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Exchange rate forecasting and the performance of currency portfolios*

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Abstract

We examine the potential gains of using exchange rate forecast models and forecast combination methods in the management of currency portfolios for three exchange rates, the euro (EUR) versus the US dollar (USD), the British pound (GBP) and the Japanese yen (JPY). We use a battery of econometric specifications to evaluate whether optimal currency portfolios implied by trading strategies based on exchange rate forecasts outperform single-currency and the equally weighted portfolio. We assess the differences in profitability of optimal currency portfolios for different types of investor preferences, different trading strategies, different composite forecasts and different forecast horizons. Our results indicate that the benefits of integrating exchange rate forecasts from state-of-the-art econometric models in currency portfolios are sensitive to the trading strategy under consideration and vary strongly across prediction horizons.

Keywords: currency portfolios, exchange rate forecasting, trading strategies, profitability
JEL classification: G02, G11, E20

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1 Introduction

Foreign exchange risk is omnipresent in international portfolio diversification, but forecasting exchange rates is well known to be a difficult task. Since the seminal work by Meese and Rogoff (1983), which shows that econometric specifications based on macroeconomic fundamentals are unable to outperform simple random walk forecasts at short time horizons (up to one year), 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 based on exchange rate predictions (see Menkhoff and Taylor, 2007, for a review). Although the random walk specification has naturally emerged as the benchmark to beat in terms of out-of-sample predictive accuracy, it is not clear that it will also yield the most profitable trading strategy. Portfolio managers are expected to be more concerned with profitability than with out-of-sample accuracy.

Our study takes the perspective of a currency portfolio manager (investor) who follows trading strategies based on exchange rate forecasts and whose main goal is to maximize (risk-adjusted) profits, under certain types of preferences. More specifically, our currency portfolio manager considers the exchange rates of the euro against the US dollar, the British pound and the Japanese yen and, for each of these three exchange rates, creates a 'single asset'. The returns of this asset are implied by a certain trading strategy that is based on exchange rate forecasts. The optimal portfolio is then made up of these three single assets according to the manager's – or some investor's – preferences.

The two primary research questions in our study are the following. First, does the optimal currency portfolio outperform some simpler benchmark portfolios and thus is there a value added in engaging in active portfolio management – or can the portfolio manager achieve the same (risk-adjusted) profit by just investing in some simpler assets (benchmark portfolios)? As simpler assets we consider the single assets of which the optimal portfolio consists as well as the equally weighted portfolio based on forecasts from the model as well as on random walk predictions. These benchmark portfolios would not require active portfolio management and thus would represent substantially simpler investment strategies. Second, how do the different optimal currency portfolios (constructed according to different types of preferences, different trading strategies, different composite forecasts and different forecast horizons) compare to each other and is there one optimal portfolio which systematically outperforms the others?

Relating to the first research question, we find some evidence indicating that simpler portfolios, like equally weighted portfolios, are not necessarily outperformed (e.g., in terms of the Sharpe ratio) by more complex portfolios (see DeMiguel et al., 2009 and Jacobs et al., 2014). The existing evidence in the literature, however, relates to equity markets (DeMiguel et al., 2009) and equity, bond and commodity markets (Jacobs et al., 2014), and it is not obvious that these findings carry over to foreign exchange markets. Our study contributes to enlarge this body of empirical evidence by concentrating on foreign exchange markets.

In order to compare the different currency portfolios, we employ a number of (risk-adjusted) performance measures, including the Omega measure, the Sharpe ratio and the Sortino ratio. In order to generate the exchange rate forecasts, we consider all the multivariate time series models and the methods of forecast combinations entertained in Costantini et al. (2014, 2016).[1] While they examine exclusively the predictability of individual exchange rates[2] in terms of out-of-sample accuracy, directional accuracy and profitability of trading strategies, we go a step further and build optimal currency portfolios, which we analyze in terms of risk-adjusted profitability. In order to generate the out-of-sample exchange rate forecasts required for the trading strategies, we also employ averaged predictions based on different loss and profit measures over a certain time span (mean-squared-error, directional value and returns) leading to different so-called composite forecasts. As far as the forecast horizon is concerned, we look at horizons of one month and three months. To obtain optimal portfolios, we consider a wide range of different types of preferences, including the mean-variance investor, the conditional value-at-risk investor, the linear investor, the linear loss aversion investor and the quadratic loss aversion investor. These preferences are also used, e.g., in Fortin and Hlouskova (2011) and Fortin and Hlouskova (2015). While these pieces of research investigate optimal asset allocation among sectoral stock indices, government bonds and commodities, we look here solely at assets based on trading strategies applied to different exchange rates.

In order to assess the performance of optimal currency portfolios versus benchmark portfolios (single assets, equally weighted portfolio), we use a data snooping bias free test, which is based on an extensive bootstrap-procedure. By employing this test we want to ensure that the performance superiority of certain optimal portfolios – if any – is systematic and not merely due to luck. The test identifies which optimal portfolios significantly beat the benchmark portfolio in terms of certain risk-adjusted performance measures.

We look at two different trading strategies in constructing the single assets. The first one is the simple 'buy low, sell high' trading strategy described, e.g., in Gençay (1998), where the trading signal is based on the spot exchange rate and its forecast. The second one is based on exploiting the forward rate unbiased expectation hypothesis and is similar to the carry trade strategy (implemented using forward contracts) used, e.g., in Burnside et al. (2008). In this case the trading signal is based on the forward exchange rate and the exchange rate forecast.

Returns implied by trading strategies have also been investigated in other exchange rate

[1]See also Crespo Cuaresma and Hlouskova (2005), Crespo Cuaresma (2007), Costantini and Pappalardo (2010) and Costantini and Kunst (2011).

[2]Costantini et al. (2014) consider the euro against the US dollar, the British pound, the Swiss franc and the Japanese yen, Costantini et al. (2016) consider the euro against the US dollar.

studies. Burnside et al. (2008), for example, examine the returns implied by the carry trade strategy, which determines to sell (buy) a currency forward when it trades at a forward premium (discount). This trading strategy is similar to our second trading strategy. The authors apply the carry trade strategy to individual currencies as well as to an equally weighted portfolio of 23 currencies and find that that constructing a portfolio improves the performance of the carry trade strategy substantially: the Sharpe ratio of the equally weighted carry trade strategy is more than 50% higher than the median Sharpe ratio across currency specific carry trade strategies. Unlike our study, Burnside et al. (2008) do not test the statistical significance of the portfolio outperformance with respect to the single currency based asset. While they use a simple, equally weighted portfolio, we take the investor's preferences into account explicitly and optimize the portfolio according to these preferences. Another fundamental difference with respect to their work is that we include exchange rate forecasts in the definition of our trading strategies with the aim of improving their performance. Burnside et al. (2008), on the other hand, use bid and ask spot and forward exchange rates. In a related paper, Burnside et al. (2011) examine carry trade and momentum strategies for single currencies and equally weighted currency portfolios, and review possible explanations for the profitability of these strategies.

There are only few existing studies which explicitly deal with optimal currency portfolios. Recently, the work by Barroso and Santa-Clara (2015) aims at maximizing the expected return of a portfolio in the forward exchange market, given preferences described by the power utility and using the parametric portfolio policies approach of Brandt et al. (2009). This approach models the asset weights as a function of their characteristics, and the relevance of these characteristics in forming portfolios is the focus of the study. The authors find that carry, momentum, and value reversal contribute to portfolio performance, whereas the real exchange rate and the current account do not. They argue that besides risk, currency returns reflect the scarcity of (speculative) capital. The study is related to ours since it deals with currency portfolio optimization according to given preferences, however, the focus – and also the assets from which portfolios are built – are very different.

Another paper dealing with currency portfolio optimization, using the mean-variance approach, is by Papaioannou et al. (2006). The authors are mainly interested in how the introduction of the euro as a new currency has changed, if at all, the optimal composition of portfolios of foreign exchange reserves and how the optimal holdings compare to actual reserve portfolios held by central banks. The expected returns in the different currencies depend on the domestic interest rates and the expected changes in foreign exchange rates. Except for the random walk forecast, no exchange rate forecasts are used in the analysis, while in our study exchange rate forecasts are one of the central ingredients of the analysis. The authors find, among other results, that the optimal shares in the US dollar match its large shares in actual foreign reserves and that the optimal euro shares are much smaller that the shares observed. The optimization results are sensitive to the reference currency, which – for the main analysis – is the US dollar.

Our analysis reveals that for a forecast horizon of one month, the mean-variance currency portfolio outperforms the single asset based on the EUR/JPY exchange rate in terms of the Omega measure, for all three composite forecasts. The equally weighted portfolio, however, is never outperformed for this forecast horizon. For a forecast horizon of three months, on the other hand, the equally weighted portfolio is always outperformed (for all composite forecasts and both trading strategies) – and most often not only in terms of the Omega measure but in terms of all four performance measures. This is also true for longer forecast horizons (six and twelve months). In general, the benchmark portfolios based on the random walk, i.e., the benchmark portfolios which do not make use of any (non-trivial) exchange rate forecasts, are more often outperformed than the benchmark portfolios based on composite forecasts.

For a given trading strategy and a given composite forecast, the best and second best performances (in terms of the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio) are mostly achieved by the mean-variance and conditional value-at-risk portfolios. This is true for both the forecast horizon of one month and the forecast horizon of three months. For forecast horizons of six and twelve months, however, also the linear and quadratic loss aversion portfolios are among the best and second best performing portfolios.

For a given type of investor and a given composite forecast, the 'buy low, sell high' strategy shows the better performance, with only few exceptions. This is true for forecast horizons of one, three, six and twelve months. Note that for a forecast horizon of three months and directional-value-based composite forecasts, the difference between the 'buy low, sell high' strategy and the carry trade based strategy is quite substantial. In general, the optimal portfolio performance and its allocation seems to be quite sensitive to the trading strategy under consideration.

For a given type of investor and a given trading strategy, the MSE-based composite forecast yields the best performance, provided the forecast horizon is one month. For a forecast horizon of three months, however, best performances are rather achieved by directional-value-based and return-based composite forecasts.

The paper is structured as follows. In Section 2 we present the analytical framework required for exchange rate forecasting and portfolio optimization. First we introduce the individual exchange rate forecast models and forecast combinations methods which we use to generate the exchange rate predictions. Then we describe the loss and profit measures employed to compute the *best* forecasts (and thus the composite forecasts). The different types of preferences and the corresponding optimization problems are presented. We conclude Section 2 by describing the data snooping bias free test for equal performance and presenting the risk-adjusted performance measures we consider. Section 3 discusses the empirical results, first for the forecast horizon of one month and then for the forecast horizon of three months.

Section 4 concludes.

2 Analytical framework: Exchange rate forecasting and optimal currency portfolios

2.1 Exchange rate specifications

We start by describing the modelling framework used to obtain ensembles of exchange rate predictions which can then be used to construct currency portfolios. The class of specifications we entertain in order to obtain forecasts of the exchange rate can be conceptualized in the context of the so-called monetary model of exchange rates originally developed in the work by, for example Frenkel (1976), Dornbusch (1976) or Hooper and Morton (1982). The monetary model of exchange rate determination has been often used as a theoretical framework to create exchange rate predictions based on macroeconomic fundamentals (see Crespo Cuaresma and Hlouskova, 2005; Costantini et al. 2016). Starting with standard Cagan money demand equations for the domestic and foreign economy, the monetary model of exchange rate formation assumes that purchasing power parity acts as a long-run equilibrium and thus leads to a relationship between the exchange rate on the one hand and the money supply levels, interest rates and income levels in the two economies on the other hand.

Such a relationship tends to be routinely specified empirically in the form of vector autoregressive (VAR) and vector error-correction (VEC) models. Defining the vector y_t, which contains the (log) exchange rate, the (log) money supply in the domestic and foreign economy, the (log) production index in the domestic and foreign economy and the respective short and long term interest rates, this implies that its dynamics are given by

$$y_t = \Phi_0 + \sum_{l=1}^{p} \Phi_l y_{t-l} + \varepsilon_t, \qquad \varepsilon_t \sim \mathbf{NID}(\mathbf{0}, \Sigma_\varepsilon), \tag{1}$$

where Φ_l for $l = 1, \ldots, p$ are matrices of coefficients and Φ_0 is a vector of constants. Alternatively, if the variables of the model are linked by one or more cointegration relationships which act as a long-run attractor of the data, the specification given by equation (1) can be written in vector error correction (VEC) form,

$$\Delta y_t = \Theta_0 + \delta\psi' y_{t-1} + \sum_{l=1}^{p-1} \Theta_l \Delta y_{t-l} + \varepsilon_t. \tag{2}$$

In this specification the cointegration relationships are given by $\psi' y_t$ and δ quantifies the speed of adjustment to the long-run equilibrium. Alternatively, if the variables in y_t are unit-root nonstationary but no cointegration relationship exists among them, a VAR model in first differences (DVAR) would be the appropriate representation, which amounts to the model given in equation (2) with $\delta = 0$.

2.2 Forecast combinations

The set of methods used to create forecast combinations from individual multivariate time series models are similar to those in Costantini et al. (2016). Let S_t^j be the spot exchange rate of euros (EUR) per foreign currency unit (FCU) of currency j, i.e., EUR/FCU, at time t, and let $\hat{S}^j_{m,t+h|t}$ be the exchange rate forecast of euros per foreign currency unit of currency j obtained using model m, $m = 1, \ldots, M$, for time $t+h$ conditional on the information available at time t (i.e., h is the forecast horizon). In the following we drop superscript j to keep the exposition simpler. The combinations of forecasts entertained in this study, $\hat{S}_{c,t+h|t}$, take the form of a linear combination of the predictions of individual specifications,

$$\hat{S}_{c,t+h|t} = w^h_{c,0t} + \sum_{m=1}^{M} w^h_{c,mt} \hat{S}_{m,t+h|t}, \tag{3}$$

where c is the combination method, M is the number of individual forecasts, and the weights are given by $\{w^h_{c,mt}\}_{m=0}^M$.

Since several combination methods require statistics based on a hold-out sample where the relative predictive ability of models is assessed, let us introduce here some notation on 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 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.

In order to pool the forecasts of individual specifications, we consider a large number of combination methods proposed in the literature. These are the same methods have been recently used in Costantini et al. (2016) to evaluate exchange rate predictability:[3]

- *Mean, trimmed mean, median.* For the mean prediction, $w^h_{\text{mean},0t} = 0$ and $w^h_{\text{mean},mt} = \frac{1}{M}$ in equation (3). The trimmed mean uses $w^h_{\text{trim},0t} = 0$ and $w^h_{\text{trim},mt} = 0$ for the individual models that generate the smallest and largest forecasts, while $w^h_{\text{trim},mt} = \frac{1}{M-2}$ for the remaining individual models. For the median combination method, $\hat{S}_{c,t+h|t} = \text{median}\{\hat{S}_{m,t+h|t}\}_{m=1}^M$ is used (see Costantini and Pappalardo, 2010).

- *Ordinary least squares (OLS) combination.* Weights of this method coincide with estimated coefficients obtained by regressing actual exchange rates on a constant and corresponding exchange rate forecasts. In our application we use a rolling window over the hold-out sample. Granger and Ramanathan (1984) provide more detail on this simple forecast pooling methodology.

[3]Costantini et al. (2016) provide a more detailed discussion of these forecast averaging methods.

- *Combination based on principal components (PC).* This method allows to overcome multicollinearity of predictions across models by reducing them to a few principal components (factors). The method is identical to the OLS combining method by replacing forecasts with their principal components. In our application, we choose the number of principal components using the variance proportion criterion, which selects the smallest number of principal components such that a certain fraction of variance is explained. We set the proportion to 80%.[4]

- *Combination based on the discount mean square forecast errors (DMSFE).* Following Stock and Watson (2004), the weights in equation (3) depend inversely on the historical forecasting performance of individual models,

$$w^h_{\text{DMSFE},m,t} = \frac{\text{WMSE}^{-1}_{mth}}{\sum_{l=1}^{M} \text{WMSE}^{-1}_{lth}}, \tag{4}$$

where

$$\text{WMSE}_{mth} = \sum_{\tilde{t}=T_1-1+h}^{t} \theta^{T-h-\tilde{t}} \left(S_{\tilde{t}+h} - \hat{S}_{m,\tilde{t}+h|\tilde{t}} \right)^2, \tag{5}$$

for $t = T_2 - h, \ldots, T_3 - h$, $m = 1, \ldots, M$, $w^h_{\text{DMSFE},0,t} = 0$ and θ is a discount factor. In the empirical application, we use $\theta = 0.95$.

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

$$w^h_{\text{HR},mt} = \frac{\sum_{\tilde{t}=T_1+h-1}^{t} DA_{m,\tilde{t}h}}{\sum_{l=1}^{M} \left(\sum_{j=T_1+h-1}^{t} DA_{l,\tilde{t}h} \right)} \tag{6}$$

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

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

$$w^h_{\text{EHR},mt} = \frac{\exp\left(\sum_{\tilde{t}=T_1+h-1}^{t} (DA_{m,\tilde{t}h} - 1) \right)}{\sum_{l=1}^{M} \exp\left(\sum_{\tilde{t}=T_1+h-1}^{t} (DA_{l,\tilde{t}h} - 1) \right)} \tag{7}$$

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

[4] More details on the method are provided in Hlouskova and Wagner (2013), where the principal components augmented regressions are used in the context of the empirical analysis of economic growth differentials across countries. Except for Costantini et al. (2016), we are not aware of the existence of any study using this approach in the context of the exchange rate forecasts.

- *Combination based on the economic evaluation of directional forecasts (EEDF).* The weights in this method capture the ability of models to predict the direction of change of the exchange rate while also taking into account the magnitude of the realized change,

$$w^h_{\text{EEDF},mt} = \frac{\sum_{\tilde{t}=T_1+h-1}^{t} DV_{m,\tilde{t}h}}{\sum_{l=1}^{M}\left(\sum_{\tilde{t}=T_1+h-1}^{t} DV_{l,\tilde{t}h}\right)} \tag{8}$$

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

- *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), and Feldkircher (2012).

$$w^h_{\text{BMA},mt} = P(\mathbb{M}_m | \mathbf{S}_{T_1+h-1:t}) = \frac{P(\mathbf{S}_{T_1+h-1:t}|\mathbb{M}_m)P(\mathbb{M}_m)}{\sum_{l=1}^{M} P(\mathbf{S}_{T_1+h-1:t}|\mathbb{M}_l)P(\mathbb{M}_l)}, \tag{9}$$

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

$$w^h_{\text{BMA},mt} = \frac{(t - T_1 - h + 2)^{\frac{p_1 - p_m}{2}} \left(\frac{\sum_{\tilde{t}=T_1+h-1}^{t} MSE_{1,\tilde{t}h}}{\sum_{\tilde{t}=T_1+h-1}^{t} MSE_{m,\tilde{t}h}}\right)^{\frac{t-T_1-h+2}{2}}}{\sum_{l=1}^{M} (t - T_1 - h + 2)^{\frac{p_1 - p_l}{2}} \left(\frac{\sum_{\tilde{t}=T_1+h-1}^{t} MSE_{1,\tilde{t}h}}{\sum_{\tilde{t}=T_1+h-1}^{t} MSE_{l,\tilde{t}h}}\right)^{\frac{t-T_1-h+2}{2}}} \tag{10}$$

  where $MSE_{m,\tilde{t}h}$ is the mean squared error of model m, namely $MSE_{m,\tilde{t}h} = \left(\hat{S}_{m,\tilde{t}|\tilde{t}-h} - S_{\tilde{t}}\right)^2$.

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

$$w^h_{\text{FMA},mt} = \frac{\exp\left(-\frac{1}{2} IC_{mt}\right)}{\sum_{l=1}^{M} \exp\left(-\frac{1}{2} IC_{lt}\right)} \tag{11}$$

  where IC_{mt} stands for an information criterion of model m 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.[5]

[5] See Raftery et al. (1997) and Sala-i-Martin et al. (2004).

2.3 Predictive accuracy: Loss and profit measures

Exchange rate forecasts are evaluated in our application using an ensemble of performance measures based on both predictive loss minimization and profit maximization in the context of trading rules.

2.3.1 Predictive loss measures

The loss measures include the standard squared error

$$SE_{m,t,h} = \left(\hat{S}_{m,t|t-h} - S_t\right)^2$$

and the absolute error

$$AE_{m,t,h} = \left|\hat{S}_{m,t|t-h} - S_t\right|$$

obtained considering rolling-window estimation, 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 and forecast combination method are thus calculated over the out-of-sample period for a given forecast horizon and aggregated as follows:[6]

- Mean square error for horizon h
  $MSE_{mh} = \frac{1}{T_3-T_2+1}\sum_{j=0}^{T_3-T_2} SE_{m,T_2+j,h}$
- Mean absolute error for horizon h
  $MAE_{mh} = \frac{1}{T_3-T_2+1}\sum_{j=0}^{T_3-T_2} AE_{m,T_2+j,h}$

In addition, we also entertain composite forecasts based on the relative performance of predictions from all models and combination methods over certain out-of-sample periods. In particular, for this technique at each time point t we choose the model or forecast combination method (and thus also the forecast for time point $t + h$) with the best performance (i.e. minimum MSE and/or MAE) over a time window ending at time point t,

$$\hat{S}^{MSE,l}_{t+h|t} = \hat{S}_{m^{MSE}_{lth},t+h|t} \qquad \text{where} \qquad m^{MSE}_{lth} = \text{argmin}_m \sum_{j=l}^{t} SE_{m,j,h}. \tag{12}$$

Time point l, such that $T_2 \leq l \leq t$, defines the beginning of the window over which the performance is evaluated. The evaluation window is $[l, t]$ where $l \leq t \leq T_3$. In a similar way

$$\hat{S}^{MAE,l}_{t+h|t} = \hat{S}_{m^{MAE}_{lth},t+h|t} \qquad \text{where} \qquad m^{MAE}_{lth} = \text{argmin}_m \sum_{j=l}^{t} AE_{m,j,h}. \tag{13}$$

[6] The term model and thus also its abbreviation m is used in a broader sense that includes forecasting rules and methods (like forecast combinations and composite forecasts).

2.3.2 Profit measures

The profit measures include the directional accuracy measure (DA), the directional value measure (DV) and returns from two different trading strategy based on our forecasts. The directional accuracy measure is given by

$$DA_{m,t,h} = I\left(\text{sgn}(S_t - S_{t-h}) = \text{sgn}(\hat{S}_{m,t|t-h} - S_{t-h})\right)$$

where $I(\cdot)$ is the indicator function which codes whether the direction of the price change was correctly forecast at horizon h. The economic value of directional forecasts can be incorporated into the measure by assigning to each correctly predicted change its magnitude (see Blaskowitz and Herwartz, 2011). The directional value statistic, defined as

$$DV_{m,t,h} = |S_t - S_{t-h}| DA_{m,t,h}$$

is used for this purpose. We aggregate these measures to create the following predictive accuracy statistics:

- Hit rate for horizon h,
  $DA_{mh} = 100 \sum_{j=0}^{T_3-T_2} \frac{DA_{m,T_2+j,h}}{T_3-T_2+1}$
- Share of exchange rate change captured by forecasts,

$$DV_{mh} = 100 \frac{\sum_{j=0}^{T_3-T_2} DV_{m,T_2+j,h}}{\sum_{j=0}^{T_3-T_2} |S_{T_2+j} - S_{T_2+j-h}|} = 100 \frac{\sum_{j=0}^{T_3-T_2} |\hat{S}_{T_2+j} - S_{T_2+j-h}| DA_{m,T_2+j,h}}{\sum_{j=0}^{T_3-T_2} |S_{T_2+j} - S_{T_2+j-h}|}$$

Similarly as in the case of loss measures, we also create aggregate/composite forecasts based on forecasts from all models and forecast combination methods. At each time point t we choose the model or forecast combination method, and thus also the forecast for time point $t+h$, with the largest DA or DV over certain time window ending at time point t. That is,

$$\hat{S}^{DA,l}_{t+h|t} = \hat{S}_{m^{DA}_{lth},t+h|t} \qquad \text{where} \qquad m^{DA}_{lth} = \text{argmax}_m \sum_{j=l}^{t} DA_{m,j,h} \tag{14}$$

where l, $T_2 \leq l \leq t$, defines the beginning of the window over which is the performance evaluated; i.e., the evaluation window is $[l, t]$ where $l \leq t \leq T_3$. In a similar way

$$\hat{S}^{DV,l}_{t+h|t} = \hat{S}_{m^{DV}_{lth},t+h|t} \qquad \text{where} \qquad m^{DV}_{lth} = \text{argmax}_m \sum_{j=l}^{t} DV_{m,j,h} \tag{15}$$

The time window over which the performance is maximized is given by $[l, t]$ with time point l defined as above.

The performance of exchange rate forecasts based on their profitability is evaluated by constructing two simple trading strategies based on the predictions: trading strategy 1 (TS1) which is based on buying the foreign currency if its price is forecast to rise and selling it when its price is forecast to fall ('buy low, sell high strategy'), and trading strategy 2 (TS2) which exploits the forward rate unbiased expectation hypothesis and is related to the so-called carry trade strategy ('carry trade based strategy').

Trading strategy 1 is a simple 'buy low, sell high' trading strategy as described in Gençay (1998), where the selling/buying signal is based on the current exchange rate. Forecast upward movements of the exchange rate with respect to the actual value (positive returns) are executed as long positions, while forecast downward movements (negative returns) are executed as short positions. For each exchange rate model and forecast combination method m and forecast horizon h is the trading strategy 1 defined by the following trading signal, $y_{th}^{jm,TS1}$, payoff, $p_{t+h}^{jm,TS1}$ (in euros), and (discrete) return, $r_{t+h,h}^{jm,TS1}$:

$$y_{th}^{jm,TS1} = \begin{cases} 1, & \text{if } \hat{S}_{t+h|t}^{jm} < S_t^j \text{ (one FCU of currency } j \text{ is sold at } t \text{ and bought at } t+h) \\ -1, & \text{if } \hat{S}_{t+h|t}^{jm} > S_t^j \text{ (one FCU of currency } j \text{ is bought at } t \text{ and sold at } t+h) \end{cases}$$

$$p_{t+h}^{jm,TS1} = \begin{cases} S_t^j - S_{t+h}^j, & \text{if } y_{th}^{jm,TS1} = 1 \\ S_{t+h}^j - S_t^j, & \text{if } y_{th}^{jm,TS1} = -1 \end{cases}$$

$$r_{t+h,h}^{jm,TS1} = \begin{cases} \frac{1}{S_t^j}\left(S_t^j - S_{t+h}^j\right) = 1 - \frac{S_{t+h}^j}{S_t^j}, & \text{if } y_{th}^{jm,TS1} = 1 \\ \frac{1}{S_t^j}\left(S_{t+h}^j - S_t^j\right) = \frac{S_{t+h}^j}{S_t^j} - 1, & \text{if } y_{th}^{jm,TS1} = -1 \end{cases}$$

Trading strategy 2 is based on exploiting the forward rate unbiased expectation hypothesis. In perfect markets, the forward exchange rate is an unbiased predictor of the corresponding future spot exchange rate. If this hypothesis does not hold, a trading strategy based on exchange rate forecasts may earn positive trading profits. This trading strategy thus depends on whether the exchange rate forecast is above or below the forward rate. The trading signal,

$y_{th}^{jm,TS2}$, payoff, $p_{t+h}^{jm,TS2}$ (in euros), and return, $r_{t+h,h}^{jm,TS2}$, are defined as follows:

$$y_{th}^{jm,TS2} = \begin{cases} 1, & \text{if } \hat{S}_{t+h|t}^{jm} < F_{t+h|t}^{j} \quad \text{(one FCU of currency } j \text{ is sold forward at } t \text{ and bought at } t+h) \\ -1, & \text{if } \hat{S}_{t+h|t}^{jm} > F_{t+h|t}^{j} \quad \text{(one FCU of currency } j \text{ is bought forward at } t \text{ and sold at } t+h) \end{cases}$$

$$p_{t+h}^{jm,TS2} = \begin{cases} F_{t+h|t}^{j} - S_{t+h}^{j}, & \text{if } y_{th}^{jm,TS2} = 1 \\ S_{t+h}^{j} - F_{t+h|t}^{j}, & \text{if } y_{th}^{jm,TS2} = -1 \end{cases}$$

$$r_{t+h,h}^{jm,TS2} = \begin{cases} \frac{1}{F_{t+h|t}^{j}} \left(F_{t+h|t}^{j} - S_{t+h}^{j} \right) = 1 - \frac{S_{t+h}^{j}}{F_{t+h|t}^{j}}, & \text{if } y_{th}^{jm,TS2} = 1 \\ \frac{1}{F_{t+h|t}^{j}} \left(S_{t+h}^{j} - F_{t+h|t}^{j} \right) = \frac{S_{t+h}^{j}}{F_{t+h|t}^{j}} - 1, & \text{if } y_{th}^{jm,TS2} = -1 \end{cases}$$

where $F_{t+h|t}^{j}$ is the forward exchange rate (EUR/FCU) at time t with respect to currency j, maturing at time $t+h$.

These returns are aggregated in terms of total returns, which are derived for each trading strategy i, $i = 1, 2$, and each model and forecast combination method m over n periods, i.e. over interval $[t, t+n]$ and with respect to all realized $h-$period returns ($h \leq n$) as follows

$$R_{h,[t,t+n]}^{m,TS} = \frac{1}{h} \sum_{i=0}^{h-1} \Pi_{k=0}^{n_i} \left(r_{t+i+kh,h}^{jm,TS} + 1 \right) - 1 \tag{16}$$

where n_i, $i = 1, \ldots, h-1$, is the largest integer such that $t + i + n_i h \leq n$.[7]

As in the previous cases, we create an aggregate/composite forecast with the maximum averaged or realized return – based on forecasts from all models and forecast combination methods. At each time point t we choose the model or forecast combination method, and thus also the forecast for time point $t+h$, with the largest average return over time window $[l, t]$, namely

$$\hat{S}_{t+h|t}^{TS,l} = \hat{S}_{m_{lth}^{TS},t+h|t} \qquad \text{where} \qquad m_{lth}^{TS} = \text{argmax}_m \sum_{k=l}^{t} r_{kh}^{m,TS} \tag{17}$$

[7]Note that for $h = 1$ is the total return over $[t, t+n]$ given by $\Pi_{k=0}^{n} \left(r_{t+k,1}^{jm,TS} + 1 \right) - 1$. Note in addition that the total return given by equation (16) is the average of all possible $h-$period returns. We decided to do so as we wanted to take into account for all $h-$step ahead forecasts.

and the largest total realized return until time point t, namely

$$\hat{S}^{TS}_{t+h|t} = \hat{S}_{m^{TS}_{th},t+h|t} \qquad \text{where} \qquad m^{TS}_{th} = \text{argmax}_m R^{m,TS}_{h,[1,t]} \tag{18}$$

2.4 Optimal portfolios

In order to assess whether exchange rate forecasts based on macroeconomic fundamentals improve the profitability of currency portfolios, we investigate the performance of (optimal) currency portfolios of returns implied by two strategies described above, which exploit the potential predictability of exchange rate changes. The optimal portfolio consists of returns implied by a certain trading strategy applied to the three foreign exchange rates EUR/USD, EUR/GBP and EUR/JPY. We refer to these individual returns as *(single) assets* based on the EUR/USD, EUR/GBP and EUR/JPY exchange rates, respectively. In building optimal portfolios, investors behave according to particular preferences. We model the following types of preferences: mean-variance (MV), conditional value-at-risk (CVaR), linear, linear loss aversion (LLA) and quadratic loss aversion (QLA). As benchmark portfolios, relative to which the optimal portfolios are evaluated, we consider both (i) the single assets based on individual exchange rates from which the optimal portfolios are composed, as well as (ii) equally weighted (EW) portfolios.[8]

Consider an investor who dynamically (e.g., on a monthly basis) re-balances her portfolio. Let $\mathbf{r}^{m,TS}_{th} = \left(r^{1m,TS}_{th}, r^{2m,TS}_{th}, r^{3m,TS}_{th}\right)'$ where $r^{1m,TS}_{th}$ is the return at time t implied by trading strategy TS, exchange rate forecasts of the EUR/USD for horizon h and model (or forecast combination method) m or some aggregate composite forecast. Similarly, $r^{2m,TS}_{th}$ is the return-based on EUR/GBP exchange rate forecasts and $r^{3m,TS}_{th}$ is the return-based on EUR/JPY exchange rate forecasts. Let $\mathbf{x}^{m,TS}_{th} = \left(x^{1m,TS}_{th}, x^{2m,TS}_{th}, x^{3m,TS}_{th}\right)'$ where $x^{im,TS}_{th}$ denotes the proportion of wealth invested at time t in trading strategy TS, whose returns are implied by forecasts based on method m for horizon h, where exchange rates are defined in euros per one unit of foreign currency i, so that it is USD for $i = 1$, GBP for $i = 2$ and JPY for $i = 3$.

We base our predictive performance analysis on the MSE, the DV as well as returns with respect to the two trading strategies.[9] This implies that forecasting models (or forecast combination methods) are chosen such that a certain (preselected) performance measure is the best over a span of 12 months, a period that appears to be appropriate in order to capture changing market conditions.[10]

[8] A portfolio with equal weights was also investigated in Burnside et al. (2008, 2011), using the carry trade strategy (exploiting the forward rate unbiased expectation hypothesis) and the momentum strategy (stipulating to sell when it was profitable to sell before).

[9] An extensive analysis with similar returns (implied by trading strategies) has shown that the portfolio performance derived from the MAE based composite forecasts is similar to that derived from the MSE-based composite forecasts, and the portfolio performance derived from the DA based composite forecasts is similar to that derived from the DV-based composite forecasts. Thus, we concentrate on MSE-based, DV-based and return-based composite forecasts.

[10] In a related analysis using similar returns, we also examined longer and shorter time periods to determine

In our application the returns are available from January 2005 until January 2016 at a monthly frequency and the optimization exercises are performed for a three years rolling window, i.e., we optimize over 36 observations. The evaluation period is therefore January 2008 to January 2016 (97 observations). The portfolio optimization exercises are carried out under the following preference schemes:

Mean-variance (MV) preferences. We consider investors that minimize the variance of their portfolio,

$$\min_{\mathbf{x}_{th}^{m,TS}} \left\{ \left(\mathbf{x}_{th}^{m,TS}\right)' \hat{\mathbf{\Sigma}}_{t+h|t}^{m,TS} \mathbf{x}_{th}^{m,TS} \,|\, \mathbf{0} \leq \mathbf{x}_{th}^{m,TS} \leq \mathbf{1}, \mathbf{1}'\mathbf{x}_{th}^{m,TS} = 1 \right\} \tag{19}$$

where $\mathbf{0}= (0,0,0)'$, $\mathbf{1}= (1,1,1)'$ and $\hat{\mathbf{\Sigma}}_{t+h|t}^{m,TS}$ is the estimate of the $(3\times 3)-$dimensional conditional covariance matrix of returns implied by the trading strategy TS and model (or forecast combination method or composite forecasts) m.[11]

Conditional value-at-risk (CVaR) preferences. We consider an investor that maximizes the conditional expectation of the left tail of portfolio return distribution such that portfolio returns do not exceed the β's quantile of of portfolio return, i.e.

$$\max_{\left(\mathbf{x}_{th}^{m,TS},\alpha_\beta\right)} \left\{ \mathbb{E}\left(\left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{th}^{m,TS} \right) \,\Big|\, \left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{th}^{m,TS} \leq \alpha_\beta,\ \mathbf{0} \leq \mathbf{x}_{th}^{m,TS} \leq \mathbf{1},\ \mathbf{1}'\mathbf{x}_{th}^{m,TS} = 1 \right\} \tag{20}$$

where $\beta \in (0,1)$ and α_β is the $\beta-$quantile of the portfolio return. Problem (20) is equivalent to[12]

$$\max_{\left(\mathbf{x}_{th}^{m,TS},\alpha_\beta\right)} \left\{ \alpha_\beta - \frac{1}{t\beta}\sum_{l=1}^{t}\left[\alpha_\beta - \left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{lh}^{m,TS}\right]^+ \,\Big|\, \mathbf{0} \leq \mathbf{x}_{th}^{m,TS} \leq \mathbf{1},\ \mathbf{1}'\mathbf{x}_{th}^{m,TS} = 1 \right\} \tag{21}$$

where $[t]^+$ denotes the maximum of 0 and t. In our application we take $\beta = 0.05$.

Linear preferences. Investors with linear utility functions maximize the expected return of their portfolio,

$$\max_{\mathbf{x}_{th}^{m,TS}} \left\{ \mathbb{E}\left(\left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{th}^{m,TS} \right) \,\Big|\, \mathbf{0} \leq \mathbf{x}_{th}^{m,TS} \leq \mathbf{1},\ \mathbf{1}'\mathbf{x}_{th}^{m,TS} = 1 \right\} \tag{22}$$

We denote this investor a 'linear' investor.

Linear loss aversion (LLA) preferences. Loss aversion, which is a central finding of prospect theory (see Kahneman and Tversky, 1979) describes the fact that people are more sensitive to losses than to gains, relative to a given reference point $\hat{y}_t$. The simplest form

the composite forecast. First we looked at the performance results based on using the total period up to time t, which were usually worse than for $j = 12$. Then we experimented with a period of six months, which in most cases resulted in similar or lower performance measures.

[11] For a seminal presentation of the mean-variance model, see Markowitz (1952).

[12] See Rockafellar and Uryasev (2000) for more details.

of such loss aversion is linear loss aversion, where the marginal utility of gains and losses is fixed.[13] Linear loss aversion preferences can be modelled as

$$\max_{\mathbf{x}_{th}^{m,TS}} \left\{ \mathbb{E}\left(\left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{th}^{m,TS} - \lambda \left[\hat{y}_t - \left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{th}^{m,TS} \right]^+ \right) \Big| \mathbf{0} \leq \mathbf{x}_{th}^{m,TS} \leq \mathbf{1},\ \mathbf{1}'\mathbf{x}_{th}^{m,TS} = 1 \right\} \tag{23}$$

where $\lambda > 0$ is the loss aversion (or penalty) parameter. Under the given utility, investors face a trade-off between return on the one hand and shortfall below the reference point on the other hand. Interpreted differently, the utility function contains an asymmetric or downside risk measure, where losses are weighted differently from gains.In our application we take the zero return as the reference point, i.e., $\hat{y}_t = 0$, and $\lambda = 1.25, 5$.

Quadratic loss aversion (QLA) preferences. Under quadratic loss aversion preferences, large losses are punished more severely than under linear loss aversion preferences.[14] The quadratic loss aversion preferences can be modelled as

$$\max_{\mathbf{x}_{th}^{m,TS}} \left\{ \mathbb{E}\left(\left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{th}^{m,TS} - \lambda \left(\left[\hat{y}_t - \left(\mathbf{x}_{th}^{m,TS}\right)' \mathbf{r}_{th}^{m,TS} \right]^+ \right)^2 \right) \Big| \mathbf{0} \leq \mathbf{x}_{th}^{m,TS} \leq \mathbf{1},\ \mathbf{1}'\mathbf{x}_{th}^{m,TS} = 1 \right\} \tag{24}$$

where notation is the same as in the LLA preferences, i.e. in our application we take again the zero return as the reference point, i.e., $\hat{y}_t = 0$ and $\lambda = 1.25, 5$. The problems given by equations (23) and (24) are equivalent to higher dimensional linear programming problems (see Fortin and Hlouskova, 2015).

Figure 1 plots the utility functions of a linear and a quadratic loss averse investor for $\hat{y} = 0$ and $\lambda = 1.25$.

2.5 Performance measures and data snooping bias free test for equal performance

In order to assess whether the performance superiority of certain (optimal) portfolios is systematic and not due to luck, we perform the bootstrap stepwise multiple superior predictive ability test (stepM-SPA) by Hsu et al. (2010) for the comparison of optimal portfolio performance with respect to the benchmark models. The test is based on the bootstrap method of Politis and Romano (1994), the stepwise test of multiple check by Romano and Wolf (2005) and the test for superior predictive ability of Hansen (2005).[15]

The following relative performance measures, $d_{opt,th}^{m,TS}$, opt =MV, CVaR, linear, LLA and QLA with $\lambda = 1.25, 5$, t = January 2008 to January 2016, $h = 1, 3, 6, 12$, are computed and

[13] The optimal asset allocation decision under linear loss aversion has been extensively studied, see, for example, Gomes (2005), He and Zhou (2011), and Fortin and Hlouskova (2011).

[14] The penalty on losses under quadratic loss aversion is also referred to as quadratic shortfall.

[15] For more details on the test, see Hsu et al. (2010).

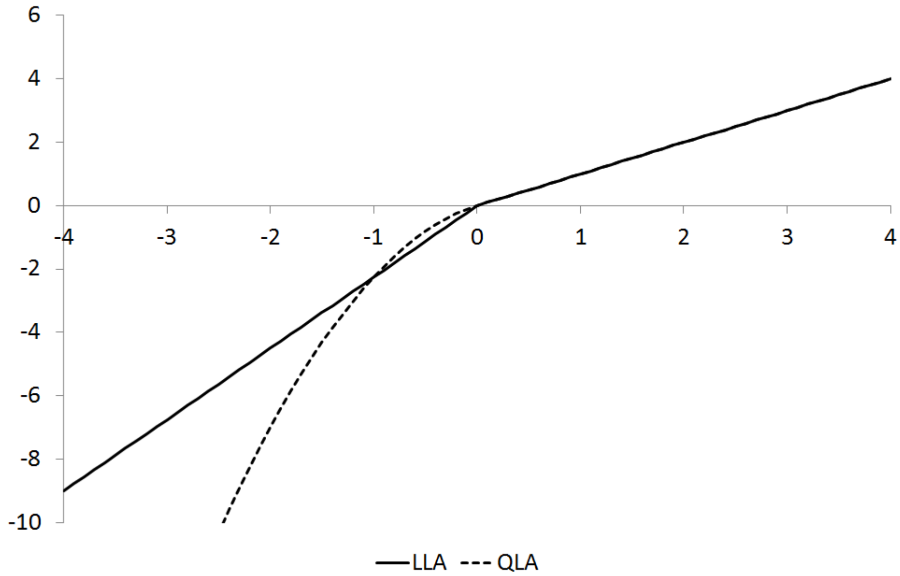

Figure 1: Linear and quadratic loss aversion.
The graph shows the utility functions of a linear (solid line) and quadratic (broken line) loss averse investor, where $\hat{y} = 0$ and $\lambda = 1.25$.

the tests are defined based on them

$$d^{m,TS}_{opt,th} = \begin{cases} r^{m,TS}_{opt,th} & - \quad r^{m,TS}_{B,th} \\ Omega^{m,TS}_{opt,th} & - \quad Omega^{m,TS}_{B,th} \\ SR^{m,TS}_{opt,th} & - \quad SR^{m,TS}_{B,th} \\ SoR^{m,TS}_{opt,th} & - \quad SoR^{m,TS}_{B,th} \end{cases} \tag{25}$$

where SR stands for Sharpe ratio and SoR stands for Sortino ratio. As benchmark portfolios, for which corresponding measures (denoted by subindex B) are calculated, we consider the *single assets* based on returns implied by a certain trading strategy which is applied to single exchange rates,[16] as well as the equally weighted portfolio (EW). The performance measures are defined as follows[17]

$$Omega_t = \frac{\max\{r_t, 0\}}{\frac{1}{n}\sum_{i=1}^{n} |\min\{r_i, 0\}|} \tag{26}$$

$$SR_t = \frac{r_t}{\sigma} \tag{27}$$

$$SoR_t = \frac{r_t}{\sigma_D} \tag{28}$$

[16]Benchmark returns will be $r^{1m,TS}_{th}$ when the returns are implied by trading strategy TS for EUR/USD, $r^{2m,TS}_{th}$ for EUR/GBP and $r^{3m,TS}_{th}$ for EUR/JPY.

[17]To simplify the notation we skip indices and superscripts.

where σ is the standard deviation of r_t calculated with respect to the sample January 2008 through January 2016 and σ_D is the downside volatility calculated as

$$\sigma_D = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\min\{r_i, 0\})^2}$$

where $i = 1$ corresponds to January 2008 and $i = n$ to January 2016.[18] The natural benchmark return in the definition of the Sharpe and Sortino ratios for our application appears to be a zero return, reflecting that the investor does not take any position in the foreign exchange market. Note finally that the Omega measure as reported in our empirical results is the upside potential of return with respect to its downside potential relative to the zero return,

$$Omega = \frac{\sum_{i=1}^{n}|\max\{r_i, 0\}|}{\sum_{i=1}^{n}|\min\{r_i, 0\}|}.$$

A larger ratio indicates that the asset provides the chance of more gains relative to losses. It is a risk-return performance measure which considers all moments of the return distribution, whereas the Sharpe ratio considers only the first two moments.[19]

The bootstrap stepM-SPA test is a comprehensive test across all portfolio optimization models under consideration 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. The following individual testing problems are considered for the seven optimization models *opt* =MV, CVaR, linear, LLA with $\lambda = 1.25, 5$ and QLA with $\lambda = 1.25, 5$

$$H_0^{opt} : \mathbb{E}\left(d_{opt,th}^{m,TS} \leq 0\right), \quad \text{versus} \quad H_A^{opt} : \mathbb{E}\left(d_{opt,th}^{m,TS} > 0\right). \tag{29}$$

In our empirical application we use the output of the test to identify those optimal portfolios that outperform the benchmark portfolio at a certain significance level.

3 Empirical results

3.1 Data, estimation and predictions

We base our empirical analysis on monthly data spanning the period from January 1980 until January 2016 for the EUR/USD, EUR/GBP and EUR/JPY exchange rates. The beginning of the sample is thus T_0 = January 1980, the beginning of the hold-out forecasting sample

[18] In our empirical results we present also the performance measure labeled as 'downside volatility ratio' that gives the proportion of downside volatility to the downside and upside volatility σ_U, where namely $\sigma_U = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\max\{r_i, 0\})^2}$ and thus the ratio is calculated as $\frac{\sigma_D}{\sigma_D+\sigma_U}$.

[19] The formal definition of the Omega measure is $\frac{\int_t^{\infty}(1-F(x))dx}{\int_{-\infty}^{t}F(x)dx} = \frac{\mathbb{E}(X-t|X>t)P(X>t)}{\mathbb{E}(t-X|X\leq t)P(X\leq t)}$, where $F(\cdot)$ is the cumulative distribution function of returns and t is the target return, which in our case is zero.

for individual models used in order to obtain weights based on predictive accuracy is given by T_1 = January 2000. The beginning of the actual out-of-sample forecasting sample is T_2 = January 2005, and the end of the data sample is T_3 = January 2016. All data are obtained from Thomson Reuters Datastream.[20]

As in Costantini et al. (2016), we entertain several types of vector autoregressive (VAR) and vector error correction (VEC) models as specifications for exchange rate forecasting. On the one hand, we differentiate between restricted and unrestricted models depending on whether the foreign and domestic covariates are included as individual variables in the model or as a single covariate measuring the domestic-foreign difference. We refer to models containing the latter as *restricted* models (r-VAR, r-DVAR, r-VEC), while the models based on separated domestic and foreign variables are labeled *unrestricted* models (VAR, DVAR, VEC). We also consider subset-VAR models, where statistically insignificant lags of the variables are omitted, and label them s-VAR, s-DVAR, rs-VAR and rs-DVAR. In addition, we use forecast combination methods aggregating the forecasts of the individual models. A list of all individual forecast models as well as a list of all forecast combination methods are provided in the Appendix.

In terms of estimation method, we consider multivariate models estimated using standard frequentist methods and Bayesian VARs. Bayesian VARs are estimated using the standard Minnesota prior (see Doan et al., 1984, and Litterman, 1986). The lag length of all multivariate model specifications under consideration is selected using the AIC criterion for potential lag lengths ranging from 1 to 12 lags. For the VEC models, selection of the lag length and the number of cointegration relationships is carried out simultaneously using the AIC criterion.

Given the large set of statistics computed for the analysis, we start by describing how the results are depicted in the tables. We first report results on the performance of optimal currency portfolios constructed by different types of investors, namely MV, CVaR, linear, linear loss averse ($LLA_{\lambda=1.25}$, $LLA_{\lambda=5}$) and quadratic loss averse ($QLA_{\lambda=1.25}$, $QLA_{\lambda=5}$) investors (the first seven data columns in the tables of results). The optimal portfolios consist of three single assets, the returns of which are implied by a certain trading strategy (from the two trading strategies described above) based on a certain composite exchange rate forecast of the EUR against the USD, GBP and JPY. In addition, we present results on how these optimal portfolios compare to benchmark portfolios, which are based on the three single assets that compose the portfolio as well as on the equally weighted portfolio (the following four data columns in the tables of results). We also consider as benchmark portfolios the three single assets, the returns of which are implied by a certain trading strategy but based on the simple random walk (RW) model to forecast the same exchange rates, as well as the equally weighted portfolio of these three assets (the last four data columns).

The tables are structured in four vertical blocks. The first block presents the performance

[20]Details on the sources for all variables used are given in the Appendix.

measures – mean return, the Omega measure, the Sharpe ratio and the Sortino ratio – for which the bootstrap based stepM-SPA test of Hsu et al. (2010) was performed. The second block shows additional performance measures, namely, median, volatility, downside volatility, downside volatility ratio, CVaR, skewness, and kurtosis. The third block presents the realized returns over the last five, three and one year(s), and the last block gives the mean portfolio allocations.

The sub-indices in the first block of the benchmark portfolios show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio) that specific benchmark portfolio. If no sub-index is present, no null hypothesis is rejected, i.e., the benchmark portfolio is not outperformed by any of the particular optimal portfolios used. If there is only one sub-index, its value indicates the number of optimal portfolios that outperform the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios that outperform the benchmark portfolio at the 5% significance level and the second one at the 10% significance level. In general, statements relating to the bootstrap test will be made using the 10% significance level.

The results are reported for forecast horizons of one and three months, for both trading strategies, and for composite exchange rate forecasts based on the mean-squared error, the directional value and the return. This yields a total of 12 tables. Tables 1–4 report the results for the MSE-based composite forecasts, on which we will concentrate our discussion. The corresponding results for DV-based composite forecasts (Tables 7–10) and return-based composite forecasts (Tables 11–14) can be found in the Appendix.

We proceed to describe the results at different forecast horizons in detail for the forecast horizons of one and three months. Additional results for forecast horizons of six and twelve months are not be discussed in detail but we point out the main differences with respect to shorter forecast horizons. The corresponding tables are presented in the appendix (Tables 15–26). When describing issues related to performance, we usually mean the four performance measures: mean return, Omega measure, Sharpe ratio and Sortino ratio. If we only mean one particular performance measure we explicitly state this.[21]

3.2 A snapshot example: From composite forecasts to single asset returns to the optimal portfolio

To get a better picture of the process leading up to the optimal portfolio choice, we start by presenting an example of the models and forecast combination methods that are chosen

[21]For a better reading flow, we sometimes simply state USD when we mean the single asset based on the EUR/USD exchange rate for a given trading strategy and given composite forecasts (analogously for GBP and JPY). Similarly, we sometimes use MSE to denote the MSE-based composite forecast (analogously for DV and return). To simplify the notation, we sometimes skip the word portfolio and just refer to MV instead of MV portfolio (analogously for CVaR, linear, LLA and QLA).

as the 'best' based on the minimum MSE over the last 12 months (and the forecasts of which are then aggregated into the composite forecasts). We then show the returns implied by these MSE-based forecasts and trading strategy 1, both for the single assets, the optimal portfolio and the equally weighted portfolio, and finally look at the resulting optimal portfolio weights. We consider a forecast horizon of one month and the mean-variance (and conditional value-at-risk) investor.

The left part of Figure 2 present how the models with the smallest MSE over the last twelve months change over the period January 2008 to January 2016, while the right part presents aggregated information on the number of times (in percent) a given forecast model is chosen over time. From top to bottom we present the EUR/USD, the EUR/GBP and the EUR/JPY exchange rates. Each currency selects 14 forecast models/forecast combinations from the total list of 25, but not all these 14 models coincide across currencies. Even though it is visible how models change, sometimes very quickly (although most of the time best models remain the best for a while), some appear to be chosen quite frequently. The principal components (PC) method, for example, is the model most often selected as the best one for the USD (27%) and for the GBP (25%). On the other hand, it does not appear a single time as the best model for the JPY. This observation, however, is not true with a forecast horizon of three months, where PC is the third best forecasting model (for the JPY) and picked up approximately 10% of the time. The random walk is chosen as the best forecast model only 2% of the time for the USD, 11% of the time for the GBP and 15% of the time for the JPY.

If one is interested in how often single models are chosen as opposed to forecast combination methods, rather surprisingly, the single models appear particularly powerful in forecasting most of the time. For the USD, single models are chosen in 62% of the time and for the JPY even in 95% of the time. For the GBP, on the other hand, single models are only selected in 38% of the time.[22]

[22]The results for the USD and the JPY (approximately) carry over to a forecast horizon of three months, while the results for the GBP are reversed. For the longer forecast horizon individual models beat the forecast combination methods in all three currencies.

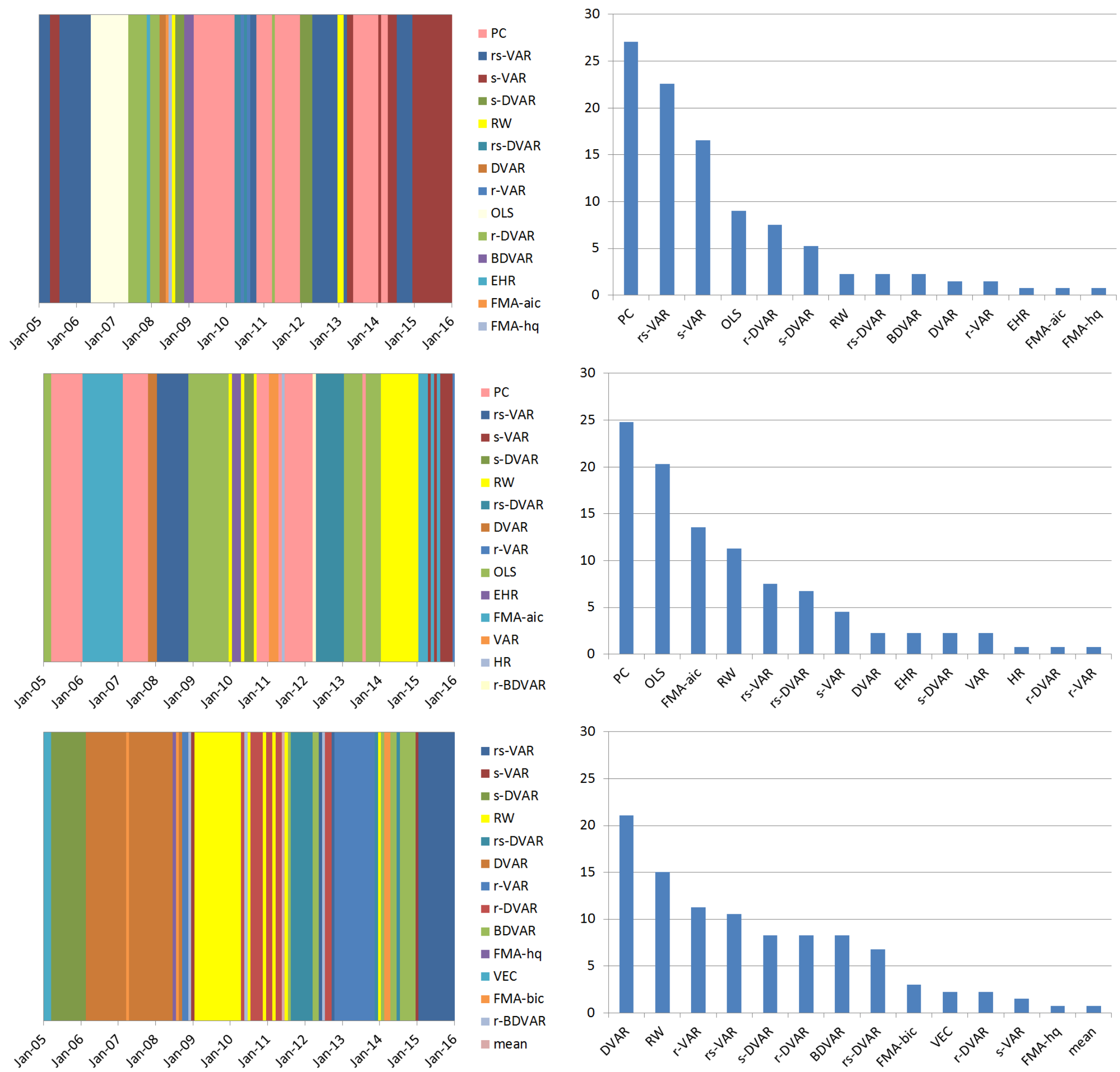

Figure 2: MSE-based best forecast models for one-month ahead forecasts.
The figure shows the best forecast models, i.e., the models generating the composite forecasts, (left) and the distribution of the best models, i.e., the number of times different forecast models are selected over the total period, in percent (right). From top to bottom the figure presents the EUR/USD, the EUR/GBP and the EUR/JPY.

Figure 3 plots the indices corresponding to the cumulated returns of the optimal MV portfolio together with those of the three single assets that make up the portfolio and the equally weighted portfolio for MSE-based composite forecasts, trading strategy 1 and a forecast horizon of one month. The starting values of the indices are set to 100.[23] The graph suggests that, as compared to single assets and the EW portfolio, the optimal MV portfolio achieves the highest total return over the evaluation period, which ranges from January 2008 to January 2016. Among the three single assets, the one based on the EUR/USD exchange rate shows the lowest total return while the ones based on the EUR/JPY and EUR/GBP exchange rates show substantially higher total returns. The volatility of the asset based on the EUR/JPY exchange rate is quite high, while that based on the EUR/GBP exchange rate appears clearly lower. Descriptive statistics relating to these returns are shown in Table 1. The mean return of the MV optimal portfolio is 4.17%, which is very similar to the mean return of the asset based on the EUR/JPY exchange rate (4.19%).[24] The mean return of the asset based on the EUR/USD exchange rate, on the other hand, is considerably lower, amounting to a rate of 1.60%. The visual impression that the optimal portfolio beats (at least some of) the single assets is confirmed by the result of the bootstrap test, which concludes that the MV optimal portfolio outperforms both the USD and the GBP at the 10% significance level in terms of the Omega measure.

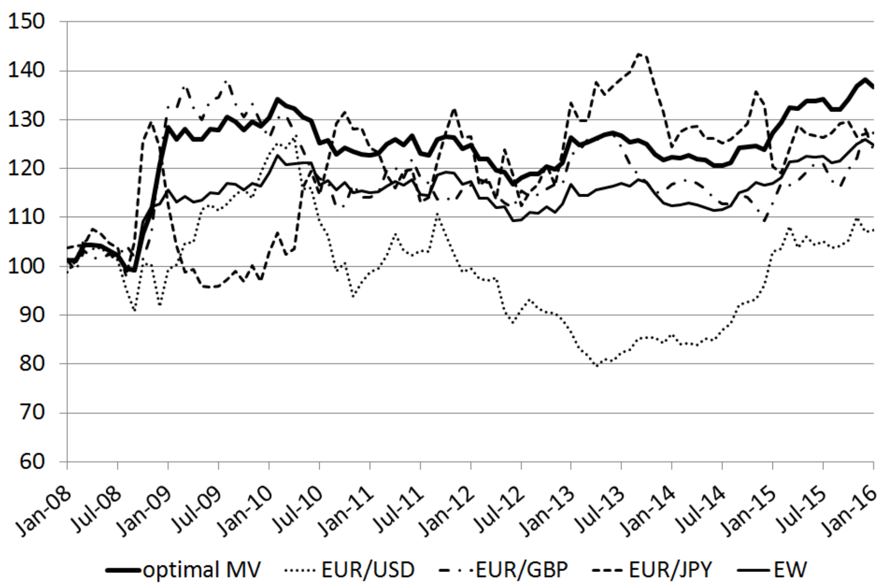

Figure 3: Optimal MV portfolio, single assets and EW portfolio based on TS1

Figure 4 depicts the optimal weights of the single assets based on the three exchange

[23]The full performance results of these returns are presented in Table 1.

[24]Note that the tables report mean returns, i.e., arithmetic averages. The geometric average of the MV portfolio over the total evaluation period would also be higher than that of the JPY.

rates for the mean-variance (MV) and the conditional value-at-risk (CVaR) investors. We again consider MSE-based composite forecasts, trading strategy 1 and a one-month forecast horizon. On average the optimal weights are 28.3%, 48.4% and 23.3% for the USD, the GBP and the JPY in the MV portfolio. The CVaR portfolio puts slightly more weight to the GBP (56.2%) on average, thereby reducing the optimal weights in the USD (22.8%) and the JPY (21.1%). The two graphs show how the optimal weights evolve over time. We can see that the MV optimal weights change more smoothly over time than the CVaR optimal weights, which remain rather constant over relatively long periods of time.

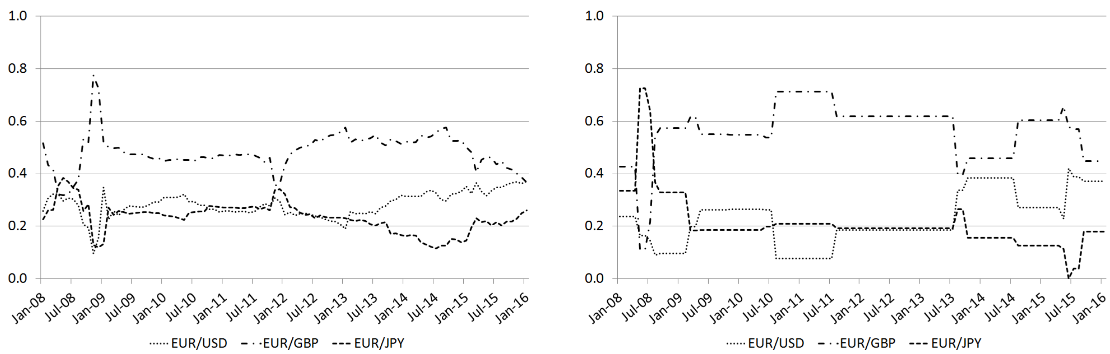

Figure 4: Optimal portfolio weights, MSE-based composite forecasts, TS1, one-month ahead. The figure shows the weights of the three single assets in the mean-variance optimal portfolio (left) and in the conditional value-at-risk optimal portfolio (right), for trading strategy 1, MSE-based composite forecasts and a forecast horizon of one month.

3.3 Results for the forecast horizon of one month

Single assets and portfolio composition

For the MSE-based composite forecasts, the best performing single asset is the one given by the EUR/GBP exchange rate for TS1. This is true in terms of the Omega measure, the Sharpe ratio and the Sortino ratio.[25] For TS2, the asset based on the EUR/USD exchange rate performs the best. The worst performing single asset is the USD for TS1 and the JPY for TS2. Considering the DV-based composite forecast, the best performing single asset is the USD for both strategies, while the worst performing single asset is the JPY for both strategies. Considering the return-based composite forecast, the best performing single asset is the USD for TS1 and the JPY for TS2. The worst performance is shown by the GBP for TS1, for all performance measures except the mean return, and by the JPY for the mean return. For TS2, the USD yields the worst performance.

The results clearly show that single assets may show a substantially different performance

[25] For the mean return, the single asset based on the EUR/JPY exchange rate shows the best performance.

depending on the trading strategy and the composite forecasts they are based on. Consider, for example, the single asset based on the EUR/USD exchange rate for the return-based composite forecasts. Applying TS1 yields a mean return of 4.32% and an Omega of 1.32 (best performance among the three single assets) while applying TS2 yields a mean of -0.84% and an Omega of 0.95 (worst performance among the three single assets).[26] This property of the USD (i.e., its different performance under TS1 and TS2) is also reflected in the composition of the corresponding optimal portfolios: its weight in the optimal portfolios is rather high under TS1 (roughly between 30% and 50%) while it is much smaller under TS2 (approximately 10% to 30%).

Note that the USD based on the random walk outperforms the USD based on the composite forecast under TS2 for MSE-based and return-based composite forecasts (in terms of the mean return, the Omega measure, the Sharpe and the Sortino ratios), where in the case of the return-based forecasts the difference in profitability is substantial. Also the JPY based on the random walk outperforms its counterpart based on the composite forecasts (TS1, return- and DV-based forecasts, for all four performance measures), while in case of the GBP we observe a rather equal performance (TS1, return-based composite forecasts).

Bootstrap analysis

Benchmark portfolios based on composite forecasts: Considering trading strategy 1, the MV portfolio outperforms the single asset based on the EUR/GBP exchange rate in terms of the Omega measure, for any given composite forecasts. If we consider MSE-based and DV-based forecasts, also the CVaR portfolio outperforms the GBP (in terms of Omega). In addition, the USD (MSE-based composite forecasts) and the JPY (DV-based composite forecasts) are outperformed by the MV portfolio (in terms of the Omega measure). Looking at trading strategy 2, on the other hand, none of the single benchmark portfolios (single assets or equally weighted portfolio) is outperformed by any optimal portfolio, for MSE-based and return-based composite forecasts. Only for DV-based composite forecasts (and TS2) the GBP is outperformed by the MV portfolio (again in terms of Omega). While optimal portfolios based on TS1 do beat single assets, optimal portfolios based on TS2 practically never beat a single asset, with the only exception being the GBP for DV-based composite forecasts.

The equally weighted portfolio is never outperformed by any optimal portfolio, for any composite forecast and any trading strategy. This will be fundamentally different for a forecast horizon of three, six and twelve months, where the equally weighted portfolio is always outperformed by some optimal portfolio, and nearly always in terms of all four performance measures.

Benchmark portfolios based on the random walk: Regarding the benchmark portfolios

[26] Note that the opposite is true for single assets based on the EUR/USD exchange rate implied by the RW forecasts: in this case the performance of the USD is clearly better under TS2 than under TS1.

based on the random walk, we observe more rejections by optimal portfolios than in the case of benchmark portfolios based on composite forecasts, except for the return-based composite forecasts. In general there are more rejections for TS1 than for TS2. For MSE-based composite forecasts and trading strategy 1, all RW-based benchmark portfolios are outperformed in terms of the Omega measure by the MV and CVaR portfolios.

Note that for MSE-based composite forecasts and TS1, all benchmark portfolios based on the random walk show worse performance than the corresponding benchmark portfolios based on composite forecasts (in terms of the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio). This is also true for TS2 with the exception of the USD, where the USD based on the RW in fact shows a better performance than the USD based on composite forecasts (in terms of all four performance measures).

Optimal portfolios across investors, trading strategies and composite forecasts

Comparison across investors: For a given trading strategy and a given composite forecast, the best performance (in terms of the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio) is always achieved by the MV portfolio. There is only a single instance when this is not true, namely for return-based composite forecasts and trading strategy 2. In this case the CVaR optimal portfolio yields the best performance. The second best optimal portfolio is CVaR or $\text{LLA}_{\lambda=5}$ in the case of MSE-based composite forecasts, and CVaR for DV-based or return-based composite forecasts. In fact, the MV and CVaR portfolios show a quite similar performance in terms of the Omega measure, the Sharpe and Sortino ratios for return-based composite forecasts and trading strategy 2.

Comparison across trading strategies: Optimal portfolios based on trading strategy 1 perform better than those based on trading strategy 2, for any given type of investor, for MSE-based composite forecasts. However, for DV-based and return-based forecasts, the picture is not so clear. While the MV portfolio based on TS1 still performs better than the MV portfolio based on TS2, this is not always true for the other optimal portfolios. Sometimes trading strategy 2 yields better performance measures than trading strategy 1, but if this is the case then the difference between the two trading strategies is usually very small (at least for the Omega measure, the Sharpe and Sortino ratios).

Comparison across composite forecasts: For trading strategy 1 and a given type of investor, the portfolios with the best performance (in terms of the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio) are always determined by MSE-based composite forecasts. For trading strategy 2, MSE-based composite forecasts yield the highest return (in terms of all four performance measures) only for certain types of investors, namely for the MV, the CVaR and the $\text{LLA}_{\lambda=1.25}$ investors. For the other types of investors the DV-based composite forecasts lead to the best performance.

3.4 Results for the forecast horizon of three months

Single assets and portfolio composition

For any given composite forecast and for both trading strategies, the best performing asset is always the one based on the EUR/GBP exchange rate (in terms of the mean return, the Omega measure, the Sortino ratio and the Sharpe ratio). The worst performing asset is the USD for TS1 and the JPY for TS2, under MSE-based composite forecasts. For DV-based composite forecasts, the worst performing asset is for both trading strategies the JPY, while for return-based composite forecasts it is the USD (for both trading strategies). All these statements are true independently of whether we concentrate on the mean return, the Omega measure, the Sortino ratio and the Sharpe ratio. These results are slightly different from those for a forecast horizon of one month, where, for example, the GBP is only the best single asset for MSE-based composite forecasts (in most other cases it is the USD). The worst performing single assets, however, are the same for both forecast horizons, except for TS1, return-based composite forecasts (where the worst asset is the USD for a forecast horizon of three months and the GBP (Omega measure, Sharpe ratio and Sortino ratio) and JPY (mean return, Sharpe ratio) for a forecast horizon of one month).

As in the case of the one-month ahead forecast horizon, the performance of single assets seems to be quite sensitive to the trading strategy and, in particular, to the composite forecasts. The difference is not so large, however, as for the one-month forecast horizon.

In three out of six situations,[27] the USD based on the random walk shows a better performance (sometimes only slightly better) than its counterpart based on the composite forecast, in terms of the mean return and all three risk-adjusted performance measures. On the other hand, the GBP based on the RW only performs better once (and only marginally) and the JPY never. Even if these results are not based on statistical tests they probably indicate that the USD is harder to predict than other currencies.

Bootstrap analysis

Benchmark portfolios based on composite forecasts: As opposed to the one-month forecast horizon, all three single assets are now outperformed, although not necessarily at the same time. Whether they perform worse than some optimal portfolio depends on the composite forecast as well as on the trading strategy. The USD, for example, is outperformed for MSE-based composite forecasts, under TS2 for the Omega measure, for DV-based composite forecasts and under TS1 for the Omega measure, Sharpe and Sortino ratios, and for return-based composite forecasts, under both trading strategies. The GBP is never (significantly) outperformed, with a performance which appears better than that of optimal portfolios. The JPY is outperformed for return-based and DV-based composite forecasts, under both trading

[27] For TS1 and TS2, return-based composite forecasts, as well as for TS2, DV-based composite forecasts.

strategies, as well as for MSE-based composite forecasts for TS2.

The equally weighted portfolio is outperformed in terms of all measures and for all composite forecasts (MSE, DV, return) for TS2. For TS1, however, it is outperformed in terms of all measures only for the DV- and return-based composite forecasts. If MSE-based composite forecasts are considered then the EW portfolio is outperformed only in terms of the Omega measure. These results indicate that investors should in fact engage in active optimal portfolio management rather than just follow the naive equally weighted portfolio approach. Note that for the one-month ahead forecast horizon the equally weighted portfolio is never outperformed, which implies that the gains from building optimal currency portfolios based on exchange rate forecasts (with respect to the naive EW portfolio) appear to be sensitive to the forecast horizon considered.

Benchmark portfolios based on the random walk: Here we observe a similar number of rejections by optimal portfolios as in case of benchmark portfolios based on composite forecasts. For all composite forecasts (MSE, DV, return) and both trading strategies, both the equally weighted portfolio and the JPY are outperformed (in terms of the Omega measure) by some optimal portfolio – in most cases by a larger number of portfolios, sometimes even by all seven portfolios.[28] For return-based composite forecasts, under both trading strategies, all four benchmark portfolios are outperformed (in terms of Omega) by some optimal portfolio.

Note that mostly the RW-based benchmark portfolios show a worse performance (in all four performance measures) than the benchmark portfolio based on composite forecasts. This is different for the USD, where the RW-based single asset quite often beats the single asset based on the composite forecast or otherwise perform only marginally worse.[29]

Optimal portfolios across investors, trading strategies and composite forecasts

Comparison across investors: For a given trading strategy and a given composite forecast the best performance is mostly achieved by CVaR and MV portfolios – a result rather similar to the one-month forecast time horizon. Other optimal portfolios being best or second-best include the linear, the $LLA_{\lambda=5}$ and the $QLA_{\lambda=5}$ portfolios.

Comparison across trading strategies: Again, as for the one-month forecast horizon, the optimal portfolios based on TS1 usually perform better than those based on TS2, for a given composite forecast and a given type of investor. Note that for the DV-based composite forecasts trading strategy 1 performs substantially better than trading strategy 2. There are only few exceptions when the TS2 based optimal portfolios show a better performance,

[28]The EW portfolio and the JPY are outperformed by all optimal portfolios for MSE-based composite forecasts under TS2, for DV-based composite forecasts under TS1, and for return-based composite forecasts under TS2.

[29]More precisely, the RW-based benchmark portfolios show a better performance (in terms of the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio) for return-based composite forecasts (TS1 and TS2) and for DV-based composite forecasts (TS2); in all other cases their performance is only marginally worse.

namely CVaR (mean return) and $QLA_{1.25}$ for the MSE-based composite forecasts, and CVaR and LLA (all four performance measures) for the return-based forecasts. In all these cases, however, TS2 performs only marginally better.

Comparison across composite forecasts: For a given type of investor and trading strategy 1, the portfolios with the best performance are based on DV-based composite forecasts, except for the linear investor, where the best performance is based on return-based forecasts. For a given type of investor and trading strategy 2, on the other hand, the best-performing portfolios are based on return-based composite forecasts. This is rather different from the one-month forecast horizon, where the portfolios with the best performance are most often determined by MSE-based composite forecasts.

3.5 Summary for the forecast horizons of six and twelve months

A crucial observation with respect to the forecast horizon in general is that the performance of the single assets, as well as of the optimal portfolios, (in terms of all four performance measures) seems to decrease with the forecast horizon. For horizons of six and twelve months the mean returns (of both benchmark and optimal portfolios) are in fact mostly negative.

For forecast horizons of six and twelve months, the equally weighted portfolio and the single asset based on the EUR/JPY exchange rate are practically always outperformed, for any given composite forecast and for both trading strategies. In most of the cases, this is true in terms of all four performance measures. In general, there seem to be more outperformances with an increasing forecast horizon. The USD, which was outperformed in some cases for forecast horizons of one and three months, however, is never outperformed for longer horizons.

Regarding the types of investors, we observe that with an increasing forecast horizon the group of investors achieving the best performance seems to be widening to include (in addition to the MV and CVaR investors) also the linear and QLA investors. While for a forecast horizon of six months the MV and CVaR portfolios are still the best or second best performing optimal portfolios in most cases,[30] the linear and QLA investors seem to be taking over for a forecast horizon of twelve months.[31]

Note that the number of cases when the performance of benchmark portfolios (single assets and equally weighted portfolio) based on the random walk exceeds the performance of benchmark portfolios based on the composite forecasts increases with the forecast horizon.[32] In particular, for a twelve-months forecast horizon, this number is considerably large. The

[30]This holds for MSE-based composite forecasts under both trading strategies, for DV-based composite forecasts under TS1, and for return-based composite forecasts under TS1 and TS2. The linear and QLA investors are among the best and second best portfolios for DV-based composite forecasts (TS1 and TS2) and for return-based composite forecasts (TS1 and TS2).

[31]They are among the best or second best portfolios in nearly all cases, i.e., in all cases except for MSE-based composite forecasts under TS2. CVaR portfolios, on the other hand, are among the best or second-best portfolios only for MSE-based composite forecasts (TS1 and TS2).

[32]This is in contrast to the stylized fact that non-naive exchange rate forecasts beat the random walk, if at all, at longer time horizons.

EW portfolio based on the random walk, for example, always shows a better performance than the EW portfolio based on the composite forecast (for all composite forecasts and both trading strategies, except for the return-based composite forecasts for TS1). The same applies to the single asset based on the EUR/JPY exchange rate. Sometimes it is also true for the GBP but it never applies to the USD. For the performance of the single asset based on the EUR/USD exchange rate, applying an exchange rate forecast rather than the simple random walk seems to provide a clear value added – for a forecast horizon of twelve months. Note that this was different for forecast horizons of one and three months.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	4.17	3.54	0.54	0.92	2.70	0.16	0.73	1.60	3.12	4.19	2.97	-3.18	-1.41	1.83	-0.94_{2}
Omega	1.72	1.60	1.03	1.10	1.42	1.01	1.05	1.11_{2}	1.30_{2}	1.24	1.54	$0.81_{3,3}$	$0.89_{3,3}$	1.10_{2}	$0.90_{3,3}$
Sharpe ratio	0.18	0.17	0.01	0.03	0.12	0.00	0.02	0.04	0.09	0.08	0.14	-0.08_{2}	-0.04_{2}	0.03	-0.04_{2}
Sortino ratio	0.38	0.32	0.02	0.05	0.22	0.01	0.03	0.06	0.18	0.13	0.26	-0.10_{2}	-0.06_{2}	0.05	-0.06_{2}
Median	0.75	1.06	2.49	-0.82	0.77	1.15	-1.75	4.67	0.38	3.11	2.07	-2.33	-4.64	2.49	-1.17
Volatility	6.69	6.03	14.44	9.26	6.26	13.82	12.44	11.88	9.68	15.21	6.00	11.86	9.71	15.25	6.46
Down. vol.	3.08	3.10	9.16	5.01	3.54	8.74	7.26	8.19	5.04	9.20	3.27	9.01	6.34	9.59	4.56
Down. vol. ratio	0.34	0.37	0.45	0.39	0.41	0.45	0.42	0.49	0.38	0.43	0.39	0.54	0.46	0.45	0.50
CVaR, $\beta = 0.05$	-29.12	-29.49	-65.71	-44.74	-33.05	-64.24	-56.10	-62.05	-37.10	-65.71	-31.68	-66.58	-50.64	-63.97	-36.55
Skewness	1.63	1.07	0.98	3.06	0.85	1.12	1.71	0.02	1.69	0.85	1.68	-0.19	1.24	0.89	0.33
Kurtosis	7.56	5.57	6.88	23.01	5.19	8.01	11.15	3.89	8.92	5.99	12.06	3.84	9.66	6.10	3.73
Realized return															
Last 5 years	2.19	2.51	-1.63	0.96	1.73	-1.39	0.34	1.69	1.62	0.49	1.65	0.43	-4.93	-2.68	-2.07
Last 3 years	2.65	2.88	-2.76	0.41	1.76	-3.29	-1.31	7.48	0.20	-1.52	2.28	0.14	-3.08	-1.25	-1.16
Last year	7.43	7.05	1.76	5.68	6.90	1.48	4.08	4.29	9.46	5.69	6.72	4.29	-1.51	2.52	1.93
Mean allocation															
EUR-USD	28.31	22.78	12.37	20.15	24.42	12.88	13.88	100	0	0	33.33	100	0	0	33.33
EUR-GBP	48.35	56.16	21.65	40.76	44.64	24.05	33.66	0	100	0	33.33	0	100	0	33.33
EUR-JPY	23.34	21.06	65.98	39.09	30.95	63.08	52.46	0	0	100	33.33	0	0	100	33.33

Table 1: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=1, MSE).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a one-month forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	2.97	0.90	-4.28	-2.53	0.67	-4.52	-3.12	2.63	1.92	1.28	1.94	3.87	-2.68	-6.75_{1}	-1.94
Omega	1.38	1.10	0.78	0.78	1.08	0.76	0.80	1.19	1.16	1.07	1.26	1.28	$0.81_{1,1}$	$0.69_{1,3}$	$0.83_{1,1}$
Sharpe ratio	0.11	0.03	-0.08	-0.09	0.03	-0.09	-0.07	0.06	0.05	0.02	0.08	0.09	-0.07	-0.13_{1}	-0.07
Sortino ratio	0.16	0.03	-0.11	-0.11	0.04	-0.12	-0.09	0.09	0.07	0.04	0.12	0.15	-0.08	-0.16	-0.09
Median	2.68	0.81	-0.99	-0.34	1.74	-1.38	0.84	5.22	1.52	2.32	3.08	2.51	-0.89	-2.27	2.36
Volatility	8.01	9.35	15.15	8.64	7.56	14.68	13.15	11.89	11.86	15.17	7.17	11.86	11.85	15.04	8.58
Down. vol.	5.13	7.47	11.29	6.78	5.52	10.97	9.67	8.05	8.38	10.15	4.74	7.26	9.42	12.47	6.47
Down. vol. ratio	0.45	0.57	0.53	0.56	0.52	0.53	0.52	0.48	0.50	0.48	0.47	0.44	0.57	0.59	0.54
CVaR, $\beta = 0.05$	-50.16	-62.94	-75.64	-57.43	-52.16	-75.30	-72.24	-62.12	-62.09	-70.25	-45.64	-58.53	-70.11	-79.49	-55.36
Skewness	0.10	-2.69	0.08	-0.32	-0.48	0.11	0.28	0.01	-0.93	0.53	0.38	0.39	-1.17	-0.88	-0.02
Kurtosis	7.54	20.69	9.15	6.98	5.13	10.26	13.35	3.99	15.09	6.07	9.07	3.85	14.66	5.76	5.84
Realized return															
Last 5 years	4.09	3.28	-0.53	1.70	2.40	-0.96	-0.20	3.24	4.42	1.14	3.32	3.42	2.56	-4.38	0.73
Last 3 years	7.20	7.60	1.15	4.73	6.11	0.12	2.12	11.89	4.85	-1.50	5.24	6.82	4.46	3.13	4.99
Last year	7.75	7.74	4.17	6.18	7.97	3.62	3.83	4.89	9.80	5.71	7.04	4.89	-0.76	1.27	1.99
Mean allocation															
EUR-USD	32.55	38.06	32.99	28.82	30.47	33.22	29.73	100	0	0	33.33	100	0	0	33.33
EUR-GBP	44.30	45.54	12.37	39.32	42.51	16.97	30.27	0	100	0	33.33	0	100	0	33.33
EUR-JPY	23.15	16.40	54.64	31.86	27.01	49.81	40.00	0	0	100	33.33	0	0	100	33.33

Table 2: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=1, MSE).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a one-month forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	1.31	1.43	-0.82	0.58	1.23	-0.24	0.85	-0.49	2.07	-0.41	0.38	-0.64	-0.66	-3.13	-1.48
Omega	1.33	1.29	0.92	1.09	1.25	0.98	1.11	0.94	1.39	0.97	1.09_{1}	0.93	$0.90_{2,3}$	0.76_{4}	$0.74_{4,6}$
Sharpe ratio	0.09	0.08	-0.03	0.02	0.07	-0.01	0.03	-0.02	0.12	-0.01	0.03	-0.03	-0.04	-0.10	-0.10
Sortino ratio	0.14	0.12	-0.03	0.03	0.10	-0.01	0.04	-0.03	0.21	-0.02	0.04	-0.04	-0.06	-0.12	-0.12
Median	0.69	0.02	-0.08	0.70	0.53	-0.08	0.12	-0.61	0.58	1.32	0.25	0.86	-2.96	1.81	-0.69
Volatility	7.19	8.89	14.92	11.57	9.02	14.50	12.71	11.61	8.49	16.18	6.88	11.61	8.54	16.11	7.36
Down. vol.	4.80	5.97	12.01	8.98	6.32	11.57	9.65	8.65	4.78	12.72	5.22	8.94	5.40	13.58	6.33
Down. vol. ratio	0.47	0.48	0.58	0.55	0.50	0.57	0.54	0.53	0.40	0.56	0.54	0.55	0.45	0.61	0.63
CVaR, $\beta = 0.05$	-31.24	-35.76	-66.41	-52.71	-41.35	-65.38	-55.61	-46.22	-24.90	-66.84	-32.43	-49.29	-27.31	-69.26	-40.71
Skewness	-0.33	-0.53	-1.66	-2.05	-0.82	-1.68	-1.59	-0.47	0.95	-1.29	-1.53	-0.71	1.12	-1.40	-2.04
Kurtosis	13.04	12.45	9.97	17.18	11.23	10.22	12.33	4.92	5.48	7.66	13.73	4.88	6.04	7.26	11.54
Realized return															
Last 5 years	2.05	2.35	-1.05	1.24	1.94	0.17	0.56	1.52	2.92	-3.14	0.76	1.80	-2.57	-2.91	-0.90
Last 3 years	2.10	3.28	-2.03	1.97	2.21	-1.37	0.11	2.75	4.24	-7.15	0.12	2.09	-0.77	-3.44	-0.45
Last year	9.48	11.16	12.93	11.75	11.76	12.93	12.74	11.10	12.93	-5.50	6.27	11.10	5.57	-6.37	3.63
Mean allocation															
EUR-USD	27.03	8.93	3.09	14.16	20.15	3.24	5.34	100	0	0	33.33	100	0	0	33.33
EUR-GBP	53.70	75.79	56.70	58.34	56.76	63.20	63.51	0	100	0	33.33	0	100	0	33.33
EUR-JPY	19.26	15.28	40.21	27.51	23.09	33.56	31.15	0	0	100	33.33	0	0	100	33.33

Table 3: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=3, MSE).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a three-months forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	0.42	1.45	-1.04	0.26	0.75	-0.11	0.66	-1.08	2.31	-6.87$_{7,7}$	-1.94$_{3,4}$	-1.98	-0.16	-7.25$_{7,7}$	-3.16$_{1,4}$
Omega	1.09	1.27	0.88	1.04	1.13	0.99	1.09	0.88$_{1}$	1.44	0.53$_{7,7}$	0.67$_{7,7}$	0.80$_{1}$	0.97	0.51$_{7,7}$	0.57$_{7,7}$
Sharpe ratio	0.03	0.08	-0.04	0.01	0.04	0.00	0.03	-0.05	0.14	-0.23$_{7,7}$	-0.13$_{5,6}$	-0.08	-0.01	-0.24$_{7,7}$	-0.20$_{1,7}$
Sortino ratio	0.04	0.12	-0.05	0.01	0.05	-0.01	0.04	-0.06	0.24	-0.26$_{7,7}$	-0.16$_{4,6}$	-0.10	-0.01	-0.27$_{4,7}$	-0.21$_{5}$
Median	0.58	1.18	-1.43	1.12	0.94	-0.91	0.65	-0.60	1.39	-6.45	-1.05	-1.69	2.25	-5.17	0.28
Volatility	7.83	8.99	13.00	12.48	10.53	12.62	11.46	11.49	8.43	15.44	7.26	12.48	8.51	15.40	8.21
Down. vol.	5.67	6.09	10.81	10.19	8.14	10.32	8.80	8.66	4.75	13.79	6.05	9.97	6.59	14.06	7.46
Down. vol. ratio	0.51	0.48	0.60	0.59	0.55	0.59	0.55	0.54	0.40	0.64	0.60	0.57	0.55	0.66	0.67
CVaR, $\beta = 0.05$	-35.54	-35.06	-61.53	-57.84	-46.04	-58.36	-49.45	-45.55	-24.13	-67.40	-35.93	-55.96	-38.80	-67.76	-44.41
Skewness	-0.78	-0.50	-2.23	-2.52	-2.29	-2.42	-1.87	-0.40	0.91	-1.14	-1.10	-0.90	-0.91	-1.24	-1.55
Kurtosis	12.67	11.13	13.82	16.82	20.61	15.86	15.35	4.70	5.43	6.68	9.94	5.64	5.78	6.58	7.11
Realized return															
Last 5 years	1.55	2.94	0.99	2.14	2.46	1.60	1.55	0.94	3.34	-8.60	-1.24	1.13	3.27	-4.69	0.22
Last 3 years	2.54	3.89	3.45	4.26	4.38	3.81	4.14	2.97	4.07	-7.14	0.11	2.68	4.57	-2.03	2.07
Last year	8.28	10.63	9.84	9.58	9.90	10.12	9.84	11.65	9.84	-5.47	5.48	11.65	6.34	-4.39	4.77
Mean allocation															
EUR-USD	30.87	15.93	13.40	14.33	22.14	12.37	9.76	100	0	0	33.33	100	0	0	33.33
EUR-GBP	54.15	74.09	67.01	72.57	66.81	74.06	77.24	0	100	0	33.33	0	100	0	33.33
EUR-JPY	14.98	9.98	19.59	13.10	11.05	13.56	13.00	0	0	100	33.33	0	0	100	33.33

Table 4: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=3, MSE).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a three-months forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

4 Conclusion

Using a comprehensive set of exchange rate models, we analyse whether investors in the foreign exchange markets, whose goal is to maximize risk-adjusted profits, should engage in active portfolio management rather than just follow the naive equally weighted portfolio approach or simply invest in one of the simple assets composing the portfolio. These simple assets are defined through returns implied by a trading strategy based on exchange rate forecasts. We consider the following foreign exchange markets: euro versus US dollar, British pound and Japanese yen. We focus on three different criteria for assessing the predictive ability of exchange rate models: the mean-squared error (MSE), the directional value (DV) and the return implied by simple trading strategies. Concerning the forecast horizon, we investigate one-month, three-, six- and twelve-months ahead forecasts. The corresponding results are often similar but in some instances may also be very different. In terms of the performance of optimal portfolios at a forecast horizon of one month, the mean-squared error provides the highest performance, while best performance results with respect to certain benchmark portfolios are achieved for DV- and return-based returns for forecast horizons of three and twelve months. We consider two trading strategies, where the first one is the 'buy low, sell high' trading strategy, and the second one is very similar to the so-called carry trade strategy, which borrows low-interest rate currencies and lends high-interest rate currencies and which is implemented using forward contracts.

Investors choose their optimal portfolio every month, according to their preferences. We consider a large variety of different types of investors, ranging from the traditional mean-variance (MV) investor to the more modern conditional value-at-risk (CVaR) investor and to the very recent (linear and quadratic) loss aversion investor. Among these different preferences, the best and the second best performances (in terms of the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio) are nearly always achieved by the MV and CVaR portfolios – for both trading strategies, any given composite forecast, and any given forecast horizon.

We apply the bootstrap stepwise multiple superior predictive ability test by Hsu et al. (2010) in order to identify better performing portfolios, in terms of a given (risk-adjusted) performance measure, relative to a benchmark portfolio. This test is one without a potential data snooping bias. The benchmark portfolios to which we compare the optimal portfolio are the single assets (which compose the optimal portfolio) as well as the equally weighted portfolio, and the performance measures we employ include the mean return, the Omega measure, the Sharpe ratio and the Sortino ratio.

We find that, for a forecast horizon of one month, the MV currency portfolio tends to outperform the single asset based on the EUR/GBP exchange rate in terms of the Omega measure. The equally weighted portfolio, however, is never outperformed for a one-month forecast horizon. If we increase the forecast horizon to three months then the equally weighted portfolio is always outperformed – mostly in terms of all four performance measures, for all three composite forecasts and for both trading strategies. This is also true for even longer forecast horizons (six, twelve months). In general, the number of benchmark portfolios being outperformed by optimal portfolios increases with an increasing horizon. These results thus indicate that investors should in fact engage in active optimal management rather than just follow the naive equally weighted portfolio approach, in particular for long forecast horizons. This outcome is in contrast to studies on equity and equity/bond/commodity portfolios which have found that complex portfolios do not usually outperform equally weighted portfolios (see DeMiguel et al. (2009) and Jacobs et al., 2014).

In general, the benchmark portfolios based on the random walk, i.e., the benchmark portfolios which do not make use of any (non-trivial) exchange rate forecasts, are more often outperformed by optimal portfolios than benchmark portfolios based on composite forecasts. This indicates indirectly that the use of exchange rate forecasts adds to improving the (risk-adjusted) profitability of the benchmark portfolios we consider, i.e., of the single assets and the equally weighted portfolio. However, in the case of the USD, the benchmark portfolios based on the random walk are less often outperformed than in the case of the other currencies (for forecast horizons of one and three months). Looking at it from a different angle, the USD based on the random walk often shows a better performance than the USD based on the composite forecast, while for the JPY and the GBP this is rarely the case. These results suggest that the degree of predictability of the different exchange rates varies significantly, in spite of the fact that all three exchange markets are known to be flexible and liquid. Note, however, that the situation is different for longer forecast horizons, where the USD based on the random walk actually performs worse than the USD based on the composite forecast.

The 'buy low, sell high' trading strategy on the one hand and the carry trade based trading strategy on the other hand are rather different by construction and also yield different results in terms of profitability of the single assets and the resulting optimal portfolio. The picture is not crystal clear but in general (with only few exceptions) the 'buy low, sell high' strategy seems to beat the carry trade based trading strategy, for any given type of investor, any given composite forecast, and any given forecast horizon.

Finally, we want to answer our initial question "Is there any value added of exchange rate forecasts in currency portfolios": Yes, there is, but not in all situations, and the extent of this value added depends on concrete aspects like the assets considered (i.e., the particular exchange rates and trading strategies), the forecast horizon taken, the criteria used in determining the best forecasts and, of course, the preferences of the investor. There is still the need to understand the determinants of the returns implied by currency trading strategies like the ones we employ in more detail. Some of our current results in terms of the best performing optimal portfolios, for example, are fundamentally different from the results obtained in Fortin and Hlouskova (2011, 2015), where equity classes (plus bonds and commodities) are considered. One difference, for example, relates to the best performing type(s) of investors. While we find that for shorter forecast horizons investors with mean-variance or conditional value-at-risk preferences achieve highest risk-adjusted returns, the findings in Fortin and Hlouskova (2011, 2015) are not so clear-cut but tend to provide evidence that loss averse investors perform best (which is more in line with our results for longer forecast horizons).

5 References

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6 Appendix

6.1 Data description and sources

All time series have monthly periodicity (January 1980 to January 2016), and have been extracted from Thomson Reuters Datastream. The spot (forward) exchange rates are mid exchange rates of the WM/Reuters closing spot (forward) rates. The variables used for the Euro area, Japan, 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 government bond yield.

The values of the variables used for the Euro area before the introduction of the Euro are as calculated and provided by Thomson Reuters Datastream.

6.2 Individual forecast models and forecast combination methods

We entertain several types of vector autoregressive (VAR) and vector error correction (VEC) models as specifications for exchange rate forecasting. On the one hand, we differentiate between restricted and unrestricted models depending on whether the foreign and domestic covariates are included as individual variables in the model or as a single covariate measuring the domestic-foreign difference. We refer to models containing the latter as *restricted* models (r-VAR, r-DVAR, r-VEC), while the models based on separated domestic and foreign variables are labelled *unrestricted* models (VAR, DVAR, VEC). We also consider subset-VAR models, where statistically insignificant lags of the variables are omitted, and label them s-VAR, s-DVAR, rs-VAR and rs-DVAR.

In terms of estimation method, we consider multivariate models estimated using standard frequentist methods and Bayesian VARs. Bayesian DVARs are estimated using the standard Minnesota prior (see Doan et al., 1984, and Litterman, 1986). The lag length of all multivariate model specifications under consideration is selected using the AIC criterion for potential lag lengths ranging from 1 to 12 lags. For the VEC models, selection of the lag length and the number of cointegration relationships is carried out simultaneously using the AIC criterion.

Table 5 lists the 12 individual forecast models used.

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

Table 5: Individual forecast models.

The combinations of forecasts entertained in this study, $\hat{S}_{c,t+h|t}$, take the form of a linear combination of the predictions of individual specifications,

$$\hat{S}_{c,t+h|t} = w_{c,0t}^{h} + \sum_{m=1}^{M} w_{c,mt}^{h} \hat{S}_{m,t+h|t},$$

where c is the combination method, M is the number of individual forecasts, the weights are given by $\{w_{c,mt}^{h}\}_{m=0}^{M}$, and $\hat{S}_{m,t+h|t}$ is the individual exchange rate forecast. Table 6 lists the 13 forecast combination methods used.

	Forecasting combination based on
mean	mean of individual predictions
tmean	trimmed mean of individual predictions
median	median of individual predictions
OLS	pooling using OLS
PC	principal components
DMSFE	discounted mean square forecast errors
HR	hit rates
EHR	exponential of hit rates
EEDF	the economic evaluation of directional forecasts
BMA	Bayesian model averaging weights using the predictive likelihood
FMA-aic	frequentist model averaging with AIC weights
FMA-bic	frequentist model averaging with BIC weights
FMA-hq	frequentist model averaging with Hannan-Quinn weights

Table 6: Forecast combination methods.

6.3 Results for DV- and return-based composite forecasts (TS1, TS2)

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	2.44	1.98	-2.20	-1.11	0.47	-1.91	-1.04	4.62	0.50	-1.05	1.33	-3.18	-1.41	1.83	-0.94
Omega	1.39	1.29	0.88	0.89	1.06	0.88	0.92	1.35	$1.04_{1,2}$	0.95_{1}	1.20	$0.81_{2,2}$	$0.89_{2,2}$	1.10	$0.90_{1,2}$
Sharpe ratio	0.11	0.09	-0.05	-0.04	0.02	-0.04	-0.03	0.11	0.01	-0.02	0.06	-0.08	-0.04	0.03	-0.04
Sortino ratio	0.18	0.14	-0.07	-0.05	0.03	-0.06	-0.04	0.17	0.02	-0.03	0.10	-0.10	-0.06	0.05	-0.06
Median	2.70	1.58	-4.34	2.54	1.78	-2.30	-0.42	4.82	1.16	1.15	2.79	-2.33	-4.64	2.49	-1.17
Volatility	6.25	6.27	13.99	8.13	6.91	12.90	11.56	11.82	9.72	15.25	6.21	11.86	9.71	15.25	6.46
Down. vol.	3.83	4.09	9.32	6.11	5.15	8.55	7.45	7.56	6.17	10.00	3.80	9.01	6.34	9.59	4.56
Down. vol. ratio	0.44	0.46	0.47	0.53	0.53	0.47	0.46	0.45	0.45	0.47	0.44	0.54	0.46	0.45	0.50
CVaR, $\beta = 0.05$	-40.31	-41.33	-66.48	-53.21	-49.86	-64.65	-60.74	-61.22	-48.31	-67.65	-34.93	-66.58	-50.64	-63.97	-36.55
Skewness	0.55	0.12	1.05	-0.15	-0.82	1.28	1.74	0.08	1.14	0.91	1.44	-0.19	1.24	0.89	0.33
Kurtosis	6.15	4.92	7.87	7.35	7.17	10.14	14.59	3.88	9.36	6.29	11.28	3.84	9.66	6.10	3.73
Realized return															
Last 5 years	2.42	2.72	-1.86	2.20	2.38	-0.64	0.26	5.88	1.68	-2.84	1.90	0.43	-4.93	-2.68	-2.07
Last 3 years	2.77	3.84	1.02	1.78	2.68	0.65	0.32	5.59	3.91	-4.49	1.88	0.14	-3.08	-1.25	-1.16
Last year	3.99	4.98	-1.06	3.60	4.40	-1.23	-0.20	4.29	8.88	-7.96	1.74	4.29	-1.51	2.52	1.93
Mean allocation															
EUR-USD	33.39	29.10	46.39	41.27	37.72	49.29	47.47	100	0	0	33.33	100	0	0	33.33
EUR-GBP	50.39	55.25	14.43	32.55	41.75	16.52	21.43	0	100	0	33.33	0	100	0	33.33
EUR-JPY	16.22	15.64	39.18	26.18	20.53	34.19	31.10	0	0	100	33.33	0	0	100	33.33

Table 7: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=1, DV).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a one-month forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	2.21	0.58	-2.03	-0.03	0.54	-0.49	-0.86	5.93	-1.14	-2.08	0.84	3.87	-2.68	-6.75	-1.94
Omega	1.35	1.07	0.89	1.00	1.07	0.97	0.94	1.47	$0.91_{1,1}$	0.90	1.12	1.28	$0.81_{1,1}$	$0.69_{1,1}$	0.83_{1}
Sharpe ratio	0.10	0.02	-0.04	0.00	0.02	-0.01	-0.02	0.14	-0.03	-0.04	0.04	0.09	-0.07	-0.13	-0.07
Sortino ratio	0.17	0.04	-0.06	0.00	0.04	-0.02	-0.03	0.23	-0.05	-0.06	0.06	0.15	-0.08	-0.16	-0.09
Median	1.39	-0.44	-2.83	3.03	2.22	-1.71	1.63	5.22	-0.54	0.87	2.55	2.51	-0.89	-2.27	2.36
Volatility	6.47	6.89	13.93	10.20	6.67	13.04	11.92	11.79	9.71	15.16	6.31	11.86	11.85	15.04	8.58
Down. vol.	3.70	4.41	9.42	6.36	4.35	8.36	7.89	7.18	6.38	10.25	4.00	7.26	9.42	12.47	6.47
Down. vol. ratio	0.41	0.46	0.48	0.45	0.46	0.46	0.47	0.43	0.47	0.48	0.45	0.44	0.57	0.59	0.54
CVaR, $\beta = 0.05$	-39.15	-43.78	-66.75	-56.12	-41.64	-63.12	-61.64	-60.09	-48.48	-67.40	-37.70	-58.53	-70.11	-79.49	-55.36
Skewness	1.22	0.96	0.94	2.32	1.15	1.22	1.40	0.19	1.23	0.87	1.44	0.39	-1.17	-0.88	-0.02
Kurtosis	8.29	9.54	7.76	20.96	11.02	9.19	12.28	3.92	9.69	6.27	12.30	3.85	14.66	5.76	5.84
Realized return															
Last 5 years	1.93	2.04	-3.49	1.27	1.90	-0.60	-0.04	5.06	1.39	-2.84	1.54	3.42	2.56	-4.38	0.73
Last 3 years	2.60	3.56	-4.65	1.63	2.57	-2.16	-0.98	5.85	3.91	-4.49	1.96	6.82	4.46	3.13	4.99
Last year	3.97	5.97	-0.70	3.43	4.29	0.16	1.37	4.89	8.80	-7.94	1.92	4.89	-0.76	1.27	1.99
Mean allocation															
EUR-USD	32.94	27.50	55.67	42.14	39.66	55.69	55.23	100	0	0	33.33	100	0	0	33.33
EUR-GBP	51.16	59.00	5.15	27.23	37.86	7.22	13.87	0	100	0	33.33	0	100	0	33.33
EUR-JPY	15.91	13.50	39.18	30.62	22.48	37.09	30.89	0	0	100	33.33	0	0	100	33.33

Table 8: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=1, DV).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a one-month forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	2.11	2.92	2.16	2.41	2.86	2.86	3.97	-0.43	4.42	$-1.74_{1,2}$	$0.72_{2,2}$	-0.64	$-0.66_{1,5}$	-3.13	-1.48_{6}
Omega	1.64	1.61	1.31	1.50	1.77	1.46	1.78	$0.95_{5,7}$	2.04	$0.86_{7,7}$	$1.17_{2,3}$	$0.93_{5,7}$	$0.90_{6,7}$	$0.76_{7,7}$	$0.74_{7,7}$
Sharpe ratio	0.19	0.14	0.08	0.12	0.19	0.11	0.16	-0.02_{1}	0.26	$-0.05_{3,7}$	$0.06_{1,2}$	-0.03	$-0.04_{2,5}$	-0.10_{1}	-0.10_{6}
Sortino ratio	0.32	0.22	0.12	0.16	0.32	0.17	0.26	$-0.03_{1,2}$	0.51	$-0.07_{4,7}$	$0.09_{1,2}$	-0.04	$-0.06_{2,4}$	-0.12_{3}	-0.12_{6}
Median	1.42	2.69	4.15	2.50	2.09	4.51	4.89	-2.05	4.51	-1.31	-0.39	0.86	-2.96	1.81	-0.69
Volatility	5.65	10.39	13.23	10.27	7.51	12.76	11.97	11.61	8.27	16.16	6.02	11.61	8.54	16.11	7.36
Down. vol.	3.31	6.62	9.17	7.41	4.41	8.56	7.51	8.39	4.26	11.87	3.86	8.94	5.40	13.58	6.33
Down. vol. ratio	0.42	0.45	0.49	0.51	0.42	0.47	0.44	0.51	0.37	0.52	0.46	0.55	0.45	0.61	0.63
CVaR, $\beta = 0.05$	-20.55	-39.61	-56.79	-41.55	-27.92	-51.07	-42.06	-45.87	-25.07	-60.84	-21.78	-49.29	-27.31	-69.26	-40.71
Skewness	0.21	0.27	-0.09	-1.78	0.13	0.01	0.25	-0.31	0.76	0.10	0.38	-0.71	1.12	-1.40	-2.04
Kurtosis	3.55	18.70	15.75	21.71	8.17	17.66	21.71	4.94	5.48	7.77	3.87	4.88	6.04	7.26	11.54
Realized return															
Last 5 years	2.24	2.59	3.08	3.93	3.03	3.81	4.22	0.14	4.72	-3.41	0.72	1.80	-2.57	-2.91	-0.90
Last 3 years	4.75	5.16	6.51	4.83	5.10	6.04	5.93	4.85	6.51	-4.96	2.23	2.09	-0.77	-3.44	-0.45
Last year	11.61	11.20	13.71	13.64	12.97	13.71	13.67	11.10	13.71	1.03	8.70	11.10	5.57	-6.37	3.63
Mean allocation															
EUR-USD	29.16	23.92	0.00	14.39	23.51	0.92	3.64	100	0	0	33.33	100	0	0	33.33
EUR-GBP	50.46	53.32	84.54	69.89	61.24	84.56	81.07	0	100	0	33.33	0	100	0	33.33
EUR-JPY	20.38	22.76	15.46	15.72	15.24	14.52	15.29	0	0	100	33.33	0	0	100	33.33

Table 9: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=3, DV).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a three-months forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	-1.25	-0.83	-3.34	-2.47	-1.61	-2.83	-2.14	-2.29	-0.36	$-6.88_{1,6}$	$-3.21_{1,2}$	-1.98	-0.16	$-7.25_{2,7}$	-3.16
Omega	0.79	0.87	0.66	0.69	0.76	0.68	0.72	0.76	0.94	$0.53_{1,4}$	$0.55_{3,5}$	0.80	0.97	$0.51_{1,4}$	$0.57_{1,1}$
Sharpe ratio	-0.08	-0.05	-0.13	-0.11	-0.09	-0.12	-0.10	-0.10	-0.02	-0.23_{1}	$-0.20_{1,2}$	-0.08	-0.01	-0.24_{1}	-0.20_{1}
Sortino ratio	-0.10	-0.06	-0.14	-0.13	-0.11	-0.13	-0.11	-0.13	-0.03	-0.25	$-0.22_{1,1}$	-0.10	-0.01	-0.27	-0.21
Median	0.40	1.03	-0.73	0.20	0.74	-0.91	0.94	-4.19	1.39	-6.67	-2.03	-1.69	2.25	-5.17	0.28
Volatility	7.48	8.84	12.89	10.91	8.86	11.80	10.80	11.44	8.50	15.44	8.22	12.48	8.51	15.40	8.21
Down. vol.	6.09	7.21	11.70	9.70	7.42	10.64	9.59	8.92	6.57	13.86	7.27	9.97	6.59	14.06	7.46
Down. vol. ratio	0.58	0.59	0.68	0.66	0.61	0.67	0.66	0.55	0.55	0.65	0.64	0.57	0.55	0.66	0.67
CVaR, $\beta = 0.05$	-35.99	-43.85	-66.25	-56.05	-45.96	-62.13	-55.37	-48.28	-38.80	-67.76	-45.04	-55.96	-38.80	-67.76	-44.41
Skewness	-0.88	-1.21	-2.60	-2.71	-1.25	-2.62	-2.82	-0.45	-0.85	-1.23	-1.32	-0.90	-0.91	-1.24	-1.55
Kurtosis	5.68	6.64	13.35	16.64	6.86	14.05	17.37	4.62	5.75	6.60	7.86	5.64	5.78	6.58	7.11
Realized return															
Last 5 years	1.84	2.82	2.51	2.38	2.40	2.84	2.37	0.35	2.83	-4.44	-0.20	1.13	3.27	-4.69	0.22
Last 3 years	3.67	4.76	3.84	3.51	3.88	3.86	3.86	5.12	4.39	-5.45	1.44	2.68	4.57	-2.03	2.07
Last year	10.26	11.07	9.44	11.03	11.39	9.50	10.77	11.65	11.19	1.05	8.09	11.65	6.34	-4.39	4.77
Mean allocation															
EUR-USD	29.23	27.84	12.37	20.39	26.26	12.33	13.19	100	0	0	33.33	100	0	0	33.33
EUR-GBP	59.66	61.78	72.16	67.29	63.98	75.20	75.27	0	100	0	33.33	0	100	0	33.33
EUR-JPY	11.10	10.38	15.46	12.31	9.76	12.47	11.54	0	0	100	33.33	0	0	100	33.33

Table 10: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=3, DV).* The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a three-months forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	1.54	0.75	-2.10	-0.04	0.40	-2.53	-0.71	4.32	-1.45	-1.85	0.30	-3.18	-1.41	1.83	-0.94
Omega	1.23	1.10	0.88	1.00	1.05	0.85	0.95	1.32	0.88_1	0.91	1.04	0.81	0.89	1.10	0.90
Sharpe ratio	0.07	0.03	-0.04	0.00	0.02	-0.06	-0.02	0.10	-0.04	-0.04	0.01	-0.08	-0.04	0.03	-0.04
Sortino ratio	0.12	0.05	-0.07	0.00	0.03	-0.08	-0.03	0.16	-0.07	-0.05	0.02	-0.10	-0.06	0.05	-0.06
Median	1.00	-1.49	-3.26	2.12	1.38	-2.36	-1.80	5.29	-0.90	1.15	1.55	-2.33	-4.64	2.49	-1.17
Volatility	6.36	6.26	13.86	9.83	6.58	13.34	12.09	11.83	9.71	15.24	6.13	11.86	9.71	15.25	6.46
Down. vol.	3.71	4.07	9.22	6.17	4.38	8.97	7.66	7.68	6.35	10.15	3.92	9.01	6.34	9.59	4.56
Down. vol. ratio	0.42	0.46	0.47	0.45	0.47	0.48	0.45	0.46	0.47	0.47	0.46	0.54	0.46	0.45	0.50
CVaR, $\beta = 0.05$	-37.30	-40.90	-66.48	-53.42	-41.03	-65.26	-61.26	-61.22	-48.31	-67.65	-34.93	-66.58	-50.64	-63.97	-36.55
Skewness	1.11	0.34	1.06	1.98	0.67	1.17	1.60	0.05	1.27	0.92	1.52	-0.19	1.24	0.89	0.33
Kurtosis	6.98	4.86	8.13	17.64	7.02	9.24	12.58	3.89	9.68	6.35	12.13	3.84	9.66	6.10	3.73
Realized return															
Last 5 years	2.02	2.52	-1.97	2.15	2.13	-2.62	-0.11	5.88	1.27	-4.89	1.04	0.43	-4.93	-2.68	-2.07
Last 3 years	2.46	3.85	0.83	2.25	2.72	1.18	1.81	5.59	3.91	-7.81	0.67	0.14	-3.08	-1.25	-1.16
Last year	4.26	6.92	-1.06	4.25	5.15	-1.23	-0.29	4.29	8.88	-7.96	1.74	4.29	-1.51	2.52	1.93
Mean allocation															
EUR-USD	31.87	27.81	51.55	43.75	38.29	52.90	50.83	100	0	0	33.33	100	0	0	33.33
EUR-GBP	51.09	57.80	12.37	26.57	38.12	12.09	15.76	0	100	0	33.33	0	100	0	33.33
EUR-JPY	17.05	14.39	36.08	29.68	23.59	35.01	33.41	0	0	100	33.33	0	0	100	33.33

Table 11: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=1, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a one-month forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	1.30	1.49	-1.90	-0.56	0.64	-1.23	-1.41	-0.84	0.27	1.41	0.28	3.87	-2.68	-6.75	-1.94
Omega	1.17	1.17	0.90	0.95	1.07	0.93	0.91	0.95	1.02	1.08	1.04	1.28	0.81_{2}	$0.69_{1,3}$	0.83
Sharpe ratio	0.06	0.06	-0.04	-0.02	0.02	-0.03	-0.03	-0.02	0.01	0.03	0.01	0.09	-0.07	-0.13	-0.07
Sortino ratio	0.08	0.08	-0.06	-0.03	0.04	-0.04	-0.05	-0.03	0.01	0.04	0.02	0.15	-0.08	-0.16	-0.09
Median	2.03	2.51	0.87	0.25	1.47	1.56	1.17	2.51	1.55	2.32	2.51	2.51	-0.89	-2.27	2.36
Volatility	6.59	7.65	14.36	7.98	7.68	14.11	12.48	11.91	9.71	15.17	6.61	11.86	11.85	15.04	8.58
Down. vol.	4.69	5.07	9.54	5.63	5.21	9.36	8.05	9.00	6.21	9.58	4.92	7.26	9.42	12.47	6.47
Down. vol. ratio	0.51	0.47	0.47	0.50	0.48	0.47	0.46	0.54	0.46	0.45	0.53	0.44	0.57	0.59	0.54
CVaR, $\beta = 0.05$	-44.91	-44.80	-65.74	-45.73	-45.26	-65.74	-59.85	-68.36	-48.19	-65.74	-45.14	-58.53	-70.11	-79.49	-55.36
Skewness	-0.80	0.00	0.99	0.10	0.00	0.98	1.50	-0.51	1.16	0.89	-0.76	0.39	-1.17	-0.88	-0.02
Kurtosis	6.71	6.26	6.88	5.87	5.90	7.26	10.77	3.94	9.47	6.03	7.08	3.85	14.66	5.76	5.84
Realized return															
Last 5 years	3.65	3.89	-2.82	2.17	3.07	-2.44	1.00	6.18	2.72	-1.06	2.90	3.42	2.56	-4.38	0.73
Last 3 years	2.51	4.04	-4.70	1.47	2.46	-4.05	0.92	7.74	3.13	-7.29	1.25	6.82	4.46	3.13	4.99
Last year	2.94	4.59	3.49	4.53	4.67	3.45	5.87	10.64	2.54	-6.40	2.20	4.89	-0.76	1.27	1.99
Mean allocation															
EUR-USD	27.40	17.94	8.25	19.83	22.01	8.61	11.97	100	0	0	33.33	100	0	0	33.33
EUR-GBP	50.85	64.73	26.80	47.05	50.28	28.58	36.26	0	100	0	33.33	0	100	0	33.33
EUR-JPY	21.75	17.33	64.95	33.12	27.70	62.82	51.77	0	0	100	33.33	0	0	100	33.33

Table 12: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=1, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a one-month forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	0.79	1.74	2.30	1.02	0.90	1.65	2.90	-2.73_{4}	2.55	-1.65_{2}	$-0.63_{1,1}$	-0.64	-0.66	-3.13	-1.48
Omega	1.19	1.42	1.27	1.16	1.18	1.23	1.49	$0.72_{7,7}$	1.50	$0.87_{4,7}$	$0.88_{3,7}$	0.93_{1}	$0.90_{1,4}$	$0.76_{2,7}$	$0.74_{7,7}$
Sharpe ratio	0.06	0.12	0.08	0.05	0.05	0.06	0.12	-0.12_{3}	0.15	-0.05_{2}	$-0.04_{1,1}$	-0.03	-0.04_{1}	-0.10	-0.10
Sortino ratio	0.08	0.19	0.11	0.06	0.06	0.09	0.18	-0.15_{1}	0.25	-0.07_{2}	$-0.06_{1,1}$	-0.04	-0.06_{1}	-0.12	-0.12
Median	0.83	1.30	4.15	3.13	2.49	3.43	4.15	-2.50	3.03	-0.77	-0.35	0.86	-2.96	1.81	-0.69
Volatility	6.76	7.04	14.96	11.00	8.72	13.47	12.20	11.53	8.46	16.16	7.14	11.61	8.54	16.11	7.36
Down. vol.	4.68	4.55	10.50	8.76	7.04	9.52	7.95	9.28	5.02	11.87	5.58	8.94	5.40	13.58	6.33
Down. vol. ratio	0.49	0.46	0.50	0.57	0.58	0.50	0.46	0.57	0.42	0.52	0.56	0.55	0.45	0.61	0.63
CVaR, $\beta = 0.05$	-29.84	-29.87	-60.84	-54.11	-43.11	-59.17	-45.47	-49.29	-28.42	-60.84	-34.73	-49.29	-27.31	-69.26	-40.71
Skewness	-0.26	-0.01	-0.20	-2.19	-2.68	-0.11	0.23	-0.59	0.64	0.09	-0.83	-0.71	1.12	-1.40	-2.04
Kurtosis	5.47	5.17	10.30	16.12	18.89	14.83	20.22	4.74	5.60	7.76	6.73	4.88	6.04	7.26	11.54
Realized return															
Last 5 years	2.93	3.57	4.85	4.22	4.24	3.73	4.63	1.22	4.72	-3.27	1.13	1.80	-2.57	-2.91	-0.90
Last 3 years	5.34	5.54	4.93	5.32	5.87	6.37	6.27	5.58	6.51	-4.73	2.55	2.09	-0.77	-3.44	-0.45
Last year	11.68	12.03	15.20	12.68	12.86	14.13	13.74	11.10	13.71	1.03	8.70	11.10	5.57	-6.37	3.63
Mean allocation															
EUR-USD	28.44	20.52	4.12	13.83	24.88	4.25	4.69	100	0	0	33.33	100	0	0	33.33
EUR-GBP	55.87	69.54	50.52	63.38	57.73	69.47	74.42	0	100	0	33.33	0	100	0	33.33
EUR-JPY	15.69	9.94	45.36	22.79	17.39	26.28	20.90	0	0	100	33.33	0	0	100	33.33

Table 13: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=3, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a three-months forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	0.55	2.17	0.31	1.43	1.72	0.44	1.60	$-2.95_{1,5}$	2.32	-2.65_{4}	$-1.12_{2,4}$	-1.98_{1}	-0.16	$-7.25_{7,7}$	$-3.16_{4,7}$
Omega	1.11	1.42	1.03	1.21	1.29	1.05	1.23	$0.70_{7,7}$	1.44	$0.79_{4,7}$	$0.82_{7,7}$	$0.80_{4,7}$	0.97_{1}	$0.51_{7,7}$	$0.57_{7,7}$
Sharpe ratio	0.04	0.13	0.01	0.06	0.08	0.02	0.07	$-0.13_{1,7}$	0.14	-0.08_{4}	$-0.07_{2,4}$	-0.08_{1}	-0.01	$-0.24_{7,7}$	$-0.20_{7,7}$
Sortino ratio	0.05	0.21	0.01	0.08	0.11	0.02	0.09	$-0.17_{1,7}$	0.24	-0.10_{3}	$-0.09_{2,4}$	-0.10_{1}	-0.01	$-0.27_{4,7}$	$-0.21_{4,7}$
Median	0.79	0.82	2.53	1.87	1.54	2.53	1.81	-4.78	2.25	-0.83	-1.39	-1.69	2.25	-5.17	0.28
Volatility	7.49	8.58	14.05	11.60	10.46	13.83	11.67	11.40	8.43	15.79	8.36	12.48	8.51	15.40	8.21
Down. vol.	5.10	5.05	11.25	8.90	7.57	11.12	8.69	8.99	4.86	12.76	6.54	9.97	6.59	14.06	7.46
Down. vol. ratio	0.48	0.42	0.58	0.55	0.51	0.58	0.53	0.56	0.41	0.58	0.56	0.57	0.55	0.66	0.67
CVaR, $\beta = 0.05$	-32.38	-30.52	-64.95	-53.04	-44.59	-64.88	-49.74	-48.28	-25.68	-65.76	-41.31	-55.96	-38.80	-67.76	-44.41
Skewness	0.09	0.66	-1.86	-1.94	-1.35	-1.96	-1.70	-0.37	0.81	-1.09	-0.90	-0.90	-0.91	-1.24	-1.55
Kurtosis	6.17	5.95	11.12	15.14	13.09	11.83	14.48	4.64	5.48	6.96	7.67	5.64	5.78	6.58	7.11
Realized return															
Last 5 years	2.31	3.45	2.25	3.31	3.24	2.48	3.25	1.81	2.49	-3.17	0.62	1.13	3.27	-4.69	0.22
Last 3 years	3.86	4.50	4.67	3.65	3.90	4.95	4.51	7.11	3.47	-5.20	1.86	2.68	4.57	-2.03	2.07
Last year	10.35	10.61	11.65	11.46	11.15	11.65	11.52	11.65	11.19	1.05	8.09	11.65	6.34	-4.39	4.77
Mean allocation															
EUR-USD	32.33	18.88	20.62	14.53	15.95	19.68	17.75	100	0	0	33.33	100	0	0	33.33
EUR-GBP	58.03	66.61	62.89	67.78	67.87	65.69	66.56	0	100	0	33.33	0	100	0	33.33
EUR-JPY	9.64	14.52	16.49	17.70	16.18	14.63	15.69	0	0	100	33.33	0	0	100	33.33

Table 14: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=3, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a three-months forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

6.4 Results for forecast horizons of six and twelve months

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	-0.04	-0.09	-1.13	-0.48	-0.49	-0.23	-0.60	-1.34	0.30	-1.99	-1.01	-2.24	-0.44	-3.28	-1.99
Omega	0.99	0.98	0.82	0.91	0.89	0.96	0.89	0.82	1.06	0.78	0.76_{2}	0.72	0.91	0.66	$0.52_{1,7}$
Sharpe ratio	0.00	-0.01	-0.06	-0.03	-0.04	-0.01	-0.04	-0.08	0.02	-0.09	-0.10	-0.13	-0.04	-0.14	-0.22
Sortino ratio	-0.01	-0.01	-0.08	-0.04	-0.05	-0.02	-0.05	-0.10	0.04	-0.11	-0.13	-0.15	-0.05	-0.16	-0.24
Median	-0.51	-0.08	-1.70	-1.24	-0.74	-0.75	-0.75	0.71	-2.21	0.03	-1.05	1.71	-2.21	0.40	-1.10
Volatility	6.13	7.89	13.73	12.06	9.59	13.23	11.51	12.44	8.70	16.41	7.05	12.38	8.70	16.30	6.43
Down. vol.	4.41	5.62	10.46	9.16	6.97	9.65	8.77	9.82	5.54	12.74	5.54	10.47	5.97	14.18	5.96
Down. vol. ratio	0.51	0.51	0.54	0.54	0.52	0.52	0.54	0.56	0.45	0.55	0.56	0.61	0.49	0.63	0.69
CVaR, $\beta = 0.05$	-20.13	-26.89	-52.05	-42.46	-34.94	-46.69	-42.65	-39.69	-21.94	-54.03	-25.87	-39.69	-22.91	-59.45	-30.37
Skewness	-0.34	-0.30	-0.65	-1.13	-0.28	-0.58	-0.95	-0.44	0.42	-0.39	-0.56	-0.69	0.35	-1.21	-1.73
Kurtosis	5.57	9.41	10.82	13.60	10.88	11.85	10.39	3.04	2.94	5.93	5.35	2.83	3.03	5.44	7.43
Realized return															
Last 5 years	0.47	-0.08	-0.28	0.32	-0.05	0.66	0.35	0.08	0.22	-1.63	-0.08	-0.66	-0.93	-2.48	-0.94
Last 3 years	1.62	0.56	-0.49	0.82	1.00	1.06	1.32	-2.53	3.84	-2.64	-0.14	-2.20	1.22	-4.94	-1.60
Last year	2.82	-0.09	3.08	2.74	2.60	2.71	3.20	-10.52	10.81	-1.49	-0.35	0.31	6.79	-1.49	2.23
Mean allocation															
EUR-USD	32.52	26.42	36.08	33.27	27.34	38.96	37.63	100	0	0	33.33	100	0	0	33.33
EUR-GBP	54.68	50.13	44.33	45.20	55.59	44.25	43.01	0	100	0	33.33	0	100	0	33.33
EUR-JPY	12.79	23.45	19.59	21.54	17.07	16.79	19.35	0	0	100	33.33	0	0	100	33.33

Table 15: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=6, MSE).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a six-months forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	-0.98	-0.18	-2.60	-1.51	-1.43	-1.31	-1.10	-1.73	-0.51	-5.89$_{7,7}$	-2.73$_{2,2}$	-2.41	-0.87	-6.54$_{6,7}$	-3.29$_{1,2}$
Omega	0.74	0.96	0.63	0.73	0.71	0.79	0.81	0.78	0.90	0.46$_{3,7}$	0.47$_{4,6}$	0.70	0.84	0.41$_{4,7}$	0.49$_{1,4}$
Sharpe ratio	-0.11	-0.02	-0.14	-0.09	-0.11	-0.07	-0.07	-0.10	-0.04	-0.28$_{3,5}$	-0.27$_{6,7}$	-0.14	-0.07	-0.31$_{1,4}$	-0.26$_{1}$
Sortino ratio	-0.14	-0.02	-0.17	-0.11	-0.13	-0.09	-0.08	-0.13	-0.06	-0.31$_{1,5}$	-0.30$_{1,6}$	-0.18	-0.09	-0.33$_{1}$	-0.28$_{1}$
Median	-1.40	1.33	-2.61	-1.17	-0.46	-1.33	-0.39	0.75	-2.58	-4.51	-1.62	-1.43	1.15	-3.88	-1.08
Volatility	6.30	7.55	12.90	11.86	9.55	12.68	11.47	12.20	8.57	15.23	7.21	12.14	8.55	15.09	8.98
Down. vol.	5.09	6.02	10.94	9.71	8.01	10.24	9.25	9.81	6.13	13.56	6.56	9.65	6.78	14.37	8.40
Down. vol. ratio	0.58	0.57	0.61	0.59	0.61	0.58	0.58	0.57	0.51	0.63	0.65	0.56	0.57	0.69	0.69
CVaR, $\beta = 0.05$	-23.48	-28.29	-53.59	-48.72	-41.28	-50.67	-46.62	-38.33	-25.45	-53.59	-29.71	-38.33	-26.64	-56.00	-36.54
Skewness	-0.71	-1.35	-1.19	-1.38	-1.41	-1.18	-1.13	-0.43	0.00	-0.44	-0.89	-0.13	-0.48	-1.04	-1.17
Kurtosis	5.38	7.80	9.77	13.00	10.12	10.34	9.32	2.91	2.89	5.41	5.00	3.02	2.75	4.72	4.77
Realized return															
Last 5 years	0.64	0.92	0.29	0.50	0.43	1.39	1.10	0.22	0.49	-2.14	-0.15	2.41	2.48	-3.76	0.60
Last 3 years	1.48	0.84	-0.33	0.88	1.27	1.37	1.47	-3.25	3.68	-2.66	-0.47	3.96	4.13	-2.29	2.20
Last year	3.62	2.91	6.13	5.78	3.60	6.13	5.41	-10.38	11.30	-1.45	-0.12	13.38	7.55	-4.87	5.42
Mean allocation															
EUR-USD	33.68	35.73	38.14	38.36	28.81	41.21	41.93	100	0	0	33.33	100	0	0	33.33
EUR-GBP	55.54	50.23	42.27	45.73	59.18	42.51	42.18	0	100	0	33.33	0	100	0	33.33
EUR-JPY	10.78	14.04	19.59	15.91	12.02	16.29	15.89	0	0	100	33.33	0	0	100	33.33

Table 16: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=6, MSE).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a six-months forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	-2.22	-1.87	-2.23	-1.96	-2.29	-2.05	-1.79	-1.41	-2.10	$-5.64_{7,7}$	$-3.05_{2,3}$	-2.02	-3.21_{3}	0.32	-1.64
Omega	0.42	0.49	0.60	0.57	0.49	0.58	0.59	0.74	0.57	0.35_{3}	$0.32_{7,7}$	0.65	0.41_{1}	1.06	0.45
Sharpe ratio	-0.33	-0.27	-0.20	-0.21	-0.26	-0.21	-0.19	-0.12	-0.24	-0.41	$-0.45_{7,7}$	-0.18	-0.38	0.02	-0.29
Sortino ratio	-0.36	-0.31	-0.25	-0.26	-0.31	-0.25	-0.24	-0.16	-0.29	-0.43	$-0.46_{2,7}$	-0.21	-0.42	0.03	-0.33
Median	-1.90	-1.50	-2.32	-1.52	-1.78	-1.28	-1.31	-1.38	-2.98	-5.08	-3.85	-0.11	-3.93	-0.08	-2.52
Volatility	6.80	6.86	10.92	9.37	8.72	9.90	9.36	11.52	8.72	13.80	6.79	11.43	8.37	14.91	5.58
Down. vol.	6.19	5.98	8.92	7.62	7.47	8.13	7.54	8.82	7.30	13.19	6.59	9.69	7.69	10.36	5.02
Down. vol. ratio	0.64	0.61	0.57	0.57	0.60	0.58	0.57	0.54	0.59	0.66	0.66	0.61	0.63	0.49	0.64
CVaR, $\beta = 0.05$	-19.06	-17.83	-23.03	-23.02	-21.29	-23.02	-23.02	-23.02	-17.27	-33.11	-18.91	-24.92	-17.87	-31.11	-18.65
Skewness	-0.22	-0.14	0.17	0.16	0.03	0.11	0.13	0.12	0.15	0.04	0.08	-0.32	0.27	-0.07	-0.72
Kurtosis	3.46	3.45	2.75	3.93	3.37	3.41	3.94	2.41	2.27	2.72	3.60	2.10	2.42	2.70	5.58
Realized return															
Last 5 years	-0.84	-1.02	-1.07	-0.85	-1.09	-0.75	-0.52	-0.04	-1.42	-5.54	-1.98	-4.34	-0.30	-4.67	-2.64
Last 3 years	-2.04	-2.28	-2.09	-1.82	-2.28	-1.80	-1.36	-3.59	-1.11	-8.98	-4.17	-6.84	1.46	-10.07	-4.69
Last year	-0.83	-2.72	-3.93	-2.73	-2.96	-3.08	-1.67	-8.28	0.59	0.38	-2.02	-18.72	7.43	-4.98	-5.25
Mean allocation															
EUR-USD	32.48	37.19	68.04	53.79	48.08	68.16	59.58	100	0	0	33.33	100	0	0	33.33
EUR-GBP	48.39	48.73	30.93	44.87	49.52	31.48	39.75	0	100	0	33.33	0	100	0	33.33
EUR-JPY	19.13	14.09	1.03	1.34	2.41	0.36	0.68	0	0	100	33.33	0	0	100	33.33

Table 17: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=12, MSE).* The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a 12-months forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	-2.66	-1.89	-3.19	-2.93	-2.35	-3.22	-2.81	-0.64	-3.12	$-6.37_{7,7}$	$-3.38_{1,3}$	-1.59	-1.17	-2.57	-1.78
Omega	0.31	0.48	0.49	0.43	0.48	0.45	0.46	0.87	0.41	0.27_{2}	$0.25_{7,7}$	0.71	0.73	0.62	0.57
Sharpe ratio	-0.43	-0.27	-0.28	-0.30	-0.26	-0.31	-0.29	-0.06	-0.38	-0.52_{4}	$-0.55_{7,7}$	-0.14	-0.14	-0.19	-0.23
Sortino ratio	-0.44	-0.32	-0.33	-0.36	-0.33	-0.35	-0.35	-0.08	-0.42	-0.50	$-0.53_{2,7}$	-0.20	-0.17	-0.23	-0.26
Median	-2.07	-1.94	-3.75	-2.27	-2.36	-2.73	-2.85	-0.81	-4.65	-5.71	-4.07	-3.97	-2.02	-2.58	-1.29
Volatility	6.20	6.95	11.33	9.64	9.03	10.54	9.65	11.29	8.13	12.27	6.16	11.20	8.63	13.60	7.78
Down. vol.	5.99	5.85	9.71	8.11	7.20	9.10	8.05	8.15	7.51	12.74	6.31	8.03	6.77	11.07	6.82
Down. vol. ratio	0.66	0.59	0.60	0.58	0.55	0.60	0.58	0.51	0.63	0.71	0.68	0.50	0.56	0.57	0.63
CVaR, $\beta = 0.05$	-17.68	-18.85	-28.16	-23.42	-21.46	-25.75	-23.04	-21.55	-17.01	-29.50	-17.29	-18.62	-16.73	-29.19	-18.98
Skewness	-0.03	0.11	0.18	0.50	0.65	0.29	0.50	0.15	0.27	0.00	0.30	0.64	-0.01	0.05	-0.37
Kurtosis	3.83	4.48	3.19	4.34	4.96	3.60	4.24	2.51	2.34	2.39	3.96	2.82	2.12	2.55	2.40
Realized return															
Last 5 years	-0.65	-0.44	-1.05	-0.75	-0.17	-0.91	-0.78	1.00	-1.91	-5.76	-1.87	0.56	2.02	1.46	1.66
Last 3 years	-0.48	-0.15	0.56	0.10	0.62	0.66	0.49	0.74	-1.59	-9.07	-2.92	4.50	4.47	5.18	5.15
Last year	0.17	-1.74	-4.89	-4.70	-2.39	-4.89	-4.36	-4.89	0.52	0.37	-0.82	13.90	10.60	-5.00	6.74
Mean allocation															
EUR-USD	34.60	35.03	65.98	52.83	49.42	63.60	55.77	100	0	0	33.33	100	0	0	33.33
EUR-GBP	50.45	53.06	27.84	39.58	44.21	29.65	36.67	0	100	0	33.33	0	100	0	33.33
EUR-JPY	14.95	11.91	6.19	7.58	6.37	6.76	7.55	0	0	100	33.33	0	0	100	33.33

Table 18: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=12, MSE).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a 12-months forecast horizon, and MSE-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	0.66	1.06	1.27	0.78	0.49	1.19	1.39	0.51	0.41	$-3.56_{7,7}$	$-0.89_{2,3}$	-2.24	-0.44	-3.28	-1.99_{3}
Omega	1.24	1.31	1.22	1.16	1.12	1.21	1.29	1.08	1.09	$0.64_{7,7}$	$0.78_{7,7}$	$0.72_{5,7}$	0.91	$0.66_{7,7}$	$0.52_{7,7}$
Sharpe ratio	0.08	0.09	0.07	0.05	0.04	0.06	0.08	0.03	0.03	$-0.16_{7,7}$	$-0.09_{3,7}$	-0.13	-0.04	-0.14	-0.22_{7}
Sortino ratio	0.13	0.14	0.09	0.08	0.06	0.09	0.13	0.04	0.05	$-0.20_{7,7}$	$-0.12_{2,7}$	-0.15	-0.05	-0.16	-0.24_{7}
Median	-0.48	0.26	0.19	0.16	-0.13	0.19	1.29	1.78	-2.21	-4.72	-1.05	1.71	-2.21	0.40	-1.10
Volatility	5.95	8.75	13.63	10.98	9.00	13.49	11.71	12.47	8.70	16.27	6.93	12.38	8.70	16.30	6.43
Down. vol.	3.57	5.36	9.73	7.19	5.68	9.64	7.51	8.86	5.53	12.88	5.07	10.47	5.97	14.18	5.96
Down. vol. ratio	0.43	0.44	0.51	0.47	0.45	0.51	0.46	0.50	0.45	0.56	0.52	0.61	0.49	0.63	0.69
CVaR, $\beta = 0.05$	-15.75	-27.95	-45.62	-32.78	-25.83	-45.41	-35.97	-35.83	-21.94	-54.73	-22.87	-39.69	-22.91	-59.45	-30.37
Skewness	0.89	0.82	-0.82	0.37	0.72	-0.79	0.38	-0.17	0.39	-0.20	0.34	-0.69	0.35	-1.21	-1.73
Kurtosis	6.62	9.15	10.72	9.63	7.68	10.85	8.97	3.20	2.93	6.04	7.43	2.83	3.03	5.44	7.43
Realized return															
Last 5 years	0.12	1.03	2.02	0.56	0.26	1.99	1.49	-1.17	0.09	-2.21	-0.74	-0.66	-0.93	-2.48	-0.94
Last 3 years	-0.05	-0.55	0.45	-0.80	-1.12	0.46	0.48	-4.73	2.99	-6.15	-2.37	-2.20	1.22	-4.94	-1.60
Last year	2.62	3.03	2.62	3.30	2.49	3.86	4.52	-11.16	9.38	-4.53	-2.03	0.31	6.79	-1.49	2.23
Mean allocation															
EUR-USD	25.50	26.57	49.48	45.49	34.00	50.15	46.55	100	0	0	33.33	100	0	0	33.33
EUR-GBP	55.87	42.81	34.02	43.27	48.64	35.81	41.32	0	100	0	33.33	0	100	0	33.33
EUR-JPY	18.63	30.61	16.49	11.24	17.36	14.04	12.13	0	0	100	33.33	0	0	100	33.33

Table 19: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=6, DV).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a six-months forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	-2.10	-2.05	-1.02	-1.51	-1.70	-0.82	-0.94	-1.14	-2.40	$-5.43_{7,7}$	-3.00_{7}	-2.41	-0.87	$-6.54_{7,7}$	-3.29_{1}
Omega	0.55	0.59	0.84	0.75	0.68	0.86	0.84	0.85	$0.61_{1,3}$	$0.49_{4,5}$	$0.46_{5,7}$	0.70	0.84	$0.41_{5,6}$	$0.49_{4,5}$
Sharpe ratio	-0.21	-0.19	-0.06	-0.11	-0.14	-0.05	-0.07	-0.07	-0.20	-0.25_{3}	$-0.26_{5,5}$	-0.14	-0.07	$-0.31_{3,4}$	-0.26_{3}
Sortino ratio	-0.25	-0.22	-0.08	-0.13	-0.17	-0.06	-0.08	-0.09	-0.25	-0.28_{2}	$-0.28_{3,5}$	-0.18	-0.09	-0.33_{3}	-0.28_{3}
Median	-1.98	-1.11	0.31	-1.21	-1.22	1.31	0.31	1.10	-3.54	-3.69	-1.60	-1.43	1.15	-3.88	-1.08
Volatility	7.07	7.66	11.37	9.69	8.55	10.88	9.94	12.23	8.40	15.32	8.08	12.14	8.55	15.09	8.98
Down. vol.	6.05	6.76	9.59	8.03	7.19	9.15	8.16	9.45	6.95	13.79	7.62	9.65	6.78	14.37	8.40
Down. vol. ratio	0.61	0.64	0.61	0.60	0.61	0.61	0.59	0.55	0.58	0.65	0.69	0.56	0.57	0.69	0.69
CVaR, $\beta = 0.05$	-27.14	-30.56	-45.89	-35.07	-30.99	-43.10	-36.84	-36.57	-26.64	-56.00	-36.54	-38.33	-26.64	-56.00	-36.54
Skewness	-0.50	-1.00	-1.58	-0.80	-0.77	-1.55	-1.08	-0.25	-0.11	-0.85	-1.56	-0.13	-0.48	-1.04	-1.17
Kurtosis	4.28	4.64	6.97	3.69	3.99	6.79	4.93	3.02	2.79	4.97	6.88	3.02	2.75	4.72	4.77
Realized return															
Last 5 years	-0.66	-0.03	1.98	1.21	0.78	2.02	1.81	-1.34	-0.08	-1.92	-0.76	2.41	2.48	-3.76	0.60
Last 3 years	-0.80	-0.60	0.27	-0.98	-1.67	0.35	0.07	-5.10	2.49	-6.17	-2.66	3.96	4.13	-2.29	2.20
Last year	2.13	3.75	3.10	4.74	2.57	3.61	5.78	-11.07	10.02	-4.50	-1.77	13.38	7.55	-4.87	5.42
Mean allocation															
EUR-USD	27.12	29.65	50.52	47.24	40.57	52.13	49.23	100	0	0	33.33	100	0	0	33.33
EUR-GBP	58.94	53.40	30.93	38.70	45.52	32.68	37.91	0	100	0	33.33	0	100	0	33.33
EUR-JPY	13.94	16.95	18.56	14.06	13.91	15.19	12.85	0	0	100	33.33	0	0	100	33.33

Table 20: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=6, DV).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a six-months forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	-2.18	-1.63	1.18	-0.73	-1.16	1.15	0.00	1.18	$-3.34_{7,7}$	$-4.44_{6,7}$	$-2.20_{3,4}$	-2.02	$-3.21_{4,6}$	0.32	-1.64_{2}
Omega	0.36	0.51	1.28	0.82	0.69	1.28	1.00	1.28	$0.39_{4,6}$	$0.45_{4,4}$	$0.41_{5,5}$	$0.65_{2,3}$	$0.41_{4,5}$	1.06	$0.45_{3,4}$
Sharpe ratio	-0.35	-0.25	0.10	-0.07	-0.13	0.10	0.00	0.10	$-0.40_{5,6}$	$-0.31_{3,4}$	$-0.33_{5,5}$	-0.18_{2}	$-0.38_{5,5}$	0.02	$-0.29_{2,3}$
Sortino ratio	-0.38	-0.29	0.16	-0.10	-0.18	0.16	0.00	0.16	$-0.43_{4,5}$	$-0.35_{2,3}$	$-0.36_{4,5}$	-0.21	$-0.42_{3,4}$	0.03	$-0.33_{2,2}$
Median	-1.87	-1.52	1.19	-0.76	-1.33	1.19	-0.11	1.19	-4.02	-4.30	-2.53	-0.11	-3.93	-0.08	-2.52
Volatility	6.24	6.51	11.55	9.80	9.06	11.54	10.35	11.55	8.32	14.23	6.74	11.43	8.37	14.91	5.58
Down. vol.	5.75	5.68	7.40	7.05	6.55	7.42	7.17	7.40	7.71	12.54	6.08	9.69	7.69	10.36	5.02
Down. vol. ratio	0.64	0.62	0.45	0.51	0.51	0.46	0.49	0.45	0.63	0.61	0.63	0.61	0.63	0.49	0.64
CVaR, $\beta = 0.05$	-18.05	-17.99	-19.54	-20.25	-20.21	-19.54	-19.85	-19.54	-17.52	-33.11	-19.09	-24.92	-17.87	-31.11	-18.65
Skewness	-0.26	-0.42	0.07	0.38	0.64	0.06	0.21	0.07	0.31	0.14	-0.21	-0.32	0.27	-0.07	-0.72
Kurtosis	4.58	4.08	2.33	3.84	4.85	2.34	3.16	2.33	2.48	2.83	4.00	2.10	2.42	2.70	5.58
Realized return															
Last 5 years	-0.40	-0.12	2.79	1.63	0.77	2.78	2.05	2.79	-2.74	-1.59	-0.17	-4.34	-0.30	-4.67	-2.64
Last 3 years	-0.94	-0.29	0.89	0.90	0.43	0.89	0.91	0.89	-3.02	-2.33	-1.08	-6.84	1.46	-10.07	-4.69
Last year	-0.77	-0.53	0.14	0.16	1.22	0.14	0.18	0.14	-3.95	0.76	-0.55	-18.72	7.43	-4.98	-5.25
Mean allocation															
EUR-USD	30.31	28.76	100.00	74.55	55.19	99.69	85.03	100	0	0	33.33	100	0	0	33.33
EUR-GBP	52.39	57.93	0.00	19.82	33.88	0.04	12.02	0	100	0	33.33	0	100	0	33.33
EUR-JPY	17.29	13.32	0.00	5.62	10.93	0.27	2.95	0	0	100	33.33	0	0	100	33.33

Table 21: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=12, DV).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a 12-months forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	-2.86	-2.32	0.01	-1.23	-2.21	-0.18	-0.70	0.53	$-3.89_{7,7}$	$-5.00_{6,7}$	$-2.79_{3,4}$	-1.59	-1.17	-2.57	-1.78
Omega	0.29	0.40	1.00	0.74	0.50	0.96	0.84	1.12	$0.31_{4,4}$	$0.38_{4,4}$	$0.34_{4,5}$	0.71_{2}	0.73_{1}	0.62_{2}	$0.57_{3,3}$
Sharpe ratio	-0.46	-0.36	0.00	-0.12	-0.26	-0.02	-0.07	0.05	$-0.50_{6,6}$	$-0.39_{4,4}$	$-0.42_{5,5}$	-0.14	-0.14	-0.19	-0.23_{1}
Sortino ratio	-0.47	-0.39	0.00	-0.16	-0.33	-0.02	-0.10	0.07	$-0.50_{4,4}$	$-0.42_{2,3}$	$-0.44_{4,4}$	-0.20	-0.17	-0.23	-0.26
Median	-2.74	-2.78	-1.65	-2.87	-2.49	-1.65	-1.94	-0.91	-5.04	-5.25	-3.26	-3.97	-2.02	-2.58	-1.29
Volatility	6.21	6.46	11.27	10.44	8.67	11.06	10.52	11.30	7.78	12.90	6.65	11.20	8.63	13.60	7.78
Down. vol.	6.05	5.92	7.43	7.47	6.80	7.38	7.27	7.28	7.81	11.99	6.33	8.03	6.77	11.07	6.82
Down. vol. ratio	0.66	0.63	0.47	0.50	0.54	0.47	0.49	0.46	0.67	0.64	0.65	0.50	0.56	0.57	0.63
CVaR, $\beta = 0.05$	-16.37	-17.72	-19.37	-19.46	-18.98	-19.37	-19.28	-19.37	-17.01	-29.19	-17.52	-18.62	-16.73	-29.19	-18.98
Skewness	0.18	-0.08	0.35	0.56	0.82	0.38	0.48	0.24	0.29	0.22	0.08	0.64	-0.01	0.05	-0.37
Kurtosis	3.85	3.49	2.49	3.25	4.71	2.65	3.09	2.43	2.38	2.77	3.28	2.82	2.12	2.55	2.40
Realized return															
Last 5 years	-1.01	-1.02	1.51	1.04	-0.09	1.51	1.21	1.51	-2.85	-1.72	-0.69	0.56	2.02	1.46	1.66
Last 3 years	-1.63	-1.52	-1.07	-0.89	-0.96	-1.07	-0.93	-1.07	-3.15	-2.43	-1.81	4.50	4.47	5.18	5.15
Last year	-1.10	-1.47	-0.15	0.41	1.83	-0.15	0.28	-0.15	-4.13	0.68	-0.70	13.90	10.60	-5.00	6.74
Mean allocation															
EUR-USD	27.81	31.21	93.81	80.96	56.54	93.33	86.24	100	0	0	33.33	100	0	0	33.33
EUR-GBP	56.05	58.29	5.15	12.97	35.91	5.53	9.43	0	100	0	33.33	0	100	0	33.33
EUR-JPY	16.14	10.50	1.03	6.07	7.55	1.14	4.33	0	0	100	33.33	0	0	100	33.33

Table 22: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=12, DV).* The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a 12-months forecast horizon, and DV-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	0.16	1.03	0.31	0.49	0.30	0.62	0.86	-0.62	0.99	-2.45_{1}	-0.70_{1}	-2.24	-0.44	-3.28	-1.99_{2}
Omega	1.06	1.32	1.05	1.10	1.08	1.11	1.17	0.91	1.22	$0.74_{2,7}$	0.82_{4}	0.72_{2}	0.91	0.66_{7}	$0.52_{7,7}$
Sharpe ratio	0.02	0.09	0.02	0.03	0.03	0.03	0.05	-0.04	0.08	$-0.11_{1,1}$	-0.08_{1}	-0.13	-0.04	-0.14	-0.22_{7}
Sortino ratio	0.03	0.15	0.02	0.05	0.04	0.04	0.08	-0.05	0.13	$-0.14_{1,1}$	-0.10_{1}	-0.15	-0.05	-0.16	-0.24
Median	-0.70	-0.47	0.37	0.58	0.09	0.37	0.19	1.80	-0.75	-4.06	-1.38	1.71	-2.21	0.40	-1.10
Volatility	5.43	8.53	13.93	10.98	7.98	13.55	11.88	12.47	8.67	16.37	6.51	12.38	8.70	16.30	6.43
Down. vol.	3.59	4.88	10.28	7.32	5.53	9.79	7.70	9.63	5.21	12.57	4.89	10.47	5.97	14.18	5.96
Down. vol. ratio	0.47	0.41	0.53	0.47	0.49	0.51	0.46	0.55	0.43	0.54	0.53	0.61	0.49	0.63	0.69
CVaR, $\beta = 0.05$	-15.65	-25.60	-48.92	-32.45	-24.43	-46.35	-35.68	-37.84	-19.71	-54.73	-22.87	-39.69	-22.91	-59.45	-30.37
Skewness	0.31	1.17	-0.75	0.29	-0.23	-0.62	0.46	-0.40	0.46	-0.27	-0.26	-0.69	0.35	-1.21	-1.73
Kurtosis	4.35	9.69	9.92	8.70	5.14	9.82	8.59	3.12	2.83	5.97	5.91	2.83	3.03	5.44	7.43
Realized return															
Last 5 years	0.09	0.15	-0.05	-0.01	0.36	0.45	0.17	-0.14	0.09	-2.21	-0.39	-0.66	-0.93	-2.48	-0.94
Last 3 years	0.46	-0.77	-1.06	-0.42	-0.63	0.35	0.16	-3.08	2.99	-6.15	-1.79	-2.20	1.22	-4.94	-1.60
Last year	2.06	1.51	-2.15	-0.65	0.90	-0.46	0.62	-11.16	9.38	-4.53	-2.03	0.31	6.79	-1.49	2.23
Mean allocation															
EUR-USD	27.26	26.68	39.18	38.83	33.18	39.50	38.38	100	0	0	33.33	100	0	0	33.33
EUR-GBP	55.16	47.74	47.42	47.55	48.27	48.63	48.81	0	100	0	33.33	0	100	0	33.33
EUR-JPY	17.58	25.58	13.40	13.62	18.55	11.87	12.81	0	0	100	33.33	0	0	100	33.33

Table 23: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=6, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a six-months forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	-0.86	-1.27	-2.55	-1.77	-1.76	-2.19	-1.29	-2.39	0.36	$-5.50_{1,7}$	$-2.52_{1,1}$	-2.41	-0.87	$-6.54_{6,7}$	-3.29_{1}
Omega	0.76	0.69	0.65	0.70	0.64	0.68	0.77	0.70	1.08	0.48_{2}	$0.48_{4,7}$	0.70	0.84	$0.41_{4,7}$	$0.49_{1,3}$
Sharpe ratio	-0.10	-0.13	-0.13	-0.12	-0.15	-0.13	-0.09	-0.14	0.03	-0.26	-0.26_{2}	-0.14	-0.07	-0.31_{1}	-0.26
Sortino ratio	-0.13	-0.16	-0.16	-0.14	-0.17	-0.15	-0.11	-0.17	0.05	-0.29	-0.28	-0.18	-0.09	-0.33	-0.28
Median	-1.64	-0.32	-2.72	-1.43	-1.86	-2.34	-1.89	-1.40	-1.42	-5.44	-1.56	-1.43	1.15	-3.88	-1.08
Volatility	6.00	6.85	13.50	10.47	8.19	12.16	10.16	12.14	8.57	15.31	6.97	12.14	8.55	15.09	8.98
Down. vol.	4.73	5.69	11.50	9.05	7.20	10.37	8.36	10.04	5.49	13.71	6.36	9.65	6.78	14.37	8.40
Down. vol. ratio	0.56	0.60	0.62	0.63	0.64	0.62	0.59	0.59	0.46	0.64	0.66	0.56	0.57	0.69	0.69
CVaR, $\beta = 0.05$	-22.23	-26.04	-56.00	-45.36	-35.09	-49.41	-39.57	-38.33	-20.93	-56.00	-30.69	-38.33	-26.64	-56.00	-36.54
Skewness	-0.61	-1.07	-1.44	-1.81	-1.93	-1.26	-1.36	-0.45	0.39	-0.80	-1.04	-0.13	-0.48	-1.04	-1.17
Kurtosis	5.34	7.25	8.14	8.94	10.42	6.23	7.90	2.84	2.84	5.02	5.14	3.02	2.75	4.72	4.77
Realized return															
Last 5 years	-0.23	-0.54	-0.48	0.40	-0.22	-0.48	0.12	-0.24	-0.11	-2.55	-0.62	2.41	2.48	-3.76	0.60
Last 3 years	0.29	-0.71	-1.26	0.51	-0.75	-0.31	0.50	-3.02	2.76	-6.56	-2.00	3.96	4.13	-2.29	2.20
Last year	2.23	-1.47	3.10	3.70	2.49	3.36	2.91	-11.07	10.02	-4.50	-1.77	13.38	7.55	-4.87	5.42
Mean allocation															
EUR-USD	26.50	26.32	24.74	28.87	26.92	29.00	29.97	100	0	0	33.33	100	0	0	33.33
EUR-GBP	55.76	52.73	45.36	46.47	50.70	47.07	48.07	0	100	0	33.33	0	100	0	33.33
EUR-JPY	17.74	20.95	29.90	24.66	22.38	23.93	21.96	0	0	100	33.33	0	0	100	33.33

Table 24: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=6, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a six-months forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β	linear	LLA, λ		QLA, λ		EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD	EUR-GBP	EUR-JPY	EW
		0.05		1.25	5.00	1.25	5.00					RW	RW	RW	RW
Mean	-1.86	-1.13	-0.08	-0.82	-0.83	-0.19	-0.56	0.84	-2.33_{1}	$-4.44_{7,7}$	-1.98_{4}	-2.02	$-3.21_{6,7}$	0.32	-1.64
Omega	0.44	0.63	0.98	0.78	0.77	0.96	0.86	1.19	$0.53_{2,3}$	$0.45_{3,4}$	$0.46_{6,6}$	0.65	$0.41_{6,6}$	1.06	$0.45_{3,4}$
Sharpe ratio	-0.29	-0.17	-0.01	-0.09	-0.09	-0.02	-0.06	0.07	-0.27_{2}	$-0.31_{1,4}$	$-0.29_{5,6}$	-0.18	$-0.38_{5,6}$	0.02	-0.29
Sortino ratio	-0.33	-0.21	-0.01	-0.12	-0.13	-0.03	-0.08	0.11	-0.31	-0.35_{1}	$-0.33_{2,5}$	-0.21	$-0.42_{1,6}$	0.03	-0.33
Median	-1.38	-0.64	-0.76	-0.63	-1.10	-0.76	-0.76	-0.34	-3.15	-4.30	-2.11	-0.11	-3.93	-0.08	-2.52
Volatility	6.35	6.61	11.23	9.44	8.93	10.78	9.74	11.58	8.66	14.23	6.76	11.43	8.37	14.91	5.58
Down. vol.	5.63	5.50	7.60	6.70	6.29	7.34	6.78	7.46	7.45	12.54	5.96	9.69	7.69	10.36	5.02
Down. vol. ratio	0.62	0.59	0.48	0.50	0.50	0.48	0.49	0.46	0.60	0.61	0.62	0.61	0.63	0.49	0.64
CVaR, $\beta = 0.05$	-18.11	-17.57	-19.54	-20.25	-19.90	-19.54	-19.80	-19.54	-17.52	-33.11	-19.09	-24.92	-17.87	-31.11	-18.65
Skewness	-0.25	-0.46	0.30	0.51	0.58	0.34	0.45	0.15	0.10	0.14	-0.21	-0.32	0.27	-0.07	-0.72
Kurtosis	4.40	4.03	2.56	4.31	4.67	2.85	3.84	2.32	2.21	2.83	3.88	2.10	2.42	2.70	5.58
Realized return															
Last 5 years	-0.59	-0.52	0.89	0.36	0.38	0.54	0.47	2.22	-2.74	-1.59	-0.36	-4.34	-0.30	-4.67	-2.64
Last 3 years	-1.30	-1.23	-0.11	-0.11	-0.05	-0.11	-0.05	-0.11	-3.02	-2.33	-1.41	-6.84	1.46	-10.07	-4.69
Last year	-0.91	-1.16	0.14	0.16	1.77	0.14	0.34	0.14	-3.95	0.76	-0.55	-18.72	7.43	-4.98	-5.25
Mean allocation															
EUR-USD	30.69	28.39	86.60	66.69	54.00	81.54	73.43	100	0	0	33.33	100	0	0	33.33
EUR-GBP	51.59	58.54	13.40	29.69	36.99	18.44	23.71	0	100	0	33.33	0	100	0	33.33
EUR-JPY	17.72	13.07	0.00	3.62	9.01	0.02	2.85	0	0	100	33.33	0	0	100	33.33

Table 25: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS1, h=12, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 1, a 12-months forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.

	MV	CVaR, β 0.05	linear	LLA, λ 1.25	LLA, λ 5.00	QLA, λ 1.25	QLA, λ 5.00	EUR-USD	EUR-GBP	EUR-JPY	EW	EUR-USD RW	EUR-GBP RW	EUR-JPY RW	EW RW
Mean	-2.04	-1.80	0.43	-0.56	-1.14	0.21	-0.35	1.35	$-3.40_{7,7}$	$-5.31_{7,7}$	$-2.45_{4,5}$	-1.59	-1.17	-2.57	-1.78
Omega	0.44	0.52	1.10	0.87	0.72	1.05	0.92	1.34	$0.37_{6,6}$	$0.35_{5,5}$	$0.38_{6,6}$	$0.71_{2,2}$	$0.73_{2,2}$	$0.62_{2,2}$	$0.57_{4,4}$
Sharpe ratio	-0.31	-0.25	0.04	-0.05	-0.12	0.02	-0.03	0.12	$-0.42_{7,7}$	$-0.42_{5,5}$	$-0.37_{5,6}$	-0.14	-0.14	-0.19	-0.23_{2}
Sortino ratio	-0.35	-0.30	0.05	-0.08	-0.17	0.03	-0.05	0.19	$-0.45_{5,7}$	$-0.43_{4,4}$	$-0.41_{5,5}$	-0.20	-0.17	-0.23	-0.26_{2}
Median	-1.79	-2.23	0.98	-0.56	-1.18	0.78	-0.81	1.50	-4.83	-5.25	-2.37	-3.97	-2.02	-2.58	-1.29
Volatility	6.62	7.19	11.96	10.46	9.57	11.11	10.64	11.23	8.01	12.77	6.57	11.20	8.63	13.60	7.78
Down. vol.	5.80	5.98	8.23	7.21	6.72	7.53	7.33	7.13	7.58	12.31	6.05	8.03	6.77	11.07	6.82
Down. vol. ratio	0.61	0.58	0.49	0.49	0.50	0.48	0.49	0.45	0.64	0.67	0.63	0.50	0.56	0.57	0.63
CVaR, $\beta = 0.05$	-16.30	-17.18	-25.03	-20.03	-18.55	-22.14	-20.50	-19.37	-16.90	-29.50	-17.52	-18.62	-16.73	-29.19	-18.98
Skewness	0.14	0.19	-0.04	0.47	0.76	0.15	0.34	0.05	0.34	0.00	0.06	0.64	-0.01	0.05	-0.37
Kurtosis	3.56	3.36	2.89	3.19	4.09	2.99	3.10	2.44	2.47	2.42	3.49	2.82	2.12	2.55	2.40
Realized return															
Last 5 years	-0.04	0.09	2.78	2.32	1.50	2.78	2.44	2.78	-1.58	-5.52	-1.12	0.56	2.02	1.46	1.66
Last 3 years	-0.34	0.04	0.99	1.14	1.11	0.99	0.88	0.99	-1.03	-9.35	-2.76	4.50	4.47	5.18	5.15
Last year	2.16	2.77	-0.15	0.38	2.30	-0.15	0.30	-0.15	2.73	-3.24	0.30	13.90	10.60	-5.00	6.74
Mean allocation															
EUR-USD	31.10	34.80	79.38	75.24	61.35	84.25	80.36	100	0	0	33.33	100	0	0	33.33
EUR-GBP	55.49	53.30	4.12	11.84	23.91	5.20	9.24	0	100	0	33.33	0	100	0	33.33
EUR-JPY	13.42	11.91	16.49	12.92	14.74	10.55	10.39	0	0	100	33.33	0	0	100	33.33

Table 26: *Optimal currency portfolios: Out-of-sample evaluation and comparison with benchmark portfolios (TS2, h=12, return).*
The table reports statistics of a monthly reallocated optimal currency portfolio and mean optimal weights, based on an optimization period of 36 months (rolling window), trading strategy 2, a 12-months forecast horizon, and return-based composite forecasts with respect to the period of the last 12 months. The evaluation period covers January 2008 to January 2016. Statistics are calculated on the basis of monthly returns and then annualized assuming discrete compounding. The same statistics are reported for the benchmark portfolios based on composite forecasts (i.e., the single assets of which the portfolios are constructed and the equally weighted portfolio) and for the benchmark portfolios based on the random walk. The sub-indices show the results of the bootstrap test. Their values indicate how many optimal portfolios outperform (in terms of the respective performance measure) that specific benchmark portfolio. If no sub-index is present, the benchmark portfolio is not outperformed by any of the optimal portfolios. If there is only one sub-index, its value indicates the number of optimal portfolios outperforming the benchmark portfolio at the 10% significance level. In the case of two sub-indices, the first one indicates the number of optimal portfolios outperforming the benchmark portfolio at the 5% significance level and the second one at the 10% significance level.