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The Role of Technical Indicators in Exchange Rate Forecasting

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Abstract

Forecasting exchange rates is a subject of wide interest to both academics and practitioners. We aim at contributing to this vivid research area by highlighting the role of both technical indicators and macroeconomic predictors in forecasting exchange rates. Employing monthly data ranging from January 1974 to December 2014 for six widely traded currencies, we show that both types of predictors provide valuable information about future currency movements. To efficiently summarise the information content in candidate predictors, we extract the principal components of each group of predictors. Our findings suggest that combining information from both technical indicators and macroeconomic variables significantly improves and stabilises exchange rate forecasts versus using either type of information alone.

JEL classification: C53, C58, F31, G17

Keywords: exchange rate predictability; principal components; forecast combination; technical indicators; macroeconomic fundamentals

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*Highlights (for review)

Highlights

- We highlight the role of both technical indicators and macroeconomic predictors in forecasting exchange rates.
- We show that both types of predictors provide valuable information about future currency movements.
- We employ principal components and combination forecasting techniques.
- Our strategy significantly improves and stabilises exchange rate forecasts.

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Forecasting exchange rates is a subject of wide interest to both academics and practitioners. We aim at contributing to this vivid research area by highlighting the role of both technical indicators and macroeconomic predictors in forecasting exchange rates. Employing monthly data ranging from January 1974 to December 2014 for six widely traded currencies, we show that both types of predictors provide valuable information about future currency movements. To efficiently summarise the information content in candidate predictors, we extract the principal components of each group of predictors. Our findings suggest that combining information from both technical indicators and macroeconomic variables significantly improves and stabilises exchange rate forecasts versus using either type of information alone.

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1 Introduction

Exchange rate forecasting is one of the most fascinating and academically vivid research areas. The large number of currency crises during the past years have stimulated and challenged the existing academic literature. Numerous researchers tried to answer the generic question "Can exchange rates be predicted and under what assumptions?" This question led to a continuous effort for identification of deterministic relationships, primarily between economic fundamentals and exchange rates. In a very influential paper, Meese and Rogoff (1983) claim that structural models cannot outperform the random walk model, giving rise to the disconnect puzzle of exchange rates from fundamentals.

Rossi (2013) provides a comprehensive literature review on exchange rate forecasting showing that the choice of predictors is important for a good forecast, along with the type of the forecasting models and the evaluation methods employed, concluding that none of the predictors, models, or tests systematically produce superior exchange rate forecasts across all countries and time periods. Mark (1995) and more recently Chen and Chou (2010) claim that exchange rates can be predicted in the long run, in contrast to Molodtsova and Papell (2009), who find mixed evidence of exchange rate predictability dependent on the predictor under consideration. Engel, Mark and West (2008) adopt an interesting approach focusing on the impact of expectations of fundamentals and find that expectations of future monetary conditions play an important role in determining current exchange rates. A stream of the literature focuses on capturing non-linearities in the predictive models and employ methodologies such as neural networks (see Sermpinis, Stasinakis and Dunis, 2014; Gradojevic, 2007; Preminger and Franck, 2007; Qi and Wu, 2003; Kuan and Liu, 1995), genetic programming (see Sermpinis, Stasinakis, Theofilatos and Karathanasopoulos, 2015), markov switching models (see Panopoulou and Pantelidis, 2015; Dunis, Laws and Sermpinis, 2011; Dueker and Neely, 2007; Engel, 1994), nearest neighbor regressions (see Gencay, 1999) etc. However, linear models tend to outperform non linear ones in general (Rossi, 2013). More recent approaches aiming at capturing uncertainty and time-varying predictability in a Bayesian framework deliver encouraging results (see Byrne, Korobilis and Ribeiro, 2016, 2018).

Apart from macroeconomic predictors stemming from exchange rate fundamentals, technical indicators are an additional tool mainly used by professionals. Despite the fact that many technical indicators have been in use for more years than the most prominent macroeconomic models (Brock, Lakonishok and LeBaron, 1992; Neely and Weeler, 2011; Park and Irwin, 2007), academia has paid little attention. Gehrig and Menkhoff (2006) suggest that both technical analysis and order flow analysis have gained ground during the last decades at the expense of fundamentals. As a matter of fact, this relatively new forecasting approach has been reported to produce significant statistical and economic gains when applied to equity, bond and exchange rate markets (Buncic and Piras, 2016; Lin, 2018; Neely, Rapach, Tu and Zhou, 2014; Goh, Jiang, Tu and Zhou, 2013; Neely and Weller, 2011; Neely, Weller and Ulrich, 2009; De Zwart, Markwat, Swinkels, van Dijk, 2009; Park and Irwin, 2007), but with unstable performance over time (Olson, 2004; De Zwart, Markwat, Swinkels and van Dijk, 2009).[1] A recent comprehensive review including numerous technical indicators over a large period of time by Hsu, Taylor and Wang (2016) provides evidence of their performance in both developed and emerging markets. The authors find that technical indicators exploit irrationalities in the financial markets; hence, they are able to generate statistically significant and profitable strategies. In addition, the authors argue that more volatile currencies are able to deliver equally profitable excess returns to less volatile ones, if the latter are subject to leverage. In a similar manner, Zarrabi, Snaith and Coakley (2017) employ 7,650 rules on six widely traded currencies and find that there are profitable opportunities, which do not persist over time as the performance of technical trading rules fluctuates throughout the sample. Their findings support Lo's (2004) adaptive market hypothesis more than the efficient markets hypothesis.

Theoretical support in favor of the technical indicators grew recently based on the following arguments. First, due to the difference in the response timing of the investors (Han, Zhou and Zhu, 2016), it takes time for the prices to adjust to their efficient level (Lo, 2004). For example, during the recent crisis, the stock market was trending downwards for almost two years before reaching the bottom. Second, investors are not always rational and are subject to cognitive biases, rules of thumb, herding behavior and overconfidence. These irrationalities create or maintain ongoing trends and momentums (Daniel, Hirshleifer and Subrahmanyam, 1998). Third, information is expensive and not presumably available to all, leading to heterogeneity among traders and deviations from implied efficient market prices. Fourth, technical analysis can be viewed as a method of learning (Menkhoff and Taylor, 2007) rather than chaotic behavior, given its popularity among practitioners (Menkhoff, 2010). Fifth, technical analysis is so popular among practitioners that creates observed self-fulfilling outcomes (see among others Menkhoff, 2010; Neely, Weller and Ulricht, 2009; Menkhoff and Taylor, 2007; Cheung and Chinn, 2001 and Taylor and Allen, 1992). Large scale trades, based on signals, distort prices from the efficient level, making fundamentals lose predictive ability. Finally, exchange rates are affected by Central Banks' interventions (Charles, Darné and Kim, 2012). LeBaron (1999) and Silber (1994) find a positive correlation between central bank intervention and profitability of technical analysis. Such interventions are able to create trends or alter expectations on fundamentals. Menkhoff and Taylor (2007) claim that interventions distort markets and technical traders profit from this "inefficiency". Reitz and Taylor (2008) give a different perspective by arguing in favor of a coordination channel from central banks to restore exchange rates when departing from their fundamental values.

In this paper, we use monthly data from January 1974 to December 2014 in order to construct forecasts for six widely traded currencies; namely the British Sterling, Japanese Yen, Norwegian Krone, Swiss Franc, Australian Dollar and Canadian Dollar. The base currency is the US

[1] Early contributions to the field include Taylor and Allen (1992) and Cheung and Chinn (2001) among others.

Dollar, which is fairly standard in the literature. Our set of predictors includes both the most widely used macroeconomic (fundamental) predictors and technical indicators. Fundamental predictors stem from the Uncovered Interest Rate Parity, Purchasing Power Parity, Monetary fundamentals and Taylor rules.[2] The technical indicators we employ are also the most widely employed in both academia and industry. These are simple moving average, momentum, relative strength index and exponential moving average rules. Following the literature we employ the Random Walk (RW) model as benchmark and evaluate the performance by the out-of-sample R^2 statistic and the MSFE-adjusted statistic (Clark and West, 2007).

The contribution of this paper to the exchange rate forecasting literature is that it brings together and evaluates the information that can be extracted from the most commonly used macroeconomic predictors and that of technical indicators on a monthly basis over an extensive period of time. In addition, it provides a comparative analysis of the two groups of predictors and the respective combined forecasts and principal components extracted from each group. In order to get a better insight on the sources of predictability, we check the performance over time with the use of the cumulative difference between the mean squared forecast errors of the random walk model and the candidate predictive model, identifying certain time periods when the rivals fail to outperform the benchmark. Interestingly, these periods seem to be closely connected to key developments in exchange rate markets. Our findings suggest that combining information from both technical indicators and macroeconomic variables (amalgam forecasts) significantly improves and stabilizes exchange rate forecasts versus using either type of information alone. Following, among others Abhyankar, Sarno and Valente (2005), Della Corte, Sarno and Tsiakas (2009), Della Corte and Tsiakas (2012); Li, Tsiakas and Wang (2015); Ahmed, Liu and Valente (2016), we assess the economic value of our forecasting strategy for two levels of risk aversion and find that our amalgam forecasts deliver sustainable economic benefits in comparison to their rivals, consistent with the statistical evaluation. Finally, we test whether our findings remain robust by changing the evaluation period, forecast horizon and extending the number of currencies by considering additional developed and emerging countries.

The remainder of the paper is organized as follows. In Section 2 we present the candidate predictors. The first part of the section is related to macroeconomic/ fundamental predictors and the second to technical indicators. Section 3 presents the predictive models, the forecast construction and the evaluation methods. In Section 4 we report the out-of-sample statistical evaluation findings, while Section 5 outlines our economic evaluation framework and results. Section 6 presents the robustness tests and Section 7 concludes the paper.

[2] For a coherent approach on Taylor rules, see among others Orphanides, 2003 and 2008; Molodtsova and Papell, 2009; Byrne, Korobilis and Ribeiro, 2016 and 2018.

2 Candidate predictors

2.1 Fundamental predictors

Following the literature that links exchange rates with macroeconomic fundamentals (Engel and West, 2005; Molodtsova and Papell, 2009, 2012; Byrne, Korobilis and Ribeiro, 2016), we employ 13 predictors, denoted by $x_{i,t}$, $i = 1, .., 13$. We briefly describe them below.

1. The first candidate predictor is given by the uncovered Interest Rate Parity (IRP) as follows:

$$x_{1,t} = i_t - i_t^* \tag{1}$$

where i_t is the nominal interest rate in the domestic country and i_t^* denotes the nominal interest rate for the foreign country.[3]

2. The second predictor is given by the deviation of the nominal exchange rate from the Purchasing Power Parity (PPP) condition:

$$x_{2,t} = p_t - p_t^* - s_t \tag{2}$$

where p_t (p_t^*) is the logarithm of domestic (foreign) national price levels and s_t is the logarithm of the nominal exchange rate.

3. The third predictor relates to the flexible price version of the monetary model, known as Frenkel-Bilson (FB) model (Meese and Rogoff, 1983). Under the assumption that PPP holds, the FB predictor is as follows:

$$x_{3,t} = a(m_t - m_t^*) - b(y_t - y_t^*) + c(i_t - i_t^*) - s_t \tag{3}$$

where m_t (m_t^*) is the log of the domestic (foreign) money supply, y_t (y_t^*) is the log of the domestic (foreign) real output, proxied by the Industrial Production Index (IPI) and s_t is the log of the nominal exchange rate. Due to first degree homogeneity of relative money supply, the parameter $a = 1$ (see Meese and Rogoff, 1983; Mark and Sul, 2001; Rapach and Wohar, 2002; Rossi, 2013). We further assume that the income elasticity of money demand and the interest rate semi-elasticity are 1, thus $b = c = 1$.

4. Under the assumption that both PPP and IRP hold, we get the basic form of the monetary model, denoted as BMF:[4]

$$x_{4,t} = a(m_t - m_t^*) - b(y_t - y_t^*) - s_t \tag{4}$$

[3] In what follows, "*" denotes the variable in the foreign country.
[4] For a more detailed discussion, see Rapach and Wohar, 2002.

where a and b are also assumed to be equal to 1.

Candidate predictors x_5 to x_{13} are all Taylor rule variants (Taylor, 1993). Taylor rules unveil the mechanism with which each central bank determines the short-term nominal interest rate by taking into account variables, such as the inflation rate, the target inflation rate and the percentage deviation of actual real GDP from an estimate of its potential level. Assuming that both the domestic and the foreign central bank employs a Taylor rule and IRP holds, the general form of our Taylor rule predictors is given by the respective differences of short-term interest rates, as follows:

$$x_t = i_t - i_t^* = a_0 + a_1\pi_t - a_1^*\pi_t^* + a_2 g_t - a_2^* g_t^* + a_3 e_t + a_4 i_{t-1} - a_4^* i_{t-1}^* + \eta_t \tag{5}$$

where π_t (π_t^*) is the domestic (foreign) inflation rate, g_t (g_t^*) is the domestic (foreign) output gap, e_t is the real exchange rate, i.e. $e_t = s_t - p_t + p_t^*$, and η_t is the error term. The output gap is measured as the (percentage) deviation of real output from an estimate of its potential level and is computed with the use of the Hodrick-Prescott filter. At each point of the out-of-sample period, equation (5) is re-estimated to give the predictor (in general form) as follows:

$$x_t = \hat{\varphi}_0 + \hat{\varphi}_1\pi_t - \hat{\varphi}_1^*\pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2^* g_t^* + \hat{\varphi}_3 e_t + \hat{\varphi}_4 i_{t-1} - \hat{\varphi}_4^* i_{t-1}^* \tag{6}$$

Several specifications, nested in equation (6), give rise to our predictors.[5] First, Taylor rules can be homogeneous or heterogeneous depending on the response of central Banks to deviations from inflation rate, output gap and interest rate targets. If $\hat{\varphi}_1 = \hat{\varphi}_1^*$, $\hat{\varphi}_2 = \hat{\varphi}_2^*$, $\hat{\varphi}_4 = \hat{\varphi}_4^*$, the rule is homogeneous, otherwise, the rule is heterogeneous. Second, Central Banks may want to avoid abrupt changes in the level of interest rates and choose to follow a smoothing interest rate adjustment policy, i.e. $\hat{\varphi}_4 \neq 0$ and $\hat{\varphi}_4^* \neq 0$. Finally, if Central Banks do not take into account possible deviations of the real exchange rate from its targeted level, so that $\hat{\varphi}_3 = 0$, the specification is called symmetric ($\hat{\varphi}_3 \neq 0$ for asymmetric). Specifically, we employ the following predictors:

5. the homogeneous asymmetric Taylor rule without interest rate smoothing and fixed weights (HOAfw):

$$x_{5,t} = \hat{\varphi}_1(\pi_t - \pi_t^*) + \hat{\varphi}_2(g_t - g_t^*) + \hat{\varphi}_3 e_t \tag{7}$$

   The parameters $[\hat{\varphi}_1, \hat{\varphi}_2, \hat{\varphi}_3]$ are set equal to $[1.5, 0.1, 0.1]$ (Engel, Mark and West, 2008; Chen and Chou, 2010; Beckmann and Schüssler, 2016; Della Corte and Tsiakas, 2012).

6. the homogeneous symmetric Taylor rule without interest rate smoothing (HOS):

$$x_{6,t} = \hat{\varphi}_1(\pi_t - \pi_t^*) + \hat{\varphi}_2(g_t - g_t^*)$$

[5] For a detailed discussion on Taylor rules, see Molodtsova and Papell (2009, 2012).

7. the homogeneous symmetric Taylor rule with interest rate smoothing (HOSS):

$$x_{7,t} = \hat{\varphi}_1 (\pi_t - \pi_t^*) + \hat{\varphi}_2 (g_t - g_t^*) + \hat{\varphi}_4 (i_{t-1} - i_{t-1}^*) \tag{8}$$

8. the homogeneous asymmetric Taylor rule without interest rate smoothing (HOA):

$$x_{8,t} = \hat{\varphi}_1 (\pi_t - \pi_t^*) + \hat{\varphi}_2 (g_t - g_t^*) + \hat{\varphi}_3 e_t \tag{9}$$

9. the homogeneous asymmetric Taylor rule with interest rate smoothing (HOAS):

$$x_{9,t} = \hat{\varphi}_1 (\pi_t - \pi_t^*) + \hat{\varphi}_2 (g_t - g_t^*) + \hat{\varphi}_3 e_t + \hat{\varphi}_4 (i_{t-1} - i_{t-1}^*) \tag{10}$$

10. the heterogeneous symmetric Taylor rule without interest rate smoothing (HES):

$$x_{10,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* \tag{11}$$

11. the heterogeneous symmetric Taylor rule with interest rate smoothing (HESS):

$$x_{11,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* + \hat{\varphi}_4 i_{t-1} - \hat{\varphi}_4^* i_{t-1}^* \tag{12}$$

12. the heterogeneous asymmetric Taylor rule without interest rate smoothing (HEA):

$$x_{12,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* + \hat{\varphi}_3 e_t \tag{13}$$

13. the heterogeneous asymmetric Taylor rule with interest rate smoothing (HEAS):

$$x_{13,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* + \hat{\varphi}_3 e_t + \hat{\varphi}_4 i_{t-1} - \hat{\varphi}_4^* i_{t-1}^* \tag{14}$$

2.2 Technical Indicators

Technical rules can be split into two broad categories; charting and mechanical methods. Charting is the oldest method of the two and relies on graphs of historical prices over a specific time period. Chartists use subjective criteria to understand and identify patterns in spot prices. On the other hand, mechanical rules, which are the focus of our study, generate buy/sell signals based on simple or more complex mathematical functions of past and current data. We employ a few well-known mechanical rules, such as moving average rules, momentum indicators and relative strength indices.[6] Moving average rules and momentum indicators signal a directional

[6] For a comprehensive review of technical indicators see Zarrabi, Snaith and Coakley (2017), Nazário, Silva, Sobreiro and Kimura, (2017) and Hsu, Taylor and Wang (2016).

change subject to past prices, while relative strength indices take into account both the velocity and magnitude of directional price movements.

More in detail, we employ eleven technical indicators based on four simple and widely used trend following rules. The first rule is a moving-average (MA) rule that generates buying and selling signals comparing the moving averages of a long period with a short period. This rule is formed as follows:

$$x_{i,t} = \left\{ \begin{array}{c} 1 \; if \; MA_{s,t} \succeq MA_{l,t} \\ 0 \; if \; MA_{s,t} \prec MA_{l,t} \end{array} \right\}, MA_{j,t} = (1/j) \sum_{i=0}^{j-1} S_{t-i} \; for \; j = s, l$$

where S_t is the spot exchange rate and s, l denote the short and long period, respectively. The MA rule aims at identified changes in spot price trends. By construction, the indicator shifts more rapidly when it is created in the short-run, as recent price changes have comparatively more weight. For example, if during one period prices increase, then MA_s gets a faster upward trend and if it exceeds (crosses) MA_l, it creates a buy signal, and vice versa. We consider s equal to [1,2,3] months and l equal to [9,12] months and denote the related rule by $MA(s, l)$.

The second rule we apply is the momentum (MOM) technical indicator (see, for example, Buncic and Piras, 2016 and Neely, Rapach, Tu and Zhou, 2014). The signal is generated according to the relationship of current prices with the past prices, as follows:

$$x_{i,t} = \left\{ \begin{array}{c} 1 \; if \; S_t \succeq S_{t-k} \\ 0 \; if \; S_t \prec S_{t-k} \end{array} \right\}$$

If current prices are higher than k periods before, then a buy signal is generated, and vice versa. We set the k month lag equal to [9,12] and denote the related predictors by $MOM(k)$.

The third rule is the Relative Strength Index (RSI).[7] This rule is a momentum oscillator that measures the speed and change of price movements by taking into account the magnitude of recent gains or losses. It takes values between 0 to 100 and is given by the following formula:

$$x_{i,t} = 100 - \frac{100}{1 + \frac{MA_t^{(n)}(dc_t)}{MA_t^{(n)}(uc_t)}}$$

where $MA_t^{(n)}$ denotes the n-period Moving Average of upclose or downclose measures, defined as:

$$uc_t = \left\{ \begin{array}{cc} \Delta S_t \; if \; \Delta S_t > 0 \\ 0 \quad otherwise \end{array} \right\} \text{ and } dc_t = \left\{ \begin{array}{cc} -\Delta S_t \; if \; \Delta S_t < 0 \\ 0 \quad otherwise \end{array} \right\}$$

The higher the value of the index, the more intense the signal is regarding the presence of overbought conditions in the market, and vice versa. We employ two versions of the index for

[7] See, for example, Buncic and Piras, 2016.

$n = [7, 14]$, i.e. 7 and 14 months.

The last rule we apply is the Exponential Moving Average (EMA). This rule gives more weight on the more recent observations and as a result it responds faster in recent changes. The signals are generated by comparing the EMA of a long period with that of a short period, similar to the case of the simple MA, i.e.

$$x_{i,t} = \left\{ \begin{array}{l} 1 \; if \; EMA_{s,t} \succeq EMA_{l,t} \\ 0 \; if \; EMA_{s,t} \prec EMA_{l,t} \end{array} \right\}, EMA_t = (S_t - EMA_{t-1}) * m + EMA_{t-1}$$

where m is a weighting multiplier, or else an accelerator, given by $m = \frac{2}{j+1}$where $j = s, l$. The $EMA(s, l)$ rule we employ sets $s = 5$ and $l = 12$.

3 Predictive Models, Forecast Construction and Evaluation

In this section, we describe the forecasting approaches we follow. One step ahead forecasts are generated by continuously updating the estimation window, i.e. following a recursive (expanding) window.[8] More specifically, we divide the total sample of T observations into an in-sample portion of the first M observations and an out-of-sample portion of $P = T - M$ observations used for forecasting. The estimation window is continuously updated following a recursive scheme, by adding one observation to the estimation sample at each step. Proceeding in this way through the end of the out-of-sample period, we generate a series of P out-of-sample forecasts for the exchange rates returns.

3.1 Univariate models

Our empirical analysis is based on the simple linear predictive model:

$$\Delta s_{i,t+1} = a_i + \beta_i \Delta x_{i,t} + u_{i,t+1} \tag{15}$$

where $\Delta s_{i,t+1}$ is the 1-month log return of the exchange rate, $\Delta x_{i,t}$ are the candidate predictors i, in first differences, with $i = 1, ..., 13$ for macroeconomic predictors and $i = 14, ..., 24$ for technical indicators, a_i, β_i are constants to be estimated and $u_{i,t+1}$ is the error term. Typically, equation (15) is estimated by least squares at each point of the out-of-sample period giving one-month ahead forecasts as follows;

$$\Delta \hat{s}_{i,t+1} = \hat{a}_i + \hat{b}_i \Delta x_{i,t} \tag{16}$$

[8] In the robustness section we also include different out-of-sample periods and alternative forecast horizons.

3.2 Principal Component models

In order to incorporate information from multiple variables/predictors, we estimate predictive regressions based on principal components. Extracting principal components is a simple technique that summarizes and extracts information from a large group of variables and at the same time reduces dimensionality. Via principal components, our set of predictors $\Delta \mathbf{x}_t = (\Delta x_{1,t}, ..., \Delta x_{N,t})$ are transformed to new uncorrelated variables, $\hat{F}_t^j = (\hat{F}_{1,t}^j, ..., \hat{F}_{N,t}^j)$. We consider three pools of predictors, $j = ECON, TECH, ALL$, for macroeconomic/ fundamental predictors, technical indicators or the entire set of predictors taken together, respectively. In practice, we need to take into account the first few K principal components which incorporate most of the predictors' information. To this end, at each point of the out-of-sample period, we select the optimal number of components (K) via the Schwarz Information Criterion (SIC).[9] The monthly out-of-sample forecasts of principal component models extracted from the j-th pool of predictors are denoted as $PC - ECON, PC - TECH$ and $PC - ALL$ and are given by the following equation:

$$\Delta \hat{s}_{t+1}^{(j)} = \hat{a} + \sum_{k=1}^{K} \hat{b}_k \hat{F}_{k,t}^{(j)} \qquad for\ j = ECON, TECH, ALL \tag{17}$$

where $\hat{F}_{k,t}^{(j)}$ is the k-th principal component of the j-th pool of predictors recursively estimated until time t, $\hat{a}$ and $\hat{b}_k$ are constants estimated via least squares and K is the SIC-selected number of principal components.

3.3 Combined Forecasts

Another popular approach aiming at reducing model uncertainty and efficiently incorporating information from a large set of potential predictors is forecast combination (see, inter alia, Timmermann, 2006; De Zwart, Markwat, Swinkels and van Dijk, 2009; Rapach, Strauss and Zhou, 2010; Beckmann and Schüssler, 2016; Buncic and Piras, 2016). We employ the simplest combination scheme proposed in the literature, namely the naive equally weighted one and employ it for the three sets of predictors considered. Specifically, the combination forecasts are given by the following formula;

$$\Delta \hat{s}_{t+1}^{(j)} = \sum_{i=1}^{N_j} \frac{1}{N_j} \Delta \hat{s}_{i,t+1}^{(j)} \qquad for\ j = ECON, TECH, ALL \tag{18}$$

where $\Delta \hat{s}_{t+1}^{(j)}$ is the combined forecast of the respective group j, N_j is the number of predictors included in group j ($N_{ECON} = 13$, $N_{TECH} = 11$ and $N_{ALL} = 24$) and $\Delta \hat{s}_{i,t+1}^{(j)}$ is the forecast

[9] For alternative ways of principal components' selection, see Bai and Ng (2002). Neely, Rapach, Tu and Zhou (2014) select K via the adjusted R^2.

computed from predictor i that belongs to the group j. We refer to these forecasts as $POOL-j$.

Finally, we create an amalgamation of forecasts (see Rapach and Strauss, 2012; Meligkotsidou, Panopoulou, Vrontos and Vrontos, 2014). Specifically, we combine the $POOL-ALL$ and $PC-ALL$ forecasts computed from the forecast combination and principal component approaches under a naive combination scheme and form a new forecast, $FC-AMALG$. This forecasting strategy can prove beneficial in the event that information contained in the two forecasting approaches is discrete.[10]

3.4 Statistical evaluation

We evaluate the forecasting ability of our proposed models/ specifications by comparing their forecasting performance relative to the random walk (RW) model, which sets $\beta_i = 0$ in equation (15). This model is the standard benchmark in the literature on exchange rate predictability since the seminal work of Meese and Rogoff (1983). We first calculate the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OOS}) metric as follows;

$$R^2_{OOS} = 1 - \frac{MSFE_q}{MSFE_{RW}} \tag{19}$$

R^2_{OOS} measures the proportional reduction in Mean Square Forecast Error ($MSFE_q$) of the q competing model/ specification relative to that of the RW ($MSFE_{RW}$). If $R^2_{OOS} > 0$ then the proposed model has better forecasting ability than the benchmark.

To test for the statistical significance of forecast improvements we employ the Clark and West (2007) $MSFE-adjusted$ statistic. This statistic is suitable for comparisons of nested models, as it accounts for additional parameter estimation (bias) introduced by the larger model. In our case, the benchmark RW model is nested in all competing specifications. The test is calculated as follows:

$$MSFE-adjusted = \left(\frac{1}{P}\right)\sum_{t=M+1}^{T-1}\{(\Delta s_{t+1}-\Delta\hat{s}^{(RW)}_{t+1})^2-[(\Delta s_{t+1}-\Delta\hat{s}^{(q)}_{t+1})^2-(\Delta\hat{s}^{(RW)}_{t+1}-\Delta\hat{s}^{(q)}_{t+1})^2]\}$$

where P is the number of out-of-sample forecasts, M is the number of in-sample observations, T is the total number of observations and q is the proposed model under consideration. The null hypothesis of the test is $H_0 : MSFE_{RW} \leq MSFE_q$ against the alternative $H_1 : MSFE_{RW} > MSFE_q$. Clark and West (2007) show that critical values based on the standard normal distribution can provide a good approximation to the distribution of the test.

Following, among others, Meligkotsidou, Panopoulou, Vrontos and Vrontos (2014); Neely, Rapach, Tu and Zhou (2014); Bergman and Hansson (2005); Rapach and Wohar (2002), we use encompassing tests in order to check whether the principal components and the combined forecasts contain distinct information or encompass each other. Specifically, consider forming a

[10] We address this issue in Section 3.4 where we present the test for model encompassing.

composite forecast, $\hat{r}_{c,t+1}$, as a convex combination of model A forecasts, $\hat{r}_{A,t+1}$, and the ones of model B, $\hat{r}_{B,t+1}$, in an optimal way so that $\hat{r}_{c,t+1} = \lambda_A \hat{r}_{A,t+1} + \lambda_B \hat{r}_{B,t+1}, \lambda_A + \lambda_B = 1$. If the optimal weight attached to model A forecasts is zero ($\lambda_A = 0$), then model B forecasts encompass model A forecasts in the sense that model B contains a significantly larger amount of information than that already contained in model A. Harvey, Leybourne and Newbold (1998) developed the encompassing test, denoted as $ENC-T$, based on the approach of Diebold and Mariano (1995) to test the null hypothesis that $\lambda_A = 0$, against the alternative hypothesis that $\lambda_A > 0$. Let $u_{A,t+1} = r_{t+1} - \hat{r}_{A,t+1}$, $u_{B,t+1} = r_{t+1} - \hat{r}_{B,t+1}$ denote the forecast errors of the competing models A and B, respectively and define $d_{t+1} = (u_{B,t+1} - u_{A,t+1})u_{B,t+1}$. The $ENC-T$ statistic is given by:

$$ENC-T = \sqrt{P}\frac{\overline{d}}{\sqrt{\widehat{Var}(d)}}$$

where $\overline{d}$ is the sample mean, $\widehat{Var}(d)$ is the sample-variance of $\{d_{s+1}\}_{s=M}^{T-1}$ and P is the length of the out-of-sample evaluation window. The $ENC-T$ statistic is asymptotically distributed as a standard normal variate under the null hypothesis. To improve the finite sample performance, the authors recommend employing Student's t distribution with $P-1$ degrees of freedom. To render a model as superior in forecasting ability, one also needs to test whether model A forecasts encompass model B forecasts ($\lambda_B = 0$) by employing the $ENC-T$ statistic based on $d_{t+1} = (u_{A,t+1} - u_{B,t+1})u_{A,t+1}$. When both null hypotheses are rejected, then the competing models contain discrete information about the future and an optimal convex ($\lambda_A, \lambda_B \in (0,1)$) combination forecast can be formed. In the event that none of the hypotheses of interest is rejected, both models contain similar information and the competing models are equivalent in terms of forecasting ability. When one of the null hypotheses is rejected, then the respective model forecasts dominate the forecasts of the competing model.

4 Empirical Findings

In this section we provide a brief description of the data used in the empirical analysis and discuss key developments in the exchange rate market. Next, we present our findings regarding the statistical evaluation of our forecasting approaches. We also describe the performance of predictors/ models over time, as well as the factors driving it.

4.1 Data

Our sample consists of monthly post-Bretton Woods data spanning from January 1974 to December 2014. We employ six of the most frequently traded currencies among industrialized economies that float freely; namely the British Sterling (GBP), the Japanese Yen (YEN), the

Swiss Franc (CHF), the Norwegian Krone (NOK), the Australian Dollar (AUD) and the Canadian Dollar (CAD). Following the standard convention in the literature, we employ the US dollar as the base currency. Our main datasources are the OECD, IMF and FRED databases. Exchange rate returns are log-returns computed from differences in the log spot prices. Price levels are proxied by the Consumer Price Index (CPI) and inflation rates are calculated from the y-o-y growth rates of prices. We employ the industrial production index and the M3 monetary aggregate for the income and money supply levels. Interest rates are short-term rates. In order to estimate the output gap, we apply the Hodrick-Prescott filter on the monthly industrial production index. The data sources and codes of the variables employed are presented in Table 1.[11]

[TABLE 1 AROUND HERE]

Table 2 (Panel A) presents the descriptive statistics of the exchange rate returns under consideration. Over the period under examination, AUD has the highest return (for a US investor), while CAD is the least volatile one. On the other hand, CHF and YEN are associated with significant negative returns of -0.24% and -0.17% per month, respectively. CAD and AUD are the most leptokurtic ones, while YEN and CHF are negatively skewed.

[TABLE 2 AROUND HERE]

In order to get a better understanding of the evolution of exchange rates over time, we plot the respective spot exchange rates in Figure 1. Overall, the post-Bretton Woods era (1973) is marked with events that significantly affected exchange rate markets such as the establishment of the Exchange Rate Mechanism (ERM, 1979) in Europe, the Plaza Accord (1985), the United States productivity boom in the 90's, the ERM crisis (1992-1994), and finally the recent financial turmoil in 2008. A closer look at Figure 1 shows that at the early 80's, USD experienced an intense appreciation for a few years exerting pressure on all the exchange rates we consider. This depreciation is more pronounced for GBP, NOK, CHF and AUD, while milder for YEN and CAD. The Plaza Accord in 1985 triggered a sharp depreciation of the US dollar. This behavior of the US dollar is characterized as the "dollar cycle" by Qi and Wu (2003).[12] This trend dies out a few years later followed by a relatively stable period until 1992-1994, when the ERM crisis and the events of Black Wednesday in September 1992 flamed uncertainty in the exchange rate market, triggering another appreciation of the USD. In the nineties, the fast growth of the US economy in relation to the other developed countries led to an increased demand for US assets (both private equities and bonds), which in turn led to a continuous dollar appreciation until 2001 (Blanchard, Giavazzi and Sa, 2005). The burst of the dotcom

[11] Table 1 also presents the datasources for an extensive set of currencies employed in the robustness section (Section 6.3).

[12] The authors attribute the inability of non-linear models to forecast accurately exchange rates to this phenomenon.

bubble in 2001 led to another prolonged period of dollar depreciation until roughly the outburst of the financial crisis in 2008, a year flagged by the collapse of Lehmann Brothers in September and the vast quantitative easing program of the Fed two months later. Moreover, the recent financial crisis coincides with a huge rise in the crude oil and commodity prices in general that seem to also have an impact on the currency market (see, inter alia, Lizardo and Mollick, 2010). A spillover effect between commodities and the US dollar has been documented (Akram, 2004) and currencies, such as NOK, CAD and AUD, are found to be linked with commodity prices (see among others Ferraro, Rogoff and Rossi, 2015). It is noteworthy that both YEN and CHF seem to be immune to the recent financial crisis. As far as CHF is concerned, uncertainty over the eurozone outlook has triggered a huge overvaluation of the currency, considered as a safe haven and resulting in further appreciation. Finally, the Japanese YEN has further depreciated during 2013 following the announcement of an "aggressive monetary easing" program that was expected to double money supply and push the exchange rate even lower.

4.2 Out-of-sample performance

One step ahead forecasts are generated by continuously updating the estimation window, i.e. following a recursive (expanding) window. More specifically, we divide the total sample of $T =$ 492 observations (January 1974 to December 2014) into an in-sample portion of the first $M = 60$ observations (January 1974 to December 1978) and an out-of-sample portion of $P = T - M$=432 observations used for forecasting (January 1979 to December 2014).[13]

Table 3 reports the out-of-sample performance (R^2_{OOS} and level of statistical significance) of the proposed models/ specifications. The Table is divided into four Panels. Panel A shows the forecasting performance of the individual predictors. Panels B and C report the pooled and principal components forecasts (Equations (18) and (17)). Specifically, Panel B presents the performance of principal component forecasts extracted from two distinct groups of predictors; macroeconomic predictors and technical indicators, as well as the corresponding combined forecasts. Panel C reports the related forecasts extracted from both macroeconomic predictors and technical indicators, along with the respective combined forecasts. Finally, Panel D presents the results for the amalgam of forecasts.

[TABLE 3 AROUND HERE]

Our findings with respect to individual predictors (Table 3, Panel A) suggest that a few predictors provide consistently superior forecasts (relative to RW) irrespective of the currency under consideration. Overall, the best predictors in terms of R^2_{OOS} are BMF, PPP, $MA(1,9)$, $RSI(7)$ and $RSI(14)$. Depending on the currency, the best predictor varies. For example, for

[13] In the robustness section we also include different out-of-sample periods, alternative forecast horizons and an extended currency dataset.

GBP, YEN and CHF, the highest R^2_{OOS} is attained by PPP, while for NOK and AUD $RSI(14)$ emerges as the most accurate one.[14]

More in detail, regarding macroeconomic predictors, BMF and PPP improve forecasts in all currencies under consideration, while IRP and PPP in three out of six currencies; namely GBP, NOK and CHF. Taylor rules emerge as the worst performing predictors. In particular, among this set of predictors the best performing ones are $HOAfw$ and HFA improving forecasts in all currencies but YEN and CAD. However, five Taylor rule variants are useful in predicting AUD and to a lesser extent CHF. On the other hand, most currencies tend to be predicted by technical indicators. $MA(1,9)$, $RSI(7)$ and $RSI(14)$ emerge as superior as they improve forecasts in all currencies under examination, followed by $MA(1,12)$, $MA(2,9)$ and $MOM(12)$. It is interesting to note that the highest R^2_{OOS} values are achieved by the RSI predictors exceeding 4.5% in all cases.

Overall, our findings so far suggest that both individual macroeconomic predictors and technical indicators can help forecasting exchange rates with the overall performance of technical indicators being superior to that of macroeconomic predictors. However, since a considerable amount of uncertainty exists with respect to the choice of the predictor, we next check whether combined forecasts and principal components forecasts can deliver a more consistent and reliable performance. Panel B reports the related findings. With the exception of the $PC-ECON$ predictors for CAD, combined forecasts and principal components ones extracted from both groups of predictors are associated with high positive R^2_{OOS} values which are statistically significant at the 1% level. For $POOL-ECON, R^2_{OOS}$ values range from 0.98% (CAD) to 5.65% (AUD), while the respective values for $PC-ECON$ are 3.50% (NOK) and 11.04% (AUD). Interestingly, both $POOL-TECH$ and $PC-TECH$ are superior to $POOL-ECON$ and $PC-ECON$, with a few exceptions. Specifically, $PC-TECH$ improves forecast accuracy by 2.40% (CAD) to 6.95% (NOK) and $POOL-TECH$ by 1.33% (CAD) to 4.80% (CHF).

Next, we consider combined forecasts and principal components extracted from the entire set of predictors, shown in Panel C. Combined forecasts generated from all the predictors ($POOL-ALL$) show significant predictive accuracy, since R^2_{OOS} values range from 1.18% to 5.10% and are statistically significant at the 1% level. More importantly, principal components extracted from the full information set ($PC-ALL$) dominate all specifications considered so far. For GBP, YEN, NOK and CHF, R^2_{OOS} values are almost equally high at 6.06% , 6.49%, 7.76% and 6.67%, respectively. Even for CAD that was hard to predict so far, we get a respectful value of 3.63%. As expected, the corresponding value for AUD increases to 12.05%. Finally, when combining both $POOL-ALL$ and $PC-ALL$ into a 'grand' forecast ($FC-AMALG$), our findings (Panel D) point to increased forecasting benefits for GBP, YEN and CHF, since R^2_{OOS} rises to 7.81%, 6.81% and 7.57%, respectively. For NOK and AUD, R^2_{OOS} are quite high

[14] Our findings with respect to macroeconomic predictors are in line, among others, with Li, Tsiakas and Wang (2015), Della Corte and Tsiakas (2012).

at 7.38% and 10.17% respectively, although they are lower than the $PC-ALL$ counterparts of 7.76% and 12.05%.

Overall, there is compelling evidence so far that macroeconomic predictors and technical indicators work complementarily, i.e. they include different types of information that is mainly exploited by principal components, in contrast to combined forecasts. Furthermore, amalgam forecasts seem to offer a superior and consistent performance across the majority of the exchange rates considered. In order to shed light on these issues, we report the encompassing test results in Table 4.

[TABLE 4 AROUND HERE]

Focusing on principal components, we observe that no $PC-TECH$ encompasses $PC-ECON$, with the exception of CAD, and no $PC-ECON$ encompasses any $PC-TECH$, with the exception of AUD. Hence, $PC-TECH$ and $PC-ECON$ contain discrete information about the future for the majority of currencies. Recall that AUD is the only currency where $PC-ECON$ delivers significantly higher R^2_{OOS} values than $PC-TECH$ and $PC-TECH$ delivers a positive R^2_{OOS} for CAD as opposed to a negative one for $PC-ECON$. Looking at the combined forecasts, our findings suggest that for all currencies, apart from AUD, $POOL-TECH$ encompasses $POOL-ECON$ (and not vice versa), i.e. $POOL-TECH$ contain information beyond that provided by $POOL-ECON$. In the case of AUD, $POOL-ECON$ encompasses $POOL-TECH$. These findings confirm our earlier ones. In a nutshell, $POOL-TECH$ outperforms both $POOL-ECON$ and $POOL-ALL$ for all currencies, except for AUD. Following the positive findings for $FC-AMALG$, we also test between $POOL-ALL$ and $PC-ALL$. We find that $POOL-ALL$ does not encompass $PC-ALL$ for any currency, whereas, the respective test reveals that $PC-ALL$ encompasses $POOL-ALL$ for NOK, CAD and AUD. These currencies are the ones for which $FC-AMALG$ does not outperform $PC-ALL$. Overall, our results corroborate the complementarity between information embedded in the two types of predictors that can enhance foreign exchange predictability further.

4.3 What drives the forecasting performance?

The statistical evaluation of our candidate predictors showed that technical indicators perform better than macroeconomic predictors and that the two groups of predictors contain different types of information that is exploitable if we extract principal components from all candidate predictors. Hence, $PC-ALL$ constitutes a fairly strong forecasting strategy. Moreover, the 'grand' predictor $FC-AMALG$ demonstrates better forecasting ability when $POOL-ALL$ and $PC-ALL$ do not encompass each other. In this section, we check whether the corresponding performance is consistent over time or our results tend to be sensitive to particular periods of time. As reported in section 4.1, there are various historical periods considered as rather important for the course of exchange rates. To this end, we report the difference between the cumulative squared prediction error of the benchmark and the respective predictor. Over times of increase in this metric, the benchmark model is outperformed by the rival, and vice versa. In addition, since the metric is by default constructed as a cumulative difference between squared errors, a positive end-of-period value points to a better out-of-sample performance of the candidate specification over the RW benchmark model.

We begin the analysis with GBP. Figure 2 presents the three best performing predictors (PPP, $RSI(14)$ and BMF) and the three worst performing ones (HFS, HEA and $MA(3,12)$). As shown in Figure 2, the best performing predictors tend to outperform the benchmark almost throughout the entire period under consideration. However, the predictors experience some boosts in their performance, closely related to significant events around those periods. Specifically, these periods are during mid-1985, at the second half of 1992 and the second half of 2008, coinciding with the Plaza Accord, the events of Black Wednesday ending in the withdrawal of British sterling from the ERM mechanism, and finally, the recent financial crisis. It seems that the respective predictors react quicker than the benchmark during periods of crisis and abrupt changes. Excluding the turbulent periods, the benchmark and the candidate predictors do not deviate significantly in terms of squared errors over time. Quite importantly, while $RSI(14)$ is overall one of the best individual predictors, we have to note that during the period between mid-1992 to mid-2001, $RSI(14)$ is outperformed by the benchmark pointing to a quite unstable performance. Its performance further picks up with the outburst of the financial crisis, where significant gains are observed. Turning to the worst performing predictors, we observe that this is quite erratic showing some gains in the beginning of the out-of-sample period, but failing to adapt for the most part of the sample.

[FIGURE 2 AROUND HERE]

Since our focus is on alternative ways of summarizing predictor information, we report in Figures 3 - 8 the performance of $POOL-j, PC-j$ and $FC-AMALG$ (for $j = ECON$, $TECH$, ALL) for all the currencies considered. Figure 3 shows the respective performance for GBP. Overall, it is evident that combined forecasts and $FC-AMALG$ have a much smoother increasing path over time in comparison to principal components. All specifications benefit from crises but in calm periods, they display either modest improvements ($POOL$) or even losses (PC) in forecasting accuracy if compared to the benchmark. The performance over time for $POOL-ECON$, $POOL-TECH$ and $POOL-ALL$ is more or less similar. Likewise, the paths of $PC-j$ are quite similar. In particular, $PC-TECH$ manages to generate better forecasts during periods of crisis but loses predictability during relatively tranquil periods, in contrast to $PC-ECON$. $PC-ALL$ is much smoother than $PC-TECH$, but at the same time, suffers during periods when returns do not fluctuate extensively. Observing closer the performance of $FC-AMALG$ that generates the highest R^2_{OOS} performance, we note that $FC-AMALG$ follows a stable and increasing path with jumps during the 1992 and 2008 turmoils.

[FIGURE 3 AROUND HERE]

Next we turn to the respective results for YEN (Figure 4). As the figure shows, combined forecasts maintain a stable upward trend throughout the whole period. Neither the YEN depreciation at the beginning of the sample, nor the ten-year appreciation after the Plaza Accord until 1995 seem to affect the forecasting superiority of combined forecasts over the benchmark. On the other hand, although principal components deliver higher R^2_{OOS} values than combined forecasts and benefit from peaks and troughs, they are not consistently better than the RW. While the performance of $FC-AMALG$ is obviously smoother, it is still affected by the abrupt changes of $PC-ALL$. What is intriguing in this feature is that $POOL-ALL$ corrects the bad performance of $PC-ALL$ during the period 2004 to 2012 when combined.

[FIGURE 4 AROUND HERE]

In Figure 5, we display the results for NOK. Overall, $POOL-j$ follow a steady and increasing path beating the benchmark in all periods followed by a significant jump at the outburst of the 2007-2009 crisis. Among the principal components under consideration, $PC-ECON$ suffers from losses at the beginning of the period that are reversed during the recent financial crisis. $PC-TECH$ outperforms the RW until 1995 when a five-year period of failures begins, ending in 2001. As far as $PC-ALL$ is concerned, it manages to neutralize the losses of $PC-ECON$ at the beginning of the sample and those of $PC-TECH$ at the period 2001-2008 and maintains a positive performance throughout the remaining periods. The path for $FC-AMALG$ does not differ significantly from that of $POOL-ALL$, exhibiting superior and stable performance over time.

[FIGURE 5 AROUND HERE]

The next currency considered is CHF (Figure 6). Among the combined forecasts reported, the smoothest is $POOL-ALL$. The most noticeable features are the strong upward trends after 1992 for all specifications and the negative trend after 2011 for principal components forecasts. Overall, PC forecasts appear more volatile that the $POOL$ ones. On the other hand and similar to our findings so far, $FC-AMALG$ rises steadily without any significant failures.

[FIGURE 6 AROUND HERE]

Turning to CAD (Figure 7), we note that all combined forecasts, as well as $PC-TECH$ and $PC-ALL$ demonstrate some common patterns. There is no sizeable forecast improvement over the benchmark until 2007, when we start to observe a prolonged period of sizable benefits until the end of the sample. Extracting principal components from macroeconomic predictors shows the worst performance with a negative trend for almost the full out-of-sample period. $FC-AMALG$ neither beats nor is beaten by RW for the entire period until October 2008 when it picks up and significantly outperforms the benchmark up to the end of the sample.

[FIGURE 7 AROUND HERE]

The last currency under consideration is AUD, illustrated in Figure 8. Apparently, our models benefit from the 1986 and 2008 AUD depreciations. Similar to the currencies considered so far, principal components appear to follow more volatile paths than combined forecasts, although they provide more sizable forecasting gains. The performance of $FC - AMALG$ is quite similar to the $POOL$ ones, attaining a positive increasing path throughout the out-of-sample period.

[FIGURE 8 AROUND HERE]

Summarizing our findings, we note that our proposed specifications can exploit periods of turbulence much more efficiently than the benchmark (we should not neglect that the RW with drift is by construction a slow adjusting predictor unable to capture abrupt changes). Aggregating predictor information via combination of pooled and principal components forecasts ($FC - AMALG$) can deliver not only superior forecasts in terms of R^2_{OOS} but also forecasts that can consistently beat the RW without being significantly affected by long or short swings in exchange rates.

5 Economic Evaluation

5.1 Univariate Portfolio Allocation

So far, we have evaluated the statistical significance of our proposed specifications. We now focus on the economic performance of our models, since statistical significance does not always imply profitability.[15] We follow the most recent literature (e.g. Buncic and Piras, 2016; Ahmed, Liu and Valente, 2016; Panopoulou and Pantelidis, 2015; Della Corte and Tsiakas, 2012; Thorton and Valente, 2012; Della Corte, Sarno and Tsiakas, 2009) and focus on the maximization of the investor's expected utility. The investor relies on the information given by the one-month-ahead forecasts of our proposed specifications (equations (16), (17) and (18)) to rebalance her portfolio, which is compared to the portfolio created by the benchmark RW forecasts.

We assume that the investor is US based and allocates part of (or the entire) her portfolio to the US risk free asset (giving return i_t) and the rest on the risk free asset of the foreign country. In this case, her return is the sum of the foreign risk free rate (i^*_t) and the realized exchange rate return. Thus, the only risk the investor is exposed to are fluctuations of the exchange rates. Specifically, the investor re-balances her portfolio every month in the out-of-sample period and allocates the following portion of her wealth (w_t) to the risky (foreign) asset:

[15] Even modest statistically significant out-of-sample performance or small R^2_{OOS} values may have significant gains (Buncic and Piras, 2016 and Neely, Rapach, Tu and Zhou, 2014; Della Corte and Tsiakas, 2012).

$$w_t = (\frac{1}{\gamma})(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}})$$

where γ is the risk aversion coefficient, $\hat{r}_{t+1}$ denotes the expected return of the investment in the risky asset and is calculated as the sum of the foreign risk free rate (i^*_t) and the forecast of the exchange rate return, i.e. $\hat{r}_{t+1} = i^*_t + \Delta \hat{s}_{t+1}$, and $\hat{\sigma}_{t+1}$ is the forecast of the variance computed by calculating the variance of the actual exchange rate returns under a rolling window of 60 observations. Intuitively, higher values of γ correspond to a more risk averse investor, resulting in lower exposure to the foreign risky position. We conduct the experiment for two levels of risk aversion (γ=2 and 5).[16] Consistent with the literature (e.g. Welch and Goyal, 2008; Ferreira and Santa Clara, 2011; Ahmed, Liu and Valente, 2016), the weights are winsorized, i.e. $-1 \leq w_t \leq 2$ in order to prevent extreme and unrealistic investments and also to allow for 200% leverage and 100% short sales. Under this setting, the optimally constructed portfolio return over the out-of-sample period is equal to

$$r_{p,t+1} = w_t(i^*_t + \Delta s_{t+1}) + (1 - w_t)i_t$$

In order to assess the economic value of the candidate predictors, we calculate the Certainty Equivalent Return (CER) as follows;

$$CER = \hat{r}_p - \frac{1}{2}\gamma\hat{\sigma}^2_p$$

where $\hat{r}_p$ is the average return of the portfolio (equal to $\frac{1}{P}\sum_{t=0}^{P-1}(r_{p,t+1})$) and $\hat{\sigma}^2_p$ is the variance of the investor's portfolio over the out-of-sample period. The difference between the CER of the proposed specification and that of the benchmark (denoted as ΔCER) can be interpreted as the maximum fee that the investor is willing to pay in order to switch from the RW to the competing model. To test the statistical significance of ΔCER, we compute the p-value of ΔCER relying on the asymptotic properties of functional forms of the estimators for means and variances (see also, Jobson and Korbie (1981), Memmel (2003) and DeMiguel, Garlappi and Uppal (2009)).[17]

[16] Abhyankar, Sarno and Valente (2005) set $\gamma = [2, 5, 10, 20]$; Neely, Rapach, Tu and Zhou (2014) set $\gamma = 5$; Buncic and Piras (2016) set $\gamma = 6$; Panopoulou and Pantelidis set $\gamma = [2, 5]$.

[17] Let the vector of moments be $u = (r_{p,i}, r_{p,RW}, \sigma^2_{p,i}, \sigma^2_{p,RW})$ and their estimates $\hat{u} = (\hat{r}_{p,i}, \hat{r}_{p,RW}, \hat{\sigma}^2_{p,i}, \hat{\sigma}^2_{p,RW})$. The difference in the certainty equivalent return of the predictor i and the benchmark is given by the function $f(u) = \left(\hat{r}_{p,i} - \frac{1}{2}\gamma\hat{\sigma}^2_{p,i}\right) - \left(\hat{r}_{p,RW} - \frac{1}{2}\gamma\hat{\sigma}^2_{p,RW}\right)$ and the asymptotic distribution of the function is calculated as $\sqrt{T}\left(f(\hat{u}) - f(u)\right)$ with a distribution $N(0, \frac{\partial f}{\partial u}^{\intercal}\Theta\frac{\partial f}{\partial u})$, where $\Theta = \begin{bmatrix} \hat{\sigma}^2_{p,i} & \hat{\sigma}_{p,i,RW} & 0 & 0 \\ \hat{\sigma}_{p,i,RW} & \hat{\sigma}^2_{p,RW} & 0 & 0 \\ 0 & 0 & \hat{\sigma}^4_{p,i} & 2\hat{\sigma}^2_{p,i,RW} \\ 0 & 0 & 2\hat{\sigma}^2_{p,i,RW} & \hat{\sigma}^4_{p,RW} \end{bmatrix}$. The variance of the distribution is given as follows; $\sigma^2 = \frac{\partial f}{\partial u}^{\intercal}\Theta\frac{\partial f}{\partial u} =$

5.2 Multivariate Portfolio Allocation

We also evaluate the economic significance of our strategies by forming a portfolio of the six risky foreign assets and the US risk-free asset. Similarly to the univariate case, the US investor dynamically rebalances the weights of each asset at the end of each period in order to maximize the portfolio returns by solving the following problem:

$$\max_{w_t} \hat{r}_{p,t+1|t} = \mathbf{w}_t^\top \hat{\mathbf{r}}_{t+1} + (1 - \mathbf{w}_t^\top \boldsymbol{\iota}) i_t$$

$$\text{subject to } (\sigma_p^*)^2 = \mathbf{w}_t^\intercal \Sigma_{t+1|t} \mathbf{w}_t,$$

where $\hat{r}_{p,t+1}$ is the expected portfolio return, $\hat{\mathbf{r}}_{t+1}$ is a 6x1 vector of expected exchange rate returns, σ_p^* is the target conditional volatility of the portfolio returns and $\Sigma_{t+1|t}$ is a 6x6 conditional variance-covariance matrix calculated as $\Sigma_{t+1|t} = (\mathbf{r}_{t+1} - \hat{\mathbf{r}}_{t+1})(\mathbf{r}_{t+1} - \hat{\mathbf{r}}_{t+1})'$. The expected return of the risky asset is equal to the return of the foreign riskless asset plus the return of the exchange rate, calculated by $E_t[r_{t+1}] = i_t^* + \hat{r}_{t+1}$. $\boldsymbol{\iota}$ is a 6x1 vector of ones. Following Li, Tsiakas and Wang (2015), we set $\sigma_p^* = 10\%$. The solution to the optimization problem gives the following weights on the risky assets:

$$\mathbf{w}_t = \frac{\hat{\sigma}_p^*}{\sqrt{C_t}} \Sigma_{t+1|t}^{-1} (\hat{\mathbf{r}}_{t+1} - \boldsymbol{\iota} i_t),$$

where $\hat{\mathbf{r}}_{t+1} - \boldsymbol{\iota} i_t$ is the 6x1 vector of excess returns, $\boldsymbol{\iota}$ is a 6x1 vector of ones, and $C_t = (\hat{\mathbf{r}}_{t+1} - \boldsymbol{\iota} i_t) \Sigma_{t+1|t}^{-1} (\hat{\mathbf{r}}_{t+1} - \boldsymbol{\iota} i_t)$. As previously, we winsorize the weights as $-\boldsymbol{\iota} \leq \mathbf{w}_t \leq 2\boldsymbol{\iota}$.

The investor at the end of each period receives a realized return equal to

$$r_{p,t+1} = \mathbf{w}_t^\top (\mathbf{r}_{t+1} - \boldsymbol{\iota} i_t) + i_t.$$

We assess the economic value of our forecasts by computing the out-of-sample performance fee (ΔCER) for two levels of risk aversion, $\gamma = [2, 5]$. We also report the annualized portfolio excess return and annualized volatility, denoted as $(\%)\mu$ and $(\%)\sigma$, before and after accounting for transaction costs. We follow Chang and Osler (1999) and Neely, Weller and Dittmar (1996) that use 5 basis points (bps) per change of position.[18] Finally, we report the Sharpe Ratio (SR) of the portfolio given by

$$SR = \frac{\overline{r_p - i_t}}{\sigma_p},$$

$$\begin{bmatrix} 1 & -1 & -\gamma\hat{\sigma}_{p,i} & \gamma\hat{\sigma}_{p,RW} \end{bmatrix} \begin{bmatrix} \hat{\sigma}_{p,i}^2 & \hat{\sigma}_{p,i,RW} & 0 & 0 \\ \hat{\sigma}_{p,i,RW} & \hat{\sigma}_{p,RW}^2 & 0 & 0 \\ 0 & 0 & 2\hat{\sigma}_{p,i}^4 & 2\hat{\sigma}_{p,i,RW}^2 \\ 0 & 0 & 2\hat{\sigma}_{p,i,RW}^2 & 2\hat{\sigma}_{p,RW}^4 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ -\gamma\hat{\sigma}_{p,i} \\ \gamma\hat{\sigma}_{p,RW} \end{bmatrix}.$$

[18] Neely, Weller and Ulricht (2009) argue that "Since the mid-1990s, electronic trading has lowered transaction costs...Recently, spot market participants have faced spreads of 2 bps or less for transactions in the $5 million to $50 million range." The authors assume a linear decline from 10 bps in 1973 to 1.88 bps in 2005. In our case, we assume that the costs are stable over the entire sample period to 5bps.

where $\overline{r_p - i_t}$ is the portfolio's average excess return and σ_p is the standard deviation of the corresponding returns. We compute SR for each predictive model and test its statistical significance based on the asymptotic distribution of the difference in SRs between the proposed model and the RW benchmark.[19] We also evaluate a Naive Portfolio (see DeMiguel, Garlappi and Uppal, 2009) formed ignoring the related exchange rate forecasts. In this case, the investor forms an equally weighted portfolio containing $N = 7$ assets (including the US risk free asset as well), so each asset is given a weight of $1/N$.

5.3 Economic Evaluation Findings

Table 5 reports the annualized ΔCER fees related to the univariate portfolios. Our findings are discussed with two perspectives; the first is connected to the performance of the models against the Random Walk, and the second is linked to the performance of the models by increasing the level of risk aversion. Overall, our findings are consistent with the statistical evaluation findings. For currencies that proved hard to predict, such as YEN and CAD, we get either negative ΔCER or small positive values. In addition, we observe that models performing poorly in terms of R^2_{OOS} do also in terms of ΔCER.

[TABLE 5 AROUND HERE]

With respect to individual predictors, we note that PPP, $RSI(7)$ and $RSI(14)$ provide statistically significant CER gains irrespective of the currency under consideration and risk aversion degree. In general, technical indicators do not generate negative ΔCER values as frequently as macroeconomic predictors. Especially in the cases of CAD and AUD, all technical indicator strategies outperform the benchmark, which however are not statistically significant. The performance of PPP is outstanding as it delivers substantial gains ranging from 3.21% (CAD) to 16% (GBP) in the case of for $\gamma = 2$. In addition, macroeconomic predictors fail significantly to generate positive fees for YEN and NOK, irrespective of the level of risk aversion. With respect to the level of risk aversion, we observe that in the majority of cases, the performance of almost all predictors deteriorates when risk aversion increases.

Turning to the performance of combined and principal components forecasts, we note that $PC-ECON$ and $PC-TECH$ generate significantly high gains, up to 11.15% for $PC-ECON$ (AUD) and 11.21% for $PC-TECH$ (GBP). More importantly, $PC-TECH$ forecasts are associated with substantial gains that range from 2.17% (1.87%) for CAD to 11.21% (9.82%) for GBP for $\gamma = 2$ ($\gamma = 5$). For almost all currencies, principal components generate higher

[19] Specifically, we test whether the Sharpe ratio of the benchmark is equal to its rival, so that $H_0 : \frac{\hat{r}_{p,i}}{\hat{\sigma}_{p,i}} - \frac{\hat{r}_{p,RW}}{\hat{\sigma}_{p,RW}} = 0$. The respective test statistic is given by $\hat{z} = \frac{\hat{\sigma}_{p,RW}\hat{r}_{p,i} - \hat{\sigma}_{p,i}\hat{r}_{p,RW}}{\sqrt{\theta}}$, where

$$\theta = \frac{1}{P}\left(2\hat{\sigma}^2_{p,i}\hat{\sigma}^2_{p,RW} - 2\hat{\sigma}_{p,i}\hat{\sigma}_{p,RW}\sigma_{i,RW} + \frac{1}{2}\hat{r}^2_{p,i}\hat{\sigma}^2_{p,RW} + \frac{1}{2}\hat{r}^2_{p,RW}\hat{\sigma}^2_{p,i} - \frac{\hat{r}_{p,i}\hat{r}_{p,RW}}{\hat{\sigma}_{p,i}\hat{\sigma}_{p,RW}}\sigma_{i,RW}\right)$$

.

performance fees than combined forecasts. In addition, a further piece of evidence regarding the superiority of technical indicators is given by comparing $PC - ECON$ to $PC - TECH$. We observe that $PC - TECH$ outperform $PC - ECON$ for four currencies out of six. The results are qualitatively the same when we compare combined forecasts.

The most interesting feature of Table 5 is Panel C, where we report the results for $POOL - ALL$ and $PC - ALL$ with $PC - ALL$ generating high economic gains, irrespective of the level of risk aversion. Except for CHF, the aforementioned model is able to result in higher economic gains than the other principal components. These gains reach 14.37% for GBP and 13.79% for AUD. Even in the case of YEN for $\gamma = 5$, where eight out of thirteen macroeconomic predictors and four out of eleven technical indicators generate losses, $PC - ALL$ delivers essential gains, equal to 376 basis points. With respect to $POOL - ALL$ we observe that this strategy favors more a relatively less risky investor, pointing to gains for four out of six currencies. The results for the combination of these two predictors, as shown in Panel D, are very promising, although the respective gains do not outperform $PC - ALL$ for any currency. $FC - AMALG$ generates sizable utility gains of 11.9% and 8.41% for $\gamma = 2$ and GBP and AUD, respectively.

Turning to the multivariate asset allocation framework, our findings, reported in Table 6, clearly support our proposed forecasting approaches. Similar to the univariate evaluation, PPP, $RSI(7)$ and $RSI(14)$ generate the highest utility gains (over the benchmark random walk) which can reach 776 bps (after transaction costs) per year for $\gamma = 2$. As expected, annualized mean returns are quite high and exceed 18% per year. Overall, more risk averse investors are willing to pay higher fees in order to have access to our forecasts in these cases. Pooling information of macroeconomic variables or technical indicators results in utility gains that range from 182 bps ($POOL - ECON$, $\gamma = 2$) to 244 bps ($POOL - TECH$, $\gamma = 2$). In these cases, SRs exceed one and are statistically greater than the benchmark RW. More importantly, pooling information from both sets of predictors achieves similar performance to $POOL - TECH$, making it a valid alternative strategy not associated with uncertainty over the predictor set choice. Contrary to our univariate evaluation findings, $PC - ECON$ and $PC - TECH$ do not provide any statistically significant gains to the investor after accounting for transaction costs. However, $PC - ALL$ is superior to $PC - ECON$ and $PC - TECH$ along with $POOL - ALL$ generating positive $\Delta CERs$ of 372 bps and higher than the benchmark SR value of 1.18. More importantly, our proposed amalgam forecasts are superior to all aforementioned sets of forecasts providing the investor with an annualized return that exceeds 15% and is associated with a significant SR of 1.22, while ΔCER gains exceed 409 bps. Finally, Panel C of Table 6 reports the performance of the naive $1/N$ portfolio, which provides gains of 202 bps for a risk averse investor; albeit not statistically significant and is associated with losses for a less risk averse investor. To conclude, our univariate and multivariate economic evaluation findings suggest that by exploiting the information from the two groups of predictors we are able to provide sizable economic gains.

[TABLE 6 AROUND HERE]

6 Robustness tests

In this section we assess further the statistical performance of the candidate predictors/ specifications by conducting a series of robustness tests. First, we consider alternative forecasting horizons. Second, we change the beginning of the evaluation period to January 1990 and January 2000. Third, we employ an extended dataset of developed and emerging countries' exchange rates and test whether our findings pertain to this dataset as well.

6.1 Alternative forecast horizons

Table 7 reports our findings for alternative forecast horizons. Specifically, we consider $h-$month-ahead forecasts for $h = [3, 6, 12]$. Our results show that statistical significance weakens as we move to higher forecast horizons. This effect is more pronounced for technical indicators, since by construction they are trend following predictors and past trends have less impact as we move further. However, when aggregating the information content in all candidate predictors via $FC-AMALG$, $PC-ALL$ and $POOL-ALL$ we still attain a very good performance for all currencies and especially for the 3- and 6- month forecast horizons.

More in detail, for the 3-month-ahead forecasts, our findings remain qualitatively similar to the benchmark one-month forecasts. Technical indicators perform better than macroeconomic predictors, especially for combined and principal components forecasts. By comparing $POOL-j$, $PC-j$ and $FC-AMALG$, we observe that the best performing predictors are $FC-AMALG$ for GBP, which generates out-of-sample R^2_{OOS} values of 3.15%, $PC-TECH$ for YEN (1.79%), $PC-TECH$ for NOK (2.47%), $POOL-ECON$ for CHF (1.78%), $PC-ALL$ for CAD (2.04%) and $PC-ALL$ for AUD (2.11%). It is interesting to note that $FC-AMALG$ outperforms both $PC-ALL$ and $POOL-ALL$ in all currencies considered with the exception of CAD.

Turning to the 6-month forecasts, we observe that the forecasting ability of most technical indicators deteriorates significantly, while the deterioration in the forecasting ability of macroeconomic predictors is not that intense. The predictors that yield the best performance are $FC-AMALG$ for GBP (1.53%), $FC-AMALG$ for YEN (0.32%), $PC-TECH$ for NOK (0.52%), $POOL-ECON$ for CHF (0.69%), $FC-AMALG$ for CAD (1.48%) and $PC-ALL$ for AUD (0.56%).

Finally, for the 12-month horizon we note that technical indicators are outperformed by the benchmark with the exception of a few cases. Interestingly, despite the bad performance of individual technical indicators, $PC-TECH$ still beats $PC-ECON$. Specifically, the best performing model for GBP is $PC-ECON$ (1.62%), $PC-TECH$ for YEN (1.62%), $PC-TECH$ for NOK (0.09%), $FC-AMALG$ for CHF (1.36%), $FC-AMALG$ for CAD (1.01%) and $PC-TECH$ for AUD (0.09%). It is interesting to note that $FC-AMALG$ loses gradually its superiority over $PC-ALL$ and $POOL-ALL$, but still manages to deliver accurate forecasts.

[TABLE 7 AROUND HERE]

Overall, the performance of individual technical indicators deteriorates as the forecasting horizon increases (in line with the results of Menkhoff and Taylor, 2007; Park and Irwin, 2007; Neely and Weller, 1999). However, principal components, combined and amalgam forecasts improve forecastability lending support to our main finding that both technical indicators and macroeconomic fundamentals incorporate useful information.

6.2 Alternative evaluation periods

The next check we perform is to evaluate the robustness of our model to changes in the out-of-sample period. We consider two more evaluation periods by setting the beginning of our forecasts to January 1990 and January 2000, respectively.

Our findings, when the out-of-sample period starts in January 1990 are reported in Table 8 and remain qualitatively similar to the long out-of-sample period. The predictors that provided statistical significant results remain robust and some of them even enhance their forecasting ability. For example, macroeconomic predictors for GBP display improved forecasting performance. $PC-ALL$ outperforms both $PC-ECON$ and $PC-TECH$, with the exception of GBP and AUD. In addition, $FC-AMALG$ also emerges as superior for GBP, YEN and CHF. However, we observe that $PC-ECON$ and $POOL-ECON$ perform even better in this more recent period.

[TABLE 8 AROUND HERE]

Next, we focus on the more recent period (out-of-sample forecasts begin in January 2000). Our findings, reported in Table 9 suggest that our proposed specifications remain robust to this part of the sample. Specifically, $PC-ALL$ shows improved forecast accuracy for NOK (12.08%), CAD (5.41%), GBP (3.66%) and AUD (14.53%), relative to $POOL-ALL$, while the opposite is true for YEN and CHF. More importantly, $FC-AMALG$ still provides statistically significant forecasts and high forecast accuracy ranging from 2.05% (YEN) to 11.10% (AUD).

[TABLE 9 AROUND HERE]

6.3 Extended currency dataset

In this subsection, we check whether our forecasting strategy survives when tested on an extended set of currencies including both developed and emerging markets. Specifically, we include 13 additional currencies; namely the Colombian peso (COP), Danish krone (DKK), Eurozone's euro (EUR)[20], Indian rupee (INR), Malaysia ringgit (MYR), Mexican peso (MXN), New Zealand dollar (NZD), Peruvian sol (SOL), Philippine peso (PHP), South African rand (ZAR), Swedish

[20] Data prior to its inception are proxied by the Deutche mark.

krona (SEK) and Thai baht (THB) and Brazilian real (BRL). Data were collected from several sources (given in Table 1) such as Datastream, FRED, IMF, OECD and Central Banks databases. In Table 2 (Panel B) we report the related descriptive statistics along with the start date of the sample period which is the month/year that each currency started to float freely or entered a crawling peg.

Table 10 (left panel) reports the results for DKK, EUR, MYR, ZAR and SEK for the out-of-sample period that begins in January 1979 and ends in December 2014. Overall, our findings are consistent with our main dataset pointing to superior forecasting ability of the technical indicators employed. To this end, pooling or extracting information from the set of technical indicators always leads to statistically significant positive R^2_{OOS}. On the other hand, pooling information about fundamentals leads to benefits in all currencies but MYR and extracting the related factors benefits only EUR and ZAR. More importantly, when both predictor sets are employed (Panel E), R^2_{OOS} are positive and statistically significant for all currencies but MYR and $POOL-ALL$. $PC-ALL$ is associated with higher R^2_{OOS} values reaching 8.47% for DKK, followed by 7.11% for SEK. Consequently, our proposed amalgam approach succeeds in improving forecasts in all currencies generating improvements ranging from 2.57% to 7.13%. Turning to the shorter out-of-sample period starting in 1990 (right Panel), our findings are qualitatively similar. In this set of results we also add NZD, since data are available. Overall, Panels D, E and F convey the same message. Information from both sets of predictors via principal components or amalgam forecasts generate superior forecasts for all currencies at hand.

[TABLE 10 AROUND HERE]

Despite the short out-of-sample period of Table 11 (out-of-sample period begins in January 2000), we are able to come into some very interesting conclusions. The Table contains an adequate number of currencies, thirteen in total, from both emerging and developed markets, from almost every geographical continent. Overall, we observe that aggregating information from both sets of predictors works positively for all currencies with the exception of COP, MXN, PHP, THB and BRL, which are all currencies of developing countries. On the other hand, the remaining developing currencies, i.e. INR, MYR, SOL and ZAR benefit from both macroeconomic and technical information aggregation as depicted in the positive and statistically significant R^2_{OOS} of $FC-AMALG$, $PC-ALL$ and $POOL-ALL$. Finally, our findings with respect to the developed countries, i.e. DKK, EUR, NZD and SEK, are similar to our main set up and promote the use of either technical indicators or both sets of predictors. Specifically, R^2_{OOS} for $PC-ALL$ range from 5.58% (NZD) to 11.66% (SEK) and for FC-AMALG from 5.10% (NZD) to 9.22% (SEK). Overall, our forecasting approach succeeds in all developed countries, while evidence is mixed for the developing ones.

[TABLE 11 AROUND HERE]

6.4 Further Robustness Tests

We also check whether a specification including common information across currencies can prove valuable in forecasting exchange rates. Since all currencies we employ are denominated in US dollar, we employ US macroeconomic and financial variables as candidate predictors. To save space, we report our findings in the online Appendix to accompany our paper. Overall, this set of variables fails to consistently outperform the Random Walk benchmark. Consequently, *PC*, *POOL* and amalgam forecasts fail to greatly improve the related forecasts. Extracting principal components appears inferior to pooling information and longer horizons become even harder to predict. Finally, in unreported results, we also consider kitchen sink models of macroeconomic predictors, technical indicators and the full set of variables. The performance of these models is inferior to the random walk and as a consequence, our forecasting approaches are superior to these alternative benchmarks.[21]

7 Conclusions

The importance of forecasting exchange rates extends beyond academia, to policymakers, practitioners and international financial market participants. In our study, we use the most widely used macroeconomic predictors and technical indicators in order to construct reliable exchange rate forecasts against the Random Walk benchmark. Overall, our findings suggest that both groups of predictors can provide superior forecasts. However, technical indicators demonstrate superior predictive ability, irrespective of being used individually, in a forecast combination or a principal components framework. More importantly, forecasts generated from the first few principal components of the two sets of predictors do not encompass each other, suggesting that these predictors capture different types of information and work complementarily. In this respect, forecasts constructed employing principal components of the whole information set, both fundamental and technical can further improve predictability reaching 12.05% over the random walk benchmark. Finally, we propose a forecasting strategy generated by the combination of combined and principal components forecasts from the entire group of predictors. Our findings suggest that in the cases that combined and principal components forecasts from the full information set do not encompass each other, this approach is superior to its rivals and outperforms the random walk model by 10.17%.

Interestingly, the financial turmoils of 1994 and 2008 enhance the predictability of our models, as they tend to be more flexible than the benchmark and adjust faster during crisis periods. Our proposed approaches tend to outperform the random walk throughout the entire out-of-sample period delivering increasing and relatively smooth performance signalling that the investor should take into account both types of predictors in order to consistently benefit. Indeed, our economic evaluation findings show that the combined use of technical indicators

[21] This set of results is available from the authors upon request.

and macroeconomic predictors can provide significant gains irrespective of the currency under consideration. Our findings are robust to the evaluation period, forecast horizon and pertain to an extended dataset of currencies from both developed and emerging markets.

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Table(s)

Table 1: Dataset and sources

Country	Nominal Exchange Rates	Industrial Production Index	Money Supply
Australia	FRED,EXUSAL	OECD,AUSPROINDQISMEI	OECD,MANMM101AUM189S
Canada	FRED,EXCAUS	OECD,CANPROINDMISMEI	OECD,MANMM101CAM189S
Japan	FRED,EXJPUS	OECD,JPNPROINDMISMEI	IMF,MYAGM2JPM189S
Norway	FRED,EXNOUS	OECD,NORPROINDMISMEI	Norges Bank
Switzerland	FRED,EXSZUS	OECD,CHEPROINDQISMEI	OECD,MABMM301CHM189S
UK	FRED,EXUSUK	FRED,GBRPROINDMISMEI	FRED,MABMM402GBM189N
US	-	FRED,INDPRO	IMF,MYAGM2USM052S
Denmark	FRED,EXDNUS	FRED,DNKPROINDMISMEI	FRED,MANMM101DKM189S
Eurozone	FRED,EXGEUS+EXUSEU	IMF,EA28+EA19,AIP_IX	IMF,FM3_SA_EUR
Malaysia	FRED,EXMAUS	IMF,AIP_IX	IMF,FM1_XDC
South Africa	FRED,EXSFUS	DATASTREAM,SAINPRODH	IMF,FM1_XDC
Sweden	FRED,EXSDUS	FRED,SWEPROINDMISMEI	FRED,MABMM301SEM189S
New Zealand	FRED,EXNZUS	FRED,NZLPROINDQISMEI	FRED,MABMM301NZM189S
Colombia	IMF,ENDE_XDC_USD_RATE	DATASTREAM,CBIPTOT.H	IMF,FM2_XDC
India	FRED,EXINUS	IMF,AIP_IX	FRED,MANMM101INM189S
Mexico	IMF,ENDE_XDC_USD_RATE	IMF,AIP_IX	FRED,MABMM301MXM189S
Peru	IMF,ENDE_XDC_USD_RATE	DATASTREAM,PECIND..G	DATASTREAM,PEM0CURRA
Philippines	IMF,ENDE_XDC_USD_RATE	IMF,AIPMA_IX	IMF,FM3_XDC
Thailand	IMF,ENDE_XDC_USD_RATE	IMF,PPPI_IX	IMF,FM1_XDC
Brazil	IMF,ENDE_XDC_USD_RATE	FRED,BRAPROINDMISMEI	IMF,FM1_XDC
Country	**Interest Rates**	**Consumer Price Index**	
Australia	OECD,IRLTLT01CHM156N	OECD,CCRETT01AUM661N	
Canada	IMF,INTGSTCAM193N	OECD,CANCPIALLMINMEI	
Japan	IMF,INTGSTJPM193N	OECD,JPNCPIALLMINMEI	
Norway	OECD,IRLTLT01NOM156N	OECD,NORCPIALLMINMEI	
Switzerland	OECD,IRLTLT01CHM156N	OECD,CHECPIALLMINMEI	
UK	FRED,INTGSTGBM193N	OECD,GBRCPIALLMINMEI	
US	FRED,INTGSBUSM193N	OECD,USCPIALLMINMEI	
Denmark	IMF,FIMM_PA	FRED,DNKCPIALLMINMEI	
Eurozone	IMF,EA19,FIGB_PA	IMF,EA19,AMPLITUD	
Malaysia	IMF,FIGB_PA	IMF,PCPI_IX	
South Africa	FRED,INTGSBZAM193N	IMF,PCPI_IX	
Sweden	IMF,FIGB_PA	FRED,SWECPIALLMINMEI	
New Zealand	OECD,NZLSTINTTOTPC_PAM	FRED,NZLCPIALLQINMEI	
Colombia	IMF,FID_PA	IMF,PCPI_IX	
India	IMF,FIGB_PA+FIMM_PA+FID_PA	IMF,PCPI_IX	
Mexico	FRED,INTGSTMXM193N	FRED,MEXCPIALLMINMEI	
Peru	IMF,FID_PA	IMF,PCPI_IX	
Philippines	IMF,FITB_PA	IMF,PCPI_IX	
Thailand	IMF,FID_PA	IMF,PCPI_IX	
Brazil	IMF,FITB_PA	IMF,PCPI_IX	

Notes: The data for the first six currencies are collected for the period January 1973 to December 2014. The sample period for the remaining currencies starts in the month they adopted the free floating scheme.

Table 2: Descriptive statistics

	Mean	Median	Standard deviation	Skewness	Kurtosis	Max	Min	ACF(1)	Starting Date
Panel A									
GBP	0.08	0.03	2.42	0.25	4.67	11.08	-9.52	0.35	01:1974
YEN	-0.17	0.01	2.72	-0.46	3.88	8.07	-10.52	0.32	01:1974
NOK	0.05	0.02	2.43	0.36	[illegible]	12.95	-6.33	0.36	01:1974
CHF	-0.24	-0.13	2.87	-0.02	3.69	11.69	-8.24	0.28	01:1974
CAD	0.03	0.00	1.42	0.60	11.36	11.29	-6.01	0.26	01:1974
AUD	0.12	-0.08	2.60	1.29	8.87	17.31	-7.12	0.33	01:1974
Panel B									
DKK	0.11	0.01	2.55	0.75	5.76	13.81	-7.12	0.38	01:1974
EUR	-0.16	-0.05	3.06	[illegible]	42.01	8.52	-36.51	0.25	01:1974
MYR	0.07	0.00	1.81	0.95	27.65	15.12	-14.48	0.27	09:1975
ZAR	0.58	0.10	3.42	0.97	9.72	19.15	-13.38	0.33	06:1974
SEK	0.11	0.01	2.55	0.75	5.76	13.81	-7.12	0.38	01:1974
NZD	0.07	0.08	2.75	0.51	5.63	14.34	-8.11	0.34	06:1979
COP	0.50	0.59	3.16	-0.03	5.61	13.08	-12.49	0.18	01:1991
INR	0.27	0.05	1.63	0.71	6.01	6.56	-5.94	0.32	01:1994
MXN	0.60	0.02	4.28	4.48	45.34	43.41	-16.42	0.03	12:1994
SOL	0.46	0.03	2.14	2.13	15.03	14.55	-7.04	0.34	10:1991
PHP	0.22	0.05	2.50	1.47	9.77	14.28	-8.48	0.11	01:1993
THB	0.12	-0.20	[illegible]	0.24	23.11	21.78	-24.66	0.18	07:1997
BRL	0.48	0.51	5.54	3.31	29.92	49.48	-18.16	0.01	02:1995

Notes: Panel A shows the summary statistics of the six currency returns considered in the main out-of-sample exercise for the total sample period (January 1974 to December 2014). Panel B reports the same statistics for the currencies used in the robustness section. The start date of the dataset is reported in the last column of the table. The statistics presented are the mean, median, standard deviation, skewness, kurtosis, maximum, minimum and first order autocorrelation.

Table 3: Out-of-sample Performance

Macroeconomic Predictors							Technical Indicators						
Predictor	GBP	YEN	NOK	CHF	CAD	AUD	Predictor	GBP	YEN	NOK	CHF	CAD	AUD
Panel A: Bivariate Predictive Regression Forecasts													
IRP	[illegible]	[illegible]	1.23***	1.18**	-1.05	-0.28	MA(1,9)	2.29***	1.95***	0.80***	2.09***	0.03*	0.91**
FB	[illegible]	-0.41	[illegible]	1.81***	-1.09	-0.03	MA(1,12)	0.45**	1.74***	2.04***	0.70**	0.15	0.38***
BMF	8.64***	[illegible]	[illegible]	6.54***	4.57***	10.19***	MA(2,9)	0.36*	0.84**	0.72**	1.59***	0.25	0.28
PPP	9.77***	[illegible]	[illegible]	7.07***	5.52***	10.16***	MA(2,12)	-0.53	-0.59	1.15**	2.72***	0.17	-0.27
HOAfw	1.42***	0.11	[illegible]	[illegible]	0.01	5.27***	MA(3,9)	-0.18	-0.03	0.87**	2.42***	-0.33	0.32
HOS	-0.03	-1.27	0.02	0.44	-0.57	6.63***	MA(3,12)	-0.90	-0.60	0.00	0.16	-0.45	1.01**
HOSS	0.28	-0.92	-0.49	0.27	-0.68	0.03	MOM(9)	-0.69	-0.43	1.60***	0.04	-0.02	0.06**
HOA	-0.83	0.42*	0.35	[illegible]	[illegible]	7.89***	MOM(12)	0.45***	0.07*	0.47	2.28***	0.25	-0.98*
HOAS	0.34	-0.86	-0.49	[illegible]	[illegible]	0.09	RSI(7)	7.30***	9.11***	11.38***	6.61***	4.53***	9.83***
HES	-1.12	0.02	0.32	-0.18	[illegible]	4.68***	RSI(14)	8.73***	9.68***	13.05***	6.56***	4.80***	10.34***
HESS	0.42*	-0.69	-0.35	0.32	[illegible]	[illegible]	EMA(5,12)	0.29*	0.41*	-0.07	-0.03	0.09	0.70
HEA	-0.97	0.38	1.46**	1.46***	0.41*	[illegible]							
HEAS	0.03	-0.65	-0.21	0.25	-0.58	-0.05							
Panel B: Principal Components and Combination Forecasts per Group (Macro vs Tech)													
POOL-ECON	3.60***	2.68***	3.05***	4.19***	0.98***	5.65***	POOL-TECH	[illegible]	4.30***	4.65***	4.80***	1.33***	4.10***
PC-ECON	4.35***	3.53***	3.50***	5.93***	-0.22	11.04***	PC-TECH	[illegible]	[illegible]	6.95***	5.13***	2.40***	6.47***
Panel C: Principal Components and Combination Forecasts per Group (All predictors)													
POOL-ALL	4.19***	3.53***	3.92***	4.60***	1.18***	5.10***							
PC-ALL	6.06***	6.49***	7.76***	6.67***	3.63***	12.05***							
Panel D: Amalgam Forecasts													
FC-AMALG	7.81***	6.81***	7.38***	7.57***	2.70***	10.17***							

Notes: The table reports the R^2_{OOS}, which measures the reduction in $MSFE_i$ relative to the MSFE of the benchmark RW model. The bivariate predictive regression forecast in Panel A is given by: $\Delta s_{t+1} = a_i + b_i \Delta x_{i,t}$, where $x_{i,t}$ is each of the 24 predictors, taken individually. PC-ECON, PC-TECH and PC-ALL forecasts are given by the formula of equation (17), such as: $\Delta \hat{s}^{(j)}_{t+1} = \hat{a}_i + \Sigma^K_{k=1} \hat{b}_k F^{(j)}_{k,t}$. $F^{(j)}_{k,t}$ is the recursively calculated, to time t, kth principal component extracted from the 13 macroeconomic predictors ($j = ECON$), 11 technical rules ($j = TECH$) and 24 regressors taken together ($j = ALL$) for $k = 1, .., K$. Panel D is estimated by taking the naive combined forecasts of PC-ALL and POOL-ALL. We apply the CW-statistic, which tests the null that the benchmark forecast MSFE is less or equal to the regressor's forecast MSFE against the one-sided alternative that the RW's forecast MSFE is greater to the MSFE of its rival. "***", "**" or "*" indicate significance at the level of 1%, 5% and 10%, respectively, of the MSFE-adjusted statistic.

Table 4: HLN - encompass test

HLN (1998)	GBP	YEN	NOK	CHF	CAD	AUD
POOL-ECON encompasses POOL-TECH	0.10	0.00	0.00	0.05	0.05	0.87
POOL-TECH encompasses POOL-ECON	0.64	0.96	0.95	0.55	0.72	0.00
PC-ECON encompasses PC-TECH	0.00	0.00	0.00	0.00	0.00	0.12
PC-TECH encompasses PC-ECON	0.00	0.04	0.03	0.00	0.80	0.00

Notes: The table reports the p-values of the HLN(1998) test.

Table 5: Univariate Economic Evaluation

Predictor	ΔCER, $\gamma = 2$						ΔCER, $\gamma = 5$					
	GBP	YEN	NOK	CHF	CAD	AUD	GBP	YEN	NOK	CHF	CAD	AUD
Panel A: Macroeconomic predictors												
RW	-7.33	4.27	-2.97	6.17	-4.85	-8.43	-5.98	2.88	-3.41	4.62	-5.36	-7.26
IRP	1.36	-1.65	1.23	1.77	0.28	0.83	1.62*	-1.19	1.12	1.57	0.21	0.39
FB	2.03	-1.66	1.88	2.24	0.28	1.02*	2.19**	-1.20	1.89*	1.87	0.21	0.60
BMF	14.19***	2.65	1.23	4.55**	1.85*	12.33***	11.62***	2.77	1.78*	4.61**	1.63*	9.78***
PPP	[illegible]	6.23***	12.10***	5.36***	3.21***	10.32***	13.47***	5.79***	10.81***	4.92***	2.96***	9.12***
HOAfw	[illegible]	-0.37	1.17	-0.07	0.24	6.57***	1.47*	-0.23	1.97*	0.47	0.14	5.16***
HOS	[illegible]	-1.46	-0.35	-0.49	-0.33	7.83***	0.28	-0.88	-0.45	-0.42	-0.34	6.46***
HOSS	[illegible]	[illegible]	-0.13	0.48	0.49	-0.05	1.67*	-0.61	-0.29	0.43	0.56	0.46
HOAfw	[illegible]	[illegible]	-0.28	1.42**	-0.16	9.72***	1.03	0.36	-0.34	1.06**	0.00	6.85***
HOAS	1.49	-0.42	[illegible]	0.52	0.36	-0.03	1.97**	-0.46	-0.26	0.47	0.48	0.50
HES	-0.31	[illegible]	[illegible]	-0.71	-0.38	5.06***	-0.08	0.27	0.22	-0.58	-0.44	3.92***
HESS	1.70	-0.34	-0.16	[illegible]	0.32	-0.04	2.11**	-0.31	-0.15	0.50	0.39	0.37
HEA	1.18	0.16	0.64	[illegible]	0.79	6.48***	0.31	0.27	0.60	0.85*	0.24	5.62***
HEAS	0.31	-0.35	-0.04	[illegible]	[illegible]	0.07	0.24	-0.34	0.04	0.46	0.31	0.42
POOL-ECON	2.72***	0.29	1.58**	[illegible]	1.27***	4.26***	3.51***	0.31	1.98***	1.74***	0.88**	3.45***
PC-ECON	10.00***	1.43	1.64	5.54**	[illegible]	[illegible]	8.64***	1.41	1.94	5.70***	0.71*	9.26***
Panel B: Technical Indicators												
MA(1,9)	3.64***	1.04	1.42	1.01	0.54	1.04	[illegible]	0.76	1.05	0.94	0.61	0.74
MA(1,12)	1.89**	0.42	1.83*	0.75	0.67*	3.65**	[illegible]	0.26	1.84**	0.44	0.50	3.13***
MA(2,9)	1.71**	0.07	0.62	1.61**	0.21	0.36	[illegible]	[illegible]	0.38	1.23*	0.11	0.15
MA(2,12)	-0.35	-0.33	0.70	2.44***	0.51	0.65	[illegible]	[illegible]	0.34	2.08***	0.44	0.61
MA(3,9)	1.18	0.06	0.68	1.35	0.23	0.89	0.47	[illegible]	[illegible]	1.15	0.22	0.39
MA(3,12)	0.36	0.00	-0.16	0.23	0.15	2.07***	0.03	[illegible]	[illegible]	0.10	0.10	1.49*
MOM(9)	0.03	-0.02	0.80	-0.38	0.42	1.54*	-0.08	-0.16	[illegible]	[illegible]	0.19	1.12
MOM(12)	1.43*	-0.26	0.25	1.76**	0.71	1.89**	1.12	-0.14	[illegible]	[illegible]	0.43	1.49*
RSI(7)	14.36***	6.66***	9.08***	4.31**	2.65**	12.42***	12.24***	5.82***	8.69***	3.98****	[illegible]	11.20***
RSI(14)	14.61**	6.58***	9.60***	4.48**	3.03***	10.11***	12.41***	5.91***	9.54***	[illegible]	[illegible]	9.44***
EMA(5,12)	1.20	0.39	-0.12	-0.08	0.45	1.09**	0.61	0.27	-0.32	[illegible]	[illegible]	0.68
POOL-TECH	4.68***	0.64	2.88**	2.43***	0.95*	2.53***	4.85***	0.85	3.10***	2.16***	[illegible]	[illegible]
PC-TECH	11.21***	3.97**	5.58***	3.49**	2.17**	7.55***	9.82***	3.68**	6.23***	3.11**	[illegible]	7.24***
Panel C: All Predictors												
POOL-ALL	3.46***	0.18	2.23***	2.00***	0.94**	3.24***	4.30***	0.65*	2.63***	2.04***	0.78**	2.84***
PC-ALL	14.37***	4.59**	7.93***	5.37***	2.59**	13.79***	12.38***	3.76**	7.58***	4.91***	2.38***	11.59***
Panel D: Amalgam Forecasts												
FC-AMALG	11.90***	1.60	3.73**	3.49**	2.22**	8.41***	10.80***	2.09*	5.57***	3.60***	1.81***	7.95***

Notes: The table reports the portfolio performance for a mean-variance investor with relative risk aversion coefficient $\gamma = 2$ and $\gamma = 5$, who rebalances her portfolio between the risky asset and the risk free asset. The investor uses either the Random Walk with drift model or the forecasts generated by the proposed approaches. For each level of risk aversion we compute the measures for the forecasts of the 13 macroeconomic predictors and 11 technical indicators, PC-ECON, PC-TECH, PC-ALL and FC-AMALG. ΔCER is the annualized difference of the Certainty Equivalent Return for the investor that uses our proposed approaches instead of the RW model. "***", "**" or "*" denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 6: Multivariate Economic Evaluation

Predictor	ΔCER_{tc} $\gamma = 2$	ΔCER_{tc} $\gamma = 5$	$(\%)\mu_{tc}$	$(\%)\sigma_{tc}$	SR_{tc}	ΔCER $\gamma = 2$	ΔCER $\gamma = 5$	SR
Panel A: After Transaction Costs						Panel B: No Transaction Costs		
RW	1.01	1.01	11.61	12.89	0.90	1.01	1.01	0.92
IRP	-1.38	-1.57	10.35	13.36	0.77	-0.48	-0.67	0.86
FB	-1.71	-1.90	10.02	13.34	0.75	-0.66	-0.84	0.85
GMF	-0.46	-0.24	11.00	12.33	0.89	1.76	2.02	1.10
PPP	7.74***	7.56***	19.46	13.33	1.46***	9.70***	9.59***	1.64***
HOAfw	-2.79	-2.84	8.85	13.02	0.68	-1.49	-1.52	0.80
HOS	-0.86	-0.86	10.75	12.91	0.83	0.13	0.15	0.93
HOSS	-0.88	-0.75	10.63	12.52	0.85	-0.37	-0.23	0.91
HOA	-3.00	-2.74	8.43	12.18	0.69	-1.76	-1.48	0.81
HOAS	-0.83	-0.69	10.68	12.50	0.85	-0.31	-0.16	0.91
HES	-0.13	-0.16	11.50	13.00	0.88	0.64	0.61	0.96
HESS	-0.81	-0.68	10.71	12.55	[illegible]	-0.29	-0.17	0.91
HEA	-0.99	-0.92	10.57	[illegible]	0.83	0.24	0.33	0.95
HEAS	-0.50	-0.41	11.04	12.63	0.87	-0.05	0.05	0.93
POOL-ECON	1.82**	1.84**	13.42	[illegible]	1.04**	2.43***	2.47***	1.11***
PC-ECON	-2.68	-2.60	8.88	12.69	0.70	-0.51	-0.40	0.89
MA(1,9)	-0.32	-0.29	11.26	12.78	0.88	1.25	1.31	1.02
MA(1,12)	-0.40	-0.23	11.10	12.42	0.89	1.12	1.32	1.04
MA(2,9)	0.13	0.26	11.66	12.56	0.93	1.25	1.39	1.04*
MA(2,12)	-1.68	-1.56	[illegible]	12.55	0.78	-0.75	-0.62	0.88
MA(3,9)	-1.85	-1.65	9.62	12.34	0.78	-0.85	-0.63	0.88
MA(3,12)	-1.10	-1.07	10.48	12.79	0.82	-0.49	-0.44	0.89
MOM(9)	-1.23	-1.26	[illegible]	12.96	0.80	-0.25	-0.27	0.90
MOM(12)	-2.53	-2.57	[illegible]	12.96	0.70	-1.48	-1.50	0.80
RSI(7)	6.58***	6.40***	18.31	13.33	1.37***	8.57***	8.45***	1.56***
RSI(14)	7.76***	[illegible]	19.48	13.30	1.46***	9.62***	9.52***	1.64***
EMA(5,12)	-1.47	-1.57	10.20	13.11	0.78	-0.79	-0.87	0.85
POOL-TECH	2.44***	2.40***	14.07	13.00	1.08***	3.34***	3.33***	1.17***
PC-TECH	2.31	2.29	13.93	12.93	1.08	4.31***	4.35***	1.26***
POOL-ALL	2.34***	2.30***	13.97	13.00	1.07***	3.01***	2.99***	1.15***
PC-ALL	[illegible]	3.65**	15.37	13.02	1.18*	5.84***	5.82***	1.37***
AMALG	[illegible]	4.09***	15.74	12.94	1.22***	5.74***	5.76***	1.37***
Panel C: Naive portfolio								
1/N	-9.45	2.02	0.16	1.52	0.10			

Notes: The table reports the portfolio performance for a mean-variance investor with relative risk aversion coefficient $\gamma = 2$ and $\gamma = 5$, who invests her portfolio in the risky assets and the risk free asset. The investor uses either the Random Walk with drift model or the forecasts generated by the proposed approaches to rebalance her portfolio. For each level of risk aversion we compute the measures for the forecasts of the 13 macroeconomic predictors and 11 technical indicators, PC-ECON, PC-TECH, PC-ALL and FC-AMALG. ΔCER is the annualized difference in the Certainty Equivalent Return for the investor that uses our proposed approaches instead of the RW model. SR is the annualized Sharpe ratio values. μ denotes the annualized portfolio excess return in percentage points and σ denotes the annualized standard deviation in percentage points. The subscript tc denotes that we account for transaction costs equal to 5 basis points. In Panel B, we do not account for transaction costs. In Panel C, we show the economic performance of the Naive Portfolio, according to which the investor equally weights her wealth among the risky assets. "***", "**" or "*" denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 7: Robustness tests: Alternative Forecast Horizons

Predictor	h=3						h=6						h=12					
	GBP	YEN	NOK	CHF	CAD	AUD	GBP	YEN	NOK	CHF	CAD	AUD	GBP	YEN	NOK	CHF	CAD	AUD
Panel A: Macroeconomic predictors																		
IRP	1.55**	[illegible]	0.47**	0.99**	-1.15	-0.22	1.21**	-2.17	0.13	0.09	-0.70**	-0.54	1.02*	-2.28	0.05	0.36	-0.38*	-0.40
FB	1.84**	[illegible]	[illegible]	1.40**	-1.13	-0.06	1.36**	-2.03	0.24	0.29*	-0.62**	-0.54	1.14*	-2.19	0.06	0.58*	-0.34*	-0.43
BMF	[illegible]	[illegible]	[illegible]	2.89***	1.57***	2.23***	-0.77	-0.12**	0.09	1.28***	1.24**	0.07	-2.06	1.26***	-0.73	1.23***	0.25	-0.58
PPP	2.71***	[illegible]	2.86***	[illegible]	1.99**	1.38**	0.59**	-0.19**	0.40*	0.57**	1.00**	0.02	-0.53*	1.97***	-0.49	0.91**	0.03	-0.52
HOAfw	0.05	-0.07	[illegible]	[illegible]	-0.37	0.05	-0.48	-0.20	0.23*	0.22	-0.38	-0.57	-2.48	-0.23	-0.06	0.26	0.18	-0.48
HOS	-0.75	-1.94	-0.34	-0.27	[illegible]	0.81*	-0.70	-1.68	-0.85	-0.40	-0.49	-0.32	-2.57	-1.54	-1.06	0.21	-0.36	-0.25
HOSS	0.43	-1.28	-0.55	[illegible]	0.47	0.76	0.05	-1.97	-0.47	-0.64	-0.43**	-0.48	0.92*	-1.52	-0.27	-0.08	-0.07*	-0.18
HOA	-1.12	-0.06	-0.21	0.30	-0.21	[illegible]	-0.39	-0.41	-0.52	-0.26	-0.38	0.16	-1.74	-0.45	-0.75	0.58**	-0.39	-0.16
HOAS	0.49*	-1.26	-0.60	-0.33	0.44	[illegible]	[illegible]	-1.80	-0.49	-0.64	-0.41*	-0.47	0.98*	-1.48	-0.26	-0.09	-0.06*	-0.17
HES	-0.82	-0.15	0.56**	0.02	[illegible]	1.57***	[illegible]	-0.29	-0.38	-0.19	0.49*	0.56	-0.25**	-0.34	-0.82	0.28	0.75**	0.05
HESS	0.69*	-0.82	-0.49	-0.35	-0.24*	-0.76	0.26	[illegible]	-0.49	-0.64	-0.18**	-0.48	1.13*	-0.78	-0.33	-0.06	0.11**	-0.18
HEA	-0.59	-0.26	0.57	0.48	2.14***	[illegible]	[illegible]	-0.10	-0.45	-0.19	1.24**	1.66***	0.30**	-0.35	-0.74	0.81**	0.70*	0.16
HEAS	0.79*	-0.84	-0.41	-0.36	-0.24*	-0.94	[illegible]	[illegible]	-0.44	-0.65	-0.19**	-0.53	1.06*	-0.70	-0.33	-0.09	0.09**	-0.26
POOL-ECON	1.55***	0.84**	0.91***	1.78***	0.85***	1.12**	1.47**	[illegible]	[illegible]	[illegible]	0.93***	0.13	1.45**	0.11	-0.11	1.01***	0.66***	-0.06
PC-ECON	0.37	-0.83	-0.57	0.90***	-0.43	0.87**	0.95**	[illegible]	-0.45	[illegible]	-0.42***	-0.02	1.62**	-0.55	-0.63	0.46*	0.06**	-0.13
Panel B: Technical Indicators																		
MA(1,9)	0.01	0.55*	0.80**	1.57***	-0.64	0.33*	-0.73	-0.35	-0.01	[illegible]	[illegible]	[illegible]	-0.62	-0.26	-0.13	-0.15	-0.80	-0.06
MA(1,12)	-0.21	0.31*	0.62	0.26*	-0.46	0.43**	-0.82	-0.44	-0.28	-0.41	[illegible]	[illegible]	-0.63	-0.05	-0.10	0.02	-0.68	-0.41
MA(2,9)	-0.38	-0.21	0.29	0.36*	-0.73	0.22*	-0.75	-0.54	-0.24	-0.63	[illegible]	[illegible]	[illegible]	-0.53	-0.26	-0.02	-0.62	-0.27
MA(2,12)	-0.51	-0.44	0.35	0.47*	-0.56	-0.21**	-0.85	-0.72	-0.19	-0.27	-0.62	[illegible]	-0.69	-0.64	-0.15	0.24	-0.35	-0.78
MA(3,9)	-0.56	-0.66	-0.12	-0.25	-0.84	-0.12	-0.83	-0.42	-0.14	-0.50	-0.76	-0.30	-0.74	[illegible]	-0.29	-0.14	-0.64	-0.30
MA(3,12)	-0.52	-0.39	-0.24	-0.16	-0.67	-0.50*	-0.74	-0.68	-0.26	-0.48	-0.82	-0.46	[illegible]	[illegible]	-0.29	-0.14	-0.44	-0.62
MOM(9)	-0.50	-0.20	0.23	-0.02	-0.52	0.63*	-0.78	-0.51	-0.15	-0.33	-0.69	-0.31	-0.80	[illegible]	-0.19	-0.08	-0.20	-0.28
MOM(12)	-0.93**	-0.02	0.58*	0.16	-0.41	-0.69	-1.38	0.35*	-0.20	-0.02	-0.28	-0.40	-1.03	[illegible]	-0.20	[illegible]	-0.29	-0.65
RSI(7)	1.48***	3.25***	3.67***	1.65***	1.42**	1.82***	0.65**	-0.05	1.24***	-0.06*	0.25	0.35	-1.28*	1.64**	0.06	[illegible]	0.29	0.38*
RSI(14)	2.86***	3.90***	3.88***	1.83***	1.53***	1.96***	1.40***	0.14**	1.14***	0.21**	0.38*	0.61*	-1.39**	2.29***	[illegible]	[illegible]	[illegible]	0.50*
EMA(5,12)	0.41**	0.92**	-0.24	-0.42	-0.77	-0.41	-0.31	0.79**	-0.38	-0.92	-0.68	-0.18	-0.35	1.09**	-0.26	-0.59	[illegible]	[illegible]
POOL-TECH	1.86***	1.36***	1.44***	1.47***	0.00	1.15***	0.38	0.31	0.24	0.10	-0.24	0.01	0.56*	1.15***	-0.02	0.50*	[illegible]	[illegible]
PC-TECH	0.62***	1.79***	2.47***	1.09***	0.29	2.11***	-0.29*	-0.12	0.52	-0.42	-0.18	0.51*	-1.00**	1.62***	0.09	0.81**	[illegible]	0.09*
Panel C: All predictors Taken Together																		
POOL-ALL	1.85***	1.15***	1.21***	1.70***	0.55**	1.22***	1.13***	0.32	0.16	0.45*	0.54**	0.10	1.27**	0.68**	-0.03	0.83***	0.40**	0.04
PC-ALL	2.04***	0.66**	1.12***	0.90***	2.04***	1.42***	0.38**	0.06	0.27*	-0.03	1.35***	0.56*	-2.34*	-0.21*	-0.61	1.32**	0.83**	-0.18
Panel D: Amalgam Forecasts																		
FC-AMALG	3.15***	1.35***	1.51***	1.73***	1.74***	1.73***	1.53**	0.32	0.29*	0.41*	1.48***	0.38	0.60**	0.55*	-0.21	1.36***	1.01**	-0.01

Notes: The table reports the R^2_{OOS} for h-month-ahead forecasts. For further details see Table 3.

Table 8: Robustness Test : Out-of-sample period begins in 1990

Macroeconomic Variables							Technical Indicators						
Predictor	GBP	YEN	NOK	CHF	CAD	AUD	Predictor	GBP	YEN	NOK	CHF	CAD	AUD
Panel A: Bivariate Predictive Regression Forecasts													
IRP	2.06**	0.75**	2.21***	[illegible]	-0.21	0.06	MA(1,9)	3.79***	0.41**	0.58**	0.86***	0.85**	1.34***
FB	2.67**	1.06**	[illegible]	1.85**	-0.23	0.41***	MA(1,12)	0.31*	0.59**	2.75***	-0.23*	0.75**	0.76***
BMF	9.51***	2.74***	3.38***	[illegible]	5.44***	10.16***	MA(2,9)	0.63*	1.21**	1.19*	2.39***	0.54*	0.66**
PPP	9.39***	9.97***	13.19***	[illegible]	[illegible]	11.57***	MA(2,12)	-1.09	-0.19	1.19**	1.27***	0.46*	-1.01
HOAfw	2.24***	-0.28	3.09***	1.03**	0.24	5.58***	MA(3,9)	-0.65	0.44	1.15**	1.46***	-0.07	0.25
HOS	0.71	-0.20	0.25	-0.29	0.36	6.96***	MA(3,12)	-2.19	-0.17	0.09	0.33	-0.32	-0.11
HOSS	-1.16	-0.14	0.16	0.39	-0.67	0.16	MOM(9)	-0.96	-0.23	1.52	0.02	0.15	-1.69
HOA	-1.19	1.07***	0.63	2.64***	-0.32	[illegible]	MOM(12)	0.32**	0.09	0.52	3.04***	0.53	1.27*
HOAS	-1.19	-0.17	0.15	0.39	-0.67	[illegible]	RSI([illegible])	6.57***	8.08***	13.13***	5.62***	5.09***	9.41***
HES	-0.73	0.14	0.79*	-0.21	-0.44	5.53***	RSI(14)	7.87***	8.55***	15.01***	5.57***	5.33***	10.56***
HESS	-1.23	-0.36	0.15	0.44	-0.66	0.19	EMA(5,12)	0.02*	0.58*	-0.15	0.00	0.25	1.39*
HEA	-0.20	0.95**	2.64**	2.44***	0.59*	8.89***							
HEAS	-0.96	-0.39	0.17	0.42	-0.60	0.21							
Panel B: Principal Components and Combination Forecasts per Group (Macro vs Tech)													
POOL-ECON	3.16***	2.68***	3.34***	3.48***	1.08***	6.03***	POOL-TECH	4.48***	4.31***	[illegible]	4.51***	1.57***	3.71***
PC-ECON	5.17***	5.43***	5.52***	4.70***	-0.12	12.74***	PC-TECH	4.96***	[illegible]	7.82***	3.98***	3.33***	5.62***
Panel C: Principal Components and Combination Forecasts per Group (All predictors)													
POOL-ALL	3.96***	3.53***	4.25***	4.08***	1.32***	5.10***							
PC-ALL	3.71***	6.22***	10.21***	4.90***	4.34***	12.25***							
Panel D: Amalgam Forecasts													
FC-AMALG	6.40***	6.75***	8.63***	5.97***	3.11***	10.09***							

Notes: The table reports the R^2_{OOS} values for each currency. For further details see Table 3. The out-of-sample period begins in January 1990.

Table 9: Robustness Test : Out-of-sample period begins in 2000

Macroeconomic Variables							Technical Indicators						
Predictor	GBP	YEN	NOK	CHF	CAD	AUD	Predictor	GBP	YEN	NOK	CHF	CAD	AUD
Panel A: Bivariate Predictive Regression Forecasts													
IRP	0.55	-0.16	0.78*	-[illegible].15	-0.41	0.11**	MA(1,9)	3.88***	-4.22	1.16**	1.07**	1.10**	1.10**
FB	0.99	-0.15	[illegible]**	-5.5[illegible]	-0.43	0.52***	MA(1,12)	0.14	-0.05	3.97***	-0.49	0.72**	2.69***
BMF	7.34***	-7.52	3.81[illegible]	-0.[illegible]8**	6.27***	11.55***	MA(2,9)	0.22	0.41	1.40*	1.14**	0.75*	0.86**
PPP	8.53***	4.83***	12.88***	1.12[illegible]	7.3[illegible]***	13.14***	MA(2,12)	-0.24	0.00	1.41*	0.98**	0.71**	-0.46
HOAfw	2.67**	-0.92	3.66**	-1.88	0.[illegible]7*	5.88***	MA(3,9)	0.26	1.08*	1.30*	1.51**	-0.04	0.51
HOS	1.06	1.04*	0.57	-0.34	0.35	7.43***	MA(3,12)	-0.15	0.06	0.06	0.82**	-0.19	1.13
HOSS	-0.13	-0.02	0.28	-0.23	-0.29	-0.0[illegible]	MOM(9)	-1.50	-0.14	2.81**	0.01	0.20	-0.52
HOA	-1.55	1.58**	1.07*	2.34***	-0.37	10.[illegible]7***	MOM(12)	-1.12	-0.49	0.61	0.33**	0.61	2.17*
HOAS	-0.14	-0.04	0.29	-0.25	-0.28	-0.01	RSI([illegible])	4.76***	-2.33**	13.50***	1.71***	5.74***	10.61***
HES	-0.49	0.76*	1.28	-0.52	-0.48	5.75***	RSI(14)	7.51***	-0.80***	15.72***	1.43***	6.01***	11.65***
HESS	-0.10	-0.18	0.25	-0.22	-0.26	0.02	EMA(5,12)	2.82	-0.46	-0.14	-1.46	0.29	2.04*
HEA	-0.20	1.47**	3.09**	1.84**	0.83**	10.65***							
HEAS	-0.06	-0.20	0.29	-0.24	-0.22	0.03							
Panel B: Principal Components and Combination Forecasts per Group (Macro vs Tech)													
POOL-ECON	3.03***	1.73***	3.31***	1.21*	1.32***	6.43***	POOL-TECH	3.59***	2.18***	5.[illegible]3***	3.32***	1.75***	4.00***
PC-ECON	7.27***	0.09*	7.66***	-2.96*	0.07	13.75***	PC-TECH	3.38***	-2.0[illegible]**	10.25***	1.33***	3.78***	8.23***
Panel C: Principal Components and Combination Forecasts per Group (All predictors)													
POOL-ALL	3.45***	2.08***	4.34***	2.31***	1.53***	5.43***							
PC-ALL	3.66***	-1.97**	12.08***	0.06***	5.41***	14.53***							
Panel D: Amalgam Forecasts													
FC-AMALG	5.44***	2.05**	9.47***	2.69***	3.75***	11.10***							

Notes: The table reports the R^2_{OOS} values for each currency. For further details see Table 3. The out-of-sample period begins in January 2000.

Table 10: Out-of-sample Estimates for Additional Currencies; Out-of-sample period begins in 1979 & 1990

Predictor	DKK	EUR	MYR	ZAR	SEK	DKK	EUR	MYR	NZD	ZAR	SEK
OOS period starts in 1979						OOS starts in 1990					
Panel A: Bivariate Predictive Regression Forecasts, ECON											
IRR	-0.10	1.17***	-0.43	-0.56	0.68**	0.02	1.34***	0.03	0.69**	-0.40	1.45**
FB	-0.13	1.90***	-0.44	-0.75	1.28***	-0.01	2.13***	0.00	0.93**	-0.43	2.12***
GMF	3.50***	4.22***	-0.39	1.06***	4.54***	3.88***	4.08***	0.08	7.24***	0.52**	5.49***
PPP	8.55***	5.22***	-4.58	10.49***	14.94***	8.61***	3.53***	-5.50	10.40***	10.78***	16.40***
HOAfx	[illegible]	2.56***	-0.42	0.49*	1.14**	0.41	2.37***	-0.26	2.45***	0.84*	1.16**
HOS	-0.10	-0.40	-0.36	-0.29	-0.29	-0.04	-0.14	-0.20	0.36	-0.48	-0.41
HOSS	-0.09	[illegible]	-0.33	-0.35	-1.52	-0.04	-0.59	0.17	-0.45	0.17	-0.24
HOA	[illegible]	[illegible]	-0.69	-0.39	-0.14	-0.09	-0.46	-0.30	1.50**	-0.56	-0.19
HOAS	-0.06	-0.28	[illegible]	-0.36	-1.58	-0.02	-0.59	0.24	-0.49	0.18	-0.23
HES	-0.39	[illegible]	[illegible]	-0.28	-0.15	-0.11	-0.58	-0.20	0.13	-0.36	-0.24
HESS	-0.15	[illegible]	[illegible]	[illegible]	-1.72	-0.04	-0.60	0.42	-0.18	0.13	-0.22
HEA	-0.17	0.93**	[illegible]	[illegible]	0.35	-0.08	0.15	-0.24	0.75*	0.36**	0.40
HEAS	-0.14	-0.37	-0.02	[illegible]	[illegible]	-0.03	-0.64	0.38	-0.26	0.02	-0.21
Panel B: Principal Components and Combination Forecasts, ECON											
POOL-ECON	1.62***	2.55***	0.50	1.93**	[illegible]	1.65***	2.05***	0.68	3.08***	2.09***	3.24***
PC-ECON	0.06	6.63***	-0.16	1.59***	[illegible]	0.21	6.25***	0.22	4.35***	3.44***	8.01***
Panel C: Bivariate Predictive Regression Forecasts, TECH											
MA(1,9)	2.07***	0.21**	0.89***	0.30	2.07***	[illegible]	[illegible]	1.00***	-1.29	1.27**	2.33***
MA(1,12)	2.59***	1.22***	0.38***	1.38***	2.59***	2.93***	[illegible]	[illegible]	-1.98	1.81***	2.93***
MA(2,9)	1.85***	0.54**	0.13*	0.30**	1.85***	1.99**	0.64*	[illegible]	-1.17	0.24	1.99**
MA(2,12)	1.15**	-0.02	0.70***	0.18	1.15**	1.58**	0.49**	[illegible]	-1.55	0.38*	1.58**
MA(3,9)	0.62*	0.23	-0.15	0.06	0.62*	0.86*	0.57**	[illegible]	-0.71	0.14	0.86*
MA(3,12)	1.10**	0.36*	0.50**	0.00	1.10**	1.64**	0.64**	0.92***	[illegible]	[illegible]	1.64**
MOM(9)	1.73***	0.73**	0.56***	-0.53	1.73***	2.05**	0.95**	0.18***	[illegible]	-0.37	2.05**
MOM(12)	0.04*	1.40***	-0.87	0.19	0.04*	0.84*	2.15***	0.07	0.07	[illegible]	0.84*
RSI(7)	4.59***	1.98***	3.14***	1.40***	4.59***	5.67***	2.07***	2.97***	2.96***	[illegible]	[illegible]
RSI(14)	6.64***	3.53***	0.14***	3.97***	7.23***	7.95***	3.72***	0.25***	5.06***	[illegible]	[illegible]
EMA(5,12)	2.10***	0.35**	-0.94	0.30*	1.83***	2.96***	0.66**	0.17*	1.36**	0.79**	[illegible]
Panel D: Principal Components and Combination Forecasts, TECH											
POOL-TECH	3.76***	1.89***	1.57***	1.10***	3.87***	4.55***	2.17***	1.47***	1.87***	1.38***	4.63***
PC-TECH	7.54***	3.31***	2.80***	1.51***	7.59***	9.18***	4.19***	2.33***	-0.13***	1.98***	9.24***
Panel E: Principal Components and Combination Forecasts, All Predictors Taken Together											
POOL-ALL	2.72***	2.33***	1.08	1.59***	3.39***	3.11***	2.18***	1.11	2.65***	1.81***	3.98***
PC-ALL	8.47***	5.03***	3.10***	2.31***	7.11***	10.56***	5.50***	3.48***	4.07***	3.81***	11.84***
Panel F: Amalgam Forecasts											
AMALG	6.59***	4.61***	2.57***	2.83***	7.13***	8.06***	4.79***	2.70**	4.64***	4.21***	9.69***

Notes: The table reports the R^2_{OOS} values for each currency. For further details see Table 3.

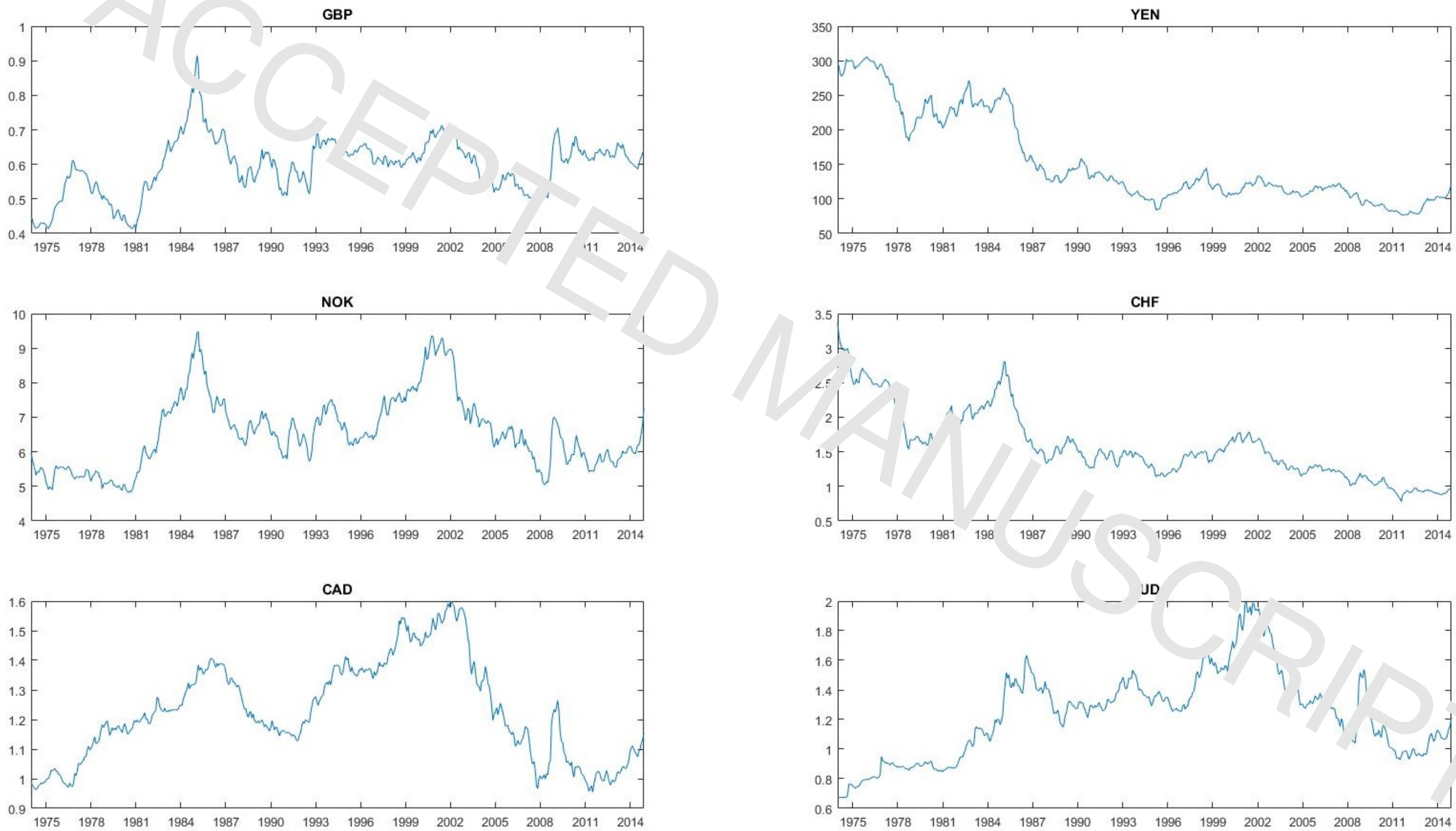
Table 11: Out-of-sample Estimates for Additional Currencies; Out-of-sample period begins in 2000

Predictor	COP	DKK	EUR	INR	MYR	MXN	NZD	SOL	PHP	ZAR	SEK	THB	BRL
Panel A: Bivariate Predictive Regression Forecasts, ECON													
IRR	0.06	0.02	1.79**	0.09	0.09	0.61*	0.39	1.75***	-1.74	-0.02	0.30	0.01	0.69***
FB	0.05	-0.01	2.73***	0.10	0.05	0.67*	0.65	1.73***	-1.72	-0.13	0.92*	0.05	0.70***
GMF	-0.79	3.36**	4.39***	-1.13	0.09	-8.28	9.12***	1.53***	0.86*	0.38	5.27***	2.79***	-2.81
PPP	[illegible]	6.84***	7.57***	4.80**	10.26***	-4.18	11.72***	1.87	-0.79	9.28***	12.81***	3.42***	-0.38
HOAfw	[illegible]	[illegible]	2.45**	0.39	-0.71	0.39*	2.40***	4.91***	1.01*	1.02*	0.64	-1.6	0.39*
HOS	-0.45	[illegible]	-0.09	-0.35	-0.15	0.28	0.53	2.87***	0.95*	-1.03	-0.23	-15.14	0.49
HOSS	[illegible]	[illegible]	0.15	0.02	-0.17	0.53***	-0.27	2.23***	-1.98	0.25	-0.07	-1.09	0.34**
HOA	-1.08	[illegible]	[illegible]	-0.18	-0.22	-1.72	1.68**	2.27***	1.18*	-1.24	-0.37	-11.8	0.97
HOAS	-0.46	[illegible]	[illegible]	-0.03	-0.27	0.60***	-0.32	2.32***	-1.91	0.25	-0.05	-1.23	0.28*
HES	-0.03	-0.15	[illegible]	[illegible]	-0.48	1.19**	0.16	2.50***	0.61	-0.96	-0.06	-5.25	-0.01
HESS	-0.37	0.11	[illegible]	[illegible]	-0.59	0.35*	0.06	2.30***	-1.81	0.25	-0.05	-0.46	0.21**
HEA	-0.72	-0.13	[illegible]	-0.22	[illegible]	1.37**	0.81*	2.39***	-0.1	1.47**	-0.37	-1.57	0.27
HEAS	-0.35	0.10	0.16	-0.08	-0.51	0.36*	-0.01	2.28***	-1.81	0.18	-0.03	-2.03	0.23**
Panel B: Principal Components and Combination Forecasts, ECON													
POOL-ECON	0.04	1.41***	2.91***	0.60**	[illegible]	[illegible]	3.29***	2.65***	0.31	1.89***	2.66***	-0.56	0.33
PC-ECON	-0.62	0.27	10.49***	0.26	-0.82	-3.16	5.37***	2.61***	-0.3	3.06**	5.84***	-4.96	0.23
Panel C: Bivariate Predictive Regression Forecasts, TECH													
MA(1,9)	-0.95	0.55*	1.74**	4.05**	3.93***	-0.93	[illegible]	[illegible]	-2.76	1.30*	0.55*	-1.16	-4.35
MA(1,12)	-0.28	3.53**	0.78**	2.44**	2.81***	-0.89	-0.9	[illegible]	[illegible]	1.99**	3.53**	-1.29	-0.7
MA(2,9)	-0.84	2.22**	1.95**	0.85**	-1.38	-0.74	-1.29	[illegible]	[illegible]	0.25	2.22**	-0.59	-6.01
MA(2,12)	-0.23	2.80**	1.51**	4.84**	3.12**	-0.73	-0.46	1.26**	[illegible]	[illegible]	2.80**	-19.8	-3.06
MA(3,9)	0.92	1.86**	1.31*	2.43**	-0.46	-0.47	-1.42	0.78*	-0.7	[illegible]	1.86**	-3.57	-7.43
MA(3,12)	1.60*	2.45**	1.92**	0.52*	2.85**	-0.64	-0.43	1.54***	-0.2	[illegible]	[illegible]	0.38	-3.9
MOM(9)	-0.41	3.25**	2.93**	1.37**	1.41*	-0.43	1.33**	2.15***	-2.36	[illegible]	[illegible]	-13.39	-1.42
MOM(12)	0.19	-1.59	1.51**	0.32	0.76**	-1.68	0.40*	2.27***	-0.67	[illegible]	[illegible]	-1.82	-1.01
RSI(7)	0.86	5.17***	4.44***	4.97***	3.22***	-3.22	3.13***	1.28**	-0.46	0.57	[illegible]	-0.37	-1.3
RSI(14)	-0.15	4.02**	3.94***	1.72*	-13.93**	-1.35	5.73***	0.89	-0.93	3.09***	[illegible]	-0.39*	[illegible]
EMA(5,12)	0.06	3.32**	1.49**	-0.35	0.70	-0.25	2.01**	2.76***	-0.23	0.73**	3.09**	-6.08	[illegible]
Panel D: Principal Components and Combination Forecasts, TECH													
POOL-TECH	0.75	4.21***	3.76***	3.25***	2.84***	-0.01	1.67***	1.90***	-0.11	1.17***	4.22***	-0.4	[illegible]
PC-TECH	1.32	9.79***	7.77***	7.80***	5.41***	-1.32	0.65**	1.36**	-0.98	1.76**	9.80***	-2.32	-6.62
Panel E: Principal Components and Combination Forecasts, All Predictors Taken Together													
POOL-ALL	0.43	2.82***	3.40***	1.90***	2.04***	0.01	2.63***	2.35***	0.29	1.59***	3.47***	-0.21	0.28
PC-ALL	0.57	10.71***	9.54***	7.94***	3.77**	0.26	5.58***	2.65***	-0.14	4.61***	11.66***	-5.78	0.14
Panel F: Amalgam Forecasts													
AMALG	0.56	7.87***	8.17***	5.89***	4.17***	0.15	5.10***	2.57***	0.45	4.54***	9.22***	-2.48	0.26

Notes: The table reports the R^2_{OOS} values for each currency. For further details see Table 3.

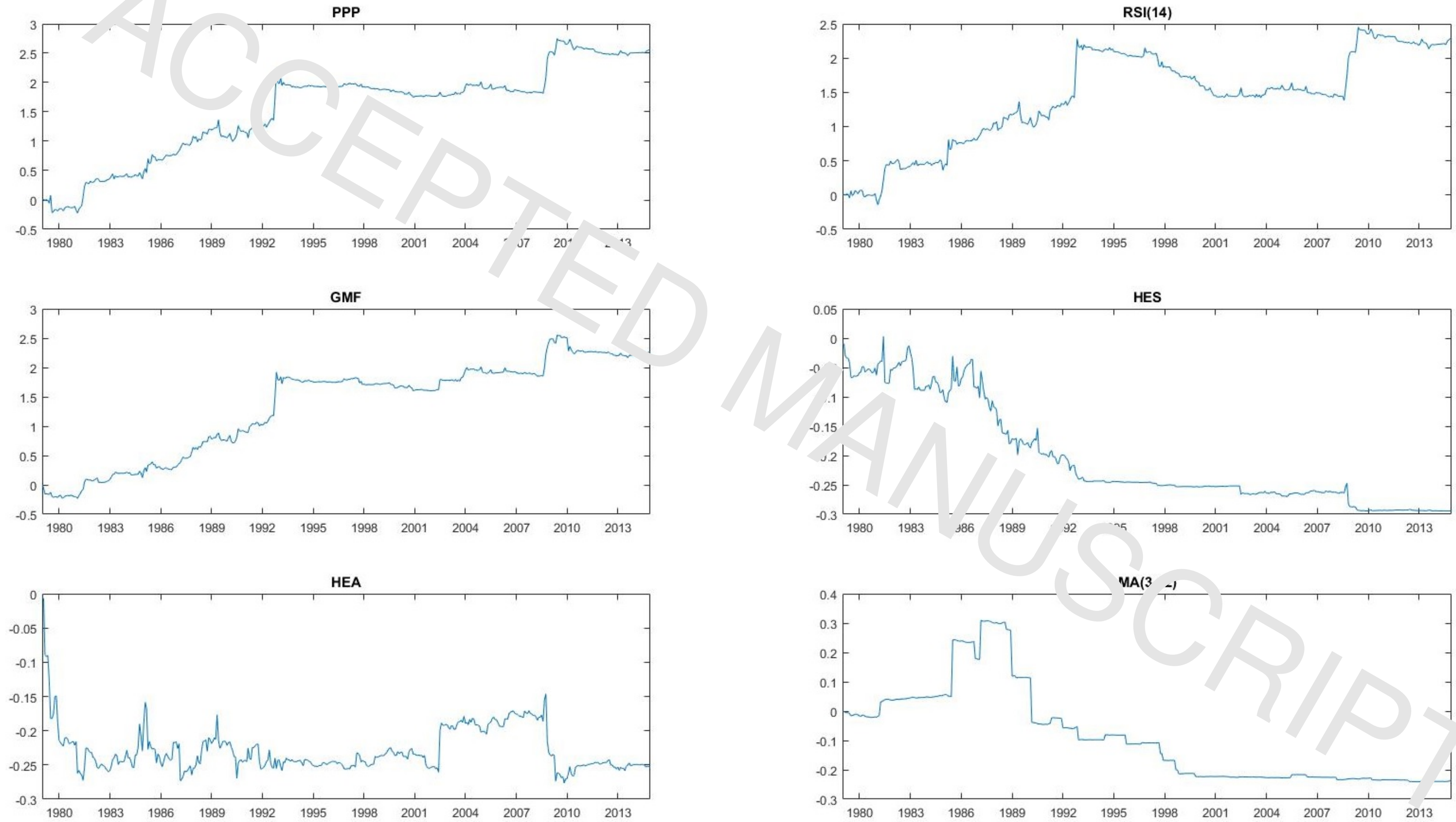
Figure(s)

Figure 1: Spot Exchange Rates



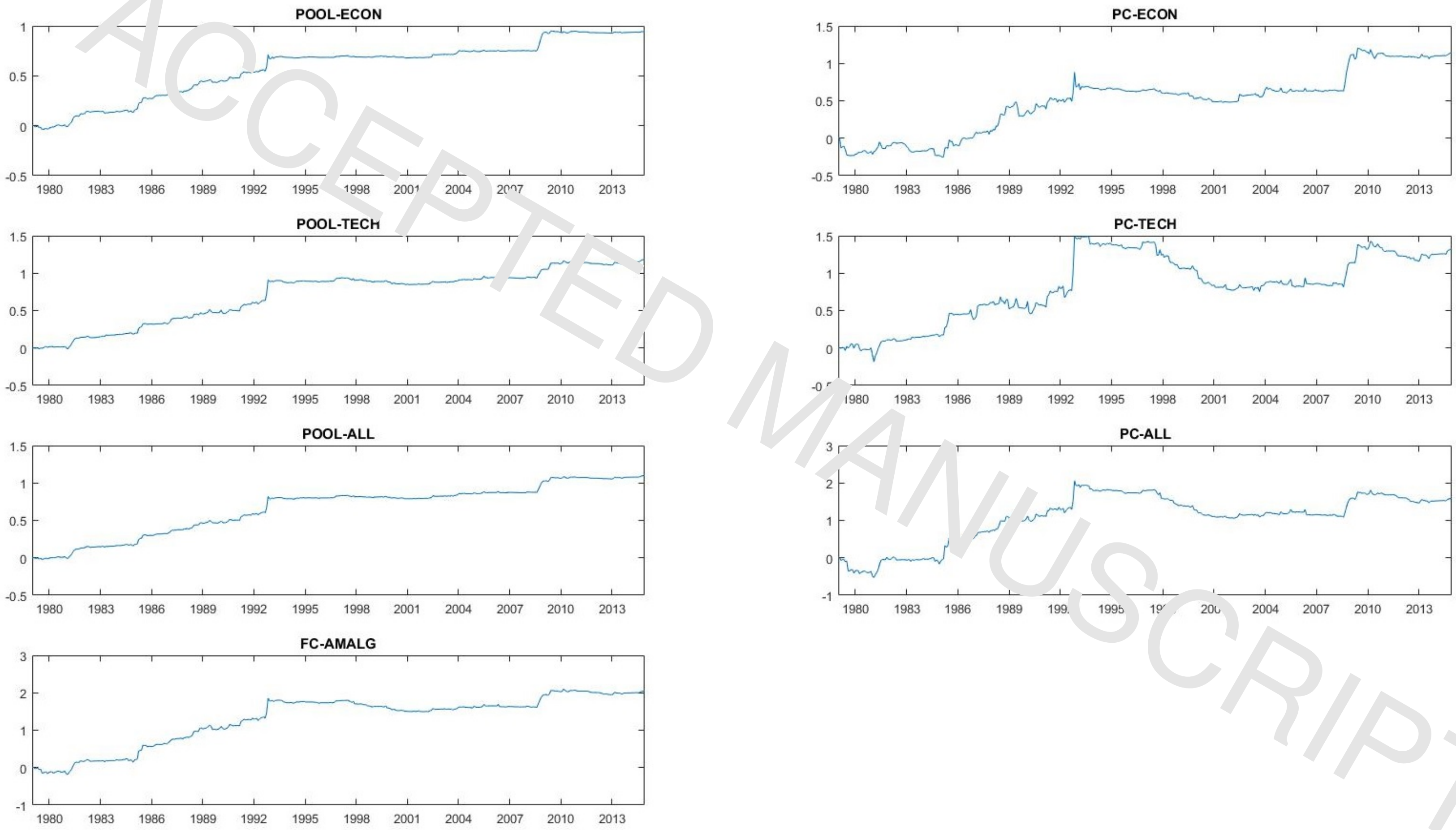
Notes: Figure 1 presents the time series of the six spot exchange rates (vs USD).

Figure 2: GBP forecasts



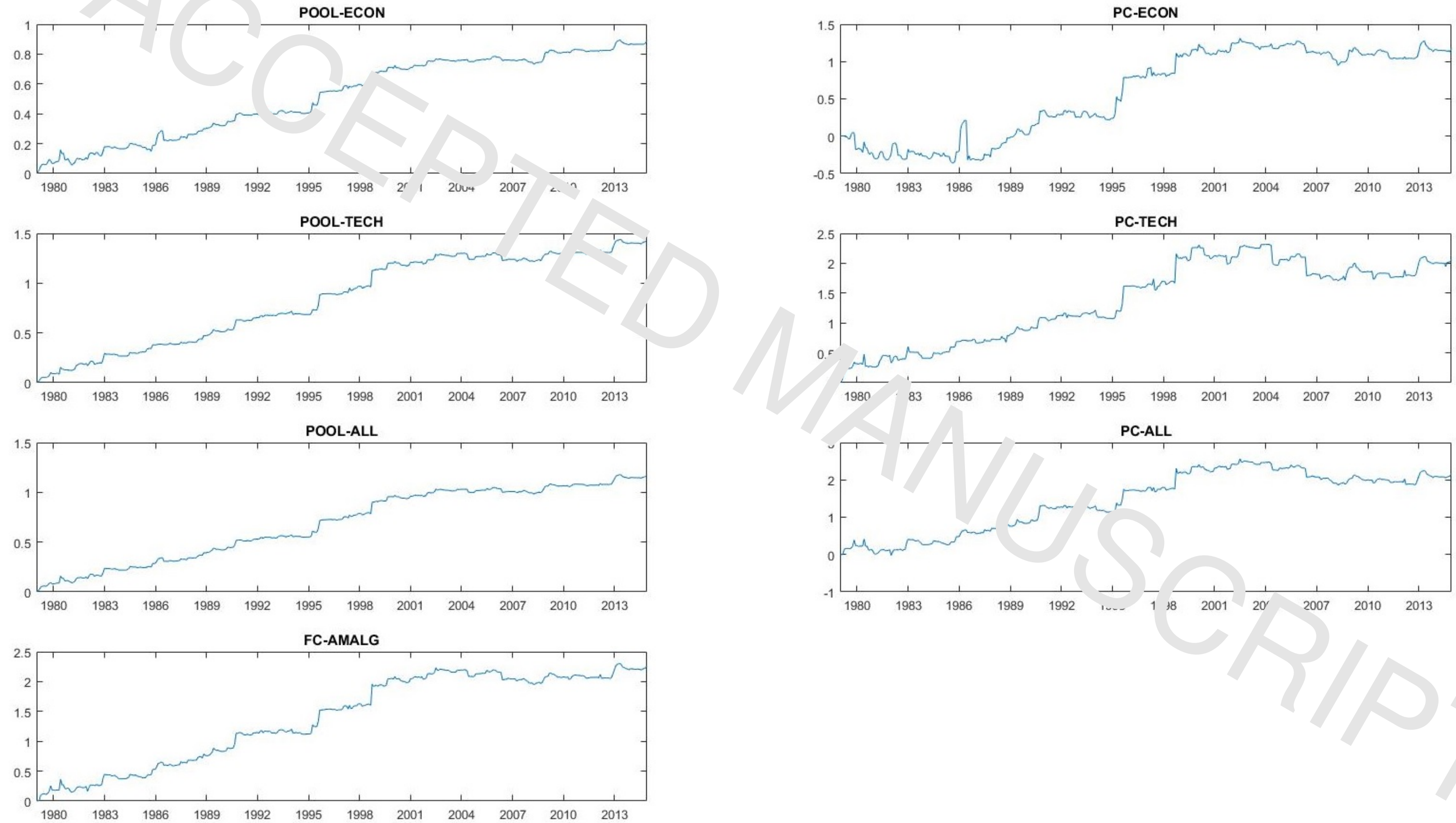
Notes: The Figure plots the cumulative squared error difference between the benchmark and the best and worst performing predictors. The best performing predictors are PPP, RSI(14) and BMF, and the worst performing ones are HES, HEA and MA(3,12).

Figure 3: GBP forecasts (PC, POOL, AMALG)



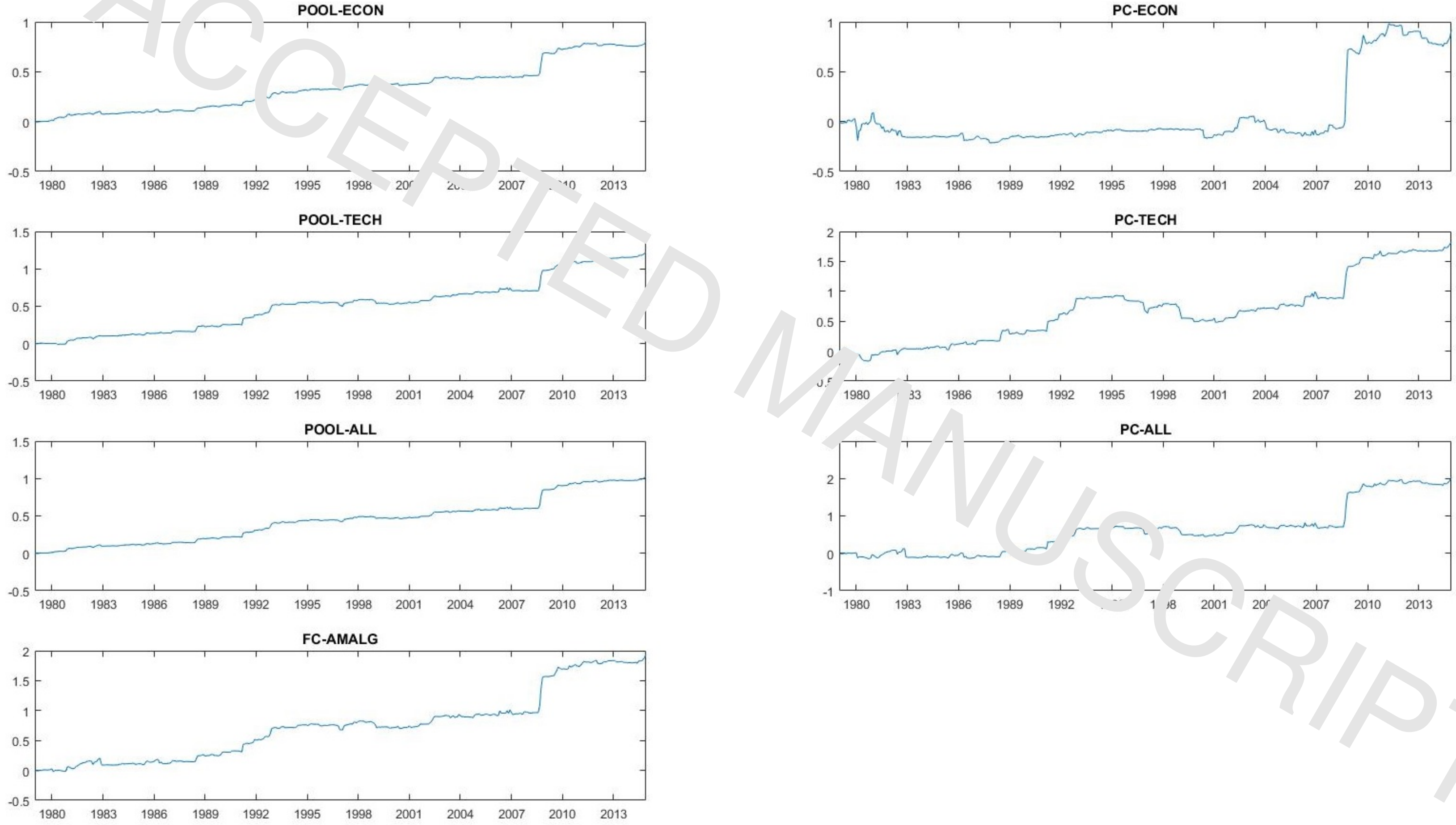
Notes: The Figure plots the cumulative squared error difference between the RW benchmark and the Combined forecasts (POOL-j), Principal Components (PC-j) and amalgam forecasts. j= ECON for macroeconomic predictors, j=TECH for technical Indicators and j=ALL for all individual predictors taken together.

Figure 4: YEN forecasts (PC, POOL, AMALG)



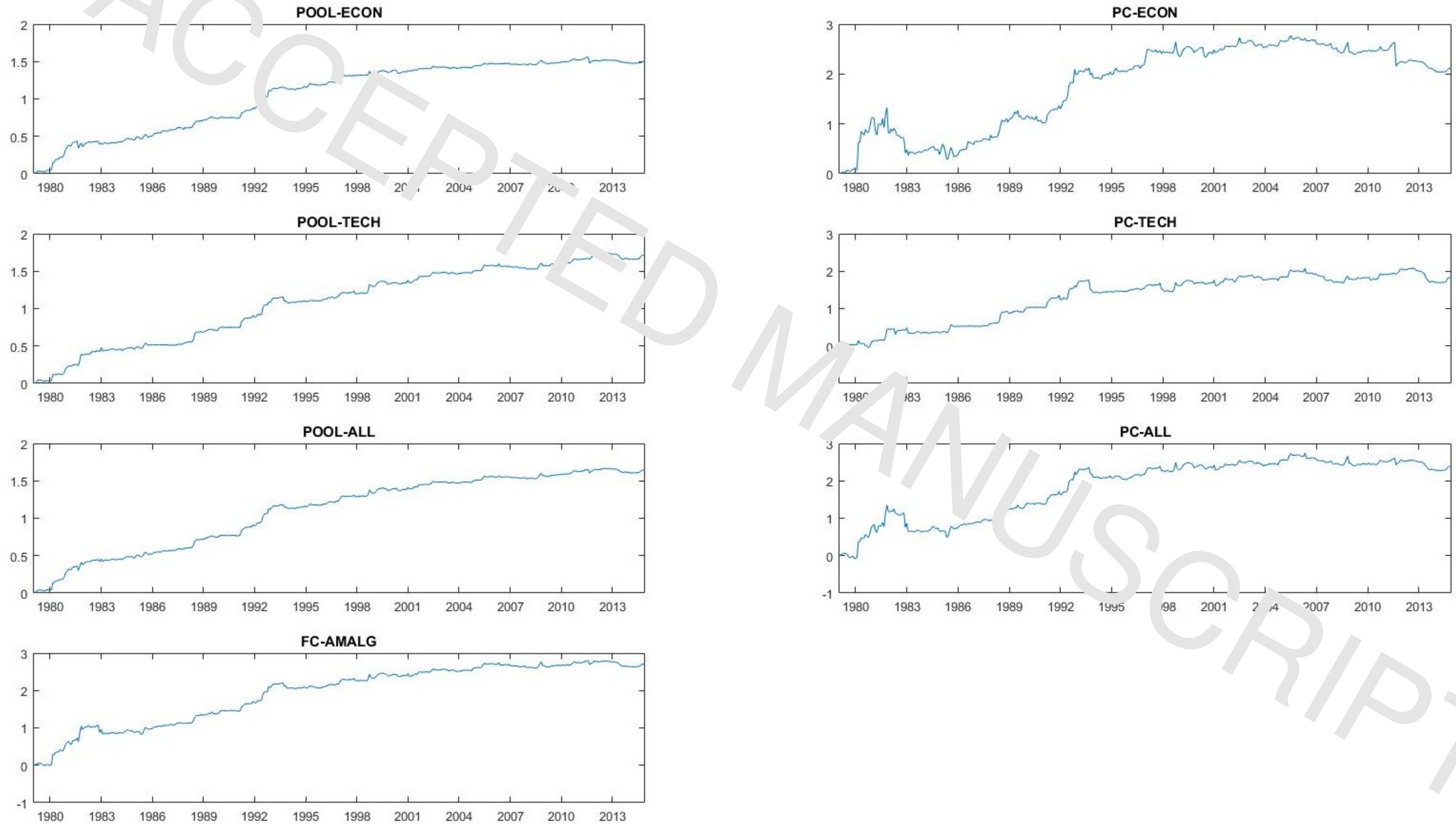
Notes: See notes in Figure 3.

Figure 5: NOK forecasts (PC, POOL, AMALG)



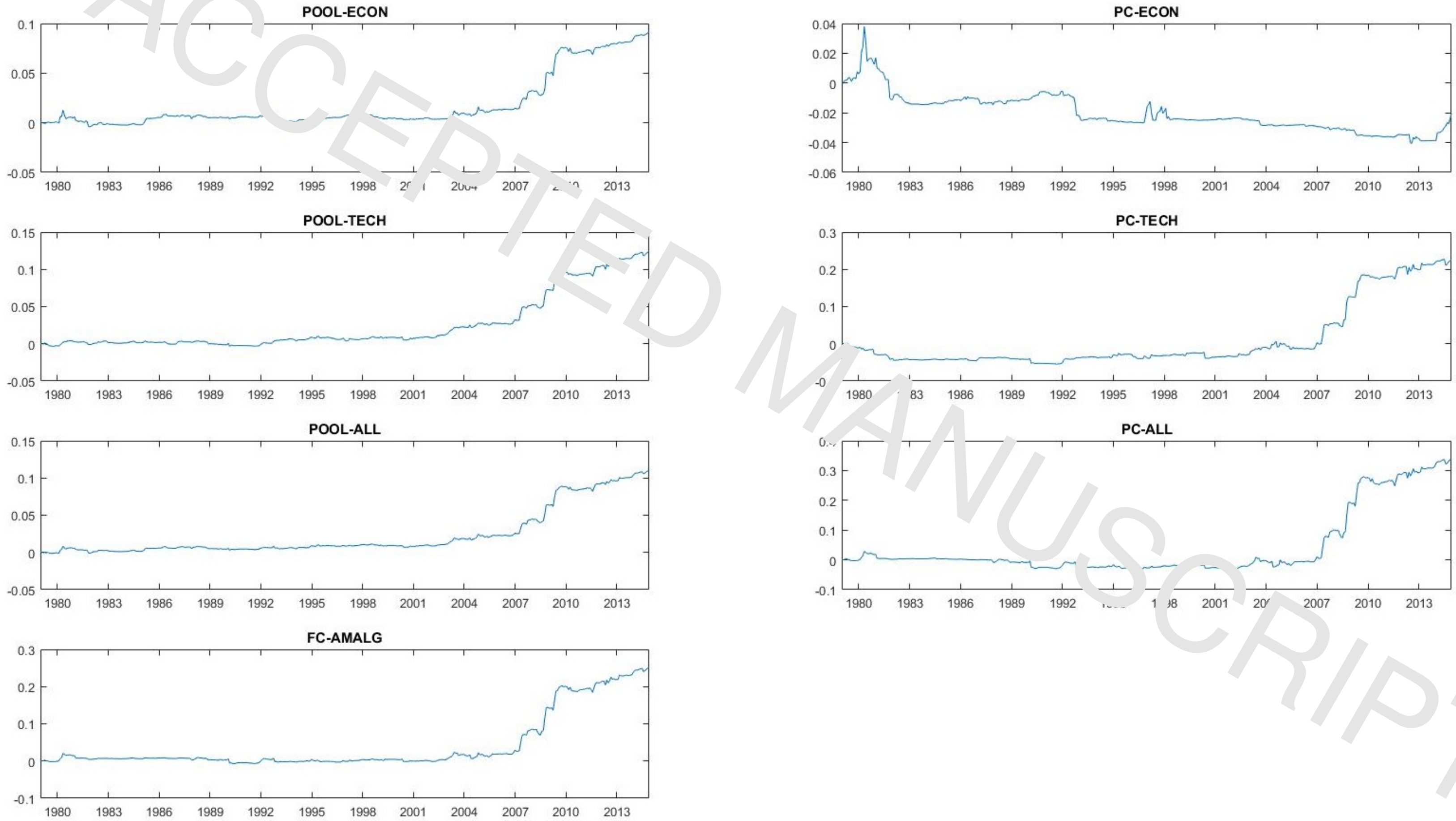
Notes: See notes in Figure 3.

Figure 6: CHF forecasts (PC, POOL, AMALG)



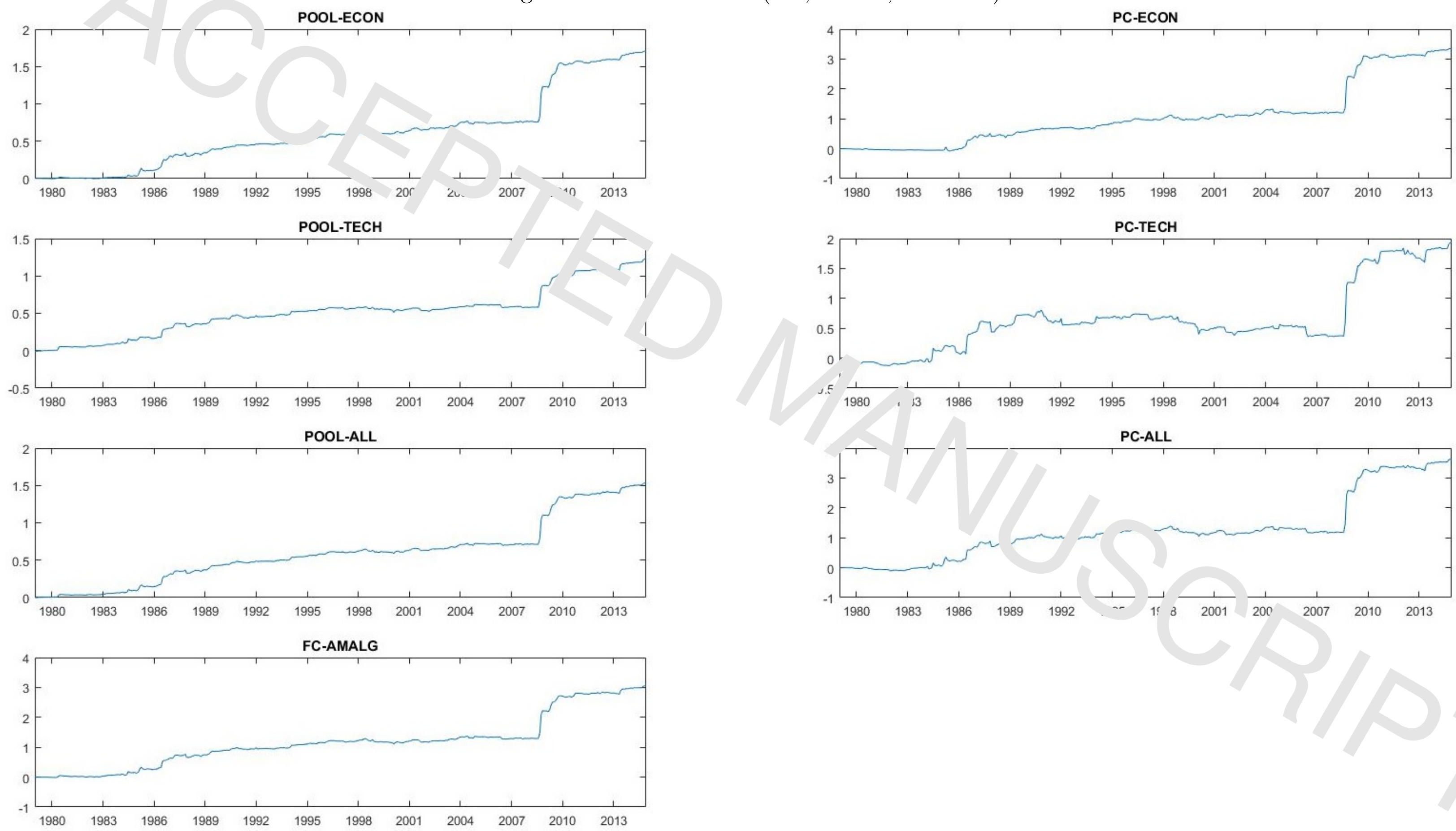
Notes: See notes in Figure 3.

Figure 7: CAD forecasts (PC, POOL, AMALG)



Notes: See notes in Figure 3.

Figure 8: AUD forecasts (PC, POOL, AMALG)



Notes: See notes in Figure 3.