Essays on Exchange Rate Forecasting

by

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Abstract

The literature in exchange rate forecasting has met a lot of interest from the academia and practitioners, as well. Since most exchange rates entered the free floating regime, the forecasting ability of the models has been challenged. In this thesis, we explore several aspects of exchange rate forecasting. We first examine the contribution of technical indicators to exchange rate forecasting. Next, we create a new methodological approach that is a hybrid of the Iterated Model Combination and the Constrained Predictors approach, on which we also apply positivity constraints in the forecasts. Last, we focus on the realized volatility of exchange rates.

In Chapter 2, we test the forecasting ability of several theoretically motivated models along with the forecasting ability of technical indicators, an atheoretical tool that identifies patterns and produces market signals. We use 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.

In Chapter 3, we focus on forecasting daily exchange rate returns of six widely traded currencies using financial predictors and combination and dimensionality reduction methods. We propose a hybrid Iterated Combination with Constrained Predictors (ICCP) approach. In addition, we examine the impact of positivity constraints on the forecasting ability of each method. Our results indicate that the proposed hybrid method outperforms the simple linear bivariate method and both the Iterated Combination and the Predictor Constrained approaches. Furthermore,

positivity constraints significantly improve the forecasting ability of all methods. We provide several robustness tests by changing several specifications of the forecasting experiment.

Chapter 4 provides empirical evidence in forecasting realized volatility in exchange rates. Forecasting realized volatility in exchange rates is very important for practitioners and has been vividly discussed among academics. Our target is to contribute to this dialogue by providing a comprehensive analysis of forecasting realized volatility in exchange rates. For the purposes of our analysis, we use data from January 1986 to December 2012 for four widely traded currencies, GBP, CHF, YEN, EUR and a composite one (FX Aggregate). We show that macroeconomic and financial variables provide additional information to the autoregressive term and can benefit the forecasting accuracy. We apply a large set of 38 variables, supported by the literature, which shed light on different macroeconomic aspects. We answer the question of variables selection by extracting all available information with the use of several shrinkage methods, machine learning techniques, dimensionality reduction techniques and combination forecasts. In order to resolve the problem of method selection the forecaster faces, we aggregate all methods and form an amalgamation of forecasts. We test whether outliers drive the performance of this type of naive combination. We apply different specifications of naive combination by trimming the first, second and third outlier from the top and bottom. Our findings suggest that macroeconomic variables should be accounted when forecasting realized volatility. Moreover, the amalgamation of forecasts benefits the forecasting experiment significantly, irrespective of the specification under consideration.

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Chapter 1

Introduction

1.1 Motivation

Over the last few decades, after the Bretton Woods, most exchange rates have adopted the free-floating regime. The huge traded turnover has placed exchange rates in the first place of all asset classes. Moreover, the relatively often currency crises around the world had serious effects in many levels. The implications of the fluctuations have stimulated the interest of both practitioners, policy makers and academics. The list of those affected by the fluctuations is infinite. However, a few sound cases of those are companies purchasing goods from foreign markets, financial dealers trading huge amounts of leveraged money and portfolio managers acquiring assets from different markets.

Empirical work has advanced over the last decades and academic dialogue has been inflamed regarding the forecasting ability of deterministic models. The often currency crises worldwide have stimulated the academic interest even more. On the other hand, academic literature benefited by the availability of extensive time series, high-quality data and advancements in econometric toolboxes. Still, the disconnect puzzle (Meese and Rogoff, 1983) remains unsoved until now; according to which, macroeconomic models are unable to forecast better than a naive random walk.

Modelling exchange rates has proven to be a rigorous task, so far. During the last fourty years of extensive research, academic literature has passed from different

stages. Hence, in the early literature, in the 1980s, we come across more scepticism regarding the out-of-sample performance of the available models. While, after the mid-1990s we observe a shift in the academic literature, starting with Mark (1995). The author argues that exchange rates can be forecast in longer horizons. The toolbox of fundamentalists is enhanced by Taylor rules (1993). After 2000, several studies claim that Taylor rules can outperform existing deterministic models (among others, see Molodtsova and Papell, 2009; and more recently Byrne, Korobilis and Ribeiro, 2016). However, the puzzling inconsistences between fundamentals and exchange rates are not met only in the forecasting of the returns, but also affect the forecasting of realized volatility (Paye, 2012).

Rossi (2013) argues that there are several aspects of the research forecasting exercise that have an actual impact on the outcome. These are the choice of predictors, the forecast horizon, sample period, model, forecast evaluation method and, finally, the choice of benchmark. We observe predictors that lose predictive power over the time; also there are some evaluation methods that accept and others reject one predictor. Similarly, we observe predictors that are able to fit well in-sample, but forecast poorly out-of-sample. A sub-branch of exchange rate forecasting is trying to answer the existing puzzle by attributing the lack of performance to the existence of nonlinearities in the data generation process.

All these questions have triggered a vast number of publications that try to shed light on every single aspect of the issue. There are promising results in the literature, but lack of stability in the long run. This dissertation contributes to the existing dialogue by experimenting through different frequencies, different types of datasets, which had not been taken into account so far, and hybrid types of technologies.

1.2 Thesis Contribution and Outline

The aim of this thesis is to contribute to the existing literature on exchange rates forecasting. We conduct the experiment by testing the out-of-sample performance of less common types of predictors in the exchange rate forecasting literature. We

apply our testing in the most widely traded currencies. We enhance the dialogue in favour of the argument that exchanges rates can be forecast. The three chapters spin around this central question.

In Chapter 2, we measure the out-of-sample performance of the most prominent fundamental models and test different types of specifications. On top, we apply several common technical indicators. We use an extensive dataset that covers almost the entire period since the main currencies started free floating. We provide evidence that the two groups of predictors contain different types of information, which can provide superior forecasts. Despite the fact that technical indicators exist far more than macroeconomic tools, academia has not given much attention due to their atheoretical framework; apart from a few recent studies (among which see Neely, Rapach, Tu and Zhou (2014); Buncic and Piras, 2016). We recursively generate our forecasts for an extensive sample period on a monthly data sample. In order to take into account all relative information we use naive combination forecasts and principal component analysis. With respect to our findings, we support that aggregating the information of the two types of predictors can provide superior forecasts. We also account for the economic performance of the results and provide robustness tests by altering the specifications. In order to understand deeper the path of the performance, we follow the performance of each predictor against the benchmark through time. Remarkably, there are some predictors that are able to outperform the benchmark almost throughout the entire sample period; and benefit from unforeseen events and crises.

In Chapter 3, we forecast daily exchange rates. Our sample size consists of more than 3,500 observations. In this chapter, we propose a hybrid approach based on the Iterated Model Combination of Lin, Wu and Zhou (2017) and the Constrained Predictor approach of Pan, Pettenuzzo and Wang (2018). We consider simple bivariate regressions, which due to the large number of predictors we complement with equally-weighed combination forecasts, principal components and partial least squares methodologies. The proposed hybrid approach integrates the properties of the two state-of-the-art methods, so that the former weighs the predictors and

the benchmark's forecasts in order to generate a new forecast, whereas the latter constrains the predictors in order to take into account only the abrupt fluctuations from the predictors side. Moreover, given that investors are interested in positive returns, we apply an additional constraint. We constrain the forecasts to maintain only positive values; and zero, otherwise. Remarkably, the proposed hybrid approach outperforms the unconstrained bivariate approach significantly.

We provide evidence that the model is specification free by conducting several robustness tests. Briefly, initially, we change the control window, according to which we determine whether the predictor undergoes an abrupt change; second, we alter the out-of-sample period, in order to view whether our results are biased towards a specific out-of-sample period; finally, we change the frequency into monthly (and replicate the experiment under two control windows). We also evaluate whether our results are economically meaningful, in both daily and monthly frequencies. Last, in order to illustrate the superiority of our approach, we show the path of the related forecasting performance over time.

The objective of Chapter 4 is to test whether macroeconomic variables benefit the forecasting experiment on realized volatility of exchange rates. We use an extensive dataset of 38 common variables in four exchange rates. The dataset accounts for different aspects of the economic activity. When we consider individual predictors, we report mixed results. The large dataset calls us to aggregate information by applying several machine learning, model combination, dimensionality reduction and shrinkage methods. The plethora of models and methods challenges the investor to select one model in order to conduct the forecasting experiment. Following Rapach and Strauss (2012), among others, we iteratively combine the information of all forecasts and create a grand predictor, an amalgamation of forecasts. We observe that this approach is able to outperform all rivals and provide superior forecasts. Finally, Chapter 5 concludes the thesis and provides intuition for further research.

Chapter 2

The Role of Technical Indicators in Exchange Rate Forecasting

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 predictability is achieved only for short periods of time and only for certain countries. 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 neighbour 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, atheoretical 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 atheoretical forecasting approach has been reported to produce significant statistical and economic gains when applied to equity and exchange rate markets (Buncic and Piras, 2016; Neely, Rapach, Tu and Zhou, 2014; Neely and Weller, 2012; 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 sta-

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

tistically 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 this chapter, 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 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) 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 chapter 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 significantly improves and stabilises exchange rate

[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.

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 model for two levels of risk aversion and find that principal components extracted from the entire group of predictors 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 and the forecast horizon.

The remainder of the chapter 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 empirical findings, namely the out-of-sample statistical and economic forecast evaluation results. Section 5 presents the robustness tests. Finally, Section 6 concludes the chapter.

2.1 Candidate predictors

2.1.1 Fundamental predictors

Following the literature that links exchange rates with macroeconomic fundamentals (Engel and West, 2005; Molodtsova and Papell, 2009; 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:

$$x_{1,t} = i_t - i_t^* \tag{2.1}$$

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]

[3]In what follows, "*" denotes the variable in the foreign country.

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

$$x_{2,t} = p_t - p_t^* - s_t \tag{2.2}$$

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:

$$x_{3,t} = a(m_t - m_t^*) - b(y_t - y_t^*) + c(i_t - i_t^*) - s_t \tag{2.3}$$

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]

$$x_{4,t} = a(m_t - m_t^*) - b(y_t - y_t^*) - s_t \tag{2.4}$$

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

[4]For a more detailed discussion, see Rapach and Wohar, 2002.

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:

$$x_t = i_t - i_t^* = a_0 + a_1\pi_t - a_1^*\pi_t^* + a_2 g_t - a_2^* g_t^* + a_3 e_t + a_4 i_{t-1} - a_4^* i_{t-1}^* + \eta_t \quad (2.5)$$

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 (2.5) is re-estimated to give the predictor (in general form) as follows:

$$x_t = \hat{\varphi}_0 + \hat{\varphi}_1\pi_t - \hat{\varphi}_1^*\pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2^* g_t^* + \hat{\varphi}_3 e_t + \hat{\varphi}_4 i_{t-1} - \hat{\varphi}_4^* i_{t-1}^* \quad (2.6)$$

Several specifications, nested in equation (2.6), 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

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

fixed weights (HOAfw):

$$x_{5,t} = \hat{\varphi}_1 (\pi_t - \pi_t^*) + \hat{\varphi}_2 (g_t - g_t^*) + \hat{\varphi}_3 e_t \tag{2.7}$$

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):

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

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

$$x_{7,t} = \hat{\varphi}_1 (\pi_t - \pi_t^*) + \hat{\varphi}_2 (g_t - g_t^*) + \hat{\varphi}_4 (i_{t-1} - i_{t-1}^*) \tag{2.8}$$

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

$$x_{8,t} = \hat{\varphi}_1 (\pi_t - \pi_t^*) + \hat{\varphi}_2 (g_t - g_t^*) + \hat{\varphi}_3 e_t \tag{2.9}$$

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

$$x_{9,t} = \hat{\varphi}_1 (\pi_t - \pi_t^*) + \hat{\varphi}_2 (g_t - g_t^*) + \varphi_3 e_t + \hat{\varphi}_4 (i_{t-1} - i_{t-1}^*) \tag{2.10}$$

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

$$x_{10,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* \tag{2.11}$$

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

$$x_{11,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* + \hat{\varphi}_4 i_{t-1} - \hat{\varphi}_4^* i_{t-1}^* \tag{2.12}$$

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

$$x_{12,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* + \hat{\varphi}_3 e_t \tag{2.13}$$

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

$$x_{13,t} = \hat{\varphi}_1 \pi_t - \hat{\varphi}_1^* \pi_t^* + \hat{\varphi}_2 g_t - \hat{\varphi}_2 g_t^* + \hat{\varphi}_3 e_t + \hat{\varphi}_4 i_{t-1} - \hat{\varphi}_4^* i_{t-1}^* \tag{2.14}$$

2.1.2 Technical Indicators

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:

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

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).[6] 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 $n = [7, 14]$, 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.

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

where m is a weighting multiplier, or else an accelerator, given by $m = \frac{2}{j+1}$where

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

$j = s, l$. The $EMA(s, l)$ rule we employ sets $s = 5$ and $l = 12$.

2.2 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.[7] 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.

2.2.1 Univariate models

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

$$\Delta s_{i,t+1} = a_i + \beta_i \Delta x_{i,t} + u_{i,t+1} \tag{2.15}$$

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 (2.15) is estimated by least squares at each point of the out-of-sample period giving one-month ahead forecasts as follows;

$$\Delta \hat{s}_{i,t+1} = \hat{a}_i + \hat{b}_i \Delta x_{i,t} \tag{2.16}$$

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

2.2.2 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 summarises 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).[8] 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:

$$\Delta \hat{s}_{t+1}^{(j)} = \hat{a} + \sum_{k=1}^{K} \hat{b}_k \hat{F}_{k,t}^{(j)} \qquad for \;\; j = ECON, TECH, ALL \tag{2.17}$$

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.

2.2.3 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

[8]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.

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;

$$\Delta\hat{s}_{t+1}^{(j)} = \sum_{i=1}^{N_j} \frac{1}{N_j} \Delta\hat{s}_{i,t+1}^{(j)} \quad for\ j = ECON, TECH, ALL \tag{2.18}$$

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 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 predictor, $FC - AMALG$. This predictor can prove beneficial in the event that information contained in the two forecasting approaches is discrete.[9]

2.2.4 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 (2.15). This model is the standard benchmark in the literature on exchange rate predictability since the seminal work of Meese and Rogoff (1983).[10] We first calculate the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OOS}) metric as follows;

$$R^2_{OOS} = 1 - \frac{MSFE_q}{MSFE_{RW}} \tag{2.19}$$

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

[10]The RW with drift is considered to be the toughest benchmark for exchange rates forecasting (see, for example, Della Corte, Sarno and Tsiakas, 2009).

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:

$$\begin{aligned} MSFE - adjusted = (\frac{1}{P})\{ \sum_{t=M+1}^{T-1} \{(\Delta s_{t+1} - \Delta \hat{s}^{(RW)}_{t+1})^2 \\ -[(\Delta s_{t+1} - \Delta \hat{s}^{(q)}_{t+1})^2 - (\Delta \hat{s}^{(RW)}_{t+1} - \Delta \hat{s}^{(q)}_{t+1})^2]\}\} \end{aligned} \tag{2.20}$$

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 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 et al. (1998) de-

veloped 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, Harvey et al. (1998) 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.

2.3 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 and economic evaluation of our forecasting approaches. We also describe the performance of predictors/ models over time, as well as the factors driving it.

2.3.1 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 2.1.

Table 2.1: 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

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

Notes: The data are collected for the period January 1973 to December 2014.

Table 2.2 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

Table 2.2: Descriptive statistics

	GBP	YEN	NOK	CHF	CAD	AUD
Mean	0.08	-0.17	0.05	-0.24	0.03	0.12
Median	0.03	0.01	0.02	-0.13	0.00	-0.08
Stdv	2.42	2.72	2.43	2.87	1.42	2.60
Skew	0.25	-0.46	0.36	-0.02	0.60	1.29
Kurt	4.67	3.88	4.36	3.69	11.36	8.87
Max	11.08	8.07	12.95	11.69	11.29	17.31
Min	-9.52	-10.52	-6.33	-8.24	-6.01	-7.12
ACF(1)	0.35	0.32	0.36	0.28	0.26	0.33

Note: The table reports the summary statistics of all exchange rate returns under consideration for the total sample period (January 1974 to December 2014). The statistics presented are the mean, median, standard deviation, skewness, kurtosis, maximum, minimum and first order autocorrelation.

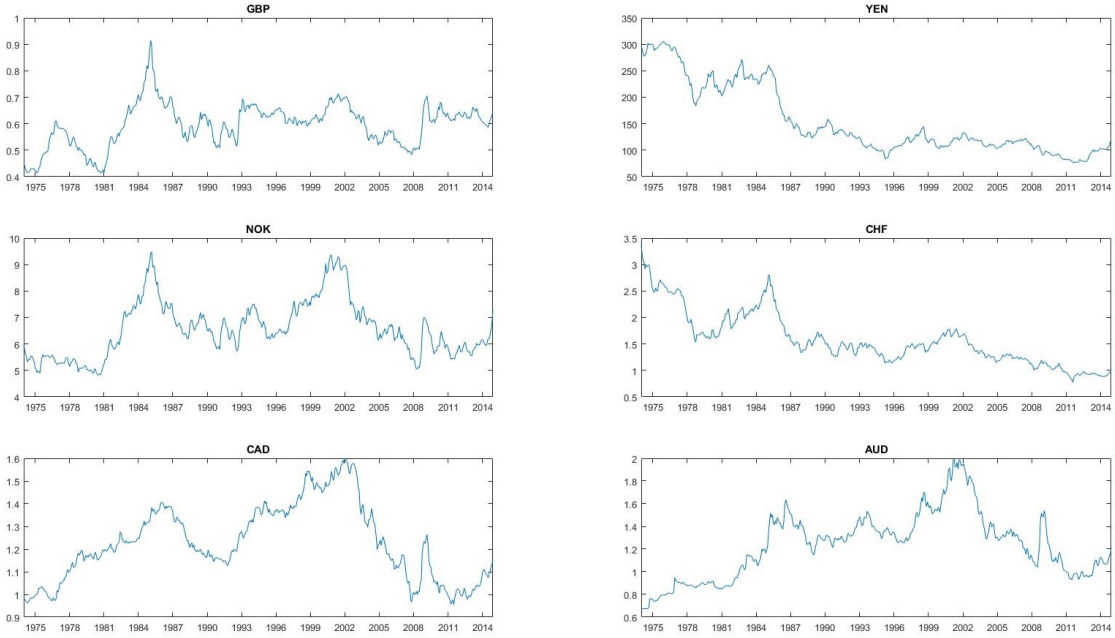
CHF are negatively skewed.

In the Figure below, we illustrate the path of the spot prices for the six currencies under consideration, thoughout the sample period. We observe similarities in the trend, namely, there is evidence that particular events may drive the fluactuations in the exchange rates. We will try to answer this issue in a next section of the chapter.

In order to get a better understanding of the evolution of exchange rates over time, we plot the respective spot exchange rates in Figure 2.1. 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 2.1 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 behaviour of the US dollar is characterised as the "dollar cycle" by Qi and Wu (2003).[11] This trend dies out a few years later followed by

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

Figure 2.1: Spot Exchange Rates



Notes: Figure 2.1 presents the time series of the six spot exchange rates (vs USD).

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 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 NOK, CAD and AUD (see, inter alia, Akram, 2004; Lizardo and Mollick, 2010; 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 euro zone outlook has triggered a huge overvaluation of the currency, considered as a safe haven and resulting in further appreciation. Finally, the Japanese YEN was 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.

2.3.2 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).[12]

Table 2.3 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 (2.18) and (3.9)). 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.

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

Table 2.3: 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	1.51**	-0.88	1.23***	1.18**	-1.05	-0.28	MA(1,9)	2.29***	1.95***	0.80***	2.09***	0.03*	0.91**
FB	2.07**	-0.41	1.93***	1.81***	-1.09	-0.03	MA(1,12)	0.45**	1.74***	2.04***	0.70**	0.15	0.38***
BMF	8.64***	4.81***	2.07***	6.54***	4.57***	10.19***	MA(2,9)	0.36*	0.84**	0.72**	1.59***	0.25	0.28
PPP	9.77***	10.51***	12.72***	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	2.62***	1.40***	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	1.48***	-0.54	7.89***	MOM(12)	0.45***	0.07*	0.47	2.28***	0.25	-0.98*
HOAS	0.34	-0.86	-0.49	0.29	-0.65	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	-0.39	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	-0.59	0.02	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*	7.66***							
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	4.52***	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	5.04***	6.18***	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: $\Delta\hat{s}_{i,t+1} = \hat{a}_i + \hat{b}_i \Delta x_{i,t}$, where $x_{i,t}$ is each of the 24 predictors, taken individually. PC-ECON, PC-TECH and PC-ALL forecasts are given by equation (17), i.e. $\Delta\hat{s}^{(j)}_{t+1} = \hat{a} + \Sigma_{k=1}^{K} \hat{b}_k \hat{F}^{(j)}_{k,t}$. $F^{(j)}_{k,t}$ is the recursively calculated (up 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 reports 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 alternative specification'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.

Our findings with respect to individual predictors (Table 2.3, 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 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.[13]

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 HEA 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%

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

(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 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 2.4.

Table 2.4: Encompassing tests

	GBP	YEN	NOK	CHF	CAD	AUD
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
POOL-ECON encompasses POOL-TECH	0.01	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
POOL-ALL encompasses PC-ALL	0.00	0.00	0.00	0.00	0.00	0.00
PC-ALL encompasses POOL-ALL	0.01	0.07	0.19	0.02	0.87	0.57

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

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.

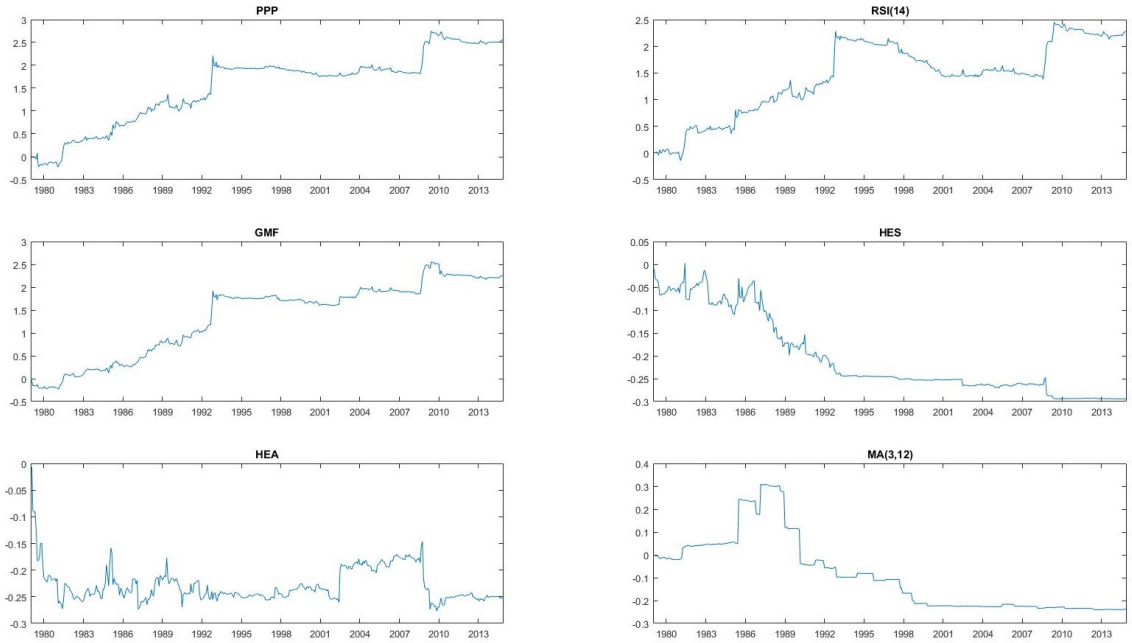
2.3.3 What drives the forecasting performance?

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 2.2 presents the three best performing predictors (PPP, $RSI(14)$ and BMF) and the three worst performing ones (HES, HEA and $MA(3,12)$). As shown in Figure 2.2, 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 2.2: GBP forecasts

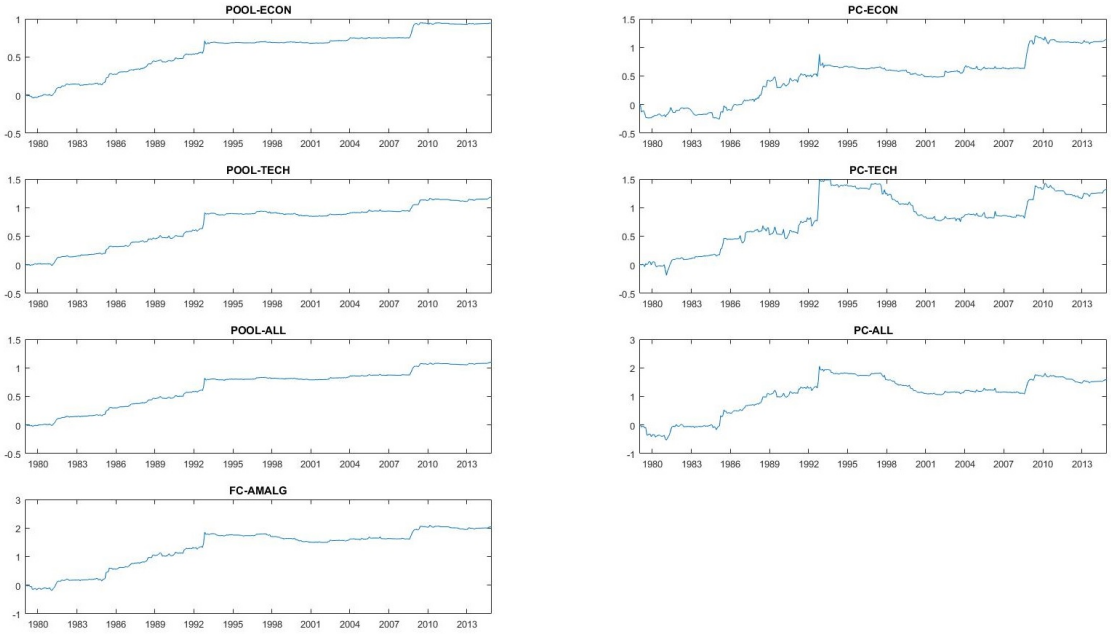


Notes: The Figure plots the cumulative squared error difference between the benchmark and the best and worst performing predictors. The best performing predictors are PPP, RSI(14) and BMF, and the worst performing ones are HES, HEA and MA(3,12).

Since our focus is on alternative ways of summarising predictor information, we report in Figures 2.3 - 2.8 the performance of $POOL-j$, $PC-j$ and $FC-AMALG$ (for $j = ECON$, $TECH$, ALL) for all the currencies considered. Figure 2.3 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 2.3: GBP forecasts (PC, POOL, AMALG)

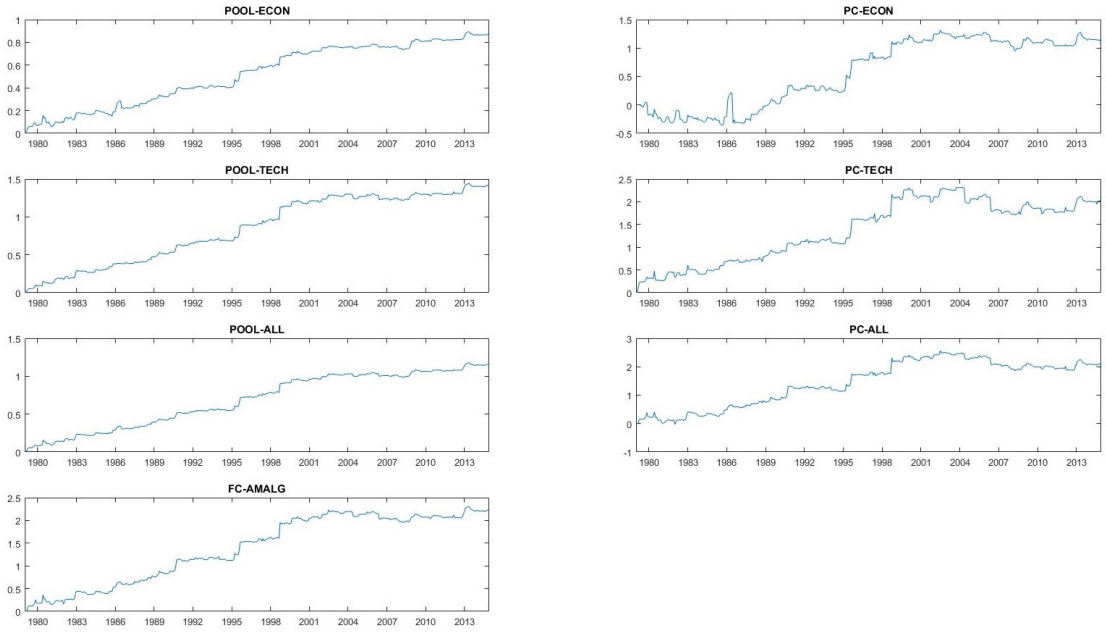


Notes: The Figure plots the cumulative squared error difference between the RW benchmark and the Combined forecasts (POOL-j), Principal Components (PC-j) and amalgam forecasts. j= ECON for macroeconomic predictors, j=TECH for technical Indicators and j=ALL for all individual predictors taken together.

Next we turn to the respective results for YEN (Figure 2.4). 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 2013 when

combined.

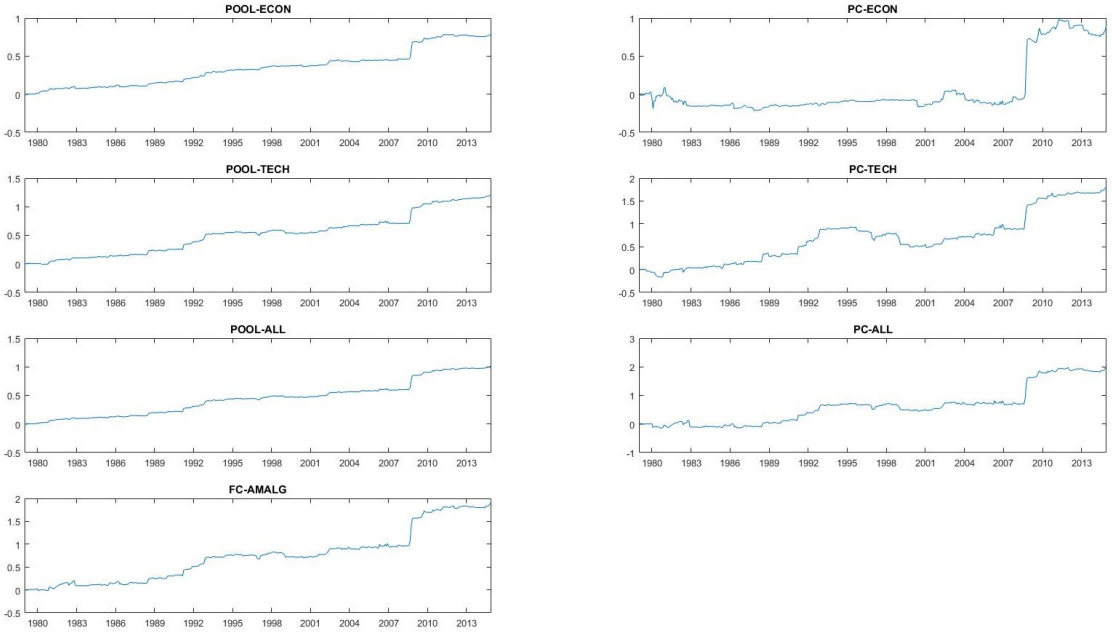
Figure 2.4: YEN forecasts (PC, POOL, AMALG)



Notes: See notes in Figure 2.3.

In Figure 2.5, 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.

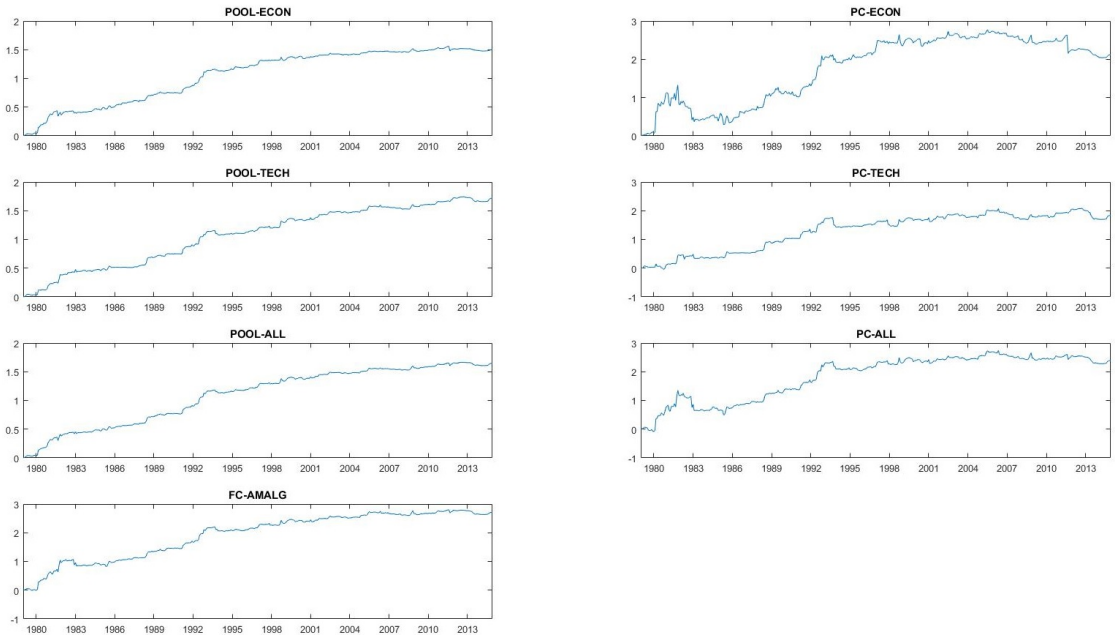
Figure 2.5: NOK forecasts (PC, POOL, AMALG)



Notes: See notes in Figure 2.3.

The next currency considered is CHF (Figure 2.6). 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.

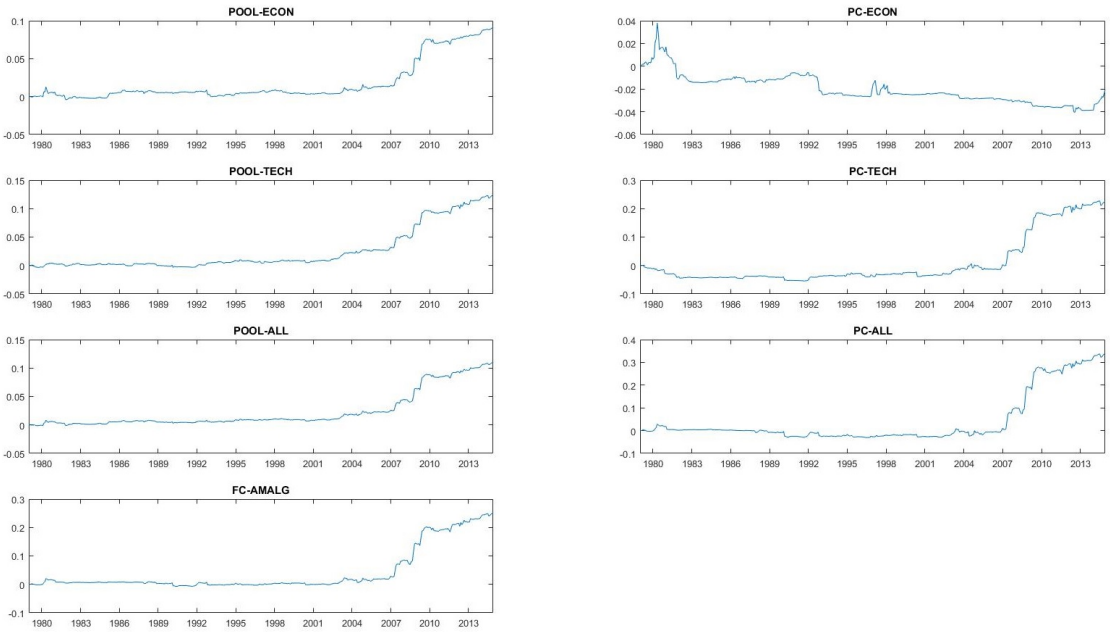
Figure 2.6: CHF forecasts (PC, POOL, AMALG)



Notes: See notes in Figure 2.3.

Turning to CAD (Figure 2.7), 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.

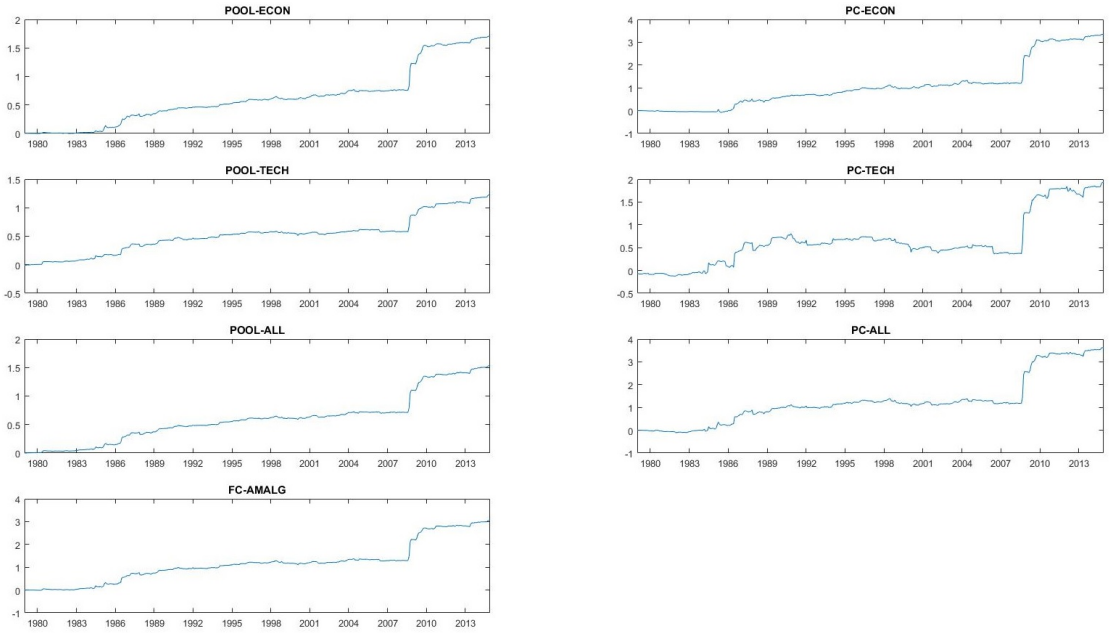
Figure 2.7: CAD forecasts (PC, POOL, AMALG)



Notes: See notes in Figure 2.3.

The last currency under consideration is AUD, illustrated in Figure 2.8. 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 2.8: AUD forecasts (PC, POOL, AMALG)



Notes: See notes in Figure 2.3.

Summarising 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.

2.4 Economic Evaluation

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.[14] 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 ex-

[14]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).

pected utility. The investor relies on the information given by the one-month-ahead forecasts of our proposed specifications (equations (2.16), (3.9) and (2.18)) 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 realised exchange rate return. Thus, the only risk the investor is exposed to are fluctuations of the exchange rates. Specifically, the investor rebalances 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:

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

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).[15] 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. Winsorizing the weights between $2 < w_t < -1$ is farely standard in the literature in order to prevent extreme investments while conducting the empirical analysis (see among others Ahmed, Liu and Valente, 2016; Neely, Rapach, Tu and Zhou, 2014). Under this setting, the

[15] 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 $\gamma = [2, 5]$; Diris, Palm and Schotman (2014) set $\gamma = [2, 5, 10]$

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;

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

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 $\hat{\sigma}_p^2$ 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.

2.4.1 Statistical Significance of ΔCER

To test the statistical significance of ΔCER, we follow Jobson and Korbie (1981), Memmel (2003) and DeMiguel, Garlappi and Uppal (2009). We compute the p-value of the ΔCER by acomputing the variance of the assymptotic distribution. Let assume a vector of moments be $u = (r_{p,i}, r_{p,RW}, \sigma_{p,i}^2, \sigma_{p,RW}^2)$ and its estimate $\hat{u} = (\hat{r}_{p,i}, \hat{r}_{p,RW}, \hat{\sigma}_{p,i}^2, \hat{\sigma}_{p,RW}^2)$, which have already been computed in previous section. The difference in the certainty equivalent return of the predictor i and the benchmark is given by the function $f(u) = \left(\hat{r}_{p,i} - \frac{1}{2}\gamma\hat{\sigma}_{p,i}^2\right) - \left(\hat{r}_{p,RW} - \frac{1}{2}\gamma\hat{\sigma}_{p,RW}^2\right)$ and the asymptotic distribution of the function is calculated as $\sqrt{T}\left(f(\hat{u}) - f(u)\right)$ with a distribution $N(0, \frac{\partial f}{\partial u}^\top \Theta \frac{\partial f}{\partial u})$ where

$$\Theta = \begin{bmatrix} \hat{\sigma}_{p,i}^2 & \hat{\sigma}_{p,i,RW} & 0 & 0 \\ \hat{\sigma}_{p,i,RW} & \hat{\sigma}_{p,RW}^2 & 0 & 0 \\ 0 & 0 & \hat{\sigma}_{p,i}^4 & 2\hat{\sigma}_{p,i,RW}^2 \\ 0 & 0 & 2\hat{\sigma}_{p,i,RW}^2 & \hat{\sigma}_{p,RW}^4 \end{bmatrix}$$

We calculate the variance part of the distribution, so that:

$$\sigma^2 = \frac{\partial f}{\partial u}^{\top} \Theta \frac{\partial f}{\partial u} = \begin{bmatrix} 1 & -1 & -\gamma\hat{\sigma}_{p,i} & \gamma\hat{\sigma}_{p,RW} \end{bmatrix} \begin{bmatrix} \hat{\sigma}^2_{p,i} & \hat{\sigma}_{p,i,RW} & 0 & 0 \\ \hat{\sigma}_{p,i,RW} & \hat{\sigma}^2_{p,RW} & 0 & 0 \\ 0 & 0 & 2\hat{\sigma}^4_{p,i} & 2\hat{\sigma}^2_{p,i,RW} \\ 0 & 0 & 2\hat{\sigma}^2_{p,i,RW} & 2\hat{\sigma}^4_{p,RW} \end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ -\gamma\hat{\sigma}_{p,i} \\ \gamma\hat{\sigma}_{p,RW} \end{bmatrix}$$

Knowing the variance we can now normalize the differential of CERs, so that the t-statistic is given by $\frac{\Delta CER}{\sigma/\sqrt{T}}$.

2.4.2 Empirical Results: Economic Evaluation

We report the annualized ΔCER fees and the respective t-statistic, in Table 2.5. 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 2.5: 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	15.97***	6.23***	12.10***	5.36***	3.21***	10.32***	13.47***	5.79***	10.81***	4.92***	2.96***	9.12***
HOAfw	1.24	-0.37	1.17	-0.07	0.24	6.57***	1.47*	-0.23	1.97*	0.47	0.14	5.16***
HOS	-0.10	-1.46	-0.35	-0.49	-0.33	7.83***	0.28	-0.88	-0.45	-0.42	-0.34	6.46***
HOSS	1.33	-0.69	-0.13	0.48	0.49	-0.05	1.67*	-0.61	-0.29	0.43	0.56	0.46
HOAfw	0.57	0.24	-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	-0.15	0.52	0.36	-0.03	1.97**	-0.46	-0.26	0.47	0.48	0.50
HES	-0.31	0.19	-0.49	-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	0.57	0.32	-0.04	2.11**	-0.31	-0.15	0.50	0.39	0.37
HEA	1.18	0.16	0.64	1.27*	0.79	6.48***	0.31	0.27	0.60	0.85*	0.24	5.62***
HEAS	0.31	-0.35	-0.04	0.53	0.31	0.07	0.24	-0.34	0.04	0.46	0.31	0.42
POOL-ECON	2.72***	0.29	1.58**	1.89**	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**	0.63	11.15***	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	2.78***	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***	1.61**	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	1.12	0.07	0.38	1.23*	0.11	0.15
MA(2,12)	-0.35	-0.33	0.70	2.44***	0.51	0.65	-0.40	-0.29	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	0.14	0.55	1.15	0.22	0.39
MA(3,12)	0.36	0.00	-0.16	0.23	0.15	2.07***	0.03	-0.10	-0.49	0.10	0.10	1.49*
MOM(9)	0.03	-0.02	0.80	-0.38	0.42	1.54*	-0.08	-0.16	0.94	-0.26	0.19	1.12
MOM(12)	1.43*	-0.26	0.25	1.76**	0.71	1.89**	1.12	-0.14	-0.04	1.38**	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****	3.09***	11.20***
RSI(14)	14.61**	6.58***	9.60***	4.48**	3.03***	10.11***	12.41***	5.91***	9.54***	4.45***	3.23***	9.44***
EMA(5,12)	1.20	0.39	-0.12	-0.08	0.45	1.09**	0.61	0.27	-0.32	-0.37	0.25	0.68
POOL-TECH	4.68***	0.64	2.88**	2.43***	0.95*	2.53***	4.85***	0.85	3.10***	2.16***	0.73**	2.42***
PC-TECH	11.21***	3.97**	5.58***	3.49**	2.17**	7.55***	9.82***	3.68**	6.23***	3.11**	1.87***	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 invests her portfolio in 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 in the Certainty Equivalent Return for the investor that uses our proposed approaches instead of the RW model.

With respect to individual predictors, we note that $BMF, PPP, RSI(7)$ and $RSI(14)$ provide essential CER gains which are also statistically significant at 1% level, irrespective of the currency under consideration. In general, technical indicators do not generate negative ΔCER values as frequently as macroeconomic predictors. However, only the predictors with solid positive ΔCER values are statistically significant. Especially in the cases of CAD and AUD, all technical indicator strategies outperform the benchmark. Additionally, technical indicators demonstrate more robust positive behavior against the benchmark for GBP and AUD. An outstanding feature for macroeconomic predictors is the performance of PPP, which delivers a substantial gain of almost 16% for GBP. Notably, eight out of thirteen macroeconomic predictors for AUD are statistically significant. 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 for $\gamma = 5$, the performance of macroeconomic predictors is partially improved. On the other hand, the performance of almost all technical indicators deteriorates when risk aversion increases.

The last part of Panels A and B demonstrate the performance of combined and principal components forecasts. In general, $PC - ECON$ and $PC - TECH$ generate high gains, up to 11.15% for $PC - ECON$ (AUD) and 11.21% for $PC - TECH$ (GBP). For almost all currencies, principal components generate higher fees than combined forecasts. The features of the Table show clearly that aggregating information is much more efficient than using single predictors in the forecasting experiment, also proven by the fact that almost each one of the two predictors under consideration is statistically significant for every currency. 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 2.5 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, and statistically significant, 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 the predictor 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. The results for $FC - AMALG$ that stand out are those for GBP (11.9%) and for AUD (8.41%). Nevertheless, apart from the tough case of YEN, all results are statistically significant, irrespective of the level of risk aversion. To conclude, our economic evaluation findings suggest that by exploiting the information from the two groups of predictors we are able to obtain sizable economic gains.

2.5 Robustness tests

In this section we assess further the statistical performance of the candidate predictors/ specifications by conducting two robustness tests. First, we consider alternative forecast horizons and second we change the beginning of the evaluation period to January 1990 and January 2000.

2.5.1 Alternative forecast horizons

Table 2.6 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. Hence, it is not surprising that technical indicators do poorly at longer horizons, since they provide

short-term market signals. 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-months 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 2.6: 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**	-2.16	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**	-1.93	0.68**	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	1.97***	2.35***	0.46*	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***	4.21***	2.86***	2.45***	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	1.07**	0.37*	-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	-0.56	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	-0.34	-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	2.15***	-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	-0.75	0.08	-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	0.90**	1.57***	0.05**	-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	-0.87	-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***	3.49***	0.03**	-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	0.18	-0.81	-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**	0.16	0.04	0.69**	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**	-0.43	-0.45	-0.83	-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	-0.61	-0.66	-0.03	-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	-0.51	-0.20	-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	-0.50	-0.18	-0.55	-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	-0.58	-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	-0.78	-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	-0.61	-0.48	-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	-0.43	-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	0.20	-0.20	0.10	-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	0.42*	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***	-0.18	0.53**	0.39	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	-0.44	-0.38
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*	-0.11	0.05
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**	-0.05	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. See also Notes in Table 2.3.

Overall, the performance of individual technical indicators deteriorates for higher forecast horizons (in line with the results of Menkhoff and Taylor, 2007; Park and Irwin, 2007; Neely and Weller, 1999), despite the fact that principal components and combined forecasts improve forecasts. However, this finding does not exclude them from the list of predictors that incorporate useful information.

2.5.2 Alternative evaluation periods

The last 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 2.7 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 2.7: 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***	1.21**	-0.21	0.06	MA(1,9)	3.79***	0.41**	0.58**	0.86***	0.85**	1.34***
FB	2.67**	1.06**	3.02***	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***	4.54***	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***	5.21***	6.43***	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	8.71***	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	0.19	RSI(7)	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***	5.08***	4.51***	1.57***	3.71***
PC-ECON	5.17***	5.43***	5.52***	4.70***	-0.12	12.74***	PC-TECH	4.96***	5.55***	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. The out-of-sample period begins in January 1990. For further details see Notes in Table 2.3.

Next, we focus on the more recent period (out-of-sample forecasts begin in January 2000). Our findings, reported in Table 2.8, 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 2.8: 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*	-5.15	-0.41	0.11**	MA(1,9)	3.88***	-4.22	1.16**	1.07**	1.10**	1.10**
FB	0.99	-0.15	1.66**	-5.56	-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**	-0.58**	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***	7.30***	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	0.37*	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	-0.03	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	10.57***	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(7)	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**	5.36***	3.32***	1.75***	4.00***
PC-ECON	7.27***	0.09*	7.66***	-2.96*	0.07	13.75***	PC-TECH	3.38***	-2.01**	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***							

Note: The table reports the R^2_{OOS} values for each currency. The out-of-sample period begins in January 2000. For further details see Notes in Table 2.3.

2.6 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 and macroeconomic predictors can provide significant gains irrespective of the currency under consideration.

Chapter 3

Forecasting Exchange Rates: An Iterated Combination Constrained Predictor Approach

3.1 Introduction

Exchange rate (FX) forecasting is a hot topic of discussion in academic literature. In their seminal paper, Meese and Rogoff (1983) have risen the issue of no predictability in the exchange rates. This gave rise to a voluminous literature on the so called exchange rate disconnect puzzle. Mark (1995) overturned this finding in favor of FX predictability. In a recent review, Rossi (2013) argues that exchange rate predictability is affected by several factors, such as the model under consideration, forecast horizon and so on.

In light of this puzzle, academia has turned to more sophisticated techniques, which stimulated the research and led to more promising results. There are several studies which discuss and implement both linear and nonlinear approaches in forecasting FX and other asset classes, as well. Nonlinear approaches mainly belong to the machine learning literature and include neural networks, genetic programming, support vector machines and related hybrid models.[1] Recently, we observe a

[1]For neural networks and hybrid applications see Kuan and Lieu, 1995; Satchell and Timmermann, 1995; Gencay, 1999;.Qi and Wu, 2003; Preminger and Franck, 2007; Gradojevic, 2007;

backward shift in the literature in favor of fairly simpler/ standard models in order to predict exchange rates. For a more detailed discussion, see among others, Orphanides (2003, 2008), Molodtsova and Papell (2009, 2012), Rossi (2013), Byrne, Korobilis and Ribeiro (2016, 2018) and Beckmann and Schüssler (2016).

This study investigates whether daily exchange rates can be forecasted with the use of financial variables. The frequency is selected because it is a natural selection for investors using technical indicators. We propose a novel forecasting approach by creating a hybrid model combining two recently developed state-of-the-art methodologies. The first is an extension of the simple combination approach and was proposed by Lin, Wu and Zhou (2017). This methodology combines the forecasts with those of the benchmark by attributing weights according to their past performance and creates an iterated combination forecast. The second is also a recently introduced methodology, proposed by Pan, Pettenuzzo and Wang (2018). The authors set constraints directly to the predictors in order to take advantage of extreme shifts in the information set that may have an actual impact on the forecasting process. Our approach, namely the Iterated Combination Constrained Predictor (ICCP) approach, generates forecasts by transforming the predictor series in line with the Constrained Predictors approach and then applying the Iterated Combination approach. Our set of specifications range from simple univariate models including one predictor at a time to dimensionality reduction and forecast combination techniques. Specifically, we employ simple combination methods, Principal Component Analysis (PCA) (see, among other Neely, Rapach, Tu and Zhou, 2014) and Partial Least Squares (PLS) (see Kelly and Pruitt; 2013, 2015). In order to incorporate the reluctance of an investor to bet on a negative return forecast, we also consider the Campbell and Thompson (2008) framework and truncate negative

Bekiros and Georgoutsos, 2007; Dhamija and Bhalla, 2010; Khashei and Bijari, 2010, 2011; Dunis, Laws and Sermpinis, 2011; Khashei, Bijari and Ardali, 2012; Choudhry, McGroarty, Peng and Wang, 2012; Jammazi and Aloui, 2012; Majhi, Rout, Majhi, Panda and Fleming, 2012; Tiwari, Dar and Bhanja, 2013; Sermpinis, Theofilatos, Karathanasopoulos, Georgopoulos and Dunis, 2013; De Oliveira, Nobre and Zárate, 2013; Krauss, Do and Huck, 2017. For Genetic Network Programming and hybrids see Neely, Weller and Dittmar, 1997; Evans, Pappas and Xhafa, 2013; Chen and Wang, 2015; Sermpinis, Stasinakis, Theofilatos and Karathanasopoulos, 2015; Hu, Feng, Zhang, Ngai and Liu, 2015; Manahov, 2016a. For Support Vector Machines and hybrids see Kara, Boyacioglu and Baykan, 2011; Patel, Shah, Thakkar and Kotecha, 2015a; Patel, Shah, Thakkar and Kotecha, 2015b; Fan, Pan, Li and Li, 2016; Oztekin, Kizilaslan, Freund and Iseri, 2016.

return forecasts at zero,

Our dataset consists of daily observations of six widely traded currencies for the period extending from February 02, 1999 to December 31, 2017 with the out-of-sample period starting in January 1st, 2004. The exchange rates we consider are the British Sterling (GBP), Japanese Yen (YEN), Swiss Franc (CHF), Euro (EUR), Canadian Dollar (CAD) and Australian Dollar (AUD) against the US Dollar (USD). We employ predictors that contain different types of information that approximate macroeconomic and financial conditions on a daily basis. Our set of 14 candidate predictors is related to risk aversion (Buncic and Piras, 2016), global trading and activity (Calvet, Fisher and Thompson, 2006; Ferraro, Rogoff and Rossi, 2015; Baumeister, Guerin and Kilian, 2015), yield curve data (Buncic and Piras, 2016), national stock indices (Christiansen, Schmeling and Schrimpf; 2012) and the respective trading volumes.

Our findings suggest that the proposed hybrid ICCP approach can actually deliver very consistent and robust forecasts and that positivity constraints in the forecasts significantly improve the forecasting ability of all predictors and combination or dimensionality reduction methods for all approaches. Our robustness checks, which include the change of the length of the control window, the frequency of the data and the out-of-sample period verify the superiority of our forecasting approach.

The remainder of the chapter is organized as follows. Section 2 presents our forecasting approaches. Section 3 describes our dataset and Section 4 presents the empirical findings. In Section 5, we present the economic evaluation approach and findings. Section 6 presents the Robustness checks, while Section 7 concludes the chapter by providing a brief summary of our results.

3.2 Methodology

Our aim is to forecast exchange rate returns for six widely traded currencies. We employ the information contained in 14 financial variables in order to generate forecasts on a daily basis. First we compute the daily log returns of the exchange

rates. Under the bivariate framework, we initially test each predictor individually. Then we apply combination forecasts and dimensionality reduction techniques.

For each of the predictive variables we estimate the following bivariate model:

$$r_{t+1} = a + bx_t + u_{t+1}$$

where r_{t+1} is the daily exchange rate log return, b is the slope coefficient, x_t is the predictor under consideration and u_{t+1} is the disturbance term. Hence, we generate the daily out-of-sample forecasts for each predictor with the use of simple OLS, such as:

$$\hat{r}_{t+1} = \hat{a} + \hat{b}x_t \tag{3.1}$$

We denote as C_i^0 the simple bivariate model for each individual predictor i.

3.2.1 Forecast Combination Approaches

3.2.1.1 Iterated Combination

We apply the Iterated Combination (IC) approach in the context of exchange rate returns forecasting. This method was recently introduced by Lin, Wu and Zhou (2017) in the context of corporate bond returns forecasting. The proposed methodology is an extension of existing combination approaches. The final forecast is a weighted average of the generated forecast and the benchmark; in our case, the Random Walk (RW)with drift:

$$r_{t+1} = (1 - \delta)\bar{r}_t + \delta\hat{r}_{t+1} + u_{t+1} \tag{3.2}$$

where δ is the weight, $\bar{r}_t$ is the RW forecast and $\hat{r}_{t+1}$ is the forecast of the individual predictor. The closer δ is to zero, the less information is contained in the candidate forecasting model. The values of δ are estimated by minimizing the in-sample

squared error, so that:

$$\delta = \frac{cov_t(r_{t+1} - \bar{r}_t, \hat{r}_{t+1}^{fitted} - \bar{r}_t)}{var_t(\hat{r}_{t+1} - \bar{r}_t)} \tag{3.3}$$

where δ is iteratively computed, $\bar{r}_t$ is the sample mean of r_t using all observations until time t (RW) and $\hat{r}_{t+1}^{fitted}$ are the fitted values (in-sample) of the individual predictor. Then, the iterated combination forecasts are calculated by:

$$\hat{r}_{t+1}^{IC} = (1 - \hat{\delta})\bar{r}_t + \hat{\delta}\hat{r}_{t+1} \tag{3.4}$$

where the process is iterated until the end of sample.
We denote this method as $C_i^{IC,0}$ for each predictor i.

3.2.1.2 Predictor Constrained

The second method that we adapt in our setting is the Constrained Predictor (CP) method that set constraints directly to the predictors and was proposed by Pan, Pettenuzzo and Wang (2018). Following the notation of the original paper, the predictors are transformed according to the following relation:

$$x_t^*(n) = \left\{ \begin{array}{c} x_t \text{if } x_t > \max(x_{t-1,}x_{t-2,}.., x_{t-n}) \text{ or } x_t < \min(x_{t-1,}x_{t-2,}.., x_{t-n}) \\ 0, \text{ otherwise} \end{array} \right\} \tag{3.5}$$

where n is the "look-back" period. In this study we apply a 25 day control window roughly corresponding to a one-month trading period. Hence, a constrained out-of-sample forecast is generated by:

$$\hat{r}_{t+1}^*(n) = \hat{a}^*(n) + \hat{b}^*(n)x_t^*(n) \tag{3.6}$$

where $\hat{r}_{t+1}^*(n)$ is the constrained out-of-sample forecast for $t+1$ of the individual predictor and $\hat{a}^*(n)$ and $\hat{b}^*(n)$ are the estimated parameters of the regression. The

procedure is repeated for each out-of-sample step. A drawback of this method is that only a few periods with abnormal behaviour on the predictors have an actual impact on the model. To alleviate this, Pan, Pettenuzzo and Wang (2018) include the information of "normal" periods and propose a revised constrained forecast, $\hat{r}_{t+1}^{CP}(n)$, as follows:

$$\hat{r}_{t+1}^{CP}(n) = 0.5\hat{r}_t + 0.5\hat{r}_{t+1}^{*}(n) \tag{3.7}$$

We denote this method as $C_i^{CP,0}$ for each predictor i.

3.2.1.3 Constrained Predictor with Iterated Combination Forecasts

In this study we propose a new method in the context of exchange rate forecasting. The proposed method is a hybrid approach of the Iterated Combination and the Predictor Constrained methods; namely the Iterated Combination Constrained Predictor (ICCP) approach. Forecasts are generated in a three step process. Initially, we create two series of forecasts. The first one is calculated as shown in equation (3.1), and the second one is calculated after constraining the predictors following the relationship (3.5). Next, we apply the IC methodology on both the constrained and unconstrained predictors, according to equations (3.3) and (3.4). As a last step, we generate the forecasts using equations (3.6) and (3.7). We denote the hybrid method as $C_i^{ICCP,0}$ for each predictor i.

The proposed method has two significant advantages against the alternatives. First, it takes into account only the significant past information, excluding the noisy data that do not contain useful information, at the same time, it winsorizes the predictors according to the past performance by allocating weights. Hence, the predictors that do not have go past performance are getting zero weight and pressed to zero, namely they are not taken into account.

3.2.1.4 Forecast Combination Approach

In our exercise, we also apply a forecast combination approach (see Timmermann, 2006; De Zwart, Markwat, Swinkels and van Dijk, 2009; Rapach, Strauss and

Zhou, 2010; Beckmann and Schüssler, 2016; Buncic and Piras, 2016; Jordan, Vivian, Wohar, 2018). We generate forecasts on the basis of each individual predictor and then combine the individual forecasts using a simple average. The general form for combining N individual forecasts is given by:

$$\hat{r}_{t+1}^{POOL} = \sum_{i=1}^{N} w_i \hat{r}_{i,t+1} \tag{3.8}$$

We assume an equal weight for each predictor, $w_i = \frac{1}{N}$ where in our case $N = 14$. Despite its simplicity, the naive combination of forecasts is widely used in the literature. In this framework, we take advantage of the aforementioned diversification by simply merging all forecasts and calculating a simple average. We denote this method as C^0_{POOL}. When Iterated Combination, Predictor Constrained or the hybrid $ICCP$ approach is applied the notation changes to $C^{IC,0}_{POOL}$, $C^{CP,0}_{POOL}$ or $C^{ICCP,0}_{POOL}$, respectively.

3.2.2 Dimensionality Reduction Techniques

Our dataset consists of a large number of predictors. Hence, dimensionality reduction techniques may help us extract the relevant information from the dataset. In this study we apply the Principal Component Analysis (PCA) and the Partial Least Squares (PLS) to transform our large set of variables to generate new predictors by extracting all relevant information.

3.2.2.1 Principal Components

Following, among others, Neely, Rapach, Tu and Zhou (2014), we use Principal Component Analysis (PCA) in order to reduce the dimensionality of the data and model complexity. PCA decreases the large number of predictors by transforming closely related variables to new uncorrelated features that capture maximum variability. Hence, this approach filters out the noise in the predictive variables.

The daily out-of-sample forecast at time $t + 1$ obtained from the principal com-

ponents is denoted as $\hat{r}_{t+1}^{PCA}$ and is given by the following formula:

$$\hat{r}_{t+1}^{PCA} = \hat{a} + \sum_{k=1}^{K} \hat{b}_k \hat{F}_{k,t} \tag{3.9}$$

where $\hat{F}_{k,t}$ is the k-th principal component estimated at time t.

By construction, most of the available information is concentrated at the first few components. We take into account at most the first $K = 4$ principal components, i.e. $\hat{F}_t = (\hat{F}_{1,t}, ..., \hat{F}_{K,t})$. The regression parameters $\hat{b}_k$ are recursively calculated with the OLS method. The optimal number of principal components is chosen using the adjusted $\overline{R}^2$of the in-sample period.

We denote this method as C_{PCA}^0. When Iterated Combination, Predictor Constrained or the hybrid $ICCP$ approach is applied, the notation changes to $C_{PCA}^{IC,0}$, $C_{PCA}^{CP,0}$ or $C_{PCA}^{ICCP,0}$, respectively.

3.2.2.2 Partial Least Squares

A method closely related to PCA and multiple linear regression is Partial Least Squares (PLS), introduced by Wold (1966) and more recently successfully extended and adopted in finance by Kelly and Pruitt (2013, 2015). The methodology is applicable in problems with extensive datasets and demonstrates promising results (see, for instance, Stivers 2018). Contrary to PCA, PLS takes into account the relationship between the dependent and independent variables by explaining the maximum variation in the target variable. Hence, theoretically, PLS is superior to PCA.

We follow Stivers (2018) and apply the de Jong (1993) SIMPLS algorithm to extract one target relevant factor (z_t) from the set of potential predictors. The daily out-of-sample forecast at time $t + 1$ obtained from the principal components is denoted as $\hat{r}_{t+1}^{PLS}$ and is given by the following formula:

$$\hat{r}_{t+1}^{PLS} = \hat{a} + \hat{b}_1 z_t \tag{3.10}$$

We denote this method as C_{PLS}^0. When Iterated Combination, Predictor Con-

strained or the hybrid $ICCP$ approach is applied the notation changes to $C_{PLS}^{IC,0}$, $C_{PLS}^{CP,0}$ or $C_{PLS}^{ICCP,0}$, respectively.

3.2.3 Positivity Constraints

In this last part of the experiment, we follow a growing part of literature supporting different types of constraints (see among others Ang and Piazzesi, 2003; Campbell and Thompson, 2008; and Pettenuzzo, Timmermann and Valkanov, 2014). These studies have proven that constraints can enhance the out-of-sample performance, significantly. We adopt the approach proposed by Campbell and Thompson (2008) and truncate the forecasts of returns at zero if the forecast is negative.

The intuition behind this truncation is that investors are not interested in negative returns. Moreover, empirically, we have witnessed the coefficients to have a sign different than the expected. Campbell and Thompson (2008) argue that such pervasive results should be truncated to zero. The forecasts are transformed under the following positivity constraint:

$$\hat{r}_t^+ = \begin{cases} \hat{r}_t \text{ if } \hat{r}_t > 0 \\ 0 \; otherwise \end{cases} \tag{3.11}$$

Our notation changes to C_i^+, $C_i^{IC,+}$, $C_i^{CP,+}$ or $C_i^{ICCP,+}$ for each predictor/ model specification i.

3.3 Dataset

In this study we forecast six widely traded currencies; the British Sterling (GBP), Japanese Yen (YEN), Swiss Franc (CHF), Eurozone's Euro (EUR), Canadian Dollar (CAD) and Australian Dollar (AUD) against the US Dollar (USD). FX spot prices were collected from Bloomberg database. Our sample contains daily observations that extend from February 02, 1999 to December 31, 2017. The total number of observations is 4,940. The first 25 observations of the sample serve as a control window ("look-back period"), in order to generate the constrained predictors, as

illustrated in equation (3.5). The following 1,257 observations are considered as the in-sample period and the remaining 3,658 are used as the out-of-sample period.

Panel A of Figure 3.1 shows the daily spot exchange rates of the six currencies under consideration against the US dollars for the period under examination (February 02, 1999 to December 31, 2017). Similarly, Panel B of Figure 3.1 depicts the daily returns of the six currencies. In Table 1 the descriptive statistics of the returns of the six currencies are presented. The mean for all currencies is similar and almost zero. On the other hand, significant differences are observed in the standard deviation, the skewness and the kurtosis. More precisely, the lowest standard deviations are observed in the GBP and CAD (0.58 and 0.56 respectively) while the largest ones in the CHF and the AUD (0.73 and 0.80 respectively). Small negative skewness is observed in the cases of YEN, -0.09 and EUR, -0.05, while positive ones for GPB, 0.83, CAD, 0.11, and AUD, 0.35. Finally, larger negative skewness is observed in the case of CHF. Similarly, CHF exhibits very large kurtosis, 112.13. The kurtosis in the remaining currencies range from 4.45 in the case of EUR to 14.20 in the case of GBP.

Table 3.1: Descriptive statistics of currency returns

	Mean	Std	Skew	Kurt	Max	Min
GBP	0.003	0.58	0.83	14.20	8.40	-3.00
YEN	-0.002	0.64	-0.09	6.69	5.50	-3.78
CHF	-0.008	0.73	-3.57	112.13	9.09	-19.38
EUR	-0.002	0.62	-0.05	4.45	2.52	-3.45
CAD	-0.004	0.56	0.11	5.97	3.25	-4.00
AUD	-0.004	0.80	0.35	12.37	7.29	-8.28

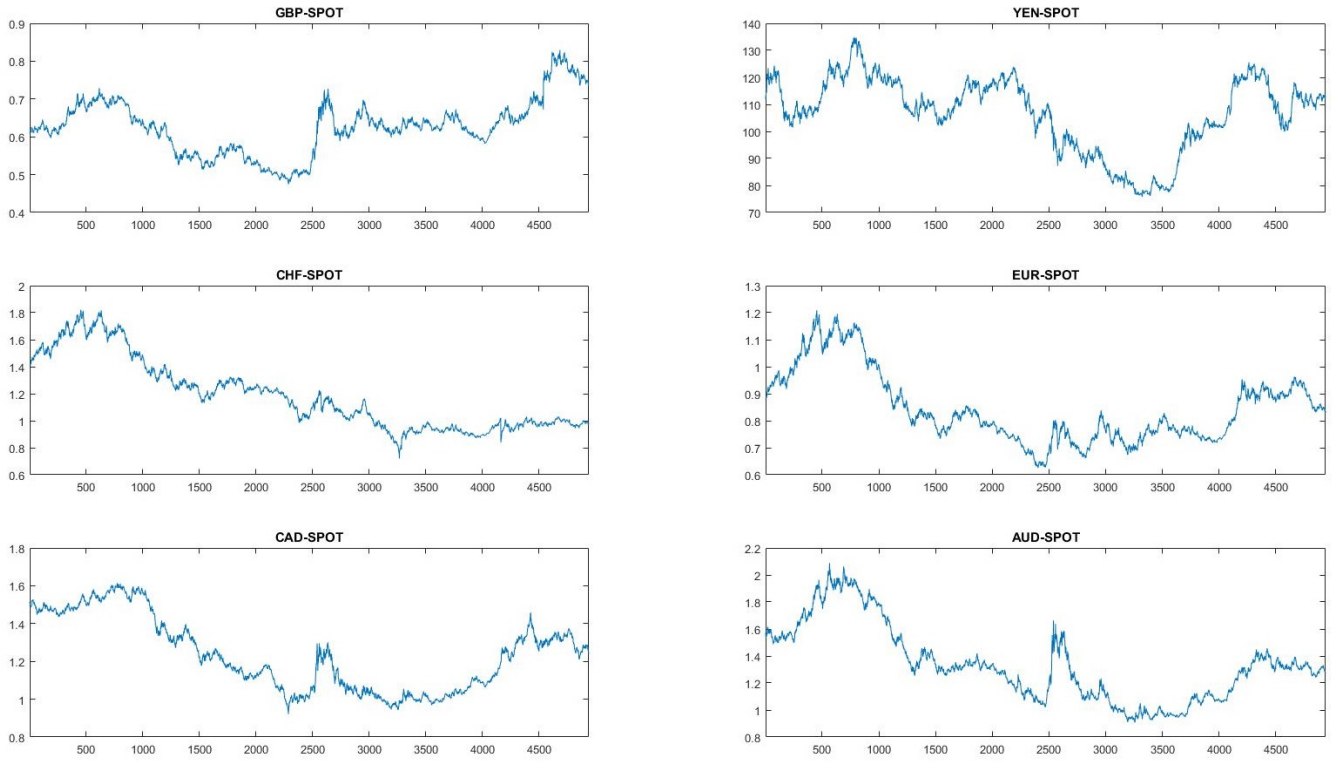
Std: Standard Deviation, Skew: Skewness, Kurt: Kurtosis

Our set of predictors contains three groups of financial variables which can be viewed as proxies for the state of the economy. These candidate predictors related to risk aversion and global trading/ economic activity, stock market data and yield curve data.

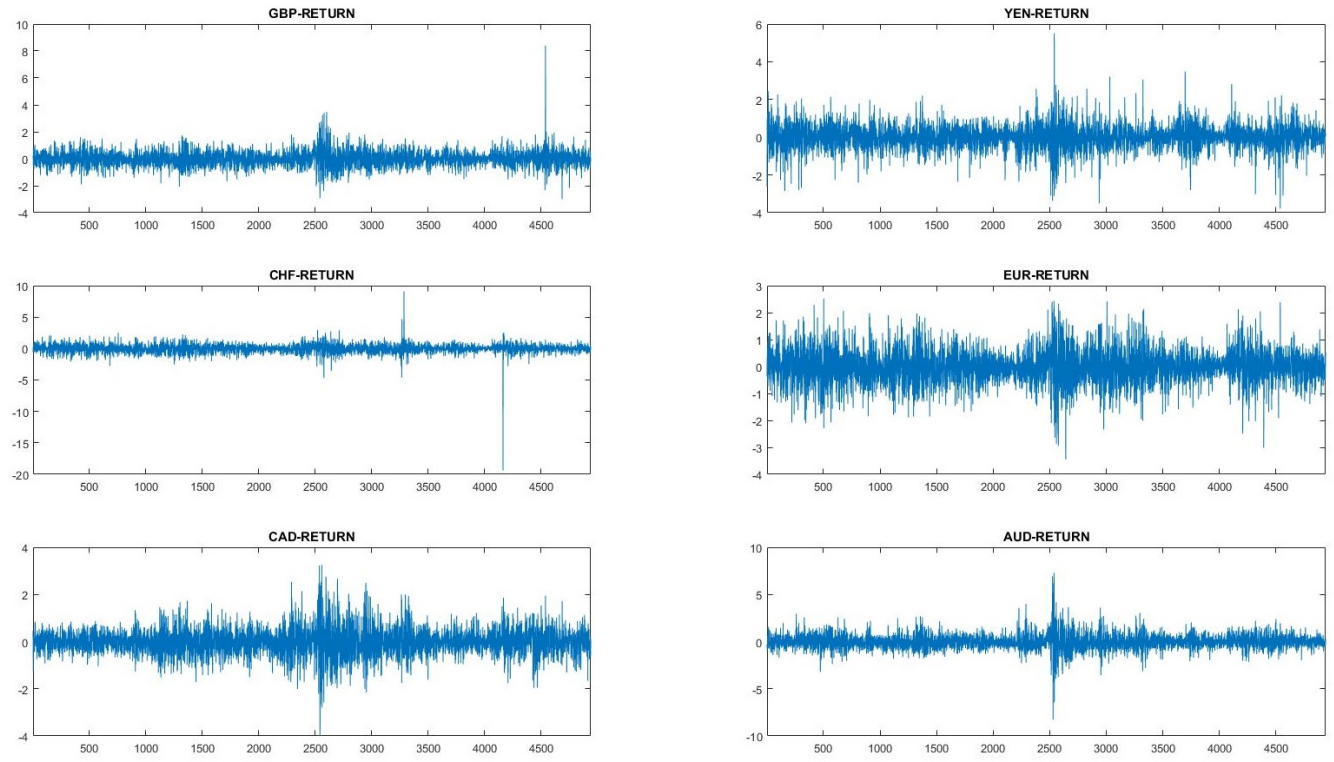
More in detail, we employ the VIX (CBOE) and the TED spread in order to gain a measure of 'risk aversion' in the markets (see among others, Cheung, Chinn, Pascual & Zhang (2018)). VIX measures the volatility implied by option prices on

Figure 3.1: Spot exchange rates and returns

(a)



(b)



Notes: (a) The first part of the figure illustrates the spot prices throughout the total sample period, from February 1999 to December 2017, for the six currencies uder consideration. (b) The second part of the Figure presents the evolution of actual returns through time for all six currencies under consideration.

the S&P500 and can gauge investors' expectations about stock market volatility over the next month. The TED spread is calculated as the difference between the 3-month LIBOR rate and the 3-month Treasury Bill rate and is related to credit risk in the US economy. In general, an increase in VIX and/or the TED spread indicates negative financial outlook. Following Jordan, Vivian, Wohar (2018) in equity returns forecasting, we consider gold returns (GOLD), which is a safe haven against shocks in risky assets and complements VIX and TED as risk measures (Capie, Mills and Wood, 2005; recently). Following Calvet, Fisher and Thompson (2006) and Ferraro, Rogoff and Rossi (2015), we employ the returns of Crude Oil (OIL) which is closely linked with the macroeconomic environment via inflation and changes in the interest rates. To proxy for trade activity and future demand (Baumeister, Guerin and Kilian, 2015; for a very recent and more extended discussion on how commodities impact on exchange rates see Baumgäertner & Klose, 2018). Next, we employ the Baltic Dry Index returns (BDI), which is composed by four indices, the Baltic Capesize, Panamax, Handysize and Supramax, illustrating shipping activity. Finally, we examine the predictive performance of the Commodity Research Bureau (CRB) Index, which is particularly important for commodity export/import countries. CRB is the arithmetic average of the futures prices of 19 commodities and is structured as follows; 39% of the commodities are related to energy, 41% to agriculture, 7% to precious metals and the remaining to base/industrial metals.

The next set of predictors is related to equity markets, which contain information about the macroeconomic outlook of the countries considered. Specifically, we include the returns of the MSCI global index, which represents large and mid-cap equity performance across 23 developed markets countries. We also take into account the information embedded in the returns and trading volume of S&P500 (denoted as SP500 and VSP500) and the leading equity market indices of the respective currencies (hereafter, denoted as EquityM and VEquityM)[2]. The equity indices we employ are FTSE100, NIKKEI225, SPI, DAX30, SPTSX and AllOrds for GBP, YEN, CHF, EUR, CAD and AUD, respectively.

[2]A very recent study of Chen and Hsu (2018) finds that there is a negative relationship between the exchange rate and the differential of the rival and US equity markets

Following Bekaert and Hodrick (1992), Clarida, Sarno, Taylor and Valente (2003) and Buncic and Piras (2016) we include a set of predictors related to the yield curve. We construct the level, slope and curvature factors (see Diebold, Rudebusch and Aruoba, 2006), denoted as L_t, S_t and C_t as a combination of yields of zero coupon bonds with various maturities, denoted as $y_t^{(m)}$ as follows:

$$\begin{aligned} L_t &= \left(y_t^{(3)} + y_t^{(24)} + y_t^{(120)}\right)/3 \\ S_t &= \left(y_t^{(3)} - y_t^{(120)}\right) \\ C_t &= \left(2y_t^{(24)} - y_t^{(3)} - y_t^{(120)}\right) \end{aligned} \tag{3.12}$$

Candidate predictors are generated by taking the differences between the respective factor for the US and each country under consideration, so that:

$$\begin{aligned} \Delta L &= \Delta(L^{US} - L^i) \\ \Delta S &= \Delta(S^{US} - S^i) \\ \Delta C &= \Delta(C^{US} - C^i) \end{aligned}$$

for $i = [GBP, YEN, CHF, EUR, CAD, AUD]$. Table 3.2 provides a more detailed description of the predictors we employ, their construction and the respective data sources.

3.4 Out-of-sample Performance

In order to evaluate the out-of-sample forecasting performance of candidate FX return models we split our dataset into two parts. The first part is called in-sample and is used for the fitting of our models. The second part is called out-of-sample and is used for the evaluation of the proposed models. The in-sample part ranges over 1,282 values (5 years), 25 of which correspond to the control window. The out-of-sample dataset consists of the remaining 3,658 values. We produce 1-day-ahead

Table 3.2: Candidate predictors and data sources

No	Abbrev.	Construction	Source
1	ΔVIX	First Differences on VIX	Fred Database.
2	ΔTED	First Differences on TED Spread	Fred Database.
3	GOLD	Log returns of Gold Prices	Fred Database.
4	OIL	Log returns of Crude Oil	Fred Database.
5	BDI	Log returns of Baltic Dry Index	Bloomberg.
6	CRB	Log returns of CRB commodities index	Bloomberg.
7	MSCI	Log returns of MSCI global stock market index	Bloomberg.
8	SP500	Log returns of SP500	Bloomberg.
9	VSP500	Growth of volume of SP500	Bloomberg.
10	EquityM	Log returns of 6 equity markets (FTSE100, NIKKEI225, SPI, DAX30, SPTSX, AllOrds	Bloomberg.
11	VEquityM	Growth of volume of the 6 equity markets	Bloomberg.
12	ΔL	Level of yield curve factor $\Delta(L_t^{US} - L_t^i)$ where $L_t = (r_t^{(3)} + r_t^{(24)} + r_t^{(120)})$	Bloomberg.
13	ΔS	Slope of yield curve factor $\Delta(S_t^{US} - S_t^i)$ where $S_t = (r_t^{(3)} - r_t^{(120)})$	Bloomberg.
14	ΔC	Curvature of yield curve factor $\Delta(C_t^{US} - C_t^i)$ where $C_t = (2r_t^{(24)} - r_t^{(3)} - r_t^{(120)})$	Bloomberg.

Notes: The predictors are collected for the sample period extending from February 02, 1999 to December 31, 2017.

out-of-sample forecasts recursively, i.e. the in-sample dataset is expanding at each time t. We only use data up to time t in order to forecast the FX returns at the next day, $t+1$.

The forecasting accuracy is measured by the Mean Square Forecasting Error (MSFE). The MSFE of each proposed model is compared against the MSFE of the random walk (RW) with drift, that is the historical average. This benchmark has proven very difficult to outperform and is calculated as follows:

$$\hat{r}_{t+1}^{RW} = \frac{1}{T}\sum_{t=1}^{T} r_t$$

We evaluate the forecasts of the proposed specifications j over the benchmark by calculating the Campbell and Thompson (2008) out-of-sample R^2, denoted as R^2_{OOS},which is given by:

$$R^2_{j,oos} = 1 - \frac{MSFE_j}{MSFE_{RW}}$$

We can interpret R^2_{OOS} as the proportional change in the Mean Square Forecast Error (MSFE) of the competing predictor j against the MSFE obtained by the benchmark. When R^2_{OOS} is positive the model under consideration generates superior forecasts

than the benchmark, and vice versa.

To test for the statistical significance of positive R^2_{OOS} we employ the adjusted MSFE, MSFE_{adj}, proposed by Clark and West (2007). The test is computed as follows:

$$\begin{aligned} MSFE-adjusted = (\frac{1}{P})\{ \sum_{t=M+1}^{T-1} \{(\Delta s_{t+1} - \Delta \hat{s}_{t+1}^{(RW)})^2 \\ -[(\Delta s_{t+1} - \Delta \hat{s}_{t+1}^{(q)})^2 - (\Delta \hat{s}_{t+1}^{(RW)} - \Delta \hat{s}_{t+1}^{(q)})^2]\}\} \end{aligned} \tag{3.13}$$

where P is the number of out-of-sample observations, T is the number of the total sample size, r_{t+1} is the actual return at time $t+1$, $\hat{r}_{t+1}^{RW}$ is the forecast generated by the benchmark and $\hat{r}_{t+1}$ is the forecast of candidate models. MSFE_{adj} is composed of two terms, the first one is the MSFE of the parsimonious model and the second is composed by the MSFE of the extended model and the average squared difference between the forecasts of the parsimonious model and those of the extended model. MSFE_{adj} is an one-sided test where H_0 is given by $MSFE_{RW} \leq MSFE_j$ against the alternative. Standard normal distribution can provide a very good approximation of the critical values.

3.4.1 Empirical Findings

In this section, we evaluate the out-of-sample performance of different forecasting methods. Initially we examine whether individual predictors or combinations can provide consistently superior forecasts, irrespective of the currency under consideration. Secondly, we examine whether the proposed methodologies, namely Iterated Combination, Constrained Predictor and ICCP Approaches, enhance the forecasting performance. Finally, we examine whether the application of positivity constraints on forecasts further improves forecast accuracy.

Table 3.3 shows the out-of-sample performance of all predictors and all proposed methods for the six currencies. By examining Table3.3 we can make the following general observations: 1) Applying positivity constrains improves the forecasting ability of each method, 2) $C^{ICCP,0}$outperforms the alternative unconstrained speci-

fications C^0, $C^{IC,0}$ and $C^{CP,0}$, 3) $C^{ICCP,+}$produces the highest R^2_{OOS} in most cases, outperforming all other methods, 4) it is very difficult to forecast the returns of some currencies, and 5) for each currency we can identify the predictors that outperform the remaining ones, however, their performance is not constant across all currencies.

Focusing on GBP in Panel A of Table 3.3 we observer that SP500, MSCI and the curvature yield curve factor outperform the remaining predictors. Combining the forecast of each individual predictor (POOL forecast) improves the R^2_{OOS} (0.12%). On the other hand, the R^2_{OOS} of both PCA and PLS are negative. Applying the Iterated Combination approach we observe an increase in terms of R^2_{OOS}, however, only MSCI and SP500 have positive and statistically significant R^2_{OOS}. R^2_{OOS} further increases for most predictors when the Predictor Constrained method is used. For example, the MSCI increased from 0.05% in the C^0 to 0.10% in the $C^{IC,0}$ and to 0.17% in the $C^{CP,0}$. Nevertheless, the overall performance in relatively poor with only 6 predictors with positive R^2_{OOS}. We observe the odd fact that negative R^2_{OOS} values (PLS) are accompanied by statistically significant CW critical values.[3] Finally, when $ICCP$ is used, R^2_{OOS} further increases in most cases, e.g. the R^2_{OOS} for the SP500 increases from 0.10% to 0.28%. However, again in most cases the R^2_{OOS} is negative. A closer inspection of Table 3 reveals that the application of positivity constraints significantly improves the forecasting ability of each method. For C^+ there are only two negative R^2_{OOS} while in the case of $C^{IC,+}$ and $C^{ICCP,+}$ all R^2_{OOS} are positive. For example we observe that ΔVIX returns a very low -0.32% R^2_{OOS} in the case of C^0 while it increases to a statistically significant (at 5%) 0.10% for C^+ and to a statistical significant (at 5%) 0.17% for $C^{ICCP,+}$. Similar changes are observed for all individuals predictors. Furthermore, the dimensionality reduction techniques (PCA and PLS) are now positive and statistically significant for all methods. In general $C^{ICCP,+}$ outperforms alternative methods when positivity constraints are applied followed by C^+, $C^{CP,+}$ and $C^{IC,+}$.

Focusing on YEN in Panel B of Table 3.3 we observe mixed results for the forecasting ability of each predictor and method. In general MSCI, SP500, OIL,

[3]This can be expected as CW tests for equal performance in the population, while R^2_{OOS} presents the performance in a finite sample.

Table 3.3: Out-of-sample results

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel A: GBP								
ΔVIX	-0.32	**0.10****	-0.16	**0.11***	-0.22	**0.16****	-0.02	**0.17****
ΔTED	-0.07	**0.04**	-0.02	**0.03**	-0.07	**0.04***	-0.02	**0.03**
GOLD	-0.01	**0.06**	-0.02	**0.04**	**0.02**	**0.05**	-0.02	**0.03**
OIL	-0.01	**0.03**	-0.01	**0.02**	0.00	**0.02**	-0.01	**0.02**
BDI	-0.06	**0.13***	-0.05	**0.07**	-0.04	**0.06**	-0.03	**0.06**
CRB	-0.02	**0.00**	-0.01	**0.02**	-0.01	-0.01	**0.01**	**0.03**
MSCI	**0.05****	**0.11****	**0.10****	**0.12***	**0.17****	**0.15****	**0.12****	**0.12***
SP500	**0.10****	**0.14****	**0.16****	**0.15****	**0.13****	**0.09***	**0.28****	**0.19****
VSP500	-0.02	**0.05****	-0.01	**0.02***	-0.02	**0.04****	-0.01	**0.02***
EquityM	-0.03	**0.02**	-0.03	**0.01**	-0.03	**0.00**	-0.02	**0.01**
VEquityM	-0.14	-0.03	-0.01	**0.03***	-0.12	-0.02	0.00	**0.03***
ΔL	-0.06	-0.01	-0.01	**0.02**	-0.06	**0.00**	0.00	**0.02**
ΔS	-0.01	**0.09****	-0.02	**0.05****	**0.07***	**0.09****	-0.02	**0.05****
ΔC	**0.02**	**0.09***	-0.01	**0.04***	**0.04**	**0.12****	0.00	**0.05***
POOL	**0.12***	**0.13****	**0.09**	**0.10****	**0.08***	**0.10****	**0.09**	**0.10****
PCA	-0.12	**0.11****	-0.03	**0.12***	-0.09	**0.07***	**0.02**	**0.13***
PLS	-0.23**	**0.04****	-0.11**	**0.09****	-0.12*	**0.06****	-0.09**	**0.10****
Panel B: YEN								
ΔVIX	**0.12****	**0.05***	**0.12***	**0.05**	**0.14****	**0.05***	**0.12***	**0.05**
ΔTED	-0.19	-0.21	-0.04	-0.04	-0.14	-0.13	-0.02	-0.02
GOLD	-0.03	**0.01**	0.00	**0.03**	-0.05	**0.02**	**0.00**	**0.03**
OIL	**0.20****	**0.20****	**0.12****	**0.12****	**0.13****	**0.14****	**0.10****	**0.11****
BDI	-0.33	-0.21	-0.08	-0.02	-0.26	-0.15	-0.06	-0.01
CRB	**0.04**	**0.16****	**0.04**	**0.11***	**0.04**	**0.16****	**0.03**	**0.09****
MSCI	**0.34****	**0.17***	**0.29****	**0.15***	**0.32****	**0.16***	**0.33****	**0.18***
SP500	**0.30****	**0.21****	**0.26****	**0.16***	**0.28****	**0.24****	**0.24****	**0.14***
VSP500	-0.01	**0.05***	0.00	**0.04***	0.00	**0.05***	0.00	**0.04***
EquityM	**0.05**	**0.04**	**0.05**	**0.03**	**0.05**	**0.04**	**0.07**	**0.04**
VEquityM	-0.03	**0.03**	0.00	**0.04***	-0.03	**0.03**	0.00	**0.04***
ΔL	-0.27	-0.07	-0.10	**0.01**	-0.24	-0.05	-0.04	**0.03**
ΔS	**0.07***	-0.01	**0.07**	**0.03**	**0.05**	**0.01**	**0.05**	**0.04**
ΔC	-0.03	**0.01**	0.00	**0.04***	-0.03	**0.02**	0.00	**0.04***
POOL	**0.24*****	**0.12***	**0.16****	**0.09***	**0.14****	**0.09***	**0.14****	**0.08***
PCA	**0.40*****	**0.22****	**0.39*****	**0.21****	**0.38*****	**0.25****	**0.40*****	**0.20***
PLS	**0.20*****	-0.01**	**0.38*****	**0.11****	**0.14*****	**0.01****	**0.47*****	**0.17****

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel C: CHF								
ΔVIX	-0.40	-0.15	-0.13	-0.06	-0.25	-0.09	0.00	**0.02**
ΔTED	-0.06	-0.05	-0.01	**0.03**	-0.06	-0.02	**0.00**	**0.03**
GOLD	-0.05	**0.03**	**0.01**	**0.03**	-0.03	**0.03**	**0.01**	**0.03**
OIL	-0.05	**0.02**	**0.02**	**0.03**	-0.04	**0.01**	**0.02***	**0.03**
BDI	0.00*	**0.05***	-0.03	**0.01**	**0.03**	**0.06***	-0.07	**0.00**
CRB	-0.05	**0.03**	**0.00**	**0.03**	-0.05	**0.03**	**0.02****	**0.03**
MSCI	-0.34	-0.14	-0.15	-0.06	-0.14	-0.05	-0.11	-0.06
SP500	-0.37*	-0.14	-0.20*	-0.07	-0.12	-0.01	-0.03*	-0.03
VSP500	-0.06	**0.02**	-0.01	**0.03**	-0.06	**0.02**	-0.01	**0.03**
EquityM	-0.06	**0.10***	-0.05	**0.04**	-0.02	**0.05**	-0.09	**0.03**
VEquityM	-0.05	**0.01**	-0.02	**0.03**	-0.03	**0.03**	-0.01	**0.03**
ΔL	-0.07	-0.04	**0.01**	**0.03**	-0.04	-0.02	**0.01**	**0.03**
ΔS	**0.12****	**0.06***	**0.02**	**0.03**	**0.01**	**0.02**	-0.05	**0.01**
ΔC	-0.06	**0.04**	-0.01	**0.04**	-0.07	**0.03**	-0.01	**0.04**
POOL	**0.07**	**0.06**	**0.08**	**0.06**	**0.03**	**0.05**	**0.08**	**0.05**
PCA	-0.33	-0.09	-0.13	-0.01	-0.28	-0.08	-0.07	-0.01
PLS	-0.59	-0.31	-0.37	-0.18	-0.44	-0.22	-0.30	-0.15
Panel D: EUR								
ΔVIX	-0.88	-0.30	-0.36	-0.05	-0.46	-0.01	-0.04	**0.11***
ΔTED	-0.13	-0.01	**0.02**	**0.06****	-0.14	**0.01**	**0.03***	**0.06****
GOLD	-0.02	**0.02**	**0.02**	**0.05***	-0.02	**0.04**	**0.00**	**0.05***
OIL	-0.06	**0.03**	**0.03****	**0.05***	-0.04	**0.03**	**0.02****	**0.05***
BDI	-0.05	**0.15***	-0.06	**0.05**	**0.02**	**0.12***	-0.07	**0.05**
CRB	-0.07	**0.01**	**0.00**	**0.05***	-0.03	**0.04**	**0.01**	**0.05***
MSCI	-0.83	-0.46	-0.43	-0.26	-0.49	-0.28	-0.41	-0.26
SP500	-1.02	-0.55	-0.68	-0.38	-0.5	-0.29	-0.31	-0.21
VSP500	-0.05	**0.04***	**0.00**	**0.05***	-0.04	**0.05***	**0.01**	**0.05***
EquityM	-0.34	-0.11	-0.09	-0.01	-0.18	-0.03	-0.05	**0.01**
VEquityM	**0.06***	**0.09****	-0.04	**0.04**	**0.08****	**0.10****	-0.02	**0.04**
ΔL	0.00	**0.01**	**0.02**	**0.05***	-0.03	**0.03**	0.00	**0.05***
ΔS	**0.01**	**0.07****	0.00	**0.06****	-0.03	**0.03**	0.00	**0.06****
ΔC	-0.01	**0.05***	**0.00**	**0.06****	-0.02	**0.04***	0.00	**0.06****
POOL	**0.02**	**0.05**	**0.04**	**0.06**	**0.01**	**0.06**	**0.05**	**0.07**
PCA	-1.17	-0.44	-0.67	-0.23	-0.77	-0.25	-0.48	-0.14
PLS	-1.50	-0.74	-1.09	-0.52	-1.04	-0.46	-0.99	-0.47

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel E: CAD								
ΔVIX	-0.11	**0.03**	-0.11	**0.01**	**0.11**	**0.11***	-0.03	**0.04**
ΔTED	-0.07	-0.01	-0.01	**0.05***	-0.03	**0.02**	0.00	**0.04**
GOLD	**0.08**	**0.06**	**0.04**	**0.03**	**0.05**	**0.06**	**0.03**	**0.03**
OIL	-0.02	**0.01**	-0.01	**0.04**	-0.02	**0.01**	-0.01	**0.04**
BDI	-0.07	**0.05**	-0.06	**0.03**	-0.07	0.00	**0.01**	**0.06**
CRB	**0.01**	**0.06***	0.00	**0.04**	**0.04**	-0.02	**0.01**	**0.05***
MSCI	-0.27	-0.03	-0.15	**0.02**	-0.23	**0.02**	-0.08	**0.05**
SP500	-0.25	-0.01	-0.14	**0.02**	-0.11	**0.05**	**0.08**	**0.12**
VSP500	-0.01	**0.05***	0.00	**0.04**	0.00	**0.05***	0.00	**0.04**
EquityM	-0.21	-0.01	-0.12	**0.02**	-0.14	**0.03**	-0.09	**0.05**
VEquityM	-0.05	**0.04**	-0.02	**0.04**	-0.05	**0.05**	-0.01	**0.04**
ΔL	-0.04	**0.03**	-0.01	**0.05***	-0.03	**0.03**	**0.01**	**0.05***
ΔS	-0.08	**0.05**	-0.04	**0.04**	-0.07	**0.05***	-0.01	**0.05***
ΔC	-0.09	**0.06***	-0.03	**0.06***	-0.07	**0.06***	-0.01	**0.06***
POOL	**0.01**	**0.06**	-0.05	**0.05**	**0.01**	**0.06**	-0.01	**0.06**
PCA	-0.38	-0.06	-0.27	**0.01**	-0.24	**0.06**	-0.21	**0.03**
PLS	-0.59	-0.18	-0.49	-0.14	-0.29	-0.09	-0.47	-0.12
Panel F:AUD								
ΔVIX	-0.51	-0.21	-0.33	-0.13	-0.27	-0.06	-0.23	-0.09
ΔTED	-0.14	-0.01	-0.07	**0.00**	-0.15	**0.01**	-0.04	**0.02**
GOLD	-0.08	-0.06	-0.01	-0.01	-0.08	-0.03	**0.01**	**0.02**
OIL	**0.05**	**0.00**	**0.01**	**0.01**	**0.04**	**0.01**	0.00	**0.01**
BDI	-0.33	-0.27	-0.32	-0.25	-0.29	-0.26	-0.19	-0.15
CRB	-0.09	-0.04	0.00	**0.04***	-0.01	-0.12	-0.02	**0.01**
MSCI	-0.71	-0.42	-0.50	-0.30	-0.56	-0.33	-0.44	-0.27
SP500	-0.48	-0.17	-0.34	-0.10	-0.29	-0.17	**0.03**	**0.10**
VSP500	-0.02	**0.03**	**0.00**	**0.04***	-0.02	**0.04***	**0.00**	**0.04***
EquityM	-0.25	-0.08	-0.10	**0.01**	-0.13	-0.09	-0.11	**0.02**
VEquityM	-0.10	**0.02**	-0.01	**0.04***	-0.06	**0.03**	**0.01****	**0.05****
ΔL	**0.04**	**0.08**	0.00	**0.04**	**0.03**	**0.08***	**0.00**	**0.04**
ΔS	-0.12	**0.01**	**0.00**	**0.05***	-0.10	**0.04**	-0.01	**0.04***
ΔC	-0.01	**0.05***	-0.01	**0.04***	**0.02**	**0.05***	-0.01	**0.04***
POOL	-0.05	-0.02	-0.19	**0.00**	-0.04	-0.02	-0.16	**0.02**
PCA	-0.73	-0.41	-0.54	-0.30	-0.47	-0.33	-0.53	-0.30
PLS	-1.67	-1.22	-1.48	-1.10	-1.19	-0.93	-1.48	-1.10

Notes: The Table illustrates the out-of-sample performance of the models employed against the RW with drift benchmark. We use the first 25 observations in order to create the constrained predictor approach. Column 2 displays the results for the individual predictor models, naive combination forecasts (POOL), Principal Components (PCA) and Partial Least Squares (PLS), without applying any restrictions or constraints, denoted as C^0. C^+ denotes constraining forecasts to positive or zero values. $C^{IC,0}$ refers to the Iterated Combination approach (Li et al, 2017. $C^{IC,+}$ denotes the IC methodology with positivity constraints. $C^{CP,0}$ refers to the constrained predictor approach of Pan et al (2017). $C^{CP,+}$ refers to the constrained predictor approach with positivity constraints. $C^{ICCP,0}$ denotes the hybrid method, i.e. the iterated combination constrained predictor approach and $C^{ICCP,+}$ refers to the hybrid approach with positivity constraints. The performance is measured by the R^2_{OOS}, which measures the reduction in MSFE of the rival model against that of the benchmark. Statistical significance is tested via the Clark and West (2007) one-sided upper-tailed statistic. Three, two and one asterisks denote the 1%, 5% and 10% level of statistical significance, respectively.

ΔVIX, and the slope of the yield curve deliver positive and statistical significant R^2_{OOS} while on the other hand the R^2_{OOS} from ΔTED, GOLD, BDI, VSP500 and ΔL is negative and in general large in absolute values. Finally, R^2_{OOS} for POOL, PCA and PLS are 0.24%, 0.40% and 0.20%, respectively and statistically significant at the 1% level. In general, we observe that $C^{ICCP,0}$ outperforms the alternative methods while comparing C^0, $C^{IC,0}$ and $C^{CP,0}$ we get mixed results. Applying positivity constraints improves the performance of all four methods. For example, R^2_{OOS} for CRB increases from 0.04% to 0.16%. On the other hand, we observe that the R^2_{OOS} of POOL, PCA and PLS decrease when the positivity constraint is applied although it is still positive and statistically significant. For example, in the case of POOL, R^2_{OOS} decreases from 0.40% to 0.20%. Again, $C^{ICCP,+}$ outperforms the alternative methods followed by $C^{CP,+}$,C^+ and $C^{IC,+}$. Finally, it is worth noting that PCA outperforms all other specifications for all methods followed by MSCI, SP500, POOL, PLS and OIL.

Moving to CHF we observe poor forecasting ability from all predictors with an exception of ΔS, which delivers a statistically significant R^2_{OOS} of 0.12%. As previously, $C^{ICCP,0}$ outperforms all unconstrained methods followed by $C^{IC,0}$. On the other hand $C^{CP,0}$ and C^0 show poor forecasting ability. Applying positivity constraints significantly improves the forecasting accuracy of all methods. For example, out of 14 individual predictors and 3 combination methods, only 2 have a positive R^2_{OOS} in the case of C^0 while this number rises to 10 in the case of C^+. Similarly, we observer 6 positive R^2_{OOS} in the case of $C^{ICCP,0}$ while there are 13 in the case of $C^{ICCP,+}$. Observing Panel C of Table 3 we conclude that $ICCP$ with positivity constraints produces the best results, the Iterated Combination approach outperforms the Predictor Constrained approach while the simple bivariate models rank last.

Focusing on the EUR we observe similar results to CHF. A closer inspection of Panel D of Table 3.3 reveals that only the volume of DAX, the slope and POOL have a positive R^2_{OOS} for C^0. However, only the volume of the equity market (DAX) is statistically significant. We observe similar poor performance for $C^{CP,0}$. When we

focus on $C^{IC,0}$ and $C^{ICCP,0}$ we clearly observe more positive R^2_{OOS} however statistical significance is obtained only in the case of OIL for $C^{IC,0}$ and ΔTED and OIL for $C^{ICCP,0}$. Positivity constrains significantly improve the results for all methods and the majority of predictors have a positive R^2_{OOS}. The proposed hybrid $C^{ICCP,+}$ approach clearly outperforms all other methods obtaining the highest R^2_{OOS} in 13 cases out of 17. Furthermore, the R^2_{OOS} of 9 predictors is statistically significant, i.e. ΔVIX, ΔTED, GOLD, OIL, CRB, VSP500, ΔL, ΔS and ΔC. Comparing the simple bivariate model with the proposed advanced method, it is clear that significant gains are obtained, e.g. for ΔVIX the R^2_{OOS} increased from -0.88% for C^0 to 0.11% for $C^{ICCP,+}$. Finally, POOL is constantly positive for all methods,while PCA and PLS are always negative.

Next, we focus on the Canadian Dollar. The results are presented in Panel E of Table 3.3. In all unconstrained specifications we observe very few positive R^2_{OOS} values. It is worth mentioning that GOLD outperforms the benchmark across all methods. $C^{ICCP,0}$outperforms the remaining unconstrained methods. It is also clear that positivity constraints significantly improve the forecasting power of all methods. In the cases of $C^{IC,+}$ and $C^{ICCP,+}$ all models, with an exception of PLS, outperform the benchmark. The results of $C^{CP,+}$ and C^{+} are similar where the majority of predictors have a positive R^2_{OOS}. The proposed hybrid $C^{ICCP,+}$ approach ranks first followed by $C^{CP,+}$, $C^{IC,+}$ and C^{+}. It is noteworthy that by combining the iterated combinations and predictor constrained approach yields better results compared to each approach separately. For example in the case of SP500 the R^2_{OOS} is –0.25%, 0.14% and -0.11% for $C^{IC,0}$ and $C^{CP,0}$ respectively while it is 0.08% for the $C^{ICCP,0}$ and 0.12% for $C^{ICCP,+}$. As previously, we also find that POOL always outperforms both dimensionality reduction approaches.

Finally, we examine the performance of the predictors and the proposed approaches in forecasting Australian Dollar returns. The results are presented in Panel F of Table 3.3. In general, for the unconstrained specifications all predictors have poor performance across all methods, nevertheless, ICCP outperforms all other methods. Positivity constraints improve the results however when we focus

on $C^{CP,+}$, $C^{IC,+}$ and C^{+} we observe only 7, 10, 6 positive R^2_{OOS}, while in the case of $C^{ICCP,+}$ there are 12 positive R^2_{OOS}. In general, we can conclude that $C^{ICCP,+}$ significantly outperforms all other methods, however, it is clear that is more difficult to forecast the returns of the Australian Dollar FX returns than other currencies. Furthermore, POOL, PCA and PLS have a poor performance although POOL outperforms both PCA and PLS.

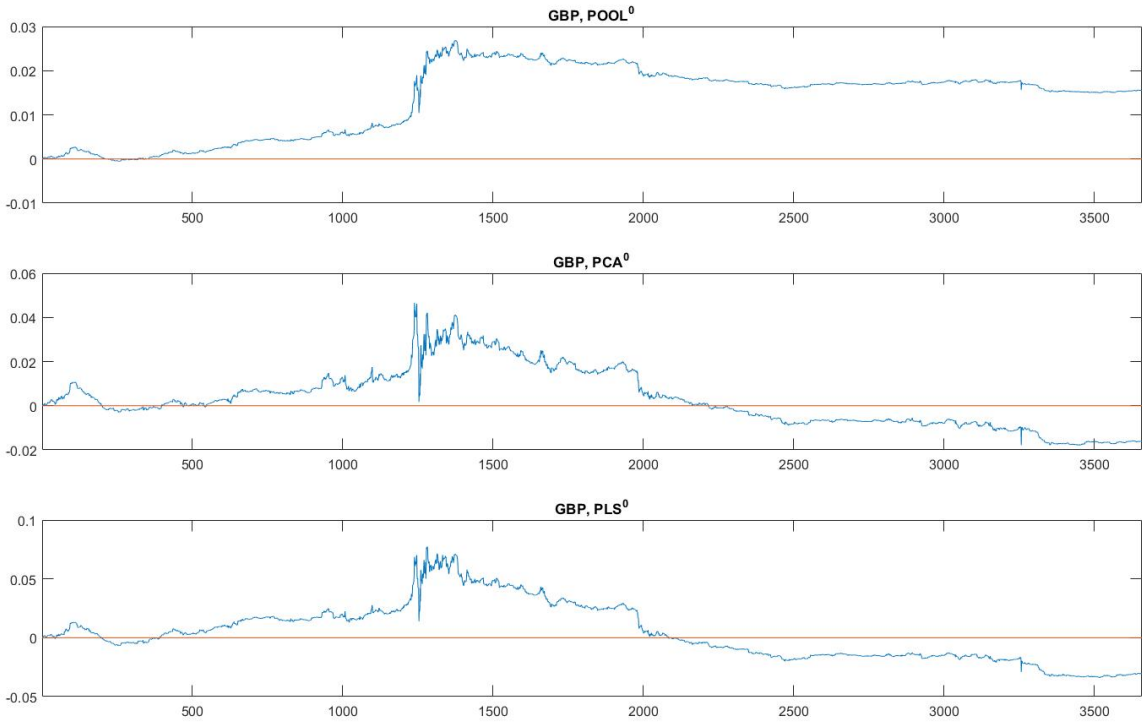
Overall, the results presented in Table 3.3 show evidence of predictability of daily exchange rate returns. The performance of individual predictors is not similar across currencies and methods. Predictors may outperform the benchmark in one currency however they may not generate consistently good forecasts for every currency. Hence, the investor faces a predictor selection problem. For this reason, we construct three set of forecasts that take into account information from all predictors, i.e. POOL, PCA and PLS. Among the three, we observe that R^2_{OOS} of POOL is larger for all currencies under consideration. On the other hand, when positivity constraints are applied we observe that OIL, the volume of S&P 500 (VSP500) and ΔC have constantly positive R^2_{OOS} for all currencies and methods. Similarly, GOLD and POOL have always positive R^2_{OOS} when positivity constraints are applied for all methods and currencies except for AUD. In general, positivity constraints significantly improve the forecasting ability of all methods. Finally, the proposed hybrid approach that combines iterated combination and predictor constrained outperforms all methods for all currencies both in the unconstrained and positivity constrained setting.

We complement our analysis by examining the evolution of the cumulative squared error difference between the benchmark and the proposed methods. Our results are presented in Figure 3.2. Due to space limitations, we only present the relative figures for the combination and dimensionality reduction techniques. As a general remark, we outline the obvious importance of the Lehman Brother collapse in 2008. The event has a remarkable impact on every currency, affecting the performance of all predictors. Apart from some rare cases, such as AUD, most predictors and models are able to benefit from this event. In Panel (a) and (b) the results for GPB are

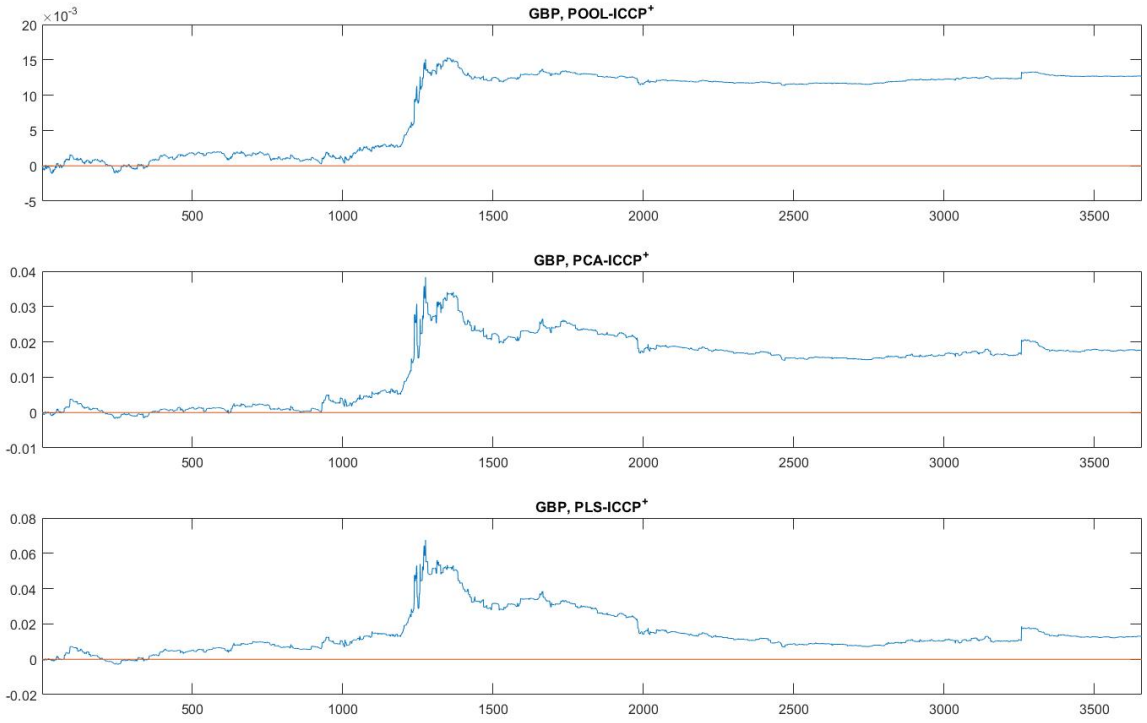
presented. More precisely, Panel (a) presents the results of the POOL, PCA and PLS techniques for GBP using the C^0 method while the $C^{ICCP,+}$ is used in Panel (b). Panel (a) reveals that POOL is always above the benchmark while PCA and PLS show negative cumulative results at the end of the period. On the other hand, in Panel (b) we observe that all three methods are always positive, however the performance of POOL is superior to PCA and PLS as the slope is almost consistently positive. The same results are observed in Panel (c) for YEN. On the other hand, the superiority of POOL is clear in panels (d)-(g). POOL is almost always positive and always outperforms the benchmark at the end of the period for all currencies. It is worth mentioning that cumulative squared difference between the benchmark and the POOL is almost always positive even in the case of AUD which is the most difficult to predict currency. On the other hand both PCA and PLS start positive but they perform worse than the benchmark for CHF, EUR, CAD and AUD.

Figure 3.2: Dynamic evolution of out-of-sample forecasts

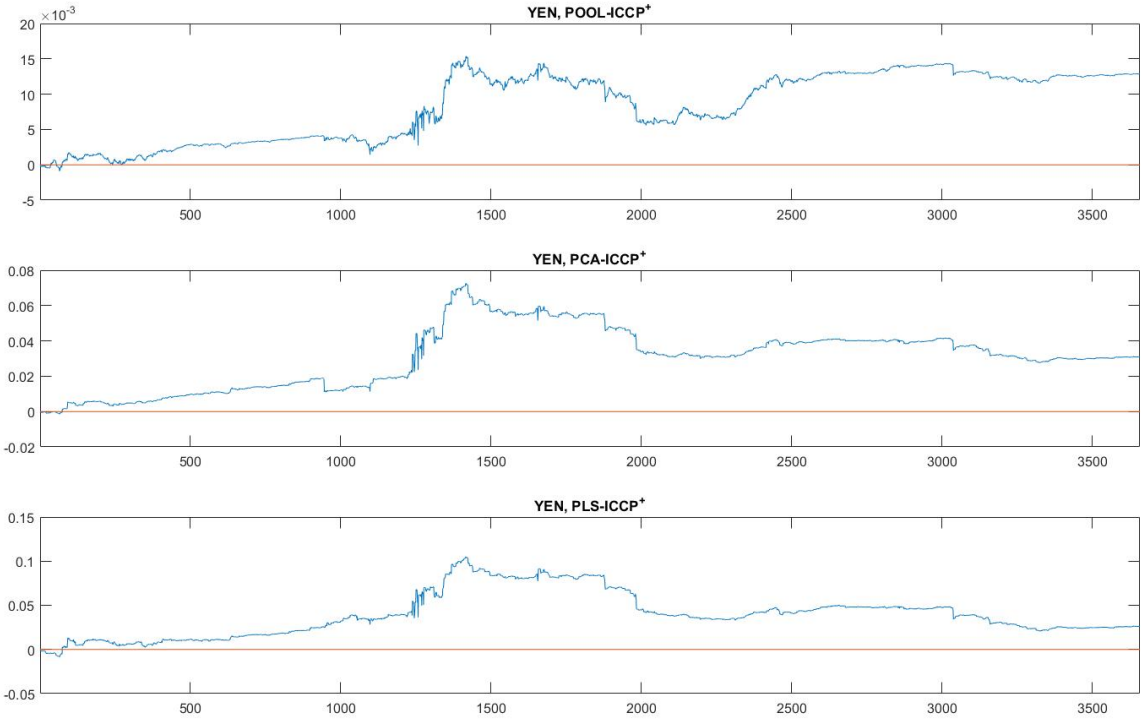
(a)



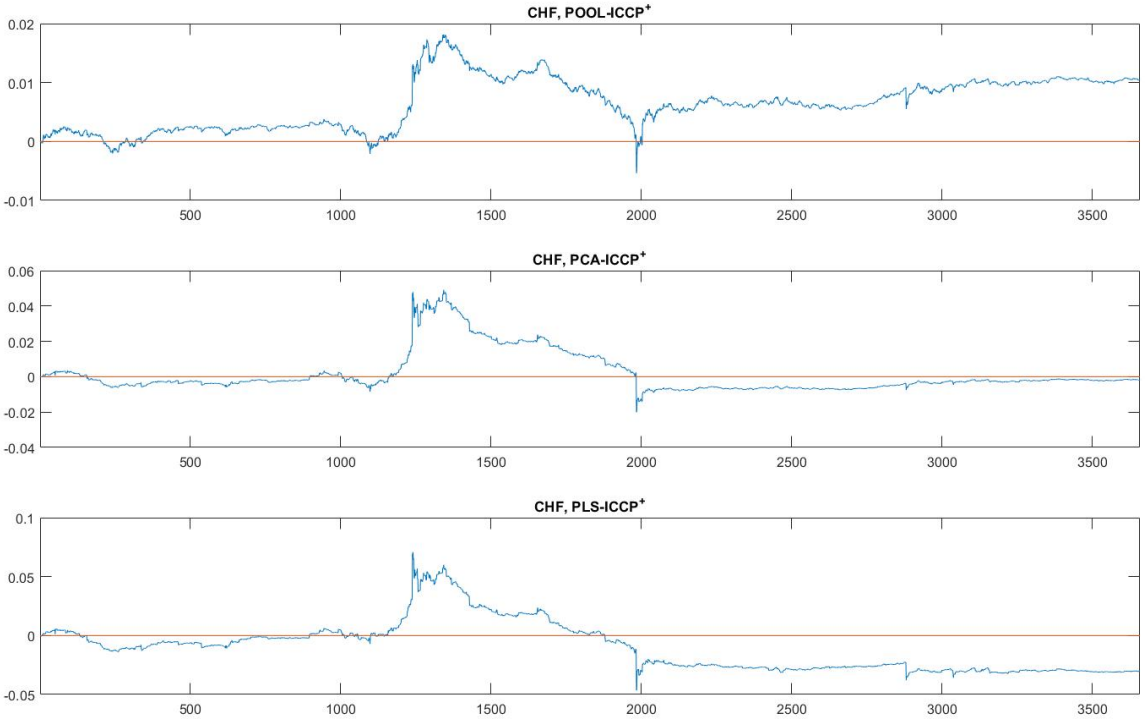
(b)



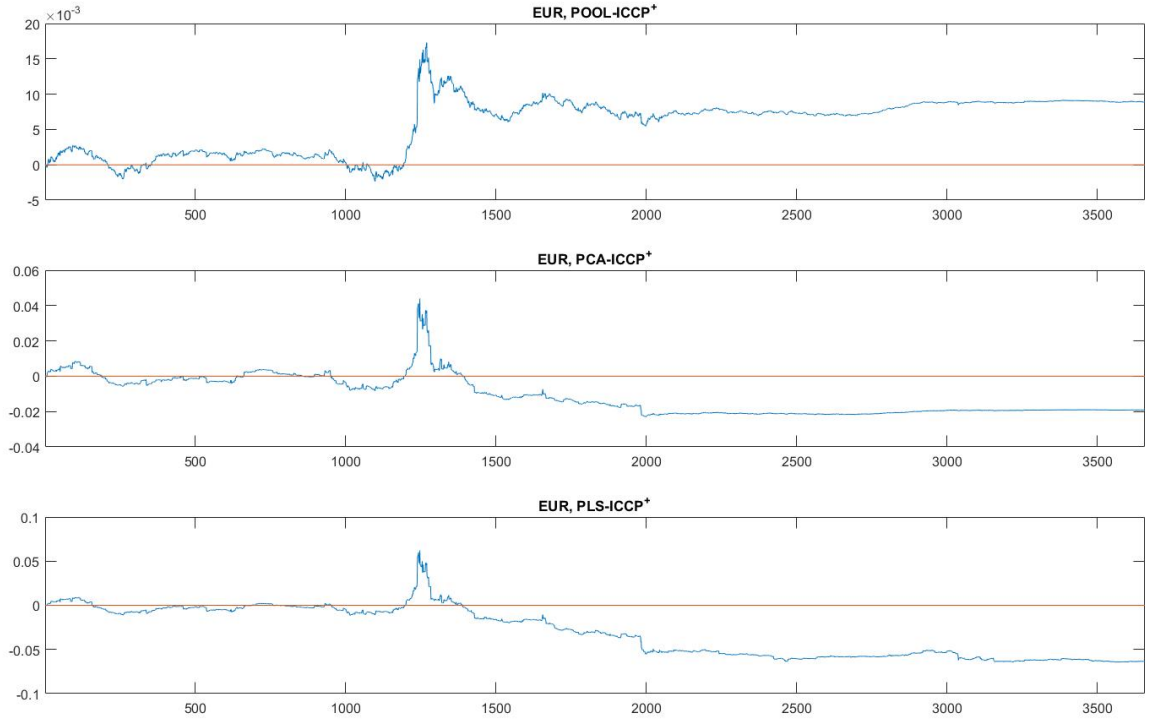
(c)


YEN, POOL-ICCP+
×10-3
20
15
10
5
0
-5
500
1000
1500
2000
2500
3000
3500
YEN, PCA-ICCP+
0.08
0.06
0.04
0.02
0
-0.02
YEN, PLS-ICCP+
0.15
0.1
0.05
0
-0.05

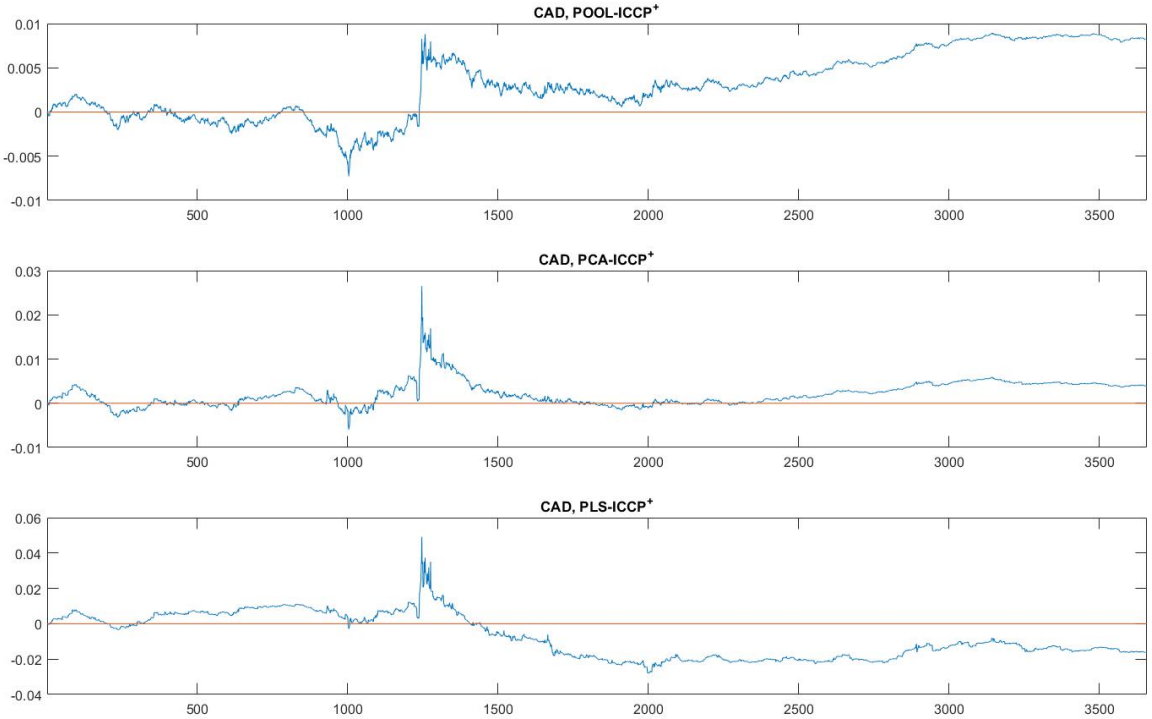
(d)


CHF, POOL-ICCP+
0.02
0.01
0
-0.01
500
1000
1500
2000
2500
3000
3500
CHF, PCA-ICCP+
0.06
0.04
0.02
0
-0.02
-0.04
CHF, PLS-ICCP+
0.1
0.05
0
-0.05

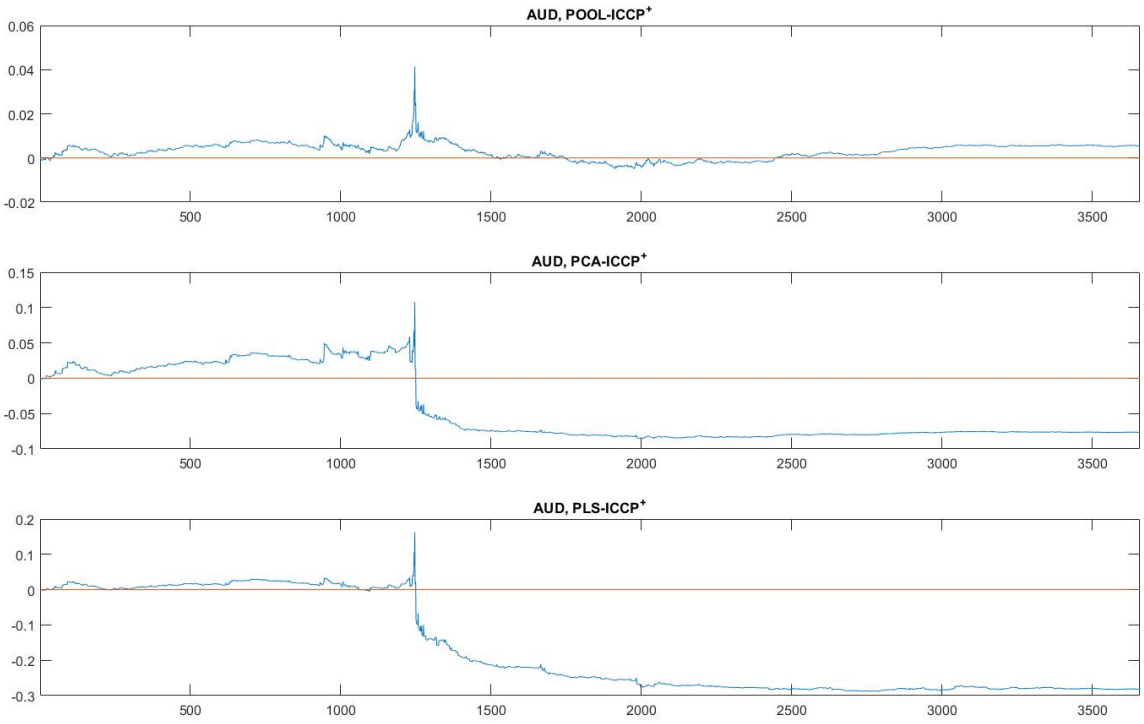
(e)


EUR, POOL-ICCP+
×10-3
EUR, PCA-ICCP+
EUR, PLS-ICCP+

(f)


CAD, POOL-ICCP+
CAD, PCA-ICCP+
CAD, PLS-ICCP+

(g)



Notes: The Figure plots the cumulative squared error difference between the benchmark and the rivals, following the specifications of the initial experiment. Due to the large set of predictors and methods, we demonstrate the performance of the combination and dimensionality reduction techniques. Only for GBP, in subplot (a), we report the respective values for C^0 and $C^{ICCP,+}$.

3.5 Economic Evaluation

In this section we examine the economic value of our forecasts and proposed methods. An investor can form a portfolio of six risky and one risk-free asset. The portfolio is rebalanced dynamically at the end of each period, i.e. new weights for each asset are computed. In this study we follow the methodology proposed in Della Corte, Sarno and Tsiakas (2009, 2011), Li, Tsiakas and Wang (2015) and Ahmed, Liu and Valente (2016).

More in detail, a US based investor allocates part of her wealth in the US riskless asset and the other part in the foreign risk free asset. Hence, the investor is exposed to exchange rate risk. The investor generates daily forecasts of FX returns using the predictors/ specifications presented in the previous section. Next, conditionally

on the forecasts, she can solve the optimisation problem in order to rebalance the portfolio between the domestic riskless and foreign risky assets. The domestic and foreign riskless assets are the respective risk free interest rates, denoted as r_t^f and y_t^f respectively. The following optimization problem is solved:

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

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

where $\hat{r}_{t+1}^p$ is the expected portfolio return, $\hat{\mathbf{r}}_{t+1}$ is a 6x1 vector of the exchange rate expected return. The expected return of the risky asset at the end of period is equal to the return of the foreign riskless asset plus the return of the exchange rate, calculated by $E_t[r_{t+1}] = y_t^f + \hat{r}_{t+1}$, ι is a 6x1 unit vector, σ_p^* is the target conditional volatility of the portfolio returns. Following Buncic and Piras (2016) and Li, Tsiakas and Wang (2015) we set $\sigma_p^* = 10\%$. $\Sigma_{t+1|t}$ is a 6x6 conditional variance-covariance matrix, $\Sigma_{t+1|t} = (\mathbf{r}_{t+1} - \hat{\mathbf{r}}_{t+1})(\mathbf{r}_{t+1} - \hat{\mathbf{r}}_{t+1})'$. By solving the optimisation problem we get the optimal weights on the risky assets:

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

where $\hat{\mathbf{r}}_{t+1} - \iota r_t^f$ is the 6x1 vector of excess returns and $C_t = (\hat{\mathbf{r}}_{t+1} - \iota r_t^f) \Sigma_{t+1|t}^{-1} \left(\hat{\mathbf{r}}_{t+1} - \iota r_t^f \right)$. Following Ahmed, Liu and Valente (2016) we winsorise the weights as $-\iota \leq \mathbf{w}_t \leq 2\iota$ in order to prevent from extreme positions in both sides, while allowing the investor to take both short positions and leverage her positions.

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

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

The gross portfolio return is $R_{p.t+1} = 1 + r_{p,t+1}$. Portfolio returns are generated by investing to all six available currencies until December 31st, 2017.

Following Della Corte, Sarno and Tsiakas (2009, 2011), Thorton and Valente

(2012) and Ahmed, Liu and Valente (2016) we compute the out-of-sample performance fee that shows the investor's gains from the proposed models over those generated by the benchmark. The average mean-variance utility function is given by:

$$\bar{U}(R_p) = \bar{R}_p - \frac{\gamma}{2P} \sum_{t=R+1}^{T-1} \left(R_{p,t+1} - \bar{R}_p\right)^2 \tag{3.14}$$

where $\bar{R}_p$ is the average gross portfolio return, given by $\bar{R}_p = \frac{1}{P}\sum_{t=R+1}^{T-1} R_{p,t+1}$ and γ is the investor's level of risk aversion. A lower γ indicates a lower level of risk aversion. In our analysis, we examine two levels of risk aversion $\gamma = [2, 5]$. P is the number of observations in the out-of-sample period. We calculate the difference between the proposed model $\bar{U}(R_p)$ and the benchmark $\bar{U}(R_{p,RW})$, which can be viewed as the Certainty Equivalent of the portfolio Returns (CER). It can also be interpreted as the maximum fee that the investor is willing to pay in order to switch from the RW portfolio to the competing model and is given by:

$$\Delta U = \bar{U}(R_p) - \bar{U}(R_{p,RW})$$

The second and most common measure of economic performance we employ is the Sharpe Ratio (SR) (Della Corte, Sarno and Tsiakas, 2009; DeMiguel, Garlappi and Uppal, 2009) and is given by:

$$SR = \frac{\overline{r_p - r_t^f}}{\sigma_p}$$

where $\overline{r_p - r_t^f}$ is the average excess return of a portfolio and σ_p is the standard deviation of the corresponding portfolio return. We compute the annualized SR for each predictive model/ specification.[4] Finally, we consider the cumulative return of the portfolio at the end of the sample (end-of-period wealth). At each time step t the portfolio is reinvested for a gross return $R_{p,t}$. At the end of the period the investor accumulates wealth equal to $TW = W_0 * R_{p,t+1} * R_{p,t+2} * ... * R_{p,P}$. For

[4]It is worth noting that SR does not take into account the effects of non-normality and it can underestimate the performance of dynamic strategies (Ahmed, Liu and Valente, 2016; Thorton and Valente, 2012; Jordeau and Rockinger, 2006; Han, 2006; Marquering and Verbeek, 2004), as it overestimates the conditional risk an investor faces at every t.

simplicity we assume that $W_0 = 1$.

3.5.1 Economic Evaluation Findings

It is well known that good forecasting ability does not necessarily imply profitability. We assess the economic value of each predictor and each method according to the ΔU, SR and TW. The evaluation period is the same as the out-of-sample forecasting period, i.e. January 1^{st}, 2004 to December 31^{st}, 2017. The investor aims at maximizing portfolio returns with a target volatility of 10%. For robustness we assume two levels of risk aversion, $\gamma = [2, 5]$. Our results are summarised in Table 3.4 .

A closer inspection of Table 3.4 reveals that positivity constraints in the forecasts play a significant role in portfolio management. ΔL and ΔVIX demonstrate significant economic gains irrespective of the level of risk aversion. We also observe poor performance for PLS, especially in the case of unconstrained forecasts. The results of POOL and PCA are similar. PCA outperforms POOL when positivity constraints are applied while POOL outperforms PCA in the unconstrained setting. By comparing the various methods, we observe that $C^{CP,+}$ and $C^{ICCP,+}$ outperform the remaining approaches. In general increasing the level of risk aversion leads to an increase in the economic gains of $C^{CP,+}$and $C^{ICCP,+}$. On the other hand, methods that do not use positivity constraints in general are negatively affected.

In Panel B of Table 3.4 the cumulative return at the end of the out-of-sample period is computed. Our results indicate that no method clearly outperforms the remaining ones although almost all predictors outperform the benchmark. It is noteworthy that $C^{CP,0}$, $C^{ICCP,0}$ and $C^{IC,+}$ in general have a poor performance since for most predictors the end of period cumulative returns are lower than the ones obtained by the RW benchmark. Among the individual predictors we are able to identify the very good overall performance of ΔL, $MSCI$ and ΔVIX. Similar to the statistical evaluation findings, POOL, PCA and PLS always provide higher cumulative returns although it seems that PCA outperforms the other two. The

same qualitative results hold in terms of SR which is presented in Panel C of Table 3.4. Overall, the proposed $C^{ICCP,+}$ specification generates SRs that range from 0.24 (PLS) to 0.44 (PCA).

Table 3.4: Economic Evaluation: Multivariate Portfolio

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel A: ΔU																
	$\gamma = 2$								$\gamma = 5$							
ΔVIX	14.34	15.88	16.46	11.90	11.62	16.82	10.52	10.56	15.40	20.13	17.10	14.08	11.25	21.08	9.21	12.78
ΔTED	4.22	6.87	-1.87	5.09	-2.33	4.99	-4.37	6.83	3.93	10.85	-2.57	7.83	-1.43	9.85	-3.08	11.85
GOLD	6.70	2.95	-0.38	10.34	1.93	8.24	0.24	7.20	4.93	1.64	0.44	9.45	1.33	11.94	0.97	12.71
OIL	6.11	11.93	4.66	5.98	2.31	8.16	4.26	4.79	5.39	15.88	4.01	7.53	2.16	11.76	3.06	7.33
BDI	-8.03	-0.62	-4.64	-0.59	-1.00	5.61	3.53	2.58	-10.22	1.45	-5.34	-0.35	-2.55	9.47	4.92	4.79
CRB	-8.42	1.82	3.19	-1.35	9.50	12.97	7.15	8.73	-11.30	2.94	1.67	-1.54	10.47	17.94	8.05	10.64
MSCI	16.08	13.93	10.32	15.55	10.97	14.47	13.56	12.39	16.45	17.29	10.58	16.87	12.79	19.11	14.94	16.93
SP500	0.52	2.39	7.04	12.18	-1.74	2.63	5.48	16.73	-3.95	2.08	5.08	10.31	-3.85	4.38	5.92	19.69
VSP500	6.44	7.20	2.96	6.37	0.49	10.92	1.07	8.48	6.94	13.40	3.18	12.03	0.84	17.21	1.51	14.13
EquityM	-10.92	5.41	-3.63	-0.15	-8.22	-2.29	-3.64	-7.07	-10.65	8.76	-3.05	1.70	-7.39	1.39	-2.58	-5.43
VEquityM	-8.28	0.13	-2.12	0.23	2.91	11.65	3.98	10.79	-8.41	4.97	-1.69	4.77	2.96	17.67	3.86	16.58
ΔL	25.33	9.68	19.37	10.47	14.60	8.82	7.39	2.26	23.26	13.06	18.10	12.63	13.83	12.91	6.81	4.84
ΔS	9.21	1.96	6.94	10.20	2.28	0.38	3.69	-0.15	8.81	4.05	7.27	11.61	3.79	5.11	5.90	3.11
ΔS	3.03	0.70	2.64	7.03	-0.42	7.16	0.17	9.03	2.31	2.99	2.40	8.45	0.81	14.05	1.14	15.63
POOL	6.68	3.46	6.79	6.92	4.20	9.66	2.93	14.08	7.35	-5.64	7.69	-0.87	5.05	7.58	3.36	11.46
PCA	5.02	12.45	-2.37	10.22	1.78	14.77	1.05	16.19	2.18	12.88	-4.40	8.49	0.49	16.81	-0.28	18.30
PLS	6.29	5.92	9.52	8.66	7.73	8.17	7.26	7.02	-1.29	0.04	2.40	-0.09	0.45	2.55	-0.46	0.95
	Panel B: Cumulative Return								Panel C: Sharpe Ratio							
RW	0.43								-0.06							
ΔVIX	3.31	3.53	4.59	2.19	2.39	4.05	2.13	1.80	0.38	0.41	0.45	0.29	0.31	0.45	0.29	0.24
ΔTED	0.81	0.97	0.34	0.79	0.30	0.70	0.21	0.91	0.08	0.08	-0.10	0.05	-0.16	-0.01	-0.24	0.06
GOLD	1.27	0.71	0.40	2.05	0.60	1.20	0.44	0.94	0.18	0.06	-0.09	0.28	0.01	0.14	-0.07	0.06
OIL	1.05	2.00	0.85	0.91	0.61	1.14	0.86	0.73	0.14	0.27	0.10	0.10	0.01	0.14	0.09	0.04
BDI	0.15	0.36	0.23	0.39	0.40	0.81	0.68	0.57	-0.25	-0.13	-0.19	-0.08	-0.06	0.04	0.02	-0.03
CRB	0.14	0.51	0.72	0.34	1.64	2.21	1.18	1.35	-0.24	-0.03	0.07	-0.10	0.22	0.30	0.15	0.19
MSCI	4.40	2.78	1.92	3.90	1.95	2.83	2.91	2.10	0.44	0.35	0.26	0.42	0.26	0.36	0.35	0.28
SP500	0.58	0.62	1.33	2.78	0.37	0.58	0.94	4.27	0.04	0.02	0.19	0.34	-0.07	-0.02	0.10	0.45
VSP500	1.08	0.91	0.66	0.83	0.46	1.56	0.50	1.13	0.13	0.05	0.03	0.03	-0.05	0.20	-0.04	0.11
EquityM	0.09	0.81	0.25	0.39	0.13	0.26	0.24	0.14	-0.41	0.04	-0.19	-0.11	-0.35	-0.24	-0.20	-0.34
VEquityM	0.13	0.35	0.31	0.36	0.66	1.76	0.78	1.57	-0.32	-0.19	-0.14	-0.18	0.03	0.23	0.07	0.20
ΔL	19.04	1.50	7.71	1.79	3.75	1.28	1.30	0.53	0.73	0.20	0.55	0.24	0.40	0.15	0.18	-0.05
ΔS	1.68	0.52	1.17	1.77	0.56	0.36	0.66	0.36	0.23	-0.05	0.15	0.24	-0.02	-0.18	0.01	-0.15
ΔS	0.70	0.41	0.64	1.07	0.38	0.88	0.42	1.16	0.05	-0.09	0.03	0.14	-0.10	0.03	-0.08	0.11
POOL	1.11	1.11	1.11	1.72	0.77	1.94	0.65	3.77	0.14	0.19	0.14	0.26	0.05	0.27	0.02	0.40
PCA	1.01	2.52	0.33	2.00	0.58	3.27	0.52	3.98	0.14	0.33	-0.09	0.28	0.02	0.39	0.00	0.44
PLS	1.51	1.31	2.36	2.24	1.83	1.80	1.74	1.55	0.24	0.21	0.32	0.31	0.28	0.27	0.27	0.24

Notes: * Panel A reports the average utility differential for two levels of Risk Aversion, $\gamma = [2,5]$. Panels B and C report the Cumulative Return and Sharpe Ratio, respectively.

3.6 Robustness Checks

In this section, we evaluate the robustness of our findings. Specifically, we examine whether our results are sensitive to particular settings considered in the forecasting experiment and whether the proposed methods can provide superior forecasts when these settings change. The tests conducted are related to the control window, the data frequency and the out-of-sample period.

3.6.1 Monthly Frequency

In this section we examine the impact of the frequency to our results. More precisely, we change the frequency from daily to monthly observations. In this case we use a control window of 3 and 6 months. The objective is to confirm that the forecasting performance of the proposed methods is qualitatively consistent irrespective of the frequency. The out-of-sample period remains the same, from January 2004 and ends at December 2017.

The results are presented in Table 3.5. A closer inspection of Table 3.5 reveals that positivity constraints improve the performance of each method as in the case of the initial results. POOL, PCA and PLS show high positive R^2_{OOS} values for GBP, CHF, EUR and CAD. Finally, the majority of the predictors, for all currencies except YEN, benefit in terms of R^2_{OOS} values from the 6 month control window.

For the GPB the predictors with the highest R^2_{OOS} values are obtained by CRB and OIL. The R^2_{OOS} further increases when the PCA and PLS are considered together with positivity constraints. In general C^+ and $C^{CP,+}$ show are the best performing specifications irrespective of the control window used.

In the case of YEN we observe that $C^{ICCP,+}$ outperforms the remaining methods followed by $C^{IC,+}$. Most predictors have a negative R^2_{OOS} in the unconstrained setting for all methods, however, they improve when positivity constraints are applied in the cases of $C^{ICCP,+}$ and $C^{IC,+}$. Comparing the results between the 3 and 6 months control window, we observe that forecasting ability is decreased with the employment of a larger window. It is also remarkable that PCA and PLS, which were

among the most robust predictors in the initial experiment, lose their forecasting ability when applied to monthly data.

Focusing on CHF, AUD and EUR, we note that there is compelling evidence that $C^{IC,+}$ and $C^{ICCP,+}$ provide the best forecasts, irrespective of the frequency under consideration. In the case of CAD we observe that almost all R^2_{OOS} are negative for C^0, $C^{IC,0}$, $C^{CP,0}$ $C^{ICCP,0}$. On the other hand, when positivity constraints are applied all R^2_{OOS} become positive and most of them statistically significant. We also observe that $C^{CP,+}$ significantly outperforms alternative methods in both frequencies.

Overall, the results between daily and monthly frequency data are qualitatively similar. Some predictors enhance their forecasting ability, but the methods aggregately perform the same, albeit with some remarkable high R^2_{OOS} values especially for GBP.

Table 3.5: Robustness Tests, Monthly Frequency

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
	3m control window								6m control window							
GBP																
ΔVIX	-4.22	**2.97***	-4.30	**1.23**	-4.62	**3.21**	-3.32	**1.94***	-4.16	**2.66***	-3.66	**1.57**	-4.58	**2.64***	-2.63	**2.16***
ΔTED	-2.79	**3.23**	-3.86	**0.93****	-3.24	**2.11***	-4.53	**0.95****	-2.06	**3.89**	-3.01	**1.40****	-3.07	**2.54***	-3.44	**1.21****
GOLD	-1.08	**1.19**	-0.89	**0.69***	-1.17	**0.84**	-0.77	**0.93****	-0.88	**1.25***	-0.51	**0.78***	-0.85	**0.96***	-0.08	**1.01****
OIL	**2.74****	**5.05****	**2.20***	**3.82****	**2.88****	**5.65****	**2.38***	**3.92****	**2.72****	**4.83****	**2.16***	**3.68****	**2.87***	**5.03****	**2.29***	**3.64****
BDI	-1.42	**2.23**	-1.88	**0.98**	-1.60	**1.69**	-2.25	**1.44**	-1.33	**2.28**	-1.13	**1.12**	-2.19	**1.80**	-0.67	**1.31**
CRB	**3.69****	**5.60****	**2.89***	**4.07***	**3.73***	**5.46***	**1.77***	**3.49***	**3.69****	**5.38****	**2.91***	**4.05***	**3.22***	**4.68***	**2.27***	**3.51***
MSCI	**0.02**	**2.19**	-0.84	**1.34**	-0.37	**2.20**	-0.95	**1.13**	**0.04**	**2.11**	-0.53	**1.49**	-0.11	**2.79**	-0.67	**1.25**
SP500	-0.89	**0.78**	-1.40	**0.50**	-0.97	**1.22**	-1.11	**0.70**	-0.91	**0.75**	-0.93	**0.71**	-0.97	**1.16**	-0.90	**0.68**
VSP500	-0.42	**0.86***	-0.44	**0.67***	-0.36	**0.81***	-0.48	**0.71***	-0.29	**1.05****	-0.21	**0.91****	-0.03	**0.99****	-0.21	**0.92****
EquityM	**0.53**	**2.60**	**0.10**	**1.83**	-0.10	**2.47**	**0.59**	**1.94**	**0.61**	**2.59***	**0.27**	**1.94**	**0.34**	**2.60***	**0.18**	**1.68**
VEquityM	-3.75	-1.19	-0.38	**0.43**	-4.26	-0.85	-0.68	**0.12**	-3.68	-1.01	-0.83	**0.22**	-4.11	-0.89	-0.94	**0.22**
ΔL	-1.33	**0.69***	**0.04**	**0.81****	-1.04	**0.70***	**0.28**	**0.85****	-0.90	**0.77***	-0.12	**1.01****	-0.51	**0.71***	-0.01	**1.01****
ΔS	-1.87	**0.90****	-0.37	**0.69***	-1.98	**0.92****	-0.45	**0.70***	-1.72	**1.20****	-0.72	**0.97****	-2.07	**0.89***	-0.61	**1.00****
ΔC	-1.09	**1.07**	-1.39	**0.78**	-1.21	**0.65**	-1.49	**0.78**	-1.04	**0.95**	-0.87	**0.98***	-1.50	**0.71**	-0.68	**1.07***
POOL	**1.86**	**3.29***	-0.96	**2.20***	**1.20**	**2.94***	-0.62	**2.17***	**1.82**	**3.24***	0.00	**2.28***	**0.94**	**2.75***	**0.20**	**2.15***
PCA	**1.65***	**6.91***	**1.73***	**5.86***	**0.78**	**6.65***	**1.26**	**5.14***	**1.98***	**6.57***	**1.98***	**5.53***	**0.81**	**5.81***	**0.57**	**3.80***
PLS	**0.97***	**6.33***	**1.11***	**5.73***	**0.32**	**6.23***	**1.23***	**5.68***	**1.27***	**6.43***	**1.36***	**5.77***	-0.14	**4.94***	**1.31***	**5.44***
YEN																
ΔVIX	-1.96	-1.23	-0.40	**0.42**	-1.83	-0.94	-0.12	**0.71**	-1.52	-1.82	-0.36	-0.30	-1.51	-1.53	-0.20	-0.17
ΔTED	-3.53	-1.74	-0.16	**0.96***	-3.32	-1.76	-0.14	**0.91**	-3.33	-2.25	-1.35	-0.10	-3.73	-2.79	-1.36	-0.12
GOLD	-1.56	-0.65	-0.31	**0.72**	-1.26	-0.23	-0.21	**0.85**	-1.54	-0.81	-0.65	**0.23**	-1.42	-0.60	-0.61	**0.28**
OIL	-4.76	-3.31	-1.60	-0.49	-3.15	-2.01	-1.00	**0.07**	-4.03	-2.80	-1.79	-0.72	-3.42	-2.28	-1.64	-0.57
BDI	**0.19**	**0.59**	-0.17	**0.86**	**0.14**	**0.33**	**0.05**	**0.84**	**0.26**	**0.55**	**0.87**	**0.97**	**0.48**	**0.48**	**1.00**	**0.94**
CRB	-6.16	-4.03	-1.94	-0.53	-4.11	-2.05	-0.91	**0.24**	-5.39	-3.46	-2.20	-0.89	-4.45	-2.74	-1.95	-0.69
MSCI	-1.09	**0.47**	-0.34	**0.98***	-1.44	-0.01	-0.28	**0.98***	-0.61	**0.42**	-0.24	**0.86**	-0.91	0.00	-0.22	**0.87**
SP500	-0.52	**0.59**	-0.40	**0.96***	-0.90	**0.26**	-0.32	**0.98***	-0.19	**0.18**	**0.02**	**0.80**	-0.63	**0.01**	**0.08**	**0.82**
VSP500	-0.62	**0.63**	-0.07	**0.97***	-0.76	**0.43**	-0.07	**0.99***	-0.38	**0.54**	-0.15	**0.98***	-0.31	**0.56**	-0.14	**0.98***
EquityM	-2.57	-0.41	-0.34	**0.93**	-3.28	-1.37	-0.53	**0.84**	-1.55	**0.28**	-0.63	**0.78**	-1.89	-0.16	-0.64	**0.77**
VEquityM	-0.99	**0.35**	-0.19	**0.99***	-0.82	**0.41**	-0.14	**0.98***	-0.57	**0.37**	-0.24	**0.82**	-0.43	**0.46**	-0.23	**0.83**
ΔL	-0.85	**0.73**	-0.30	**0.99***	-0.75	**0.76**	-0.32	**0.97***	-0.96	**0.57**	-0.30	**0.89**	-0.85	**0.18**	-0.33	**0.88**
ΔS	-0.55	**0.89**	**0.02**	**1.01***	-0.31	**0.67**	**0.06**	**1.01***	-0.49	**0.59**	-0.20	**0.90**	-0.70	-0.04	-0.24	**0.86**
ΔC	-0.90	-0.19	-0.34	**0.60**	-0.49	**0.19**	-0.30	**0.77**	-0.40	**0.22**	-0.06	**0.72**	-0.24	**0.33**	-0.01	**0.78**
POOL	-0.43	-0.03	-0.12	**0.80**	-0.50	-0.02	-0.11	**0.88**	-0.07	**0.00**	-0.04	**0.59**	-0.12	-0.07	-0.04	**0.61**
PCA	-7.29	-3.58	-3.17	-0.96	-7.31	-4.82	-2.27	-0.50	-4.80	-1.97	-2.12	-0.14	-8.97	-6.32	-2.30	-0.29
PLS	-12.06	-6.07	-7.87	-3.57	-9.52	-5.17	-6.99	-3.16	-7.04	-1.87	-3.28	**0.02**	-5.66	-2.10	-3.34	-0.04

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
	3m control window								6m control window							
CHF																
ΔVIX	-3.82	-1.32	-1.24	-0.14	-4.52	**0.23**	-1.34	-0.06	-2.57	-0.82	-1.61	**0.06**	-3.56	**0.62**	-1.52	**0.10**
ΔTED	-1.74	**1.00**	-0.07	**0.91**	-1.33	**0.78**	**0.01**	**0.91**	-1.13	**1.60***	-0.55	**1.14**	-0.84	**1.22**	-0.46	**1.14**
GOLD	-1.60	**1.29***	-0.30	**1.04**	-1.41	**1.14**	-0.21	**0.98**	-1.29	**1.49***	-0.44	**1.32***	-1.29	**1.31***	-0.27	**1.24***
OIL	-2.66	-1.71	-1.43	-0.31	-2.52	-0.80	-1.45	-0.49	-1.95	-1.10	-1.29	**0.05**	-1.77	-0.15	-1.17	-0.02
BDI	-1.38	**0.80**	**0.20**	**0.91**	-1.25	**0.85**	**0.22**	**0.91**	-1.16	**1.00**	-0.19	**1.14**	-1.25	**0.90**	-0.23	**1.14**
CRB	-3.07	-1.72	-1.07	-0.35	-2.41	-0.46	-1.37	-0.51	-2.25	-1.13	-1.00	-0.12	-1.51	-0.29	-1.17	-0.24
MSCI	-0.62	**0.40**	**0.02**	**0.88**	-0.74	**0.80**	**0.10**	**0.90**	-0.32	**1.12**	**0.03**	**0.91**	-0.47	**1.32***	**0.19**	**1.03**
SP500	**0.36**	**1.46***	**0.38**	**0.68**	**0.24**	**1.26***	**0.14**	**0.79**	**0.74**	**1.82***	**0.57**	**1.10**	**0.42**	**1.65***	**0.60**	**1.16**
VSP500	-1.16	**0.73**	**0.10**	**0.91**	-1.01	**0.74**	**0.12**	**0.91**	-1.11	**0.77**	-0.16	**1.17**	-0.71	**0.80**	-0.13	**1.15**
EquityM	-1.60	**0.51**	**0.32****	**0.91**	-1.37	**0.45**	**0.24****	**0.91**	-1.09	**0.94**	-0.04	**1.14**	-1.66	**0.52**	-0.10	**1.14**
VEquityM	-2.66	-1.50	-0.24	**0.85**	-2.40	-1.73	-0.26	**0.83**	-2.16	-1.47	-0.99	**0.59**	-2.95	-1.72	-0.94	**0.52**
ΔL	-0.99	**0.90**	**0.26***	**0.91**	-0.91	**0.88**	**0.28***	**0.91**	-0.72	**0.87**	-0.08	**1.14**	-0.57	**0.96**	**0.00**	**1.14**
ΔS	-1.25	**0.73**	**0.24***	**0.91**	-1.02	**0.88**	**0.23****	**0.91**	-0.75	**0.78**	-0.13	**1.14**	-0.38	**0.94**	-0.03	**1.14**
ΔC	-1.08	**0.91**	**0.14***	**0.91**	-1.20	**0.83**	**0.10**	**0.91**	-1.01	**1.14**	-0.01	**1.14**	-1.01	**1.11**	-0.04	**1.14**
POOL	-0.75	**0.50**	-0.17	**0.73**	-0.74	**0.69**	-0.15	**0.70**	-0.26	**0.81**	-0.31	**0.95**	-0.42	**0.90**	-0.23	**0.92**
PCA	-2.85	**1.64***	-1.16	**1.27**	-3.46	**1.13***	-1.05	**1.31**	-2.00	**1.63***	-1.23	**1.51***	-2.37	**1.71***	-0.73	**1.71***
PLS	-7.58	-3.87	-3.87	-1.65	-7.37	-2.20	-3.78	-1.49	-5.67	-2.80	-3.40	-1.48	-5.68	-1.30	-3.09	-1.21
EUR																
ΔVIX	-5.55	-0.94	-2.82	-0.95	-7.04	**1.64**	-3.73	-1.24	-4.58	-0.78	-2.48	-0.36	-6.23	**1.81**	-3.22	-0.67
ΔTED	-5.2	**0.63**	-0.43	**1.14***	-4.23	**0.65**	-0.42	**1.07***	-3.99	**1.11***	-1.25	**1.47****	-3.70	**1.18***	-1.21	**1.45****
GOLD	-1.38	**1.21***	-0.72	**1.21***	-1.28	**1.19***	-0.65	**1.20***	-1.05	**1.48****	-0.56	**1.49****	-0.90	**1.42***	-0.43	**1.49****
OIL	-1.40	-0.69	-1.24	**0.40**	-0.95	**0.51**	-1.15	**0.25**	-1.16	-0.29	-0.96	**0.72**	-0.89	**0.55**	-0.90	**0.64**
BDI	-3.05	-1.40	-1.46	**0.49***	-3.30	-1.43	-1.30	**0.68***	-2.85	-1.20	-1.74	**0.25***	-3.51	-1.26	-1.47	**0.51***
CRB	-2.14	-1.24	-2.09	-0.68	-1.51	-0.25	-2.46	-0.80	-1.76	-0.95	-1.67	-0.41	-1.24	-0.03	-1.77	-0.45
MSCI	-0.71	**0.59**	**0.25**	**1.35****	-0.85	**0.88**	**0.04**	**1.22***	-0.42	**1.21***	**0.25**	**1.68****	-0.59	**1.36***	**0.07**	**1.52****
SP500	**1.62***	**2.29****	**1.44****	**1.60****	**1.04**	**2.24****	**0.94****	**1.46****	**2.04***	**2.73****	**1.83****	**1.93****	**1.20***	**2.48****	**1.29****	**1.80****
VSP500	-0.39	**1.03***	**0.06**	**1.16***	-0.36	**1.07***	**0.09**	**1.16***	-0.26	**1.20***	-0.07	**1.44***	-0.23	**1.24***	-0.04	**1.46****
EquityM	-1.19	**0.77**	-0.01	**1.19***	-1.05	**0.84**	**0.03**	**1.19***	-0.91	**1.10**	-0.30	**1.48****	-0.77	**1.15***	-0.21	**1.48****
VEquityM	-0.71	**1.18***	**0.20****	**1.20***	-0.60	**1.22***	**0.18****	**1.19***	-0.44	**1.46****	-0.02	**1.48****	-0.33	**1.45****	-0.02	**1.48****
ΔL	-0.39	**1.17***	**0.16***	**1.18***	-0.57	**1.13***	**0.15***	**1.19***	-0.66	**1.04**	-0.24	**1.48****	-0.68	**1.13***	-0.22	**1.48****
ΔS	**1.15****	**1.28***	**0.52****	**1.21***	**0.71***	**1.21***	**0.44****	**1.20***	**3.25*****	**1.74****	**2.15*****	**1.63****	**2.30****	**1.17***	**1.94*****	**1.55****
ΔC	-0.49	**1.17***	**0.11****	**1.20***	-0.24	**1.13***	**0.06***	**1.20***	-0.20	**1.24***	-0.06	**1.48****	**0.37***	**1.38***	-0.05	**1.48****
POOL	-0.47	**0.89**	-0.33	**0.94**	-0.63	**1.17**	-0.38	**0.88**	**0.13**	**1.22**	-0.21	**1.28***	-0.29	**1.40***	-0.28	**1.21***
PCA	-2.80	-0.90	-2.23	-0.70	-3.52	-0.49	-2.16	-0.70	-2.01	-0.54	-1.65	-0.38	-4.21	-1.21*	-1.79	-0.67
PLS	-6.09	-2.01	-3.43	-1.07	-4.84	0.04	-3.50	-1.08	-5.14	-2.08	-3.24	-1.06	-3.50	-0.13*	-2.99	-0.90

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
	3m control window								6m control window							
CAD																
ΔVIX	-1.85	**1.78***	-3.07	**0.71**	-2.11	**2.38***	-2.88	**0.75**	-2.15	**2.11***	-3.26	**0.49**	-3.15	**2.07***	-3.56	**0.58**
ΔTED	-8.19	**1.17***	-4.49	**1.20***	-8.48	**1.22***	-4.40	**1.12***	-8.88	**1.11***	-5.11	**1.19***	-9.88	**1.03***	-5.23	**1.14***
GOLD	-1.12	**1.26***	-0.66	**1.37***	-0.83	**1.10***	-1.02	**1.11***	-1.54	**1.29***	-0.70	**1.26***	-1.43	**1.16***	-1.15	**1.14***
OIL	-0.37	**1.96***	-0.75	**1.14***	-0.53	**2.23****	-0.70	**1.10***	-0.17	**2.16***	-0.56	**1.69***	-0.39	**2.70***	-0.36	**1.70***
BDI	-3.74	**1.11**	-2.16	**2.06**	-3.76	**1.43**	-1.69	**2.23**	-4.24	**1.25**	-2.51	**1.89**	-4.00	**2.38**	-2.45	**1.86**
CRB	-0.64	**1.67**	-1.44	**1.39**	-0.36	**2.31***	-1.26	**1.38**	-0.71	**2.00**	-1.19	**1.47**	-0.29	**2.66***	-1.52	**1.39**
MSCI	-1.30	**1.01**	-1.9	**0.97**	-0.35	**1.63**	-1.48	**1.03**	-1.32	**1.28**	-1.80	**0.92**	**0.76**	**2.88***	-1.60	**0.95**
SP500	-1.65	**0.72**	-1.25	**0.79**	-0.97	**1.37**	-1.14	**0.79**	-1.60	**0.58**	-1.41	**0.69**	**0.17**	**2.09***	-1.44	**0.67**
VSP500	-0.57	**1.33***	**0.16**	**1.35***	-0.21	**1.10***	**0.22**	**1.35***	-0.84	**1.29***	**0.31****	**1.29***	-0.67	**0.91**	**0.18****	**1.29***
EquityM	-0.11	**0.89**	-1.92	**0.38**	**1.35**	**1.87**	-1.58	**0.28**	-0.13	**1.11**	-1.41	**0.25**	**1.92**	**2.46**	-1.15	**0.34**
VEquityM	-0.90	**1.37***	-0.03	**1.35***	-0.86	**1.33***	-0.06	**1.35***	-1.03	**1.28***	**0.13**	**1.29***	-0.93	**1.27***	**0.16**	**1.31***
ΔL	-0.83	**1.21***	-1.13	**1.39***	-0.82	**1.31***	-1.23	**1.39***	-1.14	**1.20***	-1.20	**1.38***	-1.16	**1.20***	-0.68	**1.33***
ΔS	-0.14	**1.30***	-0.17	**1.34***	**0.22**	**1.40***	-0.03	**1.34***	-0.52	**1.19***	**0.15**	**1.29***	**0.27**	**1.48***	**0.09**	**1.29***
ΔC	-0.37	**0.92**	-0.52	**1.32***	-0.56	**0.97**	-0.50	**1.28***	-0.51	**0.83**	-0.52	**1.22***	-0.47	**0.94**	-0.45	**1.24***
POOL	-0.44	**1.62***	-1.39	**1.40***	-0.20	**1.87***	-1.59	**1.38***	-0.39	**1.77***	-1.55	**1.44***	**0.07**	**2.27***	-1.91	**1.43***
PCA	-2.03	**1.22**	-3.32	**0.66**	-1.24	**2.58**	-2.72	**0.63**	-2.29	**1.63**	-3.33	**0.16**	-0.56	**3.21**	-3.20	**0.36**
PLS	-3.68	**0.07**	-2.47	**0.84**	-2.33	**1.46**	-2.43	**0.92**	-2.38	**0.91**	-1.80	**1.15**	-0.81	**2.41***	-1.92	**1.05**
AUD																
ΔVIX	-7.15	-0.40	-5.97	-1.42	-8.04	**1.94**	-6.32	-1.15	-7.75	-0.30	-6.24	-1.52	-8.92	**1.74**	-6.92	-1.53
ΔTED	-7.77	-0.17	-2.57	**0.60**	-7.36	-0.21	-2.94	**0.61**	-8.27	-0.25	-2.06	**0.64**	-9.25	-0.32	-2.71	**0.58**
GOLD	-1.58	**0.88**	-0.30	**0.94***	-1.46	**0.69**	-0.15	**0.94***	-1.92	**0.85**	-0.17	**0.90***	-1.65	**0.72**	**0.08**	**0.91***
OIL	-1.01	**0.30**	-0.51	**0.57**	-0.51	**0.83**	-0.45	**0.54**	-0.69	**0.16**	-0.40	**0.41**	-0.55	**0.74**	-0.33	**0.45**
BDI	-3.39	-1.09	-1.75	-0.57	-3.35	-1.11	-1.63	-0.44	-3.78	-1.14	-1.48	-0.47	-4.00	-1.18	-1.75	-0.56
CRB	-2.32	-0.46	-0.70	**0.27**	-1.93	**0.06**	-0.83	**0.20**	-2.08	-0.62	-0.49	**0.19**	-1.95	**0.08**	-0.71	**0.10**
MSCI	-2.33	-0.54	-1.25	**0.06**	-2.45	**0.08**	-1.63	-0.17	-2.62	-0.71	-1.58	-0.17	-1.74	**0.81**	-2.00	-0.41
SP500	-1.78	-0.96	-0.80	**0.18**	-1.42	**0.14**	-1.04	**0.15**	-2.14	-1.00	-0.95	-0.01	-1.52	**0.20**	-1.23	-0.09
VSP500	-0.75	**0.05**	-0.15	**0.95***	-0.82	**0.02**	-0.10	**0.95***	-0.96	-0.14	-0.05	**0.83***	-1.52	-0.35	-0.05	**0.82***
EquityM	-2.70	-1.72	-1.50	-0.33	-1.66	-0.59	-1.25	-0.25	-2.65	-1.99	-1.78	-0.67	-1.87	-0.91	-1.51	-0.43
VEquityM	-0.58	**0.82***	**0.07**	**0.95***	-0.73	**0.68**	**0.05**	**0.95***	-1.00	**0.63**	-0.01	**0.78***	-1.08	**0.56**	**0.01**	**0.81***
ΔL	**0.25**	**0.96**	-0.53	**0.78**	-0.01	**1.02**	-0.41	**0.77**	-0.07	**0.77**	-0.34	**0.73**	**0.51**	**1.65***	-0.20	**0.67**
ΔS	-0.83	**0.62**	**0.14**	**0.96***	-0.64	**0.71**	**0.13**	**0.96***	-1.00	**0.59**	**0.08**	**0.84***	-0.69	**0.67**	**0.05**	**0.85***
ΔC	-0.23	**0.82**	-0.08	**0.94***	-0.28	**0.82**	-0.05	**0.94***	-0.39	**0.74**	**0.04**	**0.84***	-0.46	**0.77***	**0.08**	**0.84***
POOL	-1.38	**0.30**	-0.98	**0.51**	-1.29	**0.67**	-1.20	**0.51**	-1.40	**0.27**	-0.82	**0.41**	-1.31	**0.80**	-1.02	**0.38**
PCA	-5.43	-1.97	-3.94	-1.31	-3.78	-0.08	-4.03	-1.36	-7.35	-2.47	-4.61	-1.73	-6.24	-0.45	-5.17	-1.93
PLS	-11.91	-4.96	-8.30	-2.69	-9.04	-2.66	-8.29	-2.68	-11.27	-4.78	-6.92	-2.23	-9.24	-3.53	-7.27	-2.44

Notes: In this Table we illustrate the results for monthly frequency. See Notes in Table 3.3.

Moreover, in order for the excercise to be more complete, we evaluate the economic performance of the forecasts generated by the methods under discussion. We only use the forecasts after accounting for a 3-month control window. Additionally, we iterate the experiment by taking into account two different levels of risk aversion, $\gamma = [2, 5]$ as experiment. According to our results, reported in Table 3.6, we view that they qualitatively similar to those presented in Table 3.4. Irrespective of the level of risk aversion, the investor is eager to pay a higher fee in order to change from the Random Walk strategy to $C^{ICCP,+}$. To conclude, there are some predictors that stand out for their extremely good performance, such as Δ VIX, CRB and PCA.

We observe that the predictors performing well in ΔCER measure, maintain good performance on the other measurement presented. For example, we see that the investor who uses PCA to aggregate information from individual predictors overdoubles the initial capital at the end of the period (2.64) by applying the $C^{ICCP,+}$ method, in comparison to 1.08 in the case of the simple bivariate method, C^0. Last, we observe that the Sharpe Ratio for 12 out of seventeen predictors are positive values for $C^{ICCP,+}$. Overall, we see that ΔVIX and PCA generate the best economic results, irrespective of the level of risk aversion or measure applied to compare the results.

Table 3.6: Economic Evaluation: Multivariate Portfolio, Monthly Data

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel A: ΔU																
	$\gamma = 2$								$\gamma = 5$							
ΔVIX	3.94	13.87	0.25	12.16	1.17	12.58	1.99	11.61	2.51	13.67	-0.92	12.74	1.15	15.28	0.94	13.54
ΔTED	-9.87	-7.34	-9.81	-6.51	-9.71	-2.18	-10.47	-3.21	-12.12	-3.64	-10.78	-3.97	-10.52	1.01	-11.43	-0.06
GOLD	-8.89	-7.57	-9.52	-9.95	-7.40	-0.14	-9.93	-0.56	-9.85	-5.35	-10.55	-7.14	-8.70	3.95	-10.27	2.22
OIL	3.29	5.02	0.38	3.43	5.60	6.81	5.00	6.90	5.09	7.22	2.17	4.67	7.37	10.43	6.63	9.92
BDI	2.90	-2.73	1.29	-1.70	-3.49	0.96	-0.85	2.43	-0.94	-1.54	-1.38	-2.16	-3.20	4.23	-0.20	5.20
CRB	5.96	6.09	3.82	7.76	7.49	8.82	6.14	9.25	8.61	8.87	5.84	10.33	10.28	11.77	9.73	11.92
MSCI	2.65	6.45	0.59	2.53	-3.00	4.93	-2.18	4.97	5.91	9.99	3.22	5.73	-1.10	8.00	0.05	8.52
SP500	6.54	11.59	1.06	6.78	1.94	8.85	0.32	8.03	10.18	15.04	4.64	9.88	3.66	13.03	0.54	11.26
VSP500	-4.64	1.08	-4.95	-0.85	-3.30	-2.54	-4.01	-4.30	-2.91	3.27	-4.23	0.07	-3.26	1.27	-3.71	-0.56
EquityM	0.85	1.00	2.50	1.35	-0.31	3.46	1.25	3.81	1.41	2.80	0.57	3.42	0.27	6.68	1.87	7.47
VEquityM	-0.61	-0.19	-3.86	-0.78	0.80	0.26	1.57	-0.65	-4.86	4.58	-8.28	2.65	0.52	3.71	1.83	2.76
ΔL	-4.46	-3.67	-5.43	-5.18	-0.67	3.80	-1.65	5.10	-9.07	-3.16	-11.15	-5.75	-0.61	7.04	-1.13	7.83
ΔS	-6.00	4.22	-6.23	1.99	-0.88	7.27	-0.61	6.97	-5.91	8.58	-7.68	3.97	-0.92	11.86	-0.22	11.39
ΔC	3.69	6.67	3.22	8.74	-5.38	1.64	-7.11	-2.28	3.42	10.26	3.91	12.31	-5.64	5.85	-7.38	1.05
POOL	-2.68	-2.82	-4.64	-3.83	0.49	3.90	0.36	5.53	-0.65	-2.73	-2.82	-4.30	3.80	5.82	3.55	6.49
PCA	2.92	7.77	2.58	5.06	5.70	8.90	2.88	9.96	3.78	9.60	3.09	6.01	6.82	11.63	4.09	12.91
PLS	-0.39	4.54	1.80	3.05	0.02	2.65	0.39	3.52	-0.42	4.55	1.03	2.33	0.91	2.98	1.23	3.96
	Panel B: Cumulative Return								Panel C: Sharpe Ratio							
RW	0.75								-0.02							
ΔVIX	1.45	5.45	0.85	4.10	0.90	3.85	1.06	3.52	0.17	0.56	0.02	0.49	0.03	0.52	0.09	0.47
ΔTED	0.20	0.22	0.19	0.27	0.20	0.47	0.18	0.41	-0.33	-0.58	-0.38	-0.44	-0.39	-0.26	-0.41	-0.31
GOLD	0.22	0.23	0.20	0.16	0.28	0.60	0.18	0.61	-0.35	-0.47	-0.37	-0.64	-0.28	-0.20	-0.42	-0.15
OIL	1.08	1.36	0.72	1.14	1.50	1.63	1.39	1.70	0.08	0.15	-0.06	0.10	0.19	0.22	0.16	0.23
BDI	1.36	0.48	1.03	0.62	0.45	0.73	0.64	0.92	0.17	-0.18	0.09	-0.08	-0.18	-0.09	-0.08	0.00
CRB	1.52	1.54	1.16	1.96	1.87	2.23	1.49	2.41	0.19	0.19	0.09	0.28	0.26	0.33	0.18	0.35
MSCI	0.93	1.56	0.72	0.92	0.45	1.29	0.49	1.27	0.00	0.20	-0.08	-0.01	-0.23	0.13	-0.20	0.12
SP500	1.57	3.22	0.73	1.67	0.91	2.12	0.78	1.98	0.20	0.48	-0.10	0.22	0.01	0.33	-0.01	0.29
VSP500	0.36	0.79	0.36	0.63	0.47	0.43	0.42	0.34	-0.30	-0.04	-0.26	-0.09	-0.16	-0.32	-0.20	-0.41
EquityM	0.81	0.78	1.15	0.81	0.70	1.04	0.86	1.07	0.00	-0.03	0.12	-0.03	-0.05	0.04	0.01	0.05
VEquityM	0.85	0.58	0.53	0.56	0.85	0.66	0.92	0.59	0.06	-0.25	-0.05	-0.20	0.02	-0.14	0.04	-0.19
ΔL	0.50	0.42	0.46	0.36	0.67	1.09	0.58	1.33	-0.06	-0.20	-0.07	-0.22	-0.05	0.06	-0.11	0.14
ΔS	0.32	1.09	0.33	0.90	0.65	1.67	0.67	1.61	-0.28	0.05	-0.22	0.01	-0.06	0.23	-0.06	0.21
ΔC	1.27	1.61	1.13	2.15	0.34	0.77	0.27	0.46	0.14	0.21	0.10	0.32	-0.24	-0.10	-0.31	-0.27
POOL	0.46	0.50	0.36	0.45	0.68	1.18	0.67	1.55	-0.22	-0.14	-0.30	-0.16	-0.12	0.10	-0.12	0.20
PCA	1.08	2.04	1.05	1.45	1.58	2.29	1.06	2.63	0.08	0.29	0.08	0.17	0.20	0.34	0.07	0.39
PLS	0.71	1.41	1.00	1.18	0.72	1.06	0.76	1.20	-0.04	0.17	0.07	0.12	-0.05	0.08	-0.03	0.12

Notes: * Panel A reports the average utility differential for two levels of Risk Aversion, $\gamma = [2,5]$. Panels B and C report the Cumulative Return and Sharpe Ratio, respectively.

3.6.2 Alternative Control Window

In this section, we examine the performance of the proposed methods after adjusting the control window to 75 days, roughly corresponding to 3 trading months. In this case, constrained predictors are much smoother than the case of the shorter window. Intuitively, at each point of time t, it is more difficult for predictors to exceed the maximum or minimum value of the last 50, 75, 100, 150 and 200 observations than of the last 25 observations.

In our analysis, the out-of-sample period remains the same but we change the in-sample period by discarding observations in order to create the control window. The results are reported in Tables 3.7 to 3.11. Comparing the results of Tables 3.3 and those presented in this section, we observe only minor changes in the values of the R^2_{OOS}. Irrespective of the currency, methods showing superior forecasting ability in the initial setting continue to outperform the benchmark. Similarly, the forecasting accuracy of candidate predictors are almost unaffected by the control window.

For example, for GBP we observe a small increase in some predictors but a small decrease in POOL, PCA and PLS for most methods. Similarly, in the case of EUR, by increasing the control window we observe a small improvement in the results of $C^{CP,+}$ while we observe a small deterioration in the case of $C^{ICCP,+}$. Finally, the results of AUD confirm the difficulty in predicting the FX returns of the Australian Dollar.

Table 3.7: Robustness Tests, Control Window, 50 days

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GBP								
ΔVIX	-0.33	**0.10****	-0.18	**0.10***	-0.22	**0.14****	**0.02**	**0.13***
ΔTED	-0.07	**0.04**	-0.04	**0.03**	-0.08	**0.03**	-0.05	**0.02**
GOLD	-0.01	**0.06**	-0.06	**0.02**	**0.01**	**0.05**	-0.03	**0.03**
OIL	-0.01	**0.03**	-0.04	**0.01**	-0.03	**0.01**	-0.03	**0.02**
BDI	-0.06	**0.13***	-0.13	**0.03**	-0.05	**0.05**	-0.20	**0.02**
CRB	-0.02	**0.00**	-0.04	**0.01**	-0.03	-0.00	-0.01	**0.02**
MSCI	**0.05****	**0.12****	**0.09****	**0.12***	**0.21****	**0.18****	**0.11***	**0.12***
SP500	**0.10****	**0.14****	**0.15****	**0.15****	**0.24****	**0.20****	**0.19****	**0.15****
VSP500	-0.03	**0.05****	-0.02	**0.02**	-0.02	**0.04****	-0.02	**0.03***
EquityM	-0.04	**0.02**	-0.06	-0.00	**0.00**	**0.02**	-0.07	-0.00
VEquityM	-0.14	-0.02	**0.04**	**0.05****	-0.12	-0.02	**0.05***	**0.06****
ΔL	-0.06	-0.01	-0.01	**0.03***	-0.04	**0.00**	-0.01	**0.04***
ΔS	-0.01	**0.09****	-0.07	**0.02**	**0.04**	**0.08****	-0.08	**0.02**
ΔC	**0.02**	**0.09***	-0.06	**0.03**	**0.02**	**0.08***	-0.05	**0.03**
POOL	**0.12***	**0.13****	**0.08**	**0.09****	**0.08***	**0.10****	**0.07**	**0.09****
PCA	-0.13	**0.10****	-0.05	**0.11***	-0.05	**0.12***	-0.01	**0.11***
PLS	-0.23**	**0.05****	-0.13**	**0.08****	-0.03*	**0.12****	-0.10*	**0.09****
YEN								
ΔVIX	**0.12****	**0.05***	**0.10***	**0.04**	**0.17****	**0.07**	**0.07***	**0.02**
ΔTED	-0.18	-0.20	-0.02	-0.02	-0.09	-0.09	-0.00	**0.00**
GOLD	-0.02	**0.02**	-0.01	**0.03**	-0.00	**0.05**	-0.00	**0.03**
OIL	**0.20****	**0.19****	**0.09***	**0.11****	**0.15****	**0.14****	**0.04**	**0.08****
BDI	-0.30	-0.20	-0.05	**0.00**	-0.21	-0.10	-0.02	**0.02**
CRB	**0.04**	**0.15****	**0.01**	**0.10***	**0.03**	**0.13****	**0.00**	**0.07***
MSCI	**0.34****	**0.17***	**0.28****	**0.14***	**0.38*****	**0.18***	**0.24****	**0.13**
SP500	**0.30****	**0.21****	**0.25****	**0.15***	**0.25****	**0.20****	**0.18****	**0.12**
VSP500	-0.02	**0.04***	-0.00	**0.04***	-0.02	**0.04***	-0.00	**0.04***
EquityM	**0.04***	**0.04**	**0.04**	**0.02**	**0.08**	**0.02**	**0.04**	**0.03**
VEquityM	-0.03	**0.03**	-0.00	**0.04***	-0.02	**0.03**	-0.00	**0.04***
ΔL	-0.26	-0.06	-0.10	**0.01**	-0.23	-0.05	-0.04	**0.04**
ΔS	**0.07***	-0.01	**0.06**	**0.03**	**0.07**	**0.02**	**0.03**	**0.04**
ΔC	-0.03	**0.02**	**0.00**	**0.04***	-0.03	**0.03**	**0.00**	**0.04***
POOL	**0.25*****	**0.12***	**0.17****	**0.09***	**0.15*****	**0.10***	**0.12****	**0.08***
PCA	**0.41*****	**0.23****	**0.39*****	**0.21****	**0.36*****	**0.22****	**0.36****	**0.18***
PLS	**0.22*****	-0.00**	**0.37*****	**0.10****	**0.22*****	**0.04****	**0.41*****	**0.13****

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CHF								
ΔVIX	-0.43	-0.16	-0.14	-0.06	-0.24	-0.08	-0.01	**0.02**
ΔTED	-0.06	-0.04	-0.01	**0.03**	-0.04	-0.01	-0.00	**0.03**
GOLD	-0.05	**0.03**	**0.00**	**0.03**	-0.03	**0.03**	**0.01**	**0.03**
OIL	-0.06	**0.02**	**0.01**	**0.03**	-0.10	-0.01	**0.02**	**0.03**
BDI	-0.00*	**0.05***	-0.02	**0.01**	**0.03**	**0.05***	-0.04	**0.01**
CRB	-0.06	**0.02**	**0.01**	**0.03**	-0.02	**0.06***	**0.02**	**0.03**
MSCI	-0.35	-0.15	-0.15	-0.06	-0.13	-0.05	-0.14	-0.07
SP500	-0.39*	-0.14	-0.21*	-0.07	-0.11	**0.02**	-0.04*	-0.04
VSP500	-0.06	**0.02**	-0.01	**0.03**	-0.06	**0.02**	-0.01	**0.03**
EquityM	-0.06	**0.10***	-0.04	**0.04**	-0.03	**0.06**	-0.07	**0.03**
VEquityM	-0.05	**0.02**	-0.01	**0.03**	-0.01	**0.03**	-0.01	**0.03**
ΔL	-0.07	-0.04	**0.01**	**0.04**	-0.08	-0.02	**0.02**	**0.04**
ΔS	**0.12****	**0.06***	**0.02**	**0.03**	**0.06**	**0.04**	**0.00**	**0.03**
ΔC	-0.06	**0.04**	-0.01	**0.04**	-0.06	**0.04**	-0.01	**0.04**
POOL	**0.07**	**0.06**	**0.08**	**0.06**	**0.03**	**0.05**	**0.06**	**0.05**
PCA	-0.34	-0.08	-0.13	**0.00**	-0.27	-0.07	-0.12	-0.01
PLS	-0.61	-0.32	-0.38	-0.19	-0.42	-0.18	-0.33	-0.17
EUR								
ΔVIX	-0.91	-0.31	-0.41	-0.06	-0.43	**0.02**	-0.13	**0.08**
ΔTED	-0.13	-0.01	**0.01**	**0.05***	-0.13	**0.02**	**0.01**	**0.05***
GOLD	-0.02	**0.03**	**0.02**	**0.05***	-0.02	**0.03**	**0.01**	**0.05***
OIL	-0.06	**0.03**	**0.02****	**0.05***	-0.07	**0.03**	**0.02****	**0.05***
BDI	-0.05	**0.15***	-0.04	**0.07**	**0.02**	**0.11***	-0.03	**0.06**
CRB	-0.08	**0.01**	**0.01**	**0.05***	-0.07	**0.04**	**0.01**	**0.05***
MSCI	-0.82	-0.45	-0.43	-0.26	-0.39	-0.22	-0.46	-0.27
SP500	-1.03	-0.55	-0.69	-0.38	-0.40	-0.14	-0.44	-0.27
VSP500	-0.05	**0.05***	**0.00**	**0.05***	-0.04	**0.05***	**0.00**	**0.05***
EquityM	-0.34	-0.10	-0.10	-0.02	-0.22	-0.05	-0.10	-0.01
VEquityM	**0.06***	**0.10****	-0.02	**0.04***	**0.09****	**0.12*****	-0.01	**0.04***
ΔL	-0.01	**0.01**	**0.03***	**0.05***	-0.05	**0.01**	**0.01**	**0.05***
ΔS	-0.01	**0.07****	**0.00**	**0.06****	**0.01**	**0.06***	**0.01**	**0.06****
ΔC	-0.01	**0.05***	**0.00**	**0.06****	-0.03	**0.05***	**0.00**	**0.05****
POOL	**0.02**	**0.05**	**0.03**	**0.06**	**0.01**	**0.07**	**0.02**	**0.05**
PCA	-1.19	-0.44	-0.71	-0.23	-0.76	-0.17	-0.60	-0.19
PLS	-1.52	-0.75	-1.11	-0.53	-0.94	-0.33	-1.03	-0.49

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CAD								
ΔVIX	-0.10	**0.02**	-0.12	**0.01**	**0.14***	**0.15****	-0.04	**0.04**
ΔTED	-0.07	-0.01	-0.00	**0.04**	-0.03	**0.02**	**0.01**	**0.04**
GOLD	**0.08**	**0.06**	**0.04**	**0.02**	**0.04**	**0.06**	**0.01**	**0.03**
OIL	-0.02	**0.01**	-0.00	**0.04**	-0.02	**0.02**	-0.01	**0.04**
BDI	-0.08	**0.04**	-0.07	**0.02**	-0.06	-0.00	**0.02**	**0.04**
CRB	**0.01**	**0.06***	-0.01	**0.04**	**0.02**	**0.02**	**0.00**	**0.05***
MSCI	-0.27	-0.03	-0.14	**0.02**	-0.23	**0.03**	-0.06	**0.05**
SP500	-0.26	-0.02	-0.14	**0.02**	-0.14	**0.07**	**0.15**	**0.13**
VSP500	-0.01	**0.05***	-0.01	**0.04**	**0.00**	**0.05***	-0.00	**0.04**
EquityM	-0.22	-0.01	-0.12	**0.02**	-0.12	**0.06**	-0.06	**0.05**
VEquityM	-0.05	**0.04**	-0.02	**0.04**	-0.04	**0.06***	-0.02	**0.04**
ΔL	-0.05	**0.03**	-0.00	**0.05***	-0.02	**0.04**	**0.01**	**0.05***
ΔS	-0.08	**0.05**	-0.04	**0.04**	-0.07	**0.05***	-0.01	**0.04**
ΔC	-0.09	**0.06***	-0.03	**0.06***	-0.07	**0.06***	-0.00	**0.06***
POOL	**0.01**	**0.06**	-0.05	**0.05**	**0.01**	**0.07***	-0.01	**0.06**
PCA	-0.39	-0.06	-0.27	**0.01**	-0.28	**0.05**	-0.11	**0.07**
PLS	-0.60	-0.18	-0.49	-0.14	-0.28	**0.05***	-0.46	-0.12
AUD								
ΔVIX	-0.51	-0.21	-0.29	-0.11	-0.31	-0.07	-0.17	-0.06
ΔTED	-0.15	-0.01	-0.06	**0.00**	-0.15	-0.01	-0.03	**0.02**
GOLD	-0.08	-0.06	-0.01	-0.00	-0.08	-0.04	**0.01**	**0.02**
OIL	**0.05**	**0.00**	**0.02**	**0.02**	**0.01**	**0.01**	**0.01**	**0.03**
BDI	-0.35	-0.28	-0.30	-0.24	-0.29	-0.28	-0.19	-0.14
CRB	-0.09	-0.04	-0.01	**0.03***	-0.03	-0.09	-0.02	**0.02**
MSCI	-0.73	-0.43	-0.47	-0.28	-0.53	-0.30	-0.38	-0.23
SP500	-0.51	-0.18	-0.32	-0.09	-0.27	-0.11	-0.03	**0.07**
VSP500	-0.02	**0.03**	-0.00	**0.04***	-0.02	**0.04***	-0.00	**0.04***
EquityM	-0.25	-0.08	-0.08	**0.01**	-0.20	-0.06	-0.08	**0.03**
VEquityM	-0.09	**0.02**	-0.01	**0.04***	-0.05	**0.07****	-0.01	**0.04***
ΔL	**0.03**	**0.07**	**0.01**	**0.05**	**0.02**	**0.07***	**0.02**	**0.05***
ΔS	-0.12	**0.01**	-0.01	**0.04***	-0.06	**0.06***	-0.02	**0.03***
ΔC	-0.01	**0.05***	-0.01	**0.04***	-0.01	**0.05***	-0.00	**0.04***
POOL	-0.05	-0.02	-0.12	**0.00**	-0.05	-0.01	-0.10	**0.02**
PCA	-0.74	-0.40	-0.50	-0.27	-0.59	-0.38	-0.49	-0.27
PLS	-1.69	-1.24	-1.43	-1.07	-1.32	-0.85	-1.43	-1.07

Notes: See Table 3.3. We change the control window to 50 days.

Table 3.8: Robustness Tests, Control Window, 75 days

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GBP								
ΔVIX	-0.32	**0.10****	-0.16	**0.10***	-0.23	**0.13****	-0.01	**0.12***
ΔTED	-0.07	**0.04**	-0.03	**0.02**	-0.09	**0.03**	-0.03	**0.02**
GOLD	-0.01	**0.06**	-0.04	**0.02**	**0.03**	**0.07***	-0.02	**0.03**
OIL	-0.01	**0.03**	-0.02	**0.01**	-0.02	**0.02**	-0.02	**0.02**
BDI	-0.06	**0.14***	-0.09	**0.05**	-0.06	**0.04**	-0.09	**0.04**
CRB	-0.03	**0.00**	-0.02	**0.01**	-0.04	-0.01	**0.01**	**0.03***
MSCI	**0.05****	**0.11****	**0.10***	**0.12***	**0.20****	**0.18****	**0.12***	**0.11***
SP500	**0.11****	**0.14****	**0.16****	**0.15****	**0.25****	**0.19****	**0.19****	**0.14****
VSP500	-0.03	**0.05****	-0.01	**0.02**	-0.02	**0.04****	0.00	**0.03**
EquityM	-0.04	**0.02**	-0.04	**0.00**	-0.02	**0.01**	-0.04	**0.00**
VEquityM	-0.14	-0.03	**0.02**	**0.04****	-0.13	-0.03	**0.03***	**0.03***
ΔL	-0.06	-0.01	0.00	**0.03***	-0.04	**0.00**	-0.01	**0.03***
ΔS	-0.01	**0.09****	-0.04	**0.03***	**0.01**	**0.07****	-0.04	**0.02**
ΔC	**0.02**	**0.09***	-0.03	**0.03***	**0.00**	**0.07***	-0.03	**0.03***
POOL	**0.12**	**0.13****	**0.07**	**0.09****	**0.06**	**0.09****	**0.05**	**0.08****
PCA	-0.12	**0.10****	-0.03	**0.11***	-0.04	**0.12***	**0.02**	**0.11***
PLS	-0.22	**0.05****	-0.10*	**0.09****	-0.08*	**0.10***	-0.06*	**0.10****
YEN								
ΔVIX	**0.11****	**0.05***	**0.09***	**0.04**	**0.17****	**0.08**	**0.08***	**0.03**
ΔTED	-0.18	-0.19	-0.02	-0.01	-0.11	-0.09	0.00	**0.01**
GOLD	-0.03	**0.02**	-0.01	**0.04**	**0.00**	**0.07***	0.00	**0.04**
OIL	**0.20****	**0.20****	**0.08***	**0.11****	**0.15****	**0.14****	**0.04**	**0.08****
BDI	-0.32	-0.19	-0.04	**0.02**	-0.14	-0.06	-0.02	**0.03**
CRB	**0.04**	**0.16****	**0.01**	**0.10****	**0.04**	**0.14****	-0.01	**0.08****
MSCI	**0.34****	**0.17**	**0.26****	**0.14***	**0.35****	**0.18***	**0.26****	**0.15**
SP500	**0.30****	**0.21**	**0.23****	**0.14***	**0.25****	**0.20****	**0.17***	**0.11***
VSP500	-0.01	**0.05**	0.00	**0.05***	-0.01	**0.05***	0.00	**0.05***
EquityM	**0.04***	**0.04**	**0.04**	**0.03**	**0.08**	**0.03**	**0.04**	**0.04**
VEquityM	-0.03	**0.04**	0.00	**0.05***	-0.01	**0.04**	0.00	**0.05***
ΔL	-0.26	-0.06	-0.08	**0.02**	-0.21	-0.05	-0.02	**0.05**
ΔS	**0.07***	-0.02	**0.06**	**0.04**	**0.08***	**0.02**	**0.02**	**0.04**
ΔC	-0.04	**0.02**	**0.00**	**0.05***	**0.01**	**0.05***	**0.00**	**0.05***
POOL	**0.24*****	**0.12***	**0.14****	**0.09***	**0.15*****	**0.10***	**0.09****	**0.08***
PCA	**0.42*****	**0.23****	**0.37*****	**0.20****	**0.39*****	**0.21****	**0.35****	**0.18***
PLS	**0.20****	-0.01**	**0.39****	**0.12****	**0.31*****	**0.11****	**0.42*****	**0.14****

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CHF								
ΔVIX	-0.43	-0.15	-0.13	-0.05	-0.24	-0.08	**0.02**	**0.05**
ΔTED	-0.06	-0.04	-0.01	**0.03**	-0.05	-0.01	**0.00**	**0.03**
GOLD	-0.05	**0.03**	**0.01**	**0.04**	-0.03	**0.03**	**0.01**	**0.04**
OIL	-0.06	**0.03**	**0.02**	**0.03**	-0.08	**0.02**	**0.03**	**0.03**
BDI	0.00*	**0.05***	-0.05	**0.01**	**0.04**	**0.05***	-0.11	0.00
CRB	-0.06	**0.03**	**0.01**	**0.04**	-0.06	**0.04**	**0.02**	**0.03**
MSCI	-0.35	-0.14	-0.14	-0.05	-0.14	-0.05	-0.14	-0.07
SP500	-0.39*	-0.14	-0.20*	-0.06	-0.11	**0.01**	-0.03*	-0.03
VSP500	-0.06	**0.02**	-0.01	**0.03**	-0.05	**0.02**	-0.01	**0.03**
EquityM	-0.06	**0.10***	-0.05	**0.04**	-0.04	**0.05**	-0.09	**0.02**
VEquityM	-0.05	**0.02**	-0.02	**0.03**	**0.00**	**0.03***	-0.01	**0.03**
ΔL	-0.07	-0.04	**0.01**	**0.04**	-0.08	-0.02	**0.02**	**0.04**
ΔS	**0.12****	**0.07***	**0.01**	**0.03**	**0.06**	**0.04**	-0.02	**0.02**
ΔC	-0.05	**0.04**	-0.01	**0.04**	-0.09	**0.02**	-0.02	**0.04**
POOL	**0.07**	**0.06**	**0.08**	**0.06**	**0.03**	**0.05**	**0.05**	**0.05**
PCA	-0.34	-0.08	-0.12	**0.00**	-0.27	-0.04	-0.09	-0.01
PLS	-0.61	-0.32	-0.37	-0.18	-0.44	-0.19	-0.29	-0.15
Panel D: EUR								
ΔVIX	-0.90	-0.30	-0.38	-0.04	-0.40	**0.04**	-0.10	**0.09**
ΔTED	-0.13	-0.01	**0.01**	**0.06***	-0.16	**0.01**	**0.02***	**0.06***
GOLD	-0.02	**0.03**	**0.02**	**0.05***	-0.02	**0.04**	**0.02***	**0.05***
OIL	-0.06	**0.04**	**0.02****	**0.05***	-0.06	**0.04***	**0.02****	**0.05***
BDI	-0.05	**0.16****	-0.04	**0.07**	**0.04**	**0.13***	-0.05	**0.06**
CRB	-0.08	**0.01**	**0.01**	**0.06***	-0.09	**0.03**	**0.01**	**0.06***
MSCI	-0.82	-0.44	-0.41	-0.24	-0.40	-0.17	-0.42	-0.25
SP500	-1.04	-0.54	-0.67	-0.36	-0.40	-0.15	-0.41	-0.25
VSP500	-0.05	**0.05***	**0.00**	**0.05***	-0.04	**0.05***	**0.01**	**0.05***
EquityM	-0.33	-0.10	-0.09	-0.01	-0.21	-0.06	-0.08	**0.00**
VEquityM	**0.06**	**0.10****	-0.02	**0.04***	**0.07****	**0.10****	-0.03	**0.05***
ΔL	0.00	**0.01**	**0.03***	**0.05***	-0.08	**0.00**	**0.02**	**0.05***
ΔS	0.00	**0.07****	**0.00**	**0.06****	-0.04	**0.04**	**0.00**	**0.06****
ΔC	-0.01	**0.06***	**0.00**	**0.06****	-0.03	**0.05***	**0.00**	**0.06***
POOL	**0.03**	**0.05**	**0.04**	**0.06**	**0.00**	**0.07**	**0.02**	**0.06**
PCA	-1.18	-0.44	-0.68	-0.22	-0.82	-0.17	-0.52	-0.15
PLS	-1.52	-0.75	-1.08	-0.51	-0.98	-0.32	-0.97	-0.45

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CAD								
ΔVIX	-0.11	**0.02**	-0.12	**0.00**	**0.14***	**0.14***	-0.05	**0.02**
ΔTED	-0.07	-0.01	0.00	**0.04**	-0.03	**0.01**	**0.01**	**0.04**
GOLD	**0.08**	**0.06**	**0.05**	**0.03**	**0.05**	**0.06***	**0.06**	**0.04**
OIL	-0.01	**0.00**	**0.00**	**0.04**	0.00	**0.01**	**0.00**	**0.04**
BDI	-0.07	**0.05**	-0.07	**0.02**	-0.06	-0.01	**0.01**	**0.05**
CRB	**0.00**	**0.06***	0.00	**0.04**	**0.00**	**0.02**	**0.00**	**0.04**
MSCI	-0.28	-0.04	-0.16	**0.01**	-0.22	**0.02**	-0.05	**0.05**
SP500	-0.27	-0.02	-0.16	**0.01**	-0.14	**0.07**	**0.11**	**0.12**
VSP500	-0.01	**0.05***	-0.01	**0.04**	0.00	**0.05***	-0.01	**0.04**
EquityM	-0.22	-0.02	-0.13	**0.01**	-0.11	**0.06**	-0.09	**0.03**
VEquityM	-0.05	**0.03**	-0.03	**0.04**	-0.04	**0.07***	-0.03	**0.04**
ΔL	-0.05	**0.03**	0.00	**0.04**	-0.02	**0.04**	**0.00**	**0.04**
ΔS	-0.07	**0.04**	-0.04	**0.03**	-0.05	**0.05***	-0.02	**0.04**
ΔC	-0.09	**0.06***	-0.04	**0.05***	-0.07	**0.06***	-0.02	**0.05***
POOL	**0.01**	**0.05**	-0.05	**0.04**	**0.01**	**0.06**	-0.02	**0.05**
PCA	-0.38	-0.06	-0.26	**0.00**	-0.18	**0.08**	-0.10	**0.07**
PLS	-0.62	-0.19	-0.51	-0.15	-0.23	**0.08***	-0.48	-0.14
AUD								
ΔVIX	-0.54	-0.23	-0.31	-0.13	-0.36	-0.09	-0.16	-0.06
ΔTED	-0.15	-0.01	-0.07	**0.01**	-0.15	-0.01	-0.04	**0.03**
GOLD	-0.09	-0.07	-0.01	**0.00**	-0.09	-0.05	**0.01**	**0.02**
OIL	**0.05**	0.00	**0.01**	**0.01**	**0.02**	**0.01**	**0.00**	**0.02**
BDI	-0.34	-0.28	-0.33	-0.26	-0.28	-0.29	-0.23	-0.17
CRB	-0.09	-0.05	**0.01**	**0.04***	-0.05	-0.09	0.00	**0.02**
MSCI	-0.74	-0.44	-0.48	-0.30	-0.54	-0.29	-0.36	-0.23
SP500	-0.53	-0.20	-0.34	-0.11	-0.25	-0.11	**0.05**	**0.11**
VSP500	-0.02	**0.03**	-0.01	**0.04***	-0.02	**0.03**	-0.01	**0.04***
EquityM	-0.25	-0.09	-0.1	**0.01**	-0.18	-0.07	-0.11	**0.03**
VEquityM	-0.08	**0.01**	**0.02***	**0.04***	-0.05	**0.05**	**0.02****	**0.04***
ΔL	**0.03**	**0.08**	-0.02	**0.04**	**0.02**	**0.07**	-0.02	**0.04**
ΔS	-0.12	**0.01**	**0.02***	**0.05****	-0.09	**0.03**	**0.00**	**0.04***
ΔC	-0.01	**0.05**	-0.01	**0.04***	-0.04	**0.03**	-0.01	**0.04***
POOL	-0.05	-0.02	-0.15	**0.00**	-0.06	-0.02	-0.14	**0.02**
PCA	-0.76	-0.41	-0.52	-0.28	-0.70	-0.36	-0.51	-0.28
PLS	-1.73	-1.25	-1.48	-1.10	-1.39	-0.88	-1.47	-1.09

Notes: See Table 3.3. We change the control window to 75 days.

Table 3.9: Robustness Tests, Control Window, 100 days

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GBP								
ΔVIX	-0.34	**0.10****	-0.16	**0.11***	-0.20	**0.15****	-0.01	**0.10***
ΔTED	-0.07	**0.04**	-0.02	**0.03**	-0.08	**0.04***	-0.03	**0.03***
GOLD	-0.01	**0.06**	-0.04	**0.03**	**0.02**	**0.07***	-0.01	**0.04**
OIL	-0.01	**0.03**	-0.02	**0.02**	-0.01	**0.03**	-0.02	**0.02**
BDI	-0.07	**0.14***	-0.09	**0.05**	-0.04	**0.08**	-0.12	**0.02**
CRB	-0.02	**0.00**	-0.02	**0.01**	-0.01	**0.03**	**0.01**	**0.03***
MSCI	**0.05****	**0.12****	**0.10***	**0.12***	**0.24****	**0.24****	**0.11***	**0.12***
SP500	**0.10****	**0.14****	**0.16****	**0.15****	**0.24****	**0.20****	**0.21****	**0.15****
VSP500	-0.03	**0.06****	-0.01	**0.03***	-0.02	**0.04****	-0.00	**0.03***
EquityM	-0.04	**0.03**	-0.04	**0.01**	-0.02	**0.02**	-0.04	**0.01**
VEquityM	-0.15	-0.03	**0.02**	**0.05****	-0.13	-0.02	**0.03**	**0.04****
ΔL	-0.06	-0.00	-0.00	**0.03***	-0.03	**0.00**	-0.01	**0.03***
ΔS	-0.01	**0.09****	-0.03	**0.03***	**0.00**	**0.07****	-0.04	**0.03***
ΔC	**0.01**	**0.09***	-0.03	**0.03***	-0.00	**0.06***	-0.03	**0.03***
POOL	**0.12***	**0.13****	**0.08**	**0.09****	**0.07**	**0.11****	**0.05**	**0.08****
PCA	-0.13	**0.10****	-0.03	**0.11***	-0.04	**0.13***	**0.02**	**0.11***
PLS	-0.23**	**0.04****	-0.10*	**0.09****	-0.03*	**0.16****	-0.07*	**0.10****
YEN								
ΔVIX	**0.11****	**0.05***	**0.11***	**0.05**	**0.16****	**0.05**	**0.10***	**0.04**
ΔTED	-0.16	-0.18	-0.03	-0.03	-0.07	-0.07	-0.02	-0.01
GOLD	-0.03	**0.01**	-0.00	**0.03**	-0.01	**0.06***	-0.00	**0.03**
OIL	**0.20****	**0.20****	**0.12****	**0.13****	**0.14****	**0.14****	**0.10****	**0.11****
BDI	-0.26	-0.15	-0.06	**0.00**	-0.16	-0.05	-0.04	**0.02**
CRB	**0.04**	**0.16****	**0.04**	**0.12****	**0.05**	**0.15****	**0.04**	**0.10****
MSCI	**0.33****	**0.17***	**0.28****	**0.15***	**0.36****	**0.19***	**0.30****	**0.16***
SP500	**0.29****	**0.20***	**0.23****	**0.15***	**0.23****	**0.18***	**0.23****	**0.14***
VSP500	-0.01	**0.05***	-0.00	**0.05***	-0.01	**0.05***	-0.00	**0.05***
EquityM	**0.04**	**0.04**	**0.06**	**0.03**	**0.07**	**0.02**	**0.07**	**0.05**
VEquityM	-0.03	**0.04**	-0.00	**0.05***	-0.03	**0.03**	-0.00	**0.05***
ΔL	-0.26	-0.06	-0.10	**0.01**	-0.23	-0.07	-0.05	**0.03**
ΔS	**0.06***	-0.03	**0.07***	**0.03**	**0.08***	**0.02**	**0.07***	**0.04**
ΔC	-0.04	**0.01**	-0.00	**0.04***	**0.02**	**0.03**	-0.00	**0.04***
POOL	**0.24*****	**0.12***	**0.16****	**0.09***	**0.14****	**0.09***	**0.13****	**0.08***
PCA	**0.43*****	**0.24****	**0.40*****	**0.22****	**0.39*****	**0.22****	**0.41*****	**0.21****
PLS	**0.22*****	**0.01****	**0.39*****	**0.13****	**0.29*****	**0.09****	**0.43*****	**0.16****

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CHF								
ΔVIX	-0.45	-0.15	-0.16	-0.06	-0.23	-0.05	**0.00**	**0.03**
ΔTED	-0.06	-0.04	-0.01	**0.04**	-0.04	-0.01	**0.01**	**0.04**
GOLD	-0.06	**0.03**	-0.00	**0.04**	-0.03	**0.04**	**0.00**	**0.04**
OIL	-0.05	**0.03**	**0.01**	**0.04**	-0.08	**0.01**	**0.02**	**0.03**
BDI	-0.01*	**0.06***	-0.04	**0.01**	**0.03**	**0.05***	-0.09	-0.01
CRB	-0.05	**0.03**	**0.00**	**0.04**	-0.05	**0.07***	**0.03**	**0.03**
MSCI	-0.35	-0.13	-0.16	-0.05	-0.13	-0.04	-0.15	-0.07
SP500	-0.39*	-0.13	-0.22*	-0.06	-0.11	**0.02**	-0.05*	-0.03
VSP500	-0.07	**0.02**	-0.02	**0.04**	-0.05	**0.02**	-0.01	**0.04**
EquityM	-0.06	**0.10***	-0.05	**0.04**	-0.05	**0.05**	-0.10	**0.02**
VEquityM	-0.05	**0.02**	-0.02	**0.03**	-0.02	**0.03**	-0.01	**0.04**
ΔL	-0.06	-0.04	**0.01**	**0.04**	-0.09	-0.02	**0.03**	**0.04**
ΔS	**0.11***	**0.07***	**0.01**	**0.03**	**0.05**	**0.05***	-0.02	**0.02**
ΔC	-0.05	**0.05**	-0.02	**0.04**	-0.09	**0.03**	-0.02	**0.04**
POOL	**0.07**	**0.07**	**0.08**	**0.06**	**0.02**	**0.05**	**0.06**	**0.05**
PCA	-0.35	-0.07	-0.15	-0.00	-0.26	-0.02	-0.11	-0.01
PLS	-0.61	-0.32	-0.40	-0.20	-0.44	-0.17	-0.33	-0.17
EUR								
ΔVIX	-0.92	-0.29	-0.42	-0.05	-0.33	**0.07**	-0.09	**0.05**
ΔTED	-0.12	**0.02**	**0.02**	**0.07****	-0.15	**0.03**	**0.02****	**0.07****
GOLD	-0.02	**0.03**	**0.01**	**0.06***	-0.02	**0.04**	**0.02**	**0.06***
OIL	-0.06	**0.05***	**0.03****	**0.06***	-0.06	**0.05***	**0.03****	**0.06***
BDI	-0.05	**0.17****	-0.05	**0.07**	**0.02**	**0.14****	-0.09	**0.05**
CRB	-0.08	**0.02**	**0.01**	**0.06***	-0.07	**0.08****	**0.03***	**0.06***
MSCI	-0.81	-0.42	-0.44	-0.24	-0.38	-0.14	-0.46	-0.26
SP500	-1.03	-0.52	-0.71	-0.37	-0.40	-0.12	-0.38	-0.23
VSP500	-0.05	**0.05***	-0.00	**0.06***	-0.04	**0.06***	**0.00**	**0.06***
EquityM	-0.32	-0.08	-0.09	**0.01**	-0.22	-0.05	-0.07	**0.01**
VEquityM	**0.05***	**0.09****	-0.03	**0.05***	**0.07****	**0.11****	-0.03	**0.05***
ΔL	**0.00**	**0.02**	**0.02**	**0.06***	-0.05	**0.03**	-0.00	**0.06***
ΔS	**0.00**	**0.08****	-0.00	**0.07****	-0.00	**0.07***	-0.00	**0.06****
ΔC	-0.01	**0.07****	**0.00**	**0.06****	-0.03	**0.06***	-0.00	**0.06***
POOL	**0.02**	**0.06**	**0.04**	**0.07**	**0.01**	**0.08***	**0.03**	**0.06**
PCA	-1.17	-0.41	-0.70	-0.21	-0.79	-0.15	-0.54	-0.15
PLS	-1.50	-0.74	-1.12	-0.53	-0.93	-0.25	-1.05	-0.49

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CAD								
ΔVIX	-0.10	**0.03**	-0.13	-0.00	**0.15***	**0.14***	-0.07	**0.05**
ΔTED	-0.07	-0.01	**0.00**	**0.04**	-0.04	**0.01**	**0.02**	**0.03**
GOLD	**0.08**	**0.06**	**0.04**	**0.03**	**0.04**	**0.06***	**0.05**	**0.04**
OIL	-0.01	**0.01**	**0.00**	**0.04**	**0.02**	**0.02**	**0.01**	**0.04**
BDI	-0.07	**0.05**	-0.09	**0.01**	-0.04	-0.01	-0.01	**0.04**
CRB	**0.00**	**0.06***	-0.02	**0.03**	**0.04**	**0.03**	-0.00	**0.04**
MSCI	-0.28	-0.03	-0.15	**0.01**	-0.24	**0.02**	-0.07	**0.05**
SP500	-0.28	-0.02	-0.15	**0.02**	-0.14	**0.06**	**0.19***	**0.10**
VSP500	-0.01	**0.05***	-0.01	**0.04**	-0.01	**0.05***	-0.01	**0.04**
EquityM	-0.22	-0.02	-0.13	**0.02**	-0.13	**0.05**	-0.08	**0.04**
VEquityM	-0.05	**0.04**	-0.04	**0.04**	-0.06	**0.04**	-0.04	**0.04**
ΔL	-0.05	**0.03**	**0.00**	**0.05***	-0.03	**0.03**	**0.02**	**0.05***
ΔS	-0.07	**0.04**	-0.04	**0.03**	-0.04	**0.05***	-0.02	**0.06***
ΔC	-0.08	**0.06***	-0.04	**0.05***	-0.06	**0.06***	-0.02	**0.07***
POOL	**0.01**	**0.05**	-0.07	**0.04**	**0.01**	**0.06**	-0.02	**0.06**
PCA	-0.37	-0.06	-0.25	**0.00**	-0.22	**0.04**	-0.06	**0.08**
PLS	-0.61	-0.19	-0.51	-0.15	-0.19	**0.04***	-0.49	-0.14
AUD								
ΔVIX	-0.53	-0.22	-0.32	-0.13	-0.32	-0.09	-0.19	-0.08
ΔTED	-0.15	-0.02	-0.07	-0.01	-0.17	-0.02	-0.04	**0.01**
GOLD	-0.08	-0.06	-0.01	-0.00	-0.07	-0.04	**0.02**	**0.02**
OIL	**0.05**	-0.00	**0.02**	**0.01**	**0.02**	**0.01**	**0.02**	**0.03**
BDI	-0.33	-0.27	-0.30	-0.24	-0.33	-0.29	-0.20	-0.15
CRB	-0.09	-0.04	-0.01	**0.03**	**0.03**	-0.06	-0.02	**0.01**
MSCI	-0.74	-0.44	-0.51	-0.31	-0.55	-0.28	-0.41	-0.25
SP500	-0.53	-0.19	-0.36	-0.11	-0.27	-0.13	**0.00**	**0.09**
VSP500	-0.02	**0.03**	-0.00	**0.04***	-0.02	**0.03***	-0.00	**0.04***
EquityM	-0.25	-0.08	-0.10	**0.00**	-0.15	-0.03	-0.11	**0.01**
VEquityM	-0.06	**0.02**	-0.00	**0.04***	-0.04	**0.06****	-0.00	**0.04***
ΔL	**0.03**	**0.07**	**0.01**	**0.05**	**0.04**	**0.08***	**0.02**	**0.06***
ΔS	-0.12	**0.02**	-0.02	**0.04***	-0.10	**0.02**	-0.02	**0.03***
ΔC	-0.01	**0.05***	-0.01	**0.04***	-0.05	**0.03**	-0.00	**0.04***
POOL	-0.05	-0.02	-0.14	-0.00	-0.05	-0.01	-0.14	**0.02**
PCA	-0.78	-0.41	-0.55	-0.29	-0.65	-0.46	-0.57	-0.30
PLS	-1.73	-1.25	-1.50	-1.11	-1.39	-0.95	-1.51	-1.11

Notes: See Table 3.3. We change the control window to 100 days.

Table 3.10: Robustness Tests, Control Window, 150 days

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GBP								
ΔVIX	-0.36	**0.10****	-0.18	**0.12****	-0.17	**0.13****	-0.05	**0.13****
ΔTED	-0.07	**0.04**	-0.02	**0.03**	-0.08	**0.04***	-0.03	**0.03**
GOLD	-0.01	**0.06**	-0.01	**0.04**	-0.00	**0.05**	**0.01**	**0.05***
OIL	-0.02	**0.03**	-0.01	**0.03**	-0.01	**0.02**	-0.00	**0.03***
BDI	-0.07	**0.14***	-0.04	**0.08**	-0.03	**0.08**	-0.04	**0.07**
CRB	-0.03	**0.01**	-0.01	**0.02**	-0.02	**0.03**	**0.00**	**0.03**
MSCI	**0.03****	**0.11****	**0.10****	**0.13***	**0.21****	**0.21****	**0.13***	**0.13***
SP500	**0.09****	**0.14****	**0.16****	**0.15****	**0.22****	**0.20****	**0.24****	**0.17****
VSP500	-0.03	**0.06****	-0.01	**0.04***	-0.01	**0.05****	-0.01	**0.04***
EquityM	-0.04	**0.03**	-0.02	**0.02**	-0.04	-0.01	-0.02	**0.02**
VEquityM	-0.14	-0.02	-0.02	**0.03**	-0.13	-0.02	-0.02	**0.03***
ΔL	-0.07	-0.01	-0.01	**0.02**	-0.03	**0.03**	-0.01	**0.02**
ΔS	-0.02	**0.11****	-0.01	**0.07****	**0.00**	**0.08***	-0.01	**0.06****
ΔC	**0.02**	**0.10***	**0.00**	**0.06****	**0.01**	**0.08****	**0.00**	**0.05****
POOL	**0.12***	**0.14****	**0.10**	**0.11****	**0.07**	**0.10****	**0.08**	**0.09****
PCA	-0.14*	**0.10****	-0.02*	**0.12****	-0.06	**0.11***	**0.03**	**0.12***
PLS	-0.27**	**0.04****	-0.12**	**0.09****	-0.07*	**0.14****	-0.09**	**0.11****
YEN								
ΔVIX	**0.11****	**0.03**	**0.09***	**0.02**	**0.14***	**0.02**	**0.07**	**0.00**
ΔTED	-0.18	-0.21	-0.02	-0.02	-0.09	-0.10	-0.00	-0.01
GOLD	-0.03	**0.01**	-0.01	**0.02**	-0.00	**0.05**	-0.00	**0.02**
OIL	**0.19****	**0.18****	**0.07**	**0.08***	**0.13****	**0.13****	**0.03**	**0.06***
BDI	-0.27	-0.18	-0.03	**0.00**	-0.12	-0.06	-0.01	**0.02**
CRB	**0.04**	**0.14***	**0.01**	**0.08***	**0.03**	**0.12****	-0.00	**0.06***
MSCI	**0.34****	**0.16***	**0.26****	**0.13**	**0.36****	**0.18***	**0.27****	**0.13**
SP500	**0.29****	**0.19***	**0.21****	**0.12***	**0.23****	**0.14***	**0.16****	**0.10**
VSP500	-0.00	**0.04***	-0.00	**0.03***	-0.01	**0.03***	-0.00	**0.03***
EquityM	**0.04**	**0.03**	**0.04**	**0.02**	**0.07**	-0.02	**0.04**	**0.02**
VEquityM	-0.03	**0.02**	**0.00**	**0.03***	-0.03	**0.01**	**0.00**	**0.03***
ΔL	-0.26	-0.07	-0.07	**0.02**	-0.19	-0.07	-0.02	**0.04**
ΔS	**0.07***	-0.02	**0.05**	**0.03**	**0.03**	-0.01	**0.03**	**0.03**
ΔC	-0.04	-0.02	-0.00	**0.03***	**0.03***	**0.01**	-0.00	**0.03***
POOL	**0.23*****	**0.11***	**0.12****	**0.07***	**0.14****	**0.07***	**0.09****	**0.06***
PCA	**0.41*****	**0.20****	**0.35*****	**0.18***	**0.31****	**0.17***	**0.33****	**0.15***
PLS	**0.22*****	**0.01****	**0.40*****	**0.13****	**0.31*****	**0.07***	**0.44*****	**0.16****

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CHF								
ΔVIX	-0.52	-0.19	-0.19	-0.06	-0.24	-0.04	-0.02	**0.02**
ΔTED	-0.05	-0.03	-0.00	**0.04**	-0.08	-0.02	**0.00**	**0.04**
GOLD	-0.06	**0.03**	-0.00	**0.04**	-0.02	**0.04**	-0.00	**0.04**
OIL	-0.06	**0.03**	**0.01**	**0.04**	-0.06	**0.03**	**0.01**	**0.04**
BDI	-0.00*	**0.06***	-0.01	**0.02**	**0.03**	**0.06***	-0.02	**0.02**
CRB	-0.06	**0.03**	-0.00	**0.03**	-0.06	**0.05***	**0.01***	**0.03**
MSCI	-0.39	-0.15	-0.16	-0.05	-0.17	-0.07	-0.15	-0.07
SP500	-0.44*	-0.15	-0.23*	-0.07	-0.10	**0.01**	-0.06*	-0.04
VSP500	-0.07	**0.02**	-0.01	**0.04**	-0.05	**0.02**	-0.01	**0.04**
EquityM	-0.06	**0.10***	-0.03	**0.04**	-0.05	**0.06**	-0.02	**0.04**
VEquityM	-0.04	**0.03**	-0.00	**0.04**	-0.01	**0.04***	-0.00	**0.04**
ΔL	-0.07	-0.04	**0.00**	**0.04**	-0.09	-0.01	**0.01***	**0.04**
ΔS	**0.13****	**0.07***	**0.03**	**0.03**	**0.03**	**0.04**	-0.01	**0.03**
ΔC	-0.05	**0.05**	-0.02	**0.04**	-0.08	**0.04**	-0.01	**0.04**
POOL	**0.08**	**0.07**	**0.08**	**0.06**	**0.03**	**0.06**	**0.06**	**0.05**
PCA	-0.37	-0.08	-0.14	**0.01**	-0.33	-0.04	-0.07	**0.00**
PLS	-0.67	-0.36	-0.40	-0.20	-0.53	-0.18	-0.34	-0.16
EUR								
ΔVIX	-1.07	-0.36	-0.52	-0.09	-0.40	**0.05**	-0.19	**0.07**
ΔTED	-0.11	**0.03**	-0.00	**0.06***	-0.16	**0.02**	**0.00**	**0.06***
GOLD	-0.02	**0.03**	**0.01**	**0.05***	-0.02	**0.04**	**0.02**	**0.05***
OIL	-0.06	**0.05***	**0.01***	**0.06***	-0.06	**0.05***	**0.01****	**0.06***
BDI	-0.05	**0.17****	-0.01	**0.08**	**0.02**	**0.13***	-0.01	**0.08***
CRB	-0.08	**0.02**	-0.00	**0.06***	-0.08	**0.05***	**0.01**	**0.06***
MSCI	-0.88	-0.47	-0.47	-0.27	-0.41	-0.18	-0.47	-0.27
SP500	-1.12	-0.58	-0.75	-0.39	-0.37	-0.14	-0.45	-0.26
VSP500	-0.05	**0.05***	-0.00	**0.06***	-0.03	**0.06***	-0.00	**0.06***
EquityM	-0.35	-0.10	-0.12	-0.01	-0.24	-0.07	-0.09	**0.00**
VEquityM	**0.04**	**0.08****	**0.00**	**0.05***	**0.04***	**0.09****	-0.00	**0.06***
ΔL	**0.00**	**0.01**	**0.02***	**0.06***	-0.08	**0.03**	**0.03****	**0.06***
ΔS	**0.04**	**0.09****	**0.00**	**0.06****	**0.08***	**0.11****	**0.01**	**0.06****
ΔC	-0.01	**0.06***	-0.00	**0.06***	-0.01	**0.06***	-0.00	**0.06***
POOL	**0.02**	**0.06**	**0.04**	**0.07**	**0.01**	**0.08**	**0.03**	**0.06**
PCA	-1.23	-0.46	-0.73	-0.24	-0.75	-0.16	-0.57	-0.17
PLS	-1.60	-0.80	-1.15	-0.55	-0.94	-0.32	-1.05	-0.50

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CAD								
ΔVIX	-0.12	**0.02**	-0.13	**0.01**	**0.09**	**0.09**	-0.05	**0.05**
ΔTED	-0.07	-0.01	-0.01	**0.05***	-0.03	**0.02**	**0.00**	**0.04**
GOLD	**0.08**	**0.06**	**0.04**	**0.03**	**0.04**	**0.07***	**0.04**	**0.04**
OIL	-0.01	**0.01**	-0.00	**0.05***	**0.03***	**0.03**	**0.00**	**0.05***
BDI	-0.06	**0.05**	-0.08	**0.02**	-0.04	-0.00	**0.01**	**0.05**
CRB	**0.00**	**0.07***	-0.01	**0.04**	**0.02**	**0.02**	**0.00**	**0.05***
MSCI	-0.29	-0.03	-0.16	**0.02**	-0.24	**0.03**	-0.03	**0.06**
SP500	-0.29	-0.02	-0.17	**0.02**	-0.14	**0.06**	**0.12**	**0.08**
VSP500	-0.01	**0.05***	-0.01	**0.05***	-0.00	**0.05***	-0.00	**0.05***
EquityM	-0.23	-0.01	-0.13	**0.03**	-0.12	**0.06**	-0.07	**0.05**
VEquityM	-0.06	**0.04**	-0.03	**0.04**	-0.06	**0.04**	-0.02	**0.05***
ΔL	-0.05	**0.03**	-0.00	**0.05***	-0.02	**0.04**	**0.01**	**0.05***
ΔS	-0.07	**0.05**	-0.03	**0.04**	-0.04	**0.05***	-0.01	**0.06***
ΔC	-0.07	**0.07***	-0.03	**0.05***	-0.06	**0.06***	-0.01	**0.06***
POOL	**0.01**	**0.06**	-0.06	**0.05**	**0.01**	**0.06**	-0.02	**0.06**
PCA	-0.38	-0.08	-0.26	-0.01	-0.23	**0.04**	-0.13	**0.05**
PLS	-0.63	-0.20	-0.53	-0.16	-0.26	**0.01**	-0.50	-0.14
AUD								
ΔVIX	-0.59	-0.24	-0.37	-0.14	-0.36	-0.13	-0.22	-0.10
ΔTED	-0.15	-0.01	-0.07	-0.00	-0.16	-0.02	-0.04	**0.01**
GOLD	-0.08	-0.06	-0.01	-0.01	-0.06	-0.01	**0.02**	**0.02**
OIL	**0.05**	**0.00**	**0.03**	**0.02**	**0.02**	**0.01**	**0.02**	**0.03**
BDI	-0.33	-0.27	-0.30	-0.24	-0.38	-0.33	-0.21	-0.16
CRB	-0.10	-0.04	-0.02	**0.03**	-0.03	-0.10	-0.02	**0.01**
MSCI	-0.77	-0.45	-0.54	-0.32	-0.52	-0.29	-0.36	-0.21
SP500	-0.56	-0.20	-0.39	-0.12	-0.28	-0.14	**0.02**	**0.12**
VSP500	-0.02	**0.03**	-0.01	**0.04***	-0.02	**0.04***	-0.00	**0.04***
EquityM	-0.26	-0.08	-0.11	-0.00	-0.18	-0.04	-0.11	**0.01**
VEquityM	-0.07	**0.02**	-0.01	**0.05***	-0.05	**0.04***	-0.00	**0.05***
ΔL	**0.03**	**0.08**	**0.01**	**0.05**	**0.03**	**0.09***	**0.02**	**0.06***
ΔS	-0.12	**0.03**	-0.02	**0.04***	-0.11	**0.02**	-0.03	**0.04***
ΔC	-0.02	**0.05***	-0.01	**0.04***	-0.01	**0.05****	-0.01	**0.04***
POOL	-0.05	-0.02	-0.14	**0.00**	-0.06	-0.02	-0.14	**0.03**
PCA	-0.81	-0.42	-0.58	-0.30	-0.69	-0.52	-0.60	-0.31
PLS	-1.80	-1.30	-1.58	-1.16	-1.45	-1.03	-1.57	-1.15

Notes: See Table 3.3. We change the control window to 150 days.

Table 3.11: Robustness Tests, Control Window, 200 days

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GBP								
ΔVIX	-0.37	**0.09****	-0.19	**0.11***	-0.16	**0.13****	-0.08	**0.10***
ΔTED	-0.08	**0.04**	-0.04	**0.03**	-0.10	**0.04***	-0.04	**0.03**
GOLD	-0.03	**0.06**	-0.03	**0.02**	-0.02	**0.05**	-0.01	**0.03**
OIL	-0.01	**0.03**	-0.02	**0.02**	-0.01	**0.02**	-0.01	**0.02**
BDI	-0.08	**0.12**	-0.10	**0.04**	-0.05	**0.06**	-0.13	**0.02**
CRB	-0.03	**0.00**	-0.01	**0.01**	-0.03	**0.01**	**0.01**	**0.03**
MSCI	**0.02****	**0.11****	**0.09****	**0.12***	**0.22****	**0.22****	**0.10***	**0.10***
SP500	**0.09****	**0.13****	**0.15****	**0.14****	**0.23****	**0.20****	**0.17***	**0.14***
VSP500	-0.03	**0.06****	-0.01	**0.02**	-0.01	**0.05****	-0.00	**0.02**
EquityM	-0.04	**0.02**	-0.04	**0.00**	-0.06	-0.01	-0.03	**0.03**
VEquityM	-0.16	-0.03	**0.01**	**0.04****	-0.13	-0.03	**0.02**	**0.04***
ΔL	-0.06	-0.01	-0.00	**0.03***	-0.03	**0.01**	-0.02	**0.03***
ΔS	-0.02	**0.10****	-0.05	**0.04***	-0.01	**0.06****	-0.06	**0.03***
ΔC	**0.02**	**0.10***	-0.04	**0.04***	**0.02**	**0.08****	-0.04	**0.03**
POOL	**0.12***	**0.14****	**0.08**	**0.10****	**0.06**	**0.10****	**0.04**	**0.07****
PCA	-0.13*	**0.11****	-0.02*	**0.12****	-0.09	**0.06**	**0.06**	**0.13***
PLS	-0.29**	**0.03****	-0.15*	**0.08****	-0.12*	**0.12****	-0.11*	**0.09****
YEN								
ΔVIX	**0.09****	**0.01**	**0.00**	-0.04	**0.10***	-0.02	-0.15	-0.07
ΔTED	-0.18	-0.22	-0.00	-0.01	-0.03	-0.12	-0.03	-0.07
GOLD	-0.03	**0.00**	-0.06	-0.01	**0.03**	**0.08***	-0.02	**0.01**
OIL	**0.20****	**0.19****	**0.02**	**0.06**	**0.15****	**0.14****	-0.21	-0.07
BDI	-0.21	-0.14	**0.02**	**0.01**	-0.11	-0.04	**0.06**	**0.01**
CRB	**0.03***	**0.14***	-0.00	**0.09***	**0.03**	**0.13****	-0.23	-0.04
MSCI	**0.33****	**0.16***	**0.21****	**0.09**	**0.36****	**0.20***	**0.09***	**0.02**
SP500	**0.28****	**0.18***	**0.17****	**0.09**	**0.19****	**0.10**	**0.02**	**0.06**
VSP500	-0.00	**0.03***	-0.01	**0.03***	-0.01	**0.02***	-0.02	**0.03***
EquityM	**0.04**	**0.02**	-0.02	-0.03	**0.07**	-0.04	-0.08	-0.05
VEquityM	-0.04	**0.00**	-0.00	**0.03**	-0.03	**0.01**	-0.00	**0.03**
ΔL	-0.24	-0.07	-0.09	**0.02**	-0.19	-0.07	**0.02**	**0.06***
ΔS	**0.07***	-0.01	**0.01**	**0.01**	**0.04**	-0.01	-0.10	-0.09
ΔC	-0.04	-0.02	-0.00	**0.03***	**0.02**	**0.01**	**0.00**	**0.03***
POOL	**0.23*****	**0.11***	**0.13***	**0.06**	**0.14****	**0.07**	**0.04**	**0.02**
PCA	**0.39*****	**0.18****	**0.34*****	**0.15***	**0.29****	**0.15***	**0.27****	**0.11**
PLS	**0.23*****	**0.03****	**0.36*****	**0.11****	**0.36*****	**0.11***	**0.39*****	**0.13****

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CHF								
ΔVIX	-0.48	-0.16	-0.17	-0.06	-0.23	-0.04	-0.04	**0.02**
ΔTED	-0.05	-0.01	-0.01	**0.04**	-0.01	**0.01**	-0.00	**0.04**
GOLD	-0.05	**0.03**	**0.00**	**0.04**	-0.04	**0.03**	**0.00**	**0.04**
OIL	-0.05	**0.04**	**0.01**	**0.04**	-0.10	**0.02**	**0.02***	**0.04**
BDI	-0.01*	**0.06***	-0.02	**0.02**	**0.03**	**0.06***	-0.06	**0.01**
CRB	-0.06	**0.04**	**0.00**	**0.04**	-0.07	**0.08****	**0.02****	**0.04**
MSCI	-0.38	-0.14	-0.16	-0.05	-0.17	-0.06	-0.17	-0.07
SP500	-0.42*	-0.14*	-0.22*	-0.06	-0.10	**0.01**	-0.05*	-0.04
VSP500	-0.08	**0.02**	-0.02	**0.04**	-0.05	**0.02**	-0.01	**0.04**
EquityM	-0.06	**0.11***	-0.04	**0.05**	-0.07	**0.04**	-0.04	**0.04**
VEquityM	-0.03	**0.05***	-0.00	**0.04**	-0.03	**0.01***	-0.00	**0.04**
ΔL	-0.07	-0.04	**0.01**	**0.04**	-0.08	**0.00**	**0.01**	**0.04**
ΔS	**0.13****	**0.07***	**0.03**	**0.03**	**0.08***	**0.06***	**0.00**	**0.03**
ΔC	-0.04	**0.06***	-0.03	**0.05**	-0.07	**0.06***	-0.02	**0.05**
POOL	**0.08**	**0.08***	**0.09**	**0.07***	**0.03**	**0.06**	**0.06**	**0.05**
PCA	-0.27*	-0.05*	-0.07*	**0.02***	-0.28	-0.08	-0.06	**0.01**
PLS	-0.63	-0.32	-0.39*	-0.18	-0.48	-0.19	-0.34	-0.15
EUR								
ΔVIX	-1.02	-0.32	-0.42	-0.04	-0.36	**0.06**	-0.14	**0.05**
ΔTED	-0.11	**0.05***	-0.01	**0.06****	-0.13	**0.05***	-0.01	**0.06****
GOLD	-0.02	**0.02**	-0.01	**0.06***	-0.02	**0.03**	-0.01	**0.06***
OIL	-0.06	**0.05***	**0.02****	**0.06****	-0.04	**0.06***	**0.02****	**0.06****
BDI	-0.05	**0.18****	-0.04	**0.07**	**0.01**	**0.12***	-0.03	**0.07***
CRB	-0.08	**0.02**	**0.01**	**0.07****	-0.09	**0.07***	**0.02***	**0.06****
MSCI	-0.87	-0.45	-0.41	-0.23	-0.39	-0.17	-0.42	-0.23
SP500	-1.09	-0.55	-0.67	-0.35	-0.39	-0.14	-0.37	-0.22
VSP500	-0.06	**0.06***	**0.00**	**0.06***	-0.04	**0.06***	**0.00**	**0.06***
EquityM	-0.39	-0.10	-0.11	-0.00	-0.23	-0.04	-0.04	**0.03**
VEquityM	**0.00**	**0.07****	**0.01**	**0.06***	**0.03**	**0.09****	**0.01**	**0.06***
ΔL	-0.01	**0.01**	**0.02**	**0.07****	-0.09	**0.03**	**0.03****	**0.07****
ΔS	**0.01**	**0.09****	-0.00	**0.07****	**0.08***	**0.13****	**0.01**	**0.08****
ΔC	-0.01	**0.06***	**0.00**	**0.07****	-0.02	**0.06***	**0.00**	**0.07****
POOL	**0.02**	**0.06**	**0.04**	**0.08**	**0.01**	**0.09***	**0.02**	**0.06**
PCA	-1.20	-0.42	-0.64	-0.17	-0.76	-0.15	-0.47	-0.10
PLS	-1.57	-0.77	-1.06	-0.49	-0.89	-0.30	-0.97	-0.44

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CAD								
ΔVIX	-0.13	**0.02**	-0.14	**0.00**	**0.07**	**0.10**	-0.08	**0.04**
ΔTED	-0.08	-0.01	-0.01	**0.04**	-0.04	**0.01**	-0.00	**0.04**
GOLD	**0.07**	**0.06**	**0.05**	**0.03**	**0.03**	**0.07***	**0.04**	**0.04**
OIL	-0.01	**0.01**	**0.00**	**0.05***	**0.02**	**0.02**	**0.01**	**0.05***
BDI	-0.07	**0.05**	-0.09	**0.02**	-0.03	-0.00	-0.00	**0.05**
CRB	-0.00	**0.07***	-0.01	**0.04**	**0.01**	**0.01**	-0.00	**0.05***
MSCI	-0.30	-0.03	-0.17	**0.01**	-0.23	**0.03**	-0.02	**0.06**
SP500	-0.30	-0.02	-0.18	**0.02**	-0.13	**0.06**	**0.07**	**0.08**
VSP500	-0.01	**0.05***	-0.01	**0.04***	-0.00	**0.05***	-0.01	**0.04**
EquityM	-0.23	-0.02	-0.14	**0.02**	-0.14	**0.06**	-0.08	**0.05**
VEquityM	-0.06	**0.04**	-0.04	**0.04**	-0.06	**0.03**	-0.04	**0.04***
ΔL	-0.05	**0.03**	**0.00**	**0.05***	-0.02	**0.05**	**0.01**	**0.05***
ΔS	-0.07	**0.05**	-0.04	**0.04**	-0.03	**0.06***	-0.03	**0.07***
ΔC	-0.07	**0.06***	-0.03	**0.05***	-0.06	**0.06***	-0.02	**0.06***
POOL	**0.01**	**0.06**	-0.07	**0.05**	**0.01**	**0.06**	-0.02	**0.06**
PCA	-0.39	-0.09	-0.28	-0.02	-0.19	**0.04**	-0.10	**0.05**
PLS	-0.67	-0.21	-0.57	-0.17	-0.30	**0.04***	-0.54	-0.16
AUD								
ΔVIX	-0.59	-0.24	-0.37	-0.14	-0.33	-0.11	-0.19	-0.09
ΔTED	-0.16	-0.01	-0.08	-0.01	-0.21	-0.04	-0.04	**0.02**
GOLD	-0.08	-0.06	-0.00	-0.00	-0.06	-0.02	**0.03**	**0.02**
OIL	**0.05**	**0.00**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.03**
BDI	-0.33	-0.27	-0.31	-0.25	-0.41	-0.38	-0.23	-0.18
CRB	-0.10	-0.04	-0.00	**0.04***	-0.05	-0.11	-0.00	**0.02**
MSCI	-0.78	-0.46	-0.55	-0.33	-0.52	-0.29	-0.33	-0.19
SP500	-0.58	-0.20	-0.40	-0.12	-0.29	-0.13	**0.11**	**0.16**
VSP500	-0.02	**0.04***	-0.01	**0.05***	-0.01	**0.04***	-0.00	**0.05***
EquityM	-0.26	-0.07	-0.11	**0.02**	-0.28	-0.04	-0.10	**0.04**
VEquityM	-0.09	**0.02**	**0.01**	**0.05***	-0.07	**0.03***	**0.02****	**0.05****
ΔL	**0.03**	**0.08**	-0.00	**0.05**	**0.02**	**0.07**	**0.01**	**0.05***
ΔS	-0.12	**0.03**	-0.01	**0.04***	-0.14	**0.00**	-0.02	**0.04***
ΔC	-0.02	**0.05***	-0.01	**0.04***	-0.01	**0.05***	-0.01	**0.05***
POOL	-0.05	-0.01	-0.17	**0.00**	-0.08	-0.03	-0.16	**0.03**
PCA	-0.83	-0.43	-0.60	-0.31	-0.80	-0.55	-0.61	-0.31
PLS	-1.90	-1.36	-1.67	-1.22	-1.55	-1.12	-1.65	-1.21

Notes: See Table 3.3. We change the control window to 200 days.

3.6.3 Alternative Out–of-sample Period

In this section we examine whether a different in-sample and out-of-sample period have a significant impact in our results. Specifically, the out-of-sample period starts at January 1^{st}, 2009. Hence, the in-sample period was extended by 10 years and now includes the 2008-2010 financial crisis. The results are reported in Table

3.12. In general we observe an improvement in the performance of $C^{CP,+}$ while the $C^{ICCP,+}$ outperforms the alternative methods in most cases. Again, positivity constraints greatly improve the forecasting ability of all methods considered, while the dimensionality reduction techniques, PLS and PCA, show poor performance. On the other hand, we observe a small deterioration in the performance of each method in the cases of GPB and YEN. Furthermore, POOL rarely outperforms the benchmark although it was one of the best specifications in our initial setup.

Table 3.12: Robustness Tests, OOS period

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel A: GBP								
ΔVIX	-0.64	-0.26	-0.4	-0.18	-0.32	-0.11	-0.16	-0.06
ΔTED	**0.01**	**0.01**	-0.01	**0.01*****	-0.01	-0.01	**0.01**	**0.01****
GOLD	-0.3	-0.14	-0.16	-0.07	-0.2	-0.08	-0.15	-0.07
OIL	-0.01	-0.04	-0.01	-0.01	**0.01**	-0.02	-0.01	-0.01
BDI	-0.44	-0.03	-0.26	-0.02	-0.23	-0.03	-0.16	-0.01
CRB	-0.04	-0.03	-0.02	-0.01	-0.03	-0.04	**0.01**	**0.01**
MSCI	-0.39	-0.16	-0.27	-0.12	-0.1	**0.01**	-0.24	-0.11
SP500	-0.81	-0.43	-0.66	-0.36	-0.41	-0.25	-0.45	-0.27
VSP500	**0.01**	**0.05****	-0.01	**0.01**	-0.01	**0.04****	-0.01	**0.01**
EquityM	-0.02	**0.02**	-0.01	**0.01**	-0.03	**0.01**	-0.01	**0.01**
VEquityM	-0.16	-0.05	-0.01	**0.01****	-0.15	-0.06	-0.01	**0.01***
ΔL	-0.01	**0.01**	-0.01	**0.01***	**0.01**	**0.02**	-0.01	**0.01****
ΔS	**0.04**	**0.02**	**0.012**	**0.02**	**0.02**	-0.01	**0.02**	**0.02**
ΔC	-0.03	**0.02**	-0.02	**0.02**	-0.03	**0.04**	-0.02	**0.02**
POOL	-0.09	-0.03	-0.12	-0.02	-0.05	-0.01	-0.08	-0.01
PCA	-0.49	-0.21	-0.34	-0.15	-0.3	-0.15	-0.25	-0.12
PLS	-1.09	-0.56	-0.9	-0.48	-0.67	-0.37	-0.87	-0.46
Panel B: YEN								
ΔVIX	-0.51	-0.17	-0.22	-0.02	-0.38	-0.18	-0.2	-0.02
ΔTED	-0.01	**0.06***	**0.012**	**0.07***	-0.01	**0.06***	**0.01**	**0.07***
GOLD	-0.02	**0.08***	**0.012**	**0.06***	-0.02	**0.07***	**0.01**	**0.07***
OIL	-0.21	**0.04**	-0.07	**0.08**	-0.12	**0.04**	-0.04	**0.09**
BDI	-0.15	**0.05**	-0.04	**0.07***	-0.13	**0.05**	-0.03	**0.07***
CRB	-0.36	**0.04**	-0.15	**0.08**	-0.19	**0.07**	-0.12	**0.08**
MSCI	-1.05	-0.42	-0.69	-0.24	-0.74	-0.39	-0.55	-0.18
SP500	-0.61	-0.14	-0.36	-0.05	-0.34	-0.09	-0.26	-0.01
VSP500	**0.03**	**0.08***	**0.012**	**0.07***	**0.03**	**0.07***	**0.01**	**0.07***
EquityM	-0.46	-0.06	-0.21	**0.01**	-0.35	-0.05	-0.15	**0.03**
VEquityM	-0.01	**0.07***	-0.01	**0.07***	-0.02	**0.06***	-0.01	**0.07***
ΔL	**0.16****	**0.12****	**0.06**2**	**0.08****	**0.08****	**0.1****	**0.04****	**0.08****
ΔS	**0.05**	**0.13****	**0.062**	**0.09***	**0.07**	**0.12****	**0.05**	**0.08***
ΔC	-0.04	**0.04**	-0.01	**0.07***	-0.01	**0.06**	-0.01	**0.07***
POOL	-0.05	**0.06**	-0.03	**0.06**	-0.06	**0.04**	-0.01	**0.06**
PCA	-0.94	-0.4	-0.6	-0.22	-0.66	-0.33	-0.52	-0.18
PLS	-1.41	-0.82	-1.05	-0.6	-0.98	-0.63	-0.86	-0.48

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel C: CHF								
ΔVIX	-1.02	-0.44	-0.62	-0.29	-0.71	-0.37	-0.4	-0.15
ΔTED	**0.01**	**0.04**	-0.01	**0.04**	**0.01**	**0.03**	-0.01	**0.04**
GOLD	-0.04	**0.04**	-0.03	**0.04**	-0.02	**0.04**	-0.02	**0.04**
OIL	-0.07	**0.02**	**0.022**	**0.04**	-0.08	-0.01	**0.02***	**0.04**
BDI	-0.23	-0.02	-0.08	**0.01**	-0.08	**0.04**	-0.02	**0.02**
CRB	-0.13	-0.02	**0.022**	**0.04**	-0.08	-0.04	**0.04****	**0.04**
MSCI	-1.16	-0.39	-0.85	-0.28	-0.84	-0.35	-0.75	-0.27
SP500	-1.67	-0.6	-1.39	-0.5	-1.01	-0.41	-1.1	-0.42
VSP500	-0.03	**0.02**	-0.02	**0.04**	-0.03	**0.02**	-0.02	**0.04**
EquityM	-0.16	**0.09**	-0.08	**0.04**	-0.11	**0.04**	-0.06	**0.04**
VEquityM	-0.05	**0.02**	**0.012**	**0.04**	-0.03	**0.03**	**0.01**	**0.04**
ΔL	-0.04	**0.03**	**0.02*2**	**0.04**	-0.08	**0.01**	**0.01**	**0.04**
ΔS	**0.1***	**0.07**	**0.042**	**0.03**	**0.08***	**0.05**	-0.04	**0.01**
ΔC	-0.09	**0.03**	-0.01	**0.04**	-0.12	**0.02**	-0.01	**0.04**
POOL	-0.23	-0.05	-0.26	-0.04	-0.18	-0.05	-0.16	-0.03
PCA	-1.12	-0.42	-0.82	-0.31	-0.94	-0.46	-0.71	-0.29
PLS	-1.69	-0.75	-1.39	-0.6	-1.28	-0.66	-1.28	-0.55
Panel D: EUR								
ΔVIX	-1.37	-0.59	-0.72	-0.26	-0.68	-0.25	-0.23	-0.07
ΔTED	-0.01	**0.06***	**0.01*2**	**0.06***	-0.01	**0.06***	**0.01***	**0.06***
GOLD	-0.07	**0.01**	-0.02	**0.05***	-0.03	**0.04**	-0.02	**0.05***
OIL	-0.03	**0.05***	**0.012**	**0.06***	-0.04	**0.03**	**0.01**	**0.06***
BDI	-0.72	-0.12	-0.3	-0.03	-0.32	-0.02	-0.06	**0.05**
CRB	-0.09	**0.03**	**0.022**	**0.06***	-0.06	**0.03**	**0.02**	**0.06***
MSCI	-1.43	-0.52	-0.91	-0.32	-1.12	-0.47	-0.87	-0.3
SP500	-2.4	-1.03	-1.92	-0.82	-1.48	-0.68	-1.36	-0.58
VSP500	-0.04	**0.06***	-0.01	**0.06***	-0.03	**0.06***	-0.01	**0.06***
EquityM	-0.52	-0.09	-0.17	**0.03**	-0.35	-0.05	-0.09	**0.05**
VEquityM	**0.11****	**0.12****	-0.02	**0.05**	**0.11****	**0.12****	**0.01**	**0.05***
ΔL	**0.21*****	**0.12****	**0.022**	**0.07****	**0.12*****	**0.09****	-0.04	**0.06***
ΔS	**0.12****	**0.06***	-0.02	**0.06***	**0.13****	**0.06**	-0.01	**0.06***
ΔC	**0.06***	**0.08****	-0.02	**0.06***	**0.04***	**0.07****	-0.03	**0.05***
POOL	-0.31	-0.08	-0.27	-0.05	-0.21	-0.05	-0.16	-0.02
PCA	-1.68	-0.63	-1.08	-0.38	-1.19	-0.52	-0.82	-0.27
PLS	-2.69	-1.11	-2.17	-0.87	-1.85	-0.82	-2.04	-0.81

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel E: CAD								
ΔVIX	-0.04	**0.02**	-0.03	**0.03**	**0.26****	**0.13**	-0.01	**0.04**
ΔTED	**0.03**	**0.05**	-0.01	**0.05**	**0.01**	**0.04**	**0.01**	**0.05**
GOLD	-0.03	**0.03**	**0.012**	**0.04**	-0.01	**0.04**	**0.02**	**0.04**
OIL	**0.03**	**0.02**	-0.03	**0.05**	**0.01**	**0.01**	-0.03	**0.04**
BDI	-0.3	**0.03**	-0.21	**0.03**	-0.14	**0.04**	-0.11	**0.04**
CRB	**0.13***	**0.06**	**0.052**	**0.05**	**0.07**	-0.02	**0.08***	**0.06**
MSCI	-0.36	-0.11	-0.17	-0.02	-0.22	-0.05	-0.09	**0.02**
SP500	-0.85	-0.38	-0.61	-0.27	-0.34	-0.14	-0.22	-0.1
VSP500	-0.03	**0.05**	-0.01	**0.05**	-0.01	**0.06**	**0.01**	**0.05**
EquityM	-0.17	-0.04	-0.04	**0.02**	-0.04	**0.04**	-0.02	**0.04**
VEquityM	-0.05	**0.04**	-0.01	**0.05**	-0.05	**0.04**	-0.01	**0.05**
ΔL	-0.1	**0.01**	-0.01	**0.05**	-0.07	**0.02**	**0.02***	**0.05**
ΔS	-0.1	-0.03	-0.04	**0.03**	-0.05	**0.01**	**0.01**	**0.05**
ΔC	-0.04	**0.03**	**0.012**	**0.05**	-0.01	**0.04**	**0.01**	**0.05**
POOL	-0.08	-0.01	-0.11	**0.02**	-0.01	**0.03**	-0.08	**0.04**
PCA	-0.41	-0.19	-0.26	-0.08	-0.08	-0.02	-0.24	-0.07
PLS	-1.09	-0.47	-0.95	-0.4	-0.18	-0.15	-0.93	-0.39
Panel F: AUD								
ΔVIX	-0.28	-0.16	-0.08	-0.02	**0.1**	**0.06**	-0.07	-0.01
ΔTED	**0.05**	**0.07***	**0.022**	**0.04**	**0.01**	**0.04**	**0.02**	**0.04**
GOLD	-0.13	-0.09	-0.05	-0.04	-0.06	-0.03	**0.01**	-0.01
OIL	-0.04	-0.11	-0.02	-0.05	-0.02	-0.08	-0.01	-0.03
BDI	-0.31	-0.13	-0.16	-0.04	-0.14	-0.07	-0.06	-0.01
CRB	-0.03	-0.03	-0.03	**0.02**	-0.15	-0.19	-0.02	-0.01
MSCI	-0.54	-0.31	-0.29	-0.17	-0.43	-0.24	-0.26	-0.16
SP500	-1.17	-0.7	-0.92	-0.56	-0.56	-0.34	-0.31	-0.24
VSP500	-0.03	**0.03**	**0.01*2**	**0.03**	-0.03	**0.03**	**0.01***	**0.03**
EquityM	-0.07	-0.03	-0.02	**0.02**	-0.28	-0.11	-0.03	**0.01**
VEquityM	-0.02	**0.02**	**0.01**2**	**0.03**	-0.01	**0.02**	**0.01****	**0.03**
ΔL	-0.12	**0.03**	-0.06	**0.04**	-0.02	**0.05**	-0.01	**0.04**
ΔS	**0.01**	**0.02**	-0.01	**0.03**	**0.02**	**0.02**	-0.01	**0.03**
ΔC	-0.02	**0.04**	-0.01	**0.03**	**0.02**	**0.05**	-0.01	**0.03**
POOL	-0.11	-0.08	-0.12	-0.04	-0.06	-0.04	-0.12	-0.02
PCA	-0.44	-0.27	-0.25	-0.14	-0.33	-0.26	-0.28	-0.16
PLS	-1.99	-1.17	-1.78	-1.05	-1.08	-0.77	-1.79	-1.05

Notes: See Table 3.3. The out-of-sample period begins in January 1st, 2009.

3.7 Conclusions

Forecasting exchange rates at a daily frequency can be a rigorous task due to the difficulty of capturing the dynamics of such volatile assets and due to the availability of a large number of potential predictors which are difficult to be chosen a priori. In this study we examine the forecasting ability of 14 financial predictors and three combination and dimensionality reduction techniques in the context of forecasting

daily exchange rate returns of six widely traded currencies. We propose a hybrid Iterated Combination with Constrained Predictors (ICCP) approach and further consider positivity constraints. Our proposed methods are compared with the simple RW model, the simple linear bivariate model and the two recently developed methodologies, the Iterated Combination and the Constrained Predictor proposed by Lin, Wu and Zhou (2017) and Pan, Pettenuzzo and Wang (2018), respectively. Lastly, we examine the impact of positivity constraints on the performance of each method.

Our results indicate that the proposed hybrid ICCP approach outperforms alternative methods in both the constrained and the unconstrained settings indicating that ICCP can be an important tool in daily FX return predictions. For all six currencies, ICCP shows higher forecasting ability in terms of R^2_{OOS} and MSFE_{adj}. Imposing positivity constraints enhances significantly the forecasting ability of all methods. Daily CHF and AUD returns prove the most difficult to predict. Yet, in the case of $C^{ICCP,+}$ 13 and 12 predictors have a positive R^2_{OOS} respectively, while this number falls to 12 and 8 respectively for the $C^{IC,+}$ and 10 and 7 respectively for $C^{CP,+}$. Finally, POOL generates consistently very good forecasts while we observe a poor performance by PLS and PCA. We also examine whether our forecasting approach deliver economic benefits and find that the economic evaluation supports the statistical results. Under the mean-variance framework we three measures of economic evaluations: the average utility, the Sharpe Ratio and the Cumulative Wealth. For robustness purposes we use two different levels of risk aversion. Our results indicate that the predictors generate economic meaningful results. The level of risk aversion have an impact of the values of the three evaluation measures, however the results and conclusions are similar for both levels. First, we observe that $C^{ICCP,+}$ and $C^{CP,+}$ outperform the remaining methods with the proposed hybrid method to deliver significant and consistent good results. Finally, we observe that PCA outperforms both POOL and PLS.

Finally, we perform a series of robustness tests including the change of the length of the control window, the frequency of the data and the out-of-sample period. Our

results hold over all the robustness checks, supporting the initial findings: 1) positivity constraints in the forecasts significantly improve the forecasting ability of all predictors and combination or dimensionality reduction methods for all approaches and 2) the proposed hybrid ICCP approach can actually deliver very consistent and robust forecasts.

Chapter 4

Forecasting Exchange Rate Realized Volatility; An Amalgamation Approach

4.1 Introduction

Forecasting volatility plays a central role in derivative pricing, developing trading strategies, pricing and trading volatility derivatives and hedging portfolios. A strand of the literature focuses on the potential financial and macroeconomic drivers of volatility. Early contributions focus mainly on stock market volatility and include Schwert (1989), Glosten, Jagganathan & Runkle (1993), Whitelaw (1994) and Brandt and Kang (2002). These studies find evidence of a significant link between mainly interest rate variables and future market volatility. More recent contributions, such as Paye (2012), Christiansen, Schmling & Schrimpf (2012), Conrad and Loch (2014), Mittnik, Robinzonov & Spindler (2015) and Nonejad (2017), employ a richer dataset of financial and macroeconomic variables and also focus on stock market volatility.

More in detail, Paye (2012) employs a variety of variables and finds an in-sample link between these variables and stock market volatility. However, out-of-sample improvements in forecasting accuracy mainly stem from simple combinations of in-

dividual forecasts. Christiansen, Schmling & Schrimpf (2012) focus on forecasting four different asset classes: equities, commodities, foreign exchange rates, and bonds by employing a comprehensive set of macro-finance variables. Employing Bayesian estimation techniques the authors find the strongest predictive ability in variables associated with time-varying risk premia, leverage or financial distress. Their Bayesian Model Averaging forecasting models beat autoregressive benchmarks although this performance varies across asset classes and over time. Conrad and Loch (2015) disentangle short- and long-term volatility via the GARCH-MIDAS[1] component model (Engle, Ghysel & Sohn 2013) and confirm the counter-cyclical behavior of stock market volatility for a broad set of macroeconomic variables. Long-term volatility is mainly driven by information related to the current state of the economy as well as to expectations regarding future macroeconomic conditions. Using boosting techniques, Mittnik, Robinzonov & Spindler (2015) substantially improve out-of-sample volatility forecasts for short- and longer-run horizons and confirm the nonlinear link between financial variables and future volatility. Finally, Nonejad (2017) employs a variety of Bayesian models and finds that Bayesian Model Averaging with time-varying regression coefficients provides superior density and point forecasts compared to traditional approaches.

Despite the fact that exchange rates is the most widely traded asset, little or no attention has been paid to the impact of financial and macroeconomic variables on future exchange rate volatility. It is this gap in the literature that we aim to fill in this study. We employ four widely traded currencies; the British Sterling, Japanese Yen, Swiss Franc and Euro along with an aggregate basket of exchange rates and calculate monthly realised volatility from daily exchange rate returns. Our set of candidate predictors contains 38 potential financial and macroeconomic predictors that have been typically employed in exchange rate/ stock market forecasting literature. First, we assess the in-sample ability of candidate predictors by employing simple autoregressive models augmented with one predictor at a time. Then, we focus on out-of-sample forecasting using a variety of machine learning[2], dimensionality reduc-

[1]For more recent apprach on MIDAS approaches see Foroni, Guérin and Marcellino (2018).

[2]Amat, Michalski and Stoltz (2018) argue in favor of machine learning methods that avoid

tion and forecast combination approaches. To avoid uncertainty associated with the employment of a specific predictor/ model, we propose forming amalgam/consensus forecasts by simply averaging forecasts generated by the aforementioned approaches.

Our in-sample findings suggest that exchange rate related variables, bond and liquidity related ones and macroeconomic variables improve volatility prediction in all currencies. Specifically, the exchange rate related variables are the carry trade factor and the average forward discount factor. With respect to the macroeconomic variables; the monthly inflation rate, the commodity index return and capacity utilisation appear to successfully anticipate volatility developments. Finally, liquidity and bond market developments are important as suggested by the significance of TED and long term bond returns. However, out-of-sample, no single candidate predictor can improve volatility forecasts in all the exchange rates considered. Machine learning techniques such as Lasso and Elastic Net along with combination of forecasts show superior forecasting ability and to a lesser extent dimensionality reduction approaches such as Partial Least Squares. More importantly, aggregating forecasts from all the forecasting approaches by simply taking an equally weighted (or trimmed) forecast enables us to achieve superior forecasting ability with a stable performance over time.

The remainder of the chapter is structured as follows. Section 2 describes the data and presents the in-sample analysis, while Section 3 presents the out-of-sample forecasting methodology. Section 4 discusses our out-of-sample empirical findings and Section 5 concludes the chapter.

4.2 Data and In-sample Analysis

The purpose of this chapter is to propose a new and simple technique against a more elaborate technique. We aim at pointing out the superiority of simplest techniques that capture different features of other model. For comparability, we use the same dataset and time period as Christiansen et al (2012). Our sample covers the

overfitting.

period extending from January 1986 to December 2010 ($T = 300$ observations). We consider four widely traded exchange rates; namely the British Sterling (GBP), the Japanese Yen (YEN), the Swiss Franc (CHF) and the eurozone common currency (EUR) against the US dollar.[3] Following Lustig, Roussanov & Verdelhan (2011) and Christiansen, Schmling & Schrimpf (2012), we also construct an aggregate basket of currencies (FXAggr.). Specifically, we form an equally weighted portfolio (from the perspective of a US investor) consisting of all currencies with available data at a given point in time. When data is not available, the currency is discarded and the average is calculated among the remaining.[4]

We compute a proxy of the realized variance as the sum of squared daily returns, $\sum_{i=1}^{n} r_i^2$, where r_i is the daily logarithmic return of the currency under examination and n is the number of trading days of each month. Following, among others, Paye (2012), Xiao, (2017) and Nonejad (2017), we define Realized Volatility (RV) to be the square root of the realized variance as follows:

$$RV_t = \sqrt{\sum_{i=1}^{n} r_i^2}, \quad t = 1, 2, .., T$$

where T is the whole sample period.

Table 4.1 shows summary statistics for the realized volatility series of the exchange rates employed. Average exchange realised volatility fluctuates between 9.26% (GBP) and 11.11% (CHF), while aggregate FX volatility is substantially lower at 6.32% consistent with portfolio diversification benefits arising from holding a basket of currencies. As expected, the standard deviation of aggregate FX volatility is substantially lower at 2.59 compared for example with YEN which exhibits the highest standard deviation at 3.81. All series are positively skewed and exhibit excess kurtosis. Surges in volatility can result in realised volatility levels ranging

[3]Prior to the EUR inception, the German mark is employed.

[4]The country exchange rates we consider are; Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine and UK.

from 18.15% (FXAggr) to 31.90% (YEN).

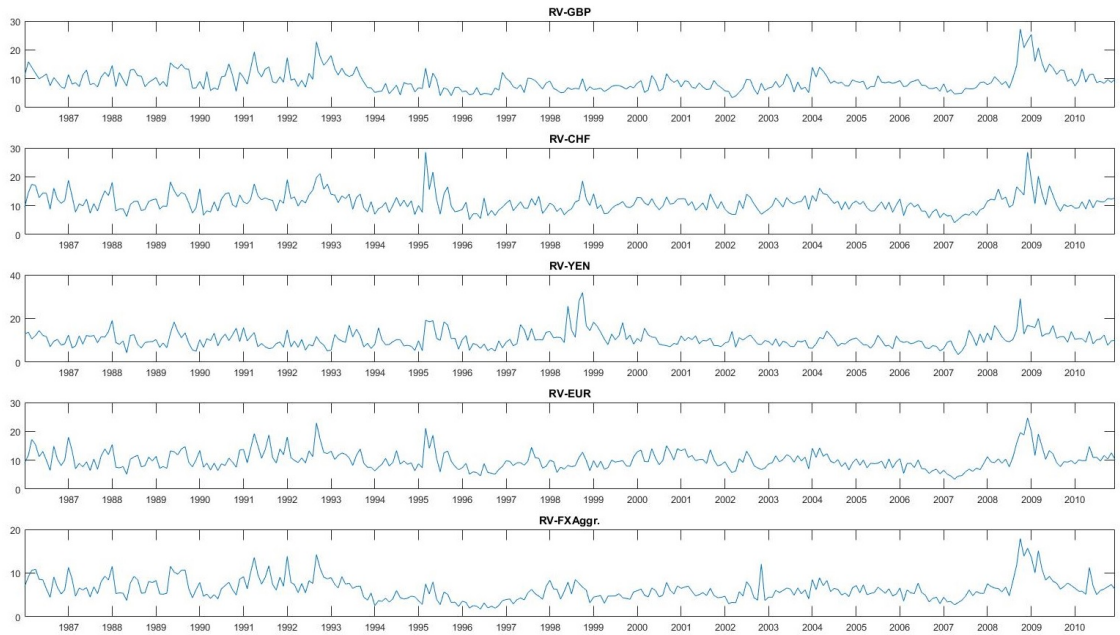
Table 4.1: Descriptive statistics of realized volatility

	MEAN	STD	SKEW	KURT	MAX	MIN
RV_{GBP}	9.26	3.67	1.71	7.43	27.23	3.43
RV_{CHF}	11.11	3.38	1.50	7.57	28.54	4.11
RV_{YEN}	10.51	3.81	1.81	9.03	31.90	3.46
RV_{EUR}	10.12	3.32	1.28	5.70	24.68	3.42
$RV_{FXAggr.}$	6.32	2.59	1.38	6.12	18.15	1.75

Note: The table reports summary statistics of GBP, CHF, YEN, EUR and Aggregate realized volatilities between January 1986 and December 2010. The realized volatilities for month t are calculated as the sum of n daily squared logarithmic returns within one month: $RV_t = \sqrt{\Sigma_{i=1}^{n} r_i^2}$ where $t = 1, 2, .., T$. Annualized and percentage values are reported.

Figure 4.1 plots the evolution of realised volatility for the currencies under investigation. Overall, we observe that all currencies behave very similarly qualitatively as calm periods alternate with turbulent ones. Turbulent periods include the collapse of Exchange Rate Mechanism (1992-1993), the Asian financial crisis (1997), the Russian financial crisis (1998), and the recent financial turmoil (2008 -2010).

Figure 4.1: Historical realized volatility of the 4 currencies and the FX Aggregate



4.2.1 Candidate Predictors

We are interested in identifying financial and macroeconomic drivers of volatility in exchange rate markets. Our dataset is presented in Table 2 and briefly described below.

First, we consider predictors associated with equity market developments. We employ the Dividend Price ratio (D-P) and the Earnings Price ratio (E-P) calculated as the 12-month moving sum relative to current S&P500 prices. We also employ the Fama French factors, i.e. the US stock market excess returns (MKT), the size (SMB), value (HML) and short-term reversal (STR) factors. Finally, we use the S&P turnover (TURN) to reveal uncertainty on the equity market (see Baker and Wurgler, 2007) and the world stock market MSCI index return (see Christiansen, Schmling & Schrimpf, 2012) to capture global stock market developments.

Second, we employ interest rates, spreads and bond market factors. Specifically, we employ the 3-month US Treasury Bill rate (T-B), the relative treasury bill (RTB) calculated as the difference of T-B from its 12-month moving average and the long term US bond return (LTR) along with its deviation from its 12-month average (RBR). Our set of bond market variables also includes the term spread (TS) calculated as the difference between the 3-month LIBOR rate (US dollar base) and the 3-month Treasury Bill rate (Campbell and Shiller, 1991) and the Cochrane Piazzesi Factor (C-P), which is based on the term structure of forward rates (Cochrane and Piazzesi, 2005).

Third, we consider three foreign exchange specific forecasting variables. These are the average forward discount (AFD), which measures interest rate differentials vis à vis the US for a broad range of currencies, the dollar risk factor (DOL) and a carry trade factor (HMLFX) from Lustig, Roussanov & Verdelhan (2011)[5].

Fourth, we consider liquidity and credit risk factors. The first factor is the default spread (DEF) that proxies for credit risk and is calculated as the yield spread between BAA and AAA rated bonds. We also include a common measure of funding

[5]Also see the most recent approaches for common factors in exchange rates by Greenwaway-McGrevy, Mark, Sul and Wu (2017) and Verdelhan (2018).

(il)liquidity in interbank markets (Brunnermeier, Nagel & Pedersen, 2009), the TED spread, which is the difference between the three month LIBOR rate and the T-Bill rate. To proxy for FX and stock market (il)liquidity, we also consider an aggregate measure of bid–ask spreads (BAS) in foreign exchange markets (Menkhoff, Sarno, Schmeling & Schrimpf, 2012) and the liquidity measure of Pastor and Stambaugh (2003) Factor (PS).

Finally, turning to macroeconomic variables, our dataset includes the annual and monthly US inflation growth rate (INFA and INFM, respectively), the annual and monthly US industrial production growth rate (IPGA and IPM, respectively), the monthly change in Housing Starts (H-S), the monthly and annual changes in the new orders of goods and materials (ORDM and ORDA), and the annual and monthly money supply growth rate (M1A and M1M, respectively). Since commodity prices play an instrumental role to economic activity, we also consider the annual growth difference of the Commodity Research Bureau index (CRB). Finally, we also employ a series of useful US economy indicators, such as the Capacity Utilization (CAP), Employment Growth (EMPL), Consumer Sentiment (SENT), Consumer Confidence (CONF), Diffusion Index (DIFF), Purchasing Manager Index (PMI) and the Chicago Business Barometer (PMBB).

Table 4.2: Candidate predictors and sources

No	Variable	Abbrev.	Source and Construction
Panel A: Equity Market Variables and Risk Factors			
1	Divident Price Ratio	D-P	Dividends over the past year (12-month moving sum) relative to current market prices (in logs) applied in S&P 500; Robert Shiller's website
2	Earnings Price Ratio	E-P	Earnings over the past year (12-month moving sum) relative to current market prices (in logs) applied in S&P 500; Robert Shiller's website
3	US Market Excess Return	MKT	Fama-French's market factor. U.S. stock market return minus one-month T-Bill rate; Kenneth French's website
4	Size Factor	SMB	Fama-French's size factor. Return on small stocks minus return on big stocks; Kenneth French's website
5	Value Factor	HML	Fama-French's value factor. Return on value stocks minus return on growth stocks; Kenneth French's website
6	Short Term Reversal Factor	STR	Fama-French's short term reversal factor. Return on stocks that demonstrated low prior one-month return minus return on stock with high prior return; Kenneth French's website
7	S&P 500 Turnover	TURN	Turnover of the S&P 500
8	MSCI Return	MSCI	Return on the MSCI world stock market index; Datastream
Panel B: Interest rates, Spreads and Bond Market Factors			
9	T-Bill rate	T-B	Three-month T-Bill rate; Goyal/Welch dataset and Datastream
10	Relative T-Bill rate	RTB	T-Bill rate minus its 12 month moving average; Goyal/Welch dataset and Datastream
11	Long Term Bond Return	LTR	Rate of return on long term government bonds; Goyal/Welch data and Datastream
12	Relative Bond Rate	RBR	Long-term bond yield minus its 12 month moving average; Goyal/Welch data and Datastream
13	Term Spread	T-S	Difference of long-term bond yield and three-month T-Bill rate; Goyal/Welch data and Datastream
14	Cochrane Piazzesi Factor	C-P	Measure of bond risk premia; recursively estimated based on Fama-Bliss data; CRSP
Panel C: FX variables and Risk Factors			
15	Dollar Risk Factor	DOL	FX risk premium measure; Average premium for bearing FX risk; BBI/Reuters (Datastream)
16	Carry Trade Factor	HMLFX	Return on high interest rate currencies minus return on low interest rate currencies; BBI/Reuters (Datastream), construction Christiansen et al (2012)
17	Average Forward Discount	AFD	Aggregate predictor of FX returns calculated from forward rates and spot rates; BBI/Reuters FX data, Datastream, construction Christiansen, Schmeling & Schrimpf (2012)

No	Variable	Abbrev.	Source and Construction
Panel D: Liquidity and Credit Risk Variables			
18	Default Spread	DEF	Measure of default risk of corporate bonds; difference of BAA and AAA bond yields; Goyal-Welch Data and Datastream
19	FX Average Bid-ask Spread	BAS	Measure of illiquidity in the foreign exchange market calculated from quoted bid-ask spreads; BBI/Reuters (Datastream), construction Christiansen, Schmeling & Schrimpf (2012)
20	Pastor-Stambaugh Liquidity Factor	PS	Measure of stock market liquidity based on price reversals; CRSP
21	TED Spread	TED	Measure of funding Illiquidity, difference of 3 Month Libor rate minus 3 month T-Bill rate; Datastream
Panel E: Macroeconomic Variables			
22	Inflation Rate, MoM	INFM	Month-over month (log) growth rate of the U.S. consumer price index; Datastream
23	Inflation Rate, YoY	INFA	Year-over year (log) growth rate of the U.S. consumer price index; Datastream
24	Industrial Production Growth, Monthly	IPM	Monthly (log) growth rate of U.S. industrial production; Datastream
25	Industrial Production Growth, YoY	IPGA	Year-over year (log) growth rate of U.S. industrial production; Datastream
26	Housing Starts	H-S	Monthly change in housing started; Datastream
27	M1 Growth, Monthly	M1M	Monthly (log) growth rate of U.S. M1; Datastream
28	M1 Growth, YoY	M1A	Year-over-year (log) growth rate of U.S. M1; Datastream
29	Orders, Monthly	ORDM	New orders of consumer goods and materials; Year-over year (log) growth rate, Datastream
30	Orders, YoY	ORDA	New orders of consumer goods and materials; Monthly (log) growth rate, Datastream
31	Return CRB	CRB	Measure of growth in commodity prices; annual log difference of CRB spot index; Datastream
32	Capacity Utilization	CAP	Datastream
33	Employment Growth	EMPL	Datastream
34	Consumer Sentiment	SENT	Monthly change in University of Michigan consumer sentiment; Datastream
35	Consumer Confidence	CONF	Monthly change in consumer confidence index; Datastream
36	Diffusion Index	DIFF	Philadelphia Fed Business Outlook Survey Diffusion Index, Datastream
37	Chicago PM Business Barometer	PMBB	Datastream
38	ISM PMI	PMI	Monthly change in purchasing manager index; Datastream

Notes: The Table presents the candidate predictors used in this study along with the abbreviations and the construction processes.

4.2.2 In-sample Predictive Ability

We first focus on the in-sample predictive ability of candidate predictors. Since volatility is quite persistent (see, among others, Müller, Dacorogna, Davé, Olsen, Pictet & von Weizsäcker, 1997; Chernov, 2007 and Corsi, 2009) we consider an AR(p) model augmented with one of the candidate predictors. In this respect, the predictive regression is given by the following regression:

$$RV_t = b_0 + \sum_{i=1}^{p} b_{1,i} RV_{t-i} + b_{2,j} x_{j,t-1} + \eta_t,\ j = 1, .., 38 \tag{4.1}$$

where RV_t is the realised volatility in each of the exchange rate markets considered, $b_{1,i}$ and $b_{2,j}$ are the slope coefficients for the autoregressive process and the candidate predictor x_j, respectively and $\eta_{j,t}$ is the error term. We set the maximum number of lags (p) equal to six and select the optimal one by minimising the Schwartz Information Criterion (SIC). The null hypothesis of no predictive ability for predictor j is $H_0 : \hat{b}_{2,j} = 0$ and the alternative is $H_1 : \hat{b}_{2,j} \neq 0$. We compute the Newey-West standard errors in order to take into account biases due to heteroscedasticity and persistence in the series.

Our in-sample estimates for each predictive variable are reported in Table 3. Our findings suggest that CHF volatility is more persistent than the other currencies as SIC selects an AR(3) model compared to an AR(2) one for the remaining series. Overall, we identify a set of predictors that are important drivers of future realised volatility in all currencies. This set mainly includes exchange rate related variables, bond and liquidity related ones and macroeconomic variables. Specifically, the exchange related variables are the carry trade factor (HMLFX) and the average forward discount factor (AFD). With respect to the macroeconomic variables, the monthly inflation rate, the commodity index return and capacity utilisation appear to successfully anticipate volatility developments. Finally, liquidity and bond market developments are important as suggested by the significance of TED and LTR. Overall, CHF volatility is the hardest to predict as only 13 (out of 38) predictors appear useful as opposed to 24 (out of 38) for EUR volatility, followed by 22 for

FXAggr.

More in detail, equity market related variables appear weak in capturing future volatility developments as only D-P, STR and MSCI are significant in four, one and three cases, respectively. On the other hand, interest rate related variables contribute significantly. With the exception of T-B and C-P, all other variables considered improve predictability in four or more cases. For example, the term spread is positive and significant in all cases, but CHF. Turning to FX related variables, the carry trade factor is negative and significant in all series under consideration suggesting that increases in the factor point to future volatility reductions, while the opposite is true for AFD. Similarly, increases in DEF, BAS and TED variables are associated with future FX volatility increases in all but CHF, CHF and YEN and all currencies, respectively. The effect of PS is negative and significant in all but CHF and YEN. Finally, improvements in the macroeconomic environment are in general associated with further volatility reductions. For example, industrial production increases, inflation increases, money supply decreases, housing starts increases, order increases, employment increases, capacity utilisation increases are all linked to future volatility dissipation. Quite interestingly, indicators like SENT, CONF, DIFF, PMBB and PMI do not show a substantial link with future volatility developments.

Table 4.3: In-Sample estimates

Predictor	GBP	CHF	YEN	EUR	FXAggr.
Panel A: Equity Market Variables and Risk Factors					
D-P	0.0050***	0.0002	0.0050***	0.0035**	0.0032***
E-P	0.0002	-0.0019	-0.0001	-0.0005	0.0003
MKT	-0.0209	-0.0206	-0.0093	-0.0195	-0.0121
SMB	-0.0078	-0.0225	-0.0080	-0.0107	-0.0089
HML	0.0031	-0.0058	-0.0143	0.0029	-0.0026
STR	-0.0163	-0.0187	-0.0249	-0.0242*	-0.0148
TURN	0.0029	0.0033	0.0001	0.0019	0.0038
MSCI	-0.0336**	-0.0300*	-0.0186	-0.0262**	-0.0157
Panel B: Interest rates, Spreads and Bond Market Factors					
T-B	-0.0162	-0.0022	-0.0119	-0.0150	-0.0045
RTB	-0.0918	-0.0515	-0.1238*	-0.1329**	-0.0729*
LTR	0.0405***	0.0549***	0.0720***	0.0650***	0.0239**
RBR	-0.0719	-0.1685**	-0.2877***	-0.2439**	-0.1141*
T-S	0.0819**	-0.0332	0.1024***	0.0916**	0.0448*
C-P	-0.0001	-0.0008**	0.0003	0.0002	0.0001
Panel C: FX variables and Risk Factors					
DOL	-0.0005	-0.0004	0.0002	-0.0001	-0.0003
HMLFX	-0.0007**	-0.0009***	-0.0007***	-0.0007***	-0.0004**
AFD	0.0058**	0.0057**	0.0109***	0.0093***	0.0058***
Panel D: Liquidity and Credit Risk Variables					
DEF	0.5930***	0.2133	0.4346**	0.4853***	0.4585***
BAS	-0.0097	0.0746***	0.0235**	0.0144	-0.0012
PS	-0.0137**	-0.0119	-0.0109	-0.0139**	-0.0112**
TED	0.5535***	0.5085**	0.3240**	0.3685***	0.3569***
Panel E: Macroeconomic Variables					
INFM	-0.4810***	-0.3401**	-0.6056**	-0.7203***	-0.3798***
INFA	0.0873**	-0.0242	0.0191	0.0566	0.0626**
IPM	-0.3603**	-0.2892	-0.3017***	-0.3346***	-0.2771***
IPGA	-0.0368**	-0.0099	-0.0220	-0.0315**	-0.0268**
H-S	-0.0076***	-0.0038	-0.0043	-0.0056**	-0.0057***
M1M	0.3045***	0.0508	0.2821***	0.2808***	0.1712**
M1A	0.0333***	-0.0016	0.0388***	0.0302***	0.0233***
ORDM	-0.0599*	-0.0268	-0.0543*	-0.0603*	-0.0399*
ORDA	-0.0204*	-0.0134	-0.0079	-0.0169*	-0.0130*
CRB	-0.0613**	-0.0468*	-0.0573***	-0.0768***	-0.0513***
CAP	-0.3050**	-0.3453**	-0.2795***	-0.3048***	-0.2346**
EMPL	-0.9520**	-0.4037	-0.8686**	-1.0093***	-0.6824***
SENT	0.0080	-0.0081	-0.0129	-0.0091	-0.0065
CONF	-0.0034	-0.011*	-0.0065	-0.0052	-0.0038
DIFF	-0.0001	-0.0002***	-0.0001	-0.0001*	-0.0001
PMBB	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
PMI	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002

Notes: The Table illustrates the in-sample performance of the predictors under consideration for each currency. We repoort only the coefficients of the financial and macroeconomic predictors coefficients and the level of statistical significance according to the heteroscesasticity-consistent t-statistic. The asterisks "*", "**"' and "***" indicate the level of significance at 10%, 5% and 1%, respectively. The bivariate regression model is given by $RV_t = b_{0j} + \sum_{i=1}^{p} b_{1,i} RV_{t-i} + b_{2,j} x_{j,t-1} + e_t$, where $j = 1, .., 38$; $RV_{i,t}$ is the Realized Volatility and $x_{j,t}$ is the individual predictor. The BIC criterion selects two lags from the autoregressive term for GBP, YEN, EUR and FX Aggregate and three lags for CHF.

4.3 Forecast Construction and Evaluation

In this section, we describe the forecasting approaches we follow, which include machine learning, dimensionality reduction and forecast combination methodologies that take into account a large number of predictors. The majority of these methods have already been applied in the forecasting literature in different types of assets with relative success.

One step ahead forecasts are generated by continuously updating the estimation window, i.e. following a recursive (expanding) window. More in detail, we divide the total sample of T observations into an in-sample portion of the first R observations and an out-of-sample portion of $P = T - R$ observations used for forecasting. The observations of the first seven years are used as our in-sample period, i.e. $R = 85$ observations and the remaining $P = 215$ monthly observations form the out-of-sample period. The total sample period initiates in January 1986 and expands until December 2010, while the out-of-sample period starts in February 1993.

4.3.1 Univariate Models

Our benchmark forecasting model is the AR(p) model with lags selected using SIC up to a maximum of six lags. This is given by the following equation:

$$RV_t = b_0 + \sum_{i=1}^{p} b_{1,i} RV_{t-i} + e_t \tag{4.2}$$

where RV_t is the realised volatility, RV_{t-p} are the AR(p) terms and e_t the error term. The forecasts generated from the autoregressive benchmark model are given as follows:

$$\hat{f}_t^{(AR(p))} = \hat{b}_0 + \sum_{i=1}^{p} \hat{b}_{1,i} RV_{t-i} \tag{4.3}$$

We assess the predictive ability of each of the candidate predictors by augmenting the benchmark model with one predictor at a time, i.e. we estimate the following model:

$$RV_t = b_{0j} + \sum_{i=1}^{p} b_{1,i} RV_{t-i} + b_{2,j} x_{j,t-1} + e_t,\ j = 1, .., 38 \tag{4.4}$$

where $x_{j,t}$ is the candidate predictor. Forecasts are generated as follows:

$$\hat{f}_{j,t} = \hat{b}_{0j} + \sum_{i=1}^{p} \hat{b}_{1,i} RV_{t-i} + \hat{b}_{2,j} x_{j,t-1} \tag{4.5}$$

Similar to our in-sample experiment, we set the maximum number of lags (p) equal to six and select the optimal one by minimising SIC.

4.3.2 Kitchen-Sink Regression

Following Goyal and Welch (2008) and Li, Tsiakas & Wang (2015), among others, we evaluate the predictive power of a kitchen-sink (KS) regression that takes all predictors under consideration simultaneously. Forecasts formed on the basis of this simple linear multivariate regression are as follows:

$$\hat{f}_t^{(KS)} = \hat{b}_{0j} + \sum_{i=1}^{p} \hat{b}_{1,i} RV_{t-i} + \sum_{j=1}^{N} \hat{b}_{2,j} x_{j,t-1} \tag{4.6}$$

where $x_{j,t}$ are the $N = 38$ candidate predictors. The KS model suffers from in-sample overfitting, with ambiguous out-of-sample forecasting ability. To this end, we employ the following techniques that aim to efficiently summarise the information content in a large set of candidate predictors.

4.3.3 Machine Learning Techniques

4.3.3.1 Lasso

A quite common machine learning method is the Lasso estimation (Least absolute shrinkage and selection operator) introduced by Tibshirani (1996). Lasso is a linear regularization technique, extensively employed in experiments using high dimensional datasets. This method performs shrinkage to the estimates by penalizing the related coefficients via the L_1 penalty function. Specifically, coefficient estimates

are obtained by solving the following minimisation problem:

$$\min_{b_{2,j}} \left(\frac{1}{2} \sum_{t=1}^{T} \left(RV_t - b_0 - \sum_{i=1}^{p} b_{1,i} RV_{t-i} - \sum_{j=1}^{N} b_{2,j} x_{j,t-1} \right)^2 + \lambda_1 \sum_{j=1}^{N} |b_{2,j}| \right)$$

where RV_t is the realised volatility at time t, $x_{j,t}$ are the candidate predictors, N is the number of predictors and λ_1 is a positive regularization parameter. As the value of λ_1 increases so does the number of coefficients that shrink to zero resulting in a more parsimonious model. We use several estimates for λ_1 ranging from 0.01 to 100 by 0.04 intervals and then select the one according to the minimum SIC.

4.3.3.2 Ridge

Ridge regression was proposed by Hoerl and Kennard (1970) and performs shrinkage to the parameters via the L_2 penalty term. By construction, Ridge does not allow for parameter exclusion, like Lasso does, since parameters cannot approach zero. The model is estimated by minimizing the following objective function:

$$\min_{b_{2,j}} \left(\frac{1}{2} \sum_{t=1}^{T} \left(RV_t - b_0 - \sum_{i=1}^{p} b_{1,i} RV_{t-i} - \sum_{j=1}^{N} b_{2,j} x_{j,t-1} \right)^2 + \lambda_2 \sum_{j=1}^{N} b_{2,j}^2 \right)$$

where λ_2 is the ridge regularisation parameter. The estimator is biased but manages to reduce the variance of the estimates. As previously, we use several potential values for λ_2 and then select the one that corresponds to the minimum SIC.

4.3.3.3 Elastic Net

The Elastic Net (EN) regression, proposed by Zou and Hastie (2005), combines both Ridge and Lasso as it uses both L_1 and L_2 penalty terms in order to perform both model selection and shrinkage. The model is estimated by minimizing the

following objective function:

$$\min_{b_{2,j}} \left(\frac{1}{2} \sum_{t=1}^{T} \left(RV_t - b_0 - \sum_{i=1}^{p} b_{1,i} RV_{t-i} - \sum_{j=1}^{N} b_{2,j} x_{j,t-1} \right)^2 + \lambda_1 \sum_{j=1}^{N} |b_{2,j}| + \lambda_2 \sum_{j=1}^{N} b_{2,j}^2 \right)$$

where λ_1, λ_2 are the regularisation parameters. Apparently, setting $\lambda_2 = 0$ we get the Lasso estimator while for $\lambda_1 = 0$ we get the Ridge estimator.

4.3.3.4 Neural Networks

Neural Networks (NN) have recently attracted attention in forecasting applications (see, for example, Sermpinis, Theofilatos, Karathanasopoulos, Georgopoulos & Dunis, 2013; and Qi and Wu, 2003). The architecture of the proposed NN consists of three layers. In the first layer the inputs (candidate predictors) are introduced, the middle layer is the hidden layer consisting of neurons (hidden units) while the final layer is the output layer. The NN is trained by minimising the mean squared error loss function (i.e. the squared difference of the actual and the forecast value). We found that only one hidden unit and the Bayesian Regularization (BR) algorithm that pushes non-relevant weights to zero in order to avoid overfitting is enough in order to forecast the realised volatility. Furthermore, to avoid the loss function to be trapped in local minima, we repeat the training 50 times with different random initial parameters and use the median value. We split the in-sample period into two subsets; the first is used for training while the second one is the validation set.

4.3.3.5 Support Vector Regression

A method that has been broadly used in forecasting processes (see among others Ince and Trafalis 2007; Lu, Lee & Chiu, 2009; Sermpinis, Stasinakis, Theofilatos & Karathanasopoulos, 2015; Plakandaras, Papadimitriou, & Gogas, 2015; Fan, Pan, Li & Li, 2016) is Support Vector Regression (SVR). SVR can be considered as a regression problem which has as a main objective the determination of a function $f(x)$ that can provide accurate forecasts on a targeted value. The main advantage of this technique is its ability to generate nonlinear decision boundaries through

linear classifiers, while having a simple geometric interpretation. Additionally, the solution is global and unique and does not suffer from multiple local minima, such as the solution of NNs. In this respect, SVR can balance between model accuracy and complexity and show a remarkable forecasting ability.[6]

4.3.4 Dimensionality Reduction Techniques

4.3.4.1 Principal Component Analysis

A successful and widely used dimension reduction technique is Principal Components Analysis (PCA) (see Dunis, Kellard & Snaith, 2013; Neely, Rapach, Tu & Zhou, 2014). Employing PCA, the large set of candidate predictors (x_j, $j = 1, .., 38$) are transformed into new uncorrelated latent factors $\hat{F}_t = (\hat{F}_{1,t}, .., \hat{F}_{N,t})$ that are able to capture maximum variability. The generated principal components filter big datasets from noise and reduce the hazard of over-fitting. By construction, the first principal component aggregates most information, followed by the second, etc. We estimate the following model (via OLS) and select among the first 4 principal components according to SIC:

$$RV_t = b_0 + \sum_{i=1}^{p} b_{1,i} RV_{t-i} + \sum_{k=1}^{K} b_{2,k} \hat{F}_{k,t-1} + e_t, : K = 1, .., 4 \tag{4.7}$$

4.3.4.2 Independent Component Analysis

Independent Component Analysis (ICA), proposed by Jutten and Herault (1991), is a recent method for isolating different types of mixed signals without knowing the mixing mechanism (see for example, Lu, Lee & Chiu, 2009). Similar to PCA, ICA creates components that maximise the independence rather than the variance. The components are mutually statistically independent. Once the independent components $\hat{G}_t = (\hat{G}_{1,t}, .., \hat{G}_{N,t})$ are obtained, we estimate the following model via OLS selecting among the first 4 independent components according to SIC:[7]

[6] Please refer to the Appendix for a detailed analysis of SVRs.
[7] Please refer to the Appendix for a detailed analysis of ICA.

$$RV_t = b_0 + \sum_{i=1}^{p} b_{1,i} RV_{t-i} + \sum_{k=1}^{K} b_{2,k} \hat{G}_{k,t-1} + e_t, : K = 1, .., 4 \tag{4.8}$$

4.3.4.3 Partial Least Squares

Partial Least Squares (PLS), introduced by Wold (1966), is linked with both PCA and multiple linear regression. This technique aims at condensing a large set of variables/predictors into a small set of factors, while simultaneously maximizing the covariance with the dependent variable, RV in our case. It is superior to simple Kitchen-Sink regression, due to the fact that it protects from over-fitting and provides more stable forecasts over time. While PCA-generated components aim at capturing the variability of the predictors, PLS-extracted orthogonal components take into account the covariance of the predictors with the target variable. Kelly and Pruitt (2013, 2015) were the first to apply a generalized version of PLS, the three-pass regression filter, in finance followed by Stivers (2018). We follow Stivers (2018) and apply the de Jong (1993) SIMPLS algorithm (detailed in the Appendix) to extract one target relevant factor from the set of potential predictors. The forecasting regression is given by:

$$RV_t = b_0 + \sum_{i=1}^{p} b_{1,i} RV_{t-i} + b_2 z_{t-1} + e_t \tag{4.9}$$

where b_2 is the PLS regression coefficient and z_t is the target factor.

4.3.5 Combination Forecasts

An efficient way to reduce the uncertainty associated with a single candidate predictor is to combine the respective individual forecasts. Bates and Granger (1969) claim that model combination can outperform individual predictors if the latter are not perfectly correlated. Forecast combination methods have been used in several forecast experiments (see, for example, Timmermann, 2006; De Zwart, Markwat, Swinkels and van Dijk, 2009; Rapach, Strauss & Zhou, 2010; Beckmann and Schüssler, 2016; Li and Tsiakas, 2017) with relative success despite their simplicity.

The concept behind this method is that the forecaster pools forecasts rather than pooling information. In this study, we consider mean, trimmed mean and median forecast combination schemes. Specifically, the mean (equally weighted) combination scheme attaches equal weight to all j forecasts generated by the univariate models given by Equation (4.5). In this respect, the mean combination forecast, $\hat{f}_t^{(POOL)}$, is given as follows:

$$\hat{f}_{t+1}^{(POOL)} = \sum_{j=1}^{N} \frac{1}{N} \hat{f}_{j,t+1} \tag{4.10}$$

We also consider two versions of Trimmed mean (TRIM) combination forecasts by discarding the 10% and 30% higher and lower forecasts (recently, Crespo Cuaresma, Fortin and Hlouskova 2018; Jordan, Vivian and Wohar, 2017; Constantini and Pappalardo, 2010), so that excluded forecasts are equal to $k = [3, 10]$. In this way, we exclude the extreme values that might have a severe impact on $POOL$. We also employ the simple average of the trimmed vector of individual forecasts, so that:

$$\hat{f}_{t+1}^{(TRIM,k)} = \sum_{j=k+1}^{N-k} \frac{1}{N-k} \hat{f}_{j,t+1} \tag{4.11}$$

where $\hat{f}_{k+1:N-k,t+1}$ is the column vector of the sorted returns that takes into account the $k+1$ element up to $N-k$ one of the vector.

Finally, we employ the median combination scheme (see Jordan, Vivian and Wohar, 2017). In this case, each element of the row of the vector of forecasts is the median of the column vector of the individual forecasts, i.e.

$$\hat{f}_{t+1}^{(MEDIAN)} = median[\hat{f}_{j,t+1}]$$

where $\hat{f}_{j,t+1}$ is the matrix containing the entire set of forecasts for the individual predictors $j = 1, .., 38$.

4.3.6 Amalgam Forecasts

Following, among others, Rapach and Strauss (2012), Meligkotsidou, Panopoulou, Vrontos & Vrontos (2014) and Li and Tsiakas (2017), we construct an amalgamation of forecasts. Pooling information by combining the forecasts generated by different forecast models is also expected to improve the forecast experiment. The new 'grand' forecast is generated by the entire set of machine learning, dimension reduction and combination forecasts, as described above. Hence, the amalgam forecast is formed as an equally weighted average of the elements of the following vector $\hat{\mathbf{f}}_{t+1} = \left[\hat{f}_{t+1}^{(POOL)} \hat{f}_{t+1}^{(MEDIAN)} \hat{f}_{t+1}^{(TRIM,3)} \hat{f}_{t+1}^{(TRIM,10)} \hat{f}_{t+1}^{(PCA)} \hat{f}_{t+1}^{(L)} \hat{f}_{t+1}^{(R)} \hat{f}_{t+1}^{(EN)} \hat{f}_{t+1}^{(ICA)} \hat{f}_{t+1}^{(PLS)} \hat{f}_{t+1}^{(NN)} \hat{f}_{t+1}^{(SVR)}\right]$:

$$\hat{f}_{t+1}^{(AMALG)} = \frac{1}{N} \sum_{n=1}^{N=12} \hat{\mathbf{f}}_{t+1}(n) \tag{4.12}$$

We also create three additional amalgam specifications, by trimming the 1,2 and 3 top and bottom forecasts at each point of the out-of-sample period and averaging the remaining forecasts. We denote these as AMTR1, AMTR2 and AMTR3, respectively.

4.3.7 Perfect Insight Forecasts

Finally, in order to get an understanding of the level of predictability we can attain, we also create a forecast by selecting the individual predictors that demonstrate lower MSFE values than the benchmark. We equally weight the forecasts produced by equation (4.4) and these predictors and generate the perfect insight forecast.

4.3.8 Forecast Evaluation

In this section we outline the forecast evaluation methodology we employ. Our benchmark model forecasts are the ones generated by equation (4.2), i.e. the AR(p) model. We use the Campbell and Thompson (2008) out-of-sample R^2 metric, denoted as R^2_{OOS}, in order to measure the performance of the candidate models/

specifications (h) relative to the benchmark, which is given by:

$$R^2_{oos} = 1 - \frac{MSFE_h}{MSFE_{AR(p)}}$$

R^2_{OOS} measures the proportional reduction in the Mean Square Forecast Error (MSFE) of model h against the MSFE of the benchmark. A positive R^2_{OOS} value means that the competing model outperforms the benchmark by providing better forecasts.

We assess the statistical significance of superior forecasting performance by the MSFE-adjusted metric proposed by Clark and West (2007). This test is computed as:

$$\begin{aligned} MSFE - adjusted = (\frac{1}{P})\{ \sum_{t=M+1}^{T-1} \{(\Delta s_{t+1} - \Delta \hat{s}^{(RW)}_{t+1})^2 \\ -[(\Delta s_{t+1} - \Delta \hat{s}^{(q)}_{t+1})^2 - (\Delta \hat{s}^{(RW)}_{t+1} - \Delta \hat{s}^{(q)}_{t+1})^2]\}\} \end{aligned} \tag{4.13}$$

where P is the number of out-of-sample observations ($P = 215$), T is the number of the total sample ($T = 300$), RV_{t+1} is the actual realized volatility, $\hat{f}^{(AR(p))}_{t+1}$ is the forecast realized volatility as computed by equation (4.3) and $\hat{f}^{(h)}_{t+1}$ is the forecast of realized volatility by the h-th candidate model/ specification. Equation (4.13) is composed of two segments, the first one is the $MSFE$ of the parsimonious model and the second one is the sum of the $MSFE$ of the large model and the average squared difference between the forecasts of the parsimonious model and the competing one. The Clark and West test is an one-sided test and the null (H_0) is given by $MSFE_{AR(p)} \leq MSFE_h$ against the alternative $(H_1) : MSFE_{AR(p)} > MSFE_h$. The test can be fairly well approximated by the critical values of the standard normal distribution.

4.4 Out-of-sample Findings

In this section we present our out-of-sample empirical findings. We first focus on the static performance of predictors/ specifications as depicted in R^2_{OOS} and then

we examine the dynamic evolution of this performance. Our aim is not only to identify the models with superior forecasting ability, but also the ones that exhibit this ability persistently over time.

4.4.1 Static Out-of-Sample Performance

Table 4.4 reports the out-of-sample forecasting performance of all models/ specifications with the exception of amalgam approaches that are reported in Table 5. Comparing the simple AR(1) process with the AR(p) one, as described in equation (4.3), we show that the chosen benchmark is significantly tougher than the AR(1) model with the exception of EUR. Benefits range from 0.16% to 6.92% as suggested by the values of R^2_{OOS}. Next, we focus on the forecasting ability of the individual candidate predictors. Table 4.4 (Panel A) reports the respective results. As expected, we observe that overall the out-of-sample forecasting ability of individual predictors is not in line with the in-sample findings. More importantly, there is no single predictor that can provide positive and statistically significant R^2_{OOS} for all the exchange rates considered. Contrary to our in-sample findings, YEN is the most difficult exchange rate to forecast (7 out of 38 significant R^2_{OOS}) followed by CHF (10 out of 38), GBP and EUR (11 out of 38). Interestingly, FXAggr. emerges as the easiest series to forecast with 13 out of 38 predictors generating more accurate forecasts than the benchmark.[8]

[8]Please note that in two occasions, negative R^2_{OOS} are statistically significant on the basis of the MSFE-adjusted test (Clark and West, 2007). This occurs because the CW test tests for equal performance in the population, while R^2_{OOS} embodies the performance in a finite sample (see also Li and Tsiakas, 2017).

Table 4.4: Out-of-sample performance: Individual predictors

Predictor	GBP	CHF	YEN	EUR	FXAggr.
AR(p) vs AR(1)	**6.92*** **	**2.73** **	**0.16***	-1.00	**2.21***
Panel A: Equity Market Variables and Risk Factors					
D-P	**1.26*** **	**2.03*** **	-3.16	**0.45*** **	**2.21*** **
E-P	-2.00	-2.48	-0.73	-2.77	-1.32
MKT	-0.40	-0.82	-1.30	-0.94	-2.09
SMB	-0.45	-0.49	-1.57	-0.15	**0.26***
HML	-2.59	-1.38	-1.86	-1.73	-2.63
STR	-1.16	**1.10**	**0.53** **	**0.02**	-0.94
TURN	-1.42	-0.23	-0.43	**0.16**	-0.97
MSCI	**0.21**	-0.05	-0.94	-0.22	-1.02
Panel B: Interest rates, Spreads and Bond Market Factors					
T-B	-3.09	-2.42	-1.97	-3.21	-1.82
RTB	**0.65**	-0.51	-0.47	-2.21	-0.80
LTR	**2.34** **	**3.72** **	**2.17** **	**2.17** **	-1.43
RBR	**0.17**	**0.53***	**1.05** **	-1.50	-1.35
T-S	-0.56	**1.41** **	-1.04	**1.18** **	-0.41
C-P	-2.03	-1.55	-0.63	-2.23	-0.70
Panel C: FX variables and Risk Factors					
DOL	-0.79	-0.69	-0.79	-0.66	-0.23
HMLFX	**1.33**	**0.38**	**1.73***	**1.44** **	**0.55**
AFD	-1.50	**1.35** **	-0.60	-0.56	-0.18
Panel D: Liquidity and Credit Risk Variables					
DEF	**2.26***	-0.35	-2.05	**3.32***	**4.88*** **
BAS	-0.09	-1.31	**5.48** **	-0.74	-0.68
PS	**0.20**	-0.73	-1.01	**0.03**	**0.24**
TED	**6.11***	**1.08**	**1.20**	**1.32**	**5.06** **
Panel E: Macroeconomic Variables					
INFM	**0.90**	-0.71	**0.89***	-1.21	-5.03
INFA	**0.44**	-1.68	-1.16	-0.35	**1.45***
IPM	**6.20***	**2.89** **	**0.34**	**2.72** **	**7.47** **
IPGA	**1.19***	-1.17	-1.36	-1.52	-0.26**
H-S	**3.74** **	-0.02	**0.23**	**0.81**	**3.43** **
M1M	**10.16** **	**2.34** **	-2.77	**1.24** **	**1.69** **
M1A	**2.59*** **	**2.73** **	-1.00	**2.61*** **	**3.62*** **
ORDM	**0.10**	-0.21	-0.78	**0.16**	**0.13**
ORDA	-0.62	-3.03	-0.31	-0.09	-0.51
CRB	**1.54** **	**0.47** **	-1.55	**3.48*** **	-0.10**
CAP	**2.75**	**1.65***	**2.21**	**0.94***	**4.02***
EMPL	**1.59***	**0.22**	-0.53	**0.18***	**0.68***
SENT	-2.24	-0.37	-0.69	-0.84	-1.51
CONF	-5.81	-1.12	-0.73	-2.28	-2.50
DIFF	-0.05	**0.02**	**0.83** **	**0.73**	**0.20**
PMBB	-0.20	-1.34	-0.24	-0.63	-0.98
PMI	-0.08	-0.82	**0.58**	-0.71	-1.13

Out-of-sample performance of the predictors under consideration against the bechmark, the AR(p) process. We set the maximum number of lags (p) equal to six and select the optimal one by minimising the Schwartz Information Criterion (SIC). We test whether the financial and macroeconomic predictors enhance the forecasting performance according to the following equation: $\hat{f}_{j,t} = \hat{b}_{0.j} + \sum_{i=1}^{p} b_{1,j,i} RV_{t-i} + \hat{b}_{2,j} x_{j,t-1}$. The performance is measured by the R^2_{OOS}, which measures the reduction in MSFE of the rival model against that of the benchmark. The asterisk stand for the Clark and West (2007) one-sided upper-tailed statistic, which tests the H_0 that the MSFE of the benchmark is less or equal to that of the rival against H_1 that the forecast MSFE of the benchmark is greater than that of the competing model. The three, two and one asterisks denote the level of 1%, 5% and 10% level of statistical significance, respectively.

More in detail, D-P emerges as the most useful predictor in the set of equity market variables as can improve forecasts in all currencies but the YEN. The respective R^2_{OOS} values range from 0.45% (EUR) to 2.21% (FXAggr.). SMB improves forecasts only for FXAggr., while STR is important only for YEN. Moving to interest rate related predictors, our findings suggest that LTR is the most successful predictor for all the currencies except for FXAggr. Benefits range from 2.17% (YEN and EUR) to 3.72% (CHF). On the other hand, RBR and T-S offer modest improvements for only two of the series under consideration. Turning to FX related variables, we note that HMLFX improves forecasts for YEN and EUR, while AFD for GBP. High R^2_{OOS} are attained by some of the liquidity and credit risk variables. For example, R^2_{OOS} for BAS and YEN is equal to 5.48% and for TED and GBP and FXAggr., the related values are 6.11% and 5.06%, respectively. In this category, DEF also improves the forecasting ability in three series; GBP (2.26%), EUR (3.32%) and FXAggr. (4.88%). We now focus on macroeconomic variables. Our forecasting findings suggest that the economic environment is important and leads developments in exchange rate volatility. Specifically, monthly industrial production growth, monthly and annual money supply growth and commodity returns can improve forecasts in four out of five exchange rates considered . The most impressive performance is achieved by monthly supply growth for GBP (10.16%) followed by monthly industrial production growth for FXAggr. and GBP with R^2_{OOS} values equal to 7.47% and 6.20%, respectively. Modest forecasting benefits can be achieved when employing housing starts, employment and DIFF but these are concentrated in two or three series.

Given the considerable heterogeneity and uncertainty regarding the choice of the predictor for the currencies under consideration, we now consider the forecasting methodologies outlined in Sections 3.2 to 3.8. Table 4.5 reports the related findings. As expected, the performance of the Kitchen Sink model (Panel A) is worse that any individual predictor with large negative R^2_{OOS} values. Our findings with respect to the machine learning techniques (Panel B) are quite encouraging. Lasso and Elastic Net both generate high positive statistically significant R^2_{OOS} for all curren-

cies, ranging from 3.01% (EN for YEN) to 10.50% (Lasso for GBP). NNs and SVR improve forecasts for all series at hand with the exception of YEN delivering lower R^2_{OOS} than Lasso and EN in the majority of cases. On the other hand, Ridge fails to improve forecasts for any currency.

Table 4.5: Out-of-sample performance: Aggregate information methods

Predictor	GBP	CHF	YEN	EUR	FXAggr.
Panel A: Kitchen Shink					
KS	-29.90	-27.04	-23.82	-36.92	-17.72
Panel B: Machine Learning					
LASSO	**10.50*** **	**3.52** **	**3.17** **	**8.16*** **	**6.50*** **
RIDGE	-4.63	-11.38	-7.19	-7.49	-4.14
EN	**10.18*** **	**3.20** **	**3.01** **	**7.26*** **	**5.61*** **
NN	**10.34** **	**0.39*** **	-27.36	**3.30*** **	**7.28*** **
SVR	**0.98***	**2.58*** **	-1.64	**2.58*** **	**1.04*** **
Panel C: Dimensionality Reduction					
PCA	**1.56**	-0.26	-0.76	**1.67***	**2.73** **
ICA	**12.26***	-5.96	-11.29	**6.41** **	-7.72
PLS	**11.63*** **	**4.15*** **	-3.28	**6.51*** **	**8.97*** **
Panel D: Forecast Combinations					
POOL	**2.52*** **	**1.72*** **	**0.98*** **	**2.43*** **	**2.64*** **
MEDIAN	**0.77*** **	**0.75** **	**0.41** **	**0.89** **	**0.76*** **
TRIM3	**2.68*** **	**1.80*** **	**1.03*** **	**2.33*** **	**2.75*** **
TRIM10	**3.59** **	**2.08*** **	**0.37**	**3.12** **	**3.81*** **
Panel E: Amalgamation Forecasts					
AMALG	**11.32** **	**4.69*** **	**2.80** **	**9.70*** **	**8.96*** **
AMTR1	**12.36** **	**4.80*** **	**2.86** **	**10.17*** **	**9.34*** **
AMTR2	**12.48** **	**4.46*** **	**3.04** **	**10.29*** **	**8.89*** **
AMTR3	**11.79** **	**3.21*** **	**2.52***	**9.84*** **	**7.41*** **
Panel F: Perfect Insight Forecast					
PI	**3.77*** **	**1.38*** **	**2.11*** **	**2.66*** **	**3.64*** **

Notes: The Table above illustrates the results of the techniques that aggragate information. In Panel A, we show the results for the amalgamation of forecasts. The amalgamation of forecasts is an equally weighted average of the forecasts generated by the illustrated methods in Panel B to D of the Table 5. The forecast series for the predictors AMTR1, AMTR2 and AMTR3 are generated by trimming the 1,2 and 3 top and buttom outiers of the original predictors included in the AMALG, at each time t. The Perfect Insight predictor is generated as follows; we assume that the forecaster is able to view at the end of the out-of-sample period, which individual predictors, among those included in Panels A to E, outperformed the benchmark. In other words, the forecaster has Perfect Insight on the performance of each predictor. Then the forecaster equally weights those predictors and generates a new series of forecasts, which is evaluated. For the evaluation measures see notes in Table 4.4.

We now focus on the dimensionality reduction techniques (Panel C) which demonstrate moderate performance that is subject to the currency under consideration.

ICA and PLS are the best performing ones with high positive R^2_{OOS} values reaching 12.26% and 11.63% for GBP and ICA and PLS, respectively. The overall performance of PLS is the best among this set of models, since it outperforms the benchmark in four out of five series. Finally, PCA succeeds in delivering positive and significant R^2_{OOS} values only for EUR and FXAggr. Panel D reports the results for the forecast combination methods. We observe that all forecast combination methods successfully outperform the benchmark for all the exchange rate series. Admittedly, R^2_{OOS} values are moderate but the overall picture suggests that uncertainty associated with the choice of predictors and models is reduced. Even for CHF and YEN that so far have been the most difficult currencies to forecast, combination methods generate statistically significant positive R^2_{OOS}.

To further alleviate the problem of selecting a particular forecasting approach, we propose combining the forecasts of all the employed techniques. In this way, we create an amalgam or consensus forecast that takes advantage of all the information at hand. Our findings (reported in Panel E) suggest that the combination of information from different types of forecasting methods further improves the forecasting accuracy as AMALG R^2_{OOS} values are quite high. For example, for GBP, the R^2_{OOS} value is 11.32%, only slightly lower than PLS (11.63%), for CHF the respective value is higher than any other approach, 4.69%, outperforming PLS (4.15%). Turning to YEN, R^2_{OOS} is positive and among the highest ones, while for EUR, AMALG R^2_{OOS} is the highest among all approaches at 9.70%, outperforming Lasso at 8.16%. Last, for FX-Aggr. the R^2_{OOS} value is again the highest among all approaches at 8.96% outperforming neural networks (8.97%). In order to verify whether the promising results are subject to biases stemming from outliers, we replicate the experiment by trimming the outliers. We observe that the R^2_{OOS} values do not change much and even increase for the majority of cases. Overall, we get evidence that the simple amalgamation of forecasts can provide more efficient and robust forecasts than using single methods, irrespective of the number of models included.

Finally, in order to gain an intuition on the level of predictbility we might expect, we form Perfect Insight (PI) forecasts. Specifically, we assume that the best perform-

ing individual predictors are known a priori and only their forecasts are combined. Panel F reports the related findings. We observe that the forecasting performance of PI is moderate but similar for all currencies delivering R^2_{OOS} values that range between 1.38% (YEN) to 3.77% (GBP). More importantly, our proposed amalgam approach provides significantly better forecasts irrespective of the currency under consideration.

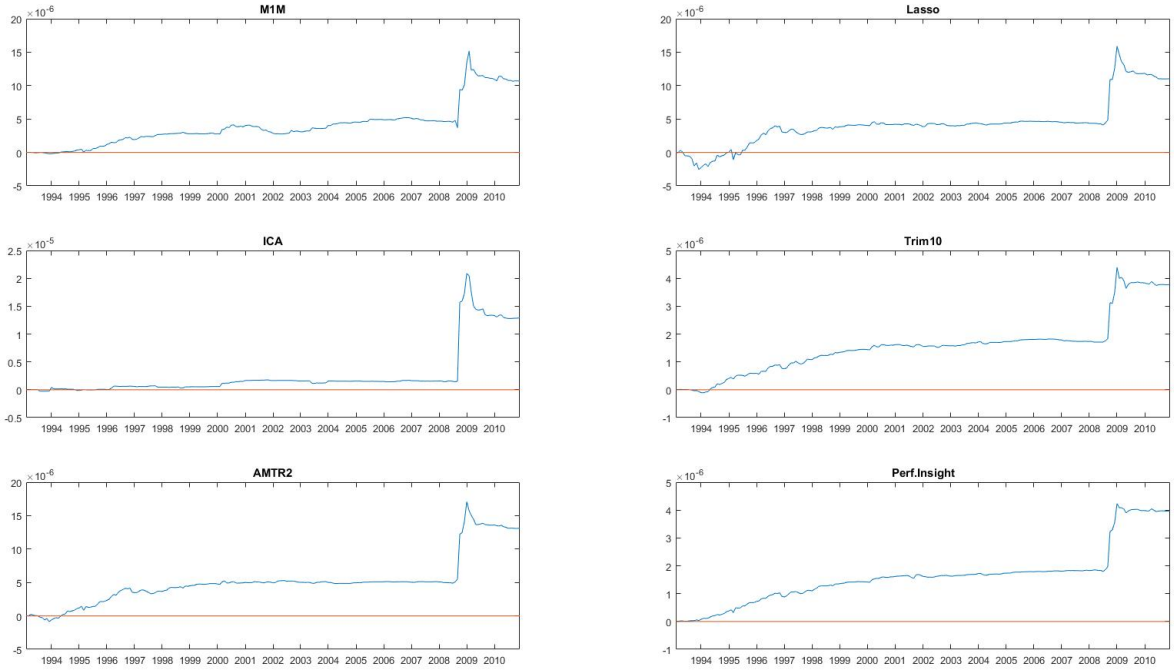
4.4.2 Dynamic Out-of-Sample Performance

The next step in our analysis is to evaluate the performance of candidate predictors/ models through time. It is very important to identify the forecasting approaches that consistently outperform the benchmark over time. The problem of the R^2_{OOS} (and MSFE) metric is that it shows the average performance over a specific time period and thus can be affected by peaks and troughs that may result is high R^2_{OOS} values for an approach exhibiting unstable performance over time. In order to identify which approaches consistently outperform the benchmark, we calculate the difference between the cumulative sum of squared errors of the proposed model/ specification and the benchmark model (ΔSSE). An upward sloping ΔSSE curve implies that the rival model outperforms the benchmark and vice versa. Figures 4.2 to 4.6 plot ΔSSE_s for the best performing specification in each category; i.e. the single best predictor, the best machine learning approach, etc; and the series of exchange rate volatilities under consideration.

Specifically, Figure 4.2 plots the related figures for GBP. We note that all specifications behave similarly; as the majority of approaches demonstrate gains during the first period of 1993 to 1996. This period coincides with the withdrawal of GBP from the ERM mechanism. After that period all specifications accumulate gains which become more apparent and abrupt during the recent financial turmoil in 2008. Part of these gains are lost after a few months for the majority of specifications. The approach showing the lowest losses in the aftermath of the recent financial crisis is the PI one, which is unrealistic followed by TRIM10 and AMTR2. On the other hand, forecasts based on Lasso and the money supply model exhibit substantial loss

of forecasting accuracy in the more recent period.

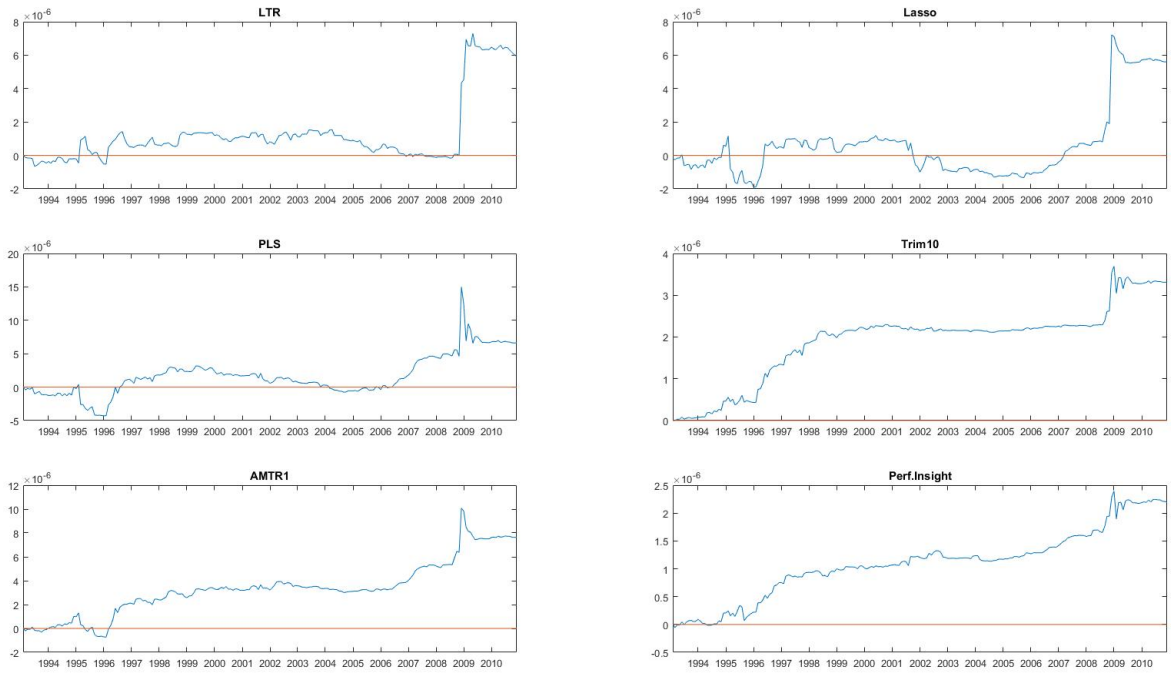
Figure 4.2: Difference between the cumulative squared error of the rival and the benchmark (ΔSSE) model over time: GBP



Notes: The Figure reports the first differences of the Sum of Squared Errors between the best forecasts in terms of R^2_{OOS} for each group of predictors, namely individual predictors, machine learning predictors, dimensionality reduction, combination forecasts, amalgamation and perfect insight forecasts.

Regarding the Swiss Franc realised volatility forecasts, shown in Figure 4.3, we observe that similar to GBP, the recent financial crisis reveals shortfalls in forecasting performance. Specifically, large gains are observed for all the superior forecasting approaches followed by losses that can be sizable for PLS, Lasso and AMTR1. It is also worth noting that the strenghtening of the dollar which edged up in 1996 posed challenges to all the models as for this early period, all specifications, but PI and TRIM10, are inferior to the benchmark.

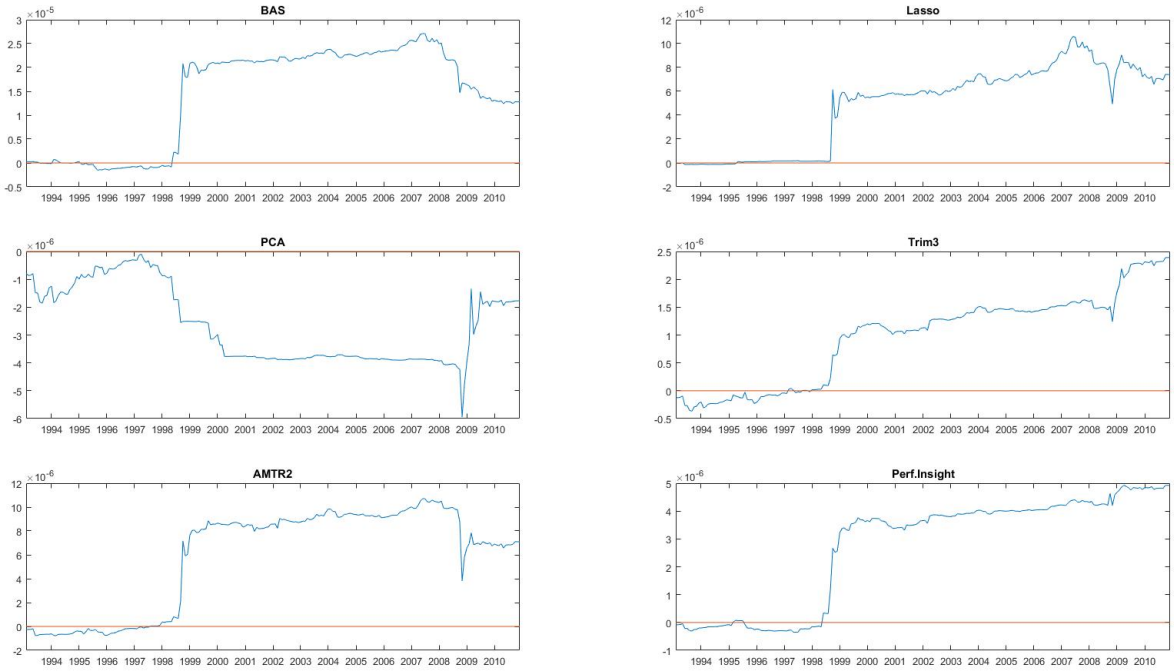
Figure 4.3: Difference between the cumulative squared error of the rival and the benchmark (ΔSSE) model over time: CHF



Notes: See Figure 4.2.

Turning to YEN, the so called "Once-in-a-generation" yen volatility in 1998 is evident in Figure 4.4. Cai, Cheung, Lee & Melvin (2001) identify three main sources of increases in YEN volatility. In brief, these are "*announcements related to macroeconomic fundamentals; intervention by the Bank of Japan, the US Treasury, and the Federal Reserve; and portfolio position switches by large institutions*" and encouraged the momentum of the Yen's appreciation in mid-1998. Our plots reveal the impact of this period on the forecasting performance of the proposed models. Specifically, with the exception of PCA, all models manage to achieve gains against the benchmark. For the period 1998-2008, we have to note that all models (except for PCA) show a relatively smooth upward sloping path. Contrary to GBP, the period after the financial crisis is beneficial for PI and TRIM3, while AMTR2 and Lasso exhibit sizable losses followed by considerable gains.

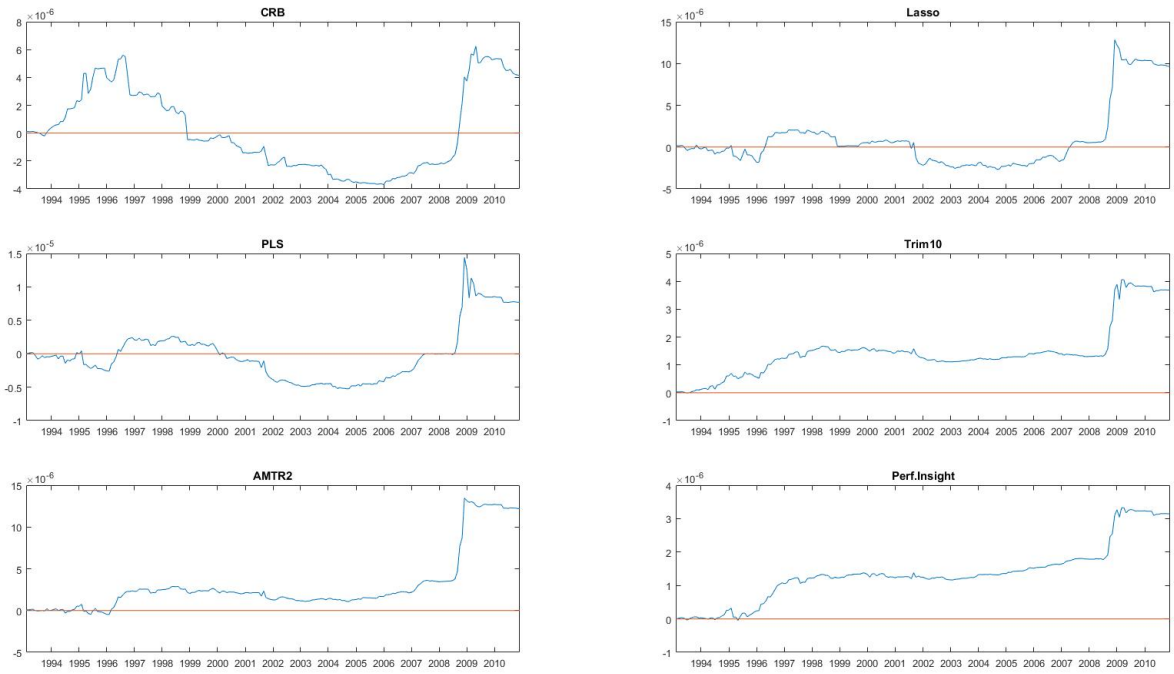
Figure 4.4: Difference between the cumulative squared error of the rival and the benchmark (ΔSSE) model over time: YEN



Notes: See Figure 4.2.

EUR is a relatively new currency and is constructed by splicing DEM until end of 1998 and EUR after 1999. The evolution of forecasts of the best performing methods is shown in Figure 4.5. Overall, the best performance is achieved by TRIM10, AMTR2 and PI which have curves that are positive and upward sloping for the full sample. As with GBP and CHF, the period during the financial crisis boosts their forecasting accuracy while the aftermath mildly deteriorates it. CRB, PLS and Lasso suffer from inferior forecasting performance relative to the benchmark in the period that follows the introduction of the euro.

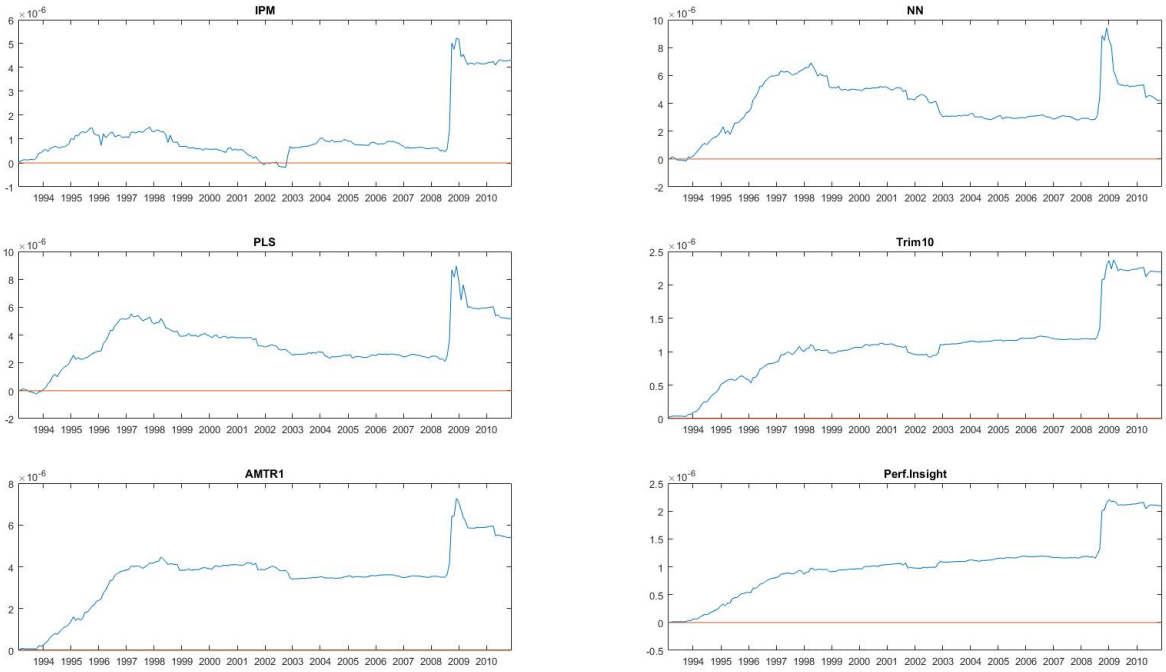
Figure 4.5: Difference between the cumulative squared error of the rival and the benchmark (ΔSSE) model over time: EUR



Notes: See Figure 4.2.

Finally, in Figure 4.6 we focus on FXAggr. Given the heterogeneity of its components, the analysis of FXAggr is more complicated. We need to focus on global scale effects rather than regional factors. By construction, the objective of this basket of currencies is to illustrate a global path of the realized volatility. We observe an almost similar behaviour of all predictors. There is an increase in the gains until the events of the Asian crisis (1997). The negative impact on the predictors is clear (with an exception of PI) although the magnitude and scale is different for each predictor. We don't observe any impact of the introduction of euro on the performance of the predictors. In early 200s there are several events (e.g. dotcom bubble, the Turkish Lira in 2001, Argentinian crisis in 2001 and its spillover in Brazil a year later). However, there are no additional gains from our predictors during this period. Finally, a large positive jump in gains for all predictors is evident for all predictors after the events of the global financial crisis in 2008.

Figure 4.6: Difference between the cumulative squared error of the rival and the benchmark (ΔSSE) model over time: FXAggr



Notes: See Figure 4.2.

Overall, we observe that the Amalgam approach outperforms alternative methods in the sense of performance through time. From the empirical analysis, it can be seen that several events have impact on the performance of predictors, although the magnitude and the scale is different. Finally, we observe a smoother performance through time. On the other hand, more abrupt changes are evident in the cases of machine learning and dimensionality reduction techniques and their performance is conditional on the currency and the period under consideration.

4.5 Conclusions

In this study we examine the contribution of financial and macroeconomic variables on forecasting exchange rate volatility. We consider 38 potential financial and macroeconomic predictors that have been typically employed in exchange rate/ stock market forecasting literature. We examine simple autoregressive models augmented with one predictor at a time and a variety of machine learning, dimension-

ality reduction and forecast combination approaches. Finally, to avoid uncertainty associated with the employment of a specific predictor/ model, we propose forming amalgam/consensus forecasts by simply averaging forecasts generated by the aforementioned approaches. We test our methodology in four widely traded currencies; the British Sterling, Japanese Yen, Swiss Franc and Euro along with an aggregate basket of exchange rates and calculate monthly realised volatility from daily exchange rate returns.

Our in-sample findings suggest that exchange rate, liquidity and credit risk related as well as macroeconomic variables improve volatility prediction in all currencies. Out-of-sample no single candidate predictor is positive and statisticall significant for all currencies. The best predictors appear to be LTR and IPM which is positive and significant for GBP, CHF, YEN and EUR but negative for FXAgrr. IPM, on the other hand is postive for all currencies but not statistically significant for YEN.

Our out-of-sample results indicate that machine learning techniques such as Lasso and Elastic Net show superior forecasting ability. Focusing on dimensionality reduction approaches we found that PLS outperforms both ICA and PCA but not machine learning approaches. Forecast combinations provide positive and statistically significant R^2_{OOS} for all currencies. Nevertheless, they cannot outperform the Elastic Net or Lasso.

Finally our out-of-sample results suggest that an amalgam of forecasts from all the forecasting approaches by simply taking an equally weighted (or trimmed) forecast enables us to achieve superior forecasting ability with a stable performance over time. More specifically, Amalgamation forecasts provide positive and statistically significant R^2_{OOS} for all currencies. They also have the highest R^2_{OOS} for CHF, EUR and FXAggr. and among the highest ones for GBP and YEN. Finally, dynamic out-of-sample performance shows that amalgamation forecasts have a stable performance over time.

Chapter 5

Concluding Remarks

The forecasting ability of existing models and methods has challenged academia, policy makers and practitioners. The fundamentals and exchange rates are challenged as disconnected. Nevertheless, the improvements in the forecasting experiment are significant, leveraged by the introduction of new variables and the proposition of new methodologies in this exercise. In this thesis, we provide evidence in favor of exchange rates forecasting. We experiment with the out-of-sample performance of several predictors in both returns and realized volatility forecasting. The predictors applied are less standard in the forecasting process. Our results are contrary to the existing literature opposing to forecasting exchange rate returns.

The study does not only aim at pointing out new approaches that could provide better forecasts, but also identifying the predictors, methods and models that demonstrate the best and most stable empirical performance. These models can be considered as reliable predictors of the exchange rates over time. We answer the problem of exchange rate forecastability by experimenting on different datasets, frequencies and moments. Our results support existing evidence of forecasting accuracy irrespective of the specification applied.

First, we test the contribution of technical indicators in the excercise. So far, the experiment of exchange rate forecasting was engaged by taking into account macroeconomic variables that have met theoretical merit. We expand the set of predictors by taking into account the information contained in technical indicators.

Due to the large number of predictors, we apply principal component analysis in order to extract most explanatory information. With respect to our results, we provide evidence that technical indicators can contribute considerably in the forecasting process. Next, we claim that by taking into account both groups of predictors we can enhance the forecasting performance. Especially, in those cases where the two sets of predictors do not encompass each other. We also find that our results are both robust and economically meaningful.

In the next Chapter, we apply the ICCP approach in daily FX data; a hybrid of two state of the art approaches, the Iterated Model Combination and Constrained Predictors. Moreover, we extend the experiment by applying positivity constraints in the forecasts. Our results suggest that taking into account abrupt changes in the predictor's side and smoothing the forecasts by weighing them with the benchmark, can actually enhance the performance of the forecasts. We provide evidence that the proposed method is robust regardless of the specifications under consideration.

In the last Chapter, we provide evidence against the disconnect puzzle between fundamentals and exchange rates, by testing the performance of a large number of predictors in forecasting realized volatility. We aggregate the information by using several linear and non-linear techniques and compare it with an AR(p) process. Next, the forecaster comes along a large number of existing tehniques with attractive properties. Hence, we respond to this question by generating an amalgamation of forecasts. Our findings report that the amalgamation of forecasts generates superior forecasts to its rivals, irrespective of the currency under consideration. We also provide evidence that this type of information aggregate is specification free.

Overall, we support that academia and future research should look upon new types of predictors that could potentially ameliorate the forecasting performance. Despite the fact that technical indicators are an atheoretical tool, it still remains one of the most widely used instruments. Moreover, exploiting the abrupt changes in the predictor's side can prove to be quite useful in the forecasting process. Short-lived abrupt changes in the fundamentals seem to play a sigificant role when forecasting extremely noisy data. In addition, given the engineering advances reported in

literature, the forecaster can benefit by aggregating information.

5.0.1 Future Research

The flourishing literature on exchange rates forecasting updates and provides new ground for future research. New technologies and databases are publicly available, allowing to consider new and more solid datasets and more elaborate methodologies. Despite the ongoing progress, while conducting this exercise, we were able to identify several potential extensions of the existing FX literature. As outlined by Rossi (2013), there are several specifications that have an impact on the forecasting performance. We came across several issues to be resolved and tested, as a future research output. In this section, we will try to map a few issues that grapped our attention and provide an intuition for further research. Thus, we could split the section into three great categories. The first one could bundle the incorporation of technical indicators in the literature and the extension of predictors in the forecasting exercise. The second is linked with the frequency of the data that are taken into account. Last but not least, given that exchange rates is an asset with extremely high turnover, it is subject to further investigation by portfolio management theory.

Taking into account technical indicators in the forecasting experiment has been ignored by academia, so far. In Chapter 2, we argue that technical indicators along with macroeconomic models are able to improve the forecasts on returns. However, it would be very useful to understand if technical indicators are able to forecast adequately realized volatility. Intuitively, the continuous switching between buying and selling signals causes more volatile movements in the prices and, consequently, returns. Hence, there seems to be an underlying relationship between these two figures. Literature doesn't seem to have paid attention in identifying such a relationship and has mainly focused on explaining the contribution of fundamentals into realized volatility forecasting. Furthermore, it would be interesting to understand if each group is able to forecast better particular frequency signals of the initial series. For this purpose we could use decomposition methods (such as wavelets, which are proven to be efficient for such type of experiments), since frequency matters (for

recent publication see Caraiani, 2017).

In addition, we observe that literature around solely technical indicators or macroeconomic predictors seems to be more extensive. There are several papers focusing on macroeconomic fundamentals, as shown in the thesis, but only recently, Hsu, Taylor and Wang (2016) provide an extensive review of the performance of several technical indicators in both developed and emerging markets over a large period of time. Nevertheless, according to our findings in Chapter 2, the interesting results come up when the two groups of predictors are taken both into account. We come across papers that take into account both predictors across different asset classes, different datasets and different methods. Despite the fact that the literature on this information combination approach is not at a mature stage, it remains vivid and unmapped. A review approach of the existing technologies taken together can provide a coherent and holistic approach and provide intuition on the progress made so far, challenges that have not taken into consideration, most successful methods etc. We should note that technical indicators should not be the single variable on which research should be focused on. Other variables to be taken into consideration, among other, an interesting approach are common factor models (see Engel, Mark and West, 2015). Moreover, we could check whether particular group of predictors (or their subsets) are able to forecast the direction of changes better than others, by applying directional tests (Pesaran and Timmermann, 1994; for economic evaluation of directional tests see Blaskowitz and Herwatz, 2011) or the asymmetric mean mixed error loss function (see Kearney, Cummins and Murphy, 2018).

Rossi (2013) argues that the choice of predictors plays a significant role in the out-of-sample performance. Hence, we could introduce new types of data, like survey based data (among others see Ince and Molodtsova, 2017), or bootstrap proccess to select variables (among other see Ribeiro, 2017) over time and data that reveal idiosyncratic risk in every currency. On the other side, there is a fast growing literature stream in identifying common factors that affect exchange rates. Such common factors could potentially be able to forecast a significant part of returns. However, given that there is a direct relationship of fundamentals and exchange

rates, these factors could be tested along with fundamentals related to each country or global factors (see among others Bekaert, 2009; recently, for global factors on market valuations see Ma, Vivian and Wohar, 2018). Moreover, among others, according to Beckmann and Czudaj (2017a, 2017b), exchange rate expectations as well as, expectations of fundamentals play an essential role in forecasting. Especially after the collapse of Lehman Brothers and the worldwide financial turmoil, we should re-consider the driving factors in exchange rates forecasting, due to time-variations in performance. Recent literature, few years before and after the events of 2008, argue that survey data could be proved relevant and helpful in forecasting (see among others Chernov and Mueller, 2012; Faust and Wright, 2013; Beckmann and Czudaj, 2017a, 2017b).

The forecasting experiment should take into account information contained in lower frequency data. Aggregating information into higher frequency has a bifold effect on the forecasting accuracy of the model. Different frequency data contain different type of noise, but also information. Hence, by using only one frequency of data does not allow to take into consideration all available information, through temporal aggregation[1]. Despite the fact that mixed frequency models are not new in literature, there is an growing stream in literature that tries to enrich and improve the existing methods (for recent study see Foroni, Guérin and Marcellino, 2018). Hence, we could examine their performance in the proposed mixed frequency VAR, unrestricted and reverse MIDAS concept or by using significantly lower frequency data. In the same spirit, we should pay a closer attention to the implications of the rolling and recursive window on the performance measurement, since the choice of window show how the model consumes the information of the past.

Given that exchange rates attracts attention from both academia and industry, we should focus on the economic performance of the asset. In this thesis, and similar papers, we applied common portfolio allocation strategies. Moreover, the existence of nonlinearities in currency returns has troubled academic research during the last two decades (see among others Clarida, Sarno, Taylor and Valente, 2003; Kilian

[1]See Andreou, Ghysels and Kourtellos (2011).

and Taylor, 2003; Anatolyev, Gospodinov, Jamali and Liu, 2017). Given the above, it is still interesting to conduct a horse-race among the elaborate machine learning techniques on a portfolio allocation exercise. It is well-documented in literature that good statistical performance does not imply economic meaningful forecasts. Hence, we should critically review the performance of thirty years of machine learning engineering advancements in economic terms.

Exchange rate forecasting is and will remain for long time a vivid subject of academic discussion. There have been steps towards the improvement of the forecasting ability of models but there is still much progress to be made. In this subsection, we point out only some proposed experiments that grapped our attention and found more fascinating for future research. We hope our findings suggest a new direction for future research in order to identify methods, variables and intuition; the latter is the most essential contribution in this continuously growing literature.

Appendix

Principal Components Analysis

Principal Component Analysis is a common dimension-reduction method in finance. It is used in order to transform the large number of available variables, say a random matrix $\mathbf{X}$, so that $\mathbf{X} = [X_1, X_2, ..., X_n]$, where each variable 1,..,n contains t number of observations, into a small set that accommodates most useful information by summarizing variance. By construction, the first component contains as much of variance as possible, and so on.

Typically, the PCA is performed on a squared symmetric matrix. In our case, we use a Correlation matrix, such as $\mathbf{R} = \frac{1}{n-1}\mathbf{X_s}'\mathbf{X_s}$, where $\mathbf{X}_s = \mathbf{CXD}^{-1}$, of which $\mathbf{C} = \mathbf{I}_n - n^{-1}\iota_n\iota_n'$ and $\mathbf{D} = diag(s_1, ..., s_n)$, s_n is the standard deviation of the adjusted series $x_n - \bar{x}_n$

The method finds a linear combination of variables, each one weighted according to its contribution, in order to generate a component that is uncorrelated with the other components and contains as much information as possible. The eigenvalues and eigenvectors of the correlation matrix are computed. The eigenvalues measure the variance for each factor. Highest eigenvalues signify highest explanatory power over total variance. The eigenvectors, v_n, serve as weights of the variables allowing to compress multiple variables into factors. Principal components are generated as a linear combination of the eigenvectors and the adjusted data series.

Next, the variance is removed and the second component is generated by iterating the process on the remaining variance. The maximum number of components equals the number of initial variables and explain 100% of the total variance, both common and unique variance.

Support Vector Regression

The methodology was proposed by Vapnik (1982). Initially the model was used in classification problems and later on non-linear regression estimation problems (Vapnik and Cortes, 1995). The target aim of SVR is to find the best possible $g(x)$

that will split data with the greatest possible deviation, say ε, from the observed targets y_t for all the training data. The parameters of a linear regression of the form $f(x) = w^\top x + b$ are obtained by the following minimisation problem:

$$\min \frac{1}{2} \|w\|^2 + c \sum_{i=1}^{N} (\zeta_i + \zeta_i^*)$$

$$\begin{aligned} s.t. \qquad (\mathbf{w}^\top \mathbf{x}_i + b) - y_i &\leq \varepsilon + \zeta_i^* \\ y_i - (\mathbf{w}^\top \mathbf{x}_i + b) &\leq \varepsilon + \zeta_i \\ \zeta_i, \zeta_i^* &\geq 0, \quad i = 1, 2, ...N \end{aligned}$$

where the entire term $\sum_{i=1}^{N}(\zeta_i + \zeta_i^*)$ can be considered as the learning capacity of the model, c is the penalty parameter (also called box constraint) that determines the trade-off between the flatness of $g(x)$ and the tolerance band ε; in this study we use the interquantile of the target variable y. ζ_i and ζ_i^* are the slack variables for the upper and lower bound of the error respectively. In order to find the extremum, we apply the Langragian multiplier and incorporate nonlinear kernel functions, suitable for approximation of nonlinear phenomena, so that:

$$g(x) = \mathbf{w}^\top \mathbf{x} + b = \sum_{i=1}^{N} (\hat{a}_i - a_i) K(x_i, x) + b$$

where a_i, $\hat{a}_i$ are the Lagrange multipliers and $K(x_i, x)$ is the kernel function. Following Ince and Trafalis (2018), Lu, Lee & Chiu (2009) and Sermpinis, Stasinakis, Theofilatos & Karathanasopoulos (2015), we use as kernel function the Radial Basis Function that can be defined as $K(x_i, x) = e^{(-\gamma \|x_i - x_k\|^2)}$. We assume that the kernel parameter $\gamma = 1$[2].

[2]For very recent SVR algorithms, see Sermpinis, Stasinakis, Rosillo and De la Fuente (2017). Despite the popularity of Radial Basis Function, the authors argue that the algorithm might not be the optimal choice for financial series.

Independent Component Analysis

Jutten and Herault (1991) proposed Independent Component Analysis (ICA) that isolates different types of mixed signals without knowing the mixing mechanism. The starting point is that the signals are independent. We assume that the mixture signal follows a process $\mathbf{X} = \mathbf{AS} = \sum_{i=1}^{N} a_i s_i$ where $\mathbf{X} = [x_1, ...x_N]^\top$ is a $N \times T$ matrix of the mixture of signals x_i, $\mathbf{A}$ is the unknown mixing matrix with a column vector a_i and $\mathbf{S}$ is the source matrix with row vector s_i, latent source signals, that are independent and unobservable. Initially, the signals x are centered and, then, whitened in order to create a new input matrix with uncorrelated rows and unit variance. The ICA solution is calculated by obtaining a de-mixing matrix $\mathbf{W}$ used for transformation of the observed mixture signals $\mathbf{X}$. The independent signals are denoted as $\mathbf{Y}$, where $\mathbf{Y} = [y_i]$ for $i = 1, ..., N$ and y_i must be independent and are called independent components. The components are calculated by $\mathbf{Y} = \mathbf{WX}$ where $\mathbf{W} = \mathbf{A}^{-1}$. In our analysis we use the FastICA algorithm in order to solve the de-mixing matrix $\mathbf{W}$ (see also Lu, Lee & Chiu, 2009) and the non-Gaussianity of the independent components is measured by the negentropy so that $J(\mathbf{y}) = H(\mathbf{y}_{gauss}) - H(y)$ and $H(\mathbf{y}) = -\int p(\mathbf{y}) \log p(\mathbf{y}) \mathrm{d}(\mathbf{y})$ where H is the entropy of a random vector $\mathbf{y}$ with density $p(\mathbf{y})$. The negentropy is non-negative and zero if and only if $\mathbf{y}$ has a Gaussian distribution. Due to the computational difficulties of negentropy we use the follwoing approximation $J(y) \approx [E\{G(y)\} - E\{G(v)\}]^2$ where v is a gaussian variable with zero mean and unit variance and $G(y) = \exp(-y^2/2)$.

Partial Least Squares

PLS aims at creating factors, similar to PCA, that maximise covariance between $\mathbf{X}$ and $\mathbf{Y}$. The algorithm elaborates as follows, the matrix of the predictive variables $\mathbf{X}$ and targeted variables $\mathbf{Y}$, namely RV are multiplied and squared. The eigenvalues are calculated, so that the first eigenvector of $\mathbf{X}^\top \mathbf{Y}\mathbf{Y}^\top \mathbf{X}$ is calculated, which is then multiplied by $\mathbf{X}^\top \mathbf{Y}\mathbf{Y}^\top \mathbf{X}$ in order to create the weights for the factor, namely the X-score. The weights and factors are normalized and generates the X-loadings and

Y-loadings (Y*X-Score). The Y-Score are obtained by multiplying the Y-loadings with Y. The loadings are orthogonalized to all previous loadings and then stored. The existing loadings are subtracted from $\mathbf{X}^\top\mathbf{Y}\mathbf{Y}^\top\mathbf{X}$ and the process is iterated for any additional factor. We apply the de Jong (1993) SIMPLS algorithm, which is far more efficient when there are many factors. The orthogonal factors of $\mathbf{X}$ that maximize the covariance with $\mathbf{Y}$ are calculated directly on the covariance matrix without multiplying $\mathbf{X}'$ and $\mathbf{Y}$ at each iteration. SIMPLS is one of the most widely used. Nevertheless, there are several other approaches, mainly differ in the deflation process.

Neural Networks

Neural networks have been vividly discussed in literature during the last year. The technology has been advanced, so there are several available specifications. We apply neural network methodology in our experiment. The architecture of our network is built by ranging the number of hidden unit from 1 to 4, so we gradually increase the complexity of our models. In theory, the more hidden units a network included the more complex functions it can capture. However, according to Evans et al (2013) the training time for models containing more than two hidden units increases crucially. We use the Bayesian Regularization (BR) algorithm that is more robust and is immune to overfitting; the main drawback is that it is quite slow. The inputs are first normalized in the range [-1,1], which are re-scaled at the end of the training period. The bias and inputs are weighted and summed. The bias is nothing else but an additional node in the input layer and hidden layer that has a fixed value of 1. This process is repeated until every input is connected with every node.

Hence, the connections can be viewed as the weights between inputs and nodes. The training process continues until the gradient is less than 1e-5, namely any further iteration does not practically improve the solution. An interesting fact with Neural Networks is that the gradient is calculated on a loss function, we have chosen Mean Squared Error, on a random point. Thus this random process can have a severe

impact on the training process, since the network can be easily trapped into local minima and extreme values (less possible for BR algorithm). In order to avoid this effect, we train the network 50 times for every time t and use the median value. So far, we have seen that every node of the hidden layer receives a weighted sum of the inputs, such as:

$$h_{i,t} = \Psi \left(b_{i,0} + \sum_{j=1}^{\infty} b_{i,j} x_{j,t} \right)$$

where $h_{i,t}$ is a hidden unit in the intermediate or a hidden layer i, j denotes the variable, $b_{i,0}$ stands for the bias term of every node i, $b_{i,j}$ is the connection of the input j to node i, and $x_{i,t}$ is the input j.

The values of the hidden units serve as an activation function, i.e. they serve as inputs to transfer function, and pass to the output layer. In our experiment the network uses the tan-sigmoid transfer, suc as:

$$S(h) = \frac{2}{1 + e^{-2h}} - 1$$

At this stage, the inputs have been transformed, including the bias. The transformed inputs are weighted again, say w_i, and summed. The last step of the architecture is the trasformation function to the output. In our example we use the simple linear purelin function, so that:

$$F(w) = \sum_{i} w_i$$

In addition, we divide the data into two subsets, the first is the training set, that is used for computing the gradient and calculating the weights and biases,and the second is the validation set (we have set the test set equal to zero. For every month the network is re-trained recursively over the sample that is equal to the out-of-sample period.

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