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Forecasting exchange rates: An iterated combination constrained predictor approach

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Abstract

Forecasting exchange rate returns is of great interest to both academics and practitioners. In this study, we forecast daily exchange rate returns of six widely traded currencies using combination and dimensionality reduction methods. We propose a hybrid iterated combination with constrained predictor 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. Positivity constraints significantly improve the forecasting ability of all methods.

KEYWORDS

constrained predictors, dimension reduction methods, exchange rates, forecast combinations, forecasting

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 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 and forecast horizon to name a few.

In light of this puzzle, academia has turned to more sophisticated techniques, which stimulated research and led to more promising results. There are several studies that 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 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), Molodtsova and Papell (2009), Molodtsova and Papell (2013), Rossi (2013), Beckmann and Schüssler (2016), and Byrne et al. (2018).

This study investigates whether daily exchange rates can be forecasted with the use of financial variables. 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 et al. (2018). This methodology combines the forecasts with those of the benchmark by attributing weights according to their past performance and creates an iterated combination (IC) forecast. The second is also a recently introduced methodology, proposed by Pan et al. (2020). 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 methodology, namely, the iterated combination constrained predictor (ICCP) approach, generates forecasts by transforming the predictor series in line with the constrained predictor (CP) approach and then applying the IC approach. Our set of specifications ranges 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 others, Neely et al., 2014) and partial least squares (PLS) (see Kelly & 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 return forecasts at zero.

Our dataset consists of daily observations of six widely traded currencies for the period extending from February 2, 1999, to December 31, 2017, with the out-of-sample period starting on January 1, 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 & Piras, 2016), global trading and activity (Baumeister et al., 2015; Calvet et al., 2006; Ferraro et al., 2015), yield curve data (Buncic & Piras, 2016), national stock indices (Christiansen et al., 2012), and their respective trading volumes.

Our findings suggest that the proposed hybrid ICCP approach can actually deliver superior forecasts. Moreover, 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 include switch from expanding to rolling window, length of the control window, the frequency of the data, the out-of-sample period, and the evaluation of the models' efficiency in predicting the actual sign of returns. The aforementioned robustness test further verify the superiority of our forecasting approach.

The remainder of the paper is organized as follows. Section 2 presents our forecasting approaches. Section 3 describes our dataset, and Section 4 presents the empirical findings. Section 5 presents the robustness checks, while Section 6 concludes the paper by providing a brief summary of our results.

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

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

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

2.1 | Forecast combination approaches

2.1.1 | IC

We apply the IC approach in the context of exchange rate returns forecasting. This method was recently introduced by Lin et al. (2018) 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:

$$r_{t+1} = (1-\delta)\bar{r}_t + \delta\hat{r}_{t+1} + u_{t+1}, \tag{2}$$

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

$$\delta = \frac{cov_t\left(r_{t+1} - \overline{r}_t, \hat{r}^{fitted}_{t+1} - \overline{r}_t\right)}{var_t\left(\hat{r}^{fitted}_{t+1} - \overline{r}_t\right)}, \quad (3)$$

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

$$\hat{r}^{IC}_{t+1} = (1-\hat{\delta})\overline{r}_t + \hat{\delta}\hat{r}_{t+1}, \quad (4)$$

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

2.1.2 | CP

The second method that we adapt in our setting is the CP method that sets constraints directly to the predictors and was proposed by Pan et al. (2020). Following the notation of the original paper, the predictors are transformed according to the following relation:

$$x_t^*(n) = \begin{cases} x_t \text{ if } x_t > \max(x_{t-1}, x_{t-2}, \ldots, x_{t-n}) \text{ or } x_t < \min(x_{t-1}, x_{t-2}, \ldots, x_{t-n}), \\ 0 \text{ otherwise}, \end{cases} \quad (5)$$

where n is the "look-back" period. In this study, we apply a 25-day control window roughly corresponding to a 1-month trading period. Hence, a constrained out-of-sample forecast is generated by

$$\hat{r}^*_{t+1}(n) = \hat{a}^*(n) + \hat{b}^*(n)x_t^*(n), \quad (6)$$

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 behavior on the predictors have an actual impact on the model. To alleviate this, Pan et al. (2020) include the information of "normal" periods and propose a revised constrained forecast, $\hat{r}^{CP}_{t+1}(n)$, as follows:

$$\hat{r}^{CP}_{t+1}(n) = 0.5\hat{r}_t + 0.5\hat{r}^*_{t+1}(n). \quad (7)$$

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

2.1.3 | CP with IC 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 IC and the CP methods, namely, the ICCP approach. Forecasts are generated in three steps. Initially, we constrain the predictors following relationship (5). Next, we apply the IC methodology on both the CP and unconstrained predictor. Last, we generate the forecasts using Equations (6) and (7). We denote the hybrid method as $C_i^{ICCP,0}$ for each predictor i.

2.1.4 | Forecast combination approach

We also apply a forecast combination approach (see Buncic & Piras, 2016; De Zwart et al., 2009; Rapach et al., 2010; Timmermann, 2006). We generate forecasts on the basis of each individual predictor and then combine the individual forecasts using a simple average. The general formula for combining N individual forecasts is given by

$$\hat{r}^{POOL}_{t+1} = \sum_{i=1}^{N} w_i \hat{r}_{i,t+1}. \quad (8)$$

We assume an equal weight for each predictor, that is, $w_i = \frac{1}{N}$ 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 IC, CP, 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.

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 PCA and the PLS methods to transform our large set of variables to a few new predictors by extracting all relevant information.

2.2.1 | Principal components

Following, among others, Neely et al. (2014), we use 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 ones that capture maximum variability.

The daily out-of-sample forecast at time $t+1$ obtained from the principal components is denoted as $\hat{r}^{PCA}_{t+1}$ and is given by the following formula:

$$\hat{r}_{t+1}^{PCA} = \hat{a} + \sum_{k=1}^{K} \hat{b}_k \hat{F}_{k,t}, \tag{9}$$

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

By construction, most of the available information is concentrated in the first few components. We take into account at most the first $K=4$ principal components, that is, $\hat{F}_t = (\hat{F}_{1,t}, \ldots, \hat{F}_{K,t}), K=1,\ldots,4$. 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 IC, CP, 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.

2.2.2 | PLS

A method closely related to PCA and multiple linear regression is the PLS, introduced by Wold (1966) and more recently successfully extended and adopted in finance by Kelly and Pruitt (2013, 2015). The methodology is applicable to 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 PLS is denoted as $\hat{r}_{t+1}^{PLS}$ and is given by the following formula:

$$\hat{r}_{t+1}^{PLS} = \hat{a} + \hat{b}_1 z_t. \tag{10}$$

We denote this method as C_{PLS}^{0}. When IC, CP, 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.

2.2.3 | Amalgamation forecasts

A priori, the investor lacks knowledge of the true data generating process required to select the most effective model. Following Rapach and Strauss (2012), Rapach et al. (2010), and Panopoulou and Souropanis (2019), we employ an amalgamation forecasting approach.

In our study, we utilize two variations of this method. In the first approach, we adopt a straightforward averaging of the three models, combining their information. This amalgamation comprises POOL, PCA, and PLS models, denoted as AMALG-PPP. In the second version, we focus on combining PCA and PLS while omitting the influence of the smooth nature of the POOL model. This variant is denoted as AMALG-PP. Our objective is to investigate whether disregarding the smoothing characteristics of POOL has any impact on the model's performance.

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 & Piazzesi, 2003; Campbell & Thompson, 2008; Pettenuzzo et al., 2014). 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. The forecasts are transformed under the following positivity constraint:

$$\hat{r}_t^{+} = \begin{cases} \hat{r}_t \text{ if } \hat{r}_t > 0, \\ 0 \text{ otherwise.} \end{cases} \tag{11}$$

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

3 | DATASET

In this study, we forecast six widely traded currencies; the GBP, YEN, CHF, EUR, CAD, and AUD against the USD as a basis currency. FX spot prices were collected from Bloomberg database. Our sample contains daily observations that extend from February 2, 1999, to December 31, 2017. The total number of observations is 4940. The first 25 observations of the sample serve as a control window ("look-back period"), in order to generate the CPs, as illustrated in Equation (5). The following 1257 observations are considered as the in-sample period, and the remaining 3658 are used as the out-of-sample period.

Panel A of Figure 1 shows the daily spot exchange rates of the six currencies under consideration against the USD for the period under examination (February 2, 1999, to December 31, 2017). Similarly, panel B of Figure 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 GBP is positive and equal to 0.3%, while the remaining currencies have

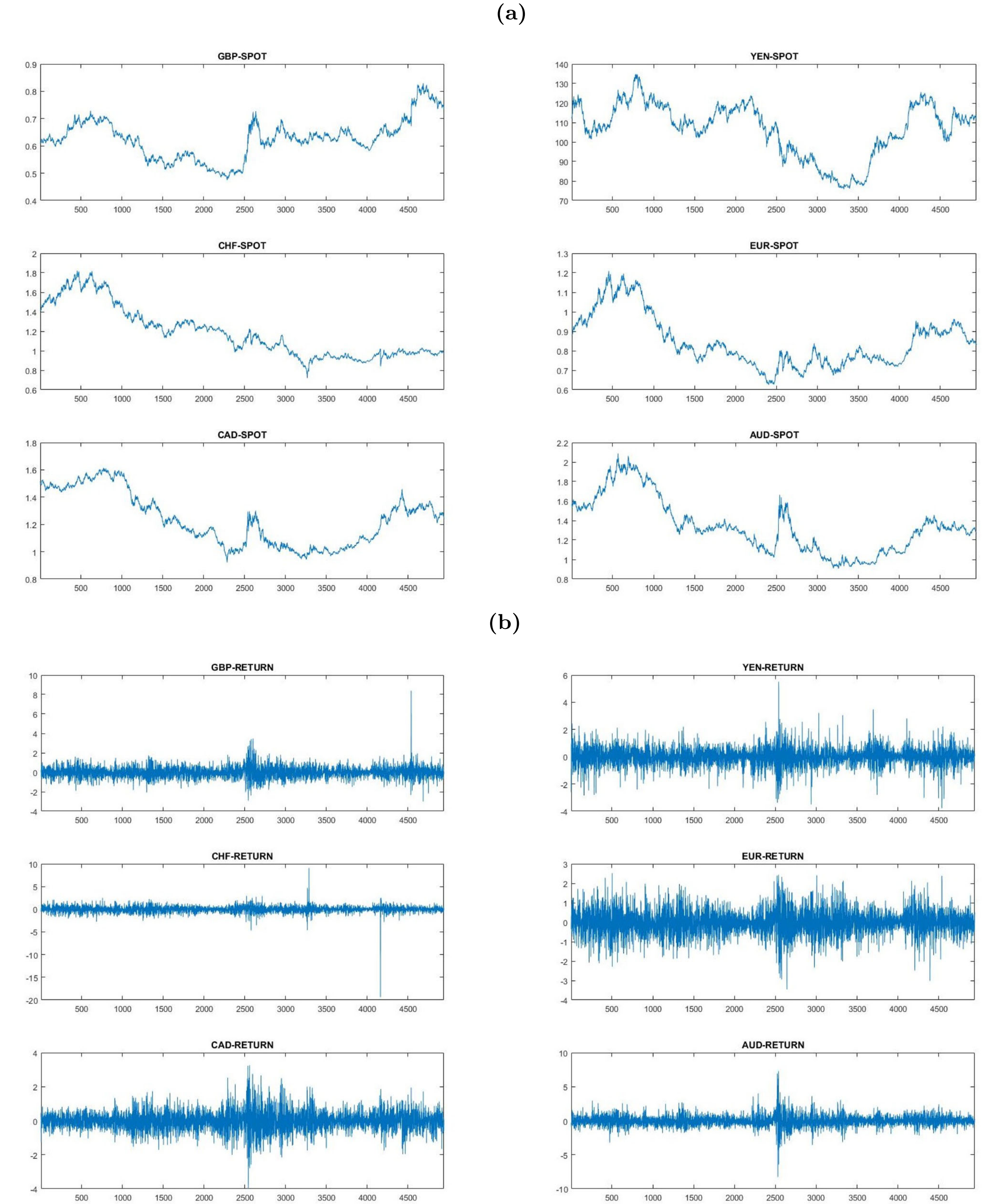


FIGURE 1 Spot exchange rates and returns. *Note*: (a) The first part of the figure illustrates the spot prices throughout the total sample period, from February 1999 to December 2017, for the six currencies under consideration. (b) The second part of the figure presents the evolution of actual returns through time for all six currencies under consideration.

TABLE 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

Abbreviations: Kurt, kurtosis; Skew, skewness; Std, standard deviation.

negative means ranging from −0.2% (YEN, EUR) to −0.8% (CHF). 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 returns (0.58 and 0.56, respectively), while the largest ones in CHF and 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.

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 are 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. VIX measures the volatility implied by option prices on 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/liquidity risk in the US economy. In general, an increase in VIX and/or the TED spread is associated with negative financial outlook. We also consider gold returns (GOLD), which is a safe haven against shocks in risky assets and complements VIX and TED as risk measures (Capie et al., 2005).

Following Calvet et al. (2006) and Ferraro et al. (2015), we employ the returns of crude oil (OIL), measured by the West Texas Intermediate (WTI) series, 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 et al., 2015), we employ the Baltic Dry Index returns (BDI), which is composed of 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 (denoted as EquityM and VEquityM). The equity indices we employ are FTSE100, NIKKEI225, SPI, DAX30, SPTSX, and AllOrds for GBP, YEN, CHF, EUR, CAD, and AUD, respectively.

Following Bekaert and Hodrick (1992), Clarida et al. (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 et al., 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:

$$
\begin{aligned}
L_t &= \left(y_t^{(3)} + y_t^{(24)} + y_t^{(120)}\right)/3, \\
S_t &= \left(y_t^{(3)} - y_t^{(120)}\right), \\
C_t &= \left(2y_t^{(24)} - y_t^{(3)} - y_t^{(120)}\right).
\end{aligned} \tag{12}
$$

Candidate predictors are generated by taking the differences between the respective factor for the United States 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 2 provides a more detailed description of the predictors we employ, their construction, and the respective data sources.

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

TABLE 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	Logarithmic returns of gold prices	Fred Database
4	OIL	Log returns of crude oil	Fred Database
5	BDI	Logarithmic returns of Baltic Dry Index	Bloomberg
6	CRB	Logarithmic returns of CRB commodities index	Bloomberg
7	MSCI	Logarithmic returns of MSCI global stock market index	Bloomberg
8	SP500	Logarithmic returns of SP500	Bloomberg
9	VSP500	Logarithmic growth of volume of SP500	Bloomberg
10	EquityM	Logarithmic returns of 6 equity markets (FTSE100, NIKKEI225, SPI, DAX30, SPTSX, AllOrds)	Bloomberg
11	VEquityM	Logarithmic growth of volume of the six equity markets	Bloomberg
12	ΔL	Level of yield curve factor $\Delta\left(L_t^{US} - L_t^i\right)$ where $L_t = \left(r_t^{(3)} + r_t^{(24)} + r_t^{(120)}\right)$	Bloomberg
13	ΔS	Slope of yield curve factor $\Delta\left(S_t^{US} - S_t^i\right)$ where $S_t = \left(r_t^{(3)} - r_t^{(120)}\right)$	Bloomberg
14	ΔC	Curvature of yield curve factor $\Delta\left(C_t^{US} - C_t^i\right)$ where $C_t = \left(2r_t^{(24)} - r_t^{(3)} - r_t^{(120)}\right)$	Bloomberg

Note: The predictors are collected for the sample period extending from February 2, 1999, to December 31, 2017.

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 1282 values (5 years), 25 of which correspond to the control window. The out-of-sample dataset consists of the remaining 3658 values. We produce 1-day-ahead out-of-sample forecasts recursively, that is, 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 RW with drift, that is, the historical average. This benchmark has proven very difficult to outperform (see Welch & Goyal, 2008) 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_{OOS}^2, which is given by

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

We can interpret R_{OOS}^2 as the proportional change in the MSFE of the competing predictor j against the MSFE obtained by the benchmark. When R_{OOS}^2 is positive the model under consideration generates superior forecasts than the benchmark and vice versa.

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

$$MSFE_{adj} = \left(\frac{1}{P}\right)\left\{\sum_{t=R+1}^{T-1}\left\{\left(r_{t+1} - \underset{t+1}{r}RW\right)2 - \left[\left(r_{t+1} - \underset{t+1}{r}\right)^2 - \left(\underset{t+1}{r}RW - \underset{t+1}{r}\right)^2\right]\right\}\right\}, \tag{13}$$

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 one is composed of 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 a one-sided test where H_0 is given by $MSFE_{RW} \leq MSFE_j$ against the alternative. The standard normal distribution can provide a very good approximation of the critical values.

4.1 | Empirical findings

In this section, we evaluate the out-of-sample performance of the forecasting methods considered in Section 2. Initially, we examine whether individual predictors or combinations can provide consistently superior forecasts, irrespective of the currency under consideration. Second, we examine whether the proposed methodologies, namely, IC, CP, and ICCP, enhance the forecasting performance. Finally, we examine whether the application of positivity constraints on forecasts further improves forecast accuracy.

Table 3 shows the out-of-sample performance of all predictors and all proposed methods for the six currencies. By examining Table 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 specifications C^0, $C^{IC,0}$, and $C^{CP,0}$; (3) $C^{ICCP,+}$ produces the highest R_{OOS}^2 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, we observe 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_{OOS}^2 (0.12%). On the other hand, the R_{OOS}^2 of both PCA and PLS are negative. Applying the IC approach, we observe an increase in terms of R_{OOS}^2; however, only MSCI and SP500 have positive and statistically significant R_{OOS}^2. R_{OOS}^2 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 is relatively poor with only six predictors with positive R_{OOS}^2. We observe the odd fact that negative R_{OOS}^2 values (PLS) are accompanied by statistically significant CW critical values.[2] Finally, when $ICCP$ is used, R_{OOS}^2 further increases in most cases, for example, the R_{OOS}^2 for the SP500 increases from 0.10% to 0.28%. However, again in most cases, the R_{OOS}^2 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_{OOS}^2 while in the case of $C^{IC,+}$ and $C^{ICCP,+}$, all R_{OOS}^2 are positive. For example, we observe that ΔVIX returns a very low -0.32% R_{OOS}^2 in the case of C^0 while it increases to a statistically significant 0.10% for C^+ and to a statistical significant 0.17% for $C^{ICCP,+}$. Similar changes are observed for all individual 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 $C^{CP,+}, C^{IC,+}$, and C^+. Both amalgamation approaches deliver statistically significant R_{OOS}^2 with the $C^{ICCP,+}$ method being the dominant methodology. Specifically, for AMALG-PPP, the R_{OOS}^2 is 0.18%, while for AMALG-PP, it is reduced to 0.14%.

Focusing on YEN in panel B of Table 3, we observe mixed results for the forecasting ability of each predictor and method. In general, MSCI, SP500, OIL, ΔVIX, and the slope of the yield curve deliver positive and statistically significant R_{OOS}^2 while on the other hand, the R_{OOS}^2 from ΔTED, GOLD, BDI, VSP500, and ΔL is negative and in general large in absolute values. Finally, R_{OOS}^2 for POOL, PCA, and PLS is 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_{OOS}^2 for CRB increases from 0.04% to 0.16%. On the other hand, we observe that the R_{OOS}^2 of POOL, PCA, and PLS decreases when the positivity constraint is applied although it is still positive and statistically significant. For example, in the case of POOL, R_{OOS}^2 decreases from 0.40% to 0.20%. Again, $C^{ICCP,+}$ outperforms the alternative methods followed by $C^{CP,+}, C^+$, and $C^{IC,+}$. It is worth noting that PCA outperforms all other specifications for all methods followed by MSCI, SP500, POOL, PLS, and OIL. Finally, both AMALG-PPP and AMALG-PP deliver superior and consistent significant results in all methodologies. For AMALG-PPP, C^0 is the best with R_{OOS}^2 of 0.56%, while for AMALG-PP, $C^{ICCP,0}$ is the best with R_{OOS}^2 of 0.52%.

Moving to CHF, we observe poor forecasting ability from all predictors with an exception of ΔS, which delivers a statistically significant R_{OOS}^2 of 0.12%. As

TABLE 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	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	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**
AMALG-PPP	0.08*	0.18**	0.09*	0.17**	0.07*	0.13**	0.12*	0.18**
AMALG-PP	−0.13*	0.10**	−0.02*	0.13**	−0.07*	0.08*	0.02*	0.14**
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**
AMALG-PPP	0.56***	0.25**	0.51***	0.25**	0.39***	0.21**	0.51***	0.25**
AMALG-PP	0.42***	0.17**	0.48***	0.21**	0.33***	0.16**	0.52***	0.23**
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

(Continues)

TABLE 3 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
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
AMALG-PPP	−0.12	−0.03	−0.04	**0.02**	−0.12	−0.03	**0.01**	**0.03**
AMALG-PP	−0.41	−0.17	−0.21	−0.08	−0.33	−0.14	−0.15	−0.06
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	−0.50	−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
AMALG-PPP	−0.64	−0.25	−0.41	−0.12	−0.43	−0.13	−0.30	−0.08
AMALG-PP	−1.26	−0.55	−0.81	−0.34	−0.86	−0.33	−0.66	−0.27
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**

TABLE 3 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CRB	**0.01**	**0.06***	0	**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
AMALG-PPP	−0.19	**0.01**	−0.17	**0.03**	−0.09	**0.05**	−0.13	**0.05**
AMALG-PP	−0.39	−0.06	−0.29	−0.02	−0.21	**0.02**	−0.24	**0.00**
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
AMALG-PPP	−0.60	−0.44	−0.58	−0.37	−0.43	−0.35	−0.56	−0.36
AMALG-PP	−1.08	−0.75	−0.90	−0.64	−0.77	−0.60	−0.89	−0.64

Note: 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), partial least squares (PLS), amalgamation of POOL-PCA-PLS (AMALG-PPP), and amalgamation of PCA-PLS (AMALG-PP), 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 (Lin et al., 2018). $C^{IC,+}$ denotes the IC methodology with positivity constraints. $C^{CP,0}$ refers to the constrained predictor approach of Pan et al. (2020). $C^{CP,+}$ refers to the constrained predictor approach with positivity constraints. $C^{ICCP,0}$ denotes the hybrid method, that is, 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. Bold numbers indicate positive R^2_{OOS}.

*10% level of statistical significance.

**5% level of statistical significance.

***1% level of statistical significance.

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 three combination methods, only two 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 observe six 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 IC approach outperforms the CP approach while the simple bivariate models rank last.

Focusing on EUR, we observe similar results to CHF. A closer inspection of panel D of Table 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 nine predictors is statistically significant, that is, 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, for example, 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, PLS, and both AMALG approaches are always negative.

Next, we focus on the CAD. The results are presented in panel E of Table 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 combining the ICs and predictor constrained approach yields better results compared with each approach separately. For example, in the case of SP500, the R^2_{OOS} is -0.25%, 0.14%, and -0.11% for $C^0, C^{IC,0}$, 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 and amalgamation approaches.

Finally, we examine the performance of the predictors and the proposed approaches in forecasting AUD returns. The results are presented in panel F of Table 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 seven, 10, and six positive R^2_{OOS}, respectively, 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 it is more difficult to forecast the returns of the AUD FX returns than other currencies. Furthermore, POOL, PCA, AMALG-PPP, AMALG-PP, and PLS have a poor performance although POOL outperforms the other methods in the majority of cases. Overall, the results presented in Table 3 show evidence of predictability in 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, that is, POOL, PCA, and PLS along with two amalgamation forecasts. We observe that the R^2_{OOS} of POOL is larger for all currencies under consideration with the exception of GBP and YEN, where the amalgamation approaches appear superior. On the other hand, when positivity constraints are applied, we observe that OIL, the volume of S&P500 (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 IC and CP 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 2. Due to space limitations, we only present the relative figures for the combination and dimensionality reduction techniques. 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

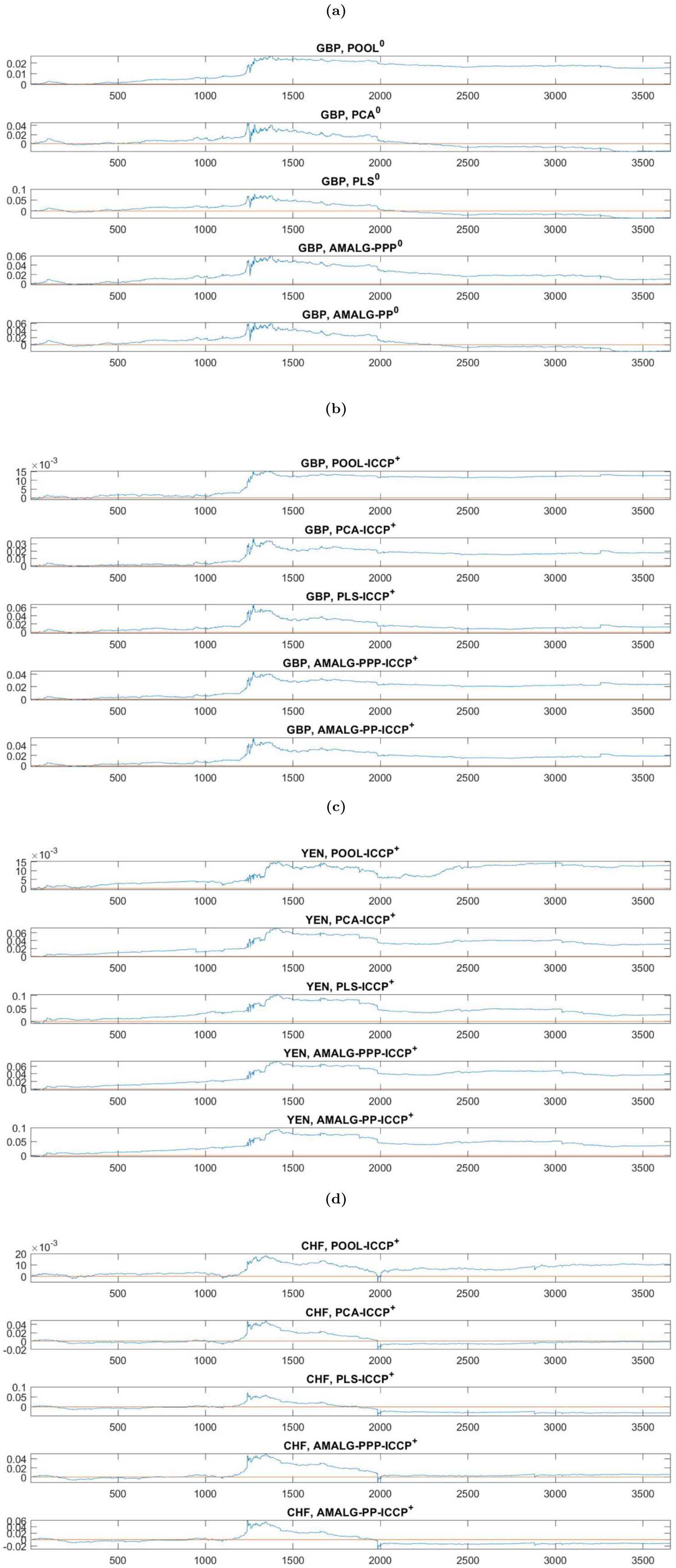
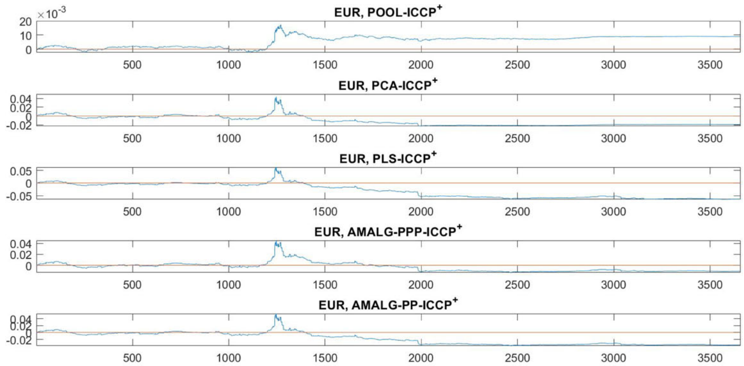
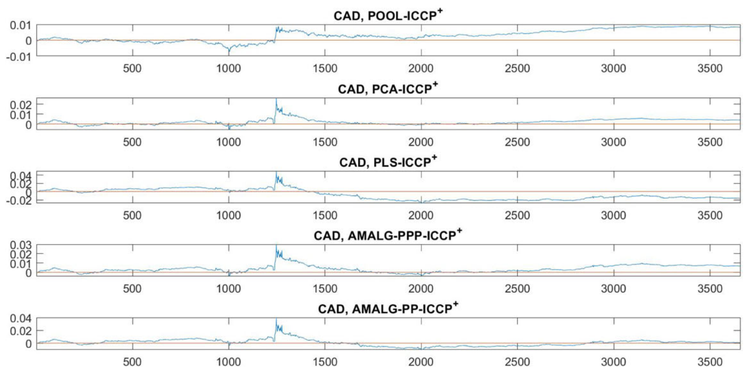


FIGURE 2 Dynamic evolution of out-of-sample forecasts.

(e)



(f)



(g)

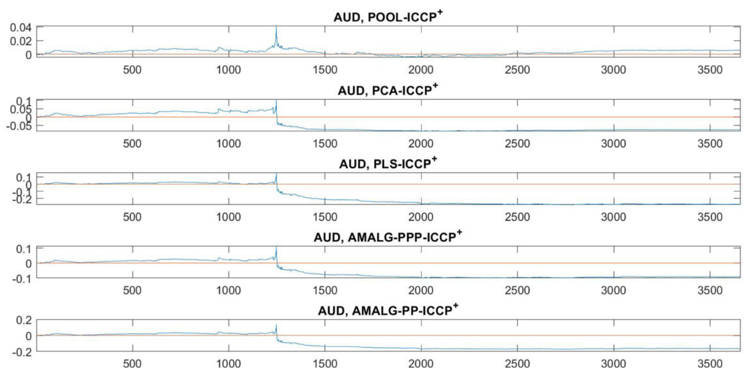


FIGURE 2 (Continued)

$C^{ICCP,+}$ 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.

5 | 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.

5.1 | Rolling window

In this part of the paper, we evaluate the robustness of our proposed methodologies by altering the information set used to generate the forecast corresponding to time $t+1$. So far, we used an expanding window. Thus, the investor updated her information set by adding one observation at every iteration, such as $1:R$ in order to forecast $t+1$, then $1:R+1$ to forecast $t+2$, and so on until the end of the sample. We now use a rolling scheme to generate forecasts. Under the rolling scheme, the parameters are re-estimated progressively by maintaining the length of the window constant over time by using most recent data. Hence, for the first forecast, we are using the information set $1:R$, for the second forecast $2:R+1$, and so on until the end of the out-of-sample period. The size of the window is set at 1257 observations. We note that the size of the sample window is sufficient to allow efficiency in the estimation of parameters.[3] Rogoff and Stavrakeva (2008) argue that the size of the window does not play a significant role in the performance of the forecasts.

Based on the results reported in Table 4, we only see sporadic changes in the performance of the methodologies for CHF and EUR. The differences are mainly in terms of the CW statistic, rather than the R^2_{OOS} metric. The performance of the candidate models in the other currencies remains qualitatively the same. The results are in line with Rossi (2013), who claims that the change in the window size affects a few countries to some extent, rather than impacting the overall performance. However, the performance of POOL, PCA, and PLS along with the two amalgamation approaches improves significantly in all currencies with the exception of AUD.

5.2 | Monthly frequency

In this section, we examine the impact of the frequency on our results. More precisely, we change the frequency from daily to monthly frequency. In this case, we use the end-of-month observation, and the size of the control window is set to 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 5. A closer inspection of Table 5 reveals that positivity constraints improve the performance of each method as in the case of the initial results. POOL, PCA, and PLS along with the amalgamation approaches show high positive R^2_{OOS} values for GBP 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 as opposed to the 3-month one.

For the GBP exchange rate, the predictors with the highest R^2_{OOS} values are CRB and OIL. The R^2_{OOS} further increases when the PCA and PLS are considered together with positivity constraints. In general, C^{+} and $C^{CP,+}$ 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, PLS, AMALG-PPP, and AMALG-PP that 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, for all frequencies under consideration. In the case of CAD, we observe that almost all R^2_{OOS} are negative for $C^{0}, C^{IC,0}, C^{CP,0}$, and $C^{ICCP,0}$. On the other hand, when positivity constraints are applied, all R^2_{OOS} become positive, and most of them are 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 on aggregate perform the same, albeit with some remarkable high R^2_{OOS} values especially for GBP.

5.3 | 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 three trading months. In this case, CPs 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 75 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

TABLE 4 Out-of-sample results, rolling window.

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel A: GBP								
ΔVIX	−0.29	0.12**	−0.25	0.14**	−0.21	0.15**	−16.87	−6.68
ΔTED	−0.23	0.03	−0.53	0.05*	−0.23	0.01	−0.47	0.09**
GOLD	−0.10	0.01	−0.76	−0.06	−0.08	−0.02	−0.55	−0.10
OIL	−0.08	0.00	−0.21	−0.05	−0.09	−0.01	−0.40	0.00
BDI	−0.15	0.07	−0.15	0.03	−0.12	0.00	−0.21	0.11**
CRB	−0.06	0.00	−0.09	−0.04	−0.06	−0.03	0.05**	0.11**
MSCI	0.01*	−0.03	−0.17*	−0.14	0.10**	0.01	−0.18	−0.17
SP500	0.14**	0.08**	0.16**	0.07**	0.19**	0.11*	0.46***	0.27**
VSP500	−0.11	0.03	−0.74	0.10**	−0.08	0.04*	−0.56	−0.01**
EquityM	−0.16	−0.08	−0.41	−0.16	−0.18	−0.08	−1.95	−0.58
VEquityM	−0.24	−0.07	−0.58	−0.37	−0.20	−0.07	−0.09*	−0.06
ΔL	−0.14	−0.02	−0.59	0.06*	−0.06	0.01	−0.13	0.13***
ΔS	−0.11	0.08**	−0.17	0.13***	0.03	0.08*	−0.16*	0.16***
ΔC	−0.04	0.11*	−0.17	−0.03*	−0.02	0.14**	−0.14	0.00
POOL	0.09	0.11**	−0.97	0.11**	0.03	0.07*	−1.74	−0.02
PCA	−0.10*	0.07*	−0.09*	0.07*	−0.04	0.09*	−0.07*	0.07*
PLS	−0.60*	−0.04**	−0.56*	−0.02**	−0.62	−0.15	−0.55*	−0.02**
AMALG-PPP	0.00*	0.15**	−0.33	0.15**	−0.06	0.07*	−0.48	0.12**
AMALG-PP	−0.26*	0.05**	−0.23*	0.06**	−0.25	−0.00*	−0.22*	0.06**
Panel B: YEN								
ΔVIX	0.26***	0.18**	0.15***	0.15**	0.36***	0.22**	0.19***	0.15**
ΔTED	−0.22	−0.23	−0.20	−0.16	−0.19	−0.15	−0.04	−0.17
GOLD	−0.07	0.03	−0.23	0.08*	−0.07	0.04	−0.69	−0.46
OIL	0.11**	0.26**	−0.21*	0.20**	0.10*	0.18**	−0.05*	0.24**
BDI	−0.23	−0.04	−0.03*	−0.07	−0.21	−0.03	−0.06**	0.02*
CRB	−0.08	0.15**	−0.19	0.04*	−0.06	0.16**	−0.41	−0.06
MSCI	0.48***	0.28**	0.35***	0.25**	0.74***	0.43***	0.36***	0.20**
SP500	0.39***	0.28**	0.34***	0.23**	0.45***	0.42***	0.18**	0.20**
VSP500	0.02*	0.15***	−0.16*	0.16***	0.05*	0.15***	−0.22*	0.16***
EquityM	0.09*	0.04	0.01*	−0.02	0.09*	0.05	−0.14	−0.01
VEquityM	−0.10	0.00	−0.27	−0.03*	−0.09	0.03	−0.12	−0.04
ΔL	−0.17	0.07*	−0.14	0.09**	−0.08	0.11*	−0.53	−0.23
ΔS	0.01	0.02	0.00	0.03	−0.05	0.00	−0.30	−0.16
ΔC	−0.08	0.03	−0.19	0.12**	−0.02	0.07*	−0.12	−0.02
POOL	0.41***	0.24**	−1.06***	0.24**	0.30***	0.22***	−1.50**	0.19**
PCA	0.54***	0.29**	0.53***	0.27**	0.58***	0.43***	0.38***	0.22**
PLS	0.61***	0.28***	0.63***	0.29***	0.60***	0.35***	0.63***	0.29***
AMALG-PPP	0.88***	0.46***	0.43***	0.45***	0.77***	0.48***	0.30***	0.42***
AMALG-PP	0.69***	0.34***	0.69***	0.33***	0.68***	0.43***	0.65***	0.32***
Panel C: CHF								
ΔVIX	−0.27	0.05*	−0.22*	0.01**	−0.18	0.14*	−0.20	0.06**
ΔTED	−0.15	−0.06	−0.06*	−0.02	−0.07	0.00	−0.09**	−0.02

TABLE 4 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GOLD	−0.12	0.07*	−0.67	0.03*	−0.06	0.08*	−0.15	0.09**
OIL	−0.56	−0.33	−0.86	−0.36	−0.54	−0.39	−0.49	−0.22
BDI	−0.00*	0.05*	−0.06*	0.07*	0.03	0.09**	−3.02	−2.24
CRB	−0.43	−0.12	−0.38	−0.16	−0.36	−0.12	−1.15	−0.54
MSCI	−0.26	−0.07	−0.22	−0.06	−0.25	0.00	−0.43	−0.26
SP500	−0.26*	−0.00*	−0.22*	0.01*	−0.11	0.11*	−0.84*	−0.40*
VSP500	−0.09	0.06*	−0.10	0.02*	−0.05	0.05*	−0.18	0.13**
EquityM	−0.22	0.07*	0.29*	0.65**	−0.29	0.02	0.05	0.27*
VEquityM	−0.03	0.08**	−0.83	−0.01	−0.02	0.08**	−0.23	0.07*
ΔL	−0.27	0.06	−0.17	0.08	−0.13	0.07	−1.09	−1.01
ΔS	0.14**	0.09**	−0.08*	0.10**	0.14**	0.04*	−0.02**	0.12**
ΔC	−0.16	0.09*	−0.15	0.14**	−0.13	0.11**	−0.12	0.14**
POOL	0.03	0.08*	−1.28	0.13*	0.01	0.08	−1.56	0.02
PCA	−0.45	−0.02*	−0.42	−0.00*	−0.40	0	−0.97	−0.36
PLS	−0.78	−0.21*	−0.74	−0.19*	−0.70	−0.25	−0.74	−0.19*
AMALG-PPP	−0.19	0.05*	−0.63	0.08*	−0.20	0.02	−0.74	−0.03*
AMALG-PP	−0.53	−0.07*	−0.49	−0.05*	−0.49	−0.09	−0.60	−0.18*
Panel D: EUR								
ΔVIX	−0.16*	0.30***	−0.12*	0.30***	0.01*	0.40***	−0.06**	0.21***
ΔTED	−0.14	0.05*	−0.99	−0.15	−0.15	0.03*	−0.59	−0.10
GOLD	−0.17	−0.05	−0.46	−0.09	−0.14	−0.02	−0.58	−0.11
OIL	−0.16	0.00	−0.24	−0.06	−0.14	0.01	−1.41	−0.16
BDI	−0.02*	0.16**	−0.04**	0.18**	0.01	0.11*	−2.32	−1.67
CRB	−0.15	0.00	−0.15	−0.07	−0.09	0.03	0.04**	0.05*
MSCI	−0.21	−0.04	−0.18	0.00	−0.21	−0.03	−0.84	−0.48
SP500	−0.23*	−0.01*	−0.14**	0.02*	−0.06*	0.09*	0.13**	0.09**
VSP500	−0.10	0.03	−0.80	0.04*	−0.08	0.04*	−0.83	0.06**
EquityM	−0.08	0.12**	−0.03	0.12**	−0.05	0.13**	−0.21	−0.00*
VEquityM	−0.02	0.07**	−0.24	0.01*	0.05*	0.10**	−0.13	0.06**
ΔL	−0.13	0.06*	−0.07	0.05*	−0.08	0.07**	0.04**	−0.14**
ΔS	0.07	0.12**	0.02*	0.13**	0.23**	0.14**	0.10*	0.13**
ΔC	−0.15	0.02	−0.10	0.03*	−0.14	0.01	−0.23	−0.02
POOL	0.14*	0.16**	−1.30	0.14**	0.11*	0.14**	−1.56	0.12**
PCA	−0.31*	0.04**	−0.31*	0.03**	−0.13*	0.22**	−0.27*	0.04**
PLS	−0.62**	−0.09**	−0.58**	−0.07**	−0.29**	0.06**	−0.57**	−0.07**
AMALG-PPP	0.01**	0.17**	−0.41*	0.18**	0.10**	0.24**	−0.47*	0.18**
AMALG-PP	−0.33**	0.04**	−0.29**	0.06**	−0.13**	0.18**	−0.28**	0.06**
Panel E: CAD								
ΔVIX	−0.31	0.08*	−0.11	0.09*	0.04*	0.14**	−0.07	0.17**
ΔTED	−0.23	−0.06	−0.25	0.01	−0.14	0.00	−0.21	0.04
GOLD	−0.03	0.02	−0.18*	0.03*	−0.05	0.04*	−0.54	0.01*
OIL	−0.09	−0.05	−0.06	−0.03	−0.11	−0.06	−0.45	−0.03
BDI	−0.12	0.03	−0.24	0.00	−0.05	0.03	−0.11	−0.05

(Continues)

TABLE 4 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CRB	−0.08	**0.03**	−0.01	**0.02**	**0.00**	−0.05	−0.03	**0.02**
MSCI	−0.20	**0.12***	−0.23	**0.09**	−0.09	**0.16****	−0.09	**0.15****
SP500	−0.32	**0.15***	−0.30	**0.16***	**0.00**	**0.22****	−1.18	−0.50
VSP500	−0.05	**0.04**	−0.99	**0.04***	−0.04	**0.05***	−0.87	−0.01
EquityM	−0.31	**0.03**	−0.38	−0.01	−0.13	**0.13****	**0.07**	**0.11**
VEquityM	−0.10	**0.02**	−0.23	**0.05***	−0.09	**0.03**	−0.47	**0.07***
ΔL	**0.05***	**0.11****	**0.05***	**0.09****	**0.04***	**0.08****	**0.06****	**0.06****
ΔS	−0.09	**0.06***	−1.87	**0.01**	−0.08	**0.02**	−0.60	**0.22****
ΔC	−0.15	**0.04***	−0.62	**0.04***	−0.10	**0.04***	−0.41	**0.02***
POOL	**0.03**	**0.11***	−1.39	**0.11***	**0.06**	**0.10****	−1.84	**0.14***
PCA	−0.34	**0.06***	−0.31	**0.07***	−0.06	**0.14****	−0.40	−0.11
PLS	−0.67	**−0.19***	−0.64	**−0.18***	**−0.29***	**0.08****	−0.63	**−0.18***
AMALG-PPP	−0.11	**0.10***	−0.52	**0.10***	**0.05***	**0.18****	−0.60	**0.07***
AMALG-PP	−0.36	**0.00***	−0.33	**0.01***	**−0.09***	**0.16****	−0.30	−0.05
Panel F: AUD								
ΔVIX	−0.36	−0.11	**0.06***	**0.02**	**0.01***	**0.02**	**0.31***	**0.27**
ΔTED	−0.46	−0.14	−0.22	−0.02	−0.46	−0.16	−0.22	−0.01
GOLD	−0.16	−0.07	−0.15	−0.13	−0.12	−0.06	**0.12****	**0.07***
OIL	−0.09	−0.14	−0.03	−0.10	−0.06	−0.10	−0.14	−0.17
BDI	−0.41	−0.32	−0.68	−0.29	−0.34	−0.30	−0.56	−0.32
CRB	−0.21	−0.15	−0.22	−0.05	−0.09	−0.22	−0.22	−0.08
MSCI	−0.33	−0.18	−0.39	−0.16	−0.14	−0.06	**0.08**	−0.01
SP500	−0.26	**0.03**	−0.26	**0.06**	**0.04**	**0.07**	**0.27**	**0.22**
VSP500	−0.11	−0.04	−0.19	**0.01**	−0.09	−0.02	−0.25	−0.05
EquityM	−0.32	−0.04	−0.62	**0.04**	−0.17	−0.13	−0.62	−0.18
VEquityM	−0.09	**0.01**	−0.27	**0.01**	−0.09	**0.01**	−0.26	**0.14*****
ΔL	−0.04	**0.04**	−0.22	**0.02**	**0.03**	**0.07***	−0.23	**0.13***
ΔS	−0.30	**0.08***	−0.39	**0.05***	−0.33	**0.02**	−0.56	**0.08***
ΔC	−0.21	−0.01	−0.47	**0.05***	**0.01**	**0.05***	−0.46	**0.04***
POOL	−0.02	**0.01**	−2.60	**0.04**	**0.02**	**0**	−2.82	**0.12**
PCA	−0.72	−0.30	−0.94	−0.25	−0.30	−0.31	−0.80	−0.26
PLS	−2.06	−1.78	−2.01	−1.75	−1.08	−1.20	−2.01	−1.75
AMALG-PPP	−0.56	−0.51	−1.45	−0.47	−0.22	−0.38	−1.46	−0.45
AMALG-PP	−1.13	−0.91	−1.21	−0.87	−0.58	−0.69	−1.15	−0.88

Note: The table presents the out-of-sample results after accounting for a rolling window. The size of the window is 1257 observations. Also, see notes in Table 3. Bold numbers indicate positive R^2_{OOS}.

observations in order to create the control window. The results are reported in Table 6. Comparing the results of Tables 3 and 6, we observe only minor changes in the values of the R^2_{OOS}. For all currencies, methods that show 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 specifications but a small decrease in POOL, PCA, PLS, and AMALG for most specifications, while for the YEN exchange rate, these methods continue to

TABLE 5 Robustness tests, monthly frequency.

Panel A:	C^0 3m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0 6m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GBP																
ΔVIX	−4.15	2.30	−4.10	0.93	−4.51	2.51	−3.19	1.58	−4.10	2.01	−3.51	1.19	−4.50	2.05	−2.53	1.74*
ΔTED	−2.64	2.75	−3.63	0.65	−3.02	1.73*	−4.25	0.66	−2.01	3.34	−2.82	1.04*	−2.93	2.09*	−3.20	0.86*
GOLD	−1.99	0.22	−1.00	0.42	−2.40	−0.18	−0.91	0.63*	−1.79	0.3	−0.79	0.42	−1.68	0.25	−0.16	0.65*
OIL	2.87**	4.53**	2.07*	3.33**	3.16**	5.10**	2.28*	3.42**	2.74**	4.23**	2.04*	3.15**	2.83*	4.39**	2.17*	3.11**
BDI	−1.43	1.54	−2.34	0.58	−1.76	1.06	−2.88	0.92	−1.42	1.52	−1.29	0.63	−2.35	1.1	−0.85	0.87
CRB	3.49**	4.86**	2.70*	3.55*	3.55*	4.78*	1.51*	2.99*	3.44**	4.64**	2.71*	3.49*	3.00*	4.04*	2.11*	2.99*
MSCI	0.30	1.81	−1.09	0.98	−0.12	1.82	−1.19	0.78	0.18	1.7	−0.52	1.12	0.03	2.31	−0.64	0.89
SP500	−0.74	0.51	−1.50	0.25	−0.87	0.92	−1.21	0.44	−0.91	0.43	−0.86	0.39	−0.98	0.81	−0.83	0.36
VSP500	−0.62	0.46	−0.32	0.41	−0.53	0.45	−0.32	0.42	−0.61	0.54	−0.26	0.58	−0.29	0.54	−0.22	0.58
EquityM	0.94	2.20	0.14	1.49	0.24	2.08	0.63	1.58	0.90	2.13	0.35	1.54	0.51	2.15*	0.22	1.30
VEquityM	−3.59	−1.38	−0.23	0.14	−4.07	−1.09	−0.52	−0.14	−3.59	−1.27	−0.76	−0.06	−3.99	−1.23	−0.88	−0.06
ΔL	−1.75	0.13	−0.19	0.51	−1.42	0.20	0.14	0.56	−1.32	0.22	−0.34	0.67*	−0.79	0.28	−0.10	0.67*
ΔS	−1.83	0.63*	−0.21	0.43	−2.02	0.58*	−0.32	0.44	−1.91	0.74*	−0.71	0.64*	−2.06	0.51	−0.57	0.66*
ΔC	−0.94	0.78	−1.34	0.51	−1.01	0.40	−1.42	0.51	−0.97	0.62	−0.81	0.64	−1.35	0.4	−0.63	0.73
POOL	1.72	2.72*	−0.92	1.81*	1.07	2.39*	−0.60	1.77*	1.59	2.63*	−0.04	1.84*	0.77	2.20*	0.16	1.72*
PCA	1.61*	6.12*	1.69*	5.18*	0.65	5.83*	1.27	4.53*	1.77*	5.87*	1.82*	4.87*	0.78	5.15*	0.51	3.27*
PLS	0.62*	5.31*	0.82*	4.83*	−0.26	4.97*	0.95*	4.80*	0.60*	5.28*	0.82	4.81*	−0.84	3.74*	0.85	4.56*
AMALG-PPP	3.23*	5.92*	1.4	5.11*	1.93	5.21*	1.44	4.82*	3.22*	5.79*	1.87	4.96*	1.55	4.44*	1.46	4.17*
AMALG-PP	1.51*	5.93*	1.57*	5.19*	0.51	5.56*	1.41	4.84*	1.62*	5.81*	1.67*	5.03*	0.35	4.65*	1.01	4.09*
YEN																
ΔVIX	−1.79	−1.17	−0.37	0.36	−1.65	−0.91	−0.12	0.63	−1.55	−1.68	−0.39	−0.29	−1.49	−1.44	−0.24	−0.17
ΔTED	−3.81	−1.78	−0.29	0.86	−3.44	−1.72	−0.2	0.81	−3.52	−2.21	−1.44	−0.12	−3.77	−2.66	−1.44	−0.13
GOLD	−1.60	−0.61	−0.30	0.64	−1.34	−0.23	−0.20	0.76	−1.65	−0.72	−0.70	0.19	−1.68	−0.51	−0.66	0.24
OIL	−2.86	−2.64	−0.74	−0.40	−1.81	−1.63	−0.50	0.08	−2.37	−2.17	−0.91	−0.60	−2.15	−1.83	−0.80	−0.48
BDI	−0.03	0.49	−0.17	0.76	−0.08	0.24	0.03	0.75	−0.01	0.46	0.69	0.86	0.18	0.34	0.81	0.84
CRB	−4.05	−3.44	−0.92	−0.39	−2.47	−1.68	−0.28	0.28	−3.5	−2.91	−1.17	−0.73	−2.82	−2.26	−0.96	−0.55
MSCI	−0.90	0.4	−0.32	0.87	−1.20	−0.04	−0.26	0.87	−0.64	0.36	−0.25	0.77	−0.81	−0.02	−0.23	0.77
SP500	−0.55	0.52	−0.36	0.86	−0.76	0.22	−0.29	0.87	−0.46	0.08	−0.09	0.71	−0.60	−0.04	−0.04	0.73
VSP500	−1.19	0.48	−0.10	0.87	−1.3	0.25	−0.14	0.88	−0.92	0.37	−0.37	0.88	−0.77	0.37	−0.37	0.87
EquityM	−3.11	−0.55	−0.62	0.81	−3.48	−1.54	−0.87	0.71	−2.08	0.09	−0.89	0.66	−2.48	−0.46	−0.93	0.65
VEquityM	−1.07	0.21	−0.20	0.89	−1.04	0.27	−0.15	0.88	−0.72	0.20	−0.29	0.73	−0.60	0.32	−0.28	0.73
ΔL	−1.06	0.54	−0.33	0.89	−1.12	0.54	−0.37	0.85	−1.39	0.29	−0.49	0.70	−1.25	0.09	−0.54	0.70

(Continues)

TABLE 5 (Continued)

Panel A:	C^0 3m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0 6m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
ΔS	−0.79	**0.78**	**0.00**	**0.90**	−0.47	**0.58**	**0.06**	**0.91***	−0.58	**0.50**	−0.23	**0.80**	−0.50	**0.18**	−0.28	**0.77**
ΔC	−0.70	−0.14	−0.26	**0.53**	−0.38	**0.18**	−0.25	**0.68**	−0.31	**0.21**	−0.02	**0.64**	−0.22	**0.30**	**0.02**	**0.69**
POOL	−0.31	−0.03	−0.10	**0.73**	−0.42	−0.05	−0.09	**0.79**	−0.06	−0.01	−0.03	**0.53**	−0.10	−0.06	−0.03	**0.55**
PCA	−5.68	−3.12	−2.38	−0.8	−5.88	−4.33	−1.71	−0.42	−3.67	−1.71	−1.53	−0.06	−7.33	−5.62	−1.68	−0.19
PLS	−10.56	−6.21	−6.77	−3.77	−8.53	−5.38	−5.97	−3.34	−5.93	−2.35	−2.57	−0.42	−4.62	−2.18	−2.63	−0.48
AMALG-PPP	−3.93	−2.31	−2.03	−0.79	−3.83	−2.65	−1.71	−0.57	−1.89	−0.67	−0.68	**0.35**	−2.85	−1.92	−0.74	**0.30**
AMALG-PP	−7.02	−4.07	−3.74	−1.88	−6.45	−4.43	−3.11	−1.52	−4.01	−1.58	−1.58	**0.01**	−5.22	−3.40	−1.70	−0.09
CHF																
ΔVIX	−3.71	−1.68	−1.19	−0.45	−4.39	−0.24	−1.29	−0.37	−2.62	−1.23	−1.56	−0.37	−3.59	**0.10**	−1.48	−0.34
ΔTED	−1.89	**0.61**	−0.02	**0.54**	−1.45	**0.40**	**0.07**	**0.54**	−1.36	**1.08**	−0.52	**0.64**	−1.00	**0.72**	−0.41	**0.64**
GOLD	−1.98	**0.61**	−0.17	**0.67**	−1.82	**0.53**	−0.04	**0.64**	−1.77	**0.74**	−0.46	**0.82**	−1.58	**0.69**	−0.24	**0.74**
OIL	−1.84	−1.88	−1.43	−0.61	−1.42	−0.96	−1.30	−0.78	−1.52	−1.47	−1.22	−0.39	−1.21	−0.53	−1.06	−0.46
BDI	−1.39	**0.43**	**0.20**	**0.54**	−1.24	**0.47**	**0.22**	**0.54**	−1.36	**0.48**	−0.18	**0.64**	−1.40	**0.40**	−0.19	**0.64**
CRB	−2.46	−1.77	−0.95	−0.64	−1.82	−0.59	−1.30	−0.8	−1.89	−1.38	−0.88	−0.55	−1.35	−0.58	−1.04	−0.67
MSCI	−0.57	**0.06**	**0.00**	**0.52**	−0.71	**0.44**	**0.08**	**0.53**	−0.47	**0.63**	−0.02	**0.43**	−0.59	**0.82**	**0.16**	**0.54**
SP500	**0.36**	**1.06**	**0.33**	**0.33**	**0.25**	**0.87**	**0.1**	**0.43**	**0.53**	**1.30***	**0.49**	**0.61**	**0.25**	**1.14**	**0.55**	**0.67**
VSP500	−1.11	**0.33**	**0.04**	**0.55**	−0.99	**0.36**	**0.04**	**0.56**	−1.23	**0.21**	−0.19	**0.67**	−0.9	**0.26**	−0.16	**0.66**
EquityM	−1.43	**0.17**	**0.25***	**0.54**	−1.16	**0.1**	**0.19***	**0.54**	−1.1	**0.45**	−0.04	**0.64**	−1.60	**0.06**	−0.11	**0.64**
VEquityM	−2.57	−1.74	−0.22	**0.49**	−2.28	−1.95	−0.24	**0.47**	−2.18	−1.82	−0.93	**0.13**	−2.91	−2.06	−0.88	**0.05**
ΔL	−1.33	**0.53**	**0.40****	**0.54**	−1.33	**0.47**	**0.40****	**0.54**	−1.04	**0.39**	−0.06	**0.64**	−1.02	**0.39**	−0.02	**0.64**
ΔS	−1.11	**0.37**	**0.17**	**0.54**	−0.81	**0.52**	**0.16**	**0.54**	−1.11	**0.21**	−0.16	**0.64**	−0.66	**0.4**	−0.02	**0.64**
ΔC	−0.97	**0.54**	**0.08**	**0.54**	−1.06	**0.46**	**0.05**	**0.54**	−1.05	**0.64**	0.00	**0.64**	−1.05	**0.61**	−0.03	**0.64**
POOL	−0.66	**0.14**	−0.19	**0.37**	−0.63	**0.32**	−0.17	**0.35**	−0.38	**0.31**	−0.30	**0.46**	−0.52	**0.41**	−0.23	**0.44**
PCA	−2.73	**1.16***	−1.10	**0.88**	−3.22	**0.75***	−0.99	**0.93**	−2.16	**1.01***	−1.24	**0.99**	−2.51	**1.13***	−0.78	**1.18**
PLS	−7.74	−4.70	−3.97	−2.29	−7.29	−2.95	−3.88	−2.14	−6.51	−3.84	−4.02	−2.30	−6.27	−2.17	−3.66	−1.99
AMALG-PPP	−2.31	−0.39	−1.00	**0.01**	−2.48	**0.02**	−0.94	**0.05**	−1.73	−0.21	−1.00	**0.08**	−2.20	**0.24**	−0.74	**0.21**
AMALG-PP	−4.67	−1.44	−2.23	−0.56	−4.77	−0.86	−2.12	−0.46	−3.67	−1.05	−2.17	−0.45	−3.91	−0.28	−1.73	−0.21
EUR																
ΔVIX	−5.39	−1.23	−2.70	−1.13	−6.84	**1.18**	−3.57	−1.42	−4.51	−1.07	−2.37	−0.67	−6.13	**1.35**	−3.09	−0.97
ΔTED	−5.24	**0.21**	−0.40	**0.85**	−4.24	**0.28**	−0.36	**0.79**	−4.11	**0.65**	−1.23	**1.07***	−3.76	**0.75**	−1.15	**1.05***
GOLD	−1.62	**0.74**	−0.62	**0.93***	−1.63	**0.74**	−0.52	**0.96***	−1.40	**0.91***	−0.52	**1.09***	−1.20	**0.94***	−0.37	**1.09***
OIL	−1.15	−0.89	−1.40	**0.12**	−0.48	**0.27**	−1.24	0.00	−1.18	−0.61	−0.90	**0.36**	−0.78	**0.2**	−0.85	**0.28**
BDI	−2.94	−1.56	−1.37	**0.23**	−3.21	−1.61	−1.22	**0.42**	−2.85	−1.47	−1.63	−0.09	−3.47	−1.53	−1.37	**0.15**

TABLE 5 (Continued)

Panel A:	C^0 3m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0 6m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CRB	−1.91	−1.37	−2.24	−0.89	−1.31	−0.44	−2.63	−1.02	−1.69	−1.22	−1.60	−0.72	−1.25	−0.35	−1.70	−0.76
MSCI	−0.74	0.33	0.26	1.05*	−0.84	0.60	0.08	0.92*	−0.64	0.80	0.18	1.27*	−0.71	0.96*	0.06	1.12*
SP500	1.49*	1.95**	1.37**	1.29**	0.95	1.90**	0.90**	1.16*	1.73*	2.27**	1.68**	1.51**	0.95	2.04**	1.20**	1.39*
VSP500	−0.39	0.74	0.05	0.89*	−0.36	0.78	0.07	0.90*	−0.38	0.81	−0.05	1.04*	−0.34	0.85	−0.01	1.06*
EquityM	−1.13	0.50	−0.01	0.90*	−0.99	0.56	0.03	0.90*	−1.02	0.72	−0.26	1.08*	−0.84	0.76	−0.18	1.08*
VEquityM	−0.65	0.89*	0.15*	0.90*	−0.51	0.93*	0.14	0.90*	−0.50	1.06*	−0.01	1.08*	−0.41	1.05*	−0.01	1.08*
ΔL	−0.45	0.88*	0.24*	0.89*	−0.70	0.85	0.21*	0.89*	−0.61	0.66	−0.25	1.08*	−0.67	0.74	−0.23	1.08*
ΔS	1.11**	0.98*	0.46*	0.91*	0.68*	0.92*	0.39*	0.91*	2.92***	1.32*	1.98***	1.22*	2.12**	0.82*	1.79**	1.15*
ΔC	−0.43	0.88*	0.05	0.90*	−0.19	0.84*	0.02	0.91*	−0.29	0.85	−0.05	1.08*	0.27	0.99*	−0.04	1.08*
POOL	−0.47	0.59	−0.30	0.66	−0.60	0.86	−0.35	0.61	−0.01	0.81	−0.2	0.89	−0.39	0.99	−0.26	0.82
PCA	−2.69	−1.09	−2.13	−0.90	−3.31	−0.70	−2.07	−0.89	−2.04	−0.85	−1.59	−0.69	−4.10	−1.48	−1.70	−0.97
PLS	−6.75	−2.87	−3.64	−1.42	−5.39	−0.79	−3.68	−1.42	−5.93	−2.95	−3.65	−1.48	−4.15	−0.98	−3.34	−1.28
AMALG-PPP	−1.83	−0.22	−1.25	−0.10	−1.83	0.57	−1.24	−0.10	−1.06	−0.05	−0.74	0.2	−1.70	0.25	−0.74	0.13
AMALG-PP	−4.01	−1.59	−2.46	−0.97	−3.81	−0.44	−2.43	−0.95	−3.08	−1.40	−1.93	−0.74	−3.43	−0.85	−1.79	−0.77
CAD																
ΔVIX	−1.86	1.40	−2.75	0.40	−2.05	1.96*	−2.62	0.43	−1.96	1.74	−3.10	0.22	−2.92	1.69*	−3.39	0.31
ΔTED	−7.81	0.82	−4.14	0.86	−8.03	0.87	−4.03	0.78	−8.37	0.80	−4.81	0.88	−9.29	0.72	−4.90	0.83
GOLD	−1.52	0.89	−0.76	1.01*	−1.22	0.75	−1.01	0.77	−1.89	0.95	−0.95	0.94	−1.78	0.83	−1.41	0.83
OIL	−0.80	1.47*	−0.71	0.80	−0.79	1.77*	−0.51	0.76	−0.24	1.79*	−0.56	1.34*	−0.37	2.29*	−0.28	1.38*
BDI	−3.63	0.55	−2.20	1.66	−3.65	0.92	−1.75	1.81	−4.03	0.65	−2.58	1.45	−3.79	1.73	−2.52	1.44
CRB	−0.76	1.26	−1.23	1.03	−0.48	1.87	−1.07	1.02	−0.57	1.63	−1.17	1.12	−0.22	2.23*	−1.52	1.04
MSCI	−1.33	0.68	−1.77	0.64	−0.47	1.25	−1.37	0.69	−1.22	0.96	−1.69	0.62	0.65	2.45*	−1.50	0.65
SP500	−1.68	0.41	−1.21	0.47	−1.02	1.02	−1.02	0.47	−1.50	0.30	−1.36	0.41	0.26	1.72	−1.35	0.39
VSP500	−0.64	0.97	0.25	1.00*	−0.29	0.76	0.32*	1.00*	−0.79	0.97	0.31**	0.97	−0.47	0.61	0.19**	0.97
EquityM	−0.18	0.56	−1.71	0.09	1.23	1.48	−1.42	−0.01	−0.04	0.8	−1.44	0.04	2.02	2.06	−1.11	0.1
VEquityM	−1.49	0.98*	−0.39	1.00*	−1.60	0.93*	−0.43	1.00*	−1.42	0.95	−0.11	0.96	−1.46	0.94	−0.12	0.98*
ΔL	−1.05	0.77	−0.89	1.03*	−1.02	0.92	−0.97	1.03*	−1.30	0.74	−1.24	1.04*	−1.17	0.8	−0.52	1.02*
ΔS	−0.18	0.94	−0.15	0.98	0.16	1.03*	−0.02	0.99*	−0.48	0.87	0.15	0.97	0.29	1.13*	0.10	0.97
ΔC	−0.34	0.59	−0.52	0.96	−0.53	0.64	−0.49	0.93	−0.43	0.53	−0.52	0.9	−0.39	0.64	−0.47	0.92
POOL	−0.59	1.22	−1.22	1.04	−0.36	1.46	−1.39	1.02	−0.41	1.39	−1.41	1.11	0.04	1.86*	−1.74	1.10
PCA	−2.08	0.87	−3.03	0.35	−1.26	2.15	−2.45	0.32	−2.35	1.29	−2.78	0.27	−0.59	2.77	−2.74	0.30
PLS	−5.10	−1.09	−3.46	0.05	−3.79	0.50	−3.37	0.16	−3.72	−0.03	−2.71	0.46	−1.81	1.50	−2.87	0.34

(Continues)

TABLE 5 (Continued)

Panel A:	C^0 3m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$	C^0 6m control window	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
AMALG-PPP	−1.71	**0.83**	−2.11	**0.84**	−0.97	**1.81**	−2.00	**0.86**	−1.08	**1.48**	−1.78	**1.11**	**0.30**	**2.64**	−1.96	**1.09**
AMALG-PP	−3.19	**0.08**	−2.94	**0.29**	−2.21	**1.46**	−2.64	**0.32**	−2.64	**0.79**	−2.46	**0.48**	−0.85	**2.27**	−2.51	**0.44**
AUD																
ΔVIX	−6.93	−0.49	−5.78	−1.42	−7.79	**1.75**	−6.12	−1.15	−7.47	−0.39	−6.13	−1.50	−8.63	**1.58**	−6.77	−1.51
ΔTED	−7.66	−0.32	−2.51	**0.53**	−7.22	−0.31	−2.82	**0.54**	−8.14	−0.38	−1.98	**0.59**	−9.03	−0.40	−2.59	**0.52**
GOLD	−1.62	**0.83**	−0.31	**0.86***	−1.53	**0.63**	−0.14	**0.89***	−1.96	**0.82**	−0.27	**0.88***	−1.69	**0.69**	−0.08	**0.90***
OIL	−1.25	**0.2**	−0.47	**0.5**	−0.63	**0.73**	−0.33	**0.47**	−0.77	**0.13**	−0.23	**0.41**	−0.56	**0.69**	−0.17	**0.44**
BDI	−3.06	−1.05	−1.89	−0.60	−3.17	−1.09	−1.79	−0.47	−3.25	−1.03	−2.19	−0.68	−3.56	−1.06	−2.40	−0.74
CRB	−2.55	−0.58	−0.7	**0.21**	−2.12	−0.07	−0.77	**0.14**	−2.18	−0.62	−0.36	**0.16**	−1.97	**0.06**	−0.56	**0.07**
MSCI	−2.32	−0.57	−1.17	**0.01**	−2.26	**0.04**	−1.55	−0.22	−2.45	−0.71	−1.65	−0.20	−1.48	**0.77**	−2.00	−0.42
SP500	−1.85	−0.97	−0.72	**0.12**	−1.44	**0.09**	−0.93	**0.10**	−2.07	−0.99	−0.89	−0.03	−1.43	**0.17**	−1.16	−0.12
VSP500	−0.74	−0.02	−0.17	**0.86***	−0.75	−0.05	−0.11	**0.86***	−0.91	−0.18	−0.12	**0.69**	−1.37	−0.42	−0.08	**0.72**
EquityM	−2.71	−1.85	−1.49	−0.37	−1.71	−0.70	−1.25	−0.29	−2.60	−1.97	−1.82	−0.74	−1.94	−1.04	−1.52	−0.48
VEquityM	−0.61	**0.73**	**0.07**	**0.87***	−0.65	**0.59**	**0.05**	**0.87***	−1.03	**0.51**	−0.09	**0.50**	−0.97	**0.45**	−0.06	**0.54**
ΔL	**0.16**	**0.88**	−0.45	**0.70**	−0.17	**0.93**	−0.36	**0.69**	−0.13	**0.72**	−0.23	**0.71**	**0.53**	**1.57***	−0.11	**0.64**
ΔS	−0.86	**0.55**	**0.17***	**0.88***	−0.78	**0.64**	**0.14**	**0.88***	−0.99	**0.55**	**0.13**	**0.82***	−0.68	**0.62**	**0.11**	**0.81***
ΔC	−0.34	**0.74**	−0.04	**0.86***	−0.37	**0.74**	**0.01**	**0.86***	−0.49	**0.69**	**0.09**	**0.80***	−0.56	**0.72**	**0.15**	**0.84***
POOL	−1.40	**0.22**	−0.93	**0.44**	−1.30	**0.58**	−1.13	**0.45**	−1.34	**0.23**	−0.80	**0.34**	−1.22	**0.73**	−0.98	**0.32**
PCA	−5.60	−1.95	−3.76	−1.31	−3.89	−0.13	−3.89	−1.36	−7.19	−2.41	−4.48	−1.75	−5.96	−0.47	−4.95	−1.90
PLS	−12.31	−5.10	−8.42	−2.72	−9.25	−2.83	−8.39	−2.69	−11.55	−4.94	−6.88	−2.22	−9.04	−3.65	−7.23	−2.42
AMALG-PPP	−5.29	−1.6	−3.69	−0.80	−3.95	−0.26	−3.83	−0.81	−5.38	−1.56	−3.39	−0.79	−4.21	−0.38	−3.70	−0.89
AMALG-PP	−8.14	−3.11	−5.59	−1.83	−6.07	−1.20	−5.68	−1.85	−8.61	−3.25	−5.30	−1.83	−6.88	−1.68	−5.70	−2.00

Note: In this table, we illustrate the results for monthly frequency. The control window we take into account in order generate the predictors is set to 3 and 6 years, as shown in columns 1–9 and 10–19, respectively. Also, see notes in Table 3. Bold numbers indicate positive R^2_{OOS}.

TABLE 6 Robustness tests, control window.

	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	0.10*	−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	−0.02	0.01	−0.04	0
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**
AMALG-PPP	0.08*	0.17**	0.08*	0.16**	0.07	0.15*	0.11*	0.16**
AMALG-PP	−0.13*	0.10**	−0.02*	0.12**	−0.04	0.12*	0.03*	0.13**
Panel B: 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	0.07*	0	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**
AMALG-PPP	0.57***	0.26**	0.49***	0.24**	0.43***	0.22**	0.46***	0.22**
AMALG-PP	0.43***	0.17**	0.48***	0.21**	0.42***	0.20**	0.48***	0.21**
Panel C: 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	0.03

(Continues)

TABLE 6 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
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**	**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
AMALG-PPP	−0.12	−0.02	−0.03	**0.03**	−0.13	−0.01	0.00	**0.02**
AMALG-PP	−0.43	−0.17	−0.21	−0.07	−0.33	−0.10	−0.15	−0.06
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**	**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**	**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
AMALG-PPP	−0.64	−0.25	−0.41	−0.12	−0.45	−0.07	−0.32	−0.09
AMALG-PP	−1.27	−0.55	−0.81	−0.33	−0.86	−0.23	−0.68	−0.26
Panel E: 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**	**0.04**
BDI	−0.07	**0.05**	−0.07	**0.02**	−0.06	−0.01	**0.01**	**0.05**

TABLE 6 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CRB	**0**	**0.06****	0.00	**0.04**	**0**	**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	**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	**0.04**	−0.02	**0.04**	**0**	**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**	−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
AMALG-PPP	−0.20	**0**	−0.17	**0.02**	−0.06	**0.11***	−0.09	**0.06**
AMALG-PP	−0.40	−0.07	−0.29	−0.03	−0.16	**0.10***	−0.19	**0.02**
Panel F: 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	**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	−0.10	**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**	**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
AMALG-PPP	−0.62	−0.45	−0.55	−0.36	−0.59	−0.35	−0.54	−0.35
AMALG-PP	−1.12	−0.77	−0.89	−0.63	−0.99	−0.59	−0.88	−0.63

Note: We change the control window to 75 days. Also, see notes in Table 3. Bold numbers indicate positive R^2_{OOS}.

outperform single-predictor models. 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 returns of the AUD.

5.4 | Alternative out-of-sample period

In this section, we examine whether a different in-sample and out-of-sample period has a significant impact on our results. Specifically, the out-of-sample period starts at January 1, 2009. Hence, the in-sample

TABLE 7 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	−0.53	−0.17	−0.31	−0.11	−0.25	−0.05	−0.11	−0.02
ΔTED	**0.00**	**0.00**	0.00	**0.00****	**0.01**	**0.00**	**0.00**	**0.00****
GOLD	−0.13	−0.03	−0.05	0.00	−0.10	**0.01**	−0.04	0.00
OIL	−0.03	0.00	−0.01	0	−0.01	0.00	−0.01	0.00
BDI	−0.25	−0.05	−0.12	−0.04	−0.10	**0**	−0.05	−0.01
CRB	−0.08	**0.02**	−0.02	**0.01**	−0.04	**0.01**	0.00	**0.01**
MSCI	−0.62	−0.04	−0.48	−0.02	−0.26	**0.1**	−0.44	−0.01
SP500	−0.98	−0.3	−0.82	−0.25	−0.50	−0.13	−0.58	−0.18
VSP500	0.00	**0.05***	−0.01	**0.00**	0.00	**0.04***	−0.01	**0**
EquityM	−0.06	**0.06**	−0.02	**0.02**	−0.03	**0.05**	−0.01	**0.01**
VEquityM	−0.17	−0.03	−0.01	**0.00**	−0.16	−0.04	−0.01	**0.00**
ΔL	**0.01**	**0.02**	0.00	**0.00**	**0.03**	**0.03***	0.00	**0.00**
ΔS	−0.04	0.00	−0.01	**0**	−0.08	−0.03	−0.01	**0.00**
ΔC	**0.01**	**0.03**	**0.00**	**0.01**	**0.02**	**0.02**	**0.01**	**0.02**
POOL	−0.12	**0.01**	−0.15	0.00	−0.06	**0.02**	−0.11	**0**
PCA	−0.61	−0.11	−0.44	−0.07	−0.33	−0.05	−0.34	−0.05
PLS	−1.14	−0.36	−0.95	−0.30	−0.66	−0.12	−0.92	−0.29
AMALG-PPP	−0.54	−0.12	−0.46	−0.09	−0.29	−0.02	−0.40	−0.08
AMALG-PP	−0.85	−0.23	−0.67	−0.17	−0.47	−0.07	−0.60	−0.15
Panel B: YEN								
ΔVIX	−0.87	−0.39	−0.47	−0.17	−0.63	−0.30	−0.43	−0.16
ΔTED	0.00	**0.06***	**0.00**	**0.07***	0.00	**0.05***	**0.00**	**0.07***
GOLD	−0.09	**0.09***	−0.01	**0.06***	−0.06	**0.08***	0.00	**0.06***
OIL	−0.24	−0.03	−0.10	**0.02**	−0.15	**0.02**	−0.06	**0.04**
BDI	−0.08	**0.06***	−0.01	**0.07***	−0.06	**0.06***	−0.01	**0.07***
CRB	−0.31	−0.03	−0.13	**0.03**	−0.20	**0.02**	−0.10	**0.04**
MSCI	−1.33	−0.67	−0.93	−0.46	−1.03	−0.54	−0.78	−0.37
SP500	−0.91	−0.28	−0.61	−0.16	−0.55	−0.16	−0.48	−0.10
VSP500	**0.01**	**0.07***	**0.00**	**0.07***	**0.01**	**0.07***	**0.00**	**0.07***
EquityM	−0.56	−0.19	−0.27	−0.08	−0.39	−0.17	−0.19	−0.05
VEquityM	0	**0.06***	0	**0.07***	−0.01	**0.06***	0.00	**0.07***
ΔL	**0.10***	**0.12****	**0.05***	**0.08****	**0.06***	**0.10****	**0.03***	**0.07***
ΔS	−0.10	**0.08***	−0.02	**0.07***	−0.01	**0.09***	0.00	**0.07***
ΔC	−0.02	**0.04**	0.00	**0.06***	**0.00**	**0.05**	0.00	**0.06***
POOL	−0.17	−0.02	−0.14	**0.00**	−0.14	−0.01	−0.10	**0.01**
PCA	−1.15	−0.59	−0.78	−0.38	−0.89	−0.45	−0.70	−0.33
PLS	−1.88	−1.14	−1.48	−0.89	−1.34	−0.81	−1.25	−0.75
AMALG-PPP	−0.92	−0.50	−0.70	−0.36	−0.70	−0.37	−0.59	−0.30
AMALG-PP	−1.46	−0.83	−1.08	−0.60	−1.09	−0.62	−0.94	−0.51
Panel C: CHF								
ΔVIX	−0.81	−0.37	−0.44	−0.24	−0.58	−0.33	−0.24	−0.10
ΔTED	**0.01**	**0.03**	0.00	**0.03**	**0.00**	**0.03**	0.00	**0.03**

TABLE 7 (Continued)

	C^{0}	C^{+}	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GOLD	−0.05	**0.04**	−0.02	**0.03**	−0.02	**0.04**	−0.01	**0.03**
OIL	−0.07	**0.02**	**0.03***	**0.03**	−0.09	**0.01**	**0.02***	**0.03**
BDI	−0.16	**0.01**	−0.05	**0.01**	−0.06	**0.02**	−0.03	**0.02**
CRB	−0.10	**0.01**	**0.02****	**0.03**	−0.06	−0.02	**0.03****	**0.03**
MSCI	−0.75	−0.22	−0.51	−0.14	−0.66	−0.26	−0.42	−0.14
SP500	−1.15	−0.34	−0.93	−0.28	−0.74	−0.28	−0.69	−0.23
VSP500	−0.01	**0.02**	−0.01	**0.03**	−0.01	**0.02**	−0.01	**0.03**
EquityM	−0.05	**0.11**	−0.05	**0.03**	−0.08	**0.04**	−0.03	**0.03**
VEquityM	−0.01	**0.03**	**0.00**	**0.03**	**0.00**	**0.03**	**0.00**	**0.03**
ΔL	−0.02	**0.03**	**0.01**	**0.03**	−0.05	**0.03**	**0.00**	**0.03**
ΔS	**0.06**	**0.05**	**0.03**	**0.02**	**0.05**	**0.04**	−0.03	**0.01**
ΔC	−0.05	**0.02**	0.00	**0.03**	−0.06	**0.02**	**0**	**0.03**
POOL	−0.17	−0.02	−0.14	−0.02	−0.14	−0.03	−0.08	−0.01
PCA	−0.76	−0.25	−0.52	−0.17	−0.77	−0.37	−0.42	−0.17
PLS	−1.24	−0.55	−0.99	−0.42	−1.03	−0.54	−0.9	−0.39
AMALG-PPP	−0.66	−0.24	−0.51	−0.18	−0.61	−0.29	−0.43	−0.17
AMALG-PP	−0.97	−0.38	−0.73	−0.28	−0.88	−0.44	−0.64	−0.27
Panel D: EUR								
ΔVIX	−1.04	−0.43	−0.43	−0.12	−0.45	−0.12	−0.07	**0.01**
ΔTED	0.00	**0.05***	**0.00**	**0.05***	0.00	**0.05***	**0.00**	**0.05***
GOLD	−0.08	−0.01	−0.01	**0.04**	−0.04	**0.02**	0.00	**0.05***
OIL	−0.02	**0.05***	**0.00**	**0.05***	−0.03	**0.04**	**0**	**0.05***
BDI	−0.64	−0.10	−0.26	−0.01	−0.28	**0**	−0.04	**0.07***
CRB	−0.05	**0.04**	**0.01**	**0.05***	−0.02	**0.05**	**0.01**	**0.05***
MSCI	−0.98	−0.30	−0.54	−0.15	−0.93	−0.34	−0.50	−0.14
SP500	−1.80	−0.73	−1.38	−0.56	−1.12	−0.47	−0.87	−0.35
VSP500	−0.02	**0.06***	−0.01	**0.05***	−0.01	**0.06***	0.00	**0.05***
EquityM	−0.29	−0.01	−0.05	**0.04**	−0.21	−0.01	−0.01	**0.05***
VEquityM	**0.08***	**0.11***	−0.01	**0.04**	**0.07**	**0.10***	**0.01**	**0.04**
ΔL	**0.20*****	**0.12****	**0.03**	**0.06****	**0.12****	**0.10****	−0.02	**0.06***
ΔS	**0.08**	**0.06***	**0.00**	**0.05***	**0.09***	**0.06**	**0.00**	**0.06****
ΔC	**0.06***	**0.07****	−0.02	**0.05***	**0.03**	**0.07****	−0.02	**0.05***
POOL	−0.24	−0.04	−0.16	−0.01	−0.16	−0.01	−0.08	**0.01**
PCA	−1.12	−0.41	−0.59	−0.20	−0.86	−0.35	−0.38	−0.11
PLS	−2.19	−0.90	−1.73	−0.68	−1.56	−0.63	−1.65	−0.64
AMALG-PPP	−1.08	−0.40	−0.75	−0.25	−0.79	−0.30	−0.62	−0.2
AMALG-PP	−1.59	−0.62	−1.09	−0.40	−1.16	−0.47	−0.93	−0.33
Panel E: CAD								
ΔVIX	**0.17****	**0.14****	**0.05**	**0.09***	**0.38****	**0.25****	**0.10****	**0.12****
ΔTED	**0.01**	**0.09***	0	**0.09***	**0.01**	**0.09***	**0**	**0.09***
GOLD	−0.09	**0.01**	−0.04	**0.03**	−0.06	**0.04**	0	**0.06**
OIL	**0.01**	**0.05**	−0.02	**0.09***	−0.02	**0.05**	−0.03	**0.07***
BDI	−0.04	**0.12***	**0.01**	**0.10***	**0.02**	**0.12***	−0.02	**0.09***

(Continues)

TABLE 7 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CRB	−0.05	**0.09**	−0.03	**0.09***	−0.11	**0.02**	−0.02	**0.09***
MSCI	−0.13	**0.04**	−0.01	**0.09***	−0.10	**0.06**	**0.01**	**0.09***
SP500	−0.55	−0.14	−0.32	−0.05	−0.18	**0.01**	−0.19	**0.02**
VSP500	−0.01	**0.09***	0.00	**0.09***	**0.00**	**0.10***	0.00	**0.09***
EquityM	−0.03	**0.09***	**0.01****	**0.09***	−0.01	**0.11***	**0.00***	**0.09***
VEquityM	−0.08	**0.07**	0.00	**0.09***	−0.13	**0.06**	−0.01	**0.09***
ΔL	−0.09	**0.08***	**0.01***	**0.09***	−0.04	**0.08***	**0.03****	**0.09***
ΔS	−0.08	**0.06**	−0.02	**0.09***	−0.05	**0.08**	**0.01**	**0.10***
ΔC	−0.05	**0.07**	**0.01**	**0.09***	−0.01	**0.08***	**0.01**	**0.09***
POOL	−0.02	**0.07**	−0.03	**0.08***	**0.01**	**0.09***	−0.02	**0.09***
PCA	−0.28	−0.05	−0.14	**0.04**	−0.05	**0.08**	−0.15	**0.03**
PLS	−0.74	−0.22	−0.63	−0.17	−0.09	−0.02	−0.61	−0.15
AMALG-PPP	−0.21	0.00	−0.15	**0.04**	**0.02**	**0.08**	−0.15	**0.04**
AMALG-PP	−0.37	−0.07	−0.26	**0.00**	−0.01	**0.06**	−0.26	**0**
Panel F: AUD								
ΔVIX	−0.08	**0.01**	**0.01**	**0.07**	**0.16**	**0.18****	−0.01	**0.05**
ΔTED	**0.00**	**0.07***	**0.00**	**0.06**	**0.01**	**0.07***	**0.00**	**0.06**
GOLD	−0.21	−0.13	−0.08	−0.05	−0.10	−0.03	0.00	**0.01**
OIL	−0.08	0.00	−0.03	**0.02**	−0.07	−0.02	−0.03	**0.03**
BDI	−0.20	−0.06	−0.06	**0.02**	−0.11	−0.02	−0.02	**0.04**
CRB	−0.08	**0.05**	−0.03	**0.06**	−0.23	−0.08	−0.04	**0.06**
MSCI	−0.26	−0.03	−0.08	**0.02**	−0.29	−0.05	−0.06	**0.03**
SP500	−0.85	−0.31	−0.62	−0.21	−0.36	−0.09	−0.15	−0.05
VSP500	−0.02	**0.06**	**0.01**	**0.06**	−0.02	**0.06**	**0.01**	**0.06**
EquityM	−0.08	**0.06**	0.00	**0.06**	−0.35	**0.05**	−0.03	**0.06**
VEquityM	−0.02	**0.05**	**0.01***	**0.06**	−0.01	**0.05**	**0.00**	**0.06**
ΔL	−0.07	**0.07**	−0.03	**0.06**	−0.02	**0.07**	**0.01**	**0.07**
ΔS	**0.01**	**0.05**	−0.01	**0.06**	0.00	**0.05**	0.00	**0.06**
ΔC	−0.04	**0.07***	−0.01	**0.06**	0.00	**0.10***	−0.01	**0.06**
POOL	−0.08	**0.02**	−0.06	**0.03**	−0.06	**0.04**	−0.07	**0.04**
PCA	−0.33	−0.11	−0.15	0.00	−0.31	−0.12	−0.18	−0.02
PLS	−1.61	−0.74	−1.42	−0.64	−1.06	−0.42	−1.42	−0.64
AMALG-PPP	−0.53	−0.21	−0.42	−0.14	−0.40	−0.12	−0.44	−0.15
AMALG-PP	−0.81	−0.35	−0.64	−0.25	−0.62	−0.23	−0.67	−0.27

Note: See Table 3. The out-of-sample period begins in January 1, 2009.

period is extended by 10 years and now includes the 2008–2010 financial crisis. The results are reported in Table 7. 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, along with the amalgamation approaches 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 8 Prediction of sign (%).

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
Panel A: GBP								
ΔVIX	49.71	75.88	49.49	74.92	49.66	65.19	49.63	65.22
ΔTED	50.86	72.76	49.03	74.60	49.90	70.06	49.38	74.00
GOLD	50.70	78.89	50.34	79.33	50.37	69.05	50.42	78.62
OIL	50.40	80.48	49.55	77.96	50.15	70.99	49.55	72.11
BDI	51.35	77.63	50.12	78.94	50.67	66.75	50.70	69.05
CRB	50.21	78.12	49.77	78.94	49.33	66.72	49.71	71.62
MSCI	50.45	77.33	50.21	77.52	50.31	68.88	50.15	77.44
SP500	50.21	77.41	50.29	77.44	50.23	66.89	50.21	76.40
VSP500	50.07	77.88	49.06	75.33	49.36	70.33	49.11	71.97
EquityM	50.23	78.86	49.74	78.84	49.88	69.67	49.52	74.16
VEquityM	49.28	72.16	49.22	75.14	49.30	69.24	49.25	74.65
ΔL	50.51	73.58	49.90	73.37	50.75	66.56	49.55	72.33
ΔS	50.04	78.12	50.81	77.88	50.83	69.32	50.83	77.25
ΔC	50.59	78.07	50.59	77.52	50.92	67.35	50.70	77.09
POOL	50.75	52.53	50.75	58.96	50.31	52.34	50.75	58.68
PCA	50.07	77.71	50.04	77.69	50.01	69.26	50.04	77.06
PLS	49.74	75.85	49.85	75.96	50.56	68.33	49.79	75.96
AMALG-PPP	50.10	52.39	49.60	57.78	50.12	51.00	49.96	57.51
AMALG-PP	50.45	72.79	50.18	72.76	50.23	59.78	50.21	72.33
Panel B: YEN								
ΔVIX	50.34	83.13	51.30	87.78	51.16	82.91	51.27	87.78
ΔTED	50.75	92.18	50.78	94.45	50.62	91.25	50.81	94.39
GOLD	50.48	86.77	50.31	94.97	50.86	85.32	50.15	94.42
OIL	50.83	81.51	49.82	86.46	50.51	80.94	50.12	86.46
BDI	50.83	86.68	50.70	92.51	51.24	84.85	50.51	92.51
CRB	50.62	80.28	50.37	86.44	50.75	79.49	50.26	86.35
MSCI	51.00	80.97	50.37	83.26	50.86	80.50	50.62	83.26
SP500	51.33	82.12	51.54	84.22	51.74	81.41	51.24	84.17
VSP500	50.92	91.66	50.42	97.62	50.07	90.73	50.62	97.59
EquityM	52.50	83.07	51.82	86.44	52.75	82.20	51.93	86.44
VEquityM	50.72	91.17	50.37	97.89	49.99	89.88	50.45	97.46
ΔL	51.27	81.68	50.72	86.77	50.56	80.39	51.11	86.57
ΔS	50.81	81.13	50.51	85.59	50.42	79.93	50.51	85.43
ΔC	49.28	90.32	50.21	97.65	49.99	88.52	50.15	97.59
POOL	51.33	52.88	50.92	58.08	51.08	52.83	50.94	58.03
PCA	51.27	79.60	51.24	80.61	51.08	77.99	51.13	80.61
PLS	51.74	77.25	51.57	77.60	51.05	70.08	51.60	77.60
AMALG-PPP	51.35	52.72	51.38	57.45	51.19	52.47	51.52	57.40
AMALG-PP	51.33	74.19	51.33	74.87	51.33	67.24	51.46	74.87
Panel C: CHF								
ΔVIX	49.14	88.35	49.17	91.77	49.60	88.21	49.47	91.28
ΔTED	49.47	96.34	49.63	99.48	49.44	95.95	49.82	99.15

(Continues)

TABLE 8 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
GOLD	49.25	95.62	50.01	99.81	49.17	94.83	49.99	99.18
OIL	49.77	96.34	49.88	99.64	50.10	95.46	49.93	99.45
BDI	50.78	85.40	49.85	94.31	50.62	84.55	49.69	87.64
CRB	49.55	95.46	49.82	99.34	50.18	93.77	49.79	98.80
MSCI	49.58	84.69	49.60	87.34	49.25	84.69	49.36	87.34
SP500	51.05	84.93	51.00	86.11	50.23	84.93	50.45	86.11
VSP500	49.85	93.60	49.77	99.95	49.74	93.60	49.74	99.56
EquityM	50.59	90.16	50.21	99.18	50.97	90.16	49.96	94.67
VEquityM	50.34	97.87	49.85	99.23	50.10	97.43	49.82	98.69
ΔL	50.45	95.76	49.99	99.67	49.85	94.53	49.77	96.86
ΔS	51.60	91.93	50.31	96.88	50.23	91.11	49.52	94.86
ΔC	50.45	97.16	49.66	99.54	50.23	96.94	49.77	99.48
POOL	50.72	61.12	49.96	75.66	50.10	59.61	49.69	68.39
PCA	50.23	86.00	49.69	88.73	50.04	85.07	49.63	88.73
PLS	49.90	76.73	49.85	77.99	50.48	71.56	49.88	77.99
AMALG-PPP	50.07	60.21	49.74	70.91	50.07	58.44	49.47	63.88
AMALG-PP	49.85	75.64	50.15	77.41	50.56	70.60	49.77	77.41
Panel D: EUR								
ΔVIX	48.92	84.52	49.71	87.94	49.79	81.54	50.37	86.16
ΔTED	50.94	93.41	50.59	96.58	50.67	92.62	50.59	96.34
GOLD	50.04	86.74	50.45	95.21	50.21	85.12	50.70	88.65
OIL	51.27	94.53	50.67	95.68	51.46	91.63	50.67	95.62
BDI	50.81	81.30	50.56	86.41	50.92	79.35	49.66	74.71
CRB	50.48	92.37	50.67	96.47	50.51	89.64	50.75	95.93
MSCI	50.18	80.07	49.99	82.58	50.12	79.57	50.01	82.55
SP500	50.42	80.61	50.31	81.27	50.72	79.74	50.67	78.84
VSP500	51.00	90.73	50.72	96.31	51.30	89.69	51.00	95.19
EquityM	50.34	83.87	49.82	90.27	50.18	82.83	50.23	87.86
VEquityM	50.94	86.00	50.26	93.25	51.16	84.91	50.26	92.07
ΔL	51.08	83.16	50.81	92.84	51.38	81.87	51.11	85.94
ΔS	50.53	89.83	50.72	96.06	50.62	88.13	50.81	95.35
ΔC	50.83	91.14	51.33	96.99	51.00	89.69	50.48	94.86
POOL	50.51	53.98	50.26	64.75	50.01	53.40	50.45	58.16
PCA	49.47	80.39	49.55	83.84	50.31	78.86	49.36	80.34
PLS	48.78	75.77	48.73	76.24	49.19	68.91	48.73	76.24
AMALG-PPP	49.33	53.76	49.11	63.33	49.74	52.94	49.25	56.93
AMALG-PP	49.28	73.07	49.47	74.13	50.18	66.89	49.41	71.34
Panel E: CAD								
ΔVIX	50.23	90.78	50.34	95.49	50.72	90.29	50.53	92.81
ΔTED	50.23	97.35	50.51	100.00	50.15	96.99	50.48	99.62
GOLD	51.22	88.79	51.11	90.70	51.11	88.49	50.67	90.68
OIL	50.40	95.41	50.59	99.59	49.96	95.24	50.26	97.32
BDI	50.37	82.94	50.12	86.68	50.31	82.28	50.34	79.05

TABLE 8 (Continued)

	C^0	C^+	$C^{IC,0}$	$C^{IC,+}$	$C^{CP,0}$	$C^{CP,+}$	$C^{ICCP,0}$	$C^{ICCP,+}$
CRB	50.92	89.09	50.92	94.78	50.83	88.90	51.19	92.12
MSCI	49.47	92.62	50.10	94.97	50.04	92.43	50.34	94.78
SP500	49.47	89.72	50.01	93.57	50.12	88.95	50.51	91.96
VSP500	50.53	98.22	50.31	99.40	50.67	98.20	50.34	99.32
EquityM	50.29	95.02	50.51	96.66	50.34	93.98	50.51	96.39
VEquityM	50.64	96.39	50.64	99.40	50.83	95.95	50.59	99.10
ΔL	49.74	96.91	50.53	99.75	50.26	96.50	50.67	99.40
ΔS	50.45	90.65	50.97	97.92	51.08	90.65	50.94	94.67
ΔC	50.83	93.22	50.62	99.04	50.67	92.67	50.75	98.50
POOL	50.48	60.08	50.07	70.33	50.45	59.12	50.12	64.37
PCA	50.12	87.12	49.96	91.96	51.35	84.74	50.29	89.72
PLS	50.56	75.75	50.64	76.57	51.19	61.33	50.59	76.48
AMALG-PPP	50.34	58.82	50.56	66.31	50.72	53.84	50.62	61.20
AMALG-PP	50.64	73.72	50.42	75.91	51.16	60.32	50.42	74.98
Panel F: AUD								
ΔVIX	52.06	89.88	52.34	93.11	52.64	89.28	52.42	90.92
ΔTED	52.04	92.48	52.37	98.25	52.80	92.18	52.37	97.54
GOLD	51.11	82.31	51.44	91.41	51.57	81.79	52.56	85.94
OIL	52.50	88.08	52.91	93.38	52.97	87.83	52.56	93.11
BDI	50.34	82.47	51.98	95.84	51.05	80.50	52.39	92.53
CRB	52.06	90.62	52.39	99.07	52.80	89.86	52.31	93.79
MSCI	50.18	84.00	51.19	89.80	51.16	84.00	51.35	89.77
SP500	50.62	82.55	50.81	84.14	50.78	81.98	51.46	80.48
VSP500	52.20	97.54	52.69	99.64	52.69	97.18	52.69	99.56
EquityM	51.49	89.36	52.12	97.95	52.39	88.54	52.39	93.14
VEquityM	51.63	95.79	52.72	99.73	52.20	94.80	52.80	99.04
ΔL	51.13	82.23	51.44	88.93	51.63	80.97	52.09	86.30
ΔS	51.96	94.80	52.80	99.70	52.45	93.85	52.64	97.79
ΔC	52.75	92.34	52.56	99.18	52.45	90.89	52.50	98.44
POOL	51.54	52.09	52.17	66.31	51.71	51.74	52.26	61.23
PCA	51.35	83.95	51.79	89.83	51.82	79.52	52.15	86.49
PLS	49.71	74.32	49.85	74.71	50.26	57.42	49.85	74.71
AMALG-PPP	50.83	51.22	50.86	62.37	50.94	48.78	50.78	57.62
AMALG-PP	50.18	71.21	50.67	73.67	50.92	56.17	50.56	72.68

Note: The table presents the prediction of sign, calculated as $POS_i = \frac{100}{T} d_t$, where $d_t = \begin{cases} 1 & y_t * \widehat{y}_t \geq 0 \\ 0 & y_t * \widehat{y}_t < 0 \end{cases}$.

5.5 | Prediction of sign

The implications of accurate and inaccurate forecasts in the financial industry are essential. Despite the importance of point forecasting, the literature has extensively acknowledged the impact of correctly predicting the sign of the forecast (the most prominent model has been proposed by Pesaran & Timmermann, (1992)), as it could generate profits that the statistical metrics could record as losses. For instance, two competing models, A and B, generate forecasts for the day $t+1, \hat{r}^A_{t+1} = 2\%$ and $\hat{r}^B_{t+1} = -0.5\%$, whereas the actual value at $t+1$ is equal to 0.1%. Statistically, model A would record higher errors in terms of point forecasting and B would win. However, an investor would prefer to realize even a small profit by choosing this model than suffer from loses that model B would result.

For this reason, we propose the prediction of sign metric,[4] such as

$$POS = \frac{100}{P}\sum_{t=1}^{P} d_t, \tag{14}$$

where

$$d_t = \begin{cases} 1 \text{if} \, \hat{r}_t \times r_t \geq 0, \\ 0 \text{if} \, \hat{r}_t \times r_t < 0. \end{cases} \tag{15}$$

Table 8 reports the results. Overall, we observe that accuracy is improved significantly after constraining the models. Specifically, in the majority of cases, models with positivity constraints succeed in predicting the direction of change. For example, in the case of GBP, C^{+} with a single predictor (OIL) captures the sign correctly in more than 80% of the cases. For YEN, $C^{ICCP,+}$ with either VSP500 or ΔC, the success rate is 97.6%. Noteworthy, currencies that were difficult to predict on the basis of R^2_{OOS} deliver promising results. For example, for the remaining exchange rates, the success rate is close to 90% or even exceeds it when positivity constraints are used along with single predictors. On the other hand, POOL, PCA, PLS, and the amalgamation techniques perform worse, in terms of sign prediction, than the single-predictor models.

6 | CONCLUSIONS

Forecasting exchange rates on a daily frequency can be a rigorous task due to the difficulty of capturing the dynamics of such volatile series and 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, three combination and dimensionality reduction techniques, and two amalgamation approaches in the context of forecasting daily exchange rate returns of six widely traded currencies. We propose a hybrid 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 IC and the CP proposed by Lin et al. (2018) and Pan et al. (2020), respectively. We also 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 good forecasts while we observe a poor performance by PLS and PCA. In order to avoid the issue of model selection, we employ two versions of amalgamation forecasts, which succeed in half the cases.

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 along with combination or dimensionality reduction methods for all approaches, and (2) the proposed hybrid ICCP approach can actually deliver very consistent and robust forecasts.

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DATA AVAILABILITY STATEMENT

The data for VIX, TED, GOLD, and OIL are publicly available on the FRED webpage. The remaining data that support the findings of this study are available from Bloomberg. Restrictions apply to the availability of these data, which were used under license for this study.

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ENDNOTES

[1] For neural networks and hybrid applications, see Kuan and Liu (1995); Satchell and Timmermann (1995); Gencay (1999); Qi and Wu (2003); Preminger and Franck (2007); Gradojevic (2007); Bekiros and Georgoutsos (2007); Dhamija and Bhalla (2010); Khashei and Bijari (2010, 2011); Dunis et al. (2011); Khashei et al. (2012); Choudhry et al. (2012); Jammazi and Aloui (2012); Majhi

et al. (2012); Tiwari et al. (2013); Sermpinis et al. (2013); De Oliveira et al. (2013); Krauss et al. (2017). For genetic network programming and hybrids, see Neely et al. (1997); Evans et al. (2013); Chen and Wang (2015); Sermpinis et al. (2015); Hu et al. (2015); Manahov (2016). For support vector machines and hybrids, see Kara et al. (2011); Patel et al. (2015a, 2015b); Fan et al. (2016); Oztekin et al. (2016).

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

[3] A short window allows the model to respond faster to structural breaks costing in terms of parameter estimation efficiency.

[4] Due to the winsorization we employ in the forecasts, we cannot employ the PT(2012) test, because the latter measures the prediction of direction of change. For example, two consecutive forecasts winsorized to zero do not change direction and the baseline assumption to use the binomial distribution properties is violated, because we have three states of changes, upward, downward, and no change.

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