J. Int. Financ. Markets Inst. Money 97 (2024) 102067

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Forecasting exchange rate volatility: An amalgamation approach

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ARTICLE INFO

JEL classification:
F31
C22
C53

Keywords:
Exchange rates
Volatility forecasting
Forecast combination
Machine learning
Dimensionality reduction
Wavelet decomposition

ABSTRACT

The importance of exchange rate volatility forecasting has both practical and academic merit. Our aim is to provide a comprehensive analysis of the forecasting ability of financial and macroeconomics variables for future exchange rate volatility. We employ seven widely traded currencies against the US dollar and examine linear models and a variety of machine learning, dimensionality reduction and forecast combination approaches, along with creating a grand forecast (amalgamation approach) from these approaches. Our findings highlight the predictive power of the amalgamation approach, as well as the positive contribution of macroeconomic and financial variables in the forecasting experiment. Furthermore, we generate forecasts on the separate frequencies of volatility using wavelet analysis, in order to extract frequency-related information and examine timing effects in the performance of the methods.

1. Introduction

Forecasting volatility plays a central role in derivative pricing, developing trading strategies, pricing, trading volatility derivatives and hedging portfolios. In this study we provide a comprehensive analysis of the forecasting ability of financial and macroeconomic variables for predicting future exchange rate volatility (RV). The study focuses on seven widely traded currencies against the USD. We evaluate the performance of various linear models, alongside advanced machine learning techniques, dimensionality reduction methods, and forecast combination approaches. Additionally, we develop a grand forecast using an amalgamation approach, which integrates the forecasts from these diverse methods to enhance predictive accuracy. Finally, we employ wavelet analysis to extract frequency-related information and investigate the timing effects on the performance of the forecasting methods. This approach allows us to capture the influence of short-, medium-, and long-term volatility components, providing deeper insights into the effectiveness of different models across varying time horizons.

Over the recent years more elaborate methods as well as various sets of candidate predictors have been proposed in the literature. Due to the fact that volatility exhibits countercyclical movements, developments in the autoregressive (AR) process of volatility has been on the spotlight of the literature (for example see, Engle (1982) and Bollerslev (1986) for the (G)ARCH family models, Taylor (2008) for stochastic volatility models and Corsi (2009) for the heterogeneous AR model). However, a different strand of literature focuses on the potential financial and macroeconomic drivers of volatility. The literature related to the so-called "disconnect puzzle" has been initiated by Schwert (1989). The argument is based on the premise that volatility makes countercyclical movements and that there is no evidence that fundamentals have any impact. More recently, a richer dataset of financial and macroeconomic variables have been employed and further insight on the research question towards the solution of the puzzle has been provided by Mele

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https://doi.org/10.1016/j.intfin.2024.102067
Received 20 March 2024; Accepted 14 October 2024
Available online 4 November 2024

(2007), Paye (2012), Christiansen et al. (2012), Conrad and Loch (2015), Mittnik et al. (2015), Nonejad (2017) and Wang et al. (2018).

The literature addresses the issue of variable selection by using methodologies that aggregate information. In brief, Paye (2012) employs a variety of variables and finds an in-sample link between these variables and stock market volatility. However, out-of-sample improvements in forecasting accuracy mainly stem from simple combinations of individual forecasts and are sensitive to the time span of the dataset. Christiansen et al. (2012) focus on forecasting four different asset classes: equities, commodities, foreign exchange rates, and bonds by employing a comprehensive set of macro-finance variables. Employing Bayesian estimation techniques the authors find that the strongest predictive ability lies in variables associated with time-varying risk premia, leverage or financial distress. Their findings indicate that the Bayesian Model Averaging forecasting models beat autoregressive benchmarks although this performance varies across asset classes and over time. Finally, Nonejad (2017) employs a variety of Bayesian models and finds that Bayesian Model Averaging with time-varying regression coefficients provides superior density and point forecasts compared to traditional approaches.

In a similar context, there is a small group of papers associating the performance of the predictors with the long- or short-term components of volatility. Conrad and Loch (2015) disentangle short- and long-term volatility via the GARCH-MIDAS component model (Engle et al., 2013) and confirm the counter-cyclical behaviour of stock market volatility for a broad set of macroeconomic variables. Long-term volatility is mainly driven by information related to the current state of the economy as well as to expectations regarding future macroeconomic conditions. Using boosting techniques, Mittnik et al. (2015) substantially improve out-of-sample volatility forecasts for short- and long-run horizons and confirm the non-linear link between financial variables and future volatility.

Despite the progress that has been made in the past, the literature provides sporadic solutions regarding individual methods or predictors and has failed to answer the problem of model selection. Second, empirical evidence around the information contained in separate frequencies remains scarce and there is little evidence towards the performance of the predictors in the separate frequency components (see among others, Baruník and Hlínková, 2016; Faria and Verona, 2018b,a, 2021; Risse, 2019; Souropanis and Vivian, 2023; Gradojevic and Tsiakas, 2021). In a relatively similar context, Niu et al. (2024) shed light on the predictive performance of different industries on the volatility driven by cash flows or discount rate fluctuations. Last, despite the fact that exchange rates are the most widely traded asset, little or no attention has been paid to the impact of financial and macroeconomic variables on future exchange rate volatility.

We contribute to the literature by filling the aforementioned gaps. First, we explore the predictive power of a large set of macroeconomic and financial predictors in forecasting volatility. Second, we explore the predictive power of a number of widely used models which aggregate information. Third, we introduce an amalgamation technique in order to alleviate the issue of model selection and uncertainty over the choice of useful predictors.[1] Fourth, we shed light on the frequency components of volatility by applying wavelet decomposition, a technique that has been barely used so far in the volatility forecasting framework.[2] Last, we build a framework on the impact of particular timing effects on the volatility forecasting performance. Hence, we evaluate the models based on their performance on different periods and market regimes.

The amalgamation approach has been highlighted as a very simple and powerful tool in forecasting. The investor has access to several models and predictors, each one of which has very appealing properties. Hence, it is made very difficult to make the "best" selection. To avoid uncertainty associated with the employment of a specific predictor/model, we construct amalgam/consensus forecasts by simply averaging forecasts generated by the aforementioned approaches. Intuitively, the outliers are cancelled out at every iteration, leaving the investor with only the relevant information.

We present the major and theoretically well-established transmission channels in order to show the impact of macroeconomic and financial variables in volatility forecasting. For this purpose, we evaluate both the in-sample and out-of-sample performance of a group of 33 potential financial and macroeconomic predictors that have been typically employed in the exchange rate/stock market forecasting literature and are associated with equity market developments, interest rates, bonds, spreads, macroeconomic conditions and liquidity, risk and economic activity. The predictive power is tested on the monthly volatility of New Zealand Dollar (NZD), Norwegian Krona (NOK), Japanese Yen (YEN), United Kingdom Pound Sterling (GBP), Canadian Dollar (CAD), Australian Dollar (AUD) and Swiss Franc (CHF); the basis currency is United States Dollar (USD). Our dataset spans from February 1986 to December 2019. The forecasting period begins in January 1993 and is recursively updated.

Initially, we assess the in-sample ability of candidate predictors by employing simple autoregressive models augmented with one predictor at a time. Our results indicate that, aside from a few consistently strong predictors like the MSCI return, the size factor, the monthly inflation rate, and monthly M1 growth, the volatility of each currency is influenced by a distinct set of predictors. Then, we focus on out-of-sample forecasting. The benchmark models of our forecasts are evaluated against is an autoregressive process. We use the R^2_{OOS} metric and the MSFE-adjusted statistic proposed by Clark and West (2007) to evaluate our forecasts. The out-of-sample forecasting performance of individual predictors aligns with the in-sample findings. Forecasting RV for GBP and CHF proves relatively easier, while predicting YEN volatility remains notably challenging. To avoid the predictor selection problem faced by the investor, we forecast RV using a variety of machine learning techniques, dimensionality reduction methods, and forecast combination approaches, including amalgamated forecasts. Our results indicate that Lasso, Neural Networks (NN), and Principal Component Analysis (PCA) provide substantial improvements over the benchmark, while the proposed amalgamation methods consistently outperform all other approaches across all currencies.

[1] See Rapach and Strauss (2012), Rapach et al. (2010) and Panopoulou and Souropanis (2019).

[2] See also (Souropanis and Vivian, 2023).

In order to understand further the sources of volatility predictability, we explore the performance of candidate predictors on the frequency components of volatility. Despite the fact that a strand of the academic literature has pointed out the importance of different components in financial time series, its main focus has been the equity premium returns. Conrad and Loch (2015) employ a GARCH-MIDAS to decompose stock returns into short-run and long-run components and examine the long-run (conditional) volatility component using macroeconomic variables. In a similar spirit, Yi et al. (2019) argue that the frequencies of the predictors contain separate information regarding the state of the economy. Ferreira and Santa-Clara (2011) employ the sum-of-the-parts method to forecast each component of stock market returns, i.e. dividend yield, earnings growth, and price-earnings ratio growth.

Wavelet decomposition is a powerful tool that has recently attracted academic interest on financial applications, providing promising results. For instance, Caraiani (2017), Faria and Verona (2018b,a, 2021) and Risse (2019) employ wavelet decomposition in exchange rates, equity markets and gold, respectively. This method allows us to obtain the time- and frequency-varying characteristics of time series, which in turn allows us to analyse each frequency separately. In our context, we apply wavelet multi-resolution decomposition on volatility and based on the forecasting performance of the predictors at each frequency component, we can identify the sources of predictability. We also examine whether the decomposed frequencies of the predictors and the volatility are aligned. We decompose RV into short-, medium-, and long-run frequency components. In the short-run, the predictive performance of most models is weak, with only a few predictors significantly outperforming the benchmark, particularly for GBP. In the medium-run, we observe substantial improvements in predictive accuracy, with more individual predictors performing well and most aggregation and amalgamation methods surpassing the benchmark. In the long-run, further enhancements are evident, with the amalgamation approach outperforming alternative methods in most cases. Macroeconomic and financial predictors capture the long-run dynamics of RV, explaining the stable, long-term volatility trends. When we extend the decomposition to both RV and the predictors, the results remain consistent. Finally, following Faria and Verona (2018b), we sum the forecasted decomposed components, leading to a marked improvement in the forecasting ability of all predictors and models. Once again, the proposed wavelet amalgamation approach outperforms all alternative methods in every case. We assess the impact of wavelets on model performance using the Model Confidence Set methodology by Hansen et al. (2011a). The results provide strong evidence supporting the use of wavelets, particularly the wavelet amalgamation approach, across all currencies.

Finally, we conduct a series of robustness checks to validate the performance of all models. Specifically, we examine their effectiveness across various dimensions, including: (a) alternative loss functions, (b) different phases of the business cycle, (c) varying sentiment periods, (d) liquidity conditions, (e) distinct out-of-sample periods, and (f) different weighting schemes in the amalgamation approach using the discounted MSFE. Our results hold in all cases.

Our findings provide evidence that macroeconomic and financial predictors should be taken into consideration in volatility forecasting, since they outforecast the benchmark. Moreover, the results verify the prevailing argument in the literature that macroeconomic variables forecast better, mainly, the long-run frequency component. In addition, we observe that this dynamic is mainly driven by the trend component of the predictors. Another important finding of the paper is related to the methods aggregating information. These methods seem to be able to outperform individual predictors, suggesting that they contain useful information, which can enhance the forecasting performance if they are considered as a group and amalgamated (i.e. averaging of the forecasts, in order to alleviate the echo related to the uncertainty of isolating one best method beforehand). Next, we sum the forecasted decomposed series and observe even higher predictive gains against the benchmark AR model. Last, we evaluate the performance of the amalgam forecasts during different sub-periods, based on theoretically supported transmission channels.

The remainder of the paper is structured as follows. Section 2 describes the conceptual background supporting the employment of macroeconomic and financial predictors in volatility forecasting. Section 3 presents the data and the respective transformations of candidate predictors. In Section 4, we outline our proposed methodology and the evaluation metrics of the forecasts, while in Section 5 we discuss our findings. In Section 6, we present further results and robustness tests and in Section 7 we discuss the main conclusions.

2. Conceptual background

In this section, we summarize the main theoretical channels between RV and fundamentals. The seminal work of Schwert (1989) has established the notorious "disconnect" puzzle. However, most recent research demonstrates positive signals in favour of establishing a theoretical and empirical relationship between fundamentals and volatility. While the main body of the literature is dealing with volatility in equity markets, rather than exchange rates, a few of these channels apply in both markets. These channels are (i) the business cycle, (ii) liquidity, (iii) sentiment and (iv) uncertainty.

Regarding the first channel, the literature suggests that market volatility is closely related with the business cycle (Schwert, 1989; Engle and Rangel, 2008; and Brandt and Kang, 2004). However, only sporadic references make the respective connection for the exchange rates. The argument that business cycle and FX volatility are related, is based on the premise that by changing the regime of the business, central banks take politically driven fiscal actions in order to amplify the effects of the change (for instance, see Lobo and Tufte, 1998).[3] Ehrmann and Fratzscher (2005) find that news about fundamentals have an essential impact during high uncertainty periods and increase further the previous exchange rate volatility. Similarly, Schwert (1989) claims that market prices react asymmetrically and fluctuate more during recessionary periods.

[3] There is a strand in the literature that supports the reverse causal relationship, by claiming that FX fluctuations impact the business cycle ((Krol, 2014; Gumus and Taşpınar, 2015; Karras and Song, 1996)).

A second important determinant of exchange rate fluctuations is the liquidity factor. Aghion et al. (2009) show that productivity growth is affected by the regime of the exchange rates, subject to the level of economic development of the country. Dornbusch (1976) has outlined the importance of monetary shocks for exchange rates via an adjustment process of exchange rates to the price levels of the economy. Alternatively, Grilli and Roubini (1992) show that bond supply shocks impact FX volatility. A financial interpretation is provided by Brunnermeier and Pedersen (2009). The authors argue that the investors' liquidity available for trading activities is tightly linked to the asset's market liquidity. Thus leveraged investors are pushed to short sales leading prices to a further decrease, generating liquidity spirals and extensive volatility. The negative relationship between liquidity and volatility is also supported by Menkhoff et al. (2012), since low interest rate currencies provide a hedge against volatility shocks.

The third channel linking volatility with fundamentals is attributed to the investor sentiment. Chu et al. (2022) find that non-fundamental variables perform better in low sentiment periods, rather than in high sentiment ones, in returns forecasting. The authors interpret the periods of high sentiment as the periods where non-fundamentalists rule over the market. Lof (2015) shows that the ratio of fundamentalists in the markets varies significantly over time. As a result, the participation of non-rational investors in the market can lead prices away from the fundamental value. Menkhoff and Rebitzky (2008) claim that adjustments of the prices towards the equilibrium level are more rapid if the distance of the current price from the fundamental value is high, and vice versa. In general, we anticipate that high sentiment periods will not benefit macroeconomic variables in terms of forecasting performance.

The last channel outlines the importance of uncertainty in the market. The impact of small or major events increase the uncertainty of the market around political decisions, disrupting the current expectations about fundamentals (Bartsch, 2019). Similarly, Pástor and Veronesi (2013) point out the essential impact of political uncertainty on the markets, as investors cannot foresee the response of the policy makers. Markiewicz (2012) supports the relationship between uncertainty and fundamentals, by demonstrating that agents assign varying degrees of importance to specific models across different time periods, even when the underlying fundamental processes remain unchanged.

These four channels map the main drivers of volatility. However, it is very difficult to avoid endogenous effects and interactions among the channels.

3. Data

Our sample covers the period extending from February 1986 to December 2019 ($T = 407$ observations) on a monthly frequency. We consider the volatility of seven widely traded exchange rates; namely the New Zealand Dollar (NZD), Norwegian Krona (NOK), Japanese Yen (YEN), United Kingdom Pound Sterling (GBP), Canadian Dollar (CAD), Australian Dollar (AUD) and Swiss Franc (CHF) against the US dollar. The data are collected from the FRED database.[4]

3.1. Exchange rate volatility

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

$$RV_t = log\sqrt{\sum_{i=1}^{n} r_i^2}, \qquad t = 1, 2, \ldots, T$$

where T is the whole sample period. The notation RV_t we employ shows the connection between the monthly volatility measure we calculate and the realized variance literature that employs intraday returns to measure return variation.[5]

Table A.1 in the Appendix shows summary statistics for the logarithm of the volatility series of the exchange rates employed. The average logarithm of exchange volatility fluctuates within a close range, i.e. between −4.09 (CAD) and −3.56 (NZD). The standard deviation of RV ranges from 0.35 (GBP) to 0.49 (CAD). The volatility of all currencies under consideration exhibits positive skewness, which ranges from 0.07 (NZD) to 0.51 (GBP) with the exception of CAD for which skewness is negative at −0.06.

Figure A.1, in the Appendix shows the evolution of volatility for the currencies under investigation. Overall, we observe that all currencies behave very similarly qualitatively as calm periods alternate with turbulent ones. Turbulent periods include the collapse of Exchange Rate Mechanism (1992–1993), the Asian financial crisis (1997), the Russian financial crisis (1998), and the recent financial turmoil (2008–2010). Such peaks and troughs are more apparent to some currencies than others.

3.2. Candidate predictors

We are interested in identifying financial and macroeconomic drivers of volatility in exchange rate markets. The importance of US fundamentals on exchange rates has been reported in the literature (Faust et al., 2007; Anderson et al., 2003; Wang et al., 2023). Our dataset, consisting of 33 candidate predictors, is presented in the Appendix, and is briefly described below.

The first set of predictors consists of variables associated with **equity market** developments. Bahmani-Oskooee and Saha (2015) provide a comprehensive literature review pointing out the relationship between stock markets and exchange rates. We employ the

[4] https://fred.stlouisfed.org/

[5] The choice of volatility frequency is dictated by data availability. Since we do not have access to intraday data, we cannot compute daily realized volatility.

Dividend Price ratio (DP) and the Earnings Price ratio (EP) calculated as the difference between the log of dividends/earnings and the log of prices. We also employ the Fama French factors, i.e. the US stock market excess returns (MKT), the size (SMB), value (HML) and short-term reversal (STR) factors. Finally, we use the world stock market MSCI index return (see Christiansen et al., 2012 and Mittnik et al., 2015) to capture global stock market developments.

Second, we employ **interest rates, spreads and bond market factors**. Interest rate-related variables enjoy a strong theoretical connection linking them with exchange rates.[6] In our case, we employ the 3-month US Treasury Bill rate (TB), the long term US bond return (LTR), the term spread (TS) calculated as the difference between the long term yield on government bonds and the Treasury-bill (Campbell and Shiller, 1991), the ΔTED (among others used by Buncic and Piras, 2016) calculated as the first differences of the gap between the 3-month LIBOR rate (US dollar base) and the 3-month Treasury Bill rate. Our set of bond market variables also includes the long-term US government bond yields (LTY) and the default yield spread (DFY) calculated as the difference between BAA- and AAA-rated corporate bond yields, (Welch and Goyal, 2008).

The third set of predictors depicts general **macroeconomic conditions** in the US market. Our dataset includes the monthly and annual US inflation growth rate (INFM and INFA, respectively), the monthly and annual US industrial production growth rate (IPM and IPA, respectively), the monthly and annual money supply growth rate (M1M and M1A, respectively), the number of employees to non-farm activities (PAYEMS) and the US Policy Uncertainty Index (EPU). Following Christiansen et al. (2012), we also use the Consumer Sentiment (SENT) Index, as published by the University of Michigan, the Capacity Utilization (CAP), the Diffusion Index (DIFF), the Consumer Confidence (CONF), the monthly change in Housing Starts (H-S), the Chicago Business Barometer (PMBB) and the Purchasing Manager Index (PMI).

The last set of predictors are considered to approximate **liquidity, risk and economic activity** related factors. The first variable considered is the (Pástor and Stambaugh, 2003) Factor (PS) that works as a liquidity proxy. Gold (GOLD) is universally considered as a "safe haven" for investors during financial turbulence. In addition, we use VIX, the so-called "fear index" in our dataset (Liang et al., 2023 use the global financial stress index, which is not available for our full sample size). Following Buncic and Piras (2016), we include Oil (WTI) as a proxy for the economic activity. Given the significant number of commodities and their role in the economic activity, we use the Commodity Research Bureau Index (CRB) to summarize the relevant information derived from commodities.

For detailed description regarding transformations of the variables, as well as the data-sources, see Table A.2, in the Appendix.[7]

4. Methodology

In this section we describe our methodology. First, we provide an overview of the in-sample analysis, then, we present the forecasting process of RV, as well as the main models used. Apart from the bivariate setup, we employ a range of models from more elaborate machine learning models to simple combination of forecasts since such models are able to concentrate on the relevant information. Next, we aggregate the forecasts from these models, since the investor is unable to know which model performs better a priori. In the last part, we describe the frequency decomposition approach to forecasting volatility. Finally, we include a description of the forecast evaluation methods.

4.1. In-sample predictive ability

First, we focus on the in-sample predictive ability of candidate predictors. Since volatility is quite persistent (see, among others, Müller et al. (1997), Chernov (2007) and Corsi (2009)) we consider an AR(p) model augmented with one of the candidate predictors at a time. In this respect, the predictive regression is given by the following regression:

$$RV_t = b_{j,0} + \sum_{i=1}^{p} b_{j,i} RV_{t-i} + \beta_j x_{j,t-1} + u_{j,t} \tag{1}$$

where RV_t is the volatility in each of the exchange rate markets considered, b_i and β_j are the slope coefficients for the autoregressive process and the candidate predictor x_j (where $j = 1, \dots, 33$) respectively and u denotes the error term. We select the optimal number of lags of the autoregressive term among the first six by maximizing the adjusted R^2 Information Criterion. The null hypothesis of no predictive ability for predictor j is $H_0 : \beta_j = 0$ against the alternative is $H_1 : \beta_j \neq 0$. We compute Newey–West standard errors in order to take into account biases due to heteroscedasticity and persistence in the series.

4.2. Forecast construction and evaluation

We now describe the forecasting approaches we follow, which include machine learning, dimensionality reduction and forecast combination methodologies that take into account a large number of predictors.

One step ahead forecasts are generated by continuously updating the estimation window, i.e. following a recursive (expanding) window. More in detail, we divide the total sample of T observations into an in-sample portion of the first R observations and an out-of-sample portion of $P = T - R$ observations used for forecasting. Similar to Christiansen et al. (2012), our out-of-sample period begins in 1993. Hence, the observations of the first seven years are used as our in-sample period, i.e. $R = 83$ observations, and the remaining $P = 324$ monthly observations form the out-of-sample period. The total sample period is February 1986 to December 2019, while the out-of-sample period starts in January 1993.

[6] Variables related to central bank news announcements are embedded in the interest rate series.

[7] Due to the large number of predictors, the descriptive statistics are not reported. However, they are available from the authors upon request.

4.2.1. Univariate models

4.2.1.1. Benchmark. Our benchmark forecasting model is the AR(p) model where $p = 1, \ldots, 6$ is selected based on the adjusted R^2 ($\bar{R}^2$) information criterion. The AR(p) is given by:

$$RV_t = b_0 + \sum_{i=1}^{p} b_i RV_{t-i} + u_t \tag{2}$$

where RV_t is the volatility at time t and u_t is the error term. The forecasts of the autoregressive benchmark model are computed as follows:

$$\hat{f}_t^{(AR(p))} = \hat{b}_0 + \sum_{i=1}^{p} \hat{b}_i RV_{t-i} \tag{3}$$

4.2.1.2. Univariate framework. We assess the predictive power of each predictor by augmenting the benchmark model:

$$RV_t = b_{j,0} + \sum_{i=1}^{p} b_{j,i} RV_{t-i} + \beta_j x_{j,t-1} + u_t \tag{4}$$

where $x_{j,t}$ is the candidate predictor j at time t, $j = 1, \ldots, 33$ and β_j is the respective slope coefficient. Similar to our in-sample experiment, we set the maximum number of lags (p) equal to six and select the optimal one by maximizing the $\bar{R}^2$. Forecasts are generated by the following linear regression model:

$$\hat{f}_{j,t} = \hat{b}_{j,0} + \sum_{i=1}^{p} \hat{b}_{j,i} RV_{t-i} + \hat{\beta}_j x_{j,t-1} \tag{5}$$

4.3. Machine learning techniques

4.3.1. Lasso

A machine learning method often proposed in the literature is the Lasso (L) estimation (Least absolute shrinkage and selection operator) introduced by Tibshirani (1996). Lasso is a linear regularization technique, extensively employed in experiments using high dimensional datasets. This method performs shrinkage to the estimates by penalizing the related coefficients via the L_1 penalty function. Specifically, coefficient estimates are obtained by solving the following minimization problem:

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

where RV is the volatility, x_j presents the candidate predictors j, N is the number of predictors and λ_1 is a positive regularization parameter. As the value of λ_1 increases so does the number of coefficients that shrink to zero resulting in a more parsimonious model.[8]

4.3.2. Neural networks

Neural Networks (NN) have recently attracted attention in forecasting applications (see, for example, Sermpinis et al., 2013 and Qi and Wu, 2003). The architecture of the proposed NN consists of three layers. In the first layer the inputs (candidate predictors) are introduced, the middle layer is the hidden layer consisting of neurons (hidden units) while the final layer is the output layer. The NN is trained by minimizing the mean squared error loss function (i.e. the squared difference of the actual and the forecast value). We employ the Bayesian Regularization (BR) algorithm that pushes non-relevant weights to zero in order to avoid over-fitting. Furthermore, to avoid the loss function to be trapped in local minima, we repeat the training 50 times with different random initial parameters and use the median value. We split the in-sample period into two subsets; the first 70% of the data is used for training while the second one is the validation set.

4.3.3. Support vector regression

A method that has been broadly used in forecasting processes (see among others Risse, 2019; Sermpinis et al., 2015; Plakandaras et al., 2015) is Support Vector Regression (SVR). SVR can be considered as a regression problem which has as a main objective the determination of a function $f(x)$ that can provide accurate forecasts on a targeted value. The main advantage of this technique is its ability to generate non-linear decision boundaries through linear classifiers, while having a simple geometric interpretation. Additionally, the solution is global and unique and does not suffer from multiple local minima (in contrast to NNs). In this respect, SVR can balance model accuracy with complexity and show a remarkable forecasting ability.

[8] The model does not suffer from a look-ahead bias, since at every iteration, we use all available information up to time t in order to select the optimal value for λ_1. The selected value is used to generate the forecast for time $t+1$. In brief, we test a number of values, ranging from 0.01 to 50 by 0.05 intervals, and then select the one according to the maximum adjusted R^2.

4.4. Dimensionality reduction techniques

4.4.1. Principal component analysis

Principal Components Analysis (PCA) has been successfully used in a variety of settings, (Dunis et al., 2013; Neely et al., 2014). In PCA, a large set of candidate predictors (x_j, $j = 1, \dots, 33$ in our case) are transformed into new uncorrelated latent factors $\hat{F}_t = (\hat{F}_{1,t}, \dots, \hat{F}_{N,t})$ that are able to capture maximum variability. The generated principal components filter noise from big datasets and reduce over-fitting. By construction, most information is aggregated by the first principal component. In order to keep our model parsimonious the number of components is selected among the first 4 according to the adjusted R^2. The model is given by:

$$RV_t^{(PCA)} = b_0 + \sum_{i=1}^{p} b_i RV_{t-i} + \sum_{k=1}^{K} \beta_k \hat{F}_{k,t-1} + u_t, \quad K = 1, \dots, 4 \tag{6}$$

4.4.2. Independent component analysis

Independent Component Analysis (ICA), proposed by Jutten and Herault (1991), isolates different types of mixed signals without knowing the mixing mechanism. The components are mutually statistically independent.

Similar to PCA, ICA creates components that maximize the independence, rather than the variance. The components are mutually statistically independent. Once the independent components $\hat{G}_t = (\hat{G}_{1,t}, \dots, \hat{G}_{N,t})$ are obtained, we estimate the following model via OLS selecting among the first 4 independent components according to the adjusted R^2:

$$RV_t^{(ICA)} = b_0 + \sum_{i=1}^{p} b_i RV_{t-i} + \sum_{k=1}^{K} \beta_k \hat{G}_{k,t-1} + u_t, \quad K = 1, \dots, 4 \tag{7}$$

4.4.3. Partial least squares

Partial Least Squares (PLS), introduced by Wold (1966), is linked with both PCA and multiple linear regression. This technique aims at condensing a large set of variables/predictors into a small set of factors, while simultaneously maximizing the covariance with the dependent variable, RV in our case. While PCA-generated components aim at capturing the variability of the predictors, PLS-extracted orthogonal components take into account the covariance of the predictors with the target variable. Kelly and Pruitt (2013, 2015) were the first to apply a generalized version of PLS, the three-pass regression filter in Finance. We follow Stivers (2018) and Rapach and Zhou (2022), in order to keep the model parsimonious and use one target relevant factor from the set of potential predictors. In order to extract the factors, we apply the (De Jong, 1993) SIMPLS algorithm. The forecasting regression is given by:

$$RV_t^{(PLS)} = b_0 + \sum_{i=1}^{p} b_i RV_{t-i} + \beta z_{t-1} + u_t \tag{8}$$

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

4.5. Combination forecasts

An efficient way to reduce the uncertainty associated with a single candidate predictor is to combine the respective individual forecasts. Bates and Granger (1969) claim that model combinations can outperform individual predictors, if the latter are not perfectly correlated. Forecast combination methods have been used in several forecast experiments (see, for example, Timmermann (2006), De Zwart et al. (2009), Rapach et al. (2010), Beckmann and Schüssler (2016), Li and Tsiakas (2017)) with relative success despite their simplicity. The aim is to pool forecasts instead of pooling information. In this study, we consider mean, trimmed mean and median forecast combination schemes.[9] Specifically, the mean combination scheme attaches equal weight to all j forecasts generated by the univariate models given by Eq. (5). In this respect, the mean combination forecast, $\hat{f}_t^{(POOL)}$, is given by:

$$\hat{f}_{t+1}^{(POOL)} = \sum_{j=1}^{N} \frac{1}{N} \hat{f}_{j,t+1} \tag{9}$$

We also consider two versions of Trimmed mean (TRIM) combination forecasts[10] by discarding the 3 and 10 higher and lower forecasts, so that excluded forecasts are equal to $k = [3, 10]$. In this way, we exclude the extreme values that might have a severe impact on $POOL$. Hence, we employ the simple average of the trimmed vector of individual forecasts:

$$\hat{f}_{t+1}^{(TRIM,k)} = \sum_{j=k+1}^{N-k} \frac{1}{N-k} \hat{f}_{j,t+1} \tag{10}$$

[9] It is beyond the scope of this paper to employ more elaborate forecast combination methodologies. For additional specifications, please refer to Rapach and Zhou (2013).

[10] Among others, see Crespo Cuaresma et al. (2018); and Della Corte and Tsiakas (2012).

where $\hat{f}_{k+1:N-k,t+1}$ is the column vector of the sorted, in increasing order, forecasts where the first and last k elements have been removed.

Finally, we employ the median combination scheme. In this case, each element of the row of the vector of forecasts is the median of the column vector of the individual forecasts, i.e.

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

where $\hat{f}_{j,t+1}$ is the matrix containing the entire set of forecasts for the individual predictors and $j = 1, \dots, 33$.

4.6. Amalgam forecasts

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

$$\hat{f}_{t+1}^{(AMALG)} = \frac{1}{N_1}\sum_{n_1=1}^{N_1=10} \hat{\mathbf{f}}_{t+1}\left(n_1\right) \tag{11}$$

We also create three additional amalgam specifications, by trimming the 1,2 and 3 top and bottom forecasts at each point of the out-of-sample period and averaging the remaining forecasts. We denote these as AMALG1, AMALG2 and AMALG3, respectively.

4.7. Perfect insight forecasts

In order to get an understanding of the level of predictability we can attain, we also create a forecast by selecting the individual predictors that demonstrate lower Mean Square Forecast Error (MSFE) values than the benchmark. We equally weight the forecasts produced by Eq. (4) for these predictors and generate the perfect insight forecast.

4.8. Frequency based forecasting

In order to examine the impact of the frequency components of the time-series, We employ wavelet analysis. Wavelet analysis is a powerful decomposition tool that has recently gained more attention in financial forecasting applications. The original time series are transformed into new orthogonal signals, which represent different frequencies. A wavelet resembles the movement of a wave. There are two main functions. One reveals the low-frequency characteristics of a signal, the father wavelet (ϕ) and the other one presents the high-frequency properties, the mother wavelet (ψ). Shifting and scaling are the two parameters that characterize a specific wavelet. Scaling denotes the level of scaling in time of a signal and it is inversely proportional to the frequency. Hence, a larger scale helps to capture gradual changes in time, while a smaller scale helps to detect abrupt changes in time. Shifting refers to moving the wavelet along the signal. Hence, wavelet analysis is a decomposition in both time and frequency. Similarity of the shape of the wavelet and the signal can lead to the extraction of additional information in each frequency. Hence, the choice of the wavelet function is important. The scaled and transformed mother and father wavelets are given by:

$$\begin{aligned}\psi_{j,k}(t) &= \frac{\psi(2^{-j}t-k)}{\sqrt{2^J}} \\ \phi_{j,k}(t) &= \frac{\phi(2^{-j}t-k)}{\sqrt{2^J}}\end{aligned} \tag{12}$$

Then the coefficients of the high frequency $d_{j,k}$ and low frequency $s_{j,k}$ have the following form:

$$\begin{aligned}s_{j,k} &= \int \psi_{j,k}\cdot y_t dt \\ d_{j,k} &= \int \phi_{j,k}\cdot y_t dt\end{aligned} \tag{13}$$

Additionally, the father and mother wavelet functions satisfy:

$$\begin{aligned}&\int_{-\infty}^{\infty}\phi(x)dx = 1 \\ &\int_{-\infty}^{\infty}\psi(x)dx = 0.\end{aligned} \tag{14}$$

where J denotes the maximum level of decomposition, $j = 1, 2, \dots, J$, i.e. the number of scales and k is the kth wavelet coefficient. A lower level of the decomposition represent a higher frequency wavelet component. For a given time series y_t with N observations the multi-resolution analysis (MRA) representation is given by Eq. (12).

$$\begin{aligned}y_t &= \sum_k s_{J,k}\cdot\phi_{J,k}(t) + \sum_k d_{J,k}\cdot\psi_{J,k}(t) + \sum_k d_{J-1,k}\cdot\psi_{J,k}(t) + \dots.. + \sum_k d_{1,k}\cdot\psi_{1,k}(t) \\ &= y_t^{S_J} + \sum_j y_t^{L_j}\end{aligned} \tag{15}$$

where $y_t^{S_J} = \sum_k s_{J,k} \cdot \phi_{J,k}(t)$ is a smooth component and $y_t^{L_j} = \sum_k d_{j,k} \cdot \psi_{j,k}(t)$ are the wavelet detailed components. In this study we use the Maximal Overlap Discrete Wavelet Transform (MODWT) which is not restricted by the sample size. We decompose the time series into five wavelet detail components, $y_t^{L_j}$ and one smooth component, $y_t^{S_5}$. Since we are using monthly data, the first detail $y_t^{L_1}$ captures oscillations between 2–4 months, the second $y_t^{L_2}$ between 4 and 8 months, while the $y_t^{L_3}$, $y_t^{L_4}$, $y_t^{L_5}$ details capture oscillation for periods of 8–16, 16–32 and 32–64 months, respectively.

Our analysis is closely related to Souropanis and Vivian (2023), Caraiani (2017) and Faria and Verona (2021). We use the MODWT and a Haar wavelet filter[11] with reflecting boundary conditions to decompose both the volatility series and the candidate predictors. We apply the MODWT at 5 levels, hence we obtain 5 details and one final smooth component. We group the decomposed signals in three frequency categories: high (short-run), medium, and low (long-run):

$$\begin{aligned} High: \quad (H) \quad RV^H &= RV^{L_1} + RV^{L_2} \\ Medium: \quad (M) \quad RV^M &= RV_t^{L_3} + RV^{L_4} + RV^{L_5} \\ Low: \quad (L) \quad RV^L &= RV^{S_5} \end{aligned} \tag{16}$$

In order to avoid any forward looking bias, we perform the wavelet decomposition at each time-step t, using only information up to time t and then we forecast the time-step $t+1$. The three calculated frequencies are denoted as RV_t^f where $f = [H, M, L]$.

Figure A.2, in the Appendix, presents the low (short-run), medium and high (long-run) frequency time series over the entire sample period for the currencies under consideration. We observe that there are country specific events that have affected the variability of RV of the respective countries, as well as events that had a universal impact on every currency in our the dataset. For example, the Black Monday event and the collapse of Lehman Brothers has raised the heat on every currency. On the other hand, the Baht crisis and its contagious effect on Asian markets, or the massive short-selling of GBP in 1992, have affected the volatility only in the respective exchange rates.

4.9. Forecast evaluation

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

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

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

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

$$MSFE_{adj} = \frac{1}{P} \sum_{t=R+1}^{T-1} \left\{ \left(RV_{t+1} - \hat{f}_{t+1}^{(AR(p))} \right)^2 - \left[\left(RV_{t+1} - \hat{f}_{t+1}^{(h)} \right)^2 - \left(\hat{f}_{t+1}^{(AR(p))} - \hat{f}_{t+1}^{(h)} \right)^2 \right] \right\} \tag{17}$$

where P is the number of out-of-sample observations ($P = 324$), T is the number of the total sample ($T = 407$), RV_{t+1} is the actual volatility, $\hat{f}_{t+1}^{(AR(p))}$ is the forecasted volatility as computed by Eq. (3) and $\hat{f}_{t+1}^{(h)}$ is the forecast of volatility by the hth candidate model/specification. Eq. (17) is composed of two segments, the first one is the $MSFE$ of the parsimonious model and the second one is the difference of the squared errors between the large model and the squared difference between the forecasts of the parsimonious model and the competing one. The Clark and West test is an one-sided test and the null (H_0) is given by $MSFE_{AR(p)} \leq MSFE_h$ against the alternative (H_1) : $MSFE_{AR(p)} > MSFE_h$. The test can be well approximated by the critical values of the standard normal distribution.

5. Empirical findings

5.1. In-sample estimates

Our in-sample estimates for each predictive variable are reported in Table A.3 in the Appendix. Our findings suggest that all currencies have persistent RV series, with an AR(6) model selected for YEN, CAD and AUD, an AR(4) for the NZD and an AR(3) for the remaining series. Our results indicate that apart from a few robust predictors, RV in each currency is driven by different predictors. For example, equity market related predictors have an impact on CAD, NZD, AUD and CHF, whereas predictors related to the macroeconomic conditions explain better NOK, GBP, AUD and CHF. There is also evidence of a couple of variables being significant for all volatility series. Specifically, the world MSCI index affects negatively volatility, while increases in the default yield lead to decreases in volatility. We also observe that MKT, INFM and M1M are statistically significant for the 6 out of 7 currencies. On the contrary, there is a number of variables with small or no significance, such as SMB, HML, ΔTED, M1A, SENT and GOLD.

[11] Berger (2016) argues that Haar filtering is optimal for such applications, since it does not suffer from look-ahead bias.

Despite the fact that we cannot argue in favour of predictors' uniform positive performance, there is evidence that the majority of financial and macroeconomic variables explain exchange rate volatility.

Focusing on the RV series, we observe that NZD, YEN and CAD volatilities are harder to predict than the other currencies with fewer significant values, mainly belonging to the equity market and liquidity and risk groups. On the other hand, predictors linked to macroeconomic conditions explain better the NOK, GBP, AUD and CHF volatility, while interest rate variables seem to have a significant impact on NOK, CAD and CHF. Notably, our results indicate that the CHF volatility is impacted more by the US variables compared to the other currencies. On the other hand, YEN is more difficult to predict since only 11 out of 33 predictors are statistically significant.

5.2. Out-of-sample results

In this section we present our out-of-sample empirical findings. As discussed in the previous section, in-sample analysis is useful in order to assess the goodness-of-fit of candidate predictors. However, in order to robustly evaluate the forecasts, we employ out-of-sample analysis. We first focus on the static performance of predictors/specifications as depicted in R^2_{OOS} and then we examine the dynamic evolution of the performance. Our aim is not only to identify the models with superior forecasting ability, but also the ones that exhibit this ability persistently over time.

5.2.1. Individual predictors

We first analyse the forecasting ability of the individual candidate predictors in order to identify potential groups of predictors that may tend to predict more accurately the RV of exchange rates. The results corresponding to each group of predictors are reported in different panels on Table 1. It is clear that the AR(p) benchmark beats the simple AR(1) process in every case. Hence, there is strong evidence that we are comparing the candidate predictors against a tougher benchmark. Overall, we observe that the out-of-sample forecasting ability of individual predictors is consistent with the in-sample estimations. Predictors that provided good in-sample estimates generate statistically significant forecasts and positive R^2_{OOS} values.

The overall results show that GBP and CHF are easier to predict, since a significant amount of predictors outperforms the benchmark. On the other hand, our results indicate that YEN volatility proves to be the most challenging one to forecast since only 4 predictors outperform the benchmark. For the remaining four currencies, around a third of the predictors prove valuable.

At a group level, we observe that predictors associated with Interest rates, Spreads and Bonds, as well as, those related to the Equity market, are performing better. The variables in Panel C demonstrate a mixed performance, though. In addition, there are some predictors that stand out due to the fact that they are able to provide positive R^2_{OOS} values in 6 out of 7 exchange rates, such as MSCI, LTY and CCONF, followed by DP, MKT, DFY and IPM (in 5 out of 7 exchange rates).[12]

5.2.2. Information aggregates

Despite the high positive R^2_{OOS} values presented in the previous subsection, the investor is facing the problem of variable selection, since there is no single predictor that robustly outperforms the benchmark in all currencies. Hence, we focus on the out-of-sample predictive performance of the information aggregation methods described earlier.

Our results are presented in Table 2. First, we observe that all methods generate positive and statistically significant R^2_{OOS} in the majority of cases. For example, even in the case of YEN (the hardest to predict in the case of individual predictors) we observe that almost all methods are able to capture additional information and outperform the benchmark.

Second, by comparing the results in Tables 1 and 2, we observe higher R^2_{OOS} in the case of information aggregation methods. More in detail, the machine learning techniques are in general successful with the exception of SVR that generates small improvements in 4 out of 7 volatility series. Lasso and NN show significant improvements over the benchmark, with R^2_{OOS} values which exceed 10% for CHF. Turning to dimensionality reduction methods, we observe that PCA is the most successful method with benefits ranging from 0.72% (YEN) to 13.67% (CAD). Finally, combining information across predictors via simple pooling schemes generates moderate benefits for all series with small positive and significant R^2_{OOS}.

Third, Table 2 reveals an increased accuracy of the amalgamation techniques, where the forecasts of all the techniques, as described in the previous section, are combined to create a grand forecast. The R^2_{OOS} is positive, statistically significant and mostly higher than the remaining methods in every case for all currencies. Overall, we provide evidence that aggregating information from both linear and non-linear models can benefit significantly RV forecasting, allowing the investor to take advantage of all the information at hand. Our results indicate that the R^2_{OOS} values among the AMALG specifications are similar and very high. This provides bi-fold evidence, first, the excellent forecasting performance is robust and is not affected by outliers, and second, the combination of information from different types of methods enhances significantly the forecasting exercise. More specifically, the AMALG3 has the highest R^2_{OOS} in the cases of NZD (7.24%) and AUD (9.44%). AMALG1 outperforms the other models in the case of YEN while AMALG in the case of NOK. However, irrespective of the specification, amalgamated forecasts are always in the group of the top performing methods.

In the last row of Table 2, we assume that the investor knows a priori the best performing individual predictors and combines their forecasts. Hence, the investor has a perfect insight (PI) on the performance of the predictors. We observe that, with the exception

[12] We observe the odd result of negative but statistically significant R^2_{OOS} in a few cases. Such results are acceptable by theory (Clark and West, 2007). According to Li and Tsiakas (2017), the CW test tests for equal performance in the population, while R^2_{OOS} embodies the performance in a finite sample. This is the underlying reason that we come across the odd feature of negative R^2_{OOS} and statistically significant MSFE-adjusted.

Table 1
Out-of-Sample Forecasts for the individual predictors.

	NZD	NOK	YEN	GBP	CAD	AUD	CHF
$AR(p)$ vs $AR(1)$	**15.38*** **	**4.91*** **	**0.45***	**4.37*** **	**10.05*** **	**4.34*** **	**6.23*** **
Panel A: Equity Market Variables							
DP	**0.35** **	−1.71	−2.15	**1.77*** **	**1.57*** **	**−0.34***	**0.32*** **
EP	−0.52	−2.18	−0.85	−0.89	**1.77*** **	−5.09	−1.42
MKT	**2.79*** **	0.37	0.01	**1.16** **	**1.67** **	**4.23*** **	**1.20*** **
SMB	−0.55	−0.75	−1.34	−0.37	−2.34	−2.19	−0.36
HML	−1.15	−2.21	−0.89	−0.76	−0.60	−1.32	−0.47
STR	**0.92** **	−0.18	0.30	−0.42	−0.26	**1.56** **	**1.30*** **
MSCI	**3.73*** **	**1.55** **	0.51	**2.44*** **	**1.41** **	**4.91*** **	**1.61*** **
Panel B: Interest rates, Spreads and Bond Market Factors							
TB	−0.17	−2.23	−1.31	−1.55	**4.71*** **	−4.41	−0.84
LTR	−0.25	−0.25	**0.16** **	**1.09** **	**1.07** **	−0.23	**3.17*** **
TS	−0.58	0.10	−1.05	−0.28	−0.20	−2.52	**0.61***
ΔTED	−0.65	−4.03	−1.26	**−0.69** **	**4.55*** **	−2.65	**−1.39***
LTY	**3.98*** **	**5.62*** **	−0.40	**5.74*** **	**3.71*** **	**7.98*** **	**2.88*** **
DFY	**0.75***	**0.83***	−0.18	**0.77***	**0.76** **	**2.27*** **	−0.19
Panel C: Macroeconomic Conditions							
INFM	−27.77	−65.00	−13.95	−21.98	−67.62	−13.35	−28.48
INFA	−0.71	−0.82	−0.93	**0.73** **	**0.62***	−0.71	−0.08
IPM	**0.83***	**3.61** **	0.05	**4.75** **	−0.54	**2.53** **	**1.52** **
IPA	−3.20	**−0.01***	−0.64	**1.29** **	−4.22	−2.28	−1.04
M1M	0.59	**−1.25***	−1.83	**1.70** **	**0.67***	0.74	**−0.03** **
M1A	−0.59	−0.57	−0.89	**0.73** **	−0.35	−0.72	−0.76
PAYEMS	−1.15	**3.69*** **	−0.04	**2.70*** **	0.23	−1.00	**0.13** **
EPU	0.01	−0.60	−0.26	**1.45** **	0.17	**0.21***	−0.29
SENT	−0.92	−0.80	−0.57	−0.42	−1.12	−0.85	−0.85
CAP	−0.71	−0.82	−0.17	0.42	**1.72*** **	−0.03	**1.55***
DIFF	−1.10	−1.02	−0.56	−1.16	−1.15	−1.29	0.43
CCONF	**0.41***	**1.31** **	**0.87***	**2.68** **	−1.36	**1.62***	**1.23** **
H-S	−0.95	**1.13** **	**0.93** **	**1.30** **	−0.28	−0.50	**1.37** **
PMBB	**−1.81***	−0.04	−0.56	**0.54***	−1.00	**−0.66***	**2.01** **
PMI	**1.89** **	−0.57	0.22	**1.38** **	**2.52*** **	**1.74** **	0.07
Panel D: Liquidity, Risk and Economic Activity							
PS	−1.71	0.56	−0.92	0.15	−0.37	0.13	−0.13
GOLD	−0.20	−0.54	−0.78	−0.55	−0.38	−0.94	−0.28
ΔVXO	0.40	**0.85***	−0.45	**3.28*** **	−0.56	**0.61***	**0.88** **
WTI	−0.45	−0.55	−0.21	−0.26	−0.35	−0.45	−0.13
CRB	**1.45*** **	0.32	−0.58	**1.60** **	−0.35	**0.91***	0.34

Notes: The Table illustrates the out-of-sample performance of the predictors under consideration against the benchmark. The benchmark is a simple AR(p) process. We set the maximum number of lags (p) equal to six. In each iteration, we select the optimal one by maximizing the adjusted-R^2. We test the performance of the forecasts based on: $\hat{f}_{j,t} = \hat{b}_{0,j} + \sum_{i=1}^{p} b_{1,j,i} RV_{t-i} + \hat{b}_{2,j} x_{j,t-1}$. In Panels A to D, we compute the results for each group of individual predictors. The performance is measured by the R^2_{OOS}, which measures the reduction in MSFE of the rival against that of the benchmark. Statistical significance is assessed by the Clark and West (2007) one-sided upper-tailed statistic, which tests the H_0 that the MSFE of the benchmark is less or equal to that of the rival against H_1 that the forecast MSFE of the benchmark is greater than that of the competing model. "***", "**" and "*" denote 1%, 5% and 10% levels of statistical significance, respectively.

of YEN, the performance of PI, regardless of the currency under consideration is moderate and similar. PCA, Lasso, NN as well as, all the AMALG specifications provide significantly better forecasts, outperforming the PI consistently, irrespective of the currency under consideration.

As a next step, we examine the dynamic evolution of the out-of-sample performance of the predictors. We compute the Scaled Net Cumulative Squared Errors (SNCSE):

$$SNCSE = \frac{\sum_1^t (RV_t - \hat{R}V_{b,t})^2 - \sum_1^t (RV_t - \hat{R}V_{j,t})^2}{\sum_1^P (RV_t - \hat{R}V_{b,t})^2}, \quad \text{where } t = 1, \dots, P \tag{18}$$

which is basically the R^2_{OOS} per time t. Upward movements indicate a period where the rival model beats the benchmark and vice-versa.

Our results are depicted in Fig. 1, below. We observe that the performance of the amalgamation specifications is relatively stable. Moreover, we observe that turbulent periods offer significant gains compared to the benchmark. The sub-prime crisis in the US and the high financial uncertainty in the Eurozone in September 2011 have benefited the performance of the majority of methods under consideration. Nevertheless, we could claim that the amalgamation forecasts follow a positive and stable performance over time.

Table 2
Out-of-Sample Forecasts for the aggregate information methods.

	NZD	NOK	YEN	GBP	CAD	AUD	CHF
LASSO	**2.39*****	**2.91*****	−1.45	**7.78*****	**7.81*****	**3.88*****	**10.06*****
NN	**3.72*****	**1.23*****	**−0.12*****	**8.65*****	**8.30*****	**6.36*****	**13.00*****
SVR	−0.01	−0.55	**0.57****	**0.98*****	**0.94****	−0.64	**1.89*****
PCA	**4.76*****	**4.51*****	**0.72*****	**9.42*****	**13.67*****	**6.97*****	**8.57*****
ICA	**−2.17*****	**−33.97****	**−1.75****	**−17.12****	**−4.89*****	**1.30****	**−12.25****
PLS	**−2.77*****	**−9.29*****	**−6.63*****	**5.86*****	**−0.99*****	**0.47*****	**6.88*****
POOL	**1.55*****	**1.88*****	**0.93*****	**2.55*****	**2.39*****	**1.81*****	**2.27*****
MEDIAN	**0.56*****	**0.55****	**0.32****	**0.88*****	**0.84*****	**0.82*****	**0.77*****
TRIM3	**1.37*****	**2.14*****	**1.08*****	**2.43*****	**2.34*****	**1.84*****	**2.45*****
TRIM10	**1.54*****	**2.91*****	**1.19****	**3.56*****	**3.14*****	**2.05*****	**3.03*****
AMALG	**5.70*****	**5.59*****	**2.91*****	**7.79*****	**7.75*****	**7.22*****	**9.98*****
AMALG1	**6.18*****	**5.38*****	**3.35*****	**7.82*****	**7.87*****	**7.83*****	**10.28*****
AMALG2	**6.33*****	**5.26*****	**3.30*****	**7.63*****	**7.86*****	**7.92*****	**9.86*****
AMALG3	**7.24*****	**4.61*****	**3.14*****	**8.36*****	**9.30*****	**9.44*****	**11.40*****
PI	**2.53*****	**1.27****	0.02	**2.94*****	**4.25*****	**2.50*****	**2.64*****

The table presents the forecasting performance of the methods aggregating information from the entire set of predictors, measured by the R^2_{OOS}. Statistical significance is assessed by the Clark and West (2007) statistic. "***", "**" and "*" denote 1%, 5% and 10% levels of statistical significance, respectively.

5.2.3. Frequency based empirical findings

In order to identify the frequency based sources of predictability, we apply the wavelet methodology. We decompose the RV signal in different frequencies and extend our experiment by aggregating the forecasted frequencies, since the investor is primarily interested in forecasting the original RV times series.

In the first step, we evaluate the performance of the individual predictors in the short-run, medium-run and long-run frequency components of RV, as shown in Tables A.4, A.5 and A.6 in the Appendix.

$$\hat{R}V_t^f = \hat{a}_j + \sum_{i=1}^{p} \hat{b}_{j,i} RV_{t-i} + \hat{\beta}_j X_{j,t-1} \tag{19}$$

To avoid any look-ahead bias, we perform the decomposition process, as described in Eq. (16), at every time-step t, using data up to this point of time, in order to forecast $t+1$.

The results regarding the short-run frequency component demonstrate a weak performance of the predictors, for almost every currency under consideration, apart from GBP. A few sporadic predictors outperform the benchmark, but there is no sufficient evidence for robust behaviour, as reported in Table A.4. On the contrary, when we focus on the medium frequency, as shown in Table A.5, there is a significant improvement in the number of individual predictors that outforecast the benchmark. Remarkably, almost every method in Panel B shows positive performance.[13] In addition, in Panel C all amalgamation specifications demonstrate significant gains against the benchmark. Finally, the results presented in Table A.6 indicate that a handful of individual predictors increase their gains in terms of performance. On the other hand, almost all methods in Panels B and C are able to outperform the benchmark significantly. The aforementioned results provide enough evidence to assume that macroeconomic and financial predictors capture information contained in the medium- and long-run frequency, namely they are able to capture relatively stable trends of the RV time series. However, we need to point out that our results are not fully aligned with the findings of Engle et al. (2013) regarding the performance of inflation and industrial production growth on the long component of volatility.

We extend our analysis by decomposing the candidate predictors in a similar way. In this respect, we focus on the impact of the predictor's frequency on the respective frequency of the RV, such as:

$$\hat{R}V_t^f = \hat{a}_j + \sum_{i=1}^{p} \hat{b}_{j,i} RV_{t-i} + \hat{\beta}_j X^f_{j,t-1} \tag{20}$$

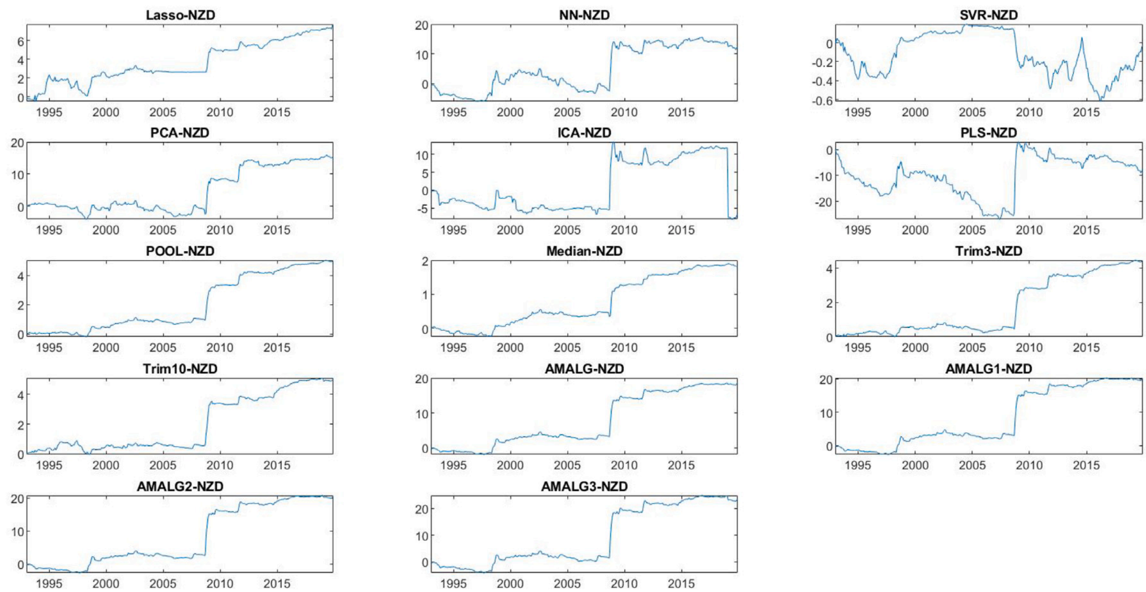
Our findings are presented in Tables A.7–A.9 for the short-run, medium-run and long-run component, respectively. We observe that the short-run (high) frequency component of the predictors is hardly statistically significant. Intuitively, this finding is attributed to the volatile nature of the high frequency components. With respect to the medium frequency, we observe that the performance is significantly improved, especially for those methods aggregating information. The amalgamation approaches, in 6 out of 7 currencies perform better than their rivals. Last, in the low frequencies, the performance is outstanding. Apparently, the long lasting patterns followed by the macroeconomic variables are able to capture long-term behaviour in the RV series.

Inspired by the work of Ferreira and Santa-Clara (2011) and, more recently, Faria and Verona (2018b) we sum the forecasted decomposed parts. The sum of forecasts of decomposed parts should approximate the actual RV series, such as:

$$\hat{R}V_{t,j} = \hat{R}V^{SS}_{t,j} + \hat{R}V^{MS}_{t,j} + \hat{R}V^{LS}_{t,j} \tag{21}$$

[13] The bizarre results of PLS and ICA, which generate a large negative but statistically significant R^2_{OOS} metric, are dictated by one outlier forecast at the end of the out-of-sample period.

(a)



(b)

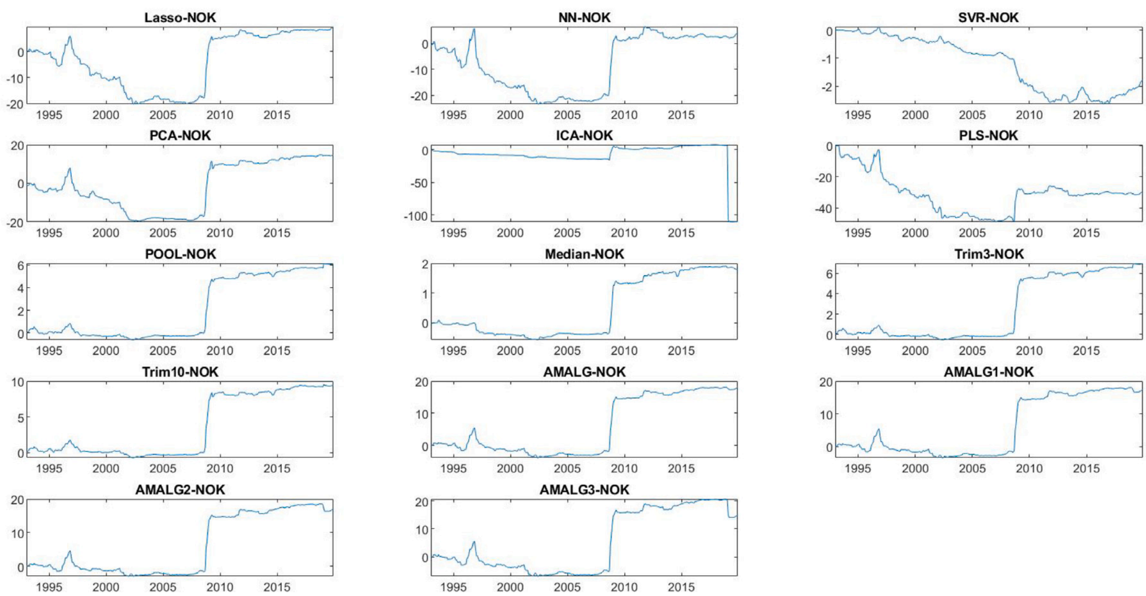
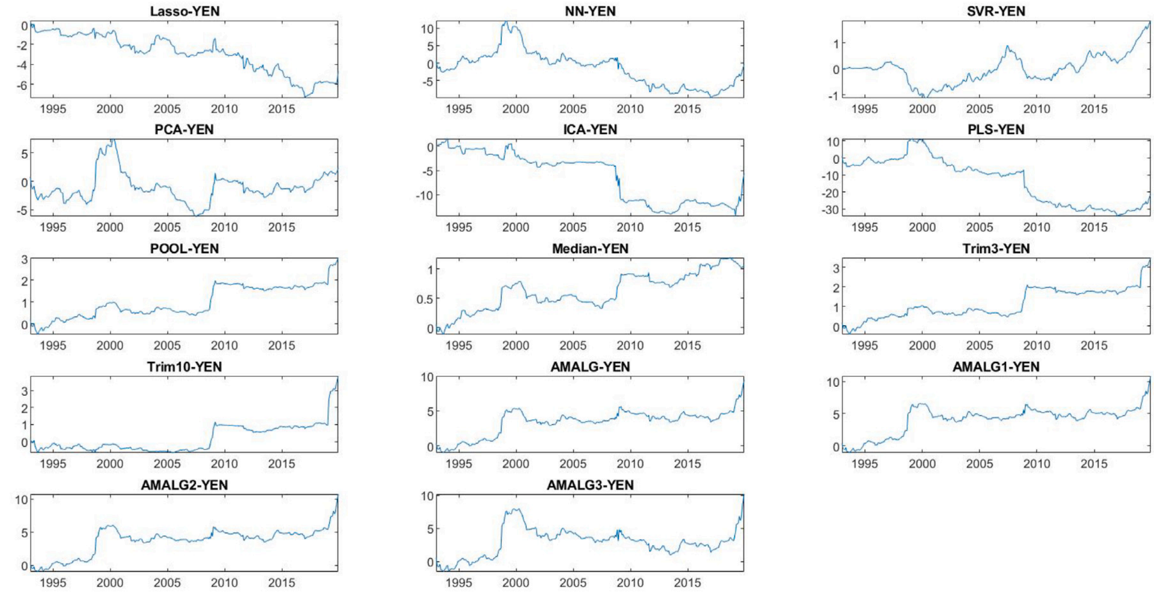


Fig. 1. Dynamic evolution of out-of-sample forecasts.
Notes: The Figure plots the Scaled Net Cumulative Squared Errors between the benchmark and the rivals, following the specifications of the initial experiment. Due to the large set of predictors and methods, we demonstrate the performance of the combination and dimensionality reduction techniques.

where $\hat{R}V_{t,j}^{SS}$, $\hat{R}V_{t,j}^{MS}$ and $\hat{R}V_{t,j}^{LS}$ are generated according to Eqs. 4 and 20. These forecasts are compared against the AR(p) process, as discussed in Eq. (3). The information derived from the former set of results is, on one hand, essential in understanding the dynamics of the RV series and the predictors, but on the other hand, these series are not directly tradable. Hence, the investor requires a model to forecast RV. For this reason, we use a naive aggregation of the sub-frequencies' forecasts, as shown in Table 4.

(c)



(d)

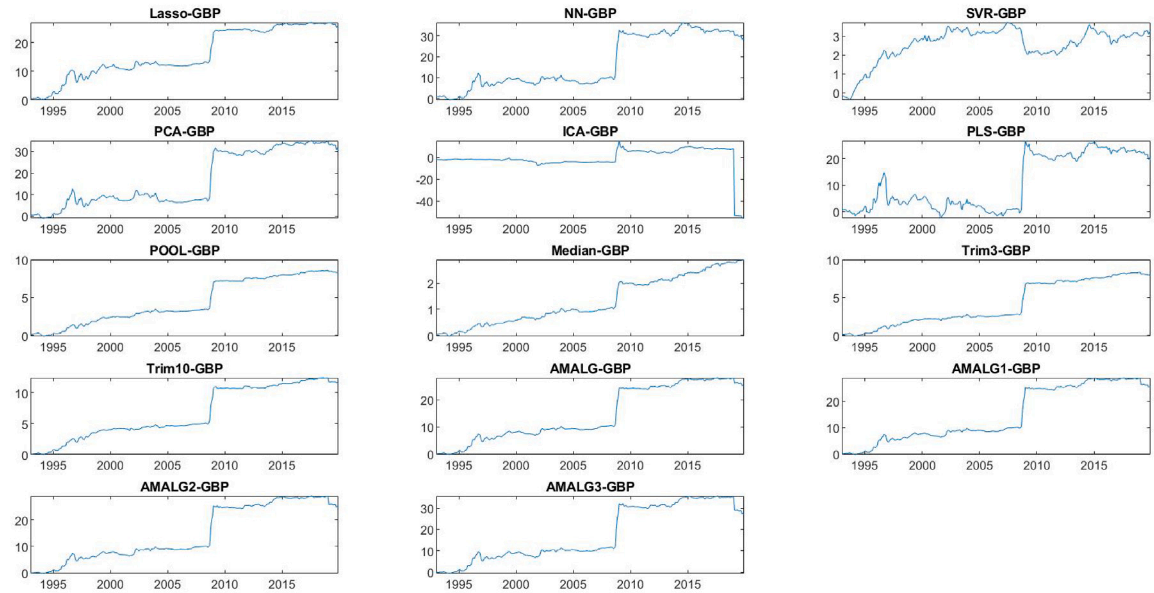
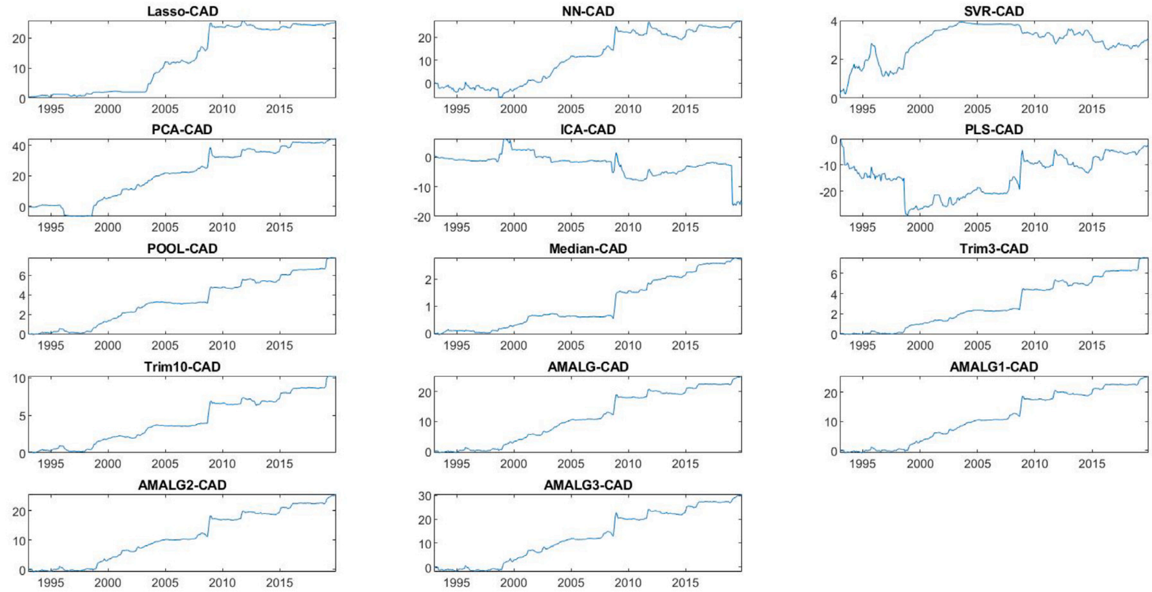


Fig. 1. (*continued*).

Overall, we see an improvement in all Panels, but this can vary among currencies and predictors. For example, by comparing the results of Table 2 with Panels B and C of Table 3, we see that the forecasts of Table 4 for NOK, CHF and, less obviously, for GBP do not improve against their rivals.

On the other hand, in Table 4 we observe an essential improvement in the overall performance of the predictors by aligning the respective frequencies of the dependent and independent variable. For instance, the predictors for GBP, CAD and AUD are almost uniformly statistically significant. Furthermore, it is noteworthy that the amalgamation forecasts demonstrate significant gains, both in terms of R^2_{OOS} and CW statistic, for every currency. More precisely, the R^2_{OOS} ranges from 4.35% for AMALG3 in YEN to 17.86%

(e)



(f)

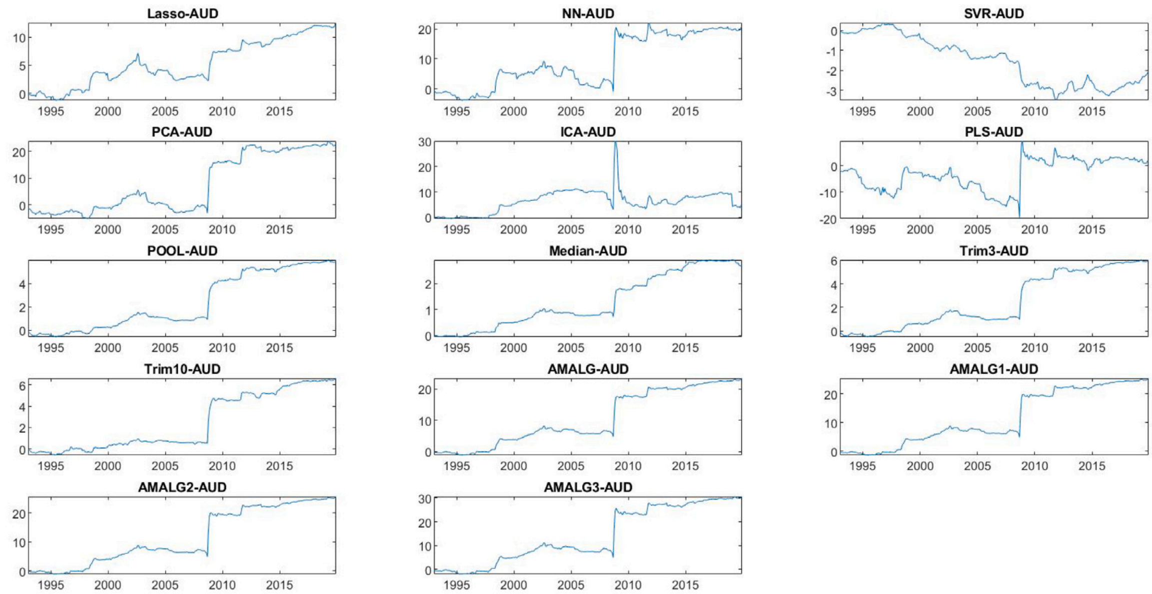


Fig. 1. (*continued*).

for AMALG3 in CAD. A close inspection of Table 4 reveals that the amalgamation forecasts outperform all other predictors under consideration.

5.3. Model confidence set

We further investigate the impact of wavelets on model performance by comparing the forecasting results of 14 models, which aggregate information in three different ways: (a) without decomposition (denoted with the subscript 1), (b) after decomposing

(g)

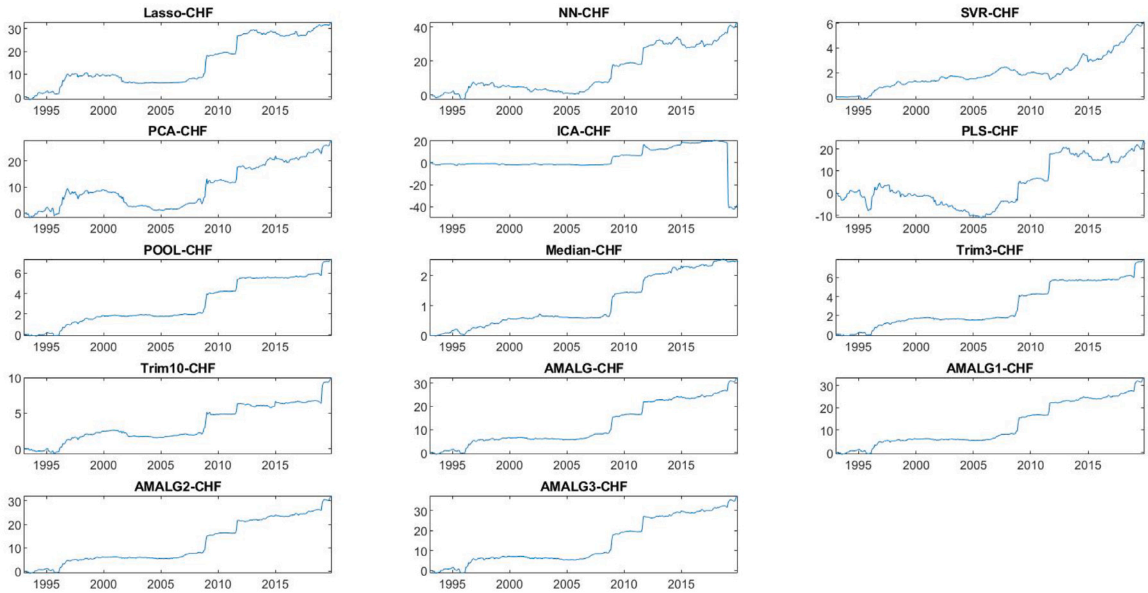


Fig. 1. (*continued*).

only the dependent variable (denoted with the subscript 2), and (c) after decomposing both X and Y (denoted with the subscript 3), using the Model Confidence Set (Hansen et al., 2011b). Similar to Bucci (2020), we use the 85% MCS to compare the models and increase it to 90%. The results reported in Table 5, provide strong evidence in favour of incorporating the wavelet methodology in the forecasting exercises. Apart from GBP and CHF, all other currencies are dominated by the models accounting for different frequencies. Overall, we observe that the AMALG approach is promoted in all currencies. Furthermore, we observe that the decomposition plays a pivotal role in forecasting, since only a handful of models are selected without any decomposition. Last, we see that aggregating the forecasts after aligning the respective frequencies of RV and X (models with subscript 3) perform better, underlining the importance of using the correct type of information to forecast inner frequencies of RV, rather than using the original series as the dependent variable.

6. Robustness checks

In this section, we examine the performance of the models under different financial conditions and periods. Such periods are related to (i) the business cycle, (ii) the market sentiment, (iii) the liquidity in the market, and, (iv) impactful events.

6.1. Alternative loss functions

The sensitivity of loss functions to a few outliers in the forecast series has been raised by the literature and thoroughly investigated by Patton (2011). In order to provide further evidence on the robustness of the results, we show the overall relative performance of the rival models, by first averaging the ranking of each model among all currencies and, as a second step, ranking the averages. A model can perform relatively poor in one currency but good in another. Hence, the forecaster trading a variety of currencies, should be able to identify which model demonstrates overall superior forecasting performance across different loss functions. Based on the results of Table 6, we observe that the specifications of amalgamation forecasts report the least losses, irrespective of the metric under consideration.

6.2. Performance during recessions and expansions

The impact of recessions/ expansions in forecasting returns and volatility has been recognized in the literature (see, among others, Neely et al., 2014 and Souropanis and Vivian, 2023). We identify business cycle periods, i.e. recessions and expansions, by the National Bureau of Economic Research (NBER) reported dates and measure the performance based on the standard R^2_{OOS} metric, adjusted to isolate for the business cycle periods.

Specifically, we employ the modified R^2_{OOS}, so that:

$$R^2_c = 1 - \frac{\sum_1^P (RV_t - \hat{R}V_t)^2 {I_t^c}^2}{\sum_1^P (RV_t - \hat{R}V_{b,t}) I_t^c}, \quad c = expansion, recession \tag{22}$$

Table 3
Out-of-Sample forecasts for the aggregated forecasted wavelet frequencies decomposing only RV.

	NZD	NOK	YEN	GBP	CAD	AUD	CHF
Panel A: Individual Predictors							
DP	**−0.00****	−3.87	−2.52	**2.39*****	**0.45*****	**1.66****	**−0.27*****
EP	−0.74	−3.73	−1.28	0.59	**1.12*****	−2.99	−1.51
MKT	**2.51*****	−1.66	0.04	**2.57*****	**1.96****	**5.74*****	**1.21****
SMB	−0.89	−2.84	−1.26	**1.22****	−1.99	**−0.25****	−0.20
HML	−1.23	−4.85	−1.03	**0.69***	−0.13	0.64	−0.42
STR	**0.71****	−2.33	0.28	**0.88****	**0.06***	**3.14*****	**1.22****
MSCI	**3.56*****	−0.47	**0.53***	**3.91*****	**1.69****	**6.38*****	**1.64*****
TB	−0.45	−4.05	−1.21	−0.10	**4.37*****	−2.35	−0.85
LTR	−0.56	−2.68	**0.08****	**2.73*****	**1.68****	**1.40****	**3.37*****
TS	−0.82	−1.70	−1.10	**0.89****	0.17	**0.03***	**0.31***
ΔTED	−0.96	−6.23	−1.24	**0.39****	**3.42*****	−1.13	**−1.00****
LTY	**3.51*****	**3.88****	**−0.28***	**6.31*****	**3.76*****	**8.95*****	**2.70*****
DFY	**0.53***	−1.26	−0.42	**2.11*****	**1.32****	**3.63*****	−0.18
INFM	**−28.37****	−67.61	**−12.83****	−19.90	**−64.31***	**−11.51*****	**−28.31***
INFA	−0.90	−3.04	−1.19	**2.20*****	**0.87****	**0.93***	0.02
IPM	**0.51***	**1.48****	−0.14	**5.80*****	−0.14	**3.62*****	**1.33*****
IPA	−3.51	−1.66	−0.76	**2.07*****	−4.17	−0.65	−1.50
M1M	0.41	−3.32	−1.69	**2.55*****	**1.15***	**2.26****	**0.04****
M1A	−0.88	−2.81	−0.66	**1.26****	0.11	**0.98****	−1.33
PAYEMS	−1.42	**1.73*****	−0.12	**4.03*****	**0.54***	**0.37***	**−0.14****
EPU	−0.32	−2.76	−0.27	**2.86*****	**0.57***	**1.81****	−0.20
SENT	−1.23	−2.90	−0.55	**1.25***	−0.66	**0.76***	−0.81
CAP	−1.15	−3.11	−0.13	**1.90****	**2.28*****	**1.57****	**1.66****
DIFF	−1.36	−2.95	−0.44	0.01	−0.81	0.33	0.38
CCONF	0.07	**−0.70***	**0.67***	**4.04*****	−0.98	**2.79****	**1.17****
H-S	−1.38	−0.82	**0.63****	**2.76*****	0.12	**0.99****	**1.42****
PMBB	**−1.91***	−1.97	**0.09***	**1.91*****	−0.84	**0.91*****	**1.96****
PMI	**1.67****	−2.75	0.27	**3.07*****	**2.96*****	**3.39*****	0.01
PS	−1.97	−1.53	−0.81	**1.59****	0.04	**1.62*****	−0.04
GOLD	−0.47	−2.62	−0.61	**1.00****	0.07	**0.67****	−0.14
ΔVXO	0.12	−0.96	−0.35	**5.10*****	−0.65	**2.33*****	**0.89****
WTI	−0.75	−2.70	−0.19	**1.15***	0.07	**1.07****	−0.27
CRB	**1.18****	−1.77	−0.43	**3.05*****	0.04	**2.63*****	**0.63***
Panel B: Aggregating Information							
LASSO	**0.93****	**3.07*****	**2.18*****	**5.83*****	**2.55*****	**4.80*****	**7.76*****
NN	**4.28*****	**−2.83****	**1.71*****	**7.46*****	**9.32*****	**8.22*****	**11.40*****
SVR	−0.39	−2.41	**0.71***	**1.90****	**0.49***	**0.83***	**0.74***
PCA	**5.96*****	**2.37*****	**1.90*****	**10.06*****	**12.81*****	**7.83*****	**9.00*****
ICA	**−3.16*****	**−34.93****	**−5.00*****	**−16.82****	**0.03*****	**0.29*****	**−15.48****
PLS	**−36.41*****	**−72.56****	**−27.40*****	**−30.07*****	**−21.49*****	**−13.52*****	**−26.70*****
POOL	**1.28*****	−0.25	**0.93****	**3.78*****	**2.59*****	**3.33*****	**2.14*****
MEDIAN	0.39	−1.73	0.32	**2.35*****	**1.04****	**2.24*****	**0.48***
TRIM3	**1.10****	−0.03	**1.09****	**3.67*****	**2.62*****	**3.34*****	**2.32*****
TRIM10	**1.25*****	**0.65***	**1.16****	**4.60*****	**3.36*****	**3.48*****	**2.80*****
Panel C: Amalgamation Forecasts							
AMLG	**5.20*****	**1.96****	**4.56*****	**7.62*****	**7.93*****	**9.89*****	**8.99*****
AMLG1	**5.63*****	**0.84****	**4.77*****	**7.41*****	**8.62*****	**10.65*****	**9.11*****
AMLG2	**5.07*****	**−0.87****	**4.38*****	**6.04*****	**8.23*****	**10.77*****	**8.04*****
AMLG3	**4.28*****	**−6.87*****	**3.22*****	**3.85*****	**9.36*****	**12.02*****	**6.80*****

Notes: Table 3 demonstrates the performance of the predictors after aggregating the forecasts of each frequency separately. The aggregate forecasts is given by: $\hat{R}V_{t,j} = \hat{R}V^{SS}_{t,j} + \hat{R}V^{MS}_{t,j} + \hat{R}V^{LS}_{t,j}$ where $\hat{R}V^{SS}_{t,j}$, $\hat{R}V^{MS}_{t,j}$ and $\hat{R}V^{LS}_{t,j}$ are generated according to $\hat{R}V^{f}_{t} = \hat{a}_j + \sum_{i=1}^{p} \hat{b}_{j,i} RV_{t-i} + \hat{\beta}_j X_{j,t-1}$ The performance is measured by the R^2_{OOS}. Statistical significance is assessed by the Clark and West (2007) statistic. "***", "**" and "*" denote 1%, 5% and 10% levels of statistical significance, respectively.

where I^c_t is a dummy variable that takes values 1 for expansion periods and 0 for recessions. The related findings are reported in Table A.10 in the Appendix. Overall, our results are in line with the existing literature for all currencies. Our models perform better during recessions than expansions. This finding complements the findings presented in Fig. 1, where we have shown that the main gains are obtained during crises periods. The only exception is YEN, which demonstrates a similar performance between the two periods. Moreover, we observe that the performance is gradually improved (in the majority of cases) as we move from Panel A to Panel C, i.e. employing decomposed RV and candidate predictors. This implies that by decomposing the series, we can elaborate on the separate frequencies distinctively and extract the most useful information. Focusing on the competing methodologies employed, we should note that our main findings hold as the amalgamation forecasts show superior predictive ability.

Table 4
Out-of-Sample forecasts for the aggregated forecasted wavelet frequencies decomposing both the RV and the X variables.

	NZD	NOK	YEN	GBP	CAD	AUD	CHF
Panel A: Individual Predictors							
DP	−2.55	−9.73	−2.75	**−2.34*****	**0.20*****	−5.17	**−3.23*****
EP	−3.29	−10.31	−5.09	−3.74	**2.50*****	−8.77	−3.98
MKT	**5.93*****	−2.64	**0.11***	**4.54*****	**3.72*****	**6.74*****	**2.07*****
SMB	−1.25	−10.62	**−0.57***	−1.17	**0.16*****	−5.25	−1.36
HML	−0.47	−5.81	−2.12	**1.36*****	**1.03*****	**0.55****	**0.03***
STR	**−0.40****	**−1.87***	**0.68****	**1.31*****	**5.52*****	**0.67*****	**1.27*****
MSCI	**5.38*****	**2.79****	**0.57****	**4.81*****	**5.88*****	**7.92*****	**3.40*****
TB	−3.37	−15.64	−1.10	−3.22	**−5.03*****	−12.62	−3.84
LTR	**0.38****	**−9.47****	**1.91*****	**0.45*****	**−2.09*****	**1.69*****	**1.69*****
TS	**0.79****	−4.43	−1.87	−0.53	**3.26*****	−3.52	−3.08
ΔTED	**−2.39****	−12.09	−1.01	**−4.41****	**−6.08*****	−6.98	**0.18*****
LTY	**3.49*****	**1.98*****	**−0.99****	**8.12*****	**6.71*****	**8.52*****	**1.93*****
DFY	**−2.13*****	−3.33	**0.56****	−1.26	**3.77*****	**3.49*****	−1.36
INFM	**1.28****	**−4.70***	**2.16*****	**1.66*****	**4.14*****	**2.01*****	**−3.18*****
INFA	−1.51	−2.26	−2.68	**1.72*****	**3.62*****	**−0.33****	**2.32*****
IPM	**2.10****	**2.47****	**0.47****	**6.95*****	**2.81****	**5.53*****	**−1.27****
IPA	−3.61	**0.44*****	**0.23***	**5.71*****	**−1.97****	−2.41	**0.80*****
M1M	**1.79****	−5.25	−2.70	**−3.75****	**0.67****	**2.23****	**−1.56***
M1A	−2.28	−5.41	−1.55	**−0.74*****	**1.04****	**3.16*****	−4.78
PAYEMS	−1.61	**0.02*****	−1.54	**3.24*****	**2.25*****	**0.60****	**−1.65***
EPU	**0.81****	**−3.24***	**0.32****	**4.78*****	**3.62*****	**−0.76****	**2.12****
SENT	−2.60	−4.38	−0.78	**1.83*****	**−1.07*****	**−0.31****	**−0.05***
CAP	**1.78*****	**−2.08***	**0.36****	**1.69****	**6.12*****	**4.51*****	**−0.74***
DIFF	−5.01	−5.08	−5.49	**−0.45***	**−0.38****	−7.72	−1.19
CCONF	**−1.07***	**−0.92****	**2.01*****	**3.61*****	**−1.29***	**1.47****	**−1.28****
H-S	−1.99	**−0.07****	**0.79****	**1.92*****	**1.34*****	**1.30*****	**2.11****
PMBB	**−0.66****	−3.05	−1.81	**1.11*****	**1.62*****	**−0.11*****	−0.40
PMI	**3.38*****	**−3.18****	**0.13*****	**6.39*****	**5.38*****	**3.80*****	**−0.64****
PS	**−2.98***	−5.31	−3.99	**1.38*****	**1.43****	**−3.57****	−3.74
GOLD	**0.54****	**−2.02****	**−1.05****	**0.23****	**6.00*****	**−1.60****	**1.15*****
ΔVXO	**2.38*****	**1.91*****	**−1.20****	**5.95*****	**2.38*****	**3.31*****	**0.88*****
WTI	−3.14	**−0.13***	−1.48	**1.39****	**2.78*****	−1.75	−1.26
CRB	**1.06****	**−0.50****	−6.56	**1.53*****	**5.35*****	**0.55*****	**0.29****
Panel B: Aggregating Information							
LASSO	**3.23*****	**−4.23*****	**4.88*****	**8.77*****	**9.44*****	**8.03*****	**8.71*****
NN	**−8.71*****	**−14.00*****	**−7.87*****	**1.08*****	**−0.70*****	**−2.84*****	**−0.06*****
SVR	**3.83*****	**−2.81*****	**1.36*****	**−2.91*****	**9.49*****	**−0.54*****	**5.24*****
PCA	**3.02*****	**−0.72*****	**−1.01*****	**6.37*****	**12.54*****	**2.03*****	**9.25*****
ICA	**−3.19****	**−9.27****	**−5.61****	**0.23*****	**−7.05****	**−1.40*****	**−6.14*****
PLS	**−28.85*****	**−30.31*****	**−21.27*****	**−6.39*****	**−11.93*****	**−16.87*****	**−5.43*****
POOL	**3.91*****	**2.20****	**1.83****	**6.72*****	**7.38*****	**5.99*****	**3.21*****
MEDIAN	**2.03*****	**1.36***	**1.24****	**4.76*****	**5.06*****	**4.04*****	**0.80****
TRIM3	**4.02*****	**2.38****	**2.08*****	**6.88*****	**7.45*****	**6.34*****	**3.46*****
TRIM10	**4.08*****	**2.98****	**1.90*****	**7.33*****	**7.98*****	**6.88*****	**3.26*****
Panel C: Amalgamation Forecasts							
AMLG	**8.82*****	**6.83*****	**5.76*****	**13.77*****	**17.06*****	**13.17*****	**11.52*****
AMLG1	**8.99*****	**6.90*****	**5.45*****	**13.40*****	**17.09*****	**13.03*****	**11.35*****
AMLG2	**9.06*****	**6.91*****	**5.68*****	**13.16*****	**17.25*****	**12.60*****	**11.17*****
AMLG3	**7.85*****	**5.61*****	**4.35*****	**14.63*****	**17.86*****	**13.70*****	**11.00*****

Notes: Table 4 illustrates the performance of the predictors after aggregating the forecasts of each frequency separately. The aggregate forecasts is given by: $\hat{R}V_{t,j} = \hat{R}V^{SS}_{t,j} + \hat{R}V^{MS}_{t,j} + \hat{R}V^{LS}_{t,j}$ where $\hat{R}V^{SS}_{t,j}$, $\hat{R}V^{MS}_{t,j}$ and $\hat{R}V^{LS}_{t,j}$ are generated according to $\hat{R}V^{f}_{t} = \hat{a}_j + \sum_{i=1}^{p} \hat{b}_{j,i} RV_{t-i} + \hat{\beta}_j X^{f}_{j,t-1}$ The performance is measured by the R^2_{OOS}. Statistical significance is assessed by the Clark and West (2007) statistic. "***", "**" and "*" denote 1%, 5% and 10% levels of statistical significance, respectively.

6.3. Performance during different sentiment periods

Next, we analyse the impact of different sentiment periods. De Long et al. (1990) argue that the existence of traders suffering from cognitive biases creates mispricing in the market. In the same spirit, Barberis et al. (1998) claim that investors are bound on their former beliefs and fail to adjust in response to new information. We measure the sentiment of the market by employing the Aligned Sentiment Index of Huang et al. (2015) and split the data into high (HSENT) and low (LSENT) sentiment periods, according to the median value of the index. The index is based on the standard investor sentiment index of Baker and Wurgler (2007) that is also employed by Stambaugh et al. (2012).

Table 5
Model Confidence Set for each exchange rate.

NZD	NOK	YEN	GBP	CAD	AUD	CHF	NZD	NOK	YEN	GBP	CAD	AUD	CHF
$MC_{85\%}$							$MC_{90\%}$						
$AMALG_3$ $AMALG1_3$ $AMALG2_3$	$LASSO_1$ PCA_2 $TRIM3_1$ $LASSO_2$ $TRIM10_1$ $AMALG3_1$ PCA_1 $AMALG2_1$ $AMALG1_1$ $AMALG3_3$	$AMALG_2$ $LASSO_3$ $AMALG1_2$ $AMALG1_3$ $AMALG2_3$ $AMALG_3$	$AMALG3_3$	$AMALG3_3$	$AMALG1_2$ $AMALG2_2$ $AMALG2_3$ $AMALG3_2$ $AMALG1_3$ $AMALG_3$ $AMALG3_3$	$AMALG1_1$ $LASSO_1$ $AMALG3_3$ $AMALG2_3$ $AMALG1_3$ NN_2 $AMALG3_1$ $AMALG_3$ NN_1	$AMALG2_3$	$AMALG_2$ $LASSO_3$ $AMALG1_2$ $AMALG1_3$ $AMALG2_3$ $AMALG_3$	$AMALG_2$ $LASSO_3$ $AMALG1_2$ $AMALG1_3$ $AMALG2_3$ $AMALG_3$	$AMALG3_3$	$AMALG3_3$	$AMALG3_3$	$AMALG1_1$ $LASSO_1$ $AMALG3_3$ $AMALG2_3$ $AMALG1_3$ NN_2 $AMALG3_1$ $AMALG_3$ NN_1

Notes: The table reports the included models in the Model Confidence Set for two different intervals, 85% and 90%, respectively. The set consists of forecasts generated by both individual predictors and dimensionality reduction techniques. The subscript "1" denotes the methods without employing any decomposition, "2" after applying wavelets only on RV, and "3" when both RV and X are decomposed.

Table 6
Alternative Loss Functions Metrics.

	QLIKE	MSE LOG	MSE SD	MSE prop	MAE	MAE LOG	MAE SD	MAE prop
AR(p)	**1**	11	**3**	7	8	5	6	9
Lasso	5	14	12	10	6	12	13	8
NN	8	13	**4**	12	15	13	15	12
SVR	7	12	11	14	14	10	14	11
PCA	13	10	15	**4**	12	11	12	6
ICA	5	**3**	14	9	13	6	10	10
PLS	8	6	13	8	7	**4**	5	13
POOL	12	8	5	13	9	8	8	**4**
MEDIAN	10	9	7	6	11	9	11	5
TRIM3	11	7	10	10	10	7	7	8
TRIM10	12	5	9	11	5	**4**	9	7
AMALG	6	**2**	8	5	**2**	**1**	**1**	**3**
AMALG1	**3**	**3**	6	**3**	**3**	**3**	**2**	**2**
AMALG2	**4**	**1**	**1**	**2**	**1**	**2**	**3**	**1**
AMALG3	**2**	**4**	**2**	**1**	**4**	**4**	**4**	**1**

Notes: The table reports the ranking of the average ranking among the currencies for each method based on alternative loss functions. As a first step, we rank each method for each currency, then we average the rankings in order to identify how well each method performs on average, last, we rank the averages.

The finding are presented in Table A.11, in the Appendix. Our results provide evidence that the models work better during high sentiment periods. Especially for some currencies, the difference in performance between the two periods is relatively significant. On the other hand this is not true for Yen, a currency that is widely characterized as a "safe haven" (see for instance, Hossfeld and MacDonald, 2015).

6.4. Performance during different liquidity periods

The importance of liquidity for realized volatility has been highlighted by Adrian and Shin (2010). The liquidity index we employ is based on the broadly used liquidity factors of Pástor and Stambaugh (2003). Similar to the previous cases, we examine the performance of the competing models during high (HLIQ) and low (LLIQ) liquidity periods, based on the median value of the index.

Our results in Table A.12 in the Appendix indicate that the impact of liquidity periods tends to affect differently the methods applied on different currencies. For instance, we observe a boost in the performance of the predictors during LLIQ when considering NZD, NOK, CHF, GBP and CAD. On the other hand, AUD and YEN demonstrate relatively different behaviour. In brief, YEN demonstrates balanced behaviour during the two liquidity periods, whereas, the predictors for AUD benefit slightly during high liquidity periods.

Overall, the results in Panel C suggest that the performance between HLIQ and LLIQ is amplified. Moreover, the candidate predictors benefit from the recommended approach. In addition, there is strong evidence in favour of using wavelet decomposition in the forecasting framework, since the results in both Panel B and C improve the forecasting performance compared to Panel A. These results suggest that the decomposition results could protect the forecaster from fluctuations in the liquidity of the market.

6.5. Performance during alternative OOS periods

Investigating further the effect of timing in the performance of our methodologies, we check the robustness of results during different out-of-sample periods (1993:1-2006:12 and 2007:1-2019:12). The effect of the sub-prime mortgage crisis on exchange rates has been well-documented by the literature. Moreover, the impact of major events on exchange rate volatility has been documented in several studies, mainly linked to changes in the uncertainty around fundamentals. Despite the fact that a large strand of the literature is using the Economic Policy Uncertainty Index to capture these effects, Bartsch (2019) argues that the EPU is mainly based on daily information updates. Hence, the effects of one month may be driven by one sole observation that has occurred from one up to thirty days ago. Thus, we split our sample into two different time periods, the last of which includes the crisis and its impact on RV forecasting.

The forecasts are mainly benefited by the last part of the period (as shown in the results in Table A.13 in the Appendix). The excess uncertainty in the financial markets and the depth of the crisis is not only reflected in the performance of the models, but also in the case of NZD and NOK, the benchmark beats the rival models. For the remaining currencies, the amalgamation approaches show superior predictive ability. Hence, the forecaster is relatively disentangled from the effect of "bad timing".

6.6. Discount MSFE

In order to see the payoff of estimating model weights at the amalgamation stage, we generate an additional ensemble methodology which allows the models to receive varying weights at each time t, based on the discount MSFE (DMSFE) combination forecast methodology (see Stock and Watson, 2004).[14] The weights are generated based on the past performance over a rolling holdout out-of-sample period, we set this period to 24 months.[15]

The results remain qualitatively the same, without demonstrating any major wins or losses (see Table A.14 in the Appendix). Hence, there is evidence that more elaborate ensemble methodologies can sporadically benefit the forecasting experiment. Apart from scattered spikes in the weights, the latter tend to equally weight the forecasts over the entire out-of-sample period.

7. Conclusions

There is a growing body of literature focusing on forecasting volatility and addressing the disconnect puzzle of RV with macroeconomic and financial variables (Schwert, 1989). Despite the progress of academic literature, there has not been a unanimous conclusion. In this study, we contribute to the growing academic dialogue by employing several financial and macroeconomic variables on exchange rate volatility forecasting.

To our knowledge, we are among the first to examine the impact of this group of predictors on exchange rate volatility forecasting. Our second contribution is related to the fact that the investor has at her disposal numerous methods and predictors in order to aggregate information. Thus, she needs an ensemble technique to take advantage of the properties of each model. Hence, we apply a variety of machine learning, dimensionality reduction and forecast combination approaches in order to aggregate all available information from the predictors at hand. Moreover in order to avoid uncertainty associated with the employment of a specific predictor/ model, we propose an amalgam of forecasts by simply averaging forecasts generated by the aforementioned approaches. Finally, our third contribution is to show that information contained at different frequencies can enhance the forecasting performance of the model significantly, by employing the wavelet decomposition methodology.

We test our methodology in seven widely traded currencies; NZD, NOK, YEN, GBP, CAD, AUD and CHF, and calculate monthly volatility from daily exchange rate returns, from February 1986 to December 2019. We use 33 candidate predictors that enjoy theoretical merit in terms of being related with exchange rates. With respect to the frequency decomposition, we use the maximal overlap discrete wavelet transform and the Haar wavelet filter. The predictors and methodologies proposed are evaluated both in sample and out of sample. As a benchmark, we use a simple AR(p) model, the toughest benchmark reported in the literature. Last, we measure the performance in different timing periods associated with (a) the business cycle, (b) sentiment periods, (c) liquidity and (d) major financial crisis.

Our in-sample findings suggest that equity market and a few macroeconomic variables are able to predict volatility in a number of currencies. However, the in-sample results are not consistent across currencies and predictors belonging in the same group. The out-of-sample results demonstrate promising forecasting behaviour, especially the amalgamation approach. The latter seems to achieve superior forecasting ability in, almost, every currency, as well as to demonstrate a stable performance over time. More specifically, amalgam forecasts provide positive and statistically significant R^2_{OOS} for all currencies, due to the fact that extreme opposite forecasts are cancelled out. They also have the highest R^2_{OOS} for NZD, NOK, YEN and AUD and among the highest ones for CAD and CHF.

We also focus on the relationship of the frequency components of volatility and the candidate predictors. First, we find that macroeconomic variables demonstrate good performance when it comes to the long frequency component, as intuitively expected. Second, our findings suggest aggregating the forecasts after aligning the frequencies of the predictor with those of volatility can qualitatively improve the forecasts. With respect to timing effects of the forecasting performance, we see that the business cycle and the crisis periods have the main impact on the forecasts, as well as the low liquidity and low sentiment periods. Remarkably, the amalgamation forecasts is able to amplify major differences in the performance during different periods. Hence, the investor is less concerned on the timing effect of investment.

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[14] For an alternative combination rules, see among other Taylor (2020) and Amendola et al. (2020)

[15] Instead of naively averaging the forecasts, we allocate the respective weights such as: $\omega_{i,t} = \phi_{i,t}^{-1} / \sum_{k=1}^{K} \phi_{k,t}^{-1}$, where $\phi_{i,t} = \sum_{s=R}^{t-1} \theta^{t-1-s}(r_{s+1} - \hat{r}_{i,s+1})^2$. We denote as $R+1$ the beginning of the out-of-sample (and consequently, that of the holdout period), θ is the discount factor; following Rapach and Zhou (2013) we set $\theta = 0.75$

CRediT authorship contribution statement

Antonios K. Alexandridis: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ekaterini Panopoulou:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ioannis Souropanis:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) have not used generative AI and AI-assisted technologies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.intfin.2024.102067.

Data availability

Data will be made available on request.

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