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by Leonardo Morales-Arias and Alexander Dross

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Kiel Institute for the World Economy, Hindenburgufer 66, 24105 Kiel, Germany

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Keywords: Exchange rate forecasting, panel data, forecast combinations, market timing

JEL classification: C20, F31, G12

Leonardo Morales-Arias
Kiel Institute for the World Economy
24100 Kiel, Germany
Phone: +49 431-8814 267
E-mail: leonardo.morales@ifw-kiel.de

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*Corresponding author. University of Kiel (Chair of Monetary Economics and International Finance) and Kiel Institute for the World Economy, Kiel, Germany. Email: moralesarias@economics.uni-kiel.de. We would like to thank Carl Chiarella, Tony He, Helmut Herwartz, Nils Jannsen, Harmen Lehment, Thomas Lux, Henning Weber and seminar participants at the Quantitative Finance Research Center (QFRC), University of Technology Sydney (UTS), May 2010 for valuable comments and suggestions. Part of this research was conducted at the QFRC-UTS whose excellent hospitality is also hereby acknowledged. The usual disclaimer applies.

1 Introduction

Forecasting exchange rates is of particular importance for investors and policy makers. Accurate forecasts of exchange rates allow investors, for instance, to design trading strategies and to hedge exchange rate risk. The future evolution of exchange rates is also important for policy makers at central banks as it can point to the appropriate interest rate policy to be set (Groen and Matsumoto, 2004; Gali, 2008).

In this paper we contribute to the empirical exchange rate literature by analyzing the statistical and economic implications of adaptive forecasting of exchange rates with panel data and several alternative predictors. The candidate exchange rate predictors are drawn from (i) macroeconomic 'fundamentals', (ii) returns/volatility of asset markets and (iii) cyclical and confidence indices. The proposed forecasting design allows us to generate alternative exchange rate forecasts at various horizons from each of the potential predictors using single market, mean group and pooled estimates by means of rolling window and recursive forecasting schemes. The capabilities of single predictors and of adaptive techniques for combining the generated exchange rate forecasts are subsequently analyzed by means of statistical and economic performance measures.

Our study is motivated by previous theoretical and empirical findings of the conventional and behavioral exchange rate literature, the risk-return literature and the forecasting literature. More precisely, the conventional theoretical literature on exchange determination suggests several potential macroeconomic predictors of exchange rates. Some of the most conventional predictors are usually based upon the Purchasing Power Parity (PPP) hypothesis, Uncovered Interest Rate Parity (UIP) condition and the Monetary Model (MM). However, the forecasting contribution of such macroeconomic 'fundamentals' of exchange rates has been questioned since the highly influential study of Meese and Rogoff (1983). The latter study finds that these predictors may not perform better out-of-sample than a random walk model in particular at lower forecasting horizons.

Subsequent studies suggest that under certain conditions (e.g. small sample corrections, recursive forecasting, measurement improvement, alternative estimation approaches), macro fundamentals may improve forecasting accuracy at longer horizons (Mark, 1995; Chen and

Mark, 1996; Kilian, 1999; Berkowitz and Giorgianni, 2001; Faust et al., 2003; Engel et al., 2007). Nevertheless, even if there is some predictability of a bilateral exchange rate from a particular macro 'fundamental' at a certain horizon, the same variable may show no predictability at different horizons or for other bilateral exchange rates (Cheung et al., 2005).

Recently, however, new predictors have shed more positive light on the capabilities of macro 'fundamentals' for forecasting exchange rates. In particular, predictors derived from Taylor (TAY) rule specifications have been proposed to forecast exchange rates, motivated by the fact that monetary policy can be more appropriately modeled by taking the interest rate as the policy instrument as opposed to money supply (Molodtsova and Papell, 2009; Molodtsova et al., 2008; Engel et al., 2009). Predictors based on alternative versions of the Taylor rule have shown promising out-of-sample forecasting power over a random walk model at short and long horizons (Molodtsova and Papell, 2009; Engel et al., 2009). In addition, a predictor constructed by extracting latent factors from a panel of exchange rates (along with pooled coefficient estimates) has shown superior out-of-sample performance than the random walk when complemented with predictors based on PPP, MM and TAY (Engel et al., 2009). The forward premium (which stems from the UIP condition) has also recently shown promising results in a portfolio allocation setting (Della-Corte et al., 2009).

In response to the puzzling explanatory power of predictors derived from conventional macro models, the behavioral finance literature suggests an alternative explanation to ex-ante exchange rate fluctuations, namely, that future exchange rates can be modeled as a weighted average of forecasts from 'fundamentalists' and 'chartists' (Kirman, 1993). For instance, chartists forecast exchange rates by extrapolating recent trends whereas fundamentalists forecast on the basis of macro 'fundamentals' (Frankel and Froot, 1986). Indeed, the advantages of forecast combinations and of adaptive strategies for combining forecasts have been highlighted in several studies in the forecasting literature (Granger, 1989; Newbold and Harvey, 2002; Granger and Jeon, 2004; Aiolfi and Timmermann, 2006; Kisinbay, 2007; Costantini and Pappalardo, 2009) and recently in the exchange rate literature (Della-Corte et al., 2009). In addition, the assumptions of behavioral exchange rate models also seem to be more in line with the behavior of traders in reality (Taylor and Allen, 1992; Cheung and Chinn, 2001; Grauwe and Grimaldi, 2006).

Also along the behavioral finance line, various empirical studies have shown that asset prices have a close relationship with economic or investor sentiment and that several sentiment indicators can predict asset returns (Neal and Wheatley, 1998; Lee et al., 2002; Brown and Cliff, 2004; Lux, 2010). Nevertheless, there seems to be a lack of empirical studies that analyze the capabilities of alternative confidence or economic indicators to forecast exchange rates, although the behavioral view of asset price determination (and economics as a whole) is becoming stronger (Akerlof and Shiller, 2009). Predictors based on returns and volatility of asset markets have also not been thoroughly investigated so far although previous empirical studies have highlighted their importance (Campbell and Hentschel, 1992; Ludvigson and Ng, 2007; Bollerslev et al., 2008; Akerlof and Shiller, 2009).

From a methodological perspective, another recent issue of interest in the empirical literature of exchange rates is the evaluation of exchange rate models with panel data (Mark and Sul, 2001; Rapach and Wohar, 2004; Groen, 2005; Engel et al., 2007, 2009). The handful of studies available show that using panel data may increase estimation precision, improve forecasting accuracy and give more power to statistical tests. In contrast to single-country exchange rate models based on macro 'fundamentals' or other variables, panel models are often able to outperform a random walk in out-of sample tests. However, the recent forecasting literature shows that considering different types of estimation approaches and their complementarities in out-of-sample studies is important as forecasting with the 'wrong' parameter estimate (e.g. forecasting with a parameter estimate based on a heterogeneous panel model when the true data generating process (DGP) is a homogeneous panel model) may lead to forecasting distortions which can be mitigated by averaging the alternative estimates (Trapani and Urga, 2009). In addition, forecasts generated from rolling window or recursive schemes can also lead to alternative forecasting results, but combining such forecasts can improve their forecasting accuracy (Clark and McCracken, 2009).

Thus, our study is 'rich' in the sense that it brings together many proposals put forward in asset pricing and forecasting studies to better understand exchange rate dynamics. To preview some of our results, we find that the forward premium and a predictor based on a Taylor rule (along with panel coefficient estimates) yield the most promising forecasting results out of the macro 'fundamentals' considered. For recursive forecasting, confidence indices and volatility in-mean (along with panel coefficient estimates) yield more accurate forecasts than most of the macro 'fundamentals'. Adaptive forecast combination techniques improve forecasting precision and yield better market timing than most single predictors at higher horizons.

The rest of the paper is organized as follows: In section 2 we explain the empirical model and predictors considered. In sections 3 and 4 we describe our dataset and the forecasting methodology employed, respectively. Section 5 presents the results of our analysis. Section 6 concludes with some final remarks.

2 The model

For our subsequent forecasting analysis of exchange rates we consider the so-called long-horizon regression approach (LHR henceforth) for country $i = 1, ..., N$ and $t = 1, ..., T$ time periods:

$$\Delta^{(h)} s_{it+h} = \alpha_{h,i} + \beta_{h,i} x_{it} + u_{it+h}, \tag{1}$$

where $\Delta^{(h)} s_{it+h} = (1 - L^h) s_{it+h} = (s_{it+h} - s_{it})$ with $s_{it} = \ln S_{it}$ the log spot exchange rate of country i measured as (log) of foreign currency units in terms of United States (US) dollar, $\alpha_{h,i}$ is a fixed effect, $\beta_{h,i}$ is the parameter attached to the observed predictor x_{it} and u_{it} is a zero-mean disturbance term most likely heteroskedastic and serially correlated due to overlapping observations for $h > 1$. The LHR approach has been used in many empirical studies in economics and finance to analyze predictability (Fama and French, 1988; Mark, 1995; Stock and Watson, 1999; Berkowitz and Giorgianni, 2001). Model (1) assumes a heterogeneous parameter $\beta_{h,i}$ for each i, indicating that the regressor x_{it} has a heterogeneous effect on $\Delta^{(h)} s_{it+h}$. Alternatively, we may assume a homogeneous β_h for all i, i.e.

$$\Delta^{(h)} s_{it+h} = \alpha_{h,i} + \beta_h x_{it} + u_{it+h}, \tag{2}$$

so that the regressor x_{it} has a homogeneous effect on $\Delta^{(h)} s_{it+h}$ (Engel et al., 2007, 2009). In this study, we use three main groups of predictors for x_{it}, namely, predictors based on (i) macroeconomic ‘fundamentals’, (ii) returns and volatility of asset markets and (iii) cyclical and confidence indicators. Moreover, as will be discussed subsequently, we consider three different estimation approaches based on (1) and (2): single market (SM), mean group (MG) and pooled (PO). Forecasting is done by means of recursive (RE) or rolling (RO) schemes. It is noteworthy, however, that our analysis can be applied to any other potential predictor or group of predictors. In what follows, we describe the alternative predictors x_{it} considered in this study which are summarized in Table 1.

2.1 Predictors based on macroeconomic fundamentals

A usual way to forecast exchange rates in the conventional (empirical) exchange rate literature is to consider a predictor of the form:

$$x_{it} = (z_{it} - s_{it}), \tag{3}$$

where z_{it} is a measure of central tendency or ‘fundamental’ of the exchange rate (Mark, 1995; Berkowitz and Giorgianni, 2001; Engel et al., 2007, 2009; Della-Corte et al., 2009). The variable z_{it} can be obtained, for instance, from the PPP hypothesis, i.e.

$$z_{it} = (p_{it} - p_t^{US}), \tag{4}$$

where $p_{it} = \ln P_{it}$ is the country i’s (log) price level and $p_t^{US} = \ln P_t^{US}$ is the (log) price level of the US (Engel et al., 2009). According to the PPP hypothesis, a relative price level increase in the home country leads to a depreciation of the domestic currency. The PPP hypothesis also suggests that future exchange rates can be predicted by the real bilateral exchange rate.

We may also obtain z_{it} based on the well-known and often tested MM:

$$z_{it} = (m_{it} - m_t^{US}) - (y_{it} - y_t^{US}), \tag{5}$$

where $m_{it} = \ln M_{it}$ is the country i’s (log) money supply, $m_t^{US} = \ln M_t^{US}$ is the (log) money supply of the US, $y_{it} = \ln Y_{it}$ is the country i’s (log) real output and $y_t^{US} = \ln Y_t^{US}$ is the (log) real output of the US. In a nutshell, MM presumes that money and output differentials should predict subsequent movements in the exchange rate. It is worth noting that the above equation is a restricted version of the flexible price MM, which is also employed in other studies (Frenkel, 1976; Mussa, 1976; Mark, 1995; Engel et al., 2009). In contrast to the original flexible price model, the interest rate differential is assumed to be zero and the domestic and foreign money-demand income elasticity is equal to one.

Another natural candidate for the set of possible z_{it} is the h-maturity forward rate of the spot exchange rate s_{it}, i.e.

$$z_{it} = g_{h,it}. \tag{6}$$

This stems from the UIP condition which proposes that the h-maturity interest rate differential between two nations should predict future h-horizon changes of their exchange rate. That is, $x_{it} = (b_{h,it} - b_{h,t}^{US})$ where $b_{h,it}$ is the h-maturity interest rate of country i and $b_{h,t}^{US}$ is the h-maturity US interest rate. In the absence of riskless arbitrage opportunities the Covered Interest Rate Parity (CIP) holds so that $x_{it} = (g_{h,it} - s_{it}) = (b_{h,it} - b_{h,t}^{US})$. Thus, $x_{it} = (g_{h,it} - s_{it})$ can be used to test the UIP (Della-Corte et al., 2009). The UIP is usually rejected in in-sample studies at short horizons which is sometimes attributed to the existence of risk-premia (Engel, 1996) or to heterogeneous exchange rate expectations (Kirman, 1993). However, the rejection of UIP may become harder for certain asset classes as the horizon increases (Chinn and Meredith, 2004).

Predictors based on PPP, MM and UIP are the most conventional macro fundamentals to forecasting exchange rates. Alternatively, as proposed recently by Engel et al. (2009), we could use a Factor Model (FM) and extract z_{it} directly from the data, i.e.

$$z_{it} = \hat{F}_{it} = \hat{\gamma}_{1,i}\hat{f}_{1t} + \hat{\gamma}_{2,i}\hat{f}_{2t} + \hat{\gamma}_{3,i}\hat{f}_{3t}, \tag{7}$$

where the $\hat{f}_{j,t}$, $j = 1, 2, 3$ are estimated latent factors obtained from the panel of exchange rates s_{it}, $i = 1, ..., N$ and $\hat{\gamma}_{j,i}$, $j = 1, 2, 3$ are the corresponding factor loadings.[1]

Another recently proposed candidate for z_{it} is based on an open economy Taylor rule which

[1]We use three latent factors as in Engel et al. (2009) to keep our analysis similar to the latter study.

can be derived from the UIP condition (Molodtsova and Papell, 2009). In this study we use the Taylor-rule specification for $x_{it} = (b_{h,it} - b_{h,t}^{US}) = (z_{it} - s_{it})$ proposed in the panel data framework of Engel et al. (2009):

$$z_{it} = 1.5(\pi_{it} - \pi_t^{US}) - 0.5(\tilde{y}_{it} - \tilde{y}_t^{US}) + s_{it}, \tag{8}$$

where π_{it} and π_t^{US} are the inflation rates of country i and the US and $\tilde{y}_{it}$ and $\tilde{y}_t^{US}$ are the output gaps of country i and the US, respectively.

2.2 Predictors based on returns and volatility of asset markets

In this section we consider predictors inspired by the behavioral finance literature and the risk-return literature. The first predictor we consider is the exchange rate return (ERR) at time t:

$$x_{it} = \Delta^{(1)} s_{it}, \tag{9}$$

where $\Delta^{(1)} s_{it} = s_{it} - s_{it-1}$. This follows from studies which suggest that chartists in the foreign exchange market rely on exchange rate changes to predict exchange rate movements (Taylor and Allen, 1992; Cheung and Chinn, 2001; Grauwe and Grimaldi, 2006).

Asset prices should theoretically incorporate information about (stochastic) discount factors and the economy in general (Campbell and Shiller, 1987, 1988; Akerlof and Shiller, 2009). In addition, countries with large stock market returns in excess of the returns of (say) the US stock market can attract foreign investors and could experience an appreciation of their currency. Thus, we also consider stock market return differentials (SRD):

$$x_{it} = (q_{it} - q_t^{US}), \tag{10}$$

where q_{it} and q_t^{US} are the stock market (log) returns for country i and the US, respectively.

As proposed in the equity and exchange rate literature, time-varying second order moments in-mean or other risk-premium measures, may play an important role in describing asset price fluctuations (Campbell and Hentschel, 1992; Dumas and Solnik, 1995; Engel, 1996). Along the latter lines, the principle of volatility-in-mean computed from daily returns has been applied recently in out-of-sample studies of the risk-return relationship in stock markets yielding promising results which motivates us to use it for exchange rates (Ludvigson and Ng, 2007; Bollerslev et al., 2008). Thus, as alternative predictor we consider the volatility of the exchange rate return (ERV) computed from daily squared returns:

$$x_{it} = \hat{\upsilon}_{it} = \sum_{d \in t} \Delta s^2_{d,it}, \tag{11}$$

where $\Delta s^2_{d,it} = (\ln S_d - \ln S_{d-1})^2_{it}$ is the day d squared (log) return of the exchange rate for cross-section member i at time t with $d \in t$. Note that this approach is similar to the realized volatility notion formalized in Andersen et al. (2003), which assumes that $\Delta s^2_{d,it}$ follow (semi)-martingale processes. This requirement should also apply to our context empirically since it is well known in the finance literature that daily asset returns follow martingales approximately (Bollerslev and Mikkelsen, 1996; Baillie, 1996).

Moreover, we consider stock market volatility differentials (SVD):

$$x_{it} = (\hat{\nu}_{it} - \hat{\nu}^{US}_t), \tag{12}$$

where $\hat{\nu}_{it}$ and $\hat{\nu}^{US}_t$ are the stock market volatilities of country i and the US, respectively. The latter variables are computed as in (11) with $q^2_{d,it}$ (the day d squared (log) return of the pertinent stock market i at time t) replacing $\Delta s^2_{d,it}$. Intuitively, differentials of stock market volatility could proxy various sorts of risk-premia if stock markets price investors' expectations of future macroeconomic and financial variables.

2.3 Predictors based on cyclical and confidence indicators

In this section we turn to other potential candidate predictors of exchange rates that draw their inspiration from the behavioral finance literature which suggests that asset price movements (and possibly many macro factors) can be explained by 'animal spirits' (Akerlof and Shiller, 2009). A usual variable used to proxy economic sentiment in the (empirical) behavioral finance literature are confidence indicators obtained from surveys of alternative economic agents such as investors, consumers, businessmen, etc (Neal and Wheatley, 1998; Lee et al., 2002; Brown and Cliff, 2004; Lux, 2010). In this study we use cyclical and confidence indicators. More precisely, we focus on business confidence, consumer confidence and a general economic indicator to have distinct sentiment measures.

Note, however, that in the context of exchange rates we want to predict changes in a relative price of currency units between two particular countries, thus we use differentials of the pertinent cyclical and confidence indicators. We consider a business sentiment differential (BSD):

$$x_{it} = (BS_{it} - BS_t^{US}), \tag{13}$$

where BS_{it} is a business confidence index for country i and BS_t^{US} is a business confidence index for the US. Similarly for the consumer sentiment differential (CSD):

$$x_{it} = (CS_{it} - CS_t^{US}), \tag{14}$$

where CS_{it} is a consumer confidence index for country i and CS_t^{US} is a consumer confidence index for the US. Lastly, we consider differentials of economic indicators (EID) to capture 'perceived' economic differentials between countries. However, since we employ levels in BSD and CSD, we employ first differences for EID in order to account for 'momentum' in the perceived economic differentials (Ghonghadze and Lux, 2008; Lux, 2009):

$$x_{it} = (\Delta EI_{it} - \Delta EI_t^{US}), \tag{15}$$

where $\Delta EI_{it} = EI_{it} - EI_{it-1}$ is the change of a main economic indicator for country i and ΔEI_t^{US} is the change of a main economic indicator for the US.

3 Data description

The dataset used in this study is obtained from Datastream and the bilateral exchange rates (measured as foreign currency units/US dollar), data frequency and time periods were selected based upon data availability. The forecasting strategy explained in the next section requires that we have the same predictors for each cross-section member i in order to be able to compare models over the panel dimension and to compute forecast combinations from the same set of potential forecasts per country. These restrictions brought about several difficulties to build a dataset with a large number of exchange rates with large time spans.[2]

Moreover, in order to have a somewhat more 'homogeneous' dataset for the cyclical and confidence indicators (since surveys, data frequency, measurement units, methodology and other issues may differ across data providers), we use business confidence, consumer confidence and the main economic indicator published by the OECD (also available in Datastream). However, cyclical indicators and confidence indices published by the OECD (or other data sources) were particularly difficult to find for several countries. When available, cyclical indicators and confident indices mostly start in 1996, and for Canada, data on business confidence were unavailable for January 2008 onwards.[3]

The other difficulty faced was the inclusion of Eurozone currencies in our panel. In order to evaluate the predictors considered for Eurozone currencies we would need to restrict our sample period from January 1996 (the starting time for the data on cyclical indicators and confidence indices) to January 1999 (the starting time of the Euro currency). This would result in very few data points to perform relevant out-of-sample evaluation at higher horizons. However, since the Euro is a major currency player, it would be unusual not to include it in our forecasting exercises. Thus, we use aggregated data for the Eurozone which is available for all predictors.

In order to have as many currencies and observations as possible given our data restrictions, we consider a panel of 12 countries with monthly data for the sample period January 1999 to January 2008 which gives us a total of 109 observations per country. The countries are: Australia, Canada, Czech Republic, Denmark, Eurozone, Japan, New Zealand, South Africa, Sweden, Switzerland, United Kingdom and United States.

We use M1 and CPI to measure money supply and price levels, respectively. In the case

[2] In fact, because of our different dimensions (e.g. time, countries and predictors) we often faced the following trade-off: given the number of predictors to be tested, an increase in the time dimension would be connected to a decrease in the cross-section dimension.

[3] To save on space, we refer the interested reader to detailed information on confidence and cyclical indicators published by the OECD at *http://www.oecd.org*.

of Australia and New Zealand, CPI is only published on a quarterly basis. Therefore, we use an interpolation technique as suggested by Molodtsova and Papell (2009) in order to compute monthly series from the quarterly data. We employ h-maturity forward rates of the exchange rates. The interest rate variables used when economically evaluating our forecasts (as explained in section 4.3.2) are h-maturity interbank rates which were available for all pertinent maturities, time periods and countries.

We are aware that one of the most common approaches to proxy GDP at the monthly frequency is (seasonally adjusted) industrial production. Unfortunately, these data were unavailable for several countries of our panel in the sample period selected. Thus, we use real seasonally adjusted GDP at the quarterly frequency to measure output which is transformed to the monthly frequency by means of the same interpolation technique we use for the quarterly CPI series. In order not to include future data to forecast (as a forecaster will, most likely, only have interpolated information from the previous quarters), we lag by three months the interpolated value for a particular month.

We use all-share Datastream calculated stock market indices at the daily (monthly) frequency to compute the monthly volatilities (returns). The factors $\hat{f}_{j,t}$ and factor loadings $\hat{\gamma}_{j,i}$ are estimated by means of Principal Component Analysis and the factors have been standardized (Engel et al., 2009). The estimated factors are computed using data available up to the forecast origin. The output gaps are computed recursively by Hodrick-Prescott detrending using only data from periods prior to the forecast origin (Engel et al., 2009).

4 Forecasting methodology

In the following subsections we describe the forecasting strategy designed for this study. To save on space, we concentrate on the most relevant issues. Specific details that are not described here can be provided upon request.

4.1 Forecasting design

We use recursive and rolling window forecasting schemes and consider forecasting horizons $h = 1, 3, 6, 12$, i.e. monthly, quarterly, semi-annual and annual. Let τ denote the forecast origin, that is, the time instance from which a forecast iteration is implemented. The recursive forecasting scheme consists of estimating parameters by recursively increasing the forecast origin from $\tau = K = 30$ to $\tau = T - h$. In the second scheme of rolling window forecasting, we sequentially update a fixed window of size $K = 30$ that ends at the forecast origin τ and begins at time $\tau - K + 1$.[4]

It is noteworthy that the literature on forecasting exchange rates usually focuses on recursive estimation for subsequent forecasting (Mark, 1995; Berkowitz and Giorgianni, 2001; Engel et al., 2009). A priori, however, rolling forecasting schemes could be better immunized against the adverse effects of falsely imposing structural invariance as they build upon a fixed time window of observations. Moreover, combining forecasts generated by recursive or rolling window schemes can improve forecasting precision which motivates us to use both schemes here (Clark and McCracken, 2009). The forecasting strategy is as follows:

1. At each recursion, we regress $\Delta^{(h)} s_{i\tau}$ on a constant $\alpha_{h,i}$ and a predictor $x_{i\tau-h}$. We obtain single market estimates $\hat{\alpha}^{(1)}_{h,i\tau}$ and $\hat{\beta}_{h,i\tau}$ of model (1) via Ordinary Least Squares (Mark, 1995). At the aggregate level, we compute a mean group estimate $\bar{\beta}_{h,\tau}$ by averaging single market estimates $\hat{\beta}_{h,i\tau}$ over all $i = 1, ..., N$. MG estimation is consistent for an average impact under parameter heterogeneity (Pesaran and Smith, 1995). In order to identify the fixed effects $\hat{\alpha}^{(2)}_{h,i\tau}$ that best whiten the data given the MG estimate $\bar{\beta}_{h,\tau}$, we compute the mean of $(\Delta^{(h)} s_{i\tau} - \bar{\beta}_h x_{i\tau-h})$. The fixed effect $\hat{\alpha}^{(3)}_{h,i\tau}$ and pooled estimate $\hat{\beta}_{h,\tau}$ of model (2) are obtained by means of a pooled Least Squares Dummy Variable regression (Engel et al., 2007, 2009).

2. We employ the alternative estimates $\hat{\beta}_{h,i\tau}$, $\bar{\beta}_{h,\tau}$ or $\hat{\beta}_{h,\tau}$ along with the corresponding fixed effects $\hat{\alpha}^{(1)}_{h,i\tau}$, $\hat{\alpha}^{(2)}_{h,i\tau}$, $\hat{\alpha}^{(3)}_{h,i\tau}$ detailed previously to forecast the quantities $\Delta^{(h)} s_{i\tau+h}$. More precisely, let $\Delta^{(h)} \widehat{s}_{i\tau+h|\tau}(PMR)$ denote a forecast conditional on information

[4]Note that $K = 30$ is about 2.5 years of data. We have experimented with other window sizes but the results remain qualitatively similar.

available up to period τ for estimator $P = \{\mathrm{SM}, \mathrm{MG}, \mathrm{PO}\} = \{1,2,3\}$, predictor $M = \{\mathrm{PPP}, \mathrm{MM}, \mathrm{UIP}, \mathrm{FM}, \mathrm{TAY}, \mathrm{ERR}, \mathrm{SRD}, \mathrm{ERV}, \mathrm{SVD}, \mathrm{BSD}, \mathrm{CSD}, \mathrm{EID}\} = \{1, ..., 12\}$ and forecasting scheme $R = \{\mathrm{RE}, \mathrm{RO}\} = \{1,2\}$. Table 1 summarizes all the PMR models. For each model M and forecasting scheme R, ex-ante forecasts at horizon h with single market estimates are obtained as

$$\Delta^{(h)}\widehat{s}_{i\tau+h|\tau}(1MR) = \hat{\alpha}^{(1)}_{h,i\tau} + \hat{\beta}_{h,i\tau}x_{i\tau}, \tag{16}$$

with mean group estimates as

$$\Delta^{(h)}\widehat{s}_{i\tau+h|\tau}(2MR) = \hat{\alpha}^{(2)}_{h,i\tau} + \bar{\beta}_{h,\tau}x_{i\tau}, \tag{17}$$

and with pooled estimates as

$$\Delta^{(h)}\widehat{s}_{i\tau+h|\tau}(3MR) = \hat{\alpha}^{(3)}_{h,i\tau} + \hat{\beta}_{h,\tau}x_{i\tau}. \tag{18}$$

3. The previous step yields at each τ a total of $P^{max} \times M^{max} \times R^{max} = 3 \times 12 \times 2 = 72$ forecasts generated from 'heterogeneous' information sets for each horizon h and cross-section member i which can be examined separately. However, forecasts may include independent and useful information so that a linear combination of two or more forecasts may yield more accurate predictions than using only a single prediction (Granger, 1989; Newbold and Harvey, 2002; Aiolfi and Timmermann, 2006). Thus, we also construct forecast combinations i.e.

$$\Delta^{(h)}\widehat{s}_{i\tau+h|\tau}(C) = \widehat{\boldsymbol{\omega}}'_{i\tau+h|\tau}\widehat{\boldsymbol{\mu}}_{i\tau+h|\tau}, \tag{19}$$

where $\widehat{\boldsymbol{\mu}}_{i\tau+h|\tau}$ is a vector containing exchange rate forecasts $\Delta^{(h)}\widehat{s}_{i\tau+h|\tau}(PMR)$ and the weights in the vector $\widehat{\boldsymbol{\omega}}_{i\tau+h|\tau}$ are computed with alternative procedures which are discussed in the following section.

4.2 Forecast combination schemes

Most of the forecast combination schemes considered are adaptive, meaning that the forecasts included in $\widehat{\boldsymbol{\mu}}_{i\tau+h|\tau}$ and/or corresponding weights $\widehat{\boldsymbol{\omega}}_{i\tau+h|\tau}$ are based on alternative selection criteria within a sub-sample of *realized* observations. Adaptive strategies for combining forecasts might mitigate structural breaks and model misspecification and thus improve forecasting precision over single forecasts (Newbold and Harvey, 2002; Granger and Jeon, 2004).

Note that since a forecaster would only have information available up to the forecast origin τ, the sub-sample for forecast selection and computation of weights must contain data on or before that period. Thus, we start by setting equal weights to all forecasts until the selection of forecasts and weighting schemes could be based on the evaluation of realized forecast errors. This procedure guarantees that we use only information available up to a particular period τ to set weights of forecasts for period $\tau + h$. The following 6 alternative combination strategies $C = \{1, 2, ..., 6\}$ are considered:

1. *Simple average (AFC)*: Various studies have demonstrated that simple averaging of a multitude of forecasts works well in relation to more sophisticated weighting schemes (Newbold and Harvey, 2002; Clark and McCracken, 2009). Therefore, the first scheme considered consists of averaging all the $P^{max} \times M^{max} \times R^{max} = 72$ forecasts obtained from the forecasting design at each τ, horizon h and cross-section member i.

2. *Rank-weighted combinations (RFC)*: The RFC scheme, suggested by Aiolfi and Timmermann (2006), consists of first computing the root mean square error (RMSE) of all models in the sub-sample period for evaluation at horizon h. Defining $RANK_{h,i\tau}(j)$ as the rank of the j-th model based on its historical RMSE performance up to time τ for horizon h, the weight for the j-th forecast is then calculated as: $\widehat{\omega}_{j,i\tau+h|\tau} = RANK_{h,i\tau}(j)^{-1}/\sum_j RANK_{h,i\tau}(j)^{-1}$.

3. *Hierarchical forecast combinations (HFC)*: Recent studies have proposed hierarchical strategies for the combination of forecasts which work relatively well in other applications (Kisinbay, 2007; Costantini and Pappalardo, 2009). The HFC procedure works as follows:

a. Take the sub-sample period for evaluation and calculate the RMSE of each model. Rank the models according to their past performance based on RMSE.

b. Select the best forecasting model (in terms of RMSE) and test sequentially whether the best model forecast encompasses other models using the forecast encompassing test of Harvey et al. (1998). If the best model encompasses the alternative model at the significance level $\varsigma = 0.05$, delete the alternative model from the list.[5]

c. Repeat step 2 with the second best model. The list of models includes those which are not encompassed by the best model. Continue with the third best model, and so on, until no encompassed model remains in the list.

d. Obtain the HFC with all the previously selected models by simple averaging.[6]

4. *Thick-modeling approach with OLS weights (OFC)*: A study by Granger and Jeon (2004) proposes the so-called thick modeling approach (TMA) which consists of selecting the z-percent of the best forecasting models according to the RMSE criterion in the sub-sample period for model evaluation. We use the selection process of Granger and Jeon and subsequently compute weights by means of OLS regressions along with the constraint that the weights are all positive and sum up to one. The z-percent of top forecasts selected is set to 25% (i.e. the upper quartile).

5. *Thick-modeling approach with RMSE-weights (MFC)*: The MFC scheme consists of selecting models by means of TMA, then computing the RMSE of all selected models j and setting the weight of the j-th model as $\widehat{\omega}_{j,i\tau+h|\tau} = RMSE_{h,i\tau}(j)^{-1}/\sum_j RMSE_{h,i\tau}(j)^{-1}$.

6. *Thick-modeling approach with MSE-Frequency weights (FFC)*: The FFC scheme consists of selecting models by means of TMA and assigning to each j-th forecast, a weight equal to a model's empirical frequency of minimizing the squared forecast error over realized forecasts.

[5]Other significance levels yielded qualitatively similar results and can be provided upon request.

[6]We have also experimented with alternative weighting schemes to simple average of the hierarchical forecasts but found that the latter yield better forecast than other approaches (Kisinbay, 2007).

4.3 Forecast evaluation

In this section we describe the different forecast evaluation methods used in this study. We consider statistical as well as economic performance measures of the forecasts generated by our forecasting design.

4.3.1 Statistical performance measures

In order to evaluate forecasts, we employ mean squared forecast errors (MSE) and mean absolute forecast errors (MAE). MSE and MAE of a particular model are given in percentage of the MSE and MAE of a random walk model with rolling drift of size K. Our choice for the latter benchmark follows from evidence that traders in foreign exchange markets rely on moving averages to 'forecast' the evolution of the exchange rate (Taylor and Allen, 1992; Grauwe and Grimaldi, 2006). More precisely, let $\tilde{\tau} = 1, ..., \mathcal{T}$ denote an out-of-sample forecast observation with $\mathcal{T} = T - K - h$. Moreover, let '$\bullet$' and '0' indicate a particular competing model and the benchmark, respectively. Forecast errors of model '$\bullet$' are computed as

$$\hat{e}_{i\tilde{\tau}}(\bullet) = \Delta^{(h)} s_{i\tilde{\tau}} - \Delta^{(h)} \widehat{s}_{i\tilde{\tau}}(\bullet). \tag{20}$$

The MSE and MAE of model '$\bullet$' are:

$$\bar{d}_i(\bullet) = \mathcal{T}^{-1} \sum_{\tilde{\tau}} d_{i\tilde{\tau}}(\bullet), \tag{21}$$

with $d_{i\tilde{\tau}}(\bullet) = \hat{e}_{i\tilde{\tau}}(\bullet)^2$ for MSE or $d_{i\tilde{\tau}}(\bullet) = |\hat{e}_{i\tilde{\tau}}(\bullet)|$ for MAE. The average performance of a competing model specification is given in relation to $\bar{d}_i(0)$, obtaining relative MSEs or MAEs:

$$\overline{dr}_i(\bullet) = \frac{\bar{d}_i(\bullet)}{\bar{d}_i(0)}, \tag{22}$$

where $\bar{d}_i(0)$ is defined as in (21). Thus, $\overline{dr}_i(\bullet)$ values below one indicate a superior performance of a particular model '$\bullet$' against the benchmark '0' in terms of MSE or MAE. At the aggregate level we compute mean and standard errors of $\overline{dr}_i(\bullet)$.[7] Moreover, we employ the modified

[7]Note that (22) computed with $d_{i\tilde{\tau}}(\bullet) = \hat{e}_{i\tilde{\tau}}(\bullet)^2$ and $d_{i\tilde{\tau}}(0) = \hat{e}_{i\tilde{\tau}}(0)^2$ in (21) is related to the so-called out-of-sample R^2 as $R^2_{OS,i} = 1 - \overline{dr}_i(\bullet)$.

Diebold Mariano (DM) test of Harvey et al. (1997) in order to analyze for each i (with respect to MSE or MAE), whether model '0' has the same predictive ability as model '•', against the alternative that model '•' has a better predictive ability. At the aggregate level we provide the number of rejections of the null hypothesis of equal forecasting accuracy via the DM test at the 10% significance level.

4.3.2 Economic performance measures

Recent studies by Han (2006), Della-Corte et al. (2009) and Chiquoine and Hjalmarsson (2009) suggest to evaluate the economic value of forecasts obtained from asset pricing models by 'simulating' a portfolio allocation choice of a representative investor (RI). In our analysis, we follow a similar *univariate* approach to the latter studies. Therefore we keep the following discussion short to save on space.

For simplicity of exposition, we consider for now a representative investor (RI) in country i with an investment horizon $h = 1$ and mean-variance preferences. Let $\lambda_{\tau+1|\tau} \equiv \mathbb{E}[r_{\tau+1}|I_\tau]$ and $\eta_{\tau+1|\tau} \equiv \mathbb{E}[(r_{\tau+1} - \lambda_{\tau+1|\tau})^2|I_\tau]$ denote, respectively, the conditional mean and variance given the current information set I_τ of the return of a US asset at $\tau + 1$ denoted $r_{\tau+1}$. Similar to Della-Corte et al. (2009), we assume that the RI invests in a US bond where the only risk involved is exchange rate risk, i.e. we set $r_{\tau+1} = r_f + \Delta^{(1)}s_{i\tau+1}$ with r_f the risk-free rate and thus $\lambda_{\tau+1|\tau} = r_f + \mathbb{E}[\Delta^{(1)}s_{i\tau+1}|I_\tau]$, $\eta_{\tau+1|\tau} = \mathbb{V}\text{ar}[\Delta^{(1)}s_{i\tau+1}|I_\tau]$. Moreover, let $\lambda_{p,i\tau+1}$ and $\eta_{p,i\tau+1}$ be the conditional mean and variance of the portfolio returns $r_{p,i\tau+1}$ of investor i at $\tau + 1$, respectively. Then, assuming that the RI in country i invests 1 unit of the domestic currency at time τ, she solves the following maximization problem:

$$\max_{\delta_{i\tau}} \left\{ \mathbb{E}[\mathcal{U}(W_{i\tau+1})] = \lambda_{p,i\tau+1} - \frac{\gamma_i}{2}\eta_{p,i\tau+1} \right\}, \tag{23}$$

with

$$\lambda_{p,i\tau+1} = \delta_{i\tau}\lambda_{\tau+1|\tau} + (1 - \delta_{i\tau})r_{f,i} \text{ and } \eta_{p,i\tau+1} = \delta_{i\tau}^2\eta_{\tau+1|\tau}, \tag{24}$$

where $\mathcal{U}(W_{i\tau})$ is the utility of wealth, $\delta_{i\tau}$ is the portfolio weight, γ_i the coefficient of absolute risk aversion, and $r_{f,i}$ the return on the domestic riskless asset. The optimal portfolio weights are given by

$$\delta^*_{i\tau} = \frac{\lambda_{\tau+1|\tau} - r_{f,i}}{\gamma_i \eta_{\tau+1|\tau}}. \tag{25}$$

Thus, the key issue in the above set up is to have estimates $\hat{\lambda}_{\tau+1|\tau}$ and $\hat{\eta}_{\tau+1|\tau}$ to obtain $\hat{\delta}^*_{i\tau}$. For this purpose, we set $\hat{\lambda}_{\tau+1|\tau} = r_f + \Delta^{(1)}\widehat{s}_{i\tau+1|\tau}(\bullet)$ with alternative models '$\bullet$'. Since modeling the conditional variance of exchange rates is out of the scope of this paper, we follow a similar approach to Chiquoine and Hjalmarsson (2009) and approximate $\hat{\eta}_{\tau+1|\tau}$ by using an estimate of the variance up to the forecast origin τ obtained from the residuals of the regression corresponding to a particular predictor, estimation approach (single market, mean group or pooled) and forecasting scheme (recursive or rolling). The variances of the forecast combinations are computed by weighting the estimated variances of the alternative models in the forecast combination with the computed weights.

To evaluate the performance of the portfolio allocation strategy the so-called *ex-post* Sharpe Ratio can be used which is defined as $\mathcal{SR}_i = (r_{p,i} - r_{f,i})/\sigma_{p,i}$, where $r_{p,i}$ is the sample mean and $\sigma_{p,i}$ the sample standard deviation from the realized portfolio returns. However, $\mathcal{SR}_i$ cannot quantify the economic gains over an alternative strategy. For this purpose, we use the $\mathcal{M}2_i$ measure developed by Modigliani and Modigliani (1997) and applied, for instance, in the portfolio allocation framework by Han (2006). The $\mathcal{M}2_i$ measure can be interpreted as the abnormal return that a particular strategy '$\bullet$' would have earned if it had the same risk as a benchmark strategy '0'. $\mathcal{M}2_i$ is given by

$$\mathcal{M}2_i = \frac{\sigma_{p,i}(0)}{\sigma_{p,i}(\bullet)}(r_{p,i}(\bullet) - r_{f,i}) - (r_{p,i}(0) - r_{f,i}), \tag{26}$$

which suggests that the portfolio of strategy '$\bullet$' is levered upwards or downwards so that it has the same volatility as the portfolio of strategy '0'. $\mathcal{M}2_i$ is directly related to the Sharpe Ratio as $\mathcal{M}2_i = \sigma_{p,i}(0)(\mathcal{SR}_i(\bullet) - \mathcal{SR}_i(0))$. To be consistent with Han (2006), we take as benchmark '0' a buy-and-hold strategy. At the aggregate level we compute mean and standard errors of

$\mathcal{M}2_i$.[8]

One of our main issues of interest is the forecasting performance of the predictors considered and the adaptive forecasting strategies for horizons $h > 1$. For this purpose we assume that the RI rebalances her portfolio not only at $h = 1$ but also at $h = 3, 6, 12$. To account for higher horizons, we set $\hat{\lambda}_{\tau+h|\tau} = r_{hf} + \Delta^{(h)}\widehat{s}_{i\tau+h|\tau}(\bullet)$ and approximate $\hat{\eta}_{\tau+h|\tau}$ by using an estimate of the residual h-period variance up to time τ to obtain $\hat{\delta}^*_{h,i\tau}$.

Note that we need to calibrate the free parameter space $\Gamma_{h,i} = \{r_{hf,i}, r_{hf}, \gamma_i\}$ for each i and the different horizons h. To have a somewhat realistic calibration, we use the sample mean of interbank rates with maturity h up to period $\tau = K$ to calibrate $r_{hf,i}$ and r_{hf}.[9] We use $\gamma_i = 3, 6$ for the coefficient of absolute risk aversion as in previous studies (Han, 2006; Chiquoine and Hjalmarsson, 2009; Della-Corte et al., 2009).

5 Results

In what follows we discuss the main results of our analysis. We first consider the forecasting results of single predictors and subsequently those of combined forecasts.

5.1 Single predictors

Tables 2 and 3 provide information on the cross-sectional average of the relative MSE and MAE obtained from a particular predictor x_{it} (see Table 1 for acronyms) for horizons $h = 1, 3, 6, 12$ and the three different estimation approaches (SM, MG, PO). To illustrate the potential benefits of combining forecasts resulting from alternative estimates, we also report relative MSE and MAE of forecasts obtained by using an average of the SM, MG, PO estimates at each forecast iteration, denoted AV. This is in line with Trapani and Urga (2009) who find that averaging estimates obtained from heterogeneous and homogeneous panel models can improve forecasting

[8] Similar to the portfolio allocation set up by Chiquoine and Hjalmarsson (2009), we restrict ourselves to the case of no transaction costs as we want to keep the computations and the comparison of market timing across all our dimensions (country, model, horizon, etc) as tractable as possible.

[9] Government bond indices or yields for maturities $h = 1, 3, 6, 12$ were unavailable for many countries. In order to have a 'homogeneous' dataset for the calibration across markets we use interbank rates since these were available for all markets and horizons.

accuracy.

In the case of recursive forecasting (Table 2) we find that the macro 'fundamentals' PPP, MM and FM yield relative MSEs and MAEs that are greater than one on average. On the other hand, the relative MSEs and MAEs of UIP and TAY are lower than one on average at $h = 3, 6, 12$ for the alternative estimation approaches.

Recursive forecasts of predictors based on asset returns and volatility (ERR, SRD, ERV, SVD) or cyclical and confidence indices (BSD, CSD, EID) yield relative MSEs and MAEs that are mostly below one on average and lower than the fundamental predictors PPP, MM, and FM. Recursive forecasts of the predictors ERR, SRD, ERV, SVD, BSD, CSD, EID are qualitatively similar to each other in terms of (average) relative MSEs and MAEs.

Turning to rolling window forecasts (Table 3) we find that the macro 'fundamentals' PPP, MM and FM yield relative MSEs and MAEs that are (still) generally greater than one on average. The predictors UIP and TAY continue to yield relative MSEs and MAEs mostly lower than one at higher horizons and evidently lower than those of the other macro 'fundamentals'. Interestingly, the forecasting power of asset returns and volatility (ERV, SRD, ERR, SVD) or cyclical and confidence indices (BSD, CSD, EID) with rolling window forecasting is less promising in terms of (average) relative MSEs and MAEs than with recursive forecasting.

Tables 4 and 5 show the frequency of rejections of the null hypothesis of equal forecasting accuracy to a rolling drift model via the DM test. The frequency of rejections is usually highest for TAY, ERV, SVD and CSD in terms of MSEs and MAEs and qualitatively similar for rolling versus recursive schemes. The highest number of rejections (5) is obtained from TAY with MG estimates and rolling forecasting at horizon $h = 12$.

Relative MSEs and MAEs obtained from the panel estimates (MG, PO) are usually lower on average than those obtained from single market estimates (SM) in both recursive and rolling forecasting and across predictors. This result corroborates findings of previous studies on the benefits of forecasting exchange rates with panel estimates (Engel et al., 2007, 2009). Forecasts obtained by averaging the SM, MG, PO estimates usually seem to improve upon the 'worst' performer and many times upon the 'best' performer. The latter result hints at the possible benefits of combining forecasts of the alternative estimation approaches.

Turning to the results of the Sharpe Ratio differentials $\mathcal{M}2$ in Tables 6 and 7, we find that a dynamic strategy based on forecasts of the alternative predictors considered usually generates positive abnormal returns over a buy-and-hold strategy at various horizons. Overall, we find that UIP, FM, TAY, ERV, SVD and CSD generate on average the highest $\mathcal{M}2$ out of the predictors considered. This result is generally true for either recursive or rolling window forecasting. However, in contrast to relative MSEs and MAEs, $\mathcal{M}2$ measures are generally higher on average for rolling than for recursive forecasting which might be due to the different estimates for $\eta_{\tau+h|\tau}$. We obtain higher $\mathcal{M}2$ on average at lower levels of absolute risk aversion γ and higher horizons h.

Summing up, we find that the forecasts generated by rolling window forecasting differ in terms of relative MSEs and MAEs to those generated by recursive forecasting. The alternative results for recursive and rolling forecasting corroborate recent findings of the econometrics literature (McCracken, 2007; Clark and McCracken, 2009). For both forecasting schemes, however, UIP and TAY provide reasonably good forecasts which is in line with findings of recent studies (Chinn and Meredith, 2004; Molodtsova and Papell, 2009; Engel et al., 2009). Indeed, UIP proves to be quite successful for 'market timing' in relation to other predictors which corroborates results by Della-Corte et al. (2009). The recursive forecasting performance of predictors based on cyclical and confidence indicators as well as asset returns and volatility yield promising results: relative MSEs and MAEs are usually less than one for most horizons and most estimation approaches. Thus, it seems that forecasting asset returns with sentiment indicators based on survey data (along the lines of CSD) results in promising statistical and economic performance measures (cf. Lux (2010)). To visualize some of our findings, Figure 1 and 2 display (by means of boxplots) the cross-sectional distribution of relative MSEs and $\mathcal{M}2$ of the 'best' single models for each group of predictors.

In general, we find that the forecasting capabilities of the alternative predictors for exchange rates considered in terms of relative MSEs and MAEs as well as $\mathcal{M}2$ vary depending on the predictor, horizon, forecasting scheme, bilateral exchange rate and estimation approach. This can be appreciated in Figure 3 which displays the frequency in which a particular model considered falls within the top 25% performers according to a root MSE criteria. However, the latter figure also shows that models conditioned upon UIP, TAY, ERV, SRD and CSD with panel estimates (MG or PO) usually maintain their top rank over time, horizon and cross-section. In what follows, we explore the potential benefits from combining alternative forecasts.

5.2 Combined forecasts

Table 8 displays the results of the forecast combination strategies considered. The results are promising in terms of relative MSEs and MAEs which are usually lower than those obtained from most single predictors, forecasting schemes and estimation approaches. In fact, the different forecast combination schemes yield relative MSEs and MAEs that are usually lower than one on average at most forecasting horizons.

In line with previous studies, we find that simple averaging of forecasts AFC works relatively well in relation to the other schemes considered (Newbold and Harvey, 2002; Clark and McCracken, 2009). The rank based strategy RFC yields qualitatively similar results to AFC in terms of (average) relative MSEs and MAEs. However, in terms of relative MSEs and MAEs, other forecast combination schemes that select forecasts of top performing models by means of the thick modeling approach (OFC, MFC, FFC) do not usually outperform those that consider all forecasts (AFC an RFC). Surprisingly, the hierarchical forecast combination scheme HFC yields the least promising forecasting results in terms of relative MSEs and MAEs on average. The variability of the relative MSEs and MAEs over the cross-section are generally lower than those of single predictors which suggests that combining forecasts may reduce forecast uncertainty (Newbold and Harvey, 2002). This result can be partially visualized in Figure 1 which displays a lower cross-sectional variation for AFC and RFC than other single 'best' models in terms of relative MSEs. In general, forecast combination schemes increase the number of rejections of the null hypothesis of equal forecasting accuracy to a rolling drift model in relation to most single models according to the DM test (Table 8).

With respect to Sharpe Ratio differentials ($\mathcal{M}2$), we find that combining forecasts usually yields higher $\mathcal{M}2$ values than single predictors, forecasting schemes and estimation approaches at higher horizons (Table 9). Interestingly, while the hierarchical strategy HFC yields the least promising results in terms of relative MSEs and MAEs, it yields the best results in terms of

$\mathcal{M}2$ on average. Similarly, thick modeling strategies (OFC, MFC, FFC) yield better results in terms of $\mathcal{M}2$ on average than AFC and RFC. Thus, it seems that it could be beneficial to make investment decisions based on adaptive combination schemes. Although UIP together with panel estimates MG or PO seems to be the most successful model in terms of $\mathcal{M}2$, hierarchical and frequency based combinations HFC and FFC generate qualitatively similar results to other 'best' single models as displayed in Figure 2.

Summing up, we find that various forecast combination strategies of the forecasts generated by our panel forecasting design are generally more accurate than single forecasts and also yield higher Sharpe Ratios in relation to a buy-and-hold strategy than most single models. Given the variation in 'best' performing models over time and cross-section as shown in Figure 3, it seems from our results that combining forecast should mitigate model misspecification and 'smooth' the forecasting accuracy and market timing ability of single models. Our results are in line with previous studies which have found that combining forecasts yields more accurate predictions and profitable investment opportunities than using only a single prediction (Granger, 1989; Newbold and Harvey, 2002; Aiolfi and Timmermann, 2006; Pesaran and Timmermann, 2007; Della-Corte et al., 2009). Our findings also corroborate theoretical evidence of behavioral exchange rate models that a combination of alternative 'expectations' of exchange rates that build upon different information sets can provide a more accurate depiction of ex-ante exchange rate movements (Kirman, 1993).

6 Conclusion

This article examined the statistical and economic implications of adaptive forecasting of exchange rates with panel data where candidate predictors are drawn from macro 'fundamentals', asset returns/volatility as well as cyclical and confidence indicators. Out of the macro 'fundamentals' considered, the forward premium (UIP) and a predictor based on a Taylor rule (TAY) yield good results in terms of relative MAEs and MSEs on average. The cyclical and confidence variables yield promising results in terms of relative MAEs and MSEs when recursive forecasting is employed. The same applies qualitatively for the predictors based on returns and volatility of asset markets. The PPP, MM and FM models usually yield the least promising forecasting results out of all predictors considered in the full sample. In terms of relative MSEs and MAEs as well as $\mathcal{M}2$, the predictors UIP, TAY, ERV, SVD and CSD yield the most promising forecasting results on average.

The adaptive forecasting design shows that combining forecasts generated from our various predictors, estimators and estimation schemes generally improves forecasting accuracy in relation to most single models. This is not only evident in the magnitudes of the relative MAEs and MSEs but also in the number of rejections of the null hypothesis of equal forecasting accuracy to a rolling drift model according to the DM test. Sharpe Ratio differentials $\mathcal{M}2$ are also improved on average when compared against those obtained from most single models. The latter result is important as it points out that our forecasting strategy could be potentially tested in practice. Moreover, our results suggest that combining forecasts based upon 'heterogeneous' information sets can improve forecasting accuracy and reduce ex-ante uncertainty which corroborates not only the forecasting literature but also the behavioral exchange rate literature. It would be interesting to investigate whether the proposed forecasting design performs well for other types of forecasting exercises such as volatility, GDP, inflation, etc. We leave these issues for future research.

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Predictor	**Acronym**	x_{it}
Purchasing Power Parity	PPP	$p_{it} - p_t^{US} - s_{it}$
Monetary Model	MM	$(m_{it} - m_t^{US}) - (y_{it} - y_t^{US}) - s_{it}$
Uncovered Interest Rate Parity	UIP	$g_{h,it} - s_{it}$
Factor Model	FM	$\hat{F}_{it} - s_{it}$
Taylor Rule	TAY	$1.5(\pi_{it} - \pi_t^{US}) - 0.5(\tilde{y}_{it} - \tilde{y}_t^{US})$
Exchange Rate Return	ERR	$s_{it} - s_{it-1}$
Stock Market Return Differential	SRD	$q_{it} - q_t^{US}$
Exchange Rate Volatility	ERV	$\hat{v}_{it}$
Stock Market Volatility Differential	SVD	$\hat{\nu}_{it} - \hat{\nu}_t^{US}$
Business Sentiment Differential	BSD	$BS_{it} - BS_t^{US}$
Consumer Sentiment Differential	CSD	$CS_{it} - CS_t^{US}$
Economic Indicator Differential	EID	$\Delta EI_{it} - \Delta EI_t^{US}$
Model no.	**Features**	PMR
1	SM, PPP, RE	$(1, 1, 1)$
2	SM, MM, RE	$(1, 2, 1)$
3	SM, UIP, RE	$(1, 3, 1)$
4	SM, FM, RE	$(1, 4, 1)$
5	SM, TAY, RE	$(1, 5, 1)$
6	SM, ERR, RE	$(1, 6, 1)$
7	SM, SRD, RE	$(1, 7, 1)$
8	SM, ERV, RE	$(1, 8, 1)$
9	SM, SVD, RE	$(1, 9, 1)$
10	SM, BSD, RE	$(1, 10, 1)$
11	SM, CSD, RE	$(1, 11, 1)$
12	SM, EID, RE	$(1, 12, 1)$
13	MG, PPP, RE	$(2, 1, 1)$
14	MG, MM, RE	$(2, 2, 1)$
15	MG, UIP, RE	$(2, 3, 1)$
16	MG, FM, RE	$(2, 4, 1)$
17	MG, TAY, RE	$(2, 5, 1)$
18	MG, ERR, RE	$(2, 6, 1)$
19	MG, SRD, RE	$(2, 7, 1)$
20	MG, ERV, RE	$(2, 8, 1)$
21	MG, SVD, RE	$(2, 9, 1)$
22	MG, BSD, RE	$(2, 10, 1)$
23	MG, CSD, RE	$(2, 11, 1)$
24	MG, EID, RE	$(2, 12, 1)$
25	PO, PPP, RE	$(3, 1, 1)$
26	PO, MM, RE	$(3, 2, 1)$
27	PO, UIP, RE	$(3, 3, 1)$
28	PO, FM, RE	$(3, 4, 1)$
29	PO, TAY, RE	$(3, 5, 1)$
30	PO, ERR, RE	$(3, 6, 1)$
31	PO, SRD, RE	$(3, 7, 1)$
32	PO, ERV, RE	$(3, 8, 1)$
33	PO, SVD, RE	$(3, 9, 1)$
34	PO, BSD, RE	$(3, 10, 1)$
35	PO, CSD, RE	$(3, 11, 1)$
36	PO, EID, RE	$(3, 12, 1)$
37	SM, PPP, RO	$(1, 1, 2)$
38	SM, MM, RO	$(1, 2, 2)$
39	SM, UIP, RO	$(1, 3, 2)$
40	SM, FM, RO	$(1, 4, 2)$
41	SM, TAY, RO	$(1, 5, 2)$

42	SM, ERR, RO	$(1, 6, 2)$
43	SM, SRD, RO	$(1, 7, 2)$
44	SM, ERV, RO	$(1, 8, 2)$
45	SM, SVD, RO	$(1, 9, 2)$
46	SM, BSD, RO	$(1, 10, 2)$
47	SM, CSD, RO	$(1, 11, 2)$
48	SM, EID, RO	$(1, 12, 2)$
49	MG, PPP, RO	$(2, 1, 2)$
50	MG, MM, RO	$(2, 2, 2)$
51	MG, UIP, RO	$(2, 3, 2)$
52	MG, FM, RO	$(2, 4, 2)$
53	MG, TAY, RO	$(2, 5, 2)$
54	MG, ERR, RO	$(2, 6, 2)$
55	MG, SRD, RO	$(2, 7, 2)$
56	MG, ERV, RO	$(2, 8, 2)$
57	MG, SVD, RO	$(2, 9, 2)$
58	MG, BSD, RO	$(2, 10, 2)$
59	MG, CSD, RO	$(2, 11, 2)$
60	MG, EID, RO	$(2, 12, 2)$
61	PO, PPP, RO	$(3, 1, 2)$
62	PO, MM, RO	$(3, 2, 2)$
63	PO, UIP, RO	$(3, 3, 2)$
64	PO, FM, RO	$(3, 4, 2)$
65	PO, TAY, RO	$(3, 5, 2)$
66	PO, ERR, RO	$(3, 6, 2)$
67	PO, SRD, RO	$(3, 7, 2)$
68	PO, ERV, RO	$(3, 8, 2)$
69	PO, SVD, RO	$(3, 9, 2)$
70	PO, BSD, RO	$(3, 10, 2)$
71	PO, CSD, RO	$(3, 11, 2)$
72	PO, EID, RO	$(3, 12, 2)$

Table 1: Alternative predictors and forecasting models for exchange rates. The table summarizes all the predictors used for forecasting exchange rates as well as all the possible models that arise from our forecasting design. SM = single market estimates; MG = mean group estimates; PO = pooled estimates; RE = recursive forecasting; RO = rolling forecasting. PMR refers to estimation approach $P = \{\text{SM}, \text{MG}, \text{PO}\} = \{1, 2, 3\}$, predictor $M = \{\text{PPP}, \text{MM}, \text{UIP}, \text{FM}, \text{TAY}, \text{ERR}, \text{SRD}, \text{ERV}, \text{SVD}, \text{BSD}, \text{CSD}, \text{EID}\} = \{1, ..., 12\}$ and forecasting scheme $R = \{\text{RE}, \text{RO}\} = \{1, 2\}$. Models in **bold** are those that most frequently fall within the top 25% of models with lowest root MSE according to the Thick Modeling Approach at the various horizons $h = 1, 3, 6, 12$. See Figure 3 for further details.

x_{it}	h	$\bar{dr}$, MSE				$\bar{dr}$, MAE			
		SM	MG	PO	AV	SM	MG	PO	AV
PPP	1	1.034	1.010	1.010	1.014	1.015	1.009	1.008	1.009
		(0.041)	(0.052)	(0.047)	(0.047)	(0.026)	(0.031)	(0.029)	(0.028)
	3	1.093	1.033	1.035	1.042	1.043	1.020	1.019	1.024
		(0.093)	(0.130)	(0.118)	(0.105)	(0.058)	(0.084)	(0.076)	(0.070)
	6	1.139	1.046	1.046	1.056	1.080	1.046	1.046	1.052
		(0.102)	(0.223)	(0.221)	(0.157)	(0.056)	(0.128)	(0.127)	(0.092)
	12	1.497	1.324	1.325	1.330	1.239	1.192	1.194	1.194
		(0.426)	(0.708)	(0.709)	(0.553)	(0.219)	(0.424)	(0.427)	(0.338)
MM	1	1.083	1.116	1.026	1.052	1.041	1.054	1.015	1.028
		(0.060)	(0.169)	(0.061)	(0.050)	(0.034)	(0.066)	(0.028)	(0.028)
	3	1.282	1.284	1.091	1.161	1.113	1.121	1.038	1.073
		(0.196)	(0.440)	(0.196)	(0.151)	(0.074)	(0.181)	(0.103)	(0.080)
	6	1.451	1.357	1.200	1.229	1.188	1.161	1.090	1.111
		(0.277)	(0.617)	(0.450)	(0.235)	(0.079)	(0.230)	(0.174)	(0.091)
	12	2.392	2.009	1.761	1.628	1.464	1.358	1.268	1.243
		(0.985)	(1.578)	(1.294)	(0.528)	(0.257)	(0.537)	(0.463)	(0.214)
UIP	1	1.009	1.004	**0.994**	**0.999**	1.015	1.005	1.000	1.005
		(0.019)	(0.027)	(0.024)	(0.023)	(0.015)	(0.017)	(0.016)	(0.015)
	3	**0.960**	**0.928**	**0.925**	**0.931**	**0.990**	**0.974**	**0.974**	**0.976**
		(0.081)	(0.083)	(0.085)	(0.080)	(0.063)	(0.062)	(0.064)	(0.062)
	6	**0.907**	**0.827**	**0.837**	**0.840**	**0.963**	**0.933**	**0.939**	**0.938**
		(0.161)	(0.158)	(0.166)	(0.153)	(0.092)	(0.100)	(0.105)	(0.098)
	12	**0.980**	**0.784**	**0.862**	**0.820**	**0.962**	**0.892**	**0.940**	**0.914**
		(0.406)	(0.303)	(0.317)	(0.310)	(0.199)	(0.195)	(0.196)	(0.196)
FM	1	1.043	1.020	1.016	1.016	1.025	1.013	1.010	1.012
		(0.065)	(0.055)	(0.059)	(0.057)	(0.034)	(0.029)	(0.033)	(0.029)
	3	1.157	1.054	1.052	1.063	1.057	1.020	1.016	1.021
		(0.186)	(0.135)	(0.147)	(0.140)	(0.101)	(0.084)	(0.097)	(0.085)
	6	1.223	1.079	1.120	1.105	1.094	1.036	1.054	1.041
		(0.336)	(0.280)	(0.312)	(0.274)	(0.161)	(0.145)	(0.174)	(0.136)
	12	1.787	1.414	1.350	1.429	1.295	1.171	1.156	1.176
		(0.794)	(0.730)	(0.697)	(0.614)	(0.345)	(0.413)	(0.426)	(0.333)
TAY	1	1.005	**0.990**	**0.988**	**0.991**	1.004	**0.992**	**0.992**	**0.994**
		(0.034)	(0.038)	(0.036)	(0.033)	(0.030)	(0.024)	(0.023)	(0.024)
	3	**0.981**	**0.968**	**0.970**	**0.969**	**0.987**	**0.977**	**0.977**	**0.978**
		(0.068)	(0.078)	(0.078)	(0.073)	(0.046)	(0.045)	(0.045)	(0.043)
	6	**0.958**	**0.926**	**0.929**	**0.934**	**0.970**	**0.953**	**0.955**	**0.958**
		(0.104)	(0.122)	(0.123)	(0.111)	(0.066)	(0.066)	(0.067)	(0.064)
	12	**0.979**	**0.940**	**0.945**	**0.949**	**0.961**	**0.944**	**0.947**	**0.947**
		(0.196)	(0.191)	(0.194)	(0.185)	(0.136)	(0.152)	(0.155)	(0.147)
ERR	1	1.019	1.003	1.000	1.005	1.013	1.003	1.001	1.005
		(0.025)	(0.030)	(0.027)	(0.025)	(0.022)	(0.019)	(0.018)	(0.018)
	3	**0.993**	**0.975**	**0.974**	**0.978**	**0.987**	**0.978**	**0.978**	**0.980**
		(0.054)	(0.062)	(0.062)	(0.060)	(0.030)	(0.036)	(0.036)	(0.034)
	6	**0.954**	**0.941**	**0.944**	**0.945**	**0.979**	**0.973**	**0.974**	**0.975**
		(0.107)	(0.097)	(0.098)	(0.100)	(0.061)	(0.053)	(0.053)	(0.056)
	12	**0.965**	**0.952**	**0.960**	**0.958**	**0.942**	**0.935**	**0.939**	**0.938**
		(0.155)	(0.159)	(0.160)	(0.158)	(0.106)	(0.111)	(0.111)	(0.109)
SRD	1	**0.993**	**0.985**	**0.984**	**0.986**	1.003	1.000	**0.999**	1.000
		(0.030)	(0.027)	(0.025)	(0.026)	(0.024)	(0.021)	(0.020)	(0.022)
	3	**0.975**	**0.964**	**0.963**	**0.966**	**0.981**	**0.974**	**0.974**	**0.976**
		(0.061)	(0.059)	(0.058)	(0.061)	(0.034)	(0.032)	(0.032)	(0.033)

	6	**0.933**	**0.920**	**0.921**	**0.923**	**0.967**	**0.963**	**0.963**	**0.964**
		(0.068)	(0.084)	(0.084)	(0.082)	(0.042)	(0.048)	(0.048)	(0.046)
	12	**0.924**	**0.914**	**0.912**	**0.915**	**0.927**	**0.920**	**0.919**	**0.921**
		(0.123)	(0.141)	(0.142)	(0.137)	(0.092)	(0.101)	(0.102)	(0.098)
ERV	1	1.045	1.005	1.011	1.004	**0.998**	**0.999**	1.005	**0.997**
		(0.146)	(0.040)	(0.044)	(0.046)	(0.044)	(0.029)	(0.024)	(0.030)
	3	**0.966**	**0.977**	**0.967**	**0.954**	**0.977**	**0.974**	**0.974**	**0.966**
		(0.047)	(0.064)	(0.063)	(0.047)	(0.038)	(0.038)	(0.037)	(0.030)
	6	**0.929**	**0.935**	**0.925**	**0.918**	**0.963**	**0.970**	**0.965**	**0.960**
		(0.094)	(0.090)	(0.106)	(0.091)	(0.056)	(0.053)	(0.062)	(0.051)
	12	**0.952**	**0.960**	**0.924**	**0.934**	**0.929**	**0.937**	**0.914**	**0.921**
		(0.155)	(0.144)	(0.160)	(0.154)	(0.097)	(0.102)	(0.104)	(0.093)
SVD	1	1.007	1.001	1.001	1.000	1.011	1.003	1.003	1.004
		(0.029)	(0.027)	(0.027)	(0.029)	(0.021)	(0.016)	(0.016)	(0.018)
	3	**0.983**	**0.967**	**0.967**	**0.969**	**0.984**	**0.975**	**0.975**	**0.975**
		(0.054)	(0.055)	(0.056)	(0.056)	(0.035)	(0.031)	(0.031)	(0.033)
	6	**0.954**	**0.933**	**0.932**	**0.937**	**0.978**	**0.969**	**0.969**	**0.971**
		(0.112)	(0.091)	(0.090)	(0.095)	(0.051)	(0.048)	(0.048)	(0.047)
	12	**0.942**	**0.922**	**0.926**	**0.926**	**0.933**	**0.921**	**0.923**	**0.924**
		(0.159)	(0.151)	(0.153)	(0.151)	(0.121)	(0.108)	(0.109)	(0.112)
BSD	1	1.003	**0.996**	**0.996**	**0.996**	1.006	1.001	1.001	1.001
		(0.024)	(0.027)	(0.027)	(0.028)	(0.022)	(0.021)	(0.020)	(0.023)
	3	**0.990**	**0.969**	**0.968**	**0.964**	**0.989**	**0.980**	**0.979**	**0.978**
		(0.077)	(0.061)	(0.060)	(0.070)	(0.047)	(0.035)	(0.034)	(0.042)
	6	**0.971**	**0.928**	**0.930**	**0.925**	**0.995**	**0.975**	**0.974**	**0.972**
		(0.149)	(0.095)	(0.093)	(0.117)	(0.080)	(0.057)	(0.055)	(0.070)
	12	1.043	**0.967**	**0.960**	**0.968**	**0.985**	**0.950**	**0.948**	**0.949**
		(0.178)	(0.177)	(0.176)	(0.178)	(0.111)	(0.120)	(0.126)	(0.118)
CSD	1	**0.999**	**0.996**	**0.989**	**0.987**	**0.999**	**0.999**	**0.992**	**0.993**
		(0.032)	(0.026)	(0.036)	(0.026)	(0.018)	(0.014)	(0.016)	(0.013)
	3	**0.970**	**0.975**	**0.948**	**0.941**	**0.977**	**0.978**	**0.964**	**0.961**
		(0.107)	(0.062)	(0.089)	(0.075)	(0.061)	(0.035)	(0.042)	(0.037)
	6	**0.945**	**0.951**	**0.919**	**0.891**	**0.959**	**0.961**	**0.943**	**0.931**
		(0.162)	(0.099)	(0.149)	(0.109)	(0.100)	(0.054)	(0.086)	(0.059)
	12	1.008	**0.935**	**0.972**	**0.886**	**0.979**	**0.938**	**0.961**	**0.924**
		(0.248)	(0.201)	(0.290)	(0.164)	(0.110)	(0.124)	(0.174)	(0.096)
EID	1	1.014	**0.996**	**0.996**	**0.996**	1.010	1.002	1.002	1.000
		(0.043)	(0.030)	(0.029)	(0.037)	(0.022)	(0.020)	(0.019)	(0.021)
	3	1.025	**0.972**	**0.972**	**0.978**	1.008	**0.980**	**0.978**	**0.982**
		(0.090)	(0.071)	(0.068)	(0.079)	(0.040)	(0.040)	(0.039)	(0.038)
	6	1.034	**0.936**	**0.943**	**0.944**	1.001	**0.974**	**0.978**	**0.975**
		(0.125)	(0.105)	(0.099)	(0.101)	(0.063)	(0.054)	(0.052)	(0.059)
	12	1.093	**0.934**	**0.926**	**0.948**	**0.973**	**0.908**	**0.914**	**0.921**
		(0.348)	(0.182)	(0.169)	(0.155)	(0.137)	(0.127)	(0.117)	(0.119)

Table 2: Recursive forecasting results (relative MSE and MAE). The table shows the cross-sectional average and standard errors obtained from the MSE or MAE of a particular predictor x_{it} standardized to the MSE or MAE of a random walk with rolling drift for horizons $h = 1, 3, 6, 12$. Entries in **bold** denote average relative MSE or MAE lower than one. SM = single market estimates; MG = mean group estimates; PO = pooled estimates; AV = average of the SM, MG, PO estimates.

		$\bar{d}r$, MSE				$\bar{d}r$, MAE			
x_{it}	h	SM	MG	PO	AV	SM	MG	PO	AV
PPP	1	1.095	1.047	1.026	1.043	1.051	1.029	1.019	1.027
		(0.036)	(0.060)	(0.042)	(0.045)	(0.027)	(0.038)	(0.026)	(0.028)
	3	1.251	1.092	1.074	1.096	1.118	1.060	1.053	1.061
		(0.127)	(0.151)	(0.114)	(0.104)	(0.087)	(0.097)	(0.074)	(0.076)
	6	1.250	**0.982**	1.045	1.016	1.123	1.002	1.039	1.018
		(0.298)	(0.225)	(0.205)	(0.163)	(0.139)	(0.136)	(0.119)	(0.098)
	12	1.383	**0.980**	1.144	1.049	1.126	0.972	1.039	1.007
		(0.401)	(0.291)	(0.376)	(0.185)	(0.181)	(0.180)	(0.229)	(0.140)
MM	1	1.115	1.217	1.068	1.097	1.057	1.108	1.037	1.050
		(0.048)	(0.208)	(0.081)	(0.084)	(0.041)	(0.101)	(0.050)	(0.053)
	3	1.399	1.553	1.197	1.284	1.162	1.274	1.116	1.156
		(0.246)	(0.543)	(0.224)	(0.207)	(0.109)	(0.253)	(0.139)	(0.137)
	6	1.588	1.597	1.353	1.374	1.232	1.284	1.185	1.188
		(0.309)	(0.648)	(0.463)	(0.303)	(0.138)	(0.296)	(0.228)	(0.165)
	12	1.985	1.648	1.736	1.531	1.322	1.238	1.263	1.192
		(0.769)	(0.898)	(1.008)	(0.478)	(0.361)	(0.385)	(0.420)	(0.250)
UIP	1	1.049	1.015	1.003	1.011	1.030	1.009	1.000	1.010
		(0.033)	(0.019)	(0.015)	(0.018)	(0.012)	(0.011)	(0.011)	(0.010)
	3	1.077	**0.965**	**0.927**	**0.971**	1.045	**0.987**	**0.971**	**0.993**
		(0.140)	(0.039)	(0.040)	(0.055)	(0.072)	(0.045)	(0.043)	(0.047)
	6	1.225	**0.952**	**0.891**	**0.983**	1.085	**0.976**	**0.949**	**0.992**
		(0.295)	(0.152)	(0.133)	(0.167)	(0.099)	(0.068)	(0.065)	(0.072)
	12	1.559	**0.905**	**0.910**	**0.998**	1.150	**0.921**	**0.940**	**0.962**
		(0.657)	(0.298)	(0.264)	(0.345)	(0.232)	(0.146)	(0.146)	(0.165)
FM	1	1.101	1.053	1.044	1.049	1.053	1.029	1.031	1.032
		(0.050)	(0.047)	(0.044)	(0.039)	(0.026)	(0.032)	(0.032)	(0.023)
	3	1.438	1.225	1.186	1.230	1.209	1.139	1.121	1.142
		(0.337)	(0.155)	(0.132)	(0.165)	(0.157)	(0.102)	(0.089)	(0.111)
	6	1.451	1.310	1.269	1.301	1.213	1.147	1.137	1.152
		(0.293)	(0.355)	(0.269)	(0.265)	(0.127)	(0.160)	(0.136)	(0.128)
	12	1.349	1.245	1.179	1.195	1.119	1.093	1.070	1.071
		(0.308)	(0.435)	(0.367)	(0.324)	(0.145)	(0.244)	(0.219)	(0.185)
TAY	1	1.042	1.000	**0.999**	1.007	1.025	**0.997**	**0.997**	1.003
		(0.050)	(0.022)	(0.023)	(0.025)	(0.039)	(0.020)	(0.018)	(0.023)
	3	1.063	1.008	1.008	1.011	1.032	1.004	1.006	1.009
		(0.085)	(0.033)	(0.040)	(0.029)	(0.043)	(0.018)	(0.023)	(0.021)
	6	1.064	**0.996**	1.002	1.006	1.023	**0.995**	**0.999**	1.002
		(0.123)	(0.046)	(0.054)	(0.034)	(0.072)	(0.029)	(0.032)	(0.029)
	12	1.031	**0.955**	**0.959**	**0.966**	1.011	**0.971**	**0.973**	**0.981**
		(0.165)	(0.032)	(0.038)	(0.048)	(0.077)	(0.019)	(0.027)	(0.036)
ERR	1	1.053	1.015	1.017	1.023	1.027	1.006	1.006	1.011
		(0.031)	(0.009)	(0.012)	(0.010)	(0.022)	(0.006)	(0.009)	(0.009)
	3	1.061	1.039	1.040	1.042	1.029	1.017	1.019	1.019
		(0.019)	(0.012)	(0.015)	(0.013)	(0.009)	(0.009)	(0.010)	(0.009)
	6	1.067	1.059	1.061	1.060	1.035	1.032	1.035	1.033
		(0.034)	(0.023)	(0.025)	(0.023)	(0.019)	(0.013)	(0.015)	(0.013)
	12	1.069	1.041	1.049	1.051	1.025	1.017	1.022	1.021
		(0.057)	(0.014)	(0.016)	(0.021)	(0.022)	(0.007)	(0.009)	(0.009)
SRD	1	1.030	1.001	1.005	1.005	1.011	1.005	1.005	1.005
		(0.033)	(0.024)	(0.021)	(0.024)	(0.017)	(0.014)	(0.011)	(0.013)
	3	1.029	1.008	1.013	1.013	1.021	1.006	1.008	1.009
		(0.024)	(0.005)	(0.007)	(0.008)	(0.016)	(0.002)	(0.003)	(0.006)

	6	1.016	**0.999**	1.002	1.003	1.003	**0.998**	1.000	**0.999**
		(0.017)	(0.008)	(0.006)	(0.010)	(0.012)	(0.005)	(0.004)	(0.006)
	12	1.015	1.007	1.005	1.007	1.009	1.004	1.003	1.004
		(0.019)	(0.011)	(0.008)	(0.009)	(0.017)	(0.007)	(0.005)	(0.007)
ERV	1	1.318	1.034	1.039	1.060	1.024	1.002	1.012	1.005
		(0.962)	(0.080)	(0.073)	(0.182)	(0.083)	(0.023)	(0.020)	(0.036)
	3	1.082	1.044	1.022	1.017	1.022	1.011	1.005	0.999
		(0.201)	(0.114)	(0.029)	(0.074)	(0.060)	(0.053)	(0.014)	(0.040)
	6	1.043	1.029	1.029	1.014	1.014	1.014	1.020	1.008
		(0.065)	(0.040)	(0.041)	(0.028)	(0.036)	(0.019)	(0.023)	(0.018)
	12	1.137	1.037	1.030	1.036	1.046	1.012	1.019	1.016
		(0.220)	(0.051)	(0.025)	(0.021)	(0.066)	(0.024)	(0.022)	(0.018)
SVD	1	1.039	1.021	1.012	1.012	1.028	1.018	1.010	1.013
		(0.052)	(0.027)	(0.013)	(0.021)	(0.030)	(0.021)	(0.014)	(0.012)
	3	1.052	1.007	1.002	1.007	1.030	1.004	**0.999**	1.005
		(0.059)	(0.023)	(0.019)	(0.023)	(0.039)	(0.012)	(0.010)	(0.019)
	6	1.092	1.035	1.013	1.029	1.038	1.014	1.004	1.011
		(0.110)	(0.064)	(0.042)	(0.063)	(0.054)	(0.043)	(0.027)	(0.038)
	12	1.029	1.036	1.020	1.020	1.015	1.011	1.001	1.003
		(0.053)	(0.074)	(0.058)	(0.046)	(0.048)	(0.031)	(0.026)	(0.027)
BSD	1	1.054	1.032	1.026	1.031	1.037	1.021	1.016	1.022
		(0.043)	(0.021)	(0.021)	(0.029)	(0.036)	(0.025)	(0.024)	(0.028)
	3	1.135	1.082	1.067	1.076	1.068	1.038	1.028	1.036
		(0.118)	(0.075)	(0.054)	(0.060)	(0.063)	(0.035)	(0.032)	(0.040)
	6	1.372	1.238	1.229	1.241	1.163	1.125	1.111	1.119
		(0.193)	(0.134)	(0.127)	(0.126)	(0.081)	(0.075)	(0.064)	(0.058)
	12	1.465	1.344	1.325	1.334	1.231	1.204	1.180	1.191
		(0.238)	(0.226)	(0.227)	(0.188)	(0.100)	(0.132)	(0.129)	(0.109)
CSD	1	1.070	1.040	1.020	1.033	1.037	1.018	1.010	1.019
		(0.044)	(0.023)	(0.021)	(0.021)	(0.026)	(0.016)	(0.016)	(0.015)
	3	1.121	1.109	1.043	1.056	1.064	1.051	1.023	1.033
		(0.110)	(0.082)	(0.050)	(0.055)	(0.067)	(0.045)	(0.028)	(0.038)
	6	1.131	1.149	1.048	1.065	1.061	1.071	1.019	1.026
		(0.168)	(0.129)	(0.110)	(0.094)	(0.081)	(0.066)	(0.053)	(0.050)
	12	1.333	1.213	1.146	1.143	1.142	1.122	1.086	1.086
		(0.437)	(0.256)	(0.315)	(0.274)	(0.202)	(0.155)	(0.184)	(0.174)
EID	1	1.049	1.014	1.012	1.014	1.019	1.008	1.008	1.006
		(0.049)	(0.018)	(0.013)	(0.026)	(0.034)	(0.013)	(0.010)	(0.016)
	3	1.109	1.037	1.034	1.036	1.063	1.025	1.024	1.024
		(0.151)	(0.048)	(0.037)	(0.063)	(0.089)	(0.033)	(0.023)	(0.046)
	6	1.141	1.071	1.066	1.050	1.058	1.035	1.036	1.026
		(0.202)	(0.124)	(0.089)	(0.102)	(0.113)	(0.078)	(0.056)	(0.070)
	12	1.389	1.132	1.089	1.145	1.138	1.057	1.043	1.057
		(0.648)	(0.162)	(0.117)	(0.219)	(0.196)	(0.083)	(0.060)	(0.099)

Table 3: Rolling forecasting results (relative MSE and MAE). The table shows the cross-sectional average and standard errors obtained from the MSE or MAE of a particular predictor x_{it} standardized to the MSE or MAE of a random walk with rolling drift for horizons $h = 1, 3, 6, 12$. Entries in **bold** denote average relative MSE or MAE lower than one. SM = single market estimates; MG = mean group estimates; PO = pooled estimates; AV = average of the SM, MG, PO estimates.

x_{it}	h	DM-MSE SM	DM-MSE MG	DM-MSE PO	DM-MSE AV	DM-MAE SM	DM-MAE MG	DM-MAE PO	DM-MAE AV
PPP	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
MM	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
UIP	1	0	0	1	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
FM	1	1	1	1	1	0	0	0	0
	3	1	0	1	1	1	0	1	1
	6	0	0	0	0	1	0	0	1
	12	0	0	0	0	0	0	0	1
TAY	1	0	0	1	0	0	3	3	2
	3	0	0	0	0	0	0	0	0
	6	1	2	2	0	2	2	2	2
	12	0	0	0	0	1	1	1	1
ERR	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
SRD	1	0	2	2	2	0	0	1	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	1	0	0
	12	0	1	0	0	0	0	0	0
ERV	1	1	1	0	2	1	1	0	3
	3	1	0	1	1	0	1	0	2
	6	1	0	1	1	1	0	1	0
	12	1	0	2	2	1	0	2	2
SVD	1	0	0	0	0	0	0	0	0
	3	0	1	1	0	0	1	1	0
	6	2	2	2	2	2	1	1	2
	12	1	0	0	0	2	0	0	2
BSD	1	0	0	0	0	0	1	1	0
	3	0	0	0	1	0	0	0	0
	6	0	0	0	1	0	0	0	1
	12	0	0	0	0	0	0	0	0
CSD	1	0	0	1	0	1	1	2	2
	3	0	1	1	0	0	1	1	0
	6	0	1	0	0	0	2	2	0
	12	0	0	0	0	0	0	0	0

EID	1	0	0	0	0	0	1	1	1
	3	0	0	0	0	0	0	0	0
	6	0	1	1	0	0	1	1	0
	12	0	1	1	1	0	1	2	0

Table 4: Recursive forecasting results (DM). The table shows the number of rejections of the Diebold Mariano test (DM) with respect to MSE or MAE for a particular predictor x_{it} for horizons $h = 1, 3, 6, 12$ at the 10% significance level (critical value = 1.28). SM = single market estimates; MG = mean group estimates; PO = pooled estimates; AV = average of the SM, MG, PO estimates.

x_{it}	h	DM-MSE				DM-MAE			
		SM	MG	PO	AV	SM	MG	PO	AV
PPP	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	1	0	0	0	1	0	0
	12	0	0	0	0	0	0	0	0
MM	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
UIP	1	0	0	0	0	0	0	1	0
	3	0	1	1	0	0	2	3	2
	6	0	0	0	0	0	1	1	0
	12	0	0	0	1	0	1	1	1
FM	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
TAY	1	0	2	2	2	0	3	2	2
	3	0	0	1	0	0	0	0	0
	6	1	2	1	0	1	3	2	2
	12	1	5	3	4	0	4	3	4
ERR	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
SRD	1	0	1	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	1	0	0	0	1	0	0
	12	0	1	0	0	0	1	1	0
ERV	1	0	0	0	1	1	0	0	1
	3	1	1	0	1	1	1	0	2
	6	0	0	0	1	0	0	0	1
	12	0	0	0	0	0	0	0	0
SVD	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	1	0
	6	1	1	1	1	1	2	2	1
	12	2	0	1	2	2	0	0	1
BSD	1	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	0	0	0	0	0	0	0	0
CSD	1	0	0	0	0	0	0	0	0
	3	0	0	1	0	0	0	0	0
	6	0	0	0	0	0	0	0	0
	12	1	0	0	0	1	0	1	1

EID	1	0	1	0	1	0	0	0	0
	3	0	0	0	1	0	0	0	1
	6	1	1	0	1	1	1	0	0
	12	0	0	0	0	0	0	0	0

Table 5: Rolling forecasting results (DM). The table shows the number of rejections of the Diebold Mariano (DM) test with respect to MSE or MAE for a particular predictor x_{it} for horizons $h = 1, 3, 6, 12$ at the 10% significance level (critical value = 1.28). SM = single market estimates; MG = mean group estimates; PO = pooled estimates; AV = average of the SM, MG, PO estimates.

x_{it}	h	$\mathcal{M}2$, $\gamma = 3$ SM	MG	PO	AV	$\mathcal{M}2$, $\gamma = 6$ SM	MG	PO	AV
PPP	1	0.996	0.830	-0.300	0.808	0.498	0.415	-0.150	0.404
		(4.719)	(2.233)	(2.227)	(3.928)	(2.359)	(1.116)	(1.113)	(1.964)
	3	0.745	-0.164	-1.169	-0.686	0.373	-0.082	-0.584	-0.343
		(6.382)	(4.690)	(3.671)	(5.216)	(3.191)	(2.345)	(1.835)	(2.608)
	6	0.865	0.498	1.701	0.475	0.432	0.249	0.851	0.237
		(8.544)	(7.821)	(10.536)	(8.148)	(4.272)	(3.910)	(5.268)	(4.074)
	12	6.858	5.622	5.725	5.081	3.429	2.811	2.863	2.540
		(11.301)	(14.324)	(13.747)	(10.680)	(5.651)	(7.162)	(6.873)	(5.340)
MM	1	2.255	-0.185	-0.392	-0.739	1.127	-0.093	-0.196	-0.369
		(5.110)	(2.362)	(4.363)	(4.489)	(2.555)	(1.181)	(2.181)	(2.244)
	3	0.882	0.494	0.897	0.293	0.441	0.247	0.448	0.147
		(8.410)	(4.805)	(4.722)	(5.011)	(4.205)	(2.403)	(2.361)	(2.505)
	6	1.593	0.862	2.953	0.958	0.796	0.431	1.477	0.479
		(13.707)	(10.213)	(10.230)	(7.257)	(6.853)	(5.107)	(5.115)	(3.629)
	12	10.594	5.905	5.990	6.530	5.297	2.953	2.995	3.265
		(14.147)	(7.332)	(8.038)	(9.941)	(7.074)	(3.666)	(4.019)	(4.971)
UIP	1	2.683	2.915	2.412	2.681	1.342	1.457	1.206	1.340
		(5.352)	(4.617)	(5.214)	(4.952)	(2.676)	(2.309)	(2.607)	(2.476)
	3	35.895	34.947	37.170	36.126	17.948	17.474	18.585	18.063
		(28.008)	(25.270)	(25.854)	(26.643)	(14.004)	(12.635)	(12.927)	(13.321)
	6	53.758	53.968	55.111	55.038	26.879	26.984	27.555	27.519
		(38.228)	(32.313)	(33.292)	(34.569)	(19.114)	(16.157)	(16.646)	(17.285)
	12	79.203	84.038	77.807	82.215	39.602	42.019	38.904	41.107
		(58.432)	(70.493)	(60.895)	(64.682)	(29.216)	(35.247)	(30.447)	(32.341)
FM	1	4.001	0.990	0.489	2.250	2.001	0.495	0.245	1.125
		(3.767)	(2.103)	(1.239)	(3.099)	(1.884)	(1.051)	(0.619)	(1.550)
	3	4.654	3.244	3.214	3.420	2.327	1.622	1.607	1.710
		(4.165)	(3.173)	(2.129)	(3.012)	(2.082)	(1.586)	(1.064)	(1.506)
	6	7.560	7.456	7.618	8.305	3.780	3.728	3.809	4.153
		(16.043)	(20.997)	(18.263)	(22.034)	(8.022)	(10.498)	(9.131)	(11.017)
	12	7.604	11.947	11.393	7.306	3.802	5.973	5.697	3.653
		(11.012)	(25.396)	(26.895)	(9.969)	(5.506)	(12.698)	(13.447)	(4.985)
TAY	1	3.423	4.749	4.792	4.207	1.712	2.374	2.396	2.103
		(5.387)	(5.237)	(5.154)	(5.236)	(2.694)	(2.618)	(2.577)	(2.618)
	3	6.364	5.907	5.825	6.053	3.182	2.953	2.913	3.027
		(6.914)	(5.669)	(5.606)	(5.706)	(3.457)	(2.834)	(2.803)	(2.853)
	6	4.848	4.535	4.419	4.344	2.424	2.268	2.210	2.172
		(9.937)	(10.647)	(10.573)	(10.293)	(4.969)	(5.324)	(5.287)	(5.146)
	12	10.541	11.993	12.048	11.448	5.271	5.996	6.024	5.724
		(8.667)	(9.985)	(10.072)	(9.430)	(4.334)	(4.992)	(5.036)	(4.715)
ERR	1	2.010	1.314	1.675	1.511	1.005	0.657	0.838	0.756
		(4.810)	(5.356)	(5.348)	(5.177)	(2.405)	(2.678)	(2.674)	(2.589)
	3	5.066	5.521	6.336	5.580	2.533	2.761	3.168	2.790
		(5.513)	(5.367)	(5.689)	(5.388)	(2.756)	(2.684)	(2.845)	(2.694)
	6	5.469	5.280	5.286	5.304	2.734	2.640	2.643	2.652
		(12.498)	(12.829)	(12.968)	(12.734)	(6.249)	(6.415)	(6.484)	(6.367)
	12	11.039	11.835	11.676	11.502	5.519	5.918	5.838	5.751
		(11.193)	(11.692)	(11.617)	(11.470)	(5.597)	(5.846)	(5.809)	(5.735)
SRD	1	5.273	5.330	4.835	5.293	2.637	2.665	2.418	2.647
		(5.680)	(5.106)	(5.161)	(5.200)	(2.840)	(2.553)	(2.580)	(2.600)
	3	3.935	4.256	4.238	4.130	1.968	2.128	2.119	2.065
		(7.342)	(7.308)	(7.221)	(7.320)	(3.671)	(3.654)	(3.611)	(3.660)

	6	5.057	5.333	5.408	5.258	2.528	2.667	2.704	2.629
		(10.909)	(10.687)	(10.679)	(10.773)	(5.454)	(5.344)	(5.339)	(5.387)
	12	11.835	11.759	11.842	11.818	5.918	5.879	5.921	5.909
		(9.471)	(9.018)	(9.296)	(9.302)	(4.735)	(4.509)	(4.648)	(4.651)
ERV	1	5.261	4.208	1.141	3.563	2.630	2.104	0.570	1.782
		(5.809)	(4.291)	(5.044)	(4.501)	(2.905)	(2.146)	(2.522)	(2.251)
	3	9.195	7.466	5.081	7.091	4.598	3.733	2.540	3.546
		(8.844)	(8.829)	(8.600)	(8.985)	(4.422)	(4.415)	(4.300)	(4.492)
	6	9.497	7.078	7.333	7.610	4.749	3.539	3.667	3.805
		(17.000)	(15.703)	(18.945)	(17.159)	(8.500)	(7.851)	(9.473)	(8.580)
	12	13.040	15.372	15.544	14.742	6.520	7.686	7.772	7.371
		(13.376)	(20.208)	(18.234)	(17.532)	(6.688)	(10.104)	(9.117)	(8.766)
SVD	1	2.209	2.184	2.021	2.002	1.105	1.092	1.011	1.001
		(5.368)	(5.582)	(5.655)	(5.526)	(2.684)	(2.791)	(2.827)	(2.763)
	3	4.649	4.345	4.378	4.427	2.325	2.172	2.189	2.213
		(7.849)	(6.466)	(6.557)	(6.860)	(3.925)	(3.233)	(3.279)	(3.430)
	6	5.935	5.919	5.599	5.803	2.968	2.960	2.800	2.902
		(9.732)	(11.000)	(10.937)	(10.496)	(4.866)	(5.500)	(5.469)	(5.248)
	12	11.469	12.276	12.213	12.025	5.735	6.138	6.106	6.012
		(10.050)	(10.436)	(10.322)	(10.210)	(5.025)	(5.218)	(5.161)	(5.105)
BSD	1	2.734	1.693	1.643	1.952	1.367	0.847	0.821	0.976
		(5.540)	(5.861)	(5.776)	(5.965)	(2.770)	(2.930)	(2.888)	(2.983)
	3	5.352	3.628	3.776	4.057	2.676	1.814	1.888	2.029
		(6.740)	(6.881)	(6.809)	(7.349)	(3.370)	(3.440)	(3.405)	(3.674)
	6	7.848	4.938	4.951	5.724	3.924	2.469	2.475	2.862
		(10.976)	(11.213)	(10.900)	(11.332)	(5.488)	(5.607)	(5.450)	(5.666)
	12	12.707	12.654	11.893	12.184	6.353	6.327	5.946	6.092
		(12.994)	(12.816)	(11.107)	(12.276)	(6.497)	(6.408)	(5.554)	(6.138)
CSD	1	4.778	3.459	4.434	4.071	2.389	1.730	2.217	2.036
		(6.830)	(5.559)	(6.092)	(6.242)	(3.415)	(2.779)	(3.046)	(3.121)
	3	8.302	6.052	7.598	7.402	4.151	3.026	3.799	3.701
		(8.061)	(6.883)	(8.442)	(7.527)	(4.030)	(3.442)	(4.221)	(3.764)
	6	12.212	9.552	12.333	11.769	6.106	4.776	6.167	5.884
		(15.670)	(11.847)	(13.546)	(13.248)	(7.835)	(5.924)	(6.773)	(6.624)
	12	21.266	16.051	17.653	19.456	10.633	8.025	8.826	9.728
		(16.154)	(16.848)	(19.180)	(18.361)	(8.077)	(8.424)	(9.590)	(9.180)
EID	1	2.520	2.852	2.605	2.583	1.260	1.426	1.302	1.291
		(6.927)	(6.059)	(5.807)	(7.034)	(3.463)	(3.030)	(2.904)	(3.517)
	3	5.728	5.659	4.968	5.326	2.864	2.830	2.484	2.663
		(10.800)	(7.286)	(6.787)	(8.463)	(5.400)	(3.643)	(3.393)	(4.232)
	6	4.512	5.453	4.419	4.520	2.256	2.727	2.209	2.260
		(9.738)	(11.566)	(11.379)	(10.878)	(4.869)	(5.783)	(5.689)	(5.439)
	12	17.945	13.575	12.876	15.044	8.973	6.788	6.438	7.522
		(16.600)	(12.003)	(11.019)	(13.044)	(8.300)	(6.002)	(5.509)	(6.522)

Table 6: Recursive forecasting results ($\mathcal{M}2$). The table shows the cross-sectional average and standard errors of the Sharpe Ratio differentials ($\mathcal{M}2$) in annualized basis points obtained from a portfolio constructed by using forecasts and residual variance of a particular predictor x_{it} versus a buy-and-hold portfolio for horizons $h = 1, 3, 6, 12$. SM = single market estimates; MG = mean group estimates; PO = pooled estimates; AV = average of the SM, MG, PO estimates.

x_{it}	h	$\mathcal{M}2$, $\gamma=3$ SM	MG	PO	AV	$\mathcal{M}2$, $\gamma=6$ SM	MG	PO	AV
PPP	1	3.442 (4.718)	3.176 (3.809)	3.999 (4.323)	3.641 (5.072)	1.721 (2.359)	1.588 (1.904)	2.000 (2.162)	1.821 (2.536)
	3	8.679 (6.553)	8.753 (9.292)	8.087 (8.855)	8.711 (8.468)	4.340 (3.277)	4.376 (4.646)	4.044 (4.427)	4.355 (4.234)
	6	14.750 (9.772)	16.563 (14.662)	13.591 (14.182)	14.567 (10.457)	7.375 (4.886)	8.281 (7.331)	6.795 (7.091)	7.284 (5.229)
	12	11.005 (13.044)	7.687 (12.386)	5.792 (10.879)	8.012 (12.284)	5.503 (6.522)	3.844 (6.193)	2.896 (5.439)	4.006 (6.142)
MM	1	4.145 (3.961)	1.567 (2.567)	2.784 (3.644)	1.693 (3.305)	2.073 (1.981)	0.784 (1.283)	1.392 (1.822)	0.847 (1.652)
	3	5.418 (6.695)	3.590 (2.905)	4.984 (3.553)	4.230 (3.812)	2.709 (3.347)	1.795 (1.452)	2.492 (1.776)	2.115 (1.906)
	6	7.653 (10.097)	5.659 (4.874)	8.001 (6.173)	4.868 (7.037)	3.826 (5.048)	2.830 (2.437)	4.001 (3.086)	2.434 (3.518)
	12	10.630 (13.018)	8.040 (9.946)	5.541 (9.866)	7.430 (10.968)	5.315 (6.509)	4.020 (4.973)	2.770 (4.933)	3.715 (5.484)
UIP	1	5.506 (4.756)	5.926 (4.957)	6.196 (5.197)	5.786 (4.980)	2.753 (2.378)	2.963 (2.478)	3.098 (2.599)	2.893 (2.490)
	3	28.064 (22.660)	28.842 (23.143)	32.965 (24.500)	29.814 (23.330)	14.032 (11.330)	14.421 (11.571)	16.483 (12.250)	14.907 (11.665)
	6	37.986 (35.937)	40.105 (27.225)	45.618 (28.222)	41.297 (30.295)	18.993 (17.968)	20.052 (13.612)	22.809 (14.111)	20.648 (15.147)
	12	65.904 (53.779)	78.596 (48.066)	78.531 (46.791)	70.403 (45.183)	32.952 (26.889)	39.298 (24.033)	39.266 (23.395)	35.202 (22.591)
FM	1	5.265 (4.162)	4.330 (2.850)	3.980 (2.668)	4.896 (3.400)	2.633 (2.081)	2.165 (1.425)	1.990 (1.334)	2.448 (1.700)
	3	9.063 (6.992)	7.797 (5.440)	6.557 (4.696)	7.802 (5.720)	4.532 (3.496)	3.898 (2.720)	3.278 (2.348)	3.901 (2.860)
	6	15.160 (14.195)	14.979 (14.098)	12.937 (12.092)	14.635 (13.461)	7.580 (7.097)	7.489 (7.049)	6.468 (6.046)	7.317 (6.730)
	12	13.295 (16.935)	16.145 (17.622)	15.581 (17.565)	14.116 (15.885)	6.647 (8.467)	8.072 (8.811)	7.790 (8.783)	7.058 (7.943)
TAY	1	5.594 (5.323)	6.661 (4.989)	6.641 (4.938)	6.330 (4.937)	2.797 (2.662)	3.331 (2.495)	3.321 (2.469)	3.165 (2.469)
	3	8.499 (7.330)	8.794 (6.949)	8.412 (6.826)	8.658 (6.851)	4.250 (3.665)	4.397 (3.475)	4.206 (3.413)	4.329 (3.426)
	6	10.911 (7.376)	10.647 (8.787)	10.179 (8.710)	10.443 (7.967)	5.455 (3.688)	5.323 (4.394)	5.089 (4.355)	5.221 (3.984)
	12	14.163 (12.076)	15.315 (12.214)	15.418 (12.288)	14.802 (11.870)	7.081 (6.038)	7.658 (6.107)	7.709 (6.144)	7.401 (5.935)
ERR	1	4.545 (5.097)	5.177 (4.922)	5.317 (5.049)	4.962 (5.075)	2.273 (2.549)	2.588 (2.461)	2.659 (2.524)	2.481 (2.538)
	3	5.038 (6.120)	5.502 (5.899)	6.092 (6.054)	5.492 (6.012)	2.519 (3.060)	2.751 (2.949)	3.046 (3.027)	2.746 (3.006)
	6	12.667 (10.871)	11.978 (9.992)	11.835 (10.221)	12.113 (10.260)	6.333 (5.435)	5.989 (4.996)	5.918 (5.111)	6.056 (5.130)
	12	15.470 (14.333)	16.109 (14.134)	15.989 (13.970)	15.841 (14.116)	7.735 (7.167)	8.055 (7.067)	7.995 (6.985)	7.920 (7.058)
SRD	1	7.449 (5.550)	7.378 (5.112)	7.002 (5.163)	7.373 (5.302)	3.724 (2.775)	3.689 (2.556)	3.501 (2.581)	3.686 (2.651)
	3	7.217 (7.315)	7.239 (7.247)	7.191 (7.454)	7.208 (7.402)	3.608 (3.657)	3.620 (3.624)	3.596 (3.727)	3.604 (3.701)

	6	11.727	11.758	11.812	11.805	5.864	5.879	5.906	5.903
		(8.277)	(8.618)	(8.613)	(8.505)	(4.139)	(4.309)	(4.306)	(4.253)
	12	15.707	15.317	15.474	15.530	7.853	7.658	7.737	7.765
		(12.717)	(12.043)	(12.198)	(12.364)	(6.359)	(6.022)	(6.099)	(6.182)
ERV	1	6.731	6.992	4.907	6.034	3.366	3.496	2.454	3.017
		(6.277)	(5.270)	(4.471)	(5.174)	(3.139)	(2.635)	(2.236)	(2.587)
	3	10.603	10.245	9.126	10.008	5.302	5.123	4.563	5.004
		(8.918)	(9.128)	(8.187)	(8.743)	(4.459)	(4.564)	(4.094)	(4.372)
	6	14.855	14.194	13.627	14.302	7.428	7.097	6.813	7.151
		(13.895)	(14.117)	(15.069)	(14.093)	(6.948)	(7.059)	(7.535)	(7.046)
	12	14.687	16.233	16.052	15.388	7.344	8.116	8.026	7.694
		(9.790)	(13.459)	(12.096)	(10.953)	(4.895)	(6.730)	(6.048)	(5.476)
SVD	1	6.103	6.083	5.971	6.093	3.052	3.042	2.986	3.047
		(5.013)	(5.108)	(5.089)	(5.058)	(2.507)	(2.554)	(2.545)	(2.529)
	3	7.739	8.051	8.231	8.021	3.870	4.025	4.115	4.010
		(8.145)	(7.252)	(7.182)	(7.547)	(4.072)	(3.626)	(3.591)	(3.773)
	6	13.747	13.015	12.926	13.295	6.873	6.508	6.463	6.647
		(9.707)	(9.517)	(9.224)	(9.392)	(4.853)	(4.759)	(4.612)	(4.696)
	12	18.339	16.062	16.416	16.896	9.169	8.031	8.208	8.448
		(13.886)	(13.049)	(12.926)	(13.074)	(6.943)	(6.525)	(6.463)	(6.537)
BSD	1	6.217	6.199	6.263	6.253	3.109	3.100	3.131	3.126
		(5.291)	(5.421)	(5.353)	(5.378)	(2.645)	(2.711)	(2.677)	(2.689)
	3	8.781	8.657	8.930	8.730	4.390	4.329	4.465	4.365
		(7.449)	(7.393)	(7.296)	(7.389)	(3.724)	(3.697)	(3.648)	(3.694)
	6	11.668	11.494	11.807	11.684	5.834	5.747	5.903	5.842
		(10.229)	(9.763)	(9.498)	(9.842)	(5.115)	(4.881)	(4.749)	(4.921)
	12	19.291	16.525	15.297	16.823	9.646	8.263	7.649	8.412
		(15.215)	(13.742)	(12.475)	(14.000)	(7.608)	(6.871)	(6.237)	(7.000)
CSD	1	5.003	4.569	5.239	4.902	2.502	2.285	2.620	2.451
		(5.141)	(4.551)	(4.728)	(4.885)	(2.571)	(2.276)	(2.364)	(2.442)
	3	8.855	6.582	7.482	7.637	4.427	3.291	3.741	3.819
		(6.559)	(6.354)	(6.364)	(6.362)	(3.279)	(3.177)	(3.182)	(3.181)
	6	14.771	9.453	11.527	12.062	7.386	4.727	5.763	6.031
		(9.663)	(11.469)	(11.297)	(10.772)	(4.831)	(5.734)	(5.648)	(5.386)
	12	23.111	15.318	16.999	18.935	11.556	7.659	8.499	9.468
		(14.332)	(13.043)	(13.795)	(14.537)	(7.166)	(6.522)	(6.897)	(7.268)
EID	1	4.992	5.609	5.522	5.336	2.496	2.805	2.761	2.668
		(6.755)	(5.299)	(5.268)	(6.124)	(3.377)	(2.649)	(2.634)	(3.062)
	3	7.715	8.406	7.691	7.865	3.858	4.203	3.846	3.933
		(10.166)	(7.505)	(7.377)	(8.351)	(5.083)	(3.753)	(3.689)	(4.176)
	6	11.941	13.117	12.123	12.566	5.971	6.558	6.061	6.283
		(9.399)	(10.642)	(10.172)	(9.612)	(4.700)	(5.321)	(5.086)	(4.806)
	12	18.254	17.939	17.834	18.077	9.127	8.970	8.917	9.039
		(17.885)	(14.862)	(14.825)	(15.864)	(8.943)	(7.431)	(7.413)	(7.932)

Table 7: Rolling forecasting results ($\mathcal{M}2$). The table shows the cross-sectional average and standard errors of the Sharpe Ratio differentials ($\mathcal{M}2$) in annualized basis points obtained from a portfolio constructed by using forecasts and residual variance of a particular predictor x_{it} versus a buy-and-hold portfolio for horizons $h = 1, 3, 6, 12$. SM = single market estimates; MG = mean group estimates; PO = pooled estimates; AV = average of the SM, MG, PO estimates.

Method	h	$\bar{d}r$, MSE				$\bar{d}r$, MAE				DM-MSE				DM-MAE			
		1	3	6	12	1	3	6	12	1	3	6	12	1	3	6	12
AFC		**0.990** (0.015)	**0.958** (0.046)	**0.909** (0.073)	**0.858** (0.110)	**0.997** (0.012)	**0.977** (0.030)	**0.964** (0.043)	**0.898** (0.086)	1	3	3	4	1	4	3	4
RFC		**0.997** (0.020)	**0.974** (0.048)	**0.940** (0.077)	**0.898** (0.126)	**0.999** (0.014)	**0.987** (0.031)	**0.976** (0.045)	**0.932** (0.088)	1	3	3	3	2	3	3	2
HFC		1.028 (0.044)	1.060 (0.143)	1.103 (0.264)	1.156 (0.311)	1.016 (0.023)	1.027 (0.082)	1.048 (0.105)	1.076 (0.188)	0	2	2	2	0	2	0	2
OFC		**0.997** (0.022)	**0.966** (0.063)	**0.993** (0.144)	1.063 (0.249)	**0.999** (0.017)	**0.990** (0.042)	**0.999** (0.073)	1.033 (0.156)	2	2	2	2	2	3	1	1
MFC		1.002 (0.024)	**0.982** (0.074)	**0.942** (0.118)	**0.961** (0.196)	1.001 (0.017)	**0.996** (0.048)	**0.976** (0.060)	**0.983** (0.141)	1	4	4	2	1	3	3	2
FFC		1.013 (0.030)	1.028 (0.131)	**0.967** (0.128)	**0.966** (0.200)	1.005 (0.022)	1.017 (0.071)	**0.993** (0.065)	**0.989** (0.148)	1	2	3	2	1	2	4	2

Table 8: Forecast combination results (MSE, MAE, DM). The table shows the cross-sectional average and standard errors obtained from a combination method standardized to the MSE or MAE of a random walk with rolling drift for horizons $h = 1, 3, 6, 12$. Entries in **bold** denote average relative MSE or MAE lower than one. The table also shows the number of rejections of the Diebold Mariano (DM) test with respect to MSE or MAE of a particular predictor x_{it} for horizons $h = 1, 3, 6, 12$ at the 10% significance level (critical value = 1.28). AFC = Simple average; RFC = Rank-weighted combinations; HFC = Hierarchical forecast combinations; OFC = TMA with OLS weights; MFC = TMA with RMSE weights; FFC = TMA with MSE-Frequency weights.

Method	h	$\mathcal{M}2$, $\gamma = 2$				$\mathcal{M}2$, $\gamma = 6$			
		1	3	6	12	1	3	6	12
AFC		3.327	5.888	9.774	14.502	1.664	2.944	4.887	7.541
		(5.251)	(6.744)	(12.244)	(11.202)	(2.625)	(3.372)	(6.122)	(5.526)
RFC		3.870	6.026	10.503	14.346	1.935	3.013	5.252	7.469
		(4.835)	(5.717)	(11.619)	(11.614)	(2.418)	(2.859)	(5.810)	(5.700)
HFC		5.405	10.408	15.355	14.134	2.703	5.204	7.677	7.281
		(5.651)	(9.104)	(10.786)	(17.497)	(2.826)	(4.552)	(5.393)	(8.361)
OFC		4.394	10.199	10.086	13.072	2.197	5.099	5.043	6.793
		(5.361)	(7.281)	(13.557)	(11.590)	(2.680)	(3.640)	(6.778)	(5.664)
MFC		4.217	7.707	12.194	13.475	2.109	3.854	6.097	7.006
		(5.265)	(7.277)	(12.501)	(12.624)	(2.633)	(3.638)	(6.251)	(6.150)
FFC		3.735	6.845	13.017	14.536	1.868	3.422	6.508	7.477
		(5.408)	(7.184)	(14.767)	(13.615)	(2.704)	(3.592)	(7.383)	(6.650)

Table 9: Forecast combination results ($\mathcal{M}2$). The table shows the cross-sectional average and standard errors of the Sharpe Ratio differentials ($\mathcal{M}2$) in annualized basis points obtained from a portfolio constructed by using forecasts and residual variance of a particular forecast combination method versus a buy-and-hold portfolio for horizons $h = 1, 3, 6, 12$. AFC = Simple average; RFC = Rank-weighted combinations; HFC = Hierarchical forecast combinations; OFC = TMA with OLS weights; MFC = TMA with RMSE weights; FFC = TMA with MSE-Frequency weights.

Figure 1: Boxplots of relative MSEs from the ‘best’ performing models. The box has lines at the lower quartile, median, and upper quartile values. The whiskers show the extent of the rest of the data. Outliers are data with values beyond the ends of the whiskers. Boxplots are in the same scale for easy comparability.

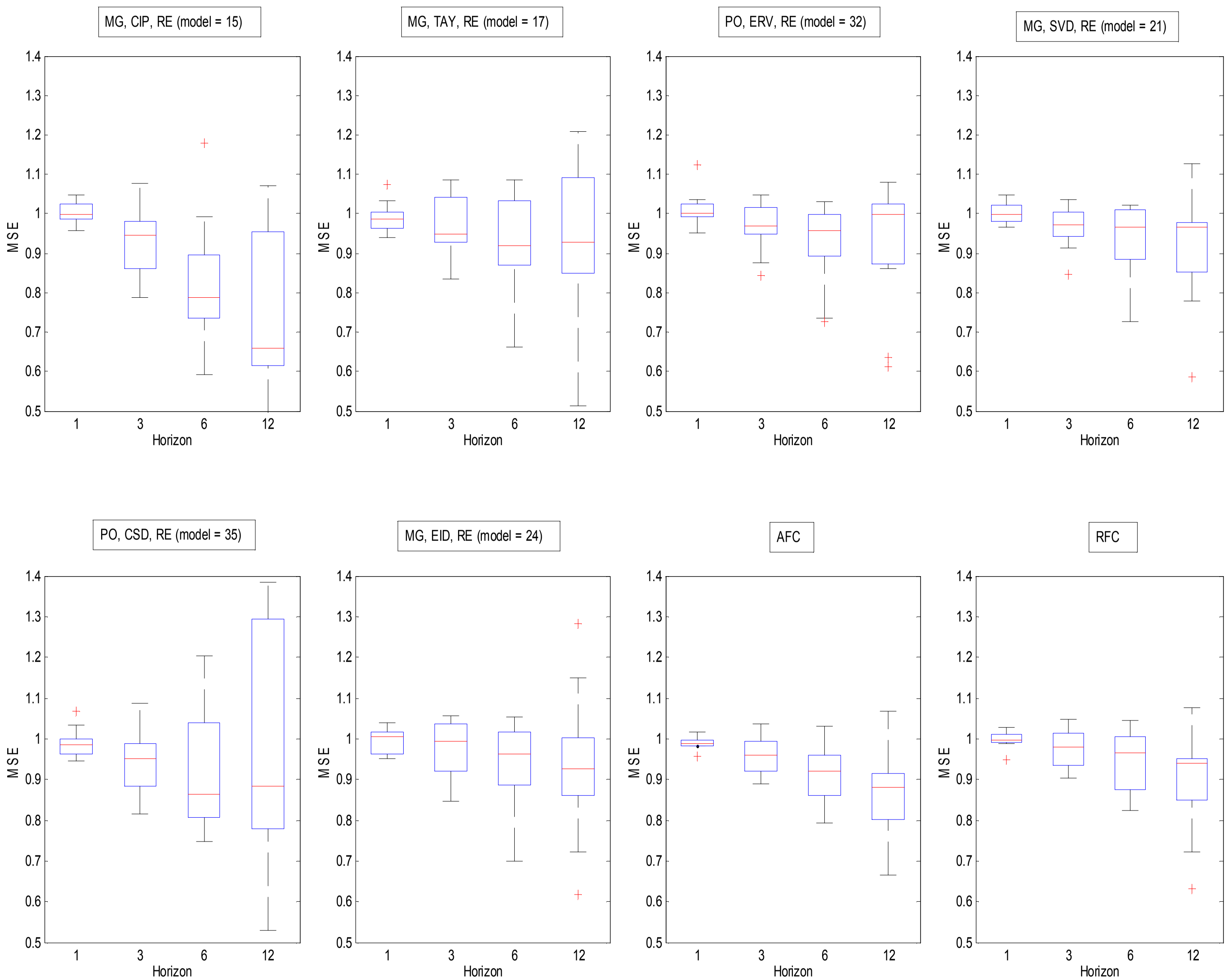

Figure 2: Boxplots of $\mathcal{M}2$ from the 'best' performing models.

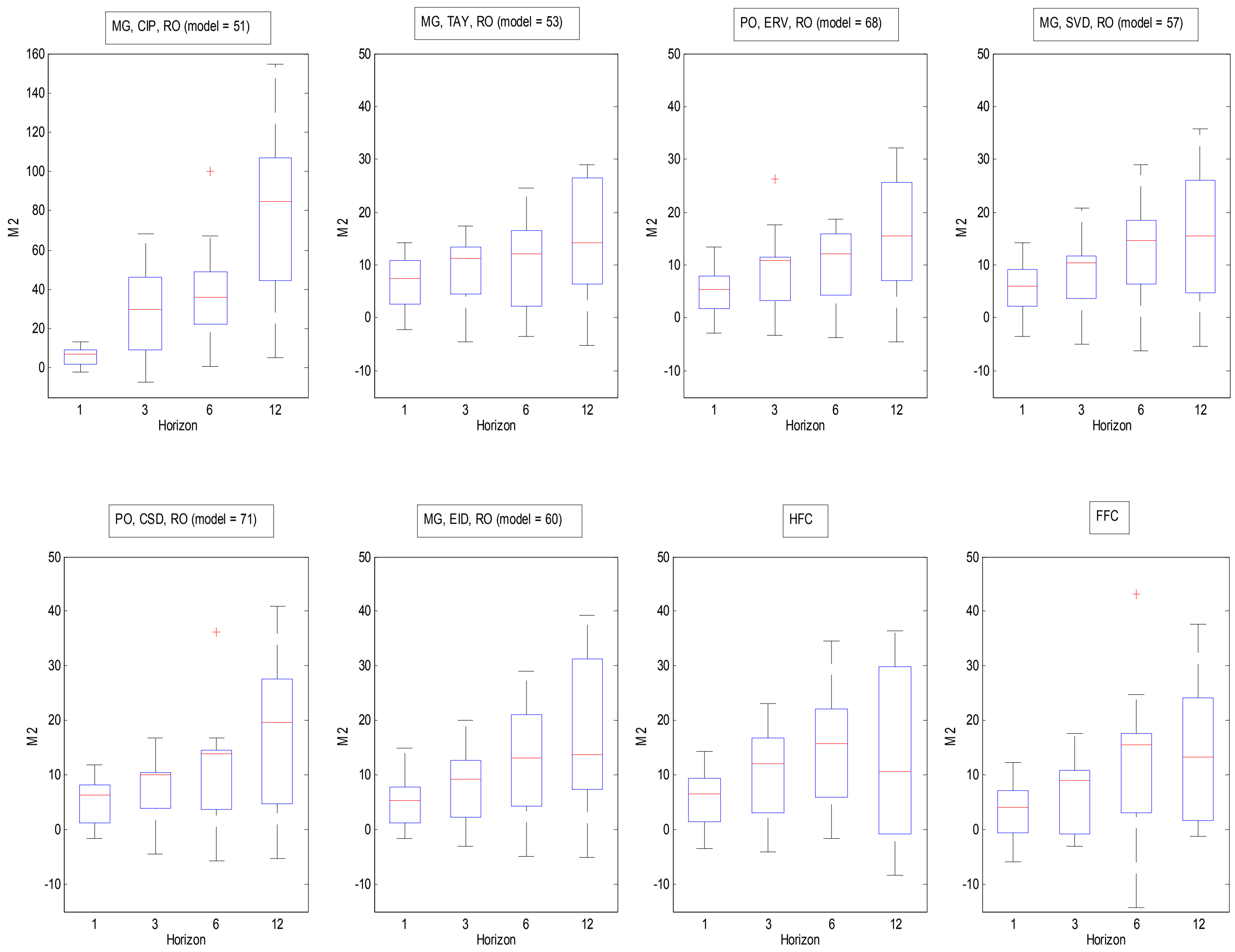

Figure 3: Histogram of models selected by the Thick Modeling Approach. The figure shows the frequency (over time and cross-section) in which a particular model=$\{1, 2, ..., 72\}$ was in the upper 25% of models with lowest RMSE according to the Thick Modeling Approach. Note: the 10 most frequently chosen models at $h = 1$ are $\{8, 11, 19, 31, 35, 44, 53, 55, 56, 67\}$, at $h = 3$ are $\{3, 11, 13, 15, 27, 35, 39, 44, 51, 63\}$, at $h = 6$ are $\{3, 11, 15, 27, 35, 39, 49, 51, 61, 63\}$ and at $h = 12$ are $\{3, 15, 27, 35, 39, 49, 51, 53, 63, 65\}$. Model descriptions can be found in Table 1.