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'Foreign currency forecasting: What can stock and bond markets tell us?'

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Foreign currency forecasting: What can stock and bond markets tell us?*

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Abstract

This paper provides a comprehensive statistical and economic evidence on the forecasting power of local-currency equity and bond returns in predicting exchange rate returns. We first construct out-of-sample (OOS) forecasts using various model specifications of equity and bond returns, and assess their statistical accuracy against the naïve random walk (RW) model. Next, we test their economic value by designing a trading strategy based on the sign of our OOS forecasts. Using a sample of 28 countries, we find three key results: (1) our in-sample forecasts show that all the slope estimates of our predictive regressions are significant, indicating that the RW model is misspecified; (2) the statistical accuracy criteria suggest that our OOS forecasts outperform the RW model; and (3) our trading strategies, that use stock and bond returns, generate high and significant Sharpe ratios which are uncorrelated with the traditional risk factors and other popular determinants of currency returns, and outperform markedly carry trade and currency momentum.

JEL classification: G15, G17, F31.

Keywords: exchange rates, out of sample predictability, equity returns, bond market returns, financial crisis

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1. Introduction

Exchange rate predictability has attracted considerable attention in the academic literature.[1] Following the seminal work of Meese and Rogoff (1983), research has found it difficult to beat the RW model for currencies. Prior research has generally focused on examining the predictive power of economic fundamentals of a country, such as inflation rate, interest rate, GDP growth rate differentials, and others (Engel *et al.*, 2007; Molodtsova and Papell, 2009; Li *et al.*, 2015).[2]

In this paper, we take a new perspective and examine the exchange rate predictability of financial market returns. More specifically, we investigate whether stock and bond market information provide not only statistical but also economic value in forecasting the exchange rate. As far as we know, this is the first paper that takes such a novel perspective in the exchange rate forecasting literature. We use monthly data spanning the period from November 1989 to December 2019 to examine a sample of 28 currency markets, which includes 10 of the most liquid currency markets amongst the developed world versus the U.S. Dollar (USD), which have been widely used in the literature (e.g. Della Corte and Tsiakas, 2012), and 18 emerging markets with wide geographical allocation and, which have adopted currently a managed floating exchange rate regime.

We assess the value of equity and bond information in currency markets using two types of analyses: statistical and economic. In our statistical analysis, we use equity and bond returns to generate n-step ahead OOS exchange rate forecasts for the currencies. We assess their statistical accuracy against competing models, such as the RW model. The question then arises whether statistical significance translates into economic benefits for investors. These forecasts are thus used to implement trading positions within a simulated investment portfolio, where investors long (short) the foreign currency if the predicted OOS return from the forecasting model is positive (negative). This trading strategy is inspired by the return chasing hypothesis, which has been confirmed empirically for both developed and emerging markets (Froot *et al.*, 2001; Griffin *et al.*,

[1] For a survey of exchange rate predictability see Rossi (2013).
[2] The predictive power of technical indicators has also been examined. For a survey, see Park and Irwin (2007) and for recent studies see Neely and Weller (2013) and Jamali and Yamani (2019).

2004; Froot and Ramadorai, 2008; Richards, 2005; Fuertes *et al.*, 2019). Theoretically, the return chasing hypothesis predicts a positive relation between exchange rate and stock return differentials in a bilateral setting, where a positive return differentials of the host foreign capital market over the U.S. capital market should be associated with an appreciation of the host foreign currency (vis-à-vis the USD). In addition to the three trading strategies mentioned above - bonds, equities, bonds and equities together, we also formulate a further trading rule by which agents can switch between using stock and bond information over time, which is consistent with the empirical evidence on the time-varying comovement between stock and bond returns within the same country (see Chordia *et al.*, 2005; Connolly *et al.*, 2005; Boyer *et al.*, 2006; Boucher and Tokpavi, 2019).

Our main results can be summarized as follows. First, our overall in-sample predictive results suggest that local-currency equity and bond returns carry significant information for the spot rate changes, indicating that the benchmark RW is misspecified. Second, we find strong evidence on the statistical power of stock and bond returns in predicting currency returns. Statistical accuracy criteria continue to suggest that our models outperform the RW model, as evidenced by the high adjusted R-squares for all our forecasting models. Third, we document the economic success of our trading rules in generating high statistical and economic average returns (net of transaction costs) for individual currencies and portfolios. Our strategies also compare favorably to carry trade and momentum strategies as attested by generating higher Sharpe ratios. Overall results also show that the combined strategies do better than individual strategies, confirming Della Corte and Tsiakas (2012) results. We subject our results to a battery of robustness tests, and we show that the significant returns generated from our trading strategies are pervasive phenomena and persist despite changing the method of forecast construction, trading rules, sample period, different numeraire currency, other than the USdollar,or conditioning on popular determinants of currency returns.

In this paper, bearing in mind the above, we contribute to the extant exchange rate literature in several important respects from both academic and practitioner perspectives. First, our work contributes to the cross–market literature. The interconnections between the various financial markets have become more complex with the increase in financial integration both domestically and internationally, rendering studies, which examined the relationship between two markets only, such as currency and stock returns (Cappiello and De Santis, 2007; Curcuru *et al.*, 2014; and Fuertes et al., 2019) as well as currency and bond returns (Uribe and Yue, 2006, Hartelius *et al.*, 2008) rather incomplete. In contrast to this separate approach which ignores cross–market effects, we take a new view by examining exchange rate predictability of stock and bond returns as well as their cross-asset relation, lending credence to the theoretical research on the interrelatedness of equity, bond and FX markets (Bansal and Dahlquist, 2000; Pavlova and Rigobon, 2007; Christiansen *et al.*, 2011).

Second, we add to the literature on exchange rate predictability. As far as we know, we provide the first evidence on the statistical power of equity and bond returns in predicting exchange rate returns in an OOS context. While the existing literature has focused its attention on examining fundamentals (Engel *et al.*, 2007; Molodtsova and Papell, 2009; Della Corte and Tsiakas, 2012; Li *et al.*, 2015) and technical indicators (Park and Irwin, 2007; Neely and Weller, 2013; Jamali and Yamani, 2019), no such exploration has been undertaken using financial market indicators.

Lastly, our evidence, that the statistical evidence of exchange rate forecasting translates to economic profits, provide important insights to the practice of currency trading. From a practitioner perspective, we show that using currency trading rules that condition on stock and bond information not only generates highly significant economic profits but also outperforms markedly carry trade and currency momentum which are popular trading strategies in the FX market (see Menkhoff *et al.*, 2012). This new evidence implies that currency traders can manage their currency portfolios more effectively when stock and bond returns are taken into account.

The remainder of the paper is organized as follows. Section 2 outlines the research design and trading strategies (i.e., economic test). Our data and variables are presented in section 3. The forecasting results and the trading strategies findings are reported in section 4. Section 5 seeks to explain our results. Section 6 reports robustness results, while section 7 concludes.

2. Research Design

In this section, we assess the value of equity and bond information in forecasting currency returns using two types of analysis: statistical and economic. Our forecasting framework is similar to the existing research on exchange rate predictability (Della Corte and Tsiakas, 2012 and Li *et al.*, 2015). We present our statistical analysis where we construct OOS forecasts using various model specifications of equity and bond returns, and then describe our economic analysis, where we investigate whether both types of information can be exploited economically to implement profitable currency trading strategies.

2.1. Predictive regressions

Our forecasting model is cast within the general framework of a predictive regression. Our focus is on using the information content of equity and bond returns in predicting currency returns using three model specifications. For notational purposes, we use variable $\chi = \{\mathrm{E}, \mathcal{B}, \mathrm{C}\}$ to refer to the three sets of predictor variables for which we construct the forecast: equity returns(E), bond returns $(\mathcal{B})$ and combined equity and bond returns(C). Denote by Δs_{it+1} the currency returns to be predicted at time t over the period t until $t+1$ which is given by spot rate changes: $\Delta s_{it+1} = \ln(S_{it+1}) - \ln(S_{it}) = s_{it+1} - s_{it}$ where S_{it} denotes the nominal exchange rate expressed in terms of the US Dollar (USD) price per unit of the foreign currency i. Given such setup, we follow the Kitchen-Sink regression approach for forecasting exchange rate returns (Welch and Goyal, 2008) that allows set of predictive variables χ to influence the value of a single forecast as follows

$$\Delta s_{it+1} = \alpha + \beta \chi_{it} + \varepsilon_{it+1}, \tag{1}$$

The first model that we consider is the 'equity-model', where we assume that the relationship between currency and equity returns is given by the following predictive regression framework

$$\Delta s_{it+1} = \alpha + \beta \mathrm{E}_{it} + \varepsilon_{it+1}, \tag{2}$$

where E_{it} is the equity based predictor set: $\mathrm{E}_{it} = \left[r_{it}^{E}, r_t^{\mathrm{E,US}}, r_t^{\mathrm{E,Global}}\right]$, where $r_t^{\mathrm{E}}, r_{it}^{\mathrm{E,US}}$ and $r_t^{\mathrm{E,Global}}$ denote, respectively, the ith foreign equity market, the return on the US equity market, and the global equity market. Theoretically, the relationship between local-currency equity returns r_{it}^{E} and spot rate changes Δs_{it+1} stems from the *return chasing hypothesis* and the *portfolio-rebalancing* *hypothesis*.[3] The inclusion of $r_t^{\mathrm{E,US}}$ is motivated by the findings of Phylaktis and Ravazzolo (2005) who emphasize that US market returns act as a conduit in linking stock and currency markets. Bearing in mind that the global equity information is the same for all currencies, which are defined with respect to the US dollar, we also include $r_t^{\mathrm{E,Global}}$ given that prior research shows that currency returns are related to global equity returns (e.g Ülkü *et al.*, 2012).[4]

Our second model is the 'bond-model'. We examine the relation between currency returns and the domestic government bond market index returns using the following predictive regression

$$\Delta s_{it+1} = \alpha + \beta \mathcal{B}_{it} + \varepsilon_{it+1}, \tag{3}$$

We use three financial variables as proxies to obtain information about the bond market: $\mathcal{B}_{it} = \left[r_{it}^{\mathcal{B}}, r_t^{\mathcal{B},US}, r_t^{\mathcal{B},\mathrm{Global}}\right]$, where $r_{it}^{\mathcal{B}}$ represents the returns on foreign markets local currency sovereign debt which is a government bond denominated in the domestic currency of the foreign issuer, $r_t^{\mathcal{B},US}$ is the return on the U.S. government bond index, and $r_t^{\mathcal{B},\mathrm{Global}}$ is the global bond returns. In theory, our analysis in Equation (3) is inspired by the Uncovered Interest Rate Parity (UIP) which states that exchange rate changes are equal to the interest rate differential between two economies under the assumptions that agents are risk-neutral and form rational expectations (see Della Corte and Tsiakas, 2012 and Li *et al.*, 2015). Another view, which has influenced our analysis, is that causality runs from the local currency bond market to the FX market because foreign investors

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[3] The return-chasing hypothesis largely derives the uncovered equity disparity phenomenon (Fuertes et al., 2019), while the portfolio-rebalancing hypothesis stems from the uncovered equity parity theory of Hau and Rey (2004, 2006), Cappiello and De Santis (2007), and Curcuru *et al.* (2014). Both hypotheses predict that the direction of the relation between equity returns and equity flows determines the sign of the relationship between equity and currency returns, but they predict a different relationship. On one hand, the return-chasing hypothesis predicts a *positive* relation because any surge in $\mathrm{r}_\mathrm{t}^\mathrm{E}$ induces foreign investors to invest in local equity markets, which, in turn, induces the local currency to appreciate (Fuertes *et al.*, 2019). On the other hand, the portfolio-rebalancing hypothesis predicts a *negative* relation because equity investors tend to reduce their FX exposure by rebalancing away from countries whose equity/FX markets are performing well (Hau and Rey, 2004, 2006; Cappiello and De Santis, 2007).

[4] One wonders whether this global equity information is a kind of dollar factor. Verdelhan (2018) investigates the dollar factor, which corresponds to the average change in the exchange rate between the U.S. dollar and all other currencies and finds it to be an important driver of exchange rates in most markets in his sample. In our robustness tests, we condition our model to the dollar factor to test the possibility that our results are not due to this dollar risk.

tend to rely on FX instruments to hedge their holdings of local currency bonds, which in turn lead the variability of the exchange rate (see, for instance, Pericoli and Taboga, 2012).

Our third forecasting model is the 'combined model', in which we form a model combining exchange rate forecast using the information content of both sets of equity variables E_{it} and bond variables $\mathcal{B}_{it}$ to test the interrelatedness of equity, bond, and FX markets, as follows[5]:

$$\Delta s_{it+1} = \alpha + \beta_2 \mathrm{E}_{it} + \beta_2 \mathcal{B}_{it} + \varepsilon_{it+1}, \tag{4}$$

Equation (4) is inspired by the theoretical models of Pavlova and Rigobon (2007) and Christiansen *et al.* (2011) which have confirmed the interconnections between the stock, bond and currency markets. Pavlova and Rigobon (2007) develop a two good asset pricing model in which the terms of trade and the exchange rate play an important role in determining the dynamics of countries' stock and bond markets generating a rich set of implications on how stock, bond, and foreign exchange (FX) markets co-move. Christiansen *et al.* (2011) take a different perspective to examine the relationship between FX, stock and bond markets. They model currency returns as an asset pricing factor model with stocks and bonds being the basic factors in which factor loadings are regime dependent on FX volatility. They further explain traditional factor models for exchange rates which are exposed to equity and bond markets (e.g. Bansal and Dahlquist, 2000).

In support, there have been empirical studies, such as Andersen *et al.* (2007) and Ehrmann *et al.* (2011), that confirm these interconnections between stock, bond and currency markets. They approach the issue, however, differently rather than developing a comprehensive model to capture all linkages. Andersen *et al.* (2007), on the one hand, use high frequency data to explore the response of US, German and British stock, bond, and FX markets to real-time US macroeconomic

[5] Equation (4) adds a different perspective to look at the relation between FX, stock and bond markets. Various econometric methodologies along the line of correlations have been employed in the literature to analyze cross market linkages such as partial bilateral correlations, GARCH models, Granger causality tests, Copula, and panel fixed-effect. Other studies model currency returns as an asset pricing model with stocks and bonds being risk factors, and the factor loadings being static (Bansal and Dahlquist, 2000) or dynamic (Christiansen *et al*., (2011) depending on FX volatility. In Equation (4), we take a different approach and approach the interrelatedness of the FX, stock and bond markets in a forecasting manner by considering the predictive cross-asset relation, rather than seeking to establish a causal/correlation relation with an integration/contagion interpretation in the strict sense, as in the previous research.

news and find that news announcements produce conditional mean jumps concluding that high-frequency stock, bond, and exchange rate dynamics are linked to fundamentals. They also pursue a generalized estimation approach that documents highly significant contemporaneous cross-market and cross-country linkages, even after controlling for macroeconomic announcement effects. Their findings generally point toward important direct spillover effects among foreign and US equity markets. Ehrmann *et al.* (2011), on the other hand, investigate the impact of monetary and other shocks on the degree of financial transmission between money, bond, equity markets and exchange rates within and between the US and the euro area. Using a structural VAR approach, they find that asset prices react strongest to monetary and other domestic asset price shocks, and that there are also substantial international spillovers, both within and across asset classes.

As a benchmark, we compare the performance of our forecasting models to the RW model with drift which has received a broad attention in the international finance literature (see Della Corte and Tsiakas, 2012 and Li *et al.*, 2015). Under the RW model, the spot exchange rate changes are not predictable since they are expected to revert to the mean α in the short run, as follows

$$\Delta s_{it+1} = \alpha + \varepsilon_{it+1}, \tag{5}$$

2.2. Statistical Evaluation of Predictability

Fitting and evaluation periods: The implementation of the OOS forecasting using models (2)-(4) is straightforward. We divide our full sample period ($t = 1$ to $t = T - 1$) into an in-sample (IS) period spanning observations $t = 1$ to $t = M$, and an OOS period spanning observations $t = M + 1$ to $t = T - 1$. This results in $P = (T - 1) - M$ out-of-sample forecasts. The IS period is employed to estimate the predictive regressions while the OOS is preserved to evaluate the statistical accuracy of the three competing models. We follow Della Corte and Tsiakas (2012) and Li *et al.* (2015) and obtain the OOS monthly forecasts using rolling regressions. More specifically, we use the first 120 monthly observations as the in-sample period – which corresponds to a ten-year time horizon – and then we roll through the rest of the OOS period using a fixed window size of 120 observations to generate rolling one-step-ahead forecasts from the competing models.

The starting date for the sample period is constrained by data availability on currency, equity and bond returns for some of our sample currencies, and therefore the starting date for the both the IS and OOS periods differs by currency. Hence, Table 1 lists the IS and OOS periods employed in these rolling regressions along with entire sample period for every individual currency.

Forecast evaluation criteria: Let $\widehat{\Delta s}^{\chi}_{t+1|t}$ refers to the individual one-month ahead exchange rate forecast constructed from the three sets of χ information up to time t. We begin assessing the statistical accuracy of our models with calculating the Mean Square Forecast Error (MSFE):

$$MSFE^{\chi} = \frac{1}{T}\sum_{t=M+1}^{T}\left(\Delta s_{t+1} - \widehat{\Delta s}^{\chi}_{t+1|t}\right)^2, \tag{6}$$

where $\left(\Delta s_{t+1} - \widehat{\Delta s}^{\chi}_{t+1|t}\right)^2$ is the rolling one-step ahead forecast errors from model χ, where $\chi = \{\mathrm{E}, \mathcal{B}, \mathrm{C}\}$. Our main goal is to examine whether there are substantial differences in the forecast performance between our three models and the RW "no-predictability" benchmark model. To do so, we employ three statistical tests of equal predictive ability. Our first test is the relative *MSFE* statistic of equal predictive accuracy used by Buncic and Piras (2016), given by

$$Relative\ MSFE\ = \frac{MSFE^{\chi}}{MSFE^{RW}}, \tag{7}$$

where $MSFE^{RW}$ is Mean Square Forecast Error from the RW (with drift) benchmark forecast. We also use the OOS R^2 which is widely used in the equity (Campbell and Thompson, 2008; Welch and Goyal, 2008; Rapach *et al.*, 2010) and the FX prediction literature (Anatolyev *et al.*, 2017; Della Corte and Tsiakas, 2012; Li *et al.*, 2015). The OOS R^2 equals

$$R^2_{oos} = 1 - \frac{MSFE^{\chi}}{MSFE^{RW}}, \tag{8}$$

In general, the lower the MSFE value the better the forecasting predictions. Hence, if the relative MSE-F statistic is any number less (higher) than one, or equivalently the OOS R^2 is positive (negative), then that means our forecasting models are expected to produce better predictions than the benchmark RW model. The third test we employ is Clark and West (CW) (2007) test of equal predictive ability which is obtained as the *t*-statistic of the following regression on a constant:

$$CW\ test\colon \hat{f}_{t+1} = \left(\Delta s_{t+1} - \widehat{\Delta s}^{RW}_{t+1|t}\right)^2 - \left[\left(\Delta s_{t+1} - \widehat{\Delta s}^{\chi}_{t+1|t}\right)^2 - \left(\widehat{\Delta s}^{RW}_{t+1|t} - \widehat{\Delta s}^{\chi}_{t+1|t}\right)^2\right] \qquad (9)$$

where $\widehat{\Delta s}^{RW}_{t+1|t}$ refers to the individual one-step ahead forecast of currency returns constructed from the RW model up to time t. A significant CW statistic, therefore, implies that the alternative competing forecasting outperforms the RW model.

2.3. Economic Evaluation of Predictability

In the second part of our analysis, we examine whether the statistical significance translates to economic benefits for investors. For that purpose, we examine whether information can be exploited to implement profitable currency trading strategies. The rationale for such test is that existing research establishes that forecast (in)accuracy need not automatically imply (lack of) profitability (Leitch and Tanner, 1991; Satchell and Timmermann, 1995).

It is thus natural to examine the profitability of currency trading based on stock and bond returns. Several authors have documented the diversification benefits of incorporating foreign stocks (e.g., DeSantis and Gerard, 1997) and foreign bonds (e.g. Levich and Thomas, 1993) in an investor international portfolio. In the backdrop of a lack of consensus regarding the empirical cross-market relationship, however, it is unclear how investors could leverage gains by investing across these asset classes. In order to elucidate our trading strategies, we build on the established approaches on exchange rate behavior which use generally a two-country framework where the relative macroeconomic, or financial variable differentials of two countries are linked to their exchange rate (see De Zwart *et al.*, 2009, Doukas and Zhang, 2013). We run our analysis from the perspective of a US-based investor[6], and employ a two-country currency trading strategy (US and

[6] The rationale for such focus is twofold. On one hand, several papers show that the US stock market acts as a channel for the relation between exchange rate movements and stock returns (Phylaktis and Ravazzolo, 2005). As noted in

a foreign country) in a world with open economies with intertemporal trade so that a country can borrow resources from the rest of the world, or invest them abroad.

The dynamic FX strategy: Our simple trading strategy is described as follows. Motivated by the evidence on the empirical failure of uncovered equity parity (Hau and Rey, 2004 and 2006; Cappiello and De Santis, 2005; Curcuru *et al.*, 2014), we design a simple bias-exploiting trading strategy, where investor trades in the spot market and goes long (short) currency i if the predicted return of currency i is positive (negative). Put differently, we condition our investment decision on trading signals based on the sign of the one-month ahead forecasts from the three empirical models we estimate. The OOS predictability-based signal can be defined as

$$Signal_t = \mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi} = \begin{cases} 1 & if \quad \widehat{\Delta s}_{t+1|t}^{\chi} > 0, \\ -1 & if \quad \widehat{\Delta s}_{t+1|t}^{\chi} < 0, \end{cases} \tag{10}$$

Where $\mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi}$ is the active position at time t conditional on the forecasts from the three sets of χ predictor variables, and it equals $+1$ or -1 for taking a long or short positions in foreign currencies, respectively. Given such setup, we calculate the dynamic return from trading currency i based on model χ's forecast Δs_{it}^{χ} as the currency return Δs_{it} multiplied by the trading signal

$$\Delta s_{it}^{\chi} = Signal_t \times spot\ rate\ changes_t = \mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi} \times \Delta s_{it} \tag{11}$$

The rationale of implementing this simple trading strategy is to examine the use of equity and bond returns as a timing signal for the currency trading when applied in real-investment portfolios. The investors condition their investment decision on the sign of our one-month ahead forecasts only. Hence, investors invest by default in the currency, but close that position when our forecasts

Hau and Rey (2006), US cross border capital mobility transactions increased significantly from 4% of GDP in 1975 to 245% by 2000, with a growing proportion consisting of equity flows. On the other hand, the U.S. entities are the largest and the most significant players in international bond markets (International Monetary Fund (2018): Table 12). Previous research finds that U.S. monetary policy had a significant influence on capital spillovers to local currency bond markets (see Uribe and Yue, 2006; Hartelius *et al.*, 2008; Albagli *et al.*, 2019). An open economy with a temporary income deficit can thus avoid sharp contraction in investment with the aid of equity and bond capital inflows from U.S. investors, who can participate in investment portfolios overseas.

predict losses from currency trading. The intuition behind such trading strategy is simple: The investor realizes a gain when the sign of the predicted currency return is the same as that of the actual return while the investor records a loss otherwise (Anatolyev *et al.*, 2017; Jamali and Yamani, 2019). As pointed out by Leitch and Tanner (1991), among others, correctly forecasting the *direction* of asset price movements is more crucial than forecasting their *magnitude* when it comes to economic forecast evaluation measures, such as the performance of trading strategies.

The key mechanism that brings about our trading strategy is the evidence, both theoretical and empirical, on the return chasing hypothesis. Theoretically, the return chasing hypothesis model predicts a positive relation between exchange rate and stock market return in a bilateral setting, where a positive return of the host foreign stock market should be associated with an appreciation of the host foreign currency (vis-à-vis the USD). Empirically, the return chasing hypothesis has been confirmed for both developed and emerging markets (Froot *et al.*, 2001; Griffin *et al.*, 2004; Froot and Ramadorai, 2008; Richards, 2005; Fuertes *et al.*, 2019).

Transaction costs: Equation (11) indicates how dynamic returns are calculated when transaction costs are not taken into account. A realistic assessment of the economic value of exchange rate predictability of our forecasting models profitability takes into account the effect of transaction costs which can diminish, or erode the profitability of a trading strategy. We account for transaction costs by calculating the net-of-transaction costs dynamic return (which we denote by $\Delta s_{it,\tau}^{\chi}$) defined as the dynamic currency return Δs_{it}^{χ} minus the proportional transaction costs τ_{it}

$$\Delta s_{it,\tau}^{\chi} = \begin{Bmatrix} \Delta s_{it}^{\chi} - \tau_{it}^{long} & if \quad \mathbb{Z}_{it}^{\chi} \middle| \widehat{\Delta s}_{t+1|t}^{\chi} = 1, \\ -\left(\Delta s_{it}^{\chi} - \tau_{it}^{short}\right) & if \quad \mathbb{Z}_{it}^{\chi} \middle| \widehat{\Delta s}_{t+1|t}^{\chi} = -1, \end{Bmatrix} \tag{12}$$

The proportional transaction cost equals $\tau_{it+1}^{long} = ln(1 + c_{it}/1 - c_{it+1})$ for long positions, and $\tau_{it+1}^{short} = ln(1 - c_{it}/1 + c_{it+1})$ for short positions, where $c_{it+1} = \left(0.5\left(S_{it+1}^{a} - S_{it+1}^{b}\right)/S_{it+1}\right)$ is the one-way proportional transaction cost and the letters b and a indicate bid and ask quotes, respectively. We follow Neely *et al.* (2009) in assuming that c_{it+1} is half of the bid-ask spread.

Therefore, the net return from buying currency i at the spot exchange rate at time t (s_{it}^{a}) and selling at time $t+1$ at the spot rate $\left(s_{it+1}^{b}\right)$ is equal to $s_{it+1}^{b} - s_{it}^{a} = r_{it} - \tau_{it}^{long}$. Similarly, the net return from selling currency i at time t and buying it at time $t+1$ at the spot rate is equal to $s_{it}^{b} - s_{it+1}^{a} = -\left(\Delta s_{it}^{\chi} - \tau_{it}^{short}\right)$. This approach to account for transaction costs has been used in several studies (Neely *et al.*, 2009; Della Corte and Tsiakas, 2012; Li *et al.*, 2015; Jamali and Yamani, 2019). We focus on the net-of-transaction costs dynamic return in Equation (12) to assess the economic value of exchange rate predictability of our forecasting models.

3. Data and Variables

Sample description: We use a panel dataset that enables us to construct monthly observations for the variables of interest per country i=1,……, N for each of $t = 1, \ldots.., T$ months. We collect data for 28 countries (i.e., the cross-section dimension is $N = 28$) from November 1989 to December 2019 (i.e., the time-series dimension is $T = 362$) (although the data availability varies by the country, see Table 1), to build three baskets of currencies – developed, emerging and global. Our sample of developed markets includes 10 of most liquid currency markets amongst the developed world versus the USD, which have been widely used in the literature (Della Corte and Tsiakas, 2012). Those are Australia, Canada, Germany/EURO, Japan, New Zealand, Norway, Switzerland, Sweden, Denmark and the UK. This way we benchmark our results against those of influential studies in the literature. Our cross-section of emerging countries includes 18 markets with wide geographical allocation and, which have currently a managed floating exchange rate regime. These are Argentina, Brazil, Chile, Colombia, Czech Republic, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippine, Poland, Romania, Singapore, South Africa, and Turkey. The global portfolio includes all the 28 currencies in the sample.[7]

[7] We have included emerging markets in our sample unlike other studies on exchange rate forecasting because of their heterogeneous response to financial variables. Compared to developed market currencies, trading in emerging market currencies exposes investors to higher transaction costs, higher idiosyncratic volatility due to threats of sudden capital account restrictions, non-convertibility of currency, as well as higher country risk because of higher inflation, higher transaction costs, more limits to arbitrage, more government intervention, and more political instability. Nevertheless, U.S. investors seeking greater yields have been showing a growing preference for emerging market currencies which

Our dataset consists of the end of month values of exchange rates, national stock and bond market indices (expressed in local currency). For each asset class, we convert all data by taking logs and multiplying by 100 to construct currency, equity, and bond return series. To examine the dynamics between currency returns, equity returns and bond returns, we express all the return data in a pooled sample in the local currency. All data are obtained from DataStream.

Currency data: We collect the WMR/Reuters spot exchange rates for our 28 currencies against the USD. The nominal spot exchange rates S_{it} are expressed in terms of the USD per unit of the foreign currency. Data on the Euro spot rates are not available prior to January 1999. To extend the Euro spot data backwards to December 1996 (which is the starting date of our forecasting sample), we splice the Euro with Deutsche Mark spot and forwards using the fixed conversion rate of January 1999. The latter approach to extending the EUR data backwards is commonly employed in existing studies (Anatolyev *et al*., 2017; Della Corte and Tsiakas, 2012).

Equity and bond data: Besides using currency returns, we also consider stock and bond index returns that represent broad price movements in each market. For country-level equity index returns ($r_t^{E,US}$and r_{it}^{E}), we use the Datastream global equity indices. For country-level bond index returns ($r_t^{\mathcal{B},US}$ and $r_{it}^{\mathcal{B}}$), we employ government bond index returns which represent the returns on the safest asset in a country. We measure bond returns for the developed markets using the five-year Datastream government bond indices, while we base our bond returns for the emerging markets on the JPMorgan Government Bond Index-Emerging Markets (GBI-EM) Broad which is a comprehensive global local Emerging Markets index that tracks local currency bonds issued by Emerging market governments. We use the Morgan Stanley Capital International (MSCI) world stock market index to control for global stock returns ($r_t^{\mathrm{E,Global}}$), and the Citibank world government bond index (WGBI) to control for world bond returns ($r_t^{\mathcal{B},\mathrm{Global}}$).

4. Results

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appear to provide better profit opportunities because they have lower turnover (Bank of International Settlements, 2016), lesser competition among traders and more easily-identified trends (Frankel and Poonawala, 2010). Furthermore, portfolio debt and equity flows to emerging economies have continued to develop and become global asset classes, and they are closely monitored by financial market participants and international policy makers alike.

4.1. Statistical Evaluation Results

In-Sample Predictability: A natural starting point for our predictability analysis is that we examine first the estimation results of our in-sample predictive regressions. The regressions include the 'Equity' model as defined in (2), the 'Bond' model as defined in (3), and the combined model as defined in (4). Table 2 summarizes the coefficient estimates of these models with Newey and West (1987) standard errors. If the RW holds, all estimates should be insignificantly different from zero. In contrast, positive (negative) beta indicates that currencies whose stock and/or bond index returns are high (low) tend to appreciate (depreciate), which contradicts the RW model, which states that exchange rates are unpredictable. Note that an increase in exchange rate means an appreciation of the foreign currency. Our tables are organized in three panels, with each panel corresponding to different sample of currencies. Panel A reports the results for the 10 developed currencies; Panel B reports the results for the 18 emerging currencies; and Panel C presents the results for three equally weighted portfolios (developed, emerging and global). This will enable us to make comparative remarks between developed and emerging market portfolios.

Several interesting findings stand out from our empirical exercise in Table 2. First, the equity-model results (Equation 2) show that local-currency stock index returns are negatively related to the spot rate changes for both developed and emerging market currencies. In panel A, we find that almost all the r_{it}^{E} coefficients are significantly negative in the equity model. In panel B, the overall negative r_{it}^{E} coefficients show that the inclusion of the emerging market currencies makes almost no difference and does not change the interpretation of the findings. A similar finding is observed in panel C. Second, the bond-model results (Equation 3) show that the expected spot rate changes appear to be predictable with bond returns. We find a significant negative relation between local-currency bond returns r_{it}^{B} and expected spot rate changes for all the ten developed currencies (panel A), but the relation becomes significantly positive when emerging currencies are employed (panel B). Third, it is also notable that such statistical significance in both r_{it}^{E} and r_{it}^{B} coefficients remains when we use the combined model which expands the equity model to also include the bond variables. In support, the R^2 values are high for all models and are the highest for the combined model. Furthermore, the results show that $r_t^{\mathrm{E,Global}}$ and $r_t^{\mathcal{B},\mathrm{Global}}$ carry significant information for the spot rate changes for both developed and emerging market currencies.

In a nutshell, our overall in-sample predictive results suggest that local-currency equity and bond returns carry significant information for the spot rate changes, a finding that motivates our exercise on the OOS forecasting power of equity and bond returns in predicting currency returns.

Out-of-Sample Predictability: Table 3 reports the results of a comprehensive set of statistical forecast accuracy criteria for evaluating the one-month ahead OOS forecasts for the equity, bond and combined empirical exchange rate models. The forecast accuracy measures include the MSFEs as defined in (6), the MSFEs relative to the RW benchmark as defined in (7), the OOS R^2 as defined in (8), and the Clark and West (2007) test of equal predictive ability as defined in (9). In order to interpret the statistical significance of the differences in the forecast performance between our three models and the RW benchmark model, a model with a relative MSEF statistic of less (more) than one, a positive (negative) R_{oos}^2, and a significant (insignificant) Clark and West (2007) t-statistic indicates that the competing model outperforms (underperforms) the RW model.

In Table 3, it is evident that the equity, bond and combined forecasts produce lower MSFEs than the benchmark RW model, as shown by our finding that the values of the Relative-MSFEs corresponding to the various models, are consistently less than one, and hence generating positive and high OOS R^2 values. Furthermore, the Clark and West (2007) statistics reject the null of equal predictive ability between our three predictive models and the benchmark RW with drift at the 1% level for all currencies. It is notable that the combined model forecasts as a whole perform better than equity and bond forecasts, as evidenced by producing the smallest MSFEs.

To understand how such statistical results, translate into visual evidence, Figure 1 plots the individual one-step ahead forecast of currency returns constructed from both the combined model and the benchmark RW model, alongside with the actual spot rate changes. Figure 1 provides a visual illustration of the success of our rolling forecasts in predicting actual spot rate changes. The time series fluctuations show that the combined model forecasts and the actual spot rate changes almost coincide together overtime, while the RW forecasts show a mean reversion pattern.

Taken together, the results in Table 3 and the visual assessment in Figure 1 contribute to the literature on the exchange rate predictability by providing the first evidence on the statistical power of equity and bond returns in predicting exchange rate returns. While the existing literature has focused its attention on examining fundamentals (Molodtsova and Papell, 2009; Della Corte and Tsiakas, 2012; Li *et al.*, 2015) and technical indicators (Park and Irwin, 2007; Jamali and Yamani, 2019), no such exploration has been undertaken for predictors based on financial markets.

4.2. Economic Evaluation Results

Turning now to examining the central idea in our analysis, we extend our statistical analysis to the use of economic criteria. As noted in Della Corte *et al.* (2009), the statistical evidence of exchange rate forecasting does not necessarily guarantee economic profits. Table 4 reports profitability measures for our three FX long-short trading strategies (equity, bond, and combined) which are all conditional on the one-month ahead forecasts generated from our predictive regression in Equations (2) - (4). The key mechanism that characterizes our strategies is defined in (10) where an investor trades in the spot market and goes long (short) in currency i if its predicted return is positive (negative). We examine the null hypothesis that our trading rules do not generate statistically significant profits. For each strategy, we thus report the monthly % mean (μ), % volatility(σ), skewness (γ), and kurtosis (K). Further, we report two measures of risk-adjusted returns: the Sharpe ratio (SR, the ratio of net monthly return to monthly standard deviation) and the Sortino ratio (SO, the ratio of net monthly return to monthly standard deviation of only the negative returns). Unlike the SR, the SO differentiates between 'up' and 'down' volatility. A large SO thus implies a low risk of large losses. We also report the Sharpe ratio of the RW model (SR_{RW}) to compare it with the Sharpe ratios of the competing models.

Consider first the economic evaluation for bilateral currency pairs against the USD. Overall, our results in Panels A and B provide consistent results and clearly indicate the economic success of our three trading rules in predicting individual currency returns. It is notable that our three strategies have several appealing diversification characteristics for currency traders. In terms of payoffs, the three strategies consistently yield a high statistical and economic average returns (net of transaction costs) in all currencies. It is also notable that our strategies perform well in terms of risk-adjusted returns as evidenced by rendering a high and positive Sharpe ratios. It is further evident that our three strategies compare favorably to the benchmark RW returns as attested by generating higher Sharpe ratios compared to those of the RW model (SR_{RW}). Moreover, the large values of the SR suggest that the profitability of our trading rules are associated with low risk of large losses. In support, the returns on our strategies exhibit positive skewness, suggesting that they are relatively stable during market crashes. This may be an appealing characteristic for investors who are concerned about higher moments beyond mean and variance. The sizeable number of currencies for which our indicators generate positive net-of-transaction cost returns is indicative of the success of our trading rules in generating economic profits.

For completeness, we take our trading strategies to the portfolio-level data to ensure the robustness of our results in a cross section of currencies. In Panel C, we combine individual currencies in an equally weighted portfolio to yield a return $r_{t,\tau}^{\chi}$ calculated simply as average net-of-transaction costs return on individual currencies $r_{it,\tau}^{\chi}$ (i.e., $r_{t,\tau}^{\chi} = {}^{1}\!/_{n_t} \sum_{i \epsilon \rho \Omega_t} r_{it,\tau}^{\chi}$) where Ω_t is the set of available currencies at time t, and $n_t$is the number of currencies in Ω_t at time t. For comparison, we also report the performance measures for three benchmark portfolios: RW, momentum, and carry trade portfolios. The first benchmark portfolio that we consider is the RW with drift model that is conditional on the one-month ahead forecasts generated by rolling regressions of Equation (1) that sets $\beta = 0$ (i.e., Δs_{it+1}=α+ε_{t+1}, as defined in Equation 5). We also form momentum (carry trade) portfolio, and sort currencies into five portfolios based on their lagged one-month return (interest rate)[8] and then rank them from small to large lagged returns (lagged interest rate) (Menkhoff *et al.*, 2012). The momentum portfolio goes long in the ''winner'' portfolio (the top portfolio with the highest lagged return), and goes short in the ''loser'' portfolio

[8] Data for interest rates are obtained directly from Verdelhan website. We exclude Argentina, Brazil, Chile, Colombia and Peru) (from the emerging sample) when forming the carry trade portfolios due the unavailability of interest rate data from Verdelhan website.

(the bottom portfolio with the lowest lagged return). Similarly, the carry trade portfolio goes long (short) in the top (bottom) portfolio with the highest (lowest) lagged interest rate.

Our overall results show that our exchange rate strategies outperform all the benchmark portfolios. The Equity-based strategy has average monthly payoffs of 1.82%, 1.46% and 1.49% (compared to 1.81%, 1.60% and 1.51% for the bond-based strategy) for developed, emerging and global portfolios, respectively. Our combined strategy also performs well as evidenced by generating positive and statistically significant monthly returns of 1.82%, 1.61% and 1.52% for the developed, emerging, and global portfolio, respectively. Furthermore, our trading strategies produce higher Sharpe and Sortino ratios than the three benchmark portfolios. In comparison, the benchmark portfolios are not profitable, except the carry trade portfolio. It is also notable that all our strategies in all portfolios exhibit positive skewness suggesting that they are relatively stable during market crashes. This is not the case with some of the benchmark portfolios.[9]

In short, therefore, our empirical evidence allows us to conclude that our trading strategies outperforms the RW on a country and portfolio level.

5. Understanding the results

5.1. Carry and Dollar risk factors

The results in Table 3 and 4 show that our strategies deliver high statistical and economic average returns. A natural question to ask is whether systematic risk plays a role for these abnormal returns. To address this question, we explore whether risk factors can explain our abnormal returns. We explore whether the *Dollar* and *Carry* risk factors (which are found to be successful in pricing the bilateral exchange rates in Verdelhan (2018)) can explain our abnormal returns. In order to explore that, we expand our predictive regressions in Equations (2) - (4), to include also the *Dollar* and $Carry$ risk factors. Finding that statistical significance of stock and bond variables disappears

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[9] Interestingly, our overall results in Table 4 show that the implementation of the three strategies lead to very similar mean returns in the order of magnitude. Bearing in mind that our trading strategies yield a return calculated as the actual spot rate changes multiplied by a timing signal (defined in Equation 10) based on the sign of the one-month ahead forecasts from the empirical models we estimate, such similarity in mean returns thus indicates that our trading strategies provide very consistent signals for the currency trading.

when we use such expanded specification of our models would imply that systematic risk (proxied by the two risk factors) drives the profitability of our strategies. Table 1A in Appendix A of the SSRN online paper reports the results from such expanded specification of our predictive models (i.e., with the same stock and bond variables, but augmented by the $Dollar$ and $Carry$ risk factors).[10] We observe that the statistical significance of stock and bond variables remains when we expand our base models to include the two risk factors. This finding implies that currency risk factors, albeit significant, do not drive the profitability of our strategies.

5.2. Global equity volatility risk

Global equity volatility risk has been found to impact the relationship between international equity returns and currency returns (e.g. Cenedese *et al.*, 2016). Hence, we now perform the same analysis as above but this time we augment our predictive regression in Equations (2) - (4) to include global equity volatility risk.[11] Table 2A in Appendix A examines the relative importance of VIX data versus stock and bond returns in predicting currency returns by reporting predictive regression results similar to those in Table 2, but augmented by the VIX factor. Looking over the overall results in Table 2A, it is evident that they are in line with those reported in Table 2, in the sense that stock and bond variables appear to be appealing predictors of currency returns even after controlling for VIX. Hence, there is no evidence that VIX is able to account for our returns.

5.3. Business cycle effects

[10] The *Dollar* factor is constructed as the average spot rate changes on several currencies, while the $Carry$ factor is generated by sorting currencies based on their forward discount. Data for both risk factors are obtained directly from Verdelhan website. It is important to note that the sign of the coefficients in Table 5 should be interpreted with caution, given that Verdelhan defines the exchange rate in units of foreign currency per USD.

[11] For robustness, we follow Ang *et al.* (2006) and Cenedese *et al.* (2016) and use three alternative measures of global equity risk: (a) volatility changes, defined as the monthly change in the values of the VIX index, an index of the implied volatility of the US equity market; (b) volatility shocks, measured by regressing VIX_t on VIX_{t-1} and then retrieving the residuals which are the unexpected component of VIX; and (c) volatility innovations, measured by first-differencing the VIX time series and then retrieving the residuals. The results from the three measures are similar and, therefore, we only report the results using the first measure to save space. The data for VIX are obtained from the Federal Reserve Bank economic database (FRED).

We also examine whether the profitability of our strategies can be explained by relying on their covariance with macroeconomic variables. Colacito *et al.* (2020) use the cross-sectional properties of currency returns to provide evidence on the relationship between currency returns and country-level macroeconomic conditions, measured by the business cycle which constitutes a key building block in theoretical models of exchange rates. They find that business cycles are key driver and powerful predictor of currency returns in the cross-section. Hence, we augment our predictive regressions in Equations (2) - (4) by the logarithmic values of the monthly changes of the industrial production (IP).[12] Following Colacito *et al.* (2020), we use IP data to measure output gap as a proxy of the business cycle. The results are reported in Table 3A in Appendix A. Again, looking across stock and bond coefficient estimates, results continue to show that stock and bond returns continue to be significant determinants of currency returns. As it can be seen that there is basically no additional explanatory power, in the sense that we show that IP is not a useful predictor of future currency returns and that a change in IP does not explain our findings.

For completeness, Table 5 reports the time-series regression estimates of our OOS returns (generated from long-short trading rules based on rolling one-month-ahead forecasts using the equity, bond and combined models) on $Dollar$, $Carry$, VIX, and IP factors. A similar regression has been done by Menkhoff *et al.* (2012) to explain currency momentum returns. Once again, the results in Table 5 reveal that our returns are not primarily driven by risk factors, as attested by several findings. First, the alphas are fairly high and significant at 1% level in all regressions. Second, there is little evidence that exposure to these factors is able to account for our abnormal returns. Third, the R-squares are small in all regressions across Table 5.

5.4. Multicollinearity

It is important to note that we acknowledge that our aforementioned results may be interpreted subject to multicollinearity caveat due to the possible correlation between our various explanatory

[12] We obtain IP data from the IMF data bank (https://data.imf.org/regular.aspx?key=61545849). We exclude Australia, New Zealand, Switzerland, Argentina and Singapore due the unavailability of IP data at the monthly level.

variables, justifying the importance of further assessing whether our results in Tables 2, 3 and 4 are driven my multicollinearity. To address potential multicollinearity, we run two sets of tests.

In our first test, we examine whether our predictive results (reported in Table 2) are driven by multicollinearity by estimating four alternative specifications of our equity-predictive model defined in Equation (2) ($\Delta s_{it+1} = \alpha + \beta \mathrm{E}_{it} + \varepsilon_{it+1}$) that differ in the set of predictor variables. In the first specification, we regress spot rate changes on local-currency equity returns r_{it}^{E} only without any control variables. The second model expands the first specification to also include the return on the U.S. equity market $r_t^{E,US}$. The third model expands the second specification to include all three right-hand side controls in Equation (2) $\left[r_{US,t}^{\mathrm{E}}, r_{it}^{\mathrm{E}}, r_t^{\mathrm{E,Global}}\right]$. In the last model, we use return differentials between the U.S. and local stock markets ($r_{it}^{E} - r_t^{\mathrm{E,US}}$).

Table 6 report the results of these four predictive models. In the first specification, we do find that all the regression coefficients are significantly positive. Such statistical significance remains positive when we use a second specification which expands the first specification to also include the return on the US equity market. These findings are in line with the previous research on return chasing hypothesis which predict a positive relationship between local-currency equity returns and currency returns (Kim, 2011; Cho *et al.*, 2016; Fuertes *et al.*, 2019). Interestingly, such association becomes negative when we expand the second specification to include all our three right-hand side controls in Equation (2). Thus, conditional on controlling for global equity returns, local currency depreciation follows a bullish local stock market, a finding which is more consistent with the portfolio-rebalancing hypothesis (Curcuru *et al.*, 2014). However, such statistical significance mostly disappears in our last model when we follow Cenedese *et al.* (2016) and use *return differentials* between the U.S. and local stock markets, rather than using local-currency equity returns (as in the first three models). This finding is consistent with the evidence reported by Cenedese *et al.* (2016) who find no relation between equity return differentials and currency returns. In sum, these results may help in reconciling several mixed results in the literature, providing a unified framework, which relates currencies to their corresponding local-currency equity markets, through careful attention to model specification.

In our second test, we examine whether our statistical and economic results (reported in Tables 3 and 4, respectively) are driven by multicollinearity. To this end, we estimate four different predictive combined models, that differ in the set of predictor variables: (1) r_{it}^{E} and $r_{it}^{\mathcal{B}}$ (Model 1); (2) $r_t^{\text{E,Global}}$ and $r_t^{\mathcal{B}\text{,Global}}$ (Model 2) ; (3) $(r_{it}^{E} - r_t^{\text{E,Global}})$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B}\text{,Global}})$ (Model 3); and $r_{it}^{E}, (r_{it}^{E} - r_t^{\text{E,Global}})$, $r_{it}^{\mathcal{B}}$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B}\text{,Global}})$ (Model 4). The statistical and economic results are reported in Tables 7 and 8, respectively. The overall results in Table 7 are analogue to Table 3 for our baseline model, suggesting that all four forecasting models are able to predict exchange rate returns as evidenced by the three predictability signals (i.e., the Relative-MSFEs are less than one; the OOS R^2 values are positive; and the Clark and West (2007) MSFE adjusted t-statistics are significant at 1% level). Moreover, the economic results in Table 8 are analogue to Table 4, indicating that our long-short trading rule performs well across all our four proposed models as evidenced by the high net average returns and high Sharpe ratios in all currencies.

5.5. Time variation in forecast performance – subsample analysis

Next, we are interested in examining the stability of currency returns generated from our strategies over time. Our goal is to examine whether our results are driven by certain periods in our entire sample period. We thus extend our analysis further and re-examine the statistical and economic performance of our forecasts over different sub-sample periods to evaluate the time-varying stability of our forecasts. The choice of the length of each sub-sample period is triggered by the length of the OOS period.[13] The OOS rolling forecasting exercise generates 242 forecasts, where the first OOS forecast is for November 1999 and the last forecast is for December 2019. Hence, we examine three equal sub-periods so that each sub-period corresponds to 80 months in length as follows: (1) the first sub-period covers the period from January 2000 to August 2006; (2) the second sub-period covers the period from September 2006 to April 2013[14]; and (3) the third

[13] Our OOS monthly forecasts obtained from rolling and recursive regressions are very similar and, therefore, we focus on the rolling regressions results The results for the recursive regressions are available upon request.

[14] Note that the second period covers the period surrounding the 2008 financial crisis. It will be interesting to see whether our findings in normal times generalize to crises times, given that the crisis has led to an unexpected sharp appreciation of the USD against all currencies after a period of extreme weakness (Fatum and Yamamoto, 2016).

sub-period is from May 2013 to December 2019 (i.e., our last 80 forecasts).[15] The results are not reported here but, but they can be accessed in Appendix B Tables 1B (statistical results) and 2B (economic results) of the SSRN online paper.

The statistical results in Table 1B (that is the analogue to Table 3 for the full sample period) continue to support the ability of our forecasting models to predict exchange rate returns for all three sub-periods as evidenced by the three predictability signals (i.e., the Relative-MSFEs are less than one; the OOS R^2 values are positive; and the Clark and West (2007) MSFE adjusted t-statistics are statistically significant at 1% level). Similarly, the economic results in Table 2B (that is the analogue to Table 4 for the full sample period) show that our three strategies perform well across the three subsample periods as evidenced by the high average returns (net of transaction costs), and high Sharpe ratios in all currencies. Interestingly, our strategies are profitable during the second sub-sample period, albeit to a lesser extent, which covers the global financial crisis period.

Summarizing this subsection, our subperiod analysis documents the time varying *stability* of our forecasts, in particular for the developed market currencies, where the availability of data has allowed us to do the analysis for all three sub-periods. We have shown in our analysis that stock and bond markets have predictive information for currency market for a relatively large number of countries, and for a long period even during the turbulent time of the GFC.[16]

6. Robustness analyses

In this section, we consider a rich set of robustness checks including different predictive model specifications to control for the choice of numeraire currency, a different method of forecast construction, and different trading rules.

[15] We require a country to have at least one year of OOS forecasts (i.e., 12 observations) in any sub-period to be included in our sub-sample period analysis We were able to perform the exercise for all the developed market currencies. However, this was more challenging for the emerging currencies. For all the emerging market currencies, it was not possible to estimate the first sub-period and for a few countries in the second sub-period as well.

[16] This finding contrasts with the findings by Rossi (2013) who in surveying the literature on exchange rate forecasting find that "the predictability of fundamentals varies not only across countries, models and predictors but also over time. None of the predictors, models, or tests systematically finds empirical support or superior exchange rate forecasting ability across all countries and time periods. When predictability appears typically it does so occasionally for some countries and for short periods of time".

6.1. Alternative numeraire currency – Euro

So far, we have taken the perspective of a US-based investor to provide a statistical and economic evidence on the forecasting power of equity and bond returns in predicting exchange rate returns. For robustness, we also run our statistical and economic analyses for an European investor. More specifically, we collect the WMR/Reuters spot exchange rates for 10 developed market currencies (Australia, Canada, Japan, New Zealand, Norway, Switzerland, Sweden, Denmark, UK and the US) against the Euro, so that the nominal spot exchange rates S_{it} are expressed in terms of the Euros per unit of the foreign currency. Furthermore, we replace $r_t^{\mathrm{E},US}$ and $r_t^{\mathcal{B},US}$ in our predictive regressions (2) and (3) with the return on Dutch equity and government bond markets, respectively, and we also convert $r_t^{\mathrm{E,Global}}$ and $r_t^{\mathcal{B},\mathrm{Global}}$ data such that they are quoted against Euro. Results are shown in Tables 9 and 10 for statistical and economic results, respectively. It can be seen that statistical results in Table 9 are basically unchanged relative to the benchmark results reported in Table 3. It is also notable in Table 10 that changing the numeraire currency has no effect on the profitability of our trading strategies. Hence, the forecasting power of equity and bond returns in predicting exchange rate returns is not a US dollar phenomenon.

6.2. Alternative forecasting methodology – recursive regressions

Once again, we test the robustness of the statistical and economic results reported in Tables 3 and 4, respectively, by using recursive regressions based on Della Corte and Tsiakas (2012) to obtain the OOS monthly forecasts. We generate forecasts using recursive regressions that initially use the first 120 monthly observations (i.e., the same first 10-year window) as the in-sample period for every individual currency and then re-estimate the model parameters every time a new monthly observation is added to the sample. The results are surpassed to save space, but they can be accessed in Appendix C Tables 1C (statistical results) and 2C (economic results) of the SSRN online paper. The overall findings in Table 1C are in line with those reported in Table 3, and continue to support the ability of our forecasting models in predicting exchange rate returns as attested by three findings: (1) the Relative-MSFEs corresponding to the three models, are less than one; (2) the OOS R^2 values are high and positive; and (3) the Clark and West (2007) MSFE adjusted t-statistics are statistically significant at 1% level. These findings are robust for bilateral exchange rates in Panels A and B and for equally weighted portfolios in panel C. Furthermore, our empirical evidence in Table 2C continues to show that our trading strategies are profitable. In summary, both rolling and recursive regressions provide consistent results and corroborate the in-sample estimation results in that, for the equity, bond, and combined models outperform markedly the benchmark RW model for the developed and emerging market currencies.

6.3. Alternative trading rules

To further assess the robustness of our economic results, we propose two alternative FX trading rules. First, we propose a long-only trading rule which takes no position in the currency instead of short position, as follows

$$Signal_t = \mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi} = \begin{cases} 1 & if \quad \widehat{\Delta s}_{t+1|t}^{\chi} > 0, \\ 0 & if \quad \widehat{\Delta s}_{t+1|t}^{\chi} < 0, \end{cases} \tag{16}$$

Where $\mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi}$ is the active position at time t conditional on the forecasts from the three sets of χ predictor variables, and it equals $+1$ or 0 for taking a long or no positions in foreign currencies, respectively. We then recalculate dynamic returns as defined in Equation 11 ($\Delta s_{it}^{\chi} = \mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi} \times \Delta s_{it}$). In contrast to the long-short trading rule that we implement in Equation (12), the long only trading rule in Equation (16) recommends taking no position in the currency (instead of short position) if the predicted return of currency i is negative. This alternative trading rule is less aggressive given that it is not designed to benefit from negative returns. A similar trading rule has been used by Egbers and Swinkels (2015). Results are reported in Appendix D Table 1D of the SSRN online paper, and they are consistent with those reported in Table 4, and continue to support the ability of our models in generating OOS profits.

For completeness, we also formulate a time varying combined model defined as the *'The Heterogeneous Agent-based strategy'* (henceforth, simply HA). In contrast to the naïve combined strategy described in Equation (4) where traders put equal value on equity and bond information, for robustness, the HA strategy assumes that agents can switch between using stock and bond information over time using relative weights assigned to equity and bond signals based on their past performance.[17] More specifically, our HA strategy requires an investor to take two steps in every period t. First, she uses predictive regressions (2) and (3) to forecast the one-month ahead exchange rate returns conditional on equity and bond returns, respectively. Second, she forms a portfolio by placing dynamic weights on stock and bonds trading rules where the relative weights assigned to stock and bonds signals vary over time based on the last period profit. More specifically, the weight given to the stock trading rule (w_t^{E}) increases relative to the weight given to the bond trading rule $\left(w_t^{\mathcal{B}}\right)$ when the last period currency return conditional on equity return $\left(r_{it-1,\tau}^{\mathrm{E}}\right)$ increases relative to the last period currency return conditional on bond return$\left(r_{it-1,\tau}^{\mathcal{B}}\right)$, and vice versa. This procedure can be specified as

$$w_t^{\mathrm{E}} = \frac{\exp\left(\delta r_{it-1,\tau}^{\mathrm{E}}\right)}{\exp\left(\delta r_{it-1,\tau}^{\mathrm{E}}\right) + \exp\left(\delta r_{it-1,\tau}^{\mathcal{B}}\right)} \tag{13}$$

$$w_t^{\mathcal{B}} = \frac{\exp\left(\delta r_{it-1,\tau}^{\mathcal{B}}\right)}{\exp\left(\delta r_{it-1,\tau}^{\mathrm{E}}\right) + \exp\left(\delta r_{it-1,\tau}^{\mathcal{B}}\right)} = 1 - w_t^{\mathrm{E}} \tag{14}$$

The parameter δ measures the intensity with which agents switch the weights from stock to bond. The realized return on the investor's portfolio (which we denote by $\Delta s_{it,\tau}^{HA}$) is then computed as

$$\Delta s_{it,\tau}^{HA} = w_t^{\mathrm{E}} r_{it,\tau}^{\mathrm{E}} + w_t^{\mathcal{B}} r_{it,\tau}^{\mathcal{B}} \tag{15}$$

[17] The heterogeneous agent modeling approach is well suited for our purposes because it allows investors to switch from 'equity traders' to 'bond traders', depending on changing market conditions. The HA strategy is inspired by the literature on heterogeneous agent models (Grauwe and Grimaldi, 2006; De Zwart *et al.*, 2009; Buncic and Piras, 2016) suggesting that agents switch their behavior over time to the more profitable strategy. For example, De Zwart *et al.* (2009) consider a combined investment strategy with dynamic weights placed on fundamental and technical information. Further, Buncic and Piras (2016) use an empirical heterogeneous agent model to combine OOS exchange rate forecasts using fundamentalist and technical signals.

The HA strategy optimally combines forecasts of equity and bond returns. The rationale for using the dynamic weighting is based on the idea that a naïve combination of stock and bond in an equally weighted portfolio (i.e., $\delta = 0$) does not seem to add sufficient value for an investor during times of turbulence when the risky equity investment appears less attractive, since traders would have no reason to close their eyes to stock crashes during times of stress and to equal-weight stock and bond signals. This idea is consistent with the empirical evidence on the time-varying comovement between stock and bond returns within the same country (see Chordia *et al.*, 2005; Connolly *et al.*, 2005; Boyer *et al.*, 2006; Li *et al.*, 2015; Boucher and Tokpavi, 2019). In times of financial stress, bond and stock market returns of the same country become negatively correlated if investors engage in a "flight to quality" by substituting safer government bonds for their risky stocks. In contrast, bond and stock returns become positively correlated if there is a capital flight from the country and international investors withdraw capital from both equity and bond markets.

Results for the HA strategy are reported in Appendix D Table 2D of the SSRN online paper. The figures in Table 2D are based on a particular switching parameter $\delta = 50$ that represents the maximum 'aggressiveness' of the dynamic weights on both stock and bonds trading rules, as defined in (13) and (14), respectively. Once again, results are similar to those reported for the combined model in Table 4, supporting the ability of our models in generating OOS profits.

7. Conclusion

In this study, we have used a novel approach to exchange rate forecasting. Inspired by the theoretical and empirical studies which show the importance of the interrelationships of stock, bond, and foreign exchange markets, we test whether there is statistical and economic value in the information emanating from these markets separately, and combined to take account of the cross-asset relations, for forecasting exchange rates. Our sample, consists of 28 markets, which includes both developed and emerging in order to confirm the robustness of our findings and covers a long period from November 1989 to December 2019, using monthly data.

We focus on OOS exchange rate forecasts and assess their statistical accuracy against the RW model (with a drift). The question then arises whether statistical significance translates into economic benefits for investors. These forecasts are used to implement trading positions within a simulated investment portfolio, where investors long (short) the foreign currency if the predicted OOS return from the forecasting model is positive (negative). This trading strategy is inspired by the return chasing hypothesis, which has been confirmed empirically for both developed and emerging markets. In addition to the three trading strategies mentioned above - bonds, equities, bonds and equities together, we formulate a trading rule by which agents can switch between using stock and bond information over time, which is consistent with the empirical evidence on the time-varying comovement between stock and bond returns within the same country. We check the robustness of our analysis, by evaluating the time-varying stability of our forecasts by dividing our sample period into three equal sub-periods.

Our main results are: (i) our OOS forecasts show that all the slope estimates of our predictive regressions are significant, indicating that the RW benchmark is misspecified. Furthermore, the adjusted R-square is high for all the models and is highest for the combined model. Statistical accuracy criteria continue to suggest that our empirical models outperform the benchmark RW model; (ii) our four strategies yield high statistical and economic average returns (net of transaction costs), and they outperform the benchmark RW model, as shown by the higher Sharp Ratios; (iii) similar results are obtained when assessing the profitability of our trading strategies at the portfolio level not only against the RW portfolio but also against the momentum and carry trade portfolios; (iv) it seems that combined strategies do better than individual strategies confirming Della Corte and Tsiakas (2012) results; (v) there is no difference in our results between developed and emerging markets; and (vi) Our results seem to be robust to a different a method of forecast construction, and time periods. We further show that there is little evidence that dollar and carry risk factors proposed by Verdelhan (2018), equity volatility (Cenedese *et al.*, 2016), and standard business cycle variables (Colacito *et al.*, 2020) help to account for our findings.

In summary, our analysis shows that there is statistical and economic value in stock and bond market information for forecasting foreign currency returns, and the abnormal returns generated from our trading strategies are pervasive phenomena that persist despite changing the forecasting method, the choice of numeraire currency, the trading strategy, the sample period, or conditioning our models on global risk factors, such as carry and dollar risk factors, global equity volatility risk and business cycles effects. This could be exploited by investors in their investment strategies.

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TABLE 1. Sample description

	Panel A. Developed Market Currencies									
	Equity Model Sample					Bond Model Sample				
	Beg. date	End date	Obs.	IS Obs.	OOS	Beg. date	End date	Obs.	IS Obs.	OOS
Australia	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
Canada	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
Denmark	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
Germany	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
Japan	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
New Zealand	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
Norway	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
Sweden	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
Switzerland	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
UK	11/30/1989	12/31/2019	362	120	242	11/30/1989	12/31/2019	362	120	242
	Panel B. Emerging Market Currencies									
	Beg. date	End date	Obs.	IS Obs.	OOS	Beg. date	End date	Obs.	IS Obs.	OOS
Argentina	12/31/1990	12/31/2019	349	120	229	8/31/2007	12/31/2019	149	120	29
Brazil	8/31/1994	12/31/2019	305	120	185	2/28/2002	12/31/2019	215	120	95
Chile	12/31/1990	12/31/2019	349	120	229	12/31/2002	12/31/2019	205	120	85
Colombia	1/31/1994	12/31/2019	312	120	192	2/28/2003	12/31/2019	203	120	83
Czech	12/31/1993	12/31/2019	313	120	193	2/28/2002	12/31/2019	215	120	95
Hungary	7/31/1993	12/31/2019	318	120	198	2/28/2002	12/31/2019	215	120	95
India	6/30/1990	12/31/2019	355	120	235	2/28/2002	12/31/2019	215	120	95
Indonesia	12/31/1990	12/31/2019	349	120	229	2/28/2003	12/31/2019	203	120	83
Malaysia	11/30/1989	12/31/2019	362	120	242	2/28/2002	12/31/2019	215	120	95
Mexico	6/30/1990	12/31/2019	355	120	235	2/28/2002	12/31/2019	215	120	95
Peru	2/28/1994	12/31/2019	311	120	191	10/31/2006	12/31/2019	159	120	39
Philippine	6/30/1992	12/31/2019	331	120	211	11/30/2010	12/31/2019	110	**NA**	**NA**
Poland	4/30/1994	12/31/2019	309	120	189	2/28/2002	12/31/2019	215	120	95
Romania	1/31/1997	12/31/2019	276	120	156	4/30/2013	12/31/2019	81	**NA**	**NA**
Singapore	11/30/1989	12/31/2019	362	120	242	8/31/2002	12/31/2019	209	120	89
S. Africa	11/30/1989	12/31/2019	362	120	242	2/29/2000	12/31/2019	239	120	119
S. Korea	6/30/1990	12/31/2019	355	120	235	1/31/2001	12/31/2019	228	120	108
Turkey	6/30/1990	12/31/2019	355	120	235	5/31/2004	12/31/2019	188	120	68

TABLE 2. Predictive Regressions for Models with Equity and Bond Returns

The table reports the estimates of the predictive regression $\Delta s_{it+1} = \alpha + \beta\chi_{it} + \varepsilon_{it+1}$, where Δs_{it+1} is the monthly % exchange rate return to be predicted at time $t+1$ for the currency i; and χ refers to the three sets of predictor variables for which we construct the forecast: (1) the equity model sets $\chi_{it} = [r_{US,t}^{\mathrm{E}}, r_{it}^{\mathrm{E}}, r_t^{\mathrm{E,Global}}]$, where $r_{US,t}^{\mathrm{E}}$ is the return on the US equity market, r_{it}^{E} represents the return on the ith foreign equity market, and $r_t^{\mathrm{E,Global}}$ is the global MSCI stock returns; (2) the bond model sets $\chi_{it} = [r_t^{\mathcal{B},US}, r_{it}^{\mathcal{B}}, r_t^{\mathcal{B},\mathrm{Global}}]$, which denote, respectively, the return on the US government bond market, the ith foreign government bond market denominated in the domestic currency, and the global WGBI bond market; and (3) the combined model sets $\chi_{it} = [r_{US,t}^{\mathrm{E}}, r_{it}^{\mathrm{E}}, r_t^{\mathrm{E,Global}}, r_t^{\mathcal{B},US}, r_{it}^{\mathcal{B}}, r_t^{\mathcal{B},\mathrm{Global}}]$. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Developed Market Currencies

	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
		Australia			Canada			Denmark			Germany	
r_{it}^{E}	-0.146***		-0.027	-0.091***		-0.014	-0.147***		-0.021**	-0.175***		-0.002
$r_t^{E,US}$	-0.465***		-0.169***	-0.345***		-0.118***	-0.478***		-0.083***	-0.586***		-0.207***
$r_t^{E,\mathrm{Global}}$	0.685***		0.248***	0.553***		0.2***	0.647***		0.101***	0.807***		0.192***
$r_{it}^{\mathcal{B}}$		-0.152***	-0.115**		-0.063	-0.113**		-0.256***	-0.234***		-0.108	-0.088
$r_t^{\mathcal{B},US}$		-0.628***	-0.357***		-0.635***	-0.347***		-0.397***	-0.318***		-0.651***	-0.491***
$r_t^{\mathcal{B},\mathrm{Global}}$		0.733***	0.483***		0.653***	0.443***		0.665***	0.574***		0.812***	0.639***
R-square	0.875	0.912	0.93	0.754	0.821	0.85	0.86	0.963	0.966	0.903	0.942	0.948
		Japan			New Zealand			Norway			Sweden	
r_{it}^{E}	-0.207***		-0.064***	-0.12***		-0.03**	-0.091***		0.002	-0.153***		-0.04***
$r_t^{E,US}$	-0.578***		-0.21***	-0.526***		-0.184***	-0.522***		-0.13***	-0.439***		-0.128***
$r_t^{E,\mathrm{Global}}$	0.728***		0.215***	0.695***		0.241***	0.692***		0.149***	0.683***		0.204***
$r_{it}^{\mathcal{B}}$		-0.241***	-0.199***		-0.141***	-0.073		-0.168***	-0.165***		-0.215***	-0.158***
$r_t^{\mathcal{B},US}$		-0.385***	-0.262***		-0.639***	-0.401***		-0.554***	-0.397***		-0.496***	-0.339***
$r_t^{\mathcal{B},\mathrm{Global}}$		0.699***	0.505***		0.737***	0.505***		0.704***	0.567***		0.71***	0.512***
R-square	0.9	0.932	0.946	0.873	0.919	0.933	0.861	0.941	0.948	0.903	0.946	0.955
		Switzerland			UK							
r_{it}^{E}	-0.248***		-0.078***	-0.306***		-0.154***						
$r_t^{E,US}$	-0.443***		-0.128***	-0.328***		-0.15***						
$wr_t^{E,\mathrm{Global}}$	0.654***		0.16***	0.627***		0.287***						
$r_{it}^{\mathcal{B}}$		-0.149***	-0.099**		-0.346***	-0.159***						
$r_t^{\mathcal{B},US}$		-0.435***	-0.339***		-0.43***	-0.262***						
$r_t^{\mathcal{B},\mathrm{Global}}$		0.694***	0.541***		0.66***	0.388***						
R-square	0.883	0.947	0.957	0.886	0.903	0.931						

TABLE 2. Predictive Regressions for Models with Equity and Bond Returns (continued)

	Panel B. Emerging Market Currencies											
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Argentina			Brazil			Chile			Colombia		
r_{it}^{E}	-0.027***		-0.019*	-0.071***		-0.068***	-0.016		-0.044**	-0.015		-0.041***
$r_{t}^{E,US}$	-0.858***		-0.636***	-0.779***		-0.41***	-0.596***		-0.483***	-0.684***		-0.16***
$r_{t}^{E,\text{Global}}$	0.915***		0.552***	0.896***		0.446***	0.702***		0.505***	0.767***		0.144***
$r_{it}^{\mathcal{B}}$		0.001	-0.002		0.24***	0.169***		0.04***	0.023***		0.311***	0.284***
$r_{t}^{\mathcal{B},US}$		-0.986***	-0.547***		-0.523***	-0.199***		-0.726***	-0.261***		-0.347***	-0.3***
$r_{t}^{\mathcal{B},\text{Global}}$		0.932***	0.402***		0.417***	0.141***		0.716***	0.282***		0.251***	0.188***
R-square	0.94	0.936	0.964	0.96	0.971	0.982	0.842	0.915	0.944	0.915	0.979	0.984
	Czech			Hungary			India			Indonesia		
r_{it}^{E}	-0.04***		-0.031***	-0.035***		-0.03***	-0.028***		-0.022***	-0.047***		-0.043***
$r_{t}^{E,US}$	-0.693***		-0.284***	-0.67***		-0.218***	-0.532***		-0.279***	-0.831***		-0.249***
$r_{t}^{E,\text{Global}}$	0.768***		0.316***	0.776***		0.23***	0.617***		0.318***	0.919***		0.252***
$r_{it}^{\mathcal{B}}$		0.095***	0.071***		0.233***	0.202***		0.272***	0.217***		0.178***	0.161***
$r_{t}^{\mathcal{B},US}$		-0.575***	-0.287***		-0.371***	-0.241***		-0.329***	-0.065		-0.433***	-0.269***
$r_{t}^{\mathcal{B},\text{Global}}$		0.621***	0.369***		0.363***	0.22***		0.28***	0.076**		0.342***	0.202***
R-square	0.913	0.964	0.974	0.922	0.982	0.986	0.766	0.921	0.944	0.942	0.922	0.935
	Malaysia			Mexico			Peru			Philippine		
r_{it}^{E}	-0.003		-0.014	-0.015		-0.048***	-0.028***		-0.037***	-0.005		-0.033*
$r_{t}^{E,US}$	-0.487***		-0.081***	-0.636***		-0.161***	-0.487***		-0.174***	-0.615***		-0.233***
$r_{t}^{E,\text{Global}}$	0.561***		0.092***	0.751***		0.19***	0.539***		0.153***	0.666***		0.252***
$r_{it}^{\mathcal{B}}$		0.398***	0.37***		0.344***	0.297***		0.189***	0.178***		0.182***	0.144***
$r_{t}^{\mathcal{B},US}$		-0.193***	-0.135***		-0.367***	-0.245***		-0.315***	-0.305***		-0.368***	-0.162*
$r_{t}^{\mathcal{B},\text{Global}}$		0.097***	0.056***		0.182***	0.097***		0.26***	0.202***		0.299***	0.159***
R-square	0.68	0.971	0.973	0.86	0.969	0.973	0.674	0.85	0.874	0.746	0.849	0.881

TABLE 2. Predictive Regressions for Models with Equity and Bond Returns (continued)

Panel B. Emerging Market Currencies

	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Poland			Romania			Singapore			South Africa		
r_{it}^{E}	-0.013*		-0.018**	-0.019***		-0.014*	-0.036***		-0.004	-0.089***		-0.109***
$r_{t}^{E,US}$	-0.643***		-0.146***	-0.773***		-0.131***	-0.336***		-0.03**	-0.62***		-0.501***
$r_{t}^{E,\text{Global}}$	0.755***		0.163***	0.82***		0.118***	0.455***		0.041***	0.781***		0.564***
$r_{it}^{\mathcal{B}}$		0.356***	0.312***		0.3***	0.268***		0.444***	0.426***		0.109***	0.065***
$r_{t}^{\mathcal{B},US}$		-0.306***	-0.207***		-0.351***	-0.33***		-0.116***	-0.085***		-0.815***	-0.227***
$r_{t}^{\mathcal{B},\text{Global}}$		0.197***	0.12***		0.265***	0.219***		0.05***	0.034***		0.666***	0.204***
R-square	0.935	0.988	0.989	0.942	0.982	0.987	0.689	0.984	0.985	0.897	0.955	0.977
	South Korea			Turkey								
r_{it}^{E}	-0.048***		-0.007	-0.025***		-0.038***						
$r_{t}^{E,US}$	-0.647***		-0.102***	-0.773***		-0.283***						
$r_{t}^{E,\text{Global}}$	0.779***		0.126***	0.862***		0.313***						
$r_{it}^{\mathcal{B}}$		0.421***	0.384***		0.249***	0.213***						
$r_{t}^{\mathcal{B},US}$		-0.192***	-0.097***		-0.465***	-0.213***						
$r_{t}^{\mathcal{B},\text{Global}}$		0.1***	0.037*		0.326***	0.114***						
R-square	0.873	0.987	0.989	0.915	0.974	0.98						

Panel C. Equally Weighted Portfolios

	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
r_{it}^{E}	-0.359***		-0.083***	-0.052***		-0.052***	-0.155***		-0.035***
$r_{t}^{E,US}$	-0.256***		-0.083***	-0.366***		-0.251***	-0.325***		-0.097***
$r_{t}^{E,\text{Global}}$	0.613***		0.189***	0.525***		0.344***	0.551***		0.158***
$r_{it}^{\mathcal{B}}$		-0.431***	-0.336***		0.21***	0.128***		0.18***	0.142***
$r_{t}^{\mathcal{B},US}$		-0.288***	-0.161***		-0.402***	-0.096***		-0.488***	-0.338***
$r_{t}^{\mathcal{B},\text{Global}}$		0.609***	0.429***		0.332***	0.131***		0.483***	0.357***
R-square	0.922	0.954	0.965	0.782	0.937	0.964	0.832	0.921	0.935

TABLE 3. Statistical Evaluation of Exchange Rate Forecasts: Rolling Regressions

The table provides the OOS statistical forecast accuracy for the rolling one-month-ahead forecasts generated from the equity, bond and combined models. The OOS monthly forecasts are obtained with rolling regressions that use the first 120 monthly observations as the in-sample period – which corresponds to a ten-year time horizon – and then roll through the rest of the OOS period using a fixed window size of 120 observations. The IS and OOS periods employed in the rolling regressions along with entire sample period for every individual currency are listed in Table 1. The table reports the mean squared forecast errors (MSFEs) as defined in (6), the MSFEs relative to the random walk benchmark as defined in (7), the OOS R^2 as defined in (8), and the Clark and West (2007) test of equal predictive ability as defined in (9). *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Developed Market Currencies												
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Australia			Canada			Denmark			Germany		
MSFE	0.597	0.675	0.43	0.799	0.764	0.566	0.615	0.303	0.227	0.467	0.313	0.279
Rel.-MSFE	0.046	0.052	0.033	0.117	0.112	0.083	0.075	0.037	0.028	0.056	0.038	0.034
R^2_{OOS}	0.954	0.948	0.967	0.883	0.888	0.917	0.925	0.963	0.972	0.944	0.962	0.966
CW	7.632***	7.662***	7.556***	7.487***	6.53***	6.543***	8.538***	8.734***	8.757***	8.67***	8.618***	8.715***
	Japan			New Zealand			Norway			Sweden		
MSFE	0.745	0.806	0.523	0.812	0.834	0.588	0.594	0.66	0.488	0.547	0.477	0.351
Rel.-MSFE	0.099	0.107	0.069	0.057	0.059	0.042	0.056	0.063	0.046	0.051	0.045	0.033
R^2_{OOS}	0.901	0.893	0.931	0.943	0.941	0.958	0.944	0.937	0.954	0.949	0.955	0.967
CW	9.609***	9.382***	9.654***	8.162***	8.178***	8.097***	8.632***	8.988***	8.921***	9.722***	9.897***	9.676***
	Switzerland			UK								
MSFE	0.696	0.584	0.381	0.356	0.726	0.337						
Rel.-MSFE	0.078	0.066	0.043	0.056	0.115	0.053						
R^2_{OOS}	0.922	0.934	0.957	0.944	0.885	0.947						
CW	7.611***	7.928***	8.082***	7.667***	8.281***	7.99***						

Panel B. Emerging Market Currencies												
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Argentina			Brazil			Chile			Colombia		
MSFE	8.184	10.469	2.49	0.931	0.329	0.246	0.947	7.907	3.467	0.871	0.198	0.178
Rel.-MSFE	0.179	0.11	0.026	0.044	0.017	0.013	0.08	0.809	0.355	0.055	0.012	0.011
R^2_{OOS}	0.821	0.89	0.974	0.956	0.983	0.987	0.92	0.191	0.645	0.945	0.988	0.989
CW	3.167***	2.12**	2.441**	7.582***	6.324***	6.412***	5.999***	7.063***	6.971***	8.713***	6.718***	6.731***

TABLE 3. Statistical Evaluation of Exchange Rate Forecasts: Rolling Regressions (continued)

Panel B. Emerging Market Currencies (continued)												
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Czech			Hungary			India			Indonesia		
MSFE	0.755	5.457	5.416	0.761	0.151	0.139	0.632	0.266	0.198	1.281	0.443	0.462
Rel.-MSFE	0.063	0.762	0.756	0.045	0.017	0.016	0.143	0.056	0.042	0.125	0.086	0.09
R^2_{OOS}	0.937	0.238	0.244	0.955	0.983	0.984	0.857	0.944	0.958	0.875	0.914	0.91
CW	7.698***	4.91***	4.939***	6.153***	5.239***	5.171***	7.097***	5.018***	5.144***	4.862***	5.011***	4.967***
	Malaysia			Mexico			Peru			Philippine		
MSFE	0.617	0.061	0.062	0.963	0.259	0.226	0.797	0.295	0.267	0.63	NA	NA
Rel.-MSFE	0.176	0.011	0.011	0.101	0.024	0.021	0.318	0.193	0.174	0.227	NA	NA
R^2_{OOS}	0.824	0.989	0.989	0.899	0.976	0.979	0.682	0.807	0.826	0.773	NA	NA
CW	6.103***	4.451***	4.497***	6.343***	6.073***	6.026***	5.822***	4.012***	4.167***	10.05***	NA	NA
	Poland			Romania			Singapore			South Africa		
MSFE	0.682	0.11	0.11	0.783	NA	NA	0.433	0.021	0.025	0.946	0.276	0.214
Rel.-MSFE	0.041	0.012	0.012	0.064	NA	NA	0.167	0.007	0.009	0.041	0.016	0.012
R^2_{OOS}	0.959	0.988	0.988	0.936	NA	NA	0.833	0.993	0.991	0.959	0.984	0.988
CW	6.827***	5.263***	5.189***	6.725***	NA	NA	6.737***	4.403***	4.454***	10.15***	6.487***	6.389***
	South Korea			Turkey								
MSFE	0.852	0.103	0.091	1.553	0.607	0.483						
Rel.-MSFE	0.084	0.017	0.015	0.054	0.024	0.019						
R^2_{OOS}	0.916	0.983	0.985	0.946	0.976	0.981						
CW	6.161***	4.965***	4.959***	5.797***	2.351**	2.348**						

Panel C. Equally Weighted Portfolios									
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
MSFE	0.137	0.212	0.097	0.408	0.27	0.18	0.279	0.226	0.156
Rel.-MSFE	0.024	0.036	0.017	0.083	0.052	0.035	0.059	0.048	0.033
R^2_{OOS}	0.976	0.964	0.983	0.917	0.948	0.965	0.941	0.952	0.967
CW	8.481***	8.93***	8.74***	7.39***	6.011***	5.998***	7.87***	7.302***	7.455***

TABLE 4. Economic Evaluation of Exchange Rate Predictability

The table reports the economic value of OOS exchange rate predictability by analyzing the performance of three long-short trading rules (equity, bond, and combined) conditional on the one-month ahead forecasts (obtained from rolling regressions). The key trading signal that characterizes these three long-short trading rules is that investor goes long (short) currency i if the predicted return of currency i ($\widehat{\Delta s}^{\chi}_{t+1|t}$) for the three sets of χ predictor variables is positive (negative), as defined in Equation (10). This gives us the net of transaction cost return on these three dynamic strategies $\Delta s^{\chi}_{it,\tau}$ as the realized exchange rate return Δs_{it+1} multiplied by the trading signal, as defined in Equation (11). For each trading rule, we report the monthly % mean (μ), % volatility(σ), skewness (γ), kurtosis (K), Sharpe ratio (SR), Sharpe ratio of the random walk model (SR_{RW}), and Sortino ratio (SO). Panel C reports the performance measures for the three equally weighted portfolios and for three benchmark portfolios: the random walk, momentum, and carry trade (CT). The figure reported for the CT and MOM portfolios refer to currency excess returns defined as interest rate differentials minus spot rate changes. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Panel A. Developed Market Currencies											
	Equity	*Bond*	*Comb*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*
		Australia			*Canada*			*Denmark*			*Germany*	
μ	2.63***	2.62***	2.65***	1.84***	1.81***	1.86***	2.05***	2.09***	2.09***	2.09***	2.10***	2.10***
σ	2.43	2.45	2.41	1.83	1.87	1.82	1.98	1.94	1.94	1.95	1.95	1.94
γ	1.72	1.68	1.76	1.84	1.72	1.90	1.33	1.44	1.44	1.41	1.42	1.43
K	5.44	5.30	5.61	6.85	6.33	7.12	2.25	2.49	2.49	2.39	2.42	2.44
SR	1.08	1.07	1.10	1.00	0.96	1.03	1.03	1.08	1.08	1.07	1.08	1.08
SR_{RW}	-0.04	-0.04	-0.04	-0.02	-0.02	-0.02	-0.00	-0.00	-0.00	0.04	0.04	0.04
SO	8.28	7.16	11.29	3.97	3.85	4.65	4.74	8.00	8.15	7.21	9.25	13.17
		Japan			New Zealand			Norway			Sweden	
μ	1.97***	2.04***	2.03***	2.78***	2.73***	2.77***	2.40***	2.42***	2.42***	2.49***	2.49***	2.52***
σ	1.89	1.82	1.84	2.51	2.56	2.52	2.16	2.13	2.14	2.09	2.09	2.06
γ	0.96	1.10	1.08	1.58	1.47	1.56	1.18	1.25	1.23	1.08	1.08	1.17
K	1.06	1.32	1.25	3.81	3.50	3.75	2.62	2.79	2.77	1.69	1.72	1.85
SR	1.04	1.12	1.10	1.11	1.07	1.10	1.11	1.14	1.13	1.19	1.19	1.23
SR_{RW}	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03	-0.04	-0.04	-0.04	0.01	0.01	0.01
SO	4.57	5.60	7.46	6.23	5.22	5.47	7.99	9.99	8.31	5.15	3.87	5.30

TABLE 4. Economic Evaluation of Exchange Rate Predictability (continued)

Panel A. Developed Market Currencies (continued)

	Equity	*Bond*	*Comb*	*Equity*	*Bond*	*Comb.*
	Switzerland			*UK*		
μ	2.16***	2.16***	2.19***	1.91***	1.85***	1.91***
σ	2.04	2.04	2.01	1.63	1.70	1.64
γ	1.59	1.60	1.69	1.75	1.47	1.73
K	4.75	4.80	5.10	5.24	4.47	5.16
SR	1.06	1.06	1.09	1.17	1.08	1.17
SR_{RW}	0.04	0.04	0.04	0.03	0.03	0.03
SO	6.53	6.13	6.54	10.77	3.17	10.51

Panel B. Emerging Market Currencies

	Equity	*Bond*	*Comb*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*
	Argentina			Brazil			Chile			Colombia		
μ	2.60***	6.47***	6.47***	3.28***	3.34***	3.33***	2.54***	2.50***	2.48***	2.91***	3.16***	3.16***
σ	6.44	8.18	8.18	3.11	2.85	2.87	2.28	1.85	1.89	2.62	2.47	2.48
γ	5.48	1.94	1.94	1.39	1.02	0.99	2.33	0.72	0.63	1.09	0.89	0.89
K	39.68	3.36	3.36	2.81	0.69	0.65	13.05	0.02	0.03	0.83	0.06	0.06
SR	0.40	0.79	0.79	1.05	1.17	1.16	1.11	1.35	1.31	1.11	1.28	1.28
SR_{RW}	0.26	0.44	0.44	-0.07	-0.00	-0.00	-0.02	-0.01	-0.01	-0.04	0.01	0.01
SO	3.52	99.82	99.82	8.94	15.18	18.01	5.37	10.70	3.69	9.58	39.63	22.00
	Czech			Hungary			India			Indonesia		
μ	2.54***	2.02***	2.02***	2.93***	2.32***	2.32***	1.24***	1.52***	1.53***	1.83***	1.58***	1.57***
σ	2.32	1.71	1.72	2.86	1.86	1.86	1.69	1.59	1.58	2.51	1.66	1.67
γ	1.29	1.49	1.48	2.49	1.86	1.86	1.39	1.51	1.54	2.63	1.43	1.40
K	2.54	4.10	4.06	9.81	6.16	6.16	2.19	2.61	2.67	10.93	1.59	1.54
SR	1.09	1.18	1.18	1.03	1.25	1.25	0.73	0.95	0.97	0.73	0.95	0.94
SR_{RW}	0.01	-0.10	-0.10	-0.03	0.10	0.10	0.04	0.18	0.18	-0.00	0.19	0.19
SO	5.90	.	12.03	7.43	.	.	2.75	5.80	9.74	3.51	13.31	10.22

TABLE 4. Economic Evaluation of Exchange Rate Predictability (continued)

	Panel B. Emerging Market Currencies											
	Equity	Bond	Comb	Equity	Bond	Comb.	Equity	Bond	Comb.	Equity	Bond	Comb.
	Malaysia			Mexico			Peru			Philippine		
μ	1.05***	1.64***	1.64***	2.04***	2.46***	2.46***	0.90***	0.85***	0.92***	1.09***	NA	NA
σ	1.51	1.65	1.65	2.29	2.18	2.18	1.27	0.91	0.83	1.17	NA	NA
γ	1.89	2.06	2.06	1.99	1.30	1.29	0.95	0.73	1.00	0.35	NA	NA
K	5.44	5.90	5.90	7.24	1.37	1.36	4.13	-0.14	0.06	-0.15	NA	NA
SR	0.69	1.00	1.00	0.89	1.13	1.13	0.71	0.94	1.11	0.94	NA	NA
SR_{RW}	-0.04	-0.07	-0.07	0.10	0.12	0.12	-0.23	-0.04	-0.04	-0.07	NA	NA
SO	2.99	7.64	7.64	4.18	20.92	16.18	1.14	3.32	12.53	2.36	NA	NA
	Poland			Romania			Singapore			South Africa		
μ	2.89***	2.27***	2.27***	2.52***	NA	NA	1.06***	1.22***	1.22***	3.66***	3.27***	3.28***
σ	2.80	2.01	2.00	2.40	NA	NA	1.20	1.17	1.17	3.08	2.65	2.63
γ	1.78	1.46	1.48	1.87	NA	NA	1.55	2.37	2.37	1.15	0.93	0.96
K	4.87	4.64	4.69	5.34	NA	NA	5.70	10.15	10.15	1.98	0.77	0.81
SR	1.04	1.13	1.14	1.05	NA	NA	0.88	1.05	1.05	1.19	1.23	1.25
SR_{RW}	-0.03	0.03	0.03	-0.04	NA	NA	-0.04	0.02	0.02	0.03	0.10	0.10
SO	5.63	14.58	13.89	8.40	NA	NA	2.51	134.89	134.89	14.07	12.73	20.09
	South Korea			Turkey								
μ	2.08***	1.91***	1.91***	3.39***	3.39***	3.42***						
σ	2.36	1.57	1.57	3.93	3.98	3.95						
γ	2.35	2.09	2.09	3.91	4.04	4.11						
K	7.88	8.16	8.16	24.14	23.57	24.10						
SR	0.88	1.22	1.22	0.86	0.85	0.87						
SR_{RW}	-0.17	-0.05	-0.05	0.19	0.30	0.30						
SO	4.26	34.63	34.63	13.50	25.00	327.59						

TABLE 4. Economic Evaluation of Exchange Rate Predictability (continued)

	Panel C. Equally Weighted Portfolios								
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Developed Portfolio			Emerging Portfolio			Developed and Emerging Portfolio		
μ	1.82***	1.81***	1.82***	1.46***	1.60***	1.61***	1.49***	1.51***	1.52***
σ	1.57	1.59	1.57	1.54	1.48	1.46	1.50	1.49	1.48
γ	1.46	1.41	1.47	1.76	1.51	1.56	1.66	1.71	1.75
K	3.03	2.91	3.07	5.90	3.46	3.62	5.39	5.57	5.72
SR	1.16	1.14	1.16	0.94	1.08	1.10	0.99	1.01	1.03
SO	0.04	0.04	0.04	0.04	0.04	0.04	0.00	0.00	0.00

	RW	Momentum	CT	RW	Momentum	CT	RW	Momentum	CT
	Developed Portfolio			Emerging Portfolio			Developed and Emerging Portfolio		
μ	0.10	0.23	0.35*	0.08	-0.22	1.21***	0.01	-0.03	0.94***
σ	2.4	2.57	2.86	2.12	3.46	3.19	2.12	2.24	2.36
γ	-0.35	-0.41	0.51	0.3	-0.28	0.89	0.01	-0.48	0.78
K	1.21	2.71	1.3	3.04	1.16	3.07	2.55	1.34	2.44
SR	0.04	0.09	0.12	0.04	-0.06	0.38	0	-0.01	0.4
SO	0.06	0.13	0.23	0.06	-0.1	0.77	0	-0.02	0.88

TABLE 5. Macro risk

The table reports the time-series regression estimates of our OOS returns (generated from long-short trading rules based on rolling one-month-ahead forecasts using the equity, bond and combined models) on various risk and macro factors. $Dollar$ factor is constructed as the average spot rate changes on several currencies; $Carry$ factor is generated by sorting currencies based on their forward discount; VIX factor refers to the monthly change in the values of the VIX index; and IP factor that denotes monthly change in the values of industrial production. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Developed Market Currencies												
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Canada			Denmark			Germany			Japan		
Intercept	1.843***	1.803***	1.858***	2.043***	2.093***	2.093***	2.026***	2.03***	2.032***	1.999***	2.082***	2.058***
Carry	5.041	5.312	5.988	31.223***	29.368***	29.341***	26.387***	26.713***	26.905***	6.662	4.351	5.952
Dollar	-6.266	-4.956	-6.454	-1.08	0.027	-0.07	1.261	0.822	1.026	9.482	7.971	7.868
VIX	0.084**	0.086**	0.091***	-0.031	-0.04	-0.04	-0.028	-0.026	-0.028	0.027	0.038	0.036
IP	-0.092	-0.081	-0.079	-0.003	-0.002	-0.003	-0.005	-0.006	-0.005	-0.012	-0.01	-0.008
R-square	0.04	0.042	0.049	0.102	0.093	0.093	0.079	0.082	0.083	0.031	0.028	0.029
	Norway			Sweden			UK					
Intercept	2.356***	2.382***	2.38***	2.452***	2.452***	2.484***	1.884***	1.821***	1.878***			
Carry	17.076**	16.946**	16.116**	13.672**	14.062**	13.897**	12.099**	10.685**	12.491**			
Dollar	-6.468	-7.341	-7.25	0.725	-0.476	-0.274	-3.133	-3.477	-3.327			
VIX	0.103***	0.1***	0.104***	0.066*	0.069*	0.068*	0.05*	0.045	0.049			
IP	-0.022	-0.021	-0.02	-0.019*	-0.017*	-0.018*	-0.012	-0.019	-0.011			
R-square	0.082	0.08	0.079	0.062	0.062	0.064	0.055	0.043	0.056			

Panel B. Emerging Market Currencies												
	Czech			Hungary			India			Indonesia		
Intercept	2.464***	1.96***	1.956***	2.863***	2.25***	2.25***	1.222***	1.443***	1.45***	1.835***	1.664***	1.653***
Carry	24.467***	11.593	11.716	19.675**	3.352	3.352	6.404	12.637	12.16	16.162*	-3.94	-4.297
Dollar	7.86	11.883	11.844	34.48***	25.344*	25.344*	18.596***	17.68	19.344*	-5.54	5.482	6.005
VIX	-0.043	0.021	0.022	-0.062	0.006	0.006	0.022	0.056	0.049	0.09*	0.001	-0.009
IP	-0.009	-0.012	-0.013	0.026	0.016	0.016	0.011	-0.011	-0.009	0.014	-0.016	-0.016
R-square	0.063	0.049	0.049	0.082	0.053	0.053	0.074	0.095	0.096	0.053	0.005	0.006

TABLE 5. Macro risk (continued)

Panel B. Emerging Market Currencies

	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
	Malaysia			Mexico			Philippine			Poland		
Intercept	1.004***	1.578***	1.578***	2.041***	2.39***	2.388***	1.098***	NA	NA	2.845***	2.228***	2.233***
Carry	15.299***	23.843***	23.843***	4.692	7.905	7.725	4.873	NA	NA	16.241*	7.243	7.069
Dollar	11.934**	10.537	10.537	22.784**	24.528	24.132	7.448	NA	NA	24.468*	8.301	9.018
VIX	-0.056**	0.03	0.03	0.12***	0.107	0.109	-0.009	NA	NA	0.03	0.058	0.054
IP	0.013	0.04	0.04	0.035	0.137*	0.134*	0.022	NA	NA	-0.036	-0.002	-0.003
R-square	0.071	0.128	0.128	0.124	0.12	0.117	0.042	NA	NA	0.077	0.024	0.024
	South Africa			South Korea			Turkey					
Intercept	3.651***	2.891***	2.908***	2.008***	1.865***	1.865***	3.384***	3.194***	3.222***			
Carry	20.653*	36.979**	37.186**	22.92***	0.916	0.916	13.025	35.467	35.517			
Dollar	14.102	47.574**	47.27**	4.704	16.229	16.229	29.563*	76.294**	76.483**			
VIX	0.037	-0.083	-0.083	-0.071	-0.079*	-0.079*	0.063	-0.252	-0.253			
IP	-0.042*	-0.058	-0.058	0.034	0.048**	0.048**	-0.013	-0.045	-0.043			
R-square	0.052	0.139	0.141	0.052	0.086	0.086	0.044	0.09	0.091			

Panel C. Equally Weighted Portfolios

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
Intercept	1.777***	1.763***	1.78***	1.414***	1.494***	1.506***	1.454***	1.466***	1.477***
Carry	16.696***	16.738***	16.707***	13.465***	15.938**	16.182**	15.454***	15.926***	15.573***
Dollar	-1.899	-1.871	-1.867	19.074***	22.037**	21.809**	12.116**	11.016*	10.977*
VIX	0.024	0.02	0.023	0.017	-0.044	-0.048	0.012	0.021	0.02
IP	-0.028	-0.027	-0.027	0.018	0.03	0.033	-0.005	-0.005	-0.004
R-square	0.073	0.069	0.073	0.131	0.16	0.165	0.102	0.11	0.108

TABLE 6. Predictive Regressions using alternative model specifications

The table reports the estimates of the predictive regression $\Delta s_{it+1} = \alpha + \beta\chi_{it} + \varepsilon_{it+1}$, where Δs_{it+1} is the monthly % exchange rate return to be predicted at time $t+1$ for the currency i; and χ refers to the three sets of predictor variables for which we construct the forecast: (1) the equity model sets $\chi_{it} = [r^{E}_{US,t}, r^{E}_{it}, r_t^{E,\text{Global}}, r^{E}_{it} - r_t^{E,US}]$, where $r^{E}_{US,t}$ is the return on the US equity market, r^{E}_{it} represents the return on the ith foreign equity market, and $r_t^{E,\text{Global}}$ is the global MSCI stock returns. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Developed Market Currencies

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Australia				Canada				Denmark				Germany			
r^{E}_{it}	0.317***	0.116**	-0.146***		0.261***	0.096**	-0.091***		-0.066**	-0.192***	-0.147***		0.015	-0.161**	-0.175***	
$r_t^{E,US}$		0.273***	-0.465***			0.202***	-0.345***			0.258***	-0.478***			0.312***	-0.586***	
$r_t^{E,\text{Global}}$			0.685***				0.553***				0.647***				0.807***	
$r^{E}_{it} - r_t^{E,US}$				-0.132**				-0.088**				-0.21***				-0.173***
R-square	0.135	0.202	0.875	0.017	0.2	0.252	0.754	0.011	0.013	0.1	0.86	0.092	0	0.04	0.903	0.02
	Japan				New Zealand				Norway				Sweden			
r^{E}_{it}	-0.112***	-0.126***	-0.207***		0.165***	0.026	-0.12***		0.093***	0.007	-0.091***		0.002	-0.164***	-0.153***	
$r_t^{E,US}$		0.038	-0.578***			0.271***	-0.526***			0.2***	-0.522***			0.398***	-0.439***	
$r_t^{E,\text{Global}}$			0.728***				0.695***				0.692***				0.683***	
$r^{E}_{it} - r_t^{E,US}$				-0.106***				-0.128***				-0.006				-0.173***
R-square	0.041	0.043	0.9	0.03	0.041	0.126	0.873	0.025	0.031	0.072	0.861	0	0	0.149	0.903	0.064
	Switzerland				UK											
r^{E}_{it}	-0.181***	-0.394***	-0.248***		-0.032	-0.318***	-0.306***									
$r_t^{E,US}$		0.314***	-0.443***			0.363***	-0.328***									
$r_t^{E,\text{Global}}$			0.654***				0.627***									
$r^{E}_{it} - r_t^{E,US}$				-0.359***				-0.342***								
R-square	0.063	0.151	0.883	0.142	0.002	0.126	0.886	0.122								

TABLE 6. Predictive Regressions using alternative model specifications (continued)

Panel B. Emerging Market Currencies																
	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Argentina				Brazil				Chile				Colombia			
r_{it}^{E}	-0.092***	-0.114***	-0.027***		0.259***	0.167***	-0.071***		0.141***	0.071**	-0.016		0.159***	0.114***	-0.015	
$r_{t}^{E,US}$		0.161*	-0.858***			0.281***	-0.779***			0.232***	-0.596***			0.272***	-0.684***	
$r_{t}^{E,\text{Global}}$			0.915***				0.896***				0.702***				0.767***	
$r_{it}^{E} - r_{t}^{E,US}$				-0.114***				0.148***				-0.026				0.005
R-square	0.028	0.037	0.94	0.036	0.106	0.137	0.96	0.024	0.058	0.143	0.842	0.002	0.074	0.174	0.915	0
	Czech				Hungary				India				Indonesia			
r_{it}^{E}	0.061**	0.019	-0.04***		0.092***	0.022	-0.035***		0.017	0	-0.028***		0.081**	0.031	-0.047***	
$r_{t}^{E,US}$		0.17***	-0.693***			0.252***	-0.67***			0.134***	-0.532***			0.222**	-0.831***	
$r_{t}^{E,\text{Global}}$			0.768***				0.776***				0.617***				0.919***	
$r_{it}^{E} - r_{t}^{E,US}$				-0.007				0.034				-0.012				0.022
R-square	0.016	0.053	0.913	0	0.045	0.102	0.922	0.004	0.004	0.053	0.766	0.002	0.011	0.028	0.942	0.001
	Malaysia				Mexico				Peru				Philippine			
r_{it}^{E}	0.102***	0.084***	-0.003		0.207***	0.126***	-0.015		0.058***	0.046***	-0.028***		0.104***	0.096***	-0.005	
$r_{t}^{E,US}$		0.07**	-0.487***			0.219***	-0.636***			0.052**	-0.487***			0.035	-0.615***	
$r_{t}^{E,\text{Global}}$			0.561***				0.751***				0.539***				0.666***	
$r_{it}^{E} - r_{t}^{E,US}$				0.058***				0.092**				0.02				0.082***
R-square	0.091	0.105	0.68	0.026	0.121	0.161	0.86	0.017	0.054	0.073	0.674	0.007	0.098	0.101	0.746	0.051
	Poland				Romania				Singapore				South Africa			
r_{it}^{E}	0.137***	0.055**	-0.013*		0.029	0.004	-0.019***		0.107***	0.076***	-0.036***		0.191***	0.079*	-0.089***	
$r_{t}^{E,US}$		0.328***	-0.643***			0.178***	-0.773***			0.066***	-0.336***			0.3***	-0.62***	
$r_{t}^{E,\text{Global}}$			0.755***				0.82***				0.455***				0.781***	
$r_{it}^{E} - r_{t}^{E,US}$				0.046				0.004				0.059***				-0.014
R-square	0.094	0.204	0.935	0.008	0.006	0.036	0.942	0	0.139	0.156	0.689	0.026	0.06	0.125	0.897	0

TABLE 6. Predictive Regressions using alternative model specifications (continued)

Panel B. Emerging Market Currencies (continued)

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	South Korea				Turkey			
r_{it}^{E}	0.147***	0.093***	-0.048***		0.074***	0.048**	-0.025***	
$r_{t}^{E,US}$		0.228***	-0.647***			0.247***	-0.773***	
$r_{t}^{E,\text{Global}}$			0.779***				0.862***	
$r_{it}^{E} - r_{t}^{E,US}$				0.08***				0.047**
R-square	0.094	0.142	0.873	0.022	0.032	0.066	0.915	0.011

Panel C. Portfolios

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Developed Portfolio				Emerging Portfolio				Developed and Emerging Portfolio			
r_{it}^{E}	0.091***	-0.162***	-0.359***		0.191***	0.13***	-0.052***		0.189***	0.103***	-0.156***	
$r_{t}^{E,US}$		0.296***	-0.256***			0.108***	-0.363***			0.117***	-0.326***	
$r_{t}^{E,\text{Global}}$			0.613***				0.516***				0.547***	
$r_{it}^{E} - r_{t}^{E,US}$				-0.251***				0.053*				-0.006
R-square	0.023	0.122	0.922	0.075	0.206	0.236	0.776	0.01	0.162	0.19	0.828	0

TABLE 7. Statistical Evaluation using Alternative Combined Predictive Regressions

The table provides the OOS statistical forecast accuracy for the rolling one-month-ahead forecasts generated from the predictive regression defined in Equation (1) ($\Delta s_{it+1} = \alpha + \beta\chi_{it} + \varepsilon_{it+1}$). We perform the later test for four different models that differ in the set of predictor variables: (1) r_{it}^{E} and $r_{it}^{\mathcal{B}}$ (Model 1); (2) $r_t^{\text{E,Global}}$ and $r_t^{\mathcal{B},\text{Global}}$ (Model 2) ; (3) $(r_{it}^{E} - r_t^{\text{E,Global}})$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\text{Global}})$ (Model 3); and r_{it}^{E}, $(r_{it}^{E} - r_t^{\text{E,Global}})$, $r_{it}^{\mathcal{B}}$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\text{Global}})$ (Model 4). In each of the four versions, the OOS monthly forecasts are obtained with rolling regressions that use the first 120 monthly observations as the in-sample period – which corresponds to a ten-year time horizon – and then roll through the rest of the OOS period using a fixed window size of 120 observations. The IS and OOS periods employed in the rolling regressions along with entire sample period for every individual currency are listed in Table 1. The table reports the mean squared forecast errors (MSFEs) as defined in (6), the MSFEs relative to the random walk benchmark as defined in (7), the OOS R^2 as defined in (8), and the Clark and West (2007) test of equal predictive ability as defined in (9). *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Developed Market Currencies

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Australia				Canada				Denmark				Germany			
MSFE	10.963	0.821	0.703	0.645	4.865	1.046	0.743	0.692	8.164	0.525	0.343	0.297	8.359	0.56	0.383	0.34
Rel.-MSFE	0.845	0.063	0.054	0.05	0.71	0.153	0.108	0.101	0.993	0.064	0.042	0.036	1.005	0.067	0.046	0.041
R_{OOS}^2	0.155	0.937	0.946	0.95	0.29	0.847	0.892	0.899	0.007	0.936	0.958	0.964	-0.005	0.933	0.954	0.959
CW	4.342***	7.322***	7.485***	7.44***	5.688***	6.67***	6.65***	6.28***	3.546***	8.423***	8.766***	8.576***	2.145**	8.358***	8.581***	8.608***
	Japan				New Zealand				Norway				Sweden			
MSFE	6.351	0.791	0.766	0.751	13.551	1.133	0.919	0.903	8.467	0.899	0.896	0.773	9.436	0.722	0.539	0.46
Rel.-MSFE	0.841	0.105	0.101	0.1	0.959	0.08	0.065	0.064	0.806	0.086	0.085	0.074	0.886	0.068	0.051	0.043
R_{OOS}^2	0.159	0.895	0.899	0.9	0.041	0.92	0.935	0.936	0.194	0.914	0.915	0.926	0.114	0.932	0.949	0.957
CW	4.999***	9.394***	9.103***	9.396***	3.333***	8.015***	8.003***	7.939***	4.709***	8.45***	8.953***	8.799***	4.614***	9.468***	9.776***	9.438***
	Switzerland				UK											
MSFE	9.135	0.714	0.529	0.534	5.663	1.192	0.553	0.554								
Rel.-MSFE	1.029	0.08	0.06	0.06	0.894	0.188	0.087	0.087								
R_{OOS}^2	-0.029	0.92	0.94	0.94	0.106	0.812	0.913	0.913								
CW	1.445	7.947***	8.077***	8.097***	4.458***	8.106***	8.009***	8.138***								

TABLE 7. Statistical Evaluation using Alternative Combined Predictive Regressions (continued)

Panel B. Emerging Market Currencies

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Argentina				Brazil				Chile				Colombia			
MSFE	22.492	5.534	50.02	8.52	0.419	1.219	2.286	0.35	10.794	1.077	6.945	7.48	0.35	0.91	2.349	0.32
Rel.-MSFE	0.237	0.058	0.527	0.09	0.022	0.063	0.118	0.018	1.104	0.11	0.71	0.765	0.022	0.056	0.144	0.02
R^2_{OOS}	0.763	0.942	0.473	0.91	0.978	0.937	0.882	0.982	-0.104	0.89	0.29	0.235	0.978	0.944	0.856	0.98
CW	2.102**	2.463**	1.86*	2.278**	6.383***	6.197***	6.166***	6.317***	7.241***	7.038***	5.227***	6.8***	6.627***	6.394***	6.149***	6.646***
	Czech				Hungary				India				Indonesia			
MSFE	5.746	0.684	6.869	5.519	0.346	0.725	2.458	0.288	0.444	0.776	2.142	0.276	0.575	1.058	1.88	0.704
Rel.-MSFE	0.802	0.096	0.959	0.77	0.039	0.082	0.279	0.033	0.093	0.163	0.45	0.058	0.112	0.206	0.367	0.137
R^2_{OOS}	0.198	0.904	0.041	0.23	0.961	0.918	0.721	0.967	0.907	0.837	0.55	0.942	0.888	0.794	0.633	0.863
CW	4.846***	5.407***	3.029***	4.94***	5.031***	5.273***	4.375***	5.151***	5.069***	4.762***	3.852***	4.864***	4.788***	4.816***	4.292***	4.849***
	Malaysia				Mexico				Peru				Poland			
MSFE	0.091	0.612	1.336	0.079	0.458	0.974	1.745	0.379	0.323	0.528	0.663	0.341	0.21	0.573	2.044	0.21
Rel.-MSFE	0.016	0.111	0.243	0.014	0.043	0.091	0.163	0.035	0.211	0.344	0.433	0.223	0.023	0.062	0.222	0.023
R^2_{OOS}	0.984	0.889	0.757	0.986	0.957	0.909	0.837	0.965	0.789	0.656	0.567	0.777	0.977	0.938	0.778	0.977
CW	4.387***	4.339***	3.78***	4.406***	5.878***	5.955***	6.12***	6.045***	3.924***	3.592***	3.882***	3.849***	5.177***	5.21***	4.283***	5.133***
	Singapore				South Africa				South Korea				Turkey			
MSFE	0.023	0.324	1.481	0.023	0.579	1.064	2.066	0.355	0.133	0.561	1.905	0.116	1.046	1.626	3.634	0.742
Rel.-MSFE	0.008	0.112	0.511	0.008	0.033	0.06	0.117	0.02	0.021	0.091	0.308	0.019	0.041	0.064	0.142	0.029
R^2_{OOS}	0.992	0.888	0.489	0.992	0.967	0.94	0.883	0.98	0.979	0.909	0.692	0.981	0.959	0.936	0.858	0.971
CW	4.4***	5.195***	3.84***	4.409***	6.238***	6.553***	6.204***	6.391***	4.975***	5.012***	4.323***	4.921***	2.461**	2.333**	2.477**	2.416**

Panel C. Equally Weighted Portfolios

	Developed Portfolio				Emerging Portfolio				Developed and Emerging Portfolio			
MSFE	5.231	0.321	0.193	0.156	0.413	0.416	1.39	0.265	0.861	0.339	1.345	0.256
Rel.-MSFE	0.899	0.055	0.033	0.027	0.088	0.089	0.297	0.057	0.187	0.074	0.292	0.056
R^2_{OOS}	0.101	0.945	0.967	0.973	0.912	0.911	0.703	0.943	0.813	0.926	0.708	0.944
CW	4.163***	8.84***	8.871***	8.782***	5.94***	6.082***	5.419***	5.984***	6.007***	7.278***	7.012***	7.336***

TABLE 8. Economic Evaluation using Alternative Combined Predictive Regressions

The table reports the economic value of OOS exchange rate predictability by analyzing the performance of four long-short trading rules (Model 1, Model 2, Model 3 and Model 4) conditional on the one-month ahead forecasts (obtained from rolling regressions). The set of predictor variables in each of the four models for which we construct the forecast are described in the caption of Table 6. The key mechanism that characterizes the trading rule is defined in the caption of Table 4, in the sense that investor trades goes long (short) currency i if the predicted return of currency i ($\widehat{\Delta s}^{\chi}_{t+1|t}$) for the four sets of predictor variables is positive (negative). For each model, we report the monthly % mean, % volatility, skewness, kurtosis, Sharpe ratio, Sharpe ratio of the random walk model, and Sortino ratio. Panel C reports the results for the three equally weighted portfolios. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Developed Market Currencies

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Australia				Canada				Denmark				Germany			
μ	0.85***	2.58***	2.60***	2.62***	0.94***	1.79***	1.84***	1.82***	0.57**	2.05***	2.07***	2.09***	0.42**	2.05***	2.07***	2.08***
σ	3.48	2.48	2.47	2.44	2.43	1.88	1.84	1.86	2.80	1.99	1.96	1.94	2.83	2.00	1.98	1.96
γ	0.50	1.60	1.63	1.70	0.78	1.68	1.83	1.77	-0.64	1.33	1.38	1.44	-0.46	1.31	1.34	1.39
K	1.94	5.01	5.14	5.38	2.84	6.22	6.83	6.58	1.94	2.23	2.35	2.48	1.61	2.16	2.22	2.33
SR	0.24	1.04	1.05	1.08	0.39	0.95	1.00	0.98	0.20	1.03	1.05	1.08	0.15	1.03	1.04	1.06
SR_{RW}	-0.04	-0.04	-0.04	-0.04	-0.02	-0.02	-0.02	-0.02	-0.00	-0.00	-0.00	-0.00	0.04	0.04	0.04	0.04
SO	0.45	6.07	6.37	7.38	0.80	3.28	3.95	3.38	0.26	5.35	7.30	6.91	0.20	5.58	8.43	8.62
	Japan				New Zealand				Norway				Sweden			
μ	0.57***	2.05***	2.01***	2.03***	0.72***	2.75***	2.72***	2.75***	0.84***	2.40***	2.41***	2.41***	0.72***	2.42***	2.48***	2.49***
σ	2.68	1.81	1.85	1.83	3.68	2.55	2.57	2.54	3.12	2.16	2.15	2.15	3.18	2.17	2.10	2.09
γ	-0.04	1.15	0.98	1.09	-0.23	1.51	1.45	1.51	0.28	1.20	1.22	1.22	-0.16	0.92	1.07	1.08
K	0.73	1.37	1.42	1.28	1.89	3.56	3.43	3.60	0.85	2.65	2.71	2.70	0.71	1.45	1.70	1.72
SR	0.21	1.14	1.08	1.11	0.19	1.08	1.06	1.08	0.27	1.11	1.12	1.12	0.23	1.12	1.19	1.19
SR_{RW}	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-0.04	-0.04	0.01	0.01	0.01	0.01
SO	0.34	7.25	2.53	6.16	0.29	8.89	5.54	6.26	0.48	9.92	10.27	10.00	0.37	3.69	4.24	4.15

TABLE 8. Economic Evaluation using Alternative Combined Predictive Regressions (continued)

Panel A. Developed Market Currencies (Continued)

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Switzerland				UK			
μ	0.32	2.15***	2.18***	2.17***	0.62***	1.73***	1.89***	1.88***
σ	2.96	2.05	2.03	2.04	2.44	1.82	1.65	1.67
γ	-0.36	1.58	1.64	1.62	-0.06	0.98	1.66	1.60
K	2.23	4.70	4.93	4.84	2.02	4.04	4.98	4.78
SR	0.11	1.05	1.07	1.07	0.25	0.95	1.15	1.13
SR_{RW}	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03
SO	0.15	6.05	5.54	6.22	0.41	1.78	4.99	4.57

Panel B. Emerging Market Currencies

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Argentina				Brazil				Chile				Colombia			
μ	6.02***	6.47***	5.11***	6.45***	3.32***	3.21***	3.24***	3.35***	2.42***	2.36***	1.88***	2.41***	3.16***	3.11***	2.75***	3.16***
σ	8.53	8.18	9.13	8.20	2.88	3.01	2.97	2.85	1.96	2.04	2.49	1.98	2.48	2.54	2.93	2.48
γ	1.77	1.94	1.48	1.93	0.97	0.81	0.87	1.02	0.47	0.41	-0.19	0.48	0.89	0.78	0.40	0.88
K	2.89	3.36	2.60	3.33	0.63	0.45	0.47	0.70	0.12	-0.22	0.38	-0.12	0.06	-0.01	-0.34	0.05
SR	0.71	0.79	0.56	0.79	1.15	1.07	1.09	1.18	1.24	1.16	0.75	1.21	1.28	1.22	0.94	1.27
SR_{RW}	0.44	0.44	0.44	0.44	-0.00	-0.00	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01	0.01	0.01	0.01	0.01
SO	3.14	65.18	1.28	73.32	11.32	4.32	7.25	18.09	2.35	7.14	1.26	5.84	22.00	7.41	3.32	26.70
	Czech				Hungary				India				Indonesia			
μ	2.02***	1.98***	1.39***	2.02***	2.30***	2.23***	1.97***	2.27***	1.51***	1.48***	1.11***	1.52***	1.51***	1.53***	1.35***	1.58***
σ	1.71	1.77	2.27	1.72	1.89	1.97	2.23	1.92	1.60	1.63	1.90	1.59	1.73	1.71	1.85	1.66
γ	1.48	1.33	0.53	1.47	1.75	1.50	0.87	1.65	1.49	1.38	0.95	1.50	1.24	1.32	1.05	1.43
K	4.07	3.59	1.34	4.03	5.79	4.91	3.26	5.43	2.54	2.46	1.33	2.59	1.49	1.40	1.00	1.60
SR	1.18	1.12	0.61	1.17	1.21	1.13	0.88	1.18	0.94	0.91	0.58	0.95	0.87	0.89	0.73	0.95
SR_{RW}	-0.10	-0.10	-0.10	-0.10	0.10	0.10	0.10	0.10	0.18	0.18	0.18	0.18	0.19	0.19	0.19	0.19
SO	11.78	6.15	1.38	14.33	15.42	6.59	1.91	7.26	5.65	2.91	1.57	5.50	2.17	4.27	2.13	11.70

TABLE 8. Economic Evaluation using Alternative Combined Predictive Regressions (continued)

Panel B. Emerging Market Currencies (Continued)

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 1*	*Model 2*	*Model 3*	*Model 4*
	Malaysia				Mexico				Peru				Poland			
μ	1.63***	1.51***	1.48***	1.63***	2.43***	2.34***	2.29***	2.45***	0.83***	0.83***	0.68***	0.81***	2.28***	2.25***	2.10***	2.27***
σ	1.65	1.77	1.80	1.65	2.21	2.31	2.36	2.19	0.92	0.93	1.04	0.94	2.00	2.03	2.18	2.00
γ	2.04	1.67	1.59	2.04	1.23	1.03	0.97	1.27	0.71	0.68	0.54	0.66	1.48	1.39	1.07	1.48
Κ	5.80	4.43	4.25	5.80	1.27	1.09	0.86	1.33	-0.26	-0.22	-0.48	-0.30	4.70	4.43	3.30	4.68
SR	0.99	0.85	0.82	0.99	1.10	1.01	0.97	1.12	0.91	0.89	0.65	0.86	1.14	1.10	0.96	1.14
SR_{RW}	-0.07	-0.07	-0.07	-0.07	0.12	0.12	0.12	0.12	-0.04	-0.04	-0.04	-0.04	0.03	0.03	0.03	0.03
SO	6.72	4.09	2.79	6.72	5.71	2.96	3.80	16.16	4.69	3.24	2.23	3.67	22.25	4.03	2.92	12.47
	Singapore				South Africa				South Korea				Turkey			
μ	1.22***	1.17***	0.85***	1.22***	3.23***	3.20***	3.13***	3.25***	1.90***	1.85***	1.47***	1.91***	3.41***	3.36***	3.36***	3.41***
σ	1.17	1.22	1.46	1.17	2.69	2.73	2.81	2.67	1.58	1.64	2.00	1.57	3.96	4.00	4.00	3.96
γ	2.33	2.05	1.25	2.36	0.87	0.82	0.71	0.90	2.05	1.78	0.85	2.11	4.07	3.96	3.96	4.07
Κ	9.97	8.55	4.49	10.11	0.68	0.64	0.47	0.73	7.99	6.90	3.43	8.21	23.83	23.02	22.99	23.83
SR	1.04	0.96	0.58	1.05	1.20	1.18	1.11	1.22	1.21	1.13	0.73	1.22	0.86	0.84	0.84	0.86
SR_{RW}	0.02	0.02	0.02	0.02	0.10	0.10	0.10	0.10	-0.05	-0.05	-0.05	-0.05	0.30	0.30	0.30	0.30
SO	8.88	4.27	1.51	38.62	18.20	4.87	5.81	16.94	5.85	5.85	1.77	77.82	26.89	9.84	7.22	26.89

Panel C. Equally Weighted Portfolios

	Developed Portfolio				Emerging Portfolio				Developed and Emerging Portfolio			
μ	0.50***	1.79***	1.81***	1.81***	1.57***	1.59***	1.40***	1.60***	1.38***	1.50***	1.27***	1.52***
σ	2.35	1.60	1.57	1.58	1.50	1.49	1.66	1.47	1.61	1.50	1.70	1.48
γ	0.42	1.35	1.45	1.44	1.41	1.47	1.01	1.53	1.32	1.67	1.11	1.75
Κ	0.89	2.76	3.00	2.99	3.23	3.34	2.08	3.52	4.15	5.42	3.44	5.71
SR	0.21	1.11	1.15	1.15	1.04	1.07	0.84	1.09	0.85	1.00	0.74	1.02
SR_{RW}	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.00	0.00	0.00	0.00
SO	0.39	6.29	7.56	8.11	4.54	10.11	2.79	16.07	2.75	5.25	1.99	8.92

TABLE 9. Statistical Evaluation of Exchange Rate Forecasts (using Euro as the numeraire currency)

The table provides the OOS statistical forecast accuracy for the rolling one-month-ahead forecasts generated from the predictive equity, bond and combined regressions, using Euro as the numeraire currency. The setup of this table is identical to Table 3 except (1) we express the nominal spot exchange rates S_{it} in terms of the Euros per unit of the foreign currency, (2) we replace $r_t^{E,US}$ and $r_t^{\mathcal{B},US}$ in our predictive regressions with the return on Dutch equity and government bond markets, respectively, and (3) we convert $r_t^{E,\text{Global}}$ and $r_t^{\mathcal{B},\text{Global}}$ data such that they are quoted against Euro. The table reports the mean squared forecast errors (MSFEs) as defined in (6), the MSFEs relative to the random walk benchmark as defined in (7), the OOS R^2 as defined in (8), and the Clark and West (2007) test of equal predictive ability as defined in (9). *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Developed Market Currencies											
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
		Australia			Canada			Denmark			Japan	
MSFE	3.835	2.116	1.994	4.06	2.323	1.966	3.258	1.199	1.214	4.705	2.449	2.545
Rel.-MSFE	0.561	0.309	0.292	0.211	0.121	0.102	0.247	0.091	0.092	0.327	0.17	0.177
R^2_{OOS}	0.439	0.691	0.708	0.789	0.879	0.898	0.753	0.909	0.908	0.673	0.83	0.823
CW	8.044***	9.652***	10.021***	7.189***	7.674***	7.629***	6.504***	6.576***	6.697***	9.63***	10.19***	10.66***
		New Zealand			Norway			Sweden			Switzerland	
MSFE	4.818	2.206	2.195	3.477	1.596	1.549	3.72	1.648	1.467	3.312	1.596	1.582
Rel.-MSFE	0.162	0.074	0.074	0.187	0.086	0.083	0.2	0.089	0.079	0.229	0.11	0.109
R^2_{OOS}	0.838	0.926	0.926	0.813	0.914	0.917	0.8	0.911	0.921	0.771	0.89	0.891
CW	8.411***	8.782***	8.628***	7.043***	6.957***	7.164***	7.475***	7.62***	7.646***	7.153***	7.473***	7.614***
		UK			US							
MSFE	4.131	2.699	2.565	4.243	1.981	2.212						
Rel.-MSFE	0.741	0.484	0.46	0.515	0.24	0.268						
R^2_{OOS}	0.259	0.516	0.54	0.485	0.76	0.732						
CW	5.148***	5.787***	5.63***	6.67***	8.457***	8.289***						

TABLE 10. Economic Evaluation of Exchange Rate Predictability (using Euro as the numeraire currency)

The table reports the economic value of our forecasts, using Euro as the numeraire currency. The setup of this table is identical to Table 4 except (1) we express S_{it} in terms of the Euros per unit of the foreign currency, (2) we replace $r_t^{\mathrm{E},US}$ and $r_t^{\mathcal{B},US}$ in our predictive regressions with the return on Dutch equity and government bond markets, respectively, and (3) we convert $r_t^{\mathrm{E,Global}}$ and $r_t^{\mathcal{B},\mathrm{Global}}$ data such that they are quoted against Euro. For each trading rule, we report the monthly % mean (μ), % volatility(σ), skewness (γ), kurtosis (K), Sharpe ratio (SR), Sharpe ratio of the random walk model (SR_{RW}), and Sortino ratio (SO). *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Developed Market Currencies											
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
		Australia			Canada			Denmark			Japan	
μ	1.34***	1.81***	1.86***	3.02***	3.25***	3.22***	2.30***	2.64***	2.63***	2.51***	2.83***	2.72***
σ	2.23	1.86	1.81	3.14	2.90	2.94	2.79	2.47	2.48	2.80	2.47	2.60
γ	-0.01	0.30	0.40	0.98	1.32	1.25	1.10	1.70	1.68	0.08	0.54	0.33
K	0.08	0.22	0.14	3.20	4.50	4.28	3.44	5.33	5.18	0.57	0.28	0.40
SR	0.60	0.98	1.03	0.96	1.12	1.10	0.83	1.07	1.06	0.90	1.15	1.04
SR_{RW}	-0.17	-0.17	-0.17	-0.01	-0.01	-0.01	-0.03	-0.03	-0.03	-0.09	-0.09	-0.09
SO	1.16	2.34	2.94	2.99	3.76	3.38	2.10	5.26	7.74	1.65	3.41	2.36
		New Zealand			Norway			Sweden			Switzerland	
μ	3.89***	4.05***	4.04***	2.79***	3.16***	3.17***	2.81***	3.06***	3.09***	2.49***	2.77***	2.74***
σ	3.80	3.63	3.63	3.27	2.91	2.90	3.25	3.01	2.98	2.86	2.58	2.62
γ	1.03	1.23	1.22	0.95	1.44	1.47	0.98	1.27	1.31	0.93	1.33	1.25
K	2.05	2.50	2.49	3.26	5.15	5.16	2.07	2.89	3.01	1.69	2.61	2.49
SR	1.02	1.12	1.11	0.85	1.08	1.09	0.87	1.02	1.04	0.87	1.07	1.05
SR_{RW}	-0.11	-0.11	-0.11	-0.04	-0.04	-0.04	-0.08	-0.08	-0.08	0.04	0.04	0.04
SO	3.74	6.78	5.51	2.37	4.16	7.04	2.97	6.40	5.90	2.67	7.33	4.09
		UK			US							
μ	0.78***	1.27***	1.18***	1.47***	1.92***	1.86***						
σ	2.22	1.97	2.03	2.45	2.12	2.17						
γ	1.37	1.63	1.57	0.35	1.08	1.00						
K	6.42	9.36	8.34	1.84	1.72	1.56						
SR	0.35	0.65	0.58	0.60	0.90	0.86						
SR_{RW}	0.05	0.05	0.05	-0.00	-0.00	-0.00						
SO	0.79	1.35	1.37	0.98	3.07	2.68						

Figure 1. Combined Model Forecasts versus Random Walk Forecasts and Actual Returns