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

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

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Abstract

This paper provides the first comprehensive investigation on the informational role of financial market information in the profitable predictability of exchange rates in an out-of-sample (OOS) context in emerging markets. Within a comparative analysis framework across developed and emerging countries, we examine if international stock and bond returns can be exploited as a predictor for future spot exchange rate changes (statistical test), and if an economically profitable trading strategy can be executed (economic test). Our central finding is that currency traders can beat emerging markets conditionally on correctly predicting the direction of the OOS forecasted currency returns induced by emerging stock and, to a lesser extent, by bond market returns. By contrast, this profitability is not evident in developed countries data. This asymmetric evidence, on the power of stock and bond returns in the profitable predictability of currency returns across developed and emerging countries, is affected by the country-specific institutional quality.

JEL classification: G15, G17, F31.

Keywords: exchange rates, out of sample predictability, emerging markets, equity returns, bond market returns.

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1. Introduction

Exchange rate predictability has attracted considerable attention in academic literature. Following the seminal work of Meese and Rogoff (1983), research has found it difficult to beat the random walk (RW) model for currencies. Prior research has generally focused on examining the predictive power of macroeconomic fundamentals, such as inflation rate, interest rate, GDP growth rate, and others (Engel et al., 2007; Della Corte et al., 2009; Molodtsova and Papell, 2009; Li et al., 2015).[1] While economists have long understood that macroeconomic and financial variables are interrelated (see, e.g., Fama, 1990, Chiu et al., 2018), not much work has been done on investigating the informational role of financial asset returns in exchange rate predictability. For example, Camanho et al. (2022), focusing on developed markets finds that equity returns forecast exchange rate returns due to portfolio rebalancing, while Ang and Chen (2010) focusing again on developed countries find that many factors affecting the yield curve, such as changes in interest rates and term spreads predict excess foreign exchange returns.

This paper distinguishes itself from prior research on the informational role of financial asset returns in exchange rate predictability by focusing on emerging market economies, as well as on examining the exchange rate profitable predictability of financial market returns in an OOS context. We employ a three-step forecasting model that uses differential stock and bond returns between the foreign market and the U.S. market for forecasting exchange rate returns. We first examine the presence of in-sample (IS) predictability over the entire sample period, and we then implement an OOS forecast evaluation of our model using two types of analyses: statistical and economic. In our statistical analysis, we divide our full sample period into an IS period (which corresponds to a ten-year time horizon) and roll through the rest of the OOS period (which corresponds to a fixed window size of 120 observations) to generate rolling one-step-ahead OOS exchange rate forecasts from stock and bond returns, and we then assess their statistical accuracy against the RW model. In our economic analysis, we use these OOS exchange rate forecasts 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).

Within this framework, we present a comparative analysis across developed and emerging countries from November 1989 to December 2019. We are motivated by the different characteristics of the two groups of countries, which imply great heterogeneity in their responses

[1] For a survey of exchange rate predictability, see Park and Irwin (2007) and Rossi (2013).

to financial variables, and by the importance of portfolio debt and equity flows to emerging economies which have continued to develop and become global asset classes. However, despite its importance, there is little evidence in the exchange rate predictability literature on emerging countries (De Zwart et al. 2009; Jamali and Yamani, 2019), given that most of the prior research has focused on developed countries (Della Corte and Tsiakas, 2012; Neely and Weller, 2013; Li et al., 2015).

As far as we know, this is the first attempt that it takes such a novel perspective in the exchange rate forecasting literature on emerging markets. Our main results can be summarized as follows. First, our in-sample predictive results reveal a contrasting evidence across developed and emerging economies, in the sense that local-currency stock (bond) returns carry significant information for future spot rate changes but only for emerging (developed) countries. Second, our OOS predictive results provide strong evidence of the statistical power of stock returns, but not bond returns, in predicting exchange rate changes for emerging economies only. Third, our economic test results corroborate our statistical test results and document the economic success of our stock-based trading rules in generating high statistical and economic positive returns (net of transaction costs) for emerging currencies. We subject these findings to a battery of robustness tests, and we show that these findings are robust despite changing the method of forecast construction, trading rules, or conditioning on popular determinants of currency returns. Finally, we find that the profitability of our trading strategies is time-varying, in the sense that returns appear to be insignificant from September 2006 to April 2013 for all our strategies that condition on both stock and bond information, but they turn to be significantly positive between May 2013 and December 2019.

In a nutshell, our central finding is that there is an economic value in stock and, to a lesser extent, bond information for forecasting exchange rate returns for emerging countries. This new evidence, on the informational role of stock and bond returns in the profitable predictability of exchange rate movements, can be understood in the context of the recent exchange rate forecasting literature suggesting that expected currency returns are primarily driven by a missing risk premium that could account for the "real-world" currency expectation (Sarno et al., 2012; Boudoukh et al., 2016; Kremens and Martin, 2019; Balduzzi and Chiang, 2020; Chernov and Creal, 2021; Dahlquist and Penasse, 2022). Within this framework, we interpret our findings through the lens of the evidence in Sarno et al. (2012) and Kremens and Martin (2019) who show that the missing risk premium is closely linked to bond and stock returns, respectively.

In this paper, bearing in mind the above, we contribute to the extant literature on exchange rate predictability in several important respects. As far as we know, we provide the first evidence on the power of stock and bond returns in predicting currency returns for emerging markets. While the literature has focused on examining economic fundamentals (Engel et al., 2007; Della Corte and Tsiakas, 2012; Li et al., 2015) and technical indicators (Park and Irwin, 2007; Neely and Weller, 2013), no such exploration has been undertaken using financial market indicators in an OOS forecasting framework. The merit of using financial asset returns in exchange rate forecasting is that not only has it been widely documented that macroeconomic and financial variables are dynamically interrelated (Fama, 1990, Chiu et al., 2018), but also financial markets have long been known to recover faster than macroeconomic fundamentals from shocks.

From a practitioner perspective, this paper provides important insights to the practice of currency trading. We document that our currency trading rules that condition on stock returns not only generate significantly positive returns for emerging countries but also outperform popular trading strategies in the foreign exchange (FX) market such as carry trade and currency momentum (Menkhoff *et al.*, 2012). Additionally, we show that using trading rules that condition on bond information generates highly significant profits for emerging countries between 2013 and 2019. This evidence, that the statistical evidence of exchange rate forecasting translates to economic profits, implies that traders can manage their portfolios more effectively conditional on correctly predicting the direction of the forecasted currency returns induced by financial market returns.

Furthermore, our results contribute to a small but growing strand of literature that emphasizes the importance of recognizing the heterogeneity between developed and emerging currency markets (Bansal and Dahlquist, 2000; Frankel and Poonawala, 2010), suggesting that the existing evidence in the exchange rate predictability literature on developed countries does not necessarily generalize to emerging countries. Within this framework, exchange rate forecasting can serve as a good setting in which to study the different profiles of the two groups of economies[2], in the sense that information leakage is presumably more prevalent in emerging countries (Michaelides et al.,

[2] Compared to developed market currencies, trading in emerging market currencies exposes investors to 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. Accordingly, emerging market currencies appear to provide better profit opportunities because of their lower turnover (Bank of International Settlements, 2016, 2022), lesser competition among traders and more easily-identified trends (Frankel and Poonawala, 2010). By contrast, developed countries are more financially integrated than emerging countries which in turn increases the pressure on developed market currencies, leading to more noise in currency forecasting among traders (Phylaktis and Aftab, 2023).

2019) and, therefore, exchange rate predictability should be stronger in emerging countries. The latter view is validated in our evidence that there is a statistical and economic value in stock market information for forecasting exchange rate returns but only for emerging countries.

Finally, our empirical work also lends credence to the theoretical cross–market research on the interrelatedness of stock, bond and FX markets (Bansal and Dahlquist, 2000; Pavlova and Rigobon, 2007; Christiansen et al., 2011). The interconnections between various financial markets have become more complex with the increase in financial integration both domestically and internationally, rendering studies, which examined the relation 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 approach which ignores cross–market effects, we take a different view by examining exchange rate predictability of stock and bond returns, rather than seeking to make predictions based on lead–lag relationships, as in the previous research.

The remainder of the paper is organized as follows. Section 2 presents our forecasting model (i.e., statistical test) and currency trading strategy (i.e., economic test). Our data and variables are outlined in section 3. Section 4 reports our main results, while section 5 presents our robustness results. Section 6 seeks to explain our findings, and section 7 concludes.

2. Research Design

The exchange rate forecasting literature has commonly used several differential parameters, including the difference between domestic and foreign interest rates (the Uncovered Interest Rate Parity, UIP), the difference in price levels (the purchasing power parity), and the difference in real output and money supply (monetary fundamentals) (Engel et al., 2007; Della Corte and Tsiakas, 2012; Li et al., 2015). By contrast, we use differential stock and bond returns between the foreign market and the U.S. market in predicting currency returns.

Our model is cast within the general framework of currency forecasting. In this section, we employ a three-step forecasting approach. To set the stage, our analysis begins with an in-sample testing of the relation between currency, stock, and bond returns. Next, we present our statistical analysis where we construct OOS forecasts using various model specifications of stock and bond returns, and we then assess the statistical accuracy of our forecasts against the actual exchange rate returns. Finally, we describe our economic analysis, where we investigate whether our forecasts can be exploited economically to implement profitable currency trading strategies.

2.1. Forecasting Model – In-sample testing

We run our analysis from the perspective of a U.S.-based investor and employ a two-country (U.S. and a foreign country) model 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. In order to elucidate our forecasting models, we build on the established exchange rate models which use generally a two-country framework where the relative economic or financial variable differentials of two countries are linked to their exchange rate (De Zwart *et al.*, 2009, Doukas and Zhang, 2013).

Within this framework, we employ three forecasting models that use correlations between currency, stock and bond returns for forecasting exchange rate returns. 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 our forecasts: equity returns (E), bond returns ($\mathcal{B}$) and combined equity and bond returns (C). We also denote Δs_{it+1} the currency returns 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 units of the foreign currency i per one USD. Given such setup, our forecasting model allows a set of variables χ to influence future spot rate changes as follows

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

2.1.1. Equity model

Motivation: The first model that we consider is the 'equity-model', where we examine the forecasting power of local-currency stock returns for future currency returns. Theoretically, the relation between stock returns and spot rate changes stems from the portfolio balance model of exchange rates, which predicts that "a strong equity market comes with a strong currency". The portfolio balance model, proposed by Branson (1983) and Frankel (1983), views exchange rate as a variable reflecting relative demand for domestic versus foreign financial assets, suggesting that an increase in local stock prices increases the value of the equity market and results in an increase of demand for local currency by investors and a subsequent appreciation of exchange rates.

The relation between stock and currency returns can be understood also through two hypotheses – the return chasing hypothesis which largely derives the uncovered equity disparity phenomenon (Fuertes et al., 2019), and the portfolio-rebalancing hypothesis which stems from the uncovered equity parity theory (Hau and Rey, 2004, 2006; Cappiello and De Santis; 2007; Curcuru *et al.*, 2014). Both hypotheses predict that the direction of the relation between equity returns and equity flows determines the sign of the relation between equity and currency returns, but they predict a different relation. The return-chasing hypothesis predicts a *positive* relation because any surge in equity returns induces foreign investors to invest in local equity markets, which, in turn, induces local currency to appreciate (Fuertes et al., 2019). By contrast, the portfolio-rebalancing hypothesis predicts a *negative* relation because equity investors tend to reduce their FX exposure by rebalancing away from countries whose equity markets are performing well.

From a forecasting perspective, our hypothesis, that stock returns carry significant information for future currency returns, is inspired by the theoretical work of Kremens and Martin (2019) who develop a stock-based currency risk premium modeled as a function of the so-called "quanto-contract" based on the notion that currency and stock returns are correlated. Kremens and Martin (2019) document the superior predictive ability of the "quanto-contract" as a univariate predictor of currency returns, suggesting that stock returns should significantly predict currency returns.

Equity model: Motivated by these predictions, the first model that we consider is the 'equity-model', where we use the differential stock returns between the foreign market and the U.S. market as a single predictor, as follows

$$\Delta s_{it+1} = \alpha + \beta(r_{it}^{E} - r_{t}^{\mathrm{E,US}}) + \varepsilon_{it}, \tag{2}$$

Where r_t^{E} and $r_t^{\mathrm{E,US}}$ denote, respectively, the ith foreign equity market return in local-currency and the U.S. equity market return in USD.[3] It is important to note that both return chasing hypothesis and portfolio-rebalancing hypothesis are based on the relative outperformance of one market versus another. Since Δs_{it+1} is only between country i and the U.S., r_{it}^{E} only needs to outperform $r_t^{\mathrm{E,US}}$ in order to generate a positive (negative) exchange rate prediction under the return-chasing (portfolio-rebalancing) hypothesis. Note that an increase in Δs_{it+1} means an appreciation (depreciation) of the USD (foreign currency) and, therefore, positive (Negative) β in Equation (2) indicates that currency i will depreciate (appreciate) relative to the USD if the ith foreign stock market outperforms the U.S. stock market.

[3] The inclusion of $r_t^{\mathrm{E,US}}$ is motivated by prior research that emphasizes that U.S. market acts as a conduit in linking currency markets and international stock markets (Phylaktis and Ravazzolo, 2005). As noted in Hau and Rey (2006), U.S. 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.

2.1.2 Bond model

Motivation: Our second model examines the informational role of bond returns in predicting currency returns. In theory, the relation between bond and currency returns is driven from two popular models of exchange rate determination – the balance of payment model and the monetary model. The former emphasizes trade flows and capital movements as exchange rate determinants, while the latter shifts the responsibility for determining exchange rates to money markets.

The power of bond returns in forecasting currency returns is inspired by the classic literature on exchange rate predictability which has focused on predicting exchange rates in the context of UIP, suggesting that exchange rate changes are equal to interest rate differential between two economies under the assumptions that agents are risk-neutral and form rational expectations. Nevertheless, it has been widely documented that UIP does not hold (Della Corte et al., 2009; Li et al., 2015). The predictive failure of UIP has been attributed to the assumption of "risk-neutrality" expectation of currency returns, given that "real-world" expectation is what matters in forecasting.

Accordingly, the modern literature has attempted to study exchange rate predictability beyond UIP by relaxing the "risk-neutrality" assumption (Sarno et al., 2012; Boudoukh et al., 2016; Balduzzi and Chiang, 2020; Chernov and Creal, 2021; Dahlquist and Penasse, 2022). This literature decomposes currency risk premium into interest rate differential plus a missing risk premium which accounts for the "real-world" currency expectation. Within this framework, Sarno et al. (2012) relax the "risk-neutrality" assumption and derive a risk-adjusted UIP model by showing that expected exchange rate returns are driven by interest rate differentials (as in the UIP) in addition to a time-varying risk premium which compensates for both currency risk and interest rate risk. Sarno et al. (2012) document the success of this bond- and currency-based risk premium in pricing both currencies and bonds.[4]

Bond model: Viewed through this lens, we empirically formalize this intuition based on different versions of UIP and suggest that bond returns should predict exchange rate movements. More specifically, we examine the relation between bond return and future currency return using a univariate regression which use the differential domestic government bond return between the foreign market and the U.S. market as a single explanatory variable, as follows

[4] Another view, which has influenced our analysis, is that causality runs from the local currency bond market to the FX market because foreign investors tend to rely on FX instruments to hedge their holdings of local currency bonds, which in turn lead to the variability of the exchange rate (e.g., Pericoli and Taboga, 2012).

$$\Delta s_{it+1} = \alpha + \beta(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\text{US}}) + \varepsilon_{it+1}, \tag{3}$$

where $r_{it}^{\mathcal{B}}$ represents the returns on foreign markets local currency sovereign debt which is a government bond and $r_t^{\mathcal{B},US}$ is the return on the U.S. bond index denominated in the USD.[5]

2.1.3 Combined model

Motivation: Our third model combines data from both stock and bond markets to predict future currency returns. The interconnections between various financial markets have become more complex with the increase in financial integration both domestically and internationally, rendering studies, which examined the relation 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.[6]

In contrast to this separate approach which ignores cross–market effects, our 'combined' model takes a new view by examining exchange rate predictability of both stock and bond returns, lending credence to the theoretical research on the interrelatedness of stock, bond and FX markets (Bansal and Dahlquist, 2000; Pavlova and Rigobon, 2007; Christiansen et al., 2011) which has confirmed the interconnections between the three 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 FX markets co-move. Christiansen et al. (2011) take a different perspective by modeling 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.

In support, numerous empirical studies, such as Andersen *et al.* (2007) and Ehrmann et al. (2011), confirm these theoretical interconnections between stock, bond, and FX markets. They approach interconnections, 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

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[5] The rationale for including $r_t^{\mathcal{B},US}$ is that U.S. entities are the largest and the most significant players in international bond markets (International Monetary Fund (2018): Table 12). Furthermore, U.S. monetary policy exerts a significant influence on capital spillovers to local currency bond markets (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.

[6] Our combined model adds a different perspective to view 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.

the response of U.S., German and British stock, bond, and FX markets to U.S. macroeconomic news, and they find that high-frequency stock, bond, and exchange rate dynamics are linked to fundamentals. Ehrmann et al. (2011), on the other hand, investigate the impact of monetary shocks on the degree of financial transmission between money, bond, stock markets and exchange rates within and between the U.S. and the Euro area, and they find evidence on substantial international spillovers within and across asset classes.

Combined model: Our third forecasting model is the 'combined model', in which we employ the information content of both differential sets of stock and bond returns in order to test the interrelatedness of stock, bond, and FX markets in a forecasting context, as follows

$$\Delta s_{it+1} = \alpha + \beta_1(r_{it}^{E} - r_t^{\text{E,US}}) + \beta_2(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\text{US}}) + \varepsilon_{it+1}, \quad (4)$$

Equation (4) follow the Kitchen-Sink regression approach for forecasting exchange rate returns, which has been applied to stock returns (Welch and Goyal, 2008).

2.2. Statistical Evaluation of Predictability – Out-of-sample testing

Fitting and evaluation periods: To provide a deeper investigation into the value of stock and bond information in FX markets, we implement an OOS forecast evaluation of our model. The implementation of the OOS forecasting is straightforward. Let $\widehat{\Delta s}_{t+1|t}^{\chi}$ refers to the individual one-month ahead exchange rate forecast constructed from the three sets of χ information up to time t. We use the aforementioned three models in Equations (2)–(4) to generate n-step ahead OOS forecasts for currency returns as follows $\widehat{\Delta s}_{t+1|t}^{\chi} = \hat{\alpha}_{t,i} + \hat{\beta}_{t,i}\chi_{it}$, where $\hat{\alpha}_{t,i}$ and $\hat{\beta}_{t,i}$ are the OLS predictive estimates from Equations (2)–(4).

To generate $\widehat{\Delta s}_{t+1|t}^{\chi}$, we divide our full sample period ($t = 1$ to $t = T - 1$) into an in-sample 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 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 we then 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 currency.

Forecast evaluation criteria: We begin assessing the statistical accuracy of our models with calculating the Mean Square Forecast Error (MSFE), given by

$$MSFE^{\chi} = \frac{1}{T}\sum_{t=M+1}^{T}\left(\Delta s_{t+1} - \widehat{\Delta s}^{\chi}_{t+1|t}\right)^2, \tag{5}$$

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

$$Relative\ MSFE\ = \frac{MSFE^{\chi}}{MSFE^{RW}}, \tag{6}$$

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 (e.g., Campbell and Thompson, 2008; Welch and Goyal, 2008; Rapach et al., 2010) and the FX prediction literature (Della Corte and Tsiakas, 2012; Li et al., 2015). The OOS R^2 equals

$$R^2_{oos} = 1 - \frac{MSFE^{\chi}}{MSFE^{RW}}, \tag{7}$$

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

$$CW\ test: \hat{f}_{t+1} = \left(\Delta s_{t+1} - \widehat{\Delta s}^{RW}_{t+1|t}\right)^2 - \left[\left(\Delta s_{t+1} - \widehat{\Delta s}^{\chi}_{t+1|t}\right)^2 - \left(\widehat{\Delta s}^{RW}_{t+1|t} - \widehat{\Delta s}^{\chi}_{t+1|t}\right)^2\right], \tag{8}$$

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. As a benchmark, we compare the performance of our models to the RW model which has received a broad attention in the international finance literature (Della Corte and Tsiakas, 2012; Li et al., 2015). According to the RW hypothesis, spot exchange rate changes are not predictable since they are expected to revert to the mean in the short run, as follows: $\Delta s_{it+1} = \alpha + \varepsilon_{it+1}$. A significant CW statistic, therefore, implies that the alternative competing forecasting model outperforms the RW model.

2.3. Economic Evaluation of Predictability – Trading strategies

In the third part of our analysis, we examine whether statistical significance translates to economic benefits for investors, in the sense that we test whether stock and bond information can be exploited to implement profitable currency trading strategies. Our motivation for running this economic test is that forecast (in)accuracy need not automatically imply (lack of) profitability (Leitch and Tanner, 1991). While prior research documents diversification benefits of incorporating international stocks (DeSantis and Gerard, 1997) and bonds (Levich and Thomas, 1993) in international portfolios, it is unclear how investors could leverage gains by investing across various asset classes in the backdrop of a lack of consensus on cross-market relations, and, therefore, it is natural to study the profitability of currency trading based on stock and bond returns.

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

$$Signal_t = \mathbb{Z}^{\chi}_{it} \big| \widehat{\Delta s}^{\chi}_{t+1|t} = \begin{Bmatrix} 1 & if \quad \widehat{\Delta s}^{\chi}_{t+1|t} > 0, \\ -1 & if \quad \widehat{\Delta s}^{\chi}_{t+1|t} < 0, \end{Bmatrix} \tag{9}$$

Where $\mathbb{Z}^{\chi}_{it} \big| \widehat{\Delta s}^{\chi}_{t+1|t}$ 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+1} multiplied by the trading signal

$$\Delta s_{it}^{\chi} = Signal_t \times spot\ rate\ changes_t = \mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi} \times \Delta s_{it}\ , \qquad (10)$$

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

Transaction costs: Equation (10) 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}

$$\Delta s_{it,\tau}^{\chi} = \begin{Bmatrix} \Delta s_{it}^{\chi} - \tau_{it}^{long} & if \quad \mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi} = 1, \\ -\left(\Delta s_{it}^{\chi} - \tau_{it}^{short}\right) & if \quad \mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi} = -1, \end{Bmatrix} \qquad (11)$$

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 $s_{it}^{b} - s_{it+1}^{a} =$

$-\left(\Delta s_{it}^{\chi} - \tau_{it}^{short}\right)$. We focus on the net-of-transaction costs return in Equation (11) in order to assess the economic value of our forecasting models. This approach to account for transaction costs has been used in several studies (e.g., Neely et al., 2009; Della Corte and Tsiakas, 2012).

It is important to note that we take our trading strategies to the portfolio-level data to ensure the robustness of our results in a cross section of currencies. 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.

3. Data and Variables

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 $t = 1, \ldots\ldots, T$ 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 equally weighted portfolios of currencies – developed, emerging and global. Our developed portfolio 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 literature. Our emerging portfolio 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.

Our dataset consists of the end-of-the-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. We express all the return data in a pooled sample in the local currency. All data are obtained from DataStream.

For currency returns, we collect the WMR/Reuters spot exchange rates for our 28 currencies against the USD. 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 spots using the fixed conversion rate of January 1999. This latter approach is commonly used in existing studies (Della Corte and Tsiakas, 2012).

For stock and bond returns, we consider index returns that represent broad price movements in each market. For country-level equity index returns (r_{it}^{E}), we employ the Datastream global equity indices. For country-level bond index returns ($r_{it}^{\mathcal{B}}$), we use government bond index returns which represent the returns on the safest asset in a country. We measure developed market bond returns using the 5-year Datastream government bond indices, while we base our emerging market bond returns on the JPMorgan Government Bond Index-Emerging Markets (GBI-EM) Broad which is a comprehensive index that tracks local currency bonds issued by Emerging market governments.

4. Results

4.1. Statistical IS Forecast Evaluation Results

A natural starting point for our forecasting analysis is that we examine the estimation results of our in-sample regressions for 'Equity' model as defined in (2), Bond' model as defined in (3), and 'Combined' model as defined in (4). Table 2 summarizes the coefficient estimates of these three models with Newey and West (1987) standard errors with three lags. If the RW holds, all estimates should be insignificantly different from zero suggesting that currency returns are not predictable by financial market returns. In contrast, positive (negative) beta indicates that currencies, whose stock and/or bond index returns are high relative to the US stock and/or bond index returns, tend to depreciate (appreciate). To save space, we surpass country-level results and report only portfolio-level results (developed, emerging and global). For comparison purposes, all our tables employ a comparative analysis (developed vis-à-vis emerging countries) in order to make comparative remarks between developed and emerging market countries.

Overall, Table 2 results emphasize the importance of qualifying the differences between developed and emerging countries when investigating cross-market relations. Consider first equity-model results. We find that stock return differential $r_{it}^{E} - r_{t}^{\mathrm{E,US}}$ coefficients are insignificant for the developed portfolio, but they turn to be significantly negative for the emerging portfolio. It is notable that this statistical significance remains when we use the global portfolio which expands the developed portfolio to also include the emerging portfolio, suggesting that such significant effect is more likely driven by the emerging countries in our sample. This latter finding suggests that emerging market currency appreciation follows a bullish emerging stock market (relative to the U.S. stock market), a finding which is more consistent with the return chasing hypothesis that predicts a positive relation between currency returns and stock returns because any surge in local-currency stock returns induces foreign investors to invest in local equity markets, which, in turn, induces local currency to appreciate (Fuertes et al., 2019, Phylaktis and Aftab, 2023).

Analogously, bond-model results reveal that developed and emerging countries predict different conclusions on the response of future exchange rate returns to local-currency bond returns. While $r_{it}^{B} - r_{t}^{\mathrm{B,US}}$ coefficient is significantly positive for the developed portfolio, we do not find any significant relation between differential bond returns and future spot rate changes for both emerging and global portfolios. This could be due to the fact that sovereign bond markets in many emerging countries are not well developed (Kersley and Sulivan, 2014).

Similar findings are observed for the combined model that expands the equity model to also include bond variables, and the R^2 values are the highest for the combined model. The combined-model results show that local-currency stock returns carry significant information for future spot rate changes, given that $r_{it}^{E} - r_{t}^{\mathrm{E,US}}$ coefficients are consistently significant across the three baskets of currencies (-0.105, -0.129 and -0.083 for the developed, emerging and global portfolios, respectively). By contrast, $r_{it}^{B} - r_{t}^{\mathrm{B,US}}$ coefficients are significant for the developed portfolio only, a finding which is in line with bond-model results.

In a nutshell, our in-sample results suggest that stock (bond) returns carry significant information for emerging (developed) market currency returns, a finding that motivates our OOS forecasting exercise on the power of stock and bond returns in predicting currency returns.

4.2. Statistical OOS Forecast Evaluation Results

Panel A of Table 3 reports the results of a comprehensive set of statistical forecast accuracy criteria for evaluating one-month ahead OOS forecasts for the equity, bond and combined empirical exchange rate models. The forecast accuracy measures include MSFEs as defined in (5), MSFEs relative to the RW benchmark as defined in (6), OOS R^2 as defined in (7), and Clark and West (2007) test of equal predictive ability as defined in (8). In order to interpret the statistical significance of differences in 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.

Several interesting findings stand out from our OOS empirical exercise in Panel A of Table 3 which corroborates our IS results in Table 2. Once again, our results reveal a contrasting pattern across developed and emerging currencies. We observe that equity and combined model forecasts for emerging market currencies perform better than analogue forecasts for developed market currencies. For the emerging portfolio, it is obvious that equity and combined predictive models produce lower MSFEs compared to the benchmark RW model, as evidenced 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, Clark and West (2007) statistics reject the null of equal predictive ability between our equity and combined forecasts and the RW forecasts at the 1% level for the emerging portfolio. By contrast, our assessment of the statistical forecast accuracy does not reject the null of equal predictive ability between our predictive models and the RW model for the developed portfolio. Our forecasts generated from the bond model do not outperform the RW model for both developed and emerging portfolios.

In summary, our overall predictive results contribute to the literature on exchange rate predictability by providing the first evidence on the statistical power of international stock returns in predicting exchange rate returns in an OOS context, using emerging countries data. While the existing literature has focused its attention on examining fundamentals (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 market returns.

4.3. Economic Evaluation Results

The question then arises whether the statistical significance (documented in Panel A of Table 3) translates into economic benefits for investors. As noted in Della Corte et al. (2009), statistical evidence of exchange rate forecasting does not necessarily guarantee economic profits. We thus go one step further in our analysis and extend our statistical analysis to the use of economic criteria. The key mechanism that characterizes our strategies is defined in Equation (9) 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 strategies do not generate significant profits.

Panel B of Table 3 reports several profitability measures for our three long-short trading strategies (equity, bond, and combined) which are all conditional on the one-month ahead forecasts generated from our predictive regressions in Equations (2)-(4). For each strategy, we report the monthly % mean (μ), % volatility(σ), skewness (γ), and kurtosis (K). Further, we report two measures of risk-adjusted returns: Sharpe ratio (SR, the ratio of net monthly return to monthly standard deviation) and 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 our competing models.

Overall, results in Panel B of Table 3 provide consistent evidence on the economic success of our equity and combined trading strategies when emerging market currencies are employed, as attested by several appealing diversification characteristics for currency traders. In terms of payoffs, equity and combined strategies consistently yield a high statistical and economic average returns (net of transaction costs) for the emerging portfolio. The stock-based strategy has average monthly payoffs of 0.30% for emerging portfolio.[7] Our combined strategy also performs well for the emerging portfolio as evidenced by generating positive and statistically significant monthly returns of 0.59%. It is also notable that our equity and combined trading strategies perform well in terms of risk-adjusted returns as attested by rendering not only positive Sharpe ratios but also higher Sharpe ratios compared to those of the RW model, suggesting that they compare favorably to the benchmark RW model. Moreover, the large values of the SR suggest that the profitability of our trading strategies are associated with low risk of large losses. In support, returns on our equity and combined trading strategies exhibit positive skewness, suggesting that they are relatively stable during times of financial stress. This may be an appealing characteristic for investors who are concerned about higher moments beyond mean and variance.

For comparison, Panel C of Table 3 reports analogue performance measures for three popular currency trading strategies: RW, currency momentum, and carry trade. The first benchmark 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., $\Delta s_{it+1}=\alpha+\varepsilon_{t+1}$). We also form currency momentum (carry trade) strategy by sorting currencies into five portfolios based on their lagged one-month return (interest rate) and then rank them from small to large lagged currency returns (lagged interest rate) (Menkhoff *et al.*, 2012). The momentum strategy goes long in the

[7] The key mechanism underlying our stock-based trading strategy is the evidence, both theoretical and empirical, on the return chasing hypothesis. Theoretically, the return chasing hypothesis predicts a positive relation between exchange rate and stock 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 in several studies (Froot et al., 2001; Froot and Ramadorai, 2008; Richards, 2005).

‘‘winner” portfolio (the top portfolio with the highest lagged return), and goes short in the ‘‘loser” portfolio (the bottom portfolio with the lowest lagged return). Similarly, the carry trade strategy goes long (short) in the top (bottom) portfolio with the highest (lowest) lagged interest rate. Overall, results shows that our combined trading strategy outperforms all the benchmark strategies but only when emerging market currencies are employed.

In summary, our empirical findings in Table 3 point to a novel conclusion: investors in emerging currency markets not only can improve their ability in forecasting exchange rate movements by incorporating stock market information, but also they can beat the FX market by trading on the sign of exchange rate predictability induced by stock market returns.

5. Robustness Analyses

In this section, we consider a rich set of robustness checks on our statistical and economic results (reported in Table 3) including different model specifications to control for our choice of the forecast construction method, benchmark index, and trading strategy.

5.1. Alternative forecasting methodology – recursive regressions

We first test whether our results are driven by our choice of the forecast construction method (i.e., rolling regression). For robustness, we re-estimate our OOS forecasts using recursive regressions that initially use the first 120 monthly observations as the IS period for every currency and then re-estimate the model parameters every time a new observation is added to the sample.

The statistical and economic results are reported in Panels A and B, respectively, of Table 4. The overall findings in Panel A of Table 4 are in line with those reported in Panel A of Table 3, and continue to support the ability of our equity and combined models in predicting emerging market currency returns as attested by three findings: (1) the Relative-MSFEs corresponding to the two models, are less than one; (2) the OOS R^2 values are positive; and (3) the Clark and West (2007) MSFE adjusted t-statistics are statistically significant. Furthermore, our empirical evidence in Panel B of Table 4 continues to provide evidence on the profitability of our combined trading strategy using the emerging portfolio. In summary, both rolling and recursive regressions provide consistent results and corroborate the in-sample estimation results in that, for the combined model outperforms markedly the benchmark RW model using emerging market currencies.

5.2. Alternative benchmark index – Global market index

We also examine whether our statistical and economic results (reported in Table 3) are driven by our choice of the U.S. stock and bond indexes. So far, we have used $r_t^{\mathrm{E},US}$ and $r_t^{\mathcal{B},US}$ as our benchmark indexes in all our regressions. Bearing in mind that the global stock and bond information is the same for all currencies, which are defined with respect to the USD, we replace $r_t^{\mathrm{E},US}$ and $r_t^{\mathcal{B},US}$ in our regressions with returns on global equity market $r_t^{\mathrm{E,Global}}$ [8] and global bond market $r_t^{\mathcal{B},\mathrm{Global}}$, respectively. We use MSCI world stock market index to measure $r_t^{\mathrm{E,Global}}$ and Citibank world government bond index (WGBI) to control for $r_t^{\mathcal{B},\mathrm{Global}}$. We estimate three alternative specifications of our 'combined' model, that differ in the set of predictor variables as follows: (1) $r_t^{\mathrm{E,Global}}$ and $r_t^{\mathcal{B},\mathrm{Global}}$ (Model 1) ; (2) $(r_{it}^{E} - r_t^{\mathrm{E,Global}})$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\mathrm{Global}})$ (Model 2); and r_{it}^{E}, $(r_{it}^{E} - r_t^{\mathrm{E,Global}})$, $r_{it}^{\mathcal{B}}$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\mathrm{Global}})$ (Model 3).

Table 5 reports the statistical (Panel A) and economic (Panel B) evaluation results. The overall statistical results in Panel A of Table 5 are analogue to Panel A of Table 3 for our baseline model, suggesting that Models 2 and 3 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). Moreover, the economic results in Panel B of Table 5 are analogue to those reported in Panel B of Table 3, indicating that our long-short trading rule performs well across the three models for the emerging portfolio as evidenced by the significantly positive net average returns and high Sharpe ratios.

5.3. Alternative combined trading strategies

To further assess the robustness of our economic results, we propose two alternative "combined" trading strategies. In our first strategy, we use excess stock returns (instead of stock returns as in Equation 2), so that we combine stock and bond (interest rate) information, as follows

$$\Delta s_{it+1} = \alpha + \beta_1 \left(r_{it}^{E} - r_{ft} \right) + \beta_2 \left(r_t^{\mathrm{E,US}} - r_{f,t}^{\mathrm{US}} \right) + \varepsilon_{it+1} \qquad (12)$$

Where r_{ft} and $r_{f,t}^{\mathrm{US}}$ denote, respectively, the ith foreign country and the U.S. risk-free rates.[9]

[8] Prior research shows that currency returns are related to global equity returns (e.g., Ülkü et al., 2012). 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 USD 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 driven by this dollar risk.

[9] Data for interest rates are obtained directly from Verdelhan website. We exclude Argentina, Brazil, Chile, Colombia and Peru due the unavailability of interest rate data from Verdelhan website.

We also use *'Heterogeneous Agent-based strategy'* (henceforth, simply HA) which is inspired by the literature on HA models (De Zwart *et al.*, 2009; Buncic and Piras, 2016)[10], suggesting that agents switch their behavior over time to the more profitable strategy. 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 stock and bond returns, respectively. Second, she forms a portfolio by placing dynamic weights on stock and bond trading strategies where the relative weights assigned to stock and bond signals vary over time based on the last period profit. Specifically, the weight given to the stock trading strategy (w_t^{E}) increases relative to the weight given to the bond trading strategy $\left(w_t^{\mathcal{B}}\right)$ when the last period currency return conditional on stock 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 stocks to bonds. The realized return on the investor's portfolio (which we denote by $\Delta s_{it,\tau}^{HA}$) equals

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

The HA model optimally combines forecasts of stock and bond returns by allowing investors to switch from 'stock traders' to 'bond traders', depending on changing market conditions. In contrast to the naïve combined strategy outlined in Equation (4) where traders put equal value on stock 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 stock and bond signals based on their past performance. The rationale for using 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 traders during times of turbulence when the risky stock

[10] De Zwart *et al.* (2009) consider a combined investment strategy with dynamic weights placed on fundamental and technical information. Similarly, Buncic and Piras (2016) use an empirical heterogeneous agent model to combine OOS exchange rate forecasts using fundamentalist and technical signals.

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.[11]

Table 6 reports performance measures for both trading strategies. For robustness, we report monthly returns on the "long-short" trading rule (as defined in Equation 9) alongside those of the "long-only" trading rule which takes no position in the currency instead of short position, as

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

where $\mathbb{Z}_{it}^{\chi} \big| \widehat{\Delta s}_{t+1|t}^{\chi}$ equals $+1$ or 0 for taking a long or no positions in foreign currencies, respectively. In contrast to the long-short trading rule, the long-only trading rule recommends taking no position in the currency (instead of short position) if the predicted return of currency i is negative. This long-only 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).

The figures for the HA strategy in Table 6 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 in Table 6 are similar to those reported in Panel B of Table 3, supporting the ability of our combined model in generating OOS profits for emerging market currencies. The results of both "long-only" and "long-short" strategies are consistent, suggesting that investors can beat the emerging FX market by trading on the sign of currency return predictability induced by financial market returns.

6. Understanding the results

So far, our evidence suggests that our equity and combined trading rules generate sensible robust returns which are not explained by our choice of the forecast method, benchmark index, and trading rule. A relevant question to ask is what the underlying mechanism behind this profitability is which is expected to be arbitraged away. While addressing this question is beyond the scope of this paper, we examine whether systematic risk, extreme market conditions, transaction cost, and institutional quality play a role for these abnormal returns.

[11] This idea is consistent with the existing empirical evidence on the time-varying comovement between stock and bond returns within the same country (e.g., 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 within 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.

6.1. Systematic risk

Dollar and Carry factors: We first explore whether systematic risk proxied by $Dollar$ and $Carry$ risk factors (which are found to be successful in pricing the bilateral exchange rates in Verdelhan, 2018) can explain our results. In order to explore that, we expand our predictive regressions in Equations (2) - (4), to also include $Dollar$ and $Carry$ risk factors[12]. Finding that the statistical significance of our financial variables disappears when we include these risk factors would imply that systematic risk drives the profitability of our strategies. Panel A of Table 7 reports the results from this expanded specification of our predictive models and it is notable that the statistical significance of stock and bond variables remains basically unchanged, implying that currency risk factors, albeit significant, do not drive the profitability of our trading strategies.

VIX index: Global equity volatility risk has also been found to impact the relation between international stock returns and currency returns (Cenedese *et al.*, 2016). Hence, we now perform the same analysis as above but this time we augment our predictive regressions in Equations (2)-(4) to include global equity volatility risk.[13] Panel B of Table 7 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 VIX. Looking over the overall results in Panel B of Table 7, it is evident that they are in line with those reported in Table 2, in the sense that stock and bond returns continue 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 results.

Macro risk: 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 relation between currency returns and country-level macroeconomic conditions, measured by the business cycle which constitutes a key building block in the theoretical models of exchange rates. They find that business cycle is key driver and powerful predictor of currency returns in the cross-section. Hence, we augment our regressions in Equations (2)–(4) by the logarithmic values of the monthly changes of

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[12] $Dollar$ factor is the average spot rate changes of several currencies, and $Carry$ factor is generated by sorting currencies based on their forward discount. Data for both risk factors are obtained directly from Verdelhan website.

[13] 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 U.S. 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 results using the first measure to save space. Data for VIX are obtained from the Federal Reserve Bank database (FRED).

the industrial production (IP).[14] 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 Panel C of Table 7. Again, looking across stock and bond coefficient estimates, we find that all results are virtually unchanged relative to Table 2. It can be seen that there is basically no additional explanatory power, in the sense that IP is not a useful predictor of currency returns and that a change in IP does not explain our findings.

Panel D of Table 7 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, results reveal that emerging market currency returns generated from our equity and combined models are not primarily driven by risk factors, as attested by several findings. First, the alphas are fairly high and significant at 5% level. Second, there is a little evidence that exposure to these factors is able to account for our abnormal returns. Third, R-squares are small.

Currency excess returns: For completeness, Table 8 evaluates the forecasting power of stock and bond returns in currency excess returns (Panel A) and forward discounts (Panel B), rather than exchange rate changes. Note that average excess returns on currencies are decomposed into two components: average forward premiums (interest rate differentials) and average spot rate changes against the USD. While examining currency excess returns is beyond the scope of this article, it is interesting to explore whether our evidence, on the power of stock returns in forecasting exchange rate changes, also holds for currency excess returns. Looking over the results in Table 8, it is evident that this is not the case. There is no evidence that stock or bond returns can predict excess currency returns or forward discounts. Our results relate to the poor performance of carry trades noted in many papers (see e.g. Hsu, Taylor, Wang and Lee 2024).

6.2 Time variation in forecast performance

We extend our analysis further and examine the time-varying stability of our OOS forecasts over time. Our goal is to examine whether our evidence (in Table 3), on the forecasting power of equity and bond returns in predicting exchange rate returns, is driven by certain periods in our entire sample period. To this end, we re-examine the statistical and economic performance of our

[14] 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.

forecasts over several subsample periods as well as during the turbulent periods surrounding two major crises – the 2007–2008 global financial crisis (GFC) and the COVID-19 pandemic.

Subsample analysis: We first examine the statistical and economic performance of our rolling forecasts over two equal sub-sample periods so that each period corresponds to 80 months in length as follows: (1) the first sub-period covers the period from September 2006 to April 2013; and (2) the second sub-period is from May 2013 to December 2019. The choice of the length of each sub-sample period is triggered by the length of the OOS period, where the first OOS forecast is for November 1999 and the last forecast is for December 2019, in our OOS rolling forecasting exercise which generates 242 forecasts.[15] The sub-sample analysis results are reported in Table 9.

Panel A of Table 9 repeats the same statistical analysis in Panel A of Table 3 with the two periods, revealing an interesting time-varying pattern. During the first period (Panel A.1 of Table 8), none of our predictive models is able to outperform the RW model across the three portfolios as evidenced by insignificant CW t-statistics, with the only exception being the equity model which continue to outperform the RW model for the emerging portfolio. We fail to reject the null of equal predictive accuracy for the combined model across both emerging and global portfolios, a finding which contradicts our findings in Panel A of Table 3 for the whole sample period.

Moving onto the second period (Panel A.2 of Table 9), a contrasting pattern is observed. It is now seen that the statistical forecast accuracy for the combined model has been significantly improved across both emerging and global portfolios and becomes analogous to those reported in Panel A of Table 3 for the full sample period. Interestingly, the statistical forecast accuracy has been also improved for the developed portfolio. While both equity and combined models do not possess any predictive power for developed market currencies during the first period, results turn to be stronger in the second period, suggesting the success of our equity and combined models in predicting developed market currency returns. Nevertheless, we fail to reject the null of equal conditional predictive accuracy for our bond model across the two subsample periods.

To understand how such time-varying statistical performance translates into visual evidence, Figure 1 plots the one-step ahead forecast of currency returns constructed from equity, bond and combined models vis-à-vis the RW model alongside with the actual spot rate changes for both

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[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. Hence, we are not able to perform the exercise for all our sample emerging market currencies over the first sub-period covering the period from January 2000 to August 2006.

developed and emerging portfolios. Figure 1 provides a visual illustration of the time-varying pattern of our combined model forecasts in predicting actual spot rate changes for both developed and emerging countries. It can be seen that the accuracy of our forecasts appears to be higher over the second part of the sample. The time series fluctuations show that the combined model forecasts show a mean reversion pattern similar to RW forecasts during the first period, but then the forecasts and the actual spot rate changes almost coincide together overtime during the second period.

Panel B of Table 9 repeats the same economic analysis in Panel B of Table 3 with the two subsample periods. Once again, our results reveal that the profitability of our trading strategies is time-varying for emerging countries. The returns from our equity and combined trading strategies are insignificant for the emerging portfolio in the first period, but they turn to be significantly positive (at a 1% significance level) in the second period. A similar pattern is observed for the global portfolio. Interestingly, trading based on the predicted sign of the bond model results in a loss of -0.68% on the emerging portfolio during the first period, but then renders positive returns of 0.47% during the second period. This finding suggests that there is an economic value in bond market information for emerging currencies between May 2013 and December 2019.

Global financial crisis: Our subsample analysis in Table 9 points to a novel conclusion: the profitability of our trading strategies is time-varying for emerging countries over the September 2006 – April 2013 period which covers the turmoil time of the GFC which has led to an unexpected sharp appreciation of the USD against all currencies (Fatum and Yamamoto, 2016). This finding motivates us to examine the impact of the turbulent periods on the variation in our OOS forecasts. To better understand the time-varying pattern in Table 9, Table 10 reports the statistical (Panel A) and economic (Panel B) performance of our OOS forecasts during and after the GFC using two periods: (1) crisis period from August 2007 to February 2009, and (2) post-crisis period from March 2009 to December 2019. Our choice of the onset of the crisis period is motivated by the major carry trade unwinds in August 2007 (Melvin and Taylor, 2009), and the starting date of the post- crisis period is inspired by the rising of US stock market that took place in March 2009.

Interestingly, Table 10 shows that our OOS forecasts reveal a contrasting pattern when assessed during crisis and non-crisis periods. During the crisis period, Panel A shows that none of our predictive models carry forecasting information for spot rate changes across the three portfolios, and Panel B reveals that none of our trading strategies are profitable. These findings are in line with our Table 9 results for the first half of our sample period (9/2006 – 4/2013). By contrast, the expected spot rate changes appear to be profitably predictable with stock returns for emerging market currencies in the post-crisis period.

COVID-19 pandemic: To further examine the performance of our forecasting analysis over turbulent periods, we test whether the COVID-19 pandemic play any role in changing the state of profitable predictability of our OOS forecasts. We employ a longer time series sample by complementing our original data (which only end in December 2019) with more recent data that extend to October 2024. We have a smaller cross-section of 10 emerging countries (in addition to our 10 developed countries) for this longer time span. These emerging countries are: Czech Republic, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Singapore, South Africa, and Thailand. This expanded sample allows us to examine the pandemic effect on our results.

Table 11 presents the results for this analysis. The setup is the same as in Table 10 except we now focus on the COVID period (from December 2019 to November 2020) as the key event. Our choice of the ending date of this period is triggered by Pfizer Inc.'s announcement of a COVID vaccine candidate in November 9, 2020. Overall, Table 11 results are in line with Table 10 results. Panel A shows that none of our predictive models is able to outperform the RW model across the three portfolios during the COVID period, as evidenced by insignificant CW t-statistics. Further, Panel B reveals that our trading strategies do not generate any significant profits during the COVID period, a finding which corroborates our findings in Table 10 for the GFC period.

In addition to the COVID period, Table 11 also reports the results for our expanded post-GFC period from March 2009 to October 2024. Overall, Panel A supports the ability of our equity and combined models in predicting both developed and emerging market currencies even after using longer time span. Furthermore, Panel B continues to confirm the economic success of our equity and combined trading strategies when emerging market currencies are employed. Summarizing this section, we conclude that turbulent periods play an important role in changing the state of profitable predictability of our forecasts, in the sense that our equity-based models are less successful in predicting exchange rates in times of financial stress compared to normal times, suggesting that currency forecasting changes over time across tranquil and turbulent periods.

Time series frequency: Our main analysis focuses on one-month predictability, so we extend our analysis further and examine other time-series frequencies. Table 12 reports the statistical performance of our OOS forecasts using weekly (Panel A), quarterlydata (Panel B), and semiannual (Panel C) data. For our one-week, quarter, and semi-annual forecasts, we employ a ten-year IS period which corresponds to 520, 40, and 20 observations, respectively, and we then generate rolling one-step-ahead OOS roll through the rest of the OOS period. Table 12 reveals a contrasting pattern across higher (weekly) and lower (quarterly or semi-year) frequencies. Interestingly, we observe that our one-week forecasts perform better than the analogue quarter and semi-annual forecasts. These results suggest that our evidence, on foreign exchange rate predictability, is limited to higher frequencies (i.e., weekly and monthly data). Thus, our results highlight two points. First, as it has been found in earlier studies the frequency of the data is important for exchange rate forecasting(Rossi2013). Secondly, our study shows that using high frequency data increases the performance of forecasting, compared to using low frequency data. An explanation of our results compared to forecasting results related to models based on macroeconomic variables might be that financial markets, incorporate new information much faster than macroeconomic data.

6.3 Country type

Throughout our analysis, a comparison of developed and emerging market currencies reveals that exchange rate forecasting is affected by country type (developed versus emerging). Nevertheless, there is a possibility that this developed/emerging classification is arbitrary and does not truly reflect exogenous characteristic of the country. To provide a deeper investigation into the underlying mechanism behind our results, we employ alternative country type classifications.

Alternative emerging market portfolios: So far, all our tests have employed an emerging portfolio that includes a sample of 18 emerging market currencies, but there is a possibility that our results are driven by one particular currency. To alleviate this concern, we repeat the same analysis in Table 3 using 8 different samples of emerging market currencies. For each emerging portfolio, we first exclude one major emerging country (Brazil, India, Indonesia, Malysia, Mexico, Singapore, South Korea, and Turkey) from our sample, and we then check the statistical and economic performance of our OOS forecasts using the remaining 17 emerging market currencies in our sample. Table 13 reports the results of this robustness test. As shown in Panel A, similar to our results in Panel A of Table 3, the forecasting power of our equity and combined models are maintained across all portfolios. Moving onto Panel B, we further notice that positive returns from our equity and combined trading strategies remain significant across almost all portfolios. Therefore, our results for emerging countries are not driven by one particular currency.

Transaction costs: Compared to developed countries, emerging countries tend to have higher transaction costs. Hence, we examine whether our findings are driven by transaction costs. To this end, we sort each of our three baskets of currencies (developed, emerging and global) into five portfolios based on their one-way proportional transaction costs for long positions, calculated as follows: $c_{it+1} = \left(0.5\left(S_{it+1}^{a} - S_{it+1}^{b}\right)/S_{it+1}\right)$ where b and a indicate bid and ask quotes, respectively. We then use our three models in Equations (2)–(4) to generate one-month ahead OOS forecasts for currency return on each of these transaction-cost based portfolios using equally weighted portfolios of differential stock ($r_t^E - r_t^{\mathrm{E,US}}$) and bond ($r_t^{\mathcal{B}} - r_t^{\mathcal{B},\mathrm{US}}$) returns as predictors, given that r_t^E and $r_t^{\mathcal{B}}$ are calculated simply as average stock r_{it}^E and bond $r_{it}^{\mathcal{B}}$ returns on individual countries. Table 14 reports the statistical accuracy measures for this forecasting analysis. We find that none of our predictive models is able to outperform the RW model across all the developed market portfolios. By contrast, the expected spot exchange rate returns appear to be predictable with stock returns for emerging countries regardless of the respective transaction costs underlying these currencies. In sum, there is little evidence that transaction costs help us to understand our results.

Institutional quality: An important question is what role do institutional quality play for our results. Hence, we resort to an alternative classification of the country-specific financial conditions by sorting our sample countries according to their institutional quality proxied by Transparency International (TI) index (see Michaelides, Milidonis, and Nishiotis, 2019). The rank ordering is divided into 5 portfolios, C1 to C5, into which future spot exchange rates are assigned. The first portfolio (C1) includes countries with the lowest TI scores (Argentina, Brazil, Turkey, Philippine, Peru, and Mexico), while the last portfolio (C5) includes countries with highest TI scores (Denmark, Singapore, New Zealand, Norway, Switzerland, and Sweden). Data for TI index score values for each country are obtained from www.transparency.org. These results are also aligned with the results of Jeannert and Sokolovski (2023, who find that predictability of future currencies by commodity prices, is limited to high volatility, and low tradability regions, which are characteristics of currency markets in emerging economies.

Table 15 reports the statistical evaluation results for our one-month ahead OOS forecasts after using these five TI-sorted portfolios in lieu of the developed, emerging and global portfolios. While our equity model is able to outperform the RW model across the P1, P2 and P3 portfolios (low institutional quality countries), the equity model is not successful in predicting exchange rates across the P4 and P5 portfolios (high institutional quality countries). This finding shows that institutional quality could be an important factor for understanding our results, suggesting that our evidence, that differences in stock returns between a foreign country and the U.S. can predict exchange rates, is more prevalent in countries that can be categorized as low institutional quality.

6.4. Missing risk premium?

One alternative potential piece of explanation of the abnormal currency returns generated from our trading rules, is that they are explained by their sensitivity to a *missing currency risk premium* which explains most of the variation in exchange rates. While the classic predictability literature has focused on predicting exchange rates in the context of UIP (Della Corte et al., 2009; Li et al., 2015), the modern literature has studied exchange rate forecasting beyond UIP by relaxing the "risk-neutrality" assumption (Sarno et al., 2012; Boudoukh et al., 2016; Kremens and Martin, 2019; Balduzzi and Chiang, 2020; Chernov and Creal, 2021; Dahlquist and Penasse, 2022).

These studies share in common that they decompose currency risk premium into interest rate differential plus a missing risk premium which accounts for the "real-world" currency expectation. Most of these studies relate the missing currency risk premium to real exchange rates (Menkhoff *et al.*, 2017; Balduzzi and Chiang, 2020; Chernov and Creal, 2021; Dahlquist and Penasse, 2022). By contrast, Sarno et al. (2012) and Kremens and Martin (2019) show that risk premium is closely linked to bond and stock returns, respectively. Therefore, our findings may be interpreted through the lens of the evidence in Sarno et al. (2012) and Kremens and Martin (2019) who provide evidence on the superior ability of bond- and stock-based risk premiums in forecasting currency returns, and our forecasting framework empirically formalizes this intuition.

7. Conclusion

This paper presents the first evidence on the statistical and economic power of stock and, to a lesser extent, bond returns in predicting emerging market currency returns. Using a sample of 28 developed and emerging countries from November 1989 to December 2019, we construct OOS exchange rate forecasts using various model specifications of stock and bond returns, and we then assess their economic value by designing a trading strategy based on the sign of our forecasts.

Our main findings can be summarized as follows: (i) differential stock returns between the foreign market and the U.S. market carry significant information for the future spot rate changes for emerging countries (Table 2); (ii) our OOS exchange rate forecasts based on stock market information outperform the benchmark RW model when using emerging markets data (Table 3); (iii) trading based on the predicted sign of our stock-based trading strategy generates significant profits (net of transaction costs) using emerging market currencies (Table 3); (iv) these abnormal returns are pervasive phenomena that persist despite changing the forecast construction method (Table 4), benchmark index (Table 5), and trading strategy (Table 6), and they are robust even after controlling for systematic risk and macro variables (Table 7); and (v) the profitability of our trading strategies is time-varying over our entire sample period (Tables 9, 10 and 11).

In summary, our central finding is that there is a robust statistical value in stock market returns for forecasting emerging market currency returns, as well as an economic value in stock and bond returns for designing economically profitable currency trading strategies between May 2013 and December 2019. By contrast, we find a little or no evidence on the economic value of stock or bond information when using developed market currencies. Our evidence, on the informational role of international stock returns in exchange rate movements for emerging countries, can be exploited by investors in their investment strategies and can be understood in the context of the recent literature on exchange rate forecasting suggesting that a missing stock-based risk premium could explain most of the variation in currency returns (Kremens and Martin, 2019).

This paper suggests two potential directions for future research to contribute toward filling gaps in the exchange rate predictability literature. One suggestion is that future research should focus more on recognizing the differences between developed and emerging countries. Exchange rate forecasting can serve as a good setting in which to compare the informational efficiency between the two markets due to the great heterogeneity in their responses to the arrival of new information in the market. Compared to developed countries, emerging countries are presumably less efficient due to lower institutional quality (i.e., higher inflation, more government intervention, and more political instability) and, therefore, information leakage is presumably more prevalent (i.e., information is incorporated into prices more sluggishly) in emerging countries. Emerging market currencies may thus have more easily-identified trends than developed market currencies (Bansal and Dahlquist, 2000; Frankel and Poonawala, 2010), suggesting that the profitability of currency technical trading rules have migrated overtime from developed countries to emerging countries (De Zwart *et al.*, 2009; Jamali and Yamani, 2019). This latter view is validated in our evidence on the power of stock market information in forecasting currency returns for emerging countries, while the evidence seems to be weaker when using developed countries.

Another area of future research deserving additional attention concerns distinguishing between "normal" and "extreme" market conditions when examining exchange rate predictability. While we find no evidence on the profitable predictability of our trading strategies during the sample period surrounding the turmoil time of the 2007–2008 global financial crisis, we observe that our strategies generate statistically significant profits after the crisis between May 2013 and December 2019. This evidence, on the time-varying informational role of financial asset returns in the profitable predictability of currency returns over time, suggest that existing evidence in the exchange rate predictability literature based on "normal" market conditions does not necessarily generalize to "extreme" market conditions.

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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

	Equity Model Sample					Bond Model Sample				
	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. In-Sample Forecasts from Regression Models with Equity and Bond Return Differentials

The table reports estimates of the predictive regression: $\Delta s_{it+1} = \alpha + \beta\chi_{it} + \varepsilon_{it+1}$, where Δs_{it+1} is the monthly % future exchange rate return for currency i; and χ refers to the three sets of predictor variables for which we construct our forecasts: (1) equity model sets $\chi_{it} = [r_{it}^{E} - r_{t}^{E,US}]$, where r_{it}^{E} represents the return on the ith foreign stock market, and $r_{t}^{E,US}$ is the return on the U.S. stock market,; (2) bond model sets $\chi_{it} = [r_{it}^{\mathcal{B}} - r_{t}^{\mathcal{B},US}]$, which denotes, respectively, the ith foreign government bond market denominated in the USD, and the return on the U.S. government bond market; and (3) combined model sets $\chi_{it} = [r_{it}^{E} - r_{t}^{E,US}, r_{it}^{\mathcal{B}} - r_{t}^{\mathcal{B},US}]$. The table reports the coefficient estimates for three equally weighted currency portfolios (developed, emerging and global) along with their associated R-square statistics. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Dependent Variable: Δs_{it+1}									
	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
Independent Variable	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
$r_{it}^{E} - r_{t}^{E,US}$	-0.071		-0.105**	-0.06**		-0.129***	-0.079**		-0.083**
$r_{it}^{\mathcal{B}} - r_{t}^{\mathcal{B},US}$		0.364**	0.435***		-0.034	-0.014		0.021	0.041
R-square	0.006	0.018	0.03	0.013	0.002	0.033	0.015	0.000	0.016

TABLE 3. Statistical and Economic Evaluation of OOS Forecasts using Rolling Regressions

The table provides the statistical (Panel A) and economic (Panel B) evaluation results for the rolling one-month-ahead OOS forecasts generated from the equity, bond and combined models. The rolling OOS forecasts are obtained with rolling regressions that use the first 120 monthly observations as the IS period – which corresponds to a ten-year time horizon – and we then roll through the rest of the OOS period using a fixed window size of 120 observations. Panel A reports mean squared forecast errors (MSFEs) as defined in (5), MSFEs relative to the RW benchmark as defined in (6), OOS R^2 in percent units as defined in (7), and Clark and West (2007) test of equal predictive ability as defined in (8). Panel B reports the economic value of exchange rate predictability by analyzing the performance of our three long-short trading strategies (equity, bond, and combined) conditional on the one-month ahead OOS forecasts. The key trading signal that characterizes these trading strategies is that investors 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 (9). 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 (10). For each trading strategy, we report 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 analogue performance measures for three benchmark portfolios: random walk, currency momentum, and carry trade (CT). The figures reported for momentum and CT 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. Statistical Evaluation

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	6.222	5.99	5.917	4.515	4.807	4.479	4.628	5.925	4.611
Rel.-MSFE	1.069	1.029	1.016	0.965	1.019	0.95	1.001	1.282	0.997
R^2_{OOS}(%)	-0.069	-0.029	-0.016	0.035	-0.019	0.05	-0.001	-0.282	0.003
CW	0.626	-0.522	1.405	3.113***	-0.457	2.724***	2.09**	-0.1	2.347**

Panel B. Economic Evaluation

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	-0.04	0.03	0.04	0.30**	0.09	0.59***	0.21	-0.12	0.12
σ	2.41	2.41	2.41	2.10	2.19	2.11	2.11	2.12	2.12
γ	-0.08	-0.49	-0.25	0.25	0.24	0.38	-0.29	0.31	0.47
K	1.15	1.18	1.17	3.05	1.50	1.35	2.72	2.64	2.47
SR	-0.01	0.01	0.02	0.14	0.04	0.28	0.10	-0.06	0.06
SR_{RW}	0.05	0.05	0.05	0.03	0.04	0.04	-0.00	-0.00	-0.00
SO	-0.02	0.01	0.03	0.22	0.07	0.49	0.14	-0.09	0.09

Panel C. Benchmark Portfolios

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	RW	Momentum	CT	RW	Momentum	CT	RW	Momentum	CT
μ	0.10	0.18	0.34*	0.08	-0.57**	0.48**	0.01	-0.23	0.30*
σ	2.4	2.55	2.86	2.12	3.22	3.23	2.12	2.25	2.4
γ	-0.35	-0.24	-0.52	0.3	-0.27	-0.34	0.01	-0.47	-0.72
K	1.21	2.31	1.34	3.04	2.18	3.46	2.55	1.28	2.46
SR	0.04	0.07	0.12	0.04	-0.18	0.15	0	-0.1	0.13
SO	0.06	0.11	0.17	0.06	-0.26	0.2	0	-0.14	0.17

TABLE 4. Statistical and Economic Evaluation of OOS Forecasts using Recursive Regressions

The table provides the statistical forecast accuracy (Panel A) and economic value (Panel B) for the recursive one-month-ahead OOS forecasts generated from the equity, bond and combined models. The recursive OOS forecasts are obtained with recursive regressions that initially use the first 120 monthly observations (for every individual currency) as the in-sample period and then re-estimate the model parameters every time a new monthly observation is added to the sample. Panel A reports the forecast accuracy measures (MSFEs, MSFEs relative to the random walk benchmark, OOS R^2, and Clark and West (2007) statistics) for the recursive one-month-ahead OOS forecasts. Panel B presents the performance measures (% mean (μ), % volatility(σ), skewness (γ), kurtosis (K), Sharpe ratio (SR), Sharpe ratio of the random walk model (SR_{RW}), and Sortino ratio (SO)) for the three trading strategies (equity, bond, and combined) conditional on the one-month ahead OOS forecasts (obtained from recursive regressions). Both statistical accuracy measures and economic performance measures are described in the caption of Table 3. The key mechanism that characterizes these strategies is that investors long (short) currency i if the predicted return of currency i ($\widehat{\Delta s}^{\chi}_{t+1|t}$) for the three sets of predictor variables is positive (negative). *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Statistical Evaluation

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	5.789	5.9	5.865	4.535	4.772	4.427	4.415	5.595	4.613
Rel.-MSFE	1	1.019	1.013	0.973	1.029	0.955	0.969	1.228	1.012
R^2_{OOS}(%)	0	-0.019	-0.013	0.027	-0.029	0.045	0.031	-0.228	-0.012
CW	1.547	-0.131	1.54	2.683***	-1.136	2.528**	3.075***	-0.574	1.883*

Panel B. Economic Evaluation

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	-0.02	-0.11	0.07	0.24	0.3	0.56***	0.26	0.01	0.22
σ	2.41	2.4	2.41	2.11	2.16	2.11	2.11	2.12	2.11
γ	0.03	0.06	0.21	0.9	0.49	0.43	0.71	0.53	0.64
K	1.16	1.17	1.13	2.73	1.36	1.33	2.28	2.55	2.34
SR	-0.01	-0.04	0.03	0.11	0.14	0.26	0.12	0.01	0.11
SR_{RW}	0	0	0	0.11	0.17	0.17	0.07	0.07	0.07
SO	-0.01	-0.07	0.05	0.22	0.25	0.47	0.22	0.01	0.19

TABLE 5. Statistical and Economic Evaluation of OOS Forecasts using Global Market Index as the Benchmark Index

The table provides the statistical forecast accuracy (Panel A) and economic value (Panel B) for the rolling one-month-ahead OOS forecasts generated from three different specifications of the 'combined' model that differ in the set of predictor variables: (1) $r_t^{\mathrm{E,Global}}$ and $r_t^{\mathcal{B},\mathrm{Global}}$ (Model 1) ; (2) $(r_{it}^{E} - r_t^{\mathrm{E,Global}})$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\mathrm{Global}})$ (Model 2); and r_{it}^{E}, $(r_{it}^{E} - r_t^{\mathrm{E,Global}})$, $r_{it}^{\mathcal{B}}$ and $(r_{it}^{\mathcal{B}} - r_t^{\mathcal{B},\mathrm{Global}})$ (Model 3). Panel A reports four forecast accuracy measures (MSFEs, MSFEs relative to the random walk benchmark, OOS R^2, and Clark and West (2007) statistics) for the rolling monthly OOS forecasts. The implementation of the OOS forecasting using rolling regression is illustrated in the caption of Table 3. Panel B reports performance measures (% mean, % volatility, skewness, kurtosis, Sharpe ratio, Sharpe ratio of the random walk model, and Sortino ratio) for three long-short trading strategies (Model 1, Model 2 and Model 3) conditional on the one-month ahead OOS forecasts (obtained from rolling regressions). The key mechanism that characterizes these trading strategies is defined in the caption of Table 3. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Statistical Evaluation

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
MSFE	6.219	5.916	6.078	4.819	4.625	4.629	5.039	4.849	4.91
Rel.-MSFE	1.068	1.016	1.044	1.022	0.981	0.982	1.09	1.049	1.062
R^2_{OOS}(%)	-0.068	-0.016	-0.044	-0.022	0.019	0.018	-0.09	-0.049	-0.062
CW	0.522	0.861	1.563	0.391	1.975*	2.301**	0.813	0.233	1.406

Panel B. Economic Evaluation

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
μ	0.16	0.29*	0.26*	0.40**	0.37*	0.37**	-0.01	-0.00	0.09
σ	2.40	2.39	2.39	2.15	2.16	2.16	2.12	2.12	2.12
γ	0.15	-0.18	0.29	0.46	0.13	0.52	0.50	-0.68	0.63
Κ	1.12	1.28	1.05	1.29	1.54	1.26	2.56	2.55	2.46
SR	0.07	0.12	0.11	0.19	0.17	0.17	-0.00	-0.00	0.04
$\mathrm{SR}_{\mathrm{RW}}$	0.05	0.05	0.05	0.04	0.04	0.04	-0.00	-0.00	-0.00
SO	0.11	0.18	0.18	0.34	0.27	0.32	-0.01	-0.00	0.07

TABLE 6. Economic Evaluation of OOS Forecasts using Alternative Combined Trading Strategies

The table provides the economic value for the rolling one-month-ahead OOS forecasts generated from two different trading strategies based on the 'combined' model. In our first strategy, we include information from stock and bond (interest rate) markets by using excess stock returns, as defined in 12: $\Delta s_{it+1} = \alpha + \beta_1(r_{it}^E - r_{ft}) + \beta_2(r_t^{\mathrm{E,US}} - r_{f,t}^{\mathrm{US}}) + \varepsilon_{it+1}$, where r_{ft} and $r_{f,t}^{\mathrm{US}}$ denote, respectively, the ith foreign country and the U.S. risk-free rates. Our second strategy is the heterogeneous agent (HA) model conditional on the one-month ahead forecasts (obtained from rolling regressions). The key trading signal that characterizes the HA strategy is that investor forms a portfolio by placing dynamic weights on stock and bond trading rules where the relative weights assigned to stock signals (as defined in 13) and bonds signals (as defined in 14) vary over time based on the last period performance. The net of transaction cost return on the HA strategy is then computed as: $\Delta s_{it,\tau}^{HA} = w_t^{\mathrm{E}} r_{it,\tau}^{\mathrm{E}} + w_t^{\mathcal{B}} r_{it,\tau}^{\mathcal{B}}$ (as defined in 15). For each trading strategy, we report performance measures (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)) for two versions: long-only *(L)* and long-short *(L-S)* trading rules. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Developed Portfolio				Emerging Portfolio				Developed and Emerging Portfolio			
	Excess Stock Return		*HA*		*Excess Stock Return*		*HA*		*Excess Stock Return*		*HA*	
	L-S	*L*	*L-S*	*L*	*L-S*	*L*	*L-S*	*L*	*L-S*	*L*	*L-S*	*L*
μ	-0.01	-0.02	-0.12	-0.08	0.37**	0.30**	0.53***	0.48***	0.02	0.08	-0.07	0.03
σ	2.41	1.58	2.11	1.36	2.09	1.94	1.90	1.79	2.12	1.61	1.84	1.59
γ	-0.10	0.08	-0.48	-0.75	0.62	1.02	0.70	1.00	-0.49	0.31	-0.17	0.39
K	1.15	4.44	2.20	5.10	2.82	4.24	2.95	4.02	2.58	2.95	2.50	3.56
SR	-0.00	-0.01	-0.06	-0.06	0.17	0.15	0.28	0.27	0.01	0.05	-0.04	0.02
SR_{RW}	0.05	0.03	0.05	0.03	0.03	0.08	0.05	0.16	-0.00	0.04	0.00	0.04
SO	-0.01	-0.02	-0.08	-0.07	0.31	0.27	0.46	0.47	0.01	0.07	-0.05	0.03

TABLE 7. Regression Models with Equity and Bond Returns augmented with Control Variables

The table reports estimates of various expanded model specifications of our three predictive models in Equations (2)-(4), to also include Verdelhan's (2018) *Dollar* and $Carry$ risk factors (Panel A), the monthly change in the values of the VIX index (Panel B), and the monthly change in the values of industrial production (IP) (Panel C). The dependent variable is Δs_{it+1} and the two primary sets of predictor variables for which we construct our forecasts ($\left[r_{it}^{E} - r_{t}^{E,US}\right]$ and $\left[r_{it}^{\mathcal{B}} - r_{t}^{\mathcal{B},US}\right]$) are defined in the caption of Table 2. Panel D reports the time-series regression estimates of our OOS forecasts (generated from long-short trading rules based on rolling one-month-ahead forecasts using equity, bond and combined models) (i.e., the dependent variable is $\widehat{\Delta s}_{it+1}$) on *Dollar*, $Carry$, VIX and IP factors. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Regressions augmented with Carry and Dollar Factors - Dependent Variable: Δs_{it+1}

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
$r_{it}^{E} - r_{t}^{E,US}$	-0.092*		-0.116**	-0.055**		-0.125***	-0.08**		-0.095***
$r_{it}^{\mathcal{B}} - r_{t}^{\mathcal{B},US}$		0.36**	0.418***		0.081	0.1		0.147**	0.18**
$Dollar$	9.984	1.288	5.197	12.448**	14.106	14.931	11.861**	15.932**	18.686***
$Carry$	5.638	7.464	7.041	5.253	14.021*	12.818*	5.367	9.065**	8.405*
R^2(%)	0.017	0.025	0.039	0.034	0.021	0.05	0.035	0.032	0.052

Panel B. Regressions augmented with VIX - Dependent Variable: Δs_{it+1}

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
$r_{it}^{E} - r_{t}^{E,US}$	-0.073		-0.108**	-0.057**		-0.135***	-0.078**		-0.084**
$r_{it}^{\mathcal{B}} - r_{t}^{\mathcal{B},US}$		0.39***	0.462***		0.005	0.035		0.076	0.097
VIX	0.035	0.05	0.052	0.033	0.053	0.064	0.033	0.054*	0.055*
R^2(%)	0.009	0.023	0.036	0.016	0.009	0.042	0.019	0.008	0.024

Panel C. Regressions augmented with IP - Dependent Variable: Δs_{it+1}

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
$r_{it}^{E} - r_{t}^{E,US}$	-0.085*		-0.119**	-0.064**		-0.137***	-0.091***		-0.094***
$r_{it}^{\mathcal{B}} - r_{t}^{\mathcal{B},US}$		0.366**	0.443***		-0.039	-0.018		0.014	0.036
IP	-0.044*	-0.038	-0.047*	-0.058**	-0.066**	-0.073**	-0.068***	-0.061**	-0.068***
R^2(%)	0.015	0.024	0.04	0.03	0.021	0.055	0.037	0.018	0.038

Panel D. Regressions augmented with Carry, Dollar, VIX and IP - Dependent Variable: $\widehat{\Delta s}_{it+1}$

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
$Intercept$	-0.048	0.018	0.03	0.274**	0.166	0.646***	0.204	-0.109	0.122
$Carry$	4.016	0.695	4.985	10.002	-17.203	-13.141	2.067	-6.755	0.542
$Dollar$	-0.111	8.747	1.53	8.286	-0.357	-7.047	-2.758	-1.729	-7.26
VIX	-0.056	-0.032	-0.023	-0.034	0.116*	0.135**	0.038	0.108***	0.11***
IP	-0.015	0.037	0.015	-0.015	0	0.036	-0.004	0.061*	0.01
R^2(%)	0.009	0.01	0.003	0.016	0.042	0.054	0.006	0.052	0.038

TABLE 8. Statistical Evaluation of OOS Forecasts – FX currency excess returns

The table provides the statistical evaluation results for the rolling one-month-ahead OOS forecasts of currency excess returns (Panel A) and forward premium (Panel B) generated from the equity, bond and combined models. Currency excess returns are computed as the log forward rate minus the expected log spot rate against the USD, and forward premium is calculated as the log one-month forward rate minus the log spot rate. The table reports the forecast accuracy measures (MSFEs, MSFEs relative to the random walk benchmark, OOS R^2, and Clark and West (2007) statistics) for our OOS forecasts, using three equally weighted portfolios – developed emerging, and 'developed and emerging'.. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Statistical Evaluation

Panel A.1 Currency excess returns

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	0	0	0	0	0	0	0	0	0
Rel.-MSFE	1.015	1.008	1.021	1.075	1.018	1.089	1.032	1.009	1.042
R_{OOS}^2 (%)	-0.015	-0.008	-0.021	-0.075	-0.018	-0.089	-0.032	-0.009	-0.042
CW	1.114	-0.188	1.139	0.937	-0.033	0.183	1.063	-0.232	1.038

Panel A.2 Forward premium

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	0	0	0	0	0	0	0	0	0
Rel.-MSFE	1.019	1.07	23.468	1.192	1.011	4.708	1.144	1.065	7.803
R_{OOS}^2(%)	-0.019	-0.07	-22.468	-0.192	-0.011	-3.708	-0.144	-0.065	-6.803
CW	-0.472	0.394	0.912	0.722	1.248	0.912	1.116	0.495	-0.138

TABLE 9. Statistical and Economic Evaluation of OOS Forecasts – Subsample Analysis

The table provides the statistical (Panel A) and economic (Panel B) evaluation results for the rolling one-month-ahead OOS forecasts generated from the equity, bond and combined models across two subsample periods: (1) the first period consists of 80 observations, covering the period from September 2006 to April 2013; and (2) the second period is from May 2013 to December 2019, yielding 80 observations. Panel A reports the forecast accuracy measures (MSFEs, MSFEs relative to the random walk benchmark, OOS R^2, and Clark and West (2007) statistics) for our OOS forecasts, and Panel B presents the performance measures (% mean, % volatility, skewness, kurtosis, Sharpe ratio, Sharpe ratio of the random walk model, and Sortino ratio) for our trading strategies. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
Panel A. Statistical Evaluation									
Panel A.1 first half of the sample period: 09/2006 – 04/2013									
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	9.95	9.241	9.068	7.518	7.062	6.694	7.872	11.718	7.775
Rel.-MSFE	1.092	1.015	0.996	0.972	1.047	0.992	0.997	1.485	0.985
R^2_{OOS} (%)	-0.092	-0.015	0.004	0.028	-0.047	0.008	0.003	-0.485	0.015
CW	0.523	-0.496	1.157	1.994**	-0.893	0.868	1.255	-0.202	1.355
Panel A.2 second half of the sample period: 05/2013 – 12/2019									
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	3.436	3.717	3.419	3.451	3.693	3.386	3.082	3.267	3.054
Rel.-MSFE	0.965	1.044	0.96	0.929	0.994	0.912	0.935	0.991	0.926
R^2_{OOS}(%)	0.035	-0.044	0.04	0.071	0.006	0.088	0.065	0.009	0.074
CW	1.964*	-0.019	2.068**	2.429**	1.006	2.619**	2.544**	1.327	2.736***
Panel B. Economic Evaluation									
Panel B.1. first half of the sample period: 09/2006 – 04/2013									
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	0.18	0.09	-0.15	-0.03	-0.68*	0.17	0.09	-0.55**	-0.25
σ	3.01	3.01	3.01	2.76	2.52	2.60	2.79	2.74	2.78
γ	-0.14	-0.90	-0.29	0.49	0.83	0.80	-0.28	0.78	0.95
K	1.12	1.19	1.02	2.56	3.26	1.76	2.06	2.85	2.41
SR	0.06	0.03	-0.05	-0.01	-0.27	0.07	0.03	-0.20	-0.09
SO	0.09	0.04	-0.07	-0.08	-0.14	-0.14	0.05	-0.32	-0.16
Panel B.2 second half of the sample period: 05/2013 – 12/2019									
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	0.32	-0.05	0.33	0.80***	0.47**	0.79***	0.63***	0.21	0.66***
σ	1.86	1.89	1.86	1.80	1.91	1.80	1.73	1.83	1.72
γ	-0.26	-0.09	-0.25	0.15	0.12	0.16	-0.22	-0.10	-0.26
K	-0.19	-0.37	-0.20	0.51	0.45	0.49	0.08	-0.17	0.17
SR	0.17	-0.03	0.18	0.45	0.25	0.44	0.37	0.11	0.38
SO	0.27	-0.04	0.28	0.16	0.16	0.16	0.61	0.19	0.63

TABLE 10. Statistical and Economic Evaluation of OOS Forecasts – Global Financial Crisis

The table presents the statistical (Panel A) and economic (Panel B) evaluation results for the rolling one-month-ahead OOS forecasts during and after the GFC, using two subsample periods: (1) the GFC period from August 2007 to February 2009; and (2) the post-GFC period from March 2009 to December 2019. Results are reported for OOS forecasts generated from our equity, bond and combined models using three equally weighted portfolios as test assets. Panel A reports the forecast accuracy measures (MSFEs, MSFEs relative to the random walk benchmark, OOS R^2, and Clark and West (2007) statistics) for our OOS forecasts, and Panel B presents the economic performance measures (% mean, % volatility, skewness, kurtosis, Sharpe ratio, and Sortino ratio) for our trading strategies. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Statistical Evaluation

Panel A.1. GFC Period: 8/2007 – 2/2009

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	19.387	14.939	14.993	14.437	NA	NA	15.45	21.284	14.683
Rel.-MSFE	1.303	1.004	1.008	1.006	NA	NA	1.093	1.506	1.039
R^2_{OOS}(%)	-0.303	-0.004	-0.008	-0.006	NA	NA	-0.093	-0.506	-0.039
CW	-0.37	0.034	0.503	-0.385	NA	NA	-0.843	0.871	0.028

Panel A.2. Post-GFC Period: 03/2009 – 12/2019

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	5.216	5.612	5.304	4.41	4.807	4.479	4.292	5.953	4.338
Rel.-MSFE	0.957	1.03	0.973	0.933	1.019	0.95	0.924	1.281	0.934
R^2_{OOS}(%)	0.043	-0.03	0.027	0.067	-0.019	0.05	0.076	-0.281	0.066
CW	2.603**	-0.481	2.306**	3.222***	-0.457	2.724***	3.515***	-1.018	3.359***

Panel B. Economic Evaluation

Panel B.1. GFC Period: 8/2007 – 2/2009

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	-0.64	-0.76	-0.64	0.17	NA	NA	-0.35	-0.57	-1.08
σ	3.85	3.83	3.85	3.89	NA	NA	3.83	3.80	3.68
γ	-0.36	-0.52	-0.36	1.01	NA	NA	-0.83	1.03	1.46
K	0.42	0.20	0.42	1.42	NA	NA	1.04	2.23	3.77
SR	-0.17	-0.20	-0.17	0.04	NA	NA	-0.09	-0.15	-0.29
SO	-0.23	-0.25	-0.23	0.09	NA	NA	-0.11	-0.29	-0.57

Panel B.2. Post-GFC Period: 03/2009 – 12/2019

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	0.36	0.09	0.19	0.53***	0.09	0.59***	0.57***	-0.06	0.51***
σ	2.31	2.33	2.33	2.12	2.19	2.11	2.08	2.16	2.10
γ	0.19	-0.57	-0.22	-0.46	0.24	0.38	0.15	0.03	0.26
K	1.01	1.17	1.17	2.07	1.50	1.35	1.21	1.19	1.07
SR	0.16	0.04	0.08	0.25	0.04	0.28	0.27	-0.03	0.24
SO	0.26	0.05	0.11	0.35	0.07	0.49	0.44	-0.04	0.41

TABLE 11. Statistical and Economic Evaluation of OOS Forecasts – COVID-19 Pandemic

The table provides the statistical (Panel A) and economic (Panel B) evaluation results for the rolling one-month-ahead OOS forecasts across two subsample periods: (1) COVID period covering from December 2019 to November 2020; and (2) 'extended' post-GFC period spanning from March 2009 to October 2024. Results are reported for OOS forecasts generated from our equity, bond and combined models using three equally weighted portfolios as test assets. Panel A reports the forecast accuracy measures (MSFEs, MSFEs relative to the random walk benchmark, OOS R^2, and Clark and West (2007) statistics) for our OOS forecasts, while Panel B presents the economic performance measures (% mean, % volatility, skewness, kurtosis, Sharpe ratio, and Sortino ratio) for our trading strategies. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Statistical Evaluation

Panel A.1. COVID period: 12/2019 – 11/2020

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	7.08	7.794	7.21	7.257	10.04	7.291	6.495	9.503	6.697
Rel.-MSFE	1.121	1.234	1.142	1.106	1.53	1.111	1.094	1.601	1.128
R^2_{OOS}(%)	-0.121	-0.234	-0.142	-0.106	-0.53	-0.111	-0.094	-0.601	-0.128
CW	-1.281	-1.052	-1.884*	-0.571	-1.518	-0.482	-0.735	-0.949	-0.924

Panel A.2. Extended Post-GFC Period: 03/2009 – 9/2024

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	9.175	5.828	5.476	6.136	4.701	4.352	7.835	5.012	4.555
Rel.-MSFE	1.677	1.065	1.001	1.392	1.067	0.987	1.691	1.082	0.983
R^2_{OOS}(%)	-0.677	-0.065	-0.001	-0.392	-0.067	0.013	-0.691	-0.082	0.017
CW	2.34**	-1.7*	1.792*	2.355**	-1.536	2.188**	2.315**	-1.3	2.52**

Panel B. Economic Evaluation

Panel B.1. COVID period: 12/2019 – 11/2020

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	-0.84	-0.84	-1.43***	-0.73	-1.58***	-0.33	-0.53	-0.66	0.03
σ	2.43	2.43	2.11	2.53	2.06	2.62	2.44	2.40	2.50
γ	0.22	0.55	0.94	-0.71	-1.08	-0.98	-0.08	1.22	-0.34
K	-1.44	-0.78	0.49	1.93	2.60	2.06	-0.64	1.35	-0.40
SR	-0.35	-0.35	-0.68	-0.29	-0.77	-0.13	-0.22	-0.28	0.01
SO	-0.64	-0.78	-1.20	-0.38	-0.89	-0.16	-0.38	-0.65	0.02

Panel B.2. Extended Post-GFC Period: 03/2009 – 9/2024

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
μ	0.27	0.05	0	0.25	0.01	0.30*	0.34**	-0.02	0.33**
σ	2.32	2.34	2.34	2.08	2.10	2.08	2.12	2.15	2.13
γ	0.04	-0.38	-0.06	0.18	-0.60	0.22	0.15	-0.49	0.07
K	0.46	0.50	0.47	1.58	1.63	1.56	0.80	0.84	0.85
SR	0.12	0.02	-0.00	0.12	0.00	0.14	0.16	-0.01	0.16
SO	0.19	0.03	-0.00	0.20	0.01	0.24	0.28	-0.01	0.26

TABLE 12. Statistical Evaluation of OOS Forecasts – Weekly, Quarterly, and Semiannual Forecasts

The table presents the statistical evaluation results for the rolling OOS forecasts generated from the equity, bond and combined models, using various time series frequencies – weekly (Panel A), quarterly (Panel B) and semiannual data (Panel C). The one-week, quarter, and semi-annual forecasts are generated from a ten-year IS period which corresponds to 520, 40, and 20 observations, respectively. Results are reported for the three equally weighted portfolios – developed, emerging, and 'developed and emerging'. The table reports the forecast accuracy measures (MSFEs, MSFEs relative to the random walk benchmark, OOS R^2, and Clark and West (2007) statistics) for our OOS forecasts. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Weekly data

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	0	0	0	0	0	0	0	0	0
Rel.-MSFE	1.006	0.999	0.998	1.019	0.997	0.993	1.003	0.999	0.995
R^2_{OOS} (%)	-0.006	0.001	0.002	-0.019	0.003	0.007	-0.003	0.001	0.005
CW	2.432**	1.808*	3.646***	2.576**	1.98**	3.354***	3.09***	1.932*	3.833***

Panel B. Quarterly data

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	0.001	0.001	0.001	0.003	0.001	0.001	0.002	0.001	0.002
Rel.-MSFE	1.209	1.016	1.225	2.488	1.217	1.235	2.114	1.037	1.924
R^2_{OOS}(%)	-0.209	-0.016	-0.225	-1.488	-0.217	-0.235	-1.114	-0.037	-0.924
CW	0.561	0.273	0.676	1.076	-1.376	-0.656	1.062	-0.584	0.857

Panel C. Semiannually data

	Developed Portfolio			Emerging Portfolio			Developed & Emerging Portfolio		
	Equity	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
MSFE	0.008	0.003	0.006	0.005	0.008	0.004	0.006	0.004	0.004
Rel.-MSFE	5.201	1.666	3.458	2.62	6.396	3.268	3.81	2.195	2.656
R^2_{OOS}(%)	-4.201	-0.666	-2.458	-1.62	-5.396	-2.268	-2.81	-1.195	-1.656
CW	-0.228	-1.125	0.109	-0.204	-1.197	-0.535	-0.173	-1.518	0.451

TABLE 13. Statistical and Economic Evaluation of OOS Forecasts – Alternative Emerging Portfolios

The table provides the statistical (Panel A) and economic (Panel B) evaluation results for the rolling one-month-ahead OOS forecasts generated from the equity, bond and combined models, using 8 different equally weighted portfolios of emerging currencies as test assets. For each portfolio, we drop one particular emerging market currency from our sample and we then examine the performance of our OOS forecasts using the remaining 17 emerging countries. Panel A reports forecast accuracy measures (MSFEs, MSFEs relative to the RW benchmark, OOS R^2 in percent and Clark and West (2007) statistics), and Panel B presents performance measures (% mean, μ, % volatility, σ, skewness, γ, kurtosis, K, Sharpe ratio, SR, Sharpe ratio of the random walk model, SR_{RW}, and Sortino ratio, SO) for our long-short trading strategies conditional on the one-month ahead OOS forecasts. The setup of our rolling OOS forecasts and trading strategies is described in the caption of Table 3. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Panel A. Statistical Evaluation											
	Equity	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*
	Portfolio 1: w/o Brazil			Portfolio 2: w/o India			Portfolio 3: w/o Indonesia			Portfolio 4: w/o Malysia		
MSFE	4.271	4.487	4.155	4.701	4.942	4.587	4.629	5.088	4.766	4.721	4.905	4.577
Rel.-MSFE	0.968	1.018	0.942	0.964	1.02	0.947	0.968	1.02	0.955	0.965	1.019	0.951
R^2_{OOS}(%)	0.032	-0.018	0.058	0.036	-0.02	0.053	0.032	-0.02	0.045	0.035	-0.019	0.049
CW	3.177***	-0.363	2.956***	3.124***	-0.425	2.726***	2.995***	-0.385	2.627***	3.153***	-0.334	2.69***
	Portfolio 5: w/o Mexico			Portfolio 6: w/o Singapore			Portfolio 7: w/o South Korea			Portfolio 8: w/o Turkey		
MSFE	4.543	4.713	4.365	4.739	4.729	4.358	4.527	4.837	4.536	4.291	4.662	4.342
Rel.-MSFE	0.969	1.019	0.944	0.968	1.01	0.931	0.965	1.018	0.955	0.96	1.016	0.946
R^2_{OOS}(%)	0.031	-0.019	0.056	0.032	-0.01	0.069	0.035	-0.018	0.045	0.04	-0.016	0.054
CW	3.033***	-0.547	2.849***	3.051***	-0.026	2.914***	3.068***	-0.47	2.604**	3.335***	-0.121	2.805***

TABLE 13. Statistical and Economic Evaluation of OOS Forecasts – Alternative Emerging Portfolios (continued)

Panel B. Economic Evaluation												
	Equity	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*	*Equity*	*Bond*	*Comb.*
	Portfolio 1: w/o Brazil			Portfolio 2: w/o India			Portfolio 3: w/o Indonesia			Portfolio 4: w/o Malysia		
μ	0.40***	0.19	0.58***	0.29**	0.10	0.57***	0.22	0.18	0.45**	0.36**	0.24	0.51**
σ	2.02	2.11	2.04	2.15	2.22	2.14	2.14	2.24	2.20	2.14	2.20	2.15
γ	0.71	0.22	0.35	0.26	0.28	0.41	0.15	0.30	0.38	0.68	0.30	0.41
K	2.90	1.41	1.32	3.05	1.47	1.28	2.95	1.57	1.47	2.87	1.46	1.34
SR	0.20	0.09	0.28	0.14	0.04	0.27	0.10	0.08	0.21	0.17	0.11	0.24
SR_{RW}	0.06	0.08	0.08	0.02	0.02	0.02	0.02	0.02	0.02	0.05	0.07	0.07
SO	0.35	0.15	0.50	0.21	0.07	0.48	0.16	0.13	0.35	0.30	0.18	0.42
	Portfolio 5: w/o Mexico			Portfolio 6: w/o Singapore			Portfolio 7: w/o South Korea			Portfolio 8: w/o Turkey		
μ	0.38**	0.02	0.59***	0.30**	0.30	0.74***	0.30**	0.17	0.43*	0.25*	-0.05	0.57***
σ	2.09	2.17	2.08	2.15	2.17	2.06	2.11	2.19	2.16	2.07	2.15	2.08
γ	0.65	0.28	0.38	0.30	0.30	0.64	0.34	0.29	0.45	0.17	0.27	0.40
K	2.40	1.46	1.28	3.10	1.76	1.44	3.12	1.41	1.24	2.91	1.50	1.26
SR	0.18	0.01	0.28	0.14	0.14	0.36	0.14	0.08	0.20	0.12	-0.02	0.27
SR_{RW}	0.04	0.06	0.06	0.06	0.11	0.11	0.05	0.07	0.07	-0.01	0.00	0.00
SO	0.33	0.01	0.50	0.22	0.23	0.77	0.23	0.13	0.36	0.19	-0.03	0.50

TABLE 14. Statistical Evaluation of OOS Forecasts – Portfolios sorted based on transaction costs

The table reports forecast accuracy measures (MSFEs, MSFEs relative to the RW benchmark, OOS R^2, and Clark and West (2007) statistics) for the rolling one-month-ahead OOS forecasts of exchange rate changes generated from the equity, bond and combined models. The test assets are the future spot rate returns on five cross-sectional currency portfolios constructed by sorting currencies on their associated transaction costs, so that currencies with the lowest (highest) transaction costs are allocated to P1 (P5). The proportional transaction cost equals $c_{it+1} = \left(0.5\left(S^a_{it+1} - S^b_{it+1}\right)/S_{it+1}\right)$ and the letters b and a indicate bid and ask quotes, respectively. Results are reported for the three baskets of currencies – developed, emerging, and 'developed and emerging'. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

		Developed Countries			Emerging Countries			Developed & Emerging Countries		
Portfolio	Statistics	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*	*Equity*	*Bond*	*Combined*
P1	MSFE	9.018	8.655	8.635	7.945	8.474	8.004	7.019	10.234	7.448
	Rel.-MSFE	1.056	1.014	1.011	0.956	1.02	0.964	0.981	1.43	1.041
	R^2_{OOS} (%)	-0.056	-0.014	-0.011	0.044	-0.02	0.036	0.019	-0.43	-0.041
	CW	0.74	0.005	1.559	2.476**	-0.22	2.278**	2.342**	-1.206	1.829*
P2	MSFE	8.198	8.141	7.983	5.259	5.334	5.337	4.362	4.737	4.538
	Rel.-MSFE	1.044	1.037	1.017	1.002	1.016	1.017	0.957	1.039	0.995
	R^2_{OOS} (%)	-0.044	-0.037	-0.017	-0.002	-0.016	-0.017	0.043	-0.039	0.005
	CW	1.332	-1.254	1.276	1.142	-0.516	0.799	2.93***	-0.08	2.468**
P3	MSFE	10.186	9.673	10.346	5.549	6.064	5.658	4.319	4.616	4.419
	Rel.-MSFE	1.078	1.024	1.095	0.935	1.021	0.953	0.995	1.063	1.018
	R^2_{OOS} (%)	-0.078	-0.024	-0.095	0.065	-0.021	0.047	0.005	-0.063	-0.018
	CW	1.219	-0.035	1.229	2.901***	-0.476	2.535**	2.008**	-0.187	1.633
P4	MSFE	8.993	8.799	8.503	5.186	5.34	5.175	5.24	5.394	5.199
	Rel.-MSFE	1.057	1.034	0.999	0.984	1.013	0.982	1.006	1.036	0.998
	R^2_{OOS} (%)	-0.057	-0.034	0.001	0.016	-0.013	0.018	-0.006	-0.036	0.002
	CW	0.553	-1.168	1.852*	2.115**	-0.909	2.07**	1.833*	0.88	1.827*
P5	MSFE	3.903	3.792	3.884	7.137	8.167	7.459	7.899	9.296	8.091
	Rel.-MSFE	1.062	1.031	1.056	0.902	1.033	0.943	0.976	1.148	0.999
	R^2_{OOS} (%)	-0.062	-0.031	-0.056	0.098	-0.033	0.057	0.024	-0.148	0.001
	CW	-1.277	-1.015	-1.153	3.294***	-0.929	2.847***	3.095***	-0.192	1.809*

TABLE 15. Statistical Evaluation conditional on Transparency International Index

The table reports forecast accuracy measures (MSFEs, MSFEs relative to the RW benchmark, OOS R^2, and Clark and West (2007) statistics) for the rolling one-month-ahead OOS forecasts of exchange rate changes generated from the equity, bond and combined models. The test assets are the future spot rate returns on five cross-sectional currency portfolios constructed by sorting our sample currencies based on their corresponding countries' Transparency International index, in the sense that countries with the lowest (highest) index scores are allocated to C1 (C5). *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Portfolio	Statistics	Equity	Bond	Combined
C1	MSFE	6.649	6.868	6.533
	Rel.-MSFE	0.978	1.01	0.961
	R^2_{OOS} (%)	0.022	-0.01	0.039
	CW	1.717*	-0.345	1.995**
C2	MSFE	4.604	5.009	4.745
	Rel.-MSFE	0.933	1.015	0.961
	R^2_{OOS} (%)	0.067	-0.015	0.039
	CW	2.869***	-0.44	2.026**
C3	MSFE	4.829	5.114	4.981
	Rel.-MSFE	0.955	1.011	0.985
	R^2_{OOS} (%)	0.045	-0.011	0.015
	CW	2.703***	-0.176	1.837*
C4	MSFE	4.933	4.622	4.975
	Rel.-MSFE	1.089	1.02	1.098
	R^2_{OOS} (%)	-0.089	-0.02	-0.098
	CW	0.85	0.062	0.269
C5	MSFE	7.37	6.705	7.237
	Rel.-MSFE	1.118	1.017	1.098
	R^2_{OOS} (%)	-0.118	-0.017	-0.098
	CW	1.104	-0.22	0.97

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