Timing foreign exchange markets[1]

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Abstract

Priced level, slope, and volatility risk factors recently proposed in the finance literature help explain long-standing puzzles related to the cross-section of carry trade returns. In this paper, we examine whether the information contained in these global factors allows foreign market speculators in individual currencies to successfully time the direction of their carry trades, both when they can foresee the realizations of these factors one-month in advance, as in the classic exchange rate forecasting literature, and when they cannot. We find that, in stark contrast to most previous attempts to forecast monthly exchange rates, perfect foresight of these fundamentals confers statistically and economically significant market timing ability upon speculators. Conditional linear and nonparametric models based on these factors outperform the random walk. Without perfect foresight of these fundamentals, simple strategies based on the directional forecasts of conditional models still manage to outperform the random walk with respect to market timing statistics and realized Sharpe ratios for a large minority of currencies, especially when combined with information on global liquidity factors.

Keywords: foreign exchange, speculation, Bayesian treed Gaussian process, Anatolyev-Gerko statistic

JEL Classifications: F31, G15, G17

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1 Introduction

In a seminal contribution, Meese and Rogoff (1983) demonstrated that empirical (linear and VAR) models based upon the most important structural exchange rate models of the 1970s were inferior to a naive random walk in out-of-sample forecasting performance, even when the realized next-period values of independent variables were taken as given. A great deal of literature has repeatedly verified the basic conclusions of the Meese and Rogoff (1983) study, in particular for major cross-currency exchange rate pairs at the monthly frequency (Rogoff, 2001).

In a recent paper that provides a possible exception to this stylized fact, Gramacy, Malone, and ter Horst (2012) demonstrate that, in black markets for currency, while structural models of black market exchange rates still perform worse than the random walk with respect to RMSE's and MAE's, as in Meese and Rogoff's (1983) study, the exhibit superior performance with respect to directional accuracy, market timing ability, and realized out-of-sample profitability when next-period values of fundamentals are given. When next period values of fundamentals are unknown, as would be the case for currency speculators, they demonstrate moreover that a Bayesian treed Gaussian process model (BTGP) due to Gramacy and Lee (2008) outperforms both the random walk and linear models with respect to directional accuracy, market timing ability, and realized out-of-sample profitability measures, while the linear structural model does no better than a random walk. While the finding that traditional forecasting metrics such as the RMSE and the MAE are at best only distantly related to the ability of speculators to make a profit is not new in the literature, the successful application of the BTGP to predicting exchange rate returns out-of-sample in the black market context with respect to criteria more relevant to real-world speculators begs the question of whether the BTGP, which makes no assumptions regarding the stationarity of exchange rates, the stationarity of exchange rate fundamentals, or the stationarity of the relationship between the fundamentals and exchange rates, is able to achieve comparable levels of success in forecasting a broad selection of cross-rates with the US dollar.

Parallel to the work on the out-of-sample performance of structural models in the black market context, recent work in the international finance literature by Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012) has uncovered important level, slope, and volatility factors that can account for a significant fraction of the variation in the cross-section of carry trade returns across 48 currency pairs with the US dollar. The success of these level, slope, and foreign exchange volatility factors in explaining carry trade returns in the cross section raises the question of whether they would be successful in forecasting individual exchange rate time series out-of-sample.

To answer the above questions, we test the ability of linear and BTGP models based on the level, slope, and global foreign exchange volatility factors studied by Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012) to forecast the returns of individual exchange rates with the US dollar, both when the next-month values of these fundamentals are given, as in the classic Meese and Rogoff (1983) exercise, and when they are unknown, as in the exercise of Gramacy, Malone, and ter Horst (2013) for black market currency speculators.

We focus on forecasting carry trade returns, constructed as in Lustig, Roussanov, and Verdelhan (2011), for two reasons: first, because the next-period log carry trade return can be decomposed as the sum of the current forward premium, which is observed, and the next-period log exchange rate return, which is uncertain; and second, because this allows us to adapt the Anatolyev-Gerko (2005) excess profitability (EP) statistic of market timing ability to the foreign exchange rate context. As the EP statistic is based on the realized returns of a simple trading strategy that goes long if the expected return signal given by the model is positive and short if it is negative, forecasting carry trade returns directly is sensible because long and short positions in the individual currencies studied are easy to implement as carry trade (or reverse carry trade) strategies by combining positions in the forward and spot markets in the underlying currency versus the US dollar. We report RMSEs and MAEs for our models for consistency with earlier literature, but focus principally on statistics of directional accuracy, the EP test of market timing ability adapted to the foreign exchange market context, and realized out-of-sample Sharpe ratios and profitability for the simple directional trading strategies we consider.

Our results are as follows. We find that, in contrast to most previous attempts to forecast monthly exchange rates, perfect foresight of the level, slope, and volatility factors studied by Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012) confers statistically and economically significant forecasting accuracy and market timing ability upon speculators. In fact, the root mean squared errors and mean absolute errors obtained by conditional models that employ these fundamentals are significantly lower than those obtained by the random walk benchmark. This is due primarily, but not exclusively, to the information contained in the DOL level factor that measures the average cross-sectional return of carry trades that go long in foreign currencies versus the US dollar. Without perfect foresight of these fundamentals, simple strategies based on the directional forecasts of conditional models still manage to outperform the random walk with respect to market timing statistics and realized Sharpe ratios for a large minority of currencies. The directional accuracy and realized profitability of simple trading strategies based on the level, slope, and volatility factors in this setting, however, are still inferior to those of the random walk benchmark on average across the countries in our sample, although they do manage to outperform the random walk with drift on average.

The rest of this paper is organized as follows. Section II briefly summarizes the literature on empirical exchange rate models, with a focus on contributions stemming from the seminal Meese and Rogoff (1983) study. Section III briefly describes our foreign exchange rate dataset. Section IV describes the models used to forecast carry trade returns. Section V describes the trading strategy used based on the forecast signals, and the statistics used to measure model forecasting performance. Section VI reports results for the out-of-sample fit exercise, which is comparable with the exercises in the Meese and Rogoff tradition, as well as the out-of-sample forecasting exercise, in which the next-period values of fundamentals are unknown. Section VIII concludes.

2 A brief review of the literature

A great deal of work in the years directly following the publication of Meese and Rogoff's (1983) paper attempted to overturn their results, with little success. This group of contributions includes linear models with time-varying features (Alexander and Thomas (1987), Wolff (1987), and Wolff (1988)), non-parametric kernel regression models (Diebold and Nason (1990) and Meese and Rose (1990)), and Markov-switching models (Engel and Hamilton (1990) and Engel (1994)). More recently, as noted by Preminger and Frank (2007), the use of neural network models to forecast exchange rates has met with some limited success. While the application of neural networks to forecasting daily exchange rates out of sample by Kuan and Tung (1995), Brooks (1997) and Gencay (1999) seems to have outperformed the random walk, an application by Qi and Wu (2003) of a neural network model with monetary fundamentals at the 1-month and longer horizons finds that the neural network performs no better than a random walk at these longer horizons. Rogoff (2001) himself has noted that the inability of structural models to explain the movements of G3 exchange rates remains a robust stylized fact.

During the past decade, however, a handful of studies have managed to deliver more optimistic results with respect to the forecasting ability of structural models in foreign exchange. These studies have obtained their results, for the most part, either by implementing existing models using more sophisticated model selection criteria (Nag and Mitra (2002), Preminger and Franck (2007), and Sarno and Valente (2009)), or by expanding the range of exchange rates studied to include smaller country cross rates with the dollar or another major currency (Liu, Gerlow, and

Irwin (1994), Yang, Su, and Kolari (2008), and Cerra and Saxena (2010)). These papers are discussed in more detail in Gramacy, Malone, and ter Horst (2013), so we do not elaborate on them here, other than to comment briefly on the paper by Cerra and Saxena (2010). Cerra and Saxena (2010) find robust evidence for co-integrating relationships between fundamentals taken from monetary models and exchange rates, and robust evidence that monetary models achieve significantly lower RMSEs than the random walk in out-of-sample prediction, using annual data on a large panel of 98 countries. While their focus is somewhat different than ours, and they do not assess the potential profitability of trading strategies based on their models, two basic but important differences between their study and ours (as well as the original Meese and Rogoff study) are worth noting: first, their use of annual rather than monthly data, and second, their use of panel regressions (in which coefficient estimates on the fundamental variables is pooled for each sample) rather than pure time series models for exchange rate prediction.

In the present paper, while we consider a novel set of fundamentals drawn from the recent finance literature, and compare their performance to that of the set of fundamentals considered by Meese and Rogoff (1983), we maintain the exact same setup of monthly data and individual time series models in all our forecasting exercises. [2] This setup, we believe, allows us to claim that success in our out-of-sample forecasting exercises is indeed a direct answer to the challenge implied by the original Meese and Rogoff (1983) paper, which is that a random walk is better at forecasting next-month exchange rates than the best structural time-series models on offer, even when the next-month values of fundamentals are given. In order to achieve success in our exercises, we employ two primary innovations over previous literature: first, we use global level, slope, and volatility favors from the finance literature as our primary set of fundamentals, and second, we employ the Bayesian treed Gaussian process (BTGP) model due to Gramacy and Lee (2008).

The slope factor identified by Lustig, Roussanov, and Verdelhan (2011), and the global foreign exchange volatility factor identified by Menkhoff et al. (2012), have both proven highly successful at explaining the cross section of contemporaneous carry trade returns. While these factors are related, as discussed at length by Menkhoff et al. (2012), they are distinct. The slope, or high-minus-low factor introduced by Lustig, Roussanov, and Verdelhan (2011) captures the return of a portfolio that is long in high forward premium currencies versus the US dollar and short in low forward premium currencies versus the US dollar. The volatility factor of Menkhoff et al. (2012) captures innovations to global foreign exchange volatility, measured as the average absolute log spot return across all currencies in the sample and days in the month in question. Both factors, as well as the level factor (which measures the return to a portfolio that goes long all currencies versus the US dollar), are global factors, unlike the set of country-specific fundamentals considered in Meese and Rogoff (1983) and subsequent papers that focus on fundamentals drawn from monetary models of exchange rates. This distinction is important, as standard no-arbitrage logic suggests that exchange rate risk due to variations in local factors (monetary or otherwise) will not command a risk premium if sufficient diversification can be obtained by investors by holding particular currencies as part of a portfolio of foreign currencies or other traded assets. [3] Our paper is the first to our knowledge to test whether the global level, slope, and volatility factors have significant out-of-sample forecasting power in individual exchange rate time series, both when the next period values of these fundamental factors is known, and when it is not.

[2] While it is true we forecast log carry trade returns rather than spot exchange rate returns per se, this difference is largely cosmetic, as we discuss further in the following section, and our results are similar in any case when we forecast log exchange rate returns directly.

[3] While Gramacy, Malone, and ter Horst (2013) did find evidence that country-specific black market fundamentals were successful in predicting the direction of black market exchange rates at the monthly frequency, and contained value for speculators as evidenced by the performance of simple trading strategies based on those directional forecasts, it is somewhat questionable whether standard no-arbitrage logic applies to the case of black market currencies.

In making the distinction between out-of-sample forecasting when next-period fundamentals are known, versus when they are not, we follow Howrey (1994) and Gramacy, Malone, and ter Horst (2013).

In addition to the linear regression model estimated via OLS, we employ a Bayesian treed Gaussian process (BTGP) model due to Gramacy and Lee (2008) to forecast one-month-ahead exchange rates. The BTGP is a nonparametric model that can be viewed as a tree whose leaves represent random functions, with the functions modeled using Gaussian processes. The flexibility afforded by being able to classify observations into different "leaves" of the BTGP allows for the modeling of non-stationary data, in which the function relating the carry trade return and the fundamental variables in a given month may represent one of several Gaussian processes indexed by the leaves of the tree. This is consistent with earlier findings that neural network models, and methods that explicitly allow for non-stationarity in the relationship between fundamentals and exchange rates, can improve out-of-sample prediction. The Bayesian treed Gaussian process (BTGP) has been applied successfully in areas such as computational fluid dynamics, genetics, finance, climatology and political science, and can be implemented via use of open source software in the form on an R package called "tgp" available on CRAN (Gramacy, 2007). The inclusion of the linear regression model in our forecasting horse race allows us to assess whether superior forecasting ability in exercises that take the future values of fundamentals as given is due to the superior information content of our global level, slope, and volatility factors, to the superior ability of the BTGP to handle non-stationarity in the data, or both.

Finally, in contrast to many previous studies, our focus is centered not only upon the question of whether or not out-of-sample forecasting ability for structural models exists, but also on whether or not such an ability confers the capacity to generate speculative profits in simulated real-time trading. For that reason, we go beyond the usual reporting of RMSE's and measures of out-of-sample fit when next-period values of fundamentals is known (à la Meese and Rogoff, 1983). We report directional accuracy measures, following the work of Leitch and Tanner (1991), Engel (1994), and Abhayankar et al. (2005), the Anatolyev-Gerko (2005) excess profitability statistic of market timing ability, the cross-sectional distribution of realized monthly APR's from simulated trading, and the realized Sharpe ratios from simple trading strategies.

3 Description of the data

In constructing our dataset of carry trade returns and their determinants, we follow closely the papers of Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012). The dataset consists of 48 countries, including 15 developed and 33 emerging market countries, during the period from November 1983 to December 2010. For developed countries comprising the Eurozone, we use the cross-rates of their currencies versus the US dollar pre-euro as one set of time series, and the euro versus US dollar time series after the inception of the euro as a separate, non-overlapping currency time series. Spot and 1-month forward exchange rate data versus the US dollar was obtained from Reuters via Datastream. Like the aforementioned papers, we conduct our analysis at the monthly frequency, although as in Menkhoff et al. (2012), we start from daily data to construct their proxy for foreign exchange volatility risk. Following the tradition in the finance literature since Fama (1984), and in the international economics literature since Meese and Rogoff (1983), our exposition uses spot and forward rates in logarithms rather than levels. The full list of 48 countries and the subset of 15 developed countries included in our paper is listed in Section II.A of Menkhoff et al. (2012) and Appendix A of this paper.

As in Menkhoff et al. (2012), monthly excess returns for holding foreign currency k, denoted by rx^k, are given by

$$rx^k_{t+1} = i^k_t - i_t - \Delta s^k_{t+1} \approx fp^k_t - \Delta s^k_{t+1} = f^k_t - s^k_{t+1}$$

where s and f denote spot and forward exchange rates in logs, respectively. As shown by Akram, Rime, and Sarno (2008), covered interest parity holds closely in foreign exchange data at the monthly frequency, so the first approximation above uses the fact that $i_t^k - i_t \approx fp_t^k$, where the forward premium in logarithms is defined as $fp_t^k \equiv f_t^k - s_t^k$.

As in Lustig, Roussanov, and Verdelhan (2011), we focus on trading strategies that involve positions exclusively in forward and spot currency markets, as carry trades (and reverse carry trades, in which the investor goes long the foreign currency versus the dollar) are easy to implement in such markets, and forward contracts involve minimal default and counter-party risk. (Also, as noted by Lustig, Roussanov, and Verdelhan (2011), bid-ask spreads for forward currency markets are readily available, thus facilitating the calculation of realistic estimates of metrics of trading strategy performance net of transaction costs.) Unless otherwise stated, and given our focus on strategies involving the time series of individual currencies, we drop the country superscript k in the rest of the paper for ease of exposition.

3.1 The set of factors used for prediction

Our main interest in this paper is whether, given a vector X of factors we believe may have predictive power for period $t+1$ carry trade returns rx_{t+1} for a given currency versus the dollar, we can time the foreign exchange market by initiating a carry trade (going long the foreign currency) or a reverse carry trade (going short the foreign currency) based on the sign of our model predictions. The information set for the vector X of factors may include information available up to time $t+1$, so that we use X_{t+1} to form out-of-sample predictions of the dependent variable rx_{t+1}^k, or may be limited to information available only up to time t, so that we use X_t to predict rx_{t+1}^k. The former exercise corresponds to the benchmark established in the seminal paper of Meese and Rogoff (1983) in the international economics literature, whereas the latter exercise, which is the most directly relevant for the success of market timing strategies on the part of foreign exchange speculators, corresponds to the exercise considered by Gramacy, Malone, and ter Horst (2013) for the case of black markets for foreign exchange.

The vector X of factors we use to forecast one-month ahead carry-trade returns includes variables that fall into three categories: (a) three global (level, slope, and volatility) risk factors studied by Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012); (b) three currency-specific or global liquidity measures proposed and studied variously by Pastor and Stambaugh (2003) and the previous two papers; and (c) proxies for the classic variables based on early monetary models of exchange rates included in the Meese and Rogoff (1983) study. In the latter case, we focus in particular on the Dornbusch-Frankel model.

In particular, the category (a) variables are: DOL, the average return on a portfolio that goes long all foreign currencies vs. the US dollar, HML_FX, the returns on a high-minus-low interest rate FX portfolio that closely mimics the slope factor identified and discussed in detail by Lustig, Roussanov, and Verdelhan (2011), and $\Delta\sigma_t^{FX}$, the innovation of the σ_t^{FX} factor proposed by Menkhoff et al. (2012), which we denote by DVOL.[4] The category (b) variables include innovations in the TED spread, denoted as DTED, the Pastor-Stambaugh liquidity factor in differences, denoted by DPS, and the global bid-ask spread liquidity measure proposed Menkhoff et al. (2012), in differences and computed at the monthly frequency from daily data, denoted by DUSD_BASLiquidity. The category (c) variables include DLNMstarM, the log of the ratio of foreign to US money supplies in first differences, DLNYstarY, the log ratio of foreign to US output, proxied by industrial production indices, in first differences, the interest rate differential, proxied by the log forward premium fp, and a simple proxy for the expected long-run inflation

[4]Note that Menkhoff et al. (2012) label this variable as VOL; we denote it by DVOL to make a distinction between the factor in differences and the factor in levels, which we label VOL in the present paper.

differential, denoted rmeanDLNCPIstarCPI, computed as the average growth rate of CPI inflation over the preceding 12 month period in the foreign country minus the average growth rate of CPI inflation over the preceding 12 month period in the US.

4 The forecasting models

The forecasting models for exchange rate returns we consider are the random walk, the random walk with drift, a linear model in differences, and a BTGP model in differences. We apply these models to the prediction of next-period carry trade log returns as follows. First, since the random walk is equivalent to assuming $E(\Delta s) = 0$, this implies that $rx^f_{t+1} = E(rx_{t+1}) = fp_t$ by covered interest rate parity. Second, for the random walk with drift, we take the rolling mean of the past $W = 48$ months of the log spot currency return Δs, and form the forecast $rx^f_{t+1} = fp_t - \overline{\Delta s}_t$, where $\overline{\Delta s}_t = (1/W)\sum_{i=t-W+1}^{t} \Delta s_i$. It is important to note that the forecasts of the random walk and random walk with drift models, respectively, is the same in both the forecasting exercise where the next-period of fundamentals X_{t+1} is given, and the forecasting exercise where the next-period of fundamentals is unknown and we forecasting using the information set X_t, as neither model uses information on fundamentals in period $t+1$ to form expectations regarding the value of rx_{t+1}.

Third, given a vector of fundamentals X, our ex-post out-of-sample linear model forecast rx^f_{t+1}, in which the next-month values of fundamentals is given, is obtained as

$$rx^f_{t+1} = \hat{\alpha} + \hat{\gamma} fp_t + \hat{\vec{\beta}}' \vec{X}_{t+1}, \tag{1}$$

where we condition on the value of fp_t in recognition of the fact that rx_{t+1} can be decomposed as $rx_{t+1} = fp_t - \Delta s_{t+1}$, and the next-month log exchange rate return Δs_{t+1} may be correlated with the present value of the forward premium fp_t. Thus, the random walk is nested as a subcase of the above linear model in which $\alpha = 0, \vec{\beta} = \vec{0}$, and $\gamma = 1$, whereas the random walk with drift is nested as the subcase of the above model in which $\vec{\beta} = \vec{0}$ and $\gamma = 1$, but $\alpha = -\overline{\Delta s}_t$ is estimated as above. Our ex-ante linear model out-of-sample forecast, in which the next-month values of fundamentals in unknown, is obtained as

$$rx^f_{t+1} = \hat{\alpha} + \hat{\gamma} fp_t + \hat{\vec{\beta}}' \vec{X}_t, \tag{2}$$

in which the salient difference with respect to the previous model is that we condition on the period t, rather than the period $t+1$, value of X. All models are estimated using the same rolling window size of $W = 48$.

Finally, in our Bayesian treed Gaussian process model, ex-post out-of-sample forecasts are formed as

$$rx^f_{t+1} = \hat{F}(fp_t, \vec{X}_{t+1}), \tag{3}$$

whereas our ex-ante out-of-sample forecasts are formed as

$$rx^f_{t+1} = \hat{F}(fp_t, \vec{X}_t). \tag{4}$$

5 The trading strategy and measures of forecasting performance

Following Meese and Rogoff (1983), Gramacy, Malone and ter Horst (2013), and the vast majority of literature in between, we report statistics on the mean error (ME), the root mean squared error

(RMSE), and the mean absolute error (MAE) of our forecasts. In our case, we are forecasting carry trade returns rather than exchange rate log returns per se, but our inclusion of the forward premium on the RHS of our forecasting models ensures that the values we obtain for these measures should be comparable with those obtained for errors of log exchange rate return forecasts. Following Cerra and Saxena (2010) and Gramacy, Malone and ter Horst (2013), we also report statistics on the directional accuracy of our models, in particular on the percentage of months in which the prediction of the sign of the next-month carry trade return by a given model is correct.

To measure the economic value of our forecasts of next-month carry trade returns, we employ a simple directional trading strategy of the sort analyzed by Anatolyev and Gerko (2005) and adapted to the foreign exchange market context by Gramacy, Malone, and ter Horst (2013). In particular, given a forecast rx^f_{t+1} for the next-period log return of a carry trade that goes short in the US dollar and long in the foreign currency, we consider an "artificial technical analyst" who takes a position according to the sign of the forecast, going long the foreign currency versus the US dollar if the forecast is positive, and going short the foreign currency versus the US dollar if the forecast is negative. The realized (log) returns to such a strategy are given by r_{t+1}, where

$$r_{t+1} = sign(rx^f_{t+1}) rx_{t+1}. \tag{5}$$

From the log returns, we can calculate the discrete returns according to the formula

$$R_{t+1} = exp(r_{t+1}) - 1. \tag{6}$$

RX^f_{t+1} and RX_{t+1} denote the discrete forecast returns and carry trade returns, respectively, and are calculated in a similar manner. We use the discrete returns from our trading strategies to calculate the Anatolyev-Gerko excess profitability statistic and our other measures of the economic value of these strategies, such as realized profitability and Sharpe ratios.

For realized carry trade returns RX_{t+1} and return forecast RX^f_{t+1}, the Anatolyev-Gerko statistic is computed as

$$EP = \frac{A_T - B_T}{\sqrt{\hat{V}_{EP}}} \xrightarrow{d} N(0,1), \tag{7}$$

where

$$A_T = \frac{1}{T}\sum_{i=0}^{T-1} sign(RX^f_{t+1}) RX_{t+1} \text{ and } B_T = \left(\frac{1}{T}\sum_{i=0}^{T-1} sign(RX^f_{t+1})\right)\left(\frac{1}{T}\sum_{i=0}^{T-1} RX_{t+1}\right), \tag{8}$$

T is the number of out-of-sample periods, and $\hat{V}_{EP}$ is the feasible estimate of the variance of the numerator of the statistic, which is given in Anatolyev and Gerko (2005).

The EP statistic is useful because it measures the extent to which a given forecasting signal is able to generate trades whose profitability (before transactions costs) exceeds that of trades generated by a forecasting signal whose unconditional directional forecasting probabilities are equal to those of the model being tested. Models with significantly positive EP statistics, therefore, are often able to achieve a consistent market timing of nontrivial moves of the exchange rate. We report the EP statistic of Anatolyev and Gerko (2005), as well as our other statistics, for both the "ex-post" out-of-sample and "ex-ante" out-of-sample forecasting exercises. In the context of ex-post forecasts, in which the ex-post values of the independent variables are given, a positive and significant EP statistic indicates superior market timing ability, conditional upon perfect foresight of the structural model determinants one month ahead. In the context of our ex-ante out-of-sample forecasting exercise, in which future values of fundamentals are unknown, a positive EP statistic suggests a potentially profitable superiority in market timing ability.

Finally, as transparent measures of realized profitability, we compute the cumulative monthly return, expressed as an APR (compounded monthly), and the annualized Sharpe ratio for each model and country in the sample. It should be stressed that our exercises involve only time series data for each country, and that information from other currency markets is used only to the extent that it enters into the computation of our global predictor variables; all cumulative returns and Sharpe ratios reported are for averages across results for individual currencies, not portfolios. In all of our exercises, unless otherwise stated, the initial training window is set equal to the first 48 months of data, and the out-of-sample testing period comprises the last $T_k - 48$ months of data, where T_k is the total number of months for country k, with country episodes in alphabetical order by country indexed by k. Thus the monthly APR for country k, assuming an initial capital of USD 1000, is computed as

$$APR_k = 12((V_{T_k}/1000)^{1/(T_k-48)} - 1), \tag{9}$$

where V_{T_k} is the value of the portfolio after the final month of country sample period. The annualized Sharpe ratio is computed as

$$SR_k = \sqrt{12}\frac{\overline{R_k}}{\sigma(R_k)}, \tag{10}$$

where $\overline{R_k}$ represents the sample mean of the out-of-sample discrete strategy returns for country k, and $\sigma(R_k)$ represents the sample standard deviation of the out-of-sample discrete strategy returns for country k.

Note that, due to the use of a 48 month training window, the countries Cyprus, Finland, Greece, and Slovenia drop out of the sample, because the number of total carry trade return observations available for each is 45, 24, 48, and 33 months, respectively.

6 Empirical Results

In this section, we discuss the empirical performance of our models. The conditional models in all of our exercises consist of the predictive regression estimated via OLS and the BTGP model of Gramacy and Lee (2008). The forecasts of these models, in all our exercises, are benchmarked against the forecasts of the random walk (RW) and random walk with drift (RWWD) models discussed previously. The exercises we present in this section differ, therefore, along two primary dimensions: whether they are "ex-post" or "ex-ante", and based on the set of fundamentals we use to populate the X vector of predictors in our conditional models. By "ex-post", or out-of-sample fit exercises we mean those in which the $t+1$ (next-month) values of the fundamentals are given, as in Meese and Rogoff (1983); by "ex-ante", or out-of-sample forecasting exercises, we mean those in which the $t+1$ values of the fundamentals in unknown, and prediction is conditioned on the values of fundamentals at time t.

We begin our discussion of the empirical results by comparing the mean error (ME), root mean squared error (RMSE), and mean absolute error (MAE) statistics for the out-of-sample fit exercise in which the next-month values of fundamentals are given for the conditional models. Within this exercise, whose results are displayed in Table 1, we consider two sets of fundamental variables. The first, displayed in the right-most two columns of panel A, we label the Global Forex set of fundamentals, which consists of the variables DOL, HML_FX, and DVOL discussed previously. The second, displayed in the right-most columns of panel B, consists of the factors in the Dornbusch-Frankel specification tested by Meese and Rogoff (1983), constructed for each country in our more recent dataset.

Examination of Table 1 reveals three important results. First, from the results displayed in panel A, we see that both the predictive regression and BTGP model employing our Global Forex set of fundamentals are able to soundly beat both the random walk and random walk with drift benchmarks with respect to the RMSE and MAE criteria, in terms of achieving cross-sectional average RMSE and MAE figures that are around 25% lower than the cross-sectional RMSE and MAE averages for the RW and RWWD. This is a significant finding, given that no model in the literature of which we are aware has managed to beat these two benchmarks to such an extent using only time-series models on monthly exchange rate data. Second, an examination of panel B reveals that we manage to recreate the original Meese-Rogoff result, for the case of the Dornbusch-Frankel model, in our dataset, as the average RMSEs and MAEs for conditional models based on these variables are higher than those of the benchmarks. This is important, as it broadly confirms the Meese-Rogoff result on our contemporaneous sample and demonstrates that the success of our Global Forex fundamentals is not simply an artifact of the change in sample. Third, we find that within the set of conditional models, the predictive regression and the BTGP exhibit highly similar performance with respect to all three traditional measures of forecasting accuracy.

	Model	RW	RWWD	Predictive regression	BTGP
	Number of countries	43	43	43	43
Panel A: Global Forex fundamentals (DOL, HML_FX, DVOL)					
ME	Mean	6e-04	0.0014	-1e-04	3e-04
	St.Dev.	0.0041	0.0033	0.0031	0.0031
	Min	-0.0106	-0.0114	-0.0103	-0.0078
	Max	0.0141	0.008	0.0123	0.0112
RMSE	Mean	0.0317	0.0323	0.0232	0.024
	St.Dev.	0.014	0.0142	0.0176	0.0165
	Min	0.0012	0.0012	0.0014	0.0017
	Max	0.0708	0.0715	0.0782	0.0746
MAE	Mean	0.023	0.0235	0.016	0.0159
	St.Dev.	0.0095	0.0098	0.0108	0.0097
	Min	3e-04	3e-04	5e-04	6e-04
	Max	0.0445	0.0469	0.0496	0.0493
Panel B: Dornbusch-Frankel fundamentals					
ME	Mean	6e-04	0.0014	0.0011	9e-04
	St.Dev.	0.0041	0.0033	0.0041	0.0045
	Min	-0.0106	-0.0114	-0.0153	-0.0194
	Max	0.0141	0.008	0.0087	0.0126
RMSE	Mean	0.0317	0.0323	0.0345	0.0369
	St.Dev.	0.014	0.0142	0.0154	0.0208
	Min	0.0012	0.0012	0.0015	0.0015
	Max	0.0708	0.0715	0.0784	0.1306
MAE	Mean	0.023	0.0235	0.0248	0.0257
	St.Dev.	0.0095	0.0098	0.011	0.0118
	Min	3e-04	3e-04	5e-04	6e-04
	Max	0.0445	0.0469	0.0555	0.0566

Table 1: Sample error statistics for out-of-sample fit exercises: Global Forex fundamentals vs. Dornbusch-Frankel fundamentals

To build upon the results in Table 1, we next ask the question, given the success of the Global Forex fundamentals in beating the Meese-Rogoff random walk benchmark, of what is the ability of each of the three Global Forex factors to explain variation in carry trade log returns individually when the next-month values are given. The results of this exercise are displayed in Table 2. Panel A of that table reports the ME, RMSE, and MAE statistics for conditional models that employ (in addition to the value of fp_t, as is true throughout this paper) only the DOL factor, panel B reports these measures for models that employ only the HML_FX factor, and panel C reports these measures for conditional models that employ only the DVOL factor. Results for the benchmarks are reproduced in the leftmost columns for convenience.

Three additional results emerge from Table 2. First, we see that of the three factors, it is primarily the DOL factor whose information content allows the conditional models to beat the random walk by achieving lower RMSEs and MAEs. With 43 countries in the sample (five having been dropped due to data limitations), we obtain a 95% confidence interval for the average RMSE of the random walk of $[0.0275, 0.0359]$. The average RMSEs in the cross-section of the conditional models employing the DOL factor fall well below the lower end of this confidence interval. Second, we see that the cross-sectional averages of the RMSEs for the conditional models in panels B and C fall well within this confidence interval, so that conditional models employing the HML_FX factor and the DVOL factor appear to be at least as good as the random walk, if not much better. Theil U-statistics of the ratios of the MSEs by country, which we do not report here for brevity, lead to similar conclusions for each of these three factors. Third, although the average RMSEs and MAEs for the BTGP are slightly higher than those for the predictive regression in panels A-C, the differences are insignificant.

The out-of-sample forecasting accuracy of the conditional models employing the DOL factor deserves some further comment. What this result is telling us is that, conditional upon knowing the average carry trade return of all currencies against the US dollar in the following month, we can develop very accurate forecasts of any individual currency carry trade return (or to be more accurate, long position in a given foreign currency versus the US dollar) in the following month. It is not obvious that this should be the case. Many if not most currencies have data spanning a large part of the sample, so that the charge that we are using the individual carry trade return to predict itself has limited merit. Furthermore, we know from Menkhoff et al. (2012) that high forward premium currencies and low forward premium currencies tend to depreciate and appreciate, respectively, in response to positive innovations in the DVOL factor, for example, so it is not clear that knowing the current average carry trade return, given by DOL, should be so definitive in forecasting the next-month individual carry trade returns out-of-sample. Nevertheless, we find that conditioning on this factor does allow us to beat the long-standing Meese-Rogoff (1983) random walk benchmark.

Since it is now widely acknowledged that RMSE and MAE measures of forecasting accuracy are perhaps of secondary importance in gauging the economic value of forecasting models compared to measures such as those described in the latter part of Section 5, we now turn to reporting summary statistics for measures of directional accuracy, the Anatolyev-Gerko excess profitability statistic, the realized cumulative monthly strategy retuns as an APR, and realized Sharpe ratios of the simple long-short trading strategy based upon the signals from each of our models. Table 3 reports these measures for our conditional models based on the set of three Global Forex fundamentals. Panel A of the table reports values of the measures for the "ex-post" out-of-sample fit exercise, in which the next-month values of fundamentals are known, and panel B of the table reports values of the measures for the "ex-ante" out-of-sample forecasting exercise, in which ex-post values of fundamentals are unknown.

We can glean several interesting results from this table. First, in panel A, we see that the Global Forex set of fundamentals delivers a high degree of prediction accuracy, market timing ability, and realized profitability and Sharpe ratios for the simple directional strategies considered when the next-month values of the fundamentals are known. Somewhat remarkably, the EP test statistics for the conditional models are positive for all countries considered, and most are significantly different from zero at the 5% level. The realized returns and trading strategy Sharpe ratios are statistically significantly different from zero in the cross section and highly economically significant, both in absolute terms and relative to the levels obtained by the benchmarks.

Second, turning to panel B, we see that the performance of our conditional models deteriorates significantly relative to panel A when the next-month values of the set of three Global Forex fundamentals is unknown. The difference in the average cross-sectional prediction accuracy percentage of both conditional models versus that of the random walk is just significant at the 95% level. In the EP test of market timing ability, the results are similar, with the random walk exhibiting more instances of positive and significant EP statistics than the conditional models. However, in the incidence of positive EP statistics (those that are statistically significant and those that are not), we find that the BTGP beats all other models, with 27 out of 43 countries having positive EP statistics based on the trading strategy that takes signals from the BTGP conditional on the previous month values of the Global Forex fundamentals. The average realized returns and Sharpe ratios for the predictive regression and BTGP are clearly lower than those for the random walk, but generally comparable to or better than those obtained for the random walk with drift. Overall, we can conclude that conditional models based on the Global Forex fundamentals cannot beat the random walk based on economic criteria in true ("real time", or "ex-ante") forecasting exercises, although they do outperform the random walk with drift, and do nonetheless outperform the random walk in a minority of countries, if not on average.

Given the failure of conditional models based on our baseline Global Forex set of fundamentals to beat the random walk in "ex-ante" out-of-sample forecasting exercises, we close by examining whether adding additional, liquidity-based measures discussed in Menkhoff et al. (2012), denoted by DTED, DPS, and DUSD_BASLiquidity, respectively, and adding values of the global forex volatility and liquidity variables in levels (VOL, TED, PS, and USD_BASLiquidity, respectively) to the set of predictors improves their performance. These results are displayed in Table 6.

Panel A of this table displays "ex-ante" forecasting results for the conditional models after adding the three liquidity measures from Menkhoff et al. (2012) to the set of Global Forex factors. The predictive regression deteriorates marginally in performance, and the BTGP improves slightly in performance, but the overall results are similar to the models before the liquidity factors were included.

Panel B of the table displays "ex-ante" forecasting results for the conditional models after adding the VOL and liquidity variables in levels to the specification in panel A. The performance of the predictive regression deteriorates further, but the performance of the BTGP improves substantially with respect to the realized average returns and Sharpe ratios of the long-short trading strategy. In particular, besides achieving positive EP statistics for the largest number of countries in the sample of any model, we can now no longer reject at the 95% level the null hypothesis that the average monthly return (expressed as an APR) or the realized Sharpe ratio associated with the BTGP model are different from the comparable figures obtained by the random walk benchmark, respectively, on average in the cross section of countries in our sample. The set of VOL and liquidity factors in levels clearly contains additional information that the BTGP is able to capitalize on to improve the quality of its predictions, but the linear model is not.

7 Conclusion

We assess the out-of-sample forecasting performance of linear and nonparametric Bayesian treed Gaussian process (BTGP) models conditional on a set of global level, slope, and foreign exchange volatility factors recently brought to attention in the finance literature. These factors, which have proven successful in explaining the cross section of carry trade returns, also contain valuable information for forecasting individual currency carry trade returns versus the US dollar. Given next-month values of these fundamentals, as in the exercise originally performed by Meese and Rogoff (1983), we find that our conditional models beat the random walk and the random walk with drift across various measures of forecasting performance. Not only do our conditional models achieve lower RMSEs and MAEs than the random walk, but they also achieve superior directional accuracy, superior performance with respect to the Anatolyev-Gerko (2005) excess profitability statistic of market timing, and realized profitability and Sharpe ratios. Further, we show that when next-month values of fundamentals are unknown, as they would be for currency speculators, the random walk outperforms the conditional models overall. However, the conditional models outperform the random walk with drift on average, and manage to outperform the random walk itself for a nontrivial minority of countries. The BTGP slightly outperforms the linear regression in the latter context. When we add global liquidity factors as predictors and include the volatility and liquidity factors in levels as well as first differences, we find the average performance of the BTGP with respect to realized returns and Sharpe ratios becomes statistically indistinguishable from that of the random walk in the cross section of countries studied.

8 Appendices

8.1 List of countries considered

The full sample consists of the following 48 countries (referred to as our All Countries sample), as in Menkhoff et al. (2012): Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. As in Lustig et al. (2011) and Menkhoff et al. (2012), our subsample of 15 developed countries (referred to as our Developed Countries sample below) consists of: Australia, Belgium, Canada, Denmark, euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. Since the introduction of the euro in January 1999, the sample of developed countries covers 10 currencies only.

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	Model	RW	RWWD	Predictive regression	BTGP
	Number of countries	43	43	43	43
	Panel A: DOL factor				
ME	Mean	6e-04	0.0014	-3e-04	-2e-04
	St.Dev.	0.0041	0.0033	0.002	0.0028
	Min	-0.0106	-0.0114	-0.0077	-0.0083
	Max	0.0141	0.008	0.0041	0.0063
RMSE	Mean	0.0317	0.0323	0.0212	0.0222
	St.Dev.	0.014	0.0142	0.0132	0.0139
	Min	0.0012	0.0012	0.0014	0.0014
	Max	0.0708	0.0715	0.0616	0.0638
MAE	Mean	0.023	0.0235	0.015	0.0153
	St.Dev.	0.0095	0.0098	0.0086	0.0083
	Min	3e-04	3e-04	4e-04	5e-04
	Max	0.0445	0.0469	0.0411	0.0393
	Panel B: HML_FX factor				
ME	Mean	6e-04	0.0014	0.0033	0.0024
	St.Dev.	0.0041	0.0033	0.0048	0.0055
	Min	-0.0106	-0.0114	-0.0087	-0.015
	Max	0.0141	0.008	0.0161	0.0218
RMSE	Mean	0.0317	0.0323	0.0323	0.034
	St.Dev.	0.014	0.0142	0.0142	0.0173
	Min	0.0012	0.0012	0.0014	0.0015
	Max	0.0708	0.0715	0.0681	0.0991
MAE	Mean	0.023	0.0235	0.0229	0.0234
	St.Dev.	0.0095	0.0098	0.0095	0.0103
	Min	3e-04	3e-04	5e-04	5e-04
	Max	0.0445	0.0469	0.0434	0.0543
	Panel C: DVOL factor				
ME	Mean	6e-04	0.0014	5e-04	0.0012
	St.Dev.	0.0041	0.0033	0.0047	0.0042
	Min	-0.0106	-0.0114	-0.0217	-0.0103
	Max	0.0141	0.008	0.0089	0.0099
RMSE	Mean	0.0317	0.0323	0.034	0.0343
	St.Dev.	0.014	0.0142	0.0164	0.0166
	Min	0.0012	0.0012	0.0014	0.0016
	Max	0.0708	0.0715	0.0786	0.0863
MAE	Mean	0.023	0.0235	0.0245	0.025
	St.Dev.	0.0095	0.0098	0.0106	0.011
	Min	3e-04	3e-04	5e-04	5e-04
	Max	0.0445	0.0469	0.0493	0.0582

Table 2: Sample error statistics for out-of-sample fit exercises: DOL, HML_FX, and DVOL fundamentals considered separately

	Model	RW	RWWD	Predictive regression	BTGP
	Number of countries	43	43	43	43
Panel A: "Ex-post" Out-of-sample fit (Ex-post values of fundamentals known)					
Dir. accuracy (%)	Mean	0.5792	0.5601	0.7768	0.7771
	St.Dev.	0.0929	0.0951	0.0949	0.0955
	Min	0.3824	0.3636	0.5758	0.5758
	Max	0.9083	0.9	0.9091	0.9444
EP test	$EP > 0$ and p-value $< .05$	9	3	41	37
	EP insignificant	34	39	2	6
	$EP < 0$ and p-value $< .05$	0	1	0	0
	Incidence of positive EP	25	21	43	43
Cum. APR	Mean	0.0279	0.0098	0.2415	0.2346
	St.Dev.	0.0421	0.0513	0.1323	0.1262
	Min	-0.0714	-0.1701	0.0036	4e-04
	Max	0.1139	0.1306	0.5329	0.5208
Sharpe ratio	Mean	0.4044	0.2463	2.4428	2.3959
	St.Dev.	0.4597	0.4862	0.9958	1.0861
	Min	-0.2042	-0.676	0.5052	0.0917
	Max	2.2265	2.2265	4.4441	5.0249
Panel B: "Ex-ante" Out-of-sample forecasting (Ex-post values of fundamentals unknown)					
Dir. accuracy (%)	Mean	0.5798	0.559	0.5453	0.5471
	St.Dev.	0.0924	0.0956	0.0758	0.0693
	Min	0.3824	0.3636	0.3636	0.4242
	Max	0.9083	0.9	0.7417	0.8417
EP test	$EP > 0$ and p-value $< .05$	9	3	4	2
	EP insignificant	34	39	39	41
	$EP < 0$ and p-value $< .05$	0	1	0	0
	Incidence of positive EP	25	21	25	27
Cum. APR	Mean	0.0285	0.0087	0.0117	0.0133
	St.Dev.	0.0428	0.0515	0.0466	0.0429
	Min	-0.0714	-0.1701	-0.0997	-0.1025
	Max	0.1156	0.1306	0.144	0.1515
Sharpe ratio	Mean	0.4098	0.2359	0.2209	0.2231
	St.Dev.	0.4623	0.4891	0.4281	0.3582
	Min	-0.2042	-0.676	-0.694	-0.5985
	Max	2.2265	2.2265	1.467	1.0284

Table 3: Performance statistics for out-of-sample fit and forecasting exercises: Global Forex fundamentals (DOL, HML_FX, and DVOL)

	Model	RW	RWWD	Predictive regression	BTGP
	Number of countries	43	43	43	43
Panel A: "Ex-ante" exercise for Global Forex fundamentals (DOL, HML_FX, and DVOL) plus Liquidity fundamentals (DTED, DPS, and DUSD_BASLiquidity)					
Dir. accuracy (%)	Mean	0.5798	0.559	0.5443	0.549
	St.Dev.	0.0924	0.0956	0.0863	0.0744
	Min	0.3824	0.3636	0.3529	0.3636
	Max	0.9083	0.9	0.7576	0.8083
EP test	$EP > 0$ and p-value $< .05$	9	3	4	2
	EP insignificant	34	39	39	41
	$EP < 0$ and p-value $< .05$	0	1	0	0
	Incidence of positive EP	25	21	26	27
Cum. APR	Mean	0.0285	0.0087	0.0109	0.0147
	St.Dev.	0.0428	0.0515	0.0466	0.0472
	Min	-0.0714	-0.1701	-0.1224	-0.1357
	Max	0.1156	0.1306	0.0957	0.1371
Sharpe ratio	Mean	0.4098	0.2359	0.2067	0.2409
	St.Dev.	0.4623	0.4891	0.4398	0.3783
	Min	-0.2042	-0.676	-0.9496	-0.6449
	Max	2.2265	2.2265	1.6163	1.2448
Panel B: "Ex-ante" exercise for Global Forex fundamentals (DOL, HML_FX, and DVOL) plus Liquidity fundamentals (DTED, DPS, and DUSD_BASLiquidity) plus Vol and Liquidity fundamentals in levels (VOL, TED, PS, and USD_BASLiquidity)					
Dir. accuracy (%)	Mean	0.5798	0.559	0.5439	0.5537
	St.Dev.	0.0924	0.0956	0.0737	0.06
	Min	0.3824	0.3636	0.3333	0.4545
	Max	0.9083	0.9	0.7417	0.75
EP test	$EP > 0$ and p-value $< .05$	9	3	2	4
	EP insignificant	34	39	40	39
	$EP < 0$ and p-value $< .05$	0	1	1	0
	Incidence of positive EP	25	21	22	32
Cum. APR	Mean	0.0285	0.0087	0.005	0.0252
	St.Dev.	0.0428	0.0515	0.0568	0.0449
	Min	-0.0714	-0.1701	-0.1742	-0.0257
	Max	0.1156	0.1306	0.1901	0.1979
Sharpe ratio	Mean	0.4098	0.2359	0.1544	0.3194
	St.Dev.	0.4623	0.4891	0.4546	0.4099
	Min	-0.2042	-0.676	-1.2364	-0.1319
	Max	2.2265	2.2265	1.5167	1.7361

Table 4: Performance statistics for out-of-sample forecasting exercises: Global Forex fundamentals plus Liquidity fundamentals

	Model	RW	RWWD	Predictive regression	BTGP
	Number of countries	15	15	15	15
Panel A: "Ex-ante" exercise for Global Forex fundamentals (DOL, HML_FX, and DVOL) plus Liquidity fundamentals (DTED, DPS, and DUSD_BASLiquidity)					
Dir. accuracy (%)	Mean	0.5535	0.5204	0.5125	0.5247
	St.Dev.	0.0346	0.0408	0.0296	0.0305
	Min	0.5	0.4242	0.4773	0.4621
	Max	0.6123	0.5761	0.5758	0.5725
EP test	$EP > 0$ and p-value $< .05$	5	0	1	0
	EP insignificant	10	14	14	15
	$EP < 0$ and p-value $< .05$	0	1	0	0
	Incidence of positive EP	14	9	6	10
Cum. APR	Mean	0.0415	0.0048	0.0034	0.0147
	St.Dev.	0.0292	0.0207	0.0266	0.0219
	Min	0.0032	-0.0415	-0.0248	-0.0175
	Max	0.1156	0.0258	0.0539	0.0551
Sharpe ratio	Mean	0.4262	0.1061	0.0903	0.1877
	St.Dev.	0.2441	0.1972	0.2457	0.1954
	Min	0.0845	-0.3311	-0.1618	-0.0967
	Max	1.042	0.3843	0.5317	0.5394
Panel B: "Ex-ante" exercise for Global Forex fundamentals (DOL, HML_FX, and DVOL) plus Liquidity fundamentals (DTED, DPS, and DUSD_BASLiquidity) plus Vol and Liquidity fundamentals in levels (VOL, TED, PS, and USD_BASLiquidity)					
Dir. accuracy (%)	Mean	0.5535	0.5204	0.529	0.527
	St.Dev.	0.0346	0.0408	0.031	0.029
	Min	0.5	0.4242	0.4697	0.4773
	Max	0.6123	0.5761	0.6038	0.5688
EP test	$EP > 0$ and p-value $< .05$	5	0	0	1
	EP insignificant	10	14	15	14
	$EP < 0$ and p-value $< .05$	0	1	0	0
	Incidence of positive EP	14	9	9	12
Cum. APR	Mean	0.0415	0.0048	0.0069	0.014
	St.Dev.	0.0292	0.0207	0.0238	0.0186
	Min	0.0032	-0.0415	-0.0218	-0.0082
	Max	0.1156	0.0258	0.0697	0.0621
Sharpe ratio	Mean	0.4262	0.1061	0.1176	0.1764
	St.Dev.	0.2441	0.1972	0.2099	0.1646
	Min	0.0845	-0.3311	-0.1451	-0.039
	Max	1.042	0.3843	0.6469	0.5822

Table 5: Performance statistics for out-of-sample forecasting exercises: Global Forex fundamentals plus Liquidity fundamentals (Developed Countries only)

	Model	RW	RWWD	Predictive regression	BTGP
	Number of countries	28	28	28	28
Panel A: "Ex-ante" exercise for Global Forex fundamentals (DOL, HML_FX, and DVOL) plus Liquidity fundamentals (DTED, DPS, and DUSD_BASLiquidity)					
Dir. accuracy (%)	Mean	0.5939	0.5796	0.5614	0.562
	St.Dev.	0.1098	0.11	0.1013	0.0873
	Min	0.3824	0.3636	0.3529	0.3636
	Max	0.9083	0.9	0.7576	0.8083
EP test	$EP > 0$ and p-value $< .05$	4	3	3	2
	EP insignificant	24	25	25	26
	$EP < 0$ and p-value $< .05$	0	0	0	0
	Incidence of positive EP	11	12	20	17
Cum. APR	Mean	0.0216	0.0108	0.0148	0.0148
	St.Dev.	0.0475	0.0623	0.0544	0.0567
	Min	-0.0714	-0.1701	-0.1224	-0.1357
	Max	0.1139	0.1306	0.0957	0.1371
Sharpe ratio	Mean	0.401	0.3055	0.2691	0.2695
	St.Dev.	0.549	0.5811	0.508	0.4477
	Min	-0.2042	-0.676	-0.9496	-0.6449
	Max	2.2265	2.2265	1.6163	1.2448
Panel B: "Ex-ante" exercise for Global Forex fundamentals (DOL, HML_FX, and DVOL) plus Liquidity fundamentals (DTED, DPS, and DUSD_BASLiquidity) plus Vol and Liquidity fundamentals in levels (VOL, TED, PS, and USD_BASLiquidity)					
Dir. accuracy (%)	Mean	0.5939	0.5796	0.5518	0.568
	St.Dev.	0.1098	0.11	0.0881	0.0675
	Min	0.3824	0.3636	0.3333	0.4545
	Max	0.9083	0.9	0.7417	0.75
EP test	$EP > 0$ and p-value $< .05$	4	3	2	3
	EP insignificant	24	25	25	25
	$EP < 0$ and p-value $< .05$	0	0	1	0
	Incidence of positive EP	11	12	13	20
Cum. APR	Mean	0.0216	0.0108	0.004	0.0312
	St.Dev.	0.0475	0.0623	0.0687	0.0534
	Min	-0.0714	-0.1701	-0.1742	-0.0257
	Max	0.1139	0.1306	0.1901	0.1979
Sharpe ratio	Mean	0.401	0.3055	0.174	0.3959
	St.Dev.	0.549	0.5811	0.5454	0.4795
	Min	-0.2042	-0.676	-1.2364	-0.1319
	Max	2.2265	2.2265	1.5167	1.7361

Table 6: Performance statistics for out-of-sample forecasting exercises: Global Forex fundamentals plus Liquidity fundamentals (Emerging Markets only)