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Common Macro Factors and Currency Premia

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Abstract

We study the role of domestic and global factors in the payoffs of portfolios mimicking carry, dollar-carry, and momentum strategies. Using factors summarizing large data sets of macroeconomic and financial variables, we find that global equity-market factors are predictive for carry-trade returns, whereas U.S. inflation and consumption variables drive dollar-carry-trade payoffs, momentum returns are predominantly driven by U.S. inflation factors, and global factors capture the countercyclical nature of currency premia. We also find predictability in the exchange-rate component of each strategy and demonstrate strong economic value for risk-averse investors with mean-variance preferences, regardless of base currency.

I. Introduction

This article investigates the domestic and global drivers of currency premia by examining three widely used currency investment strategies: the carry-trade strategy (i.e., going long in high-interest-rate currencies and short in low-interest-rate currencies), a dollar-carry-trade strategy (i.e., a carry-trade strategy relative to the U.S. dollar), and a momentum strategy (i.e., buy and sell currencies in the forward market that were worth buying or selling in a recent time period). All of these strategies exploit deviations from the well-known uncovered interest-rate parity (UIP) condition according to which, under risk neutrality and rational expectations, the forward exchange rate should be an optimal predictor of the future spot exchange rate. However, many studies (e.g., Bilson (1981), Fama (1984), and Froot and Thaler (1990)) document the empirical rejection of UIP and

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the so-called "forward premium puzzle" (Froot and Thaler (1990), Taylor (1995), and Sarno and Taylor (2003)), and hence the apparent profitability of carry-trade and momentum strategies has captured the attention of many academics and practitioners. A particularly noteworthy feature of these strategies is the presence of downside risk, as witnessed by the strong appreciation of low-interest-rate currencies under periods of market stress.

Although a basic currency carry trade involves taking a short position in low-interest-rate (funding) currencies and a corresponding long position in high-interest-rate (investment) currencies, Lustig, Roussanov, and Verdelhan (2014) study a slightly different version of the carry trade, the dollar carry trade, where investors short the dollar when the average short-term interest rate of foreign currencies is greater than the U.S. short-term interest rate and go long in the dollar otherwise. These authors show that this strategy is driven by the U.S. business cycle because investors tend to sell the dollar just before the start of a recession as dated by the National Bureau of Economic Research (NBER) and purchase the dollar after the end of the recession. A momentum strategy, as noted previously, is based on the assumption that currencies that were appreciating well in the past will render higher excess returns in the future in comparison to currencies with poor past performances; in other words, investors buy forward foreign currency units that were worth buying forward in a recent time period.

Despite the fact that a lot of research has been carried out in recent years on carry and momentum strategies, it is still questionable whether the macroeconomic environment can explain the average time-series profitability of those strategies. If so, what is the statistical and economic value of this finding for an investor, and how can an investor protect him- or herself from erratic macroeconomic conditions? Consequently, the fundamental questions that drive our analysis are, first, whether the macroeconomic environment plays an economically significant role in determining currency excess returns and exchange-rate changes and, second, which macroeconomic or financial variables are driving this phenomenon. Answers to both issues render crucial implications for our understanding of the forward premium puzzle.

The difficulty of finding a strong empirical link between macroeconomic fundamentals and currency premia has also been documented (see, e.g., Lustig et al. (2014)) and may be explained in various ways. First, it may be argued that many macroeconomic variables are imperfectly measured and that a small number of variables cannot capture the high variability of exchange rates (Flood and Rose (1995)). Thus, the first principal component of a panel of many different proxies of the same macro variable may be more informative in this respect than one official measure of the macro variable itself. Interestingly, Lustig et al. (2014) point out that macro variables exhibit low predictive power per se, but their common movements could contain important information for carry trades. Second, carry-trade and momentum strategies exploit the disparities observed in global macroeconomic conditions and especially between debtor and creditor economies (Plantin and Shin (2011), Della Corte, Riddiough, and Sarno (2012)). Therefore, dynamic factor analysis is a valid methodology to employ in this context because it gives us the opportunity to confine those disparities in a few unobserved variables.

Taking the U.S. dollar-based investor's viewpoint, we apply dynamic factor analysis to obtain U.S. (domestic) and global (mainly from G10 countries) factors that capture the variability of a large panel of macroeconomic and financial variables. This methodology has been used extensively in different strands of the literature. In particular, Stock and Watson (2002a), (2002b), (2004), (2006) show that dynamic factor models applied to large data sets can enhance the forecasting power of many macroeconomic variables. Ludvigson and Ng (2009), (2010) find that U.S. static factors have strong predictive power for future U.S. excess government bond returns over and above the information contained in the Cochrane and Piazzessi (2005) predictor. They also show that static and dynamic factors exhibit similar predictive power. Bernanke and Boivin (2003) and Bernanke, Boivin, and Eliasz (2005) arrive at a similar conclusion regarding the forecasting ability of static and dynamic factors in their analysis of Federal Reserve policy in a data-rich environment. In the foreign exchange literature, Engel, Mark, and West (2012) develop static factors from a panel of exchange rates and employ the idiosyncratic deviations from the factors as a predictor of exchange rates, although their findings with regard to predictability are mixed.

A number of recent contributions to the research literature focus on the cross-sectional variation of carry-trade and momentum strategies. In particular, Lustig, Roussanov, and Verdelhan (2011) develop a factor model that resembles the Fama and French (1993) model for the foreign exchange market; they find that a carry-trade factor that goes long a basket of high-interest-rate currencies and short a basket of low-interest-rate currencies, together with a dollar factor that is defined as the average return across portfolios each month, can price the cross section of currency returns. In the same spirit, Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) introduce a volatility risk factor and Mancini, Ranaldo, and Wrampelmeyer (2013) a liquidity factor to explain most of the cross-sectional variation in monthly carry-trade returns. Similarly, Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) examine a momentum strategy in a cross-sectional framework. We deviate from these studies because we focus on the time-series variability of carry trades.

Our in-sample empirical results indicate that carry-trade returns are more exposed to the global economy rather than to U.S. economic conditions. In particular, we find strong evidence of predictability in global factors that capture the macroeconomy of the G7 countries as well as the global stock market. This finding might be related to the exit strategies in the G7 economies during the financial crisis and the tendency of the domestic currency to depreciate when the home equity return exceeds its foreign counterpart (Hau and Rey (2006)). Regarding the domestic economy, we find that real and inflation factors are highly significant. The dollar carry trade is mainly driven by domestic variables because, as mentioned previously, investors focus more on the U.S. economy when they form expectations with regard to the dollar carry trade. Thus, global factors do not seem to provide useful information, but U.S. inflation and consumption factors have strong predictive power with respect to dollar-carry returns. Momentum returns are mainly driven by U.S. inflation factors. We also find predictable components in exchange-rate returns gathered from the aforementioned strategies. The forecasting ability of the factors is also verified by out-of-sample tests. Moreover, combination forecasts emphasize the out-of-sample performance of the individual models and provide an overall improvement over the individual predictions.

We also consider a trading rule based on our forecasts to evaluate the economic significance of our results. We find an increase in Sharpe ratios and an improvement in the skewness of the payoffs for all three strategies as well as for a mixed strategy that invests only on strategies that are profitable according to signals obtained from our forecasts. Then, we investigate whether a risk-averse investor with mean-variance preferences would acquire economic value from the use of the factors. To do that, we estimate the certainty-equivalent return gain and find that a U.S. dollar-based investor would be willing to pay a management fee to benefit from the predictive regression forecasts.

As a point of comparison, our analysis takes into consideration other factors in the literature, such as the Bakshi and Panayotov (2013) predictors or average forward discounts, to estimate conditional predictive regressions of the common factors. We find that our factors can forecast currency excess returns over and above commodity, volatility, and liquidity factors as well as average forward discounts. We also test whether our results are due to data snooping (White (2000)) and perform various robustness checks. In addition, although for ease of exposition we largely focus on the strategies viewed from a U.S. dollar-based investor's perspective, we also demonstrate that our results are robust to using a range of alternative base currencies.

The remainder of the article is set out as follows: The carry-trade, dollar-carry-trade, and momentum strategies are presented in Section II. In Section III, we describe dynamic factor analysis, and in Section IV, we provide a brief description of the data. In Section V, we discuss the empirical results of the article. Section VI provides an economic evaluation of the forecasts, and Section VII offers a number of robustness checks on our analysis. Finally, in Section VII, we offer some concluding remarks. There is also an Internet Appendix (available at www.jfqa.org) that reports a number of additional supporting and subsidiary results, as well as a detailed description of the data sources and methods.

II. Multi-Currency Investment Strategies

In this section, we consider the currency excess returns of the most profitable investment strategies in the foreign exchange market. In particular, we construct payoffs of currency portfolios built to mimic carry-trade, dollar-carry-trade, and momentum strategies. Thus, deviating from currency-level approaches, we explore predictable components and potential commonalities in the variation of the payoffs across basket-level investment strategies.[1] As noted previously, although we largely focus on the strategies from a U.S. dollar-based investor's perspective for ease of exposition, we later show that the results are robust to using a range of alternative base currencies.

[1]Among others, Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011a), Lustig et al. (2011), (2014), and Menkhoff et al. (2012a), (2012b) provide a very clear description of these strategies.

A. Currency Excess Returns

We employ end-of-month series of the spot and 1-month forward rates. S_t represents the level of the nominal exchange rate at time t, and F_t denotes the 1-month forward rate, known at time t. Taking the U.S. dollar-based investor's perspective, all currencies are expressed in foreign currency units per U.S. dollar (the foreign price of dollars), meaning that a rise in S_t implies a depreciation of the foreign currency. The level of the currency excess return resulting from going long the foreign currency in the forward market at time t and then selling the same currency at time $t+1$ in the spot market can be expressed as follows:

$$\text{(1)} \qquad \mathrm{RX}_{t+1} = \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}.$$

As can be seen in equation (1), excess returns can be decomposed into two parts: the forward discount and the change in the spot exchange rate. In addition, under the covered interest-rate parity condition, the forward discount must be equal to the interest-rate differential: $\mathrm{FD}_t = (F_t - S_t)/S_t \approx \hat{i}_t - i_t$, where $\hat{i}_t$ is the risk-free interest rate of the foreign country, and i_t is the home-country counterpart.[2] Thus, under the assumption that covered interest parity holds, excess returns are equal to the interest-rate differential corrected for the rate of depreciation: $\mathrm{RX}_{t+1} \approx \hat{i}_t - i_t - (S_{t+1} - S_t)/S_t$.

B. Transaction Costs

Our analysis takes into account the implementation cost of the strategies to estimate the actual realized excess returns. In particular, bid and ask quotes are employed for the spot and forward contracts, and the long and short position are modified as follows. The net position of buying the foreign currency forward at time t using the bid price (F_t^b) and selling it at time $t+1$ in the spot market at the ask price (S_{t+1}^a) is given by $\mathrm{RX}_{t+1}^l = (F_t^b - S_{t+1}^a)/S_t^b$, whereas the corresponding short position in the foreign currency (or short in the dollar) will render a *net* excess return of the form $\mathrm{RX}_{t+1}^s = (F_t^a - S_{t+1}^b)/S_t^a$. Throughout the article, we consider only *net* currency excess returns and *net* exchange-rate changes.

C. Carry-Trade Portfolios

We build two baskets of currencies. The first basket, which we label "All Countries," contains a set of all 48 currencies examined; the second basket, which we label "Developed Countries," contains a subset of 15 developed-market currencies to alleviate problems in the data caused by capital controls, currency pegs, and so forth (Section IV provides a detailed description of the currency baskets). Then, we sort currency excess returns into six (five) portfolios (using the All

[2]Many studies (e.g., Taylor (1987), Burnside, Eichenbaum, and Rebelo (2006), Akram, Rime, and Sarno (2008)) have shown that deviations from covered interest parity are very small and infrequent when transaction costs are taken into consideration, and Taylor (1989) shows that deviations during a number of historical turbulent periods tend to be relatively short-lived and located in the longer maturities. Nevertheless, there is evidence that this condition was significantly violated during the 2007–2008 financial crisis for some currencies, mainly because of liquidity constraints and counterparty risk (see, e.g., Baba and Packer (2009), Levich (2013)).

Countries or Developed Countries sample) based on forward discounts.[3] The payoff of a carry-trade strategy (ψ_{t+1}^{HML}) represents a long position in the last portfolio (with the highest interest rate) while taking a short position in the first portfolio (the lowest-yielding currencies) each month. A similar procedure is carried out for the exchange-rate component of the excess return.

D. Dollar-Carry-Trade Portfolios

We also design a different version of the carry-trade strategy that was first introduced into the research literature by Lustig et al. (2014). Specifically, we consider an equally weighted portfolio that goes long all foreign (non-U.S.) currencies when the average foreign short-term interest rate of the developed countries is greater that the home country's (U.S.) analogue as inferred through the average forward discount (AFD). The AFD is defined as the mean of the forward discounts across portfolios each month. In other words, investors short the dollar when the AFD of the developed countries is positive and go long otherwise. Consequently, the payoff of a *dollar* carry trade (ψ_{t+1}^{USD}) for both samples is given by

$$(2) \qquad \psi_{t+1}^{\text{USD}} = \begin{cases} \left(\dfrac{F_t^b - S_{t+1}^a}{S_t^b}\right) & \text{if} \quad \text{AFD}_t > 0, \\ \left(\dfrac{S_{t+1}^b - F_t^a}{S_t^a}\right) & \text{if} \quad \text{AFD}_t \leq 0, \end{cases}$$

where AFD_t denotes the average forward discount at time t. Results for the subsequent exchange rate returns are reported.

E. Momentum Portfolios

We also construct portfolios of currencies based on recent performance. As before, currency excess returns are allocated into portfolios each month according to the lagged excess return over the previous period. Thus, we consider a formation period of 1 month, and investors hold the portfolio until the next month. The first portfolio corresponds to the *loser* portfolio, and the last portfolio serves as the *winner* portfolio. We focus on a momentum portfolio (ψ_{t+1}^{WML}) that buys the last portfolio and sells the first basket of currencies each month. An important feature of this strategy (which also holds for the carry trade) is that it is dollar neutral.[4,5]

[3]Our results are largely the same when sorting the currencies of the All Countries sample into 5 portfolios rather than 6. However, we follow this approach to be consistent with the literature.

[4]Our definition of momentum is slightly different from the purely trend-following definition of momentum used by some researchers, which is more akin to technical trend-following strategies (see, e.g., Pojarliev and Levich (2008), Allen and Taylor (1990), and Menkhoff and Taylor (2007)). Similarly, we do not explicitly consider "value" trading strategies based on economic fundamentals (such as purchasing power parity (PPP)) in our main analysis, although we do consider generic strategies based on carry, momentum (trend), and value, using published Deutsche Bank indices, as in Hafeez and Brehon (2010) (see, e.g., Section VII and Table 9).

[5]We also report results for the spot exchange rate component because, consistent with Menkhoff et al. (2012b), we show that it captures a significant amount of the momentum portfolio's variability.

III. Dynamic Factor Analysis

This section introduces the econometric framework. We consider two large panels of macroeconomic data[6] as well as financial variables, and we apply dynamic factor analysis to extract common factors that can capture most of the variability of each panel. The first panel consists of 127 variables from the U.S. economy, and we label the corresponding factors as *domestic factors* [7] (h_{it}). The *global factors* (g_{jt}) are estimated from the second panel, which comprises 97 variables obtained mainly from G10 countries. The main reason for making the separation between domestic and global factors is that the strategies of interest would be expected to be subject to different shocks. In particular, the carry-trade strategy might be expected to be mainly affected by disparities observed between countries, and so we expect global factors to be stronger predictors. Conversely, the dollar carry trade might be expected to be driven by U.S. economic conditions because its risk premia will be negatively correlated with the U.S. business cycle, and domestic factors should therefore be more informative for this strategy.

The profitability of the momentum strategy, however, might be expected to be subject to various factors affecting trading, such as transaction costs, liquidity levels, country risk, and idiosyncratic volatility (Menkhoff et al. (2012b)); we therefore expect both domestic and global factors to have explanatory power for the momentum payoffs.

A number of methodologies have been proposed in the literature regarding the appropriate method of estimation for factors summarizing large sets of data. In the present analysis, we apply principal component analysis (PCA), as in Stock and Watson (2002a), (2002b), (2006), for two reasons. First, in previous studies employing factor analysis, the factors obtained when other more computationally demanding methods are employed have not in general rendered stronger predictive power because the precision of the factors remains the same (e.g., the Bayesian posterior means are very close to the corresponding PCA estimates).[8] In addition, the estimation of dynamic factors using such methods as the expectation-maximization (EM) algorithm or Bayesian approaches has not improved the forecasting performance of the factors in various contexts, as is also verified in the literature.[9] Therefore, we follow a methodology that has extensively been used in many other studies (e.g., Ludvigson and Ng (2009), (2010), Bernanke and Boivin (2003), Bernanke et al. (2005), and Kim and Taylor (2012)).[10]

As discussed in Section II, we denote the payoff of a strategy at time $t+1$ as ψ_{t+1}^{i}, where $i = \text{HML}, \text{USD}, \text{WML}$ for the payoffs of a carry-trade, dollar-carry-trade, and momentum strategy, respectively. Therefore, we can assess the in-sample predictive ability of a set of K predetermined predictors at time t,

[6] The data are winsorized (i.e., outliers are excluded) so as to control against rare events.

[7] Recall that we take the U.S. dollar-based investor's perspective, which means that the U.S. dollar is the domestic currency.

[8] For more details, see Ludvigson and Ng (2010).

[9] Bai and Ng (2008) provide a very comprehensive survey of factor models.

[10] However, we need to stress here that it is harder to interpret static factors because they are unobserved. In contrast, it is easier to explain dynamic factors because the data are organized into blocks, but they do not allow for cross-sectional correlation of the idiosyncratic errors; also, the precision achieved from those factors is quite similar.

provided by a $K\times 1$ vector Z_t,[11] by estimating the following model:

$$(3)\quad \psi^i_{t+1} = \alpha+\gamma' Z_t+\varepsilon_{t+1}, \quad \text{for} \quad i = \text{HML}, \text{USD}, \text{WML}.$$

For example, consideration of the panel of the U.S. macro variables leads to a restrictive model as the cross-sectional dimension of the panel increases. In particular, assume that we have a $T\times N$ panel of macroeconomic variables, where T denotes the time dimension and N denotes the cross-sectional dimension. As N increases, the available degrees of freedom decline, and in the limit, when $N+K>T$, the model runs out of degrees of freedom, and standard econometric techniques thus are not appropriate. Let us denote by x_{it} the ith element in an $N\times 1$ vector of macro variables at time t, x_t. We conjecture that x_{it} has a factor structure of the form $x_{it}=\lambda_i' h_t+u_{it}$, where h_t denotes a $k\times 1$ vector of latent common factors ($k\ll N$), λ_i' represents the corresponding $k\times 1$ vector of factor loadings, and u_{it} is an idiosyncratic error.[12] Therefore, we consider the following regression:

$$(4)\quad \psi^i_{t+1} = \alpha+\beta' H_t+\gamma' Z_t+\varepsilon_{t+1}, \quad \text{for} \quad i = \text{HML}, \text{USD}, \text{WML},$$

where H_t is a subset of h_t, and Z_t could be a benchmark.[13] As already mentioned, the common factors (h_t), estimated by PCA, are unobserved, so we denote them by $\hat{h}_t$. The main feature of PCA is that the factor space is estimated precisely as the time-series and cross-sectional dimensions increase significantly (i.e., as $N,T\longrightarrow\infty$). More specifically, the estimated factors are linear combinations optimally obtained by minimizing the sum of squared residuals $(x_t-\Lambda h_t)$, where x_t denotes the vector of panel elements, and Λ denotes the corresponding $N\times K$ matrix of latent factor loadings.

The number of common factors ($\hat{k}$) is determined by the panel information criteria detailed by Bai and Ng (2002). More precisely, a random number $k_{\max}$ is selected in such a way that it is not greater than the minimum of T and N. Then, we obtain the optimal number of common factors by solving the following optimization problem:

$$(5)\qquad \hat{k} = \underset{0\le k\le k_{\max}}{\operatorname{argmin}}\, h(k) = \ln(V(k))+kg(N,T),$$

where $g(N,T)$ denotes a penalty function,[14] and the average sum of squared residuals with k factors ($V(k)$) could be expressed as $V(k)=(1/NT)\sum_{i=1}^{N}\sum_{t=1}^{T}(z_{it}-\hat{\lambda}_i^k\hat{h}_t^k)^2$, where $\hat{h}_t^k$ is a matrix of k factors, and $\hat{\lambda}_i^k$ is the vector of the corresponding factor loadings. Thereafter, we estimate the $\hat{k}$ common factors with PCA, as described previously. In addition, we employ different information criteria to

[11] Z_t could contain the panel of domestic or global variables. We can also include other predictive variables.

[12] A limited cross-sectional correlation among the idiosyncratic errors is allowed. Particularly, the idiosyncratic covariances are limited to the total variance of x as the cross-sectional dimension of the panel increases.

[13] We consider different benchmarks in a later section.

[14] That is, $g(N,T)=((N+T)/NT)\ln(NT/(N+T))$.

determine the most informative set of static factors for currency premia.[15] In particular, we form different subsets of the factors, and for each candidate subset we project the ψ_{t+1} onto $\hat{H}_t = [\hat{h}_1 \hat{h}_2 \ldots \hat{h}_{\hat{k}}]$ and compute the Bayesian information criterion (BIC), Akaike information criterion (AIC), log-likelihood (LL), and adjusted coefficient of determination ($\bar{R}^2$). The LL and the $\bar{R}^2$ are used as decision tools in case of inconsistency between the BIC and AIC criteria.[16] According to Stock and Watson (2002a), (2002b), (2006), we can obtain the optimal set of factors $\hat{H}_t$ by choosing the minimum BIC estimates. We also estimate the global factors in the same way by replacing $\hat{H}_t$ with $\hat{G}_t$.

Thus, our analysis focuses on two regression models. In the first model, we examine the *unconditional* predictive power of the domestic and global factors. This version of the model tests whether the coefficients of the factors in the following model are statistically different from 0:

$$\psi^i_{t+1} = \alpha + \beta' \hat{H}_t + \gamma' \hat{G}_t + u_{t+1}, \quad \text{for} \quad i = \text{HML}, \text{USD}, \text{WML}, \tag{6}$$

where $\hat{H}_t \subset \hat{h}_t$ represents the optimal subset of the U.S. static factors, and $\hat{G}_t$ represents the optimal subset of global factors, both at time t. Later, we consider the performance of the static domestic and global factors *conditional* on the information provided by other predictors in the literature. It is apparent that the use of dynamic factor analysis for the estimation of the optimal set of common factors should lead to a parsimonious model that helps capture the common trends of the major economies that are involved in our sample. Indeed, this is perhaps true almost by construction because we are explicitly building factors that are designed to explain currency premia, although it need not be assured out of sample.

IV. Data

A. U.S. Data

The domestic data set consists of a large balanced panel of 127 monthly macroeconomic and financial series for the U.S. economy spanning the time period July 1985–Mar. 2012; the data were downloaded from Datastream. Moreover, the panel covers a variety of categories of the U.S. economy: real output, employment, consumption, housing starts, orders, stock prices, exchange rates, interest rates, money and credit quality aggregates, price indices, earning, international trade, capacity utilization, and miscellaneous. In addition, the raw data have been standardized and transformed according to simple stationarity tests. Table B.1 in the Internet Appendix offers a detailed description of the data.[17]

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[15] Although nonlinear analysis is not the main focus of the present article, we include nonlinear (i.e., squared or cubed terms) as well as linear and lagged factors for completeness and to be consistent with the previous literature (see, e.g., Ludvigson and Ng (2009), (2010)).

[16] We also try to identify the optimal set of factors in a forecasting context. However, we find that the two methodologies lead to the same subset of factors in most of the cases.

[17] Our data set spans almost 3 decades. However, the inclusion of observations before 1985 leads to an unbalanced panel because many variables have missing values, which is common when dealing with macroeconomic data. There are many different ways of tackling this problem, such as interpolation, the EM algorithm, or Kalman filter methods. However, we exclude the unbalanced panel and apply the methodology only to the balanced panel because all of these methodologies smooth the data.

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B. Global Data

The global variables comprise a panel of 97 macroeconomic and financial variables collected (mainly) from G10 countries for the period July 1985–Mar. 2012. The reasoning behind the inclusion of G10 countries corresponds to the tradability of their currencies. In particular, the G10 currencies are the most actively traded currencies in the foreign exchange market, and thus we suspect that the macroeconomic and financial environments of those countries would affect the variability of our strategies and reveal potential commonalities.[18] The data cover a broad spectrum of the macroeconomic and financial environments of the economies in question, namely, real output, employment, consumption, stock prices, price indices, interest rates, international trade, reserves, and aggregate variables for the G7 countries.[19] All the series are transformed based on unit root tests and standardized prior to estimation of the global factors. Table B.2 in the Internet Appendix provides a detailed description of the global data.

C. Spot and Forward Exchange Rates

We begin with *daily* spot and 1-month forward exchange rates vis à vis the U.S. dollar for the period July 1985–Mar. 2012. The data are available on Datastream from WM/Reuters and Barclays Bank International (BBI). Moreover, we create *end-of-month* series for spot and forward rates (i.e., we take the last business day of each month) as in Burnside et al. (2011a). Afterward, bid, middle, and ask quotes are employed to take transaction costs into consideration. The whole sample consists of the following 48 currencies: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, the euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, the Netherlands, New Zealand, Norway, the Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, and the United Kingdom. We label this sample "All Countries." The inclusion of some of these currencies could, however, be problematic because of capital constraints or the fact that some of them are pegged to other currencies, so investors may experience difficulties trading some of the currencies in significant volumes despite the availability of forward contracts. To tackle this problem and make our analysis more realistic, we also consider a smaller sample of 15 "Developed Countries," namely, Australia, Belgium, Canada, Denmark, the euro area, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. The euro-area currencies are excluded from the sample after the introduction of the euro in Jan. 1999, and thus the sample is narrowed down to the G10 currencies. This sample is similar to the one employed by Lustig et al. (2011), (2014) and Menkhoff et al. (2012a). Consistent with other studies, we delete

[18]According to the Bank of International Settlements (BIS) 2010 Triennial Survey, the top 10 currencies accounted for almost 90% of the average daily foreign exchange turnover, which reached $4 trillion.

[19]United States, Japan, Germany, United Kingdom, France, Canada, and Italy.

observations for which we observe significant deviations from the covered interest parity condition.[20]

V. Empirical Results

In this section, we offer descriptive statistics of the payoffs and the common factors before turning to the in-sample and out-of-sample analysis. We also provide an economic interpretation of the factors that were selected for the optimal samples.

A. Summary Statistics of the Currency Excess Returns

1. Carry Trades

Table 1 presents descriptive statistics for the payoffs of the carry-trade (i.e., ψ^{HML}) and dollar-carry-trade (i.e., ψ^{USD}) strategies. We report annualized estimates of the mean, standard deviation, Sharpe ratio, and Sortino ratio. The annualized mean of the *carry trade* is 4.24% (2.79%), with a Sharpe ratio of 0.46 (0.27) for the sample of All Countries (Developed Countries). The currency excess returns exhibit left skewness and excess kurtosis, which is in line with other studies in the literature, such as those by Brunnermeier, Nagel, and Pedersen (2008) and Burnside, Eichenbaum, and Rebelo (2011b). AR1 represents the first-order

TABLE 1

Summary Statistics for the Payoffs of Currency Strategies

Table 1 reports descriptive statistics for the payoffs of the carry-trade, dollar-carry-trade, and momentum strategies. Panel A reports descriptive statistics for currency excess returns, and Panel B reports descriptive statistics for exchange-rate changes. In particular, ψ^{HML} denotes the carry-trade strategy that goes long (short) a basket of currencies with the highest (lowest) forward discounts, ψ^{USD} is the dollar carry trade that shorts the dollar when the average interest rate is greater than the U.S. risk-free rate, and ψ^{WML} represents the payoff of a momentum strategy that invests (borrows) on a basket of currencies with the highest (lowest) last-month return. All the payoffs are estimated in the presence of transaction costs, and the portfolios are rebalanced on a monthly basis. Finally, the mean, standard deviation, Sharpe ratio (SR), and Sortino ratio (SOR) are annualized (the means are multiplied by 12, and the standard deviation is multiplied by $\sqrt{12}$) and expressed in percentage points. The data span the period July 1985–Mar. 2012.

Payoffs	Mean	Std. Dev.	SR	SOR	Skew	Kurt	AC1
Panel A. Currency Excess Return							
All Countries							
ψ^{HML}	4.24	9.19	0.46	0.62	−1.17	5.23	0.20
ψ^{USD}	3.93	7.18	0.55	0.82	−0.39	4.71	−0.04
ψ^{WML}	5.17	9.57	0.54	0.86	0.07	5.00	−0.04
Developed Countries							
ψ^{HML}	2.79	10.47	0.27	0.36	−0.96	5.66	0.11
ψ^{USD}	5.86	8.48	0.69	1.09	−0.29	4.17	−0.03
ψ^{WML}	1.57	8.74	0.18	0.27	0.03	4.34	0.01
Panel B. Exchange-Rate Returns							
All Countries							
ψ^{HML}	7.85	9.02	0.87	1.96	1.23	5.43	0.20
ψ^{USD}	4.18	7.22	0.58	0.88	−0.40	4.80	−0.04
ψ^{WML}	2.81	10.56	0.27	0.41	0.37	5.74	−0.01
Developed Countries							
ψ^{HML}	1.63	10.53	0.15	0.26	0.98	0.13	0.01
ψ^{USD}	5.56	8.51	0.65	1.02	−0.28	0.03	0.01
ψ^{WML}	−1.14	8.71	0.13	−0.18	−0.13	0.03	0.01

[20]In particular, we remove the following data: South Africa for the periods July 1985–Aug. 1985 and Dec. 2001–May 2004; Indonesia for the periods June 1997–Mar. 1998, Jan. 2001–Sept. 2002, and Nov. 2008–Feb. 2009; and Kuwait for the period Mar. 2001–Apr. 2001.

autocorrelation coefficient and is 0.20 (0.11) for the case of All Countries (Developed Countries). Thus, we can infer that the carry-trade payoffs exhibit positive autocorrelation with low persistence. The annualized mean of the dollar-carry-trade strategy is 3.93% (5.86%) for the All Countries (Developed Countries) sample, with a Sharpe ratio of 0.55 (0.69).[21] As in the case of the carry trade, the dollar carry trade displays negative skewness and excess kurtosis with negative and low autocorrelation. We also report the corresponding summary statistics for the exchange-rate component of the strategies.

2. Momentum

Table 1 also reports summary statistics for the momentum strategy (ψ^{WML}) returns. The annualized mean is 5.17% (1.57%), and the annualized standard deviation is 9.57 (8.74), yielding a Sharpe ratio of 0.54 (0.18) for the full sample (Developed Countries). The payoffs exhibit positive skewness and excess kurtosis with almost zero first-order autocorrelation for both samples. We also report descriptive statistics for the exchange-rate changes. Figure 1 displays the annualized payoffs of the strategies; the shaded areas represent the NBER recessions for the U.S. economy.[22]

B. Summary Statistics and Optimal Subsets of the Factors

Table 2 reports summary statistics for the domestic and global factors. The Bai and Ng (2002) criterion suggests the use of nine factors in the case of the domestic data and three factors for the global data.[23] Nevertheless, as can be seen from the table, the first three domestic factors capture more than 60% of the total variation in the U.S. data, whereas three global factors capture less than 25% of the variation in the global data. Table 2 also reports the first- and second-order autocorrelation coefficients of the common factors. Thus, there is substantial heterogeneity across factors, as depicted in the high dispersion of the coefficients. In particular, the AR1 coefficients in the case of the domestic factors range from 0.03 to 0.97, whereas the corresponding range for the global factors is 0.11–0.95.

As mentioned in Section III, the optimal subset of factors represents the candidate subset that has the minimum value of the corresponding BIC and AIC. The LL function and $\bar{R}^2$ are used as decision tools if there is an inconsistency between the two information criteria. More specifically, we first estimate all the combinatorial subsets of the factors in sets of n, where $n=2,\dots,\hat{k}-1$, and then make the final decision based on BIC and AIC.

[21] As pointed out by Lustig et al. (2014), the strategies under consideration are not highly correlated (not reported in Table 1) and deliver significantly different mean returns and thus Sharpe ratios. That is, the dollar carry trade is more exposed to the U.S. economy because investors short the dollar before the NBER recessions and go long the dollar right after the end of the U.S. recessions, whereas the carry trades are more affected by global economic conditions.

[22] The summary statistics for the currency excess returns reported in this section are in line with those reported elsewhere for similar generic strategies (see, e.g., Hafeez and Brehon (2010), who use data on generic value, momentum and carry strategies available from Bloomberg).

[23] The first factor in each case explains the largest proportion of the total variation in the panel, and then each factor explains the largest fraction of the variation conditional on the information provided by the previous factors. In other words, the R_i^2 is defined as the sum of the first i largest eigenvalues divided by the sum of the eigenvalues of the panel $x'x$, which determines the total variation of the panel.

FIGURE 1

Cumulative Payoffs from Currency Strategies

Figure 1 displays the cumulative payoffs for the carry-trade (HML), dollar-carry-trade (USD), and momentum (MOM) strategies. Cumulative excess returns are expressed in percentage points per annum (% p.a.). The data span the period July 1985–Mar. 2012.

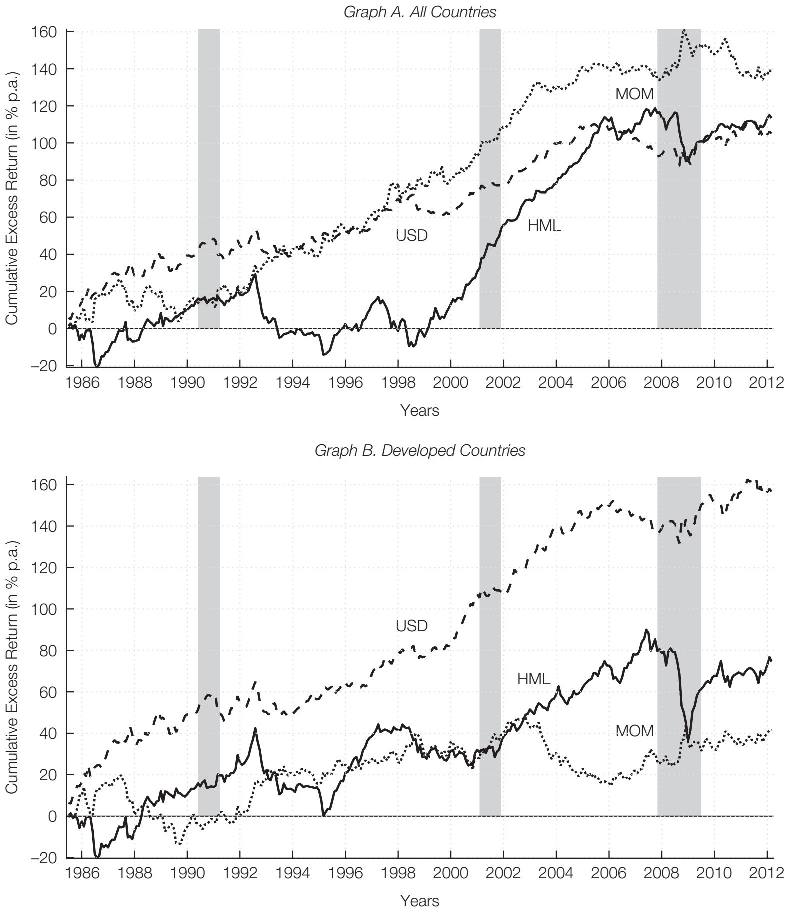

Table C.1 in the Internet Appendix presents information criteria and $\bar{R}^2$ for each competing set of factors for each strategy. Thus, the optimal subsets of global factors ($\hat{G}_t \subset \hat{g}_t$) are the following:[24] $\hat{G}_t^{\mathrm{HML}} = (\hat{g}_{2t})'$, $\hat{G}_t^{\mathrm{USD}} = (\hat{g}_{3t})'$, $\hat{G}_t^{\mathrm{WML}} = (\hat{g}_{3t})'$. The sets of domestic factors for the three currency strategies ($\hat{H}_t \subset \hat{h}_t$) are given by $\hat{H}_t^{\mathrm{HML}} = (\hat{h}_{2t}, \hat{h}_{3t}, \hat{h}_{4t}, \hat{h}_{6t})'$, $\hat{H}_t^{\mathrm{USD}} = (\hat{h}_{6t}, \hat{h}_{7t})'$, $\hat{H}_t^{\mathrm{WML}} = (\hat{h}_{1t}, \hat{h}_{4t})'$, and the corresponding subsets of all factors ($\widehat{HG}_t \subset \widehat{hg}_t$) are $\widehat{HG}_t^{\mathrm{HML}} = (\hat{h}_{6t}, \hat{g}_{2t}, \hat{g}_{3t})'$, $\widehat{HG}_t^{\mathrm{USD}} = (\hat{h}_{6t}, \hat{h}_{7t}, \hat{g}_{3t})'$, $\widehat{HG}_t^{\mathrm{WML}} = (\hat{h}_{1t}, \hat{h}_{4t}, \hat{g}_{3t})'$. Later, we also examine nonlinear and lagged forms of the factors.

[24] We report results for the full sample. Table C.1 in the Internet Appendix also shows results for the Developed Countries group.

TABLE 2

Summary Statistics for the Common Factors ($\hat{h}_{it}$, $\hat{g}_{jt}$)

Table 2 presents summary statistics for the common factors. Panel A reports results for the U.S. data, and Panel B reports results for the global data. Both data sets span the period of July 1985–Mar. 2012. The domestic panel includes 127 macroeconomic and financial variables from the U.S. economy, and the global panel consists of 98 variables from all the countries that are involved in our portfolio. We report the first- and second-order autocorrelation coefficients (AR1 and AR2) for the U.S. and global factors as well as the relative importance of the factors as measured by the R_i^2. The R_i^2 is estimated as the sum of the eigenvalues of the ith first factors divided by the sum of the eigenvalues in the data. We also present the macroeconomic or financial series that exhibit the highest correlation with the domestic and global factors along with the positions of each variable in the panel and a detailed description of the variables. The variables are transformed according to simple unit root tests (see the Internet Appendix for more details), and they are standardized prior to estimation. The data are available from Datastream.

Panel A. U.S. Data

Factors	AR1 ($\hat{h}_{it}$)	AR2 ($\hat{h}_{it}$)	$\sum R_i^2$	Positions	Correlations	Mnemonics	Description
$\hat{h}_1$	0.98	0.96	0.39	95	0.55	USOMA002B	U.S. MONEY SUPPLY-BROAD MONEY (M2) CURA (bil, U.S. $)
$\hat{h}_2$	0.97	0.95	0.52	32	0.88	USNEWCONB	U.S. EXISTING HOME SALES: SINGLE-FAMILY & CONDO (AR) VOLA
$\hat{h}_3$	0.75	0.62	0.63	7	0.76	USNAPMNO	U.S. ISM MANUFACTURERS SURVEY: NEW ORDERS INDEX SADJ
$\hat{h}_4$	0.64	0.46	0.70	7	0.4	60611444	U.S. PERSONAL INCOME LESS TRANSFER PAYMENTS (BCI 51) CONA
$\hat{h}_5$	0.65	0.54	0.75	15	0.38	870004623	U.S. UNEMPLOYED (16 YRS & OVER) VOLA
$\hat{h}_6$	0.49	0.57	0.79	20	0.44	62244022	U.S. PERSONAL CONSUMPTION EXPENDITURES - LESS FOOD & ENERGY CURA
$\hat{h}_7$	0.05	0.11	0.82	20	0.69	62244022	U.S. PERSONAL CONSUMPTION EXPENDITURES - LESS FOOD & ENERGY CURA
$\hat{h}_8$	0.12	−0.01	0.85	122	0.33	870011929	U.S. HOURLY EARN: PRIVATE SECTOR SADJ
$\hat{h}_9$	0.16	0.16	0.87	90	0.42	60200205	U.S. 3-MONTH US DEPOSITS, LONDON OFFER

Panel B. Global Data

Factors	AR1 ($\hat{g}_{jt}$)	AR2 ($\hat{g}_{jt}$)	$\sum R_i^2$	Positions	Correlations	Mnemonics	Description
$\hat{g}_1$	0.86	0.94	0.10	7	0.77	100900842	DK UNEMPLOYMENT NET (METHODOLOGY BREAK APR. 2000) VOLA
$\hat{g}_2$	0.72	0.66	0.18	83	0.60	870015830	U.S. FOREIGN NET LONG-TERM FLOWS IN SECURITIES CURN
$\hat{g}_3$	0.16	0.001	0.25	97	0.60	CNSHRPRCF	G7 MSCI (U.S.$) – PRICE INDEX

C. In-Sample Analysis

In this section, we conduct the in-sample analysis. The main advantage of this approach is that all the available information in the sample can be used, whereas the out-of-sample tests use only a part of the available information, which lowers their power and increases the forecast error significantly, a phenomenon that is amplified in smaller samples.

Tables 3 and 4 report the in-sample prediction regressions in the form of equation (6) for currency excess returns as well as exchange-rate changes. We take into consideration transaction costs in any case.[25] Thus, we present estimates of the slope coefficients of the regressions and the corresponding t-statistics and adjusted R^2 for each regression. NW denotes t-statistics[26] with asymptotic

[25]The results for logarithmic returns are very close to those presented here for raw returns.

[26]Our results are also verified by the estimation of Hansen and Hodrick (1980) standard errors. Those results are not reported but are available from the authors.

standard errors that are corrected for heteroskedasticity and autocorrelation (HAC) based on the Newey and West (1987) correction, with the optimal number of lags selected following Andrews (1991). BS denotes 2-sided p-values based on a wild bootstrap with 10,000 bootstrap iterations to account for potential small-sample bias in the inference about the models in use.[27] The use of bootstrapping

TABLE 3

In-Sample Analysis: Carry Trades and Dollar-Carry Trades

Table 3 reports the ordinary least squares (OLS) estimates for the carry-trade and dollar-carry-trade strategies. In Panel A, the dependent variable is the currency excess return based on the carry-trade strategy that goes long (short) a basket of currencies with the highest (lowest) forward discounts. Panel B reports results for the exchange-rate component of the strategy. Results for carry trades (ψ^{HML}) are reported on the left of each panel, and predictive regressions for dollar-carry trades (ψ^{USD}) are displayed on the right. NW represents Newey and West (1987) t-statistics corrected for autocorrelation and heteroskedasticity, constructed with the optimal number of lags chosen following Andrews (1991). BS denotes the bootstrap p-values based on 10,000 bootstrap iterations, and Constant is the intercept. The data span the period July 1985–Mar. 2012.

Panel A. Currency Excess Returns

	Carry Trades						Dollar-Carry Trades					
	All Countries			Developed Countries			All Countries			Developed Countries		
Factors	1	2	3	4	5	6	7	8	9	10	11	12
Constant	0.35	0.35	0.35	0.43	0.23	0.23	0.33	0.32	0.33	0.49	0.49	0.49
NW	2.16	2.16	2.22	1.34	1.35	1.41	2.90	3.11	3.13	3.74	3.87	3.90
BS	0.02	0.01	0.01	0.17	0.16	0.10	0.00	0.00	0.00	0.00	0.00	0.00
$\hat{g}_1$				0.29		0.27						
NW				1.17		1.23						
BS				0.23		0.24						
$\hat{g}_2$	0.52		0.56	0.50		0.54						
NW	2.84		3.17	3.34		2.61						
BS	0.01		0.00	0.03		0.02						
$\hat{g}_3$			−0.21				−0.12		−0.24	−0.17		−0.29
NW			−1.31				−0.92		−1.80	−1.07		−1.91
BS			0.20				0.45		0.15	0.37		0.12
$\hat{h}_2$		0.23										
NW		1.72										
BS		0.09										
$\hat{h}_3$		0.30			0.44							
NW		1.22			1.48							
BS		0.14			0.09							
$\hat{h}_4$		−0.28										0.17
NW		−1.91										1.27
BS		0.05										0.19
$\hat{h}_6$		0.21	0.36	0.32	0.37			0.28	0.36		0.29	0.39
NW		1.48	2.02	2.18	2.58			2.50	3.10		2.20	2.98
BS		0.14	0.03	0.02	0.00			0.03	0.00		0.04	0.00
$\hat{h}_7$								−0.35	−0.34		−0.38	−0.36
NW								−3.12	−3.11		−3.06	−3.05
BS								0.01	0.00		0.00	0.00
$\bar{R}^2$	0.05	0.03	0.06	0.04	0.03	0.05	0.01	0.04	0.05	0.00	0.03	0.05
NW	8.08	13.50	15.16	4.60	7.50	11.15	0.84	15.93	19.47	1.14	13.89	18.71
BS	0.00	0.00	0.00	0.00	0.02	0.01	0.45	0.00	0.00	0.37	0.00	0.00

(continued on next page)

[27] Our bootstrap procedure is similar to that used by Mark (1995), Kilian (1999), Kilian and Taylor (2003), Amihud, Hurvich, and Wang (2009), and Bakshi and Panayotov (2013). In particular, we estimate the bias-adjusted standard errors by simulating a data-generating process (DGP) that generates 10,000 samples (with replacement) of the payoffs and factors from a vector autoregression (VAR) under the null of no predictability. The number of lags in the VAR is determined by information criteria (i.e., BIC).

TABLE 3 (continued)
In-Sample Analysis: Carry Trades and Dollar-Carry Trades

Panel B. Exchange-Rate Returns

	Carry Trades						Dollar-Carry Trades					
	All Countries			Developed Countries			All Countries			Developed Countries		
Factors	1	2	3	4	5	6	7	8	9	10	11	12
Constant	0.66	0.66	0.66	0.14	0.13	0.14	0.35	0.35	0.35	0.46	0.47	0.46
NW	4.16	4.16	4.18	0.77	0.75	0.79	3.08	3.20	3.21	3.50	3.62	3.65
BS	0.00	0.00	0.00	0.43	0.41	0.41	0.00	0.00	0.00	0.00	0.00	0.00
$\hat{g}_1$				−0.18		−0.16						
NW				−0.73		−0.74						
BS				0.44		0.48						
$\hat{g}_2$	−0.48		−0.52	−0.60		−0.64						
NW	−2.75		−2.97	−2.81		−3.02						
BS	0.00		0.00	0.01		0.01						
$\hat{g}_3$			0.16				−0.17		−0.28	−0.18		−0.30
NW			1.00				−1.29		−2.20	−1.08		−1.90
BS			0.31				0.31		0.05	0.36		0.12
$\hat{h}_2$		−0.08										
NW		−0.64										
BS		0.54										
$\hat{h}_3$		−0.33			−0.47							
NW		−1.61			−1.61							
BS		0.06			0.08							
$\hat{h}_4$		0.25										
NW		1.70										
BS		0.08										
$\hat{h}_6$		−0.17	−0.29		−0.25	−0.33		0.24	0.34		0.28	0.39
NW		−1.20	−1.62		−1.61	−2.17		2.09	2.84		2.12	2.91
BS		0.27	0.09		0.07	0.03		0.04	0.00		0.04	0.01
$\hat{h}_7$								−0.31	−0.28		−0.38	−0.36
NW								−2.77	−2.72		−3.11	−3.11
BS								0.01	0.01		0.00	0.00
$\bar{R}^2$	0.03	0.02	0.05	0.04	0.02	0.06	0.01	0.03	0.03	0.00	0.03	0.04
NW	9.78	9.61	14.27	6.88	5.98	12.53	1.02	11.63	16.37	1.18	14.25	19.41
BS	0.00	0.15	0.00	0.03	0.05	0.01	0.31	0.00	0.00	0.36	0.00	0.00

is very important because of the persistence of the predictors, which can lead to biased slope coefficients with greater dispersion than the asymptotic distribution (Bekaert, Hodrick, and Marshall (1997), Stambaugh (1999)). Below the R^2s, we report the corresponding χ^2 and p-values for joint tests of parameter significance.

1. Carry Trades

Table 3 reports in-sample predictions for the carry trade using the optimal subset of factors analyzed in the previous section. Panel A reports results for the excess returns, and Panel B reports estimates for exchange-rate changes. First, we consider predictive regressions with global factors. As can be seen, the slope coefficients are highly statistically significant, yielding an adjusted R^2 of 0.05 (0.04) for All Countries (Developed Countries), which, although quite small, compares well with corresponding goodness-of-fit statistics reported in previous studies (see, e.g., Bakshi and Panayotov ((2013), p. 147), Lustig et al. (2014)). However, the domestic factors provide even smaller R^2s (i.e., 0.02–0.03), verifying our assumption concerning the exposure of carry trades to the global environment

TABLE 4
In-Sample Analysis: Momentum

Table 4 reports ordinary least squares (OLS) estimates for the momentum strategy. Panel A reports results of the predictive regressions for the momentum strategy (ψ^{WML}). Panel B displays the exchange-rate component of the strategy. NW represents Newey and West (1987) t-statistics corrected for autocorrelation and heteroskedasticity, constructed with the optimal number of lags chosen following Andrews (1991). BS denotes the bootstrap p-values based on 10,000 bootstrap iterations, and Constant is the intercept. The data span the period July 1985–Mar. 2012.

	All Countries					Developed Countries						
Models	Constant	$\hat{g}_3$	$\hat{h}_1$	$\hat{h}_4$	$\bar{R}^2$	Constant	$\hat{g}_2$	$\hat{h}_3$	$\hat{h}_4$	$\hat{h}_7$	$\hat{h}_8$	$\bar{R}^2$
Panel A. Currency Excess Return												
(a)	0.43	−0.16			0.01	0.13	−0.38					0.02
NW	3.08	−0.63			0.39	1.05	−2.80					4.15
BS	0.00	0.38			0.76	0.34	0.04					0.04
(b)	0.43		−0.17	0.28	0.01	0.13		−0.28	−0.28	−0.22	−0.24	0.03
NW	3.19		−1.23	1.60	3.95	1.05		−2.17	−2.02	−1.54	−1.48	9.56
BS	0.00		0.24	0.09	0.10	0.34		0.05	0.06	0.12	0.14	0.05
(c)	0.43	−0.14	−0.16	−0.28	0.01	0.13	−0.43			−0.18	0.30	0.04
NW	3.18	−0.55	−1.00	−1.68	3.22	1.05	−3.04			−1.31	1.81	7.62
BS	0.00	0.50	0.34	0.08	0.21	0.35	0.02			0.17	0.07	0.02
Panel B. Exchange-Rate Returns												
(a)	0.23	0.06			0.01	−0.10	0.41					0.02
NW	1.38	0.26			0.01	−0.77	2.89					4.47
BS	0.30	0.75			0.75	0.48	0.03					0.03
(b)	0.23		0.12	0.45	0.02	−0.10		0.30	−0.30	0.20	−0.22	0.03
NW	1.42		0.74	2.30	5.55	−0.77		2.29	−2.14	1.46	−1.42	9.54
BS	0.29		0.31	0.02	0.05	0.48		0.09	0.05	0.15	0.17	0.05
(c)	0.23	0.04	0.11	0.45	0.02	−0.10	0.45			0.17	−0.28	0.04
NW	1.41	0.19	0.69	2.26	6.87	−0.77	3.11			1.24	1.79	8.06
BS	0.15	0.85	0.54	0.02	0.07	0.48	0.02			0.19	0.08	0.02

rather than the domestic. The inclusion of both domestic and global factors provides similar results.

2. Dollar Carry Trades

Table 3 also displays results for the dollar-carry-trade strategy when considering the most informative set of factors. Here we observe results that are in many ways converse to those reported previously. In particular, the global factors are not statistically significant, yielding an adjusted R^2 of 1%, whereas the set of domestic factors ($\hat{h}_6, \hat{h}_7$) provides high t-statistics and R^2s of approximately 4% for both excess returns and exchange-rate changes. The consideration of both global and domestic factors leads to highly significant estimates and an R^2 of approximately 5%. These results are verified by the bootstrapped p-values, and the results are in line with our conjecture regarding the exposure of the dollar carry trade to the U.S. economy and, to a lesser extent, the global environment, consistent with Lustig et al. (2014).

3. Momentum

Table 4 provides estimates of the predictive regressions when considering momentum returns. We find that $\hat{g}_2$ (for Developed Countries) and $\hat{h}_4$ contain valuable information for currency momentum profits at the 10% significance level, offering adjusted R^2s of 2%–4%. Overall, we find weak evidence of predictability for currency momentum that is mainly driven by U.S. macro factors.

D. Economic Interpretation of the Factors

In this section, we attempt to provide some economic intuition behind the common factors. We need to be careful when analyzing the factors, because they are unobserved; they capture the variation of the whole panel and thus absorb information from all of the economic variables. Thus, labeling the predictors could be problematic because we cannot link the factors directly with specific economic series, such as unemployment or consumption. However, some factors seem to load heavily on particular economic or financial variables, which helps us make inferences with regard to the identity of the factors.[28] Graph A (Graph B) of Figure 2 provides an illustration of the marginal R^2s from regressing each of the 127 (97) economic and financial series onto each domestic (global) factor. The individual series are grouped into more general categories, as in the Internet Appendix (Tables B.1 and B.2), and follow the same numbered ordering. Table 2 displays the names of the economic series that exhibit the highest correlation with the common factors. Once again, we use this table as a verification tool of the marginal R^2s, and we do not try to link particular series with the factors.

1. Domestic Factors

Graph A of Figure 2 displays the marginal R^2s of the domestic factors that were selected for the optimal subsets. The second factor ($\hat{h}_2$) may be identified as an *interest-rate factor* because it exhibits higher marginal R^2s for interest rates. In addition, $\hat{h}_3$ and $\hat{h}_8$ load heavily on series that measure real output, employment, and consumption but also on measures of money and credit and price indices. A similar pattern is observed for $\hat{h}_5$ but with slightly lower correlations. Thus, we label $\hat{h}_3$, $\hat{h}_5$, and $\hat{h}_8$ *real factors*. The fourth factor ($\hat{h}_4$) loads heavily on price indices, money, and credit variables and to a lesser extent on real variables (e.g., U.S. personal income), and thus we label it *inflation factor*. Finally, $\hat{h}_6$ and $\hat{h}_7$ load heavily on measures of consumption, and thus we label them *consumption factors*.

2. Global Factors

Graph B of Figure 2 shows the marginal R^2s for the global factors. The first global factor ($\hat{g}_1$) loads heavily on variables that measure international trade and is highly correlated (77%) with variables that measure employment, so we label $\hat{g}_1$ as *international trade factor*. The factors $\hat{g}_2$ and $\hat{g}_3$ contain information for the global stock market, and they load heavily on interest rates and reserves. In the same vein, the marginal R^2s provide the same information; we obtain R^2s of approximately 40% for stock market indices as well as interest rates. Therefore, we label them *money and credit factors*. As we saw in the previous section, the second global factor seems to be a very strong predictor, especially for the carry trades. This is not surprising, because the link between the global stock market and the foreign exchange market is quite strong.[29]

[28] Ludvigson and Ng (2009) follow a similar procedure.

[29] For example, Hau and Rey (2006) show empirically and theoretically that under circumstances of incomplete hedging in the foreign exchange market, the foreign currency appreciates when the return in the home equity market is greater than that in the foreign counterpart.

FIGURE 2

Marginal R^2s for Each Domestic and Global Factor

Figure 2 shows the R^2s from regressing the series number given on the x-axis on each factor. Graphs A–G report results for U.S. common factors ($\hat{h}_2$–$\hat{h}_8$), and Graphs H–J display marginal R^2s for the global factors ($\hat{g}_1$–$\hat{g}_3$). The factors are estimated over July 1985–Mar. 2012.

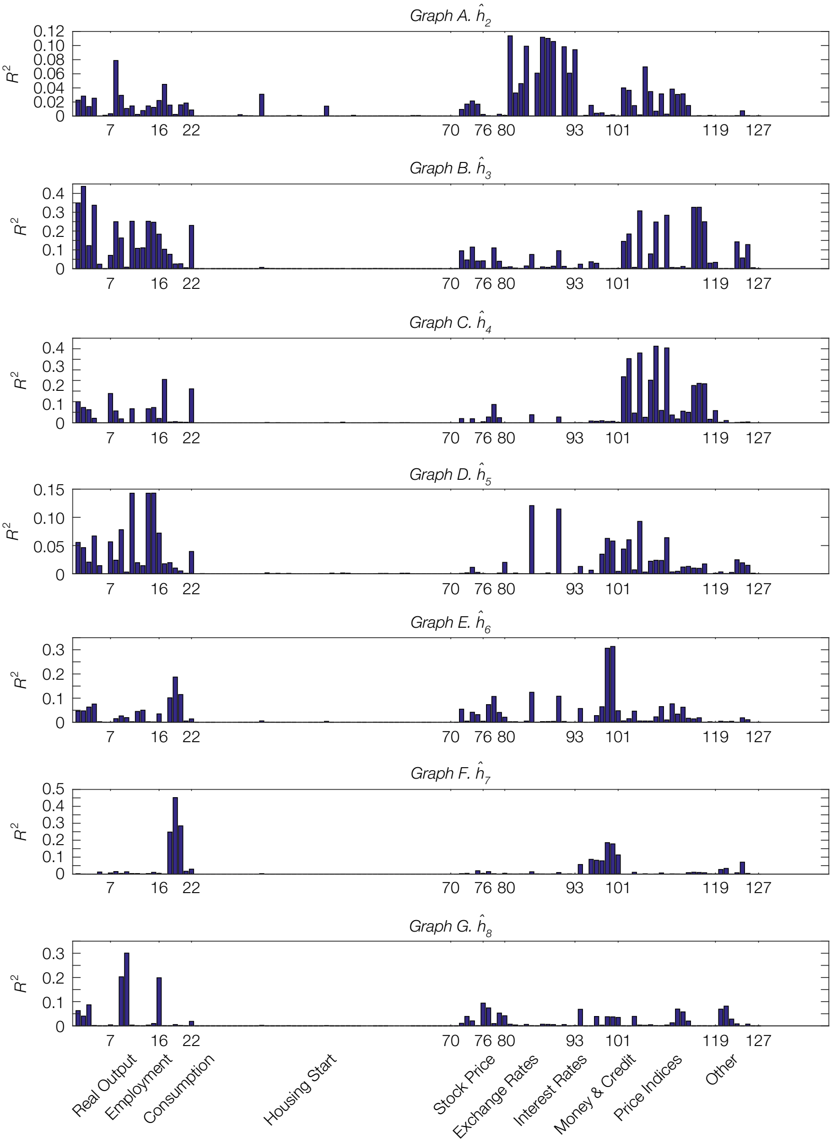

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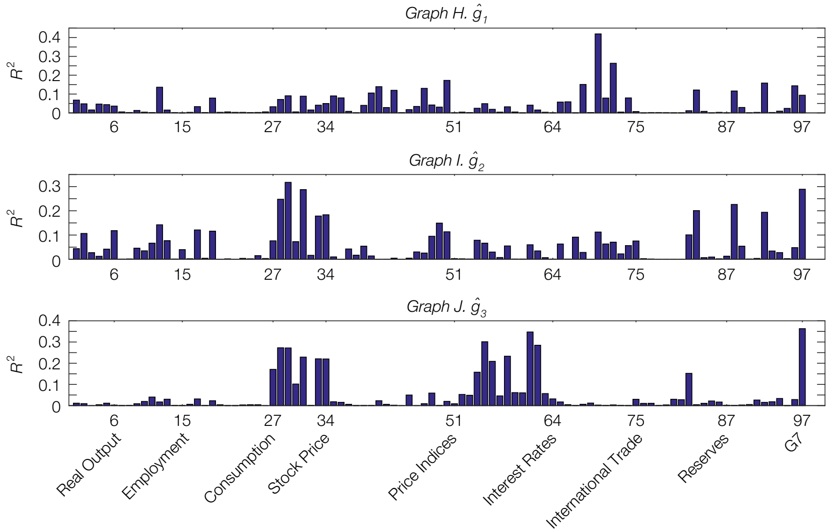
FIGURE 2 (continued)
Marginal R^2s for Each Domestic and Global Factor



E. Out-of-Sample Analysis

In this section, we report the results of out-of-sample analysis to further assess the forecasting power of the common factors.[30] More precisely, we employ recursive estimates of the factors and parameters using data up to time t to forecast at time $t+1$, accounting in this way for potential look-ahead bias. We question whether an economic agent can obtain better forecasts from the use of the factors rather than simply relying on the historical mean. Table 5 reports out-of-sample R^2 (R^2_{OOS}), as in Campbell and Thompson (2008):

$$R^2_{\text{OOS}} = 1 - \sum_{t=1}^{T-1} \frac{(\psi^i_{t+1} - \hat{\mu}_{t+1})^2}{(\psi^i_{t+1} - \mu_{t+1})^2},$$

where $\hat{\mu}_{t+1}$ represents the 1-step-ahead conditional forecast from the model of interest and μ_{t+1} is the historical mean of the payoff. Thus, a positive R^2_{OOS} statistic means that the competing model outperforms the benchmark model because it has a lower mean-squared prediction error. Then, we test the forecasting ability of the models using the mean-squared prediction error statistic (MSPE-adjusted) following Clark and West (2007). Under the null hypothesis, the mean-squared error of the competing model is expected to be greater than the mean-squared error of the benchmark model. Therefore, we construct $\hat{f}_t = (\psi^i_t - \mu_t)^2 - [(\psi^i_t - \hat{\mu}_t)^2 -$

[30]A particularly noteworthy feature of this approach involves the implications for the scapegoat theory developed by Bacchetta and Wincoop (2004), (2013) and empirically tested (in a different context) by Fratzscher, Sarno, and Zinna (2015). This approach also provides information regarding data mining, overfitting, and structural changes or model instability, and it resembles the behavior of an investor in real time.

TABLE 5

Out-of-Sample Analysis: Against the Mean

Table 5 presents out-of-sample R^2s (R^2_{OOS}) as described by Campbell and Thompson (2008) ($R^2_{\text{OOS}} = 1 - \sum_{t=1}^{T-1} (\psi^i_{t+1} - \hat{\mu}_{t+1})^2 / (\psi^i_{t+1} - \mu_{t+1})^2$), where $\hat{\mu}_{t+1}$ represents the one-step-ahead conditional forecast from the model of interest, and μ_{t+1} is the historical mean of the payoff. Thus, a positive R^2_{OOS} statistic means that the competing model outperforms the benchmark model because it has a lower mean-squared prediction error (MSPE). We also report the one-sided p-values of the MSPE-adjusted statistic for the competing models described in the article against the benchmark model following Clark and West (2007). Panel A (Panel B) reports results for currency excess returns when considering the All Countries (Developed Countries) sample. The superscript *mean* represents the mean combined forecast, and the superscript *weighted* represents the weighted counterpart. The in-sample period spans the first 180 observations (out of 321) that correspond to the period July 1985–May 2000.

Panel A. Currency Excess Returns: All Countries

	ψ^{HML}		ψ^{USD}		ψ^{WML}	
Factors	R^2_{OOS}	MSPE-Adj.	R^2_{OOS}	MSPE-Adj.	R^2_{OOS}	MSPE-Adj.
$C_1 = [\hat{g}_2]$	0.07	0.00				
$C_2 = [\hat{h}_{2,3,4,6}]$	0.01	0.01				
$C_2' = [\hat{h}_{3,6}]$						
$C_3 = [\hat{g}_{2,3}\hat{h}_{5,6}]$	0.10	0.01				
$C_{2,3}^{\text{mean}}$	0.08	0.00				
$C_{2,3}^{\text{weighted}}$	0.08	0.00				
$D_2 = [\hat{h}_{6,7}]$			0.07	0.00		
$D_3 = [\hat{g}_3\hat{h}_{6,7}]$			0.07	0.00		
$D_{2,3}^{\text{mean}}$			0.07	0.00		
$D_{2,3}^{\text{weighted}}$			0.07	0.00		
$M_2 = [\hat{h}_{1,4}]$					0.01	0.14
$M_2' = [\hat{h}_{3,4,7,8}]$						
$M_3 = [\hat{g}_3 h_4]$					0.01	0.12
$M_3' = [\hat{g}_2 h_8]$						
$M_{2,3}^{\text{mean}}$					0.01	0.12
$M_{2,3}^{\text{weighted}}$					0.01	0.12

Panel B. Currency Excess Returns: Developed Countries

	ψ^{HML}		ψ^{USD}		ψ^{WML}	
Factors	R^2_{OOS}	MSPE-Adj.	R^2_{OOS}	MSPE-Adj.	R^2_{OOS}	MSPE-Adj.
$C_1 = [\hat{g}_2]$	0.01	0.10				
$C_2 = [\hat{h}_{2,3,4,6}]$						
$C_2' = [\hat{h}_{3,6}]$	0.04	0.07				
$C_3 = [\hat{g}_{2,3}\hat{h}_{5,6}]$	0.04	0.05				
$C_{2,3}^{\text{mean}}$	0.04	0.05				
$C_{2,3}^{\text{weighted}}$	0.04	0.05				
$D_2 = [\hat{h}_{6,7}]$			0.04	0.00		
$D_3 = [\hat{g}_3\hat{h}_{6,7}]$			0.05	0.00		
$D_{2,3}^{\text{mean}}$			0.05	0.00		
$D_{2,3}^{\text{weighted}}$			0.05	0.00		
$M_2 = [\hat{h}_{1,4}]$						
$M_2' = [\hat{h}_{3,4,7,8}]$					0.04	0.03
$M_3 = [\hat{g}_3 h_4]$						
$M_3' = [\hat{g}_2 h_8]$					0.04	0.04
$M_{2,3}^{\text{mean}}$					0.05	0.03
$M_{2,3}^{\text{weighted}}$					0.05	0.03

$(\mu_t - \hat{\mu}_t)^2]$, and then $\hat{f}_t$ is regressed on a constant; rejecting the null hypothesis of a zero estimated coefficient then implies that the competing model outperforms the benchmark model, so the factors forecast better that the historical mean.

The in-sample period spans the first 180 observations (out of 321) that correspond to the period July 1985–May 2000.[31] The factors are fixed, and we fol-

[31]Many different in-sample periods have been employed and render similar results.

low an expanding-window approach. The recursively estimated factors provide positive R^2_{OOS}, but they are not as high as those obtained from the fixed factors. Table 5 offers out-of-sample R^2_{OOS} as well as one-sided p-values of the MSPE-adjusted statistic for the competing models described against the benchmark model. All the sets of factors that are statistically significant in the in-sample test pass the out-of-sample test with R^2_{OOS} that range from 1% to 10%, all statistically significant. Furthermore, most of the one-sided p-values of the MSPE-adjusted statistics are not greater than 0.05, verifying further the forecasting ability of the factors. Panel C of Table A.7 shows similar results for exchange-rate changes.

The out-of-sample results are reinforced by combination forecasts, following Stock and Watson (2004).[32] Therefore, we consider *mean* predictions as well as *weighted* predictions based on the performance of the predictions in the holdout period, p. In particular, as in Rapach, Strauss, and Zhou (2010), each prediction i at time t is associated with a weight ω_t^i, such that $\omega_t^i = (1/\phi_t^i)/\sum_{j=1}^{N}(1/\phi_t^j)$, where $\phi_t^i = \theta^{t-1-k}\sum_{k=p}^{t-1}(\psi_{k+1}^i - \hat{\mu}_{k+1}^i)^2$; $\hat{\mu}_{k+1}^i$ is the ith individual prediction for the $k+1$ month; and the discount factor θ is less than unity, providing a higher weight to the latest prediction. Here, we consider a holding period of $p=180$ months and a holdout period of 141 months. In addition, we set $\theta = 0.9$, as in a number of previous studies, although other values of θ provide similar results. Table 5 also reports results for mean and weighted forecasts and demonstrates an overall improvement in comparison to results obtained from individual forecasts.[33]

F. Testing for Data Snooping

One might raise concerns regarding the presence of data snooping in our methodology, in the sense that because we have analyzed large amounts of data in some cases more than once, the results may be attributable to selecting an apparently optimal result that is in fact due to chance rather than any merit inherent in the method yielding the results (see, e.g., White (2000)). The reasoning behind this claim might arise from the way that the factors are extracted from the large data sets, although some authors have in fact argued that because, as outlined previously, dynamic factor analysis uses a relatively small number of factors based on a simple decision rule rather than considering the very high number of possible factors, it may be largely robust *against* data snooping.[34] Nevertheless, we examine the robustness of our methodology against data snooping by utilizing a statistically more powerful approach. Specifically, we follow Clark and McCracken (2012), who have extended White's (2000) reality check by using a wild

[32]This approach is based on the idea that the weighted averages of the individual predictions obtained from different models may exhibit a significantly better performance than the individual models.

[33]Table A.7 in the Internet Appendix provides out-of-sample results for a different sample that employs information until Dec. 2007. The purpose of this exercise is to see whether the factors perform well during the recent financial crisis.

[34]See, for example, Ludvigson and Ng (2010). More precisely, in addition to following the simple selection procedure detailed in Section III, these authors consider all possible combinations of linear and nonlinear forms of the factors (over 100,000 possible models) and evaluate the best performing set of factors based on in-sample and out-of-sample information criteria (i.e., BIC); they find that the optimal set of factors resulting from this extensive search of the data is the same as the one suggested by the initial, less intense method.

fixed-regressor bootstrap to account for the fact that the competing models nest the benchmark model (i.e., the historical average).

In particular, we test the null hypothesis that the mean-squared forecast error (MSFE) of the historical mean does not exceed the minimum MSFE of all the competing models (using the maxMSFE-F statistic). To that end, we simulate the innovation term (i.e., $\hat{\varepsilon}_t$), obtained from a "kitchen sink" model estimated using the whole sample so as to generate the pseudo-payoffs (i.e., ψ_t^*) for each strategy (see, e.g., Neely, Rapach, Tu, and Zhou (2014)), such that $\psi_t^* = \alpha_{0,T} + \eta_t \hat{\varepsilon}_t$, where $\alpha_{0,T}$ is the sample mean of each strategy, and η_t is drawn from a standard normal distribution. Then, the optimal factors are used to forecast the pseudo-samples based on 1,000 replications.

For carry-trade excess returns, we find a maxMSFE-F statistic of 8.22 for All Countries and 4.98 for Developed Countries, with p-values of 0.01 and 0.03, respectively. The corresponding statistics for the dollar carry trade are 10.66 and 7.56, each of which has a p-value close to 0.01. Regarding the momentum strategy, we find an insignificant maxMSFE-F statistic for All Countries (1.21 with a p-value of 0.25) but significant results for Developed Countries momentum (a maxMSFE-F statistic of 6.07 with a p-value of 0.04); this is perhaps not surprising because our macro factors exhibit stronger predictive power when we consider the smaller group of currencies that were not subject to issues such as capital controls. Overall, however, at a nominal significance level of 5%, the Clark and McCracken (2012) reality-check procedure suggests that the out-of-sample predictive power of the factors for the currency strategies cannot be linked to data snooping but is indeed due to significant predictive information in the macro factors.

VI. Economic Evaluation of the Forecasts

A. Decision Rule

To assess the economic value of the forecasts, we develop a strategy that resembles a decision rule. In particular, the investor is involved in one of the strategies at the end of month t if the forecast of the corresponding strategy is positive for the month $t+1$; otherwise, the investor does not enter into a position. We use the forecasts of domestic and global factors as well as combination forecasts. Thereupon, we examine the performance of the factors when investing in all strategies at the same time. In this case, identical weights are assigned to each strategy.

Table 6 displays the Sharpe ratios (Panel A) and skewness (Panel B) of the conditional and unconditional payoffs. The unconditional payoff embodies the realized value of the payoff, whereas the conditional payoff is determined by a decision rule. As can be seen in the table, there is an overall significant increase in the Sharpe ratios and an improvement in the skewness profile of the payoffs for both samples. In curly brackets, we report p-values, estimated based on 10,000 stationary bootstrap samples (Politis and Romano (1994)), for the null hypothesis that the Sharpe ratios of the conditional strategy do not exceed (statistically) the unconditional counterparts, which take a position in the foreign exchange (FX) strategy regardless of the sign of the prediction. With the exception of the

TABLE 6

Out-of-Sample Performance Measures Based on Decision Rules

Table 6 presents out-of-sample (annualized) Sharpe ratios (Panel A) based on the conditional and unconditional payoffs of the strategies. The conditional strategies are based on the forecasts when considering the optimal set of factors or combined forecasts. $\hat{\psi}^{\text{HML}}$ denotes the carry-trade strategy, $\hat{\psi}^{\text{USD}}$ represents the dollar-carry trade, $\hat{\psi}^{\text{WML}}$ is the momentum strategy, and $\hat{\psi}^{\text{ALL}}$ represents the combination of the previous three strategies with equal weights. Panel B displays the corresponding skewness, and Panel C presents the certainty-equivalent return gain (ΔCER), expressed in annual percentage points. In curly braces, we report *p*-values, estimated based on 10,000 stationary bootstrap samples (BS) (Politis and Romano (1994)), for the null hypothesis that the Sharpe ratios of the conditional strategy do not exceed (statistically) the unconditional counterparts, which take a position in the foreign exchange (FX) strategy regardless of the sign of the prediction. The in-sample period spans the first 180 observations (out of 321) that correspond to the period July 1985–May 2000.

	All Countries		Developed Countries	
Payoffs	Multiple Predictors	Combined Forecasts	Multiple Predictors	Combined Forecasts
Panel A. Sharpe Ratio				
$\hat{\psi}^{\text{HML}}$	1.55	1.74	1.12	1.04
BS	{0.01}	{0.02}	{0.01}	{0.02}
$\hat{\psi}^{\text{USD}}$	0.54	0.51	0.72	0.56
BS	{0.40}	{0.45}	{0.38}	{0.22}
$\hat{\psi}^{\text{WML}}$	0.54	0.54	0.44	0.42
BS	{0.47}	{0.46}	{0.24}	{0.19}
$\hat{\psi}^{\text{ALL}}$	1.06	1.12	1.06	1.12
BS	{0.56}	{0.52}	{0.57}	{0.54}
Panel B. Skewness				
$\hat{\psi}^{\text{HML}}$	−0.52	−0.51	−0.61	−0.54
$\hat{\psi}^{\text{USD}}$	−0.11	−0.79	0.09	−0.35
$\hat{\psi}^{\text{WML}}$	0.34	0.34	0.02	−0.04
$\hat{\psi}^{\text{ALL}}$	0.75	0.93	0.75	0.93
Panel C. ΔCER				
$\hat{\psi}^{\text{HML}}$	0.10	0.09	0.04	0.05
$\hat{\psi}^{\text{USD}}$	0.12	0.12	0.06	0.06
$\hat{\psi}^{\text{WML}}$	−0.07	−0.07	−0.12	−0.06

momentum strategy, where there is no big improvement, the forecasts provide strong out-of-sample economic value for an investor who applies the strategies of interest. A mixed strategy that combines all three strategies also verifies the strong predictive power embodied in our factors.

Figure 3 illustrates rolling Sharpe ratios using a 12-month window for the carry, dollar-carry, and momentum strategies as well as the mixed strategy. The solid and dotted lines represent the rolling Sharpe ratios of conditional payoffs obtained from the forecasts of the optimal subset of factors (solid) and the combination forecasts (dotted). The dashed line displays the realized value of the payoffs. There is clearly an improvement in the rolling Sharpe ratios, especially during the crisis. Our decision rule shows that an investor could achieve very high Sharpe ratios during the recent financial turmoil (2008–2009) if the investor has taken into account the domestic and global macroeconomic environment.

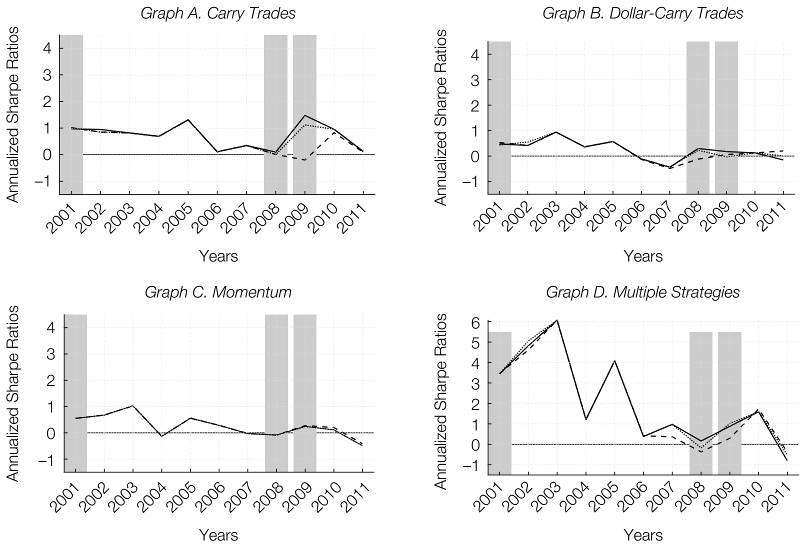
B. Dynamic Asset Allocation

The decision rule does not take account of the investor's risk preferences in the asset-allocation decision. Thus, we ask whether our forecasts can benefit a risk-averse investor with mean-variance preferences who allocates his or her wealth on a monthly basis across risky assets (i.e., equities and currency strate-

FIGURE 3

Rolling Sharpe Ratios of Conditional and Unconditional Strategies

Figure 3 displays the rolling Sharpe ratios (estimated over each year) of the conditional and unconditional strategies when using the optimal set of domestic and global factors as well as combined forecasts. The dashed line represents the unconditional payoffs, and the solid and dotted lines show the conditional payoffs when we use the optimal set of factors (solid) or combined forecasts (dotted). We consider the group of all countries. The shaded areas represent the National Bureau of Economic Research (NBER) recessions of the U.S. economy. The in-sample period spans the first 180 observations (out of 321) that correspond to the period July 1985–May 2000.



gies) and risk-free assets (i.e., U.S. Treasury bills). In particular, we ask whether an investor could benefit from a currency investment strategy that is appended by a traditional institutional investor's 60/40 (60% equities, 40% bonds) portfolio. To this end, we estimate the certainty-equivalent return (CER), following Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011). The investor rebalances his or her portfolio at the end of month t, forming the weights of the currency strategies (w_t^i) for investing at time $t+1$ as follows:

$$(7) \qquad w_t^i = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{\psi}_{t+1}^i}{\hat{\sigma}_{i,t+1}^2}\right), \quad \text{for} \quad i = \text{HML}, \text{USD}, \text{WML},$$

where $\hat{\psi}_{t+1}^i$ is the forecast of the payoff for the ith strategy, $\hat{\sigma}_{i,t+1}^2$ the corresponding forecast of the variance, and γ denotes the investor's coefficient of absolute risk aversion. Therefore, the portfolio return at time $t+1$ is given by

$$(8) \qquad R_{p,t+1}^i = w_t^i \psi_{t+1}^i + R_{p60/40_{t+1}}, \quad \text{for} \quad i = \text{HML}, \text{USD}, \text{WML},$$

where $R_{p60/40_{t+1}}$ is the return of a traditional 60/40 portfolio that allocates 60% to equities (i.e., Standard & Poor's (S&P) 500) and 40% to risk-free bonds at time $t+1$. As in Campbell and Thompson (2008), the variance of the payoffs is estimated on the basis of a 5-year rolling window, the risk-aversion coefficient is set equal to 5, and the weights for the risky asset are confined to a particular interval (i.e., between 0 and 1). In this way, we do not allow for leverage. Thus, the average realized utility or CER is defined as follows:

$$(9)\qquad \mathrm{CER}_p^i \quad = \quad \hat{\mu}_p^i - \frac{\gamma \hat{\sigma}_{i,p}^2}{2}, \quad \text{for} \quad i \quad = \quad \text{HML, USD, WML},$$

where $\hat{\mu}_p^i$ is the mean, and $\hat{\sigma}_{i,p}^2$ is the variance of the portfolio when investing in each of the three strategies over the out-of-sample period. The CER is the risk-free return that a mean-variance investor would consider sufficient to avoid investing in the strategy. The CER gain represents the difference between the average realized utility of the forecasts and the corresponding value of the historical average. It can be interpreted as the fee that an investor is willing to pay to utilize the forecasts rather than relying on the historical mean. Thus, a positive value of the CER means that the investor prefers the forecasts over the estimate of the historical mean when forming expectations with regard to the strategies of interest. Panel C of Table 6 presents positive CER gains for the carry and dollar-carry strategies but not the momentum strategy. Thus, there is a predictable component in the carry and dollar-carry-trade strategies that provides strong economic value to a risk-averse investor with mean-variance preferences.

VII. Robustness and Other Specification Tests

In this section, we offer some additional tests to evaluate the robustness of our results.

A. Non–U.S. Dollar Base Currencies

A natural question that arises from our analysis is associated with the explanatory power of our domestic and global factors when considering alternative investors' perspectives. In particular, we evaluate carry-trade strategies for alternative, non-U.S. dollar base currencies and show that our results remain robust or improved. Panel A of Table 7 reports in-sample estimates for the optimal set of factors for carry-trade strategies that employ different base currencies, namely, the British pound (GBP), Swiss franc (CHF), Canadian dollar (CAD), Swedish krona (SEK), Japanese yen (JPY), and Australian dollar (AUD). We find that our estimates are highly significant, rendering relatively high R^2s. Panel B of Table 7 assesses the economic value of the factors for the alternative payoffs on the basis of their CER values. In all cases, we find a positive ΔCER, indicating strong economic value to non-U.S. dollar based investors.[35]

B. Conditional Predictive Regressions

We assess the predictive ability of the factors conditional on the information provided by the Bakshi and Panayotov (BP) (2013) predictors, namely, commodity, volatility, and liquidity measures ($\Delta\mathrm{CRB}, \Delta\sigma^{fx}, \Delta\mathrm{LIQ}$), all estimated on a monthly basis.[36] Panel A of Table 8 provides in-sample estimates for the

[35] We also find an improvement in the out-of-sample Sharpe ratios and the skewness profiles of the corresponding strategies; these results are available on request.

[36] We offer a detailed description of the BP predictors in the Internet Appendix.

TABLE 7

In-Sample Analysis and Certainty-Equivalent Return Gain: Non-U.S. Dollar-Based Investors (carry trades)

Table 7 reports results for alternative non-U.S. base currencies, namely, the British pound (GBP), Swiss franc (CHF), Canadian dollar (CAD), Swedish krona (SEK), Japanese yen (JPY), and Australian dollar (AUD). Panel A shows ordinary least squares (OLS) estimates for the carry-trade strategy for the sample of All Countries. The dependent variable is the currency excess return (ψ^{HML}) based on the carry-trade strategy or the exchange-rate component (Δs^{HML}) of the strategy. NW represents Newey and West (1987) t-statistics corrected for autocorrelation and heteroskedasticity with the optimal number of lags following Andrews (1991). BS denotes the bootstrap p-values based on 10,000 bootstrap iterations, and Constant is the intercept. The data span the period July 1985–Mar. 2012. Panel B presents the certainty-equivalent return gain (ΔCER), expressed in annual percentage points based on the conditional and unconditional payoffs of the strategies. The conditional strategies are based on the forecasts when considering the optimal set of factors or combined forecasts. The in-sample period spans the first 180 observations (out of 321) that correspond to the period July 1985–May 2000.

Panel A. Excess Returns and Exchange-Rate Changes

Payoffs	Constant	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{g}_{3,t-3}$	$\hat{h}_2$	$\hat{h}_6$	$\bar{R}^2$	Constant	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{g}_{3,t-3}$	$\hat{h}_2$	$\hat{h}_6$	$\bar{R}^2$
	GBP							CHF						
ψ^{HML}	1.23	0.72	−0.49	−0.37	0.21	0.29	0.07	0.95	0.60	−0.37	−0.34	0.33	0.31	0.08
NW	7.85	2.87	−2.55	−2.54	1.48	2.08	27.53	6.10	2.48	−1.91	−2.22	2.27	2.22	32.80
BS	0.00	0.00	0.02	0.00	0.16	0.05	0.00	0.00	0.00	0.10	0.01	0.03	0.02	0.00
Δs^{HML}	−0.01	−0.71	0.36	0.32	0.08	−0.24	0.06	0.22	−0.62	0.28	0.31	−0.03	−0.25	0.05
NW	−0.08	−3.30	2.10	2.22	0.65	−1.85	23.21	1.55	−2.95	1.56	2.15	−0.25	−1.81	19.91
BS	0.93	0.00	0.09	0.01	0.65	0.09	0.00	0.11	0.00	0.24	0.01	0.75	0.07	0.00
	CAD							SEK						
ψ^{HML}	0.95	0.75	−0.50	−0.39	0.28	0.28	0.09	0.83	0.69	−0.49	−0.39	0.29	0.26	0.08
NW	6.02	2.93	−2.49	−2.67	1.91	1.91	32.87	5.43	2.59	−2.45	−2.59	1.91	1.81	32.76
BS	0.00	0.00	0.02	0.00	0.06	0.06	0.00	0.00	0.00	0.02	0.00	0.06	0.07	0.00
Δs^{HML}	0.23	−0.73	0.37	0.33	0.00	−0.22	0.06	0.30	−0.67	0.36	0.34	0.00	−0.21	0.05
NW	1.57	−3.45	2.08	2.20	0.00	−1.61	23.15	2.16	−3.02	2.04	2.23	0.01	−1.53	21.03
BS	0.11	0.00	0.08	0.01	0.92	0.10	0.00	0.03	0.00	0.10	0.01	0.92	0.13	0.00
	JPY							AUD						
ψ^{HML}	0.91	0.63	−0.39	−0.34	0.33	0.30	0.08	0.88	0.74	−0.51	−0.34	0.30	0.23	0.09
NW	5.65	3.04	−2.44	−2.45	2.56	2.36	36.46	5.97	2.92	−2.62	−2.67	2.11	1.73	38.82
BS	0.00	0.00	0.04	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.04	0.09	0.00
Δs^{HML}	0.24	−0.66	0.29	0.32	−0.04	−0.23	0.05	0.28	−0.71	0.35	0.29	0.02	−0.20	0.06
NW	1.64	−3.57	1.93	2.33	−0.30	−1.80	21.95	2.06	−3.38	2.04	2.22	0.14	−1.53	24.44
BS	0.09	0.00	0.17	0.01	0.72	0.09	0.00	0.04	0.00	0.08	0.02	0.98	0.13	0.00

Panel B. ΔCER

	All Countries		Developed Countries	
Payoffs	Multiple Predictors	Combined Forecasts	Multiple Predictors	Combined Forecasts
$\hat{\psi}^{\text{HML}}_{\text{GBP}}$	0.32	0.16	0.10	0.12
$\hat{\psi}^{\text{HML}}_{\text{CHF}}$	0.25	0.20	0.06	0.10
$\hat{\psi}^{\text{HML}}_{\text{CAD}}$	0.27	0.17	0.05	0.08
$\hat{\psi}^{\text{HML}}_{\text{SEK}}$	0.21	0.15	0.04	0.06
$\hat{\psi}^{\text{HML}}_{\text{JPY}}$	0.31	0.23	0.05	0.09
$\hat{\psi}^{\text{HML}}_{\text{AUD}}$	0.24	0.12	0.05	0.06

factors in the presence of the BP variables.[37] For the carry-trade strategy, the set of common factors is highly significant, rendering an adjusted R^2 of 5% (9%) for the full sample (Developed Countries). Regarding the dollar carry trade (momentum), the factors $\hat{h}_4$, $\hat{h}_6$, and $\hat{h}_7$ ($\hat{g}_2$, $\hat{h}_8$, and $\hat{h}_9$ for developed countries) are significant, and among the BP predictors, only the volatility (commodity) factor explains the behavior of the strategy of interest.

[37] To conserve space, we report results only for combined subsets of domestic and global factors. However, our results for domestic or global estimations are available on request.

Lustig et al. (2014) show that average forward discounts (AFDs) exhibit important information for dollar-carry-trade returns. Thus, we examine whether the predictability of our factors remains after including the AFD. Panel B of Table 8 displays the results of the predictive regressions for all the payoffs.

TABLE 8
Conditional Predictive Regressions

Table 8 reports ordinary least squares (OLS) estimates of conditional predictive regressions. Panel A reports results of the predictive regressions for the carry, dollar-carry, and momentum strategies (ψ^{HML}, ψ^{USD}, ψ^{WML}) in the presence of the Bakshi and Panayotov (2013) predictors (ΔCRB, $\Delta\sigma^{fx}$, ΔLIQ). Panel B presents results of in-sample estimates of the common factors conditional on the information provided by the average forward discounts (AFDs). NW represents Newey and West (1987) t-statistics corrected for autocorrelation and heteroskedasticity, constructed with the optimal number of lags chosen following Andrews (1991). BS denotes the bootstrap p-values based on 10,000 bootstrap iterations, and Constant is the intercept. The data span the period July 1985–Mar. 2012.

Panel A. Bakshi and Panayotov Predictors

	All Countries			Developed Countries		
Factors	ψ^{HML}	ψ^{USD}	ψ^{WML}	ψ^{HML}	ψ^{USD}	ψ^{WML}
Constant	0.37	0.26	0.44	0.15	0.42	0.08
NW	2.28	2.42	3.10	1.48	3.21	0.63
BS	0.01	0.03	0.00	0.39	0.00	0.57
$\hat{g}_{2,t}$	0.60			0.62		−0.59
NW	3.08			2.45		−3.08
BS	0.00			0.02		0.00
$\hat{g}_{2,t-2}$				−0.65		
NW				−3.35		
BS				0.00		
$\hat{g}_{3,t}$	−0.35	−0.29			−0.29	
NW	−1.62	−1.75			−1.38	
BS	0.05	0.09			0.14	
$\hat{h}_{3,t}$			−0.19			
NW			−1.06			
BS			0.42			
$\hat{h}_{4,t}$		0.21	0.28	0.06	0.28	0.20
NW		1.87	1.92	0.33	1.97	1.52
BS		0.08	0.06	0.76	0.05	0.20
$\hat{h}_{6,t}$	0.39	0.23				
NW	2.07	1.79				
BS	0.04	0.06				
$\hat{h}_{7,t}$		−0.27			−0.28	
NW		−2.65			−2.26	
BS		0.01			0.02	
$\hat{h}_{8,t}$			0.87			0.28
NW			0.09			1.82
BS			0.93			0.08
$\hat{h}_{9,t}$			−1.27			−0.30
NW			−0.85			−1.62
BS			0.39			0.06
$\Delta\mathrm{CRB}_t$	−7.93	6.32	−1.99	21.48	5.60	14.35
NW	−1.06	1.13	−1.12	2.10	0.80	1.71
BS	0.42	0.45	0.14	0.06	0.56	0.10
$\Delta\sigma_t^{fx}$	−1.25	−2.75	0.01	−3.09	−3.52	−1.70
NW	1.76	−1.82	6.38	−1.90	1.96	−1.19
BS	0.08	0.05	0.27	0.06	0.03	0.21
$\Delta\mathrm{LIQ}_t$	2.19	0.52		1.83	0.93	−2.27
NW	1.41	0.47		1.48	0.73	−1.65
BS	0.04	0.69		0.34	0.53	0.12
$\bar{R}^2$	0.05	0.06		0.09	0.05	0.05
NW	19.02	28.35		21.06	18.61	15.52
BS	0.00	0.00		0.00	0.00	0.02

(continued on next page)

TABLE 8 (continued)
Conditional Predictive Regressions

Panel B. Average Forward Discounts

	All Countries			Developed Countries		
Factors	ψ^{HML}	ψ^{USD}	ψ^{WML}	ψ^{HML}	ψ^{USD}	ψ^{WML}
Constant	0.50	0.34	0.36	0.41	0.55	0.01
NW	2.31	2.85	2.40	2.01	3.88	0.06
BS	0.00	0.00	0.03	0.28	0.00	0.95
$\hat{g}_{1,t}$				0.36		
NW				1.62		
BS				0.12		
$\hat{g}_{2,t}$	0.46			0.40		
NW	2.09			1.91		
BS	0.01			0.10		
$\hat{g}_{3,t}$		−0.23	−0.18		−0.28	
NW		−1.80	−0.79		−1.91	
BS		0.10	0.34		0.14	
$\hat{g}_{2,t-3}$	−0.37					
NW	−2.35					
BS	0.00					
$\hat{h}_{3,t}$						−0.25
NW						−1.92
BS						0.24
$\hat{h}_{4,t}$			0.28			0.28
NW			1.74			2.01
BS			0.08			0.07
$\hat{h}_{6,t}$	0.43	0.37		0.46	0.43	
NW	3.14	2.95		2.93	3.06	
BS	0.00	0.00		0.00	0.00	
$\hat{h}_{7,t}$		−0.34			−0.38	
NW		−2.91			−2.94	
BS		0.01			0.01	
$\hat{h}_{8,t}$						0.30
NW						1.73
BS						0.08
AFD_t	−1.63	−0.18	0.85	−2.00	−0.76	1.38
NW	−1.19	−0.22	0.20	−1.56	−0.80	1.75
BS	0.14	0.80	0.36	0.10	0.38	0.08
$\bar{R}^2$	0.07	0.05	0.01	0.05	0.04	0.03
NW	24.62	18.71	4.16	14.08	16.34	8.94
BS	0.00	0.00	0.24	0.01	0.00	0.07

In all cases, the AFD is statistically significant at the 10% significance level only for the Developed Countries sample, and our factors remain highly significant.[38]

C. Alternative Payoffs

We also look at alternative strategies, such as the Deutsche Bank (DB) global and G10 carry-trade indices. Table 9 shows that our factors provide very strong in-sample predictive power for the excess returns of these indices, as can be seen from the highly significant slope coefficients and the high R^2s (i.e., 9%–14%). In addition, we investigate the variation of two more strategies that deviate from the scope of the article, namely, DB value and DB momentum (trend-based strategies), and we again find that domestic factors exhibit strong predictive power. Moreover, we employ additional payoffs (see Table A.2 of the Internet Appendix)

[38]We obtain similar results with data obtained from Lustig et al. (2014), which are available from the authors.

TABLE 9
Robustness: In-Sample Analysis (DB indices)

Table 9 reports ordinary least squares (OLS) estimates for Deutsche Bank (DB) indices. In Panel A, the dependent variable is the currency excess returns of the DB global and G10 currency carry-trade strategies. Panel B reports results for the DB value and momentum strategies. NW represents Newey and West (1987) t-statistics corrected for autocorrelation and heteroskedasticity, with the optimal number of lags following Andrews (1991). BS denotes the bootstrap p-values based on 10,000 bootstrap iterations, and Constant is the intercept. The data span the period Dec. 2000–Mar. 2012 for the DB global and G10 carry trade and the period Sept. 1989–Mar. 2012 for value and momentum.

Panel A. Currency Harvest USD

Models	Constant	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{h}_{2,t}$	$\hat{h}_{3,t}$	$\hat{h}_{5,t}$	$\bar{R}^2$
Global							
(a)	0.52	0.82	−0.76				0.09
NW	1.77	2.64	−4.31				13.79
BS	0.11	0.01	0.00				0.00
(b)	0.34			0.40	0.53	0.64	0.07
NW	0.97			1.36	1.98	2.79	7.46
BS	0.46			0.31	0.05	0.05	0.05
(c)	0.27	0.37	−0.74	0.61	0.55	0.41	0.12
NW	0.94	1.24	−4.75	2.35	1.57	2.03	20.91
BS	0.57	0.31	0.00	0.07	0.16	0.06	0.00

Models	Constant	$\hat{g}_{1,t-1}$	$\hat{g}_{2,t}$	$\hat{g}_{2,t-3}$	$\hat{g}_{3,t-3}$	$\hat{h}_{3,t}$	$\hat{h}_{5,t}$	$\hat{h}_{6,t}$	$\bar{R}^2$
G10									
(a)	1.32	0.84	0.37	−0.84	0.40				0.14
NW	3.46	2.90	1.36	−3.98	2.04				14.49
BS	0.02	0.01	0.26	0.00	0.19				0.00
(b)	0.43					0.50	0.42	0.39	0.09
NW	2.35					1.92	1.63	2.75	9.46
BS	0.04					0.10	0.22	0.03	0.02
(c)	0.79			−0.70	0.42	0.75	0.37		0.16
NW	3.25			−3.89	2.02	3.31	1.68		12.46
BS	0.00			0.01	0.21	0.01	0.26		0.01

Panel B. Value and Momentum

Models	Constant	$\hat{g}_{1,t-3}$	$\hat{g}_{3,t}$	$\hat{h}_{2,t}$	$\hat{h}_{3,t}$	$\hat{h}_{4,t}$	$\bar{R}^2$
FX PPP							
(a)	0.20	−0.34	0.26				0.02
NW	1.22	−2.48	1.02				6.98
BS	0.21	0.04	0.17				0.03
(b)	0.21			0.26	−0.32	0.19	0.02
NW	1.30			1.66	−2.33	1.46	9.30
BS	0.19			0.11	0.02	0.18	0.03
(c)	0.17	−0.40	0.26		−0.23	0.31	0.04
NW	1.08	−2.77	1.14		−1.39	2.34	14.40
BS	0.28	0.02	0.17		0.23	0.05	0.01

Models	Constant	$\hat{g}_{3,t-2}$	$\hat{g}_{3,t-3}$	$\hat{h}_{3,t}$	$\hat{h}_{4,t}$	$\bar{R}^2$
FX Momentum						
(a)	0.17	−0.41	−0.33			0.04
NW	1.10	2.15	−2.21			3.90
BS	0.44	0.03	0.04			0.03
(b)	0.15			−0.25	0.38	0.03
NW	0.94			−0.99	3.15	5.48
BS	0.37			0.20	0.00	0.06
(c)	0.14	−0.42	−0.35	−0.13	0.44	0.07
NW	0.93	−2.42	−2.68	−0.58	3.33	16.98
BS	0.36	0.00	0.06	0.58	0.00	0.00

that are available from other studies in the literature, such as the carry-trade excess returns of Lustig et al. (2011) and Bakshi and Panayotov (2013), with qualitatively similar results.

D. Other Tests

We perform a set of additional robustness checks, the results of which are reported in the Internet Appendix. We show that the factors demonstrate strong predictive power for the long and short components of the strategies (Table A.1). Our results remain robust when considering alternative subsamples (Tables A.2 and A.4), longer horizons (Tables A.5 and A.6), and alternative asset classes (Table A.8). Figures A.1 and A.2 in the Internet Appendix show that the global factors (Graph A) incorporate information regarding the countercyclical nature of currency premia, whereas the domestic factors (Graph B) lead to acyclic or reverse results.[39] This finding might be of interest to policymakers because it could help them adjust currency premia with the appropriate monetary policy or examine the interaction among risk premia, monetary policy, and the economic environment.

VIII. Conclusions

In this article, we examine the role of the domestic and global macroeconomies on the returns to carry-trade, dollar-carry-trade, and momentum trading strategies in the foreign exchange market. We constructed domestic (U.S.) and global (G10) factors that are extracted from large panels of macroeconomic and financial variables. Thus, the main focus of the article is the time-series predictability of the payoffs and the economic value that can be earned by a U.S. dollar-based investor from the use of these domestic and global common factors. Later, we show that our results are robust to the use of other base currencies.

We find very strong evidence of in-sample predictability in the carry, dollar-carry, and momentum trading strategy returns. In particular, carry-trade variability can be explained by global variables that are exposed to G7 economies and are highly correlated with global stock markets. This finding shows that carry-trade activity depends more on the global environment than on the domestic (i.e., U.S.) economy, although U.S. real and inflation factors also provide useful information. Conversely, as one might perhaps expect, the dollar carry trade is mainly driven by the U.S. economy, and indeed, we find that only domestic inflation and consumption factors have strong predictive power for the dollar-carry-trade returns. U.S. inflation and, to a lesser extent, global money and credit factors are also strong predictors of the momentum strategy. In addition, very strong evidence of profitability is found in the exchange-rate component of these strategies.

Further, we find that our results are reinforced by out-of-sample analysis and combination forecasts and deliver strong economic value to an international investor with mean-variance preferences. Another striking feature revealed from an examination of rolling Sharpe ratios is associated with very high annualized Sharpe ratios during the recent financial crisis. Finally, our analysis shows that the common factors are able to forecast the carry and dollar-carry-trade returns over and above other factors previously considered in the literature.

[39] We come to a similar conclusion when we employ other predictors. The results are similar for U.S. and G7 industrial production (IP) growth because they are highly correlated. We also obtain similar results when we exclude the United States from the sample of the G7 countries.

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