Cross-asset Return Predictability between Currency Carry Trades and Stocks

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Abstract

Changes in either equity volatility or the world equity index return predict carry trade profits. Drops but not increases in the world equity index positively predict profits from shorting the low-yielding currencies. Changes in equity volatility negatively predict profits from both high- and low-yielding currencies and the effect is symmetric. Interestingly, the predictability effect appears to go both ways: high-yielding currencies also predict the world equity return, but only if the 2008 financial crisis is included.

JEL classifications: G11, G14, F31

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1. Introduction

Returns and risks of carry trades and stocks are closely related. They tend to both perform well when economic uncertainty is low and badly when economic uncertainly is high. Stock volatility explains currency returns (as shown by the seminal work by Lustig, Roussanov and Verdelhan, 2011a). Stock prices also co-move strongly with safe haven currencies. Low-yielding currencies (or *safe haven currencies*) tend to appreciate when equity prices drops (for example, Ranaldo and Söderlind, 2010; Campbell, Medeiros and Viceira, 2010). The rich evidence on contemporaneous correlations between these two classes of assets is important and interesting. A natural question to ask is whether there is any cross-asset return predictability between stock investments and carry trades. We find that there is, but the direction is stronger from stock markets to carry trades than from from carry trades to stock markets. Both monthly changes in equity volatility and monthly world equity index return significantly predict carry trade profits from low-yielding currencies (or *the short leg profits*) two months later. Carry trade profits from high-yielding currencies (or *the long leg profits*) also predict the world equity index return significantly three months later, but only if the 2008 financial crisis is included.

Our study is also motivated by the gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong, Torous and Valkanov (2007). The notion that information may gradually diffuse across financial markets and that this may lead to cross-asset return predictability is now backed up by substantial empirical evidence. For instance, Hong, Torous and Valkanov (2007) find that U.S. industry returns predict general market movements; Driesprong, Jacobsen and Maat (2008) document that oil price changes predict many stock markets around the world; Menzly and Ozbas (2010) find that customer and supplier firms cross-predict each other's returns; Rapach, Strauss and Zhou (2011) provide evidence that the U.S. market leads stock markets worldwide. Currency markets and stock markets appear to be natural candidates to investigate cross-asset return predictability that may be explained by the gradual information diffusion model.

Carry trades involve investing in high-yielding currencies and borrowing in low-yielding currencies. If the Uncovered Interest Parity (UIP) holds, high-yielding currencies should depreciate against low-yielding currencies and offset the difference in interest rates, making carry trades unprofitable. In the short run, however, high-yielding currencies do not tend to depreciate; instead, on average they appreciate a little[1]. This empirical violation of UIP is precisely why carry trades make money. The attractiveness of carry trades is evident in the growing number of financial products exploring interest rate differentials (or, the *carry*) among currencies.

We choose the MSCI world equity index return and changes in global equity volatility as stock market variables for this cross-asset market return predictability study. These choices are guided by the work on common currency risk factors by Lustig, Roussanov and Verdelhan (2011a), on safe haven currencies by Ranaldo and Söderlind (2010) and on global currency risk hedging by Campbell, Medeiros and Viceira (2010).

Our in-sample results show that drops but not rises in the world equity index return positively predicts carry trade profits from low-yielding currencies. If the world equity index level drops, the profit from shorting low-yielding currencies (or *the short-leg profit*) decreases two months later. Changes in equity volatility also predict carry trade profits from the short leg and the effect is more symmetric. Both rises and drops in equity volatility significantly predict short leg profit in two month time. Out-of-sample results provide more evidence for the predictability of short leg carry trade profits. Prediction models for short leg carry trade profits generate trading signals in almost half of the months. As a result, trading strategies that make trading decisions based on predicted short leg profits have higher average profits, Sharpe-ratios and improved skewnesss.

Turning to the predictability in long leg carry trade payoffs (from investing in high-yielding currencies), we find that neither the world equity index return nor changes in equity volatility strongly predict the long leg profits. If the world equity index rises, the long leg

[1] For example, Froot and Thaler (1990) survey 75 studies and show that the exchange rate moves in the opposite direction as the forward rate predicts – on average if the forward rate predicts that the exchange rate appreciates by 1%, it drops 0.9% instead..

carry trade profit (from high-yielding currencies) appear to increase on average two months later. However, this "good" market effect is sample specific and delivers poor out-of-sample performance. Neither do changes in equity volatility strongly predict the long leg carry trade profit out-of-sample.

Do carry trades and changes in currency volatility predict the world equity index return? Currency market variables generally do not predict the world equity index return. The long leg carry trade profits appear to predict changes in the world equity index, but the predictability is sample specific. Out-of-sample analysis confirms the sample-specific predictability. Stock return prediction models based on long leg carry trade profits could generate only a few trading signals during the 2008 financial crises. Changes in currency volatility do not predict carry trade profits either.

At first sight, this result may be surprising, because the main equity index levels are widely broadcast public information. If financial markets are fully efficient, one would expect that information contained in stock prices would be immediately incorporated into exchange rates. Nevertheless, even main equity index levels are highly public information. Our findings can be explained by the gradual information diffusion model developed by Hong, Torous and Valkanov (2007). If FX traders focus mostly on macro-economic information, while stock market investors consider company information as well, this exposure of FX traders to a smaller information set could explain our results. For example, traders in London and New York both state that they primarily follow macro-economic news, according to the survey by Cheung and Chinn (2001) and Cheung and Wong (2000). Evans and Lyons (2007, p.1) describe macroeconomic information as existing in "a dispersed micro-economic form in the sense of Hayek (1945)". In the process of aggregating company level micro-information, stock market returns reflect information regarding macro-economic uncertainty. Further, the predictability in carry trade profits only gradually show up after a month lag after the world equity index drops or global equity volatility changes. This pattern appears to be consistent with an explanation of delayed reaction by investors in currency markets to information in equity markets. This finding is also consistent with the intuition that equity markets service as a barometer for other asset markets.

Why do equity market variables only strongly predict the short leg carry trade profit but not profits from the long leg. Changes in equity volatility have some marginal predictive ability for the long leg profit three months later. In the sample period from 2008 onwards, the long leg carry trade profits actually significantly and positively predict movements in the world equity index. Our result suggests that the stock might only serve as a barometer for low-yielding currencies in the foreign exchange market, but not high-yielding currencies. A possible explanation is that exchange rates of high-yielding currencies are primarily driven by exogenous factors that do not originate from stock markets. As argued by Chen and Rogoff (2002), commodity currency exchange rates (high-yielding currencies typically are commodity currencies) are exposed to exogenous commodity price shocks. A recent study by Bakshi and Panayotov (2012) demonstrates the superior predictive power of commodity price movements for carry trade profits from investing in high-yielding currencies.

Our paper contributes to the literature in three respects.

The paper first relates to the carry trade return predictability literature. Bakshi and Panayotov (2012) is the first to thoroughly study the predictability in dynamic carry trades. While they focus on profits from dynamic long/short strategies and profits from the long leg, we contribute to the discussion on predictability in carry trade profits by providing strong evidence for the predictability in the short leg profits.

Second, our study is related to the exchange rate forecast literature. To date, models that use macroeconomic variables to predict exchange rates have had little success for horizons shorter than a year (for example, Meese and Rogoff, 1983; Mark, 1995; Cheung, Chinn and Pascual, 2005). There is some recent success in predicting exchange rates using currency order flow data (for example, Evans and Lyons, 2005). The mechanism through which order flows forecast exchange rates is analogous to the gradual information diffusion model by Hong and Stein (1999) and Hong, Torous and Valkanov (2007). Evans and Lyons (2005, 2007) explain that order flows forecast exchange rates by way of gradually dispersing information across the currency market. Not only order flows in the currency market forecast exchange rates. Albuquerque, Francisco and Marques (2008) document that stock market order flows also significantly explain future exchange rate movements. We contribute to this strand of literature by showing that stock returns and changes in equity volatility forecast returns of sorted currency portfolios. This result also indicates dynamic ranking and sorting currencies may have cancelled out some noise related to one specific currency so that the predictive effect strengthens.

Our paper is also related to the gradual information diffusion literature inspired by the work by Hong and Stein (1999) and Hong, Torous and Valkanov (2007). We add evidence for this hypothesis by showing that information may gradually flow from stock markets to low-yielding currencies but not the other way around.

2. Data

2.1. Construction of carry trade profits

We take the perspective of a U.S. investor in carry trades. A U.S. investor sells low-yielding currencies forward against the U.S. dollar and buys high-yielding currencies forward with the U.S. dollar. Following practitioners' practice, we implement carry trades using forward contracts and spot exchange rates after crossing bid-ask spreads, as articulated in Lustig, Roussanov and Verdelhan (2011a), Burnside, Eichenbaum, Kleshchelski and Rebelo (2011) and Bakshi & Panayotov (2012). While practitioners generally implement carry trade strategies with leverage, we study carry trade profits without leverage in order to focus on the pure lead-lag effects between stock returns and carry trade profits. Throughout this paper, we denote exchange rate as home currency per foreign currency unit (or FCU). Using this notation, an increase in exchange rates is a result of the appreciation of a foreign currency against the U.S. dollar.

We use spot and forward exchange rates provided by Barclays Capital via Datastream for G-10 currencies from January 1985 to December 2011[2]. Many investable carry trade indices use G-10 currencies as the universe of their constituent currencies3. G-10 currencies are also the ten most actively traded free float currencies in terms of daily average turnover. According to the triennial survey conducted by the Bank for International Settlements (BIS) in April 2010, the G-10 currencies account for 88% of global foreign exchange market average daily turnover in April 2010. The G-10 currencies include the Australian dollar (AUD), the Canadian dollar (CAD), the Swiss franc (CHF), the euro (EUR), the British

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[2] Forward rate data for the Australian dollar, New Zealand dollar, Norwegian krone and Swedish krona are unavailable before January 1985.

[3] For example, constituent currencies for the iPath Optimized Currency Carry ETN and the Powershares DB G10 Currency Harvest Fund are G-10 currencies.

pound (GBP), the Japanese yen (JPY), the Norwegian krone (NOK), the New Zealand dollar (NZD), the Swedish krona (SEK) and the U.S. dollar (USD). Similar to Ranaldo and Söderlind (2010), we connect the Deutsche mark (DEM) series (1985-1998) with the euro series (1999-2011) as a single time-series for the euro.

Carry trade strategies can be designed in many ways. Many retail investors consider only one foreign currency at a time. For example, the Japanese yen and U.S. dollar was a popular carry trade pair in the 1990s. Another example is that many Japanese retail investors seek higher returns by purchasing Uridashi bonds which are bonds denominated in a high-yielding currency and directly issued to Japanese household invetors. By contrast, currency investment funds take long and short positions in multiple currencies in order to generate profits with lower volatility and downside risks. We are interested in understanding carry trade returns available to both traditional retail carry trade investors and professional investors.

First, we construct nine series of fixed-pair carry trade profits. Each currency-pair includes the U.S. dollar and one fixed foreign currency. An investor buys this foreign currency forward if it is at a forward discount ($F_t^{ask} < S_t^{bid}$) and sells it forward if it is at a forward premium ($F_t^{bid} > S_t^{ask}$) [4]. The profit from betting one U.S. dollar or equivalent FCU on this currency-pair carry trade strategy is:

$$\begin{cases} P_{t+1} = \frac{1}{F_t^{bid}}\left(F_t^{bid} - S_{t+1}^{ask}\right) & if\ F_t^{bid} > S_t^{ask}, \\ P_{t+1} = -\frac{1}{F_t^{ask}}\left(F_t^{ask} - S_{t+1}^{bid}\right) & if\ F_t^{ask} < S_t^{bid}, \\ 0 & otherwise. \end{cases} \qquad (1)$$

Dynamic equal-weighted carry trade strategies studied in this paper are based on a simple rule utilized by many carry trade indices and employed by numerous studies (for example, Bakshi and Panayotov, 2012; Clarida, Davis and Pedersen, 2009). In particular,

[4] The ask (bid) exchange rate is the exchange rate the participant in the interdealer market can buy (sell) the currency to a currency dealer.

they closely resemble those employed by Bakshi and Panayotov (2012)[5]. Specifically, at the end of each month, an investor ranks currencies based on their realizable interest rate differentials inferred from spot and forward rates, and then takes equal-weighted short and long positions in one to three currencies for one month, without leverage. The portfolio is re-balanced every month.

Realizable interest rate differentials against the USD are inferred from the forward rate at the end of month t for delivery at the end of month $t+1$ (F_t) and the spot rate at the end of month t (S_t) after crossing the bid-ask spreads using Equation (2) :

$$idiff_t = \begin{cases} \frac{S_t^{ask}}{F_t^{bid}} - 1 & if\ F_t^{bid} > S_t^{ask} \\ \frac{S_t^{bid}}{F_t^{ask}} - 1 & if\ F_t^{ask} < S_t^{bid} \\ 0 & otherwise \end{cases} \tag{2}$$

All profits are scaled to a bet size of one U.S. dollar. The short (long) leg payoff is from betting one U.S. dollar on low-yielding (high-yielding) currencies. In strategy one, we sell (buy) forward the lowest-yielding (highest-yielding) currency among the G-10 currencies. In strategies two and three, we sell (buy) forward the two and three lowest (highest) yielding currencies, respectively. In three long/short strategies, we bet half of the U.S. dollar on each leg to maintain a total bet size of one U.S. dollar. Only currencies with negative (positive) realizable interest rate differentials against the U.S. dollar can be sold (bought) forward. When the U.S. dollar is included as one of the lowest-yielding currencies in any month, the weights are adjusted accordingly in order to maintain a total bet size of one U.S. dollar. We rebalance this equal-weighted strategy monthly, based on realizable interest rate differentials.

More specifically, considering a dynamic carry trade strategy K, where a total of K long and K short positions are included, the profit from this dynamic strategy is:

[5] We have replicated the carry trade strategy profits in Bakshi and Panayotov (2012) and obtained similar profits.

$\overline{P}_{t+1}^{K_{short}} = \frac{1}{K}\sum_{j=1}^{K} P_{t+1}^{j_{short}}$, $\overline{P}_{t+1}^{K_{long}} = \frac{1}{K}\sum_{j=1}^{K} P_{t+1}^{j_{long}}$,

and $\overline{P}_{t+1}^{K_{long/short}} = \frac{\overline{P}_{t+1}^{K_{short}} + \overline{P}_{t+1}^{K_{long}}}{2}$ $\quad , K = 1 \cdots 3$ (3)

where $\overline{P}_{t+1}^{K_{short}}$ ($\overline{P}_{t+1}^{K_{long}}$) is the profit over month $t+1$ from taking K short (long) positions in a total of K lowest-yielding (highest-yielding) currencies, or the short leg (long leg) payoff; and $\overline{P}_{t+1}^{K_{long/short}}$ is the long/short strategy profit (long/short profit), from simultaneously taking K long/short positions in the highest and lowest yielding currencies in month $t+1$.

2.2.Choice of stock market variables and currency volatility factor

Do changes in the equity prices and changes in equity volatility predict carry trade profits? Or, do carry trade profits and changes in currency volatility predict stock returns? We rely on existing studies to choose suitable variables in stock markets and currency markets in addition to carry trade profits, in order to answer these questions.

Motivated by the work by LRV (2011a), we consider stock market variables that capture the global risk as predictors for carry trade profits. We use monthly changes in average equity volatility, denoted as $\Delta\sigma_t^{equity}$, as a proxy for uncertainty in global equity markets. A country's equity volatility in month t is computed as the standard deviation of daily stock market index returns, with the average equity return volatility being the cross-sectional mean of the country volatility series in our sample. $\Delta\sigma_t^{equity}$, or change in average equity volatility, is the difference between the average equity volatility in month t and in month $t-1$. Similar to the global equity volatility measure by LRV (2011a), we also use stock returns in local currency terms to calculate volatility, so that it is a pure measure of equity volatility free of exchange rate movements.

In addition to monthly changes in average global equity volatility based on LRV(2011a), we also consider monthly percentage changes in the MSCI world price index as a predictor for carry trades.[6] When we investigate the profitability of equity market investment strategies, we use total return which includes dividends. All stock return data cover the same sample period as the exchange rate data (1985:01 to 2011:12).

Findings in Bakshi and Panayotov (2012) guide us to explore changes in average currency volatility as a predictor for the MSCI world index return. Bakshi and Panayotov (2012) show that changes in average currency volatility ($\Delta\sigma_t^{fx}$) strongly and negatively predict carry trade profits. This study focuses on cross-asset return predictability. Hence, we are interested in whether volatility changes in currency markets contain significant information about future stock returns. Following Bakshi and Panayotov (2012), for each G-10 currency included in this study, we calculate monthly volatility as the standard deviation of daily exchange rate percentage changes against the U.S. dollar over a month. The monthly currency volatility averaged across G-10 currencies is the average currency volatility. $\Delta\sigma_t^{fx}$ is the difference between average currency volatility in month t and month $t-1$.

2.3.Summary statistics

How profitable are different carry trade strategies and how do their risk profiles look like? How do carry trades compare with equity investments? How strong do carry trade profits co-move with stock market variables? Table 1 contains some basic characteristics of profits from each of the nine currency pairs and profits from nine dynamic strategies.

[Table 1 about here]

Dynamic rebalancing strategies are all profitable, with average annual profits ranging between 3.15% and 5.48% (shown on the last three rows in Table 1) and Sharpe Ratios between 0.40 and 0.54. By contrast, average annual profits from fixed-pair carry trades range widely between -0.7% and 6.3% with Sharpe Ratios between -0.07 to 0.55.

[6] Instead of using total return index, we use percentage changes in the MSCI world price index to predict carry trade profits, because the price index is more commonly reported in the news and more readily available than the total return index.

For a U.S. investor, buying high-yielding currencies forward appear to be more profitable than selling low-yielding currencies forward. The two winner currency-pairs are dollar carry trades against the New Zealand dollar and against the Australian dollar, generating average annual profits of 6.3% and 4.2%, respectively. The two loser currency-pairs are dollar carry trades against the Swiss franc and against the Japanese yen with -0.7% and -0.6% annual return, respectively. The pattern observed in fixed-pair carry trades also shows up in dynamic carry trades. The long leg of dynamic strategies generates average annual profits ranging between 5.36% and 9.31%. By contrast, the short leg on average makes losses ranging between -0.67% to -1.00% annually. Although *ex post* an investor on average encounters a small loss from shorting low-yielding currencies against the U.S. dollar, an investor does not have any *a priori* reason to believe that one should refrain from selling low-yielding currencies short. In fact, the Japanese yen and U.S. dollar carry trade was a most popular carry trade pair in the 1990s. Carry trade investors exploit opportunities presented by both low and high-yielding currencies.

Although the long leg profits appear to be more profitable than the short leg profits, both strategies have similar volatility and downside risk. For example, during the 2008 financial crisis, the Australian dollar depreciated almost 20% in a single month. In fact, the volatility of carry trade profits strongly and positively correlates with the size of interest rate components. In Figure 1, we plot the annualized standard deviation of carry trade profits from nine currency pairs as a function of average interest component of carry trade profits. The slope co-efficient is 3.10 and the R^2 is 0.79. In other words, if the average annual interest rate differential between two currencies widens by 1%, the annual carry trade profit volatility increase by 3% on average. This positive correlation demonstrates the importance of dynamically ranking currencies by interest rates, if we want to filter out noises and focus on systematic movements in carry trade profits. The mechanism of our dynamic strategies is the same as currency portfolio sorting. Profits from the three long (short) legs can be viewed as profits from sorted currency portfolios with one, two and three currencies. As we focus on the commonality of predictability between currency carry trades and equity market variables, we report cross-asset return predictability between dynamic carry trade profits and stock returns. Main results for fixed-pair carry trades are included in Appendix [ ].

[Figure 1. About here]

Like stock returns, carry trade profits are also negatively skewed. Profits from all dynamic rebalancing strategies are significantly negatively skewed, ranging from -0.97 to -0.36.

How much do exchange rate movements contribute to carry trade profits? Interest components are universally positive by construction, but not the currency components. The long-leg of carry trades has experienced desirable currency movements on average, ranging from 2.44% to 5.07% annually and comparable to the interest components. By contrast, appreciations of low-yielding currencies have resulted in negative currency components ranging between -2.36% and -3.49% annually, which make short leg strategies unprofitable.

Variations in carry trade profits are primarily driven by exchange rate movements because time series auto-correlations in carry trade profits are almost identical to those in their currency components, with first-order auto-correlation varying between -0.01 and 0.12. Interest components of all carry trades are highly persistent with highly significantly positive first order auto-correlation ranging from 0.51 to 0.85.

Because carry trade is a zero-investment strategy, we compare its returns with the excess return from buy-and-hold an equity index portfolio. As carry traders are exposed to global risk, we choose benchmark equity return to be the excess return from buy-and-hold the MSCI world total return index[7]. If a U.S. investor simply buys and holds the MSCI world index portfolio, he realizes an average annual excess return of 6.46% and an annualized volatility of 16.3%. Both returns and volatility from this world portfolio are higher than those from all three long/short dynamic carry trade strategies. As a result, the Sharpe-ratio from buy-and-hold the MSCI world index is 0.40, at the low-end of the range from long/short dynamic carry trade strategies (0.40-0.54).

2.3.1. Cross-correlation and serial-correlation

When the world equity index drops, the U.S. dollar tends to appreciate against all currencies contemporaneously. The effect on high-yielding currencies is stronger with positive correlations ranging between 0.41 and 0.43 (Tab D of Table 1). The U.S. dollar also appreciates against the low-yielding currencies when the world equity index rises, but less than against the high-yielding currencies, as evidence in a smaller size correlation between -

[7] MSCI developed world total return index.

0.13 to -0.23[8]. Like the world equity return, changes in equity volatility also exhibit stronger contemporaneous effects on high-yielding currencies than on low-yielding currencies (Tab D of Table 2).

Long/short carry trade profits and long leg profits series are slightly positively auto-correlated, with first order autocorrelations significant in three out of nine profits. The autocorrelation tends, however, to be small; ranging between 0.08 and 0.12. Changes in equity volatility and changes in currency volatility tend to reverse in the following month and have a significant first-order autocorrelation of -0.24 and -0.12, respectively. The world equity index series has statistically significant autocorrelation of 0.11. These variables are not highly persistent. In addition, we explicitly control for autocorrelation in the dependent variables in the remainder of this paper and the Durbin-Watson statistics show no evidence for autocorrelation in the disturbance from all predictive regressions. Hence, all our results in the remainder of this paper are based on White standard errors.

3. Cross-asset predictability between dynamic carry trades and stocks

3.1. Predicting dynamic carry trade profits in-sample

This section examines the in-sample predictability of dynamic carry trades from global stock market variables by running the regressions specified in Equation (4):

$$\overline{P}_t^{k_j} = \alpha + \beta_1 \, Z_{t-i} + \beta_2 \, \overline{P}_{t-1}^{k_j} + \mu_t$$

$$(i = 1 \cdots 3, k = 1 \cdots 3, \; j = short, long), \qquad (4)$$

where and $\overline{P}_t^{k_{short}}$ ($\overline{P}_t^{k_{long}}$) is the profit from selling (buying) K low-yielding currencies forward. Z_{t-i} is a single predictor which include the MSCI world equity price index return and changes in equity volatility, in each of the three previous months (as described in section 2.2).

[8] Contemporaneously, the U.S. dollar tends to appreciate against all currencies when the world equity index drops. The U.S. dollar appreciation against the low-yielding currencies (or, the low-yielding currency depreciation against the U.S. dollar) results in an increase to carry trade profit. Hence, the world equity index return and profit from shorting low-yielding currencies are negatively correlated.

[Table 2 about here]

Table 2 presents the estimation results for Equation (4). The results in Table 2 show that both the MSCI world index return and changes in equity volatility predict carry trade profits:

(1) r_{t-2}^{world} predicts all short leg carry trade profits in month t, with p-values below 0.05. Equally interesting, neither r_{t-1}^{world}, r_{t-2}^{world}, r_{t-3}^{world} predicts profits from the long leg in month t.

(2) The predictive effects from $\Delta\sigma_{t-i}^{equity}$ show up two months later in short-leg profits and three months later in long-leg profits. For short leg profits, all three slope estimates on $\Delta\sigma_{t-2}^{equity}$ have p-values below 0.05, but other lagged monthly volatility changes do not predict short leg profits. Similarly, for long leg profits, all three slope estimates on $\Delta\sigma_{t-3}^{equity}$ have p-values below 0.05, but other lagged monthly volatility changes do not predict long leg profits. It appears that two types of currencies react to changes in identical variables after different lengths of delay.

This result is consistent with the intuition that the broad equity market return serves as a barometer for currency markets. If we are willing to assume that currency investors demand low-risk assets in a "bad" market and risky assets in a "good" market, rises and drops in the world equity index (increases and decreases in equity volatility) may have different effects on high-yielding and low-yielding currencies. We test for the symmetry in this predictive relation using a regression specified in equation (5).

$$\overline{P}_t^{k_j} = \alpha + \beta^{LR} D_{t-i}^{LR} Z_{t-i} + \beta^{HR} D_{t-i}^{HR} Z_{t-i} + \gamma \overline{P}_{t-1}^{k_j} + \mu_t$$

$$(i = 1 \cdots 3, k = 1 \cdots 3,\ j = short, long), \tag{5}$$

where and $\overline{P}_t^{k_{short}}$ ($\overline{P}_t^{k_{long}}$) is the profit from selling (buying) K low-yielding currencies forward. Z_{t-i} is a single predictor similar to equation (4). D_{t-i}^{LR} takes the value of 1 in a low-risk state, when $r_{t-i}^{world} > 0$ ($\Delta\delta_{t-i}^{equity} < 0$), and the value of 0 otherwise. D_{t-i}^{HR} takes the value of 1 in a high-risk state, when $r_{t-i}^{world} < 0$ ($\Delta\delta_{t-i}^{equity} > 0$), and the value of 0 otherwise. We conduct the Wald test against the null that $\beta^{LR} - \beta^{HR}$ equals zero and report the p-

Values for rejecting the null. A p-Value below 0.1 suggests that drops and rises in the equity index (increases and decreases in equity volatility) mean different things for carry traders. Table 3 reports the estimation results.

[Table 3 about here]

The results in Table 3 suggest that the world equity return effect is asymmetric, while the equity volatility effect is symmetric. The world equity index return effect is asymmetric on future carry trade profits from low-yielding currencies, and to a lesser extent, on future profits from investing in high-yielding currencies. For the short leg payoff, Wald tests strongly reject the null hypothesis of symmetric effect with p-values below 0.05. For the long leg payoff, Wald tests reject the symmetric effect null with p-values of 0.03, 0.10 and 0.11.

Drops in the world equity index significantly predicts decreases in profits of all short leg carry trades in two months later, with p-values below 0.01. However, rises in world equity index do not significantly predict carry trade profits from low-yielding currencies. This result suggests that, following drops in the world equity index, low-yielding currencies tend to appreciate against the U.S. dollar and result in decreases in profits of shorting low-yielding currencies.

In regression (3), we aggregate the "bad" market and "good" market states, and the results suggest that the world equity index return does not predict profits from investing in high-yielding currencies. Once we separate these two states of equity market, we find that world equity index rises significantly predict increases in profits of all dynamic long strategies two months later, with p-values between 0.03 to 0.10. However, drops in world equity index do not significantly predict carry trade profits from high-yielding currencies.

By contrast, the equity volatility effect on future carry trade profits appears to be symmetric. Monthly changes in equity volatility negatively predict all three short leg carry trade profits two months later, regardless of the direction of volatility changes. Wald tests against the symmetric effect cannot reject the null hypothesis at a reasonable significance level (all six p-values are above 0.7).

The signs of the slope estimates all make economic sense. First, for the short leg payoff, the slope estimates on r_{t-2}^{world} are all positive in Table 2 and 3. This result is consistent with the intuition that after worldwide stock price drops investors demand more low-risk assets denoted in low-yielding currencies. Second, slope estimates for $\Delta\sigma_{t-2}^{equity}$ and $\Delta\sigma_{t-3}^{equity}$ are uniformly negative. Increases (decreases) in the level of average global equity volatility predict drops (rises) in profits of dynamic short carry trade strategies two months later, as well as drops (rises) in profits of dynamic long carry trade strategies three months later.

The magnitude of predictive coefficients is of economic significance. For example, an increase of one standard deviation of r_{t-2}^{world} (4.59) and $\Delta\sigma_{t-2}^{equity}$(0.44) can lead to an annualized change of 5.35% and -7.94% in $\overline{P}_t^{3_{short}}$ (the payoff from shorting three low-yielding currencies), respectively. In standard deviation terms, these annualized changes in short leg carry trade profits are 0.60 and -0.90.

When we use one predictor in month $t-2$ $(t-3)$ to predict carry trade profits from dynamic short (long) strategies in month t, the adjusted R^2s range between 2.6% and 6.1% (1.4% and 1.7%). The goodness-of-fit statistics appear to be comparable to those reported for predictability in carry trade profits (for example, Bakshi and Panayotov, 2012, Tables 2 and 3; Adrian, Etula and Shin, 2009, Tables 1 and 2).

Does the world equity index return or changes in equity volatility still significantly predict carry trade profits at the presence the other predictor? We test the marginal effect by including two predictors at a time in the model specified in Equation (4) and Equation (5). We present the results in Table 4. When we aggregate "bad" and "good" states (using Equation (4)), changes in equity volatility subsume the predictive power of the world equity index return. By contrast, once we separate these two states, both the mean effect and volatility effect are robust to the other predictor. This result suggests that the world equity index return and changes in volatility contain different information. It also demonstrates the relevance of state-switching return predictability, as articulated by Jacobsen, Marshall and Visaltanachoti (2011).

[Table 4 about here]

Is the discussed predictability a result of predictability in the currency movements or interest component? We replace the forward rate with currency spot rate in Equation (1) to obtain the currency component of the carry trade profit, and run regressions specified in Equation (4). Estimation results for predicting the currency components are reported in

Appendix [ ]. Slope estimates in Appendix [ ] remain almost identical to those in Table 2. Hence, predictability in carry trade profits is from their currency components.

3.2. Predicting dynamic carry trades: rolling window regression

Full-sample regressions show that carry trade profits from both the short leg and long leg are predictable by stock market variables. Drops but not increases in the world equity index significantly predict the short leg profits. Increases but not drops in the world equity index significantly predict the long leg profits. An important question to ask is how the discussed predictive effects change over time. For those significant in-sample predictive relations, we run 10-year rolling window regressions using Equation (4) and Equation (5) and plot the slope estimates over time in Figure 2. Predictability of the short leg profit appears to be stable over time: The slope estimates of the world equity index lagged by two months and the slope estimates of changes in equity volatility lagged by two months do not swing between positive and negative territories (chart a. and b. in Figure 2). By contrast, the predictability of the long leg profits from changes in equity volatility is not stable – the slope estimates have spent long periods in both the positive and negative territories (chart c in Figure 2). Now, we focus on the predictive effect during "bad" markets: drops in the world equity index consistently predict drops in the short leg carry trade profits (chart d of Figure 2). Turning to the predictive effect during "good" markets, we can see that the predictive power of rises in the world equity index for long leg profits does not exist from 2000 to 2009. Results from rolling window regressions suggest that predictive effects on the short leg profits are more stable than those on the long leg profits.

[Figure 2 about here]

3.3. Predicting dynamic carry trades: out-of-sample tests and economic significance

Could an investor have used our stock market variables to deliver better prediction of carry trade profits than simply using historical means? In order to answer this question, we rely on out-of-sample (OoS) R^2 statistics as in Goyal and Welch (2008). The $OoS\ R^2$ is computed as follows:

$$OoS\ R^2 = 1 - \frac{MSE(prediction\ model)}{MSE(benchmark\ model)} = 1 - \frac{\sum_{j=1}^{n}(\widehat{\mu_t} - \overline{P}_t\ )^2}{\sum_{j=1}^{n}(\mu_t - \overline{P}_t\ )^2} \qquad (6)$$

where $\widehat{\mu_t}$ is the predicated carry trade profits in month t and μ_t is the historical average payoff. $\overline{P}_t$ is the realized carry trade profits in month t. A positive $OoS\ R^2$ indicates that the prediction model generates a lower mean-squared prediction error than that from the prediction based on historical means, or from outperforming the benchmark model.

Further, if there is outperformance, is it statistically significant? A test for significance of forecast improvement is conducted using an adjusted mean-squared prediction error statistic (MSPE-adjusted) developed by Clark and West (2007). The MSPE-adjusted one-sided p-values are obtained by regressing $f_t = (\overline{P}_t - \mu_t)^2 - [\left(\overline{P}_t - \widehat{\mu_t}\right)^2 - (\mu_t - \widehat{\mu_t})^2]$ on a constant. The null hypothesis is that there is no significant improvement in prediction. Thus, a lower p-value indicates higher significance of outperformance.

An investor could have used the model specified in Equation (4) or Equation (5) and observations available prior to month t to predict carry trade profits in month t ($\widehat{\mu_t}$). Alternatively, he could simply use the average of carry trade profits prior to month t as a prediction (μ_t). We assume that this investor uses observations in the first 180 months of the sample to make the first prediction. Next, the prediction model is re-estimated every month using all historical observations to predict the one-month-ahead carry trade payoff. We then compute $OoS\ R^2$'s and MSPE-adjusted one-sided p-values to evaluate the model predictions against the historical means. Each predicted series run from 2000:02 to 2011:12 with a total of 142 observations.

[Table 5 –about here]

Table 5 presents the $OoS\ R^2$ and corresponding MSPE-adjusted one-sided p-values obtained using model specified in Equation (4). The out-of-sample results are consistent with the in-sample results. Both the world equity index return lagged by two months and changes in equity volatility lagged by two month have good out-of-sample performance. Using any of these two variables to predict profits from shorting low-yielding currencies, we can generate $OoS\ R^2$ ranging between 3.53% and 8.42%. These $OoS\ R^2$s are comparable to those reported for carry trade predictability by Bakshi and Payayotov (2012) and they tend to be higher than those reported for the equity market (for instance, in Goyal and Welch, 2008; Campbell and Thompson, 2008; Rapach, Strauss and Zhou, 2012). Similar to the in-sample results, predictability of the long leg profits from stock market variables is weak out-of-sample. Changes in equity volatility lagged by three months predict carry trade profits from dynamic long strategies with small positive $OoS\ R^2$'s ranging between 1.45% and 1.88%.

Turning to the MSPE-adjusted one-sided $\boldsymbol{p}$-values, the MSCI world index return lagged by two months and changes in equity volatility lagged by two months also strongly predict profits from shorting low-yielding currencies out-of-sample, as evident in that all six p-values are below 0.1 in Table 5. Changes in equity volatility three months ago also predict profits from dynamic long strategies, with p-values ranging between 0.01 and 0.04.

Prediction models conditioned on the sign of predictors (MSCI world index return or changes in equity volatility as specified in Equation (5)) do not generate better out-of-sample prediction than an unconditional model. The results are reported in Appendix [ ].

Could an investor have used the predictability low- and high-yielding currencies from stock market variables to improve his profits from dynamic carry trades? The impact of one standard deviation change in the predictors has been considered already. Here, we compare trading outcomes of market-timing strategies based on predictions from model (4) with simple carry trade strategies, where one always takes a position in carry trades. In a market-timing strategy, the trading decision is based on one-step-ahead prediction of carry trade profits. An investor goes ahead with a carry trade if the predicted payoff is positive; otherwise, he refrains from a carry trade. This decision rule is applied to each leg of carry trade. The related outcomes are reported Table 6.

[Table 6 about here]

For low-yielding currencies, we see noticeable improvements in the mean, the Sharpe-ratios and skewness across the board, if we make trading decisions based on predicted profits from r_{t-2}^{world} or from $\Delta\sigma_{t-2}^{equity}$. Mean profits from market-timing strategies conditioned on r_{t-2}^{world} ($\Delta\sigma_{t-2}^{equity}$) range between 1.14% and 1.66% (-0.10% and 1.00%) per annum and skewness ranges between 0.21 and 0.31 (0.10 and 0.20). These ranges are higher than comparable statistics for the unconditional profits from the short leg, which have average annual profits ranging between -2.12% and -1.60%, and skewness ranging between -1.01 and -0.31. Equally important, models using r_{t-2}^{world} or $\Delta\sigma_{t-2}^{equity}$ also generate 61 to 75 no-trade signals in 142 months, which further strengthen the evidence for their predictive ability. For high-yielding currencies, none of the market-timing strategies generate profits with noticeable improved mean, Sharpe-ratios or skewness. $\Delta\sigma_{t-\mathbf{3}}^{equity}$ generates merely three to four trading signals during the 142 months. Hence, the evidence for out-of-sample predictability in long leg profits, from equity market variables, is weak.

3.4. Predicting the world equity index return in-sample

Does the predictability only go one way from equity markets to currency markets? This question is motivated by Chen and Rogoff (2002), who document that commodity prices have strong effects on commodity currencies. Chen, Rogoff and Rossi (2010) further show that commodity currencies predict commodity prices. High-yielding currencies in our dynamic carry trades tend to be commodity currencies including the Australian dollar, the New Zealand dollar and the Norwegian krone. If high-yielding currencies contain information of commodity prices, profits from investing in high-yielding currencies may predict stock returns. In addition, we also investigate whether changes in currency volatility predict stock returns. We test whether these currency market variables predict world equity index by running the follow regression:

$$rx_{t}^{world} = \alpha + \beta_1 \, Z_{t-i} + \beta_2 \, rx_{t-1}^{world} + \mu_t$$

$$(i = 1 \cdots 3, k = 1 \cdots 3), \qquad (7)$$

where rx_t^{world} is the MSCI world index total return in excess of the risk free rate[9] and Z_{t-i} is a single predictor which include profits from three short leg strategies, profits from three long leg strategies and changes in currency volatility (as described in section 2.2), in each of the three previous months. Estimation results are reported in Table 7. Long leg carry trade profits from all three strategies ($\overline{P}_{t-3}^{k_{long}}$) significantly positively predict excess equity returns (rx_{t}^{world}) three months later. However, the magnitude of predictive coefficients is of marginal economic significance. For example, a change of one annualized standard deviation of $\overline{P}_{t-3}^{3_{long}}$, or profits from investing in the three highest-yielding currencies, is 9.98%. It can lead to an annualized change of 2.47% in the MSCI world index return (0.15 standard deviation). By contrast, stock market variables exhibit stronger predictive power for carry trade profits. Analysis in section 3.1 shows that a one standard deviation changes in either r_{t-2}^{world} or $\Delta\sigma_{t-2}^{equity}$ lead to half to one standard deviation change in carry trade payoffs.

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[9] We use the U.S. risk free rates downloaded from French Kenneth data library.

Turing from currency returns to currency volatility: change in currency volatility does not predict movements in the world equity index in any of the three following months.

3.5. Predicting the world equity index return: rolling-window analysis

We take the same approach as in section 3.2 in examining whether the long leg carry trade profits has positively predict the world equity index movements over our sample. It turns out this predictive effect in the world equity return from high-yielding currencies has drastically increased and stayed strong since the 2008 financial crisis (Figure 3).

[Figure 3 about here]

3.6. Predicting the world equity index return: out-of-sample tests and economic significance

Rolling-window analysis show that the predictive ability of long leg profits from three strategies ($\overline{P}_{t-3}^{k_{long}}$) is sample specific. Out-of-sample tests further confirmed that the predictability in carry trades from stock market variables is weak.

To be consistent with the analysis in section 3.3, we use $OoS\ R^2$ statistics and MSPE-adjusted one-sided p-values to gather out-of-sample evidence. We use an initial window size of 180 months (identical to that in section 3.3) and estimate regression specified in Equation (7) recursively. We also construct profits of market-timing strategies, which make trading decisions based on predicted excess stock returns from long leg carry trade profits three months ago ($\overline{P}_{t-3}^{k_{long}}$). If the predicted excess return is positive, the investor holds the world equity index and earns the total return of the MSCI world equity portfolio in excess of the risk free rate; otherwise he invests in risk-free assets and earns zero excess return.

These statistics for the out-of-sample performance and economic significance are reported in Table 8.

[Table 8 about here]

A model that uses long leg carry trade profits ($\overline{P}_{t-3}^{k_{long}}$) to predict the world equity index return outperforms historical mean by 1.02% to 1.86%. This outperformance is marginal with p-values between 0.08 and 0.21 (Tab B of Table 8). Turning to the trading outcomes (Tab B of Table 8), we see that if an investor makes trading decisions based on predicted excess equity return from past long leg carry trade profits, he makes an average annual excess return between 2.19% to 2.25%. This return is unimpressive by itself but it still compares favourably to the abysmal average return of 0.63% per annum. However, this improvement in mean return is driven by a few trading signal generated during the 2008 financial crises. These prediction models generate merely six to eight trading signals during the 142 prediction months.

4. Conclusion

We find that both the mean return and changes in volatility in the global equity market are able to predict carry trade profits from low-yielding currencies. These equity market variables do not strongly predict carry trade profits from high-yielding currencies. Instead, since the 2008 financial crisis, profits from investing in high-yielding currencies predict return of the world equity index. These findings indicate that low-yielding currencies incorporate information contained in equity market only with a lag, which may be a result of gradual information diffusion across markets (Hong, Torous and Valkanov, 2007).

Drops but not rises in the world equity index appear to serve as a barometer for exchange rates of low-yielding currencies. If the world equity index drops in a month, low-yielding currencies tend to appreciate against the U.S. dollar in the two following months, resulting in decreases in carry trade profits from selling low-yielding currencies forward.

It is puzzling that stock markets appear to be more informationally efficient than curreny markets, given that the size and liquidity of currency markets dwarf equity markets. However, if we are willing to assume that FX traders are exposed to a smaller information set than stock market investors, gradual information diffusion provides a possible explanation for this effect.

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Figure 1 Standard deviation and interest components of carry trade profits

We plot standard deviation annualized standard deviation as a function of average interest components of fixed-pair carry trade payoffs between nine currencies and the U.S. dollar. Carry trade payoffs are computed as in Equation (1). Sample period runs from 1985:01 to 2011:12.

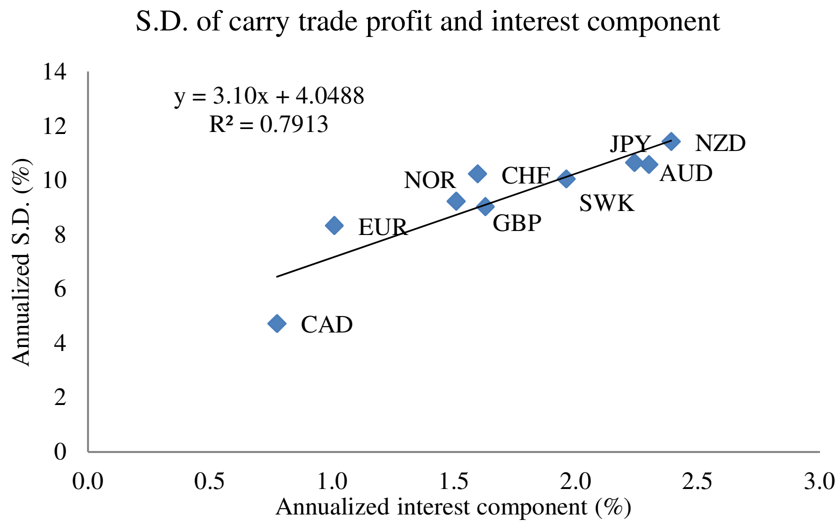
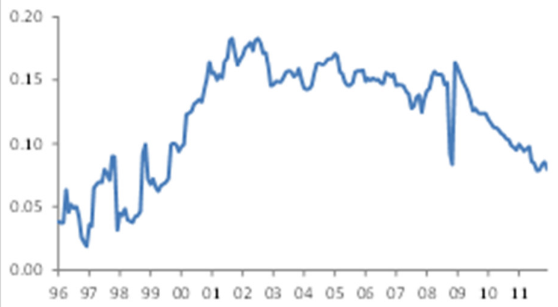


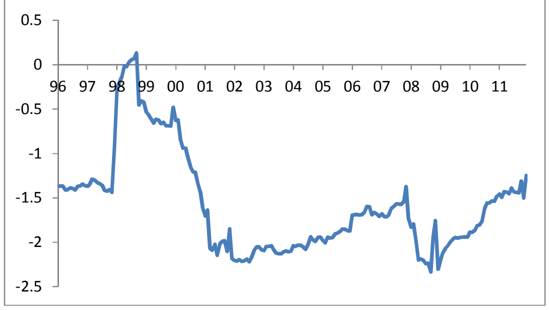
Figure 2 Rolling window regressions: predicting carry trade profits

We plot slope estimates from rolling predictive regressions as specified in Equation (4) and (5) across time. Sample period runs from 1985:01 to 2011:12.

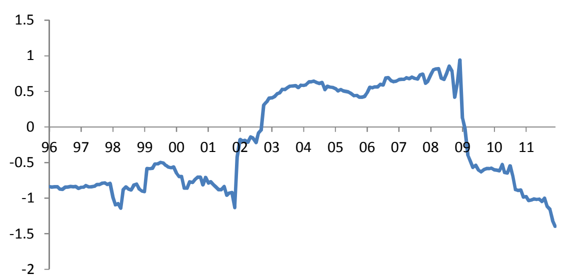
a. predicting the short leg profit (strategy 3) : slope estimates on rworld(-2)



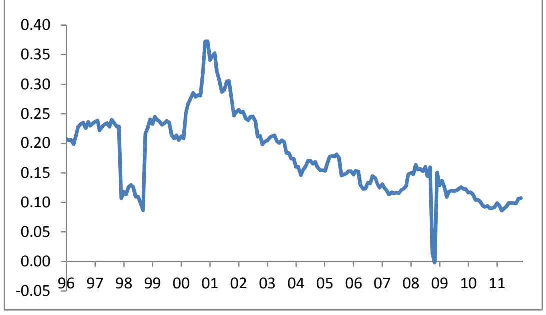
b. predicint the short leg profit (strategy 3): slope estimates on chg. in equity vol. (-2)



c. predicting the long leg profit (strategy 3): slope estimates on chg. in equity vol(-3)



d. predicting short leg profit (strategy 3): slope estimates on rworld(-2)*D^{HR}(-2)



c. predicting the long leg profit (strategy 3): slope estimates on chg. in equity vol(-3)

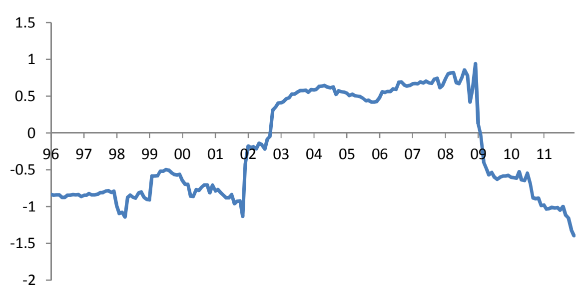
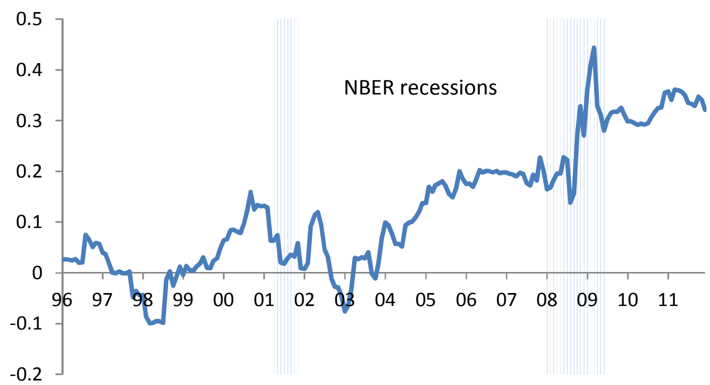


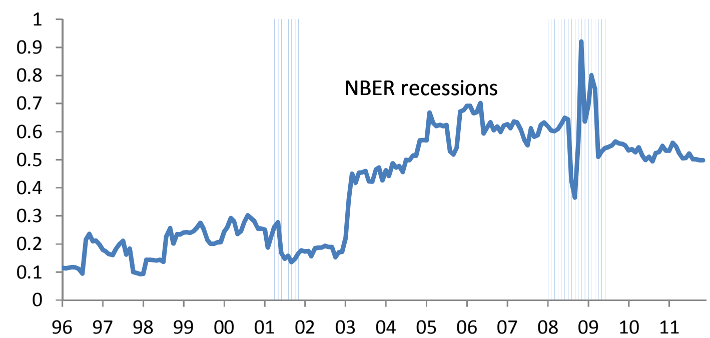
Figure 3 Rolling window regressions: predicting the world equity index return

We plot slope estimates from rolling predictive regressions as specified in Equation (6) and (7) across time. Sample period runs from 1985:01 to 2011:12.

a. slope estimates on $P^{long3}(-3)$



b. slope estimates on $P^{longt3}(-3)$*$D^{HR}(-3)$



c. slope estimates on $P^{longt3}(-1)$*$D^{HR}(-1)$

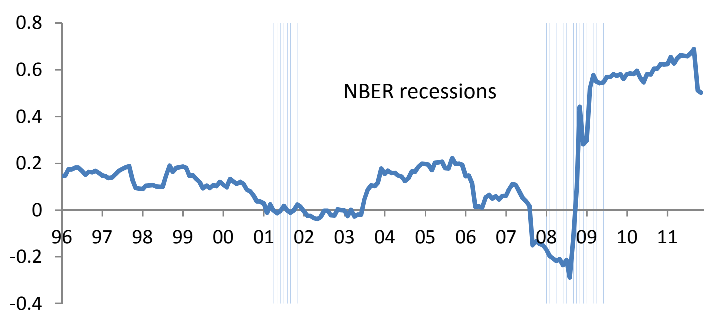


Table 1. Summary statistics

This table reports the summary statistics of carry trade profits from betting one U.S. dollar. Profits from fixed-pair carry trades (Equation (1)) are reported in Tab A. Tab B report the summary statistics of profits from betting one U.S. dollar on three long/short dynamic strategies, three dynamic strategies on the short leg and three dynamic strategies on the long leg (Equation (3)) . Tab C reports cross correlation between the long leg profit and the short leg profit. Tab D reports summary statistics for the equity market variables. Sample period runs from January 1985 to December 2011. All payoffs are denominated in USD and from a bet size of one dollar. Bold fonts indicate significance at 10%, against each of two nulls: (1)) the distribution is not skewed; and (3) there is insignificant first-order auto-correlation. Skewness tests are based on the non-normality tests in D'agostino et al. (1990).

		Carry trade					Interest component		Curreny component	
		Mean	S.D.	Sharpe Ratio	skewness	rho(-1)	mean	rho(-1)	mean	rho(-1)
A. Curreny-pair strategy			annual		monthly		annual	monthly	annual	monthly
EUR		2.35	8.33	0.28	0.00	**0.10**	1.01	**0.47**	1.34	**0.10**
GBP		3.84	9.03	0.43	**0.25**	0.06	1.63	**0.84**	2.21	0.05
JPY		-0.64	10.65	-0.06	**-0.84**	0.05	2.24	**0.70**	-2.88	0.05
CHF		-0.70	10.23	-0.07	**-0.68**	0.01	1.60	**0.51**	-2.30	0.00
CAD		1.50	4.72	0.32	**1.50**	0.03	0.78	**0.55**	0.73	0.03
AUD		4.18	10.58	0.39	**-0.87**	0.04	2.30	**0.85**	1.88	0.04
NZD		6.34	11.42	0.55	-0.18	0.00	2.39	**0.68**	3.94	-0.02
SEK		2.51	10.04	0.25	**-0.56**	0.08	1.96	**0.48**	0.55	0.07
NOK		3.42	9.22	0.37	**-0.74**	**0.12**	1.51	**0.54**	1.91	**0.12**
EW		2.53	4.54	0.56	**-0.81**	**0.21**	1.71	**0.70**	0.82	**0.21**
B. Multi-currency strategies										
Short										
	1	-1.00	10.93	-0.09	**-0.95**	-0.01	2.49	**0.60**	-3.49	-0.01
	2	-0.46	9.41	-0.05	**-0.46**	0.01	1.97	**0.66**	-2.42	0.01
	3	-0.67	9.17	-0.07	**-0.41**	0.01	1.68	**0.66**	-2.36	0.01
Long										
	1	9.31	12.56	0.74	**-0.56**	**0.10**	4.24	**0.56**	5.07	0.08
	2	7.17	10.99	0.65	**-0.36**	0.09	3.43	**0.70**	3.74	0.08
	3	5.36	9.98	0.54	**-0.46**	**0.10**	2.92	**0.67**	2.44	**0.09**
Long/short										
	1	5.48	10.19	0.54	**-0.97**	**0.11**	4.07	**0.53**	1.42	**0.12**
	2	4.39	8.48	0.52	**-0.39**	0.08	3.17	**0.65**	1.22	0.09
	3	3.15	7.79	0.40	**-0.38**	**0.10**	2.71	**0.66**	0.44	**0.11**

C.		correl(short, long)
	1	-0.24
	2	-0.33
	3	-0.36

D. equity returns and changes in average equity volatility						
MSCI total index excess return	6.46	16.34		0.40	-0.59	0.06
MSCI price index return	7.20	15.91		0.45	-0.64	**0.11**
Chg. In avg. equity volatlity	4.70E-05	0.443	n.a.		2.08	**-0.24**

Table 2. Predicting carry trade payoff in-sample with a single predictor

This table reports the coefficient estimates from regressions $\overline{P}_t^{k_j} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\, \boldsymbol{Z_{t-i}} + \boldsymbol{\beta_2}\, \overline{P}_{t-1}^{k_j} + \boldsymbol{\mu_t}$ $(i = 1 \cdots 3, k = 1 \cdots 3,\ j = short, long, long/short)$, where $\boldsymbol{Z_{t-i}}$ is a single predictor. The monthly profit from long/short positions carry trade strategy k is $\overline{P}_{t+1}^{K_{long/short}} = \frac{\overline{P}_{t+1}^{short_k} + \overline{P}_{t+1}^{long_k}}{2}$, where $\overline{P}_t^{long_K}$ ($\overline{P}_t^{short_K}$) is the profits from long (short) positions established at the end of month $t-1$ in a total of k highest (lowest) yielding currencies among the G-10 currencies, to a U.S. investor. Details of the carry trade strategies can be found in the main text.

The individual predictors for the carry trade profits are $\Delta\sigma_{t-i}^{equity}$ and r_{t-i}^{world}.

The estimates for predictive coefficient β_1 are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 10% or better significance level are bolded. The sample period runs from January 1985 to December 2011.

		month $t-1$			month $t-2$			month $t-3$		
	Strategy	β_1	p	$\bar{R}^2$	β_1	p	$\bar{R}^2$	β_1	p	$\bar{R}^2$
Tab A. Predicting short leg payoffs										
world equity	1	0.07	0.11	0.3%	0.12	**0.03**	2.7%	0.00	0.94	-0.6%
index return, $\boldsymbol{r_{t-i}^{world}}$	2	0.04	0.21	-0.1%	0.10	**0.01**	2.3%	-0.02	0.54	-0.5%
	3	0.04	0.26	-0.2%	0.10	**0.02**	2.3%	-0.03	0.48	-0.4%
chg. in equity	1	0.05	0.93	-0.6%	-1.61	**0.00**	4.7%	0.48	0.40	-0.2%
volatility, $\Delta\sigma_{t-i}^{equity}$	2	0.29	0.56	-0.4%	-1.44	**0.00**	5.0%	0.62	0.19	0.4%
	3	0.27	0.59	-0.4%	-1.49	**0.00**	5.8%	0.62	0.19	0.5%
Tab B. Predicting long leg payoffs										
world equity	1	0.02	0.69	-0.2%	0.02	0.63	-0.2%	0.01	0.92	-0.3%
index return, $\boldsymbol{r_{t-i}^{world}}$	2	0.01	0.86	-0.3%	0.03	0.44	-0.1%	0.01	0.85	-0.3%
	3	0.00	0.96	-0.3%	0.02	0.55	-0.3%	0.01	0.85	-0.3%
chg. in equity	1	-0.35	0.55	0.0%	0.75	0.10	0.7%	-1.11	**0.03**	1.7%
volatility,	2	-0.22	0.73	0.9%	0.50	0.20	1.2%	-1.03	**0.02**	2.9%
$\Delta\sigma_{t-i}^{equity}$	3	-0.27	0.66	1.3%	0.57	0.11	1.9%	-0.92	**0.01**	3.1%

Table 3. Predicting carry trade payoff in-sample: include asymmetric effects

This table reports the coefficient estimates from regressions

$$\overline{P}_t^{k_j} = \alpha + \beta^{LR} D^{LR}_{t-i} Z_{t-i} + \beta^{HR} D^{HR}_{t-i} Z_{t-i} + \gamma \overline{P}^{k_j}_{t-1} + \mu_t \quad (i = 1 \cdots 3, k = 1 \cdots 3,\ j = short, long), \textbf{(5)}$$

where and $\overline{P}_t^{k_{short}}$ ($\overline{P}_t^{k_{long}}$) is the profit from selling (buying) K low-yielding currencies forward. Z_{t-i} is a single predictor similar to equation (4). D^{LR}_{t-i} takes the value of 1 in a low-risk state, when $r^{world}_{t-i} > 0$ ($\Delta\delta^{equity}_{t-i} < 0$), and the value of 0 otherwise. D^{HR}_{t-i} takes the value of 1 in a high-risk state, when $r^{world}_{t-i} < 0$ ($\Delta\delta^{equity}_{t-i} > 0$), and the value of 0 otherwise. We conduct the Wald test against the null that $\beta^{LR} - \beta^{HR}$ equals zero and report the p-Values for rejecting the null.

Details of the carry trade strategies can be found in the main text. The individual predictors for the carry trade profits are $\Delta\sigma^{equity}_{t-i}$ and r^{world}_{t-i}.

The estimates for predictive coefficient β_1 are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 10% or better significance level are bolded. The sample period runs from January 1985 to December 2011.

	b1_LR	p1_LR	b1_HR	p1_HR	adj. R2	wald	b2_LR	p2_LR	b2_HR	p2_HR	adj. R2	wald	b3_LR	p3_LR	b3_HR	p3_HR	adj. R2	wald
rworld																		
short1	0.07	0.36	0.06	0.41	0.3%	0.98	-0.08	0.35	0.30	**0.01**	6.0%	**0.02**	0.03	0.73	-0.02	0.81	-0.6%	0.75
short2	0.08	0.25	0.01	0.87	0.0%	0.54	-0.03	0.70	0.22	**0.00**	4.1%	**0.05**	0.00	0.94	-0.04	0.60	-0.5%	0.70
short3	0.07	0.28	0.01	0.93	-0.1%	0.54	-0.03	0.64	0.22	**0.00**	4.3%	**0.05**	0.00	0.96	-0.05	0.56	-0.4%	0.68
long1	0.08	0.39	-0.03	0.77	-0.3%	0.51	0.19	**0.03**	-0.12	0.14	1.1%	**0.03**	-0.04	0.60	0.05	0.71	-0.5%	0.63
long2	0.09	0.30	-0.06	0.55	-0.1%	0.35	0.13	**0.08**	-0.06	0.38	0.4%	0.11	-0.01	0.88	0.03	0.82	-0.6%	0.82
long3	0.07	0.36	-0.06	0.58	-0.2%	0.41	0.12	**0.10**	-0.08	0.27	0.5%	**0.10**	-0.01	0.93	0.02	0.82	-0.6%	0.85
e_vol																		
short1	1.31	0.27	-0.67	0.28	0.5%	0.18	-1.41	**0.05**	-1.72	**0.02**	4.7%	0.79	-0.51	0.32	0.96	0.24	0.4%	0.18
short2	1.21	0.21	-0.24	0.68	0.4%	0.25	-1.54	**0.02**	-1.36	**0.01**	5.0%	0.85	-0.45	0.31	1.14	**0.08**	1.2%	**0.08**
short3	1.28	0.20	-0.31	0.59	0.6%	0.22	-1.50	**0.03**	-1.48	**0.00**	5.8%	0.98	-0.53	0.23	1.17	**0.07**	1.5%	**0.06**
long1	0.14	0.89	-0.75	0.42	-0.2%	0.56	1.00	0.27	0.55	0.36	0.2%	0.71	-0.91	0.29	-1.14	0.13	1.1%	0.85
long2	-0.14	0.87	-0.46	0.68	-0.4%	0.84	0.39	0.64	0.50	0.30	-0.2%	0.92	-0.96	0.22	-0.98	0.12	1.4%	0.99
long3	-0.49	0.50	-0.34	0.76	-0.3%	0.92	0.38	0.56	0.59	0.21	0.0%	0.80	-1.01	0.16	-0.76	0.11	1.2%	0.78

Table 4. Predicting carry trade payoff in-sample using two predictors

	rworld1	p1	e_vol1	p1	adj r2	rworld2	p2	e_vol2	p2	adj r2	rworld3	p3	e_vol3	p3	adj r2
short1	0.08	**0.09**	0.38	0.55	0.5%	0.07	0.16	-1.30	**0.00**	5.7%	0.02	0.64	0.50	0.33	-0.2%
short2	0.06	0.10	0.55	0.31	0.5%	0.05	0.18	-1.21	**0.00**	5.6%	0.00	0.98	0.56	0.20	0.2%
short3	0.06	0.14	0.50	0.37	0.4%	0.05	0.22	-1.29	**0.00**	6.4%	0.00	0.92	0.54	0.22	0.3%
long1	0.01	0.90	-0.39	0.53	-0.4%	0.06	0.28	0.97	**0.08**	0.7%	-0.04	0.42	-1.23	**0.01**	1.4%
long2	-0.01	0.92	-0.36	0.58	-0.4%	0.06	0.28	0.69	0.17	0.4%	-0.03	0.46	-1.12	**0.01**	1.6%
long3	-0.02	0.74	-0.46	0.48	-0.2%	0.04	0.36	0.69	0.11	0.4%	-0.03	0.44	-0.98	**0.01**	1.4%

strategy	rworld2_ LR	p	e_vol2 _LR	p	rworld2 _HR	p	e_vol 2_HR	p	adj R2	rworld3_ LR	p	e_vol3 _LR	p	rworld3_ HR	p	e_vol3 _HR	p	adj R2
short1	-0.09	0.25	-1.89	**0.01**	0.29	**0.02**	-0.28	0.60	7.6%	0.00	0.98	-0.62	0.24	0.08	0.34	1.42	**0.06**	0.1%
short2	-0.04	0.54	-1.84	**0.01**	0.19	**0.01**	-0.39	0.38	6.4%	-0.02	0.76	-0.56	0.23	0.07	0.32	1.49	**0.02**	0.9%
short3	-0.05	0.51	-1.77	**0.01**	0.17	**0.02**	-0.59	0.20	7.0%	-0.02	0.72	-0.64	0.16	0.07	0.32	1.50	**0.01**	1.1%
long1	0.20	**0.02**	1.35	0.12	-0.11	0.28	0.21	0.78	1.3%	-0.03	0.68	-0.84	0.32	-0.07	0.61	-1.56	**0.05**	0.8%
long2	0.13	**0.07**	0.55	0.49	-0.02	0.81	0.54	0.44	0.2%	0.00	0.96	-0.86	0.28	-0.08	0.53	-1.42	**0.06**	1.0%
long3	0.12	0.10	0.54	0.38	-0.04	0.69	0.54	0.39	0.4%	0.00	0.96	-0.93	0.20	-0.06	0.53	-1.11	**0.08**	0.8%

Table 5. Predicting carry trade payoff: out-of-sample performance

This table reports out-of-sample R^2s (Goyal and Welch, 2007) for predicting carry trade payoffs with two predictors and MSPE-adjusted one-sided p-values (Clark and West, 2007). The predicted variable is monthly carry trade payoffs $\overline{P}_t^{k_j}$ $(k = 1 \cdots 3,\ j = short, long,)$, where $\overline{P}_t^{long_K}$ $(\overline{P}_t^{short_K})$ is payoffs from carry trade strategies with k long (short) positions only. The sample period is from January 1985 to December 2011. The first 180 monthly observations are used to estimate the prediction models and forecast the first one-month-ahead carry trade payoffs, then models are re-estimated every month using all past observations to predict carry trade payoffs in a new month.

The $OoS\ R^2$ is computed as in Goyal and Welch (2007).

$$OoS\ R^2 = 1 - \frac{MSE(prediction\ model)}{MSE(benchmark\ model)} = 1 - \frac{\sum_{j=1}^{n}(\widehat{\mu_t} - \overline{P}_t\ )^2}{\sum_{j=1}^{n}(\mu_t - \overline{P}_t\ )^2}$$

where $\widehat{\mu_t}$ is the predicated carry trade payoff in month t and μ_t is the historical average payoff. $\overline{P}_t$ is the realized carry trade payoff in month t.

The MSPE-adjusted one-sided p-values are obtained by regressing $f_t = (\overline{P}_t^{k_j} - \mu_t)^2 - [\left(\overline{P}_t^{k_j} - \widehat{\mu_t}\right)^2 - (\mu_t - \widehat{\mu_t})^2]$ on a constant.

	rworld(-1)	e_vol(-1)	rworld(-2)	e_vol(-2)	rworld(-3)	e_vol(-3)
OoS R2 (%)						
short1	-0.50	-1.28	4.22	7.95	-1.72	-1.65
short2	-1.65	-0.23	4.06	8.21	-1.11	-1.13
short3	-2.37	-0.24	3.57	8.42	-1.12	-1.33
long1	-0.68	-1.64	-0.55	0.84	-1.00	1.45
long2	-1.53	-2.25	-0.42	0.22	-0.99	1.88
long3	-2.26	-2.42	-0.60	0.58	-0.83	1.60
one-sided p-values						
short1	0.34	0.06	**0.06**	**0.04**	0.32	0.47
short2	0.40	0.37	**0.04**	**0.02**	0.46	0.42
short3	0.26	0.37	**0.05**	**0.02**	0.42	0.43
long1	0.38	0.09	0.38	0.13	0.11	0.04
long2	0.07	0.05	0.45	0.28	0.17	**0.01**
long3	0.07	0.10	0.30	0.15	0.15	0.03

Table 6. Predicting carry trade payoff: economic significance

This table reports the annual mean, Sharpe ratio and skewness of monthly payoffs from market timing strategies conditional on predicted carry trade. Using the market timing carry trade strategy, one goes ahead with the carry trade if the predicted payoffs are positive and does nothing otherwise. The sample period is from January 1985 to December 2011. The first 180 monthly observations are used to estimate prediction models and forecast the first one-month-ahead carry trade payoffs, then models are re-estimated every month using all past observations to predict carry trade payoffs in a new month.

	simple			rworld				e_vol			
	mean	Sharpe Ratio	skewness	mean	Sharpe Ratio	skewness	# of trading signals	mean	Sharpe Ratio	skewness	# of trading signals
lag2											
short1	-1.60	-0.18	-1.10	1.14	0.21	0.87	75	-0.10	-0.02	0.10	66
short2	-0.99	-0.12	-0.45	1.66	0.31	0.47	74	1.00	0.17	0.20	61
short3	-1.03	-0.13	-0.34	1.23	0.23	0.51	76	0.69	0.12	0.20	63
lag3											
long1	8.88	0.68	-0.52	8.88	0.68	-0.52	0	9.22	0.71	-0.54	3
long2	7.19	0.59	-0.49	7.19	0.59	-0.49	0	7.59	0.63	-0.52	3
long3	5.65	0.52	-0.71	5.65	0.52	-0.71	0	5.79	0.54	-0.75	4

Table 7. Predicting the excess world equity index return carry trade payoff in-sample

This table reports the coefficient estimates from regressions

$$rx_t^{world} = \alpha + \beta_1\ Z_{t-i} + \beta_2\ rx_{t-1}^{world} + \mu_t\ \ (i = 1 \cdots 3, k = 1 \cdots 3), \tag{7}$$

where rx_t^{world} is the MSCI world index total return in excess of the risk free rate and Z_{t-i} is a single predictor which include profits from three short leg strategies, profits from three long leg strategies and changes in currency volatility (as described in section 2.2), in each of the three previous months. We use the U.S. risk free rates downloaded from French Kenneth data library. The estimates for predictive coefficient β_1 are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 10% or better significance level are bolded. The sample period runs from January 1985 to December 2011.

strategy	b1	p1	adj. r2	b2	p2	adj. r2	b3	p3	adj. r2
short1	0.06	0.53	0.2%	0.02	0.85	-0.1%	-0.08	0.44	0.1%
short2	0.00	1.00	0.0%	0.05	0.63	0.0%	-0.08	0.46	0.0%
short3	0.00	0.98	0.0%	0.04	0.73	-0.1%	-0.11	0.30	0.2%
long1	0.04	0.67	0.1%	-0.17	0.11	1.5%	0.17	**0.07**	1.5%
long2	0.07	0.56	0.2%	-0.10	0.46	0.3%	0.20	**0.06**	1.5%
long3	0.11	0.40	0.3%	-0.11	0.47	0.3%	0.25	**0.04**	1.9%
fx_vol	-3.18	0.23	1.1%	0.04	0.99	-0.1%	-1.36	0.56	0.0%

Table 8. Predicting the excess world equity index return carry trade payoff out-of-sample and economic significance

	rworld
OoS R2 (%)	
lag3	
long1	1.02
long2	1.41
long3	1.86
one-sided p-values	
long1	0.21
long2	0.14
long3	0.08

Trading outcomes

	mean	Sharpe Ratio	skewness	# of trading signals
Unconditional				
rworld	0.63	0.03	-0.41	0
Conditional (lag 3)				
long1	2.25	0.14	-0.40	6
long2	2.25	0.14	-0.40	6
long3	2.19	0.13	-0.40	8