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Cross-Asset Return Predictability:

Carry Trades, Stocks and Commodities

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Abstract

Equity returns predict carry trade profits from shorting low interest rate currencies. Commodity price changes predict profits from longing high interest rate currencies. The gradual information diffusion hypothesis (Hong & Stein, 1999; Hong, Torous, & Valkanov, 2007) provides a ready explanation for these predictability results. These results cannot be explained by time-varying risk premia as stock returns and commodity price changes significantly predict negative carry trade profits. The predictability is one-directional, from commodities to high interest rate currencies, from commodities to stocks and from stocks to low interest rate currencies.

1. Introduction

Hong and Stein (1999) and Hong et al. (2007) show that asset returns may be predictable if we are willing to assume that investors cannot process all information at the time (or, being bounded rational as described by Sims, 2003). In this case, news may affect some markets first and only reach other markets with a delay, resulting in predictive relations among different financial markets. This gradual information hypothesis is supported by substantial evidence. For example, macroeconomic information gradually disperses across industries in stock markets (Hong et al., 2007), from firms with more analyst coverage to firms with less analyst coverage (Hong, Lim, & Stein, 2000), along the supply chains (Menzly & Ozbas, 2010), from oil prices to stock markets (Driesprong, Jacobsen and Maat, 2008) and across international stock markets (Rapach, Strauss, & Zhou, 2013). While studies find return predictability that is consistent with gradual information diffusion in stock markets, little evidence exists for gradual information diffusion across different asset markets. This study investigates and finds cross-asset return predictability among carry trades, stocks and commodities that is consistent with the gradual information diffusion hypothesis.

Our investigation of this cross-asset return predictability is motivated by recent literature. Lustig, Roussanov, and Verdelhan (2011) demonstrate that low interest rate currencies are more exposed to a global risk factor and hence, on average, appreciate when global consumption risk increases. Lustig, Roussanov, and Verdelhan (2014) find that profits from shorting the United States dollar (USD) is predictable across the business cycle. Campbell, Serfaty - De Medeiros, and Viceira (2010) uncover the hedging benefits of low-interest-rate currencies for stock investors. However, while the literature suggests a possible economic link, the question of whether equity returns predict carry trade profits has received no attention in the literature. We find they do. Similarly, commodities and commodity currencies tend to move together. A large number of studies find strong co-movements of returns from these two asset classes (for example, Chen and Rogoff 2003; Kearns 2007; Chen, Rogoff, and Rossi 2010). While Bakshi and Panayotov (2013) discover that changes in commodity prices strongly predict profits from longing commodity currencies (*long leg profits*), we demonstrate that this predictive result is consistent with that information gradually flows from commodity markets to high-yielding currencies. Using vector auto regressions, we also find that the information flow appears to be from commodities to high-yielding currencies, from commodities to stocks and from stocks to low-yielding currencies.

Equity returns predict profits from shorting low-yielding currencies. Monthly carry trade profits (after crossing bid–ask spreads) from the short leg tend to be lower if equity indices drop and higher if equity indices increase over the preceding three months. The equity effect we document appears to be faster than the commodity effect. The predictive effect from stocks on the short leg carry trade is most pronounced at a two month lag. By contrast, the delay averages three months for the commodity effect on the long leg of the carry trade. These delayed predictive effects are not only statistically significant but also economically significant. For example, a movement in monthly equity returns of one standard deviation (about 4.5%) predicts same-direction changes in short leg profits after two months by 0.20 of one standard deviation[1] (about 0.59%). Similarly, a change in commodity returns of one standard deviation (about 2.78%) three months ago positively

[1] The size of 0.20 of one standard deviation is calculated as $4.55\% \times 0.13 \div 2.95\%$. The estimate for the slope coefficient on the monthly MSCI all country index return is 0.13 (Panel B in Table 2). One standard deviation of the monthly profit from shorting one currency is 2.95%.

predicts a change of 0.24 of one standard deviation (about 0.83%) in long leg profits in the present month. Using the out-of-sample R^2 statistic, as in Goyal and Welch (2008), and the Mean-Squared-Prediction-Error-adjusted (MSPE-adjusted), one-sided p-values, developed by Clark and West (2007), we find that these predictors consistently deliver better predictions than the benchmark model (up to 6.55% for predictability coming from commodity returns, and up to 4.87% for predictability coming from equity prices). Market-timing strategies based on these prediction models also deliver significantly higher Sharpe ratios than naïve carry strategies (where one always goes ahead with carry trades).

We implement carry trade strategies with G-10 currencies because they account for close to 90% of total trading volume.[2] In addition, many investable carry trade indices use G-10 currencies as their constituent currencies.[3]

Our choice of predictors is motivated by recent studies on currency portfolio returns. The world equity index returns and the Standard & Poor's (S&P) 500 Index return are employed as predictors for profits from the short leg, because low-yielding currencies (or safe-haven currencies) tend to depreciate when equity prices rise (for example, Ranaldo and Söderlind 2010; Campbell, Serfaty-De Medeiros and Viceira 2010). Studies on commodity currencies (Chen, Rogoff and Rossi 2010) motivate the choice of commodity price changes as a predictor for the long leg carry trade profit.

[2] According to the triennial survey conducted by the Bank for International Settlements (BIS) in April 2010, the G-10 currencies accounted for 88% of global foreign exchange market average daily turnover in April 2010.

[3] For example, constituent currencies for the iPath Optimized Currency Carry ETN and the Powershares DB G10 Currency Harvest Fund are G-10 currencies. G-10 currencies include: the Australian dollar (AUD), the Canadian dollar (CAD), the Swiss franc (CHF), the euro (EUR), the British 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). We connect the Deutsche mark (DEM) series (prior to January 1999) with the euro series (from January 1999 onwards) as a single time series for the euro.

Our predictability results are robust to both volatility clustering in carry trade profits and to other predictors. Other predictors considered in this study include, in particular, changes in equity volatility (Lustig et al., 2011), changes in currency volatility (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012), changes in global liquidity (as per Brunnermeier, Nagel and Pedersen (2008)), the term premium (as in Ang and Chen (2010)), and average forward premium and percentage change in industrial production of the Organisation for Economic Co-operation and Development (OECD) countries (as documented in Lustig et al. (2014)). These predictors do not explain our findings.

Equity prices and commodity prices are readily available public information. Assuming market efficiency, it seems surprising that investors can use these variables to forecast carry trade profits, time the market, and improve their profits. If, however, we assume that investors all have limited processing capacity (or are bounded rational, see Sims 2003) and that interpreting changes in these predictors is not always straightforward, then information can gradually flow across investors and markets, generating return predictability. We conduct further tests to show that our predictive results are consistent with this gradual information diffusion hypothesis introduced by Hong and Stein (1999) and Hong, Torous and Valkanov (2007). We follow the approach in Driesprong, Jacobsen and Maat (2008) and introduce different sizes of lags between carry trade profits and predictors, to examine how the explanatory power of predictive regressions changes as lag size increases. As the lag lengthens, predictability in both long leg and short leg profits initially peaks, then quickly drops. This pattern appears consistent with a gradual information diffusion explanation. Furthermore, similar to stock returns, carry trade profits also vary across business cycles (as shown by Lustig, Roussanov, Verdelhan and Sloan 2012); thus, a testable prediction of the gradual information diffusion model (following the approach suggested by Hong, Torous and Valkanov 2007, p. 372) is that variables that strongly predict carry trade profits should also forecast market fundamentals such as industrial production growth. We show that commodity returns and stock returns also predict the OECD industrial production growth rate and changes in unemployment rates. This result suggests that commodity returns and stock returns contain information related to economic fundamentals that may affect high interest rate and low interest rate currencies, with a delay.

It is puzzling that stock markets appear to be more informationally efficient given that the size and liquidity of currency markets dwarf equity markets. If currency traders focus mostly on macroeconomic information, while stock market investors consider company information as well, this exposure of currency traders to a smaller information set could explain our results. Evans and Lyons (2012) describe that macroeconomic information can exist in "a dispersed microeconomic form in the sense of Hayek (1945)." Much macro information first exists in a micro form, in the sense described by Hayek (1945). As a result, some macro-information is first impounded into stock returns, and into exchange rates with a delay, because currency traders primarily focus on macroeconomic information.[4]

Our in-sample and out-of-sample results suggest that the predictive effects go from commodities to currencies and from stocks to currencies; however, there is good reason to suspect bi-directional

[4] Surveys conducted in the late 1990s (Cheung and Wong, 2000 and Cheung , Chinn and Marsh, 2004) show that currency traders in the U.S. and the U.K. react quickly to macroeconomic news, such as the unemployment rate, trade deficits, inflation, GDP, interest rates, and money supply.

causality in each case. For example, Chen, Rogoff and Rossi (2010) find that commodity currencies predict commodity prices. Granger, Huangb and Yang (2000) show that, during the 1997 Asian financial crisis, currencies led stocks in some countries, but in other countries just the opposite occurred. It is also possible that cross-market predictive effects between commodities and stocks may be significant (Hong & Yogo, 2009; Jacobsen, Marshall, & Visaltanachoti, 2013; Jahan-Parvar, Wohar, & Vivian, 2011). We explore this issue in a simple vector auto regression (VAR) setting. First, we find that VAR innovations (or residuals in VAR models) in returns to commodities, stocks, and long leg and short leg profits are significantly correlated. These significant correlations among VAR innovations point toward common influences across markets. Second, commodity returns exhibit the strongest predictive ability for returns in other assets, followed by stock returns. Commodity returns Granger-cause both carry trade profits and stock returns. By contrast, stock returns Granger-cause only carry trade profits, and not commodity returns. Carry trade profits do *not* Granger-cause returns in other assets.

In addition to the macroeconomic fundamentals that drive commodities, stocks, and carry trades, stocks and currencies can also be connected through international equity portfolio rebalancing, as hypothesized by Hau and Rey (2006). Their uncovered equity parity hypothesis assumes that investors rebalance their international equity portfolios. Thus, if the foreign stock market outperforms the home stock market, investors reduce their holdings of foreign stocks and the foreign currency depreciates against the home currency.[5] Our paper differs from this strand of literature in terms of testable hypotheses. We begin with the assumption that macroeconomic

[5] Cenedese, Payne, Sarno, and Valente (2014) demonstrate a systematic violation of UEP using a large international panel data.

fundamentals affect carry trade profits, stock returns, and commodity price changes, but some prices are more informative about economic fundamentals than others. We find that economic information originates from commodities and stocks before it diffuses to currencies.

This paper contributes to three areas of the financial literature. First, we contribute to the literature of return predictability. Subtantial evidence exists for stock return predictability that is consistent with the gradual information diffusion hypothesis. We show that the predictability in dynamic carry trade profits appear to be more consistent with the gradual information diffusion hypothesis than a time-varying risk-premia explanation. Unlike predictability from the time-varying risk premia, the predictive effect is short-lived. More importantly, in equilibrium, expected carry trade profits should increase in the face of higher uncertainty (lower stock prices and lower commodity prices). The effect found in this study is, however, precisely the opposite: lower stock prices and lower commodity prices reduce future carry trade profits. Schwert (2003) states that, as an extreme standard, when predictability is not the result of time-varying equilibrium returns, there should be evidence that returns are predictably negative. Schwert (2003) shows that many well-known predictors for stock returns (for example, lagged dividend yield) fail to meet this extreme standard, because they predict negative excess returns only infrequently. The predictability of carry trade profits also meets this stardard. Stock returns and commodity price changes predict negative carry trade profits significantly and frequently.

A second strand literature related to our study is the recent analysis on co-movements of stocks and safe heaven currencies. While Christiansen, Ranaldo, and Söderlind (2011) focus on the comtemporaneous relation between carry trade profits and the stock market risk, we investigate the predictability in carry trade profits. Ranaldo and Söderlind (2010) uncover hourly and daily predictability of safe-haven currencies (or, Swiss franc and Japanese Yen) and attribute such short-run return predictability to shifts in risk appetites – they acknowledge that their study has "little to say about long run movements of exchange rates, which are likely also to be influenced by marco factors". By contrast, our study uncovers the monthly predictability in low-interest rate currencies and demonstrate that this predictability is consistent with the flow of macroeconomic information across markets.

Third, our study contributes to a better understanding of medium-term dynamics among stock returns, carry trade profits and movements in commodity prices. After formally controlling for a known predictive relation between stocks and commodities and a possible bi-directional relation between commodities and commodity currencies, we show that the monthly predictability is unidirectional, from commodities to currencies and from stocks to currencies, but not the other way around.

2. Profits from carry trade strategies

Taking the perspective of a U.S. investor, we use one-month forward contracts against the U.S. dollar and the spot market to implement our carry trade strategies. We consider three equal-weighted and monthly rebalanced carry trade strategies (Strategy $K, K = 1, 2, 3$) for both high interest rate currencies and low interest rate currencies. K refers to the number of long or short positions in a strategy. For example, Strategy 3 for high interest rate currencies (*long leg*) involves buying one-month forward contracts on the three highest interest rate currencies at the beginning of a month and then selling spots at the end of that month. Strategy 3 for low interest rate currencies (*short leg*) does just the opposite: It sells one-month forward contracts on the three lowest interest rate currencies at the beginning of a month, and then buys spots at the end of that month. All carry trade profits are expressed in U.S. dollars and are net of transaction costs (after crossing bid–ask spreads). Carry trade strategies in this study resemble those in Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Lustig, Roussanov and Verdelhan (2011), and Bakshi and Panayotov (2013).

To calculate carry trade profits, we use spot rates and forward rates for G-10 currencies provided by Barclays via Datastream.

We infer interest rate differentials of foreign currencies against the U.S. Dollar at the end of month t 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. The calculation is shown in Equation (1):

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

where S_t^{ask} (S_t^{bid}) is the ask (bid) exchange rate at the end of month t, and F_t^{ask} (F_t^{bid}) is the ask (bid) forward rate at the end of month t for delivery at the end of month $t+1$. Exchange rates are quoted as U.S. dollars per foreign currency unit. Therefore, a U.S. investor sells a foreign currency forward at the bid price[6] in month t for delivery at the end of month $t+1$, if its interest rate is lower than the U.S. dollar in month $t-1$ ($idiff_{t-1} < 0$, or $F_{t-1}^{bid} > S_{t-1}^{ask}$, at a *forward premium*) and buys a foreign currency forward at the ask price if its interest rate is higher than the U.S. dollar in month $t-1$ ($idiff_{t-1} > 0$, or $F_{t-1}^{ask} < S_{t-1}^{bid}$, at a *forward discount*). If the implied interest rate differential is zero, the foreign currency is neither bought nor sold against the U.S. dollar. [7] Profits from all strategies are scaled to a bet size of one U.S. dollar.

Profits from these carry trade strategies are specified in Equation set (2):

$$HIGH_t^j = -\frac{1}{F_{t-1}^{ask(j^{th}\ highest)}}\left(F_{t-1}^{ask(j^{th}\ highest)} - S_t^{bid(j^{th}\ highest)}\right) \qquad (2)$$

$$LOW_t^j = \frac{1}{F_{t-1}^{bid(j^{th}\ lowest)}}\left(F_{t-1}^{bid(j^{th}\ lowest)} - S_t^{ask(j^{th}\ lowest)}\right), j = 1 \cdots 3$$

$$HIGH(K)_t = \frac{1}{K}\sum_{j=1}^{K} PHIGH_t^j$$

$$LOW(K)_t = \frac{1}{K}\sum_{j=1}^{K} PLOW_t^j \quad , K = 1 \cdots 3$$

$HIGH_t^j$ (LOW_t^j) is the profit over month t from buying (selling) the jth highest (lowest) interest rate currencies; $HIGH(K)_t$ is the profit over month t from buying K highest interest rate currencies

[6] The ask (bid) exchange rate is the rate at which a currency dealer is willing to sell (buy) a foreign currency. In other words, the ask (bid) exchange rate is the rate at which one can buy (sell) a foreign currency from (to) a currency dealer.

[7] The construction of carry trade profits closely resembles those in Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) and in Bakshi and Panayotov (2013).

forward; and $LOW(K)_t$ is the profit over month t from selling K lowest interest rate currencies forward. Appendix I summarizes the usage frequency of each currency in our carry trade strategies. The New Zealand dollar, the Australian dollar and the British pound are the most frequently used high interest rate currencies. The long three-currency strategy includes these three currencies in approximately half to two-thirds of instances. For example, the New Zealand dollar is bought forward in 170 out of the 287 months. The most frequently used low interest rate currencies in the short three-currency strategy include the Japanese yen, the Swiss franc and the euro.

3. Predicting carry trade profits

3.1. Carry trade profits, changes in commodity prices, and equity index returns: summary statistics

To study the dynamics among commodity prices, carry trade profits, and the stock market, we consider commodity price indices and equity indices that represent broad price movements in each market. For the commodity markets, we follow Bakshi and Panayotov (2013) and consider the Commodity Research Bureau (CRB) Spot Indices. In particular, we consider the CRB Spot Index and it sub-indices, the CRB Raw Industrials Index and the CRB Metals Index.[8] For the stock market, we consider the Morgan Stanley Capital International (MSCI) All Country World Index, the MSCI World Index, and the S&P 500 Index. All equity indices are total-return indices from

[8] The CRB Spot Index is an equal-weighted geometric mean of prices of 22 basic commodities that are used widely in the initial production stage. The CRB index contains two main sub-indices: raw industrials and foodstuffs. The CRB Metals Index is a sub-index of CRB Raw Materials.

Datastream.[9] To facilitate easy comparison of predictive results across the board, we investigate all predictive effects over the same sample period, February 1988–December 2011. The start of this sample period represents the earliest time at which all six commodity index and equity index series are available.

[Insert Table 1 about here]

Panel A in Table 1 summarizes carry trade profits (after crossing bid–ask spreads) and their currency and interest components. Over the period February 1988–December 2011, carry trade strategies that long high interest rate currencies make an average monthly profit of between 0.34% and 0.49% (or, a monthly payoff in the size of 0.0034 dollar to 0.0049 dollar per USD bet). The interest rate components of carry trade profits are all positive by construction. Carry trades that long high interest rate currencies experience desirable currency movements, on average. That is, when high interest rate currencies are bought forward, they do *not* tend to depreciate and offset the interest rate differentials; instead, they tend to, on average, appreciate slightly, making carry trades even more profitable. On average, these long leg carry trade strategies achieve between 0.13% and 0.20% monthly profits from currency movements, whose sizes are comparable to those of the interest components (ranging between 0.21% and 0.29% per month, on average). By contrast, low interest rate currencies, particularly the Japanese yen, experience episodes of sudden appreciation against the U.S. dollar, making carry trades that short low interest rate currencies less profitable.

[9] Results remain qualitatively the same when we use price indices.

Currency components in short leg carry trade profits range between −0.08% and 0.01% monthly. These profits are comparable to those in Table 1 of Bakshi and Panayotov (2013).[10]

Variations in carry trade profits are driven primarily by exchange rate movements, because time series autocorrelations in carry trade profits are almost identical to those in their currency components, with first-order autocorrelation varying between −0.01 and 0.09. Interest components of all carry trades are highly persistent, with positive first-order autocorrelation ranging between 0.58 and 0.72.

Panel B in Table 1 reports summary statistics of monthly changes in commodity indices and monthly changes in equity total return indices. Monthly average returns to stocks are noticeably higher than those from commodity markets and carry trades. Means of monthly equity index returns range between 0.65% and 0.84%, higher than the mean of any commodity index returns or carry trade profits included in Table 1. However, equity returns are also volatile. Monthly equity index returns display volatility of between 4.32% and 4.55%, approximately one to two percentage points higher than the volatility of carry trade profits, as well as higher than the volatility of the CRB Index return and the CRB Raw Industrials Index return.

These asset returns are highly correlated but do not always move in the same direction (Panel C of Table 1). Long leg profits, commodity prices and equity prices tend to rise and fall together, as suggested by the highly significant and positive correlations among these asset returns. For

[10] For example, the average annualized profit to a long/short carry trade strategy using three currencies is 2.88% ((0.34%+0.14%) /2*12) in our study. This number is comparable to the annual profit of 2.70% to the three-currrency long/short strategy in Bakshi and Panayotove (2013). Their sample period largely overlaps with ours.

example, profits from buying the highest interest rate currency forward (*HIGH(1)*) strongly correlate with the CRB Index return at 0.36 (*CRB*) and with the MSCI All Country Index return (*MSCI_all*) at 0.40. The CRB Index return (*CRB*) and the MSCI All Country Index return (*MSCI_all*) also show strong correlation, 0.31. By contrast, short leg carry trade profits tend to negatively correlate with equity index returns (with six significantly negative correlation coefficients ranging between -0.14 and -0.12, out of 9).[11] Short leg carry trade profits also negatively correlate with long leg profits, and to a certain extent, with commodity index returns.

3.2. Predicting carry trade profits in-sample

Motivated by Campbell and Shiller (1988b) and Fama and French (1988), Bakshi and Panayotov (2013) employ predictors with low variability (three-month changes in predicting variables) to predict monthly carry trade profits. Following their approach, we first use normalized three-month equity index returns ending in month $t-1$ to predict short leg profits in month t. The normalized three-month index return in month $t-1$ is computed as the percentage change in the index level from month $t-4$ to $t-1$ divided by 3, or normalized to monthly. In the same spirit, we use normalized three-month percentage changes in commodity indices to predict the long leg carry trade profit. Normalized three-month returns are less volatile than monthly returns. For example, normalized three-month equity index returns have standard deviations that range between 2.58%

[11] These negative correlation coefficients do not contradict the hedging benefit of low-interest-rate currencies discussed by Campbell et al. (2010) because the optimal currency portfolio for stock investors has an negative exposure to the JPY (Table IV, p.102, Campbell et al., 2010) – JPY is the most common currency on the short leg in our carry trade strategies.

to 2.75%, lower than those of monthly equity index returns (between 4.32% and 4.55%). The first two in-sample predictive regressions are specified as follows:

$$LOW(K)_t = b_0^{Y,K} + b_1^{Y,K} Y_{t-1} + \omega_t^{Y,K}, \quad \text{for } K = 1 \cdots 3 \tag{3}$$
$$HIGH(K)_t = a_0^{Z,K} + a_1^{Z,K} Z_{t-1} + \mu_t^{Z,K}$$

where Y_{t-1} denotes a predictor for the short leg carry trade profit; Y_{t-1} is the normalized three-month MSCI All Country World Index return ($MSCI\_all\_3M_{t-1}$), the normalized three-month MSCI World Index return ($MSCI\_3M_{t-1}$), or the normalized three-month S&P 500 Index return ($SP500\_3M_{t-1}$); Z_{t-1} denotes a predictor for long leg profits; Z_{t-1} is the normalized three-month CRB Spot Index return (CRB_3M_{t-1}), the normalized three-month CRB Raw Industrials Index return ($CRB\_raw\_3M_{t-1}$), or the normalized three-month CRB Metals Index return ($CRB\_metals\_3M_{t-1}$)Y_{t-1}. We expect a positive predictive relation as a result of gradual information diffusion in this case, because stock returns, carry trade profits, and commodity returns rise on good economic news. There are three predictors for each leg of carry trades and each leg employs three strategies. Thus, we are interested in the 18 slope estimates for predicting variables (9 for each leg of carry trades).

[Insert Table 2 about here]

Panel A in Table 2 reports estimation results of Equation (3). The t-statistics are calculated with the Newey and West (1994) standard errors with three lags. We find that normalized three-month equity returns significantly predict short leg carry trade profits. If the MSCI All Country Index, the MSCI World Index, or the S&P 500 Index rises (drops) over the preceding three months, short leg carry trade profits tend to increase (decrease) in the current month. The slope estimates on lagged three-month equity returns range between 0.12 and 0.21, with p-values of 0.05. The predictability in short leg carry trade profits is also economically significant—a one-standard-deviation change in three-month equity returns predicts same-direction change of 0.14 to 0.19 standard deviation in short leg carry trade profits. The positive sign of the slope estimates for equity index returns makes sense economically. Low interest rate currencies strengthen (weaken) against the U.S. dollar following drops (rises) in world equity prices, leading to decreases (increases) in profits from shorting these currencies.[12] We also confirm the findings in Bakshi and Panayotov (2013) that normalized three-month changes in commodity price indices strongly predict carry trade profits from high interest rate currencies—all nine slope estimates for normalized three-month commodity returns (*CRB_3M*, *CRB_raw_3M*, and *CRB_metals_3M*) ending in month $t-1$ are between 0.16 and 0.34, with p-values of 0.05 or 0.01.

The predictive effect is from three-month changes in equity prices to short leg carry trade profits and from three-month changes in commodity prices to long leg carry trades. This finding raises the question whether such predictive effect appears immediately in the following month or after some delay. An answer to this question may also provide evidence regarding whether the discussed predictability is a form of gradual information diffusion (Hong & Stein, 1999; Hong et al., 2007). We test the predictive effect in each of the three months by running the regressions specified below:

[12] We also examine whether stock returns predict long leg profits in an OLS setting, and find that stock returns do not predict long leg profit. Currency markets receive economic information from both commodity markets and stock markets. Our results suggest that information from commodity markets is more important than information from stock markets for high interest rate currencies.

$$HIGH(K)_t = \alpha_0^{C,K} + \alpha_1^{C,K} C_{t-1} + \alpha_2^{C,K} C_{t-2} + \alpha_3^{C,K} C_{t-3} + \gamma^{C,K} HIGH(K)_{t-1} + \mu_t^{C,K}, \qquad (4)$$

$$LOW(K)_t = \theta_0^{E,K} + \theta_1^{E,K} E_{t-1} + \theta_2^{E,K} E_{t-2} + \theta_3^{E,K} E_{t-3} + \delta^{E,K} LOW(K)_{t-1} + \omega_t^{E,K},$$
$$\text{for } K = 1,2,3$$

where C_t denotes a predictor for the long leg profits; C_t is the monthly CRB Spot Index return (CRB_t), the monthly CRB Raw Industrials Index return (CRB_raw_t), or the monthly CRB Metals Index return (CRB_metals_t); E_t denotes a predictor for the short leg profits; E_t is the monthly MSCI All Country World Index return ($MSCI\_all_t$), the monthly MSCI World Index return ($MSCI_t$), or the monthly S&P 500 Index return ($SP500_t$).

Panel B in Table 2 reports estimation results of Equation (4). Interestingly, equity effects on short leg carry trades appear to be faster than commodity effects on long leg carry trades. Monthly equity returns strongly predict short leg profits two months later, but not in any other months. Slope estimates for equity returns lagged by two months (*L2.MSCI_all*, *L2.MSCI* and *L2.SP500*) are positive and significant for all short leg profits, with p-values of 0.05 or less. By contrast, monthly commodity returns strongly predict long leg profits only three months later, but not in earlier months. Among all 27 slope estimates for monthly commodity returns lagged by one, two, and three months, only those on monthly commodity index returns lagged by three months (*L3.CRB*, *L3.CRB_raw*, and *L3.CRB_metals*) are positive and significant at the 0.01 level, for all three carry trade strategies. These positive predictive coefficients suggest that changes in commodity prices positively predict long leg profits three months later, while movements in equity prices positively forecast short leg profits two months later. These delayed predictive effects are not only statistically significant but also economically significant. For example, a one-standard-deviation variation in monthly equity returns predicts approximately a 0.16 to 0.20 standard deviation, same-direction change in short leg profits after two months. Similarly, a one-standard-deviation change in commodity returns three months ago positively predicts a change of 0.19 to 0.27 standard deviation in long leg profits in the current month. Coefficients on lagged carry trade profits are invariably small and insignificant thus not reported in Table 2.

The in-sample adjusted R^2s in Table 2 are comparable to those reported for predictability in carry trade profits (for example, Bakshi and Panayotov 2012, Tables 2 and 3; Adrian, Etula and Shin 2010 Tables 1 and 2). The adjusted R^2s range between 1.5% and 4.7% when predictors are lagged three-month returns, and range between 1.7% and 7.5% when predictors are monthly returns in each of preceding three months.

We also show that the predictability in carry trade profits stems from their currency components. We repeat the above regressions specified in Equation (4) with the currency components of carry trade profits as dependent variables and find that slope estimates on predictors for the currency components (Appendix II) are almost identical to those in the carry trade profits reported in Table 2.

3.3. Predicting carry trade profits out-of-sample

As suggested by Welch and Goyal (2008, p. 1456),[13] we test whether the delayed predictive effect exists out-of-sample. We compute the out-of-sample R^2 ($OS\ R^2$) used by Campbell and Thompson (2008) and Welch and Goyal (2008), among others. $OS\ R^2$ is specified as:

[13] Welch and Goyal (2008, p. 1456), "the OOS performance is not only a useful model diagnostic for the IS regressions but also interesting in itself for an investor who had sought to use these models for market-timing."

$$OS\ R^2 = 1 - \frac{\sum_{j=1}^{n}(\widehat{\theta_t} - \mathrm{P}_t\ )^2}{\sum_{j=1}^{n}(\theta_t - \mathrm{P}_t\ )^2}, \tag{5}$$

where $\widehat{\theta_t}$ is the predicated carry trade profit in month t, and θ_t is historical average profit; P_t is realized carry trade profit in month t; and $OS\ R^2$ indicates percentage reduction in the forecasting error of a prediction model relative to the historical mean model. In addition to $OS\ R^2$, we follow Rapach et al. (2013) and Ferson, Nallareddy, and Xie (2013) test the significance of forecast improvement with one-sided p-values of adjusted mean-squared prediction errors (*one-sided p-values for adjusted MSPE*, Clark and West (2007)). One-sided p-values for adjusted MSPE are obtained by regressing $f_t = (P_t - \theta_t)^2 - [\left(P_t - \widehat{\theta_t}\right)^2 - \left(\theta_t - \widehat{\theta_t}\right)^2]$ 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.

Consistent with our in-sample results, we use monthly commodity index returns to predict long leg profits after three months and monthly equity index returns to predict short leg profits in two months' time. Specifically, we use all observations available prior to month t to predict carry trade profits in month t ($\widehat{\theta_t}$) and require a minimum of 120 observations to make the first forecast. All predicted carry trade profits start from April 1998 and end in December 2011.

[Insert Table 3 about here]

Panel A in Table 3 reports estimates of $OS\ R^2$ and one-sided p-values for adjusted MSPE. If an investor uses monthly commodity returns to predict long leg profits three months later, that investor can reduce forecast error by 3.83–6.55% (shown as $OS\ R^{2\prime}s$ for commodity returns as predictors). These improvements in forecast error are also significant at levels between 0.02 and

0.06 (shown as one-sided p-values for adjusted MSPE). Similarly, if an investor uses monthly equity returns to predict short leg profits, that investor can decrease forecast error by 2.48–4.87%, and these improvements are significant at levels between 0.02 and 0.05.

In addition to out-of-sample statistical tests, we also compare profits of market-timing strategies based on predicted carry trade profits with profits from naive carry trade strategies (where one always goes ahead with 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 profit is positive; otherwise, that investor refrains from a carry trade. Monthly average profits, standard deviation, and annualized Sharpe ratios[14] of market-timing strategies and naïve strategies are reported in Panel B in Table 3. During the period April 1998–December 2011, average monthly returns from market-timing strategies are universally higher than those from naïve strategies. For example, means of monthly profits from naïve short leg carry trade strategies range between -0.25 and -0.08, while means of profits from corresponding market-timing strategies range between -0.10 and 0.12. At the same time, these market-timing strategies generate returns with lower volatility than naïve strategies, resulting in significant improvements in Sharpe ratios.[15] Sharpe ratios generated by long leg market-timing strategies are between 0.54

[14] Because practitioners normally use annualized Sharpe ratios, we report annualized Sharpe ratios for ease of comparison.

[15] To test the significance level at which we can reject the null that the Sharpe ratio of the market-timing strategy is *not* higher that of the naïve strategy, we bootstrapped 1,000 pseudo time-series for profits from each market-timing strategy. We use moving block bootstrapping with a block size of $N^{1/4}$ for a one-tailed test in time-series data, to preserve the structure presented in the data (Hall, Horowitz, & Jing, 1995). The p-value to reject the null of *no*

and 0.97, and 7 out of these 9 Sharpe ratios are significantly higher than those from naïve strategies (between 0.48 and 0.62). Similarly, market-timing strategies on the short leg of carry trades also deliver significantly improved Sharpe ratios—6 out of the 9 corresponding market-timing strategies deliver significantly improved Sharpe ratios, ranging between 0.09 and 0.21. By contrast, naïve short leg carry trade strategies, on average, make losses and have negative Sharpe ratios ranging between -0.11 and -0.28 during the forecast period.

Panel C of Table 3 reports the summary of trading signals and losses avoided from applying selected market-timing rules.[16] When the above market-timing rules are used, one stays invested in carry trades about 66% to 80% of the time (or 8 to 10 months in a year, Panel C of Table 3). If carry trade profit is predicted to be negative in a month, one needs to follow this no-trading signal in that month. Trading signals are not concentrated in the period which contains the financial crisis (2007-2011). There are more signals for the long-leg carry trades during the 98-06 period than during the last five year of our sample (2007-2011). For example, during the 98-06 period 15 trading signals occur and 10 during the 07-11 period for the carry trade longing three currencies (HIGH(3). But, the rule helps to avoid larger losses on average during the second period than during the first period. For example, the out-of-sample predictability from commodities could have helped investors to avoid monthly losses of about 12% in October 2008 and in January 2009. By contrast, for short-leg carry trades, market-timing strategies generate more signals in the financial

improvement in Sharpe-ratio is computed as the percentage of Sharpe-ratios of a mark-timing strategy that are greater than or equal to those of a naïve strategy.

[16] Panel C of table 3 only report results when using CRB as a predictor for the long-leg profit and MSCI_all as a predictor for the short-leg profit. Results from other prediction models are smilar and available upon request.

crisis period than during the first period – but it helps to avoid larger losses in this first period than in the financial crisis period. Using the MSCI world index return as a predictor for the short-leg carry trade profit out-of-sample, one could have avoided the monthly loss of 16% in October 1998.

This section investigates out of sample predictability using three measures: out-of-sample R^2, p-values for a one-tailed test for adjusted MSPE improvements, and one-tailed significance for improvements in Sharpe ratios from market-timing strategies. All three measures confirm the in-sample evidence of delayed predictive effects in long leg profits from commodities and in short leg profits from stocks.

4. VAR estimation results

Because it is reasonable to expect bi-directional causality and cross-market effects (Chen et al., 2010; Granger, Huangb, & Yang, 2000; Hong & Yogo, 2009; Jahan-Parvar et al., 2011), in this section, we adopt VAR models that include four equations and four variables each. The VAR model includes long leg profits, short leg profits, commodity index returns, and world equity index returns. The VAR system is specified below in Equation set (6):

$$HIGH(K)_t = \sum_{j=1}^{3} a_{1j}E_{t-j} + \sum_{j=1}^{3} b_{1j}C_{t-j} + \sum_{j=1}^{3} c_{1j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{1j}HIGH(K)_{t-j} + \mu_t$$

$$LOW(K)_t = \sum_{j=1}^{3} a_{2j}E_{t-j} + \sum_{j=1}^{3} b_{2j}C_{t-j} + \sum_{j=1}^{3} c_{2j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{2j}HIGH(K)_{t-j} + \tau_t \qquad (6)$$

$$E_t = \sum_{j=1}^{3} a_{3j}E_{t-j} + \sum_{j=1}^{3} b_{3j}C_{t-j} + \sum_{j=1}^{3} c_{3j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{3j}HIGH(K)_{t-j} + \varphi_t$$

$$C_t = \sum_{j=1}^{3} a_{4j}E_{t-j} + \sum_{j=1}^{3} b_{4j}C_{t-j} + \sum_{j=1}^{3} c_{4j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{4j}HIGH(K)_{t-j} + \omega_t$$

The four endogenous variables in Equation set (6) include long leg profits ($HIGH(K)_t$), short leg profits ($LOW(K)_t$), equity index returns (E_t), and commodity index returns (C_t).

[Insert Table 4 about here]

Table 4 (Panel A) reports contemporaneous correlations of residual returns, or VAR innovations, among the four variables. These correlation coefficients reflect the degree to which innovations to long leg carry trades, to short leg carry trades, to equity indices, and to commodity indices occur together, after accounting for cross-market predictability.[17] We find that innovations to commodity prices, innovations to equity index returns, and innovations to high interest rate currencies are positively correlated between 0.301 and 0.439 at better than the 0.01 significance level. By contrast, both innovations to commodity prices and innovations to equity index levels are negatively associated with low interest rate currencies. Pairwise correlation coefficients among innovations to low interest rate currencies, commodity prices, and equity indices are generally negative; correlation coefficients range between -0.047 and -0.121.

Table 4 also presents pairwise Granger-causality tests among endogenous variables of the VAR. For the null hypothesis that variable x does not Granger-cause variable y, we test whether the lag

[17] Because we consider three carry trade strategies for high interest rate currencies and low interest currencies, three commodity indices and three equity indices, we estimate a total of 27 VAR models, as specified in Equation (6). For brevity, Table 4 reports results only from the nine VAR models that use the MSCI All Country World Index return as E_t and the CRB Spot Index return as C_t, which are representative of results from other VAR models. Details of correlations of VAR innovations from the other 18 models are available on request.

coefficients of x are jointly zero when y is the dependent variable. In Panel B of Table 4, the cell associated with the xth row variable and the yth column variable reports the Chi-square statistic for the tests. Panel C in Table 4 summarizes the number of tests (out of a total of 27 tests) that reject the null at 0.10 or better significance levels.[18] In the 27 VAR systems, the predictive ability of monthly commodity index returns stands out, because they Granger-cause long leg profits in all 27 cases, as well as Granger-cause equity index returns and short leg profits in 21 and 19 out of 27 cases, respectively. Second to commodity index returns are equity index returns; they significantly Granger-cause short leg profits and long leg profits in 22 and 9 out of 27 cases, respectively. Stock returns Granger-cause no commodity returns (this finding corroborates the findings regarding stock returns and industrial metals by Jacobsen, Marshall, and Visaltanachoti (2013)). By contrast, neither long nor short leg profits Granger-cause any other variables. Thus, VAR Granger-causality tests indicate that the predictive effect from commodities on high interest currencies is strongest, followed by that from stocks on low interest rate currencies.

Figure 1 plots selected impulse response functions for explanatory variables in the VAR model.[19] All of the impulse response functions in this paper are based on the generalized approach of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), which does not require orthogonalization

[18] For brevity, this appendix reports only a summary of the number of Granger-causality tests that reject the null of no causality at 0.10 or better significance level. Details of Granger-causality test results for the other 18 models are available on request.

[19] In Figure 1, we report that IRFs use CRB_raw, HIGH(1), LOW(1), and MSCI_all as endogenous variables only for brevity. Results from other VAR systems that use two and three currencies on each leg are similar and available on request. We omit IRFs for responses to shocks to carry trade profits, because responses to these shocks are insignificant.

of shocks and thus is order invariant. We do not attempt to estimate a structural VAR, because this requires a significant number of additional assumptions of the relations among exogenous shocks in different asset markets. These plots suggest that there are significant delayed predictive effects from commodities to high interest rate currencies, from commodities to world stocks, and from stocks to low interest rate currencies.

[Insert Figure 1 about here]

5. Gradual information diffusion or time-varying risk premia

5.1. Gradual information diffusion

We follow Driesprong, Jacobsen, and Maat (2008) and conduct a test for the gradual information diffusion hypothesis, for each leg of a carry trade. These authors argue that if investors react with delay to information in the predictors, the predictability effect should become stronger once a lag is introduced between carry trade profits and the predictors; the predictability effects should also peak and decrease quickly as lag size increases. First, a lag of one week (five trading days) is introduced between the long and short carry trade profits and each predictor before running the regression specified in Equation (7). Then, the procedure is repeated for different lag sizes up to 16 weeks.

$$HIGH(K)_t = a_0^{C,K} + a_1^{C,K} C_{t-1} + \mu_t^{C,K}, \tag{7}$$

$$LOW(K^{20})_t = b_0^{E,K} + b_1^{E,K} E_{t-1} + \omega_t^{E,K}, \quad \text{for } K = 1 \cdots 3$$

[20] a

where C_{t-1} is one of the three commodity index returns and E_{t-1} is one of the three equity index returns.

[Insert Figure 2 about here]

Figure 2 plots R^2 as a function of different numbers of weeks used as lags, from predictive regressions where dependent variables are profits from the short one-currency strategy and profits from the long one-currency strategy.[21] R^2s peak at different lags for short leg and long leg profits. For the short leg (charts on the right), the predictive regressions have their highest explanatory power for a lag of five weeks. By contrast, predictive regressions for the long leg carry trade profit have the highest R^2s for a lag of 10 weeks (charts on the left). For lags longer than five weeks (10 weeks), the explanatory power for profits from selling low-yielding currencies short (buying high-yielding currencies forward) quickly decreases. These results support the gradual information diffusion hypothesis.

5.2.Time-varying risk premia

5.2.1. Predictability at longer horizons

While the evidence thus far points toward a gradual information diffusion explanation, return predictability is not necessarily a result of market inefficiency. Return predictability can be an effect of time-varying risk-premia. For example, Fama and French (1988) show that many well-known predictors for stock returns, such as dividend yield, term structure, and the default premium,

[21] The results are qualitatively the same for the other strategies.

serve as proxies for business risk. For example, dividend yield is high during economic downturns, when investors expect high returns to compensate for increased business risk. Thus, dividend yield predicts stock returns as a result of time-varying risk premia. Carry trade profits, like stock returns, also display a cyclical nature (Lustig et al., 2014). Hence, it is necessary to verify whether the observed predictability is a result of time-varying risk premia.

The predictability associated with time-varying risk premia tends to strengthen at longer horizons (Cochrane, 2001). Average term premium (Ang & Chen, 2010), average forward discount, and industrial production growth rate (Lustig et al., 2014) are the most well-known economic variables to forecast carry trade profits, and their predictive power strengthens over longer horizons, persisting up to 12 months. We test whether observed predictability in carry trades survives at long horizons using regressions specified as follows:

$$HIGH(K)_t = \alpha_0^{C,K} + \sum_{j=1}^{6} \alpha_j^{C,K} C_{t-j} + \gamma^{C,K} HIGH(K)_{t-1} + \mu_t^{C,K}, \tag{8}$$

$$LOW(K)_t = \theta_0^{E,K} + \sum_{j=1}^{6} \theta_j^{E,K} E_{t-j} + \delta^{E,K} LOW(K)_{t-1} + \omega_t^{E,K}, \text{ for } K = 1,2,3$$

where monthly commodity returns between month $t-6$ and $t-1$ ($C_{t-j}, j = 1 \cdots 6$) predict long leg profits in month t and monthly equity returns between month $t-6$ and $t-1$ ($E_{t-j}, j = 1 \cdots 6$) predict short leg profits in month t. If the discovered predictability is a result of time-varying risk premia, we expect many slope estimates for commodity returns and those for equity returns to be significant and positive.

[Insert Table 5 about here]

Contrary to the predictability associated with time-varying risk premia, the results in Table 5 suggest that the predictability in short leg profits using equity returns is a short-run phenomenon. The predictability effect for the short leg carry trade disappears when one considers equity index returns lagged more than two months. Similarly, only commodity return three months ago significantly and positively predicts the long leg carry trade profit in the present month; this positive predictive effect disappears once the horizon extends over three months, and it turns negative at the sixth month. The next, and maybe more conclusive, test on whether predictability maight be attributed to time-varying risk premia, we follow the approach suggested by Schwert (2003) as implemented by Driesprong et al. (2008).

5.2.2. Negative carry trade profits

Schwert (2003) suggests an extreme standard to analyze whether a discovered predictability is a compensation for risk or a consequence of market inefficiency. In the latter case, the predicted carry trade profits should be frequently negative. Many well-known predictors for stock returns fail this negative excess return test. For instance, Eleswarapu and Thompson (2007) find that during the period from 1951 to 2000, the dividend yield and the default premium predicted negative excess returns for only 3% and 0% of the 600 months, respectively. If it was only a time-varying risk premium causing the predictability results in our study, one would expect that carry trade profits are infrequently predicted to be negative. This is not the case, however, both short leg profits and long leg profits are frequently predicted to be negative – stock returns predict negative short leg profits in many months, ranging between 30% and 36% of total observatioins in-sample and between 22% and 35% out-of-sample. Similarly, commodity price changes also predicted negative long leg profit in many months (22-28% in-sample and 20-30% out-of-sample). Thus, we reject the hypothesis that our predictability results are a consequence of time-varying risk premia.

6. Predictability and macroeconomic fundamentals

This section shows that the variables that predict carry trade profits contain information about market fundamentals, as proxied by industrial production growth and change in unemployment rate in the OECD countries. Carry trades, like stock investments, demonstrate a cyclical nature and long-run predictability driven by proxies for such economic activities as industrial production growth, as demonstrated by Lustig et al. (2014). Thus, in the context of carry trades, a testable prediction from the gradual information diffusion model in Hong, Torous and Valkanov (2007, p. 372) is that a variable that predicts carry trade profits ought to be able to forecast indicators of market fundamentals, as proxied by OECD industrial production growth and changes in OECD unemployment rate. We test whether commodity price changes and equity returns predict macroeconomic fundamentals by running the regressions specified in the equation below:

$$O_t = \varphi_i + \sum_{s=1}^{3} \lambda_{Z,s} Z_{t-s} + \sum_{s=1}^{3} \xi_s \, O_{t-s} + \mathrm{A}X_{t-1} + \omega_t \ , \qquad (9)$$

where O_t is either monthly industrial production growth or monthly percentage change in unemployment rate; and Z_{t-s} is the value of predictor *CRB*, *CRB_raw*, *CRB_metals*, *MSCI_all*, *MSCI*, or *SP500* in month $t-s$. $\boldsymbol{X_{t-1}}$ is a vector of additional predictors for macroconomic variables, including inflation rate (Fama & Schwert, 1977), the term spread (Fama & French, 1988) and the market dividend yield (Campbell & Shiller, 1988a).[22]

[Insert Table 6 about here]

Table 6 reports estimation results from Equation (9). Estimates for correlation coefficients in Panel A show that both commodity returns and equity returns contemporaneously correlate with economic fundamentals. Commodity index returns significantly and positively correlate with industrial production growth in the OECD countries, and significantly negatively correlate with changes in unemployment rates in these countries. To a lesser extent, stock returns also positively correlate with industrial production growth and negatively correlate with changes in unemployment rates. Estimates for predictive coefficients in Panel B suggest that stock returns and, to a lesser extent, commodity returns, significantly predict economic fundamentals, as proxied by industrial production growth and changes in unemployment rate, over a three-month horizon. All equity returns and three out of six commodity returns, over the three-month horizon, jointly and significantly predict economic fundamentals at 0.05 or better levels. Results from this section suggest that commodity returns and equity returns contain information related to the economy and that this information may gradually diffuse to currencies and result in cross-market predictability.

[22] We use inflation rate for OECD countries, average term spread in G-10 countries and dividend yield to the MSCI World Index portfolio.

7. Robustness to volatility clustering in carry trade profits

Prior studies have uncovered considerable evidence for volatility clustering in monthly financial time series data (for example, Ding and Granger (1996), Engle and Lee (1999), Bollerslev and Ole Mikkelsen (1996), Jacobsen and Dannenburg (2003)). We explicitly account for volatility clustering in carry trade profits by assuming a GARCH(1,1) structure for the variance term. This test enables us to verify whether discussed predictability in carry trade profits is a result of volatility clustering.

[Insert Table 7 about here]

Table 7 reports slope estimates on predictive variables after we impose a GARCH(1,1) structure on the variance term. Both the predictive effect from commodities to high interest rate currencies and that from stocks to low interest rate currencies are robust to the GARCH effect. Monthly commodity returns three months ago still significantly predict long leg profits in the present month—nine slope estimates for commodity returns lagged by three months are all positive and significant. The sizes of these predictive coefficients are comparable to those from earlier analysis without GARCH effects (Table 7). Similarly, monthly equity returns significantly and positively predict short leg profits two months later; eight out of nine slope estimates on equity returns two months earlier remain positive and significant at 0.05 or better levels. However, conditional volatility and volatility clustering account for about half the discovered predictive effect from stocks to carry trade profits from the short leg. Slope estimates for equity returns two months prior range between 0.04 and 0.05 in Table 7, where we include a GARCH(1,1) term when predicting carry trade profits from the short leg. These predictive coefficients are about half the size of those estimated without the GARCH(1,1) term (Table 2).

8. Other robustness tests

Existing studies consider many variables as predictors for currency returns and carry trade profits. This study adds equity returns as a new predictor for carry trade profits from the short leg. We also consider commodity returns in predicting carry trade profits from the long leg. The robustness of commodity returns as a predictor for carry trade profits is established by Bakshi and Panayotov (2013). This section tests whether the predictive ability of equity returns is robust to other variables related to carry trade profits discussed in the literature. These predictors include commodity returns (Bakshi and Panayotov (2013), changes in G-10 currency volatility (Menkhoff et al., 2012), changes in G-10 country equity volatility (Lustig et al., 2011), changes in global liquidity and monthly percentage change in the CBOE VOX index (Brunnermeier, Nagel, & Pedersen, 2008), term premium averaged across the sample countries (Ang & Chen, 2010), average forward discount and industrial production growth in the OECD countries (Lustig et al., 2014), and changes in the Baltic Dry Index (Ready, Roussanov, & Ward, 2013).[23] We test whether these variables individually predict carry trade profits from the short leg, using the same set of regressions specified for in-sample predictability tests (Equation (4)). None of these predictors significantly predicts the short leg profits.

9. Conclusion

The main contribution of this paper is that it is the first study to document evidence of predictability in short leg carry trade profits. Following drops (rises) in world equity index levels, profits from shorting low interest rate currencies tend to decrease (increase). Further, the predictability in the

[23] Appendix III includes a description of the construction of each of these variables.

short leg is of significant economic value to carry trade investors. By predicting short leg profits and timing investment decisions, an investor can improve short leg profits and decrease volatility, resulting in significantly improved Sharpe ratio, relative to when investors stay fully invested in carry trades. This predictability effect is faster than the commodity effect on long leg profits (as documented by Bakshi and Panayotov (2013)). Although previous studies show bi-directional effects between commodities and currencies and between equities and currencies using daily data, at monthly frequency, the predictive effects go only one way: from commodities to long leg profits and from stocks to short leg profits. This predictability does not appear to be consistent with time-varying risk premia, because the predictability is short-lived.

One possible explanation for this study's findings is that carry trade investors react at different points in time to changes in equity prices and changes in commodity prices, or carry trade investors may have difficulty in assessing the impact of these changes on exchange rates. This study's results appear to be more consistent with the gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong et al. (2007). First, the results are strongest in two to three months' time. As a lag of 1 to 12 weeks is introduced between carry trade profits and the predictors, the explanatory power of predictive regressions increases, peaks, then quickly drops. This pattern is in line with the delayed reaction of investors. Second, commodity returns and stock returns also forecast economic fundamentals, as proxied by industrial production growth and changes in unemployment rates in the OECD countries. This result suggests that these stock and commodity returns may contain information related to economic fundamentals; this information flows gradually through asset markets. Finally, plots of impulse response confirm that delayed responses in carry trade profits to shocks to commodity prices and to shocks to equity prices are short-lived rather than persistent, which is more consistent with a market inefficiency explanation for the predictability results.

References

Adrian, T., Erkko Etula, and H. S. Shin. "Risk appetite and exchange rates." FRB of New York Staff Report 361 (2010).

Ang, A., & Chen, J. (2010). *Yield curve predictors of foreign exchange returns.* Paper presented at the AFA 2011 Meeting, Denvor.

Bakshi, G., & Panayotov, G. (2013). Predictability of currency carry trades and asset pricing implications. *Journal of Financial Economics, 110*(1), 139-163.

Bollerslev, T., & Ole Mikkelsen, H. (1996). Modeling and pricing long memory in stock market volatility. *Journal of econometrics, 73*(1), 151-184.

Brunnermeier, M. K., Nagel, S., & Pedersen, L. H. (2008). Carry trades and currency crashes. *NBER working paper*.

Burnside, C., Eichenbaum, M., Kleshchelski, I., & Rebelo, S. (2011). Do peso problems explain the returns to the carry trade? *Review of Financial Studies, 24*(3), 853-891.

Campbell, J. Y., Serfaty ‐ De Medeiros, K., & Viceira, L. M. (2010). Global currency hedging. *The Journal of Finance, 65*(1), 87-121.

Campbell, J. Y., & Shiller, R. J. (1988a). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies, 1*(3), 195-228.

Campbell, J. Y., & Shiller, R. J. (1988b). Stock prices, earnings, and expected dividends. *The Journal of Finance, 43*(3), 661-676.

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*(4), 1509-1531.

Cenedese, G., Payne, R., Sarno, L., & Valente, G. (2014). What Do Stock Markets Tell Us About Exchange Rates? *working paper, (Available at SSRN: http://ssrn.com/abstract=2467707)*.

Chen, Y.-c., & Rogoff, K. (2003). Commodity currencies. *Journal of International Economics, 60*(1), 133-160.

Chen, Y.-C., Rogoff, K. S., & Rossi, B. (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics, 125*(3), 1145-1194.

Cheung, Y. W., Chinn, M. D., & Marsh, I. W. (2004). How do UK ‐ based foreign exchange dealers think their market operates? *International Journal of Finance & Economics, 9*(4), 289-306.

Christiansen, C., Ranaldo, A., & Söderlind, P. (2011). The time-varying systematic risk of carry trade strategies. *Journal of Financial and Quantitative Analysis, 46*(04), 1107-1125.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics, 138*(1), 291-311.

Cochrane, J. H. (2001). Asset pricing.

Ding, Z., & Granger, C. W. (1996). Modeling volatility persistence of speculative returns: a new approach. *Journal of econometrics, 73*(1), 185-215.

Driesprong, G., Jacobsen, B., & Maat, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics, 89*(2), 307-327.

Engle, R. F., & Lee, G. (1999). A long-run and short-run component model of stock return volatility. *Cointegration, Causality, and Forecasting: A Festschrift in Honour of Clive WJ Granger*, 475-497.

Evans, M. D., & Lyons, R. K. (2012). Exchange rate fundamentals and order flow. *The Quarterly Journal of Finance, 2*(04).

Fama, E. F., & French, K. R. (1988). Business cycles and the behavior of metals prices. *The Journal of Finance, 43*(5), 1075-1093.

Fama, E. F., & Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics, 5*(2), 115-146.

Ferson, W., Nallareddy, S., & Xie, B. (2013). The ″ out-of-sample ″ performance of long run risk models. *Journal of Financial Economics, 107*(3), 537-556.

Granger, C. W., Huangb, B.-N., & Yang, C.-W. (2000). A bivariate causality between stock prices and exchange rates: evidence from recent Asianflu. *The Quarterly Review of Economics and Finance, 40*(3), 337-354.

Hall, P., Horowitz, J. L., & Jing, B.-Y. (1995). On blocking rules for the bootstrap with dependent data. *Biometrika, 82*(3), 561-574.

Hau, H., & Rey, H. (2006). Exchange rates, equity prices, and capital flows. *Review of Financial Studies, 19*(1), 273-317.

Hayek, F. A. (1945). The use of knowledge in society. *The American economic review*, 519-530.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance, 55*(1), 265-295.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance, 54*(6), 2143-2184.

Hong, H., Torous, W., & Valkanov, R. (2007). Do industries lead stock markets? *Journal of Financial Economics, 83*(2), 367-396.

Hong, H., & Yogo, M. (2009). Digging into commodities. *working paper, Princeton University and Wharton of University of Pennsylvania*.

Jacobsen, B., & Dannenburg, D. (2003). Volatility clustering in monthly stock returns. *Journal of empirical finance*, *10*(4), 479-503.

Jacobsen, B., Marshall, B. R., & Visaltanachoti, N. (2013). Stock Market Predictability and Industrial Metal Returns. *working paper*(Available at SSRN: http://ssrn.com/abstract=1660864).

Jahan-Parvar, M. R., Wohar, M. E., & Vivian, A. J. (2011). Underreaction to New Information in Equity Returns: Evidence from Commodity Markets. *working paper*.

Kearns, J. (2007). Commodity Currencies: Why Are Exchange Rate Futures Biased if Commodity Futures Are Not? *Economic Record, 83*(260), 60-73.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, *74*(1), 119-147.

Lustig, H., Roussanov, N., & Verdelhan, A. (2011). Common risk factors in currency markets. *Review of Financial Studies, 24*(11), 3731-3777.

Lustig, H., Roussanov, N., & Verdelhan, A. (2014). Countercyclical currency risk premia. *Journal of Financial Economics*, *111*(3), 527-553.

Menkhoff, L., Sarno, L., Schmeling, M., & Schrimpf, A. (2012). Carry trades and global foreign exchange volatility. *The Journal of Finance, 67*(2), 681-718.

Menzly, L., & Ozbas, O. (2010). Market Segmentation and Cross - predictability of Returns. *The Journal of Finance, 65*(4), 1555-1580.

Newey, W. K., & West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies, 61*(4), 631-653.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters, 58*(1), 17-29.

Ranaldo, A., & Söderlind, P. (2010). Safe Haven Currencies. *Review of Finance, 14*(3), 385-407.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2013). International stock return predictability: what is the role of the United States? *The Journal of Finance, 68*(4), 1633-1662.

Ready, R., Roussanov, N., & Ward, C. (2013). Commodity Trade and the Carry Trade: A Tale of Two Countries. *NBER working paper, No. 19371*.

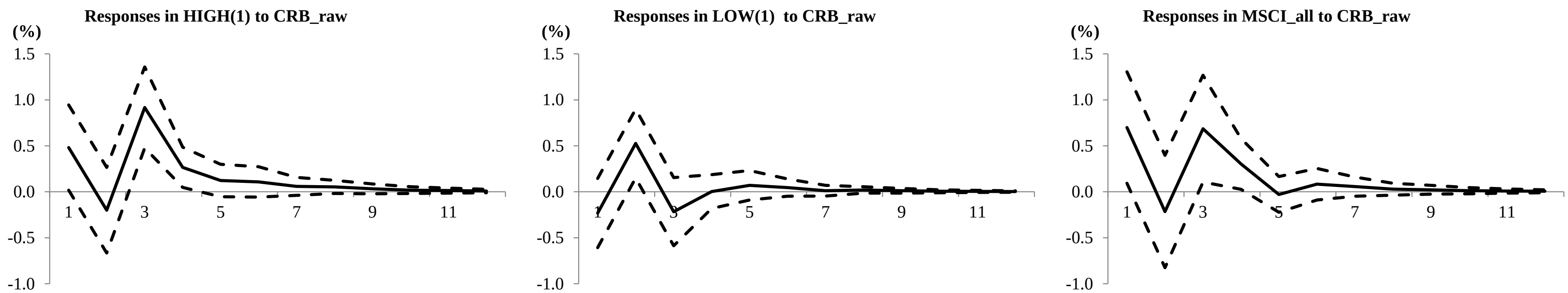
Schwert, G. W. (2003). *Anomalies and market efficiency*.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies, 21*(4), 1455-1508.

Figure 1. Impulse response functions

Plots in Panel A are cumulative responses in HIGH(1), LOW(1) and MSCI_all to a generalized one-standard-deviation innovation in CRB_raw. The solid lines plot the impulse responses to a generalized one standard deviation innovation from the VAR specification reported in Table 4. The dashed lines depict the 90% confidence intervals. HIGH(1) denotes monthly profits from longing the highest interest rate currency against one U.S. dollar using one-month forward contracts. LOW(1) denotes monthly profits from shorting the lowest interest rate currency against one U.S. dollar using one-month forward contracts. Details related to the construction of these carry trade strategies are in the main text. CRB_raw refers to monthly percentage changes in the CRB Raw Industrials Index. MSCI_all stands for the monthly percentage changes in the MSCI All Country World Index.

A.



B.

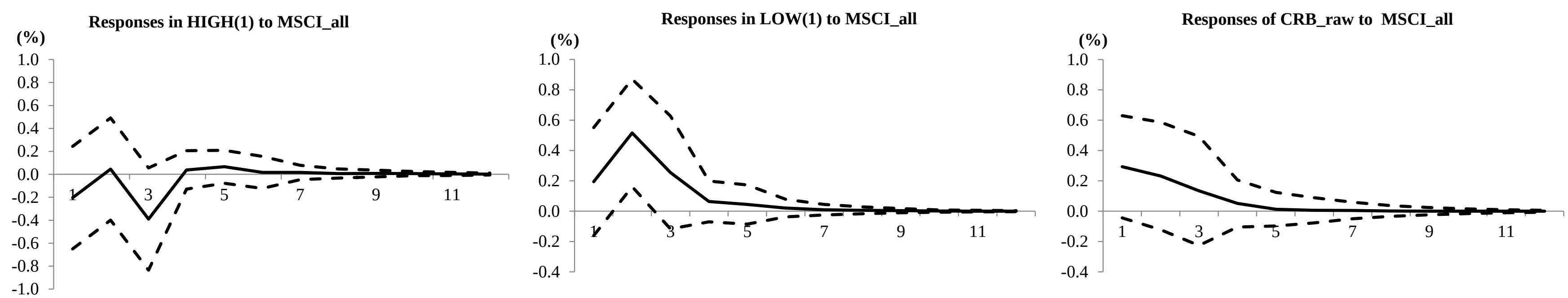


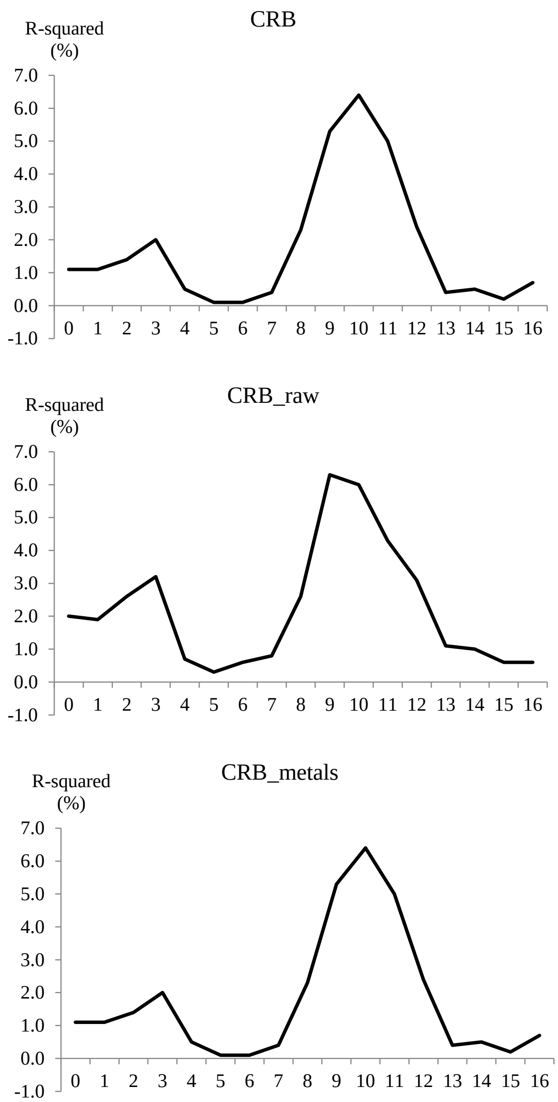
Figure 2. Predictive power with different lag sizes

This figure depicts the $\boldsymbol{R^2}$ from the regression specified in Equation (7), with different lag sizes between the predictors and carry trade profits.

$$HIGH(1)_t = a_0^{Z,K} + a_1^{Z,K} C_{t-1} + \mu_t^{Z,K}, \quad \text{for } K = 1,2,3$$
$$LOW(1)_t = b_0^{Y,K} + b_1^{Y,K} E_{t-1} + \omega_t^{Y,K}, \quad \text{for } K = 1 \cdots 3$$

where HIGH(1) denotes monthly profits from longing the highest interest rate currency against one U.S. dollar using one-month forward contracts; LOW(1) denotes monthly profits from shorting the lowest interest rate currency against one U.S. dollar using one-month forward contracts; C_{t-1} is either the monthly CRB Spot Index return (CRB_{t-1}), the monthly CRB Raw Industrials Index return (CRB_raw_{t-1}) or the monthly CRB Metals Index return (CRB_metals_{t-1}); E_{t-1} is either the monthly MSCI All Country World Index return ($MSCI\_all_{\mathrm{t-1}}$), the monthly MSCI World Index return ($MSCI_{t-1}$) or the monthly S&P 500 Index return ($SP500_{t-1}$). Details related to the construction of these carry trade strategies are in the main text.

A. Predicting long leg carry trade profits



B. Predicting short leg carry trade profits

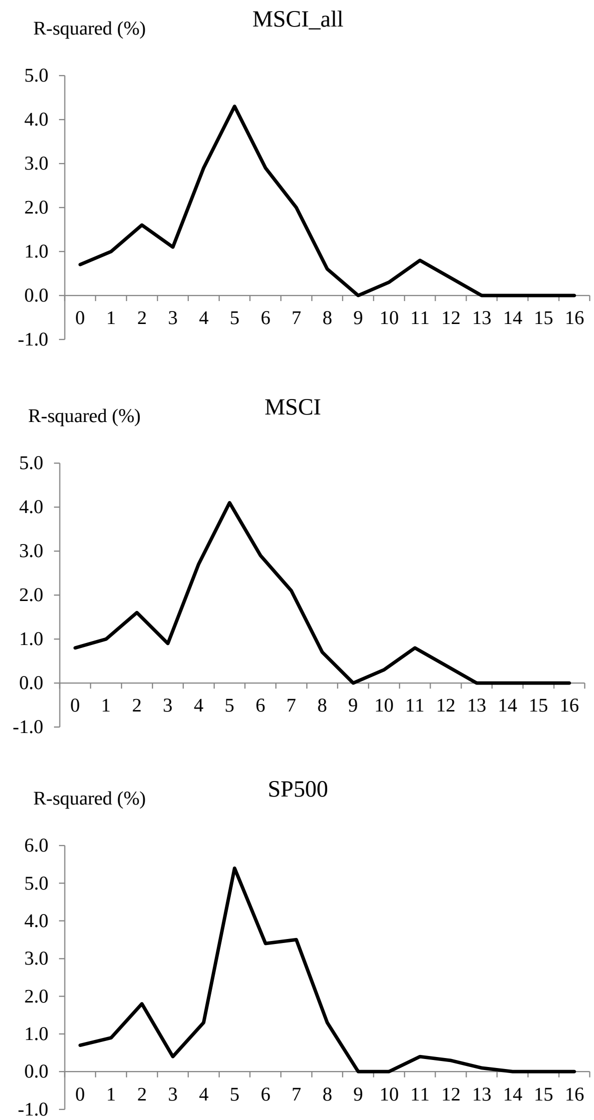


Table 1. Summary statistics and cross-correlations

Panel A in this table summarizes monthly carry trade profits, their currency components and their interest components. All profits and returns are in U.S. dollar terms. $HIGH(K)$ ($K = 1, 2, 3$) denote monthly profits from longing the K highest interest rate currencies against one U.S. dollar using one-month forward contracts. $LOW(K)$ ($K = 1, 2, 3$) denotes monthly profits from shorting the K lowest interest rate currencies against one U.S. dollar using one-month forward contracts. The interest rate component of carry trade profits is calculated based on Equation (2), with spot rate S_t replaced by S_{t-1}. Currency components of carry trade profits are calculated based on Equation (2), with forward rate F_{t-1} replaced by S_{t-1}. Details of these carry trade strategies are in the main text. rho(-1) denotes the first-order autocorrelation coefficient. *Panel B* summarizes monthly changes in equity indices and monthly changes in commodity indices. CRB, CRB_raw and CRB_metals refer to monthly percentage changes in the Commodity Research Bureau spot index, in the CRB Raw Industrials Index and in the CRB Metals Index. $MSCI\_all$, $MSCI$ and $SP500$ stand for monthly percentage changes in the MSCI All Country World Index, in the MSCI World Index and in the S&P 500 Index, respectively. All stock market indices in this study are total return indices. *Panel C* in this table reports pairwise correlation coefficients among all variables.

Sample periods of all variables run from February 1988 through December 2011. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

A. Carry trade profits

	Carry trade profits						Currency component		Interest component	
	N	Mean	SD	Skewness	Kurtosis	rho(-1)	Mean	rho(-1)	Mean	rho(-1)
HIGH(1)	287	0.49	3.52	-0.68	5.28	0.10	0.20	0.09	0.29	0.58
HIGH(2)	287	0.40	3.06	-0.46	5.15	0.08	0.17	0.07	0.24	0.72
HIGH(3)	287	0.34	2.87	-0.58	5.35	0.08	0.13	0.07	0.21	0.68
LOW(1)	287	0.12	2.95	-1.18	9.04	-0.01	-0.08	-0.01	0.21	0.62
LOW(2)	287	0.16	2.51	-0.48	5.37	-0.01	-0.01	-0.02	0.17	0.66
LOW(3)	287	0.14	2.38	-0.26	4.83	0.00	0.01	-0.00	0.14	0.67

B. Percentage changes in commodity indices and percentage changes in equity indices

	N	Mean	SD	Skewness	Kurtosis	rho(-1)
CRB	287	0.26	2.78	-1.36	13.64	0.24
CRB_raw	287	0.25	2.88	-1.88	19.09	0.32
CRB_metals	287	0.52	4.99	-1.59	18.34	0.28
MSCI_all	287	0.66	4.55	-0.60	4.42	0.08
MSCI	287	0.65	4.47	-0.57	4.24	0.09
SP500	287	0.84	4.32	-0.56	4.06	0.04

C. Cross-correlations

	HIGH(1)	HIGH(2)	HIGH(3)	LOW(1)	LOW(2)	LOW(3)	CRB	CRB_raw	CRB_metals	MSCI_all	MSCI	SP500
HIGH(1)	1.00											
HIGH(2)	0.92***	1.00										
HIGH(3)	0.91***	0.97***	1.00									
LOW(1)	-0.20***	-0.18***	-0.19***	1.00								
LOW(2)	-0.29***	-0.28***	-0.31***	0.91***	1.00							
LOW(3)	-0.30***	-0.30***	-0.33***	0.86***	0.98***	1.00						
CRB	0.36***	0.41***	0.44***	0.00	-0.08	-0.10	1.00					
CRB_raw	0.37***	0.42***	0.45***	-0.04	-0.12**	-0.14**	0.87***	1.00				
CRB_metals	0.32***	0.41***	0.43***	0.03	-0.06	-0.08	0.72***	0.85***	1.00			
MSCI_all	0.40***	0.44***	0.46***	-0.12**	-0.13**	-0.13**	0.31***	0.37***	0.38***	1.00		
MSCI	0.40***	0.43***	0.45***	-0.13**	-0.14**	-0.14**	0.30***	0.35***	0.36***	1.00***	1.00	
SP500	0.28***	0.30***	0.31***	0.02	0.05	0.05	0.27***	0.30***	0.31***	0.89***	0.89***	1.00

Table 2. Predicting carry trade profits in-sample

Panel A in this table reports coefficient estimates for $a_1^{Z,K}$ and $b_1^{Y,K}$ from regressions specified in the following equations:

$$HIGH(K)_t = a_0^{Z,K} + a_1^{Z,K} Z_{t-1} + \mu_t^{Z,K},$$

$$LOW(K)_t = b_0^{Y,K} + b_1^{Y,K} Y_{t-1} + \omega_t^{Y,K}, \quad for\ K = 1 \cdots 3$$

where Z_{t-1} is normalized three-month CRB Spot Index return (CRB_3M_{t-1}), normalized three-month CRB Raw Industrials Index return ($CRB\_raw\_3M_{t-1}$) or normalized three-month CRB Metals Index return ($CRB\_metals\_3M_{t-1}$); Y_{t-1} is normalized three-month MSCI All Country World Index return ($MSCI\_all\_3M_{t-1}$), normalized three-month MSCI World Index return ($MSCI\_3M_{t-1}$) or normalized three-month S&P 500 Index return ($SP500\_3M_{t-1}$). The normalized three-month index return in month $t-1$ is computed as percentage change in the index level from month $t-4$ to $t-1$ divided by three, or normalized to monthly. The t-statistics in Panel A are calculated from Newey-west standard errors with three lags.

Panel B in this table reports coefficient estimates for $\alpha_1^{C,K}$, $\alpha_2^{C,K}$, $\alpha_3^{C,K}$, $\theta_1^{E,K}$, $\theta_2^{E,K}$ and $\theta_3^{E,K}$ from regressions specified in the following equations:

$$HIGH(K)_t = \alpha_0^{C,K} + \alpha_1^{C,K} C_{t-1} + \alpha_2^{C,K} C_{t-2} + \alpha_3^{C,K} C_{t-3} + \gamma^{C,K} HIGH(K)_{t-1} + \mu_t^{C,K},$$
$$LOW(K)_t = \theta_0^{E,K} + \theta_1^{E,K} E_{t-1} + \theta_2^{E,K} E_{t-2} + \theta_3^{E,K} E_{t-3} + \delta^{E,K} LOW(K)_{t-1} + \omega_t^{E,K}, \text{ for } K = 1,2,3.$$

where C_t is monthly CRB Spot Index return (CRB_t), monthly CRB Raw Industrials Index return (CRB_raw_t) or monthly CRB Metals Index return (CRB_metals_t); E_t is monthly MSCI All Country World Index return ($MSCI\_all_t$), monthly MSCI World Index return ($MSCI_t$) or monthly S&P 500 Index return ($SP500_t$). The t-statistics in Panel B are calculated from heteroskedasticity-robust standard errors. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively. Sample periods of all variables run from February 1988 through December 2011.

A. Predictors are normalized three-month commodity index returns and normalized three-month equity index returns

	HIGH(1)	HIGH(2)	HIGH(3)
L.CRB_3M	0.32***	0.31***	0.27***
t-stat	(2.89)	(3.30)	(2.97)
N	284	284	284
Adj. R^2	2.60	3.40	2.90
L.CRB_raw_3M	0.34***	0.33***	0.29***
t-stat	(3.22)	(3.67)	(3.32)
N	284	284	284
Adj. R^2	3.60	4.70	4.10
L.CRB_metals_3M	0.18**	0.18***	0.16**
t-stat	(2.38)	(2.65)	(2.55)
N	284	284	284
Adj. R^2	3.00	4.00	3.60

	LOW(1)	LOW(2)	LOW(3)
L.MSCI_all_3M	0.20**	0.14**	0.12**
t-stat	(2.39)	(2.47)	(2.15)
N	284	284	284
Adj. R^2	3.20	2.10	1.60
L.MSCI_3M	0.21**	0.15**	0.12**
t-stat	(2.44)	(2.55)	(2.22)
N	284	284	284
Adj. R^2	3.20	2.20	1.60
L.SP500_3M	0.21**	0.15**	0.13**
t-stat	(2.42)	(2.45)	(2.13)
N	284	284	284
Adj. R^2	3.10	2.00	1.50

B. Predictors are three monthly commodity index returns and three monthly equity index returns

	HIGH(1)		HIGH(2)		HIGH(3)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
L.CRB	0.09	(1.04)	0.06	(0.76)	0.07	(0.94)
L2.CRB	-0.08	(-0.85)	-0.02	(-0.30)	-0.04	(-0.49)
L3.CRB	0.30***	(3.07)	0.24***	(2.83)	0.22***	(3.38)
N	284		284		284	
Adj. R^2	5.2		5.2		4.5	
L.CRB_raw	0.14*	(1.78)	0.14*	(1.93)	0.15**	(2.15)
L2.CRB_raw	-0.13	(-1.29)	-0.09	(-1.21)	-0.09	(-1.06)
L3.CRB_raw	0.33***	(3.53)	0.27***	(3.25)	0.22***	(3.73)
N	284		284		284	
Adj. R^2	6.9		7.5		6.3	
L.CRB_metals	0.07	(1.50)	0.06	(1.56)	0.06	(1.56)
L2.CRB_metals	-0.05	(-0.83)	-0.03	(-0.64)	-0.02	(-0.41)
L3.CRB_metals	0.16***	(2.66)	0.13***	(2.61)	0.11***	(2.78)
N	284		284		284	
Adj. R^2	5.3		6.00		4.7	

	LOW(1)		LOW(2)		LOW(3)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
L.MSCI_all	0.05	(1.16)	0.03	(1.00)	0.03	(0.83)
L2.MSCI_all	0.13**	(2.16)	0.11***	(2.62)	0.09**	(2.48)
L3.MSCI_all	0.03	(0.69)	0.00	(0.02)	-0.00	(-0.08)
N	284		284		284	
Adj. R^2	3.7		2.9		2.3	
L.MSCI	0.05	(1.23)	0.03	(1.06)	0.03	(0.89)
L2.MSCI	0.13**	(2.12)	0.11***	(2.61)	0.09**	(2.47)
L3.MSCI	0.03	(0.78)	0.00	(0.09)	-0.00	(-0.02)
N	284		284		284	
Adj. R^2	3.5		2.9		2.2	
L.SP500	0.05	(1.11)	0.04	(1.03)	0.03	(0.87)
L2.SP500	0.13**	(1.98)	0.10**	(2.32)	0.09**	(2.19)
L3.SP500	0.03	(0.83)	0.01	(0.25)	0.01	(0.19)
N	284		284		284	
Adj. R^2	3.3		2.4		1.7	

Table 3. Predicting carry trade profits out of sample

Panel A in this table reports $OS\ R^2$ as in Welch and Goyal (2008) and one-sided p-values for adjusted MSPE (Clark and West (2007)). *Panel B* in this table presents average profits, standard deviation and annualized Sharpe ratios of market-timing strategies and those of naive carry trade strategies. In Panel A and B, column heads are carry trade profits. Row heads are predictive variables. Asterisks next to Sharpe ratios indicate the bootstrapped significance level at which we can reject the null that the Sharpe ratio of market-timing strategy is *not* higher that of the naïve strategy. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

A. Out-of-sample R^2 and one-sided p-values for adjusted MSPE

	HIGH(1)	HIGH(2)	HIGH(3)
Out-of-sample R^2 (%)			
L3.CRB	5.36	5.49	5.07
L3.CRB_raw	5.98	6.55	5.33
L3.CRB_metals	3.43	4.71	3.83
One-sided p-values for adjusted MSPE			
L3.CRB	0.03	0.03	0.02
L3.CRB_raw	0.03	0.03	0.02
L3.CRB_metals	0.06	0.03	0.03

	LOW(1)	LOW(2)	LOW(3)
Out-of-sample R^2 (%)			
L2.MSCI_all	3.73	4.87	4.21
L2.MSCI	3.48	4.73	4.11
L2.SP500	2.48	3.80	3.26
One-sided p-values for adjusted MSPE			
L2.MSCI_all	0.05	0.02	0.03
L2.MSCI	0.05	0.02	0.03
L2.SP500	0.05	0.02	0.03

B. Monthly profits from market-timing strategies

	HIGH(1)	HIGH(2)	HIGH(3)
Trading profit (monthly)			
Naive strategy	0.65	0.51	0.43
L3.CRB	0.81	0.69	0.66
L3.CRB_raw	0.69	0.63	0.53
L3.CRB_metals	0.57	0.48	0.43
Standard deviation (monthly)			
Naive strategy	3.60	3.35	3.13
L3.CRB	2.88	2.64	2.42
L3.CRB_raw	2.99	2.75	2.62
L3.CRB_metals	3.09	2.86	2.74
Sharpe ratio (annualized)			
Naive strategy	0.62	0.52	0.48
L3.CRB	0.97**	0.90**	0.94***
L3.CRB_raw	0.80**	0.79	0.70
L3.CRB_metals	0.64**	0.58**	0.54**

	LOW(1)	LOW(2)	LOW(3)
Trading profit (monthly)			
Naive strategy	-0.25	-0.09	-0.08
L2.MSCI_all	0.11	0.09	0.05
L2.MSCI	0.08	0.12	0.09
L2.SP500	-0.10	-0.05	0.00
Standard deviation (monthly)			
Naive strategy	3.01	2.44	2.30
L2.MSCI_all	2.04	1.96	1.96
L2.MSCI	2.13	1.95	1.98
L2.SP500	2.49	2.04	2.02
Sharpe ratio (annualized)			
Naive strategy	-0.28	-0.13	-0.11
L2.MSCI_all	0.19**	0.16**	0.09*
L2.MSCI	0.13**	0.21**	0.16**
L2.SP500	-0.14	-0.08	0.00

C. Trading signals

	HIGH(1)	HIGH(2)	HIGH(3)
Predictor (L3.CRB)			
# of months	165	165	165
# of signals	40	33	36
% of time invested	76%	80%	78%
# of correct signals	25	20	25
98-06	16	12	15
07-11	9	8	10
98-06 avg. loss avoided	-1.09	-1.12	-1.30
07-11 avg. loss avoided	-5.70	-6.21	-4.90

	LOW(1)	LOW(2)	LOW(3)
Predictor (L2.MSCI_all)			
# of months	165	165	165
# of signals	56	49	41
% of time invested	66%	70%	75%
# of correct signals	38	34	29
98-06	15	15	10
07-11	23	19	19
98-06 avg. loss avoided	-3.57	-2.16	-1.81
07-11 avg. loss avoided	-1.51	-1.09	-1.05

Table 4. VAR analysis

This table presents estimation results from VAR models with endogenous variables $HIGH(K)$, $LOW(K)$, CRB and $MSCI\_all$. Each VAR model is estimated with three lags and a constant. HIGH(K) ($K = 1, 2, 3$) denote monthly profits from longing K highest interest rate currencies against one U.S. dollar using one-month forward contracts. $LOW(K)$ ($K = 1, 2, 3$) denotes monthly profits from shorting K lowest interest rate currencies against one U.S. dollar using one-month forward contracts. CRB refers to monthly percentage changes in the Commodity Research Bureau spot index. $MSCI\_all$ denotes monthly percentage changes in the MSCI All Country World Index. *Panel A* reports correlations between the VAR innovations, or the residuals in VAR models. *Panel B* reports Chi-square statistics and p-values of pairwise Granger-causality tests between endogenous variables. *Panel C* summarizes the number of Granger-causality tests that can reject the null at 0.10 or better significance levels, out of the total 27 VAR models. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively. Sample periods run from January 1988 to December 2011.

A. Contemporaneous correlations of VAR innovations

	HIGH(1)	LOW(1)	CRB
LOW(1)	-0.198***		
CRB	0.357***	-0.047	
MSCI_all	0.379***	-0.114*	0.301***

	HIGH(2)	LOW(2)	CRB
LOW(2)	-0.278***		
CRB	0.412***	-0.110*	
MSCI_all	0.425***	-0.110*	0.305***

	HIGH(3)	LOW(3)	CRB
LOW(3)	-0.319***		
CRB	0.434***	-0.121**	
MSCI_all	0.439***	-0.108*	0.301***

B. Granger-causality tests. Null hypothesis: row variable does not Granger-cause column variable.

	HIGH(1)	LOW(1)	CRB	MSCI_all
HIGH(1)		1.29	0.69	2.21
LOW(1)	1.16		4.40	1.09
CRB	15.55***	8.16**		7.43*
MSCI_all	2.93	9.15**	3.72	

	HIGH(2)	LOW(2)	CRB	MSCI_all
HIGH(2)		1.60	1.41	0.84
LOW(2)	1.10		4.83	0.68
CRB	11.04**	6.63*		6.90*
MSCI_all	4.97	8.47**	2.97	

	HIGH(3)	LOW(3)	CRB	MSCI_all
HIGH(3)		1.73	1.03	0.94
LOW(3)	0.92		4.76	0.78
CRB	10.22**	6.10		6.14
MSCI_all	3.89	6.10	2.91	

C. Summary of Granger-causality tests

	HIGH	LOW	Commodity	Stock
HIGH		0	0	0
LOW	0		0	0
Commodity	27	19		21
Stock	9	22	0	

Table 5. Predictability at longer horizons

This table reports the coefficient estimates for $a_j^{C,K}$ and $\theta_j^{E,K}$ from regressions specified in the following equations:

$$HIGH(K)_t = \alpha_0^{C,K} + a_j^{C,K} \sum_{j=1}^{6} C_{t-j} + \gamma^{C,K} HIGH(K)_{t-1} + \mu_t^{C,K},$$

$$LOW(K)_t = \theta_0^{E,K} + \theta_j^{E,K} \sum_{j=1}^{6} E_{t-j} + \delta^{E,K} LOW(K)_{t-1} + \omega_t^{E,K}, \text{ for } K = 1,2,3$$

where C_{t-j} is monthly CRB Spot Index return (CRB_{t-j}), monthly CRB Raw Industrials Index return (CRB_raw_{t-j}) or monthly CRB Metals Index return (CRB_metals_{t-j}); E_{t-1} is monthly MSCI All Country World Index return ($MSCI\_all_{t-j}$), monthly MSCI World Index return ($MSCI_{t-j}$) or monthly S&P 500 Index return ($SP500_{t-j}$). The t-statistics are calculated from heteroskedasticity-robust standard errors. ***, ** and * next to t-statistics indicate significance levels of 1%, 5% and 10%, respectively. Sample periods of all variables run from February 1988 through December 2011.

	HIGH(1)	HIGH(2)	HIGH(3)		HIGH(1)	HIGH(2)	HIGH(3)		HIGH(1)	HIGH(2)	HIGH(3)
L.CRB	0.09	0.06	0.06	L.CRB_raw	0.15*	0.16**	0.16**	L.CRB_metals	0.07	0.07*	0.07*
t-stat	(1.03)	(0.81)	(0.95)	t-stat	(1.90)	(2.26)	(2.40)	t-stat	(1.61)	(1.82)	(1.75)
L2.CRB	-0.07	-0.01	-0.03	L2.CRB_raw	-0.11	-0.07	-0.07	L2.CRB_metals	-0.05	-0.03	-0.02
t-stat	(-0.66)	(-0.12)	(-0.31)	t-stat	(-1.10)	(-0.92)	(-0.84)	t-stat	(-0.77)	(-0.51)	(-0.33)
L3.CRB	0.30***	0.25***	0.22***	L3.CRB_raw	0.33***	0.28***	0.23***	L3.CRB_metals	0.17***	0.15***	0.12***
t-stat	(3.00)	(2.76)	(3.14)	t-stat	(3.58)	(3.30)	(3.63)	t-stat	(2.77)	(2.86)	(2.93)
L4.CRB	0.02	0.00	0.01	L4.CRB_raw	0.05	0.05	0.05	L4.CRB_metals	0.05	0.04	0.04
t-stat	(0.21)	(0.01)	(0.10)	t-stat	(0.66)	(0.63)	(0.72)	t-stat	(1.03)	(0.97)	(0.87)
L5.CRB	0.02	-0.00	0.02	L5.CRB_raw	-0.02	-0.07	-0.02	L5.CRB_metals	-0.05	-0.08	-0.05
t-stat	(0.19)	(-0.04)	(0.23)	t-stat	(-0.23)	(-0.63)	(-0.20)	t-stat	(-0.91)	(-1.44)	(-0.92)
L6.CRB	-0.18**	-0.18**	-0.18**	L6.CRB_raw	-0.18**	-0.19**	-0.19**	L6.CRB_metals	-0.07*	-0.08*	-0.08*
t-stat	(-2.10)	(-2.08)	(-2.24)	t-stat	(-2.29)	(-2.24)	(-2.47)	t-stat	(-1.68)	(-1.78)	(-1.79)

	LOW(1)	LOW(2)	LOW(3)		LOW(1)	LOW(2)	LOW(3)		LOW(1)	LOW(2)	LOW(3)
L.MSCI_all	0.04	0.03	0.03	L.MSCI	0.05	0.03	0.03	L.SP500	0.05	0.04	0.03
t-stat	(1.12)	(1.00)	(0.87)	t-stat	(1.14)	(1.01)	(0.85)	t-stat	(1.04)	(1.03)	(0.87)
L2.MSCI_all	0.13**	0.11***	0.09**	L2.MSCI	0.13**	0.11***	0.09**	L2.SP500	0.14**	0.11**	0.09**
t-stat	(2.19)	(2.62)	(2.47)	t-stat	(2.18)	(2.65)	(2.51)	t-stat	(2.09)	(2.44)	(2.29)
L3.MSCI_all	0.02	-0.00	-0.01	L3.MSCI	0.03	0.00	-0.00	L3.SP500	0.03	0.01	0.01
t-stat	(0.48)	(-0.14)	(-0.22)	t-stat	(0.65)	(0.02)	(-0.08)	t-stat	(0.83)	(0.34)	(0.32)
L4.MSCI_all	0.03	0.01	0.01	L4.MSCI	0.03	0.02	0.01	L4.SP500	0.02	-0.00	-0.00
t-stat	(0.70)	(0.34)	(0.24)	t-stat	(0.80)	(0.52)	(0.45)	t-stat	(0.34)	(-0.04)	(-0.13)
L5.MSCI_all	-0.01	-0.01	-0.01	L5.MSCI	-0.01	-0.00	-0.01	L5.SP500	-0.03	-0.02	-0.02
t-stat	(-0.38)	(-0.30)	(-0.35)	t-stat	(-0.23)	(-0.13)	(-0.19)	t-stat	(-0.89)	(-0.76)	(-0.80)
L6.MSCI_all	0.02	0.00	-0.00	L6.MSCI	0.02	0.00	0.00	L6.SP500	0.02	-0.00	-0.00
t-stat	(0.53)	(0.05)	(-0.06)	t-stat	(0.58)	(0.11)	(0.03)	t-stat	(0.48)	(-0.07)	(-0.11)

Table 6. Relation with macroeconomic fundamentals

This table presents relations between predictors for carry trade profits (*CRB*, *CRB_raw*, *CRB_metals*, *MSCI_all*, *MSCI* and *SP500*) and macroeconomic variables (monthly OECD industrial production growth and monthly change in unemployment rate). *Panel A* reports contemporaneous correlation coefficients between predictors and macroeconomic variables. *Panel B* reports estimation results for predicting macroeconomic variables using the following equation:

$$O_t = \varphi_i + \sum_{s=1}^{3} \lambda_{Z,s} Z_{t-s} + \sum_{s=1}^{3} \xi_s \, O_{t-s} + \mathbf{A}\boldsymbol{X}_{\boldsymbol{t-1}} + \omega_t \, ,$$

where O_t is either monthly industrial production growth or monthly percentage changes in unemployment rate; Z_{t-s} is the value of predictor *CRB*, *CRB_raw*, *CRB_metals*, *MSCI_all*, *MSCI* or *SP500* in month $t - s$. **$\boldsymbol{X}_{\boldsymbol{t-1}}$ is a vector of additional predictors for macroconomic variables, including inflation, the term spread and the market dividend yield.**

A. Correlation coefficients

	Industrial Production Growth	Change in Unemployment Rate
CRB	0.24***	-0.16***
CRB_raw	0.27***	-0.21***
CRB_metals	0.24***	-0.20***
MSCI_all	0.11*	-0.07
MSCI	0.05	-0.08
SP500	0.11*	-0.11*

B. Predicting macroeconomic variables

	Industrial Production Growth	Change in Unemployment Rate		Industrial Production Growth	Change in Unemployment Rate
L.CRB	0.02	-0.06*	L.MSCI_all	0.01*	-0.04**
	(1.09)	(-1.82)		(1.78)	(-2.10)
L2.CRB	0.04*	-0.04	L2.MSCI_all	0.03***	-0.04**
	(1.96)	(-1.27)		(4.22)	(-2.37)
L3.CRB	0.01	-0.01	L3.MSCI_all	0.01*	-0.03**
	(0.42)	(-0.21)		(1.92)	(-2.28)
joint_significance	0.12	0.07	joint_significance	<0.01	<0.01
L.CRB_raw	0.02	-0.04	L.MSCI	0.01*	-0.04**
	(1.50)	(-1.08)		(1.71)	(-2.08)
L2.CRB_raw	0.04*	-0.06**	L2.MSCI	0.03***	-0.04**
	(1.87)	(-2.02)		(4.03)	(-2.37)
L3.CRB_raw	0.02	-0.00	L3.MSCI	0.01*	-0.03**
	(1.09)	(-0.13)		(1.74)	(-2.29)
joint_significance	0.01	0.04	joint_significance	<0.01	<0.01
L.CRB_metals	0.01	-0.02	L.SP500	0.01	-0.04**
	(1.42)	(-1.35)		(1.46)	(-2.40)
L2.CRB_metals	0.02*	-0.02	L2.SP500	0.03***	-0.03**
	(1.91)	(-1.21)		(3.50)	(-1.99)
L3.CRB_metals	0.01	-0.01	L3.SP500	0.02**	-0.03**
	(1.13)	(-1.03)		(2.48)	(-2.28)
joint_significance	0.01	0.12	joint_significance	<0.01	<0.01

Table 7. Robustness to GARCH effects

This table reports slope estimates on predicting variables for carry trade profits when we impose a GARCH(1,1) structure for the variance term. *HIGH(K)* ($K = 1, 2, 3$) denotes monthly profits from longing K highest interest rate currencies against one U.S. dollar using one-month forward contracts. *LOW(K)* ($K = 1, 2, 3$) denotes monthly profits from shorting K lowest interest rate currencies against one U.S. dollar using one-month forward contracts. *CRB*, *CRB_raw* and *CRB_metals* refer to monthly Commodity Research Bureau spot index return, monthly CRB Raw Industrials Index return and monthly CRB Metals Index return, respectively. *MSCI_all*, *MSCI* and *SP500* stand for monthly MSCI All Country World Index return, monthly MSCI World Index return and monthly S&P 500 return, respectively. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively. Sample periods run from February 1988 to December 2011.

	HIGH(1)	HIGH(2)	HIGH(3)		HIGH(1)	HIGH(2)	HIGH(3)		HIGH(1)	HIGH(2)	HIGH(3)
L.CRB	0.07	0.07	0.08	L.CRB_raw	0.06	0.13**	0.13**	L.CRB_metals	0.02	0.05	0.04
t-stat	(0.92)	(1.24)	(1.28)	t-stat	(0.72)	(2.02)	(1.99)	t-stat	(0.49)	(1.04)	(0.88)
L2.CRB	-0.07	-0.08	-0.09	L2.CRB_raw	-0.04	-0.07	-0.07	L2.CRB_metals	0.01	-0.01	-0.00
t-stat	(-0.87)	(-1.15)	(-1.32)	t-stat	(-0.50)	(-1.15)	(-1.15)	t-stat	(0.23)	(-0.33)	(-0.02)
L3.CRB	0.26***	0.25***	0.24***	L3.CRB_raw	0.24***	0.21***	0.19***	L3.CRB_metals	0.11***	0.09***	0.08***
t-stat	(3.75)	(3.98)	(3.98)	t-stat	(3.30)	(3.62)	(3.23)	t-stat	(2.82)	(2.98)	(2.72)

	LOW(1)	LOW(2)	LOW(3)		LOW(1)	LOW(2)	LOW(3)		LOW(1)	LOW(2)	LOW(3)
L.MSCI_all	0.03*	0.03	0.03	L.MSCI	0.03*	0.03	0.04	L.SP500	0.03	0.04	0.04
t-stat	(1.78)	(1.62)	(1.55)	t-stat	(1.73)	(1.59)	(1.51)	t-stat	(1.17)	(1.57)	(1.53)
L2.MSCI_all	0.05**	0.05**	0.05**	L2.MSCI	0.04**	0.05**	0.05*	L2.SP500	0.05	0.05**	0.05**
t-stat	(2.13)	(2.21)	(1.98)	t-stat	(2.04)	(2.13)	(1.91)	t-stat	(1.62)	(2.29)	(2.13)
L3.MSCI_all	0.03	0.03	0.03	L3.MSCI	0.03	0.03	0.03	L3.SP500	0.02	0.02	0.02
t-stat	(1.54)	(1.41)	(1.16)	t-stat	(1.60)	(1.45)	(1.18)	t-stat	(0.66)	(0.78)	(0.67)

Appendix I. Frequency of each currency in carry trade strategies

This table reports numbers of months that each currency is used in each carry trade strategy. $HIGH(K)$ ($K = 1, 2, 3$) denotes monthly profits from longing K highest interest rate currencies against one U.S. dollar using one-month forward contracts. $LOW(K)$ ($K = 1, 2, 3$) denotes monthly profits from shorting K lowest interest rate currencies against one U.S. dollar using one-month forward contracts. A currency is only bought (sold) forward against the U.S. dollar when it is at a forward discount (a forward premium) after crossing the bid–ask spread. Sample periods of all variables run from February 1988 through December 2011.

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
HIGH(1)	64	6	1	6	25	1	41	88	38
HIGH(2)	119	12	2	15	84	2	53	161	56
HIGH(3)	148	31	4	28	136	3	103	170	72
LOW(1)	0	1	17	1	0	184	1	0	2
LOW(2)	1	1	145	21	1	193	1	0	4
LOW(3)	1	4	158	111	2	201	2	0	12

Appendix II. Predicting currency component of carry trade profits

This table reports the slope estimates for predicting variables when they are used to predict the currency components of carry trade profits. Predictive regressions are specified in Equation (4). t-statistics are calculated from heteroskedasticity-robust standard errors. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively. Sample periods of all variables run from February 1988 through December 2011.

	HIGH(1)		HIGH(2)		HIGH(3)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
L.CRB	0.09	(1.09)	0.06	(0.79)	0.07	(0.98)
L2.CRB	-0.08	(-0.79)	-0.02	(-0.25)	-0.04	(-0.46)
L3.CRB	0.31***	(3.09)	0.25***	(2.83)	0.22***	(3.40)
N	284		284		284	
Adj. R^2	5.4		5.4		4.7	
L.CRB_raw	0.14*	(1.88)	0.15**	(1.99)	0.15**	(2.20)
L2.CRB_raw	-0.12	(-1.24)	-0.09	(-1.17)	-0.08	(-1.03)
L3.CRB_raw	0.33***	(3.56)	0.27***	(3.27)	0.22***	(3.76)
N	284		284		284	
Adj. R^2	7.2		7.8		6.6	
L.CRB_metals	0.07	(1.62)	0.07	(1.63)	0.07	(1.63)
L2.CRB_metals	-0.05	(-0.79)	-0.03	(-0.60)	-0.02	(-0.38)
L3.CRB_metals	0.16***	(2.71)	0.14***	(2.64)	0.11***	(2.81)
N	284		284		284	
Adj. R^2	5.7		6.3		4.9	

	LOW(1)		LOW(2)		LOW(3)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
L.MSCI_all	0.05	(1.25)	0.03	(1.04)	0.03	(0.85)
L2.MSCI_all	0.13**	(2.15)	0.11**	(2.59)	0.09**	(2.46)
L3.MSCI_all	0.02	(0.55)	-0.00	(-0.07)	-0.00	(-0.13)
N	284		284		284	
Adj. R^2	3.7		2.9		2.2	
L.MSCI	0.06	(1.31)	0.04	(1.10)	0.03	(0.91)
L2.MSCI	0.13**	(2.10)	0.10**	(2.56)	0.09**	(2.44)
L3.MSCI	0.03	(0.61)	-0.00	(-0.01)	-0.00	(-0.09)
N	284		284		284	
Adj. R^2	3.5		2.8		2.2	
L.SP500	0.06	(1.16)	0.04	(1.07)	0.03	(0.90)
L2.SP500	0.13*	(1.95)	0.10**	(2.26)	0.09**	(2.15)
L3.SP500	0.03	(0.65)	0.01	(0.15)	0.00	(0.13)
N	284		284		284	
Adj. R^2	3.2		2.3		1.6	

Appendix III. Summary predictors for carry trade profits

This appendix describes the predictors of currency carry trade profits investigated in this study.

1. *CRB*, *CRB_raw* and *CRB_metals*: *CRB_raw* stands for monthly percentage change in CRB Raw Industrials commodity index, based on Bakshi and Panayotov (2013), who find that three-month changes in the CRB Raw Industrials commodity index predict monthly carry trade profits both in-sample and out-of-sample. In addition to *CRB_raw*, we also examine the predictive ability of *CRB* and *CRB_metals*, which refer to the CRB Commodity Spot Index and the CRB Metals Index, respectively.
2. *MSCI_all*, *MSCI* and *SP500*: *MSCI_all* refers to monthly percentage change in MSCI All Country Total Return Index, as a proxy for world equity market performance; *MSCI* is monthly percentage change in the MSCI World Total Return Index; *SP500* refers to monthly change in the S&P 500 Index (including dividends). The choice of these equity indices is motivated by Ranaldo and Söderlind (2010) and Campbell et al. (2010).
3. *FX_vol_chg*: Changes in G-10 currency volatility, as a proxy for uncertainty in global currency markets, based on Menkhoff et al. (2012). For each G-10 currency included in this study, we calculate monthly volatility as the standard deviation of daily exchange rate changes against the U.S. dollar over a one-month period. Currency volatility averaged across these 10 currencies is G-10 currency volatility. *FX_vol_chg* is monthly percentage change in G-10 currency volatility.
4. *E_vol_chg*: Changes in G-10 country equity volatility, as a proxy for uncertainty in global equity markets, motivated by Lustig et al. (2011). A country's equity volatility in a given month is computed as the standard deviation of daily stock market index returns, and G-10 country equity return volatility is the cross-sectional mean of these country volatilities. *E_vol_chg* is monthly percentage change in G-10 country equity volatility.
5. *Liq_chg*: Changes in global liquidity, based on Brunnermeier et al. (2008). We compute an average of the equivalent of TED spread (three-month LIBOR minus three-month T-bill yields) across the G-10 currencies. *Liq_chg* is computed as $Liq\_chg_t = -(Liq_t - Liq_{t-1})$. Hence, a positive *Liq_chg* indicates that global liquidity has improved in a month.
6. *VOX_chg*: Monthly percentage change in the CBOE VOX index, following Brunnermeier et al. (2008).
7. *Term*: Term premium averaged across sample countries, based on Ang and Chen (2010), who show that term premium predicts currency returns. Individual country term premium is the difference between yield of a 10-year government bond and one-month interest rate (LIBOR or equivalent).
8. *AFD*: Average forward discount across countries, based on Lustig et al. (2014). Forward discount is computed as (S-F)/F, where S is the spot rate and F is the forward rate at the end of a given month, with the U.S. dollar as the home currency. Since exchange rates are denoted as home currency per foreign currency unit, a positive (negative) *AFD* indicates that the foreign interest rate is higher (lower) than the U.S. dollar interest rate.
9. *IP_growth*: Monthly percentage change in industrial production of the OECD countries, as a proxy for global economic growth, following Lustig et al. (2014), who find that IP growth predicts carry trade profits at long-horizon, after controlling for AFP.

10. *BDI_chg*: Monthly percentage change in the Baltic Dry Index, following Ready et al. (2013).