Cross-Asset Return Predictability:

Carry Trades, Stocks and Commodities

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Abstract

Bakshi and Panayotov (2013) find that commodity price changes predict profits from longing high interest rate currencies (long leg profits) up to three months later. We find that equity returns also predict carry trade profits, but from shorting low interest rate currencies (short leg profits). Equity effects appear to be slightly faster than commodity effects, as equity price rises predict higher short leg profits over the next two months. The predictability is one-directional from commodities and stocks to carry trades. Our evidence supports gradual information diffusion, rather than time-varying risk premia, as the most likely explanation for the predictability results.

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1. Introduction

Commodities and commodity currencies tend to move together. A large number of studies find strong co-movements and lead–lag relations between returns from these two asset classes (for example, Chen and Rogoff (2003), Kearns (2007), Chen, Rogoff, and Rossi (2010)). A recent study by Bakshi and Panayotov (2013) shows that commodity price movements predict carry trade profits from longing high interest rate currencies (*long leg profits*). Recent studies also suggest that movements in world equity prices may predict carry trade profits from shorting low interest rate currencies (*short leg profits*). For example, low interest rate currencies display safe-haven characteristics (Ranaldo and Söderlind 2010) and on average move against the main equity indices. Low interest rate currencies provide hedging benefits to equity investors (Campbell, Serfaty-De Medeiros, and Viceira 2010). 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. However, while the literature suggests this economic link, the question of whether equity returns predict carry trade profits has received no attention in the literature.

This paper intends to fill this gap by investigating whether changes in equity index levels predict short leg profits; using two world-market indices and a U.S. market index, we find that they do. 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. Our results also confirm the findings in Bakshi and Panayotov (2013) that three-month commodity returns strongly predict long leg profits one month later. The equity effect we document appears to be faster than the commodity effect. The predictive effect from stocks on the short leg carry trade significantly appears after two months. 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 a 0.20 standard deviation (about 0.59%). Similarly, a change in commodity returns of one standard deviation (about 2.78%) three months ago positively predicts a change of 0.24 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 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).

Our in-sample and out-of-sample results suggest that the predictive effects go from commodities to currencies and from stocks to currencies. There is good reason to suspect bi-directional 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 lead–lag effects between commodities and stocks may be significant (Hong and Yogo 2009; Jahan-Parvar, Wohar, and Vivian 2011; Jacobsen, Marshall, and Visaltanachoti 2013). We investigate cross-asset return dynamics in a vector autoregression (VAR) setting. First, we find that VAR innovations (or residuals in VAR models) in returns to commodities, stocks, and long- 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 stock returns and carry trade profits. 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. Third, results from impulse response functions (IRF) confirm results from ordinary least squares (OLS) regressions. IRF graphs show significant delayed predictive effects from commodities to high interest rate currencies and from stocks to low interest rate currencies. IRF graphs also depict interesting bi-directional cross-market dynamics between commodity returns and stock returns. Shocks originating from commodity markets (that are uncorrelated to variations in stock returns) affect stock returns over the following three months. Similarly, shocks originating from stock markets also ripple through to commodity markets.

We test two hypotheses for these predictability results. One explanation, often offered for return predictability based on economic variables, is that predictability is a result of time-varying risk premia. Our evidence does *not* support this hypothesis. Instead, our evidence is consistent with the gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong, Torous, and Valkanov (2007). First, we follow 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 and short leg profits initially peaks, and then quickly drops. This pattern is more consistent with a gradual information diffusion explanation. Second, we show that commodity returns and stock returns also predict the Organisation for Economic Co-operation and Development (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 reasonable to suspect that our predictability results are an artifact of volatility clustering or other known predictors for returns to sorted currency portfolios. 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, Roussanov, and Verdelhan 2011), changes in currency volatility (Menkhoff et al. 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 the industrial production of the OECD countries (as documented in Lustig, Roussanov, and Verdelhan (2014)).

This paper makes three contributions to the literature. First, this study documents statistically and economically significant predictability in carry trade profits from shorting low interest rate currencies. We also show that such predictability is from currency movement. This short-run predictability in the short leg of the carry trade is new and interesting in itself. Second, our study investigates low-frequency cross-markets dynamics among the main asset classes in a VAR setting. 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 predictability is unidirectional, from commodities to currencies and from stocks to currencies, but not the other way around. Third, existing studies uncover substantial evidence for cross-market and cross-asset return predictability consistent with the gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong,

Torous and Valkanov (2007).[1] Our study contributes to this strand of literature by showing that the predictability in short-run dynamic carry trade profits is more consistent with the gradual information diffusion hypothesis, rather 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, the 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.

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 three highest interest rate currencies at the beginning of a month and then selling spots at the end of a month. Strategy 3 for low interest rate currencies (*short leg*) does just the opposite: selling one-month forward contracts on three lowest interest rate currencies at the beginning of a month, and then buying spots at the end of a 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

[1] For example, see Hong, Lim and Stein, 2000; Hong, Torous and Valkanov, 2007; Driesprong, Jacobsen and Maat, 2008; Menzly and Ozbas, 2010; Rizova, 2012; Rapach, Strauss and Zhou, 2012.

resemble those in Burnside et al. (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 focus on 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] 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.

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):

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

[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.

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 (FCU). Therefore, a U.S. investor sells a foreign currency forward at the bid price[4] 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*).

Profits from all strategies are scaled to a bet size of one U.S. dollar. We buy (sell) a currency forward only if its implied interest differential from Equation (1) is positive (negative). If the U.S. dollar is the lowest (highest) interest rate currency at the beginning of a month, no currency is sold (bought) forward against the U.S. dollar in that month.

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

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

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

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

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

[4] 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.

$HIGH_t^j$ (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 forward; and $LOW(K)_t$ is the profit over month t from selling K lowest interest rate currencies forward. Appendix I summarises 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 approximately half to two-thirds of the time. 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 U.S. dollar, and the Swiss franc.

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 market, 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.[5] For the stock market, we consider the Morgan Stanley Capital International (MSCI) All Country World Index, the MSCI World Index and the Standard & Poor's 500 (S&P 500)

[5] 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.

Index. All equity indices are total return indices from Datastream.[6] To facilitate easy comparison of predictive results across the board, we investigate all predictive effects over the same sample period, February 1988–December 2012. The start of this sample period is 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 summarises 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%. 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. Currency components in short leg carry trade profits range between −0.08% and 0.01% monthly.

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

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 1% to 2% 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 or fall together, as suggested by the highly significant and positive correlations among these asset returns. For 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 have a 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). 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 (1988) 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 normalised three-month commodity index returns ending in month $t-1$ to predict long leg profits in month t. The normalised 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 normalised to monthly. In the same spirit, we use normalised three-month returns in equity indices to predict the short leg carry trade profit. Normalised three-month returns are less volatile than monthly returns. For example, normalised three-month equity index returns have standard deviations that range between 2.58% 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:

$$HIGH(K)_t = a_0^{Z,K} + a_1^{Z,K} Z_{t-1} + \mu_t^{Z,K} \tag{3}$$

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

where Z_{t-1} denotes a predictor for long leg profits; Z_{t-1} is either the normalised three-month CRB Spot Index return (CRB_3M_{t-1}), the normalised three-month CRB Raw Industrials Index return ($CRB\_raw\_3M_{t-1}$) or the normalised three-month CRB Metals Index return ($CRB\_metals\_3M_{t-1}$); Y_{t-1} denotes a predictor for the short leg carry trade profit; Y_{t-1} is either the normalised three-month MSCI All Country World Index return ($MSCI\_all\_3M_{t-1}$), the normalised three-month MSCI World Index return ($MSCI\_3M_{t-1}$) or the normalised three-month S&P 500 Index return ($SP500\_3M_{t-1}$). 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. Like Bakshi and Panayotov (2013), we find that normalised three-month changes in commodity price indices strongly predict carry trade profits from high interest rate currencies – all nine slope estimates for normalised 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. In addition to predictability in long leg profits, we also find that normalised 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.

The predictive effect is from three-month changes in commodity prices to long leg carry trades and from three-month changes in equity prices to short leg carry trade profits. This finding raises the question whether such predictive effect appears immediately in the

following month or after some delay. An answer to this question can also provide evidence regarding whether the discussed predictability is a form of gradual information diffusion (Hong and Stein 1999; Hong, Torous, and Valkanov 2007). We test the predictive effect in each of the three months by running the regressions specified below:

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

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

where C_t denotes a predictor for the long leg profits; C_t is either 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.

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, 2009, 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),[7] 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:

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

where $\widehat{\theta_t}$ is the predicated carry trade profit in month t and θ_t is the historical average profit; P_t is the realized carry trade profit in month t; $OS\ R^2$ indicates the 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, Strauss, and Zhou (2013) and Ferson, Nallareddy, and Xie (2013) and 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)). The 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

[7] 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."

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[8] 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

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

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.[9] Sharpe ratios generated by long leg market-timing strategies are between 0.54 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.

This section investigates out of sample predictability using three measures, namely, 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, Rogoff, and Rossi 2010; Granger, Huangb, and Yang 2000; Hong and Yogo 2009; Jahan-Parvar, Wohar, and Vivian 2011), in this section, we adopt vector autoregression (VAR)

[9] 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, and Jing 1995). The p-value to reject the null of *no* 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.

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):

$$
\begin{aligned}
HIGH(K)_t &= \sum_{j=1}^{3} a_{1j}E_{t-j} + \sum_{j=1}^{3} b_{1j}C_{t-j} + \sum_{j=1}^{3} c_{1j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{1j}HIGH(K)_{t-j} + \mu_t \\
LOW(K)_t &= \sum_{j=1}^{3} a_{2j}E_{t-j} + \sum_{j=1}^{3} b_{2j}C_{t-j} + \sum_{j=1}^{3} c_{2j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{2j}HIGH(K)_{t-j} + \tau_t \\
E_t &= \sum_{j=1}^{3} a_{3j}E_{t-j} + \sum_{j=1}^{3} b_{3j}C_{t-j} + \sum_{j=1}^{3} c_{3j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{3j}HIGH(K)_{t-j} + \varphi_t \\
C_t &= \sum_{j=1}^{3} a_{4j}E_{t-j} + \sum_{j=1}^{3} b_{4j}C_{t-j} + \sum_{j=1}^{3} c_{4j}LOW(K)_{t-j} + \sum_{j=1}^{3} d_{4j}HIGH(K)_{t-j} + \omega_t
\end{aligned}
\tag{6}
$$

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 shocks 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. 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.[10] We find that shocks to commodity prices, shocks to equity index returns and shocks 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 shocks to commodity prices and shocks to equity index levels are negatively associated with low interest rate currencies. Pairwise correlation coefficients among shocks 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 between endogenous variables of the VAR. For the null hypothesis that variable x does not Granger-cause variable y, we test whether the lag 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 summarises the number of tests (out of a total of 27 tests) that reject the null at 0.10 or better significance levels.[11] In the 27 VAR systems, the predictive ability of monthly commodity indices returns stands out, because they Granger-cause long leg profits in all 27 cases, as well as Granger-causing equity index returns and short leg profits in 22 and 19 out of 27 cases, respectively. Second to commodity indices returns are equity indices returns – they significantly Granger-cause short leg profits and long leg profits in 22 and 9 out of 27 cases, respectively. In addition, commodity returns Granger-cause stock returns in 21 out of 27 cases but stock returns do not Granger-cause any commodity returns (this finding corroborates the findings regarding stock returns and

[10] Details of correlations of VAR innovations from the other 18 models are available on request.

[11] 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.

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 other markets is strongest, followed by that from stocks on other markets.

To further understand the dynamic properties of cross-asset return predictability, we compute IRFs for a unit standard deviation shock to the commodity index returns, as well as that for equity index returns. The IRF traces the impact of a one-time and one-unit standard deviation positive shock to one variable on the current and future values of other endogenous variables in a VAR system. Because VAR innovations in different markets are contemporaneous correlations (as shown in Panel A of Table 4), we perform a Cholesky decomposition of the variance-covariance matrix of residuals to orthogonalise the impulses. Because our VAR Granger-causality results show that commodities and stocks lead currencies, when studying responses to shocks to commodities, we choose Cholesky decomposition order to be commodity index return, equity index return, long leg profits and short leg profits. When studying responses to shocks to stocks, we choose Cholesky decomposition order to be equity index return, commodity index return, long leg profits and short leg profits.

[Insert Figure 1 about here]

The plots in Panel A of Figure 1 illustrate the cumulative response of other exogenous variables to a unit standard deviation shock to commodity returns for a period of 12 months.[12] Plots in Panel B illustrate the cumulative response of other exogenous variables to a unit

[12] In Figure 1, we report IRFs use CRB_raw, HIGH(1), LOW(1) and MSCI_all as endogenous variables only for brevity. Results from other VAR systems are similar and available on request.

standard deviation shock to stocks.[13] These plots suggest that there are significant delayed predictive effects from commodities to high interest rate currencies and from stocks to low interest rate currencies. There are also significant cross-market dynamics between commodities and stocks. The first plot in Panel A indicates that the long leg profits contemporaneously increase by approximately a 0.34 standard deviation in response to a unit standard deviation shock to the CRB Raw Industrials Index return. During the following three months, the cumulative response strengthens gradually and stabilises at around a 0.60 standard deviation. By contrast, innovations in commodity returns do not significantly predict short leg profits (the second plot in Panel A). Rather, shocks to equity returns positively predict short leg profits with a delay of two months (the second plot in Panel B) – the profits from shorting low interest rate currencies appear to decrease slightly during the same month in response to a positive shock to the equity index (but the response is insignificant); after two months, the cumulative response turns significantly positive and stabilises at around a 0.25 standard deviation. The last plot in Panel A and the last plot in Panel B provide evidence of cross-market dynamics. The MSCI All Country World Index return responds positively to a shock in the CRB Raw Industrials Index return – the contemporaneous response is of a 0.30 standard deviation. Additional responses during the three following months drive the cumulative responses in the MSCI All Country World Index return to a 0.60 standard deviation. A positive shock to equity returns also forecasts an increase in commodity returns, with noticeable incremental effects in the first few months (the third plot in Panel B).

[13] We omit IRFs for responses to shocks to carry trade profits because responses to these shocks are insignificant.

5. Gradual information diffusion or time-varying risk premia

5.1. Evidence for 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 (containing 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.

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

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

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.[14] R^2s peak at different lags for the 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

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

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. Evidence against the time-varying risk premia explanation

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, 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, Roussanov, and Verdelhan 2014). Hence, it is necessary to verify whether the observed predictability is a result of time-varying risk premia. This section provides evidence against the time-varying risk premia explanation in two respects: (1) lack of predictability at longer horizons; and (2) inconsistency in predictions from equilibrium theory.

5.2.1. Predictability at longer horizons

The predictability associated with time-varying risk premia tends to strengthen at longer horizons (Cochrane 2001). The analogous question is whether observed predictability in carry trades survives at long horizons. This section tests long-run predictability using regressions specified as follows:

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

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

where six monthly commodity returns (equity returns) between month $t-6$ to $t-1$ predict long leg (short leg) profits in month t.

[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 long leg profits using commodity 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. These results suggest that predictability in carry trade profits from commodity returns and equity returns is short-lived and that neither commodity returns nor equity returns serve as an indication of time-varying risk premia.

5.2.2. Equilibrium theory

Equilibrium theory suggests that the predictability discussed in this paper is not related to risk premia. According to equilibrium theory, some variables proxy for business risk across economic cycles (for example, dividend yield and term structure) and higher risk should predict higher returns. Take the equity index return as an example: If a negative equity index return predicts carry trade profits as a result of risk, equilibrium theory suggests that drops in world equity prices, which indicate higher risk, should lead to higher average profits from carry trades. This study finds, however, that a drop in world equity prices leads to decreases

in carry trade profits. Similarly, decreases in commodity prices are related to increases in risk. If the predictive effect in long leg profits from commodity price movements is a result of risk, then decreases in commodity prices should predict increased carry trade profits, instead of drops in carry trade profits. The inference from equilibrium theory is inconsistent with findings in this study, where drops in commodity prices and drops in equity prices predict lower future carry trade profits.

6. Predictability and macroeconomic fundamentals

This section shows that the variables that predict carry trade profits contain information about market fundamentals, as proxied for 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 economic such activities as industrial production growth, as demonstrated in a study by Lustig, Roussanov, and Verdelhan (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 for 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 regressions specified in the equation below:

$$O_t = \varphi_i + \sum_{s=1}^{3} \lambda_{Z,s} Z_{t-s} + \sum_{s=1}^{3} \xi_s \, O_{t-s} + \omega_t \ , \tag{9}$$

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_metal, MSCI_all, MSCI or SP500 in month $t-s$.

[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 both commodity returns and stock returns significantly predict economic fundamentals, as proxied by industrial production growth and changes in unemployment rate, over a three-month horizon. Five out of six commodity returns and all equity 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.

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 still significantly predict long leg profits three months later – nine slope estimates for commodity returns lagged by three months are all positive and significant. 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. The present 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 carry trade predictors 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, Roussanov, and Verdelhan 2011), changes in global liquidity and monthly percentage change in the CBOE VOX index (Brunnermeier, Nagel, and Pedersen 2008), term premium averaged across the countries in the sample (Ang and Chen 2010), average forward discount and industrial production growth in the OECD countries (Lustig, Roussanov, and Verdelhan 2014), and changes in the Baltic Dry Index Ready (Ready, Roussanov, and Ward 2013).[15] 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 short leg is of significant economic value to carry trade investors. By predicting short leg profits and timing investment decisions, an investor can improve the short leg profits and lower 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

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

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. It seems unlikely that this predictability can be attributed to time-varying risk premia, because the predictability is short-lived and inconsistent with predictions from the equilibrium theory, where increased uncertainty is associated with higher expected returns. If predictors, including the world equity index return and commodity returns, indeed serve as proxies for business cycle risk, drops in world equity prices and drops in commodity prices should lead to higher carry trade profits, not lower profits as found in this study.

One possible explanation for the findings in this study 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. The results in this study appear to be more consistent with the gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong, Torous, and Valkanov (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.

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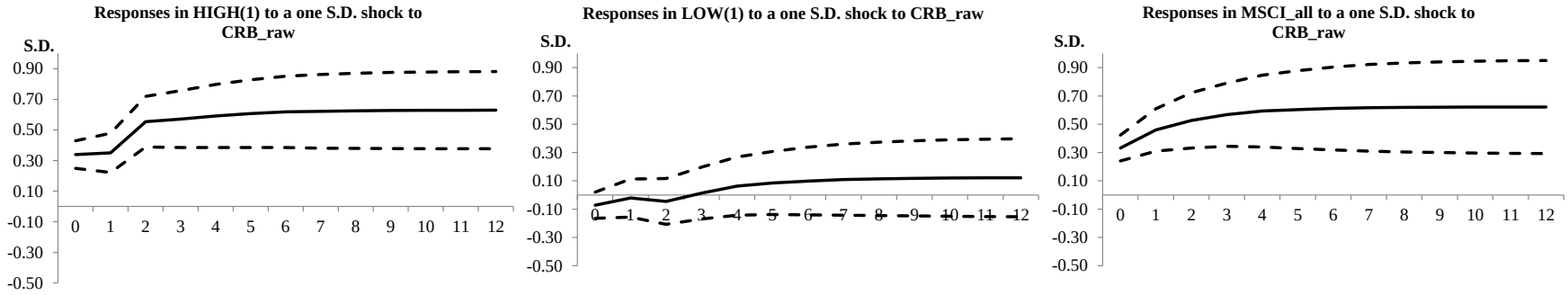
Figure 1. Cumulative impulse response functions

Plots in Panel A are cumulative responses in HIGH(1), LOW(1) and MSCI_all to a one-standard-deviation shock to the CRB_raw. Impulse response is based on an estimated vector autoregressive model that includes 12 monthly lags of endogenous variables, with a Cholesky decomposition of the shock (order CRB_raw, MSCI_all, HIGH(1) and LOW(1)). Plots in Panel B are cumulative responses in HIGH(1), LOW(1) and CRB_raw to a one-standard-deviation shock to the percentage changes in MSCI_all. The order of Cholesky decomposition is MSCI_all, CRB_raw, HIGH(1) and LOW(1). Solid lines depict the response and 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.

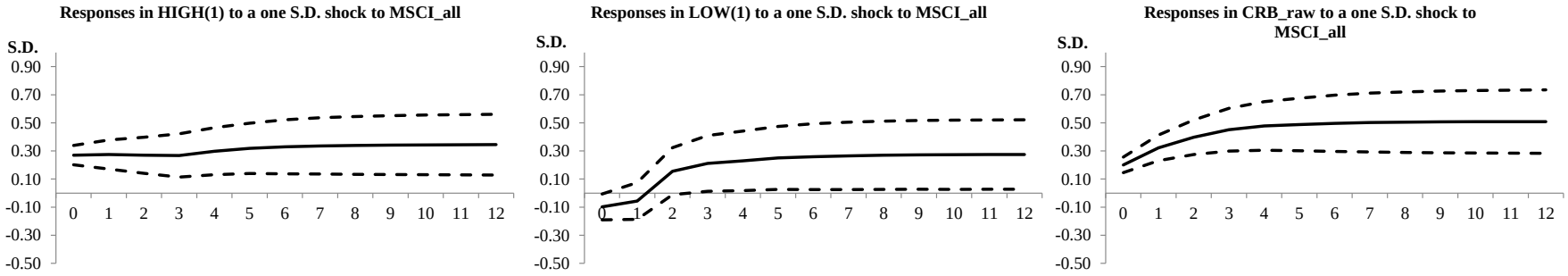


Figure 2. Predictive power with different lag sizes

This figure depicts the $\boldsymbol{R^2}$ from the regression specified in Equation (10), with different lag sizes between the predictors and carry trade profits.

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

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 ($\mathrm{CRB\_raw}_{t-1}$) or the monthly CRB Metals Index return ($\mathrm{CRB\_metals}_{t-1}$); E_{t-1} is either the monthly MSCI All Country World Index return ($\mathrm{MSCI\_all}_{t-1}$), the monthly MSCI World Index return (MSCI_{t-1}) or the monthly S&P 500 Index return ($\mathrm{SP500}_{t-1}$). Details related to the construction of these carry trade strategies are in the main text.

A. Predicting short leg carry trade profits

B. Predicting long leg carry trade profits

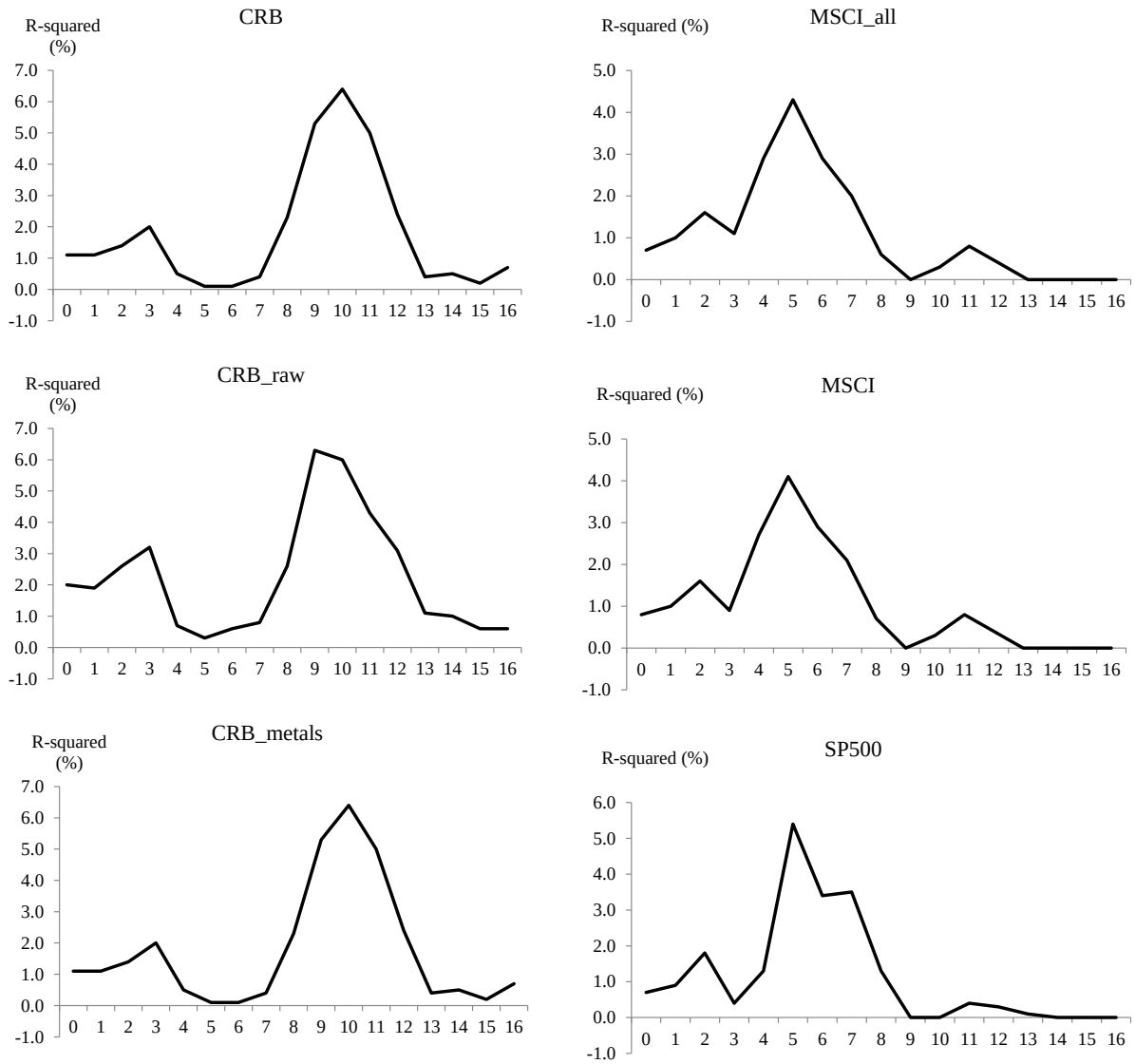


Table 1. Summary statistics and cross-correlations

Panel A in this table summarises 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* summarises 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 (CRB) 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 normalised three-month CRB Spot Index return (CRB_3M_{t-1}), normalised three-month CRB Raw Industrials Index return (CRB_raw_3M_{t-1}) or normalised three-month CRB Metals Index return ($\text{CRB\_metals\_3M}_{t-1}$); Y_{t-1} is normalised three-month MSCI All Country World Index return ($MSCI\_all\_3M_{t-1}$), normalised three-month MSCI World Index return (MSCI_3M_{t-1}) or normalised three-month S&P 500 Index return (SP500_3M_{t-1}). The normalised 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 normalised 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 normalised three-month commodity index returns and normalised 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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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. 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)
OS R2 (%)			
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)
OS R2 (%)			
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
Shape 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
Shape 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

Table 4. Vector auto regression (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 (CRB) 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* summarises 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 ($\mathrm{CRB\_raw}_{t-j}$) or monthly CRB Metals Index return ($\mathrm{CRB\_metals}_{t-j}$); E_{t-1} is monthly MSCI All Country World Index return ($\mathrm{MSCI\_all}_{t-j}$), monthly MSCI World Index return (MSCI_{t-j}) or monthly S&P 500 Index return ($\mathrm{SP500}_{t-j}$). 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:

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

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_metal, MSCI_all, MSCI or SP500 in month $t - s$.

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**
t-stat	(1.21)	(-1.95)	t-stat	(1.87)	(-2.20)
L2.CRB	0.05**	-0.05	L2.MSCI_all	0.04***	-0.04**
t-stat	(2.03)	(-1.48)	t-stat	(4.01)	(-2.47)
L3.CRB	0.01	-0.01	L3.MSCI_all	0.01*	-0.03**
t-stat	(0.48)	(-0.29)		(1.93)	(-2.34)
joint_significance	0.10	0.01	joint_significance	0.00	0.00
L.CRB_raw	0.03	-0.04	L.MSCI	0.01*	-0.04**
t-stat	(1.58)	(-1.12)	t-stat	(1.80)	(-2.18)
L2.CRB_raw	0.05*	-0.07**	L2.MSCI	0.03***	-0.04**
t-stat	(1.95)	(-2.21)	t-stat	(3.83)	(-2.47)
L3.CRB_raw	0.02	-0.01	L3.MSCI	0.01*	-0.03**
t-stat	(1.16)	(-0.18)	t-stat	(1.76)	(-2.35)
joint_significance	0.01	0.01	joint_significance	0.00	0.00
L.CRB_metals	0.01	-0.02	L.SP500	0.01	-0.04**
t-stat	(1.41)	(-1.36)	t-stat	(1.49)	(-2.47)
L2.CRB_metals	0.03**	-0.02	L2.SP500	0.03***	-0.04**
t-stat	(1.99)	(-1.43)	t-stat	(3.31)	(-2.03)
L3.CRB_metals	0.01	-0.02	L3.SP500	0.02**	-0.03**
t-stat	(1.19)	(-1.18)	t-stat	(2.42)	(-2.28)
joint_significance	0.01	0.05	joint_significance	0.00	0.00

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 (CRB) 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 Feburary 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	USD
HIGH(1)	64	6	1	6	25	1	41	88	38	17
HIGH(2)	119	12	2	15	84	2	53	161	56	53
HIGH(3)	148	31	4	28	136	3	103	170	72	96
LOW(1)	0	1	17	1	0	184	1	0	2	81
LOW(2)	1	1	145	21	1	193	1	0	4	126
LOW(3)	1	4	158	111	2	201	2	0	12	163

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. R2	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. R2	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. R2	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. R2	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. R2	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. R2	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, Serfaty-De Medeiros, and Viceira (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, Roussanov, and Verdelhan (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, Nagel, and Pedersen (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, Nagel, and Pedersen (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, Roussanov, and Verdelhan (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 FCU, 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, Roussanov, and Verdelhan (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, Roussanov, and Ward (2013)).