Speculator activity and the cross-asset predictability of FX returns

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Abstract
The gradual information diffusion hypothesis (GIDH) suggests that information flows slowly between across asset markets, thus generating return predictability. We examine the cross-asset return predictability of FX market strategies and apply the GIDH to empirically investigate the role of speculator activity in the cross-asset return predictability of FX market strategies. We hypothesize that when speculators are active in the FX market, the speed of information diffusion into the market increases, which invariably weakens predictability between the equity and commodity markets and FX strategies. Our reported results show that when speculators are active in the FX market, predictability from the equity market dissipates. Our findings suggest that speculators play a vital role in enhancing informational efficiency in the FX market.

JEL Classification: G12, G14, G15

Keywords: Speculator, FX strategy, Information

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1. Introduction

The extant literature documents ample evidence that asset returns encompass a predictable component. Conventional finance theories, which assume investors are unboundedly rational and have unlimited information processing capacity, have, however, been ineffectual in explaining this predictability. Over the past decade, behavioural economics models have gained increased prominence over conventional finance models in explaining the predictability of asset returns. In this paper, we use one such behavioural model, the gradual information diffusion hypothesis (Hong and Stein, 1999), to explain the role of speculators in the cross-asset return predictability of FX market strategies. Specifically, we examine information flow between the equity and commodity and FX markets, as well as speculative activity in the FX market, to explain predictability between the equity and commodity market and FX strategies.

The gradual information diffusion hypothesis posits that a set of economic information flows slowly across asset markets and generates return predictability. This is a consequence of investors’ inability to always process every piece of information. The extant literature has shown that the impact of economic fundamentals is pervasive across asset markets (see Campbell et al., 2010; Chen and Rogoff, 2003; Kearns, 2007; Lustig et al., 2011) and the evidence on predictability across asset classes has been shown to be consistent with the gradual information diffusion hypothesis. For example, Lu and Jacobsen (2016) find that equity returns predict the returns of the short leg of the carry trade strategy. These studies have, however, mainly focused on asset returns and not on the important primary drivers of the information diffusion process across economically linked asset markets. The drivers are, arguably, a potential and significant value source in the information diffusion process. This paper,

4(see, e.g., Hong et al., 2000; Chordia and Swaminathan, 2000; Hong et al., 2007; Hou, 2007; Cohen and Frazzini, 2008; Driesprong, Jacobsen and Maat, 2008; Menzly and Ozbas, 2010; Rapach et al., 2013; and Lu and Jacobsen, 2016).
therefore, examines the role of *speculators* as a fundamental element in the information diffusion process.

Understanding the role of *speculators* is imperative because their activities can enhance information diffusion between markets as the participants actively follow the relevant information. This is an important point because informed investors spread information more rapidly than uninformed investors (see Menzly and Ozbas, 2010). Thus, investigating the cross-asset predictability of FX market strategies in conjunction with the activity of FX market participants touches on the important question of the role of market *speculators* in the information diffusion process. In addition, by distinguishing the role of *speculators*, this paper integrates several strands of the financial literature; FX market-related return predictability (e.g., Bakshi and Panayotov, 2013; Lu and Jacobsen, 2016), the role of *speculators* in the FX market (e.g., Fong, 2013), and the role of *speculators* in the information diffusion process (Hong and Stein, 1999; Menzly and Ozbas, 2011).

The behaviour of FX market participants is state-dependent. For example, Fong (2013) documents a significant increase in hedge funds carry trade positions in *hot markets* (market-states with very high currency returns) and that optimism in the stock market has a spillover effect on hedge fund speculation in the FX market. Also, there is evidence in the literature which suggests that, as informed traders, hedge fund activity increases market efficiency (Menzly and Ozbas, 2010; Kokkonen and Suominen, 2015). Assuming that informed investors perform exceptionally well at processing information, a larger number of informed investors, or a higher degree of their activity, should increase the speed of information diffusion into the market. Therefore, we hypothesize that the gradual information flow between the equity and
commodity markets and the FX market depends on speculative activity in the FX market. That is, we expect predictability between FX strategies and the equity market to be weaker when FX speculators are more active. The FX strategies we are considering are the carry trade, momentum, and fundamental strategies, which are generally acknowledged and shown to generate significant profits (see, e.g., Kroencke et al., 2013).

We report several notable findings. First, we find that the equity market (S&P 500) predicts each strategy, and the commodity index predicts the majority of the the short and long legs of all three strategies considered in this paper. In relation to speculator activity, we find, in line with our hypothesis, that speculator activity in the AUD/JPY carry trade weakens predictability from the equity market but it does not appear to alter the predictability from the commodity market. When speculators are not actively trading the AUD/JPY carry trade, the equity market predicts each leg of the different FX strategies. Our additional analysis using hedger activity show contrasting findings compared to speculator activity that cross-asset predictability is only present when hedgers are active. These findings strongly support our hypothesis that speculator activity increases the speed of information diffusion in the FX market. These findings are further supported by the out-of-sample statistics.

Our key contribution is that we recognize FX market participants’ activity as an important and novel aspect of return predictability. To the best of our knowledge, the extant literature has not yet addressed the speculators’ role in the information diffusion process, thus leaving a gap in the literature.

The reminder of our paper is organized as follows: Section 2 presents the data, the FX strategies,
and the variables used in our study. Section 3 explains the methodology and discusses the results. Section 4 provides further analysis and Section 5 concludes the study.

2. Data and Methodology

2.1. Sample Construction

We are guided by the literature in our choice of cross-asset predictors to predict the FX strategies included in our empirical analysis. We include the two broad indexes in the equity and commodities markets, the S&P 500 Equity Index and the CRB Spot Commodity Index, as the main research variables in predicting FX strategy returns (see, e.g., Kearns, 2007; Groen and Pesenti, 2009; Bakshi and Panayotov, 2013; Chen et al., 2010; Lu and Jacobsen, 2016). We also include additional control variables known to generally impact on asset predictability, currency volatility5, and liquidity6 in our empirical analyses to control for predictability that might be related to risk premia (see, e.g., Bhansali, 2008; Brunnermeier et al., 2009; Menkhoff et al., 2011). Following the literature, we normalize every predictor used over a three-month period, computed as the percentage change in the variables from month $t-4$ to $t-1$ divided by 3 (see, e.g., Campbell and Shiller, 1988; Fama and French, 1988; Bakshi and Panayotov, 2013)7. The normalized variables exhibit low correlation apart from the correlation between the VIX

5 Following Bakshi and Panayotov (2013), we construct monthly currency volatility as the square root of the sum of squares of daily log changes in the exchange rates, averaged over the set of currencies.

6 Following Brunnermeier et al. (2009) and Byrne et al. (2018) we use the TED Spread to proxy for liquidity.

7 For robustness, we also run the entire analysis without the normalization, i.e., with simple one-month lagged variables as predictors; the results are qualitatively the same and lend even stronger support for our hypothesis than in the normalized case. We also test to normalize only the two predictors of particular interest, e.g., the S&P 500 and CRB Indexes, and find almost exactly the same results as in our presented analysis.
and the S&P 500, 0.6, which reflects the different economic nature of the predictors according to Bakshi and Panayotov (2013).

The data on the price series for the S&P 500, the CRB Spot Commodity Index, as well as the non-seasonally adjusted consumer price indices (CPI) with the base year 2010, are obtained from Thomson Reuter’s Datastream. We also obtain the daily bid, mid, and ask spot and one-month forward rates for the G-10 currencies (AUD, CAD, EUR, JPY, NOK, NZD, SEK, CHF, GBP, and DM) against the USD from the same source. Following common praxis, we use DM until the introduction of the EUR in Jan 1999. Analogous to the currency and forward data, the German CPI is used before January 1999. Thereafter, we switch to the EURO area CPI. Finally, the VIX Index and the TED spread are drawn from the CBOE web page and the Federal Reserve Bank of St. Louis web page, respectively. Our full data sample period spans from January 1997 to December 2015.¹⁸

We collect data on trader positions in futures contracts in the currency market from the U.S. Commodity Futures Trading Commission’s (CFTC) Commitment of Traders (CoT) report. These data have, typically, been used to measure speculative capital in the currency market and to proxy for carry trade positions (see, for example, Brunnermeier et al., 2009; Fong, 2013). The positions included in the reports equal 70% to 90% of a market’s total open interest.²⁹ The CFTC reports the trading positions of two trader groups, commercial and non-commercial traders. The former (latter) refers to traders using the market for hedging purposes (using the market for speculative purposes). We focus on the latter group and refer to them as speculators

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¹⁸ This excludes some variables that use lagged values starts from January 1998 or September 1998 (see Table 1 for details).

to track speculative trading positions. The data from the CFTC do not cover all of the G-10 currencies, but we find reliable data for AUD, GBP, CAD, EUR, JPY, and CHF against the USD.

2.2. Variables

2.2.a Return Calculation

We follow Menkhoff et al. (2012) in calculating currency returns. Let $s_t$ and $f_t$ be the log of the spot rate of foreign currency per USD and the log of the one-month forward contract on the same currency, respectively. The returns from buying a foreign currency, $C$, in the forward market and selling it in the spot market are then:

$$r_t^C = f_t^C - s_t^C. \tag{1}$$

Equation (1) can be re-stated in terms of the forward discount/premium as follows:

$$r_t^C = f_t^C - s_t^C - \Delta s_t^C. \tag{2}$$

The forward discount/premium approach implies that the Covered Interest Rate Parity (CIRP) holds, taking into account the interest payments. The CIRP states that the forward discount is equal to the interest rate differential:
where \( i_t^C \) is the foreign interest rates and \( i_t \) is the US interest rate. Equivalently, currency returns can be written in terms of the interest rate differential as:

\[
\begin{align*}
\Delta r_t^C &= i_t^C - i_t - \Delta s_t^C.
\end{align*}
\]

Thus, the currency returns capture changes in the spot rates as well as the interest rate component.

We consider transaction costs as in Menkhoff et al. (2012) by calculating returns to a long position and a short position as Equations (5) and (6), respectively. The superscript \( a \) and \( b \) indicates ask and bid prices, respectively. As in Lustig et al. (2011), the long returns illustrate an investor who buys the foreign currency (or sells the USD forward contract at bid) at time \( t \), and sells the foreign currency (buys USD spot at ask) in the spot market at time \( t+1 \), and vice versa, for short returns.

\[
\begin{align*}
\Delta r_t^{Long,C} &= f_t^b - s_t^a, \\
\Delta r_t^{Short,C} &= -f_t^a + s_t^b.
\end{align*}
\]
If a position is kept for more than one continuous month, the forward positions would have to be re-entered every month (as they have a maturity of one month), thus incurring transaction costs. The spot rate trade can, however, be postponed until an exit in the position. The return is, thus, calculated as:

\[
\begin{align*}
\rho^{\text{Long}, C}_{t+1} &= f_t^b - f_t^s - s_{t+1}^C \\
\rho^{\text{Short}, C}_{t+1} &= -f_t^a + s_{t+1}^C.
\end{align*}
\] (7)

Lyons (2001) reports that the bid-ask spreads from Reuters are approximately double the values of inter-dealer spreads. Thus, our return calculations are conservative.

2.2.b The Carry Trade

The carry trade is executed out by borrowing low-yield currencies and buying high-yield currencies. We carry out the strategy from the perspective of a U.S. investor, where a carry trader takes long positions in currencies with a positive forward premium, i.e., a positive interest rate differential, and short positions in currencies with a forward discount, i.e., a negative interest rate differential vis-à-vis the USD. The forward premium is defined in Equation (8).

\[
F_t^{\text{Premium}, C} = f_t^C - s_t^C
\] (8)

The decision variable, \( d_t^C \) of going long (+1) or short (-1) in foreign currency \( C \) is as follows:
\[ d_t^C = \begin{cases} +1 & \text{if } F_{t-1}^{Premium,C} > 0 \\ -1 & \text{if } F_{t-1}^{Premium,C} < 0 \\ 0 & \text{if } F_{t-1}^{Premium,C} = 0 \end{cases} \] \tag{9}

We distinguish between the short and long legs of the strategy, and the returns for the corresponding leg is calculated in Equations (10) and (11) for the two strategies, respectively.

\[ r_t^{Carry,\text{Long}} = \frac{1}{N} \sum_C d_t^C \cdot r_t^{C,\text{Long}}, \] \tag{10}

and

\[ r_t^{Carry,\text{Short}} = \frac{1}{N} \sum_C d_t^C \cdot r_t^{C,\text{Short}}, \] \tag{11}

where \( N \) is the number of currencies in the portfolio and \( r_t^C \) is the currency returns. We follow Lu and Jacobsen (2016) in forming a carry trade portfolio and form an equal-weighted portfolio by taking positions in in the 20% top and 20% bottom currencies based on the carry.

2.2.c The Fundamental Strategy

The fundamental strategy is one that takes positions in currencies based on their value in relation to some fundamental benchmark. An interesting feature of the fundamental strategy is that it yields high returns when volatility is high, unlike the carry trade strategy (see Copeland and Lu, 2016). Analogous to Copeland and Lu (2016), we evaluate the currencies in relation to their long-run average real exchange rate. The real exchange rate of any given currency is estimated in Equation (12).
\[ q_t^C = s_t^C + (p_t^C - p_t^f), \]  

(12)

where \( s_t^C \) is the log exchange rate per USD of currency \( C \), \( p_t^C \) is the Consumer Price Index (CPI) for the foreign country, and \( p_t \) is the U.S CPI. We calculate the real exchange rate based on mid-quotes. We follow Jordá and Taylor (2012), defining the long-run equilibrium real exchange rate, \( \bar{q}_t^C \), as the three-year rolling average of the real exchange rate\(^{10}\). A long (short) position is established if the real exchange rate is lower (higher) than the long-run equilibrium real exchange rate. Formally, the decision variable, \( z_t^C \), is constructed as follows:

\[
z_t^C = \begin{cases} +1 & \text{if } q_{t-1} < \bar{q}_{t-1}^C \\ -1 & \text{if } q_{t-1} > \bar{q}_{t-1}^C \\ 0 & \text{if } q_{t-1} = \bar{q}_{t-1}^C \end{cases}
\]  

(13)

We distinguish between the short and long legs of the strategy and calculate the returns for the corresponding leg in Equations (14) and (15), respectively.

\[
r_t^{Fund,Long} = \frac{1}{N} \sum_C z_t^C \cdot r_t^{C,Long},
\]  

(14)

and

\[
r_t^{Fund,Short} = \frac{1}{N} \sum_C z_t^C \cdot r_t^{C,Short},
\]  

(15)

\(^{10}\) Note that Jordá and Taylor (2012) use a five-year window.
where \( N \) is the number of currencies in the portfolio and \( r_t^C \) is the returns of currency \( C \), as explained above. For the fundamental strategy, we form an equal-weighted portfolio by taking positions in the 20% top and 20% bottom currencies based on the fundamental valuation.

### 2.2.d The Momentum Strategy

The momentum strategy is a one of buying past winners and selling past losers. We include the momentum strategy in our analyses given that institutional traders have previously been found to be momentum traders in the FX market (e.g., Fong, 2013). Consistent with Menkhoff et al. (2012), the momentum strategy that we are considering uses a 12-month formation period, a one-month skip period, and a one-month holding period. The long/short decision, \( x_t \), is formalized in Equation (15).

\[
x_t^C = \begin{cases} 
+1 & \text{if } r_{t-12:t-1}^{Cumulative,C} > 0 \\
-1 & \text{if } r_{t-12:t-1}^{Cumulative,C} < 0, \\
0 & \text{if } r_{t-12:t-1}^{Cumulative,C} = 0 
\end{cases}
\]  

(15)

where \( r_{t-12:t-1}^{Cumulative,C} \) is the cumulative return from month \( t-12 \) to month \( t-1 \) for currency \( C \). We distinguish the short strategy from the long leg of the strategy and estimate the returns for the corresponding leg as follows:

\[
r_t^{Mom,Long} = \frac{1}{N} \sum_C x_t^C \cdot r_t^{C,Long},
\]  

(16)
and

\[ r_t^{\text{Mom,Short}} = \frac{1}{N} \sum_C x_t^C \cdot r_t^C, \]

(17)

where \(N\) is the number of currencies in the portfolio and \(r_t^C\) is the returns of currency \(C\) as explained above. For the momentum strategy, we form an equal-weighted portfolio taking positions per currency in the 20% top and 20% bottom currencies based on the cumulative return performance.

2.2.e Investor Activity

Our measure of investor activity is in the carry trade strategy proxied by net open positions in the AUD/JPY (see, e.g., Fong, 2013; Brunnermeier et al., 2009). We construct the net open positions as:

\[ NOI_t^C = \frac{\text{Long}_t^C - \text{Short}_t^C}{\text{Total Open Interest}_t^C}, \]

(18)

where \(C\) is the currency of interest. The total open interest is defined as \(\text{Long}_t^C + \text{Short}_t^C\) and is labelled speculators for the group, as defined by CFTC. Thus, the measure is calculated as the long positions minus the short positions over the sum of the long and short positions in line with Brunnermeier et al. (2009) and Fong (2013). As carry traders are typically long in the AUD and short in the JPY, we calculate the final measure by subtracting the net open positions
in the JPY from those in the AUD so that higher values indicate increased carry trade activity\textsuperscript{11} as follows:

\[ POS_{t}^{\text{adj, jpy}} = \frac{(NOI_{t}^{\text{aud}} - NOI_{t}^{\text{jpy}})}{2}. \quad (19) \]

We use end-of-month observations to construct our activity measures.

In this study, we use dummy variables for activity that takes value 1 when the standardized activity measure is a positive number, and 0 otherwise. This is done to detect when \textit{speculators} are active, not necessarily how active they are.

\textbf{2.3. Descriptive Statistics}

Panel A in Table 1 presents the descriptive statistics on the returns of the S&P 500 returns and CRB Spot Commodity Index returns, the long and short strategy returns, and the total strategy returns. The statistics show that the annualized mean returns are positive for every strategy and their legs with the exception of the fundamental strategy’s long leg. Overall, the documented annualized mean return of the carry trade strategy of 2.88\% is within the range (2-4\%) suggested in Filipe and Suominen (2015) for comparable strategies. It is lower than the Sharpe ratio of 0.5 reported in Lustig et al. (2011) in their 1983-2009 sample for a larger set of currencies. The annualized mean returns of the combined momentum strategy (1.85\%) are lower than the roughly 6\% of the momentum strategy presented in Menkhoff et al. (2012). We

\textsuperscript{11} Note that we standardize the final measure.
attribute this difference to the use of 48 currencies including emerging markets and a longer data period including the 1970s and 1980s. The returns on the combined fundamental strategy reported in this paper (0.7%) are lower than those documented in Copeland and Lu (2016). This difference may possibly be due to the different valuation method.\textsuperscript{12} In this paper, we follow Jordà and Taylor (2012), defining the fundamental value as the three-year average of the real exchange rate (note that Jordà and Taylor (2012) use a five-year average).

[Insert Table 1 Here]

The highest (lowest) annualized standard deviation of 15.69\% (8.13\%) is reported for the S&P 500 Index (fundamental long). The long and short combined carry trade strategy has the highest Sharpe Ratio, 0.31, while the Sharpe Ratio for the S&P 500 is 0.27, marginally higher than the momentum strategy, which is 0.2. The carry trade returns are shown to be negatively skewed, in line with previous research (e.g., Brunnermeier et al., 2009), while the fundamental strategy returns (earning money on reversals to fundamentals) are positively skewed. The descriptive statistics on the trader groups’ activity variables are presented in Panel B in Table 1. The variable Spec POS\textsubscript{audjpy}, which is the activity in the AUD/JPY carry trade, is standardized and therefore has a mean of 0 and a standard deviation of 1.

3. Empirical Analysis

\textsuperscript{12} Copeland and Lu (2016), in their paper, use 29 OECD countries and do not explicitly state how they define the fundamental value to which they estimate over/undervaluation.

15
3.1. The Predictability of FX Returns

To evaluate whether there is predictability in the FX strategies, we estimate regressions of the following form:

\[ r_{t, \text{Strategy,Leg}} = \delta_0 + x_{t-1}' \delta_x + \eta_t \]  \hspace{1cm} (19)

where \( r_{t, \text{Strategy,Leg}} \) is the monthly strategy returns, \( \delta = [\delta_0, \delta_x] \)' is the vector of regression coefficients, and \( x_{t-1} = [\Delta SP500_{t-1}, \Delta CRB_{t-1}, \Delta FXVol_{t-1}, \Delta LIQ_{t-1}] \) are the predictors and controls. Equation (19) relates to testing the gradual information diffusion hypothesis without considering speculator activity in order to perform the analysis in the same fashion as Lu and Jacobsen (2016). We start with univariate versions of Equation (19) with predictors \( \Delta SP500_{t-1} \) and \( \Delta CRB_{t-1} \) as vector \( x_t \) and subsequently include every variable of vector \( x_t \). Similar to Bakshi and Panayotov (2013), we use Newey-West (1987) corrected standard errors (lags selected with the Akaike Information Criterion (AIC)) in every regression.

Table 2 reports the results from estimating Equation (19). The results in Panel A show a statistically significant coefficient of 0.154 for CT Short, indicating that the S&P 500 Index return predicts the short leg return of the carry trade strategy. For the CRB Commodity Index, we find that the commodity returns predict the long leg of the carry trade. We report a statistically significant coefficient of 0.292 for the CRB Index return (see Panel B). These results are consistent with the studies of Lu and Jacobsen (2016), and Bakshi and Panayotov (2013). Lu and Jacobsen (2016) document significant predictability from the equity market to the short leg of the carry trade, and Bakshi and Panayotov (2013) show the same finding for the
CRB Commodity Index and the long leg of the carry trade. We also document a novel finding that the S&P 500 Index return predicts the long leg of the fundamental strategy, FundLong, where an increase in equity returns is associated with lower future returns for undervalued currencies. We also document significant predictability from the CRB Index towards FundShort and MomShort strategies, indicating that an increase in the CRB Index is associated with lower future returns for overvalued currencies and currencies with a previously poor performance.

[Insert Table 2 Here]

We also estimate multivariate regressions with every predictor included in each regression and report the results in Table 3. Compared to the univariate analysis results, the multivariate analysis results show a general increase in the significance of the predictors and the adjusted R-squareds in the estimated regressions models. It is noteworthy that after controlling for the FX volatility, commodity returns, and funding liquidity in the multivariate analysis, the S&P 500 Index not only survives the inclusion of the control variables, it appears to be a strong predictor for other known currency strategies.\(^{13}\) The reported coefficients for every strategy are statistically significant at the 1% level. This finding implies that there is information in the U.S. equity market that diffuses slowly to the FX market and that the predictability is not associated with the control-factors related to risk-premiums in Bakshi and Panayotov (2013).

\(^{13}\) Lu and Jacobsen (2016) also show that equity returns predict the short leg of the carry trade. However, they do not use a multivariate setting to control for this. Instead, they use a set of other predictors as univariate replacements for the equity predictors and conclude that none of them can predict the short leg of the carry trade.
With regard to commodity returns as a predictor of FX returns, Lu and Jacobsen (2016) and Bakshi and Panayotov (2013) find that the CRB Index only predicts the long leg of the carry trade and the combined carry trade strategy. The results of our multivariate analysis show that the CRB Index predicts every strategy except the short leg of the carry trade. Thus, the results using the CRB Index are also in line with the slow information diffusion explanation for predictability. Overall, these results in Table 3 suggest extensive predictability from both the equity and commodity markets towards every FX strategy considered.

[Insert Table 3 Here]

3.2. Speculator Activity and FX Return Predictability

To examine our central hypothesis that speculator activity influences the predictability of the FX strategies, we estimate regressions of the following form:

\[ r_{t}^{Strategy,Leg} = d_0 + \gamma_0 + x_t' \gamma \chi + \epsilon_t, \]  

(20)

where \( r_{t}^{Strategy,Leg} \) is the monthly strategy returns, \( \gamma = [\gamma_0, \gamma']' \) is the vector of regression coefficients, \( d_0 \) is a dummy variable for speculator activity, and the set of predictors and controls variables \( x_{t-1} \) is \( x_{t-1} = [\Delta SP500_{t-1}, D_{t-1} \cdot \Delta SP500_{t-1}, \Delta CRB_{t-1}, \Delta FXVol_{t-1}, \Delta LIQ_{t-1}] \) or \( x_{t-1} = [\Delta SP500_{t-1}, \Delta CRB_{t-1}, D_{t-1} \cdot \Delta CRB_{t-1}, \Delta FXVol_{t-1}, \Delta LIQ_{t-1}] \). We estimate Equation (20) with and without controls.
The variables of interest in Equation (20) are the interaction terms involving the equity and commodity market returns, as well as the speculators’ state of activity, which indicates whether there is a significant difference in predictability when the speculators are “active”. Furthermore, we explicitly want to address whether there is predictability when the speculators are “active”, not just whether there is a difference. Therefore, we also estimate a Wald test for the hypothesis in (21):

\[ H_0: \gamma_{Pred} + \gamma_{interacted} = 0 \]

Where \( \gamma_{Pred} \) is the coefficient of the predictor of interest and \( \gamma_{interacted} \) is the coefficient of the interaction term. We thus test to confirm whether there is predictability when the speculators are active.

Panel A in Table 4 reports the results of the speculator activity effect on the predictability of the S&P 500. Examining the reported coefficients of the interaction term, \( D_{t-1} \cdot \Delta SP500_{t-1} \), we identify a statistically significant difference in the predictive ability of the S&P 500 when the speculators are active for the short leg of the carry trade strategy (CTShort), the long leg of the fundamental strategy (FundLong), and the short leg of the momentum strategy (MomShort), as is evident from the coefficients of the interaction term, \( D_{t-1} \cdot \Delta SP500_{t-1} \). The results from estimating the full model produce statistically significant coefficients of -0.340, 0.204, and 0.225 for CTShort, FundLong and MomShort, respectively (see columns 4, 6, and 12). All of these coefficients have the opposite signs, but are similar in magnitude compared to the coefficient on the prediction term for the S&P 500 (\( \Delta SP500_{t-1} \)), indicating a mitigating effect on predictability. We also find significant coefficients, the 1% level, on the S&P 500 predictors...
for most strategies and specifications (see row 1). The reported results also show statistically significant coefficients of 0.795 and 0.911, respectively, for the dummy variable for the short leg of the carry trade and fundamental strategies, $D_{t-1}$, indicating that returns for these strategies are higher when the *speculators* are active. These support the earlier results reported in Table 3, as well as our central hypothesis that *speculator* activity has a measurable influence on predictability.

Panel B in Table 4 reports the results of the estimating the Wald tests (Equation 21) in examining whether the sum of the coefficients of the predictor and interaction variable is significantly different from zero. The reported results show insignificant test statistics for every FX strategy, indicating that the predictability from the S&P 500 to any of the FX strategies is not apparent when the *speculators* are active. Therefore, we conclude that when the *speculators* are active, all traces of predictability from the S&P 500 to the FX strategies dissipate. This is in line with our hypothesis that active *speculators* increase the speed of cross-asset information diffusion, which eliminates return predictability.

[Insert Table 4]

The results from the estimation model assessing the predictability of commodity market returns, the CRB Index returns, conditioned on *speculator* activity is reported in Table 5. As in Table 4, we interact *speculator* activity with commodity index returns, CRBs, in estimating Equation (20). The coefficient of the interaction term, $D_{t-1} \cdot \Delta SP500_{t-1}$, is shown to be statistically insignificant for every FX strategy, lending credence to the hypothesis that when *speculators* are active they enhance the informational efficiency of the FX market, which reduces cross-
asset return predictability from the commodity market. Table 5 also reports contrasting results on predictability when speculators are inactive. Analogous to previous research (see, e.g., Lu and Jacobsen, 2016), we document evidence of predictability from the commodity market to the long leg of the carry trade strategy, with a statistically significant coefficient of 0.348 (see column 2) when speculators are inactive. In addition, we also document evidence of the predictability of commodity market returns to the short leg of the fundamental strategy, with a statistically significant coefficient of -0.292, as well as the long and short legs of the momentum strategy (with statistically significant coefficients of 0.203 and -0.289, respectively, at the 1% level) when speculators are inactive (see columns 8, 10, and 12). As can be seen in Table 5, returns to the short leg of the carry trade and the fundamental strategy are higher when speculators are active, as shown by the positive and statistically significant coefficient for the dummy variable, $D_{t-1}$, 0.531 and 0.761, respectively.

We run Wald tests for the sum of coefficients of the CRB predictor and interacted term, $D_{t-1} \cdot \Delta CRB_{t-1}$, thus measuring the total predictability of the CRB Index when speculators are active. The results are reported in Panel B in Table 5. We report statistically significant p-values for the long leg of the carry trade FX strategy, the long and short legs of the fundamental FX strategy, and the short leg of the momentum strategy. The results show that in every instance where the CRB Index significantly predicted a strategy’s leg, there is also predictability when the speculators are active. The predictability from the commodity market to the FX strategies are no more than mitigated, and in some cases strengthened when the speculators are active. Thus, it does not seem to matter much for the commodity market’s predictability whether the speculators are active or otherwise.
Overall, our results show that the cross-asset market predictability between the equity and commodity markets and FX strategies depends on the *speculators* actively trading the carry trade strategy. These results are reminiscent of the studies conducted in the equity market, where information availability is positively related to the speed of information diffusion. Hong et al. (2000) find that momentum in the equity market is stronger for stocks with low analyst coverage, and Chordia and Swaminathan (2000) find that high-trading volume stocks lead low-trading volume ones. Menzly and Ozbas (2010) present direct evidence that the magnitude of return cross-predictability within the equity market declines with the number of informed investors, as proxied by analyst coverage and institutional ownership. Our finding that *speculator* activity reduces the predictability of FX returns corroborates these findings and extends them to the FX market. However, we find it puzzling that *speculator* activity does not significantly affect the predictability from the commodity market to the FX market. This finding suggests that speculators in the FX market do not sufficiently exploit the predictability from the commodity market to the FX market. This could be related to the finding by Kohlscheen et al. (2016) that the predictability from commodity prices to exchange rates is not driven by changes in global risk appetite or carry.

### 3.3. Out-of-sample Statistics

We use the out-of-sample $R^2$ and MSPE-adjusted statistics to gauge out-of-sample predictability following the previous literature (Lu and Jacobsen, 2016). Following Cambell and Thompson (2008), and Welch and Goyal (2008), the out-of-sample $R^2$ is constructed as follows:
\[ OOS R^2 = 1 - \frac{\sum_{j=1}^{n}(\hat{\mu}_t - \tau_j^i)^2}{\sum_{j=1}^{n}(\mu_t - \tau_j^i)^2} \]  

(22)

where \( \hat{\mu}_{t+1} \) is the prediction of month \( t+1 \) of the model, \( \mu_{t+1} \) is the historical average return, and \( \tau_j^i \) is the realized return of strategy \( j \). The \( OOS R^2 \) statistic measures how much better the chosen model is in forecasting than the historical average, by measuring the percentage decrease in forecasting errors. Secondly, the MSPE-adjusted statistic from Clark and West (2007) is obtained by first calculating

\[ f_t = (r_t^i - \mu_t)^2 - ((r_t^i - \hat{\mu}_t)^2 - (\mu_t - \hat{\mu}_t)^2) \]

(23)

and then obtaining the one-sided p-values for \( f_t \). A low p-value thus means a rejection of the hypothesis that the model does not improve forecasting compared to the historical average model. As in Bakshi and Panayotov (2013), we use an expanding window with an initial length of 180 months.

[Insert Table 6 Here]

In Table 6, we calculate \( OOS R^2 \) for two different models. First, Equation (19) including the S&P 500 and CRB predictors and the FX volatility and liquidity control variables. Second, Equation (20), which takes into account speculator activity in the forecasting. In the table, we
label the former analysis as “No speculator” and the latter as “Speculator”.

As the positive $OOS \ R^2$, as shown in Table 6, the two models perform well at forecasting the FX returns compared to the historical averages. Further, the model with speculator activity has lower forecasting errors in terms of $OOS \ R^2$ in each case except for MomLong. This indicates that there are forecasting improvements in taking speculator activity into account. We also find the decrease in forecasting error using the model with speculator activity is quite large for some strategies, e.g., FundShort and MomShort (24.50% and 31.27%, respectively). The MSPE-adjusted p-values are consistent with $OOS \ R^2$ for every strategy, showing that the two models significantly outperform the historical average model at the 5% level. In relation to previous studies, we hereby confirm the evidence of a predictable component to the separate legs of the carry trade strategy (see, e.g., Lu and Jacobsen, 2016; Bakshi and Panayotov, 2013).

3.4. Robustness and Further Analysis

3.4.a Alternative Activity Measures

As described in Section 2, our carry-trade activity measure is based on end-of-month observations. For robustness, we re-estimate the models using monthly averages. The results of the re-estimations are qualitatively the same in the multivariate regression frameworks. To alleviate concerns that our results are driven by the choice of the two currencies used to measure activity (AUD/JPY), we also re-estimate the entire analysis using a broader measure of carry-trade activity. Using the same approach, we take an average of all the long positions in AUD, CAD, and GBP minus the short positions in JPY, CHF, and EUR, consistent with the carry-trade positions. The results obtained in the multivariate analysis are also similar to those in our main analysis.
We also re-estimate the models using an alternative *speculator* activity measure based on the sentiment index created and used in Wang (2001, 2004). The measure represents the general activity of *speculators*. It is based on past extreme values over the last three years, thus it is forward-looking and applicable to forecasting. While Wang (2001, 2004) bases the sentiment index on net positions to get a bullish/bearish sentiment, we use total open interest to capture activity. Formally, the measure is

\[
Activity_t = \frac{1}{N} \sum_c^N \frac{OIC_t - \text{Min}(OIC_t)}{\text{Max}(OIC_t) - \text{Min}(OIC_t)} \cdot 100
\] (24)

where \(OIC_t\) is the total open interest (long positions + short positions). \(\text{Max}(OIC_t)\) and \(\text{Min}(OIC_t)\) are the maximum and minimum total open interest over the previous three-year period prior to week \(t\).\(^{14}\)

The results obtained from these analyses are qualitatively similar, also leading to the conclusion that speculator activity diminishes predictability. The S&P 500 predictor loses much of its predictability in this framework and in the multivariate regressions nearly every predictor is insignificant for the vast majority of the strategies when the *speculators* are active. This would indicate that it does matter for predictability whether the *speculators* are active or not generally, but the effects are greater when the *speculators* are actively trading a carry-trade strategy, or at

\(^{14}\) The final measure is then standardized. Also note that the correlation of this measure with the “carry-trade” activity measure is around 0.35.
least have positions consistent with it. This is intuitive, as *speculators* care most about this predictability when they are invested in the strategy being predicted.

### 3.4.b Hedger Activity

In the unreported analysis, we also re-estimate the activity measure, but for the *hedger* category as reported by the CFTC. We then re-run the models to evaluate whether there is a difference in predictability when the *hedgers* are active in the carry trade. We acknowledge that *hedgers* do not actively track the carry-trade strategy, although their hedging positions may be consistent with this strategy. For this reason, we interpret *hedger* activity as “carry-trade-consistent” positions. Overall, the results are the opposite to what we found for *speculator* activity. For the S&P 500 Index, predictability is only present when the *hedgers* are active in the FX market. One possible explanation is that *hedgers* are uninformed investors who do not facilitate the information diffusion process, as they are trading to offset the risks of other positions. This explanation is line with Menzly and Ozbas (2010), who relate cross-asset predictability to uninformed traders.

### 3.4.c Other Tests

Lu and Jacobsen (2016) consider the MSCI World Index as a predictor for the short leg of carry trade. Intuitively, this suggests that currency strategy consists of international currencies and international investors and should, thus, be affected by an international equity index. Therefore, we re-estimate our models using the MSCI World Index and the NIKKEI 250 as our equity predictors. To conserve space, we state only that the same results stand, albeit somewhat weaker than when we used the MSCI World Index, which contrasts with the findings of Lu and Jacobsen (2016). The NIKKEI 250, however, does not predict any strategy in the univariate
analysis. Although we find a few instances of predictability for some strategies in some multivariate regression frameworks, no patterns are observed. As such, we suggest that the results observed for the U.S. equity market do not extend arbitrarily to other equity markets. It is noteworthy that in the carry trade specification we are using the USD as a base currency. Therefore, the effect of the U.S. equity market may be more pronounced than the MSCI World Index or the NIKKEI 250. These results are available on request.

In addition to the inclusion of liquidity and FX volatility as control variables in Tables 4 and 5, we take the VIX Index into consideration. Brunnermeier et al. (2009), for example, find that the VIX Index is important in determining carry trade profits. Therefore, we obtain data for the VIX Index from the CBOE website and normalize it over three months, as with the other predictors, including it in the regressions in the unreported analysis. The results indicate that the S&P 500 still has highly significant predictive power over FX strategy returns, apart from momentum (short and long). The estimated models conditioned on speculator activity show spatially stronger results. However, there seems to be some predictability from the S&P 500 towards the CTLong variable when the speculators are active, while controlling for VIX. It seems, therefore, that equity volatility is not driving the reported results. In line with the univariate regressions, we find that there is (no) predictability when the speculators are (active) inactive.

We also re-run the analysis with an AR(1) term of the strategies’ returns in every specification. This does not change the results in any noteworthy way.

4. Conclusion
In this study, we apply the gradual information diffusion hypothesis to address the role of speculative activity in the FX market for information flow between the equity and commodity markets to FX strategies. The information flow has important implications for the cross-asset predictability of FX strategies due to the inability of investors to always process every piece of information. We argue that informed and active speculators increase the speed of information diffusion from the equity and commodity markets into the FX strategies. Thus, speculators in the FX market should have an important role in cross-asset information diffusion, leading to the hypothesis that the gradual information flow between the equity and commodity markets and the FX market decreases when the speculators are active in the FX market.

After controlling for Bakshi and Panayotov’s (2013) factors, we find that the broad equity market predictor (the S&P 500) predicts every FX strategy, and the commodity market predictor (the CRB index) predicts the majority of the FX strategies. In line with our hypothesis, the presented results show that the predictability from the equity market evaporates when the speculators are active. For the CRB Index, the predictability is diminished when the speculators are active. These findings are novel and confirm the importance of speculators in explaining cross-asset predictability. The commodity market, however, differs from the equity market in that the predictability from the commodity market to the FX market does not disappear when speculators are active. This puzzling finding would be an interesting topic in future studies.
References


Table 1. Descriptive Statistics

This table presents the descriptive statistics for the variables used in the analysis. Panel A shows the annualized returns, standard deviation, Share Ratio (SR), skewness, all annualized, the start and end dates, and the number of observations for the short leg, long leg, and a combined carry trade strategy (CTShort, CTLong, CTHML) that takes long positions in currencies with high interest rates and short currencies with low interest rates. The data are annualized. FundLong, FundShort, and FundHML are the long leg, short leg, and the combined fundamental strategy that takes a long position in undervalued currencies and shorts overvalued currencies in relation to a three-year average real exchange rate. MomShort, MomLong, and MomHML are returns to the short leg, long leg, and a combined momentum strategy with a 12-month formation period and a one-month skip period. Panel B shows the descriptive statistics for a variable measuring the activity of Speculators using the data from CFTC. “Spec POS$_{audjpy}$” is activity in the AUD/JPY carry trade of speculators and hedgers, respectively.

### Panel A. Strategy Returns

<table>
<thead>
<tr>
<th>Variable</th>
<th>Ann. Return</th>
<th>St Dev.</th>
<th>Sharpe ratio</th>
<th>Skewness</th>
<th>Start</th>
<th>End</th>
<th>N</th>
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<tr>
<td>CTShort</td>
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<td>9.22</td>
<td>0.11</td>
<td>-0.25</td>
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<td>1.19</td>
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<td>Dec 2015</td>
<td>228</td>
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<td>Dec 2015</td>
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<td>FundLong</td>
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<td>Dec 2015</td>
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<td>0.09</td>
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<td>Dec 2015</td>
<td>228</td>
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<td>228</td>
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<td>MomShort</td>
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<td>10.07</td>
<td>0.06</td>
<td>0.24</td>
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<td>Dec 2015</td>
<td>216</td>
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<td>MomLong</td>
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<td>-0.27</td>
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<td>MomHML</td>
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<td>Dec 2015</td>
<td>216</td>
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<td>S&amp;P 500</td>
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<td>-0.79</td>
<td>Jan 1997</td>
<td>Dec 2015</td>
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<tr>
<td>CRB</td>
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<td>-1.68</td>
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### Panel B. Activity Measures

<table>
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<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Start</th>
<th>End</th>
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</thead>
<tbody>
<tr>
<td>Spec POS$_{audjpy}$</td>
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<td>-0.05</td>
<td>-2.64</td>
<td>2.18</td>
<td>Jan 1997</td>
<td>Dec 2015</td>
<td>228</td>
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</table>
Table 2. Univariate In-sample Predictability

This table presents the univariate regression results of in-sample predictability of the long and short legs of three currency strategies. The regression equation is $r_{t}^{\text{Strategy,Leg}} = \delta_0 + \mathbf{x}_{t-1}'\delta + \eta_t$ where $r_{t}^{\text{Strategy,Leg}}$ is the monthly returns of strategy $i$ where $i=$[CTLong, CTShort, FundLong, FundShort, MomLong, MomShort]. CTLong and CTShort are the long and short legs of a carry trade strategy buying currencies with high interest rates and selling currencies with low interest rates in relation to the USD. FundLong and FundShort are the long and short legs of a fundamental strategy buying undervalued currencies and selling overvalued currencies in relation to the three-year average real exchange rate. MomLong and MomShort are the long and short legs of a momentum strategy with a 12-month formation period and a one-month skip period. $\mathbf{\delta} = [\delta_0, \mathbf{\delta}']'$ is the vector of regression coefficients and $\mathbf{x}_{t-1} = \Delta SP_{500_{t-1}}$ or $\mathbf{x}_{t-1} = \Delta CRB_{t-1}$ which are the three-month normalized predictors. $\Delta SP_{500_t}$ is the S&P 500 equity returns and $\Delta CRB_t$ is the CRB Spot Commodity Index. We use Newey-West (1987) corrected standard errors and the t-statistics are in brackets; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>CTLong</th>
<th>CTShort</th>
<th>FundLong</th>
<th>FundShort</th>
<th>MomLong</th>
<th>MomShort</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta SP_{500_{t-1}}$</td>
<td>-0.020</td>
<td>0.154**</td>
<td>-0.112**</td>
<td>0.023</td>
<td>-0.054</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>[-0.204]</td>
<td>[2.164]</td>
<td>[-2.496]</td>
<td>[0.277]</td>
<td>[-0.993]</td>
<td>[0.616]</td>
</tr>
<tr>
<td>N</td>
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<td>227</td>
<td>227</td>
<td>227</td>
<td>216</td>
<td>216</td>
</tr>
<tr>
<td>Adjusted R$^2$</td>
<td>-0.004</td>
<td>0.021</td>
<td>0.12</td>
<td>-0.004</td>
<td>-0.002</td>
<td>-0.003</td>
</tr>
</tbody>
</table>

| $\Delta CRB_{t-1}$ | 0.292*** | -0.007 | 0.047 | -0.225*** | 0.103 | -0.243*** |
|                    | [3.579]   | [-0.055] | [0.506] | [-3.206] | [1.400] | [-4.053] |
| N                 | 227       | 227     | 227     | 227       | 216     | 216      |
| Adjusted R$^2$    | 0.034     | -0.004 | -0.003 | 0.028     | 0.002   | 0.031    |
Table 2. Univariate In-sample Predictability

This table presents the univariate regression results of in-sample predictability of the long and short legs of three currency strategies. The regression equation is $r_t^{\text{Strategy,Leg}} = \delta_0 + x_{t-1}'\delta_x + \eta_t$ where $r_t^{\text{Strategy,Leg}}$ is the monthly returns of strategy $i$ where $i=\{\text{CTLong, CTShort, FundLong, FundShort, MomLong, MomShort}\}$. CTLong and CTShort are the long and short legs of a carry trade strategy buying currencies with high interest rates and selling currencies with low interest rates in relation to the USD. FundLong and FundShort are the long and short legs of a fundamental strategy buying undervalued currencies and selling overvalued currencies in relation to the three-year average real exchange rate. MomLong and MomShort are the long and short legs of a momentum strategy with a 12-month formation period and a one-month skip period. $\delta = [\delta_0, \delta_x']'$ is the vector of regression coefficients and $x_{t-1} = [\Delta SP_{500,t-1}]$ or $x_{t-1} = [\Delta CRB_{t-1}]$ which are the three-month normalized predictors. $\Delta SP_{500,t}$ is the S&P 500 equity returns and $\Delta CRB_{t}$ is the CRB Spot Commodity Index. We use Newey-West (1987) corrected standard errors and the t-statistics are in brackets; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>CTLong</th>
<th>CTShort</th>
<th>FundLong</th>
<th>FundShort</th>
<th>MomLong</th>
<th>MomShort</th>
</tr>
</thead>
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<tr>
<td>$\Delta SP_{500,t-1}$</td>
<td>-0.020</td>
<td>0.154**</td>
<td>-0.112**</td>
<td>0.023</td>
<td>-0.054</td>
<td>0.048</td>
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<tr>
<td></td>
<td>[-0.204]</td>
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<tr>
<td>Adjusted R²</td>
<td>-0.004</td>
<td>0.021</td>
<td>0.12</td>
<td>-0.004</td>
<td>-0.002</td>
<td>-0.003</td>
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<tr>
<td>$\Delta CRB_{t-1}$</td>
<td>0.292***</td>
<td>-0.007</td>
<td>0.047</td>
<td>-0.225***</td>
<td>0.103</td>
<td>-0.243***</td>
</tr>
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<td>Adjusted R²</td>
<td>0.034</td>
<td>-0.004</td>
<td>-0.003</td>
<td>0.028</td>
<td>0.002</td>
<td>0.031</td>
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</table>
Table 3. Multivariate Analysis of FX Return Predictability

This table presents the multivariate regression results of in-sample predictability of the long and short legs of three currency strategies. The regression equation is \( r_{\text{Strategy,Leg}} = \delta_0 + x_{t-1}'\delta_x + \eta_t \) where \( r_{\text{Strategy,Leg}} \) is the monthly returns of strategy \( i \) where \( i=\{\text{CTLong, CTShort, FundLong, FundShort, MomLong, MomShort}\} \). CTLong and CTShort are the long and short legs of a carry trade strategy buying currencies with high interest rates and selling currencies with low interest rates in relation to the USD. FundLong and FundShort are the long and short legs of a fundamental strategy buying undervalued currencies and selling overvalued currencies in relation to the three-year average real exchange rate. MomLong and MomShort are the long and short legs of a momentum strategy with a 12-month formation period and a one-month skip period. \( \delta = [\delta_0, \delta_x'] \) is the vector of regression coefficients and \( x_{t-1} = [\Delta S^500_{t-1}, \Delta CRB_{t-1}, \Delta FXVol_{t-1}, \Delta LIQ_{t-1}] \) are the three-month normalized predictors and controls. \( \Delta S^500 \) is the S&P 500 equity returns and \( \Delta CRB \) is the CRB Spot Commodity Index. \( \Delta FXVol \) is the currency volatility and \( \Delta LIQ \) is the liquidity, as proxied by the TED spread. We use Newey-West (1987) corrected standard errors and the t-statistics are in brackets; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>CTLong</th>
<th>CTShort</th>
<th>FundLong</th>
<th>FundShort</th>
<th>MomLong</th>
<th>MomShort</th>
</tr>
</thead>
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<tr>
<td>( \Delta S^500_{t-1} )</td>
<td>-0.181***</td>
<td>0.197***</td>
<td>-0.148***</td>
<td>0.141**</td>
<td>-0.107*</td>
<td>0.181***</td>
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<tr>
<td></td>
<td>[-2.984]</td>
<td>[3.222]</td>
<td>[-2.704]</td>
<td>[2.515]</td>
<td>[-1.764]</td>
<td>[2.788]</td>
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<td>( \Delta CRB_{t-1} )</td>
<td>0.310***</td>
<td>-0.081</td>
<td>0.128*</td>
<td>-0.246***</td>
<td>0.159**</td>
<td>-0.293***</td>
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<tr>
<td>( \Delta FXVol_{t-1} )</td>
<td>-0.051**</td>
<td>0.014</td>
<td>-0.007</td>
<td>0.031*</td>
<td>-0.010</td>
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<td>[-2.482]</td>
<td>[0.991]</td>
<td>[-0.435]</td>
<td>[1.931]</td>
<td>[-0.519]</td>
<td>[2.266]</td>
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<td>( \Delta LIQ_{t-1} )</td>
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<td>0.001</td>
<td>0.018</td>
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<td>0.018</td>
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Table 4. Analysis of the Equity - FX Return Predictability and Investor Activity

This table presents the regression results of the in-sample predictability of the long and short legs of three currency strategies. The regression equation is 

$$y_{t}^{Strategy, Leg} = a_{0} + y_{t} + x_{t-1}y_{t-1} + \epsilon_{t},$$

where $r_{t}$ is the monthly returns of strategy $i$ where $i = \{CTLong, CTShort, FundLong, FundShort, MomLong, MomShort\}$. CTLong and CTShort are the long and short legs of a carry trade strategy buying currencies with high interest rates and selling currencies with low interest rates in relation to the USD. FundLong and FundShort are the long and short legs of a fundamental strategy buying undervalued currencies and selling overvalued currencies in relation to the three-year average real exchange rate. MomLong and MomShort are the long and short legs of a momentum strategy with a 12-month formation period and a one-month skip period. $y = [y_{0}, y_{0}']$ is the vector of regression coefficients, $d_{0}$ is a dummy variable for speculative activity, and $x_{t-1} = [\Delta SP500_{t-1}, D_{t-1} \cdot \Delta SP500_{t-1}, \Delta CRB_{t-1}, \Delta FXVol_{t-1}, \Delta LIQ_{t-1}]$ is the set of predictors and controls variables. The dummy variable, $D_{t}$, takes the value 1 (0) when the standardized activity measure, defined in Equation (11), is above (below) zero. The activity measure is normalized on three months and captures speculative activity in the AUD/JPY carry trade. The standard errors are Newey-West (1987) corrected. The t-statistics are in brackets; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. This table also presents the test statistics and p-values from the Wald tests. We test the hypothesis that the sum of coefficients of the predictor and its interaction with the dummy variable is equal to zero, i.e., that there is predictability when the *speculators* are active: $H_{0}: y_{pred} + y_{interacted} = 0$.

### Panel A: Regressions

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</tbody>
</table>

N | 227 | 227 | 227 | 227 | 227 | 227 | 227 | 227 | 216 | 216 | 216 | 216 | 216

Adj. R² | -0.013 | 0.043 | 0.037 | 0.039 | 0.01 | 0.022 | -0.002 | 0.05 | -0.011 | -0.002 | -0.01 | 0.042 |

### Panel B: Wald Test

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Table 5. Analysis of the Commodity - FX Return Predictability and Investor Activity

This table presents the regression results of the in-sample predictability of the long and short legs of three currency strategies. The regression equation is $\gamma_t^{Strategy, Leg} = \alpha_0 + \gamma_0 + \chi_{t-1}'\gamma_1 + \epsilon_t$, where $R_t^{i}$ is the monthly returns of strategy $i$ where $i \in \{CTLong, CTShort, FundLong, FundShort, MomLong, MomShort\}$. CTLong and CTShort are the long and short legs of a carry trade strategy buying currencies with high interest rates and selling currencies with low interest rates in relation to the USD. FundLong and FundShort are the long and short legs of a fundamental strategy buying undervalued currencies and selling overvalued currencies in relation to the three-year average real exchange rate. MomLong and MomShort are the long and short legs of a momentum strategy with a 12-month formation period and a one-month skip period. $\gamma = [\gamma_0, \gamma_1]$ is the vector of regression coefficients, $\epsilon_t$ is a dummy variable for speculator activity, and $x_{t-1} = [\DeltaSP500_{t-1}, \DeltaCRB_{t-1}, D_{t-1} \cdot \DeltaCRB_{t-1}, \DeltaFXVol_{t-1}, \DeltaLIQ_{t-1}]$ is the set of predictors and controls variables. The dummy variable, $D_t$, takes the value 1 (0) when the standardized activity measure, defined in Equation (11), is above (below) zero. The activity measure is normalized on three months and captures speculator activity in the AUD/JPY carry trade. The standard errors are Newey-West (1987) corrected. The t-statistics are in brackets; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. This table also presents the panel statistics and p-values from the Wald tests. We test the hypothesis that the sum of coefficients of the predictor and its interaction with the dummy variable is equal to zero, i.e., that there is predictability when the speculators are active: $H_0: \gamma_{pred} + \gamma_{interacted} = 0$.

### Panel A: Regressions

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### Panel B: Wald Test

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Table 6. Out-of-sample Statistics
This table presents two out-of-sample statistics. First, the out-of-sample R$^2$ of Campbell and Thompson (2008), and Welch and Goyal (2008), $OOS R^2 = 1 - \frac{\sum_{t=1}^{n}(\hat{\mu}_t - r_i^j)^2}{\sum_{j=1}^{n}(\mu_t - r_i^j)^2}$ where $\hat{\mu}_{t+1}$ is the prediction of month t+1 of the model, $\mu_{t+1}$ is the historical average return, and $r_i^j$ is the realized return of strategy j. Second, the MSPE-adjusted statistic from Clark and West (2007) is obtained by first calculating $f_t = (r_i^j - \mu_t)^2 - \left((\mu_t - \mu_t)^2 - (\frac{\mu_t - \mu_t)^2}{n}\right)$, and then obtaining the one-sided p-value from a regression of $f_t$ on a constant. “BP No speculator” is a predictive regression with the predictors $\Delta CRB_t$, $FXVol_t$, and $\Delta LIQ_t$. “With SP500” is the same predictive regression with the addition of the $\Delta SP500_t$ predictor. “Speculator” also includes a dummy variable for speculator activity and an interaction term for the $\Delta SP500_t$. These regressions are run on the monthly returns of six strategies: $CTLong$, $CTShort$, $FundLong$, $FundShort$, $MomLong$, $MomShort$. $CTLong$ and $CTShort$ are the long and short legs of a carry trade strategy buying currencies with high interest rates and selling currencies with low interest rates in relation to the USD. $FundLong$ and $FundShort$ are the long and short legs of a fundamental strategy buying undervalued currencies and selling overvalued currencies in relation to the three-year average real exchange rate. $MomLong$ and $MomShort$ are the long and short legs of a momentum strategy with a 12-month formation period and a one-month skip period. The predictive regression use an expanding window with initial length of 180 months.

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<th>CTLong</th>
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<th>FundShort</th>
<th>MomLong</th>
<th>MomShort</th>
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