The Time-Varying Systemic Risk of Carry Trade Strategies

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The Time-Varying Systematic Risk of Carry Trade Strategies

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The Time-Varying Systematic Risk of Carry Trade Strategies

Abstract: This paper suggests a factor model for carry trade strategies where the regression coefficients are allowed to depend on market volatility and liquidity. Empirical results on daily data from 1995 to 2008 show that a typical carry trade strategy has much higher exposure to the stock market and also more mean reversion in volatile periods—and that FX market volatility is a priced risk factor. The findings are robust to various extensions, including using more currencies and other proxies for volatility and liquidity (VIX, TED and a bid-ask spread).

Keywords: carry trade, factor model, smooth transition regression, time-varying betas

JEL Classifications: F31, G15, G11
1 Introduction

"(Carry trade) is like picking up nickels in front of steamrollers: you have a long run of small gains but eventually get squashed." (The Economist, “Carry on speculating”, February 22, 2007).

The common definition of currency carry trade is borrowing a low-yielding asset (for instance, denominated in Japanese yen or Swiss franc) and buying a higher-yielding asset denominated in another currency. Although this strategy has proliferated in practice, it is at odds with economic theory. In particular, the Uncovered Interest Parity (UIP) states that there should be an equality of expected returns on otherwise comparable financial assets denominated in two different currencies. Thus, according to the UIP we expect an appreciation of the low rewarding currency by the same amount as the return differential. However, there is overwhelming empirical evidence against the UIP theory, see e.g. Burnside, Eichenbaum and Rebelo (2007) for a recent study.

One of the most plausible explanations for the UIP puzzle and the long-lasting carry trade performance is a time-varying risk premium (Fama (1984)). Relying on this rationale, we analyze whether the systematic risk of a typical carry trade strategy is time-varying and if it varies across regimes. The literature proposes several explanations for the carry trade performance such as the exposure to illiquidity spirals (Plantin and Shin (2008)), crash risk (Brunnermeier, Nagel and Pedersen (2009)) and Peso problems (Farhi and Gabaix (2008))—although the latter argument is not supported by the substantial payoff remaining in hedged carry trade strategies (see Burnside, Eichenbaum, Kleshchelski and Rebelo (2008)). By applying an asset pricing approach with factor mimicking portfolios, some recent studies relate excess return of foreign exchanges to risk factors (e.g. Lustig, Roussanov and Verdelhan (2008)). Here, we propose to account for FX time-varying risk premia by adopting a related, but different, approach. We apply a multi-factor model with explicit factors, but where the risk exposures are allowed to change according the one or more state variables. This methodology provides a general framework to explain non-linear and regime-dependent risk-return payoffs. The investigation of non-linear patterns in exchange rates is not new, see Bekaert and Gray (1998), Sarno, Valente and Leon (2006) and Ichiue and Koyama (2008). However, the previous papers

2Burnside et al. (2007) also find that forward premium strategies yield very high Sharpe ratios, but they argue that the carry trade performance is not correlated with traditional risk factors.
focus on the UIP rather than the carry trade performance. We use a logistic smooth transition regression methodology to explain the systematic risk of carry trade strategies. In doing so, the state variables have straightforward economic interpretations such as market risk and illiquidity. More specifically, we model the regimes by adopting proxies commonly used to measure market risk (foreign exchange volatility and the VIX) and either market or funding illiquidity (the bid-ask spread and the TED). The explanatory financial factors include equity and bond returns.

Our results on the relevance of the regime dependency of the carry trade risk sheds light on the gamble of currency speculation. By distinguishing between low and high risk environments, the danger related to carry trade becomes fully visible. In turbulent times, carry trade significantly increases its systematic risk and the exposure to other risky allocations. This finding warns against the apparent attractiveness of carry trade depicted by simple performance measures such as the Sharpe ratio.

The structure of the remaining part of the paper is as follows: Section 2 outlines the theoretical motivation and our econometric approach, while Section 3 describes the data. Section 4 contains the empirical results; firstly, we show some preliminary results, secondly, we show the empirical results from estimating the smooth transition regression model. Finally, we conclude in Section 5.

2 Theoretical and Empirical Framework

2.1 Theoretical Background

This paper combines three strands of literature to model carry trade returns. First, traditional factor models for exchange rates (McCurdy and Morgan (1991), Dahlquist and Bansal (2000) and Mark (1988)) suggest that currencies are exposed to equity and bond markets. Second, non-linear patterns in exchange rate returns emerge from unwinding carry trade and squeezes in funding liquidity (Plantin and Shin (2008)), Peso problems (Farhi and Gabaix (2008)), limits to speculation hypothesis (Lyons (2001)) and non-linear cost of capital (Dumas (1992)) the rational inattention mechanism (Bacchetta and van Wincoop

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3Limits to speculation refers to the idea that speculators accessing a limited number of capital and investment opportunities would profit from carry trade performance only if its risk adjusted expected return is more attractive in comparative terms.

4Dumas (1992) proposes a general-equilibrium two-country model that endogenously produces nonlinearity, heteroskedasticity and mean-reverting in the cost of capital. This setting implies that the real interest rate differential incorporates a risk premium.
These arguments imply that a factor model for exchange rates should allow for different regimes. Third, the recent evidence on market volatility and liquidity risk premia (Acharya and Pedersen (2005), Ang, Hodrick, Xing and Zhang (2006) and Bhansali (2007)) highlights the need to incorporate the effects of high volatility and liquidity squeezes.

To incorporate and assess these different mechanisms, we model the currency excess return ($z$) by a factor model where S&P 500 futures returns (SP) and Treasury Notes futures returns (TN) are the basic factors

$$z = \beta_{SP}(s)SP + \beta_{TN}(s)TN + \alpha(s) + \varepsilon,$$

but where the slope coefficients ($\beta_{SP}$ and $\beta_{TN}$) as well as the “intercept” ($\alpha$) are allowed to depend on “regime” variables: measures of market volatility and liquidity ($s$). To account for the autocorrelation that exists in some exchange rates, we also include lags of all variables (see below for details on the econometric specification).

This model has the advantage of being written in terms of traditional risk factors. An alternative is to construct factors from portfolios of exchange rates (Lustig et al. (2008))—which may well give a better fit, but at the cost of making the interpretation of the results more difficult.

We study several proxies (regime variables) for market volatility and liquidity. A measure of FX volatility is used to account for market volatility risk premia (Bhansali (2007) and Ang et al. (2006)), the spread between Libor and T-bill rates (TED) is a proxy of funding liquidity (Brunnermeier et al. (2009)), CBOE’s index of equity market volatility (VIX) is often used to represent equity market volatility as well as risk aversion (Lustig et al. (2008)), and the bid-ask spread on the FX market is a natural measure of market liquidity (Roll (1984)) and asymmetric information (Glosten and Milgrom (1985)). See Section 3 for details on the data.

Our aims are to study if such a model can explain carry trade returns and to assess which of these different volatility and liquidity proxies that are most relevant for the FX market.

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Empirical evidence on non-linear patterns is provided in e.g. Bekaert and Gray (1998), Sarno et al. (2006) and Ichieu and Koyama (2008).
2.2 Econometric Approach

Our econometric model is as follows. First, let \( G(s_{t-1}) \) be a logistic function that depends on the value of some regime variables in the vector \( s_{t-1} \).

\[
G(s_{t-1}) = \frac{1}{1 + \exp[-\gamma(s_{t-1} - c)]},
\]

(2)

where the parameter \( c \) is the central location and the vector \( \gamma \) determines the steepness of the function. Then, our logistic smooth transition regression model (see van Dijk, Tersvirta and Franses (2002)) is

\[
z_t = [1 - G(s_{t-1})] \beta_1' x_t + G(s_{t-1}) \beta_2' x_t + \varepsilon_t,
\]

(3)

where the dependent variable \( z_t \) (the currency excess return) is modelled in terms of the set of explanatory variables \( x_t \) (here, stock returns, bond returns, lags, and a constant) and the regime variable \( s_{t-1} \). The parameters \((\gamma, c)\) are from the logistic function and \( (\beta_1, \beta_2) \) are from the regression function.

The effective slope coefficients in (3) vary smoothly with the state variables \( s_{t-1} \): from \( \beta_1 \) at low values of \( \gamma' s_{t-1} \) to \( \beta_2 \) at high values of \( \gamma' s_{t-1} \). This is illustrated in Figure 1. Clearly, if \( \beta_1 = \beta_2 \) then we effectively have a linear regression.

Figure 1 also illustrates how the effective slope coefficient depends on the parameters of the \( G(s_{t-1}) \) function (assuming \( s_{t-1} \) is a scalar and \( \gamma > 0 \)). A lower value of the parameter \( c \) shifts the curve to the left, which means that it takes lower a value of \( s_{t-1} \) to move from the regime where the effective slope coefficient is \( \beta_1 \) to where it is \( \beta_2 \). In contrast, a higher value of the parameter \( \gamma \) increases the slope of the curve, so the transition from \( \beta_1 \) to \( \beta_2 \) is more sensitive to changes in the regime variable \( s_{t-1} \).

The model is estimated and tested by using GMM, where the moment conditions are set up to replicate non-linear least squares. Diagnostic tests indicate weak first-order (but no second-order) autocorrelation and a fair amount of heteroskedasticity. Therefore, the inference is based on a Newey and West (1987) covariance matrix estimator with a bandwidth of two lags.

The explanatory variables are current and 1-day lagged stock and bond returns as well as the 1-day lagged currency excess return and a constant:

\[
x_t = \{SP_t, SP_{t-1}, TN_t, TN_{t-1}, z_{t-1}, 1\}.
\]

(4)

With these regressors, our regression model in equation (3) is just a factor model. The basic factors are the US equity and bond returns—although with
extra dynamics due to the lagged factors and also the lagged excess return (lagged dependent variable). The new feature of our approach is that it allows all coefficients (the betas and the intercept—the alpha) to vary according to a regime variable. The regime dependent intercept can also be interpreted as the direct effect of the regime on the currency return. In fact, we have also tried including the regime variables as factors themselves, but the results were similar to those reported before. The reason for this result is that the “effective intercept” looks like in Figure 1 discussed before—which is not very different from a linear function (over the range of data available).

Prompted by preliminary findings (see below), we are initially interested in studying if the systematic risk exposure is greater during volatile periods and if the FX volatility itself is a priced factor—but we later also use other proxies of market volatility and liquidity.

3 Data Description

The sample is based upon daily data and runs from January 1995 through December 2008, thus providing us with 3,652 observations.

3.1 Currency Excess Returns

We investigate the G10 currencies quoted against the US dollar (USD): Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), euro/German mark (EUR), UK pounds (GBP), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish kronor (SEK). The main sample is 1995–2008. In a robustness analysis we include 10 more currencies for a shorter sample 2003–2008: Brazil cruzeiro (BRC), Czech koruna (CZK), Israeli shekel (ILS), Indian rupee (INR), Icelandic krona (ISK), Mexican new peso (MXN), Polish new zloty (PLN), Russian Federation rouble (RUB), new Turkish lira (TRY), and South African rand (ZAL).

The daily WM/Reuters closing spot exchange rates are available through DataStream. For each currency pair we calculate the mid-quote log-returns, denoted $r_t^k$ for currency $k$ at day $t$. Following Brunnermeier et al. (2009), we use the exchange rate return in excess of the prediction by the UIP (i.e. the abnormal return), denoted $z_t^k$ for currency $k$ at time $t$. Thus we add the currency return and the one-day lagged interest rate differential between a given country and the US: it is the return (in USD) on a long position in the money market.
in currency $k$ minus the return on the US money market

$$z_t^k = r_t^k + i_{t-1}^k - i_{t-1}^{US}, \quad (5)$$

where $i_t^{US}$ is the log interest rate for the US and $i_t^k$ is the log interest rate for country $k$.

The interest rate data are taken from DataStream and we use the interest rate with the shortest available maturity, normally the 1-day money market rate (except for Australia and New Zealand where we use 1-week interest rates).

Table 1 (upper rows) contains summary statistics of the excess returns for the individual G10 currencies. All excess returns have fat tails, most pronounced for the Australian dollar. The average excess returns are negative for typical funding currencies (-3.7% for JPY and -1.7% for CHF, annualized) and positive for some of the typical investment/lending currencies (1.4% for NZD, annualized).

### 3.2 Carry Trade Excess Returns

A (unleveraged) carry trade strategy consists of selling low interest rate currencies and buying high interest rate currencies. To study typical carry trade strategies, we rely on the explicit strategy followed by Deutsche Bank’s “PowerShares DB G10 Currency Harvest Fund”.

It is based on the G10 currencies listed in the previous subsection. The carry trade portfolio is composed of a long position in the three currencies associated with the highest interest rates and a short position in the three currencies with the lowest interest rates (cf. Gyntelberg and Remolona (2007)). The portfolio is rebalanced every 3 months. We let $z_{t}^{CT}$ denote the excess return at time $t$ on the carry trade strategy.

Table 1 (row 10) shows that the average carry trade return is higher than for any individual currency and that the standard deviation is lower than for all except one (CAD) currency. This might explain the popularity of the strategy. As in Brunnermeier et al. (2009), we find that the distribution of the return of the carry trade strategy is left skewed (i.e. the left tail of the distribution is longer than the right tail), and that it has fat tails.

Figure 2 shows the weights for the carry trade portfolio. The weights seem to be fairly stable. The usual situation is that the carry trade strategy is long in the GBP, NZD, and a third and varying currency. Most often the carry trade strategy is short in the CHF, JPY, and a third and varying currency.

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6 More information about this index is available at the Deutsche Bank home page at www.dbfunds.db.com.
3.3 Additional Variables

The explanatory variables that we use in the empirical analysis represent the two other main financial markets, namely the stock and bond markets. We use the log-returns on the futures contract on the SP500 index traded on the Chicago Mercantile Exchange, and the futures contract on the 10-year US Treasury notes traded on the Chicago Board of Trade. Each day, we use the most actively traded nearest-to-maturity or cheapest-to-deliver futures contracts, switching to the next-maturity contract five days before expiration. We denote these returns at time $t$ by $SP_t$ and $TN_t$, respectively. The futures contracts data are also available from DataStream.

To differentiate between regimes we initially construct a foreign exchange volatility variable (denoted $FXV_t$ and called FX volatility below). We measure the FX volatility by the standardized first principal component extracted from the most liquid 1-month OTC implied volatilities from Reuters (all quoted against the USD): CAD, CHF, EUR, JPY, and GBP. The first principal component is approximately an equally weighted portfolio of the implied volatilities, in particular the weights are $\{0.25, 0.20, 0.17, 0.19, 0.19\}$. Figure 3 shows the time profile of the FX volatility. It is particularly high during spring 1995 to spring 1996 (with somewhat lower values during summer 1995), early 1998, summer 2006 and late 2008.

Table 1 (lower rows) shows that the distribution of the stock returns has a fat tail, and to a minor extent this also applies to the bond returns. The standard deviations of the currency excess returns fall between those of stocks (highest) and bonds (lowest). The distribution of the FX volatility is right skewed and has fat tails.

In further analysis we make use of three additional regime variables representing market volatility and liquidity. Firstly, the so-called TED spread, which is the difference between the 3-month USD LIBOR interbanking market interest rate and the 3-month T-Bill rate. Secondly, we use the VIX index, which is the index of implied volatilities on SP500 options which is traded at the CBOE. Thirdly, we measure market liquidity with the JPY/USD bid-ask spread computed as the average of the ask price minus the bid price divided by their average at the end of each five-minute interval during the day. We use the 10-day moving average of the daily bid-ask spreads. We cap the spread at its 95% percentile to get rid of the ten-fold increase on (fuzzy) holidays like Christmas.

Finally, we use the order flow for the JPY/USD as an additional explanatory variable which is defined as the number of buys minus the number of sells during
the day (divided 10,000). Both the JPY/USD bid-ask spread and the order flow are constructed from firm quotes and trading data obtained by the tick-by-tick data of EBS (Electronic Broking Service). We only have JPY/USD data covering the long sample period from 1997 to 2008. However, the JPY/USD is notoriously considered the exchange rate subjected to most carry trade, so it provides an interesting proxy.

4 Empirical Results

In this section we present the empirical results. First, we provide some preliminary findings that motivate the econometric framework. Then, we show the empirical results for carry trade strategies as well as for the individual currencies.

4.1 Preliminary Results

The excess return on the carry trade strategy is positively correlated with the return on the stock market (0.19) and somewhat negatively correlated with the return on the bond market (−0.06). This means that “weak currencies” like NZD (the long positions of the carry trade strategy) tend to appreciate relative to “strong currencies” like JPY and CHF (the short positions) when the stock market booms. Conversely, weak currencies tend to depreciate against strong currencies when bond prices increase (interest rates decrease). That is, when the risk appetite of investors decrease and they move to safe assets (US Treasury bonds are typically considered to be “safe havens”), then weak currencies lose value against strong currencies.

While these patterns are already relatively well understood (see, for instance, Bhansali (2007)), it is less well known that the strength of the correlations depend very much on the level of FX volatility. Table 2 (first column) shows how the correlation between the carry trade return and the SP500 varies across the top quantiles of FX volatility. The figure 0.41 is the correlation between the carry trade return and the SP500 return for days when FX volatility is in the top 5%. The table shows a very clear pattern, the higher the foreign volatility, the stronger is the correlation between the stock market and the carry trade strategy. The correlation coefficients between the stock market and the carry trade strategy for the eight top volatility quantiles are significantly higher than the correlation coefficient for the entire sample (the inference is based on GMM).

Similarly, Table 2 (second column) shows the correlations between the carry trade return and the 10-year Treasury at various top quantiles for the FX volatil-
ity. This correlation is negative and numerically stronger for higher FX volatility. However, only the correlation coefficient at the two top most volatility quantiles is significantly stronger than for the entire sample.

These preliminary results suggest that the risk exposures of the carry trade strategy are much stronger during volatile periods than during calm periods.

Table 2 (third column) reports the average excess returns of the carry trade strategy for different top quantiles of FX volatility. On average, the carry trade strategy yields positive and moderately high returns in normal periods, whereas it has dramatic losses during turbulent periods.

### 4.2 Results from the Smooth Transition Regression Model

The preliminary findings suggest that both the risk exposure and the average of the carry trade return are related to volatility of the FX markets. We now formalize this by using a linear factor model (with stocks and bonds as factors), but where the betas and the alpha (the intercept) depend on the one-day lagged FX volatility—according to the logistic smooth transition regression model discussed above.

Table 3 (first column) shows the results from estimating the logistic smooth transition regression model for the carry trade strategy. The results in the last two columns are discussed in the robustness analysis below. The top part of the table shows the parameter estimates applicable for low values of the FX volatility, denoted $\beta_1$ above, and the middle part of the table shows the parameter estimates applicable for high values of FX volatility, denoted $\beta_2$ above. The lower part of the table shows the difference between the parameter estimates for high and low FX volatility values, i.e. it shows $\hat{\beta}_2 - \hat{\beta}_1$. Moreover, the table indicates whether these differences are statistically significant.

The explanatory power of the smooth transition regression model is fairly high: The $R^2$ is 0.18. As a comparison, an OLS regression gives half of that—which suggests that it is empirically important to account for regime changes in order to describe the exchange rate movements. The estimated value of the $c$ parameter (the central location of the logistic function) is 1.25, and the estimated $\gamma$ parameter (the steepness) is 2.49, so the estimated logistic function is similar to the solid curve in Figure 1 discussed above. In practice, this means that the volatile regime starts to have an impact when the standardized FX volatility variable goes above 1 or so. The resulting time path of $G(FXV)$ is shown in Figure 4. The value is close to zero most of the time (it is less than 0.1 on 80% of the days in the sample) and it only occasionally goes above a half (6% of the days). The calm regime (when $\beta_1$ is the effective slope coefficient)
is thus the normal market situation, while the volatile regime (when \( \beta_2 \), or a weighted sum of \( \beta_1 \) and \( \beta_2 \), is the effective slope) represents periods of extreme stress on the FX market.

The results in Table 3 clearly show that the risk exposure depends on the FX volatility variable. During calm periods, the carry trade strategy is significantly positively exposed to current and lagged stock returns, but not to the bond market (a numerically small, negative, coefficient). During turmoil, the exposure to the current and lagged stock market returns is much larger. The exposure to the bond market also has a more negative coefficient, but the difference between the regimes is not significant. It is also interesting to note that the autoregressive component is small and insignificant during calm periods, but significantly negative during turmoil—which indicates considerable predictability and mean reversion during volatile periods.

The result that the currency risk exposure is larger during turbulent periods is related to the comovement literature that discusses whether financial markets comovement is stronger during financial crises, cf. Forbes and Rigobon (2002) and Corsetti, Pericoli and Sbraci (2005). In addition, the \( \alpha \) (“intercept”) is slightly positive in the low volatility state (the numerical value is small, but non-trivial—especially when annualized) and slightly negative when volatility is high—and the difference is clearly significant. This suggests that the overall performance of carry trades is negatively affected by market volatility—as discussed by Bhansali (2007) and Menkhoff, Sarno, Schmeling and Schrmpfz (2009). We discuss the economic significance of these results later on.

Table 4 shows the results from estimating the logistic smooth transition regression model for the individual currency excess returns. In these regressions, we set \( \gamma \) equal to 2.50 to guarantee a unique and consistent number across the panel (the point estimate for the carry trade return is 2.49). The table is structured similarly to Table 3. The results for the individual currencies are broadly in line with those from the carry trade. In both regimes, typical investment currencies like NZD have positive exposure to SP500, while typical funding currencies like CHF and JPY have negative risk exposure (a safe haven feature). In most cases, this pattern is even stronger in the high volatility regime (the change in the slope coefficient is significant for all currencies). Together this explains why the carry trade is so strongly exposed to SP500 risk, particularly in the high volatility regime. In addition, the negative autocorrelation in the carry trade strategy in the high volatility regime seems to be driven by the typical investment currencies. These findings on mean-reversion are consistent with Dumas (1992) in two respects: first, mean-reverting patterns of exchange
rates are non-linear; second, they should be more significant for those currencies deviating from the interest rate parity (i.e. the “investment” currencies in our case).

While the typical investment currencies are not exposed to the bond market, most funding currencies covary positively with it (in both regimes). This means that the strong currencies tend to gain value at the same time as the US bond market does. The point estimates of the carry trade are consistent with this pattern, but the values are not statistically significant.

To assess the economic importance of the systematic risk of the carry trade strategy we consider the fitted values (CT excess returns) in Figures 5–6. Figure 5 shows the fitted carry trade excess returns split up into two parts: the first part (upper graph) caused by the calm regime \((1 - G)\hat{\beta}_1 x_t\) and the second part (lower graph) caused by the volatile regime \(G\hat{\beta}_2 x_t\). The total fitted carry trade excess return adds up to the sum of the two parts. Almost all the movement in the fitted carry trade excess returns are caused by the volatile regime. So, it is during volatile FX markets that the systematic risk of the carry trade is most important. This illustrates that non-linearities and regime-dependence (see, for instance, Plantin and Shin (2008) and Mark (1988)) are important for modelling carry trade returns.

Similarly, Figure 6 shows the (annualized) fitted returns for different top quantiles of FX volatility. The upper left subfigure shows both the actual CT returns (cf. Table 2) and the fitted values from the estimated model: the fit is very good.

The other three subfigures in Figure 6 decompose the fitted values into the contribution from (contemporaneous and lagged) S&P returns, Treasury note returns and alpha (together with the lagged dependent variable). All these three subfigures point in the same direction. The contribution from S&P is negative at high FX volatility (around \(-6\%\)) since the beta of the carry trade strategy is positive—and S&P has, on average, negative returns when FX volatility is high. Treasury notes also have a negative contribution (\(-4\%\)) in those states, since the beta is negative and the bond market typically performs well when FX volatility is high. Finally, the alpha is markedly negative at high FX volatility (\(-18\%\))—which is the direct effect of FX volatility on the carry trade return.

This shows that around 1/3 of the (disastrous) carry trade return in the (extreme) high volatility state is accounted for by the exposure to traditional risk factors (equity and bonds) and 2/3 by the market volatility factor. Overall, our results suggest that it is important to model both regime dependence of traditional risk factors (see, for instance, McCurdy and Morgan (1991), Dahlquist
and Bansal (2000)) as well as the dependence on market volatility (see, for instance, Bhansali (2007), Lustig et al. (2008) and Menkhoff et al. (2009)).

4.2.1 Larger Currency Base

Constructing the carry trade strategy from a larger base of 20 currencies instead of 10 currencies does not alter the conclusion. To show that, Table 3 also reports results for a carry trade strategy based on the G10 currencies for the shorter sample 2003–2008 (instead of the 1995–2008 sample discussed above) and for a strategy based on the G10 and 10 additional currencies (also for 2003–2008) mention above. To guarantee high quality data and the existence of an active carry trade, the sample starts in 2003.

The results for the larger currency base are very much line with those for the G10 currencies—and perhaps even stronger. In particular, the negative exposure to the bond market is stronger (and more significant).

4.2.2 Other Regime Variables

So far, we have related the regime mechanism to a straight measure of risk on exchange rate markets. Here, we extend our analysis to more general proxies of global risk or risk aversion (the VIX, as used by Lustig et al. (2008) and Menkhoff et al. (2009)), of funding liquidity (the TED, as in Brunnermeier et al. (2009)) as well as market liquidity. To capture the latter, we use the JPY/USD bid-ask daily spread as a measure of transaction cost due to market illiquidity (Roll (1984)) and asymmetric information (Glosten and Milgrom (1985)). It should be noted that since we use EBS data, this measure accounts only for inter-dealer and brokered FX trading and not other trading venues such as OTC markets.

Using these other natural candidates for the regime variable does not change the results much. Table 3 shows the smooth transition regressions for the carry trade strategy for the sample 1997–2008 for different choices of the regime variable. The sample starts in 1997 (instead of 1995) due to limited data availability for some of the new regime variables. For convenience, the first column of the table uses the same specification as before: the FX volatility (FXV; now for the shorter sample period).

The second column uses the TED spread (the difference between the interbank and the treasury short interest rate), the third the VIX index, and the fourth the JPY/USD bid-ask spread. The results are similar across these different specifications.

The last column report results from a regression where we use all four state variables simultaneously. Both the FXV and the TED are highly significant,
while the VIX and bid-ask spread are not. (In this regression the state regime variables are rotated to be uncorrelated, but we get a similar result with the original variables.)

The correlations between these different regime variables are reasonably high (0.4–0.75), suggesting a well-expected co-variation between risk and illiquidity (of any nature). (The lowest correlation is between TED and the bid-ask spread and the highest is between FX volatility and the bid-ask spread). Not surprisingly, the different regimes variables generate fairly similar results for the time variation in risk exposure. However, a direct horse race favours the FX volatility and the TED over VIX and the bid-ask spread.

These findings suggest that FX market volatility and funding liquidity might be more important than risk measures related to equity markets (VIX) and direct measures of FX (inter-dealer) market liquidity (bid-ask spread). This is somewhat similar to the findings on the equity market by Bandi, Moise and Russell (2008).

4.2.3 Effects of Order Flow

In the market microstructure literature, the order flow is often thought of as representing the net demand pressure (Evans and Lyons (2002)). To investigate the importance of this in our model, Table 6 shows logistic smooth transition regressions for the Japanese yen (against the USD) for the sample 1997–2008, with and without controlling for order flow.

The results for the standard specification is very similar to those reported before (but for the sample 1995–2008): the yen appears to be a safe haven asset (the betas have the opposite sign compared to the carry trade strategy). The second column includes one more regressor: the order flow on the JPY/USD exchange rate, measured as the number of buyer initiated trades minus the number of seller initiated trades (where a trade means buying JPY and selling USD). The coefficient related to the order flow is significantly positive, so there is a significant price impact meaning that demand pressure is associated with a currency appreciation, as expected. More importantly for our paper, however, is the fact that including the order flow does not materially change the betas on the equity and bond markets.

Although limited to the JPY/USD exchange rate, this finding still suggests that our previous conclusions on the time varying risk exposure are not sensitive to the inclusion/exclusion of order flow.
4.2.4 Further Robustness Analysis

The empirical results are robust to various changes of the specification. First, rebalancing the carry trade portfolio more often than every three months does not change the qualitative results. Second, our results are robust to the number of long and short currency positions in the carry trade strategy. Third, including other variables (for instance, FX volatility) as regressors does not alter any of the main results. Fourth, a joint panel estimation of the individual currencies also give similar results.

5 Conclusion

This paper studies the risk exposure of carry trade returns by estimating factor models on daily data from 1995 to 2008. The risk factors are traditional (equity and bond markets), but the risk exposures are allowed to depend on proxies for volatility and (market and funding) liquidity. We also allow for mean-reversion and use the volatility and risk proxies as additional factors.

The results from carry trade strategies based on the G-10 currencies show that carry trade excess returns have highly regime dependent risk exposures: the beta of the stock market is positive in normal times—and much more so during turbulent times. In addition, the returns are more predictable (mean-reverting) during turmoil and have a direct exposure to a volatility factor.

The economic importance of the results is significant. For instance, the (abysmal) performance of carry trade strategies during times of high (extreme) market volatility is by 1/3 driven by exposure to traditional risk factors (equity and bonds) and by 2/3 by exposure to the volatility factor itself.

The results hold also for individual currencies: typical weak currencies have a positive exposure to equities and this exposure is much larger during periods of FX market turmoil. Typical strong currencies are the mirror image. Using a larger set of currencies including emerging market currencies and controlling for order flow does not change the main results.

By allowing several proxies for volatility and liquidity to jointly define the regimes, we find that FX market volatility and funding liquidity (the TED spread) are more important than measures of equity market volatility and risk aversion (VIX) or the FX market liquidity (bid-ask spread).

Our findings provide further evidence on the recent financial research showing that financial markets are regime dependent and have non-linear pattern with stronger comovements during financial crises (Plantin and Shin (2008), Forbes and Rigobon (2002) and Corsetti et al. (2005)), and that volatility and
liquidity have important direct effects on asset returns (Acharya and Pedersen (2005), Ang et al. (2006) and Bhansali (2007)).
References


Effective coefficient of $x_t$ for different $G$ functions

$c_1 = 1.2, \gamma_1 = 2.5$
$c_2 = 0.5, \gamma_2 = 2.5$
$c_3 = 1.2, \gamma_3 = 5$

Figure 1: Example of Smooth Transition Regression Model
Figure 2: Carry Trade Strategy Weights
Figure 3: Time Series of FX Volatility
Figure 4: Estimated $G(FXV)$ Time Series
Figure 5: Time Series of Fitted Carry Trade Excess Return
Figure 6: Fitted (Annualized) CT Returns for Different Top Quantiles of FX Volatility
the curry trade strategy (CT), the SP500 (SP), the 10-year Treasury bonds
statistics for the excess returns on 9 individual currencies (relative to the USD),

Across the top quantiles of FX volatility, this table shows the
table 2:
Carry trade characteristics across FX volatility top quantiles,

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>mean/year</th>
<th>std</th>
<th>skewness</th>
<th>exkurtosis</th>
<th>min</th>
<th>max</th>
<th>nObs</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUD</td>
<td>−0.01</td>
<td>−1.33</td>
<td>0.78</td>
<td>−1.28</td>
<td>19.47</td>
<td>−9.22</td>
<td>6.50</td>
<td>3652.00</td>
</tr>
<tr>
<td>CAD</td>
<td>0.00</td>
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<td>0.07</td>
<td>10.67</td>
<td>−4.43</td>
<td>4.93</td>
<td>3652.00</td>
</tr>
<tr>
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<td>−1.71</td>
<td>0.67</td>
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<td>3.06</td>
<td>−4.55</td>
<td>5.30</td>
<td>3652.00</td>
</tr>
<tr>
<td>EUR</td>
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<td>0.61</td>
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<td>2.46</td>
<td>−3.91</td>
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<td>GBP</td>
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<td>0.53</td>
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<td>−3.79</td>
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<td>3652.00</td>
</tr>
<tr>
<td>JPY</td>
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<td>0.70</td>
<td>0.61</td>
<td>5.05</td>
<td>−3.65</td>
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<tr>
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</tr>
<tr>
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</tr>
<tr>
<td>SEK</td>
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<td>0.65</td>
<td>0.23</td>
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<td>−3.50</td>
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</tr>
<tr>
<td>CT</td>
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<td>0.52</td>
<td>−0.90</td>
<td>11.12</td>
<td>−5.35</td>
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</tr>
<tr>
<td>SP</td>
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<td>6.64</td>
<td>1.27</td>
<td>0.20</td>
<td>12.32</td>
<td>−9.88</td>
<td>14.11</td>
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</tr>
<tr>
<td>TN</td>
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<td>−0.47</td>
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<tr>
<td>FXV</td>
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<td>0.00</td>
<td>1.00</td>
<td>2.87</td>
<td>14.85</td>
<td>−1.80</td>
<td>8.16</td>
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</table>

Table 1: **Descriptive statistics, 1995–2008.** This table shows descriptive statistics for the excess returns on 9 individual currencies (relative to the USD), the curry trade strategy (CT), the SP500 (SP), the 10-year Treasury bonds (TN), as well as for the FX volatility (FXV). All returns are in percent.

<table>
<thead>
<tr>
<th>FXV top quantile</th>
<th>Corr(z,SP)</th>
<th>Corr(z,TN)</th>
<th>Mean CT return</th>
<th>nObs</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.05</td>
<td>0.41***</td>
<td>−0.19*</td>
<td>−25.35</td>
<td>178.00</td>
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<tr>
<td>0.15</td>
<td>0.33***</td>
<td>−0.13*</td>
<td>−14.54</td>
<td>535.00</td>
</tr>
<tr>
<td>0.25</td>
<td>0.30**</td>
<td>−0.10</td>
<td>−3.96</td>
<td>892.00</td>
</tr>
<tr>
<td>0.35</td>
<td>0.27**</td>
<td>−0.09</td>
<td>−1.36</td>
<td>1248.00</td>
</tr>
<tr>
<td>0.45</td>
<td>0.24**</td>
<td>−0.08</td>
<td>0.21</td>
<td>1605.00</td>
</tr>
<tr>
<td>0.55</td>
<td>0.23**</td>
<td>−0.06</td>
<td>1.37</td>
<td>1961.00</td>
</tr>
<tr>
<td>0.65</td>
<td>0.21**</td>
<td>−0.06</td>
<td>3.01</td>
<td>2318.00</td>
</tr>
<tr>
<td>0.75</td>
<td>0.21**</td>
<td>−0.05</td>
<td>2.47</td>
<td>2674.00</td>
</tr>
<tr>
<td>0.85</td>
<td>0.20</td>
<td>−0.05</td>
<td>3.65</td>
<td>3031.00</td>
</tr>
<tr>
<td>0.95</td>
<td>0.19</td>
<td>−0.06</td>
<td>3.71</td>
<td>3388.00</td>
</tr>
<tr>
<td>1.00</td>
<td>0.19</td>
<td>−0.06</td>
<td>4.64</td>
<td>3652.00</td>
</tr>
</tbody>
</table>

Table 2: **Carry trade characteristics across FX volatility top quantiles, 1995–2008.** Across the top quantiles of FX volatility, this table shows the correlation between the carry trade excess return and the stock return (first column), the correlation between the carry trade excess return and the bond return (second column), the annualized average carry trade excess return, and the number of observations. Based on a GMM test using Newey and West (1987) standard errors, */** indicates that the correlation is significantly different from the full sample (in last line) correlation at the 10%/5% level of significance.
Table 3: Parameter estimates from the smooth transition regression, using FX\(V_{t-1}\) as regime variable. The table shows the parameter estimates arising from estimating the logistic smooth transition regression model on carry trade excess returns. Based upon Newey and West (1987) standard errors, \(*/**\) indicates that the parameter is significantly different from zero at 10%/5% level of significance.
Table 4: Parameter estimates from the smooth transition regression, 1995–2008, using $FXV_{t-1}$ as regime variable. The table shows the parameter estimates arising from estimating the logistic smooth transition regression model separately for excess returns from 9 currencies. Based upon Newey and West (1987) standard errors, */** indicates that the parameter is significantly different from zero at 10%/5% level of significance. The γ parameter is fixed to 2.5.
Based upon Newey and West (1987) standard errors, the logistic smooth transition regression model on carry trade excess returns, 1997–2008. The table shows the parameter estimates arising from estimating the logistic smooth transition regression model on carry trade excess returns.

Table 5: Parameter estimates from the smooth transition regression, 1997–2008. The table shows the parameter estimates arising from estimating the logistic smooth transition regression model on carry trade excess returns. Based upon Newey and West (1987) standard errors, */** indicates that the parameter is significantly different from zero at 10%/5% level of significance.
Table 6: Parameter estimates from the smooth transition regression, JPY/USD exchange rate, 1997–2008, using $FXV_{t-1}$ as regime variable. The table shows the parameter estimates arising from estimating the logistic smooth transition regression model. Based upon Newey and West (1987) standard errors, */** indicates that the parameter is significantly different from zero at 10%/5% level of significance.