The Time-Varying Systematic Risk of Carry Trade Strategies*

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Abstract: We explain the currency carry trade performance using an asset pricing model in which factor loadings are regime-dependent rather than constant. Empirical results show that a typical carry trade strategy has much higher exposure to the stock market and is mean-reverting in regimes of high FX volatility. The findings are robust to various extensions. Our regime-dependent pricing model provides significantly smaller pricing errors than a traditional model. Thus, the carry trade performance is better explained by a time-varying systematic risk that increases in volatile markets, suggesting a partial resolution of the Uncovered Interest Rate parity puzzle.
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I. Introduction

"[Engaging in carry trades] 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).

A currency carry trade is defined as borrowing a low-yielding asset 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 should 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 regime dependent.

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 foreign exchange returns to risk factors (e.g. Lustig, Roussanov, and Verdelhan (2008)).

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, where the risk exposures are allowed to change according to one or more state variables. This methodology provides a general framework to explain regime-dependent and non-linear risk-return payoffs. The investigation of regime-switching models for exchange rates is not new, see Bekaert and Gray (1998), Sarno, Valente, and Leon (2006), and Ichiue and Koyama (2008). Our contribution is to show that the risk exposure to the stock and bond market in the carry trade is regime dependent and that regimes are characterized by the level of foreign exchange volatility. While there have been other papers that point to the importance of volatility (e.g. Lustig, Roussanov, and Verdelhan (2008), Menkhoff, Sarno, Schmeling, and Schrimpf (2009)), the present paper is the first to demonstrate that volatility affects the exposure to stock market risk.

We use logistic smooth transition regression methodology to explain the systematic risk of carry trade strategies. In doing so, the state variables have straightforward economic interpretations. 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. The asset pricing analysis shows that the regime-dependent pricing model provides significantly smaller pricing errors.

Our results on the relevance of the regime dependency of the carry trade risk shed 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. Overall, our contribution can be seen as a partial resolution of the UIP puzzle.

This paper is topical considering the ongoing financial crisis which provides a live experiment for many of the ideas that we explore here.

The structure of the remaining part of the paper is as follows: Section II. outlines the theoretical motivation and our econometric approach, while Section III. describes the data. Section IV. contains the empirical results. Section V. concludes.

II. Theoretical and Empirical Framework

A. 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 can be explained by unwinding carry trades and squeezes in funding liquidity (Plantin and Shin (2008)), limits to speculation hypothesis (Lyons (2001)), as well as the rational inattention mechanism (Bacchetta and van Wincoop (2006)).[1] 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 return (r) by a factor model where stock (S&P 500 futures) returns (SP) and bond (Treasury Notes futures) returns (TN) are the basic factors

$$r = \beta_{SP}(s)SP + \beta_{TN}(s)TN + \alpha(s) + \varepsilon, \tag{1}$$

but where the slope coefficients (β_{SP} and β_{TN}) as well as the "intercept" (α) are allowed to depend on "regime" variables (s): measures of market volatility and liquidity. We study several proxies for market volatility and liquidity. To

[1] Empirical evidence on non-linear patterns is provided in e.g. Bekaert and Gray (1998), Sarno, Valente, and Leon (2006), Ranaldo and Söderlind (2009) and Ichiue and Koyama (2008).

account for the autocorrelation that exists in some exchange rates, we also include lags of all variables. In a robustness analysis we replace SP with various MSCI world equity indices and also include other regressors like the order flow.

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, Roussanov, and Verdelhan (2008))—which may well give a better fit, but at the cost of making the interpretation of the results more difficult.

B. 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}

$$G(s_{t-1}) = \frac{1}{1 + \exp[-\gamma'(s_{t-1} - c)]}, \tag{2}$$

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

$$r_t = [1 - G(s_{t-1})]\, \beta_1' x_t + G(s_{t-1}) \beta_2' x_t + \varepsilon_t, \tag{3}$$

where the dependent variable r_t (the carry trade or currency excess return) is modeled 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} (in our main case, the lagged FX volatility). The parameters (γ, c) are from the logistic function and (β_1, β_2) are from the regression function.

[Figure 1 about here.]

The effective slope coefficients in (3) vary smoothly with the state variables s_{t-1}: from β_1 at low values of $\gamma' s_{t-1}$ to β_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 a lower value of s_{t-1} to move from the regime where the effective slope coefficient is β_1 to where it is β_2. In contrast, a higher value of the parameter γ increases the slope of the curve, so the transition from β_1 to β_2 is more sensitive to changes in the regime variable s_{t-1}.

The model is estimated and tested by using generalized method of moments (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 return and a constant:

$$x_t = \{SP_t, SP_{t-1}, TN_t, TN_{t-1}, r_{t-1}, 1\}\,. \tag{4}$$

Thus, the regression model in equation (3) is a linear factor model, but where all coefficients can vary according to regime variables. The regime-dependent intercept (alpha) can also be interpreted as the direct effect of the regime on the currency return.[2]

III. Data Description

A. Currency Returns

In our base line analysis, 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 based upon daily data and runs from January 1995 through December 2008, providing us with 3,653 observations. The starting time is dictated by the availability of data on option-implied FX volatility. In a robustness analysis we include 10 more currencies (G20) for a shorter sample covering 2003–2008: the Brazilian real (BRL), 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 (ZAR). In another robustness analysis we consider a longer sample period, namely from 1976–2008. In this longer sample, only seven out of the 10 currencies are represented (AUD, CAD, CHF, EUR, GBP, JPY all against the USD)—due to lack of high quality data on short-term interest rates.

The daily WM/Reuters closing spot exchange rates are available through DataStream. Following Brunnermeier, Nagel, and Pedersen (2009), we use the exchange rate return in excess of the prediction by the UIP (i.e. the abnormal return). Thus, we add the currency return (based on mid-quotes) and the one-day lagged interest rate differential between a given country and the US

$$r_t^k = -(q_t^k - q_{t-1}^k) + i_{t-1}^k - i_{t-1}^{US}, \tag{5}$$

where q_t^k is the log exchange rate (the price, in currency k, of one US dollar), i_t is the log interest rate for currency k and i_t^{US} is the log interest rate for the US dollar. We therefore obtain the return on a foreign currency investment in excess of investing on the US money market.

[2] We have also used a smooth transition logistic model where FX volatility is both a regime variable (s_{t-1}) and an explanatory factor (an element of x_t). The results were similar to those where FX volatility is only used as a regime variable.

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).

All individual currency returns have fat tails, these being most pronounced for the AUD. The average returns are negative for typical funding/borrowing 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).

B. Carry Trade Returns

To study typical carry trade strategies, we rely on the explicit strategy followed by Deutsche Bank's "PowerShares DB G10 Currency Harvest Fund".[3] This 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 r_t^{CT} denote the return at time t on the carry trade strategy.

The weights for the carry trade portfolio are fairly stable. Usually, the carry trade strategy is long in the GBP, the NZD, and a third varying currency. It is most often short in the CHF, the JPY, and a third varying currency.

The average carry trade return is higher than that of any individual currency (4.64%) and the standard deviation is lower than that of any currency except the CAD. This might explain the popularity of the strategy. As in Brunnermeier, Nagel, and Pedersen (2009), we find that the distribution of the return of the carry trade strategy is left skewed and fat-tailed.

C. Additional Variables

The explanatory variables we use in the empirical analysis represent the two other main financial markets, namely the stock and bond markets. To represent the stock market we use the log-returns on the futures contract on the S&P 500 index traded on the Chicago Mercantile Exchange. The S&P 500 index is the most tracked equity index worldwide. It is replicated by a number of investment vehicles which are typically liquid and tradable at low transaction costs. Moreover, the use of future data guarantees us a consistent data set during the entire sample period. To represent the bond market we use the futures contract on the 10-year US Treasury notes traded on the Chicago Board of Trade. The rationale for using the US Treasury bond is that it is typically considered to be the broadest "safe haven," especially when "flight to quality" and "flight to liquidity" phenomena emerge. 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 available from DataStream.

[3] More information is available on the Deutsche Bank website at `www.dbfunds.db.com`.

To differentiate between regimes, we 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 close to being an equally weighted portfolio of the implied volatilities; the weights are $\{0.25, 0.20, 0.17, 0.19, 0.19\}$. This measure of FX volatility is particularly high during the period from spring 1995 to spring 1996 (with somewhat lower values during summer 1995), early 1998, summer 2006 and late 2008.

In the further analysis we use two additional stock market proxies, namely the MSCI world index in US dollars including and excluding US stocks. Both indices are recorded in USD. Moreover, we make use of three additional regime variables representing market volatility and liquidity. Firstly, we utilize the 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 CBOE VIX index, which is an index of implied volatilities on S&P 500 stocks. 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 95th percentile to eliminate the ten-fold increase on holidays or days with extremely low activity that typically occur between weekends and main holidays like Christmas or the New Year's Day.

Finally, we use the order flow for the JPY/USD as an additional explanatory variable. It is defined as the number of buyer initiated trades minus the number of seller initiated trades during the day (divided by 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. As the JPY/USD is considered to be the exchange rate subject to the most carry trades, it provides an interesting proxy.[4]

IV. Empirical Results

A. Preliminary Results

The 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 "investment currencies" like the NZD (the long positions of the carry trade strategy) tend to appreciate relative to "funding currencies" like the JPY and CHF (the short positions) when the stock market booms. Conversely, investment currencies tend to depreciate against funding currencies when bond prices increase (interest rates decrease). In other

[4]For more about yen carry trade, see e.g. Hattori and Shin (2007) and Gagnon and Chaboud (2007).

words, when the risk appetite of investors decreases and they move to safe assets such as US Treasury bonds, investment currencies lose value against funding currencies.

[Table 1 about here.]

While these patterns are already relatively well understood (see, for instance, Bhansali (2007)), it is less well known that the strength of the correlations depends very much on the level of FX volatility and liquidity. As an illustration, Table 1 (first column) shows how the correlation between the carry trade return and the SP varies across the top quantiles of FX volatility. The figure 0.41 is the correlation between the carry trade return and the SP return for days when FX volatility is in the top 5%. The table shows a very clear pattern: the higher the FX volatility, the stronger the correlation between the stock market and the carry trade strategy. In fact, 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 (GMM based inference).

Similarly, Table 1 (second column) shows the correlations between the carry trade return and TN at various top quantiles for the FX volatility. This correlation is negative and numerically stronger for higher FX volatility—although only the correlation coefficient at the second top volatility quantile 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.[5]

Table 1 (third column) reports the average 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 on average it shows dramatic losses during turbulent periods.

B. Carry Trade Strategy

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

[Table 2 about here.]

Table 2 (first column) shows the base case results from estimating the logistic smooth transition regression model for the carry trade strategy. The top part of the table shows the parameter estimates applicable for low FX volatility values, denoted β_1 in (3), and the middle part of the table shows the parameter

[5] However, the results should be read with appropriate reservations as Embrechts, McNeil, and Straumann (2002) call for caution when using correlations in risk management.

estimates applicable for high FX volatility values, denoted β_2. The lower part of the table shows the difference between the parameter estimates for high and low FX volatility values, i.e. it shows $\widehat{\beta}_2 - \widehat{\beta}_1$. 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. 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 γ parameter (the steepness) is 2.49, so the estimated logistic function is similar to the solid curve in Figure 1 discussed above. The resulting time path of the "regime function" $G(FXV)$ is shown in Figure 2 (upper panel). 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 β_1 is the effective slope coefficient) is thus the normal market situation, while the volatile regime (when β_2, or a weighted sum of β_1 and β_2, is the effective slope) represents periods of extreme stress on the FX market.

The regression results 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 (although the coefficient is numerically small), 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. 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.

These results are robust to various changes in the empirical specification. First, we get similar results by replacing the SP with either the $MSCI$ world index or the $MSCI$ world index excluding the US (see columns 2 and 3 of Table 2). In particular, the exposure to equities in the high volatility regime remains very strong. Thus, the carry trade's exposure to stock market returns appears irrespective of the country of origin of the companies' returns. Moreover, we obtain very similar results when the $MSCI$ indices are in local currencies (results not tabulated). Second, taking into account transaction costs affects the average return of the strategy (decreasing it by 1.12 percentage points per year), but does not change any of the slope coefficients.[6] The main reason is that the trading costs are fairly stable over time and that there is little rebalancing as the interest rate differentials are very persistent. Third, rebalancing the carry trade portfolio more/less often than every three months does not change the qualitative results. The main reason is that interest rates tend to change

[6] For each daily return we subtract 1/63 of half the bid-ask spread from the beginning of the investment period (rebalancing every 3 months) and half of the bid-ask spread from the end of the period. Since our return data are based on mid-quotes, the adjusted return is calculated from buying high and selling low. The data used to estimate transaction costs are bid and offered indicative WM/Reuters quotes from DataStream.

smoothly across time and so do portfolio weights. The results are also robust to the number of long and short currency positions in the carry trade strategy.[7]

[Figure 2 about here.]

To assess the economic importance of the systematic risk of the carry trade strategy, we consider the fitted values (CT returns) in Figures 2–3. Figure 2 shows the fitted carry trade returns split up into two parts: the first part (middle panel) caused by the calm regime ($(1 - G)\,\widehat{\beta}_1 x_t$) and the second part (lower panel) caused by the volatile regime ($G\widehat{\beta}_2 x_t$). The total fitted carry trade return adds up to the sum of the two parts. Almost all the movement in the fitted carry trade returns is caused by the volatile regime. So, it is during volatile FX markets that the systematic risk of the carry trade is most important. This is related to the literature that discusses whether financial market comovement is stronger during financial crises (cf. Forbes and Rigobon (2002) and Corsetti, Pericoli, and Sbracia (2005)) and also to the literature on non-linearities and regime-dependence of carry trade returns (cf. Plantin and Shin (2008) and Mark (1988)).

[Figure 3 about here.]

Figure 3 shows the (annualized) fitted returns for different top quantiles of FX volatility. The upper left subfigure shows both the actual CT returns (cf. Table 1) and the fitted values from the estimated model: the fit is very good.

The other three subfigures in Figure 3 decompose the fitted values into the contribution from (contemporaneous and lagged) SP returns, TN returns and alpha (together with the lagged dependent variable). All these three subfigures point in the same direction. The contribution from SP is negative at high FX volatility (around -6%) since the beta of the carry trade strategy is positive—and SP has, on average, negative returns when FX volatility is high. TN also has 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 combined effect of the alpha and the lagged dependent variable is remarkably negative at high FX volatility (-18%)—but somewhat positive at low FX volatility (5%). To interpret the latter finding, note that (3) shows that the alpha is

$$\alpha(s_{t-1}) = \alpha_1 + G(s_{t-1})(\alpha_2 - \alpha_1). \tag{6}$$

Since low volatility (implying $G(s_{t-1}) \approx 0$) is the typical state, we can interpret α_1 (which is positive) as the typical alpha—and $\alpha_2 - \alpha_1$ (which is negative) as the direct effect of high volatility on the on the carry trade return. This is similar to Bhansali (2007) and Menkhoff, Sarno, Schmeling, and Schrimpf (2009)

[7] Varying the rebalancing frequency between 1 and 6 months (all else equal) and varying the number of long/short positions between 2 and 4 (all else equal) gives very similar (i.e. small) coefficients in the low state. For the high state the sum of the contemporaneous and lagged coefficients is between 0.38 and 0.51 for SP and between -0.16 and -0.35 for TN.

who discuss how carry trades are negatively affected by market volatility. Note, however, that the alphas should not be taken as literal performance measures since some of the factors are managed portfolios.

The effect of the lagged dependent variable and the direct FX volatility effect imply a certain amount of predictability (as the state variable is measured in $t-1$). We leave this aspect to future research.

To sum up, our results show that around one third of the (disastrous) carry trade return in the (extreme) high volatility state is accounted for by the exposure to traditional risk factors (equities and bonds) and two thirds by the market volatility factor. This suggests 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 direct effect of market volatility on carry trade performance (see, for instance, Bhansali (2007), Lustig, Roussanov, and Verdelhan (2008) and Menkhoff, Sarno, Schmeling, and Schrimpf (2009)).

C. Individual Currencies

[Table 3 about here.]

Table 3 shows the results from estimating the logistic smooth transition regression model for the individual currency returns. In these regressions, we set γ equal to 2.50 to guarantee a unique and consistent number across the panel. The results for the individual currencies are broadly in line with those from the carry trade. In both regimes, typical investment currencies like the NZD have positive exposure to SP, while typical funding currencies like the CHF and JPY have negative SP 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 these elements explain why the carry trade is so strongly exposed to SP 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.

D. Larger Set of Currencies

Constructing the carry trade strategy from a larger base of 20 currencies (G20) instead of 10 currencies does not alter the conclusion. To show this, column 4 of Table 2 reports results for a carry trade strategy based on the G10 and 10 additional currencies for 2003–2008. The sample starts in 2003 in order to guarantee high quality data and the existence of an active carry trade market. (It can be shown that the results for the G10 in the shorter sample are very similar to those for the longer sample.)

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

G20 are also robust to the choice of stock index (see columns 5 and 6 of Table 2).

Accounting for the transaction costs decreases the carry trade performance by 1 percentage point per year, but does not affect the slope coefficients—as in the G10 case. Although the trading costs are higher for these additional 10 currencies, there is less rebalancing since some of the interest rate differentials are extremely persistent. Overall this leads to almost the same adjustment of the average performance as in the G10 case.

E. Asset Pricing Analysis

The regime-dependent risk exposures have important implications for the cross-sectional fit of the model. To illustrate this, we estimate a simplified model with the following specification: *(i)* the factors (f_t) are only contemporaneous variables; *(ii)* SP and TN are expressed as excess returns over a risk-free US interest rate; and *(iii)* the parameters of the logistic function are fixed (at the values estimated from the carry trade return).

By these simplifications, the model becomes testable (sufficient number of test assets compared to factors) and is a linear factor model with the following factors

$$f_t = [SP_t, TN_t, G_{t-1} \times SP_t, G_{t-1} \times TN_t, G_{t-1}]. \tag{7}$$

Since some of the factors are not excess returns, the asset pricing implications are tested by studying whether the cross-sectional variation in average returns is explained by the betas of the factors

$$\sum\nolimits_{t=1}^{T} r_t/T = \beta'\lambda, \tag{8}$$

where λ is a vector of factor risk premia. The model is estimated by GMM where the first set of moment conditions effectively estimate the betas (and an intercept) by regressing each currency return on the factors (time-series regressions), and the second set of moment conditions estimate the factor risk premia by a cross-sectional regression. We discipline the exercise by using the fact that the SP and TN are excess returns: these factors are included in the vector of test assets (together with the currencies) and formulate the moment conditions so that the factor risk premia for these two factors are just their average returns.

[Figure 4 about here.]

Figure 4 (upper panel) compares the results from using just SP and TN (a 2-factor model) with those from using all 5 factors in (7) for the G10 sample. While the 2-factor model explains virtually nothing of the cross-sectional variation of the currency returns, the 5-factor model is much more successful. For instance, the low return on JPY is well explained—mostly by the negative exposure to equities in the high volatility state. Similarly, the pricing error (the vertical distance to the 45 degree line) for the carry trade strategy (marked by CT) is substantially smaller in the 5-factor model, although it is not zero. Because of the few degrees of freedom, the power of formal tests of the model is low.

The lower panel of Figure 4 shows the asset pricing implication for the 20 currencies and the corresponding carry trade strategy (CT). As before, the 2-factor explains almost nothing of the cross-sectional variation of average returns, while the 5-factor works much better. In contrast to before, the formal test of the overidentifying restrictions has enough degrees of freedom to discriminate between the models: the 2-factor model is rejected at the 2% significance level, while the 5-factor model cannot be rejected even at the 20% significant level. The pricing error of the carry trade strategy is virtually zero in the 5-factor model (but almost 10% in the 2-factor model).

Overall, this gives considerable support for a model with regime-dependent risk exposures.

F. Other Regime Variables

So far, we have related the regime mechanism to a measure of risk on exchange rate markets, the FXV. Here, we extend our analysis to more general proxies of global risk or risk aversion (the VIX, as used by Lustig, Roussanov, and Verdelhan (2008) and Menkhoff, Sarno, Schmeling, and Schrimpf (2009)), to *funding* liquidity (the TED, as in Brunnermeier, Nagel, and Pedersen (2009)) as well as to *market* liquidity (the JPY/USD bid-ask spread which is a measure of transaction cost due to market illiquidity (Roll (1984)) and asymmetric information (Glosten and Milgrom (1985))).

[Table 4 about here.]

Table 4 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.

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). Not surprisingly, the different regime variables generate fairly similar results for the time variation in risk exposure.

However, a direct horse race favors the FX volatility and the TED over VIX and the bid-ask spread. The last column reports results from a regression where we use all four state variables simultaneously. Both the FXV and the TED are significant, while the VIX and bid-ask spread are not. (In this regression the state regime variables are rotated to be uncorrelated, but we obtain a similar result with the original variables).

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).

G. Further Robustness Analysis

Longer Sample Period

It is of considerable interest to see if the properties of carry trade documented above (on 1995–2008 and 2003–2008 data) also hold for earlier periods—especially during periods of marked FX market turmoil. We therefore also study the 1976–2008 sample for a reduced currency base (7 currencies).

We define a new FX volatility variable (since data on the FX options are not available before 1995), namely a 15-day moving average of the first principal component of the absolute value of the FX daily returns (see Taylor (1986)). This new FX volatility variable is backward looking and does not necessarily represent the beliefs of market participants, but it is still a reasonable approximation. For instance, over the 1995–2008 sample the correlation with the option based measure is 0.85.

For this longer sample most coefficients are numerically small (cf. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008), who find no relation between carry trade strategies and an equity factor for the same time period). However, the exposure to equities in the high volatility state is as strong as in the shorter sample (0.18 for the contemporaneous coefficient and 0.21 for the lagged coefficient). The details of these findings are available upon request.

Overall, it seems as if the time-varying exposure to equities has been an important feature during both earlier periods of FX market turbulence as well as during more recent episodes. This suggests that our findings cannot be solely driven by the current financial crisis.

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 order flow, we estimate the logistic smooth transition regressions for the JPY/USD for the sample 1997–2008 with and without adding order flow as an explanatory variable. Order flow data are constructed from firm quotes obtained by the tick-by-tick data of EBS (Electronic Broking Service). The coefficient related to the order flow is significantly positive, so there is a significant price impact meaning that demand pressure is associated with currency appreciation, as expected. More importantly for our paper, however, is the fact that the inclusion of the order flow does not materially change the betas on the equity and bond markets. The details of these findings are available upon request.

This finding suggests that our previous conclusions on the time-varying risk exposure are not sensitive to the inclusion/exclusion of order flow.

V. 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 returns), but the risk exposures are allowed to depend on proxies for volatility and (market and funding) liquidity.

The results from carry trade strategies based on the G10 currencies show that the risk exposures of the carry trade returns are highly regime-dependent: the beta related to 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 results also hold for individual currencies: typical investment currencies have a positive exposure to equities and this exposure is much larger during periods of FX market turmoil, while typical funding currencies are the mirror image. The results are robust to the application of a larger set of currencies including emerging market currencies, longer sample periods, other definitions of stock market returns, net of transaction costs, and controlling for order flow.

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 one third driven by exposure to traditional risk factors (equity and bond returns) and two thirds driven by exposure to the volatility factor itself. Moreover, the regime-dependent factor model assigns a very small pricing error to the carry trade strategy—in stark contrast to a traditional factor model, which suggests a zero risk premium for the strategy.

We test several variables in order to determine which factors govern the regime-dependency of the systematic risk inherent to the carry trade strategies. We find that FX market volatility and funding liquidity (the TED spread) are more relevant than measures of equity market volatility and risk aversion (VIX) or the FX market liquidity (bid-ask spreads).

Our findings provide further evidence on the recent research showing that financial markets are regime-dependent with stronger comovements during financial crises, and that volatility and liquidity have important direct effects on asset returns. Our results also indicate that carry trades look less attractive once correctly priced by means of regime-dependent models—suggesting a partial resolution of the UIP puzzle.

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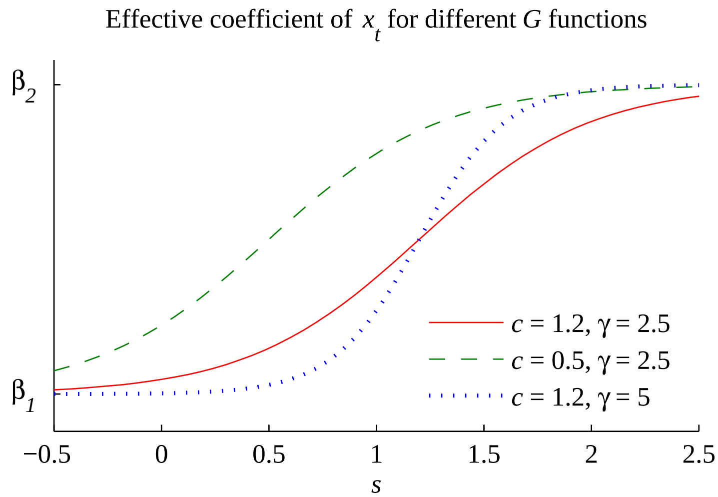

Figure 1: **Example of Smooth Transition Regression Model.** This figure illustrates the logistic $G(s)$ function in equation (2) used in the smooth transition regression in equation (3).

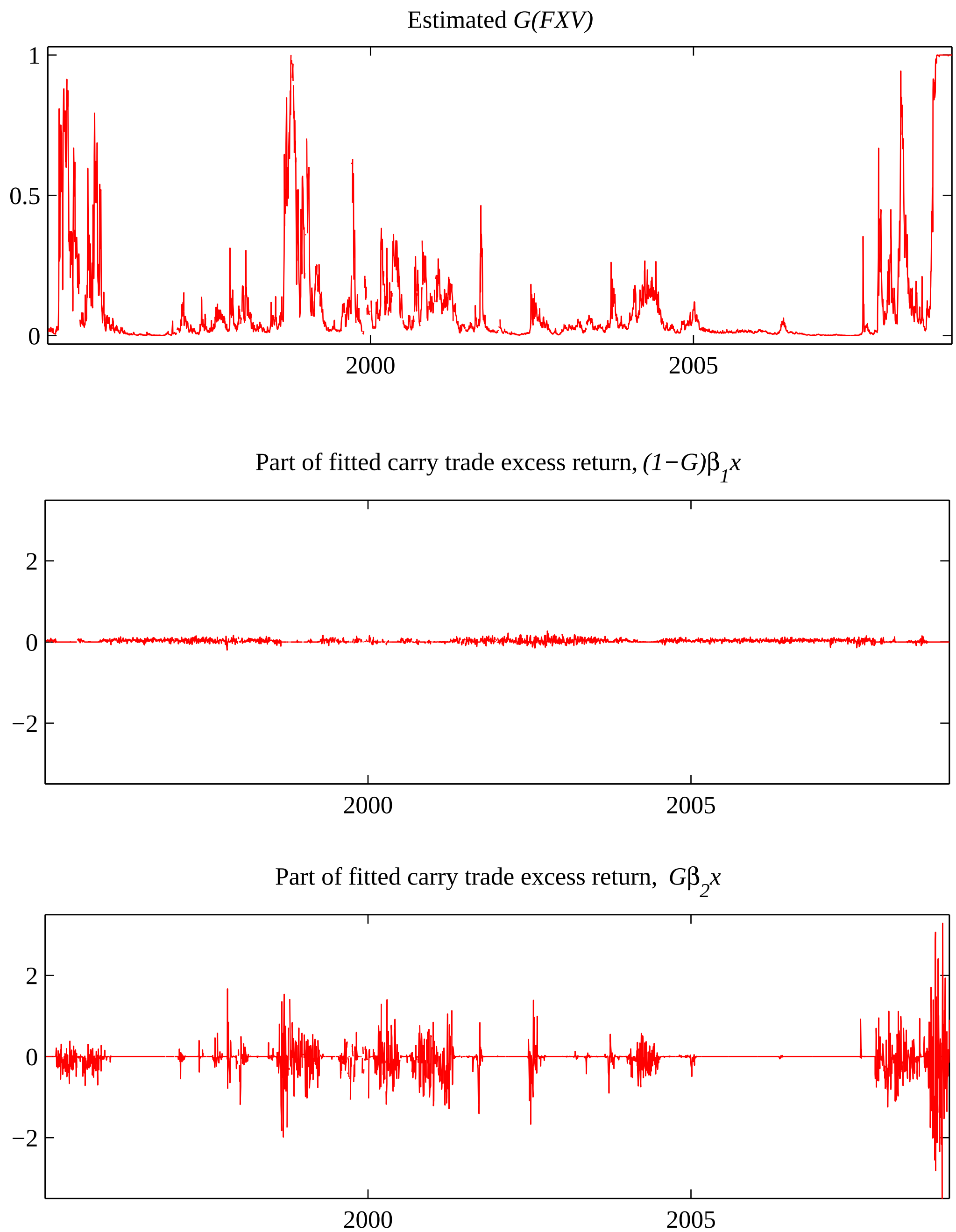

Figure 2: **Time Series of Fitted $G(FXV)$ and Carry Trade Excess Return.** The upper panel shows the fitted $G(FXV)$ function, using the point estimates for the G10 carry trade strategy in Table 2. The middle panel shows the part of the fitted carry trade return driven by the low state coefficients ($(1-G)\beta_1 x_t$). The lower panel shows the part driven by the high state coefficients ($G\beta_2 x_t$). The fitted carry trade return is the sum of the results in the middle and lower panel.

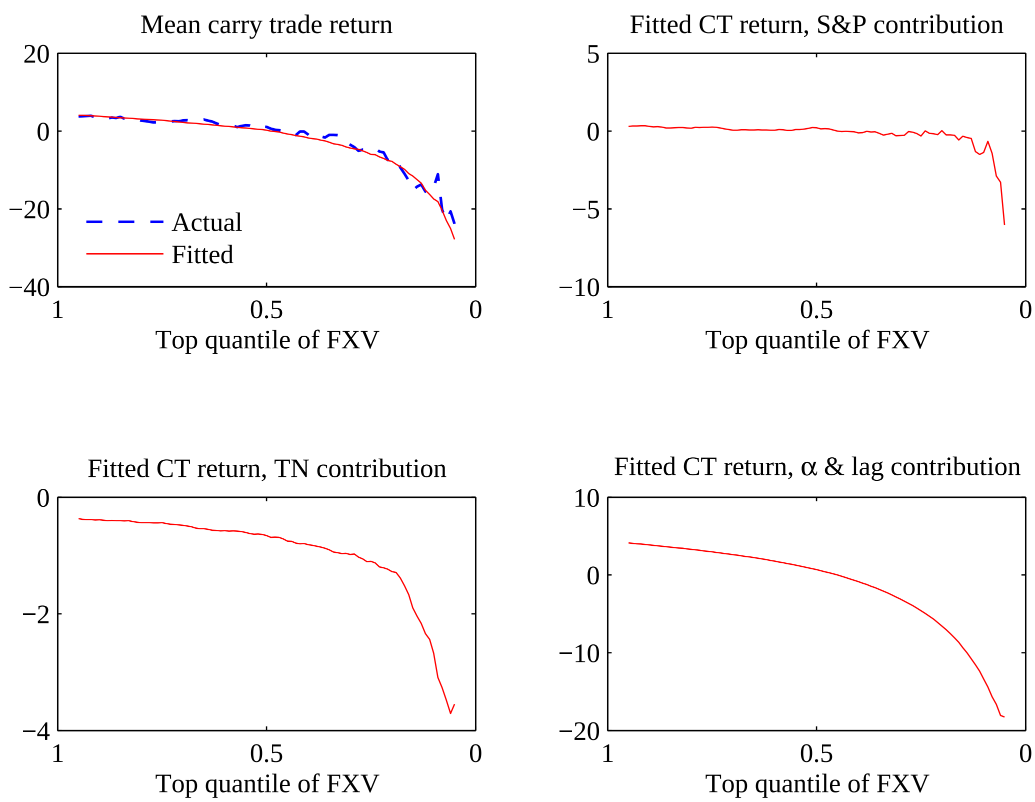

Figure 3: **Fitted (Annualized)** CT **Returns for Different Top Quantiles of** FX **Volatility.** The upper left subfigure shows how the actual and fitted G10 carry trade return depend on the FXV volatility. See Table 2 for the point estimates. The remaining three subfigures decompose the fitted carry trade return into the parts driven by the S&P 500 (upper right), the Treasury notes (lower left) and the combined effect of the "intercept" and lagged carry trade return (lower right).

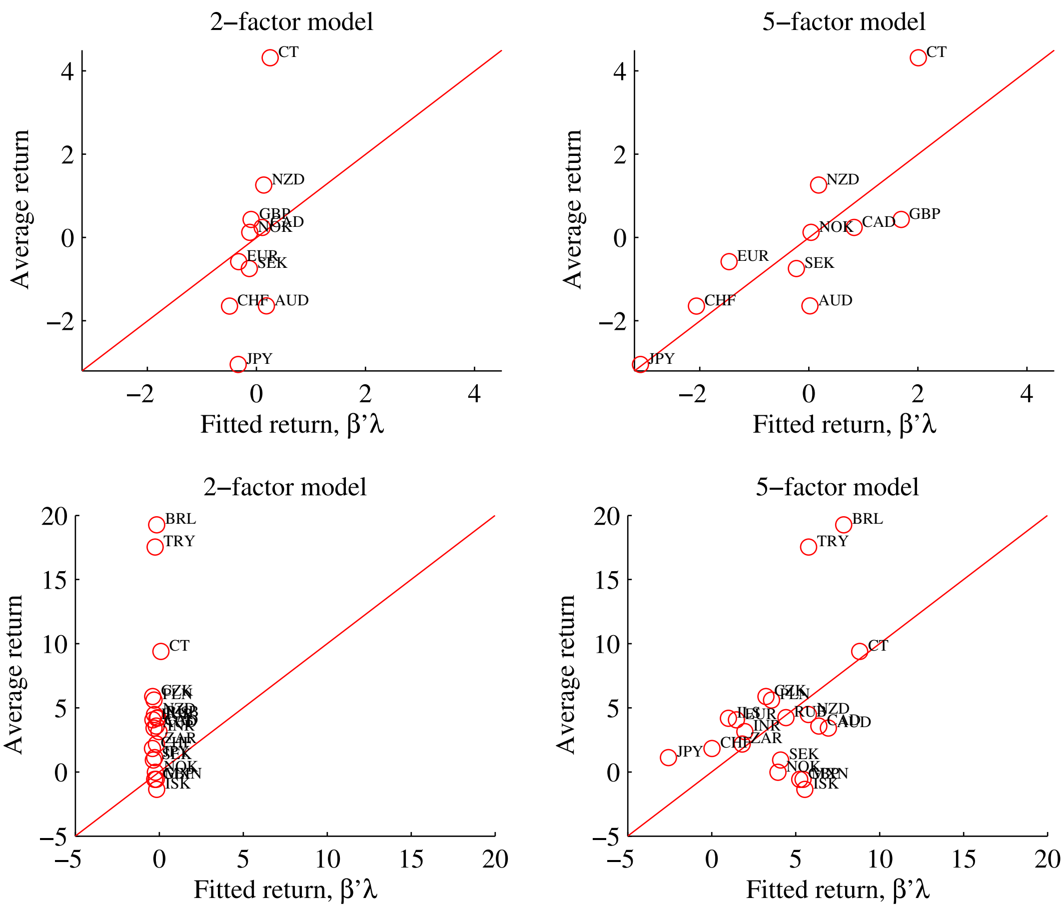

Figure 4: **Cross-Sectional Fit of Asset Pricing Model (G10 Top, G20 Bottom).** The subfigures show scatter plots of the actual average return (vertical axis) against the fitted average return (horizontal axis), $\beta'\lambda$. The upper left (right) subfigure is for the G10 currencies (1995–2008), using a 2- (5-) factor model. The lower subfigures are similar, but for the G20 currencies (2003-2008).

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

Table 1: **Carry Trade Characterstics 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, $*/**$ indicate that the correlation is significantly different from the full sample (in last line) correlation at the 5%/1% level of significance.

	CT on 10 currencies, 1995-2008			CT on 20 currencies, 2003-2008		
	SP	MSCI world	MSCI world excl US	SP	MSCI world	MSCI world excl US
γ	2.49**	1.82**	8.67**	7.14**	7.73**	8.33**
c	1.25**	1.58**	2.14**	0.56**	0.48**	0.46**
Low regime						
Equity	0.03*	0.02	0.05**	0.15**	0.22**	0.19**
Equity_{t-1}	0.04**	0.03	0.01	0.17**	0.09**	−0.01
TN	−0.01	−0.01	−0.03	−0.12*	−0.11*	−0.15**
TN_{t-1}	−0.03	−0.02	−0.05**	−0.05	−0.09*	−0.12*
z_{t-1}	0.03	0.04	−0.00	−0.02	−0.02	−0.01
α	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**
High regime						
Equity	0.20**	0.35**	0.44**	0.23**	0.37**	0.38**
Equity_{t-1}	0.26**	0.24**	0.01	0.22**	0.17*	0.03
TN	−0.20	−0.13	−0.20	−0.59**	−0.48**	−0.55**
TN_{t-1}	−0.13	−0.19	−0.14	−0.57*	−0.59**	−0.48*
z_{t-1}	−0.22**	−0.34**	−0.13	−0.27**	−0.29**	−0.21
α	−0.00*	−0.00	−0.00	−0.00*	−0.00*	−0.00**
R^2	0.18	0.19	0.22	0.25	0.28	0.29
nObs	3653.00	3653.00	3653.00	1567.00	1567.00	1567.00
High–Low regime						
SP	0.18**	0.32**	0.39**	0.08	0.16*	0.19**
SP_{t-1}	0.22**	0.21**	−0.00	0.05	0.07	0.04
TN	−0.20	−0.12	−0.17	−0.48*	−0.37*	−0.39*
TN_{t-1}	−0.11	−0.17	−0.09	−0.52*	−0.50*	−0.37
z_{t-1}	−0.24*	−0.38**	−0.12	−0.25**	−0.27*	−0.20
α	−0.00*	−0.00*	−0.00	−0.00**	−0.00*	−0.00**

Table 2: **Parameter Estimates from the Smooth Transition Regression, Using FXV_{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. The first three columns concern the G10 countries (1995–2008) and the last three columns concern the G20 countries (2003–2008). The applied equity index varies from the SP500 futures (first and fourth column), MSCI world index including the US (second and fifth columns), and MSCI world index excluding the US (third and sixth columns). Based upon Newey and West (1987) standard errors, $*/**$ indicate that the parameter is significantly different from zero at 5%/1% level of significance.

	AUD	CAD	CHF	EUR	GBP	JPY	NOK	NZD	SEK
γ	[2.50]	[2.50]	[2.50]	[2.50]	[2.50]	[2.50]	[2.50]	[2.50]	[2.50]
c	2.24*	2.28**	2.17**	1.95**	1.89**	1.01**	1.64**	2.26**	1.26*
Low regime									
SP	0.03	0.02*	−0.08**	−0.06**	−0.03**	−0.03*	−0.04**	0.03*	−0.03
SP_{t-1}	0.07**	0.06**	−0.05**	−0.01	−0.01	0.00	0.02	0.06**	0.05**
TN	−0.00	0.01	0.23**	0.18**	0.11**	0.10*	0.14**	0.01	0.13**
TN_{t-1}	0.02	−0.03	0.12**	0.09**	0.05*	0.17**	0.07*	0.07*	0.13**
z_{t-1}	0.03	−0.00	−0.03	−0.00	0.02	0.01	0.05	0.03	0.05
α	−0.00	0.00	−0.00	−0.00	0.00	−0.00*	0.00	0.00	0.00
High regime									
SP	0.27**	0.19**	−0.01	0.08**	0.14**	−0.14**	0.10**	0.23**	0.13**
SP_{t-1}	0.43**	0.21**	0.05	0.11**	0.14**	−0.11**	0.20**	0.33**	0.17**
TN	0.09	−0.03	0.24	0.12	−0.14	0.19	−0.34	0.01	0.07
TN_{t-1}	−0.20	−0.05	−0.05	0.01	−0.03	0.08	−0.05	−0.10	−0.16
z_{t-1}	−0.34*	−0.06	0.01	0.03	−0.00	−0.00	−0.14	−0.16	−0.10
α	−0.00	−0.00	0.00	−0.00	−0.00	0.00	−0.00	−0.00	−0.00
R^2	0.16	0.13	0.05	0.05	0.06	0.05	0.06	0.10	0.06
nObs	3651.00	3651.00	3651.00	3651.00	3651.00	3651.00	3651.00	3651.00	3651.00
High–Low regime									
SP	0.24**	0.17**	0.08**	0.14**	0.17**	−0.11**	0.14**	0.20**	0.16**
SP_{t-1}	0.35**	0.15**	0.10*	0.13**	0.14**	−0.11**	0.18**	0.28**	0.12*
TN	0.10	−0.04	0.01	−0.06	−0.25	0.09	−0.48*	−0.00	−0.06
TN_{t-1}	−0.22	−0.02	−0.17	−0.08	−0.09	−0.09	−0.12	−0.17	−0.30
z_{t-1}	−0.37**	−0.06	0.05	0.03	−0.03	−0.01	−0.19*	−0.19	−0.15
α	−0.00	−0.00	0.00	−0.00	−0.00	0.00	−0.00	−0.00	−0.00

Table 3: **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, $*/**$ indicate that the parameter is significantly different from zero at 5%/1% level of significance. The γ parameter is fixed to 2.50.

Regime variable:

	FXV	TED	VIX	Bid-ask spread	All
γ_{FXV}	2.83**				1.68*
γ_{TED}		1.86			1.68**
γ_{VIX}			11.84**		0.39
γ_{BA}				2.38**	−0.22
c	1.19**	1.31**	2.35**	1.81**	0.81**
Low regime					
SP	0.03*	0.02	0.05**	0.04**	0.02
SP_{t-1}	0.04**	0.04**	0.05**	0.06**	0.03**
TN	0.00	0.05	−0.04	−0.03	0.04
TN_{t-1}	−0.03	−0.02	−0.05*	−0.03	−0.02
z_{t-1}	0.02	0.04	−0.00	−0.02	0.03
α	0.00**	0.00*	0.00**	0.00*	0.00**
High regime					
SP	0.20**	0.19**	0.19**	0.20**	0.19**
SP_{t-1}	0.25**	0.24**	0.26**	0.23**	0.24**
TN	−0.25	−0.35	−0.17	−0.15	−0.30
TN_{t-1}	−0.09	−0.17	−0.10	−0.30	−0.13
z_{t-1}	−0.18*	−0.20*	−0.23*	−0.11	−0.18*
α	0.00*	−0.00*	−0.00**	−0.00	−0.00*
R^2	0.21	0.22	0.20	0.18	0.23
nObs	3132.00	3132.00	3132.00	3132.00	3132.00
High–Low regime					
SP	0.17**	0.17**	0.14**	0.16**	0.17**
SP_{t-1}	0.21**	0.21**	0.20**	0.17**	0.21**
TN	−0.25	−0.40*	−0.13	−0.12	−0.34
TN_{t-1}	−0.06	−0.15	−0.05	−0.27	−0.11
z_{t-1}	0.20*	−0.23*	−0.23*	−0.09	−0.21*
α	0.00*	−0.00*	−0.00**	−0.00*	−0.00**

Table 4: **Parameter Estimates from the Smooth Transition Regression, 1997–2008, Using Different Regime Variables.** The table shows the parameter estimates arising from estimating the logistic smooth transition regression model on carry trade excess returns. The regime variables are 1-day lagged values of the: FX volatility (first column), TED spread (second column), VIX volatility index (third column), bid-ask spread (fourth column). The last column includes all four regime variables jointly. Based upon Newey and West (1987) standard errors, $*/**$ indicate that the parameter is significantly different from zero at 5%/1% level of significance.