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The Time-Varying Systematic Risk of Carry Trade Strategies

Abstract: To capture time-variation in the risk exposure of exchange rates, this paper suggests a factor model with stock and bond markets as the explanatory factors—but where the betas are allowed to depend on the exchange rate volatility. Empirical results on daily data from 1995 to 2008 show that a typical carry trade strategy based on 10 currencies from major industrialized countries has much higher exposure to the stock market and also more mean reversion in volatile periods. The findings are robust to various extensions, including adding more currencies and other regime variables.

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.[1] 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.[2]

We contribute to the carry trade literature by analyzing whether the systematic risk of a typical carry trade strategy varies across regimes. We model the regimes by foreign exchange volatility, the TED spread, the VIX and a bid-ask spread. The explanatory financial factors are equity and bond returns. In particular, we use the logistic smooth transition regression model to describe the systematic risk of carry trade strategies changes.

The relevance of the regime dependency of the carry trade risk is twofold. First, it 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.

Second, as underlined in Sarno, Valente and Leon (2006) allowing for time-variation in the forward bias and nonlinear link between exchange rates and forward premia put the UIP puzzle in a different perspective. Consistent with Plantin and Shin (2008), we show that carry trade prospers in calm markets with slow appreciations of the high-rate currency but it occasionally turns into big drops. In highly volatile markets, unwinding carry trade becomes more difficult

[1] More about yen carry trade in i.e. Hattori and Shin (2007) and Gagnon and Chaboud (2007).

[2] Burnside 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.

because of the upward shift in its systematic risk and adverse comovements with other risky assets. Our results are also consistent with Brunnermeier, Nagel and Pedersen (2008) who find that carry traders are subject to crash risk. Ichiue and Koyama (2008) show that the UIP failure is influenced by carry trade activity.

This paper also links up with the idea that rare but extreme disasters can be a major determinant of time-varying currency risk premia and that the latter covaries positively with interest rates and negatively with equity risk premia, cf. Farhi and Gabaix (2008). Additionally, Verdelhan (2009) proposes a habit-formation model with counter-cyclical risk premia. Highly risk averse investors in low-rewarding currency countries expect excess return in bad times. Lustig, Roussanov and Verdelhan (2008) show that carry trade strategy incorporates currency risk premia related to a global risk factor. The rational inattention mechanism in Bacchetta and van Wincoop (2006) also produces a prolonged reallocation in high-rewarding currencies but then shocks causes abrupt appreciations of low-rewarding currencies.

Finally, our analysis is related to Connolly, Stivers and Sun (2005) who show that the size of the stock market volatility has important bearings upon the comovement between the stock and bond markets, in that the our analysis also allows the dependence upon other financial markets to be dependent upon financial volatility.

The structure of the remaining part of the paper is as follows: In Section 2 we describe the data. Section 3 contains the empirical results; firstly, we show some preliminary results, secondly, we introduce the econometric framework, and thirdly, we show the empirical results from estimating the smooth transition regression model. Finally, we conclude in Section 4.

2 Data Description

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

2.1 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 log-returns, denoted r_t^k for currency k at day t. Following Brunnermeier et al. (2008), 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 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

$$z_t^k = r_t^k + i_{t-1}^k - i_{t-1}^{US}, \tag{1}$$

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 for each country 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 for the excess returns for the individual G10 currencies. The excess returns have fat tails, most pronounced for the Australian dollar for which the excess kurtosis is 19. 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).

2.2 Carry Trade Excess Returns

A (unleveraged) carry trade strategy consists of selling low interest rate currencies and buying high interest rate currencies. The empirical analysis makes use of the excess return on a carry trade strategy which is constructed similarly to the carry trades in Gyntelberg and Remolona (2007). To study typical carry trade strategies, we rely on the explicit strategy followed by Deutsche Bank's "PowerShares DB G10 Currency Harvest Fund".[3] 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

[3]More information about this index is available at the Deutsche Bank home page at www.dbfunds.db.com.

rates and a short position in the three currencies with the lowest interest rates. 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. (2008), 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 1 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.

2.3 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. Similar to Ranaldo and Söderlind (2008), we think of stock and bond markets as convenient factors for capturing the market portfolio risk. 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, respectively. 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 TY_t, respectively. The futures contracts data are also available from DataStream.

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 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 2 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 extend this also applies to the bond returns. Not surprisingly, the stock returns are much more variable than the bond market returns (standard deviation of 1.27 compared to 0.39). The standard deviations of the currency excess returns fall between those of stocks and bonds. The distribution of the FX volatility is right skewed and has fat tails.

In some further robustness analysis we make use of three additional regime variables. 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. In the spirit of Brunnermeier et al. (2008), we interpret the TED as a proxy for funding liquidity and other risk premia impending on the interbanking lending market and the VIX as a broader measure of global risk or risk aversion. Thirdly, we measure market liquidity with the JPY/USD bid-ask daily 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.

3 Empirical Results

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

3.1 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 loose value against strong currencies.

While these patterns are already relatively well understood, 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 when FX volatility is in the top 5%. The table shows a very clear pattern, the higher the foreign volatility, the stronger the correlation between the stock market and the carry trade strategy is. Based on the moment conditions, the correlation coefficients between the stock market and the carry trade strategy at the eight top volatility quantiles are seen to be significantly higher than the correlation coefficient for the entire sample.

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

Table 2 (third column) reports the average excess returns of the carry trade strategy at increasing quantiles for the FX volatility. On average the carry trade strategy yields positive and moderately high returns in normal periods, whereas it turns out with sizable losses during turmoil periods. Thus, it is during turmoil periods that the carry trade strategy is dangerous and during normal periods that is advantageous return-wise.

3.2 Econometric Framework

The preliminary findings suggest that the risk exposure of the exchange rate returns is related to volatility of the FX markets. We formalize this by using a linear factor model (with stocks and bonds as factors), but where the betas depend on the one-day lagged FX volatility. In particular, we use the logistic smooth transition regression model, discussed below (see van Dijk, Teräsvirta and Franses (2002) for further details).

The dependent variable z_t (the currency excess return) is described by a non-linear equation where it depends upon the set of explanatory variables x_t (here, stock returns, bond returns, lags, and a constant) and the regime variable s_{t-1} (here, the lagged FX volatility, but later also other variables)

$$z_t = F(x_t, s_{t-1}; \gamma, c, \beta_1, \beta_2) + \varepsilon_t, \tag{2}$$

where $(\gamma, c, \beta_1, \beta_2)$ are parameters that will be described shortly and ε_t is the error term. The specification of the $F()$ function 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}

$$G(s_{t-1}) = \frac{1}{1 + \exp[-\gamma'(s_{t-1} - c)]}, \tag{3}$$

where the parameter c is the central location and the vector γ determines the steepness of the function. Then, the logistic smooth transition regression model is

$$z_t = [1 - G(s_{t-1})]\, \beta_1' x_t + G(s_{t-1}) \beta_2' x_t + \varepsilon_t. \tag{4}$$

The effective slope coefficients 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 $\gamma' s_{t-1}$. Figure 3 illustrates three possible $G(s_{t-1})$ functions in terms of a scalar s_{t-1}: a lower value of 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 β_1 is the effective slope coefficient to where β_2 is. In contrast, a higher value of 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. A linear regression is a special case where $\beta_1 = \beta_2$.

The model is estimated and tested by using a GMM framework, 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 results for the carry trade are broadly unchanged whether we estimate or impose a pre-established value of γ above 1. For the carry trade analysis, γ is estimated (the point estimate is 2.49) and for the individual exchange rates, we use γ equal to 2.50 to guarantee a unique and consistent number across the panel. The estimation is done in MatLab.

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:

$$x_t = \{SP_t, SP_{t-1}, TY_t, TY_{t-1}, z_{t-1}, 1\}. \tag{5}$$

With these regressors, our regression model in equation (4) 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) to vary according to a regime variable: the FX volatility level (FXV_{t-1}), constructed from implied volatilities from currency options. Prompted by the preliminary findings (previously reported in Table 2), we are particularly interested in studying if the systematic risk exposure is greater during volatile periods.

3.3 Results from the Smooth Transition Regression Model

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 β_1 above, and the middle part of the table shows the parameter estimates applicable for high values of FX volatility, denoted β_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 $\widehat{\beta}_2 - \widehat{\beta}_1$. Moreover, the table indicates whether these differences are statistically significant.

For the carry trade strategy, 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, so the estimated logistic function is similar to the solid curve in Figure 3 discussed above. In practice, this means that the volatile regime starts to have an impact when the 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 go 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) represent periods of extreme stress on the FX market.

The results in Table 3 clearly show that the risk exposure is different in the two regimes. 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 Corsettia, Pericolib and Sbraciab (2005).

Table 4 shows the results from estimating the logistic smooth transition regression model for the individual currency excess returns. 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, while most other currencies have no autocorrelation to speak of.

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 Figure 5 which shows the fitted carry trade excess returns split up into two parts: the first part (upper graph) caused by the calm regime ($(1-G)\,\widehat{\beta}_1 x_t$) and the second part (lower graph) caused by the volatile regime ($G\widehat{\beta}_2 x_t$). 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.

3.3.1 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 an 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) for the larger currency base.

3.3.2 Effects from Regime Variables

Using other natural candidates for the regime variable does not change the results much. Table 5 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 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 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.)

These different regime variables have different interpretations: TED is often used as a proxy for funding liquidity and other risk premia impending on the interbanking, VIX as a broader measure of global risk or risk aversion and the JPY/USD bid-ask daily spread as a measure of market liquidity and asymmetric information. Still, they generate similar results for the time variation in risk exposure (and are also highly correlated).

3.3.3 Effects from Order Flow

Including order flow improves the regression, but does not change the estimates of the risk exposure. Table 6 shows logistic smooth transition regressions on the Japanese yen (against the USD) for the sample 1997–2008. The results for the standard specification is very similar to those reported before (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). In the market micro structure literature, this variable is often thought of as representing the net demand pressure, cf. Evans and Lyons (2002).

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

3.3.4 Further Robustness Analysis

The empirical results are robust to refining the carry trade strategy in various other ways. Firstly, rebalancing the portfolio more often than every three months does not change the qualitative results (results not tabulated). Secondly, our results are robust to the number of long and short currency positions in the carry trade strategy.

4 Conclusion

This paper studies the risk exposure of exchange rate returns. Results from a sample of daily exchange rate returns from 1995 to 2008 show that typical weak currencies have a positive exposure to stock market returns and that this exposure is much larger during periods of FX market turmoil. Typical strong currencies are the mirror image. Combining these into a carry trade strategy based on interest rates, gives a return series that has strongly regime dependent risk exposure: positive covariance with the stock market in normal times—and even stronger in turbulent times. In addition, the currency returns are more predictable (mean-reverting) in turmoil periods.

These results hold also for a larger set of currencies including emerging market currencies, for other choices of the regime variable (TED spread, VIX, bid-ask spread) and also when we control for order flow.

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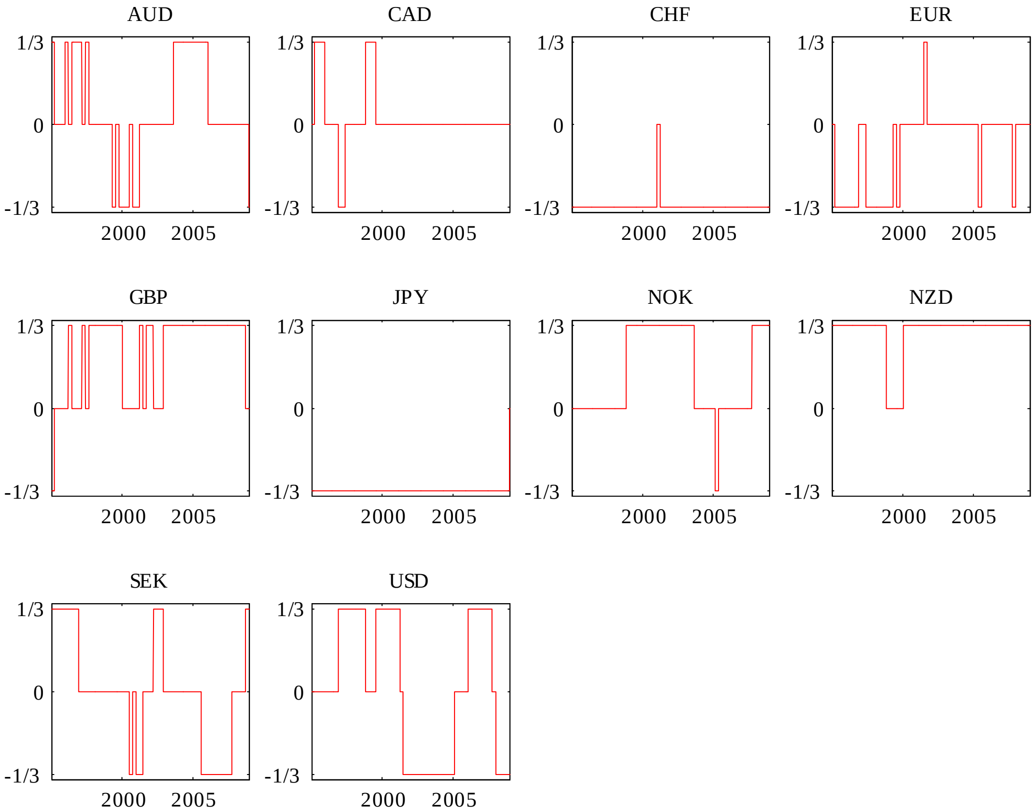

Figure 1: Carry Trade Strategy Weights

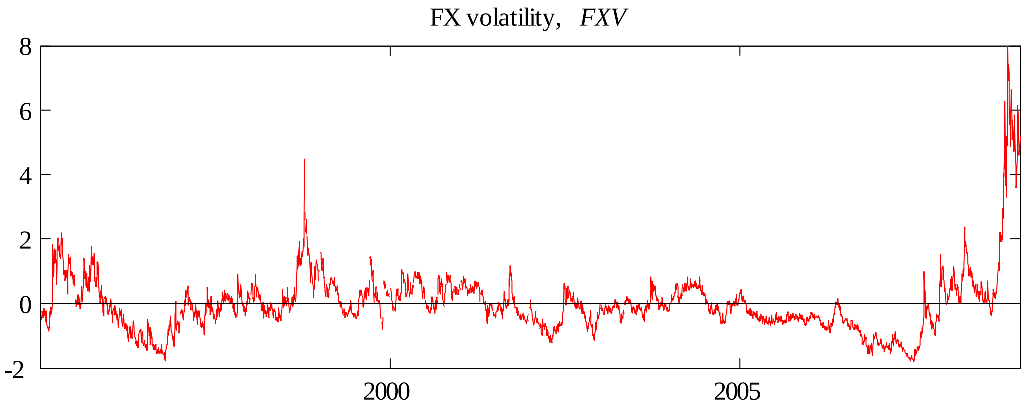

Figure 2: Time Series of FX Volatility

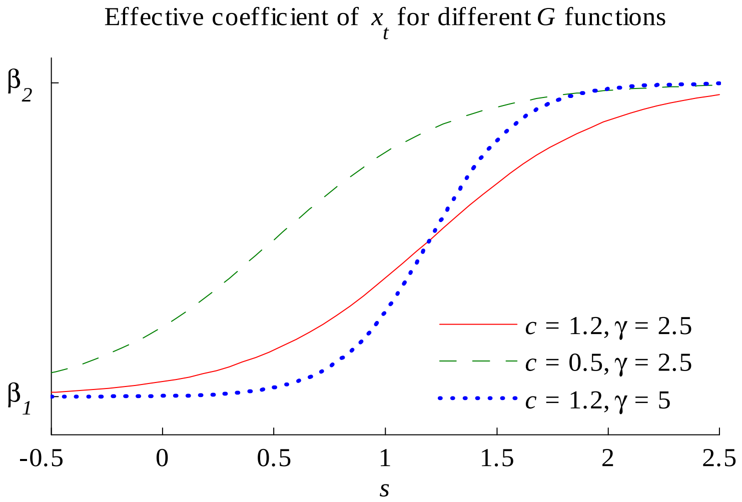

Figure 3: Example of Smooth Transition Regression Model

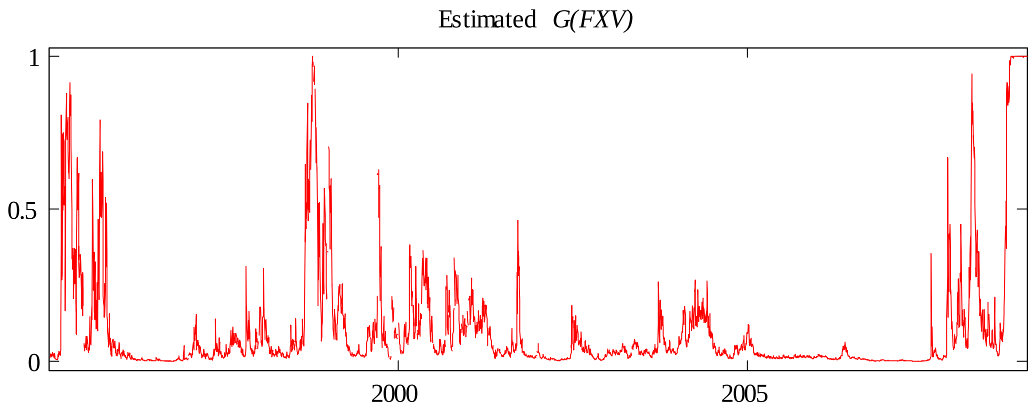

Figure 4: Estimated $G(FXV)$ Time Series

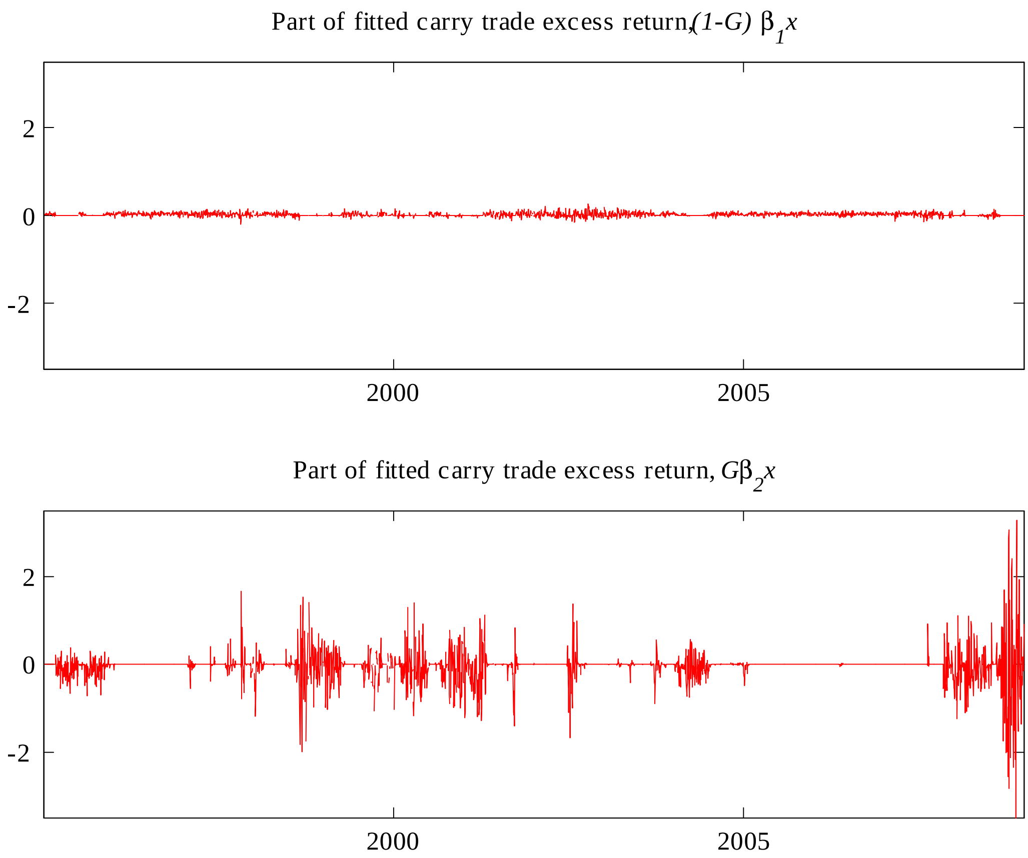

Figure 5: Time Series of Fitted Carry Trade Excess Return

	mean	mean/year	std	skewness	exkurtosis	min	max	nObs
AUD	−0.01	−1.33	0.78	−1.28	19.47	−9.22	6.50	3652.00
CAD	0.00	0.52	0.49	0.07	10.67	−4.43	4.93	3652.00
CHF	−0.01	−1.71	0.67	0.27	3.06	−4.55	5.30	3652.00
EUR	−0.00	−0.56	0.61	0.12	2.46	−3.91	3.96	3652.00
GBP	0.00	0.22	0.53	−0.13	4.23	−3.79	4.39	3652.00
JPY	−0.01	−3.72	0.70	0.61	5.05	−3.65	6.35	3652.00
NOK	0.00	0.21	0.67	−0.13	5.63	−4.90	5.34	3652.00
NZD	0.01	1.38	0.77	−0.61	7.37	−6.85	5.69	3652.00
SEK	−0.00	−0.99	0.65	0.23	4.37	−3.50	5.40	3652.00
CT	0.02	4.64	0.52	−0.90	11.12	−5.35	4.29	3652.00
SP	0.03	6.64	1.27	0.20	12.32	−9.88	14.11	3652.00
TY	0.01	2.57	0.39	−0.47	3.28	−2.82	1.76	3652.00
FXV	0.00	0.00	1.00	2.87	14.85	−1.80	8.16	3566.00

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 (TY), as well as for the FX volatility (FXV). All returns are in percent.

FXV top quantile	Corr(z,SP)	Corr(z,TY)	Mean CT return	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 2: **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, $*/**$ indicates that the correlation is significantly different from the full sample (in last line) correlation at the 10%/5% level of significance.

	CT on 10 currencies 1995–2008	CT on 10 currencies 2003–2008	CT on 19 currencies 2003–2008
γ	2.49**	17.06	7.14**
c	1.25**	0.33**	0.56**
Low regime			
SP	0.03**	0.02	0.15**
SP_{t-1}	0.04**	0.05**	0.17**
TY	−0.01	−0.07*	−0.12**
TY_{t-1}	−0.03	−0.02	−0.05
z_{t-1}	0.03	0.07**	−0.02
constant	0.00**	0.00**	0.00**
High regime			
SP	0.20**	0.19**	0.23**
SP_{t-1}	0.26**	0.25**	0.22**
TY	−0.20	−0.18	−0.59**
TY_{t-1}	−0.13	−0.08	−0.57**
z_{t-1}	−0.22**	−0.19**	−0.27**
constant	−0.00*	−0.00**	−0.00**
R^2	0.18	0.32	0.25
nObs	3653.00	1567.00	1567.00
High–Low regime			
SP	0.18**	0.17**	0.08
SP_{t-1}	0.22**	0.20**	0.05
TY	−0.20	−0.11	−0.48**
TY_{t-1}	−0.11	−0.06	−0.52**
z_{t-1}	−0.24**	−0.26**	−0.25**
const	−0.00**	−0.00**	−0.00**

Table 3: **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. Based upon Newey and West (1987) standard errors, $*/**$ indicates that the parameter is significantly different from zero at 10%/5% 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**
TY	−0.00	0.01	0.23**	0.18**	0.11**	0.10**	0.14**	0.01	0.13**
TY_{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*
constant	−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**
TY	0.09	−0.03	0.24	0.12	−0.14	0.19	−0.34	0.01	0.07
TY_{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
constant	−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**
TY	0.10	−0.04	0.01	−0.06	−0.25	0.09	−0.48**	−0.00	−0.06
TY_{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
constant	−0.00	−0.00	0.00	−0.00	−0.00*	0.00	−0.00	−0.00	−0.00

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 tran- sition 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.

Regime variable:

	FXV	TED	VIX	Bid-ask spread	All
γ_{FXV}	2.87**				1.68**
γ_{TED}		1.86*			1.67**
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**
TY	0.00	0.05	−0.04	−0.03	0.04
TY_{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
constant	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**
TY	−0.25	−0.35*	−0.17	−0.15	−0.30*
TY_{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**
constant	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**
TY	−0.25	−0.40**	−0.13	−0.12	−0.34*
TY_{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**
constant	0.00**	−0.00**	−0.00**	−0.00**	−0.00**

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. Based upon Newey and West (1987) standard errors, $*/**$ indicates that the parameter is significantly different from zero at 10%/5% level of significance.

	Standard specification	With Order flow
γ	[2.5]	[2.5]
c	1.01**	0.91**
Low regime		
SP	−0.03**	−0.02
SP_{t-1}	0.01	0.01
TY	0.11**	0.08**
TY_{t-1}	0.21**	0.20**
Order flow		0.06**
z_{t-1}	−0.01	−0.00
constant	−0.00**	0.00**
High regime		
SP	−0.13**	−0.11**
SP_{t-1}	−0.11**	−0.10**
TY	0.25	0.15
TY_{t-1}	0.11	0.11
Order flow		0.07
z_{t-1}	0.03	0.02
constant	0.00	−0.00*
R^2	0.06	0.09
nObs	3130.00	3130.00
High–Low regime		
SP	−0.11**	−0.09**
SP_{t-1}	−0.11**	−0.11**
TY	0.14	0.06
TY_{t-1}	−0.10	−0.09
Order flow		0.01
z_{t-1}	0.04	0.02
const	0.00	−0.00

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.

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