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CARRY TRADES AND EXCHANGE RATE VOLATILITY: A TVAR APPROACH

by Alessio Anzuini* and Francesca Brusa§

Abstract

Recent empirical studies have established that deviations from the Uncovered Interest Parity (UIP) condition may be different across macroeconomic regimes. We extend this work to account for possible nonlinearities and endogeneity by estimating a Threshold Vector Autoregression (TVAR) model. Using carry trade proxies as in Brunnermeier et al. (2009) alongside a measure of realized exchange rate volatility, we endogenously identify two volatility regimes: low and high. Simulating an incentive to open a carry-trade position through an orthogonal shock to the interest rate differential, we find that carry trade performance varies across different regimes. This suggests that UIP deviations are more pronounced in the low volatility state and non-linearities play a role in explaining the forward bias.

JEL Classification: C32, G15.
Keywords: Threshold Vector Autoregression, carry trade.

Contents

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1 Introduction

Carry trades are strategies in the foreign exchange market that exploit interest rate differentials across countries. Investors short a low-yielding currency and take long positions in a high-yielding currency to earn "the carry", i.e., the interest rate differential. In recent years, the extraordinary growth in carry trade activities attracted a great deal of attention in the financial press for the generous returns earned by investors. Burnside et al. (2006) estimate that carry trade returns, in the last 30 years, are of the same magnitude as those generated by investment in the S&P 500.

Carry trades are one aspect of the UIP anomaly in international finance. Under the UIP condition, carry trades are not profitable *ex-ante*, as the gain yielded by carry is expected to be offset by a commensurate depreciation of the target currency within the investment horizon. But in the data, the so called "Fama regressions" show that interest rate differential are followed by an appreciation of the high yielding currency, amplifying rather than offsetting the excess returns. This is also known popularly as the "forward premium puzzle" (Fama, 1984).[1]

Carry trades exhibit patterns over time: periods of rewarding carry trades are followed by a reversal, leading to episodes of weak carry trade activity. Empirics suggest that target currencies strengthen and funding currencies weaken as long as investors continue to accumulate their speculative positions in the foreign exchange market until the perceived risk is high. Historically, an unexpected increase in the foreign exchange market volatility, notwithstanding the nature of the shock beyond it, has prompted a rapid dismantling of carry trade positions and a sharp appreciation of the funding currency (the so-called "unwinding of the carry trades"). On the contrary, periods of low exchange rate volatility have been conducive for carry trade activities (Anzuini and Fornari, 2011). In periods of high (low) volatility, investors may unwind (increase positions) because the risk adjusted returns of carry trade strategies are perceived to be less (more) profitable.[2]

In this paper, we examine carry trade dynamics conditional on the prevailing exchange rate volatility regime. Building on the linear set-up as in Brunnermeier et al. (2009), we provide empirical evidence on the non-linear relationship between carry trade returns and exchange rate volatility with endogenously-chosen thresholds. The TVAR model employed here uses the same four variables used in Brunnermeier et al. (2009), namely the interest rate differential, excess returns, skewness and carry trade positions, alongwith a measure of realised exchange rate volatility as the threshold variable. A set of (linear) conditional impulse

[1] This puzzle is also related to Meese and Rogoff (1983)'s finding that exchange rates follow a"near random walk" allowing investors to take advantage of the interest differential without suffering an exchange rate depreciation. This is particularly true in periods in which financial market volatility is low.

[2] A widely used indicator to measure the carry trade performance is the carry-to-risk ratio, that is the ratio of the interest rate differential to volatility (implied or historical).

response functions are then adopted, to simulate an unexpected shock to the average interest rate differential.

The unconditional impulse response function used in Brunnermeier et al. (2009) documents an increase in carry trade positions, consistent with higher interest rate differentials leading to more carry trade activity. The conditional skewness gets more negative, signalling an increase in the crash risk of the target currency, followed by slow reversion towards the mean. Importantly, the exchange rate appreciates sharply adding to gains from "carry". Previewing the results, the responses to an analogous shock to the average interest rate differential differ in size and persistence across volatility regimes identified by the threshold variable. We therefore find that the dynamics documented in Brunnermeier et al. (2009) are mainly driven by the low volatility state.

Our contribution combines the methods adopted in Brunnermeier et al. (2009) and Clarida et al. (2009) in a unified empirical framework. The non-linearity is detected formally with the Tsay test (Tsay, 1998) and the threshold level is determined endogenously (with grid searches) rather than being exogenously imposed as in Clarida et al. (2009). The power of the TVAR procedure to identify variations in the extent of the UIP anomaly that are correlated with our threshold variable makes this work an important departure from the existing literature. To the best of our knowledge, this is the first study that addresses nonlinearities and endogeneity in a multivariate setting.

The paper is organized as follows: next section briefly reviews the literature, while section 3 describes data and variables. The econometric procedure is presented in section 4 and then implemented in Section 5. The empirical findings are discussed in section 6. Section 7 concludes.

2 Related literature

The forward premium puzzle, the positive mean returns of the carry trade strategy and the empirical failure of the UIP are essentially the same phenomenon. See Froot and Thaler (1990), Lewis (1995) and Engel (1996) for nice survey articles. These anomalies have spurred a large literature. In his highly influential paper, Fama (1984) noted that high interest rate currencies tend to appreciate, whereas one might suppose that investors would demand higher interest rates on currencies expected to fall in value. Since then, researchers generally report results which reject UIP and concentrate on the ultimate cause beyond this failure.

A large body of literature has explored whether excess returns can be rationalised as a compensation for risk. Lustig and Verdelhan, (2007) taking the perspective of the US investor, argue that agents are compensated for their exposure to aggregate growth risk and provide evidence about its pricing in the currency market. Lustig et al. (2010) shows that two risks are priced in the currency market so that investors are compensated for bearing both a home-country risk (i.e. dollar risk premium) and a global/common risk (i.e. carry trade risk premium). Building on this study, Menkhoff et al. (2011) show that investors are compensated for their exposure to volatility risk. Partial support for the risk-compensation-view is also provided by Fahri et al. (2009), who look at disaster risk showing that that it can account for 25 percent of the excess returns, and Jurek (2007).

Another stream of the literature concludes against a relation between risk factors and currency returns and argue in favour of the market microstructure as a reason beyond the UIP failure. Burnside et al. (2006), for example, find no evidence that carry trade generous payoffs are explained by standard measures of risk, instead, they show that gains are limited when transaction costs (e.g. bid-ask spreads) and price pressure are taken into account and conclude attributing the forward premium to these market frictions. Limit to speculation is another explanation of the UIP failure, see for example Lyons (2001). In its essence, the limits-to-speculation argument implies that, within a certain range of the Sharpe ratio, the forward bias does not attract capital and hence may potentially persist for a long time. Sarno et al. (2006) provide empirical evidence that deviations from the uncovered interest rate parity (UIP) condition display significant nonlinearities, consistent with theories based on transactions costs or limits to speculation.

Two other studies more directly related to our paper are Clarida et al (2009) and Brunnermeier et al. (2009). The former documents a strong relationship between carry trade returns and foreign exchange volatility. Using equally-weighted carry trade portfolio returns, they identify a"low volatility" regime and a "high volatility" regime, splitting their sample informally according to the 25^{th} and 75^{th} percentile of the empirical distribution of their volatility measures. Conditioning on these regimes, they show that the widely documented negative slope coefficient in regressions of exchange rate depreciation on forward currency premiums is an artefact of the volatility regime. In high volatility regimes, the so-called Fama regression produces a positive coefficient greater than unity, while the same coefficients are strongly negative in the low volatility regime.

Brunnermeier et al. (2009), instead, documents some important stylized facts regarding carry trades, namely: that currencies with positive interest-rate differentials are associated with negative conditional skewness of exchange rate movements; that an increase in interest-rate differential, is associated with positive speculator net positions in investment currencies; that the accumulation of speculators' positions increase crash risk; that an increase in global risk or risk aversion as measured by the VIX equity option implied volatility index coincides with reductions in speculator carry positions (unwind) and carry-trade losses. More generally, they argue that crash risk may discourage speculators from taking on large enough positions to enforce UIP. Crash risk may thus help explain the empirically well documented violation of the UIP.

3 Data and Variables

The sample covers the period from January 1986 to December 2010. Five major currencies are included, quoted against the US dollar: the Canadian dollar (i.e CAD), Swiss franc (i.e. CHF), pound sterling (i.e. GBP), euro or German mark[3] (i.e EUR) and Japanese yen (i.e. YEN). The addition of the indicator of carry trade activity as a variable in the analysis imposes data limitations. Tracking carry trade activities is difficult and official statistics on the amount of carry trade positions are currently not available (see Galati et al. 2007; Gagnon and Chaboud, 2007). The U.S. Commodity Futures Trading Commission (CFTC) data for non-commercial traders are widely considered the most reliable gauge of carry trade volumes. Non-commercial traders are classified by the CFTC as using futures, but not for hedging purposes, and hence most likely for speculative reasons[4]. We collect non-commercial positions from the website of the CFTC; they are available twice per month between January 1986 and September 1992 and thereafter weekly (on Tuesdays). The search for long and continuous data from futures markets forces the US dollar to be the funding currency and limits the analysis to the five currencies above.

Daily nominal exchange rates are collected from Datastream, while daily money market rates at the 3-month maturity are obtained from Global Financial Data. Daily series are converted into end-of-month series, and the analysis is run on a quarterly horizon (with monthly data).

In defining the variables embedded in the model of the carry trade, Brunnermeier et al. (2009) is used as a benchmark. Their VAR is meant to capture the key aspects of a carry trade via four proxies. Definitions are provided below and the variables are constructed for the five currency pairs of interest (e.g. CAD/USD, GBP/USD, YEN/USD, CHF/USD, EUR/USD)[5].

The first variable is the interest rate differential between the target currency and the US dollar (henceforth $idiff_t$) and represents the incentive (the carry) to build a carry trade position. This proxy represents the profit opportunity the investors seek in the foreign exchange market.

The second variable is the proxy of the intensity of carry trade activity, namely the indicator of the amount of net open speculative positions held in currency futures (henceforth $NetPos_t$). It is computed as the difference between long positions and short futures positions, scaled by the total open interest[6].

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[3] The Euro is spliced with the German mark before its introduction on 1/1/1999.

[4] The use of these data is subject to three caveats. Firstly, our indicator embeds only non-commercial traders, even if some commercial traders may take speculative positions. Secondly, it assumes that all positions held by non-commercial traders are due to the implementation of a carry trade. Thirdly, it captures only a share of the existent carry trades, as these trades are often executed through other instruments, such as foreign exchange swaps (Galati et al. 2007).

[5] Definitions differ slightly from Brunnermeier et al. (2009), who use quarterly data.

[6] Values of futures positions are re-sampled at a monthly frequency, so that the end-of-month date for which positions are sampled is equal or smaller than the date for which the

The third variable is the carry trade return, which is computed as the residuals from the UIP condition over a quarterly horizon (henceforth z_t)

$$z_t = (i_t^* - i_t) - s_{t+3}$$

where $i_t^* - i_t$ is the interest rate differential between the target currency and the funding currency at the 3-month maturity and s_{t+3} denotes the depreciation of the target currency over a quarter. Since economic theory postulates that a carry trade is not profitable ex ante, such residuals can be interpreted as the returns yielded by the foreign exchange market in excess of those predicted in equilibrium.

The last variable is a proxy of the exchange rate risk or downside risk involved in a carry trade strategy, that is, the skewness of the daily percentage change in the bilateral exchange rate, computed over overlapping windows of 63-working days (henceforth $skew_t$)[7]. By definition,

$$skew_t = skew(s_{t-63} : s_t) * 100 * \sqrt{253}$$

it is then re-sampled at the end of each month. Unlike foreign exchange volatility, this measure is not a symmetric indicator of risk, and keeps track of the expected direction of the subsequent exchange rate movements.

A proxy of foreign exchange volatility is constructed separately for each of the five currencies, in addition to the four variables used by Brunnermeier et al. (2009). Since both economic intuition and recent research suggest that foreign exchange volatility is a crucial factor behind the carry trade performance, this fifth variable is used as source of non-linearity in the TVAR analysis. The foreign exchange volatility regimes are formally and endogenously identified via a measure of realized exchange rate volatility (henceforth vol_t). This fifth variable is computed as the volatility of the daily percentage change in the bilateral exchange rate, by analogy with $skew_t$:

$$vol_t = vol(s_{t-63} : s_t) * 100 * \sqrt{253}$$

It is also re-sampled at the end of each month.

Figures 1 and 2 plot the five variables for the five currency pairs in the sample, while Table 1 reports their descriptive statistics. Concerning the four proxies of a carry trade, the distinctive features of the high-yielding currencies are evident in CAD, GBP and EUR, while the peculiarities of the low-yielding currencies are pronounced in YEN and CHF.

Typical target currencies are associated with positive mean values of $idiff_t$, $NetPos_t$, and z_t, and a negative mean value of $skew_t$; while typical funding currencies show the reverse signs. This is consistent with the idea that a positive interest rate differential leads to more carry trade activity, the target currency

moments of the foreign exchange returns are re-sampled.

[7] 63 working days are approximately 3 calendar months, while 253 working days are approximately one calendar year. The choice of 63 working days is consistent with the quarterly horizon of the analysis.

is exposed to crash risk and currency speculation may help explaining the forward premium puzzle. A negative correlation between market positioning and the downside risk of the strategy is evident also in the graphs: in the first half of the 1990s and between 2006 and 2008, both intense carry trade periods, the skewness of high yielding currencies follows persistently declining paths along with a clear accumulation of speculative positions in the futures market. The dynamics reverse in the following months consistent with the existence of an unwinding of trades.

The volatility measures provide further evidence supporting the idea that periods of low volatility have been historically conducive to carry trade activities. Comparing Figure 1 - Panel B with Figure 2, prolonged periods of low volatility are associated with positive/negative net future positions in high-yielding/low-yielding currencies. The evidence is particularly strong in the second part of the sample: the exceptional growth of carry trade activities since 2000 was likely boosted by a low perceived risk worldwide. All volatilities peaked after the well-known Lehmans default in 2008 and around 1992, the year of the crisis of the European Exchange Rate Mechanism. The movements of CHF and YEN are also clearly correlated around 1997 and 1998, which correspond to the Asian crisis and the LTCM collapse[8], respectively.

4 Methodology

The TVAR models have been applied in economics to examine the relationship between savings, openness and growth (Hoogstrate and Osang, 2005), between credit and economic activity (Balke, 2000; Calza and Sousa, 2005) and in finance, for instance in the study of index futures arbitrage (Tsay, 1998). In this paper, a TVAR model is adopted to examine the relationship between carry trades and foreign exchange volatility. Recent research indicates that the extent of the UIP anomaly is less pronounced in periods in which financial market volatility is high (Clarida et al. 2009, Christiansen et al. 2011). What past dynamics suggest is that carry trades exhibit patterns over time: periods of rewarding carry trades are followed by a reversal, leading to episodes of weak carry trade activity. Although such patterns indicate that several factors may lie behind the carry trade dynamics, an obvious candidate is risk: the higher the perceived profitability of outstanding positions (high carry-to-risk ratio/low foreign exchange volatility), the stronger the incentives for investors to build up risky positions over time.

This study captures such asymmetric dynamics via a multivariate non-linear model (a TVAR), in which a measure of foreign exchange volatility is used as source of risk. The empirical strategy follows Tsay (1998), who addresses

[8] The Long Term Capital Management (LTCM) was a speculative hedge fund that utilised absolute-return trading strategies combined with high leverage. Its collapse in 1998 led to a bailout by other financial institutions, under the supervision of the Federal Reserve.

both testing and model building issues concerning implementation of the TVAR technique. The TVAR specification he proposes is a multivariate version of the Self-Exciting Threshold Models outlined by Tong (1990). The peculiarity of the Threshold models in general is the use of a threshold variable to capture non-linearities. Within this group, TVAR models and Self-Exciting Threshold Models have two distinctive features: (i) they are linear autoregressive processes *within* each regime and (ii) they employ a delayed threshold variable to govern regime switching. In a TVAR model indeed, the regime in place at any time t depends on the observable past history of the threshold variable itself.

A s-regime TVAR model, also called a Multivariate Threshold Model, satisfies (Tsay, 1998):

$$\mathbf{y}_t = \mathbf{c}_j + \sum_{i=1}^{p} \mathbf{\Phi}_i^{(j)} \mathbf{y}_{t-i} + \sum_{i=1}^{q} \boldsymbol{\beta}_i^{(j)} \mathbf{x}_{t-i} + \boldsymbol{\epsilon}_t^{(j)} \quad \text{if} \quad \gamma_{j-1} < b_{t-d} \leq \gamma_j \qquad (1)$$

where $\mathbf{y}_t$ is a vector of endogenous variables, j = *1,..., s* indicates the regime/s, $\mathbf{c}_j$ are the constant vectors for the different regimes, $\Phi^{(j)}$ denotes the coefficient matrix of the respective lags and regime, γ_{j-1} and γ_j are threshold values and p is the number of lags included. The delayed threshold variable, b_{t-d}, determines which regime the system is in at any time. Asymmetries arise, as the coefficients of the linear VAR model can vary across the regimes defined by b_{t-d} , where d denotes the delay integer. Crucially, the model in (1) allows for an endogenous threshold variable, which can be defined as one of the endogenous variables in the model or alternatively can be computed as a function of one of them. Such peculiarity is the major innovation of this work: since a measure of realised volatility is used as threshold variable, the threshold level of volatility that induces parameter shifts is endogenous to the econometric procedure (derived via grid searches, details below) rather than exogenously imposed as in Clarida et al. (2009). Furthermore, since shocks to any element in $\mathbf{y}_t$ are potentially able to induce a regime-shift via the threshold variable itself, regime switches are themselves endogenous in the model. Concerning the statistical properties, the threshold variable b_t is required to be stationarity and to have a continuous distribution. The model in (1) is specified in the general form: it allows for s regimes, such that $-\infty = \gamma_0 < \gamma_1 < ... < \gamma_s < +\infty$ and is defined for a given vector of the exogenous variables, $\mathbf{x}_t$ with lag order q. Since the benchmark (linear) VAR model by Brunnermeier et al. (2009) does not include any exogenous variable, $\mathbf{x}_t$ is a vector of zeros in this study. Finally, the $\epsilon^{(j)}$ are sequences of white noises and are independent of each other.

Before modeling the TVAR specification, the presence of threshold non-linearity is formally assessed (using the *Tsay test*, see Appendix A). Testing the validity of a TVAR model (i.e. a linear VAR model under the null hypothesis and TVAR model under the alternative) involves non-standard inference due to the so called "nuisance parameter problem": when threshold values are unknown, the parameters $\gamma_{j=1,...,s}$ in (1) are identified under the alternative, but not under the null. In this study, the ad hoc test statistic designed by Tsay (1998) is employed to conduct inference[9]. Tsay (1998) transforms the problem of testing for a threshold into a problem of testing for a change-point. The model in (1) is re-arranged according to the increasing order of the threshold variable b_{t-d}; predictive residuals are then obtained in the new setup via recursive least squares and are used to construct a test statistic that does not involve undefined parameters[10]. The Tsay test statistic has an asymptotic Chi-squared distribution and can be also specified to allow for conditional heteroscedasticity. To assess the stability of the results, the Tsay test is generally performed for different starting values of the recursive estimation, m_0[11]. The test is designed to jointly detect the appropriate delay parameter d and the presence of non-linearity and assumes that both the threshold variable b_t and the lag parameter p are known. A standard procedure is to select the order p in the linear framework using an Information Criterion (i.e. AIC, HQ or SIB[12]).

Modelling a TVAR model includes selecting the threshold variable b_t, determining the number of regime s, and choosing the order p for each regime (Tsay, 1998). A TVAR model is estimated by using the conditional least square method, while the selection of the best TVAR specification is based on some information criteria (i.e. commonly the minimum Akaike Information Criterion or the sum of squares residuals). The threshold values $\gamma_{j=1,...,s}$ are determined according to a grid search over a range of potential values of the threshold variable. Given s, p and the threshold variable b_t and conditional on each of these potential values, the TVAR model is estimated by ordinary least squares. The best TVAR specification is then selected using the aforementioned method. To ensure that each regime contains a minimum number of observations, the grid is usually restricted. It is common practice in the literature to allow for at least 10 percent of the total number of observations in each regime (Tsay, 1998; Hansen, 2000; Clements and Galvao, 2004). Once the best TVAR model has been selected, the specification is refined choosing the appropriate number of lags p in each regime. The Information Criterion (i.e. AIC, HQ or SIB) adopted in the linear framework is generally re-applied.

Finally, we estimate a set of conditional linear impulse responses to assess whether the carry trade dynamics differ across the foreign exchange volatility regimes defined by the estimated TVAR model of the carry trade. Since conditional linear impulse responses are regime-dependent, they describe the dynamics of the system *within* each of the regimes identified by the estimated threshold values (Calza and Sousa, 2005). There is indeed a limiting assumption underlying this approach: the regime prevailing at the time of the shock

[9] See Hansen (1996, 2000), Galbraith (1996) and Balke (2000) for other approaches to conduct non-standard inference in this framework.)

[10] Refer to Appendix A for a formal and detailed description of the Tsay Test.

[11] Tsay (1998) studies the finite-sample performance of this test by simulation and recommends choosing $m_0 \sim 5\sqrt{n}$ when $\mathbf{y}_t$ is a unit root series, and $m_0 \sim 3\sqrt{n}$ under stationarity, where n is the sample size. The choice is a compromise between stable starting estimation and good power in testing.

[12] The choice of an appropriate threshold variable requires a careful investigation and remains one of the major problems in empirical applications of the method (Tsay, 1998).

is supposed to be preserved throughout the horizon of the responses (Balke, 2000). It follows that conditional impulse responses are an appropriate tool for examining the responses to an analogous shock in the presence of alternative volatility states, but are not designed to capture regime switching during the propagation of the shock. In principle a large shock could shift the system from one regime to another. Non-linear impulse-responses would overcome this issue: they are beyond the scope of this current paper and are an interesting possibility for future extensions.

5 The TVAR Model of the Carry Trade

The relationship between carry trades and foreign exchange volatility is explored by adding threshold non-linearity to the (linear) VAR model of the carry trade by Brunnermeier et al. (2009), and over a longer sample. The four variables described in Section 3 are used to proxy a carry trade strategy and are included in the TVAR model as endogenous variables, so that $\mathbf{y}_t = (\mathit{idiff}_t,\ \mathit{NetPos}_t,\ z_t,\ \mathit{skew}_t)$ in (1). Consistent with Brunnermeier et al. (2009), five currencies pairs (i.e. CHF/USD, CAD/USD, EUR/USD, YEN/USD and GBP/USD) are embedded in the TVAR model, which is estimated by pooling across currencies. The vector of endogenous variables is therefore a (4 x 5 x n) column vector, where $n = 287$ denotes the size of the sample. For clarity in the exposition, the suffix "all" is used henceforth to distinguish panel variables (i.e. five currency pairs) from individual variables (i.e. single currency)[13].

This choice to pool across currencies is focused on the ultimate purpose of this paper: to provide evidence on the importance of carry trades across macroeconomic regimes. The experiment we have in mind is designed to extend recent research on the relationship between the UIP anomaly and exchange rate volatility regimes. First, the TVAR allows the parameters of the VAR (and hence the extent of the UIP anomaly) to vary with the realised volatility of the exchange rate (i.e. our threshold variable). Second, our econometric procedure selects the threshold to determine parameter change. Finally, pooling across currencies, we assess how on average the carry trade behaves in response to an unexpected widening of the (average) interest rate differential. Since the five currencies are all associated with large industrialized countries, the parameter homogeneity assumption underlying this approach is expected to hold. Well developed countries are likely to react similarly to an analogous shock of this kind (see also Brunnermeier et al., 2009). More crucially, we use a positive shock to idiff_t to simulate an incentive to open a carry trade position. In the financial markets, such an incentive arises whatever the currency pair. The need to overcome the problem of limited data for individual currencies drives our choice further. Overall, a panel analysis generates gains in estimation.

[13]The vector of endogenous variables is specified as follows: $\mathbf{y}_t = (\mathit{idiff}_{all,t},\ \mathit{NetPos}_{all,t},\ z_{all,t},\ \mathit{skew}_{all,t})$

The validity of a multivariate analysis is supported by the need of modelling net speculative positions and exchange rates as endogenous variables. Our econometric procedure can enhance insights from previous research capturing this feature, which is a stylised fact in the data. The results of the Pairwise Granger Causality Tests and the VAR Granger Causality Tests (Appendix B1)[14] corroborate our choice. The first test always indicates a two-way causation: $NetPos_t$ helps in the prediction of z_t and vice versa, as current values of $NetPos_t$ are explained by past values of z_t with the reverse being also true. The second test shows that $NetPos_t$ is not exogenous for z_t and vice versa. This is consistent with the idea that target currencies strengthen and funding currencies weaken as long as investors continue to accumulate their speculative positions in the foreign exchange market until the perceived risk is too high and positions are suddenly dismantled. Pojarliev and Levich (2011) relate the liquidation of carry trades to the crowdedness of the strategy in currency markets. Their estimated proxy suggests that good past performances (i.e. positive carry trade payoffs) encourage new investors to gamble on the same outcome until the trade is too "crowded" and investors switch to the opposite game that is betting against the carry. Abrupt shifts in the exchange rates can be indeed observed in the absence of observable factors. In Brunnermeier et al. (2009), this finding is associated with funding liquidity constraints. In this study, we pin down exchange rate volatility as a key driver of the phenomenon. Modelling endogeneity and non-linearities jointly via a TVAR, we assess the UIP anomaly from a new angle.

5.1 Testing a TVAR model: Tsay test

Testing for threshold effects (i.e. with the Tsay test) entails selecting the lag parameter p and choosing a threshold variable b_t.

Lags. To select p, we employ the Multivariate Akaike Information Criterion (MAIC)[15]. We consider both the VAR model estimated pooling across currencies and the VAR models specified for individual currencies. CAD, EUR and CHF each require four lags, GBP requires five and the YEN seven lags (Appendix B2 - Panel A). Pooling across currencies, the optimal lag length is ten. For the full model only (Panel B), we also examine the order p using another set of criteria (i.e. LR, FPE, AIC, SC and HQ)[16]. Three out of five suggest twelve lags, while the remaining criteria suggest less than nine[17]. Consistent with conventional lag

[14] Refer to Appendix B1 for details about both tests.

[15] $MAIC = nlog|\hat{\Sigma}| + 2(k^2p + k)$ where $\hat{\Sigma}$ is the variance-covariance matrix of residuals, n is the number of observations, p is the number of lags and k is the number of endogenous variables.

[16] Acronyms are defined in Appendix B2.

[17] Results are provided by different econometric packages. The MAIC is available in RATS (Panel A), while the set of alternative criteria refers to the VAR Lag Order Selection Criteria procedure available in Eviews.

order choices (four or eight lags for quarterly data, six or twelve lags for monthly data), both $p = 10$ and $p = 12$ will be considered throughout the analysis.

Threshold variable. The choice of the threshold variable requires careful evaluation: a misspecification may invalidate the selection of the regimes, thus affecting the ultimate conclusions of the analysis. As anticipated, we capture non-linearities via a measure of realised exchange rate volatility (i.e. vol_t). The same indicator is constructed separately for each of the five currencies in the sample (see Section 3). From an economic perspective, several arguments support this choice: carry traders are exposed to exchange rate risk and exchange rate volatility is a way to proxy it, investors care about the carry-to-risk ratio and, more in general, agents are induced to underestimate the risk of their investments when volatility is persistently low. The insights from the recent carry trade literature (see Section 2) corroborate the intuition further: the UIP anomaly is found to be less pronounced when foreign exchange volatility is high. Moving to the econometric procedure, our indicator vol_t is a candidate for being a threshold variable: it is both endogenous and stationary as required by Tsay (1998). The endogeneity follows from the fact that vol_t is a function of a linear combination of endogenous variables, namely z_t and $idiff_t$. This property ensures that Tsay (1998) is applied correctly (see Section 4). The threshold values are then derived endogenously via grid searches. Stationarity is assessed via the Augmented Dickey Fueller (ADF) Test, which is carried out both on the country-specific measures and pooling the individual measures. The null hypothesis of unit root in the series is always rejected[18].

The descriptive statistics in Table 1 suggest that the measure of volatility based on CAD is likely to induce a downward bias in the estimates: $vol_{CAD,t}$ shows one of the highest maxima, but its 90th-percentile value lies close to the mean of all other currencies. To eliminate the component that is currency-dependent and allow for a sensible pooling, we compute five new indicators by expressing each volatility measure vol_t as the deviation from its mean. Comparing the new percentile values across currencies (Table 2) provides evidence of homogeneity: patterns are pretty similar around the lower bound of the grid search (10^{th} percentile), while the variability around the upper bound (90^{th} percentile) appears negligible. We adopt these five demeaned volatility measures (henceforth vol_dm_t) as threshold variables in our empirical analysis.

Tsay test. Given $p = 10$ or $p = 12$ and the five demeaned volatility measures, we run the Tsay test to assess the presence of threshold effects in the VAR model of the carry trade, $\mathbf{y}_t = (idiff_{all,t},\ NetPos_{all,t},\ z_{all,t},\ skew_{all,t})$. Rejecting the null hypothesis (i.e H_0: $\mathbf{y}_t$ is linear) means to conclude in favour of a TVAR specification. Four values of the threshold delay parameter d are considered, so that $d=(0, 1, 2, 3)$. A delay integer equal to zero implies a contemporaneous relationship between the threshold variable b_t and the other variables in the

[18]Results are available upon request. As suggested by graphical inspection (Figure 2), all tests includes a constant, with the exception of the CAD specification that embeds also a linear trend. The significance level is five percent for EUR and one percent in all other tests.

system, while a delay integer equal to three can be interpreted as a delay of a quarter. Since financial markets tend to react almost immediately to a rise in perceived risk, testing for longer delays does not seem appropriate. The stability of the results is assessed performing the test for different starting values of the recursive estimation, that is m_0 = *(110,120,130)*, where the choice of the values follows Tsay (1998)[19]. Conditional on m_0, the value of d associated with the maximum of the test statistic *C(d)* indicates the appropriate threshold delay integer. Diagnostic checks on the residuals of both country-specific and pooled VAR models always reject the null hypothesis of no heteroscedasticity at the one percent significance level (White heteroscedasticity test). Tsay test statistics which account for heteroscedasticity are therefore constructed[20]. Results are reported in Table 3 (the optimal specifications are in bold).

Pooling across currencies, the test strongly concludes in favour of a TVAR specification. The linearity assumption is rejected at the one percent significance level for any given value of d and m_0 and results are stable across alternative choices of the latter. Changes in the number of lags included in the model (i.e.$p = 10$ and $p = 12$) do not affect the outcomes. Concerning the delay integer d, the test selects $d = 1$ as the appropriate choice, which is supported by any combination of p and m_0.

The test is repeated under the null of a VAR model specified for each currency in the sample. Results are reported in the same table and show that the evidence is mixed. CAD and GBP supports a non-linear analysis for almost any threshold delay integer d (at the one percent significance level and five percent significance level, respectively), EUR strongly rejects a VAR model only under the assumption of a contemporaneous threshold variable, and YEN and CHF do not reject the linearity assumption. However, this finding is likely due to the use of the US dollar as funding currency. Threshold effects would be detected again when typical carry positions are actually built on the market i.e. YEN/CAD and or CHF/GBP. Take for example a typical position based on shorting YEN and CHF and going long in CAD and GBP. As all contracts are denominated in USD, agents sell a future contract in YEN and CHF and buy a future contract in CAD and GBP simultaneously to implement the strategy in the future market. The final position (short YEN and CHF, long CAD and GBP) is affected by the non-linear relationship between returns and volatility, but the short leg of the position (YEN and CHF) it is not. Moreover, the use of five currencies allows for immediate comparison with the linear benchmark

[19]Refer to Footnote 10: $m_0 = 3\sqrt{1485} \sim 120$, where n=1485 denotes the total number of available observations.

[20]To the knowledge of the authors, automatic routines for the Tsay test are available only under the assumption of homoscedasticity. They are downloadable by the official RATS forum and are by Tom Doan. To account for heteroscedasticity, the authors coded the Tsay test in Matlab following Remark 2 in Tsay (1998, p. 1190). Their Matlab code is available upon request. The values of the test statistics under heteroscedasticity are consistent with the values provided by the Standard test, but are always lower. This implies that the values of the delay integer d that are marginally significant under the Standard test are not statistically significant under the modified Tsay Test.

of Brunnermeier et al. (2009).

On the grounds that in pooling across currencies the Tsay test strongly detects threshold effects, both *d=0* and *d=1* are used to search for threshold values. Both values are consistent with economic intuition, as explained above.

5.2 Modeling a TVAR: threshold values

Given the five demeaned volatility measures, the delay integers $d = 0$ and $d = 1$ and the lag orders $p = 10$ and $p = 12$, the threshold value/s are selected by means of a grid search method and the AIC.

Regimes. We consider both a two-regime TVAR model ($s = 2$) and a three-regime TVAR model ($s = 3$). Equivalently, we allow for two or three foreign exchange volatility states of the economy[21]. The five demeaned volatility measures vol_dm_t are pooled together and the common threshold values are estimated following the approach by Tsay (1998). Under $s = 2$, the delayed threshold variable splits the sample endogenously into two parts: "a low volatility regime", which collects all the observations associated with values of $vol\_dm_{all,t}$ lower than the estimated threshold value $\hat{\gamma_1}$ and "a high volatility regime", which collects the remaining observations. Under $s = 3$, a third regime or "middle regime" is defined between the estimated threshold values $\hat{\gamma_1}$ and $\hat{\gamma_2}$. Periods where volatility is extremely low (high) are collected below (above) the lower (upper) threshold value $\hat{\gamma_1}$ ($\hat{\gamma_2}$). Searching for three regimes is consistent with the ad hoc regime selection approach in Clarida et al. (2009). Our econometric procedure extends previous work, as both the number of regimes and the threshold values are determined endogenously via the demeaned volatility measures.

Grid search method. We use the grid search method with 300 grid points to select the threshold value. Under $s = 2$, we limit the search between the 10^{th} percentile and the 90^{th} percentile of the empirical distribution of our threshold variable b_t, so that $\hat{\gamma_1} \in [-3.25, 4.07]$ and $b_t = vol\_dm_{all,t}$ (see Table 2). This choice ensures that each regime contains a minimum number of observations without imposing strong restrictions on the location of the estimated threshold value. Under $s = 3$, we limit the lower (upper) threshold value between the 10^{th} percentile and the 40^{th} percentile (the 60^{th} percentile and the 90^{th} percentile) of the same distribution, so that $\hat{\gamma_1} \in [-3.25, -1.29]$ and $\hat{\gamma_2} \in [-0.06, 4.07]$. This choice stems from Clarida et al. (2009): we search *formally* for threshold values around the percentiles defined by their ad hoc splitting rule (i.e. the 25^{th} percentile and the 75^{th}percentile).

Threshold values. Eight alternative TVAR specifications are estimated combining all possible values of p, d and s. Table 4 shows the mimimum Akaike

[21] Under $s > 3$, potential issues in estimation may arise due to the presence of limited data in each regime. Furthermore, economic intuition suggests that two and three volatility regimes are plausible.

Information Criterion (AIC) of each multivariate threshold model[22] and the corresponding estimates of the threshold value/s. The best specification is the one with the minimum overall AIC (AIC* = 9635.53) and selects $s = 2$, $p = 10$ and $d = 0$ with threshold value $\hat{\gamma_1} = 0.51$. The latter is robust to the number of lags p included in the model. Comparing the AIC values across specifications, two-regime TVAR models are clearly preferred over three-regime TVAR models. Two-regime TVAR models that rely on this assumption clearly perform better than their linear counterparts (VAR model), while the reverse holds *a priori* under *s=3*. This evidence corroborates the conclusions of the Tsay test and strongly supports the validity of a non-linear analysis under two foreign exchange volatility states.

The estimated threshold value $\hat{\gamma_1} = 0.51$ assigns 982 observations to the "low volatility regime" and 503 observations to the "high volatility regime" and corresponds to the 66^{th} percentile of the empirical distribution of the threshold variable. This result is consistent with economic intuition: the upper regime includes a lower number of observations than the downside counterpart, as it collects periods of high tension in the foreign exchange markets. This sub-sample is large enough to include not only rare events, like the recent financial crisis, but also periods where tensions have been considerably higher than in normal circumstances (i.e. the average exchange rate volatility).

Robustness check. Figure 3 - Panel C provides reports the results of the grid search for the best TVAR specification ($s = 2$, $p = 10$, $d = 0$). Panel A shows the threshold variable $b_t = vol\_dm_{all,t}$ and the estimated threshold value $\hat{\gamma_1} = 0.51$, while Panel B displays the ordered threshold variable. For each possible value of the threshold variable considered by the grid search (x-axis), Panel C displays the AIC of the corresponding multivariate threshold model (y-axis). The scatterplot clearly shows that the AIC is well behaved. Our TVAR model performs poorly when the threshold variable assumes low values, but the quality of fit improves as long as the volatility measure increases in value. The minimum AIC is achieved at 9635.53, while the model gradually lose explicative power as long as the threshold values move towards the upper bound of the grid search interval. In the light of this further evidence, we turn to search for asymmetries across the separate volatility states defined by our endogenously-chosen threshold level.

[22] The Akaike Information Criterion (AIC) of a multivariate threshold model is given by: $AIC(p, d, s) = \sum_{j=1}^{s} [T_j \; ln \; (|\hat{\Sigma}_j|) + 2k(kp+q)]$, where T_j denotes the number of observations in each regime j, $|\hat{\Sigma}_j|$ is the determinant of the variance-covariance matrix of residuals, k denotes the number of endogenous variables and p and q denote, respectively, the number of lags and the number of deterministic variables (fixed effects).

6 Empirical Findings

Conditional Impulse-Responses We use a set of linear conditional impulse-response functions to search for evidence of asymmetric carry trade dynamics across the separate regimes defined by our econometric procedure. The analysis follows the same logic of running linear regressions conditioning on the regimes defined by the estimated TVAR model, but it is conducted in an enriched macroeconomic framework. Regime-dependent impulse-responses are employed to examine the impact of a shock to the average $idiff_t$, (i.e. an unexpected widening of the average interest rate differential) on the other determinants of a carry trade strategy (i.e. $skew_t$, $NetPos_t$ and z_t). Since the incentive to open a carry trade position exists whatever level of volatility is prevailing, asymmetric carry trade dynamics may be interpreted as a sign that foreign exchange volatility and the failure of the UIP condition are intimately related, i.e. the UIP anomaly is more pronounced in periods in which exchange rate volatility is low. Brunnermeier et al. (2009, p. 320), working in a linear VAR framework, show that a positive shock to the average interest rate differential leads to more carry trade activity, makes the conditional skewness more negative and appreciates the foreign exchange rate. We extend the analysis to endogenously chosen volatility regimes and show that findings are regime-dependent.

Prior to estimation, the selected TVAR specification is refined using the Multivariate AIC to choose the appropriate autoregressive order p for each regime. In both cases, the optimal lag length is four. Choleski decomposition of the covariance matrix is employed as structural identification, while error bands for impulse-response functions are computed using Monte Carlo simulation. Following Brunnermeier et al. (2009, p. 320), the casual ordering is: $idiff_t$, z_t, $skew_t$ and $NetPos_t$; the most important assumption being that shocks to the interest rate differential cause contemporaneous changes in the other three variables but shocks in the other three variables do not affect the VAR innovation of the interest rate differential. This assumption is consistent with the well known fact that money markets are much larger than FX markets so that interest rates are not systematically influenced by exchange rate movements unless the central bank has an explicit target for the exchange rate. Central bank of the currencies included in our TVAR model did not have neither implicit nor explicit exchange rate target during the sample period of the estimates.

Figure 4 shows the impulse-responses for a shock to the average $idiff_t$ of 100 basis points for the VAR model. Figure 5 refers to the same exercise, but responses are computed conditioning on each volatility regime[23]. Concerning the sign of the responses, conditional responses are always consistent with the linear case. Concerning the size and the persistence of the responses, however, the propagation of the shock clearly differs across regimes. In the first year, an analogous unexpected increase in the average interest rate differential produces an average

[23] Impulse-responses for the cumulated foreign exchange return are generated by cumulating the impulse-response for the one-month foreign exchange return.

appreciation around 20 percent conditioning on a low-volatility state, but only around 6 percent conditioning on a high-volatility state. The gap is even more striking over time: after four years, the cumulated excess of returns peaks at 30 percent in the lower TVAR regime, but is less than 10 percent in the upper TVAR regime. With regard to the other variables, their movements are also volatility-dependent. The behaviour of the skewness differs sharply in the two volatility regimes: in the low volatility state the skewness is persistently negative and negatively correlated with futures positions, while in the high volatility regime it oscillates and is uncorrelated with futures positions. Concerning the intensity of carry trade activities, in a low volatility environment futures positions remain high for about one year after the shock and take a long time to become statistically insignificant. In a high volatility environment instead, speculative activity is negligible. Comparing the IRFs across scenarios, the evidence is sharp: the dynamics prevailing in the low-volatility state mainly drive the dynamics prevailing in the linear setup (VAR).

Fama regressions To address non-linearities further, we conduct a second experiment. In the spirit of Clarida et al. (2009), we run Fama regressions conditioning on the level of foreign exchange volatility. Again, the major difference is that the threshold level of volatility is endogenously determined rather than being exogenously imposed. Specifically, we test the following specification:

$$\Delta s_{t+3} = \alpha + \beta(i_t - i_t^*) + u_{t+3} \tag{2}$$

where Δs_{t+3} denotes the depreciation of the target currency against the US dollar over a quarter and $i_t - i_t^*$ is the 3-month interest rate differential between the target currency and the US dollar. Under the UIP hypothesis, $\alpha = 0$ and $\beta = 1$. Hundreds of empirical works have documented the UIP anomaly pursuing this approach (Sarno, 2005; Froot and Thaler, 1990). We restate equation (2) assuming that an investor funded in US dollars invests in the five currencies available in our sample for a quarter. Since the TVAR model has been estimated pooling across currencies, we replace Δs_{t+3} and $i_t - i_t^*$ in the equation above with their panel counterparts. The first term can be interpreted as the average depreciation of the five investment currencies against the funding currency over the horizon of the carry trade strategy, the second term represents the average yield difference between the five currencies in the panel and the US dollar over the same period. Since YEN/USD and CHF/USD show on average a negative interest rate differential (Table 1), we run the same analysis twice: firstly, using a basket of five currencies consistent with the approach so far and secondly, relying on a panel of the three currencies for which the Tsay test (Table 3) detects non-linear effect. To control for overlapping effects and heteroscedasticity in the sample, moving average terms and a robust variance-covariance matrix are used.

Table 5 - Panel A shows that estimates of β over the whole sample are negative and significant confirming the rejection of the unbiasedness hypothesis commonly found in empirical works (the so-called *forward bias*). Conditioning

on the volatility states defined by our estimated threshold value ($\hat{\gamma}_1 = 0.51$), however, asymmetries clearly arise: the estimates are negative and significant in the "low volatility state" but positive in the"high volatility state". Although above the threshold value the significance of the coefficient is statistically rejected, these results point in the same direction of our previous findings. The UIP anomaly is found to be less pronounced when financial market volatility is high. Ignoring YEN and CHF in the analysis leads to estimates consistent in sign with this discussion, though not statistically significant in the separate regimes. Panel B provides a partial explanation for this finding, reporting the results of the efficiency tests carried out on individual currencies. Conditioning on the low volatility regime, both YEN and CHF show very negative estimates of beta, which are also statistically significant at the one percent significance level. Even if these values cannot be related directly to carry trade activities, they suggest that modelling non-linearities may help explaining the forward bias.

The logic underlying this analysis is close to Clarida et al. (2009). However, (i) their investigation relies on portfolios based on G10 currencies and (ii) they focus on the lower regime and the upper regime of an implicit three-regime model. Compared to our analysis so far, they disregard a part of the sample (the "middle regime"). We repeat the exercise using their ad hoc splitting rule to identify the volatility states[24]. Panel A shows that estimates are more negative and significant in the low volatility state than previously commented and that slopes are still positive but not significant in the upper regime. Again, using only three currencies validates the outcomes[25].

Overall, both experiments confirm the findings by previous research (Clarida et al. 2009; Ichiue and Koyama 2007, and Christiansen et al. 2011). In a dynamic framework, foreign exchange excess returns are found to be sizeable in the low-volatility regime but not in the high-volatility regime (and in general carry trade dynamics are found to be more pronounced in one regime than in the other one). In a static framework, the well-known *forward bias* arises as a distinctive feature of a low volatility environment. This evidence is consistent with the idea that the accumulation of speculative positions in the foreign exchange market puts an appreciating pressure on the exchange rate of the target currency and in doing so makes the currency speculation even more appealing. This phenomenon is found to be more pronounced in a low-volatility environment, where a high carry-to-risk ratio is likely to persuade investors to renew their speculative bets over time. In a risky environment instead, the widening of the interest rate differential still provides an incentive to open a carry trade position, but the dynamic is not noticeable, as the perceived exchange risk is high. The gain offered by "the carry" is indeed negligible compared to the loss yielded by a

[24]The low and high volatility regime is determined by $\hat{\gamma}_1 \leq -2.05$ and $\hat{\gamma}_1 > 1.46$, respectively. These threshold values correspond to the 25^{th} and the 75^{th} percentile of the empirical distribution of our demeaned volatility measures (see Table 2).

[25]The number of observations differs across sub-samples, so the estimates are not directly comparable.

sudden adverse movement in the exchange rates.

7 Conclusion

Recent research indicates that the extent of the UIP anomaly is less pronounced in periods of high financial market volatility. The aim of this paper has been to provide evidence on the importance of carry trades across different macroeconomic regimes. We estimate a TVAR model with four carry trade variables, as proposed by Brunnermeier et al. (2009), and search for evidence of asymmetric carry trade dynamics across different foreign exchange volatility regimes. These variables are embedded as endogenous variables in the model and we propose an additional de-meaned measure of realised exchange rate volatility as the threshold variable.

The novelty of this study is to address endogeneity and non-linearities jointly. As a departure from the existing literature, we adopt an econometric procedure whereby the threshold level of volatility is determined endogenously. This is an important extension considering the power of the TVAR procedure to identify parameter change (i.e., variations in the extent of the UIP anomaly) that are correlated with changes in exchange rate volatility. The validity of this analysis over a VAR analysis is supported by the Tsay test, and is reinforced by the Akaike Information Criterion of a multivariate threshold model. We provide evidence about the role of non-linearities in explaining the forward bias.

Empirical results suggest that heavier carry trades in the low-volatility regime explains part of the deviation from efficiency commonly found by linear studies. The UIP hypothesis is found to be violated in an environment where the carry-to-risk ratio is high and exchange rate risk is low. Conditional impulse-responses indicate that responses to an analogous shock to the average interest rate differential differ in size and persistence in different regimes. The dynamics of carry trade are found to be more pronounced in the low volatility regime, but negligible in the higher volatility regime. Furthermore, sizeable excess returns to currencies are documented in the lower regime as opposed to limited excess returns in a high volatility environment. This is consistent with the violation of UIP hypothesis detected in the regression analysis. It also suggests that the UIP condition is more likely to hold in a high volatility environment, where the gain offered by the carry is negligible.

The asymmetry detected confirms insights from earlier research and show that the results are robust to using an econometric procedure that allows for endogenously chosen thresholds. However, we cannot draw any conclusion about factors that drive unwinding of carry-trades. Conditional impulse-responses only characterise the responses *within* each regime and do not shed light on factors that affect the transition between regimes. This is the subject matter for further investigation.

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Appendix A: The Tsay test for threshold non-linearity

The Tsay test is a test for threshold non-linearity in a multivariate framework. The vector time series $\mathbf{y}_t$ is assumed to be linear under the null hypothesis, whereas it follows the multivariate threshold model in equation (1) under the alternative. Formally,

$$H_0 : s = 1 \text{ vs } H_1 : s > 1$$

where s is the number of regimes.

Given observations for the variables $\mathbf{y}_t$, $\mathbf{x}_t$ and $\mathbf{s}_t$, where $t = 1, ..., n$, and under the assumption that p, q and d are known, the model in equation (1) is restated in the standard regression form:

$$\mathbf{y}'_t = \mathbf{X}'_t \boldsymbol{\Phi} + \boldsymbol{\epsilon}'_t \qquad t = 1, ..., n \tag{A.1}$$

where $h = \max(p,\ q,\ d)$, $\mathbf{X}'_t = (1,\ \mathbf{y}'_{t-1},\ \dots\ \ \mathbf{y}'_{t-p},\ \mathbf{x}'_{t-1},\ \dots,\ \mathbf{x}'_{t-p})$ is a $(pk{+}qv{+}1)$-dimensional regressor, $\boldsymbol{\Phi}$ denotes the parameter matrix, and the notation " ' " denotes the transpose. To transform the problem of testing for a threshold into a problem of testing for a change-point, equation (A.1) is re-arranged according to the increasing order of the threshold variable b_{t-d}:

$$\mathbf{y}'_{t(i)+d} = \mathbf{X}'_{t(i)+d} \boldsymbol{\Phi} + \boldsymbol{\epsilon}'_{t(i)+d} \qquad t = h + 1, ..., n \tag{A.2}$$

where $t_{(i)}$ denotes the time index of $s_{(i)}$, that is the i-th smallest value assumed by the threshold variable in its support $\mathrm{S} = \{s_{h+1-d}\ , \dots\ , s_{n-d}\}$. In equation A.2 (i.e. the "arranged regression"), only the ordering of the observations is affected. The dynamics of the vector series $\mathbf{y}_t$ are unchanged.

Model changes are detected by using predictive residuals and the recursive least squares method. The argument goes as follows. If $\mathbf{y}_t$ is linear (i.e. the null hypothesis holds), then the recursive least squares estimator of the "arranged regression" in equation (A.2) is consistent. In turn, the predictive residuals behave like white noise and are uncorrelated with the explanatory variables in the "arranged regression", that is variables contained in the vector $\mathbf{X}_{t(i)+d}$. If $\mathbf{y}_t$ instead follows a multivariate threshold model, the recursive least squares estimator is biased. Thus, the predictive residuals will be correlated with the regressor $\mathbf{X}_{t(i)+d}$ and the residuals will fail to be white noise. The predictive residuals $\hat{\mathbf{e}}_{t(m+1)+d}$ are obtained by estimating the "arranged regression" (A.2) via recursive least squares. The algorithm is initialised using m_0 observations. The recursive least estimate $\hat{\boldsymbol{\Phi}}_m$ of $\boldsymbol{\Phi}$ in equation (A.2) is obtained estimating the "arranged regression" using the observations associated with the m smallest values of the threshold variable b_{t-d}, so that i=1,...,m. Predictive residuals are indeed computed as

$$\hat{\mathbf{e}}_{t(m+1)+d} = \mathbf{y}_{t(m+1)+d} - \hat{\mathbf{\Phi}}'_m \mathbf{X}_{t(m+1)+d} \tag{A.3}$$

and then standardized.

In the Standard version of the Tsay test, the standardized predictive residuals $\hat{\boldsymbol{\eta}}_{t(m+1)+d}$ are determined under the assumption of homoscedasticity, that is:

$$\hat{\boldsymbol{\eta}}_{t(m+1)+d} = \frac{\hat{\mathbf{e}}_{t(m+1)+d}}{\sqrt{1 + \mathbf{X}'_{t(m+1)+d}\mathbf{V}_m\mathbf{X}_{t(m+1)+d}}} \tag{A.4}$$

where $\mathbf{V_m} = [\sum_{i=0}^{m} \mathbf{X}_{t(i)+d}\mathbf{X}'_{t(i)+d}]^{-1}$. The test can also be generalised to allow for conditional heteroscedasticity. In this case, the variances of the least square estimates have to be modified to take into account the correlation between the squared error terms and the elements of $\mathbf{X}'_t\mathbf{X_t}$. The jth element of $\hat{\boldsymbol{\eta}}_{t(m+1)+d}$ is therefore standardised as follows:

$$\hat{\eta}_{j,t(m+1)+d} = \frac{\hat{e}_{j,t(m+1)+d}}{\sqrt{\hat{\sigma}_j^2 + \mathbf{X}'_{t(m+1)+d}\mathbf{V}^*_m\mathbf{X}_{t(m+1)+d}}} \tag{A.5}$$

where $\hat{\sigma}_j^2 = \sum_{i=0}^{m} e^2_{j,t(i)+d}/(m - kp - vq - 1)$ is the residual mean squared error of the jth element of $\mathbf{y}_t$ and

$$\mathbf{V}^*_m = \mathbf{V}_m(\sum_{i=1}^{m} e^2_{j,t(i)+d}\mathbf{X}'_{t(i)+d}\mathbf{X}_{t(i)+d})\mathbf{V}_m \qquad with \qquad \mathbf{V}_m = (\sum_{i=1}^{m} \mathbf{X}'_{t(i)+d}\mathbf{X}_{t(i)+d})^{-1}. \tag{A.6}$$

Threshold non-linearity is tested exploiting the vector of standardized predictive residuals $\hat{\boldsymbol{\eta}}_{t(m+1)+d}$ in equation (A.4) or equation (A.5). The Tsay test is constructed by regressing the latter on the explanatory variables of the"arranged regression", $\mathbf{X}_{t(i)+d}$, and testing for their significance. The test has the following specification form:

$$\hat{\boldsymbol{\eta}}'_{t(l)+d} = \mathbf{X}'_{t(l)+d}\mathbf{\Psi} + \mathbf{w}'_{t(l)+d} \qquad l = m_0 + 1, ..., n - h \tag{A.7}$$

and the presence of threshold effects is assessed testing $H_0 : \mathbf{\Psi} = \mathbf{0}$ vs $H_1 : \mathbf{\Psi} \neq \mathbf{0}$. Under the null hypothesis, $\mathbf{y}_t$ is linear as the predictive residuals are uncorrelated with the explanatory variables. Under the alternative, $\mathbf{y}_t$ follows the multivariate threshold model in equation (1), as the predictive residuals are correlated with the explanatory variables. The test statistic proposed by Tsay (1998) to conduct inference in this framework is:

$$C(d) = [n - h - m_0 - (kp + vq + 1)] \times \{\ln[\det(\mathbf{S}_0)] - \ln[\det(\mathbf{S}_1]\} \quad \text{(A.8)}$$

where the notation "det" denotes the determinant of the matrix in brackets,

$$\mathbf{S}_0 = \frac{1}{n - h - m_0} \sum_{l=m_0+1}^{n-h} \hat{\boldsymbol{\eta}}_{\mathbf{t(l)+d}} \hat{\boldsymbol{\eta}}'_{t(l)+d} \quad \text{(A.9)}$$

and

$$\mathbf{S}_1 = \frac{1}{n - h - m_0} \sum_{l=m_0+1}^{n-h} \hat{\mathbf{w}}_{t(l)+d} \hat{\mathbf{w}}'_{t(l)+d} \quad \text{(A.10)}$$

are variance-covariance matrices and $\hat{\mathbf{w}}_t$ is the least squares residual of regression (A.6).Under the null hypothesis, *C(d)* is asymptotically a chi-squared random variable with $k(pk+qv+1)$ degrees of freedom. Linearity is rejected for large values of the tests statistic *C(d)*. When the predictive residuals are uncorrelated with the explanatory variables, $\hat{\mathbf{w}}_t$ and $\hat{\eta}_t$ display a similar behaviour and *C(d)* is small.

The finite-sample performance of this test is studied by simulation in Tsay (1998). The test has good power when the delay d is correctly specified, whereas it deteriorates when the adopted delay moves away from the true value. It is therefore preferable to repeat the test using different values of d in empirical applications.

Appendix B: Additional diagnostic checks

B1: Granger Causality Tests

Panel A: Pairwise Granger Casuality Tests

Currency	Null Hypothesis $NetPos_t$ does not Granger cause z_t		Null Hypothesis z_t does not Granger cause $NetPos_t$	
	F-Statistic	Prob	F-Statistic	Prob
ALL	3.84348	0.00004	65.3544	0
CAD	3.77903	0.0052	27.9867	0
GBP	2.2287	0.0517	22.7306	0
EUR	3.8142	0.0049	27.7396	0
YEN	3.44913	0.0015	16.0199	0
CHF	34.6711	0.0012	4.65403	0

Panel B: VAR Granger Casuality/Block Exogeneity Wald Tests

Currency	Dependent Variable	Excluded Variable	Chi-sq	df	Prob.
ALL	z_t	$NetPos_t$	49.589	10	0.0000
	$NetPos_t$	z_t	661.494	10	0.0000
CAD	z_t	$NetPos_t$	10.983	4	0.0268
	$NetPos_t$	z_t	111.430	10	0.0000
GBP	z_t	$NetPos_t$	12.475	5	0.0288
	$NetPos_t$	z_t	126.940	5	0.0000
EUR	z_t	$NetPos_t$	19.866	4	0.0005
	$NetPos_t$	z_t	125.760	4	0.0000
YEN	z_t	$NetPos_t$	21.436	7	0.0032
	$NetPos_t$	z_t	98.596	7	0.0000
CHF	z_t	$NetPos_t$	20.814	4	0.0003
	$NetPos_t$	z_t	138.745	4	0.0000

Table B1 reports the test statistics and the corresponding levels of significance for the Granger casuality tests. The Pairwise Granger Causality Test (Panel A) tests the joint hypothesis $\beta_1 = \beta_2 = ... = \beta_l$ for the pair (x, y)=(z_t, $NetPos_t$) in the bivariate regression of the form:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + ... + \alpha_1 x_{t-l} + \beta_1 y_{t-1} + ... + \beta_1 y_{t-l} + \epsilon_t$$
$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_1 y_{t-l} + \beta_1 x_{t-1} + ... + \beta_1 x_{t-l} + u_t$$

where l is the number of lags. Under the null hypothesis, z_t does not Granger cause $NetPos_t$ and vice versa. The VAR Granger Causality Test (Panel B) tests whether a variable in the VAR model can be treated as exogenous testing bilaterally whether the lags of the excluded variable affect the endogenous variable. Under the null, the excluded variable is exogenous (i.e. all lagged coefficients are not statistically different from zero.) Results refer to the pair (z_t, $NetPos_t$). *Notes*: z_t: foreign exchange rate excess returns over a quarterly horizon. $NetPos_t$: proxy of carry trade intensity. 1986M1 to 2010M12. ALL: panel of target currencies. *df*: number of lags.

B2: VAR Lag Order Selection Criteria

Panel A: Multivariate AIC

p	ALL	CAD	EUR	CHF	GBP	YEN
0	18789.49	3095.91	3425.78	3583.88	3412.68	3610.84
1	10673.57	1838.73	1848.19	1895.66	2127.97	1958.79
2	10504.15	1815.77	1786.32	1847.51	2086.75	1910.59
3	10265.52	1771.75	1739.67	1821.22	2061.26	1868.82
4	10043.35	**1760.67***	**1724.94***	**1780.43***	2030.56	1840.19
5	10022.93	1781.03	1728.74	1794.51	**2018.53***	1844.74
6	9971.49	1785.66	1735.63	1801.55	2033.81	1847.69
7	9834.28	1790.62	1736.31	1793.82	2030.94	**1830.81***
8	9814.96	1810.29	1748.92	1815.12	2026.54	1862.12
9	9831.49	1834.83	1766.85	1839.49	2039.03	1883.55
10	9802.68*	1839.91	1789.84	1836.54	2063.05	1888.42
11	9810.69	1855.87	1812.02	1835.2	2087.2	1915.27
12	9809.58	1849.3	1834.19	1856.3	2105.84	1952.83

Panel B

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−8962.94	NA	2.328647	12.19680	12.26869	12.22360
1	−5304.439	7272.294	0.016566	7.251106	7.380517	7.299360
2	−5200.848	205.3536	0.014709	7.132177	7.319104	7.201877
3	−5059.672	279.0934	0.012410	6.962216	7.206659	7.053363
4	−4937.297	241.2617	0.010741	6.817782	**7.119741***	6.930375
5	−4909.64	54.37525	0.010572	6.801955	7.161429	6.935994
6	−4864.033	89.41854	0.010156	6.761755	7.178745	6.917240
7	−4782.766	158.8926	0.009294	6.673137	7.147643	**6.850069***
8	−4753.798	56.48014	0.009132	6.655530	7.187552	6.853908
9	−4744.296	18.47415	0.009213	6.664354	7.253891	6.884177
10	−4714.555	57.66659	0.009043	6.645695	7.292749	6.886965
11	−4701.58	25.08504	0.009081	6.649804	7.354373	6.912520
12	−4682.401	**36.97938***	**0.009042***	**6.645486***	7.407572	6.929649

Number of lags p selected by alternative Information Criteria for a VAR model in four variables ($idiff_t$, $NetPos_t$, $skew_t$, z_t). Panel A relies on the Multivariate Akaike Information Criterion by RATS. Panel B reports the results yielded by the "VAR Lag Order Selection Criteria" procedure available in Eviews. The number of lags p selected by each criterion is in bold. *Notes*: ALL: panel of target currencies.

A set of conditional linear impulse responses from a TVAR model in the four variables ($idiff_t$, $NetPos_t$, $skew_t$, z_t) for a shock of 100 bps to the interest rate differential, $idiff_t$. The low and high volatility regime is determined by $\hat{\gamma}_1 \leq 0.51$ and $\hat{\gamma}_1 > 0.51$ with 982 and 503 observations respectively. Eleven (low regime) and seven (high regime) lags are included. Error bands are computed using Monte-Carlo simulations. Shocks are normalized.

Figure 1
Carry-trade variables

This figure shows the time-series of four carry-trade variables that are used as endogenous variables in the TVAR analysis. These variables are constructed for five currencies (GBP, EUR, CHF, CAD, YEN) from January 1986 to December 2010. Specifically, *Idiff* denotes the interest rate differentials (in percent) between each target country and the U.S. Daily interbank interest rates are collected at the 3-month maturity; the German interest rate is used prior to the introduction of the Euro. *Skew* denotes the skewness of the daily percentage change in the bilateral exchange rate computed over overlapping windows of 63 working days and re-sampled at the end of each month. *Z* denotes the carry trade returns computed as UIP residuals over a quarterly horizon. *Net Pos* denotes the net speculative positions (long minus short positions against USD) held in the foreign exchange futures market, scaled by the open interest.

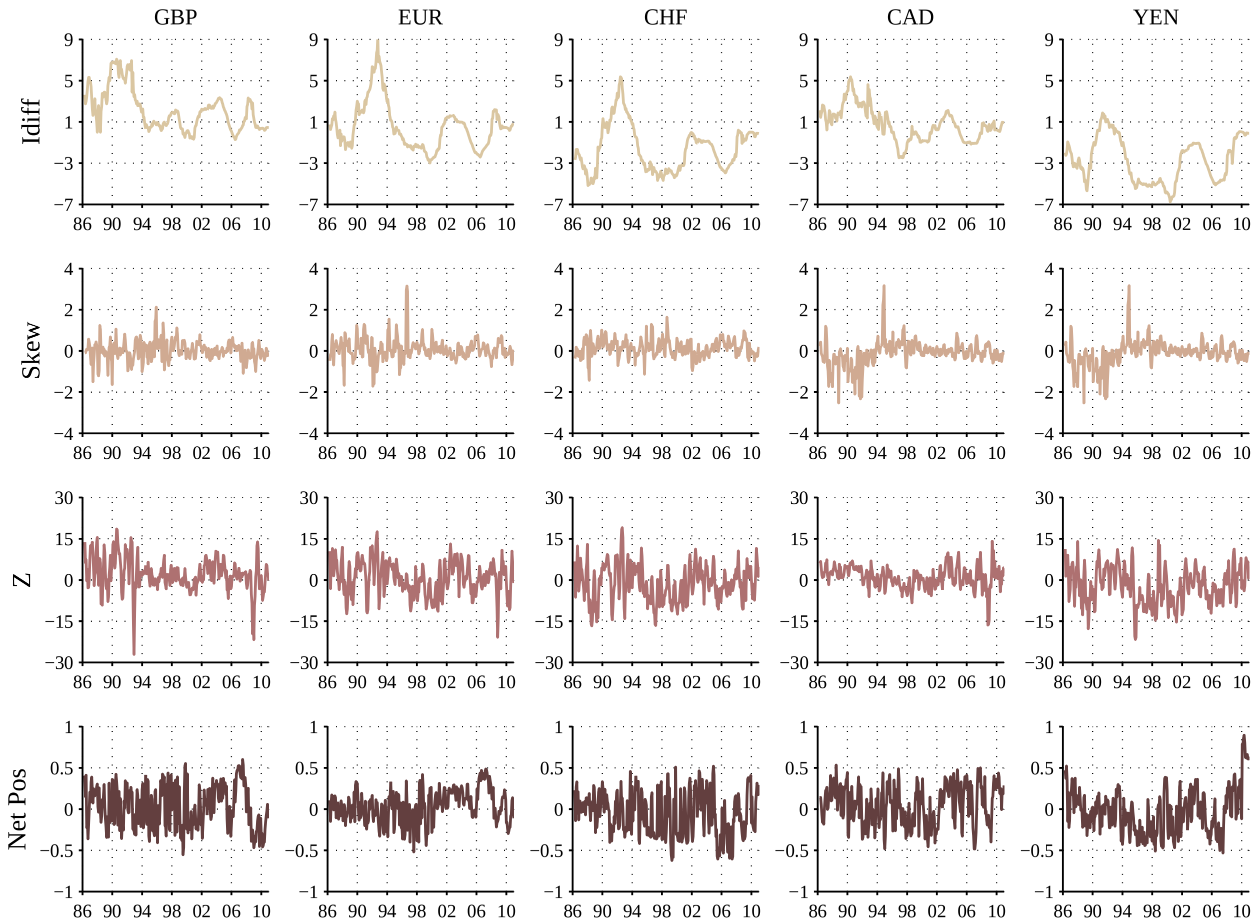

Figure 2

Volatility measures

This figure shows the demeaned measures of realized exchange rate volatility (VOL DM) that are used as source of non-linearity in the TVAR analysis. The same indicator is constructed separately for each of the five currencies in the sample. For each currency, a measure of realized exchange rate volatility (VOL) is constructed first. This measure is defined as the volatility of the daily percentage change in the bilateral exchange rate, is computed over overlapping windows of 63 working days ($vol_t = (s_{t-63} : s_t) * 100 * \sqrt{253}$) and is re-sampled at the end of each month. Demeaned volatility measures are then obtained by expressing each volatility indicator in devation from its sample mean (reported in black dashed line). The sample period is January 1986 to December 2010.

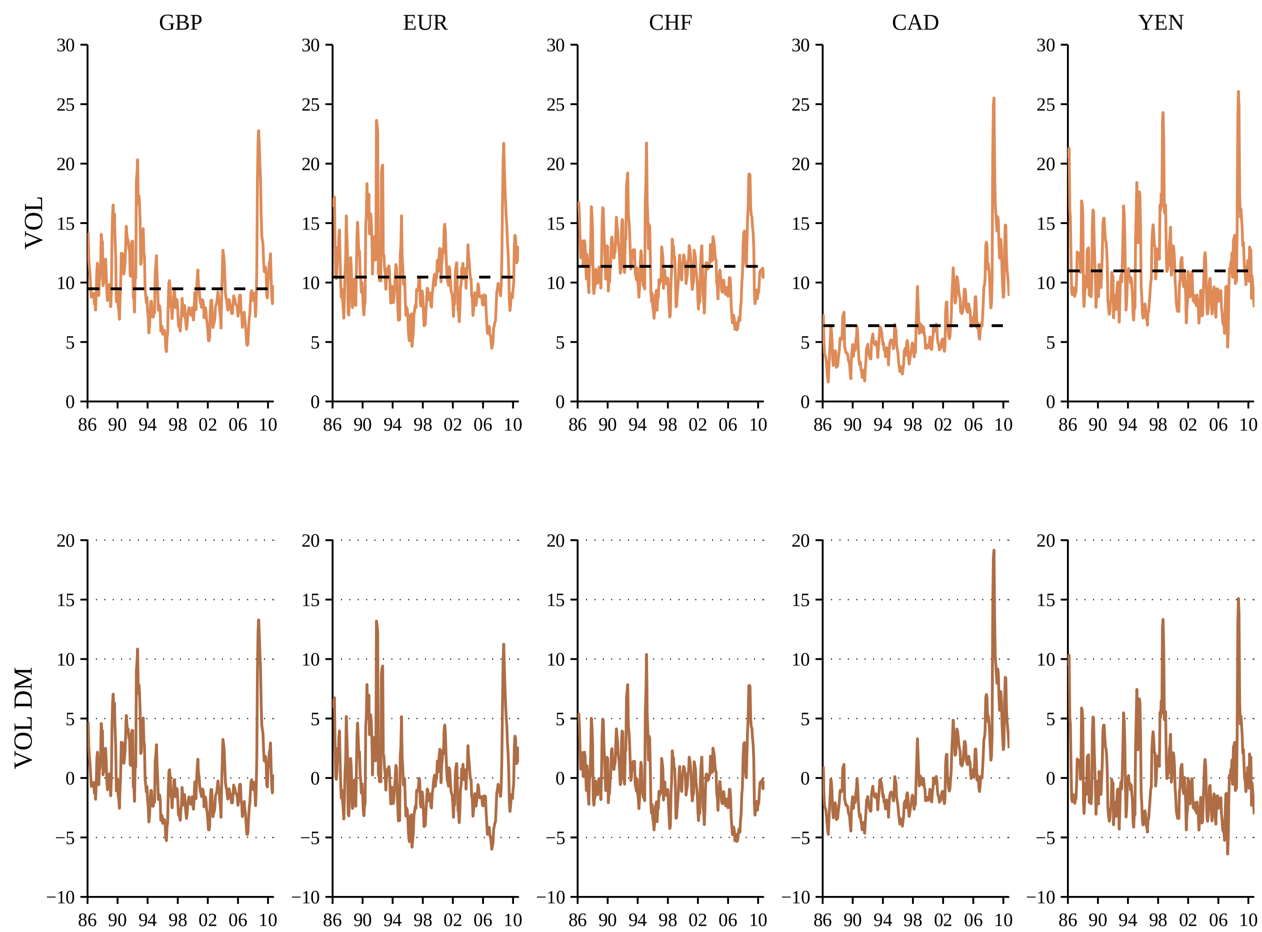

Figure 3
Estimating the threshold value

Steps to select the optimal threshold value in a two-regime TVAR model in the four variables: $idiff_t$, $NetPos_t$, $skew_t$, z_t when the five target currencies are pooled. The TVAR model includes 10 lags (*p=10*), the threshold variable is contemporaneous (*d=0*) and the variance-covariance matrix can differ across regimes (*heterog*). The model is selected as the best out of sixteen by the AIC. The alternative specifications are reported in Table 4. Panel A shows the threshold variable used to identify the foreign exchange volatility states, that is the demeaned volatility measure $vol\_dm_{all,t}$, and the estimated threshold value, $\hat{\gamma}_1$. Observations below (above) $\hat{\gamma}_1$ are assigned to the low (high) volatility regime. Panel B shows the ordered threshold variable. Panel C reports the results of the grid search (scatterplot). For each possible value of the threshold variable considered by the grid search (x-axis), the AIC of the corresponding multivariate threshold model is displayed (y-axis). Notes: $AIC = -2.0^{*}\%logl + 2(k^2p + k)$, where *logl* is the log-likelihood function, k is the number of endogenous variables and p is the number of lags.

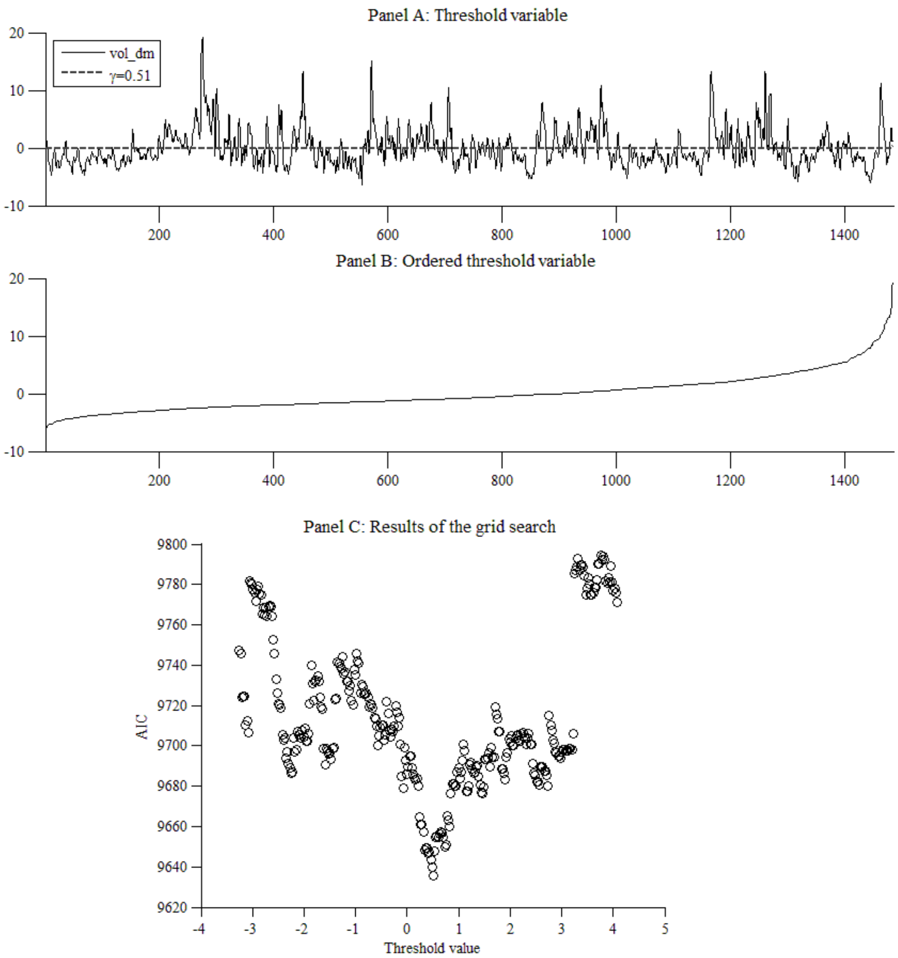

Figure 4
Impulse Responses

This figure shows impulse-responses from a VAR(10) in the four variables for a shock of 100 bps to the interest rate differential $idiff_t$. Error bands are computed via bootstrapping. The VAR Lag length is selected by MAIC (Appendix B2). There are 1485 observations from January 1986 – December 2010.

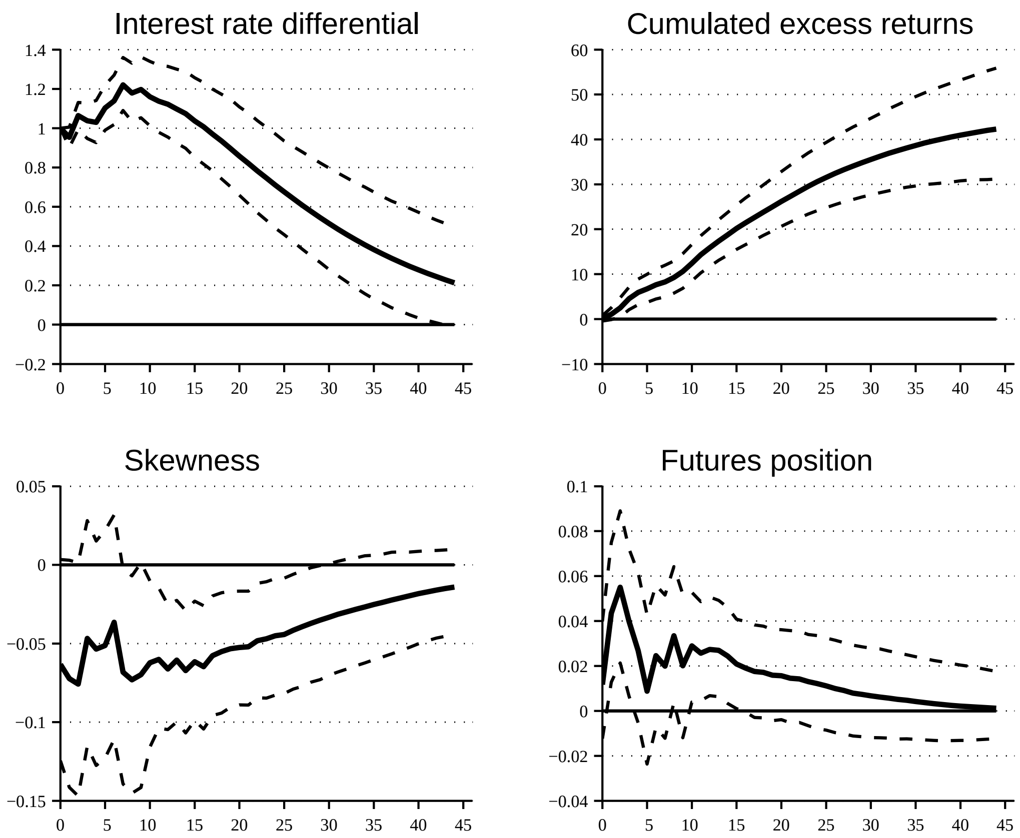

Figure 5

Conditional linear impulse responses

This figure shows a set of conditional linear impulse responses from a TVAR model in the four variables ($idiff_t$, $NetPos_t$, $skew_t$, z_t) for a shock of 100 bps to the interest rate differential, $idiff_t$. The low and high volatility regime is determined by $\hat{\gamma}_1 \leq 0.51$ and $\hat{\gamma}_1 > 0.51$ with 982 and 503 observations respectively. Four lags are included in each regime. Error bands are computed via bootstrapping. Shocks are normalized.

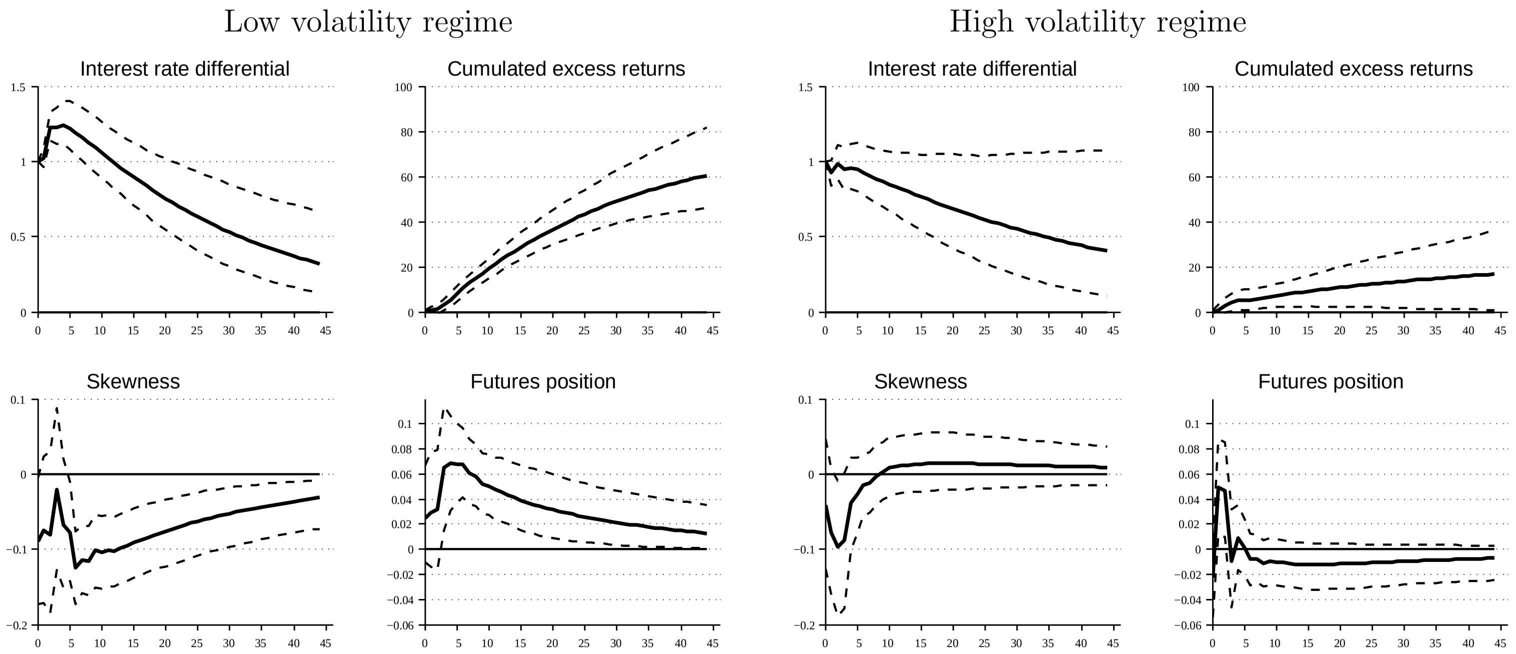

Table 1
Descriptive Statistics

This table reports descriptive statistics of the variables involved in the TVAR analysis. Monthly series; 1986M1 to 2010M12. *Notes*: $idiff_t$: three-month interest rate differential between the target currency and the US dollar; $NetPos_t$: amount of net speculative positions held in the foreign exchange futures market, scaled by the open interest; $skew_t$: skewness of the daily percentage change in the bilateral exchange rate computed over overlapping windows of 63 working days; z_t: foreign exchange rate excess returns over a quarterly horizon. ALL: panel of target currencies (GBP, EUR, CHF, CAD, YEN).

Variable	Currency	Mean	Min	Max	Skewness	Kurtosis	25^{th} perc	75^{th} perc
$idiff_t$	CAD	0.77	−2.50	5.37	0.45	3.03	−0.44	1.74
	GBP	2.14	−0.73	7.08	0.85	0.85	0.48	3.09
	EUR	0.52	−2.99	9.36	1.14	4.37	−1.31	1.49
	CHF	−1.61	−5.19	5.37	0.70	0.70	−3.58	−0.15
	YEN	−2.71	−6.76	1.87	0.16	0.16	−4.81	−1.07
	ALL	−0.19	−6.76	9.36	0.16	3.02	−1.85	1.47
z_t	CAD	1.04	−16.44	14.09	−0.52	5.39	−1.38	3.61
	GBP	2.09	−27.08	18.54	−0.54	6.07	−0.93	5.23
	EUR	0.67	−20.87	17.50	−0.21	2.89	−3.23	5.03
	CHF	−1.10	−16.70	18.98	0.04	2.81	−5.45	3.87
	YEN	−2.10	−21.63	14.38	−0.03	2.65	−7.02	2.87
	ALL	0.12	−27.08	18.98	−0.29		−3.39	4.16
$NetPos_t$	CAD	0.05	−0.48	0.53	−0.19	2.09	−0.12	0.25
	GBP	0.02	−0.55	0.60	0.04	1.96	−0.19	0.24
	EUR	0.04	−0.52	0.49	−0.09	2.65	−0.09	0.18
	CHF	−0.05	−0.62	0.52	0.00	2.08	−0.27	0.16
	YEN	−0.02	−0.53	0.89	0.61	3.24	−0.24	0.15
	ALL	0.01	−0.62	0.90	0.05	2.47	−0.19	0.20
$skew_t$	CAD	−0.12	−2.53	3.16	−0.12	8.48	−0.33	0.18
	GBP	−0.00	−1.63	2.12	0.15	5.28	−0.27	0.25
	EUR	0.07	−1.71	3.15	1.33	10.97	−0.20	0.31
	CHF	0.14	−1.43	1.63	0.04	3.86	−0.14	0.41
	YEN	0.29	−2.50	2.84	0.04	5.34	−0.10	0.63
	ALL	0.08	−2.53	3.16	0.40	7.34	−0.21	0.36
vol_t	CAD	6.37	1.63	25.52	2.09	0.71	4.29	7.66
	GBP	9.52	4.18	22.77	1.46	5.71	7.59	10.94
	EUR	10.45	4.46	23.650	1.25	5.45	8.33	11.87
	CHF	11.35	6.01	21.735	0.71	3.93	9.67	11.87
	YEN	11.00	4.57	26.068	1.49	6.10	8.65	12.60
	ALL	9.73	1.63	26.07	0.77	4.47	7.49	11.72

Table 2
Foreign exchange volatility measures: Empirical distribution

This table reports the main percentiles of the empirical distribution of two measures of realised foreign exchange volatility, which are computed for each currency in the sample (GBP, EUR, CHF, CAD, YEN). *Notes*: vol_t: volatility of the daily percentage change in the bilateral exchange rate. It is computed over overlapping windows of 63 working days and is then re-sampled at the end of each month. vol_dm_t: for each currency in the sample the volatility measure vol_t is expressed in deviation from its mean. ALL: panel of target currencies (all quoted against the US dollar).

Variable	Currency	10th	25th	40th	Median	60th	75th	90th
vol_t	CAD	3.24	4.30	4.80	5.25	6.30	7.66	10.50
	GBP	6.39	7.59	8.28	8.67	9.31	10.94	13.58
	EUR	7.22	8.33	9.37	9.88	10.87	11.87	14.56
	CHF	8.34	9.67	10.44	11.10	11.81	11.87	14.83
	YEN	7.56	8.65	9.64	10.17	11.05	12.60	15.52
	ALL	5.09	7.49	8.69	9.38	10.27	11.72	14.28
vol_dm_t	CAD	−3.13	−2.08	−1.49	−1.12	−0.07	1.29	4.13
	GBP	−3.13	−1.93	−1.23	−0.85	−0.20	1.42	4.06
	EUR	−3.23	−2.13	−1.08	−0.58	0.41	1.42	4.11
	CHF	−3.00	−1.68	−0.91	−0.25	0.47	1.50	3.48
	YEN	−3.45	−2.35	−1.36	−0.83	0.05	1.60	4.51
	ALL	−3.25	−2.05	−1.29	−0.77	−0.06	1.46	4.08

Table 3
Tsay tests

This table reports the test statistics *C(d)* and the corresponding levels of significance for the Tsay test, which is a test for threshold non-linearity in a multivariate framework (see Appendix A). The model includes four endogenous variables ($idiff_t$, $NetPos_t$, $skew_t$, z_t) and is specified both for the five currencies in the sample (GBP, EUR, CHF, CAD, YEN) and pooling them, 1986:M1 to 2010:M12. The threshold variable b_t is a demeaned measure of realized volatility (i.e. vol_dm_t, see Section 3). Under the null hypothesis, the system is linear. The test is run for different starting values of the recursive estimation, m_0, and under the assumption of heteroscedasticity. Conditional on m_0, the maximum of the test statistic *C(d)* indicates the optimal delay integer d of the threshold variable b_t. Optimal values are in bold. The number of lags p included in each model is selected by the Multivariate AIC (Appendix B2). Critical values are reported at the bottom of the table. *, **, *** denotes significance at 10%, 5% and 1% respectively.

Currency	p	df	m_0 / d	0	1	2	3
			100	246.96***	**264.82*****	242.22***	208.97**
ALL	10	164	110	249.41***	**265.49*****	239.23***	206.69**
			120	246.14***	**263.79*****	242.51***	210.32***
			100	274.65***	**303.94*****	267.84***	235.42***
ALL	12	196	110	277.43***	**306.62*****	264.76***	233.98***
			120	278.79***	**305.80*****	268.43***	235.69***
			40	111.94***	**127.06*****	107.59***	101.75***
CAD	4	68	50	116.72***	**124.98*****	128.01***	122.45***
			60	106.69***	**133.42*****	118.96***	125.07***
			40	**110.11****	106.98**	94.36	109.54**
GBP	5	84	50	**113.47****	111.48**	89.45	110.23**
			60	**108.38****	106.41**	91.23	111.49**
			40	**102.03*****	69.24	81.45	66.66
EUR	4	68	50	**102.41*****	69.15	72.18	61.14
			60	**102.75*****	70.17	68.15	59.97
			40	68.32	72.39	79.13	63.24
CHF	4	68	50	75.43	78.01	78.87	63.51
			60	81.73	72.41	79.73	62.37
			40	92.35	98.25	79.76	75.88
YEN	7	116	50	89.43	95.43	78.67	73.94
			60	88.86	96.79	76.54	78.47

C(d): Critical values

α, *df*	68	84	116	164
1% level	98.03	117.06	154.34	209.05
5% level	88.25	106.39	142.14	194.88
10% level	83.31	100.98	135.90	187.60

Table 4
Estimating the threshold values

This table shows eight alternative specifications of a TVAR model in four carry-trade variables ($idiff_t$, $NetPos_t$, $skew_t$, z_t) and their linear counterparts (VAR). For each TVAR specification, the table reports the estimated threshold values ($\hat{\gamma}_1$ and $\hat{\gamma}_2$) and the minimum AIC of the estimated model. The minimum overall AIC denotes the best TVAR specification and is in bold. The demeaned volatility measure $vol\_dm_{all,t}$ is used as threshold variable. Notes: $AIC = \sum_{j=1}^{s} [T_j \; ln \; (|\hat{\Sigma}_j|) + 2k(kp+q)]$, where T_j denotes the number of observations in each regime j, $|\hat{\Sigma}_j|$ is the determinant of the variance-covariance matrix of residuals, k is the number of endogenous variables, p is the number of lags and q is the number of deterministic variables (fixed effects); s: number of regimes, d: delay integer of the threshold variable.

Spec.	p	s	d	AIC	$\hat{\gamma}_1$	$\hat{\gamma}_2$
TVAR[1]	10	2	0	-7606.77	0.50	
TVAR[2]	10	2	1	-7476.91	-3.01	
TVAR[3]	12	2	0	-7428.77	0.50	
TVAR[4]	12	2	1	-7299.43	-3.01	
TVAR[5]	10	3	0	-7698.79	-1.96	0.51
TVAR[6]	10	3	1	-7541.65	-3.01	0.64
TVAR[7]	12	3	0	-7636.54	-1.96	0.51
TVAR[8]	12	3	1			
VAR	10	1		-7346.756		
VAR	12	1		-7330.183		

Table 5: Testing UIP hypothesis

$$\Delta s_{t+3} = \alpha + \beta(i_t - i_t^*) + u_{t+3}$$

Panel A

	5 currency pairs					3 currency pairs				
	Whole Sample	Low $\gamma_1 \leq 0.51$	High $\gamma_1 > 0.51$	Low $\gamma_1 \leq 25^{th}$	High $\gamma_1 > 75^{th}$	Whole Sample	Low $\gamma_1 \leq 0.51$	High $\gamma_1 > 0.51$	Low $\gamma_1 \leq 25^{th}$	High $\gamma_1 > 75^{th}$
β	-0.22***	−0.45***	0.18	−0.73***	0.15	−0.23**	−0.24	0.33	−0.46**	0.44
	(0.1)	(0.12)	(0.19)	(0.18)	(0.21)	(0.11)	(0.15)	(0.25)	(0.23)	(0.3)
α_{CAD}	0.11	0.45	−0.85	1.09	−0.33	−0.06	0	−0.75	0.66	−0.44
	(0.54)	(0.57)	(1.06)	(0.83)	(1.16)	(0.51)	(0.52)	(1.04)	(0.75)	(1.14)
α_{YEN}	−1.17**	−2.25***	0.55	−2.84***	1					
	(0.58)	(0.66)	(1.11)	(0.9)	(1.25)					
α_{CHF}	−1.19**	−2.24***	0.47	−3.44***	−0.25					
	(0.57)	(0.65)	(0.97)	(1.03)	(1.11)					
α_{GBP}	0.73	0.79	0.16	0.55	−0.68	0.77	0.4	−0.31	0.14	−0.63
	(0.57)	(0.61)	(1.16)	(0.87)	(1.32)	(0.56)	(0.58)	(1.25)	(0.8)	(1.47)
α_{EUR}	−0.34	−0.23	−0.65	−2.07**	−0.53	−0.42	−0.24	−0.62	−1.61***	−0.99
	(0.55)	(0.58)	(1.03)	(0.81)	(1.2)	(0.52)	(0.53)	(1.05)	(0.72)	(1.21)
DW	2	2	2	1.98	1.99	2	1.99	2.02	1.98	1.99
Obs	1485	982	503	371	372	891	602	289	226	215

Note: *, **, *** denotes significance at 10%, 5%, 1%

Table 5 reports the results of simple market efficiency tests. The UIP condition is tested by estimating the values of the α and β coefficients in the specification reported at the top of the page. Δs_{t+3} is the depreciation against the US dollar over a quarter and is replaced by panel variables $s_{t+3_{all}}$ (Panel A), while $i_t - i_t^*$ is the 3-month interest rate differential between the target currency and the US dollar and is replaced by $idiff_{t_all}$ (Panel A). Panel B (next page) refers to individual currencies. Tests are run on the whole sample and conditioning on the foreign exchange volatility regimes defined by the threshold variable $b_t = vol_{dmt_{all}}$. Notes: Robust standard errors in parenthesis. Moving average terms included to remove overlapping effects.

Table 5 (continued): Testing UIP hypothesis

$$\Delta s_{t+3} = \alpha + \beta(i_t - i_t^*) + u_{t+3}$$

Panel B

	Whole Sample				Low Volatility State				High Volatility State			
	α	β	DW	Obs	α	β	DW	Obs	α	β	DW	Obs
CAD	−0.45	−0.23*	1.99	297	0.1	−0.47***	1.98	209	−0.86	0.06	2.05	88
	(0.35)	(0.12)			(0.36)	(0.14)			(0.98)	(0.67)		
GBP	0.55	−0.51***	1.98	297	0.16	−0.2	2.01	200	0.54	0.02	1.97	97
	(0.53)	(0.15)			(0.73)	(0.28)			(1.8)	(0.44)		
EUR	−0.43	0.02	1.99	297	−0.21	−0.08	1.98	135	−1.31	0.57*	1.98	104
	(0.57)	(0.23)			(0.66)	(0.31)			(1.03)	(0.34)		
CHF	−1.3	−0.21	1.97	297	−2.80***	−0.80***	1.97	187	0.18	0.11	1.98	110
	(0.73)	(0.23)			(0.95)	(0.28)			(0.99)	(0.38)		
YEN	−2.92	−0.66***	1.97	297	−2.79	−0.58**	1.99	193	0.09	0.09	2	104
	(0.87)	(0.25)			(1.01)	(0.29)			(0.48)	(0.48)		

Note: *, **, *** denotes significance at 10%, 5%, 1% respectively.

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