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Carry Trade Activities: A Multivariate Threshold Model Analysis*

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Abstract

In this empirical study, we analyze the relationship between carry trade positions and some key financial as well as macroeconomic variables using a multivariate threshold model. It is often stated that the Swiss franc serves as a funding currency. We therefore focus on carry trades based on the USD/CHF and EUR/CHF currency pairs over the period from 1995 to mid-2008. We conclude that carry trades are driven to a large extent by changes in investors' risk sentiment, movements in stock market prices and exchange rate fluctuations. The adjustments of carry trade positions to unexpected movements in these variables vary between periods of high and low interest-rate differentials (IRD). While a positive shock to the IRD is followed by a rise in carry trade positions during a period of low IRD, it will trigger a decline in these positions during a period of high IRD. These results suggest that the shock to the IRD itself is not enough to compensate investors for the increased foreign exchange risk. Moreover, a positive stock market price shock is associated with a rise in carry trade positions, since investors may use stock portfolios as collateral for liquidity. A sudden unwinding of carry trades leads to significant Swiss franc appreciation. Furthermore, carry trade activities 'Granger-cause' the nominal exchange rate in periods of low IRD. The Granger causality test results further indicate feedback trading.

JEL Classifications: C15 C32 E44

Keywords: Carry Trades, Multivariate Threshold Model, Tsay Test, Generalized Impulse Response Functions, Bootstrap Method, Granger Causality

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1 Introduction

In this paper, we explore the relationship between speculators' currency carry trade positions and key financial variables which are of macroeconomic interest. The basic idea of a 'currency carry trade' (hereinafter 'carry trade') involves selling low-interest-rate currencies (e.g., by borrowing money) and investing simultaneously in high-interest-rate currencies. Low-interest-rate currencies, such as the Swiss franc or the Japanese yen, are called funding currencies, whereas high-yielding currencies are called target currencies.

Investment strategies to exploit the failure of uncovered interest rate parity (UIP) have become a major focus of interest not only for financial market participants;¹ carry trades also have appeared on policymakers' agendas, specifically on those of central bankers. For instance, Jean-Pierre Roth, former president of the governing board of the Swiss National Bank, pointed out the crucial role of carry trades in determining the nominal exchange rate in the medium run (Roth, 2007). In our analysis, we focus on two target currencies for which the Swiss franc (CHF) serves as the funding currency: the US dollar (USD) and the euro (EUR).

While an extensive body of the literature on carry trades examines their profitability, the main contribution of this study is the empirical investigation of the interaction between carry trade activities and financial as well as macroeconomic variables with a multivariate threshold model. Carry traders presumably react to shocks to variables which determine the profitability of their investment strategy, such as the interest-rate differential (IRD), the nominal exchange rate, the risk sentiment, the investment return, and possible liquidity constraints. In addition, these variables can move due to unexpected carry trade activities. Thus, we include these variables, or reasonable proxies, in our model covering the period from 1995 to mid-2008. Moreover, in order to assess the statistical significance of the results we extend the recursive-design wild bootstrap method for univariate models proposed by Goncalves and Kilian (2004) to multivariate models.

Therefore, our empirical study is closest to Brunnermeier et al. (2009) and Nishigaki (2007). Brunnermeier et al. (2009) show that in times of reduced funding liquidity and declining risk appetite carry traders are subject to crash risk due to the sudden unwinding of carry trades. Nishigaki (2007) examines the yen carry trade. His analysis implies that the IRD has no significant impact on carry trade movements, in contrast to US stock prices. The results also indicate USD depreciation against the Japanese yen once carry trades unwind. Both of these studies incorporate futures positions to proxy carry trade activities, as we do for the CHF/USD exchange rate. Yet, futures position data with respect to the CHF/EUR exchange rate are not available. Hence, we employ for the Euro market the carry-to-risk ratio (CTR ratio) to proxy carry trade activities, since it is an important indicator of potential carry trade profitability.

Hassan and Mano (2014) argue that carry trades are driven by persistent IRD due to asymmetries in currency risk premia reflecting relative country size or financial development. Therefore, given these asymmetries, a rise in the IRD should boost carry trades activities. On the other

¹Many empirical studies emphasize the violation of UIP. For a literature survey on this empirical anomaly of the foreign exchange market ('forward premium puzzle'), see for example Engel (1996). In fact, Fama (1984) shows that on average the target currency appreciates which makes carry trades profitable. However, this finding is challenged by the recent study of Hassan and Mano (2014).

hand, relative purchasing power parity (PPP) seems to hold in the medium to long run conditional on real shocks (Coakley et al., 2005). However, the adjustment of the (real) exchange rate to deviations from PPP is often found to be nonlinear (for a survey, see Taylor and Taylor, 2004). As a result, a widening of the (expected) inflation-rate differential that pushes the IRD above a certain threshold value may trigger a fast convergence of the exchange rate toward the PPP value, which reverses the higher returns resulting from the IRD. This, in turn, may impact the behavior of carry traders. Indeed, preliminary analyses of the IRD indicate a nonlinear relationship among the variables in our model. The results of a Tsay (1998) test confirm the assumption of nonlinearity. Therefore, we apply a multivariate threshold model to account for the possible changes in the dynamic behavior of carry trade activities dependent on the size of the IRD.

By analyzing the generalized impulse response functions (GIRFs) of the model containing the USD/CHF exchange rate, we find that carry trade positions are driven to a large extent by changes in investors' risk sentiment, movements in stock market prices and exchange rate fluctuations. Since the responses of these variables to shocks depend on the size of the IRD, these differences are carried over to the speculators' carry trade positions. We show that the probability of a sudden appreciation of the Swiss franc is higher during a period of high IRD, in line with an increased inflation-rate differential. Indeed, while during a period of low IRD a positive shock to the IRD is followed by a rise in carry trade positions, it will trigger a decline in carry trade positions during a period of high IRD. These results suggest that the shock to the IRD itself is not enough to compensate investors for the increased foreign exchange risk. Moreover, in line with the prediction of UIP, the CHF appreciates against the USD during a period of high IRD, but not in the regime of low IRD.

We also show that a positive stock market price shock is associated with a rise in carry trade positions, since investors may use stock portfolios as collateral for liquidity. Furthermore, a sudden unwinding of carry trades leads to a significant appreciation of the Swiss franc. Finally, we point out that the majority of impulse responses is similar for the CHF/USD and CHF/EUR exchange rates, although the proxy for carry trade positions differs.

Klitgaard and Weir (2004) and Mogford and Pain (2006) analyze futures position data and state that net positions do not seem to 'Granger-cause' the exchange rate movements of the following week. We follow their approach and apply the Granger causality test to our regime-dependent model and find that past position data help to predict exchange rate movements in periods with low IRD. Additionally, in samples with the USD as target currency, the exchange rate has very high predictive power for carry trade activities, pointing to feedback trading.²

The remainder of this paper is organized as follows. Section 2 contains an overview of the related literature. Data sources and variable definitions are presented in Section 3. In Section 4, we outline the methodology used for our empirical study. We provide a detailed discussion on our results for the GIRFs in Section 5 and their robustness analysis (Section 5.3). Section 5.4 shows the Granger causality test results and Section 6 concludes.

²In contrast, no prediction power is found in samples with the EUR as target currency. This might be due to the definition of the CTR ratio. This issue is discussed in greater detail in Section 5.4.

2 Related Literature

A large body of the literature on carry trades examines the profitability of potential carry trade strategies. A few studies conclude that these investment strategies lead to excess returns. These excess returns can be attributed neither to standard risk factors (Burnside et al., 2006), to the exposure to currency crashes (Jurek, 2007), nor to disaster risks (Farhi et al., 2009). Instead, market frictions such as the bid-ask spread and price pressure greatly reduce the return on these portfolios (Burnside et al., 2006), or they are not economically significant (Wagner, 2008). In contrast, Lustig et al. (2011) argue that carry trade profits are a compensation for systematic risk and Menkhoff et al. (2012) find that cross-sectional excess returns in five carry trade portfolios are largely captured by a proxy for global FX volatility. Moreover, Darvas (2009) shows that the degree of leverage is crucial for excess returns. Profitability declines with increasing leverage. Furthermore, Kohler (2007) examines the correlation dynamics between returns on global equity portfolios and simple carry trade investment strategies. Based on his results, carry trades are exposed to a severe diversification meltdown in times of global stock markets crisis.

Another stream of the carry trade literature examines other channels to detect carry trade positions that focus mainly on yen carry trades. For example, Gagnon and Chaboud (2007) emphasize the ‘canonical yen carry trade’ in contrast to the ‘derivatives carry trade’ studied by Nishigaki (2007) and Brunnermeier et al. (2009).³ Galati et al. (2007) compare low frequency data from the BIS international banking statistics with higher frequency futures data and find similar insights for carry trade positions. Cai et al. (2001) examine the effects of order flows and macroeconomic news on the dramatic yen/dollar volatility of 1998 with weekly data from the US Treasury on purchases and sales of spot, forward, and futures contracts. Finally, Hattori and Shin (2007) conclude that the waxing and waning of the balance sheets of foreign banks in Japan is related to the state of overall risk appetite. By using descriptive statistics and a simple econometric analysis, they reveal a positive relationship between the IRD and carry trades. However, McGuire and Upper (2007) argue that carry trade positions are not only difficult to detect but also to distinguish from other investment strategies.

The importance of regime-dependent results is highlighted by Clarida et al. (2009) among others. These authors examine carry trade strategies and identify a robust empirical relationship between their excess returns and exchange rate volatility. Furthermore, they show that the failure of UIP is only present in low-volatility environments. Jordà and Taylor (2012) argue that more sophisticated conditional carry trade strategies exhibit more favorable payoffs. They adopt a nonlinear regime-dependent model approach and add the fundamental equilibrium exchange rate (FEER) to their model. In distinction to our study, they choose the threshold value exogenously. Christiansen et al. (2011) provide a factor model with regression coefficients dependent on market volatility and liquidity to assess carry trade strategies. In volatile periods the excess returns have much higher exposure to the stock market and also more mean reversion.

To the best of our knowledge, there is only one theoretical contribution in the literature

³Gagnon and Chaboud (2007) define canonical carry trades as borrowing low-yielding currencies and investing the proceeds in high-interest-rate currencies. In contrast, derivatives carry trades are defined as taking on leveraged positions in derivatives markets. More on this issue is provided in Section 3.1.

that focuses specifically on carry trades. Plantin and Shin (2011) provide a model in which externalities among traders can generate the classic exchange rate price pattern ‘going up the stairs, and coming down in the elevator’. Whether carry trades are stabilizing or de-stabilizing at shorter horizons depends on the capital recipient economy’s monetary policy.

3 Data

3.1 Variables

We collected data to examine the Swiss franc (CHF) carry trade with the US dollar (USD) or the euro (EUR) as respective target currency. The variables of interest are the interest-rate differential (IRD_{USD} , IRD_{EUR}), the nominal exchange rate (FX_{USD} , FX_{EUR}), the VIX index (VIX), 10-year bond yields (Y_{USD} , Y_{EUR}), stock market prices (P_{USD} , P_{EUR}) and carry trade positions (CTF_{USD} and $CTFO_{USD}$, CT_{EUR}). All variables are described in Table 1. A similar set of variables is widely chosen in the literature (see, e.g., Nishigaki, 2007; Brunnermeier et al., 2009 or Ranaldo and Söderlind, 2010).

For the calculation of the IRD_{USD} and IRD_{EUR} we obtain 3-month interbank interest rates. The carries are defined as the difference between the respective target currency interest rate (United States or Euro area) and the Swiss interest rate. Accordingly, we employ the nominal exchange rates CHF/USD, FX_{USD} , as well as CHF/EUR, FX_{EUR} . Furthermore, the VIX volatility index, VIX , from the Chicago Board Options Exchange (CBOE) serves as a proxy for the expected stock market risk. Brunnermeier et al. (2009) argue that the index is a useful proxy for investor sentiment or ‘global risk appetite’.

For an analysis on carry trade positions based on the Swiss and US markets, prices on the

Table 1: Description and Construction of the Variables

Abbr.	Variable	Source
IRD_{USD}	Interest rate differential: 3-month US Libor - 3-month Swiss Libor	Datastream
IRD_{EUR}	Interest rate differential: 3-month EUR Libor - 3-month Swiss Libor	Datastream
FX_{USD}	Nominal exchange rate to USD: $\log(\text{CHF}/\text{USD})$	Datastream
FX_{EUR}	Nominal exchange rate to EUR: $\log(\text{CHF}/\text{EUR})$	Datastream
VIX	Implied stock market volatility index: $\log(\text{VIX index})$	Datastream
Y_{USD}	10-year constant-maturity Treasury bond yields	Datastream
Y_{EUR}	Synthetic euro benchmark bond yields	Datastream
P_{USD}	$\log(\text{S\&P 500 price index})$	Datastream
P_{EUR}	$\log(\text{Euro Stoxx 50 price index})$	Datastream
<i>Carry Trade Positions</i>		
CTF_{USD}	$\log(\text{short CHF futures}) - \log(\text{long CHF futures})$	CFTC
$CTFO_{USD}$	$\log(\text{short CHF futures \& options}) - \log(\text{long CHF futures \& options})$	CFTC
CT_{EUR}	Carry-to-risk ratio: (3-month IRD_{EUR} / implied CHF/EUR exchange rate volatility)	Datastream, Bloomberg

US stock exchange market index S&P 500, P_{USD} , and 10-year constant-maturity Treasury bond yields, Y_{USD} , were collected. If the EUR serves as target currency, prices of the euro stock exchange market index Euro Stoxx 50, P_{EUR} , and the synthetic euro benchmark bond yield series,⁴ Y_{EUR} , are used.

Trades in the currency markets are usually over-the-counter, making it difficult to find appropriate proxies for carry trade positions. Hence, we rely on data from the U.S. Commodity Futures Trading Commission (CFTC) for carry trade positions with regard to the USD. These contracts are traded on the Chicago Mercantile Exchange (CME). Since October 1992, long and short currency futures positions of non-commercial traders are published periodically. All investors are classified as non-commercial or commercial. Commercial investors have currency risk hedging purposes defined by the CFTC. We are only interested in positions held by those traders who basically trade for speculative purposes.

Burnside et al. (2006) show that a strategy of borrowing the low-interest-rate currency and lending the high-interest-rate currency yields a positive payoff if, and only if, a forward contract has a positive payoff. According to Brunnermeier et al. (2009), few investors actually implement the carry trade using the spot currency market since futures contracts are economically equivalent.

Our proxy for carry trade positions has several shortcomings. First, these data reflect only a very small fraction of currency trades.⁵ Second, they are not necessarily results from carry trades, and the classification of commercial and non-commercial traders might be inaccurate in some cases (Galati et al., 2007). Finally, Gagnon and Chaboud (2007) show that the timing of changes in these positions might not be perfectly accurate in all cases. For example, the unwinding of yen carry trades in October 1998 is not displayed in the data. Despite these shortcomings, these futures positions are the best publicly available data (Brunnermeier et al., 2009).

Furthermore, we calculate the so-called ‘success rate’. For the samples considered in our study, we count the observations for which the investors increase the net long futures positions (decrease the net long futures positions) and the CHF appreciates (depreciates) against the USD. The success rate is in the range of 69% and 87%, and above 75% three-quarters of the time. In line with the results of Klitgaard and Weir (2004), we find a strong contemporaneous correlation between changes in net futures positions and exchange rate fluctuations. Thus, knowing the traders actions gives a reasonable chance of correctly estimating the direction of the exchange rate movement during the same week.

A new data set including futures and options was launched by the CFTC at the end of March 1995. Keeping in mind that an option contract differs in several respects from a futures contract, we use these data for our robustness analysis. From Mogford and Pain (2006) we know

⁴The US benchmark bond yield series from Datastream is almost identical to the 10-year constant-maturity Treasury yields for the US market. Hence, the Euro benchmark bond yield series is a reliable proxy for our purposes.

⁵Following Klitgaard and Weir (2004) a substantial part of the high foreign exchange transaction volume reflects traders’ risk management. Hence, the global volume by itself does not preclude the possibility that participations in futures markets might cause currency movements.

that speculative future positions from the CME and risk reversals, reflecting the views of options purchasers, move a significant number of times in the same direction.

Carry trade positions are defined as the difference between short and long futures positions, CTF_{USD} , or as the difference between short and long futures and options positions, $CTFO_{USD}$.

If the net position is positive (negative), investors are involved in carry trades with the CHF as a funding (target) currency. These currency futures position data are not available for the EUR. Thus, we use the carry-to-risk ratio (CTR ratio) as a proxy for carry trade activities, CT_{EUR} . The CTR ratio is defined as the 3-month interest-rate differential divided by the implied volatility derived from 3-month at-the-money exchange rate options. Data on implied exchange rate volatility are taken from Bloomberg. Unfortunately, due to data limitations, we are not able to examine further target currencies.

The choice of the CTR ratio as proxy for carry trade positions has several caveats as the CTR ratio does not represent (carry trade) positions directly. Nevertheless, professional currency market watchers take it as an important indicator for carry trade activities. Furthermore, Galati et al. (2007) find significant correlations between the CTR ratio and futures positions traded at the CME.⁶

We take the natural logarithm of the nominal exchange rates, stock market prices, the VIX index and futures (and options) positions.

3.2 Sample Period and Frequency

The weekly sample period with the USD as target currency starts with 03/28/1995 and ends with 06/24/2008. For our robustness analysis, we estimate the model with different sample lengths. We add observations until the end of 2009 to address the recent financial crisis or start with 10/06/1992. For model specifications in which the EUR serves as the target currency, we use data for the time period from 01/06/1999 to 06/25/2008.

We determined the data frequency according to the variable with the lowest frequency published, as we expect a strong short-run relationship between the variables included in this study. Futures position data from the CME are published weekly, thus leading to a weekly frequency. To ensure comparability along the frequency dimension, we also apply weekly data for the model with the CTR ratio as a proxy for carry trade positions. In contrast, Brunnermeier et al. (2009) include quarterly data, whereas Nishigaki (2007) estimates his model with monthly data.

4 Methodology

We use a multivariate threshold model to analyze the relationship between key financial and macroeconomic variables focusing on carry trade positions. Hassan and Mano (2014) argue that carry trades are driven by persistent interest-rate differentials (IRD) due to asymmetries in

⁶These correlations always involve the USD. Moreover, Brunnermeier et al. (2009) argue that the past return of carry trades is perhaps a better measure for carry trade positions than futures data from the CME. In this case, the CTR ratio is, owing to its forward-looking nature, also a good proxy in a world with rational market participants.

currency risk premia reflecting relative country size or financial development. Therefore, given these asymmetries, a rise in the IRD should boost carry trades activities and a linear econometric model with respect to the IRD could be chosen. On the other hand, relative purchasing power parity (PPP) seems to hold in the medium to long run conditional on real shocks (Coakley et al., 2005). However, the adjustment of the (real) exchange rate to deviations from PPP is often found to be nonlinear because of transaction costs in international arbitrage, the heterogeneity of opinion concerning the equilibrium level of the exchange rate, or more likely interventions by central banks (for a survey, see Taylor and Taylor, 2004). As a result, a widening of the (expected) inflation-rate differential that pushes the IRD above a certain threshold value may trigger a fast convergence of the exchange rate toward the PPP value, which reverses the higher returns resulting from the IRD. This, in turn, may impact the behavior of carry traders. The choice of the method and the IRD as threshold variable is also based on a descriptive analysis, econometric tests and reported information.

First, the descriptive analysis serves to detect sub-periods separated by an endogenous threshold value of the IRD. The results of this analysis are presented in Figures (1) and (2). The former depicts the 3-month interest-rate differential, IRD_{USD} , between the United States and Switzerland. Until 2001, the IRD_{USD} spread was substantial (about 3% to 4.5%). Subsequently, the difference decreased to around zero percent in November 2001. The following upward trend reaches its maximum of almost 4% at the end of June 2006. The financial crises caused the IRD_{USD} to fall again. Thus, we were able to construct one sub-sample containing high IRD and another with smaller differences, allowing the sub-periods to be discontinued, i.e. one sub-period is interrupted by the other one.

Analogously, Figure (2) illustrates the IRD_{EUR} . The starting point of the sample is the euro



Figure 1: IRD between the US and Swiss 3-month interbank interest rates (IRD_{USD})

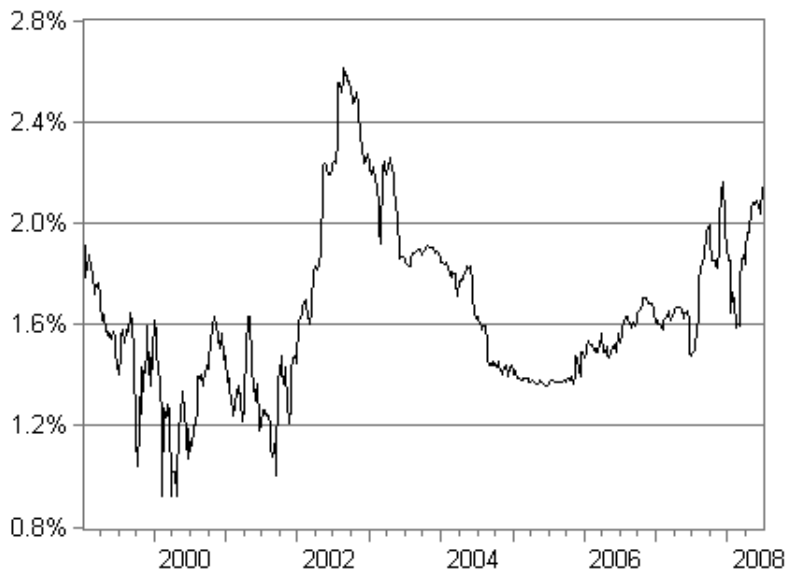


Figure 2: IRD between the Euro and Swiss 3-month interbank interest rates (IRD_{EUR})

launch. The amplitudes of the IRD_{EUR} are not as distinct as for the IRD_{USD} . Nevertheless, three time periods with higher IRD_{EUR} could be identified: the beginning of the sample, the period from mid-2002 to almost the end of 2004 and the end of the sample.

Moreover, these findings are also reflected in the residuals of a regression of the IRD on a constant and lagged values of all variables. The residuals follow a very similar pattern to the IRD themselves.

Second, the insights of the descriptive analysis are confirmed by the estimation results of a reduced vector autoregressive regression model (VAR) for the whole period. We have to reject the null hypothesis of no autoregressive conditional heteroscedasticity (ARCH) for the majority of error term variances. The results are summarized in the Tables (11) and (12) in Appendix A.1. This is not surprising, since we have high frequency financial variables in our model.⁷ Nevertheless, this result indicates a nonlinear relationship between the variables considered.

Finally, professional currency market analysts argue that there exists a threshold level for the IRD, above which investor behavior changes.⁸ We assume that the dynamic behavior of carry trade positions depends on the magnitude of the IRD, and therefore apply a multivariate threshold model for our empirical investigation (Tsay, 1998). Similar methods to study relationships where nonlinear effects are present are used by Canjels et al. (2004), Bernholz and Kugler (2011) and others.

⁷The variance of the error term might follow an ARCH/GARCH process when financial variables are included in a model with high frequency data (see, e.g., Engle, 2001).

⁸I would like to thank the Head FX Research of a major Swiss bank for this important information.

4.1 Multivariate Threshold Model and GIR Functions

Before we turn to the econometric model, we test the appropriateness of a multivariate threshold model by applying a test developed by Tsay (1998). The observations are ordered in descending order of the lagged threshold variable to estimate the recursive residuals. The lag is determined by the threshold delay parameter, d . If the dependent variables are linear, then the recursive least squares estimator of the arranged VAR model is consistent, i.e. the coefficients are zero (Tsay, 1998). Compared to the standard test, we modify its computation to account for conditional heteroscedasticity (Tsay, 1998), i.e. the correlation between the squared error terms and the elements of $X_t'X_t$. The variances of the least squares estimates are adjusted by correcting the weights to standardize the predictive residuals of the recursive least squares estimations. The test results confirm the preliminary findings, pointing to a multivariate threshold model.

The generalized multivariate threshold model can then be written as:

$$\mathbf{y}_t = \mathbf{c}^{(j)} + \Phi_1^{(j)}\mathbf{y}_{t-1} + \dots + \Phi_p^{(j)}\mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t \quad \text{if } \tau_{j-1} \leq y_{1,t-d} < \tau_j,$$

where \mathbf{y}_t denotes a (6×1) vector containing the values at date t of six variables (interest-rate differential, VIX index, carry trade positions, nominal exchange rate, bond yields, stock market index), $\mathbf{c}^{(j)}$ are the constant vectors for the different regimes, and $\Phi^{(j)}$ denotes a (6×6) coefficient matrix of the respective lag and regime. The vector of error terms is denoted as $\boldsymbol{\epsilon}$, and p is the number of lags included. Let $-\infty = \tau_0 < \tau_1 < \dots < \tau_{s-1} < \tau_s = \infty$. Then $j = 1, \dots, s$ represents the different regimes.

We concentrate on models with two regimes, hence, we have only one threshold value and $s = 2$.⁹ The multivariate threshold model applied with two regimes has the following form:

$$\mathbf{y}_t = \mathbf{c}^{(1)} + \Phi_1^{(1)}\mathbf{y}_{t-1} + \dots + \Phi_p^{(1)}\mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t \quad \text{if } y_{1,t-d} < \tau, \quad (1)$$

$$\mathbf{y}_t = \mathbf{c}^{(2)} + \Phi_1^{(2)}\mathbf{y}_{t-1} + \dots + \Phi_p^{(2)}\mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t \quad \text{if } y_{1,t-d} \geq \tau. \quad (2)$$

The observations of a specific date are included in the first regime (Equation 1) if the threshold variable y_1 is below the threshold value, τ , to the second regime (Equation 2) otherwise. The determination of the delay parameter, d , is based on the test statistic of the Tsay test. In order to determine the threshold value we use a grid search over a reasonable interval of possible values of the threshold variable. The selection of τ is based on the minimized determinant of the variance-covariance matrix. When τ is known, we can estimate the model by ordinary least squares (OLS). Concretely, we estimate the following model:

$$\mathbf{y}_t = \mathbf{c} + (\Phi_1^{(1)}\mathbf{y}_{t-1} + \dots + \Phi_p^{(1)}\mathbf{y}_{t-p})D_{t-d} + (\Phi_1^{(2)}\mathbf{y}_{t-1} + \dots + \Phi_p^{(2)}\mathbf{y}_{t-p})(1 - D_{t-d}) + \boldsymbol{\epsilon}_t,$$

where a dummy variable D is defined as being one if $y_{1,t-d} < \tau$, and zero if $y_{1,t-d} \geq \tau$.

Since Sims (1980) seminal paper, vector autoregressions (VARs) are routinely carried out to

⁹The model was also estimated with two threshold values and with the first difference of the IRD as threshold variable. In these cases, the estimation technique does not change, only the notation becomes slightly more complicated.

study dynamic systems. In numerous studies, researchers rely on the Cholesky decomposition to structure the estimation model. Both Nishigaki (2007) and Brunnermeier et al. (2009) use this approach to examine carry trade positions. The structural shocks are obtained by orthogonalizing the estimated reduced-form error terms. However, the ordering of variables in the system matters for the results (Pesaran and Shin, 1998). In many cases it is very difficult to establish a particular recursive ordering on economic theory or institutional knowledge (Stock and Watson, 2001). Therefore, we prefer to compute generalized impulse response functions (GIRFs) as proposed by Koop et al. (1996) and Pesaran and Shin (1998), whereby the variance-covariance matrix itself matters, since the interdependence of the shocks is carried over to the impulse responses.¹⁰ This alternative approach is invariant to the ordering of variables, instead, it lacks the possibility of identifying a specific shock.

4.2 Confidence Interval: Bootstrap Method

The confidence intervals of impulse responses are routinely computed with bootstrap methods. Kilian (1998b) shows that traditional bootstrap methods such as the frequently applied non-parametric approach developed by Runkle (1987) are inaccurate in the presence of bias and skewness in the small-sample distribution of impulse response estimators. Thus, we adopt his bias-correction (Kilian, 1998b), because the construction of sub-periods reduces the number of observations to a great extent. Additionally, Kilian (1998a) demonstrates the outperformance of the bias-corrected confidence intervals if there is evidence of fat tails or skewness in the error distribution, i.e. the residuals' departure from normality. The distribution of a few estimated residuals in our study suffers from non-normality, not only in the full sample but also in the regimes.

As stated earlier, by considering the full samples, we have to reject the null hypothesis of no ARCH effects for the majority of error term variances. However, we conduct the resampling of residuals only within regimes but not across them. The problem is far less severe in the regimes, but it is still present. At least partly, deviations from normality reflected by excess kurtosis could also be explained by unknown ARCH/GARCH processes. Since the bias-correction cannot account for biases introduced by ARCH/GARCH processes (Kilian, 1998a), we change the computation of the confidence intervals to deal with unknown ARCH/GARCH processes.

Based on the work by Goncalves and Kilian (2004), we modify the residuals such that we can treat them as *i.i.d.* In order to break up the time interdependence between the estimated residuals we multiply the sequence of residuals with an *i.i.d.* sequence with mean zero and variance one, drawn from a standard normal distribution. However, we extend the recursive-design wild bootstrap method for univariate models proposed by Goncalves and Kilian (2004) to multivariate models. The application of this method to a multivariate system creates a problem of correctly treating the cross interdependence between residuals of different estimation equations. To overcome this cross interdependence we rely on Pesaran and Shin (1996). In a

¹⁰We follow the approach by Pesaran and Shin (1998) as we correct the estimates for small-sample bias and departures from non-normality of the error terms (Kilian, 1998a,b). Furthermore, results from a recursive VAR consistent with Nishigaki (2007) indicate that the GIRFs are reasonable.

first step, the residuals are multiplied by the inverse of the Cholesky decomposition:

$$\boldsymbol{\xi} = \mathbf{P}^{-1}\hat{\boldsymbol{\epsilon}},$$

where $\boldsymbol{\xi}$ is a $(m \times T)$ matrix and $\hat{\boldsymbol{\epsilon}}$ are the estimated residuals. T is the number of observations and m the number of variables. The resulting terms in the matrix $\boldsymbol{\xi}$ are independent from each other for every t . The error terms for which we reject the null hypothesis of no ARCH of order one and/or two and/or four at the 5% significance level are multiplied element by element with i.i.d. sequences described above.¹¹ The resulting matrix $\boldsymbol{\Gamma}$ has dimension $(m \times T)$. We recover the contemporaneous correlation structure as follows:

$$\hat{\boldsymbol{\epsilon}}^* = \mathbf{P}\boldsymbol{\Gamma},$$

where \mathbf{P} denotes the Cholesky decomposition matrix. Finally, the matrix $\hat{\boldsymbol{\epsilon}}^*$ contains modified residuals with the same cross interdependence, but no interdependence over time.

All of these modifications have the property to enlarge the non-centered 95%-confidence intervals of our empirical study. The confidence intervals are based on 11,000 random draws, where the first 1,000 draws are used to compute the bias-correction.

5 Empirical Results

5.1 Preliminary Analysis

In this subsection, we briefly describe the results of the preliminary analysis necessary prior to the estimation of the multivariate threshold model.

5.1.1 Stationarity Tests

In a first step, the time series properties of the variables are examined. For this purpose, the test proposed by Phillips and Perron (1988) and the augmented Dickey and Fuller (1979) unit root test are applied to the variables. Tables (2) and (3) report the results for the models for which the USD serves as the target currency of carry trades. The results point clearly to stationarity of the carry trade positions and the VIX index, regardless of the sample choice. For the 10-year constant-maturity Treasury bond yields the results are borderline. Even if the null hypothesis cannot be rejected, the test statistic is very close to the critical value of the 10% significance level. For the remaining three variables, the CHF/USD exchange rate, the price of the S&P 500 and the interest-rate differential (IRD) the null hypothesis of non-stationarity cannot be rejected.

Table (4) presents the results for the sample with the EUR as target currency. Again, the proxy for carry trade activities is clearly stationary. The results for the VIX index also points

¹¹The computation of the GIRFs requires a constant variance-covariance matrix (Koop et al., 1996). The presence of unknown ARCH/GARCH processes might lead to a time-variant variance-covariance matrix. However, we assume that our results are not strongly biased, since we conduct the resampling of residuals only within regimes in which only few or even no error term variances follow an unknown ARCH/GARCH process.

Table 2: PP and ADF Unit Root Test Results with the USD as Target Currency

	March 1995 - June 2008		March 1995 - Dec 2009	
	PP	ADF	PP	ADF
FX_{USD}	-1.530	-1.539	-1.987	-2.009
P_{USD}	-2.243	-2.178	-2.284	-2.214
VIX	-3.717***	-3.612***	-3.744***	-3.507***
IRD_{USD}	-0.624	-0.720	-0.692	-0.877
Y_{USD}	-3.122	-3.109	-3.420**	-3.385*
<i>Carry Trade Positions</i>				
CTF_{USD}	-6.785***	-6.984***	-7.021***	-7.230***
$CTFO_{USD}$	-6.801***	-6.575***	-7.029***	-7.226***

Notes: FX_{USD} , P_{USD} and Y_{USD} : A deterministic trend is included. PP: Bartlett kernel, Newey-West bandwidth. ADF: Lag length selection by modified SIC (Ng and Perron, 2001). */**/** denotes significance at 10%, 5% and 1% level, respectively.

Table 3: PP and ADF Unit Root Test Results with the USD as Target Currency

	Oct 1992 - June 2008		Oct 1992 - Dec 2009	
	PP	ADF	PP	ADF
FX_{USD}	-1.568	-1.547	-1.946	-1.953
P_{USD}	-1.299	-1.238	-1.292	-1.351
VIX	-3.746***	-3.620***	-3.480***	-3.679***
IRD_{USD}	-2.354	-1.824	-2.200	-2.818
Y_{USD}	-3.197*	-3.043	-3.326*	-3.525**
<i>Carry Trade Positions</i>				
CTF_{USD}	-7.237***	-7.323***	-7.566***	-7.468***

Notes: FX_{USD} , P_{USD} , IRD_{USD} and Y_{USD} : A deterministic trend is included. PP: Bartlett kernel, Newey-West bandwidth. ADF: Lag length selection by modified SIC (Ng and Perron, 2001). */**/** denotes significance at 10%, 5% and 1% level, respectively.

to stationarity. For all other time series the unit root null cannot be rejected.

All results are confirmed by applying the Kwiatkowski et al. (1992) stationarity test and the two unit root tests from Elliott et al. (1996) and Ng and Perron (2001). Moreover, all of them point to a (weak) stationary IRD between the 3-month interbank interest rates from Switzerland and the Euro area for the period from January 1999 to June 2008, and a (weak) stationary carry-to-risk ratio for the period from January 1999 to December 2009.¹²

The outcomes of tests for non-stationarity of the time series are in line with the findings of other empirical studies (see, e.g., Nishigaki, 2007). From a theoretical point of view it is surprising that the null hypothesis cannot be rejected for the difference between the US and Swiss 3-month interbank interest rates. This result implies that the correct model specification includes the first difference of the IRD. However, there is no economic justification for a random walk behavior of the IRD, specifically in the long run. In addition, the test result might be

¹²These results are not published but can be obtained from the author upon request.

Table 4: PP and ADF Unit Root Test Results with the EUR as Target Currency

	Jan 1999 - June 2008		Jan 1999 - Dec 2009	
	PP	ADF	PP	ADF
FX_{EUR}	-2.015	-2.107	-1.998	-1.586
P_{EUR}	-1.263	-1.170	-1.519	-1.346
VIX	-2.911**	-2.746*	-2.917**	-2.705*
IRD_{EUR}	-2.098	-2.067	-1.181	-1.027
Y_{EUR}	-1.709	-1.574	-1.732	-1.649
<i>Carry Trade Positions</i>				
CT_{EUR}	-3.461***	-3.603***	-2.127	-1.748

Notes: FX_{EUR} : A deterministic trend is included. PP: Bartlett kernel, Newey-West bandwidth. ADF: Lag length selection by modified SIC (Ng and Perron, 2001). */**/** denotes significance at 10%, 5% and 1% level, respectively.

biased due to the nonlinear threshold nature of this variable. Moreover, as long as the model is stationary and no spurious regression problem arises, the coefficients are estimated consistently, even if the model contains non-stationary variables (Sims et al., 1990). Furthermore, we believe that the divergence of the IRD within the threshold model regimes is much smaller than in the full sample. Hence, the variable might be even stationary.¹³ Therefore, we assume that the IRD are stationary.¹⁴

Thus, the model contains the nominal exchange rates (ΔFX_{USD} , ΔFX_{EUR}), the prices of the stock market indices (ΔP_{USD} , ΔP_{EUR}) and ΔY_{EUR} in first differences. The interest-rate differential (IRD_{USD} , IRD_{EUR}), the VIX volatility index (VIX) and the proxies for carry trade activities (CTF_{USD} and $CTFO_{USD}$, CT_{EUR}) enter the model in levels. Furthermore, we assume the 10-year constant-maturity Treasury bond yield series to be trend-stationary and remove the linear trend from the series, Y_{USD} . Following the unit root test results, the series is at least very close to being trend-stationary.¹⁵ Table (5) displays the definitions of the samples, where the subscript to the sample notations indicates the target currency. We do not show all results for the samples constructed to analyze the robustness of the findings.¹⁶

5.1.2 Threshold Nonlinearity Test and Grid Search

Prior to testing threshold nonlinearity, we determine the number of lags included in the model. According to the Akaike & Schwarz lag length selection test results, the optimal lag length is either one or two. But with very few lags included, the estimated residuals exhibit strong serial correlations, as both multivariate and univariate Lagrange multiplier (LM) test results show.

¹³The sample sizes of the sub-periods are too small to get reasonable results from applying unit root tests. This issue is restated in Section 5.4 where the results of the Granger causality tests are discussed.

¹⁴We also estimated the model with the first difference of the IRD. In contrast to the model with the IRD in levels, we do not find nonlinear effects for all sample periods. For the periods where we do find nonlinear relationships, the results support our findings.

¹⁵It is well known that these tests have poor power properties relative to the alternative which follows a persistent stationary stochastic process (see, e.g., Christiano et al., 2003).

¹⁶These results can be obtained from the author upon request.

Table 5: Sample Definitions

Sample	Period	Variables						
		3-Month LIBOR	IRD	Carry Trade	Positions	FX	Bond Yields	Stock Market Index
<i>Main Samples</i>								
A_{USD}	March 1995 - June 2008	IRD_{USD}		CTF_{USD}		ΔFX_{USD}	Y_{USD}	ΔP_{USD}
B_{EUR}	Jan 1999 - June 2008	IRD_{EUR}		CTE_{EUR}		ΔFX_{EUR}	ΔY_{EUR}	ΔP_{EUR}
<i>Samples for Robustness Analysis</i>								
C_{USD}	March 1995 - Dec 2009	IRD_{USD}		CTF_{USD}		ΔFX_{USD}	Y_{USD}	ΔP_{USD}
D_{USD}	Oct 1992 - June 2008	IRD_{USD}		CTF_{USD}		ΔFX_{USD}	Y_{USD}	ΔP_{USD}
E_{USD}	March 1995 - June 2008	IRD_{USD}		$CTFO_{USD}$		ΔFX_{USD}	Y_{USD}	ΔP_{USD}
F_{EUR}	Jan 1999 - Dec 2009	IRD_{EUR}		CTE_{EUR}		ΔFX_{EUR}	ΔY_{EUR}	ΔP_{EUR}

Notes: The sources and more details about the variables are described in Section 3.1. All samples additionally include the VIX index. Y_{USD} is linearly detrended.

Table 6: Univariate Serial Correlation LM Test Results

Dependent Variable	Sample A _{USD}			Sample B _{EUR}		
	AR(1)	AR(2)	AR(4)	AR(1)	AR(2)	AR(4)
$\Delta FX_{USD} / \Delta FX_{EUR}$	0.040	0.101	3.150	0.081	0.117	5.153
$\Delta P_{USD} / \Delta P_{EUR}$	0.026	0.329	5.592	4.828**	6.195*	11.548**
<i>VIX</i>	0.005	0.137	5.006	5.972**	5.966*	7.404
IRD_{USD} / IRD_{EUR}	0.971	2.935	7.269	1.953	6.313**	12.804**
$Y_{USD} / \Delta Y_{EUR}$	1.382	2.011	4.522	0.731	2.594	4.238
<i>Carry Trade Positions</i>						
CTF_{USD} / CTF_{EUR}	5.408**	5.335*	5.598	1.737	5.638*	6.131

Notes: The samples are described in Table (5). The LM test results are based on four lags for sample A_{USD} and two lags for sample B_{EUR}. */**/** denotes significance at 10%, 5% and 1% level, respectively.

Therefore, we must include more lags to avoid having inconsistent estimators. Thus, the choice of the lag length is based on serial correlation tests for the error terms. We tested for serial correlation in the residuals with the multivariate and univariate LM tests of order one, two and four. The optimal lag length of the samples A_{USD}, C_{USD} and E_{USD} is four. For the sample D_{USD}, we choose five, and for sample B_{EUR} and F_{EUR}, two lags.¹⁷ Except for sample B_{EUR}, neither including more lags nor reducing the number of lags improves the serial correlation test results noticeably. We estimate sample B_{EUR} with two instead of three lags, because the threshold model cannot be estimated accurately otherwise.¹⁸ Nevertheless, a few error terms of the models estimated with the optimal lag length still exhibit serial correlation. The test results for the univariate serial correlation LM test are summarized in Table (6). Moreover, the multivariate serial correlation LM test rejects the null hypothesis of no serial correlations of order four for sample A_{USD} at the 5% significance level. For sample B_{EUR}, the null hypothesis of no serial correlations of order one, two and four is rejected at the 10% significance level. The misspecification of a simple linear model might lead to these results.

The Tsay test to detect threshold nonlinearity, corrected for the possibility of conditional heteroscedasticity, is applied with delay parameters, d , equal to one, two and three. For reasons discussed in Section 4, we choose the interest-rate differential as the threshold variable. The findings for all samples are shown in Table (7). Overall, we conclude that for the majority of model specifications we can reject the null hypothesis of parameter stability. If threshold nonlinearity is present for more than one value of d , we aim to choose d such that it corresponds to the maximum of the Chi-squared test statistic. For different reasons this is not always achievable. The threshold value for sample B_{EUR} with $d = 2$ leaves for one of the two regimes too few observations for an accurate estimation. Hence, we set the delay parameter equal to three. Sample F_{EUR} is estimated with $d = 1$ because one of the regimes has an eigenvalue greater than unity with $d > 1$. For sample A_{USD} we choose $d = 3$ instead of $d = 2$, because

¹⁷The results of sample D_{USD} are robust to the estimation with four lags.

¹⁸ The threshold value determined to detect the two regimes leaves for one regime too few observations for reliable estimations.

Table 7: Results of the Tsay Test

Sample	Delay Parameter (d)		
	1	2	3
<i>Main Samples</i>			
A_{USD}	221.2 (150)***	212.1(150)***	211.5 (150)***
B_{EUR}	219.6(78)***	274.1(78)***	273.5 (78)***
<i>Samples for Robustness Analysis</i>			
C_{USD}	225.4(150)***	190.0(150)**	247.4 (150)***
D_{USD}	238.7(150)***	206.0(150)***	222.2 (150)***
E_{USD}	214.6(150)***	220.5(150)***	183.3 (150)**
F_{EUR}	160.6 (78)***	204.3(78)***	187.6(78)***

Notes: The samples are described in Table (5). The estimated models are denoted by extra bold type. The degrees of freedom are written in brackets. */**/** denotes significance of the Chi-squared value at 10%, 5% and 1% level, respectively.

the latter value is preferred for the samples C_{USD} and D_{USD} . Sample E_{USD} is estimated with the delay parameter equal to three for purposes of comparison. As the differences between the test statistics are small, sample A_{USD} is estimated with $d = 1$ and $d = 3$ to check for possible variations in the impulse response functions. Our main model specifications are $A_{USD}^{d=3}$ and $B_{EUR}^{d=3}$. All versions estimated are denoted by extra bold type.

In order to estimate the multivariate threshold model, the threshold values for all model specifications are determined. The selection of the threshold value, τ , is based on a grid search for the minimized determinant of the variance-covariance matrix. Table (8) depicts τ for the different models.

As shown in Figures (1) and (2), IRD_{USD} and IRD_{EUR} are almost always positive over all sample periods. Therefore, we search for a value which separates two regimes depending on the

Table 8: Threshold Values (Percentage)

Sample	Delay Parameter (d)	
	1	3
<i>Main Samples</i>		
A_{USD}	2.12	2.63
B_{EUR}		1.84
<i>Samples for Robustness Analysis</i>		
C_{USD}		2.17
D_{USD}		2.94
E_{USD}		2.63
F_{EUR}		1.91

Notes: The samples are described in Table (5).

size of the IRD. One regime contains observations with values of the threshold variable greater than or equal to τ , all other observations are collected in the other regime. The threshold values are between 1.84% and 2.94%. Compared to $A_{USD}^{d=3}$, τ falls if additional observations until the end of 2009 are added (sample C_{USD}) or if a smaller delay parameter value is chosen ($d = 1$). The contrary is true for sample D_{USD} starting with 10/06/1992. The inclusion of options positions does not alter the result.¹⁹

5.2 Estimated Generalized Impulse Responses

In this section, we discuss the generalized impulse response functions (GIRFs) of the main samples $A_{USD}^{d=3}$ and $B_{EUR}^{d=3}$. For sample $A_{USD}^{d=3}$ we compute the GIRFs for the regime with values of $IRD_{USD}^{d=3}$ greater than or equal to the threshold value of 2.63%. This regime is denoted as H-regime. The GIRFs for the regime with values of $IRD_{USD}^{d=3}$ smaller than 2.63% are shown in the L-regime. The same approach determines the GIRFs of sample $B_{EUR}^{d=3}$ with the threshold variable $IRD_{EUR}^{d=3}$ and the threshold value of 1.84%. The (accumulated) GIRFs of all variables at a forecast horizon up to 40 weeks are summarized in Appendix A.2, Figures (12)-(15). We present the point estimates (solid line), the median of the bootstraps (dashed-dotted line) and the non-centered 95%-confidence interval (dotted lines).

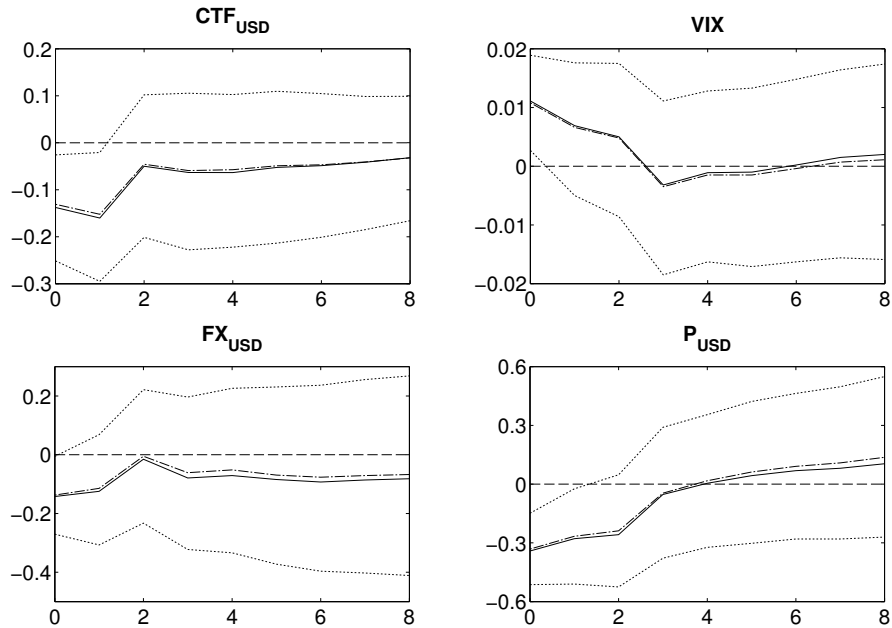


Figure 3: Sample $A_{USD}^{d=3}$: (Accumulated) GIRFs of the variables CTF_{USD} , VIX , ΔFX_{USD} and ΔP_{USD} in response to a one-standard deviation ΔIRD_{USD} shock in the H-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $A_{USD}^{d=3}$ see Table (5). Number of observations: 418

¹⁹In addition, for the main samples, we searched for two threshold values instead of one. The minimized determinant of the variance-covariance matrix of sample A_{USD} increases in the specification with two threshold values. Therefore, the model with one threshold value is preferred. For sample B_{EUR} the minimized determinant is smaller. However, as the grid search reveals that one threshold value is almost equal to 1.84% and the other is very close to the minimum value of IRD_{EUR} , we consider only models with one threshold value.

Figure (3) shows the (accumulated) GIRFs of the sample $A_{USD}^{d=3}$ VAR system in response to a one-standard deviation IRD_{USD} shock in the H-regime. An unexpected increase in IRD_{USD} , through an increase in the US interest rate and/or a decrease in the Swiss interest rate, is associated with a statistically significant contemporaneous rise in VIX , a decline in CTF_{USD} and P_{USD} , as well as an appreciation of the Swiss currency. The impacts on CTF_{USD} and P_{USD} last slightly longer than one week. While the increased IRD_{USD} improves the environment for a profitable carry trade strategy, other variables such as risk sentiment and US stock market prices indicate a rising risk for a sudden and strong unwinding of carry trades. This result echoes the finding of Brunnermeier et al. (2009) that the conditional skewness becomes more negative after an interest-rate differential shock. The response of FX_{USD} is (partially) in line with the prediction of uncovered interest parity (UIP). The immediate appreciation of the low-interest-rate currency could be affected by the fall in CTF_{USD} , among other factors such as the decrease in the investors risk appetite. The so-called ‘safe haven’ property of the CHF might be an explanation for the lack of the initial USD appreciation. Clarida et al. (2009) show that in high exchange rate volatility environments the low-yielding currency tends to appreciate even more than implied by UIP.

In the L-regime the effects are different (see Figure 4). In the short run none of the responses are statistically significant. Nevertheless, some long-run trends are revealed. The shock tends to result in a lower risk sentiment, a continuous depreciation of the CHF, pointing to the UIP puzzle, and an increase in P_{USD} . Although in the short run CTF_{USD} hardly moves, in the period

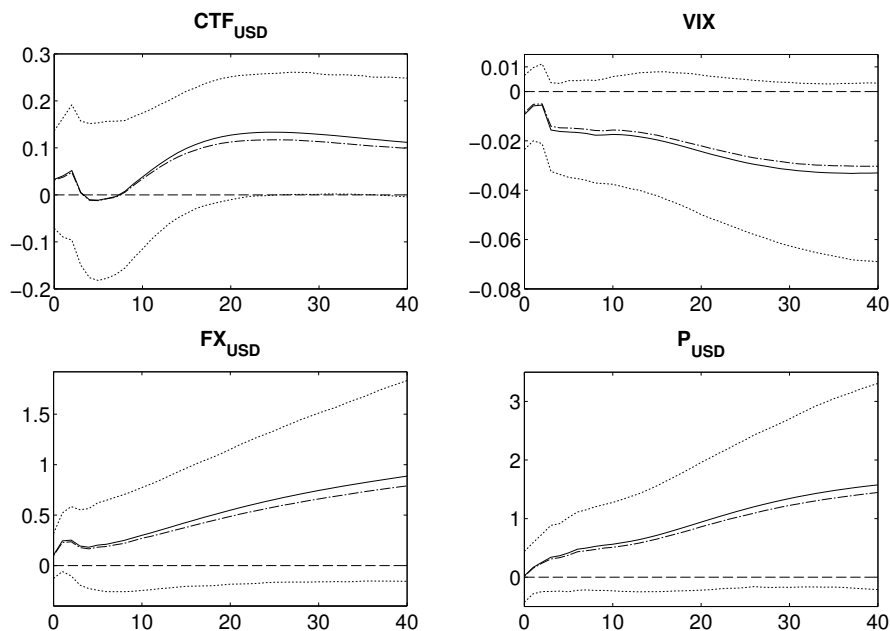


Figure 4: Sample $A_{USD}^{d=3}$: (Accumulated) GIRFs of the variables CTF_{USD} , VIX , ΔFX_{USD} and ΔP_{USD} in response to a one-standard deviation ΔIRD_{USD} shock in the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $A_{USD}^{d=3}$ see Table (5). Number of observations: 270

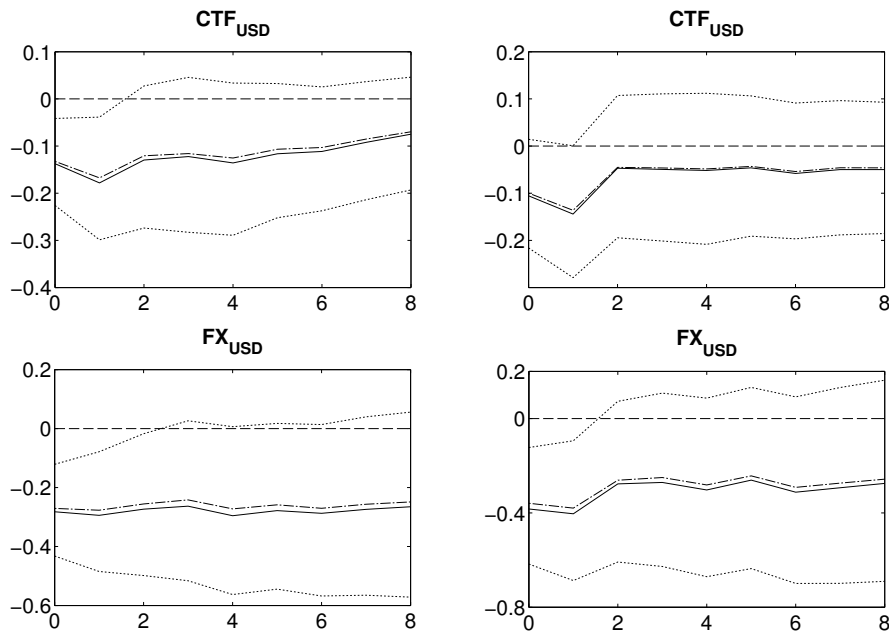


Figure 5: Sample $A_{USD}^{d=3}$: (Accumulated) GIRFs of the variables CTF_{USD} and ΔFX_{USD} in response to a one-standard deviation VIX shock. The left panel depicts the H-regime, the right panel depicts the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $A_{USD}^{d=3}$ see Table (5). Number of observations: 418 (H-regime) & 270 (L-regime)

between five and ten months after the shock, the buildup of CTF_{USD} is statistically significant. However, the *insignificant* appreciation of the USD on impact and its trend to further appreciate instead of a CHF appreciation as UIP predicts, could be due to the under reaction of carry trade activities.²⁰ Brunnermeier et al. (2009), who do not distinguish between different interest-rate differential regimes, infer that carry trade activities in response to a shock is not enough to push up the exchange rate towards the value implied by UIP. To summarize, in the H-regime a further increase in the IRD triggers a fall in CTF_{USD} in the short run and in the L-regime a rise in the long run. These opposed effects arise due to different risk environments, liquidity constraints and/or exchange rate fluctuations.²¹

A simple analysis of a sudden and strong movement of ΔFX_{USD} , approximated by $1.64\sigma_{\Delta FX_{USD}}$ and $1.96\sigma_{\Delta FX_{USD}}$, reveals that in the H-regime a strong appreciation of the Swiss currency happens twice as often as a strong depreciation, while in the L-regime the fraction is 52% and 57%, respectively. This finding mirrors the results obtained by Brunnermeier et al. (2009). The authors conclude that in times when the IRD is high, the skewness of carry trade returns is particularly negative. The higher probability of a sudden appreciation ('crash') of the Swiss franc in the H-regime might be attributed to differences in fundamentals. The average monthly CPI inflation-rate differential between the US and Switzerland is in the H-regime 0.5 percentage

²⁰Numerous empirical studies find evidence for the so-called 'delayed overshooting puzzle' (see, e.g., Eichenbaum and Evans, 1995 or Scholl and Uhlig, 2008 and the references therein).

²¹Contemporaneously, the change of the correlation coefficient between IRD and VIX from being positive in the H-regime to being negative in the L-regime seems to have a dominant effect. A comparison of the remaining correlations reveals a surprisingly stable contemporaneous relationship between the variables across both regimes.

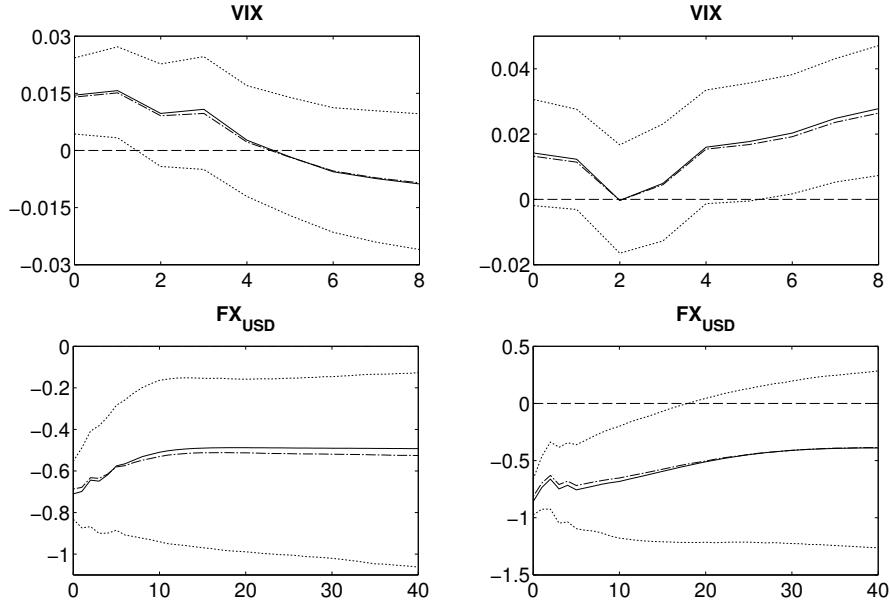


Figure 6: Sample $A_{USD}^{d=3}$: (Accumulated) GIRFs of the variables VIX and ΔFX_{USD} in response to a one-standard deviation CTF_{USD} shock. The left panel depicts the H-regime, the right panel depicts the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $A_{USD}^{d=3}$ see Table (5). Number of observations: 418 (H-regime) & 270 (L-regime)

points higher than in the L-regime (1.94% vs. 1.40%).

A shock to VIX gives rise to a statistically significant contraction of CTF_{USD} in both regimes, shown in Figure (5). This pattern is not surprising, as an increase in VIX represents a higher risk sentiment and it is in line with the results found by Nishigaki (2007) and Brunnermeier et al. (2009). The decline is slightly stronger in the H-regime (left panel), reflecting an increased risk aversion of the speculators with a higher IRD. As can be seen in Figures (12) and (13) in Appendix A.2, the effects on FX_{USD} and P_{USD} are similar across both regimes. Yet, the initial decrease in FX_{USD} is somewhat larger in the L-regime (right panel).²²

What happens to the variables in the VAR after an unexpected unwinding of carry trades? Brunnermeier et al. (2009), for instance, conjecture that sudden exchange rate fluctuations unrelated to fundamental news events can be triggered when investors near funding constraints. We expect a strong appreciation of the CHF as the demand for the Swiss currency rises sharply. Figure (6) confirms this assumption. The currency appreciates contemporaneously in both regimes of about 0.7%.²³ A more severe shock whose size is for instance twice the standard deviation of CTF_{USD} leads to an immediate appreciation of the CHF of about three percent in the H-regime (left panel) and four percent in the L-regime (right panel). In the L-regime the CHF

²²Recently, Grisse and Nitschka (2013) examined the ‘safe haven’ characteristics of the Swiss franc by applying an UIP framework that allows for time-varying relationships. In their study the Swiss franc appreciates against the euro, but depreciates against the US dollar in response to increases in global risk. Our estimates point to a strengthening of the Swiss franc against both currencies, albeit more marked against the euro (see also Figure (10).

²³The variance decomposition based on the Cholesky decomposition ordering in line with Nishigaki (2007); IRD_{USD} , VIX , CTF_{USD} , ΔFX_{USD} , Y_{USD} and ΔP_{USD} , reveals that the semi-structured carry trade activities shock explains about 25% of FX_{USD} in both regimes. It is the most important shock apart from the own shock.

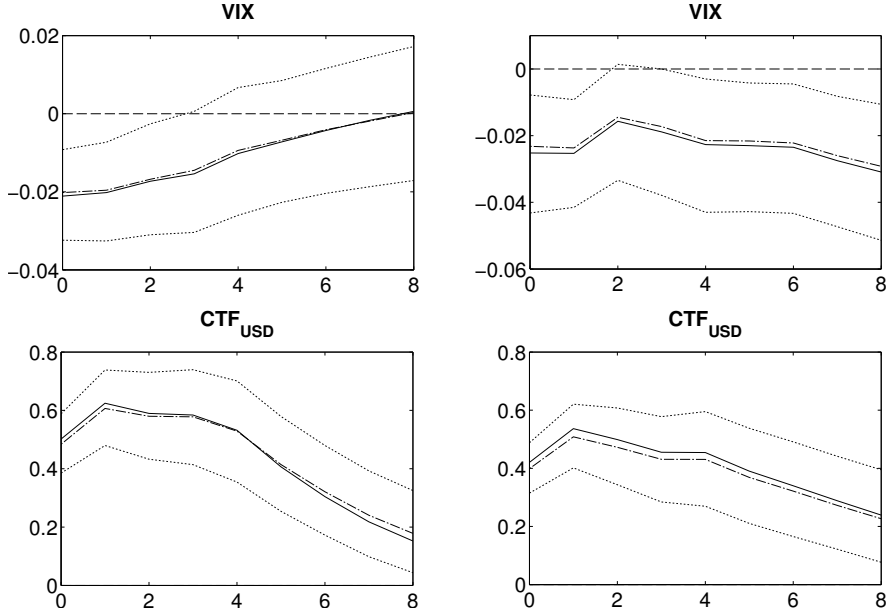


Figure 7: Sample $A_{USD}^{d=3}$: (Accumulated) GIRFs of the variables VIX and CTF_{USD} in response to a one-standard deviation ΔFX_{USD} shock. The left panel depicts the H-regime, the right panel depicts the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $A_{USD}^{d=3}$ see Table (5). Number of observations: 418 (H-regime) & 270 (L-regime)

starts to depreciate after a sudden appreciation. The effect diminishes over time and ceases to be statistically significant after four months (see Figure 13 in Appendix A.2). In contrast, we find a slight overshooting in the H-regime, and the Swiss currency remains appreciated against the US currency over the entire forecast horizon. In the study of Nishigaki (2007), the appreciation of the yen is also statistically significant and lasts for almost two years. Additionally, in both regimes we find an increase in VIX . Whereas in the H-regime the effect is statistically significant in the short run, in the other regime it is significant in the medium run too.

Figure (7) shows that an unexpected depreciation of the Swiss franc results in a large and statistically significant buildup of CTF_{USD} . The reduction of the positions over time is (marginally) slower in the L-regime (right panel). This could be due to the slower mean reversion of VIX , which falls after the shock in both regimes, and the longer statistically significant increase in Y_{USD} in the L-regime.

An unexpected rise in P_{USD} induces a sudden drop in VIX and an appreciation of the US currency in both regimes (Figure 8). Both effects last longer in the H-regime (left panel). This might be an explanation for the longer horizon over which CTF_{USD} increases, although not statistically significant for all horizons (see Figure 12 in Appendix A.2). Positive shocks to P_{USD} increase the value of a stock portfolio investors would like to use as collateral for liquidity, to engage in carry trade activities. Nishigaki (2007) finds a persistent fall in yen carry trade positions after a negative US stock market shock.

Now we turn to the results for sample $B_{EUR}^{d=3}$. Not surprisingly, a positive innovation to IRD_{EUR} results in a statistically significant rise in CT_{EUR} , which has IRD_{EUR} as its numer-

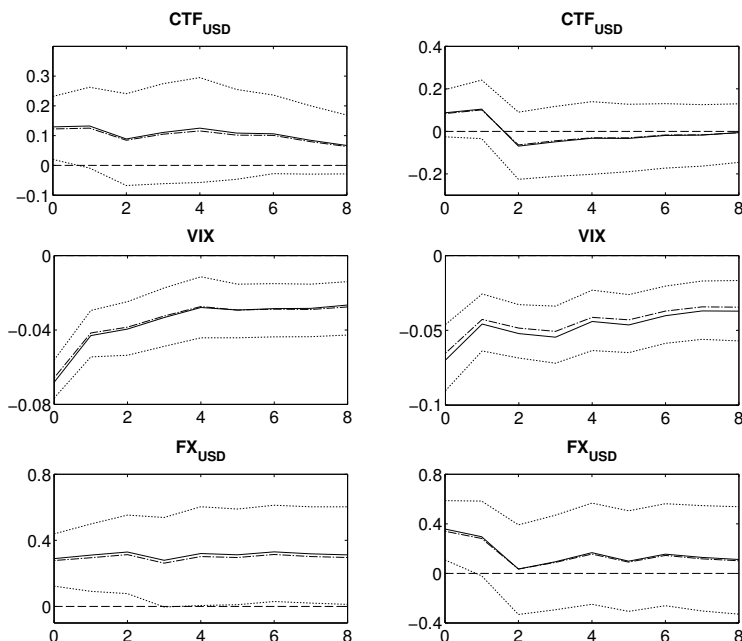


Figure 8: Sample $A_{USD}^{d=3}$: (Accumulated) GIRFs of the variables VIX , CTF_{USD} and ΔFX_{USD} in response to a one-standard deviation ΔP_{USD} shock. The left panel depicts the H-regime, the right panel depicts the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $A_{USD}^{d=3}$ see Table (5). Number of observations: 418 (H-regime) & 270 (L-regime)

ator (Figure 9). The correlation between IRD_{EUR} and CT_{EUR} amounts to 0.5. However, compared to IRD_{EUR} the rise is smaller, hence, the implicit nominal exchange rate volatility increases too. In the long run, depicted in Figure (14) in Appendix A.2, the effect on CT_{EUR} is statistically significant for a longer time span in the L-regime. Apart from the fact that the increase in IRD_{EUR} is statistically significant for a longer period, the negative trend of VIX , and the increase in FX_{EUR} , Y_{EUR} and P_{EUR} might influence this pattern (see Figure 14 in Appendix A.2). This finding is comparable to the results for sample $A_{USD}^{d=3}$.

The analysis of the exchange rate exhibits that strong appreciations of the CHF, approximated by $1.64\sigma_{\Delta FX_{EUR}}$ and $1.96\sigma_{\Delta FX_{EUR}}$, occur more probable in the H-regime than in the L-regime. With equal probability ΔFX_{EUR} should fall in one-quarter of the cases in the H-regime, determined by the number of observations. Yet, 32% ($1.64\sigma_{\Delta FX_{EUR}}$) and 44% ($1.96\sigma_{\Delta FX_{EUR}}$) of the appreciations happen in the H-regime.²⁴ However, the average monthly CPI inflation-rate differential between the Euro zone and Switzerland is only very slightly higher in the H-regime compared to the L-regime.²⁵

Compared to sample $A_{USD}^{d=3}$, the GIRFs associated with an innovation to VIX are qualitatively similar. However, Figure (10) displays that the effects are more pronounced in the L-regime (right panel). The fall in CT_{EUR} in the L-regime could be driven by the strong appreciation of the CHF against the EUR. By virtue of the faster mean reversions of VIX and

²⁴In contrast to sample $A_{USD}^{d=3}$ we do not find a higher probability for a strong appreciation compared to a strong depreciation. The probability is about equal.

²⁵The results are sensitive to some negative and positive outliers of the inflation-rate differential.

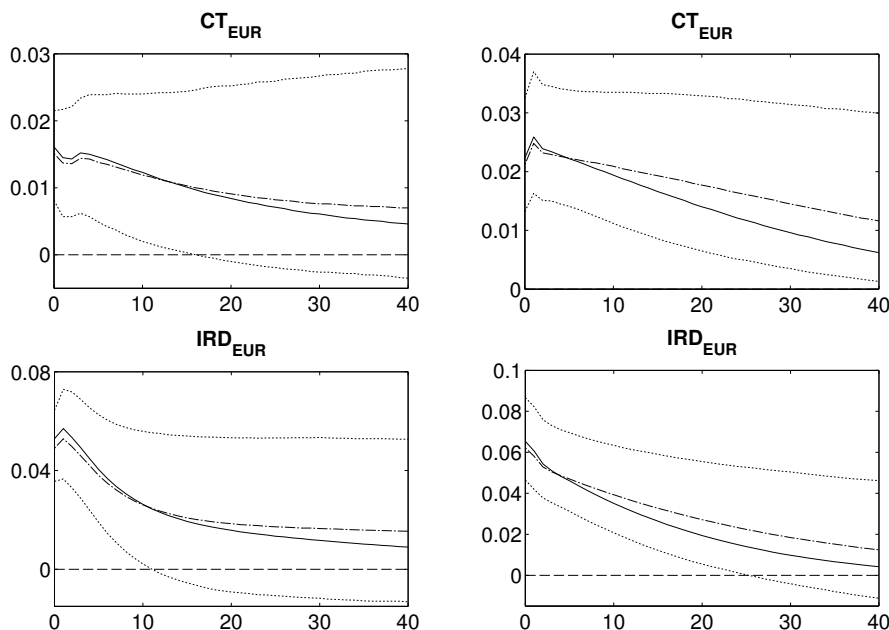


Figure 9: Sample $B_{EUR}^{d=3}$: (Accumulated) GIRFs of the variables CT_{EUR} and ΔIRD_{EUR} in response to a one-standard deviation ΔIRD_{EUR} shock. The left panel depicts the H-regime, the right panel depicts the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $B_{EUR}^{d=3}$ see Table (5). Number of observations: 125 (H-regime) & 367 (L-regime)

FX_{EUR} in the H-regime than in the L-regime, CT_{EUR} rises in the long run (see Figure 14 in Appendix A.2).

A one-standard deviation shock to CT_{EUR} gives rise to an expected appreciation of the CHF.²⁶ Figure (11) shows that the initial impact is equal for both regimes, but the mean reversion is slower in the L-regime (right panel). If the shock equals twice the standard deviation of CT_{EUR} the sudden appreciation of the CHF is slightly more than one percent in both regimes. This effect is smaller compared to the sample $A_{USD}^{d=3}$. Though, as the proxy for carry trade activities differs, a one-to-one comparison is impossible. Additionally, we find an increase in VIX in the short run and a fall in P_{EUR} . However, the impacts are only significant in the L-regime (Figures 14 and 15 in Appendix A.2).

Figures (14) and (15) in Appendix A.2 depict the GIRFs resulting from shocks to FX_{EUR} and ΔP_{EUR} . In line with sample $A_{USD}^{d=3}$, an unexpected depreciation of the Swiss currency leads to a fall in risk sentiment and an increase in CT_{EUR} and P_{EUR} . Furthermore, the short-run effects of a shock to ΔP_{EUR} are qualitatively the same as in sample $A_{USD}^{d=3}$, except for Y_{EUR} in the H-regime. In the L-regime the rise in CT_{EUR} becomes marginally statistically significant two weeks after the shock. The stronger impact compared to the H-regime may be a consequence of the severe and persistent depreciation of the Swiss currency.

²⁶The variance decomposition based on the Cholesky decomposition ordering in line with Nishigaki (2007); IRD_{EUR} , VIX , CT_{EUR} , ΔFX_{EUR} , ΔY_{EUR} and ΔP_{EUR} , reveals that the semi-structured carry trade activities shock explains about 5% of FX_{EUR} in the H-regime. Apart from the own shock it is the second most important shock. In the L-regime it is the most important shock apart from the own shock and explains about 16% of FX_{EUR} .

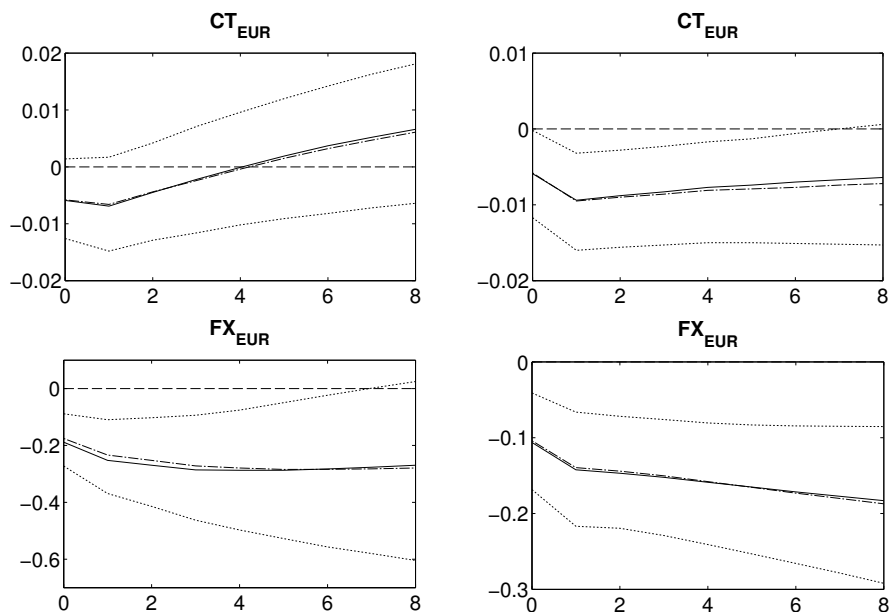


Figure 10: Sample $B_{EUR}^{d=3}$: (Accumulated) GIRFs of the variables CT_{EUR} and ΔFX_{EUR} in response to a one-standard deviation VIX shock. The left panel depicts the H-regime, the right panel depicts the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $B_{EUR}^{d=3}$ see Table (5). Number of observations: 125 (H-regime) & 367 (L-regime)

Overall, we note that there are substantial differences across regimes depending on the size of the IRD. Furthermore, the comparison of the two samples reveals that risk sentiment, exchange rates, bond yields and stock market indices show similar (qualitative) patterns with few exceptions, especially for the exchange rate and bond yields. Carry traders seem to react likewise, although the proxies for carry trade activities differ.

5.3 GIRFs: Robustness Analysis

Overall, the robustness analysis demonstrates robust findings across the different samples. In the following, we describe the changes and point out some important qualitative and quantitative divergences from sample $A_{USD}^{d=3}$ and sample $B_{EUR}^{d=3}$.

5.3.1 Delay Parameter

Since the Chi-squared test statistic for the delay parameter equal to one is the largest among the different delay parameters (see Table 7), we also estimate sample $A_{USD}^{d=1}$. While the GIRFs of the H-regime reveal no qualitative or quantitative differences, the positive long-run impact of a shock to IRD_{USD} on CTF_{USD} is not statistically significant in the L-regime. This might be due to the somewhat faster mean reversion of the IRD, a slightly smaller decline in VIX and a less pronounced depreciation of the Swiss currency.

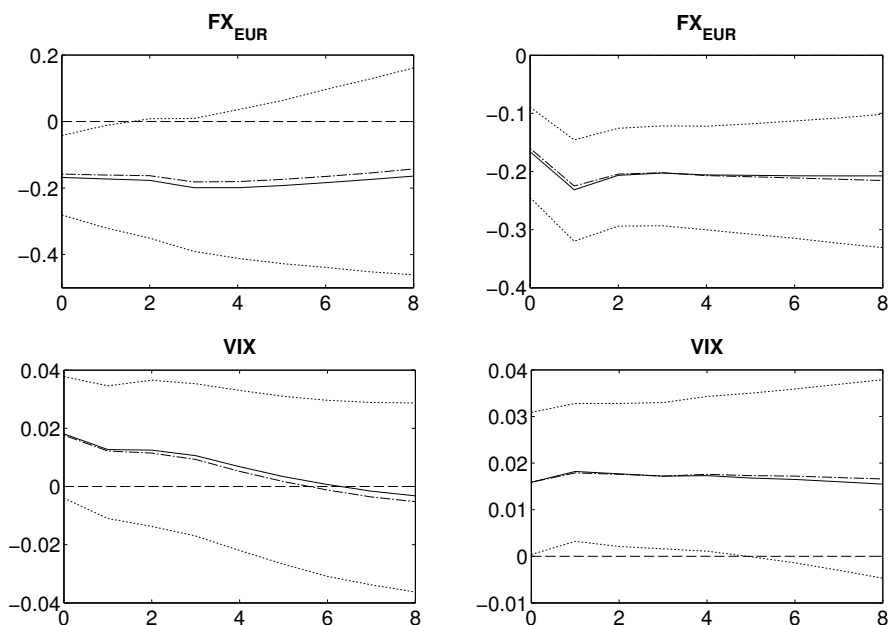


Figure 11: Sample $B_{EUR}^{d=3}$: (Accumulated) GIRFs of the variables ΔFX_{EUR} and VIX in response to a one-standard deviation CT_{EUR} shock. The left panel depicts the H-regime, the right panel depicts the L-regime. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample $B_{EUR}^{d=3}$ see Table (5). Number of observations: 125 (H-regime) & 367 (L-regime)

5.3.2 Sample Period Selection

We extended the sample period to include observations of the recent financial crises (sample $C_{USD}^{d=3}$). The GIRFs of the H-regime are very robust to this modification. Yet, several GIRFs of the L-regime exhibit distinct differences compared to the results of sample $A_{USD}^{d=3}$. A one-standard deviation shock to IRD_{USD} has no impact on VIX , FX_{USD} or P_{USD} anymore, i.e. the responses show no trend either way. The absence of these trends might explain that investors do not increase CTF_{USD} in the long run. Besides the modification of the sample length, the reduction in the threshold value determines this result (see Table 8). The mean reversion of FX_{USD} after an unexpected unwinding of carry trades takes longer in sample $C_{USD}^{d=3}$. Moreover, the impacts on VIX and P_{USD} are no longer statistically significant. This also holds when the Swiss currency depreciates unexpectedly. In general, the confidence intervals for the impulse response functions for the L-regime are expanded, pointing to increased uncertainty during the financial crisis.

The same modification for sample $B_{EUR}^{d=3}$ reveals that the results of the H-regime are qualitatively robust (sample $F_{EUR}^{d=1}$), in spite of a slight shift of the delay parameter d in addition to the change in the sample period. While in sample $F_{EUR}^{d=1}$ CTF_{EUR} asymptotes faster to its steady-state level after an IRD_{EUR} shock, the effect on carry trades is more persistent in response to an unexpected depreciation of the CHF. Moreover, the decline in CTF_{EUR} becomes statistically significant after a sudden increase in VIX . The same is true for the contemporaneous rise in VIX to a CTF_{EUR} shock. In distinction from sample $A_{USD}^{d=3}$, the GIRFs of the L-regime do not

change markedly by extending the sample period. Nevertheless, compared to the benchmark, the mean reversion of CTF_{EUR} is notably slower after a surprising increase in risk sentiment, the Euro Stoxx index and the exchange rate in sample $F_{EUR}^{d=1}$. However, these changes partly depend on the increased value of the delay parameter (see Table 8). Additionally, the exchange rate remains significantly below its steady-state level for 17 weeks in response to an unwinding of carry trades. This is about two months less than in sample $B_{EUR}^{d=3}$.

Because weekly published CME futures positions are available since October 1992, sample $D_{USD}^{d=3}$ contains data from 1992/10/06 until 2008/06/24. The GIRFs of the H-regime are robust to this modification. In contrast to sample $A_{USD}^{d=3}$, the rise in VIX in response to an unexpected decrease in CTF_{USD} only marginally fails to pass the 5% significance level. However, more substantial changes are observed for the L-regime. A shock to IRD_{USD} gives rise to a statistically insignificant increase in CTF_{USD} in the medium run. This lack of significance is somewhat surprising, because the fall in VIX is statistically significant during three weeks. Yet, after an initial tendency to depreciate, the Swiss currency does not continue to follow a depreciation trend in the long run. An unexpected rise in VIX leads to a longer appreciation of the CHF and fall in P_{USD} . Furthermore, the decline in CTF_{USD} is less pronounced and far from being statistically significant. In the medium run, VIX , Y_{USD} and P_{USD} cease to respond statistically significantly to a sudden unwinding of carry trades. Moreover, FX_{USD} exhibits a slower mean reversion. Finally, when P_{USD} goes up unexpectedly, the increase in CTF_{USD} is statistically significant on impact, in contrast to the jump in sample $A_{USD}^{d=3}$. This change arises due to the increase in the threshold value, whereas all the other deviations cannot be ascribed to a threshold value change.

5.3.3 Futures and Options Positions

The inclusion of options to the CME futures positions to proxy carry trade activities (sample $E_{USD}^{d=3}$) causes no qualitative change in either regime. However, for the L-regime, the decline in $CTFO_{USD}$ in response to an innovation to VIX is statistically significant for the first week. The same is true for the rise after a shock to P_{USD} . Furthermore, an unexpected increase in Y_{USD} has a slightly longer statistically significant impact on $CTFO_{USD}$. In the H-regime the reaction of $CTFO_{USD}$ to an unexpected increase in IRD_{USD} is slightly less pronounced.

5.3.4 Choice of the Interest Rate

Next, we assess whether the chosen interest rate has any impact on our results. Therefore, we replace the 3-month interbank interest rates with the 1-month interbank interest rates. While this replacement of the interest-rate differentials has no impact on the GIRFs with the USD as target currency, the rise in CTF_{EUR} in response to a sudden increase in IRD_{EUR} is no longer statistically significant in the H-regime.

5.4 Granger Causality Analysis

In this section, we shed light on the question of whether one variable in our models moves ahead of the others, i.e. if the variables ‘Granger-cause’ each other. Following Klitgaard and Weir (2004) and Mogford and Pain (2006), position data do not help in anticipating exchange rate movements for the subsequent week. Their insights are based on a Granger (1969) causality test with two variables, the net futures positions and the nominal exchange rate. We extend their analysis in two ways. First, we include additional variables in our model which have the potential to ‘Granger-cause’ another variable. Second and more important, we distinguish the effects between regimes, depending on the size of the interest-rate differential (IRD). If the value of the threshold variable is greater than or equal to the threshold value, the corresponding observations are assigned to the H-regime, to the L-regime otherwise.

In a first step, the proxy for carry trade positions is excluded from the multivariate threshold model to examine the power of this variable to ‘Granger-cause’ the other variables in the model. Table (9) displays the findings of all samples for each regime.²⁷

Table 9: Granger Causality Test: Carry Trade Positions Excluded

<i>Sample / Regime</i>	<i>Variable</i>				
	$IRD_{USD} /$ IRD_{EUR}	VIX	$\Delta FX_{USD} /$ ΔFX_{EUR}	$Y_{USD} /$ ΔY_{EUR}	$\Delta P_{USD} /$ ΔP_{EUR}
$A_{USD}^{d=3}$					
H	10.560**	9.865**	2.444	3.758	6.493
L	1.390	17.172***	10.206**	14.241***	16.136***
$B_{EUR}^{d=3}$					
H	1.575	0.257	0.373	7.325**	0.617
L	22.717***	1.862	8.281**	7.832**	11.539***
$C_{USD}^{d=3}$					
H	14.376***	5.547	2.563	4.288	4.806
L	2.610	10.271**	2.945	2.015	7.388
$D_{USD}^{d=3}$					
H	12.945**	8.783*	2.365	5.058	6.532
L	2.287	8.363*	6.344	9.874**	4.577
$E_{USD}^{d=3}$					
H	2.894	6.961	4.979	2.072	4.365
L	1.290	15.622***	7.904*	15.800***	14.855***

Notes: The samples and variables are described in Table (5). Observations for which the threshold variable lies above the threshold value are assigned to the H-regime; for values below the threshold values, the observations are included in the L-regime. The threshold values are given in Table (8). */**/** denotes significance of the Chi-squared value at 10%, 5% and 1% level, respectively.

²⁷If a VAR model contains one or more random walk series without cointegration relationship, the Granger causality test statistics have a nonstandard limiting distribution (Sims et al., 1990). The unit root tests reveal that the variable IRD is non-stationary. Nevertheless, we assume this series to be stationary and refer to the standard test statistics, since the spread of the IRD is smaller within the regimes compared to the full sample. Further, there is no economic reason for a random walk behavior. The sample sizes of the regimes are too small to get reasonable results from applying unit root tests.

In all three models containing futures position data as proxy for carry trade positions, these positions have predictive power for the IRD in the H-regime. The contrary is true for sample $B_{EUR}^{d=3}$, where carry trade activities lead the IRD in the L-regime. This highly statistically significant result, however, has to be interpreted with caution as the IRD is the numerator of the carry-to-risk ratio (CTR ratio), which is the proxy for carry trade positions.

However, the predictive power of the proxy for carry trade activities is often statistically (more) significant in the L-regime, for example, with respect to nominal exchange rate fluctuations. For all samples, the Chi-squared values for the L-regime are substantially larger, and in addition, in two cases statistically significant at the 5% level and once at the 10% level. This result challenges the insights of Klitgaard and Weir (2004) and Mogford and Pain (2006) in the sense that during a period of low IRDs there is the possibility that past position data help to predict exchange rate movements. The knowledge about speculative future positions seems to have incremental information about future fluctuations in the exchange rate in line with findings from the literature, pioneered by Evans and Lyons (2002, 2005), that tries to explain and empirically forecast exchange rate movements based on a microstructure approach. The microstructure approach assumes that, apart from common knowledge macroeconomic information (macro approach), heterogeneous beliefs are essential for exchange rate determination. In a hybrid view, macroeconomic information influences the exchange rate directly and indirectly through order flow which reveals price-relevant private information such as, for example, heterogeneous interpretations of news or changes in expectations (Rime et al., 2010).²⁸ Evans and Lyons (2002) provide a theoretical model that integrates both approaches and find empirically that adding order flow as an explanatory variable to a regression of changes in exchange rates on IRDs, serving as a proxy for public macroeconomic information, increases the R-squared from 1%-5% to 40%-60%. As Evans and Lyons (2005) note, order flow data have not only explanatory but also forecasting power for the exchange rate if the market learns gradually from order flow information. Following the out-of-sample studies by Evans and Lyons (2005) and Rime et al. (2010), order flow is a powerful predictor for exchange rate fluctuations. Like order flow information the CME futures position data are not discovered by the market immediately and therefore do not constitute public information. The U.S. Commodity Futures Trading Commission provides the data with a delay of some days (usually three days).

In a second step, the predictive power of all other variables on carry trade positions is determined. The findings are displayed in Table (10). They suggest that exchange rate movements are very important for anticipating carry trade activities, independent of the regime, except for sample $B_{EUR}^{d=3}$. It is therefore more likely that movements in the exchange rate precede position data rather than vice versa. This result is in line with the findings reported by Mogford and Pain (2006).²⁹ The results indicate a basic form of trend-following behavior among the speculative traders at the CME. Movements in the exchange rate FX_{EUR} do not ‘Granger-cause’ the CTR

²⁸Order flow is defined as the net of buyer and seller initiated currency transactions. Hence, it is a measure of net buying pressure (Evans and Lyons, 2002).

²⁹Klitgaard and Weir (2004) also obtain a statistically significant test statistic for the CHF, but not for most other currencies.

Table 10: Granger Causality Test: Which Variables ‘Granger-cause’ Carry Trade Positions?

<i>Sample / Regime</i>	<i>Variable excluded</i>				
	$IRD_{USD} /$ IRD_{EUR}	VIX	$\Delta FX_{USD} /$ ΔFX_{EUR}	$Y_{USD} /$ ΔY_{EUR}	$\Delta P_{USD} /$ ΔP_{EUR}
$A_{USD}^{d=3}$					
H	3.062	2.490	20.562***	7.204	1.602
L	3.455	3.565	24.868***	7.102	16.149***
$B_{EUR}^{d=3}$					
H	2.810	0.942	1.762	2.448	0.139
L	17.838***	4.398	0.144	4.067	2.586
$C_{USD}^{d=3}$					
H	4.422	3.373	22.353***	6.040	3.702
L	3.474	1.234	23.797***	5.237	10.955**
$D_{USD}^{d=3}$					
H	4.564	3.910	21.161***	6.956	1.568
L	6.349	1.841	16.781***	2.855	8.912*
$E_{USD}^{d=3}$					
H	7.098	3.167	33.024***	8.922*	2.298
L	4.998	4.376	29.220***	6.690	18.901***

Notes: The samples and variables are described in Table (5). Observations for which the threshold variable lies above the threshold value are assigned to the H-regime; for values below the threshold values, the observations are included in the L-regime. The threshold values are given in Table (8). */**/** denotes significance of the Chi-squared value at 10%, 5% and 1% level, respectively.

ratio,³⁰ but the IRD and the CTR ratio seem to ‘Granger-cause’ each other in the L-regime (see also Table 9). This might be due to the calculation of the CTR ratio with the IRD as its numerator.

Moreover, in all samples, movements in P_{USD} help to predict position data in periods with $IRD_{USD}^{d=3}$ below the threshold value. The stock market may serve as a proxy for liquidity constraints, determining the value of investor collateral portfolios.

6 Summary and Conclusions

This paper examines how shocks to variables that determine the profitability of carry trades affect carry traders’ behavior and vice versa. The set of variables consists of the interest-rate differential (IRD), the nominal exchange rate, the VIX index to capture risk sentiment, bond yields to proxy investment returns and the stock market index to model possible liquidity constraints. Preliminary analyses of the IRD point to a regime-dependent relationship between these variables. Therefore, we estimate a multivariate threshold model to allow for changes in the dynamic behavior of carry trade activities conditioned on the size of the IRD.

By analyzing the generalized impulse response functions (GIRFs) of the model containing

³⁰We assume that the CTR ratio is an important indicator for carry traders to adjust their positions. However, as long as investors do not follow strictly this indicator we cannot rule out potential feedback trading.

the USD/CHF exchange rate, we find that carry trade positions are driven to a large extent by changes in investors' risk sentiment, movements in stock market prices and exchange rate fluctuations. Moreover, the response of key financial and macroeconomic variables to shocks depends on the size of the IRD. These differences then affect carry trade positions. We show that the probability of a sudden appreciation of the Swiss franc is higher during a period of high IRD, in line with an increased inflation-rate differential. Indeed, while during a period of low IRD a positive shock to the IRD is followed by a rise in carry trade positions, it will trigger a decline in carry trade positions during a period of high IRD. These results suggest that the shock to the IRD itself is not enough to compensate investors for the increased foreign exchange risk. Moreover, we find that the CHF appreciates against the USD during a period of high IRD. This result confirms the prediction of uncovered interest rate parity (UIP). However, UIP does not hold in the regime of low IRD.

Furthermore, a positive stock market price shock is associated with a rise in carry trade positions, since investors may use stock portfolios as collateral for liquidity. Moreover, given that a sudden unwinding of carry trades leads to a significant appreciation of the Swiss franc, we conclude that carry traders can indeed play a crucial role in determining the nominal exchange rate in the short run and medium run as suggested by Roth (2007).

Finally, we show that the GIRFs of models containing the USD/CHF exchange rate are broadly similar to those with the EUR/CHF exchange rate, although the proxy for carry trade positions differs.

In addition, according to the results of Granger causality tests, past position data help to predict nominal exchange rate fluctuations in periods with low IRDs. However, we find that the exchange rate has very high predictive power for carry trade activities when the USD serves as the target currency. From this result we conclude that speculative traders at the CME mainly follow a feedback trading strategy.

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A Appendix

A.1 Additional Tables

Table 11: ARCH Test Results with USD as target currency

Dependent Variable	ARCH(1)	ARCH(2)	ARCH(4)
ΔFX_{USD}	0.559	7.213**	11.118**
ΔP_{USD}	42.735***	42.642***	55.007***
VIX	3.015*	5.083*	15.935***
IRD_{USD}	6.181**	10.394***	10.669**
Y_{USD}	4.838**	4.794*	27.997***
Carry Trade Positions			
CTF_{USD}	0.355	1.872	7.328

Notes: The model is estimated with four lags from 1995/03/28 until 2008/06/24. */**/** denotes significance at 10%, 5% and 1% level, respectively.

Table 12: ARCH Test Results with EUR as target currency

Dependent Variable	ARCH(1)	ARCH(2)	ARCH(4)
ΔFX_{EUR}	0.112	17.604***	17.728***
ΔP_{EUR}	41.793***	42.233***	56.998***
VIX	2.997*	4.845*	9.356*
IRD_{EUR}	25.200***	26.300***	32.006***
ΔY_{EUR}	1.434	1.644	5.558
Carry Trade Positions			
CT_{EUR}	14.078***	14.185***	15.454***

Notes: The model is estimated with two lags from 1999/01/06 until 2008/06/25. */**/** denotes significance at 10%, 5% and 1% level, respectively.

A.2 Additional Figures

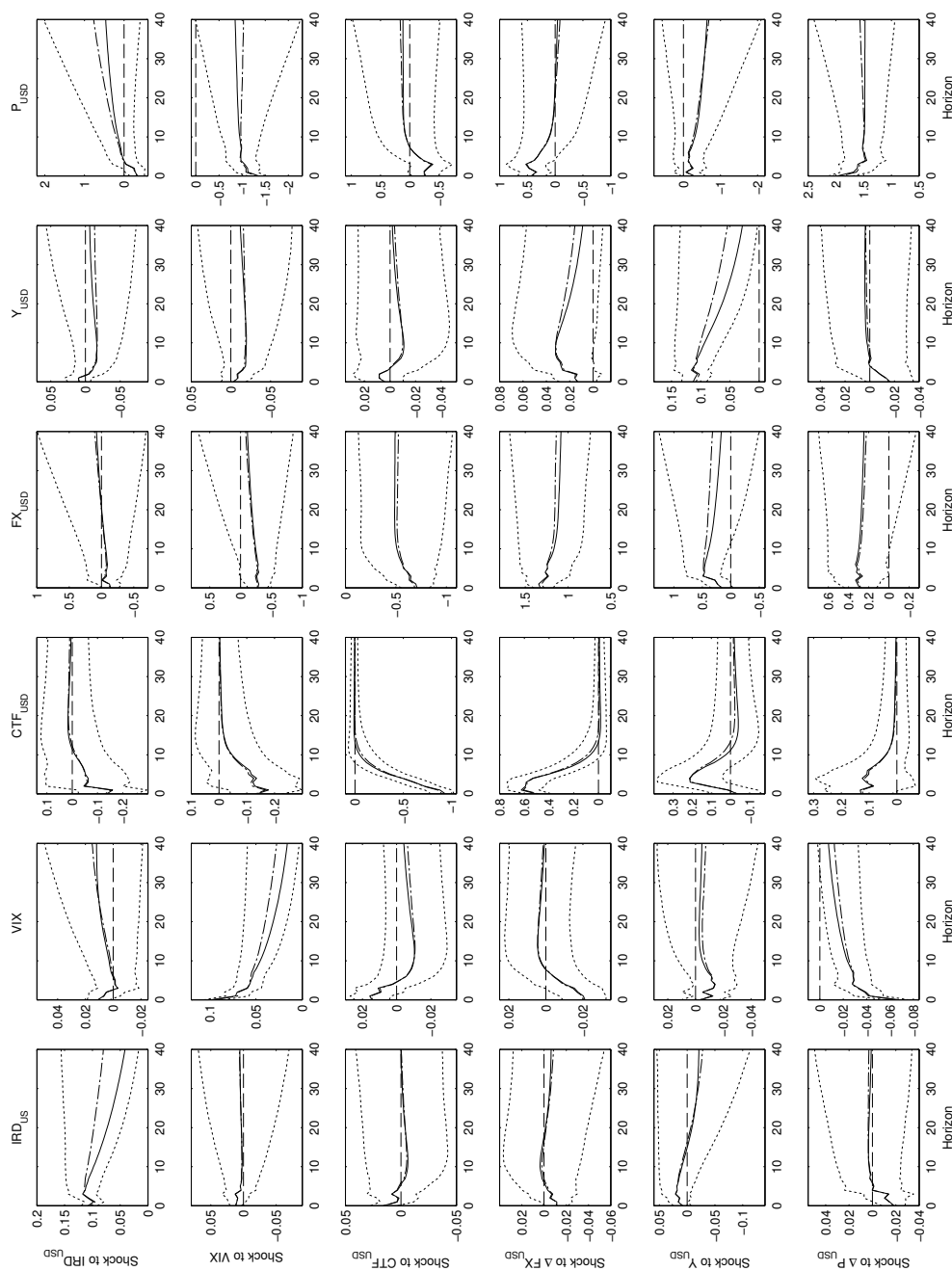


Figure 12: Sample $A_{USD}^{L=3}$: (Accumulated) generalized impulse response functions of the H-regime for all variables. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample A, see Table (5). Number of observations: 418 (H-regime) & 270 (L-regime)

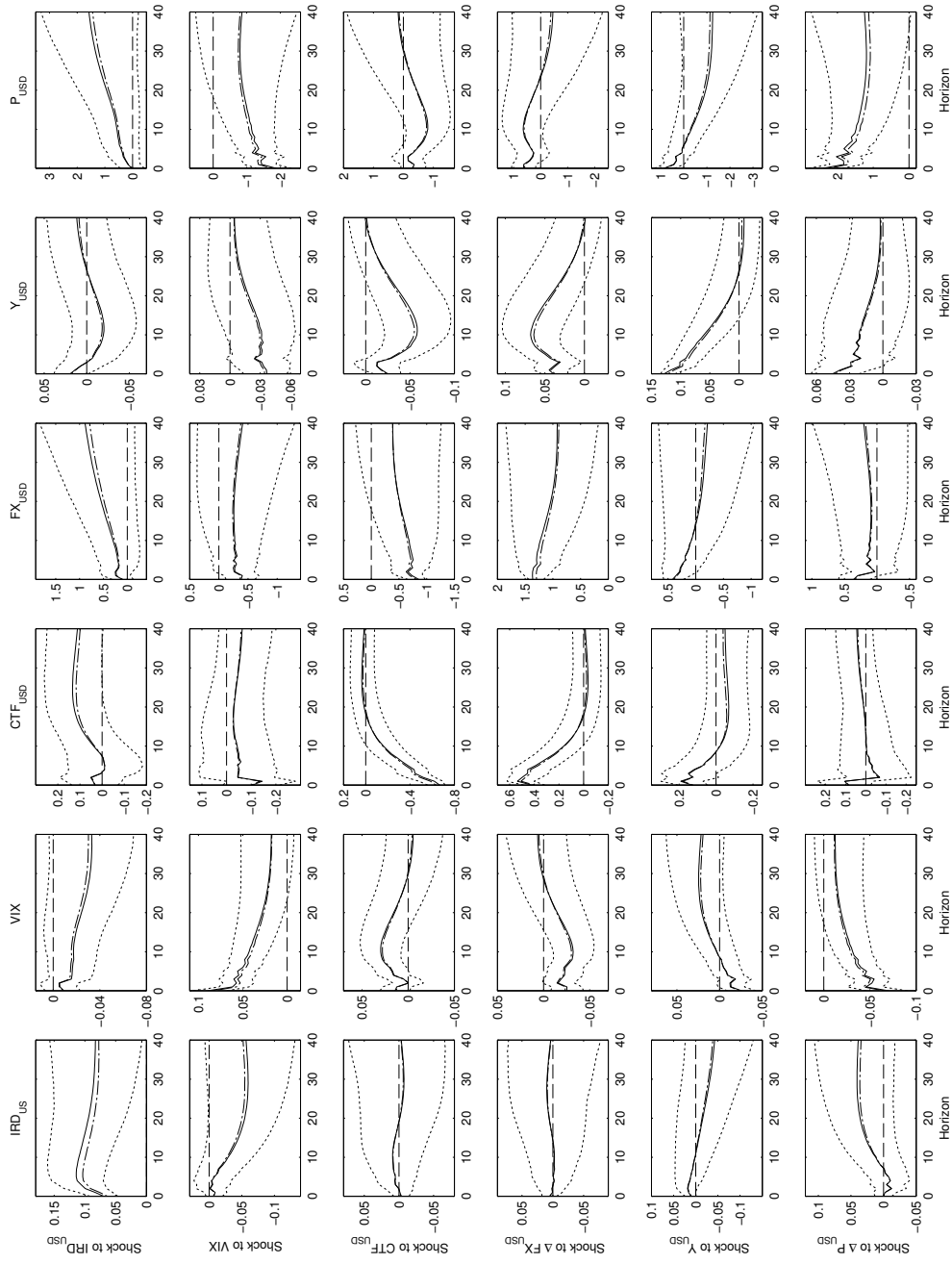


Figure 13: Sample $A_{USD}^{d=3}$: (Accumulated) generalized impulse response functions of the L-regime for all variables. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample A, see Table (5). Number of observations: 418 (H-regime) & 270 (L-regime)

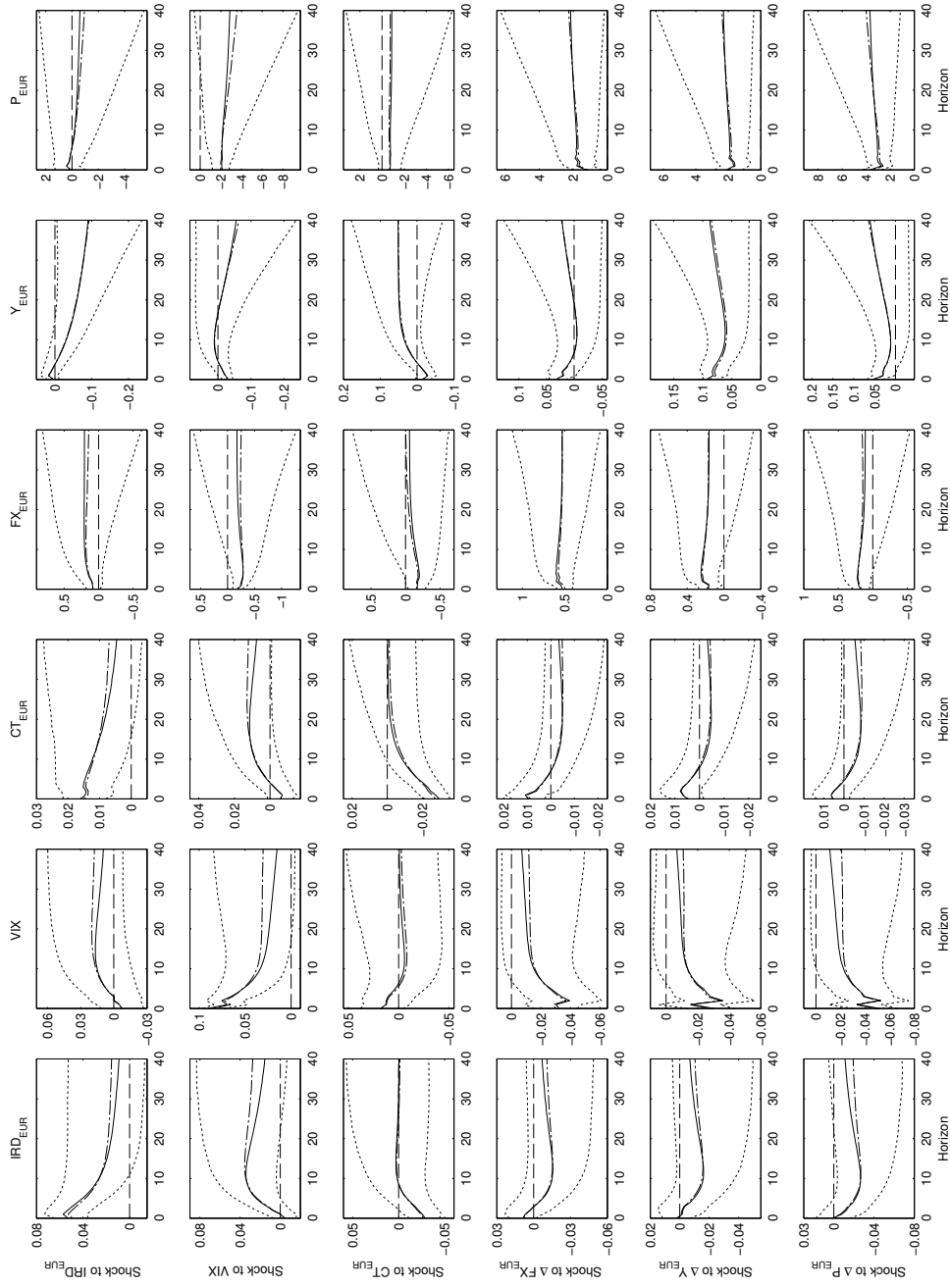


Figure 14: Sample $B_{EUR}^{L=2}$: (Accumulated) generalized impulse response functions of the H-regime for all variables. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample B, see Table (5). Number of observations: 125 (H-regime) & 367 (L-regime)

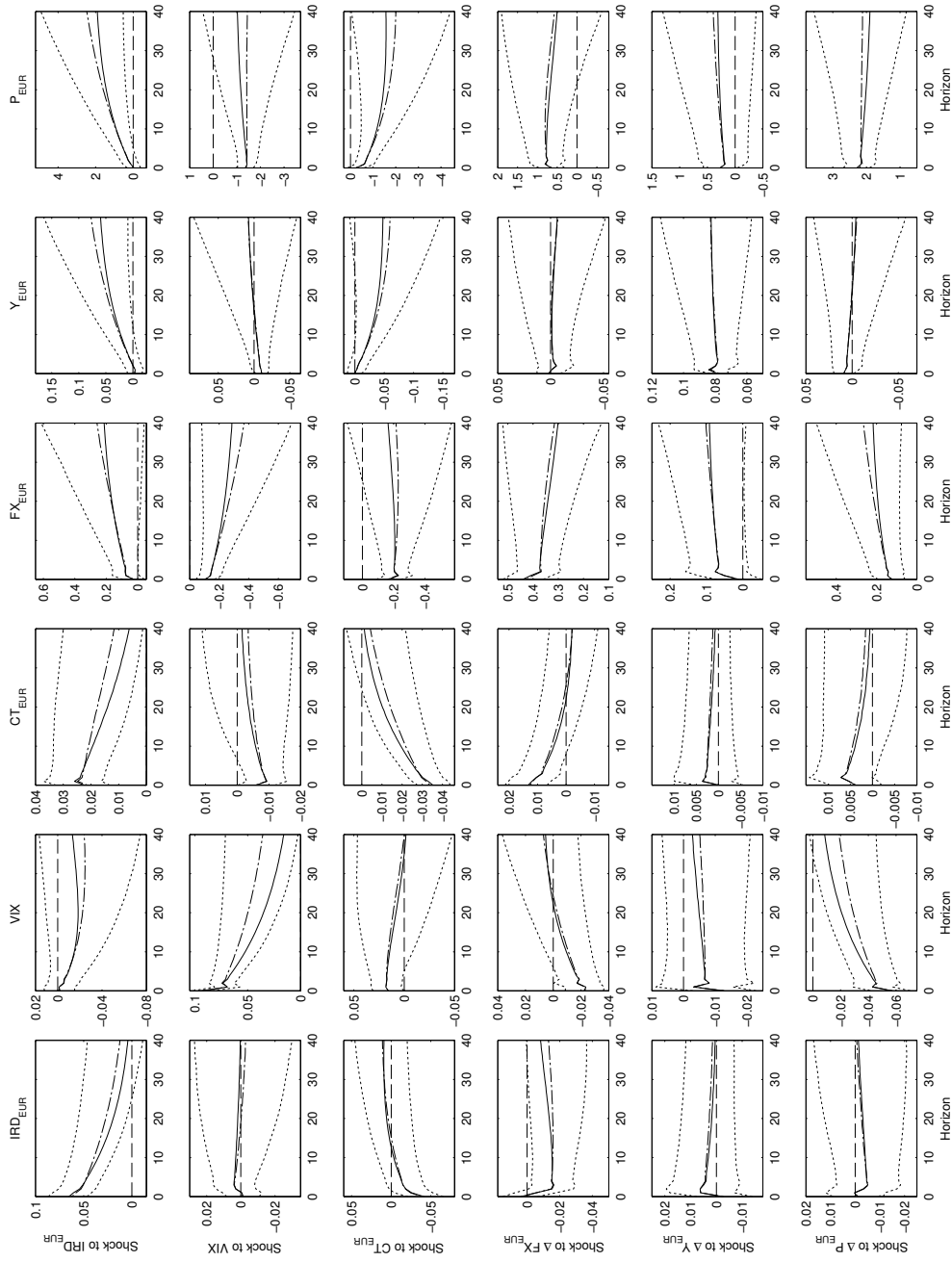


Figure 15: Sample $B_{EUR}^{d=3}$: (Accumulated) generalized impulse response functions of the L-regime for all variables. Solid line: point estimate; dashed-dotted line: bootstrap median; dotted lines: non-centered 95%-confidence interval (small sample bias and GARCH corrected, details are described in Sections 4.1 and 4.2). For more details about sample B, see Table (5). Number of observations: 125 (H-regime) & 367 (L-regime)

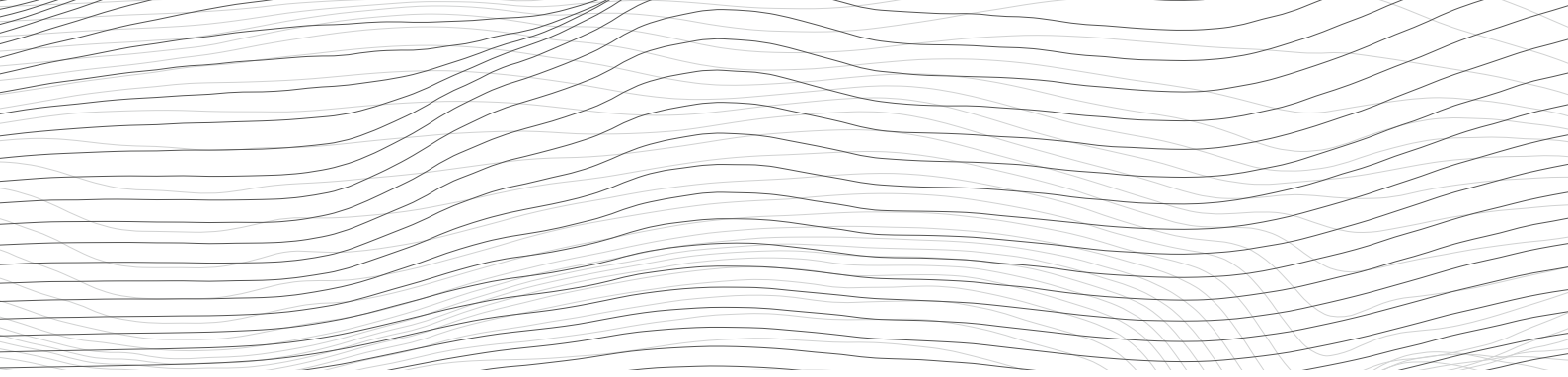
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