

# Carry trade, sudden stops and instability in emerging markets

Rob Hayward\*and Professor Jens Hölscher

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## Abstract

International financial crises disproportionately affect emerging economies and disproportionately effect emerging countries. These crises are frequently the result of the unwinding of carry-trade positions. The carry-trade is the attempt to take advantage of the apparent failure of uncovered interest parity by borrowing low interest rate currencies, exchanging for higher rate currencies and taking the interest rate differential less the depreciation of the investment currency against the funding unit. If there is fear that the investment currency will depreciation, this can trigger a sudden-stop or reversal of inbound capital flows as funds seek to exit the carry position before the collapse. A Hidden Markov Model uses the observed returns from the carry-trade to estimate the unknown probability of a shift from a state of financial stability to one of instability. This model is then used to assess the way that rising risk aversion affects the probability of switch to a regime of instability.

## 1 Introduction

As the size of international capital flow has increased in absolute terms and relative to the expansion of the trade in goods and services, it has also become subject to less regulatory constraint. Economic authorities in emerging economies have struggled repeatedly with financial instability that has an international source. An inflow of capital from abroad may appear superficially

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\*University of Brighton Business School, Lewes Road, Brighton, BN2 4AT; Telephone 01273 642586. rh49@brighton.ac.uk.

attractive but its arrival can inflate goods and asset prices; it can shape institutions, economic development and political opinion; and, the portfolio inflows can disappear even more swiftly than they arrive.

International financial conditions following the 2007-08 crisis have fuelled the growth of investments in transition and emerging economies by providing large amount of funding-currency liquidity in the financial systems of developed economies at the same time as those countries that were outside the immediate financial crisis offered relatively attractive investment opportunities. The move towards *normalisation* of monetary policy in developed nations has caused a reversal of some of these flows and concern about financial crises in emerging economies. There are three main international forces that have been identified as being potential triggers for such a reversal: US monetary policy, international risk aversion and international liquidity.

We used a Hidden Markov Model (HMM) to determine financial conditions from the returns achieved by the carry-trade invested in emerging European countries. A model with two regimes explains the data better than those with one or three in most cases. We estimated a transition matrix that identifies the probability of switching from one financial regime to another. We also estimated the transitional matrix probabilities conditional on the level of international risk (as measured by the VIX index). This is used to measure the relative importance of different types of international financial shock.

## 2 Financial crisis and sudden stops

International financial crises have been a prominent impediment to emerging economy development in the last thirty years. Globalisation of financial markets encourages capital to swiftly from one opportunity to another. The term *sudden stop* emphasises the importance of the inflow of international capital that takes place before the disruptive effects of reversal [Dornbusch and Werner \(1995\)](#), [Calvo \(1998\)](#) and [Krugman \(2000\)](#).

Following the Global Financial Crisis (GFC) the flow of finance to emerging economies has accelerated as a consequence of liquidity stoked by quantitative easing in key financial center and emerging market investment opportunities. However, the start-stop ebb and reflux has continued with changes in developed country funding conditions sometimes having as much effect as the individual circumstances of emerging states. An increased possibility of higher US interest rates and the cutting back of large-scale-asset purchase (LSAP) by the US Federal Reserve have been amongst the triggers. This has allowed a range of international factors to be added to the set of domestic

triggers of sudden-stops. Rising international risk aversion, higher interest rates and cutbacks in liquidity have been added to the role that openness to trade [Cavallo and Frankel \(2008\)](#) and overseas banking liabilities [Calvo et al. \(2004\)](#) pose to emerging economy stability. Here we assess how an increase in international risk aversion affects the probability that a range of Central and Eastern European countries will switch from a regime of stability to one of crisis. We use this analysis to try to identify risk factors.

The relative importance of each factor has been investigated. [Ceruttie et al. \(2014\)](#) ask three questions: what drives global liquidity; where does the global liquidity cycle originate; how can the recipient countries manage exposure to global liquidity? Their focus is on cross-border banking flows. They find that global liquidity is affected by uncertainty and risk aversion and that uncertainty and risk-aversion are highly correlated across countries. However, their research also shows that bank conditions and monetary policy actions in countries outside the US can also exert influence. They have three specific findings: cross-border bank-lending falls when international risk aversion increases, when US dealer bank leverage falls or when there is an increase in term premia; there is a small interest rate effect on capital flows; US and European domestic credit conditions and monetary policy affect lending to other regimes, US monetary policy is important while European leverage and credit conditions are important. They conclude that while the US drives the global liquidity cycle through its monetary policy, other financial centres (particularly in European) affect the financial cycle through the conditions of their banks. Their work suggests that global liquidity is affected by global financial conditions rather than monetary policy.

Flight-to-Safety (FTS) is the term used to describe capital flows towards international financial centres and relatively safe assets, [Baele et al. \(2014\)](#) discover that FTS are relatively rare events. Their study of 23 countries identifies FTS in less than 3% of the sample of daily data that runs from January 1980 to January 2012. In a contrast to other work, they find that most of the events are country specific (they characterise only 25% of the events as "global") and are associated with an increase in the VIX index and the TED spread.<sup>1</sup>

Consistent with the evidence of an interplay between monetary policy and

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<sup>1</sup>The VIX is an index of implied volatility on options from the S&P 500 index. It is commonly used as a measure of international risk aversion as it signals increased demand by fund managers for option protection of their equity portfolio. See [Chicago Board of Trade \(2009\)](#), [Demeterfi et al. \(1999\)](#) and [Diamond \(2012\)](#) for fuller details. The TED spread is the spread between the treasury bill and the Euro-dollar rate. It is used as a market measure of perceived credit risk of financial institutions as it records the risk premium that investors require to lend to banks relative to the risk-free rate.

international risk, and between domestic and international factors, [Ahmed and Zlate \(2014\)](#) run a multivariate panel of gross and net capital flows before and after the financial crisis, showing that economic growth, interest rate differentials and the level of global risk appetite are all important determinants of private capital flows to emerging markets. They also suggest that capital flows have been more sensitive to interest rate differentials since the financial crisis of 2007-08. There is also some evidence that quantitative easing has had some effect on capital flows.

[Alexander Klemm and Sosa \(2014\)](#) use a panel vector autoregression (VAR) method to assess the effect of US monetary policy since 1990 on capital flows to 38 emerging economies, finding evidence that the end to Federal Reserve purchase of government bonds under the quantitative easing programme, while not necessarily leading to capital outflow, could generate *new risk premium shocks*. If investors require a higher return, asset price falls are required.

While the origin of international financial crisis may be international, US monetary policy for example, the effects may vary by asset class and US policy can influence different countries in a variety of ways. Using daily data on exchange rates, stock prices and emerging market bonds, [Mishra et al. \(2014\)](#) find that exchange rates and bonds are less affected by international liquidity shocks than stock markets. They also find that stronger domestic macroeconomic fundamentals, more prudent financial policy and deeper financial markets provide some insulation against US monetary policy shocks.

The flow of international bank lending is more difficult to measure but seems to host some of the most speculative activity. One specific part of the range of international capital flows that has attracted particular attention because it is associated with speculation is the *carry-trade*. This is the attempt to take advantage of the break down in *uncovered interest parity* (UIP).<sup>2</sup> Most of the explanation of UIP revolve around the idea that what is supposed to be an excess return is actually a return for taking *crash-risk*. This is the small probability of a large, probably fatal, loss. This is the equivalent of the sudden-stop for the investor. The attempt to exit the investment in the emerging market causes the fall in the value of the investment currency that is to be avoided.

[Brunnermeier et al. \(2008\)](#) analyse a sample of carry trades and find that the returns are characterised by negative skew and a larger than normal risk of extreme loss; [Jurek \(2007\)](#) assesses the cost of purchasing option protection

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<sup>2</sup>See [Fama and French \(1993\)](#), [Froot and Frankel \(1989\)](#) and [Hayward \(2013\)](#) for an overview of the failure of UIP. This provides a rationale for borrowing low interest rate currencies and investing in units with a higher return.

against crash-risk and shows that the price of out-of-the-money puts covers a proportion of the excess returns that seem to be generated by the carry-trade; [Hayward \(2013\)](#) compares carry returns in period of stable and periods of crisis (as measured by elevated levels of the VIX index). Carry-returns are negative, skewed and fat-tailed when international risk aversion is heightened, but a more normal, positive return when conditions are stable.

[Groen and Peck \(2014\)](#) consider the effect of changes in global risk aversion on the carry-trade. They find that the initial signal from the US central bank in Fed Chairman Bernanke’s May 22 2013 testimony to Congress coincide with an increase in global risk aversion which affected global asset prices. By identifying the performance of exchange rates without a change in risk aversion, they suggest that nearly half of the depreciation of a basket of 45 carry-trade currencies with the largest one-month interest rate relative to a basket of the US dollar and other equally low rate currencies is explained by this increased risk aversion. Nearly all the decline in Emerging market equities is attributable to the increase in risk aversion.

There is evidence that the international financial cycle is increasingly global. See [Rey \(2013\)](#), [Obstfeld \(2014\)](#) and [Bruno and Shin \(2014\)](#) for example. There is evidence the correlation of cross-border credit growth has risen since the 1990s and that funds increasingly flow from the financial centres to the rest of the world. For [Ceruttie et al. \(2014\)](#), credit and liquidity contractions in the US, Euro zone, UK and Japan affect the rest of the world. This is what they call *global funding liquidity*, a feature that affects financial conditions globally by transferring credit supply in financial centre economies through the provision of cross-border credit.

## 3 The Hidden Markov Model

### 3.1 The evolution of financial instability

International financial risk and the carry-trade are beset by *peso problems*. Peso problems are cases where there is potential for discrete shifts in the distribution of variables. This can affect expectations, risk-premia and asset pricing models. In [Evans \(1996\)](#), for example, if  $s_t$  is the log of US dollars in terms of Mexican peso and the peso is fixed at 0.08 dollars with information set  $\Omega_t$ , this is state  $s^0$  with a expected probability  $\pi$  at time  $t$ , which is a fixed period ahead, that there will be a discrete exchange rate adjustment to  $s^1$ , the expected depreciation is

$$E[s_{t+1}|\Omega_t] = \pi_t s^1 + (1 - \pi_t) s^0 \tag{1}$$

Therefore, the difference between the realised and expected rate is

$$s^0 - E[s_{t+1}|\Omega_t] = \pi_t(s^0 - s^1) \quad (2)$$

Expectations are continually confounded though they are not formed in an irrational way. In these cases, modelling that identifies the two regimes and the probability of switching between them will help to capture the non-linear nature of the relationship and will allow a range of cases that can span a simple transition from one state to another to an extreme of multiple states where parameters are close to time-varying.

[Hamilton \(1988\)](#) used a Hidden Markov Model (HMM) to incorporate discrete changes in expectations about Fed policy to make a closer match between the expectations theory and the term structure of interest rates. This technique assumes that there are hidden or unobserved regimes and that the adjustment from one state to another is governed by a set of probabilities. [Hamilton \(1989\)](#) also analysed the performance of postwar US GNP with adjustments from periods of positive to negative growth. The regime shift is modelled as a first-order Markov process. In other words, state  $S_t$  depends only on the previous state  $S_{t-1}$ , with given probabilities that the state will switch or remain unchanged. The parameters of an ARIMA representation of US GNP shift between the two regimes so that in periods of recession the underlying growth rate is three percentage points lower than it is during the expansionary period.

[Schaller and Norden \(1997\)](#) extend the Hamilton model to assess stock returns in two regimes, uncovering strong evidence of regime-switching between bull and bear markets in the mean and variance of US stock returns. They also find that the response of stock returns to the price-dividend ratio is asymmetric as adjustment is much swifter during the bull market phase; [Dueker \(1997\)](#) use a model that switches from periods of low to high volatility. Markov models switching models are also typically used to understand the evolution of credit risk. A transition matrix with probabilities derived empirically provides the expectation that a rating will change from one level to another. This can be rolled forward to assess the likelihood of a default and used to incorporate credit risk in the valuation of bonds. As an extension of this, [Frydman and Schuermann \(2008\)](#) use a *mixture model*, where the underlying probabilities of adjustment come from two underlying sub-models of company type, against the alternative of a pure Markov chain. The observed rating changes relate to two different underlying Markov chains representing the evolution of credit ratings. There is a heterogeneity that seems to depend upon the industry. For example, ratings of firms in the retail and wholesale trade sectors tend to be more dynamic than the others.

The rest of the paper proceeds as follows: Section two provides an outline of the model; Section three discusses the results that have been achieved; Section Four draws some conclusions and outlines the next steps that are to be taken.

### 3.2 A Markov model of financial stability

Financial stability for each of the countries covered is presented as a first-order Markov process. Three main models are tested with one, two and three regimes. There are also sub models that allow either covariates to affect returns or to affect the probability of transferring from one regime to another. The base model with one regime is a control that assesses whether regime-switch is appropriate.

### 3.3 The HMM model

A financial crisis is hard to define.<sup>3</sup> In situations like this where the underlying financial regimes are not observable, the Markov model is not sufficient to fully describe the process. It may nonetheless be possible to identify a probabilistic relationship between the carry-trade returns and the underlying financial regime and to use this to uncover the parameters of a *Hidden Markov Model (HMM)*.

Figure 1 gives an overview of the system. The HMM has three components:  $\pi, A, B$  where,

- The prior model:  $P(S_1 = n | \theta_{prior}) (\pi)$
- The transition model:  $P(S_t | S_{t-1}, \theta_{trans}) (A)$
- The response model:  $P(Y_t | S_t, \theta_{resp}) (B)$

Where there are  $n$  states or regimes;  $y_t$  are the observed carry-trade returns; and  $\theta_{prior}, \theta_{trans}$  and  $\theta_{resp}$  are the parameters of the prior, transition and response models respectively. The unobserved financial regimes are modelled as a Markov chain that switches from a period of stability to instability. The returns to the carry-trade are more likely to take particular characteristics according to the underlying regime.

The prior or initial state probabilities give the probability of being in each of the financial regime in the first period; the transition model is the

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<sup>3</sup>Calvo (1998) defines the sudden stop as a one movement of net capital flows to two standard deviations from the mean and a return to one standard deviation from the mean.

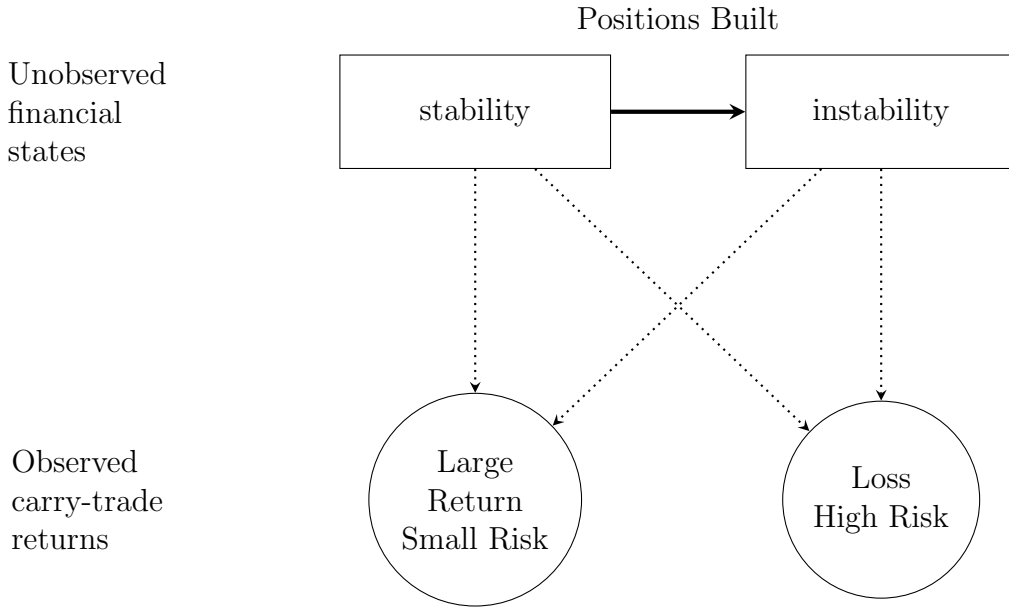


Figure 1: Two-Regime Hidden Markov Model (HMM)

probability of moving from one financial state to another; the response model is the relationship between the observed carry-returns and the unobserved financial state.

The process underlying the state transitions is assumed to be a *homogeneous first-order Markov process*. Therefore, the probabilities depend only on the previous state. This is an assumption that is used to simplify the estimation of the parameters.<sup>4</sup> Once a starting point is given, a most likely path can be determined.

The starting point of the system is given by,

$$P(S_1 = 1), \dots, P(S_1 = N)$$

as the probability of being in one of  $N$  regimes, and the state transition matrix for a two-state system is:

$$\begin{bmatrix} P(S_t = 1|S_{t-1} = 1) & P(S_t = 2|S_{t-1} = 1) \\ P(S_t = 1|S_{t-1} = 2) & P(S_t = 2|S_{t-1} = 2) \end{bmatrix}$$

Each element of the matrix shows the probability of being in a particular regime given the previous regime.

<sup>4</sup>However, this may be an over-simplification as financial crisis evolves in the fashion of Minsky through an evolution of hedge, speculative and finally Ponzi-type lending. In that case, the longer the duration of the period of stability, the greater the financial shock that is likely to be envisaged. Can this be added to the model?



In estimating the multi-regime model of financial risk, it is assumed that the carry-trade returns can be characterised as a *mixture model*, where each observation of the carry-trade profit is drawn from one of either two or three distinct sub-populations. Support for this assumption is found in [Hayward \(2013\)](#) where carry-trade returns are found to have two distinct distributions which can be characterised as *calm* and *crisis*, where the two periods are identified by the level of international risk aversion through the VIX index.

The base model assumes that there is a normal, linear relationship between the carry-trade returns and the financial regime. For the other models, it is assumed that though the distribution from which each carry-return is drawn is not immediately observable, it can be represented as a *latent* or unobserved state where this state is the unknown financial regime that is associated with a particular type of carry trade. The financial regime determines the likelihood of observing the given carry-trade return. It is assumed that when conditions are stable, the carry-trade is generally profitable and safe, when financial conditions deteriorate, there are losses and greater risk.

### 3.4 Estimation of the parameters

Estimating the HMM involves uncovering the most likely three sets of parameters for the initial probabilities ( $\pi$ ), the transitional probabilities ( $A$ ) and the conditional probabilities that a particular return will be seen given a particular financial state ( $B$ ). This gives the set of parameters to be estimated.

$$\lambda = (\pi, A_1, B_1) \tag{3}$$

This estimation is done by Maximum Likelihood. As a consequence of the Markov assumption, this is a problem that can be solved with the *Expectation-Maximization (EM) algorithm*. See [Dempster et al. \(1977\)](#) and [Hamilton \(1989\)](#) as well as [Visser and Speekenbrink \(2010\)](#) for full details of the procedure. This is a numerical optimisation. There are two steps. First *the expectation step* will iterate forward from the starting point using initial estimates of the three sets of parameter values to make an initial assessment of the probability of observing each hidden regime given the model parameters. The initial parameters can either be drawn randomly or they can be determined by some prior information.<sup>5</sup> In this way the most likely

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<sup>5</sup>In this case the parameters are drawn randomly. However, it would be possible to make initial estimates of the response model from [Hayward \(2013\)](#) using the estimates of the carry-trade returns that are identified.

unobserved regime for each period can be calculated. A variant of the EM algorithm called *the forward-backward* or *Baum-Welch* algorithm [Baum et al. \(1970\)](#) is used. The Baum-Welch algorithm will find the parameters that maximize the probability of observing the sequence of carry-trade returns.

For the dependent mixture model, the joint likelihood of observation  $Y_{1:T}$  and the latent state  $S_{1:T}$  given the model parameters is

$$P(Y_{1:T}, S_{1:T}|\theta) = \pi b_{S_1}(Y_1) \prod_{t=1}^{T-1} a_{i,j} b_{S_t}(Y_{t+1}) \quad (4)$$

where  $\pi_i$  is the initial probability of each state;  $a_{i,j} = P(S_{t+1} = j|S_t = i)$  is the transition probability; and  $b_{S_t}$  is the probability of being in a particular state given the observed carry-trade return,  $b_j = P(Y_t|S_t = j)$ .

The *maximisation step* then updates the most likely values for the three sets of parameters based on the state sequence that has just been identified. Therefore, the probabilities of starting in a particular regime ( $\pi$ ) come from the estimates just used to assess the most likely regime in each period; the transition matrix ( $A$ ) is estimated from the given sequence; and the factor weights for the response model ( $B$ ) are also updated.

For the expectations part of the iteration, the states are replaced by their expected value given the parameters of the models ( $\theta$ )

$$\log P(Y_{1:T} S_{1:T}|\theta) = \log P(S_1|\theta_1) + \sum_{t=2}^T \log P(S_t|S_{t-1}, \theta_2) + \sum_{t=1}^T \log P(Y_t|S_t, \theta_3) \quad (5)$$

It is also to iterate backwards to assess the probability that a particular sequence will be observed from a point in time to the end of the sequence. This is based on  $\beta_t(i) = P(Y_{t+1}, Y_{t+2} \dots Y_T|S_t = S_i, \lambda)$ . Setting the end probability as unity and inducting backwards,

$$\beta_i(t) = \sum_{j=1}^N a_{ij} b_j(Y_{t+1}) \beta_{t+1}(j) \quad (6)$$

The probability of being in state  $S_i$  at time  $t$  is given by

$$\gamma_t(i) = \frac{\alpha_t(i) \beta_t(i)}{P(Y|\lambda)} \quad (7)$$

Solving

$$q_i = \operatorname{argmax}[\gamma_t(i)], \quad 1 \leq i \leq N, \quad 1 \leq t \leq T \quad (8)$$

will maximise the number of correct states.

## 4 Analysis of Results

### 4.1 Data

The data are a sample of carry-trades from investments in Emerging European countries that have been compiled from exchange rate and interest rate data for the period from January 2000 to December 2013. They show a sample of possible carry-trades that could have been conducted.

The carry trade profits are calculated as follows

$$P1MEURHUF_t = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}} \times EURHUF_{t+1M}} \quad (9)$$

where  $HUF1M_t$  is the 1 month Hungarian Forint deposit rate at time  $t$ ,  $EUR1M_t$  is the 1-month euro denominated deposit rate at time  $t$ ,  $EURHUF_t$  is the exchange rate in terms of Hungarian Forint required for one euro at time  $t$  and  $EURHUF_{t+1M}$  is the spot rate in 1 month's time. This is the same as (Brunnermeier et al., 2008). When uncovered interest parity (UIP) holds,  $P1MEURHUF_t$  is equal to one.

### 4.2 Model Comparison

Three initial models of financial stability are assessed:

- Model 1 (m1) is a standard linear model  $y_t = \beta_0 + \varepsilon$
- Model 2 (m2) standard linear model with two regimes  $y_t = \beta_0 + \beta_1 S_n + \varepsilon$ ,  $n = 1, 2$
- Model 3 (m3) standard linear model with three regimes  $y_t = \beta_0 + \beta_1 S_n + \varepsilon$ ,  $n = 1, 2, 3$

There is some debate about the comparison of Markov-switching models. Standard methods that compare log-likelihood ratios adjusted for restrictions or penalise the likelihood for the number of parameters estimated. There are unidentified nuisance parameters under the null and identically zero scores (derivative of the log-likelihood function) Hansen (1992). Smith et al. (2006) propose the *Markov switching Criterion* (MSC) that will penalise the over-retention of states. The MSC performs well in Monte Carlo simulation. However, (Garcia, 1998) uses Monte Carlo simulation to assess the difference between the empirically derived likelihood and the likelihood ratio test statistic and finds that the difference is minimal for standard two-state models with constant values for the transition matrix. Psaradakis and Spagnolo

(2003) proposes a test of the number of regimes that is based on the level of auto-regression, on the basis that this is related to the number of states. In these Monte Carlo simulations, the Bayesian Information Criterion (BIC) tends to under-estimate the number of states while the Akaike Information Criterion (AIC) is generally more precise.

A combination of these measures is used here with confirmation sought across different models. Table 1 summarises the performance of the three basic models using the Akaike Information criterion and the log-likelihood ratio test. The models here are tested using the EUR as the funding currency. Results for other funding currencies are very similar and are therefore not reported. A comparison of the 2-regime response models for different funding units is presented in Table 2

The AIC is the Akaike Information Criterion (AIC) calculated as

$$AIC = 2k - 2\ln(L) \quad (10)$$

where,  $k$  is the number of free parameters and  $\ln(L)$  is the log-likelihood. Though the log-likelihood will increase when more variables are added to the model, This statistic will penalise the additional of new variables. The lower the AIC the more parsimonious the model Akaike (1981). For nested models, it is also possible to use the log-likelihood ratio. This is

$$D = 2 \times \Lambda = 2 \times (\logLik(\text{tested model}) - \logLik(\text{base model})) \quad (11)$$

Asymptotically, the likelihood ratio ( $\Lambda$ ) has a  $\chi^2$  distribution with degrees of freedom equal to the constrained parameters.

	AIC(M1)	ACI(M2)	AIC(M3)	LLR21	LLR21p	LLR31	LLR31p	LLR32	LLR32p
HUF	-404.69	-416.94	-407.23	22.25	0.0005	26.50	0.0090	4.30	0.7459
PLN	-423.98	-437.62	-428.82	23.65	0.0003	28.80	0.0042	5.20	0.6357
CZK	-427.23	-427.37	-415.61	10.14	0.0714	12.40	0.4155	2.20	0.9451
RON	-456.02	-474.81	-464.39	28.79	0.0000	32.40	0.0012	3.60	0.8264
RUB	-523.18	-567.77	-559.95	54.59	0.0000	60.80	0.0000	6.20	0.5188
BGN	-451.98	-454.32	-443.21	12.34	0.0305	15.20	0.2291	2.90	0.8945
NOK	-453.92	-449.12	-447.42	5.20	0.3922	17.50	0.1317	12.30	0.0911
ISK	-439.36	-464.24	-462.42	34.88	0.0000	47.10	0.0000	12.20	0.0947
UAH	-572.87	-643.36	-636.39	80.49	0.0000	87.50	0.0000	7.00	0.4257
HRK	-431.55	-433.37	-426.58	11.82	0.0373	19.00	0.0877	7.20	0.4068
TRY	-431.05	-441.00	-432.58	19.95	0.0013	25.50	0.0125	5.60	0.5895

Three models are initially tested. Model One (M1) is the base model with carry-trade returns explained by a normal distribution around a linear constant; Model Two (M2) is the linear model with 2 regimes; Model Three (M3) is the linear model with 3 regimes. AIC measures the Akaike Information index for the model identified, LLR is the log-likelihood ratio test statistics that compares the two named and nested models. The p indicates the probability value of the  $\chi^2$  test of the log-likelihood ratio with degrees of freedom equal to the number of parameter constraints of the base model. For example LLR32p is the probability value for the ratio between Model (M3) and Model 2 (M2).

Table 1: Comparison of models

The two-regime model is superior to the base model with one regime for all countries apart from Norway. For Norway, the AIC is just -449.12 for the two-regime model compared to -453.92 for the base model and the log-likelihood ratio test statistic is just 5.20. For the Czech Republic, there is a little ambiguity. The AIC is about equal for the two models and the ratio test is 10.14, giving a  $\chi^2$  p-value of 0.0714. These two cases will be investigated further below. Norway and Czech may be better assessed with just a single regime. For the other countries the two-regime model is superior.

The three-regime model is also superior to the base model for all but the Czech Republic, Bulgaria, Norway and, possibly, Croatia. There is less ambiguity about the Czech Republic in this case as the log-likelihood ratio statistic of model 3 over model 1 is just 12.40 and a  $\chi^2$  p-value of 0.4155. Croatia has a log-likelihood ratio of 19.00 and a p-value of 0.0877. There is no case where the model 3 with 3 regimes is seen to be superior to model 2.

An analysis of the response for the two-regimes model (see Table 2) is rather encouraging as two periods that could be termed stable and unstable can be clearly identified. During the period of stability, positive returns from the carry-trade are expected while the crash experiences losses. In all cases, the standard deviation of the crash regime is much larger than that of the period of calm. This is consistent with the idea that crash risk is part of the explanation for the apparent breakdown in UIP.

There are two other things to note. First, the funding currency that is selected does not make much difference. The average performance of stability and crash regimes across funding currencies (final column of Table 2) does not differ significantly. The rest of the results that are presented are based on EUR-funding. Secondly, the mean and standard deviation for those countries where the Information criteria and log-likelihoods raised doubt about the two-regime also suggest that a one-regime model may be more appropriate. For Turkey and Norway the difference between the returns in the two periods is much smaller. For the Czech Republic, however, there remains ambiguity and uncertainty. Outside of the JPY funding, there are two clear regimes identified by the mean and standard deviations.

Funding	Regime		HUF	PLN	CZK	RON	RUB	TRY	BGN	NOK	ISK	UAH	HRK	Mean
EUR	stable	Mean	1.0165	1.0173	1.0129	1.0150	1.0098	1.0151	1.0075	1.0092	1.0091	1.0094	1.0091	1.0119
		St-Dev	0.0519	0.0486	0.0542	0.0433	0.0310	0.0460	0.0381	0.0693	0.0532	0.0295	0.0251	0.0446
	Crash	Mean	0.9905	0.9862	0.9963	0.9969	0.9962	0.9969	1.0053	1.0008	0.9427	0.9673	1.0082	0.9897
		S-Dev	0.1085	0.1026	0.0886	0.0878	0.0779	0.1028	0.0826	0.0303	0.1871	0.1116	0.0737	0.0958
USD	stable	Mean	1.0103	1.0123	1.0072	1.0091	1.0044	1.0087	1.0041	1.0045	1.0065	1.0055	1.0054	1.0071
		S-Dev	0.0307	0.0297	0.0305	0.0080	0.0095	0.0314	0.0189	0.0050	0.0318	0.0078	0.0187	0.0202
	Crash	Mean	0.9925	0.9845	0.9983	1.0052	1.0004	1.0034	1.0016	1.0034	0.9691	0.9932	1.0036	0.9959
		S-Dev	0.0707	0.0641	0.0493	0.0389	0.0407	0.0792	0.0413	0.0364	0.0998	0.0635	0.0390	0.0566
CHF	stable	Mean	1.0052	1.0097	1.0040	1.0085	1.0033	1.0099	1.0012	1.0033	1.0048	1.0029	1.0031	1.0051
		S-Dev	0.0181	0.0235	0.0161	0.0179	0.0234	0.0313	0.0083	0.0162	0.0286	0.0307	0.0116	0.0205
	Crash	Mean	0.9994	0.9838	0.9934	0.9959	0.9373	0.9952	0.9958	0.9904	0.9760	0.9834	0.9916	0.9857
		S-Dev	0.0477	0.0459	0.0380	0.0387	0.0592	0.0792	0.0327	0.0420	0.0804	0.0900	0.0384	0.0538
JPY	stable	Mean	1.0149	1.0157	1.0125	1.0149	1.0074	1.0111	1.0092	1.0125	1.0095	1.0094	1.0091	1.0115
		S-Dev	0.0348	0.0359	0.0241	0.0291	0.0226	0.0401	0.0191	0.0226	0.0381	0.0307	0.0210	0.0289
	Crash	Mean	0.9843	0.9727	1.0012	0.9972	0.9983	1.0061	1.0002	0.9985	0.9658	0.8539	1.0028	0.9801
		S-Dev	0.0767	0.0764	0.0525	0.0580	0.0628	0.0889	0.0487	0.0510	0.1033	0.0667	0.0493	0.0668

This table outlines the linear response for Model Two (M2) for each of the regimes for all countries under consideration. Stable is the label given to the regime with the highest mean return. In all cases this is also the regime with the smallest standard deviation. This is not imposed and it is encouraging as, consistent with the idea that the carry-trade is composed of two distinct phases, it suggests that positions are built and profits are available when conditions are stable and that losses are suffered when conditions are more risky. Given the assessment of model performance that is displayed in Table 1, Norway and Iceland should be ignored; the Czech Republic may be treated with some caution. The data also suggests that the funding currency does not have a major effect on the performance of the carry-trade.

Table 2: Mean and Standard Deviation of 2 Regime Model

### 4.3 Risk aversion and financial stability

There are three exogenous forces identified in the literature that may influence financial stability: US monetary policy, the level of international risk aversion and the provision of financial market liquidity. US monetary policy is measured with the US short term interest rate (3m LIBOR), international risk aversion is measured with the VIX index, market liquidity is measured by using the Ted spread as the difference between the tbill rate and the rate that banks can borrow.

Each of these forces could affect financial stability and therefore the carry trade in two main ways: they could have a direct linear influence or they may influence the probability of switching from one regime to another. In the first case it could be added as an explanatory variable to the response model. For example,

$$y_t = \beta_0 + \beta_1 Z_t + \varepsilon \quad (12)$$

where  $y_t$  is the carry-trade return and  $Z_t$  is the exogenous influence on financial stability.

In the second case, the exogenous force is used to explain the transition probabilities using a multinomial logistic regression. For the transition model (A),

$$a_{ij}(t) = P(S_t = j | S_{t-1} = i, z) \quad (13)$$

where  $a_{ij}(t)$  is the probability that the system will be on state  $i$  at time  $t$  when it was in state  $j$  in the previous period and covariate  $z$  takes a particular value at time  $t$ . For a two-regime model, the estimation that is carried out is

$$\log(a_{t,n=2})/a_{t-1,n=1} = \beta_0 + \beta_1 z_t \quad (14)$$

State 1 is the baseline category so coefficients are set to zero for that state and the model estimates the relationship between the covariate and probability of switching to the other state.

The logistic function is

$$F(z) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 z)}} \quad (15)$$

giving a probability between zero and unit of being in the particular state. [Agresti \(2014, pp.174-75\)](#).



	AIC(M1)	ACI(M4)	AIC(M2)	AIC(M5)	LLR54	LLR54p	LLR52	LLR52p	Coeff	p-value
HUF	-404.69	-402.70	-416.94	-419.50	28.80	0.0001	6.56	0.0377	-0.00	0.9529
PLN	-423.98	-422.03	-437.62	-438.93	28.90	0.0001	5.30	0.0705	-0.00	0.8202
CZK	-427.23	-425.25	-427.37	-430.52	17.27	0.0083	7.15	0.0280	0.00	0.8935
RON	-456.02	-454.42	-474.81	-478.07	35.65	0.0000	7.26	0.0265	0.00	0.5307
RUB	-523.18	-449.98	-567.77	-566.68	128.70	0.0000	2.92	0.2328	-0.00	0.9833
BGN	-451.98	-449.98	-454.32	-459.55	21.56	0.0015	9.23	0.0099	-0.00	0.9892
NOK	-453.92	-449.98	-449.12	-445.70	7.72	0.2592	0.58	0.7472	0.00	0.7594
ISK	-439.36	-438.30	-464.24	-463.57	37.27	0.0000	3.34	0.1887	0.00	0.3343
UAH	-572.87	-571.47	-643.36	-647.67	88.20	0.0000	8.31	0.0157	0.00	0.4451
HRK	-431.55	-429.58	-433.37	-439.42	21.84	0.0013	10.05	0.0066	-0.00	0.8590
TRY	-431.05	-429.06	-441.00	-439.26	22.20	0.0011	2.26	0.3232	-0.00	0.9575

The table details the comparison of four models. Model One (M1) is the base model; Model Four (M4) adds the VIX index as a response variable (Equation 12); Model Two (M2) is the simple response model with two regimes; Model Five (M5) is the two-regime model with the VIX index as a logistic covariate of the transition matrix. LLR is the log-likelihood ratio with the p denoting the p-value for a  $\chi^2$  distribution with degrees of freedom equal to the parameter restrictions on the base model that is being compared. Therefore, LLR54p is the p-value for the log-likelihood ratio of Model Five on Model Four. This assesses the performance of the 2-regime model with the VIX influencing the transition values against the model where the VIX directly affects the carry-trade return. Coefficient is from Model Four. It is the estimate of  $\beta_1$  from a regression of Equation 12; p-value is the test of the null hypothesis that  $\beta_1$  is equal to zero.

Table 3: VIX covariate model table

Table 3 compares models using the VIX as a measure of international risk aversion. Model 1 is the base model with one state and a linear relationship (M1); Model Four (M4) adds the VIX index as a response variable like Equation 12; Model Two (M2) is the two state model; Model Five (M5) is the two-regime model with the VIX index as a logistic covariate of the transition matrix. This means that Equation 15 is used to estimate the probability of transferring between regimes, where  $z$  is the level of the VIX index. The AIC and log-likelihood ratios indicate that for every country apart from Norway, Model 5 (M5) with the VIX index as an influence on the transition matrix is a better model than Model Four (M4) where the VIX directly influences carry-trade returns. Indeed, the VIX does not seem to have a significant effect on carry-trade returns. Column 9 gives the coefficient  $\beta_1$  from a regression of Equation 12 and column 10 provides the p-value of the null hypothesis that the coefficient is equal to zero.

Columns 7 and 8 assess whether the addition of the VIX as an explanatory variable probability transition matrix as assessed in Model Five (M5) is superior to the standard two regime model (M2). The log-likelihood ratio for this comparison is in Column 7 of the table and the  $\chi^2$  p-value is in column 8. Unsurprisingly, the information criteria and log-likelihood ratio tests suggest that for Norway and Iceland the simple model without the explanation for the transition between regimes is more appropriate. This reinforces the indication made in the first tests that a two-regime model is not appropriate for these two countries (see Table 1). For Russia and Turkey, though it appears that the level of international risk aversion is best used explaining the probability of switching from one regime to another rather than as an explanation of the level of carry-trade profits, it also appears that the simple two-regime model is superior.

#### 4.4 Risk aversions on the probability of a crash

Table 3 suggests that Model Five (M5) where the measure of international risk aversion affects the probability of making the transition from the state of stable to the condition of crash is not the appropriate for Norway, Russia, Iceland and Turkey. Therefore, these countries have been left out of the more detailed analysis of the way that changes in international risk appetite affect the probabilities of a crash. The main results are detailed in Table 4. The table shows the effect of a change in the VIX on the probability that the system will switch from the state that is regarded as stable with relatively high carry-trade returns and low variance, to the region of crash where there are usually losses and large risk. The VIX has been normalised so that the mean is zero and the standard deviation is equal to unity. Therefore, the

	-3sd	-2sd	-1sd	Mean	+1sd	+2sd	+3sd
HUF	0.0020	0.0069	0.0242	0.0807	0.2375	0.5249	0.7967
PLN	0.0004	0.0016	0.0063	0.0242	0.0887	0.2766	0.6003
CZK	0.0000	0.0002	0.0034	0.0717	0.6367	0.9755	0.9989
RON	0.0014	0.0043	0.0131	0.0392	0.1119	0.2799	0.5453
BGN	0.0000	0.0001	0.0020	0.0733	0.7558	0.9918	0.9998
UAH	0.0000	0.0000	0.0000	1.0000	1.0000	1.0000	1.0000
HRK	0.0000	0.0000	0.0000	0.0001	0.4737	0.9999	1,0000

Changes in the VIX index affect the transition probabilities. The VIX index has been scaled so that it has a mean of zero and a standard deviation of one. Therefore, the central column shows the probability that the system will switch from a stable regime to one of crisis when the VIX is at its average level. It also shows how this probability changes are the VIX moves one or more standard deviations above and below this average. For example, for Hungary, there is an 8% chance that the stable will switch to a period of crash when the VIX is at its average value. This rises to 24% when the VIX is one standard deviation above average and 53% for 2 standard deviations.

Table 4: Assessing the influence of VIX index on financial risk

column with mean shows the transition probability when the VIX is at its average level, the columns show how the probability of a crash will change as the VIX moves to one or more standard deviations above or below its average.

It is possible to read across the rows to assess the way that this probability changes as the VIX moves one and more standard deviations above and below is average. For example, the first row reveals that there is a probability of about 8% of a Hungarian crash when the VIX index is close to its mean. This rises to nearly 24% when the VIX is one standard deviation above the mean and to over 52% when the VIX is two standard deviations above its mean. The probability of a crash is in the region of 80% when the VIX is three standard deviations above the mean.

## 5 Conclusions

In most cases investigated here, the carry-trade can be analysed as a system that switches between two states. Most usually there are two states that can be characterised as being period of stable, when there are positive returns to the carry-trade and relatively low levels of conventional risk, or crash when

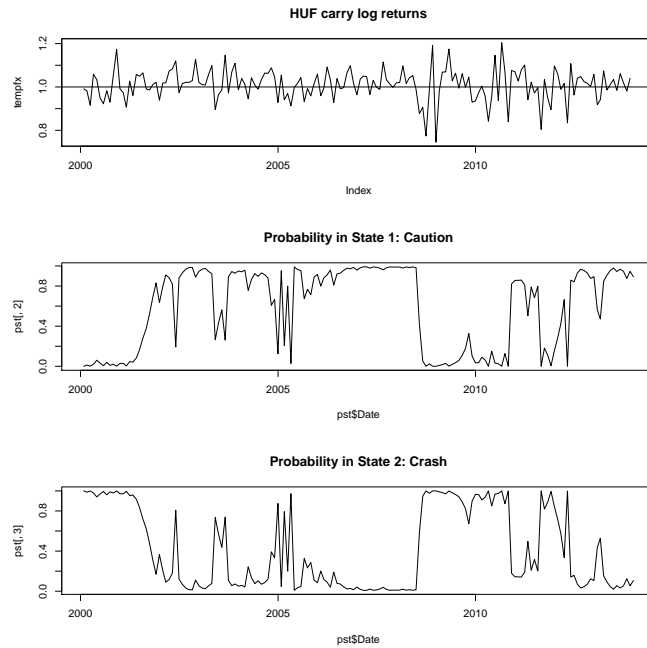


Figure 2: HUF Carry-trade probabilities

there are losses and large risks. This is consistent with the idea that international capital flows to emerging and transition economies are modelled most effectively periods of stable and then sudden stops. There is little empirical support for a more nuanced three-regime model that would distinguish, within the period of stable, between periods of stable and periods of capital surge or speculative build up in addition to the crash.

International risk aversion appears to influence carry-trade profits in many cases. However, this influence is much more likely to affect the proba-

bility of switching from one regime to another than it is of directly affecting the level of carry-trade profits.

The influence of measures of international risk aversion on the probability of moving from a state of stable to one of a crash is particularly likely to be seen in economies of central and eastern Europe. It is much less prevalent in the more developed and more periphery countries under investigation like Turkey, Norway and Iceland.

To be completed

- Pinning down the best model for Norway, Russia, Iceland and Turkey. Norway is either a one regime or three regime model; Iceland may be three. Not sure about Russia and Turkey.
- Making the same assessment using US interest rates and the Ted-spread and assessing the relative vulnerability to each of these external factors.
- Looking at the dates when the crash takes place. Which dates are the most common (Lehman's, Russian default et), which ones are unique to each country. Ratio of international to domestic.
- Looking at the applicability of the two-regime model and levels of the openness of the financial system and the exchange rate regime.

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