Carry trade and transition

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Abstract

The level of international risk aversion is shown to affect the probability of financial crash in a range of European countries. The evolution of financial stability is assessed by looking at carry-trade returns. These returns may be drawn from one, two or three financial regimes. The two-regime model is the best fit for most countries. The probability of switching from a regime of financial *calm* to a financial *crash* is affected by the level of international risk aversion for many CEE countries highlighting their vulnerability to swings in overseas investor sentiment.

1 Introduction

As the size of international capital flow has increased in absolute terms and relative to expansion of the trade in goods and services it has also become subject to less regulatory constraint. Economic authorities have struggled repeatedly with financial instability that has an international source. An inflow of capital from abroad can appear superficially attractive but its arrival can cause goods and asset price inflation, it can shape institutions, economic development and political opinion, and, most importantly, the portfolio flows 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

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the immediate financial crisis have offered relatively attractive investment opportunities. This has raised concern about the risk of a reversal in these flows. The outside of domestic considerations, 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.

Concern about changes in US monetary policy have been exacerbated by the market reaction to comments from Fed Chairman Ben Bernanke in May 2013. Bernanke's suggestion that the policy of Large Scale Asset Purchase (LSAP) could be reduced led to some reversal of emerging market capital flow and a sharp decline in value of emerging and transition economy bonds, equities and exchange rates. Risk aversion concerns the willingness of international investors to purchase more risky assets. High levels of risk aversion have caused fight-to-quality purchase of developed nation assets and an adjustment of portfolios towards towards government and fixed-income securities. International liquidity is the availability of credit for leveraged investors. It was cut back sharply during the financial crisis but efforts of developed nation central banks have sought to ensure that liquidity is restored.

These factors are, of course, interlinked. Ceruttie et al. (2014) ask three questions: what drives global liquidity; where does the global liquidity cycle originate; and, how can the borrowing country manage its 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 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 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 and 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 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 the sharp move of capital towards international financial centres and relatively safe assets.Baele et al. (2014) find that FTS are relatively rare events. Their study of of 23 countries finds that FTS represent 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.[1]

Consistent with the evidence of an interplay between monetary policy and international risk, and between domestic and international factors, Ahmed and Zlate (2014) find 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 here that quantitative easing has had some effect on capital flows.

Alexander Klemm and Sosa (2014) use a panel VAR method to assess the effect of US monetary policy since 1990 on capital flows to 38 emerging economies, finding evidence that Fed tapering 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.

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)[2] by funding an investment in relatively high yielding transition currencies with a low interest base. UIP is the theory that interest rate differentials between currencies should be matched by an equal expectation that the low rate currency will appreciate against the higher rate until expected returns from the activity are reduced to just a compensation for taking risk.

[1]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. 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.

[2]See xxx for an overview of the breakdown in UIP and .... for more on the carry trade

There is widespread evidence that UIP does not hold on average (see Froot and Thaler (1990). Froot and Frankel (1989), Hodrick (1987) and Spronk et al. (2013) for some of the discussion of the evidence against UIP) but this does not guarantee that excess returns are possible. The excess returns appear to at least partly disappear once a more multifaceted assessment of risk is applied. Carry-trade returns appear to be compensation for taking *crash-risk*. The small risk of a large loss is something that many investors wish to avoid by paying for it to transferred to other entities. Behavioural economics also suggests that these sort of large, low-probability risks are often ignored or misperceived by myopic, over-confident economic agents suffering behavioural biases. See, for example Kahneman and Tversky (1979) for an outline of *Prospect theory* as an alternative to expected utility theory derived from experiments in decision-making where there is a tendency to take risk with large losses or Odean (1998) for an overview of how over-confidence can affect asset pricing.

Brunnermeier et al. (2008) analyses 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 against crash-risk and finds 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 calm and periods of crisis (as measured by elevated levels of the VIX index) and finds that carry-returns are negative, skewed and fat-tailed when international risk aversion is heightened, but a more normal, positive return when conditions are calm.

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. They find that 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 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. This is consistent with the evidence of post-financial crisis build up of carry-like positions. As such Ceruttie et al. (2014) find that credit and liquidity contractions in the US, Euro zone, UK and Japan affect the rest of the world. Credit supply in financial centre economies affect the provision of cross-border credit. This is what they call *global funding liquidity*, a feature that affects financial conditions globally.

There are three elements to be assessed: US monetary policy, international risk aversion and provision of international liquidity.

1.1 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 Ω_t, this is state s^0 with a expected probability π 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

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

Expectations are continually confounded though they are not formed in an irrational way. In these cases, modelling that identifies two or more 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 form 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 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) analyses the change in stock market volatility that arise from different regimes. Markov models switching models are also typically used to understand the evolution of credit risk. A transition matrix with probabilities derived from empirical evidence can provide the expectation that a rating will change from one to another. This can be rolled forward to assess the probability of 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 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.

2 A Markov model of financial stability

Financial stability for each of the countries covered is presented as a first-order Markov process. There are three main possibilities: a single regime that does not change; a two-regime model that switches from calm to crisis with a sub-model that makes a one-off switch and does not return; and, a three-regime model that will switch from calm, through the building of risky investments before moving to the crash.

The base model with one regime is a control that assesses whether regime-switch is appropriate. A one-off switch from one regime to another could represent a single change in political or economic policy that contributes to a step change in financial conditions. For example, the financial crisis of 2007-08 could have caused a permanent switch to a more risky-financial state. A two-regime model may also represent a propensity to switch between periods of calm and crisis.

The two-regime model has a heritage that reaches back to Dornbusch and Werner (1995), Calvo (1998) and Krugman (2000). The term *sudden stop* emphasises the importance of the inflow of international capital that takes place before the disruptive effects of reversal. There is a focus on the factors that may make a country more or less vulnerable to sudden-stops with debate over the role that openness to trade Cavallo and Frankel (2008) and overseas banking liabilities pose Calvo et al. (2004).

A three regime model could represent a more nuanced evolution of financial instability along the lines of the Minsky (1975, 1992, 1995) where conditions of financial calm encourage excess lending and borrowing so that debt-to-income levels and an accumulation of financial risk increase to the point where there is a large risk of a crash. This is a model of financial instability where there is an evolution from caution, through the building of speculative positions and finally a crash.

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)*.

2.1 The HMM model

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

- The prior model: $P(S_1 = n|\theta_{prior})$ (π)
- 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 θ_{prior}, θ_{trans} and θ_{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 calm to crisis. 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 regimes; the transition model is the probability of moving from one financial state to another; the response model is the relationship between the carry returns and the 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

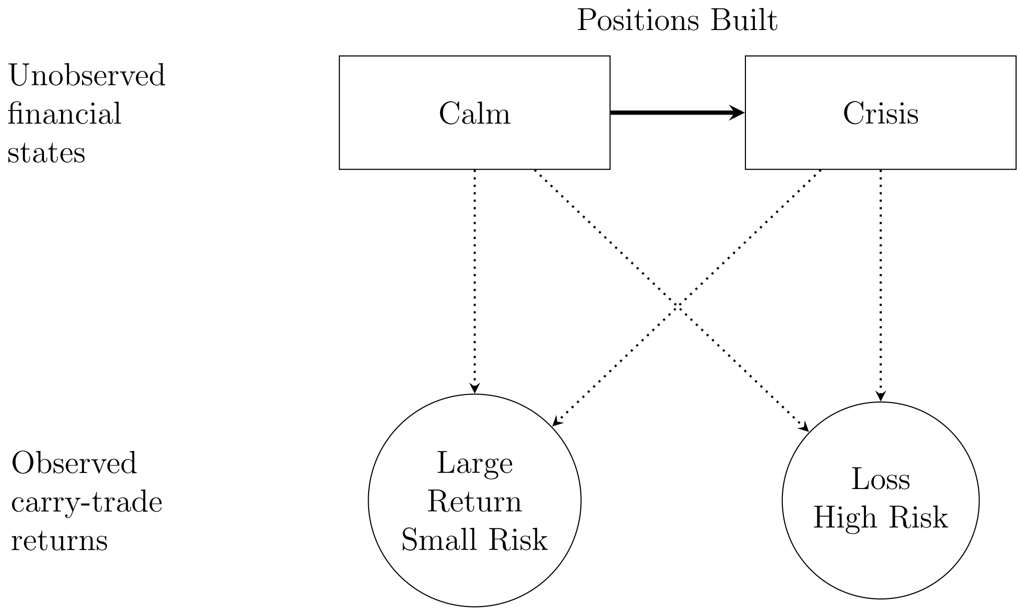

Figure 1: Two-Regime Hidden Markov Model (HMM)

estimation of the parameters. Once a starting point is given, a most likely path can be determined.

The starting point of the system is given by

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

and the state transition matrix for a two-state system is,

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

In assessing whether a multi-regime model of financial risk is applicable, it is assumed that the carry-trade returns can be characterised as a *mixture model*, where each observation of the carry-trade profit is assumed to be drawn from one of either two or three distinct sub-populations. The distribution from which the component is drawn is not immediately observable and is therefore represented as a *latent state*. Here the latent 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. Factor analysis is used to estimate the relationship.

The base model assumes that there is a normal, linear relationship between the carry-trade returns and the financial regime and the response is modelled as

$$y_t = \beta_0 + \sum_{i=1}^{i=n} S_{i,t} + \varepsilon_t \tag{3}$$

2.2 Estimation of the parameters

Estimating the HMM involves uncovering the most likely three sets of parameters for the initial probabilities (π), the transitional probabilities (A) and the conditional probabilities that a particular return will be seen given a particular financial state (B).

$$\lambda = (\pi, A_1, B_1) \tag{4}$$

This estimation is done by Maximum Likelihood using the log-likelihood function $l(\varphi, y) = \sum_{i=1}^{n} log f(y_i; \varphi)$. 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. There are two steps. The first will iterate forward from the starting point using assumptions about the parameter values (which may be drawn at random or be imposed from prior knowledge) to make and an initial assessment of the probability of observing each hidden regime given the model parameters. In this way the most likely unobserved sequence can be identified.

The Maximisation step finds the most likely values for the three sets of parameters based on the state sequence that has just been identified. 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

$$P(Y_{1:T}, S_{1:T}|\theta) = \pi b_{S_t}(Y_1) \prod_{t-1}^{T-1} a_{i,j} b_{s_t}(Y_{t+1}) \tag{5}$$

where b_{S_t} is the distribution of the observation for each latent state, $b_j = P(Y_t|S_t = j)$; π_i is the initial probability of each state; $a_{i,j} = P(S_{t+1} = j|S_t = i$ is the transition probability;

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

$$logP(Y_{1:T}S_{1:T}|\theta) = logP(S_1|\theta_1) + \sum_{t=2}^{T} logP(S_t|S_{t-1}, \theta_2) + \sum_{t-1}^{T} logP(Y_t|S_t, \theta_3) \quad (6)$$

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 $\beta_t(i) = P(Y_{t+1}, Y_{t+2} \ldots Y_T|S_t = S_i, \lambda)$. Setting the end probability as unity and inducting backwards,

$$\beta_i(t) = \sum_{j=1}^{N} a_{ij} b_j(Y_{t+1}) \beta_{t+1}(j) \quad (7)$$

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

$$\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{P(Y|\lambda})) \quad (8)$$

Solving

$$q_i = \text{argmax}[\gamma_t(i)], \qquad 1 \leq i \leq N, \qquad 1 \leq t \leq T \quad (9)$$

will maximise the number of correct states.

3 Analysis of Results

3.1 Data

The data are a sample of CEE carry-trades 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

$$P1MEURHUF_t = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}} \times EURHUF_{t+1M}} \quad (10)$$

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 fundamentally the same as (Brunnermeier et al., 2008). The forward rate is calculated as

$$EURHUF_t^{f1m} = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}}} \tag{11}$$

where $EURHUF_t^{f1m}$ is the 1 month forward rate for euro in terms of Hungarian Forint at time t, $HUF1M_t$ is 1 month Hungarian Forint deposit rate, $EUR1M_t$ is the 1 month Euro deposit rate and $EURHUF_t$ is the current rate of Euro in terms of Hungarian currency.

3.2 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 $y_t = \beta_0 + \beta_1 S_n + \varepsilon, \quad n = 1, 2$
- Model 3 (m3) standard linear model with three regimes $y_t = \beta_0 + \beta_1 S_n + \varepsilon, \quad n = 1, 2, 3$

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

$$AIC = 2k - 2ln(L) \tag{12}$$

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

$$D = 2 \times \Lambda = 2 \times (logLik(\text{tested model}) - logLik(\text{base model}) \tag{13}$$

Asymptotically, the likelihood ratio (Λ) has a χ^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 χ^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 χ^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 χ^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 calm and crash can be clearly identified. During the period of calm, 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 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 calm 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	Calm	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	Calm	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	Calm	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	Calm	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. Calm 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 calm 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

3.3 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,

$$y_t = \beta_0 + \beta_1 Z_t + \varepsilon \tag{14}$$

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),

$$a_{ij}(t) = P(S_t = j | S_{t-1} = i, z) \tag{15}$$

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

$$log(a_{t,n=2})/a_{t-1,n=1} = \beta_0 + \beta_1 z_t \tag{16}$$

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

$$F(z) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 z)}} \tag{17}$$

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 14); Model Two (M2) is the simple response model with two regimes; Model Five (M5) is the two-regime model with the VIX index a a logistic covariate of the transition matrix. LLR is the log-likelihood ratio with the p denoting the p-value for a χ^2 distribution with degrees of freedom equal to the parameter xrestrictions 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 β_1 from a regression of Equation 14; p-value is the test of the null hypothesis that β_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 14; 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 17 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 β_1 from a regression of Equation 14 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 χ^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.

3.4 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 calm 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 calm 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 calm 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 calm 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.

4 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 calm, when there are positive returns to the carry-trade and relatively low levels of conventional risk, or crash when 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 calm and then sudden stops. There is little empirical support for a more nuanced three-regime model that would distinguish, within the period of calm, between periods of calm 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 probability 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 calm 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.

References

Agresti, A. (2014), *Categorical data analysis*, John Wiley & Sons.

Ahmed, S. and Zlate, A. (2014), 'Capital flows to emerging market economies: A brave new world?', *Journal of International Money and Finance* (0), –.
URL: *http://www.sciencedirect.com/science/article/pii/S0261560614000928*

Akaike, H. (1981), 'Likelihood of a model and information criteria', *Journal of Econometrics* **16**(1), 3–14.

Alexander Klemm, A. M. and Sosa, S. (2014), Taper tantrum or tedium: How will the normalization of U.S. monetary policy affect latin-america and the caribbean?, *in* 'IMF: Regional Economic Outlook: Western Hemisphere - Rising Challenges', pp. 37 – 46.
URL: *http://www.imf.org/external/pubs/ft/reo/2014/whd/eng/pdf/wreo0414.pdf*

Baele, L., Bekaert, G., Inghelbrecht, K. and Wei, M. (2014), 'Flights to safety', *Finance and Economics Discussion Series* **2014**(46).
URL: *http://www.federalreserve.gov/pubs/feds/2014/201446/201446abs.html*

Baum, L. E., Petrie, T., Soules, G. and Weiss, N. (1970), 'A maximization technique occuring in the statistical analysis of probabilistic functions of Markov chains', *The Annals of Mathematical Statistics* **41**(1).
URL: *http://projecteuclid.org/euclid.aoms/1177697196*

Brunnermeier, M., Nagel, S. and Pedersen, L. (2008), 'Carry trades and currency crashes', *NBER Working Papers* (14473).

Bruno, V. and Shin, H. S. (2014), Cross-border banking and global liquidity. mimeo, Princeton University.

Calvo, G. A. (1998), 'Capital flows and capital-market crises : the simple economics of sudden stops', *Journal of Applied Economcs* **1**(1), 34 – 54.

Calvo, G. A., Izquierdo, A. and Mejia, L.-F. (2004), On the empiric of sudden stops: the relevance of balance-sheet effects, Technical report, National Bureau of Economic Research.

Cavallo, E. A. and Frankel, J. A. (2008), 'Does openness to trade make countries more vulnerable to sudden stops, or less? using gravity to establish causality', *Journal of International Money and Finance* **27**(8), 1430 – 1452.
URL: *http://www.sciencedirect.com/science/article/pii/S0261560607001180*

Ceruttie, E., Claessens, S. and Ratnovski, L. (2014), 'Global liquiity and drivers of cross-border bank flows', *IMF Working Paper* **14**(69).

Chicago Board of Trade (2009), 'The VIX white paper'.
URL: *http://www.cboe.com/micro/vix/vixwhite.pdf*

Demeterfi, K., Derman, E., Kamal, M. and Zou, J. (1999), 'More than you ever wanted to know about volatility swaps', *Goldman Sachs Quantitative Strategies Research Notes* .

Dempster, A. P., Laird, N. M. and Rubin, D. B. (1977), 'Maximum likelihood from incomplete data via the em algorithm', *Journal of the Royal Statistical Society. Series B (Methodological)* pp. 1–38.

Diamond, R. V. (2012), 'Vix as a variance swap'.
URL: *http://ssrn.com/abstract=2030292*

Dornbusch, R. and Werner, A. (1995), 'Currenc crises and collapses', *Brookings Papers in Economic Activity* **1995**(2), 219 – 293.

Dueker, M. J. (1997), 'Markov switching in garch processes and mean-reverting stock-market volatility', *Journal of Business & Economic Statistics* **15**(1), 26–34.

Evans, M. D. (1996), '21 Peso problems: Their theoretical and empirical implications', *Handbook of statistics* **14**, 613–646.

Froot, K. and Frankel, J. A. (1989), 'Forward discount bias: Is it an exchange rate risk premium?', *Quarterly Journal of Economics* **6**, 139 – 161.

Froot, K. and Thaler, R. (1990), 'Anomolies: Foreign exchange', *The Journal of Economic Perspectives* **4**(3), 179 – 192.

Frydman, H. and Schuermann, T. (2008), 'Credit rating dynamics and markov mixture models', *Journal of Banking & Finance* **32**(6), 1062–1075.

Groen, J. and Peck, R. (2014), 'Risk aversion, global asset prices, and fed tightening signals'.
URL: *http://libertystreeteconomics.newyorkfed.org/2014/03/risk-aversion-global-asset-prices-and-fed-tightening-signals-.html*

Hamilton, J. D. (1988), 'Rational-expectations econometric analysis of changes in regime: An investigation of the term structure of interest rates', *Journal of Economic Dynamics and Control* **12**(2), 385–423.

Hamilton, J. D. (1989), 'A new approach to the economic analysis of non-stationary time series and the business cycle', *Econometrica* **52**(2), 357 – 384.

Hayward, R. (2013), Towards a model of speculation in the forign exchange market, PhD thesis, University of Brighton Business School.

Hodrick, R. (1987), *The Empirical Evidence on the Efficiency of Forward and Futures Foreign Exchange Markets*, Harwood, New York.

Jurek, J. (2007), 'Crash-neutral currency carry trades', *AFA Atlanta Meetings Paper* .

Kahneman, D. and Tversky, A. (1979), 'Prospect theory: An analysis of decision under risk', *Econometrica* **47**(2), 263–291.

Krugman, P., ed. (2000), *Currency Crises*, University of Chicago Press, Chicago.

Minsky, H. P. (1975), *John Maynard Keynes*, Columbia University Press, NY.

Minsky, H. P. (1992), The financial instability hypothesis, *in* M. S. P. Arestis, ed., 'Handbook of Radical Political Economy', Edward Elgar, Aldershot.

Minsky, H. P. (1995), 'Longer waves in financial relations: Financial factors in the more severe depressions II', *Journal of Economic Issues* **29**(1).

Mishra, P., Moriyama, K. and N'Diaye, P. M. (2014), 'Impact of Fed tapering announcements on emerging markets', *IMF Working Paper* **14**(109).
URL: *http://www.imf.org/external/pubs/cat/longres.aspx?sk=41655.0*

Obstfeld, M. (2014), Trilemmas and tradeoffs - living with financial globalization. mimeo, University of Berkeley.

Odean, T. (1998), 'Volume, volatility, price, and profit when all traders are above average', *The Journal of Finance* **53**(6), 1887–1934.

Rey, H. (2013), Dilemma not trilemma. the global financial cycle and monetary policy independence, *in* 'Proceedings of the Federal Reseve Bank of Kansas City Economic Symposium in Jackson Hole'.
URL: *http://www.kansascityfed.org/publicat/sympos/2013/2013rey.pdf*

Schaller, H. and Norden, S. V. (1997), 'Regime switching in stock market returns', *Applied Financial Economics* **7**(2), 177–191.

Spronk, R., Vershoor, W. F. and Zwinkels, R. C. (2013), 'Carry trade and foreign exchange rate puzzles', *European Economic Review* **60**, 17–31.

Visser, I. and Speekenbrink, M. (2010), 'depmixS4: An R package for Hidden Markov Models', *Journal of Statistical Software* **36**(7), 1–21.
URL: *http://www.jstatsoft.org/v36/i07/*

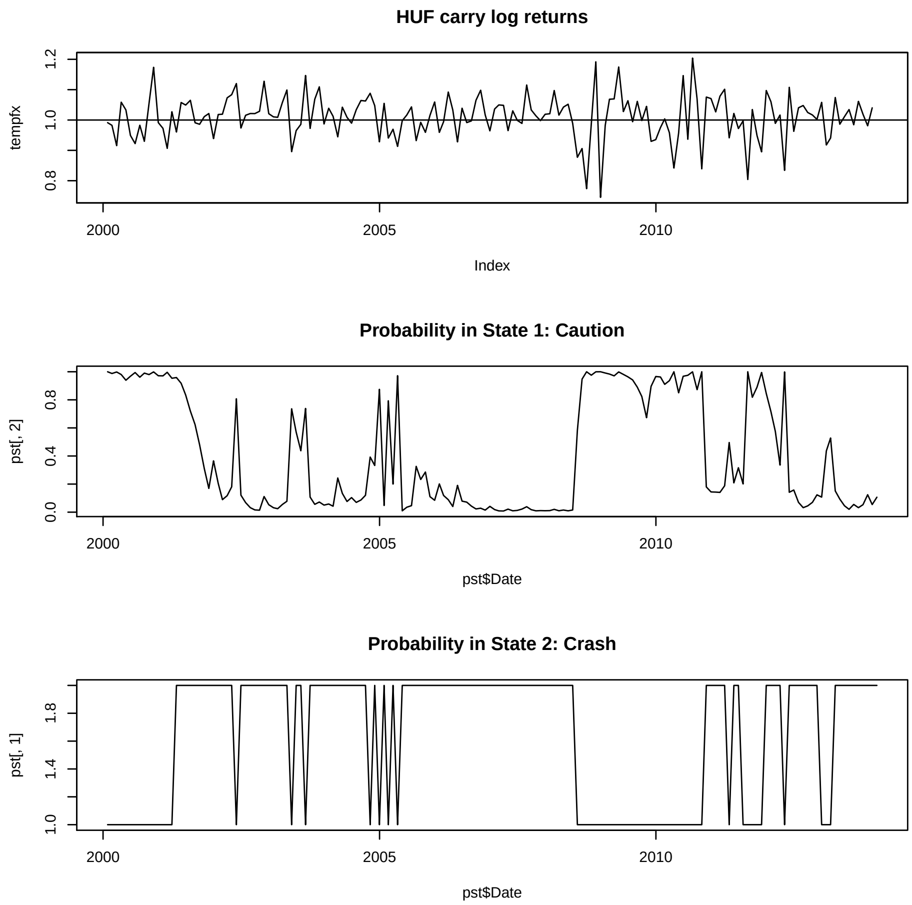

Figure 2: HUF Carry-trade probabilities