Carry trade and transmission

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Abstract

Hyman Minsky argued that financial instability would increase with an evolution that ran from caution through increasing speculation into one of precarious instability, from one characterised by *hedge financing* into successively more fragile regimes of *speculative financing* and *Ponzi financing*. Though this process is not directly observable, there are financial market outcomes that are more likely to be prevalent in each of these regimes. *Carry-trade* returns, the payment for deviations from *uncovered interest parity* (UIP), are used to identify the stages of increasing financial fragility. Return characteristics change as financial instability develops so that the process can be modeled as a Hidden Markov Model (HMM) where the states are unobserved but the probability of being in a particular regime is conditional on the carry-trade return. The parameters of the HMM can be used to learn about the evolution of financial instability, the factors that can influence instability and may also provide real-time indicators about the level of financial risk.

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 faced repeated struggles with financial instability that has an international source. An inflow of capital from abroad can appear superficially attractive but its

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arrival 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 developed economies and relatively attractive investment opportunities in many transition and emerging states. The indication from Federal Reserve Chairman Ben Bernanke on May 22nd 2013, that the central bank would cut back its pace of liquidity injection by gradually reducing its monthly bond purchase triggered a sharp sell-off in emerging bond and equity markets as well as their currencies. This market reaction has drawn attention to the risk that international capital flows will reverse and has encouraged some reassessment of the relationship between US monetary policy , international liqudity and international risk appetite with flow of capital to transition and emerging economies.

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 on 25% 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 and one that can represent all the other portfolio flows 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.

There is widespread evidence that UIP does not hold on average (see Froot and Thaler (1990). Froot and Frankel (1989), Hodrick (1987) and

[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), **?** 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

Spronk et al. (2013) for some of the discussion) but this does not guarantee that excess returns are possible. These returns disappear when a more multifaceted assessment of risk is taken. Most notably, the small risk of a large loss, is either something that is to be avoided by most investors who are willing to pay to transfer this risk to other entities or is something that misperceived by myopic, over-confident economic agents suffering behavioural biases. Carry-trade returns are compensation for taking *crash-risk*.

For example, 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) assess the cost of purchasing option protection against crash-risk and finds that it 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 a 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) assesses 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 the 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), *Trilemmas and Tradeoffs - Living with Financial Globalization* (2014) and Bruno and Shin (2014). For example, there is evidence the correlation of cross-border credit growth has increased since the 1990s and that, funds increasingly flow from the financial centres to the rest of the world. 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.

1.1 The evolution of financial instability

One common issue encountered in the assessment of finacial crises and analysis of the carry-trade, is that of *peso problems*. Peso problems are situations where there is potential for discrete shifts in the distribution of variables. This can affect expectations, risk-premia and asset pricing models 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 and this is state s^0 with a expected probability at time t of π_t that there will be an 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

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

To deal with this, Hamilton (1988, 1989) used discrete changes in Fed policy to improve modelling of term structure expectations and assessed 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}. The parameters of an ARIMA representation of US GNP shift between the two regimes so that there is a 3% decline in the US growth rate during a recession.

Schaller and Norden (1997) extends the Hamilton model to asses stock returns in two regimes, uncovering strong evidence of regim-switching in the mean and variance of US stock returns.

that that the response of stock returns to the price-dividend ratio has asymmetric effects; Dueker (1997) analyses the change in stock market volatility that arise from different regimes. Markov models switching models are also typically used to assess the evolution of credit risk. A firm with a particular credit rating has a given probability of maintaining that rating or moving to another. This can be used to estimate probability of default and value corporate bonds (reference needed). 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.

There are three main ways that the evolution of international financial risk can be modelled. The first is through a one-off transition from calm to crisis. This represents a world there has been some major event that has transformed the system and where there has been a permanent adjustment from one regime to another. This is a one-off switch that may be a function of political or policy changes that are permanent. For example, this could be caused by a move from a fixed exchange rate to something more variable or another type of shift in monetary policy regime.

The second and moris a two-regime model where there is a switch between periods of calm and crisis. This is a relatively simple system where the interest is in the factors that can trigger an adjustment from one regime to another. A more sophisticated version of this is the third model were there is an evolution of the system from a position of calm, through a time when speculative positions are build and then into a crash.

The third is a more sophistocated model that would add further dynamics.

The relatively simple model that switches between periods of calm and crisis has been discussed by 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.

2 A Markov model of financial instability

The evolution of international financial instability is presented as a first-order Markov process composed of the underlying financial regimes, a vector of probability of beginning in each regime and a transmission matrix that records the probability of switching from one regime to another.

However, in stations 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 is a composed of $\pi, A, B)$ where,

1. π Vector of initial state probabilities
2. $A = (a_{ij})$ the state transition matrix $Pr(x_{it}|x_{jt-1})$
3. $B = (b_{ij})$ the confusion matrix $Pr(y_i|x_j)$

The unobserved financial regimes are modelled as a Markov chain that runs from a period of *caution* through a speculative regime when positions are *built* and finally into the *crash*. The returns to the carry-trade are more likely to take particular characteristics according to the underlying regime.

As the financial system evolves from a position of caution into one where risk is being built and finally into a precarious state where conditions are ripe for a collapse, the nature of the returns to the carry-trade will change. During the period of caution returns are close to normal and there may be just a compensation for taking risk, as financial institutions start to increase the weight of transition and emerging market assets, the returns will tend to increase to reflect the perception that this is a profitable investment, with the building of carry positions adding a capital appreciation in the exchange rate to the interest rate carry. During the crash, there are losses and extreme risk.

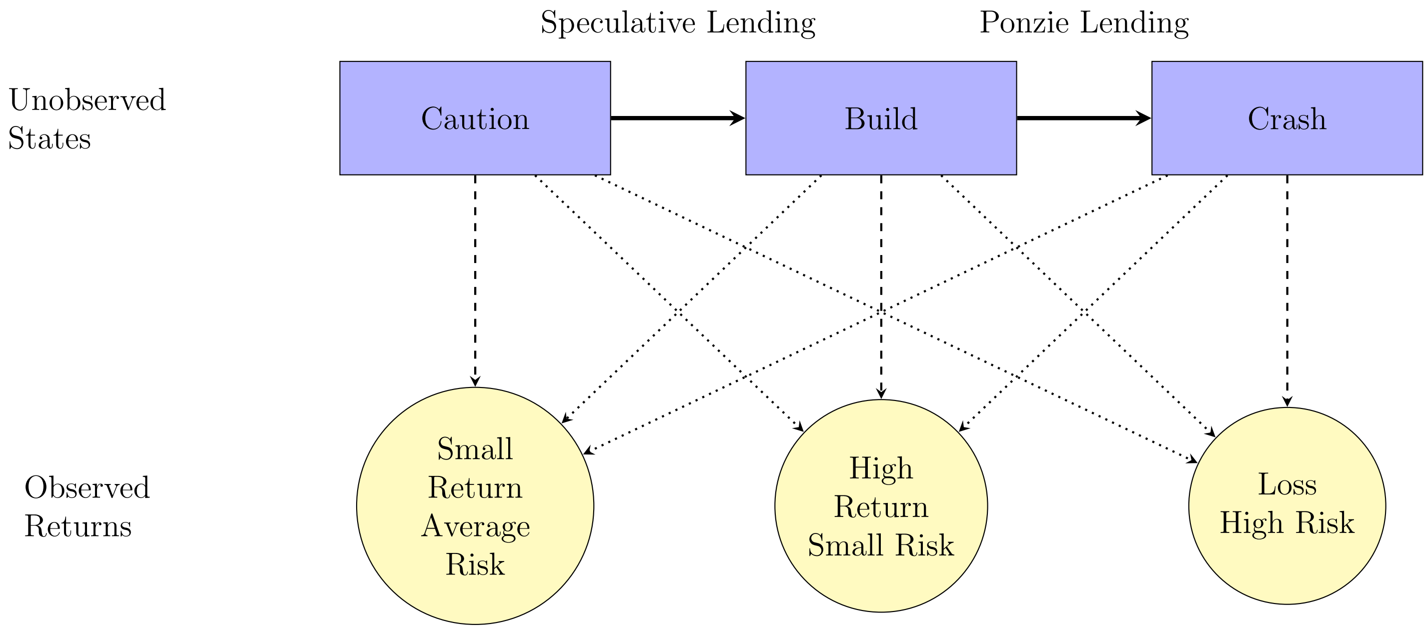

Figure 1: Hidden Markov Model (HMM)

2.2 Estimation of the parameters

The dependent mixture model is made up of three sub models.

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

Visser and Speekenbrink (2010) call this a *dependent mixture model* where the regimes are assumed to be statistically dependent on the observed carry-trade returns. The following draws from their explanation of the system and the way that the parameters are estimated.

It is assumed that the carry-trade returns can be characterised as a *mixture model*, each observation of the carry-trade profit is assumed to be drawn from a number of distinct sub-populations. These can be called *component distributions*. 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.

A mixture distribution is defined as

$$p(Y_1 = y) = \sum_{i-1}^{N} p(Y_t = y|S_t = i)P(S_t = i) \tag{3}$$

where,

- Y is the vector of carry-trade returns
- y is the particular carry-trade return that is observed
- $S_t \in 1, \ldots, N$ is the regime of observation t. One of either cautious, building or crash.
- $P(S_t = i)$ denotes the probability that the regime is in state i
- $p(Y_t = y|S_t = i)$ denotes the density of observation of Y_t conditional on regime being $S_t = i$.

$f(y_{it}|S_t)$ is assumed to have a multivariate normal density function. This distribution is characterised by $\theta_k = (\mu_k, \sigma_k^2)$. Once the number of regimes is given, the parameters of the states are estimated.

The transition matrix is estimated from the data.

The process underlying the state transitions is assumed to be a *homogeneous first order Markov process* Therefore, this process is completely defined by the initial state probabilities. This is an assumption that is used to simplify the estimation of the parameters. Once a starting point is given, a most likely path can be determined.

The prior states 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 starting point of the system is given by

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

and the state transition matrix is,

$$\begin{pmatrix} P(S_t = 1|S_{t-1} = 1) & P(S_t = 2|S_{t-1} = 1) & P(S_t = 3|S_{t-1} = 1) \\ P(S_t = 1|S_{t-1} = 2) & P(S_t = 2|S_{t-1} = 2) & P(S_t = 3|S_{t-1} = 2) \\ P(S_t = 1|S_{t-1} = 3) & P(S_t = 2|S_{t-1} = 3) & P(S_t = 3|S_{t-1} = 3) \end{pmatrix}$$

Outline the response model?

The parameters to be estimated are the mean and standard deviation of the normal distribution for each of the categories of carry-trade returns, the initial state probabilities, that assess the likelihood of being in a particular regime at the start of the time period, the transitional probabilities, that show the likelihood of moving from one regime to another, and the conditional probabilities that a particular return will be seen given a particular financial state have to be estimated.

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). There are two steps. The first will iterate forward from the initial starting point to assess the probability of observing each hidden regime given the model parameters. In this way the most likely unobserved sequence can be identified.

In other words, using a set of parameters for a HMM ($\theta = (\pi, A, B)$ estimate the probability of obtaining the sequence of carry-returns; now

The Maximisation step updates the parameters using the estimated densities of the projected hidden regimes as weights. For hidden Markov models, as special variant of the EM algorithm is proposed (called *the forward-backward* or *Baum-Welch* algorithm Baum et al. (1970). The Baum-Welch algorithm will find the parameters that maximize the probability of observing the sequence of carry-trade returns.

2.3 The HMM

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

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

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;

Assuming that there are no covariates with the initial values, the coefficients of the transition matrix or the relationship between the obsevered variables and the states, the marginal log-likelihood is computed using the formward-backward algorithm.

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

$$logP(\mathbf{Y_{1:T}} S_{1:T}|\theta) = logP(S_1|\theta_1) + \sum_{t=2}^{T} logP(S_t|S_{t-1}, \theta_2) + \sum_{t-1}^{T} logP(O_t|S_t, \theta_3) \tag{5}$$

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

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

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

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

Solving

$$q_i = argmax[\gamma_t(i)], \tag{8}$$

will maximise the number of correct states.

However, it is possible to chose a sequence that is not only not the most likely but also not even possible. The optimality criteria can therefore be changed to account for this. It could be changed to maximise the number of correct pairs or tripples. It would be best to maximise $P(Q, O|\lambda)$ (the equivalent of $P(Q, O|\lambda)$. The method that is used to find the optimal seqence path is the *Verterbi Algorithm*. This is more-or-less the same as the forward algorithm but also saves the most likely sequence to a vector and uses this to estimate the most likely sequence.

The third probme involves adjusting the model parameters to maximise the probabuility of the observed sequence. It is possible to chose $\lambda = (\pi, A, B)$ so that $P(O|\lambda)$ is locally mamimised using the Baum-Welch method.

There additional notes on this optimisation process.

The Baum-Welch procedure is then used to optimise the parameters of the model. At each point, the forward and backward sequences are combined to compute the proability that one state will be followed by another.

$$\xi_t(i, j) = P(q_t - S_t, q_{t+1} = S_j|O, \lambda) \tag{9}$$

This is equivalent to

$$\xi_t(i, j) = \frac{\alpha_t(i)a_{ij}b_j(O_{t+1}\beta_{t+1}(j)}{P(O|\lambda} \tag{10}$$

The independence assumption states that the unobserved regimes are the cause of the observed values. This implies that the observed values are independent.

Models can be assessed using the AIC, BIC and log likelihood ratio for nested models. The latter will have a χ^2 distribution.

The results will show the baseline category logistic model or the form,

$$logit[P(Y_t = 1)] = \alpha + \beta y_{t-1} + \beta_1 VIX \tag{11}$$

The interest in β_1 VIX is in the way that this affects the transition probabilities. The logit model provides an estimate of the increased odds that the system will be in system 2 rather than system 1.

The VIX could influence the returns or it could influence the transition probabilities. Each can be tested. It is possible to add some constraints on the parameters. What would be palusible? One constraint that could be tested if whether the transition between crash and caution is asymmetric. This means that the influence of the VIX will be different for the two models.

THe transition probabilities are

$$log(a_{ij}/a_{i1}) - \alpha_j + \beta_J z_t, \quad j = 2 \ldots n \tag{12}$$

where (a_{ij}/a_{i1}) is the transition probability from state i to state j. Here i is the baseline category.

Some notes .

The assumption is that the system passess through a number of states. The aim is to uncover some information about the dynamics of the system. If there is only one states, it suggests that there is a rather complex system that is difficut to understand; if there are two states, the transition parameter will say something about the probability of moving into a state of shock. It may be possible to look at the way that this parameter varies with level of economic development and exchange rate system to say something about the way that international financial risk is associated wtih these factors. It will also be important to determine whether the evolution of the system is best characterised as a one-off shift or whether there can a alterations. This can be determined by comparing the two models using the information criteria and the χ^2 difference in the log likelihood of the two models with degrees of freedome equal to the difference in the free parameters of teh two models.

Theese models are called hidden Markov models and hidden Markov models.

Look at the likelihood ratio tests. Assess the performance.

$$D = 2 \times \Lambda = 2 \times (logLik(model1) - logLik(model2)) \tag{13}$$

This can be used to test assumptions of restrictions of the model. The model with more parameters will always have a superior fit and a higher log likelihood. In most cases, the probability distribution of the test statistic can be approximated by the chi-squared distribution with (df1 - df2) degrees of freedom (where df1 and df2 are the degrees of freedom from model 1 and model 2 respectively.

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

$$P1MEURHUF_t = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}} \times EURHUF_{t+1M}} \tag{14}$$

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

$$EURHUF_t^{f1m} = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}}} \tag{15}$$

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.

Table 5 summarises the performance of the three basic models using the Akaike and Baysian information criteria and the log likelihood ratio test. It is clear that the two regime or three regime model is superior to the single regime model for most of the cases. Looking at the 5th column that shows the log-likelihood ratio for the two-regime model relative to the one-regime model, indicates that the improvement in the system is sufficient to compensate for the added complexity in every case apart from the Czech Republic and Norway. For Czech, The AIC indices are nearly the same for one and two regime models and the log-likelihood ratio test gives a score of 10.14 and a -value of 0.7; for Norway, the AIC is lower for the one regime model and the loglikelihood ratio is only 5.20.

In most cases the two-regime model appears to be superior to the three-regime model. However, for Norway, the three regime model has a lower AIC index and the log-lkelihood ratio tests suggests that the improvement in the model performance is sufficient to compensate for the added complexity with three regimes. For Icland, the information is a litte ambiguous. The AIC indices are rather similar and the log-likelihood ratio statistic is equal to 12.18 with a p-value of 0.09 using chi-squared distribution.

The VIX index is often used an measure of international risk aversion. The level of international risk could affect the model in one of two ways: it may have a general influence on carry-trade returns; it may influence the trasition probabilities. For the first of these it is added as a linear regressor on the returns, for the second, the model is augmented with a multinominal logistic model. This means that the transition probabilities can be taken from the odds for a given category given the values of the independent variables. In this case the odss of a particular regime given the level of the VIX index. Odds are the probabiluty of a particular regime divided by the probability that it is not that regime. The odds of the bianary outcome of the dependent variable are converted into nature logs and the regression is carried out, the results are then converted by to odds from the nature log with the exponential function.

The logistic function is

$$F(x) = \frac{1}{1 + e^{\beta_0 + \beta_1 x}} \tag{16}$$

n The inverse of the logistic function (logit)

$$g(x) = ln \frac{F(x)}{1 - F(x)} = \beta_0 + \beta_1 x \tag{17}$$

or

$$\frac{F(x)}{1 - F(x)} = e^{\beta_0 + \beta_1} \tag{18}$$

Therefore, for Poland, the transition matrix gives a probility of nearly 98% that the system will remain in the calm state when the VIX index is at its medium level, with just over 2% chance of a crash. However, as the VIX index moves one standard deviation from the mean, the probabilty of a switch increases to just under 9% and at two standard deviations it has risen to 28%.

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1)}} \tag{19}$$

The probability that the system will switch from calm to crash is pictured in Fig xxx. it can be seen that by three standard deviations in the VIX, the prob ability of a crash is close to 60%.

Equation 19 is the one that is used to calculate the probability.

Looking at these pictures of international financial risk it is possible to identify those countries that are more vulnerable to changes in intenational risk aversion. it may also be possile to carry out the same exercise for the changes in the interest rate.

	AIC1	BIC1	AIC2	BIC2	LR21	LR21p	AIC3	BIC3	LR31	LR31p	LR32	LR32p
HUF	-404.69	-398.46	-416.94	-395.11	22.25	0.0005	-407.23	-363.58	26.54	0.0004	4.29	0.7459
PLN	-423.98	-417.74	-437.62	-415.80	23.65	0.0003	-428.82	-385.17	28.84	0.0002	5.20	0.6357
CZK	-427.23	-421.00	-427.37	-405.54	10.14	0.0714	-413.77	-370.12	10.54	0.1599	0.40	0.9997
RON	-456.02	-449.78	-474.81	-452.98	28.79	0.0000	-464.38	-420.73	32.37	0.0000	3.57	0.8273
RUB	-523.18	-516.94	-567.77	-545.94	54.59	0.0000	-559.95	-516.30	60.77	0.0000	6.18	0.5188
BGN	-451.98	-445.75	-454.32	-432.49	12.34	0.0305	-446.12	-402.47	18.14	0.0114	5.80	0.5628
NOK	-453.92	-447.69	-449.12	-427.30	5.20	0.3922	-457.93	-414.28	28.01	0.0002	22.81	0.0018
ISK	-439.36	-433.12	-464.24	-442.41	34.88	0.0000	-462.42	-418.77	47.06	0.0000	12.18	0.0947
UAH	-572.87	-566.64	-643.36	-621.54	80.49	0.0000	-636.39	-592.74	87.52	0.0000	7.03	0.4257
HRK	-431.55	-425.41	-433.37	-411.88	11.82	0.0373	-426.58	-383.62	19.03	0.0081	7.22	0.4068
TRY	-431.05	-424.83	-441.00	-419.21	19.95	0.0013	-432.58	-389.01	25.53	0.0006	5.58	0.5895

Table 1: Comparison of models table

The next step is to assess whether the model is improved by using the measure of internatioanl risk aversion as an explanation for the carry-trade returns. There are two ways that international risk aversion could affect returns. The first is by directly affecting returns, the second is by changing the regime transition probabilities. In the first case, the VIX index is added as an explanatory variable to the regression analysis. Log-likelihood ratios and information criteria indicate that this does not improve the explanatory power of any of the models. In addition, the t-staitics of the standard linear regression model cannot reject the null hyopothesis that the VIX has a zero ifluence on returns.

Funding	Regime		HUF	PLN	CZK	RON	RUB	TRY	BGN	NOK	ISK	UAH	HRK	Mean
EUR	Caution	Mean	0.9952	1.0004	0.9953	1.0008	0.9957	1.0071	1.0074	1.0028	1.0033	1.0028	1.0030	1.0021
		S-Dev	0.1119	0.0398	0.0873	0.0341	0.0782	0.0328	0.0426	0.0469	0.0100	0.0372	0.0201	0.0559
	Build	Mean	1.0225	1.0731	1.0460	1.0573	1.0375	1.0222	1.0130	1.1187	1.0106	1.0140	1.0187	1.0390
		S-Dev	0.0490	0.0342	0.0441	0.0403	0.0212	0.0667	0.0217	0.0206	0.0572	0.0215	0.0512	0.0454
	Crash	Mean	0.9719	0.9672	0.9786	0.9956	0.9933	0.8915	1.0028	0.9020	0.9386	0.9671	0.9971	0.9583
		S-Dev	0.0518	0.1109	0.0389	0.0874	0.0233	0.1057	0.0860	0.0669	0.1791	0.1132	0.0823	0.0843
USD	Caution	Mean	0.9934	1.0093	1.0017	1.0077	1.0012	0.9996	1.0045	1.0004	0.9743	1.0025	1.0006	1.0000
		S-Dev	0.0271	0.0290	0.0475	0.0063	0.0043	0.0788	0.0190	0.0049	0.0226	0.0044	0.0120	0.0311
	Build	Mean	1.0297	1.0665	1.0354	1.0085	1.0060	1.0213	1.0190	1.0078	1.0130	1.0119	1.0194	1.0215
		S-Dev	0.0223	0.0218	0.0060	0.0252	0.0109	0.0282	0.0353	0.0308	0.0290	0.0128	0.0282	0.0231
	Crash	Mean	0.9918	0.9450	0.9942	1.0012	1.0004	0.9990	0.9712	0.9378	0.9558	0.9788	0.9773	0.9782
		S-Dev	0.0727	0.0543	0.0194	0.0518	0.0407	0.0296	0.0340	0.0332	0.1136	0.0737	0.0359	0.0515
CHF	Caution	Mean	1.0025	0.9907	1.0017	1.0019	NA	0.9956	1.0005	0.9925	0.9949	1.0023	1.0004	0.9983
		S-Dev	0.0161	0.0164	0.0230	0.0107	NA	0.0173	0.0012	0.0441	0.0202	0.0335	0.0102	0.0245
	Build	Mean	1.0383	1.0217	1.0050	1.0261	NA	1.0396	1.0015	1.0090	1.0153	1.0063	1.0134	1.0150
		S-Dev	0.0131	0.0193	0.0103	0.0182	NA	0.0201	0.0096	0.0118	0.0313	0.0105	0.0122	0.0194
	Crash	Mean	0.9946	0.9817	0.9910	0.9854	NA	0.9943	0.9941	0.9851	0.9750	0.9817	0.9885	0.9842
		S-Dev	0.0491	0.0504	0.0425	0.0362	NA	0.0735	0.0345	0.0142	0.0801	0.0916	0.0388	0.0472
CHF	Caution	Mean	1.0119	1.0101	1.0108	1.0100	1.0030	1.0041	1.0023	1.0092	0.9688	0.9984	1.0021	1.0028
		S-Dev	0.0440	0.0330	0.0235	0.0226	0.0651	0.0858	0.0147	0.0382	0.1037	0.0215	0.0131	0.0400
	Build	Mean	1.0149	1.0626	1.0555	1.0671	1.0102	1.0460	1.0307	1.0115	1.0128	1.0311	1.0315	1.0364
		S-Dev	0.0225	0.0150	0.0274	0.0189	0.0193	0.0213	0.0144	0.0074	0.0361	0.0329	0.0089	0.0205
	Crash	Mean	0.9985	0.9638	0.9837	0.9632	0.9610	0.9886	0.9977	0.9266	0.9471	0.8649	1.0019	0.9636
		S-Dev	0.0671	0.0768	0.0505	0.0454	0.0041	0.0287	0.0491	0.0530	0.0038	0.0684	0.0482	0.0491

Table 2: Mean and Standard Deviation of 3 Regime Model

Table 3 shows the estimated probability of switching from one state to another in the three state model. This is the estimation of Equation **??**. The first column is the the starting regime (either "Caution", "Build" or "Crash"), each element of the vector is the estimated probability of switching from one regime to another. In the top left corner it is the estimated probability of staying in the regime of "Caution" when the system is already in the "Caution" regime. This is 85%. The element adjacent to the right would show the estimated probability that the carry trade funded by EUR for Hungarian Forint switches from a regime of caution to one where speculative positions are being build. This is estimated at 15%. It is not considered likely that the system will switch from caution to crash.

Looking at the details of the transition matrix, the estimate of the Hungarian system suggests that things remain cautious or in the building phase for most of the time. However, there is a small probability of a crash once building has taken place. once the crash is in place, it will last a while before moving back to caution. This is consistent with the 3-stage FIH evolution of financial regimes.

For Poland there is a similar system to Hungary. However, the crash comes from the position of caution. A crash can jump back to the building of speculative positions. This is less consistent with the FIH hypothesis. For Czech, there is a small chance of a switch from caution to the building of speculative positions and a small chance that this will spillover into a crash. Once in a position of building speculative positions, the crash is quite likely. For Romania, the crash is a rare event that may evolve out of a period of caution. This is a case where the two stage regime may be a better representation of what is going on.

What else is needed in results.

- An assessment of whether the parameters of the system are consistent with the model of three stages in the evolution of financial risk. This can be a table that notes relevant characteristics (transition probabilities, proportion of time in each state, carry return characteristics).

- An assessment of those countries that are not consistent with the three regime model. Are they two-regime or transition? Do the different groups have characteristics?

- A comparison of the dates for the crash.

- Some analysis of crash dates and interest rate, liquidity or risk factors.

The parameters of the 2 regime model are given in Table 3.1. They show the returns to a two-regime model for the range of European currencies

		Proportion	To Caution	To Build	To Crash
	From Caution	0.41	0.85	0.15	0.00
HUF	From Build	0.29	0.00	0.96	0.04
	From Crash	0.30	0.27	0.00	0.73
	From Caution	0.14	0.75	0.19	0.06
PLN	From Build	0.79	0.75	0.25	0.00
	From Crash	0.07	0.00	0.22	0.78
	From Caution	0.36	0.97	0.03	0.00
CZK	From Build	0.56	0.02	0.72	0.26
	From Crash	0.08	0.00	0.60	0.40
	From Caution	0.21	0.74	0.24	0.02
RON	From Build	0.64	0.72	0.28	0.00
	From Crash	0.15	0.00	0.03	0.97
	From Caution	0.08	0.98	0.02	0.00
RUB	From Build	0.24	0.00	0.54	0.45
	From Crash	0.68	0.02	0.26	0.72
	From Caution	0.43	0.89	0.00	0.11
TRY	From Build	0.27	0.07	0.93	0.00
	From Crash	0.30	.00	0.23	0.77
	From Caution	0.48	0.09	0.09	0.82
BGN	From Build	0.39	0.00	0.99	0.01
	From Crash	0.13	1.00	0.00	0.00
	From Caution	0.03	0.91	0.07	0.03
NOK	From Build	0.77	1.00	0.00	0.00
	From Crash	0.20	0.00	0.47	0.53
	From Caution	0.05	0.35	0.60	0.06
ISK	From Build	0.09	0.09	0.91	0.00
	From Crash	0.86	0.21	0.00	0.79
	From Caution	0.03	0.14	0.00	0.86
UAH	From Build	0.72	0.00	0.91	0.09
	From Crash	0.25	0.97	0.01	0.02
	From Caution	0.57	0.26	0.73	0.02
HRK	From Build	0.32	0.86	0.00	0.14
	From Crash	0.11	0.78	0.00	0.22

Table 3: Transition probabilities funded with EUR

funded against the EUR, the US dollar, the Swiss France and the Japanese yen respectively. The mean and the standard deviation of an estimate of the normal distribution of returns for each regime is reported for the periods of

Calm and *Crash*. The average for each funding currency shows that, during the period of calm, an average monthly risk-neutral return of just over 1% is achieved for Euro-funded carry-trade positions. These range from an average of 1.65%, 1.73% and 1,59% for Hungary, Poland and Romania to just below 1% for Norway, Iceland and Croatia.

Returns for carry investments funded by US-Dollars, Swiss-Francs and Japanese Yen tend to be a little lower.

During the crash, a monthly loss of about 1.0% is experienced on average with a Euro-funded position. This compares to average losses of just 0.5% for investments funded by the US dollar and 1.5% and 2.0% for those funded by the Swiss-Franc and Japanese Yen respectively. The risk, as measured by the standard deviation of the returns, is much greater in the crash.

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

Table 4: Mean and Standard Deviation of 2 Regime Model

Some particular cases stand out. The carry-trade returns for investments in Hungary, Poland the Romania, funded by the Swiss-Franc, tend to be rather modest in nature whether in a period of calm or crash. This is a little surprising given the publicity that has been given to this activity.

However, the the Russian rouble carry-trade funded by the Swiss-Franc shows an exceptional loss in the crash, reflecting the effects of the likelihood that the Swiss currency will appreciate at the times when there is a crisis in Russia. This may reflect the effect of capital flows or the more central position of the Russian economy in international affairs.

This suggests that the crash is pretty rare as are the periods of caution.

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4 Conclusions

There are a number of ways that these methods can be used.

Does the system evolve according to the three-regimes? What are the characteristics of those cases where three-regime system does not work?

What are the dates of the crash? Which data are very similar for different currencies and which are unique. What are the characteristics of the common crashes? Do they relate to monetary, liquidity or risk shocks? What are the characteristics of the unique crashes? Do they relate to the international shocks. It is more likely that they are domestic.

What are the extensions and next steps. A sophisticated model could allow the parameters to change over time. One example would be to increase the probability of a crash as the time in the building phase or to relate the probability of a crash to some outside variables.

Have a look at the probabilities of a crash that existed on particular days (ahead of the Lehman crisis)? Do these probabilities say something about potential vuilnerability. This can go into the table that assesses the reliability of the models. What is the relatioknship between the vulnerability at the point of financial crisis and the subsequent ecomnomic outcome? What is the relationship between the vulernablity and other characteristics?

Other variables can be added to the model. There are the carry-trade crash variables. Could also add stock index. Will this add anything? Could add a variable of EU political uncertainty.

From Rabiner (1989). There are three problems:

- Given the observations, what is the probability of observing sequence given the model?

- What is the sequence of unobserved states that best describes the observed. There is an attempt to find the optimal sequence. A comparison of problem one can be used.

- Optimise the parameters to best descibe the observed sequence.

Use problem three to optimise the parameters of the observables given the latent states; use problem two to uncover the unobserved states; use problem one to calculate the probabilty of the observation given the paramers.

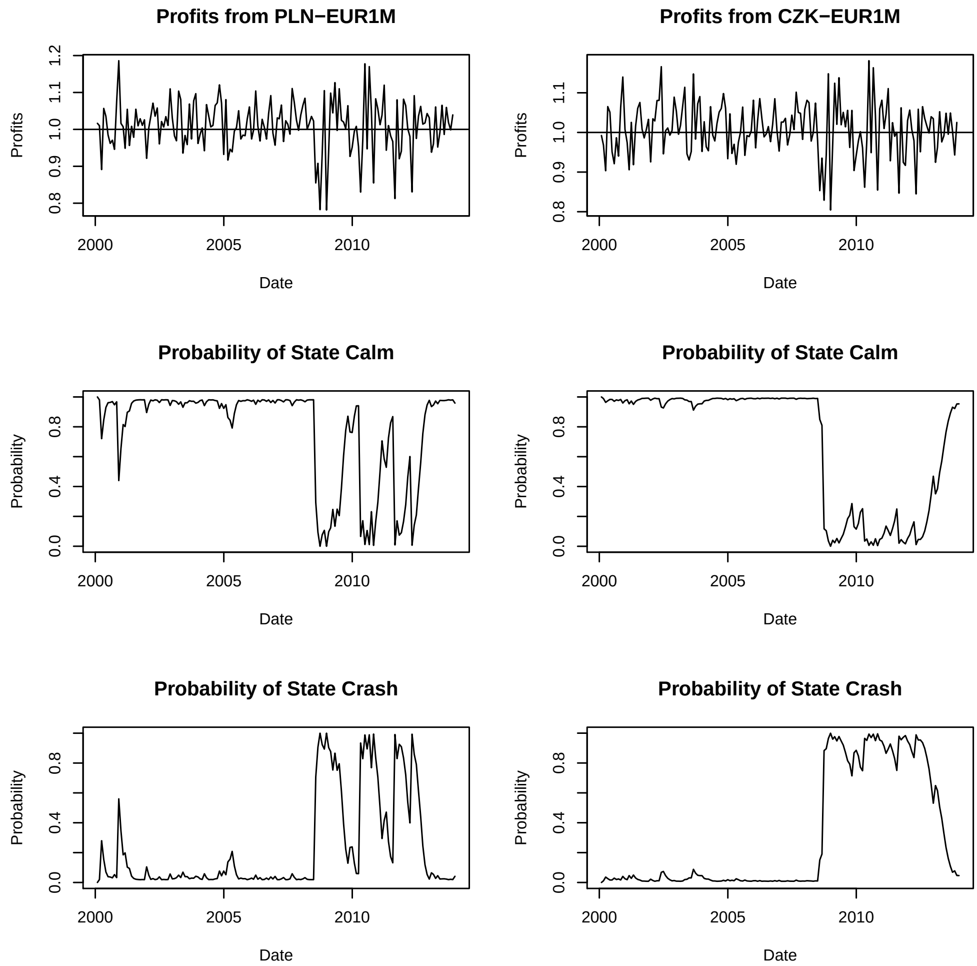
Steps.

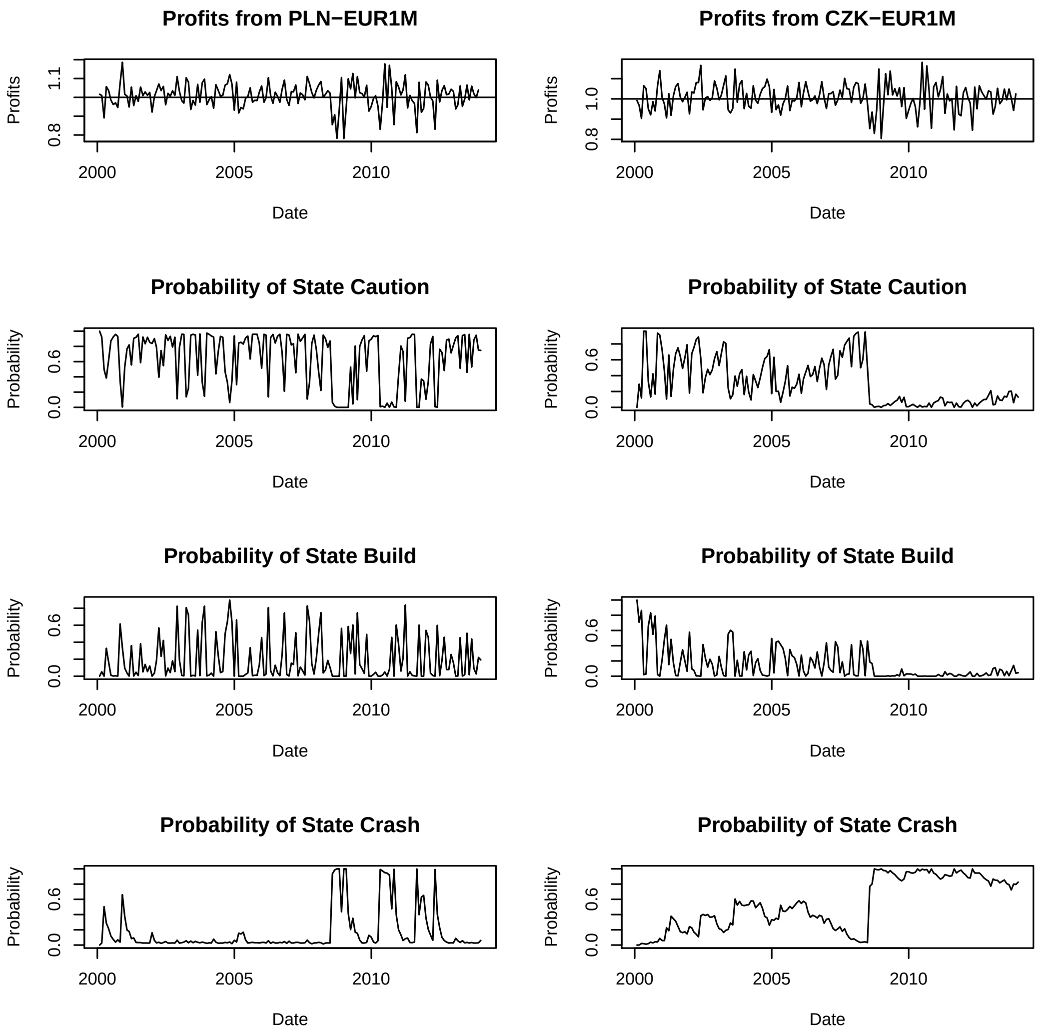
- Maximise $P(O\lambda)$, where $\lambda = (\pi, A, B)$. The probability of observing seqence O for a given set of parameters. The easiest way of doing this is to calculate the probability for each of the possible state sequences. Consider one such sequence, $Q = q_1 q_2 \dots q_T$, the probability of the observed sequence for the state sequence Q is $P(O|Q\lambda) = \prod_{t=1}^{T} P(O_t|q_t, \lambda)$. If the observations are independent, this probability $P(O|Q\lambda)$ is equal to the probabilty of observing the outcome given the state, $b_{q_1}(O_1)b_{q_2}(O_2)\dots b_{q_T}(O_T)$. At each step, the forward variable $\alpha_t(i) = P(O_1O_2\dots O_t, q_t = S_i|\lambda)$ is calculated as the product of the sum of all the probability of each state for the previous period and the probability of transition from each of those states to the current as well as the product of being in this state given the observable. $\alpha_t(i)$ is the joint probability that observation is seen and state is achieved.

- Optimise the hidden state sequence given the parameters

- From a number of λ models, chose the most optimal.

Figure 2: PLN and CZK 1m EUR funded carry profit

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Profits from CZK−EUR1M
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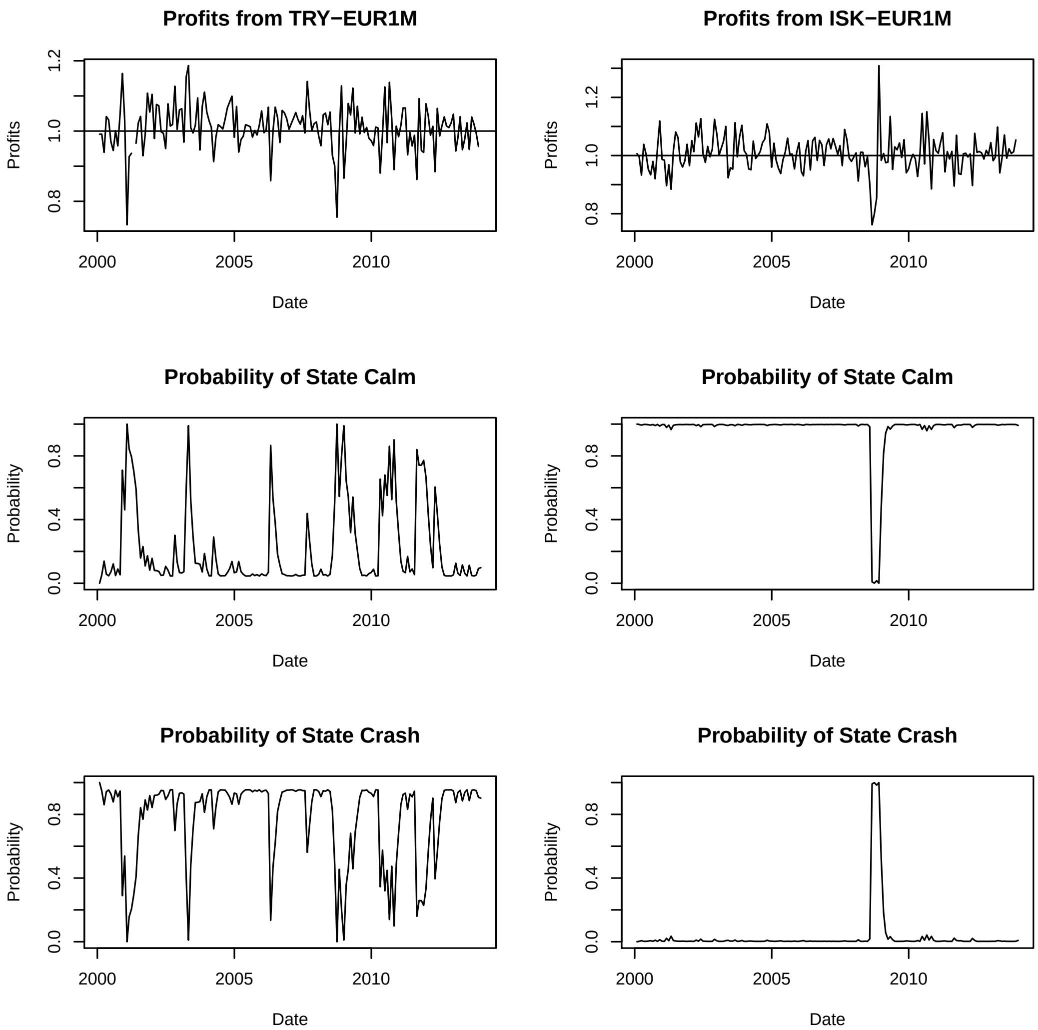
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Profits from ISK−EUR1M
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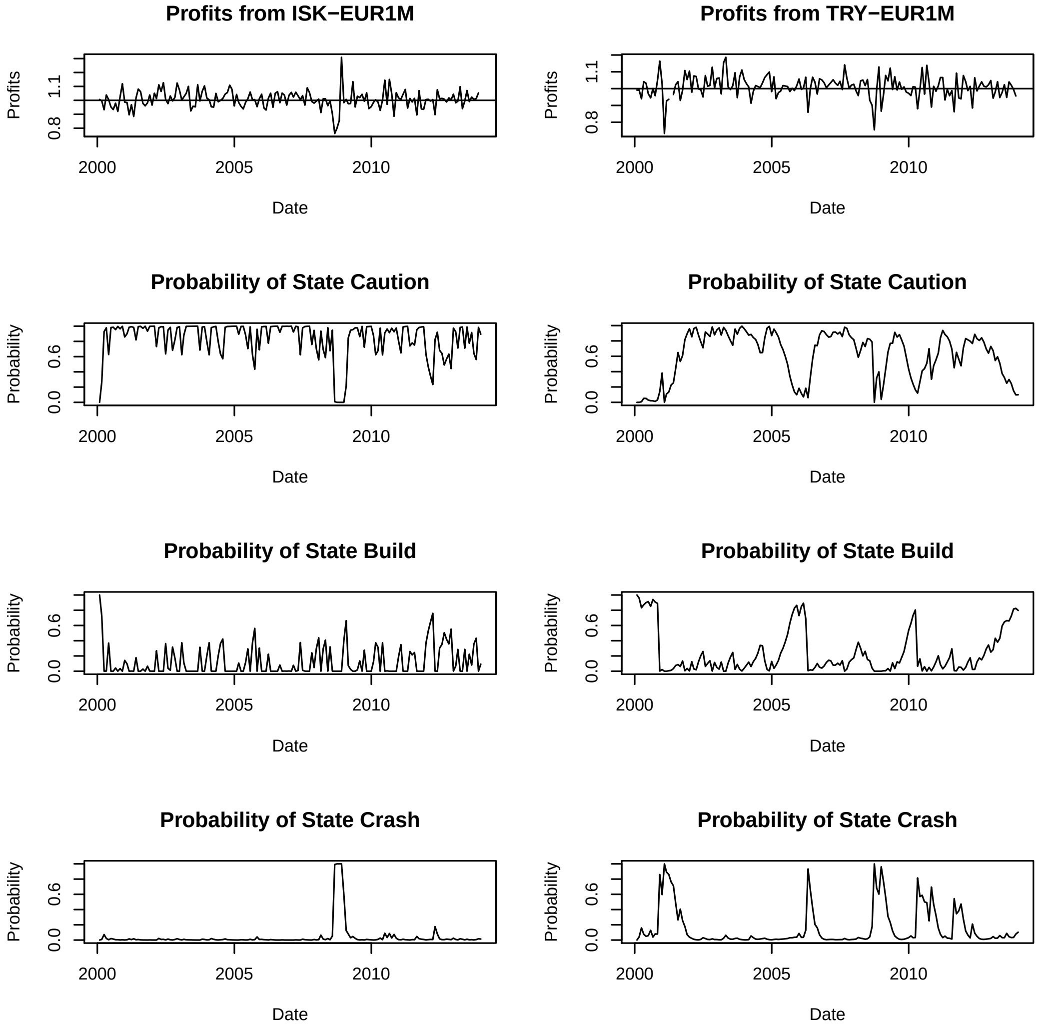
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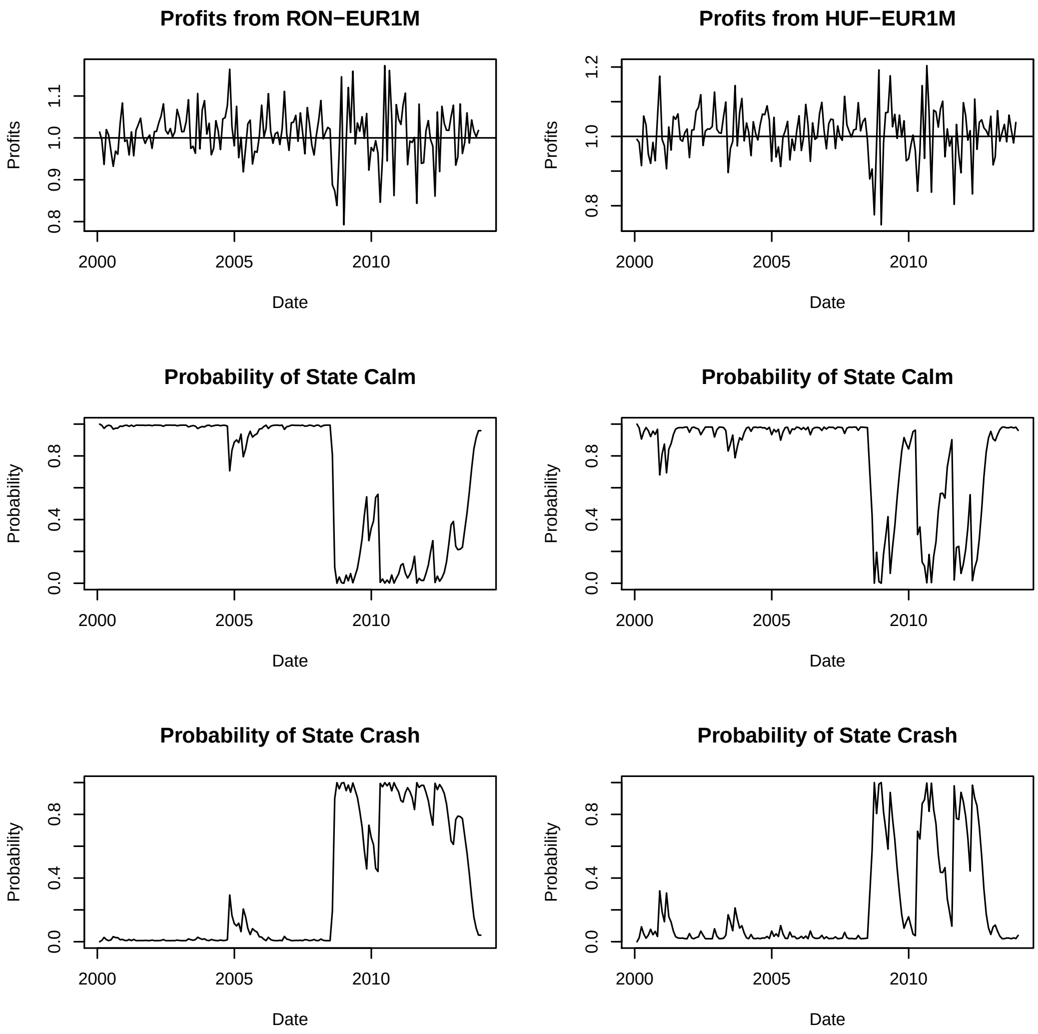
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Profits from HUF−EUR1M
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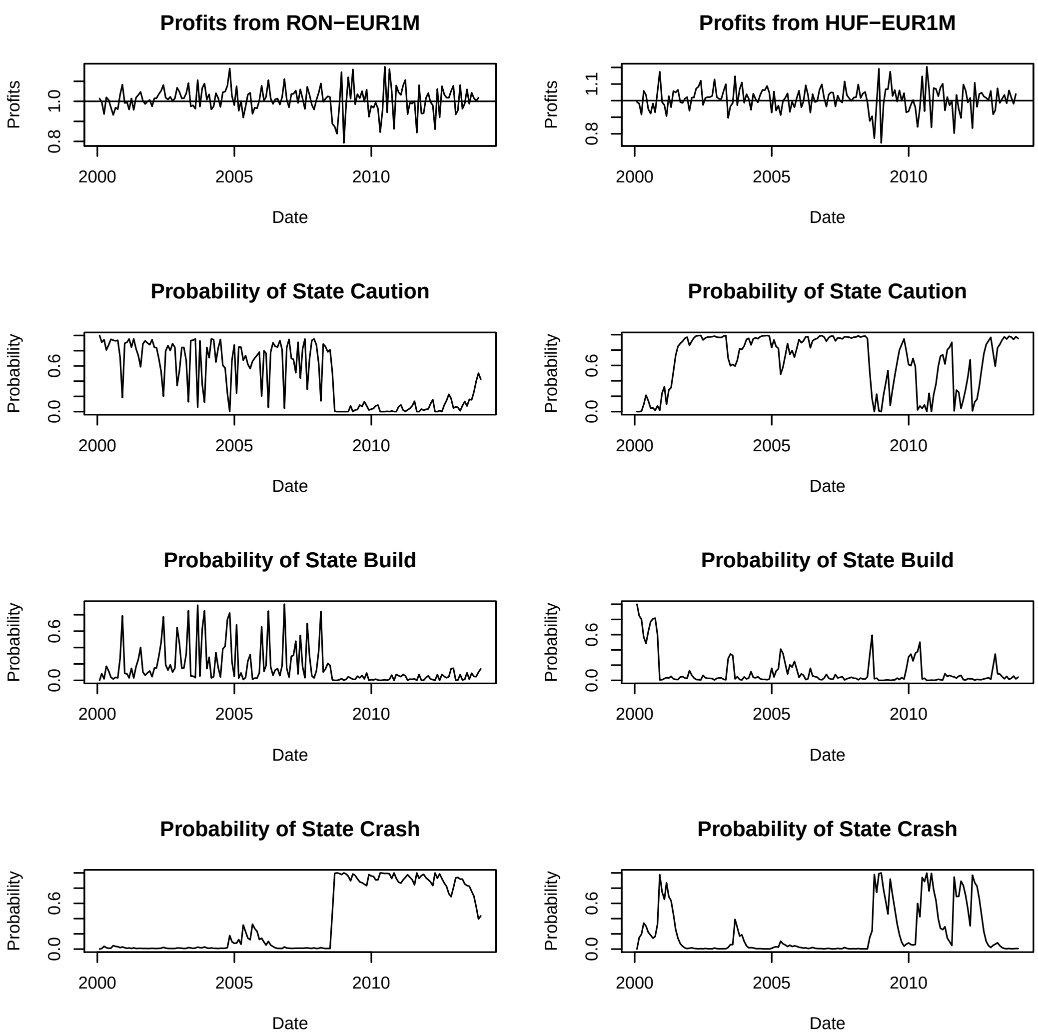
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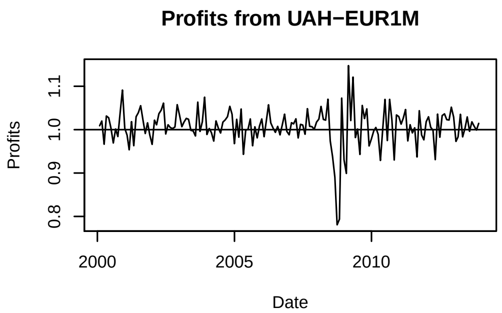
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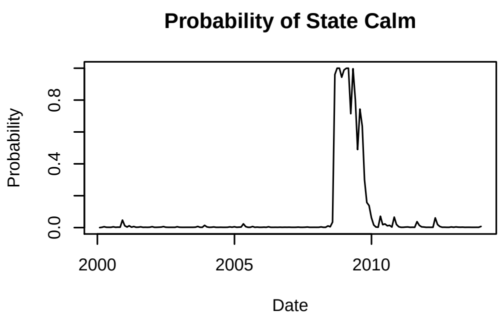
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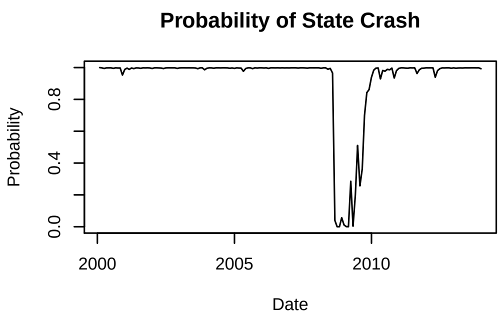
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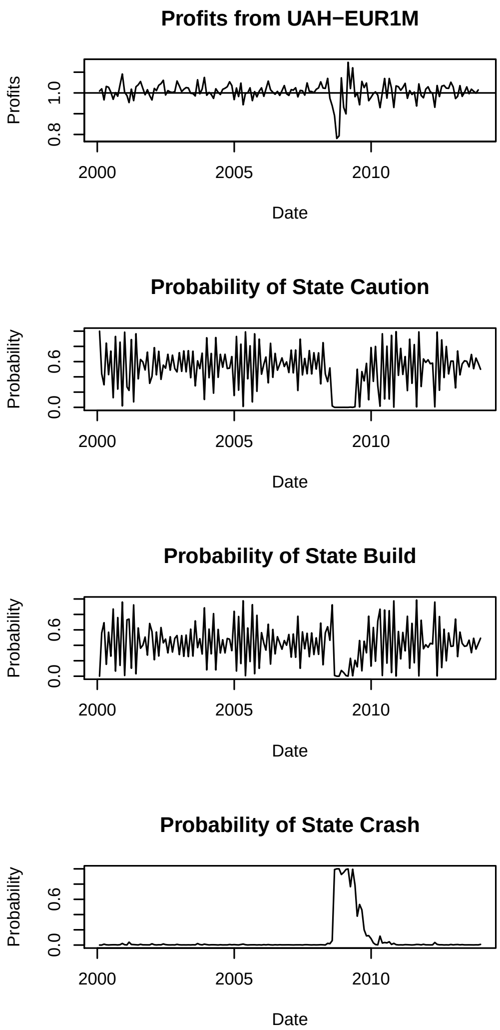
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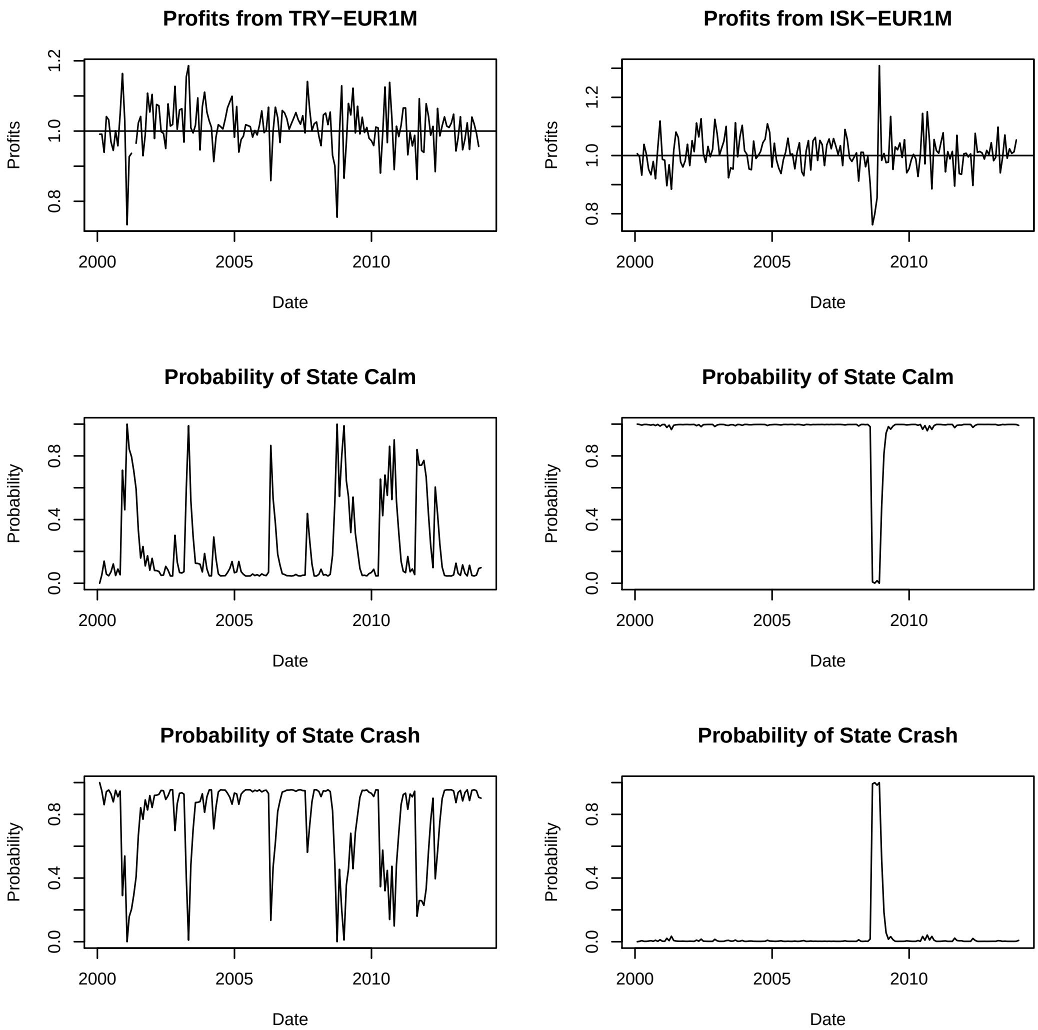
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Profits from ISK−EUR1M
Probability of State Calm
Probability of State Calm
Probability of State Crash
Probability of State Crash
Profits
Probability
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2010
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	AIC1	BIC1	AIC2	BIC2	LR21	LR21p	AIC3	BIC3	LR31	LR31p	LR32	LR32p
HUF	-404.69	-398.46	-419.50	-391.44	28.81	0.0002	-408.43	-346.07	39.74	0.0023	10.94	0.4487
PLN	-423.98	-417.74	-438.93	-410.87	28.95	0.0001	-424.77	-362.41	36.79	0.0001	7.84	0.7278
CZK	-427.23	-421.00	-430.52	-402.46	17.29	0.0156	-426.74	-364.38	35.51	0.0002	18.22	0.0766
RON	-456.02	-449.78	-478.07	-450.01	36.05	0.0000	-473.04	-410.68	53.02	0.0000	16.97	0.1087
RUB	-456.02	-449.78	-566.68	-538.62	124.67	0.0000	-556.35	-493.99	136.33	0.0000	11.66	0.3894
BGN	-451.98	-445.75	-459.55	-431.49	21.56	0.0030	-556.35	-493.99	140.37	0.0000	118.80	0.0000
NOK	-453.92	-447.69	-445.70	-417.64	5.78	0.5656	-556.35	-493.99	138.42	0.0000	132.64	0.0000
ISK	-439.36	-433.12	-463.57	-435.51	38.22	0.0000	-447.99	-385.63	44.63	0.0000	6.42	0.8441
UAH	-572.87	-566.64	-647.67	-619.61	88.80	0.0000	-447.99	-385.63	-88.88	1.0000	-177.68	1.0000
HRK	-431.55	-425.41	-439.42	-411.80	21.87	0.0027	-408.43	-346.07	12.89	0.7983	-8.99	1.0000
TRY	-431.05	-424.83	-439.26	-411.25	22.20	0.0023	-434.70	-372.46	39.65	0.0023	17.45	0.0954

Table 5: Comparison of models table

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