Carry trade and transission

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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. Analysis of *carry trade* returns, the attempt to take advantage of deviations from *uncovered interest partiy* (UIP), is 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 Markov chain where the states are unobserved but the outcomest are conditional on the financial regime. The parameters of a Hiden Markov Model (HMM) can be used to aid understanding of the evolution in the vlunerabilty of the financial system, greater knowledge of the factors that can influence the level of instability and may also provide real-time indicators about the level of financial risk.

1 Introduction

As the size of international capital flow has relative in absolute terms and relative to trade in goods and services and become subject to less regulatory constraint, countries have faced repeated struggles with financial instability that has an international source. An inflow of capital from outside can appear superficially attractive but its arrival can shape institutions, economic

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development and political opinion and the portfolio flows can disappear even more swiftly than they arrive. Transition and emerging economies are particularly affected. The financial systems of transition and emerging economies are less developed than those of the the international finance centres and therefore there is scope in these countries for the financial sector to increase in size and relative to overall level of economic activity. This process can attract financial entities from more developed economies. *Focus on European Economic Integration: Foreign Currency Loans* (2011) and Berglof (2010) survey the expansion of Euro area banks into the Central and Eastern European trasition economies; Gabor (2011) discusses the political economy of this *financialization* where the financial system expands to new sections of the economy.

Money flows in and it can retreat just as swiftly. The evolution of financial risk is familiar. Dornbusch and Werner (1995), Calvo (1998) and Krugman (2000) have been associated with the term *sudden stop* to emphasise the importance of the inflow that takes place before the currency crisis in understanding the disruptive effects of the reversal.

International financial conditions following the 2007-08 crisis have fuelled the growth of investments in emerging and transition economies by providing large amount of funding-currency liquidity and relatively attractive investment oppoprtunities. However, the indiction from Federal Reserve Chairmn Ben Bernanke on May 22nd 2013, that the central bank would cut back its pace of liquidity inject by gradully reducing its monthly bond purchase triggered a sharp sell-off in emerging bond and equity markets as well as their associated currencies. This market reaction has drawn attention to the risks associated with international capital flows as well as the relationship between US monetary policy and the flow of capital to transition and emerging economies. Amongst the debating points are questions about the relationship between capital flows and US monetary policy, international liquidity and the appetite for risk amongst international investors.

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, theor research shows that bank conditions and monetary policy actions in countries outside the US can also have an influence. They have three specific findings: an increase in the VIX index and reduction in US dealer bank leverage and a rise in the term premia reduce cross border bank lending. There is also a small interest rate effect. US and European domestic credit conditions and monetary policy affect lending to other regimes. European leverage and credit conditions are more improtant; Us monetary policy is more important. They conclude that while the US drives the global liquidity cycle through its monetary policy, other financial centers (particualrly European) affect the financial cycle through the conditions of their banks. This suggests that global liquidity is affected by global financial conditions rather than monetary policy.

Baele et al. (2014) find that Flight-to-Safety (FTS) are relatively rare events. FTS means that capital flows move towards internatioanl financial centers and relatively safe assets. This 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 and are associated with an increase in the VIX index and the TED spread.[1] These FTS eposodes are also associated with lower levels of consumer sentiment, appreciation of the Yen, Swiss franc and US dollar funding currencies. Economic growth and inflation decline in the year after a FTS event.

There is variety in the way that US monetary shocks affect transition and emerging economies. Using daily data on exchange rates, stock prics and emerging market bonds, Mishra et al. (2014) finds that exchange rates and bonds were 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.

Consistent with the evidence of an interplay between monetary policy and international risk, Ahmed and Zlate (2014) studies the determinants of private capital flows to emerging markets, finding that economic growth, interest rate differentials and the level of global risk appetite are all important. They find that capital flows have been more sensitive to interest rate differentials since the financial crisis of 2007-08. There is also some evidnece 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 likely to proceed. Similarly,

[1] The VIX index is an index of implied volatility on options from the S&P 500 index, the TED spread is the spread between the treasury bill and the Euro-dollar rate. They are used as measures of international risk aversion. The first reflects increased demand for option protection against large moves in the main US stock market, the second shows the difference in short-term borrowing costs for the US government and a representative financial institution.

Groen and Peck (2014) assesses changes in global risk aversion on strategies that borrow low interest rates to invest in higher yields. 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 find 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), (**?**) and **?**. For example, there is evidence the correlation of cross-broder credit growth has increased since the 1990s and that, funds increasingly flow from the finacial centers to the rest of the world. As such Ceruttie et al. (2014) find that credit and liquidity contractions in the US, Eurozone, UK and Japan affect the rest of the world. Credit supply in financial center economies affect the provision of cross-broder credit. This is what they call *global funding liquidity*, a feature that affects financial conditions globally.

The theme of this recent research is of an interplay between international and domestic factors. It is clear that there are a range of features, including economic, institutional and cultural that can affect this interation and teh evolution of interaction of international financial risk.

1.1 Carry trade

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 partity* (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 shoud 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. The base currencies are the US dollar, the Euro, the Swiss franc and the Japanese yen. These are the safe-haven currencies used in Habib and Stracca (2012), and they are base units that are found to appreciate during periods of FTS in Baele et al. (2014).

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

There is wide spread evidence that UIP does not hold on average but this does not mean that excess returns are possible. These returns disappear with a more multifacetted assessment of risk is taken. Most noteably, the small risk of a large loss, so-called *crash risk*, 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 mis-perceived by myopic, over-confident economic agents suffereing behavioural biases.

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.

1.2 The instability cycle

The aim of this study is to understand more about the evolution of internatonal financial instability by studying the carry trade in a number of European transition and emerging economies. There are two related areas of interest: the factors that trigger a crash, reversal or sudden-stop; the way that the financial system evolves to the point where the crash is likely to take place. There have been a number of attempts to identify levels of finacial risk. This has clearly become even more of an issue since the financial crisis. For example, Gadanecz and Jayaram (2008). The IMF have developed a range of *Financial Soundness Indications* (IMF 2006). Also - Hawkins and Klau (2000), Nelson and Perli (2005) and Gray et al (2007). There are six main strands: the real sector, including fiscal position and inflation; the corporate sector, specifically the level of debt and overseas exposure; the ability of the household sector to weather downturns; the external sector, including the foreign exchange position and the capital account; the financial sector; finacial markets.

However, While measuring debt-to-equity ratios and the scale of bank lending may provide some indication about the regime that is in place, this is imprecise and it is clear that financial services business evolve in ways that make loan counting inadequate.The recent financial crisis showed that innovations like *Collateralised Debt Obligations (CDO)* can allow an increase in debt that does not directly in bank lending.

1.3 Stops, transitions or evolution of financial instabilitys

There are three main ways that evoltion of the financial system can be modeled. The first is through a one-off transition from calm to instability. This should imply that there has been some major event that has transformed the system and that there has been a permanent adjustment from one regime to another. The second is a that there is a switch between a period of calm and crisis. In this case there are periods of calm are punctuated by crises and that there is a switch between the two systems. The third suggests an evolution of the system from a position of calm, through a time when speculative positions are build and then into a crash.

Minsky's *Financial Instability Hypothesis* (FIH) presents a model of endogenous financial crisis where a period of economic calm creates the conditions for more adventorous and risky financial behaviour that increases the fragility of the system Minsky (1975, 1986, 1992, 1995). Minsky identified three phases of financing: hedge, speculative and Ponzie.

In the first of these the system is stable as lending is not excessive, borrowers are cautious and revenues are generally sufficient to ensure that repayments of principal and interest can be made from current income. This period may be framed by memories of past financial crisis and the economic hardships that are associated with it. Violent economic shocks are among the range of possible outcomes that can readily be envisaged by creditors and debtors, encouraging them to be cautious and risk-averse.

However, in the absense of economic shocks these memories of hardship fade further into the background and all parts of the economic and financial system become more prepared to take risks. Lending becomes more speculative; decision-making gives less weight to the possibility of extereme outcomes and more weight to the immediate experience of economic calm. The increase in lending tends to improve immediate economic conditions: business investment and consumer spending rise if lending is broad-based; asset prices will appreciate where lending is directed towards financial investment. The increase in economic activity that comes from this expansion in credit will feedback to improve immediate economic conditions, exacerbating the sense of well-being and undermining the arguments of those preaching more cautious behaviour. Positive feedback effects cause a non-linear relationship between credit growth and economic activity and between credit and asset prices.

Bernanke et al. (1999), Bernanke et al. (1996) and Azaraidis and Smith (1998) present models where there is a non-linear relationship between the provision of credit and the level of economic activity. Bernanke and Gertler

(1989) provide a model where balance sheet dynamics affect the business cycle through a reduction in the agency cost of business investments and Balke (2000) has a non-linear model of credit shocks. Avdjiev and Zeng (2014) use a three regime TVAR model to identify the non-linearities in credit market shocks. They find that credit shocks have the creates impact when output growth is above its long-term trend.

While credit becomes more plentiful, household and business managers become more optimistic. There is evidence that decision-making tends to favour outcomes that can be more easily envisaged or those that are more recently arrived (see for example, Tversky and Kahneman (1973) and Schwartz and Simons (1991) for some evidence on the *availability heuristic*.

In this way, the repayment of loans becomes increasingly dependent on the continuation of above-norman economic conditions or the appreciation of asset prices. If this process is allowed to continue a speculative frenzie can take hold. Economic agents are dragged into the euphoria as households compete with the conspicuous consumption of their neighbours, businesses make investments to increase capacity to meet booming demand and endovour to increase market share, while property and financial market speculators redouble their bets. Brunnermeier and Pedersen (2009) show how the link between the availability of credit for investors and the level of liquidity in financial markets can create *liquidity spirals*. They note, that the capital of speculators can drive market iquidity, risk premia and asset prices. The ability to be able to borrow against collateral is particularly important here. As asset prices increase, the ability to borrow against their value increases the amount of trading credit that is available.

The conditions are now in place for the bubble to burst in a violent reversal. Fisher (1932, 1933) explained the way that *debt-deflation* could create a ricochet between the financial and real sectors of the economy with a decline in the availablity of credit exacerbating the financial strain on households and business, helping to reduce household and business spending thereby raising the quantity of bad loans and the sense of caution at financial instiutions. In financial markets, credit and liquidity disappear and the decline in asset values affect the ability of insitutions to raise funds. Firesales in illiquid markets exaggerates the fall in prices. Reinhart and Rogoff (2009) show how credit booms help to explain the breadth and depth of post-boom recessions. The catalist for the collapse is difficult to pin down as the build up to the excess is fragile. See Gorton (2012) and Brunnermeier and Pedersen (2009) again for financial market effects. However, the economic consequences are profound.

1.4 International portfolio flows and financial stability

As the financial system evolves from a position of caution into one where risk is being built and finanlly 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 fact that the building of carry positions will add a capital appreciation in the exchange rate to the interest rate carry. During the crash, there are losses and extreme risk.

The probability a particular type of return depends on the nature of the financial regime. The regimes of financial instability are not observed. However, the returns to the carry trade will change as the regime changes. This study aims to identify the nature of the underlying financial regime by using the returns to the carry trade to estimate the evolution of underlying conditions. Three models are assessed: a one-off transition between calm and crisis; a two-regime model that switches between caution and crash; a three-regime model that evolves from caution, through the building of speculative positions to a fragility where crash occures.

2 A Markov model of financial stability

The evolution of financial regimes can be seen as a first-order Markov process that moves from state to state depending only on the previous state. The likelihood of a transition from one state to another can be assigned a probability called a*state transition probability*. These can be collected into a *state transition matrix*. Each element of the matrix shows the probability that regime will be in a particular regime in the next perild.

For the transition model, there is a probability of shifting from calm to crisis but this is a one-off shift and there is a zero probabilty of a return to calm once the regime has made this change.

$$\begin{pmatrix} 0.8 & 0.2 \\ 0.0 & 1.0 \end{pmatrix} \tag{1}$$

Equation 1 shows the transition matrix for the transition model, With the first column representing the current regime and the first row representing calm and the second row representing crisis, there is an 80% chance that the system will remain calm if that is the current state and 20% chance of a shift to crisis if conditions are currently calm (the rows must sum to one). Once the system is in the crisis state, it doe snot shift back to calm.

$$\begin{pmatrix} 0.8 & 0.2 \\ 0.5 & 0.5 \end{pmatrix} \tag{2}$$

For the two-regime model, the transitions will determine the probability of shifting from calm to crisis and the likelihood of remaining in the existing state. For this example in Equation 2, there is an 80% chance that the regime will remain calm when it is already in that state (with a 20% chance of a shift to crisis). Once in the crisism, the system stays there with 50% probability and shifts back to calm with an equal likelihiood.

$$\begin{pmatrix} 0.7 & 0.2 & 0.1 \\ 0.4 & 0.4 & 0.2 \\ 0.5 & 0.3 & 0.2 \end{pmatrix} \tag{3}$$

Equation 3 shows a possible transition matrix For the three-regime model. The rows represent from calm, from build and from crash respectivley, the columns are to caution, to build and to crash. There is a 70% chance of staying in the caution regime if that is already in place; there is a 20% chance of switching to a regime where speculative positions are build and a 10% chance that there is a crash. The diagonals represent no chance in regime. The matrix is not necessarily symetrical.

The first order Markov process has three elements:

1. states
2. π vector
3. state tansmition matrix

However, in stuuations like this where the underlying financial regimes are not observable, the Markov model is not sufficient to fully describe the process. However, it is 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 tripple (π, 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 modeled 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.

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. The financial regime determines the carry-trade return that is seen.

A mixture distribution is defined as

$$p(Y_1 = y) = \sum_{i-1}^{N} p(Y_t = y|S_t = i)P(S_t = i) \tag{4}$$

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
- $P(S_t = i)$ denotes the probability that the regime is equals to i
- $p(Y_t = y|S_t = i)$ denotes the density of observation of Y_t conditional on regime being $S_t = i$.

$f(y_{it}|z_t)$ 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.

Visser and Speekenbrink (2010) call this a *dependent mixture model* where the regimes are assumed to be statistically dependent.

The transition matrix is estimated from the data.

The process underlying the state transitions is assumed to be a *homogenous first order Markov process* Therefore, this process is completely defined by the initial state probabilities. Once a starting point is given, a most likely path can be determined.

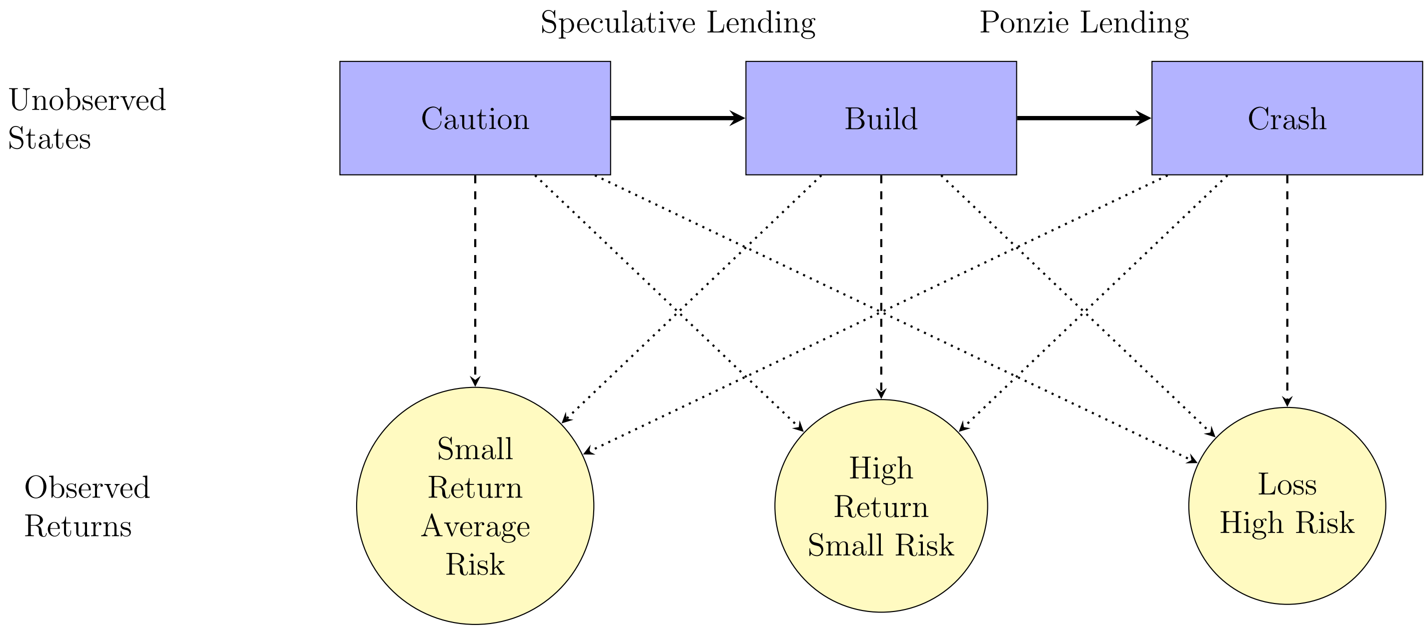

Figure 1: Hidden Markov Model (HMM)

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

and the state transition matrix,

$$\begin{pmatrix} P(S_t = 1|S_{t-1} = 1) & P(S_t = 2|S_{t-1} = 1) & \ldots & P(S_t = N|S_{t-1} = 1) \\ P(S_t = 1|S_{t-1} = 2) & P(S_t = 2|S_{t-1} = 2) & \ldots & P(S_t = N|S_{t-1} = 2) \\ \vdots & \vdots & \ddots & \vdots \\ P(S_t = 1|S_{t-1} = N) & P(S_t = 2|S_{t-1} = N) & \ldots & P(S_t = N|S_{t-1} = N) \end{pmatrix}$$

2.2 Estimation of the parameters

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

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

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 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 perild, 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 $l(\varphi, y) = \sum_{i=1}^{n} logf(y_i; \varphi)$. This is a problem that can be solved with the *Expectation-Maximization (EM) algorithm* Dempster et al. (1977). The Expectation step computes the joint conditional distribution of the latent variables given the data and the current provisional estimates of the model parameters. In other words, given a financial regime to begin the process, probabilities of traforming from this starting regime to another and the likelihood of observing the carry-trade return given a particular regime, the most likely sequence of regimes can be uncovered.

The Maximixation 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* alogorithm Baum et al. (1970). The Baum-Welch algorithm will find the parameters that maximize the probability of observing the sequence of carry-trade returns.

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

3 Literature

A common problem in estimating economic models is that the parameters do not tend to be stable over time. A HMM can be used to model a range of cases that can span a simple transition from one state to another, switching between multiple regimes with varying parameters towards the exteme where the number of regimes mean that system is close to having time-varying parameters (TVP).

Hamilton (1989) uses a two regime model to assess the performance of postwar US GNP with adjustments from periods of positive to negative growth. 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.

Other GNP examples. Stock market examples....

Standard Markov models are typically used to model 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. With the mixture model, the future depends on the past. This means that it is impant to know which of the latent sub-groups the firm is in as this will tell you more about the probability of default. The wholesale and retail trades are the most dynamic. There is clearly a hetrogeneity that is ignored by the standard Markov model of rating migration.

4 Analysis of Results

4.1 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 data are calculated as follows

$$P1MEURHUF_t = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}} \times EURHUF_{t+1M}} \tag{5}$$

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

$$EURHUF_t^{f1m} = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}}} \tag{6}$$

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.

The parameters of the 2 regime model are given in Table 4.1. They show the returns to a two-regime model for the range of European currencies 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 Eur-funded carry-trade positions. These range from an average of 1.65%, 1.73% and 1,59% for Hungary, Poland and Romania to justs 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 1: 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 central position of the Russian economy in international finance.

The parameters of the 3 regime model are given in Table 2. They show the mean and standard deviation of the carry-trade returns for each of the 3 regimes against each of the main funding currencies. There are a number of general characteristics that can be taken from the average figures in the final column that are consistent with the evolution of financial instability along the lines set out by Minsky. The While the crash has the smallest return by definition, this is associated with the largest risk as measured by the standard deviation. The average loss during the crash for carry-trade funded by Euro is a little more than 4% the regime where carry trde

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 3. 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 Florint switches from a regime of caution to one where speculative positions are being build. This is estimated at 15%. It is not cosidered likely thatthe 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 finacial 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 sepculative 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 Roumania, 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.

- A table with all the returns from the two or three regimes (using different bases). Retruns can be compared in each of the regimes (which are similar, which are different?
- A comparison of the transition matrix for each base currency
- A comparison of the percentage of time that is spent in each regime.
- A comparison of the dates for the crash.

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

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

It would be useful to have the three regimes as normal distributions on top or beneth each other. This may also give an idea of the combined distribution.

		To Caution	To Build	To Crash
HUF	From Caution	0.85	0.15	0.00
	From Build	0.00	0.96	0.04
	From Crash	0.27	0.00	0.73
PLN	From Caution	0.75	0.19	0.06
	From Build	0.75	0.25	0.00
	From Crash	0.00	0.22	0.78
CZK	From Caution	0.97	0.03	0.00
	From BUild	0.02	0.72	0.26
	From Crash	0.00	0.60	0.40
RON	From Caution	0.74	0.24	0.02
	From Build	0.72	0.28	0.00
	From Crash	0.00	0.03	0.97
TRY	From Caution	0.89	0.00	0.11
	From Build	0.07	0.93	0.00
	From Crash	.00	0.23	0.77
BGN	From Caution	0.09	0.09	0.82
	From Build	0.00	0.99	0.01
	From Crash	1.00	0.00	0.00
NOK	From Caution	0.91	0.07	0.03
	From Build	1.00	0.00	0.00
	From Crash	0.00	0.47	0.53
ISK	From Caution	0.35	0.60	0.06
	From Build	0.09	0.91	0.00
	From Crash	0.21	0.00	0.79
UAH	From Caution	0.14	0.00	0.86
	From Build	0.00	0.91	0.09
	From Crash	0.97	0.01	0.02
HRK	From Caution	0.26	0.73	0.02
	From Build	0.86	0.00	0.14
	From Crash	0.78	0.00	0.22

Table 3: Transition probabilitiews funded with EUR

It is also useful to have the conditional probabilities for the crash regime and the overall returns to the carry-trade. This could come in a box with two rows with a table and the distribution in the top row with the profits at the bottom.

It would also be useful to show the crash regimes in a way that is similar to the shading that is used by the NBER to identify recessions.

5 Conclusions

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

- There are probabilities for the system being in a crash situtation. It is possible to look at the relatioship between this probability and other variables to assess the way that other factors can affect the fragility of the regime. Examples that may be of use include the level of internatioal risk aversion (say the VIX index), the stacne of US monetary policy (either the level of rates of the expansionary nature of the policy if measured in other ways). Confidnece in the banking system of financial centers. For example, the spread between risk-free and banking assets in Us or Euro area. This can help to develop some understanding of the causes of international financial crises.

- It should be possible to determine the current level of financial fragility. The probability that the regime is in a state of crash could be used to compare countries and to assess the evolution of financial risk over time.

- THere can be a comparison of different cultures and customs. Where are the similarities and where are the differences? Different institutions may have different effects. Exchange rate regimes, level of financial development.

There are extension of the modle that can be considered.

- Can this method be used to get a fuller understanding of how the system has changed over time?

- It may be possible to say something financial bubbles.

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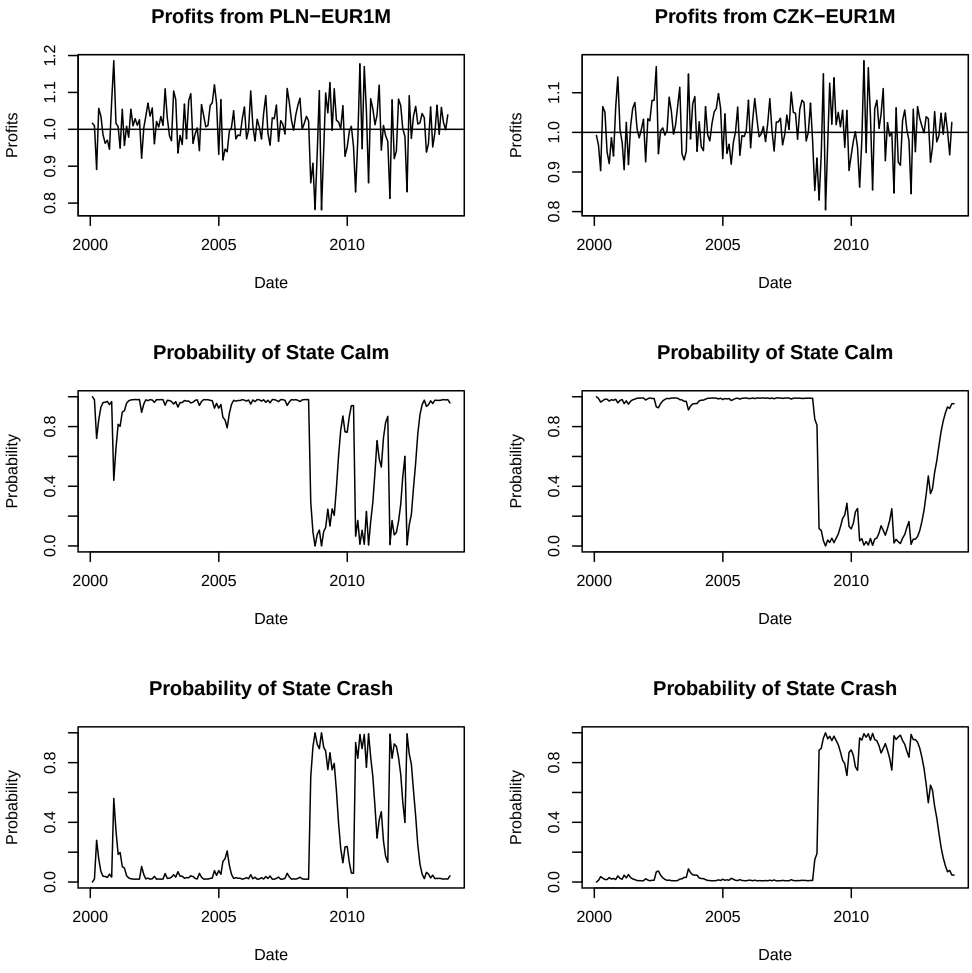
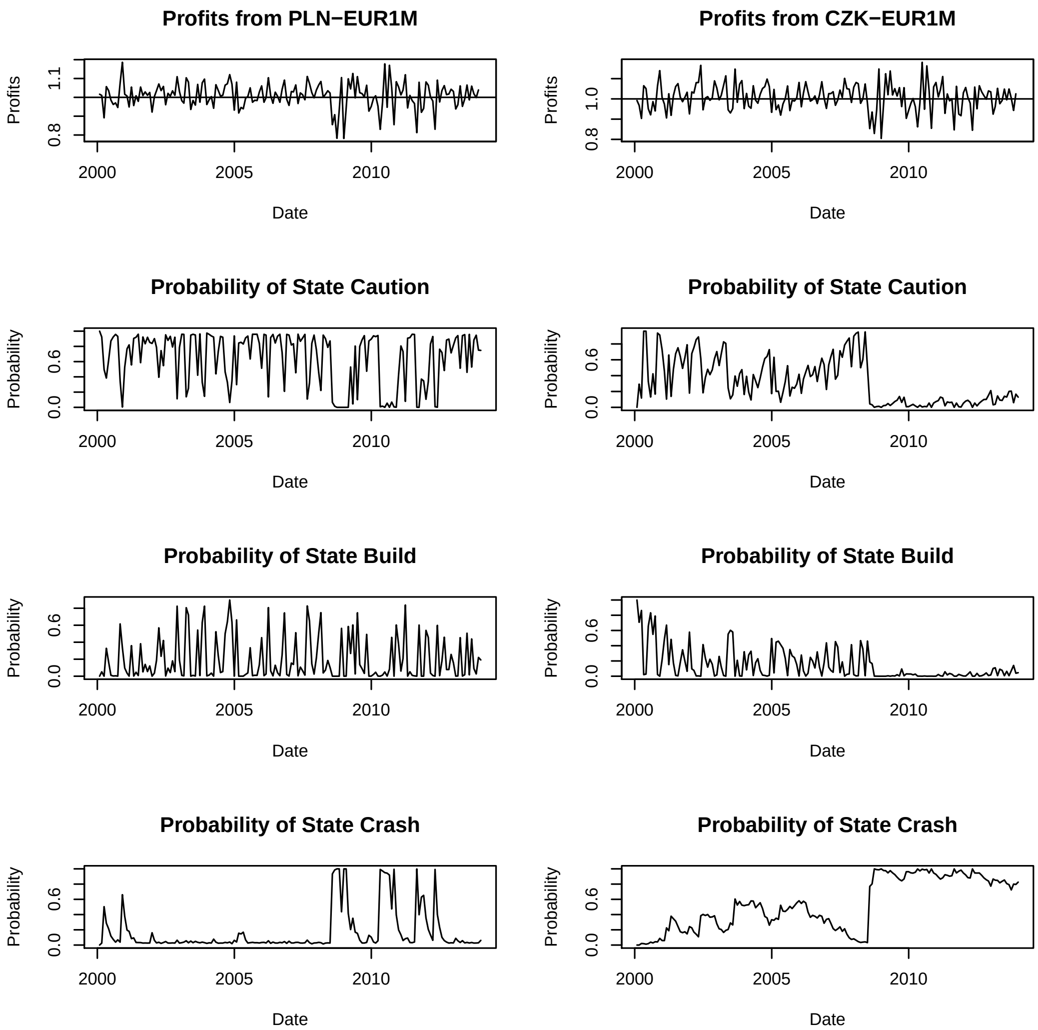
Figure 2: PLN and CZK 1m EUR funded carry profit

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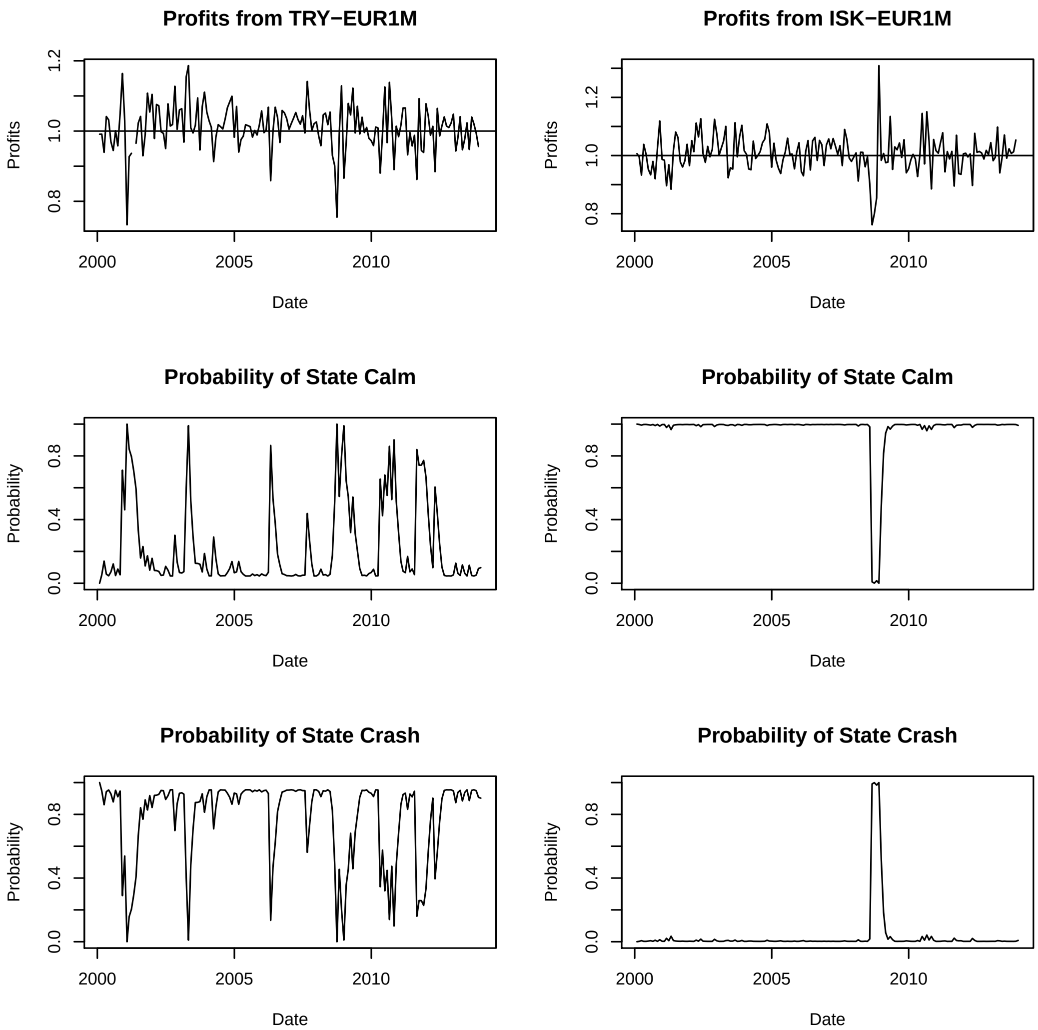
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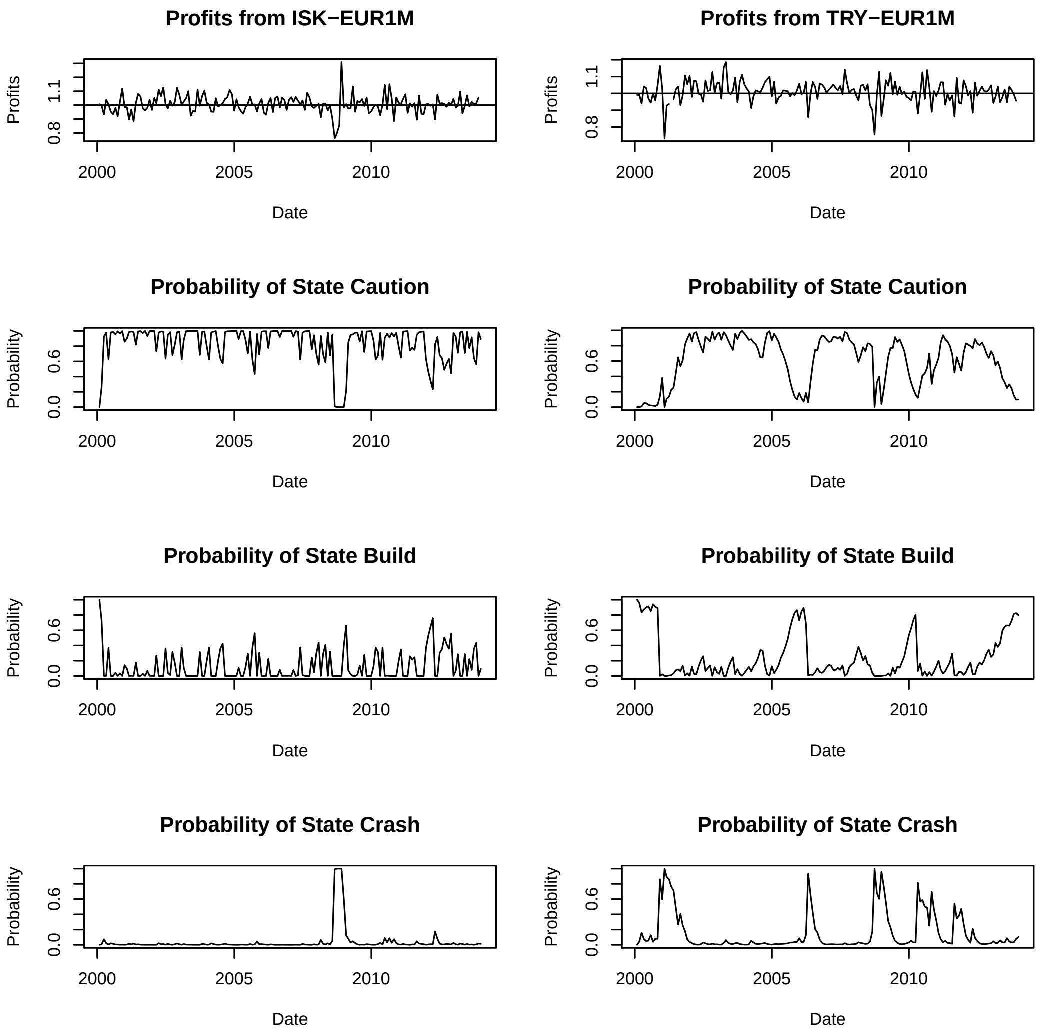
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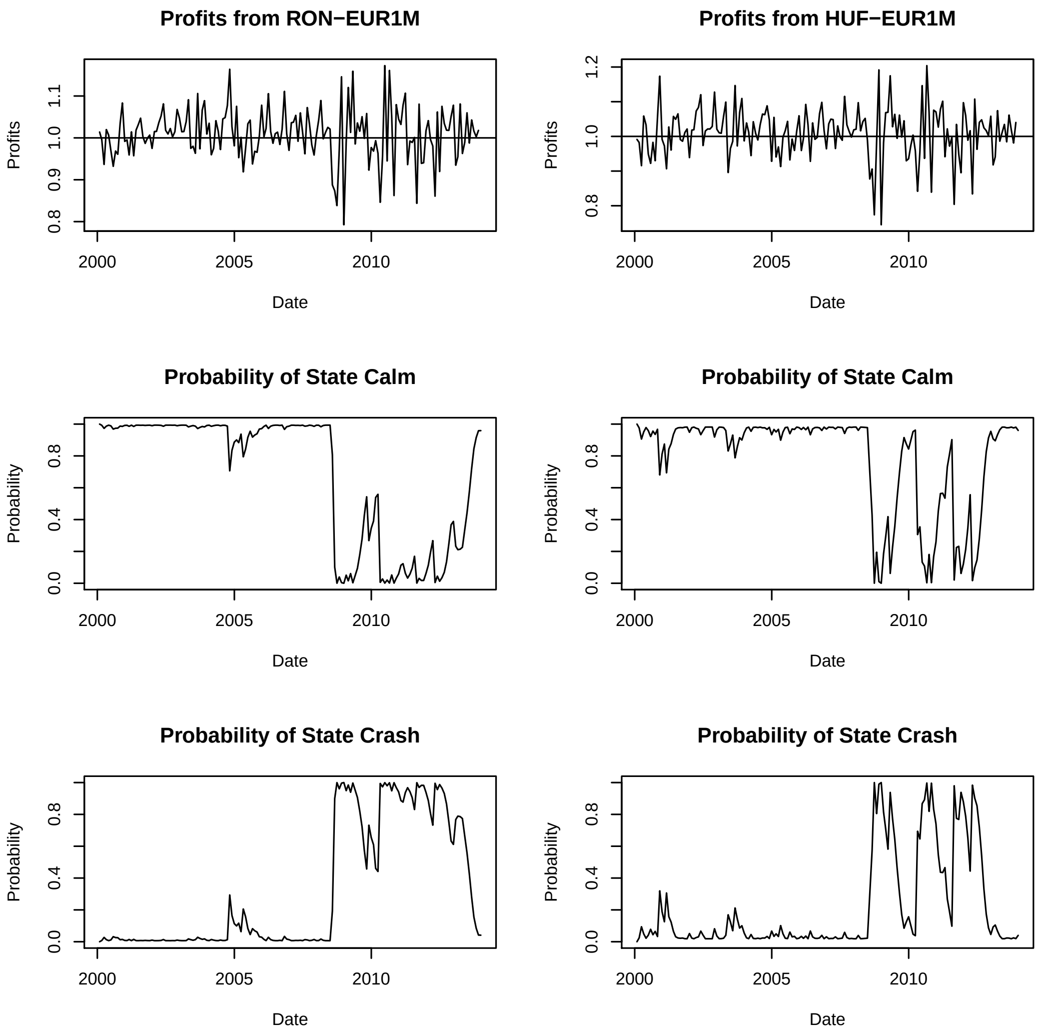
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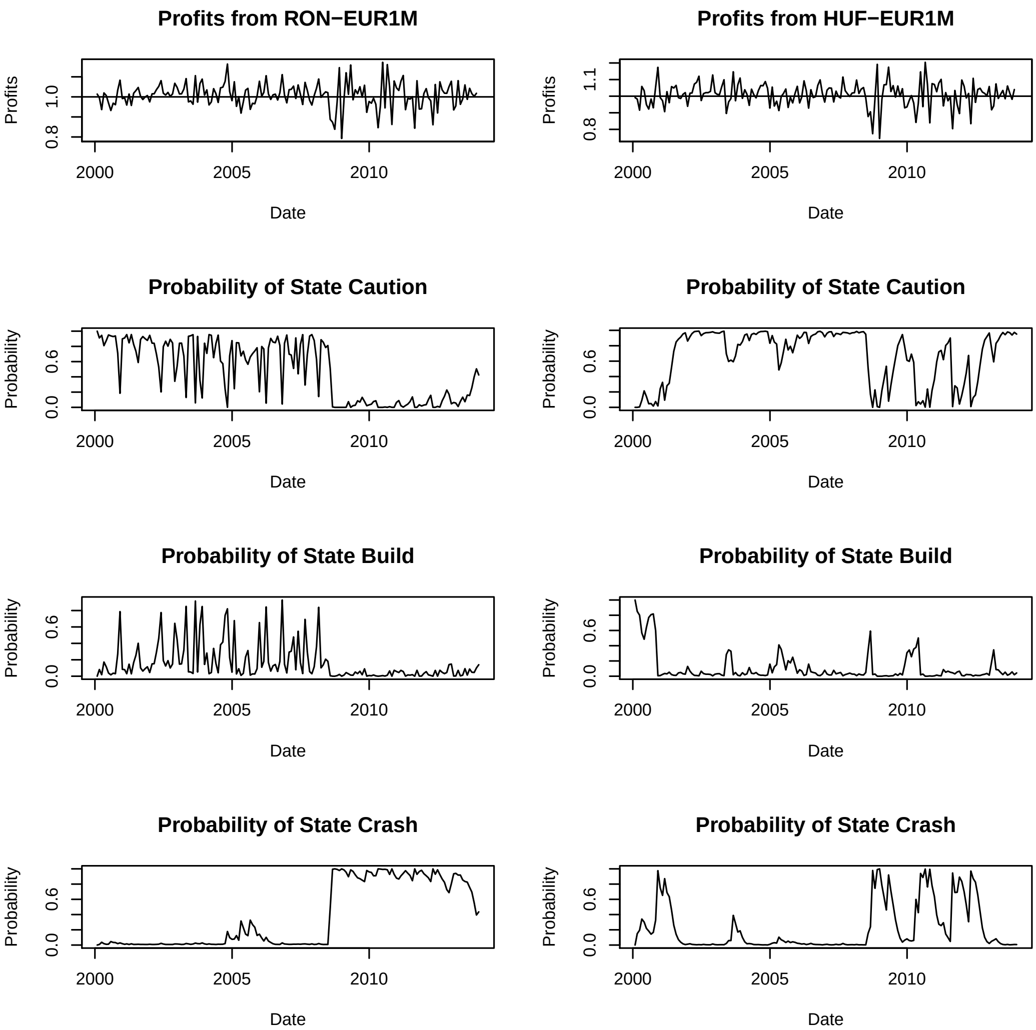
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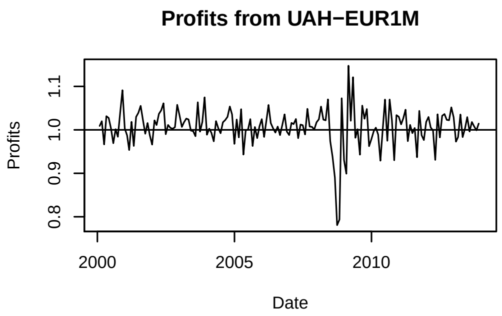
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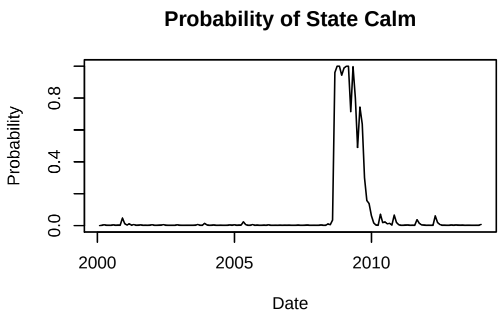
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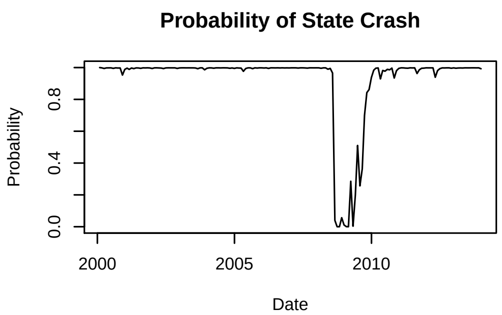
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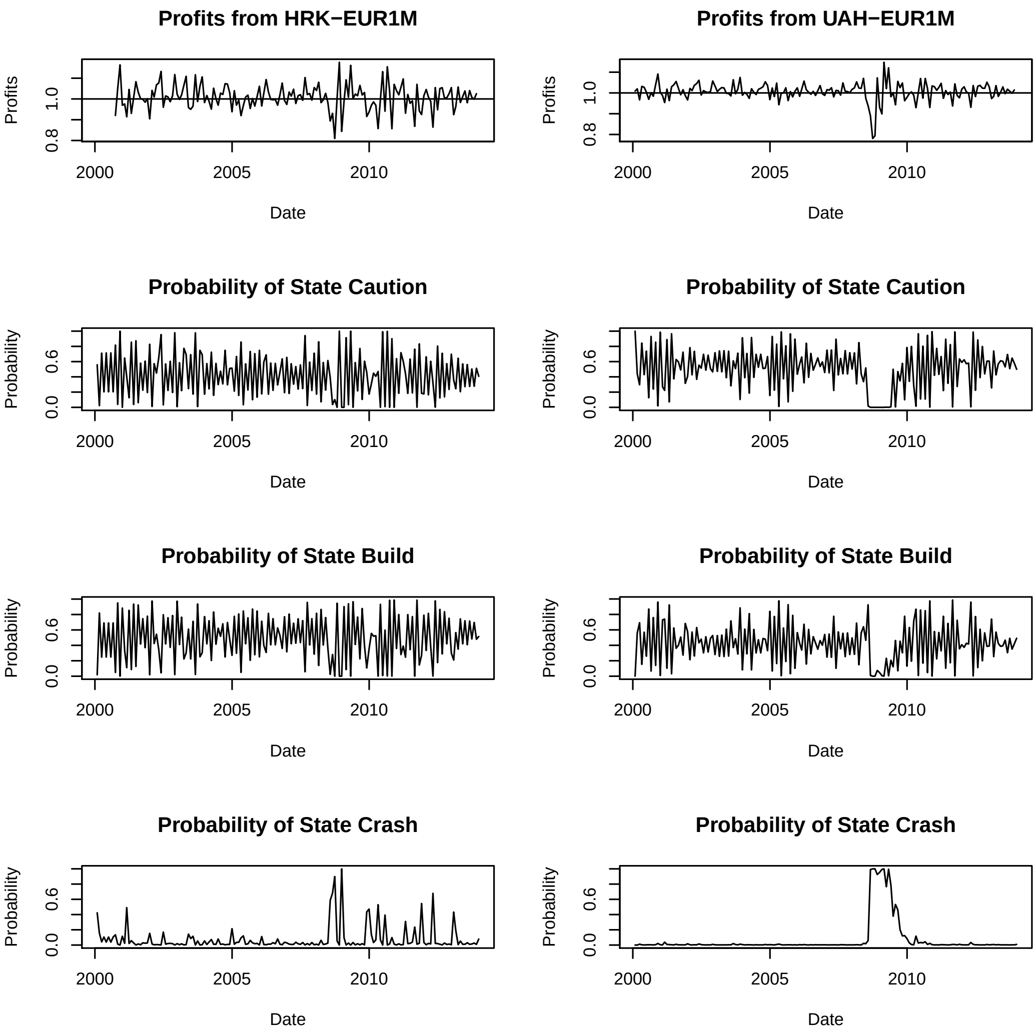
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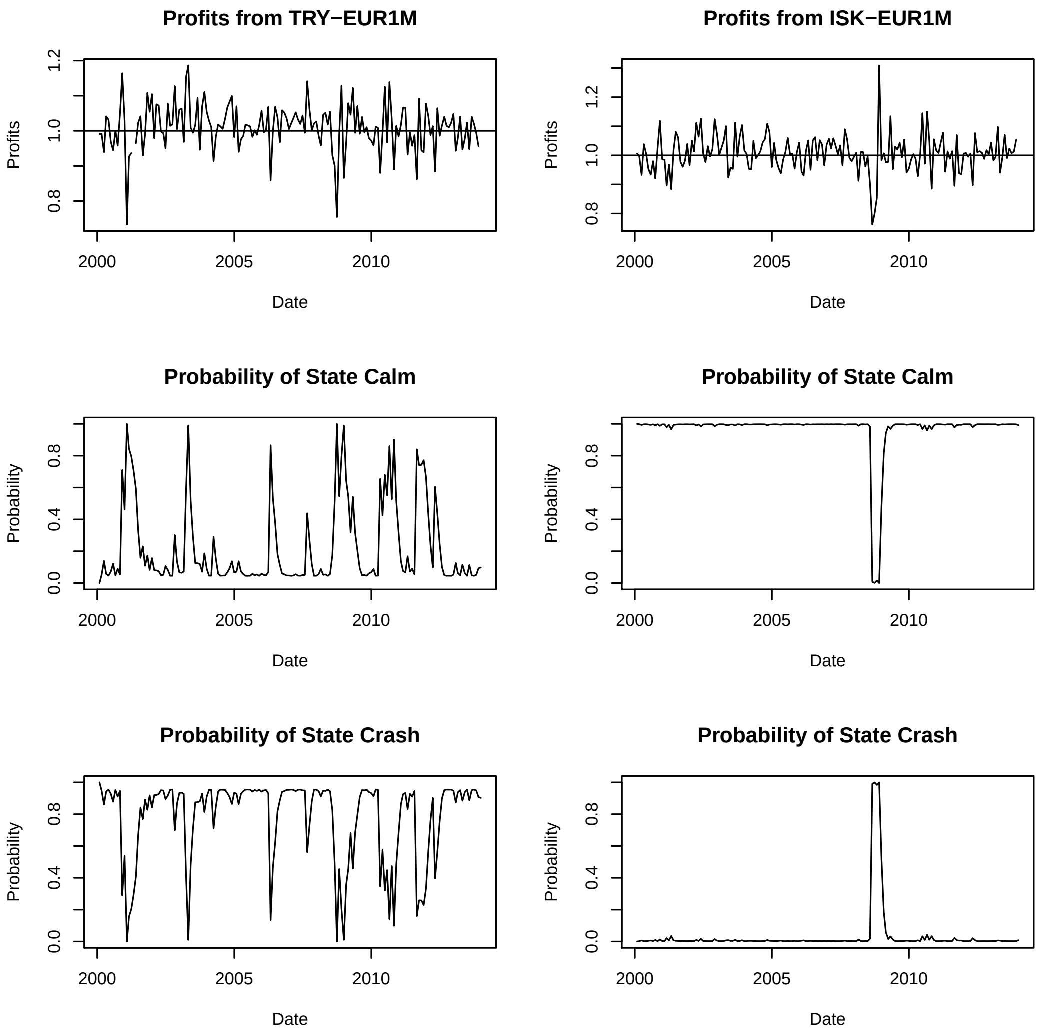
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Profits from ISK−EUR1M
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