Carry trade and transission

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Abstract

Hyman Minsky argued that financial instability would increase through an evolution that ran from stability to 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 outcome that are conditional on each state can be used to uncover the parameters of a Hiden Markov Model (HMM). Identifying financial states can be used to aid understanding of evolution in the vlunerabilty of the financial system.

1 Introduction

The financial crisis of 2007 to 2008 has provided an indication that returns to financial intermediation, like the returns to asset prices returns, have a negative skew: there is a positive mean, that could suggest super-norman profits, but there are also frequent collapses. Another way to look at this is to view the returns are being product of different regimes: some which are part of a *normal* times and others that happen in a *financial crisis*.

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 and increases the

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fragility of the system. Minsky identified three phases of financing: hedge, speculative and Ponzie.

In the first of these the system is stable as lending is not excessive, 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 are envisaged by creditors and debtors, encouraging them to be cautious and risk-averse.

However, in the absense of economic shocks these memories 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 exteremes and more weight to the immediate experience of economic calm. The increase in lending tends to improve immediate economic conditions (reference?: business investment and consumer spending increase if lending is broad-based; asset prices will rise where lending is directed towards financial investment. This increase in economic activity that comes from the 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. There is evidence that decision-making tends to favour occurances 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. Now a continuation of above-normal activity or continued asset appreciation is required. 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, business expand to meet booming demand and endovour to increase market share, while property and financial market speculators redouble their bets. Brunnermeier and Pedersen (2009) has explains how asset price appreciation incresaes the avilability of credit, reduces margins and helps to turn appreciations into bubbles.

The conditions are now in place for the bubble to burst in a violent reversal. Fisher (1932, 1933) explained the way that *debt-deflation* would bounce between financial and real sectors of the economy. 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. However, the economic consequences when it comes are profound.

When economies are in trasition, economic norms and institutions are changing and it becomes easy to downplay the likelihood that previous economic shocks will be repeated. Financial system tend to be less developed and therefore there is scope for finance to increase in absolute terms as well as relative to overall level of economic activity. This process can attract firms from more developed economies. See *Focus on European Economic Integration: Foreign Currency Loans* (2011) and Berglof (2010) for information about the expansion of Euro area banks into the Central and Eastern European trasition economies.

1.1 Carry trade

One specific part of the range of international capital flows that has been frequently evident is the *carry trade*. This is the attempt to take advantage ofthe break down in *uncovered interest partity* by funding an investment in relatively high yielding transition currencies with a low interest base. The base currencies are usually those of the US dollar, the Euro, the Swiss franc and the Japanese yen. The activity transfers credit booms in developed economies to the rest of the world and draws developed financial institutions up against the emerging financial institutions in other countries. One particular case for investing in emerging economies involves the *carry trade*. This is the attempt to take advantage of the breakdown in *unovered interest parity*: 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. There is wide spread evidence that UIP does not hold on average. However, it is debatble whether risk-free returns are possible. There is a large body of research that suggests that these returns disappear with a more sophisticated assessment of risk that is being taken. In particular, 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-coinfident economic agents suffereing behavioural biases.

1.2 CEE

Economies in transition have faced repeated struggles with financial instability. The pressure to open economies to international finance has exacerbated this risk as it has added a huge stock of international financial capital to the potential flow that can enter during the country during the optimistic expansionary stage with more significant and adverse consequences when the it retreats. Dornbusch and Werner (1995), Calvo (1998) and Krugman (2000) have been associated with the term *sudden stop* to emphasise the importane of the inflow that takes place before the currency crisis in understanding the disruptive effects of the reversal.

http://mpra.ub.uni-muenchen.de/383/

As such, there is increased skepticism about the benefit of the free flow of international capital since the dispuptive currency crises spilt from Mexico through Asia, Russia and other parts of the world in the 1990s. In addition, the story of *global imbalances* and the phenomenon of developing China lending to the US flies in face of the theory that suggests that rich developed countries will aid the progress of the less developed by providing the funding for deepening of capital.

1.3 Finance after the crisis

International financial conditions following the 2007-08 crisis have fuelled the growth of the carry-trade by providing large amount of funding-currency liquidity and relatively attractive investment oppoprtunities in emerging economies. However, the indiction from Federal Reserve Chairmn Ben Bernanke on 18th December 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 brought attention back to relationship between US monetary policy and the flow of capital to emerging economies.

This next paragraph does not work with the bibliograph. Needs fixing. There is a question about the extent to which the Fed-inspired sell-off in emerging markets is function of changes in liquidity and how much is a consequence of the change in risk-aversion. There are a number of studies that have looked at the effect of a change in Fed policy on capital flows to emerging markets. For examp le, Alexander Klemm and Sosa (2014) argue that Fed tapering while not necessarily leading to capital outflow, could generate *new risk premium shocks*. These use a panel VAR method to assess the effect of US monetary policy since 1990 on capital flows to 38 emerging economies. Similarly, Groen and Peck (2014) assess how changes in global risk aversion affects carry-trade activities. They find that the initial signal from the US central bank in Fed Chairman Bernanke's May 22 2013 testimony to Congress coinciced with an increase in global risk aversion which affected global asset prices. They use the approach presented by Karel Mertens (2013) to estimate the effect of policy changes by using a two-stage least squares appraoch to identify the SVAR model of asset price changes. 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. Using a similar method they find that nearly all the decline in Emerging market equities is attributable to the increase in risk aversion.

1.4 The instability cycle

Minsky provides a very powerful description of the financial instability cycle. It would be extremely useful to be able to identify where an economy is in the cycle and what determines when and how the economy makes the trasition from one regime to another. 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. Referenes (BIS etc measurements????).

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.[1] Therefore, this paper proposes use an analysis returns that are achieved through a sample of potentil carry-trades to get a fuller understanding of the financial instbility process.

The motivation for this research is to help to identify regimes and therefore help authorities determine the risk of financial crisis or crash. The foreign exchange market is used to get a broader understanding of some of the forces at work.

There are two ways to try to identify the regimes: use external indicators such as the VIX index or other indications of domestic economic or political uncertaintly; use the internatl structure of the data to identify the periods through which the finncial system is evolving.

1.5 The ideas of the Hidden Markov Model

One way to look at this would be to use a model that assumes that the system evolves as a Markov sequence of a series of steps. The probability a particular tupe of return depends on the type of return that was seen in the previous regime. For example, probability that the carry-trade will provide a good return with minmum risk will be greatest when that was the previous regime: if this speculative activity is profitable and others are attracted to the activity, the possibility of a crash is limited. However, there is some

[1] 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.

modest probability of a crash and some probability that there could be a return to caution. . In other words, there is a Markov sequence and there is a transition matrix which defines the probabilities of being in each regime.

A sequence of retrurned can be generated by drawing an initial state using the π values of initial probabilities and then sampling using the transition matrix. This will provide a sequence of carry trade returns.

A *Hidden Markov Model* HMM will be used to understand more about the evolution of financial instability. The MHH is a *Markov system* that evolves from one state to the next. In this case the evolution is from a situation of financial calm through financial speculation and into financial crisis. These correspond to the hedge, speculative and Ponzie financing of the Minsky model.

The regimes of financial instability are not observed. However, the returns to the carry trade will change as the regime changes: in the calm phase there may be a very small return that reflects the failure of UIP to hold; in the specualtive phase, carry-trade positions are built and this encourages high returns as the interest rate carry itself is combined with the capital appreciation that come from sales of funding currency and the purchase of investment currency. The crisis is the period of crash and reversal. The HMM aims to find the probability of a particular pattern given a particular state. The three latent states are the periods of caution, build and crash.

However, the retruns actually depend on the underlying regime. In other words, there are a series of trasition matrices that are related to different regimes because the probability of a particular type of return given the prebious type of return will depend on the regime that is in place. For example, if there are steady returns being made from the carry-trade, the probability that these returns continue in the next period or that there is a crash or a return to cautiou will depend on the underling financial regime: if the financial regime is speculative, the probability of retaining good returns or moving to a crash will be relatively high and the probabiluty of returning to caution will be relatively low; if the the financial system is in a position of calm, there is a greater probability that there can be a return to caution and a smaller chance of a crash. The transition matrix is differenet for different regimes.

There is also an *HMM emission matrix* which gives the probabilities of each return type in each of the financial regimes. For example, in the spculative phase, the probability of speculative returns is high, there is some probability of crash and some probabilty of caution.

Give this information, it is possible to construct a sample of carry-returns from the initial probabilities, the transition matrix and the emission matrix. Alternatively, it is possible to work backwards from the carry returns using the transiton matrix and the emission matrix to find the most likely sequence of financial states by applying the *viterbi* algorithm (see Chapter10.R for full details of how this works).

The *Viterbi algrithm* will create a matrix v that will contain the probability of each regime, given the type of return that is evident. This is computed from the product of the transition matrix, which gives the probability of transfering to the currnt regime from the previous regime, and the maximum value of V in row i-1. For each state, there will be a probability which is the product of the probability of seeing the regime given the returns and the most likely state in the previous period and the probability of the state given the return

```
v[i,l] <-  statelprobnucleotidei * max(v[(i-1),] * transitionmatrix[,l])
```

which is line 45 of viterbi.R

Expectations-Maximisation (EM) algorithm.

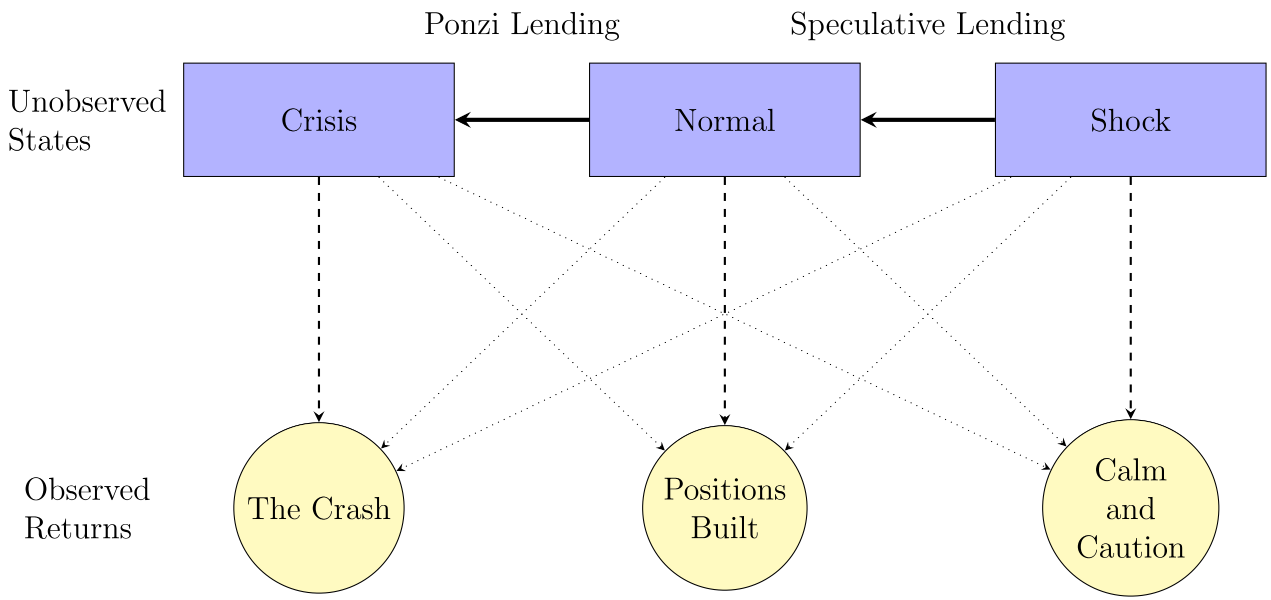


Figure 1: Carry Trade: Regime Change

1.6 Use of the model

Some history, Some examples from genetriics and speech....

Economics and finance Hamilton

The second paper (on rating agencies - incuded in the "other" folder. Uses the mixture model against the alternative of a pure Markov chain. In the pure Markov chain, the future depends only on the present. However, 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. This knowledge will be based on the whole sample of ratings. There are A and Q processs. What determines whether the rating evolves according to A or Q? It appears to be partly the result of the industry. 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.

As such, it may be possible to make a comparison of developed and less developed finncial systems or fixed and floating systems. How do they differ? What does this tell us about how vulnerble the systems are?

Agn Timmerman (2011) Looking at how abrupt changes in regime can lead to changes in the way that the system works. The different regimes can be associated with different underlying distribution of returns. This can allow the understanding of the non-liner and non–normal distribution within normal or linear framework. At the extreme, the regime switch model can incorporate a *jump model* with one change, and can also be associated with time-varying parameter models that have a large number of regimes.

The broad framework for the method is to model a discrete state $s_t \in \{0, 1, \ldots k\}$

$$y_t = \mu_{s_t} + \phi_{s_t} y_{t-1} + \sigma_{s_t} \varepsilon_t, \quad \varepsilon_t \sim iid(0, 1) \tag{1}$$

The process governing the underlying regime must also be defined.

$$Pr(s_t = 0|s_{t-1} = 0) = p_{00} \quad \text{and} \quad Pr(s_t = 1|s_{t-1} = 1) = p_{11} \tag{2}$$

More generally, the transition could be time-varying and could be dependent on the time spent in the regime. See Durland and McCurdy (1994) for example of the probbilities in the transition matrix being related to time. The longer the systemm has remained in the build phase, the greater the risk of crash. Remember that the crash phase is a period when there is risk of a sharp reversal.

See Diebold, Lee and Weinbch (1994) for examples where the transition probabilities depend on some other state variables. For example, the interest rate spread. Could the VIX index or other factors be used? Vix index would indicate heightened international tension as one element that affects the probability of transforming from one state to the next. An elevated VIX is an indication of the heightened international risk premium. This may increase the probability that the regime switches from carry build to crash. This is a theme that could be related to the bubble bursting so any information that improves the ability to identify bubbles bursting would be beneficial.

Ghysels These notes from Ghysels. There are two states of the world: crisis and moderation. If the system is in a crisis, it stays there with probability p; it switches to moderation with probability $1-p$. If in moderation, the system stays there with a probability q and switches to crisis with probability $1-q$. If the probabilities change over time, there is no longer a *homogenous Markov Chain*. Ghysels has a seasonal dummy for the probabilities that represent the months or quarters.

Can the probabilities change over time? This may be the result of changes in the resilience of the financial system. Mixture Hidden Markov Models Hidden models help to calafify the regime under which securities trade. Model takes into account the unobserved hetrogeneity across time. This could could be extended to space (for different countries). Is it possible to estimate a panel?

Can the systemm be used to compare to fixed and floating exchange rates.

The use of the regime-switch allows the transition from one regime to another to be the result of something that is more than just a deterministic process. There are a number of ways that this model could be expanded. Dueker has a model where the degrees of freedom from a Student-t distribution change with the regime.

Peso issue

1.7 The model

From Maatin's speech (can be deleted later). In a *mixture model*, each observation 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*.

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,

- $S_t \in 1, \ldots, N$ denotes the latent state or class of observation t
- $P(S_t = i)$ denots the probability of the latent state t equals i
- $p(Y_t = y|S_t = i)$ denotes the density of observation of Y_t conditional on latent state being $S_t = i$.

In the *dependent mixture model* states are assumed to be statistically dependent. This is consistent with the Minsky theory that the period of calm creates the conditions for the crash. The process underlying the state transitions is a *homogenous first order Markov process* (look this up for additional definition). This process is completely defined by the initial state probabilities.

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

and the state transition matrix,

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

The models are estimated using the Expectation-Maximisation (EM) or numerical optimisation (when parmeters are constrained). 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: $P(Y_t|S_t, x, \theta_{resp})$

See Maarten's notes to see how these are implemented.

In this case,

The regimes are

- Hedge: cautious and risk averse
- Speculative: More willing to take increased risk.
- Ponzi: Risk-loving and explosive

2 Methods

2.1 Data

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

The data are calculated as follows

$$EURHUF_t^{f1m} = \frac{(1 + HUF1M_t)^{\frac{1}{12}} \times EURHUF_t}{(1 + EUR1M_t)^{\frac{1}{12}}} \tag{4}$$

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 code for the calculation is in the function forp in the package prepareR. This will create a sample of carry-trade profits from an array of CEE investment currencies relative to standrd funding currencies. The ISK, TRY and NOK are used as reference. One month and 3 month carries are created. It would be possible to have shorter time periods for the carry-trade. This would require the addition of the appropriate times series for LIBOR or deposit rates.

2.2 Results

Running the Raw.R file, lines 22 to 24

```
mod <- depmix(PPLNUSD ~ 1, nstates = 3, data = da)
 set.seed(3)
fm2 <- fit(mod, verbose = FALSE)
depmixS4::summary(fm2)
```

gives the results

The parameters of the regimes are

	Intercept	S.Deviation
Build	1.0163	0.0200
Crash	0.9283	0.0106
Fear	0.9772	0.0156

The allocation of the regimes is based on two principles: the crash should have the lowest returns and the build should have the highert; the order of increasing financial fragility should be preserved.

In this case, the only profitable trades are those in the period of build. However, unusually, this is also the time of greatest risk (if risk is defined as the standared deviation of these returns).

The transion matrix is

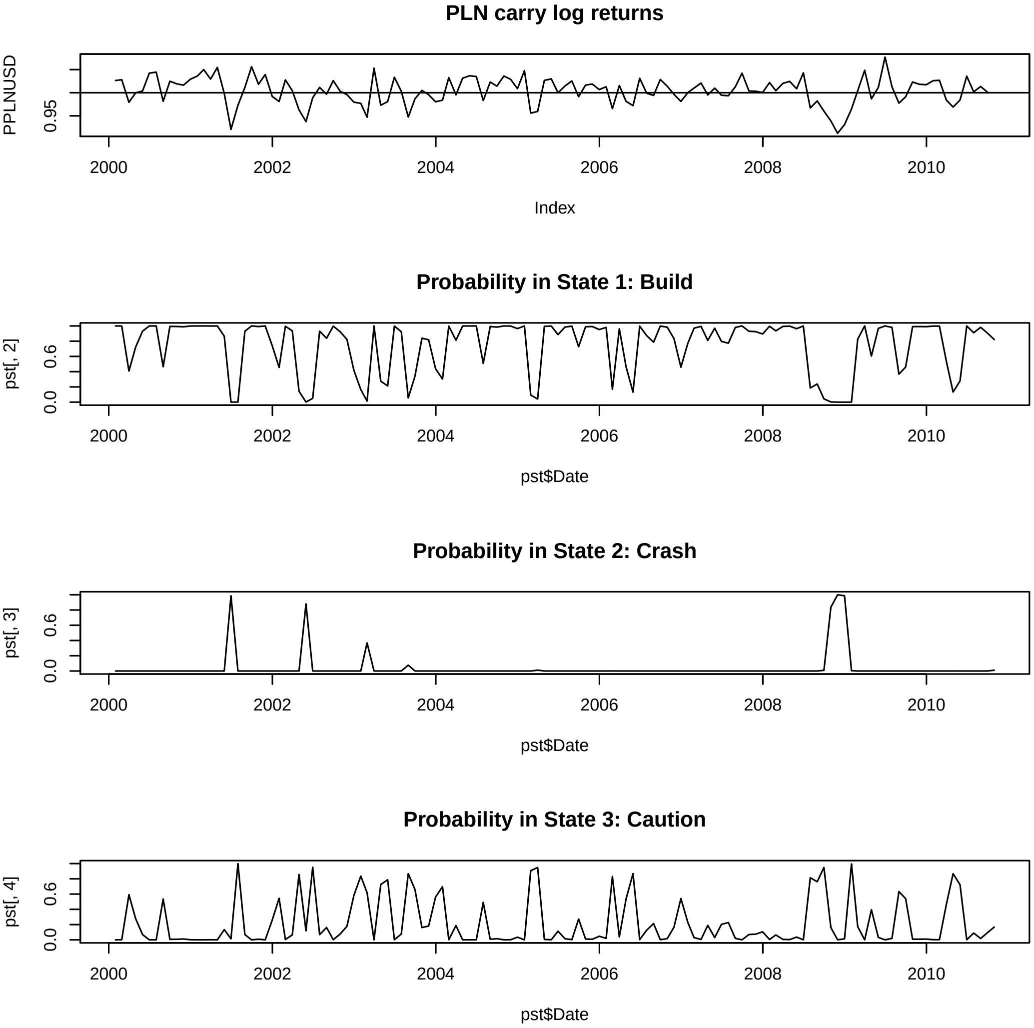
	to Build	to Crash	to Fear
From Build	0.83	0.00	0.17
from Crash	0.00	0.40	0.60
from Fear	0.55	0.10	0.34

This is rather encouraging as the probability of trasfering from one state to another is consistent with Minsky: during the building phase, the building continues with an 83% probability, there is a small chance of a crash and some chance of a move directly to fear; one in the crash, the regime remains there or moves to fear; once in fear, there is some chance of a move to building and some chance that things remain in fear. Fear does not usually lead to a crash.

2.3 Formal model again - move later

Hidden Markov Models. $f(y_{it}|z_t)$ is assumed to have a multivariate normal density function. This distribution is characterised by $\theta_k = (\mu_k, \sigma_k^2)$. Excluding the states w, there are the initial state probabilities to be determined, the 2 transition probabilities and the conditional mean and conditional variance to be estimated. Thsi 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.* Dempster, Laird and Rubin (1977). The E step computes the joint conditional distribution of the latent variables given the data and the current provisional estimates of the model parameters. The M step ML methods are used to update the parameters using the estimated densities of the latent variables 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).

Notes from the Leeds notes. The aim is to find patterns in time. This uses the examle of seaweed and traffic lights. For the traffic lights, there is a state machine where the different states follow each other. Each state is dependent only on the previous state. This is a deterministic system. The weather is not deterministic. There may be three states: wet, cloudy and sunny. The Makov assumption says that the state depends only on the previous state. This is a simplification that makes the problem easier to solve. Some information may be lost with the simplifcation. The Markov process moves from state to state, depending only on the previous n states. This is called an *order n model*, where n is the number of states affecting the choice of the h


PLN carry log returns
PPLNUSD
0.95
2000
2002
2004
2006
2008
2010
Index
Probability in State 1: Build
pst[, 2]
0.0
0.6
pst$Date
Probability in State 2: Crash
pst[, 3]
pst$Date
Probability in State 3: Caution
pst[, 4]
pst$Date

next state. With the weather example there are 9 possible transformations (M^2). The probability of each transition is assigned a probability called *state transition probability*. These are collected into a *state transition matrix*. The probabilities do not vary with time. This is a (unrealistic) assumption. To start the system, there is a *vector of initial probabilities*. This is the π vector.

The first order Markov process has three elements:

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

Sometimes the Markov model is not sufficient to fully describe the process. In the weather example, the weather may not be observable but seaweed is evident. There is a probabilistic relationship between the seaweed and the weather. More realistic is the identification of hidden states of the mouth through the sounds that can be identified. The observables are related to the hidden states. It is assumed that the hidden states (the weather) are modelled by a simple first order Markov process. The connections between the hidden states and the observable states represent the probability of generating a particular observed state given that the Markov process is in a particular state. This is the *confusion matrix* which gives the probabilites of observable states given a particular hidden state.

In our case it is assumed that the hidden states representing the evolution of financial conditions according to Minsky's Financial Instability Hypothesis evolve in a way that can be modeled by simple, first-order Markov process.

The Hidden Markov Model (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 $Pr(y_i|x_j)$

2.4 Investgations using HMM

THere are a number of problems that can be solved Once a system can be described as HMM, three problems can be solved.

1. finding the probability of an observed sequence given a HMM (evaluation)

2. finding the sequence of hidden states that most probably generated the obsered sequence (decoding)
3. generating a HMM given a sequencde of observed observations (learning)

2.4.1 Evaluation

There are a number of HMM with sets of (π, A, B) tripples, which HMM geneated the given sequence? For example, there may be 'summer model' and a 'winter model' and it may then be possible to determine the season from the seaweed sequence. The *Forward algorithm* is used to calculate the probability of an observation sequence given a particular HMM and hence the most probable HMM. In speech recognition, the HMM represent different words and the most likey HMM determines the word.

It may be that there are different models for fixed and floating exchange rates.

2.4.2 Decoding

It is most usual to find the hidden states that generated the observed sequence. Finding the hidden states is important because they are not directly observable. A blind hermit may feel the seaweed but cannot see the weather. The *Viterbi algorithm*. This could also be used to determine the syntactic class of words (noune, verb etc) from the words themselves.

What is the probability of the observed sequence given the HMM? This can evaluate risk - crash?

2.4.3 Learning

This is the most difficult task. Take a set of observations and fit the most probable HMM . The *Forward-backward algorithm* is used when the A and B matrices are not directly (empirically) measurable.

2.4.4 Forward Algorithm

With three states, three observations and the parameters of the model known, the aim is to find the most likely hidden sequence. It would be possible to find each possible sequence and sum the probabilities.

3 Results

Three regimes can be identified: number one, the cautious period; number two, the time when carry positions are being built; number three, the crash. This works for PLNUSD, HUFEUR.

The R files work as follows: prepare.R loads the data and creates the profits function; Raw(test).R will test data.

3.1 PLNUSD

For the 1-month PLN-USD carry-trade sample, a three stage HMM is fitted. The parameters of the models are

State	Mean	SD
State 1	1.0109	0.0309
State 2	0.9317	0.0486
State 3	1.040982	0.0432

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. 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.

Need to update the regimes and the figures to get an overview. Chose the countries to look at.

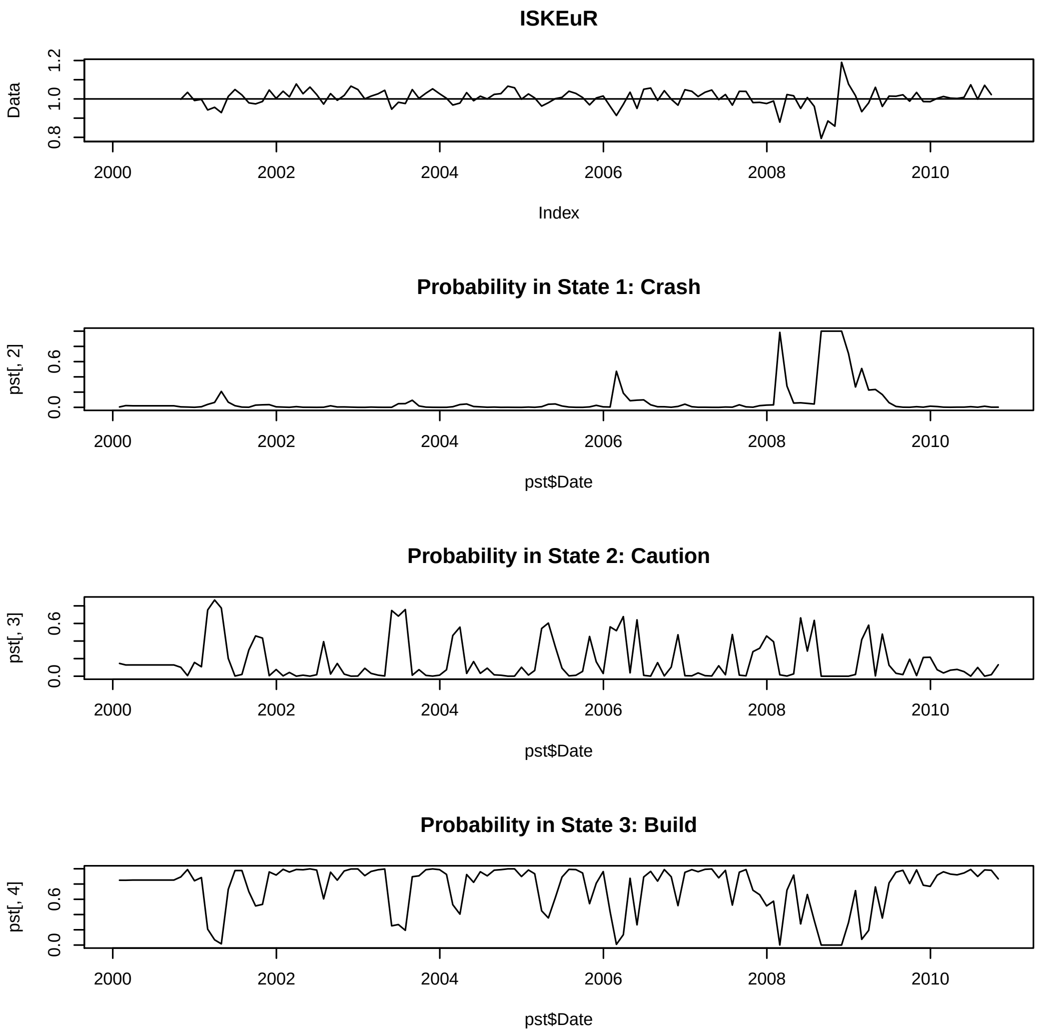
The periods that are identified as those associated with the crash are July 2008 to January 2009 and April and May 2010.

The Raw.R file works with the PLNUSD. It gives the dates and the parameters of the model but it does not produce the pdf for the figures. Now this needs to be automated so that tables and figure can be produced automatically. Test on a couple of others.

4 Conclusions

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

- Looking at the changes in the probability that there is a crash and assessing the relationship between these changes and domestic and international events. The doestic could be political opnion polls or central


ISKEuR
Data
0.8
1.0
1.2
2000
2002
2004
2006
2008
2010
Index
Probability in State 1: Crash
pst[, 2]
0.0
0.6
pst$Date
Probability in State 2: Caution
pst[, 3]
0.0
0.6
pst$Date
Probability in State 3: Build
pst[, 4]
0.0
0.6
pst$Date

bank policy; the internatinal could be international risk or changes in Fed policy.

- We may want to know whatis the evolution of underlying financial conditions given the carry return; we may want to know what is the overall level of crisis risk given the level of financial stability.

- How much of the crash is related to changes in risk aversion and how much is the provision of internationl liquidity. What is the relatinship betweenn the two forces.

- Additonal actions could assess the changes in the other moments: are TVP evident? Is there more risk of the bubble bursting when the build phase has extended more a significant period.

- It may be possible to say something about the literature on bubbles.

- THere can be a comparison of different cultures and customs. Where are the similarities and where are the differences?

- These are unseen but may be identified by other variables (such as the level of international risk aversion (VIX) or the state of domestic political uncertainty (see that buy at Yale???)). These periods can be compared to those uncovered by the crash model. How well do these periods of political instbility compare to the hidden regimes tht are uncovered. Alternatively, it may be possible to draw the states from the data and compare the information that is supplied by the data with that from what is known about political and economic developments at the time. It is also possible to assess the probability that there will be a switch from one regime to another.

- What is the probability of a particular pattern given a particular state. The three latent states are the periods of caution, build and crash. These are unseen but may be identified by other variables (such as the level of international risk aversion (VIX) or the state of domestic political uncertainty (see that buy at Yale???)). These periods can be compared to those uncovered by the crash model. How well do these periods of political instbility compare to the hidden regimes tht are uncovered. Alternatively, it may be possible to draw the states from the data and compare the information that is supplied by the data with that from what is known about political and economic developments at the time. It is also possible to assess the probability that there will be a switch from one regime to another.

Chapter 10 Biometric Text on HMM has an excellent overview of markov HMM and the R code necessary. One component of this that could be of interest is the assertion in on-line bimetrixs text that it is a problem to find the underlying state that produced the DNA outcome. The equivalent of this for the crash model is to find the underlying Minsky state that produced the market activity.

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