

# How to predict financial stress? An assessment of Markov switching versus logit models

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RiskLab/BoF/ESRB conference, 5 October 2016



Issue warnings for financial market stress, i.e. **good quality** signals **sufficiently early**

① **What are we looking for ?**

Identify turning points in the financial cycle

② **How to anticipate it ?**

Predict turning points in the financial cycle

# Where do we stand : two different strands of literatures

- Markov switching (MS) models are extensively used in the business cycle literature
  - ▶ Identify turning points in the business cycle, ultimately identify recessions
- Discrete choice models (e.g. logit/probit) are extensively used in the literature on currency, banking and financial crises
  - ▶ Identify drivers of currency/banking/financial crises, ideally provide early warning signals

⇒ Bridge the gap between both strands of literature : **identify** and **predict** episodes of financial market stress

# Focus of the paper

- 1 Can we use tools developed for the analysis of the business cycle to complement/improve existing early warning models ?
- 2 Do we gain additional information or predictive power by using a continuous measure of the intensity of financial market stress (compared to using binary crisis indicators) ?
- 3 Which variables are found to be good predictors of financial stress ?
  - ▶ Vulnerabilities associated with subsequent stress

# What do we find

## **Predicting episodes of high financial stress :**

- Markov switching model outperforms the logit model between six to one quarters prior to the onset of high financial stress episodes
- Probabilities of high financial stress obtained from the Markov switching model are less dependent on including/excluding the post-2006 data

## **Identifying leading indicators for entering/exiting a high financial stress regime :**

- Debt service ratios and housing variables indicate a transition to a high financial stress regime
- Equity price growth and economic sentiment indicators provide signals for a transition to a tranquil state

## Related literature

- **Dating business cycle turning points** : Hamilton (1989), Filardo (1994), Diebold et al (1994), Chauvet and Piger (2008), Gadea and Perez-Quiros (2012)
- **Measuring financial market stress** : Hollo et al (2012), Hartmann et al (2013), Duprey et al (2015)
- **Comparing early warning models** : Abiad (2003) evaluates the signalling ability of MS models for Asian currency crises

# Road map

- 1 Measuring financial stress
- 2 Markov-switching models for early-warning
- 3 Results on the performance of MS versus Logit
- 4 Predictors of financial stress with the MS model : horse-race

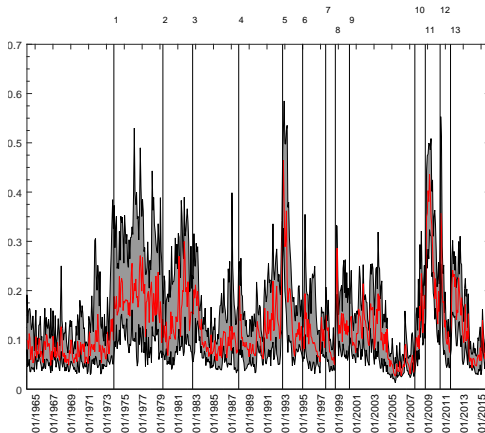
# Section 1

## Measuring financial stress



# Financial stress from Duprey et al. (2015) for EU-15

## CLIFS : Country Level Indices of Financial Stress

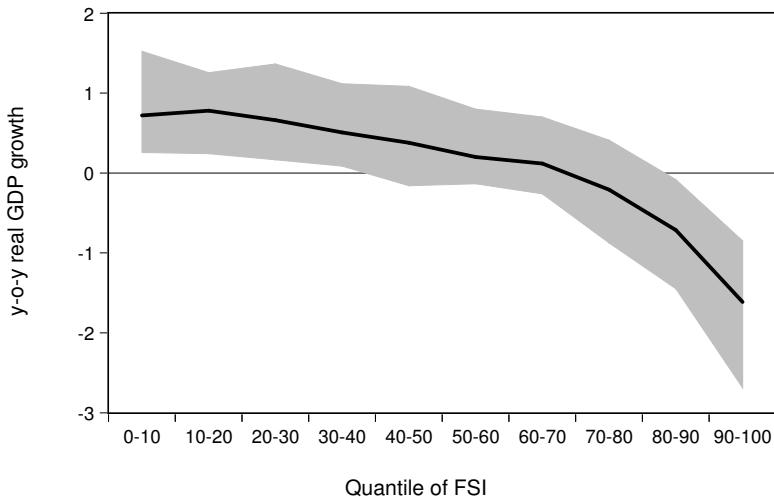


1 - first oil shock ; 2 - second oil shock ; 3 - Mexican debt crisis ; 4 - Black Monday ; 5 - crisis of the European exchange rate mechanism ; 6 - Peso crisis ; 7 - Asian crisis ; 8 - Russian crisis ; 9 - dot com bubble ; 10 - subprime crisis ; 11 - Lehman Brothers ; 12 - 1st bailout Greece ; 13 - 2nd bailout Greece

Dataset : <https://sites.google.com/site/thibautduprey/research/crisesdating>

[//sites.google.com/site/thibautduprey/research/crisesdating](https://sites.google.com/site/thibautduprey/research/crisesdating)

# Real GDP growth per quantiles of FSI



## Section 2

### Markov-switching models for early-warning

# Standard early-warning model : Logit

**Input** : Low or high financial stress state  $S_t = \{0, 1\}$

$$P(S_{c,t} = 1 | \mathbf{X}_{c,t-1}) = \frac{\exp(\theta_{l,0} + \theta_{l,1} \mathbf{X}_{c,t-1})}{1 + \exp(\theta_{l,0} + \theta_{l,1} \mathbf{X}_{c,t-1})}$$

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**Problem 1** : We need an exogenous sequence of events to predict

→ Subjectivity bias

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**Problem 2** : We want to conduct country-specific analyses

→ Crises events are rare

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**Problem 3** : We want to distinguish probability to enter/exit a crisis

→ Post-crisis bias, unconditional probabilities

# Time-Varying Transition Probability Markov Switching (TVTP-MS)

**Input** : Financial Stress Index (FSI)

$$FSI_t = \begin{cases} \mu^0 + \beta^0 FSI_{t-1} + \gamma^0 \mathbf{X}_{t-1} + \sigma^0 \epsilon_t & \text{in state } S_t = 0 \\ \mu^1 + \beta^1 FSI_{t-1} + \gamma^1 \mathbf{X}_{t-1} + \sigma^1 \epsilon_t & \text{in state } S_t = 1 \end{cases}$$

where :  $\epsilon_t \rightarrow \mathcal{N}(0, 1)$ . 2-states Markov chain :

$$P(S_t | S_{t-1}, \mathbf{X}_{t-1}) = \left[ \begin{array}{c} 1 - p_t \\ q_t = \frac{\exp(\theta_{q,0} + \theta_{q,1} \mathbf{X}_{t-1})}{1 + \exp(\theta_{q,0} + \theta_{q,1} \mathbf{X}_{t-1})} \end{array} \quad p_t = \frac{\exp(\theta_{p,0} + \theta_{p,1} \mathbf{X}_{t-1})}{1 + \exp(\theta_{p,0} + \theta_{p,1} \mathbf{X}_{t-1})} \right]$$



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**Solves 1 and 2** : no subjectivity bias + country studies

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**Solves 3** : no post-crisis bias with conditional probabilities

# Advantages and disadvantages of each model type

	Logit	MS
Simplicity	Yes	No
Easy to estimate	Yes	No
Endogenous definition of stress events	No	Yes
Captures changes in levels of stress	No	Yes
Captures changes in volatility	No	Yes
Allows for country-specific studies	No	Yes
Distinguishes prob. versus level	No	Yes
Distinguish prob. to enter/exit stress	No	Yes
Robust to post-crisis bias	No	Yes

# Compare the predictive ability of the MS with Logit

## Difficulties :

- Models are not nested
- Either predict a binary indicator or a continuous measure

## Solutions :

- Cross-country estimation
  - ▶ Assume identical financial cycle process for all countries
- Mapping binary and continuous measures of financial stress

$$S_t = \begin{cases} 1 & \text{if } ma(FSI_t) > p90 \\ 0 & \text{if } ma(FSI_t) \leq p90 \end{cases} \quad (1)$$

# Compare the predictive ability of the MS with Logit

## What we compare :

- The predicted probabilities of high financial stress  $\hat{P}_{Logit}(S_t = 1 | \mathbf{X}_{t-1})$  and  $\hat{P}_{MS}(S_t = 1 | \mathbf{X}_{t-1})$
- With the actual episodes of high financial stress  $S_t = \{0, 1\}$

## Using mainly the AUROC methodology :

- Does not need to define the thresholds above which a probability of high financial stress sends a signal
- Does not need to define preference of the regulator over missing crisis or issuing noisy signals

## Section 3

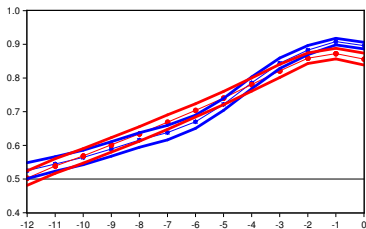
Results on the performance of MS versus  
Logit

# AUROC results

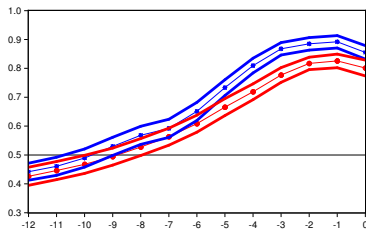
**Set of predictors X** : credit / housing / macro / market / banking

AUROC of the fitted probabilities of high financial stress

$\hat{P}_{Logit}(S_t = 1 | \mathbf{X}_{t-1})$  and  $\hat{P}_{MS}(S_t = 1 | \mathbf{X}_{t-1})$ , up to 12 quarters before a stress event



**in-sample**



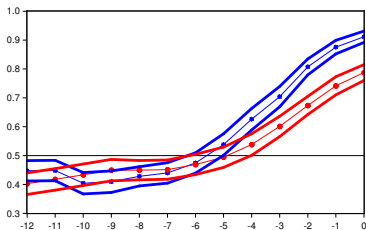
**out-of-sample (after 2006Q4)**

# AUROC results, robustness

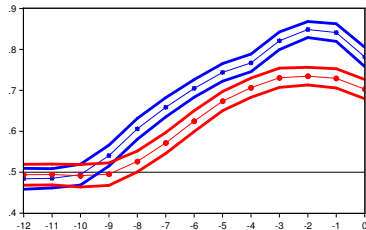
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**out-of-sample  
no moving average**



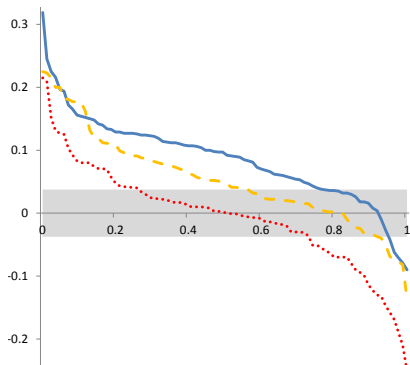
**out-of-sample (after 2006Q4)  
80th percentile definition**



# $\Delta AUROC$ results

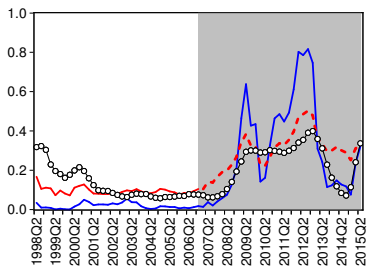
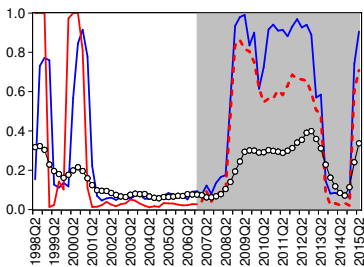
Distribution over 120 different specifications  $\Omega$

$$\Delta AUROC | \Omega = AUROC_{MS} | \Omega - AUROC_{Logit} | \Omega$$



one period ahead, one year ahead, two years ahead

## Example for Greece : MS (left) and Logit (right)



- Dotted black line : moving average of the financial stress index
- Plain blue line : in-sample fitted probability of high financial stress
- Plain red line : probability of high financial stress estimated until 2006Q4
- Dashed red line : out-of-sample probability of high financial stress after 2006Q4 (shaded area)

# Example : focus only on housing and households

Model Dependant variable	Logit	Markov switching (FSI as dependent variable)			
	$\mathbb{1}_{FSI > p90}$	FSI		FSI	
		Contribution to the level of stress		Contribution to the probability of stress	
		low	high	to enter	to exit
Constant	-3.428***	0.043***	0.155***	-3.047***	1.592
Lagged FSI		0.588***	0.589***		
<b>Credit variables :</b>					
Credit to household growth	-0.051	-0.000	0.008**	-0.155***	0.211
Credit to household gap	0.008	0.000	-0.003	0.037	0.142
DSR households	0.021	0.001	0.004*	-0.018	-0.021
<b>Housing variables :</b>					
Housing price yearly growth	-0.211***	-0.001	-0.001	-0.162***	0.429***
Housing price gap	0.043***	0.000	-0.003***	0.089***	-0.270***
Housing price to rent	0.008	0.000	0.000	0.011	0.010
<hr/>					
Log( $\sigma$ )				-2.924***	
Sum squared resid	78.18			6.56	
Mean dependent var	0.09			0.14	
S.D. dependent var	0.29			0.11	
Log likelihood	-0.243			1543	
AIC	0.50			-2.59	
Observations	1060			1060	
Stress events	106				

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## Section 4

Predictors of financial stress with the MS  
model : horse-race

# Horse race : cross-country results

- Test of 36 predictors (credit, housing, macro, market, banking) with different specifications
- With Markov-switching, fewer indicators are significant
- But a lot of heterogeneity across countries

	Predicts <b>higher</b> financial stress	Predicts <b>lower</b> financial stress
<b>Quarterly</b> multivariate 1700 obs.	3-months money market rate debt service ratio housing price to rent yearly equity growth	yearly equity growth GDP growth
<b>Monthly</b> multivariate 2400 obs.	leverage ratio of banks yearly growth of bank credit credit growth for housing yearly equity growth	(yearly equity growth) (yearly credit growth) (economic sentiment)

# Conclusion

## Why Markov switching ?

- Both event classification and prediction at the same time
- Captures the intensity of financial stress
- Distinguish the probability to enter/exit financial stress
- Distinguish the contribution to the level/to the probability
- Allow for country analyses using the time dimension only

## Good enough ?

- In-sample prediction better (a few quarters prior to event)
- Out-of-sample more robust and better

## Which predictors ?

- Bank credit (to households, for housing) related
- Market variables are also good predictors (unsurprisingly)

THANKS, QUESTIONS ?