# A Markov Switching Re-evaluation of Event-Study Methodology

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## Outline

Event-study methodology and its drawbacks

A possible solution based on Markov Switching models

An application to Credit Default Swap market

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  - 1) identification of event dates for a sample of securities and creation of equally sized event windows around each event date



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  - 3) computation of the Abnormal Returns (AR) on each security and for each event window, as  $y_t = \frac{R_t \overline{R}}{S_p}$
  - 4) use of parametric or non parametric test statistics to **test hypotheses** on the mean or variance of ARs

#### **Event-study methodology pitfalls**

T-test or other non parametric tests are used to test the null hypothesis of no abnormal returns at the time of the event

Misleading results may be obtained because of the kurtosis and volatility clustering characterizing financial time series

We propose to model abnormal returns in the event window through a Markov Switching model with two regimes:

regime 1 : normal market conditions

regime 2 : abnormal market conditions

## **Markov Switching models**

- Let  $\mathbf{y} = (y_t)_{t=t_0}^T$  be the observed data
- A MSM assumes that the distribution of an observed data point  $y_t$  depends on an unobserved (hidden) "state" or "regime"  $s_t \in \{1, ..., k\}$
- The elements of  $\mathbf{s} = (s_t)_{t=t_0}^T$  follow a Markov chain with transition matrix  $\mathbf{\Lambda} = (\lambda_{ij})$ , i.e.  $p(s_t = j | s_{t-1} = i) = \lambda_{ij}$ , and stationary distribution  $\mathbf{\pi} = (\pi_i)_{i=1}^k$



The full conditional distribution of  $y_t$  is  $P_{s_t}(y_t | \mathbf{\theta})$ 

## The model proposed

- When  $s_t = i$ , we assume that  $y_t$  is drawn from a  $N(\mu_i, \sigma_i^2)$ 
  - $\mu_i$  is the mean of the *i*-th regime
  - $\sigma_i^2$  is the variance of the *i*-th regime
- Thus the marginal distribution of  $y_t$  is a mixture of Normal distributions:

$$y_t \sim \sum_{i=1}^k \pi_i N(\mu_i, \sigma_i^2)$$



 $\pi_i$ 's are the components of the stationary vector of the transition matrix

#### **Prior distributions on the parameters**



## **Bayesian Inference**

We use MCMC to sample from the posterior joint distribution of the parameters

• update 
$$\Lambda$$
, **s**,  $\mu$ ,  $\sigma^2_{,\kappa}$  and  $\varsigma$  through Gibbs steps

From the sample  $(\Lambda^{(m)}, \mathbf{s}^{(m)}, \boldsymbol{\mu}^{(m)}, \boldsymbol{\sigma}^{(m)}, \boldsymbol{\kappa}^{(m)}, \boldsymbol{\varsigma}^{(m)})$ , for  $m = 1, \dots, M$ , we estimate quantities of interest, i.e.:

posterior probabilities of being in a certain regime at each time t

$$\hat{p}(s_t = i \mid \mathbf{y}) = \frac{1}{M} \sum_{m=1}^{M} I\{s_t^{(m)} = i\}$$

## An application to CDS market

Data set: 45 historical series of CDS and related reviews for downgrading, leading to 57 non-overlapping event windows

Event windows: starting 60 business days before a review for downgrading and ending 20 business days after the announcement, i.e.:

 $t \in [-60 ; 20]$ 

Number of regimes: 2 regimes for the CDS returns generating process in the event window, i.e.:

regime 1 : normal market conditions (low volatilities)

regime 2 : abnormal market conditions (high volatilities)

## Results

Different patterns observed for the probability of being in the high volatility regime, within each event window

Cluster analysis to enucleate typical patterns



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