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
Event-study methodology

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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 \( y = (y_t)_{t=t_0}^T \) be the observed data.

- A MSM assumes that the distribution of an observed data point depends on an unobserved (hidden) “state” or “regime” \( s_t \in \{1, \ldots, k\} \).

- The elements of \( s = (s_t)_{t=t_0}^T \) follow a Markov chain with transition matrix \( \Lambda = (\lambda_{ij}) \), i.e. \( p(s_t = j | s_{t-1} = i) = \lambda_{ij} \), and stationary distribution \( \pi = (\pi_i)_{i=1}^k \).

- The full conditional distribution of \( y_t \) is \( P_{s_t}(y_t | \theta) \).
The model proposed

- When \( s_i = i \), we assume that \( y_t \) is drawn from a \( N(\mu_i, \sigma^2_i) \)

  - \( \mu_i \) is the mean of the \( i \)-th regime
  - \( \sigma^2_i \) is the variance of the \( i \)-th regime

- Thus the marginal distribution of \( y_t \) is a mixture of Normal distributions:

\[
y_t \sim \sum_{i=1}^{k} \pi_i N(\mu_i, \sigma^2_i)
\]

- \( \pi_i \)'s are the components of the stationary vector of the transition matrix
Prior distributions on the parameters

- \( k = 2 \)
- \( \lambda_i \sim D(\delta, ..., \delta) \)
- \( \mu_i | \sigma_i^2 \sim N(\xi, \kappa \sigma_i^2) \)
- \( \kappa \sim IG(q, r) \)
- \( \sigma_i^2 \sim IG(\eta, \varsigma) \)
- \( \varsigma \sim G(f, h) \)
Bayesian Inference

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

  - update $\Lambda, s, \mu, \sigma^2, \kappa$ and $\zeta$ through Gibbs steps

- From the sample $\left(\Lambda^{(m)}, s^{(m)}, \mu^{(m)}, \sigma^{(m)}, \kappa^{(m)}, \zeta^{(m)}\right)$, for $m = 1, \ldots, M$, we estimate quantities of interest, i.e.:

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

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

Estimated mean posterior probabilities of being in the high volatility regime for series belonging to four different clusters.
References


