Chapter 3

Structural breaks for models *with path dependence*

Chapter 3

Path dependence

Chib's specification

Advantages

- Multiple breaks
- Recurrent or no recurrent states (Change-point/Markov-switching)
- MCMC with good mixing properties
- Allow to select an optimal number of regimes
- Forecast of structural breaks

→ **State of the art !**

Drawbacks

- Geometric distribution for the regime duration
- Many computation for selecting the number of regimes
- **Not applicable to models with path dependence**

Chib's specification

Why not applicable ?

- Simplification in the Forward-backward algorithm :

$$f(y_t|Y_{1:t-1}, S_{1:t}) = f(y_t|Y_{1:t-1}, s_t)$$

- If assumption does not hold :

$$\begin{aligned}
\pi(s_t|Y_{1:T}, S_{t+1:T}) &\propto f(s_t|Y_{1:t})f(S_{t+1:T}, Y_{t+1:T}|Y_{1:t}, s_t) \\
&\propto f(s_t|Y_{1:t})f(S_{t+1:T}|Y_{1:t}, s_t)f(Y_{t+1:T}|Y_{1:t}, S_{t:T}) \\
&\neq f(s_t|Y_{1:t})f(s_{t+1}|s_t)
\end{aligned}$$

Chib's algorithm not available for

State-space model with structural breaks in parameters

Example : ARMA, GARCH

Path dependent models

CP- and MS-ARMA models

$$\begin{aligned} y_t &= \mu_{s_t} + \theta_{s_t} y_{t-1} + \phi_{s_t} \epsilon_{t-1} + \epsilon_t \\ s_t | s_{t-1}, P &\sim p_{s_{t-1}, s_t} \end{aligned}$$

CP- and MS-GARCH models

$$\begin{aligned} y_t &= \sigma_t \epsilon_t \\ \sigma_t^2 &= \omega_{s_t} + \alpha_{s_t} y_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2 \\ s_t | s_{t-1}, P &\sim p_{s_{t-1}, s_t} \end{aligned}$$

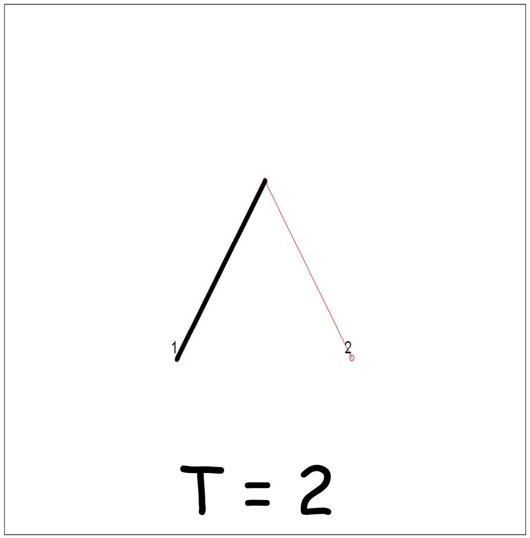
Change-point

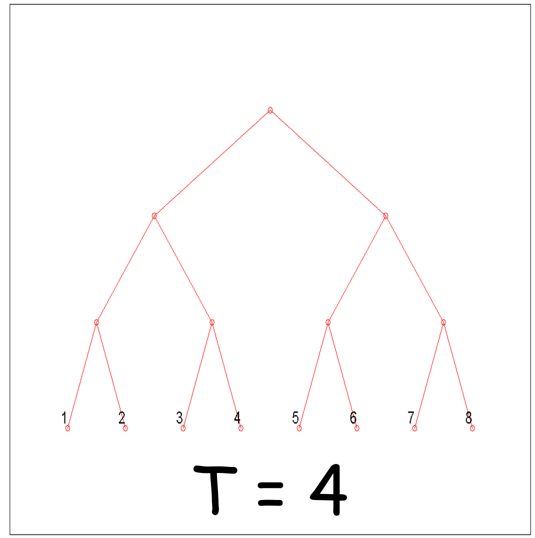
$$P = \begin{pmatrix} p_{1,1} & 1 - p_{1,1} & 0 & \ldots & 0 \\ 0 & p_{2,2} & 1 - p_{2,2} & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & \ldots & 1 \end{pmatrix}$$

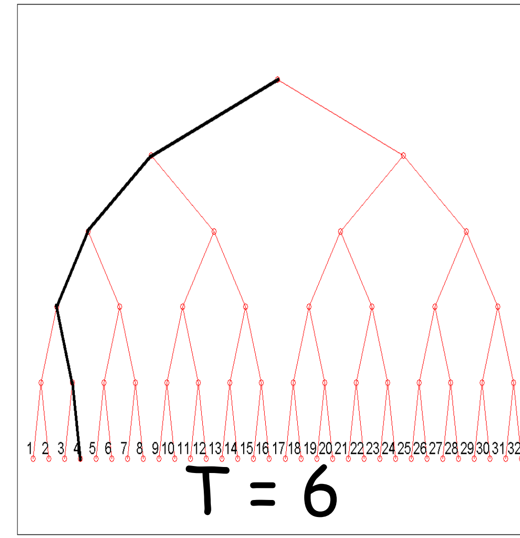
Markov-switching

$$P = \begin{pmatrix} p_{1,1} & p_{1,2} & p_{1,3} & \cdots & p_{1,K+1} \\ p_{2,1} & p_{2,2} & p_{2,3} & \cdots & p_{2,K+1} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ p_{K+1,1} & p_{K+1,2} & p_{K+1,3} & \cdots & p_{K+1,K+1} \end{pmatrix}$$

Path dependence problem







Function of $S_{1:t-1}$

ARMA $y_t = \mu_{s_t} + \theta_{s_t} y_{t-1} + \phi_{s_t} \epsilon_{t-1}(S_{1:t-1}) + \epsilon_t$

GARCH $\sigma_t^2(S_{1:t}) = \omega_{s_t} + \alpha_{s_t} y_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2(S_{1:t-1})$

Likelihood at time t depends on the whole path that has been followed so far

T	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Poss. paths	1	2	4	8	16	32	64	128	256	512	1024	2048	4096	8192	16384

Path dependence problem

Solutions ?

1) Use of approximate models without path dependence

- Gray (1996), Dueker (1997), Klaassen (2002)
- Haas, Mittnik, Poella (2004)

$$
\begin{aligned}
y_t &= \sigma_{t,s_t}\epsilon_t \\
\sigma^2_{t,1} &= \omega_1 + \alpha_1 y^2_{t-1} + \beta_1 \sigma^2_{t-1,1} \\
\sigma^2_{t,2} &= \omega_2 + \alpha_2 y^2_{t-1} + \beta_2 \sigma^2_{t-1,2} \\
&\dots \\
\sigma^2_{t,K+1} &= \omega_{K+1} + \alpha_{K+1} y^2_{t-1} + \beta_{K+1} \sigma^2_{t-1,K+1}
\end{aligned}
$$

Path dependence problem

Solutions ?

2) Stephens (1994) : Inference on multiple breaks

Drawbacks

- Time-consuming if T large
- Many MCMC iterations are required

→ **May not converge in a finite amount of time !**

3) Bauwens, Preminger, Rombouts (2011) :

- Single-move MCMC

Single-move MCMC

CP- and MS-GARCH models

$$\begin{aligned} y_t &= \sigma_t \epsilon_t \\ \sigma_t^2 &= \omega_{s_t} + \alpha_{s_t} y_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2 \\ s_t | s_{t-1}, P &\sim p_{s_{t-1}, s_t} \end{aligned}$$

Change-point

$$P = \begin{pmatrix} p_{1,1} & 1-p_{1,1} & 0 & ... & 0 \\ 0 & p_{2,2} & 1-p_{2,2} & ... & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & 0 & ... & 1 \end{pmatrix}$$

Markov-switching

$$P = \begin{pmatrix} p_{1,1} & p_{1,2} & p_{1,3} & \cdots & p_{1,K+1} \\ p_{2,1} & p_{2,2} & p_{2,3} & \cdots & p_{2,K+1} \\ ... & ... & ... & ... & ... \\ p_{K+1,1} & p_{K+1,2} & p_{K+1,3} & \cdots & p_{K+1,K+1} \end{pmatrix}$$

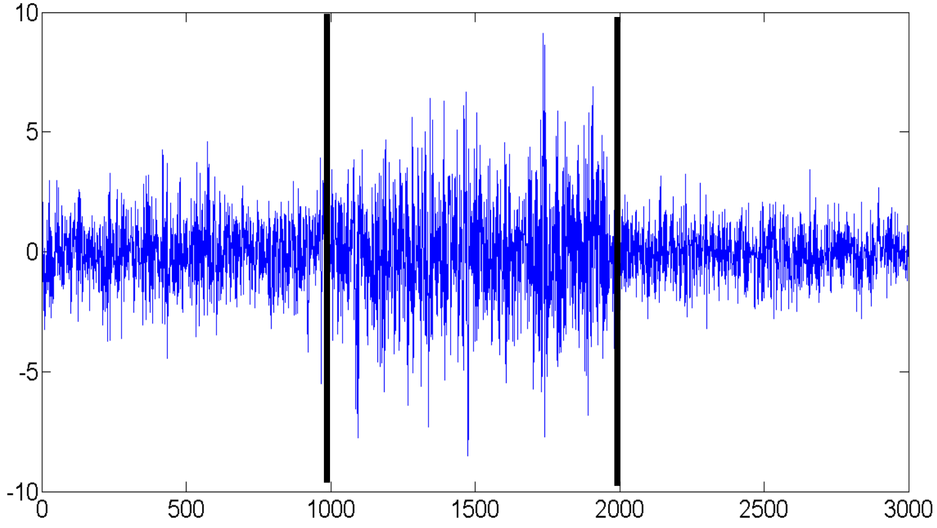
Single-move MCMC

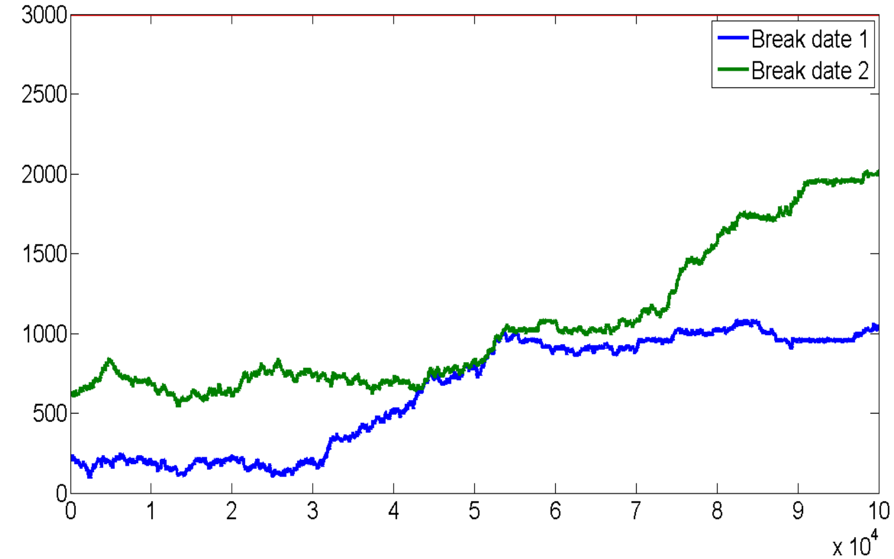
Metropolis-Hastings sampler : $\Theta = \{\omega_1, \alpha_1, \beta_1, \ldots, \omega_{K+1}, \alpha_{K+1}, \beta_{K+1}\}$

$$\begin{aligned} \theta_i | Y_{1:T}, S_{1:T}, P, \Theta_{-i} &\sim \text{Griddy-Gibbs} \\ P | Y_{1:T}, S_{1:T}, \Theta &\sim \text{Dirichlet}(\eta + n_{i,1:K+1}) \\ \underbrace{s_t | Y_{1:T}, P, \Theta, S_{1:t-1}, S_{t+1:T}}_{\text{One state updated at a time !}} &\sim \text{single-move} \end{aligned}$$

$$\begin{aligned} \pi(s_t | Y_{1:T}, P, \Theta, S_{-t}) &\propto f(Y_{1:T} | \Theta, S_{1:T}) f(s_t | s_{t-1}, P) f(s_{t+1} | s_t, P) \\ &\propto \underbrace{f(Y_{1:T} | \Theta, S_{1:T})}_{\text{Likelihood}} \underbrace{p_{s_{t-1}, s_t} p_{s_t, s_{t+1}}}_{\text{Transition matrix}} \end{aligned}$$

Example





Simulated series : $T = 3000$

Initial state : $[200 \quad 600]$

$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-200}) = 0.996$$

Convergence after 100.000 MCMC iterations !

Single-move

Advantages

- Generic method :
    - Works for many CP and MS models

Drawbacks

- No criterion for selecting the number of regimes
- Very Time-consuming if T large (especially for MS)
- Many MCMC iterations are required :

<u>Very difficult to assess convergence</u>

<u>May not converge in a finite amount of time !</u>

Questions ?

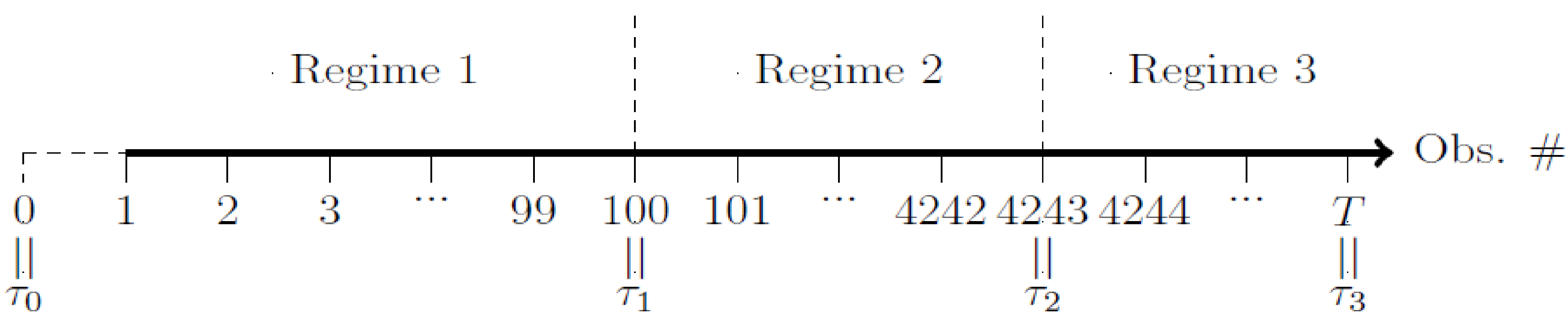
Change-point models

D-DREAM algorithm

CP-GARCH models :

$$
\begin{aligned}
y_t &= \mu_k + \epsilon_t, \\
\epsilon_t &= \sigma_t \eta_t, \; with \; \eta_t \sim i.i.d. \, N(0,1), \\
\sigma_t^2 &= \omega_k + \alpha_k \epsilon_{t-1}^2 + \beta_k \sigma_{t-1}^2,
\end{aligned}
$$

if $t \in]\tau_{k-1}, \tau_k]$, with $k = \{1, 2, ..., K+1\}$ denoting the regime.



Come back to the Stephens' specification !

D-DREAM algorithm

Problem with Stephens' inference :

- Break dates sample one at a time (single-move)

  → MCMC mixing issue

- Very demanding if T is large

Discrete-DREAM MCMC :

- Metropolis algorithm
  - Jointly sample the break dates
  - Very fast (faster than Forward-Backward)

D-DREAM algorithm

- Two sets of parameters to be estimated :

Continuous $\begin{cases} \Theta = (\theta_1, \theta_2, ..., \theta_{K+1})' \\ \theta_k = (\mu_k, \omega_k, \alpha_k, \beta_k) \end{cases}$ **Discrete** $\Gamma = (\tau_1, \tau_2, ..., \tau_K)'$

- MCMC scheme :

$\pi(\Theta | Y_{1:T}, \Gamma)$ **Iterations** $\pi(\Gamma | Y_{1:T}, \Theta)$

Not a standard dist. **Not a standard dist.**

Metropolis **Metropolis**

Proposal : DREAM **Proposal : D-DREAM**

D-DREAM algorithm

DiffeRential Adaptative Evolution Metropolis
(Vrugt et al. 2009)

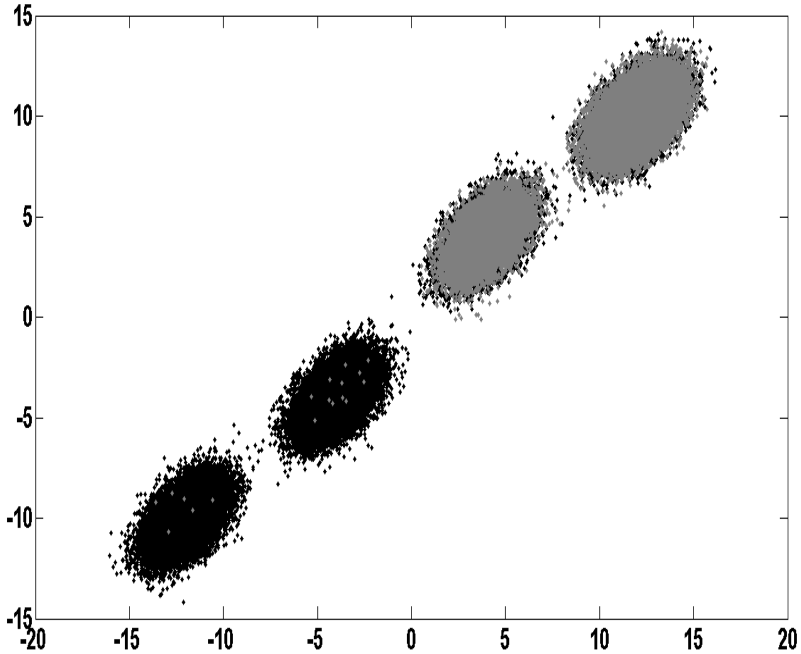
- DREAM automatically determines the **size** of the jump.
- DREAM automatically determines the **direction** of the jump
- DREAM is well suited for **multi-modal** post. dist.
- DREAM is well suited for **high dimensional** sampling
- DREAM is **symmetric** : only a Metropolis ratio

Nevertheless only applicable to continuous parameters

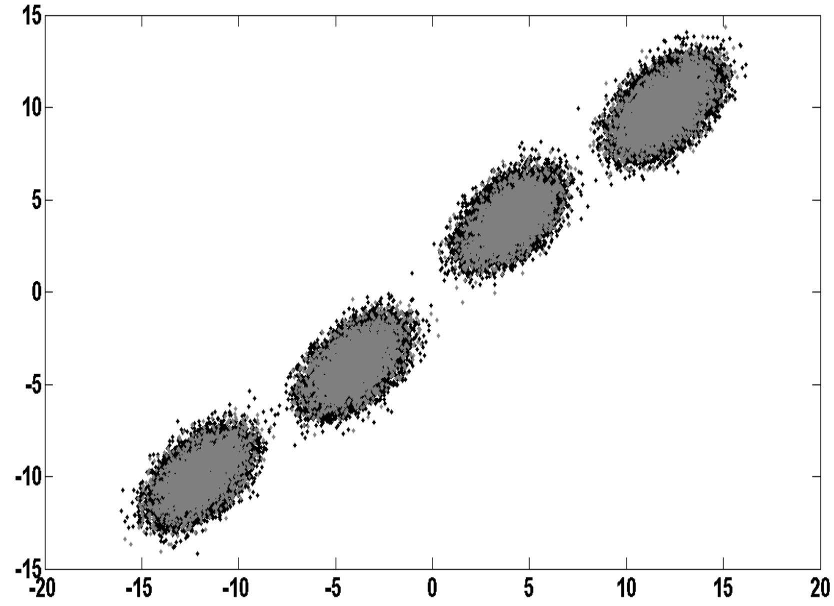
Extension for discrete parameter : Discrete-DREAM

DREAM : Example

Adaptive RW



DREAM



DREAM algorithm

M parallel MCMC chains :

$$\Theta_1^i \qquad \Theta_2^i \qquad \ldots \qquad \Theta_M^i$$

Proposal distribution :

$$\delta \in [1, \lfloor M/2 \rfloor] \qquad \zeta \sim N(0, 10^{-8})$$

$$\tilde{\Theta}_j^i = \Theta_j^i + \gamma(\delta, d)\left(\sum_{g=1}^{\delta} \Theta_{r_1(g)}^i - \sum_{h=1}^{\delta} \Theta_{r_2(h)}^i\right) + \zeta$$

$$\gamma(\delta, d) = 2.38/\sqrt{2\delta d} \qquad r_1(g) \neq r_2(h) \neq j$$

Symmetric proposal dist :

- Accept/reject the draw according to the probability

$$\min\left[\frac{f(Y_{1:T}|\tilde{\Theta}_j^i, \Gamma_j^i) f(\tilde{\Theta}_j^i)}{f(Y_{1:T}|\Theta_j^i, \Gamma_j^i) f(\Theta_j^i)}, 1\right]$$

D-DREAM algorithm

M parallel MCMC chains : $\{\Theta_j^i, \Gamma_j^i\}_{i=1,j=1}^{N,M}$

Continuous

$$\Theta = (\theta_1, \theta_2, ..., \theta_{K+1})'$$
$$\theta_k = (\mu_k, \omega_k, \alpha_k, \beta_k)$$

↓

Proposal distribution :

$$\tilde{\Theta}_j^i = \Theta_j^i + \gamma(\delta, d)(\sum_{g=1}^{\delta} \Theta_{r_1(g)}^i - \sum_{h=1}^{\delta} \Theta_{r_2(h)}^i) + \zeta$$

↓

Accept with probability

$$\min[\frac{f(Y_{1:T}|\tilde{\Theta}_j^i, \Gamma_j^i) f(\tilde{\Theta}_j^i)}{f(Y_{1:T}|\Theta_j^i, \Gamma_j^i) f(\Theta_j^i)}, 1]$$

Discrete

$$\Gamma = (\tau_1, \tau_2, ..., \tau_K)'$$

↓

Proposal distribution :

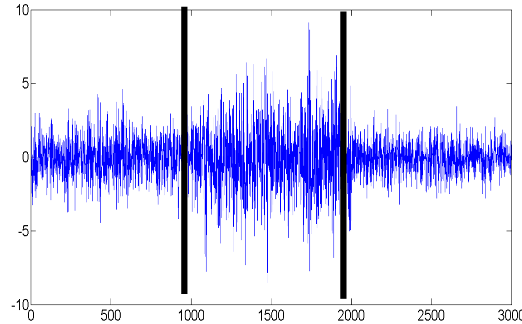
$$\tilde{\Gamma}_j^i = \Gamma_j^i + \mathrm{round}[\gamma(\delta, d)(\sum_{g=1}^{\delta} \Gamma_{r_1(g)}^i - \sum_{h=1}^{\delta} \Gamma_{r_2(h)}^i) + \zeta]$$

↓

Accept with probability

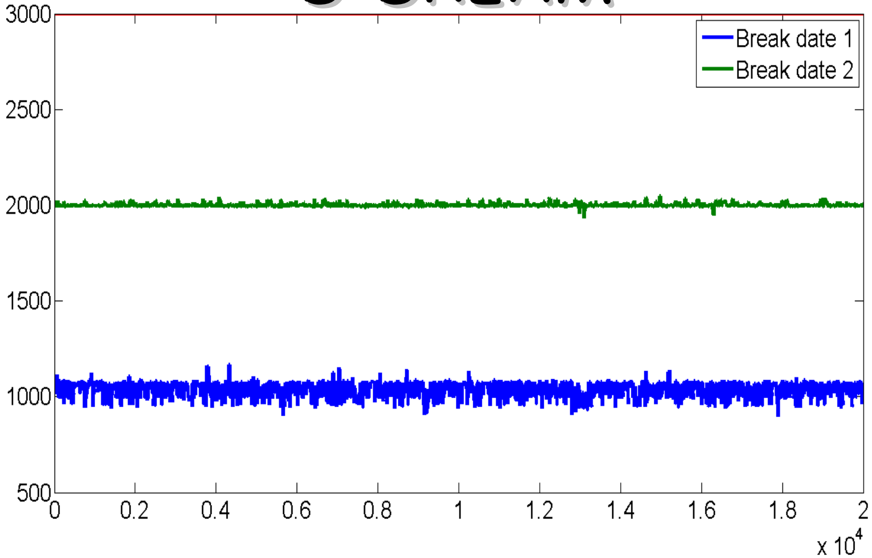
$$\min[\frac{f(Y_{1:T}|\Theta_j^i, \tilde{\Gamma}_j^i) f(\tilde{\Gamma}_j^i)}{f(Y_{1:T}|\Theta_j^i, \Gamma_j^i) f(\Gamma_j^i)}, 1]$$

Example



$$T = 3000$$

D-DREAM



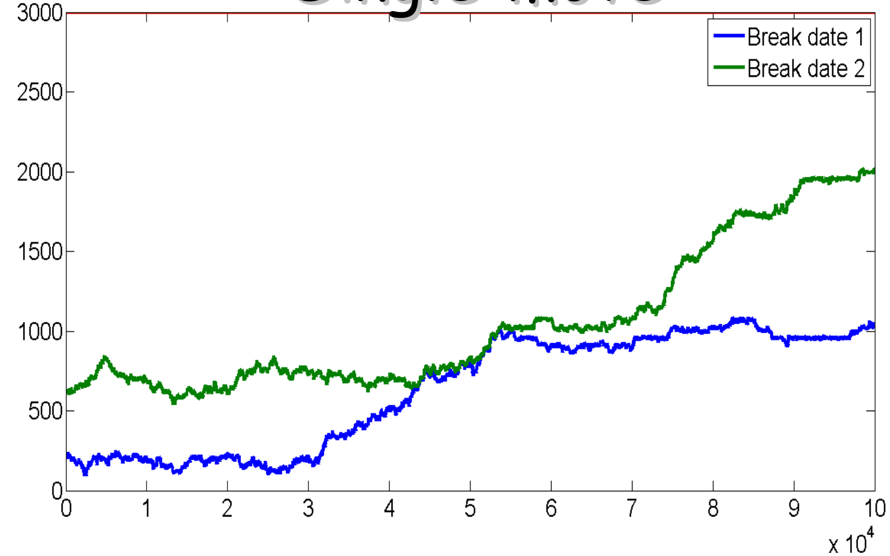
Initial states around $[200 \quad 600]$

$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-200}) = -0.005$$

$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-10}) = 0.54$$

Convergence after 3.000 MCMC iterations !

Single-move



Initial state : $[200 \quad 600]$

$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-200}) = 0.996$$

Convergence after 100.000 MCMC iterations !

D-DREAM (2014)

Advantages

- Generic method for CP models
- Inference on multiple breaks by marginal likelihood
- Very fast compared to existing algorithms

Drawbacks

- Model selection based on many estimations
- Only applicable to CP models and specific class of recurrent states

CP and MS models

Particle MCMC

CP- and MS-GARCH models

$$
\begin{aligned}
y_t &= \sigma_t \epsilon_t \\
\sigma_t^2 &= \omega_{s_t} + \alpha_{s_t} y_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2 \\
\epsilon_t &\sim \text{i.i.d.} N(0,1) \\
s_t | s_{t-1}, P &\sim p_{s_{t-1}, s_t}
\end{aligned}
$$

Change-point

$$
P = \begin{pmatrix}
p_{1,1} & 1 - p_{1,1} & 0 & \ldots & 0 \\
0 & p_{2,2} & 1 - p_{2,2} & \ldots & 0 \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 0 & 0 & \ldots & 1
\end{pmatrix}
$$

Markov-switching

$$
P = \begin{pmatrix}
p_{1,1} & p_{1,2} & p_{1,3} & \cdots & p_{1,K+1} \\
p_{2,1} & p_{2,2} & p_{2,3} & \cdots & p_{2,K+1} \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
p_{K+1,1} & p_{K+1,2} & p_{K+1,3} & \cdots & p_{K+1,K+1}
\end{pmatrix}
$$

Particle MCMC

Sets of parameters :

Continuous $\begin{cases} \Theta = (\theta_1, \theta_2, ..., \theta_{K+1})' \\ \theta_k = (\omega_k, \alpha_k, \beta_k) \\ P \end{cases}$

State var. $S_{1:T} = \{s_1, ..., s_T\}$

MCMC scheme :

1) $\Theta | Y_{1:T}, P, S_{1:T} \sim \text{Metropolis-Hastings}$

2) $P | Y_{1:T}, \Theta, S_{1:T} \sim \prod_{i=1}^{K+1} \text{Dir}(\eta_1 + n_{i,1}, ..., \eta_1 + n_{i,K+1})$

3) $S_{1:T} | Y_{1:T}, P, \Theta \sim \text{Particle-Gibbs}$

Sampling a full state vector is unfeasible
due to the path dependence issue

Particle MCMC

3) $S_{1:T}|Y_{1:T}, P, \Theta \sim \text{Particle-Gibbs}$

Idea : Approximate the distribution with a SMC algorithm

$\longrightarrow$ Does not keep invariant the posterior distribution

Andrieu, Doucet and Holenstein (2010)

- Show how to incorporate the SMC into an MCMC
- Allow for Metropolis and Gibbs algorithms
- Introduce the concept of conditional SMC

$\longrightarrow$ With a conditional SMC, the MCMC exhibits the posterior distribution as invariant one.

Particle MCMC

3) $S_{1:T}|Y_{1:T}, P, \Theta \sim \text{Particle-Gibbs}$

$$f(S_{1:t}|Y_{1:t}) \propto f(y_t|Y_{1:t-1}, S_{1:t})f(s_t|S_{1:t-1})\overbrace{f(S_{1:t-1}|Y_{1:t-1})}^{\text{Previous value}}$$

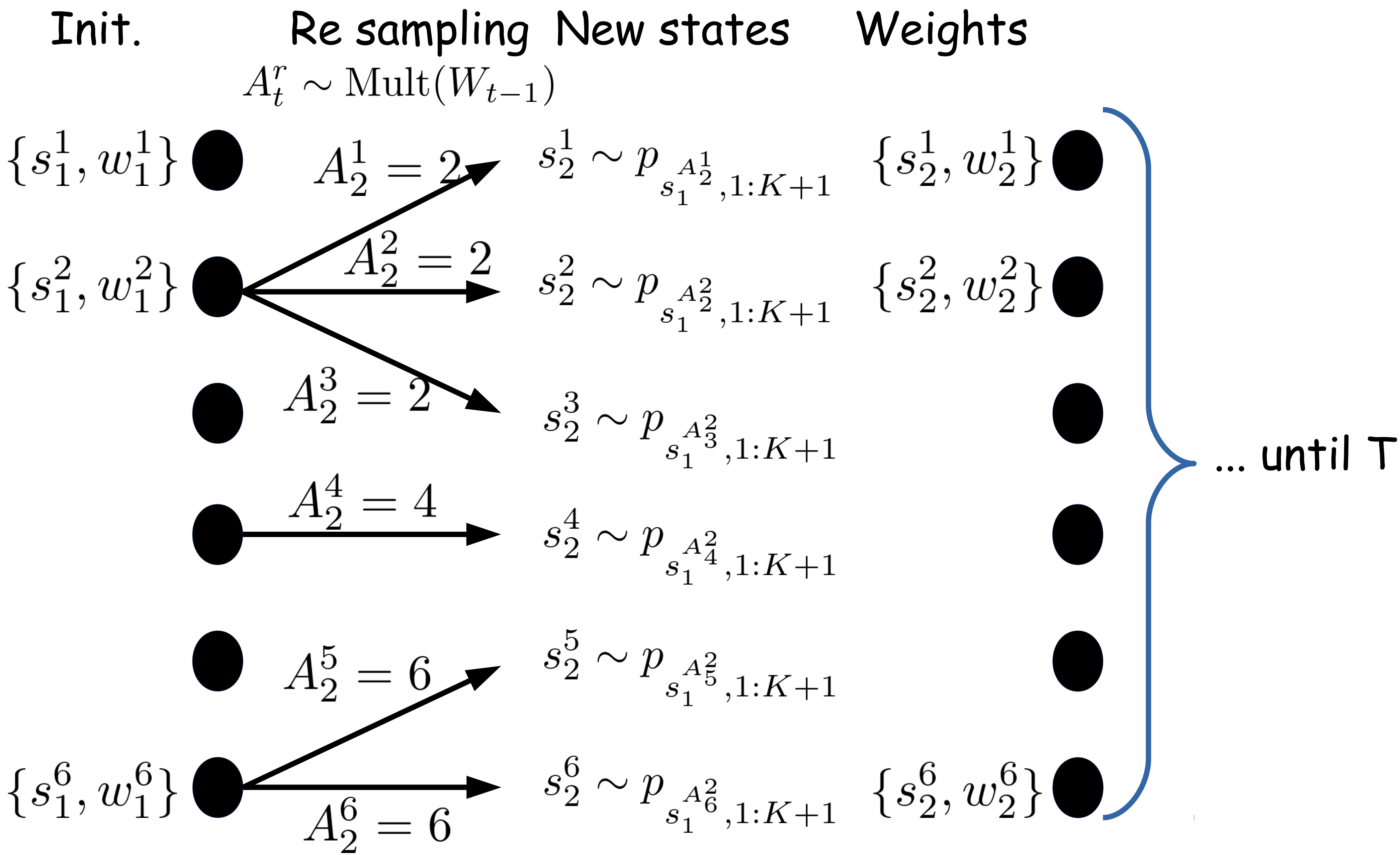
SMC :

1) Initialisation of the particles and weights: $\begin{cases} \{s_1^r\}_{r=1}^R \\ w_r \propto f(y_1|s_1^r) \end{cases}$

Iterations
$\forall t \in [2, T]$

- Re-sample the particles
  $\forall r \in [1, R]; A_t^r \sim \text{Mult}(W_{t-1})$
- Generate new states
  $\forall r \in [1, R]; s_t^r \sim \text{Mult}(p_{s_{t-1}^{A_t^r}, s_t})$
- Compute new weights
  $\forall r \in [1, R]; w_t^r \propto f(y_t|S_{1:t-1}^{A_{1:t-1}^r}, s_t^r)$ and $W_t^r = w_t^r / (\sum_{i=1}^R w_t^i)$

SMC


Init.
Re sampling
New states
Weights
$A_t^r \sim \mathrm{Mult}(W_{t-1})$
$\{s_1^1, w_1^1\}$
$\{s_1^2, w_1^2\}$
$\{s_1^6, w_1^6\}$
$A_2^1 = 2$
$A_2^2 = 2$
$A_2^3 = 2$
$A_2^4 = 4$
$A_2^5 = 6$
$A_2^6 = 6$
$s_2^1 \sim p_{s_1^{A_2^1},1:K+1}$
$s_2^2 \sim p_{s_1^{A_2^2},1:K+1}$
$s_2^3 \sim p_{s_1^{A_3^2},1:K+1}$
$s_2^4 \sim p_{s_1^{A_4^2},1:K+1}$
$s_2^5 \sim p_{s_1^{A_5^2},1:K+1}$
$s_2^6 \sim p_{s_1^{A_6^2},1:K+1}$
$\{s_2^1, w_2^1\}$
$\{s_2^2, w_2^2\}$
$\{s_2^6, w_2^6\}$
... until T

Particle Gibbs

- **Conditional SMC :** SMC where the previous MCMC state vector is ensured to survive during the entire SMC sequence.

3) $S_{1:T}|Y_{1:T}, P, \Theta \sim \text{Particle-Gibbs}$

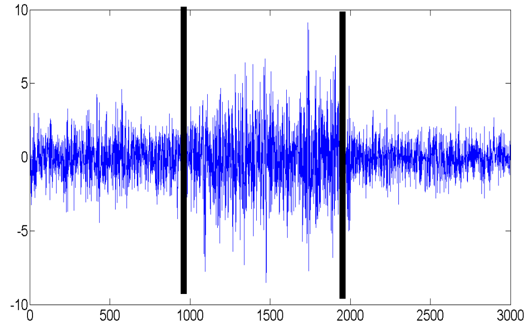
- Launch a conditional SMC
- Sample a state vector as follows :

1) $r \sim \text{Mult}(W_T^1, ..., W_T^R)$ and set $s_T = s_T^r$

2) From T-1 until 1, retrieve the path of the state : $s_t = s_t^{A_{t+1}^r}$

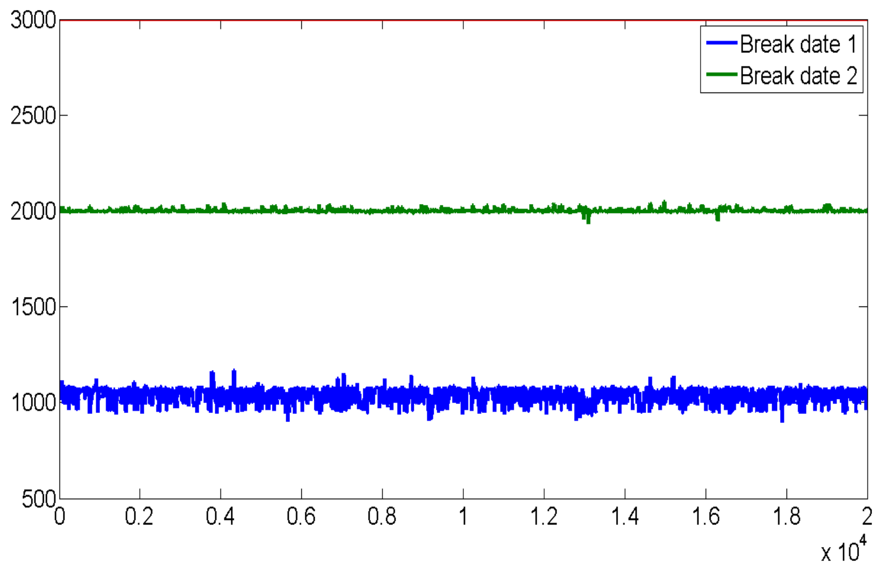
- Improvements :
  1) Incorporation of the APF in the conditional SMC
  2) Backward sampling as Godsill, Doucet and West (2004)

Example



$T = 3000$

D-DREAM

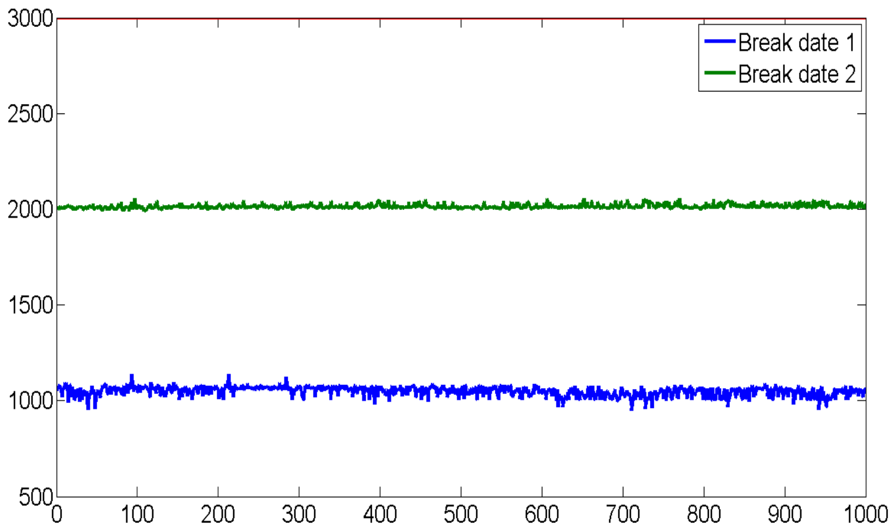


Initial states around $[200 \quad 600]$

$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-200}) = -0.005$$

$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-10}) = 0.54$$

PMCMC



Initial state : $[200 \quad 600]$

$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-200}) = 0.05$$

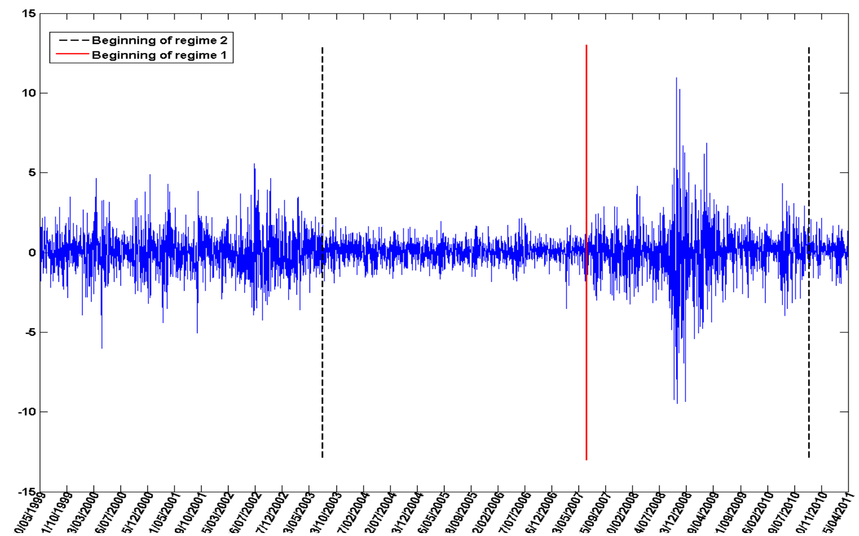
$$\mathrm{Corr}(\tau_1^i, \tau_1^{i-10}) = 0.21$$

PMCMC

S&P 500 daily percentage returns from May 20,1999 to April 25, 2011

Table: Marginal log-likelihood values for S&P 500 data

Regimes	1	2	3	4
		Change-Point		
BS	-4505.33	-4505.83	-4503.05	-4519.23
Chib	-4504.95	-4505.93	-4502.97	-4516.16
		Markov-switching		
BS	-4505.31	-4497.99	-4502.74	
Chib	-4505.08	-4496.04	-4497.73	



Regime	GARCH σ^2	GARCH α	GARCH β	CP-GARCH σ^2	CP-GARCH α	CP-GARCH β	MS-GARCH σ^2	MS-GARCH α	MS-GARCH β
1	1.55	0.075	0.915	1.95	0.0849	0.868	2.32	0.089	0.891
2				0.45	0.023	0.931	0.46	0.031	0.901
3				2.75	0.098	0.890			

PMCMC

Various financial time series

Series	Spline-GARCH		GARCH	CP-GARCH		MS-GARCH		
	knots	log-BF	MLL	K+1	log-BF	K+1	log-BF	nswitch
S&P 500	3	5.21	-4505.33	3	2.28	2	7.34	3
DJIA	3	2.99	-4333.43	1	0	2	4.7	3
NASDAQ	3	3.20	-5429.84	1	0	2	1.94	7
NYSE	3	2.40	-4380.62	1	0	2	3.91	13
BAC	4	16.62	-6127.39	3	50.12	3	79.49	11
BA	4	9.10	-6174.57	2	8.9	2	11.48	6
JPM	3	8.82	-6400.27	3	5.17	3	7.22	9
MRK	5	48.78	-6209.73	5	215.39	3	335.23	56
PG	4	16.34	-4842.02	3	24.23	2	33.6	9
Metals	2	6.66	-5267.44	2	11.33	2	14.68	5
Yen/Dollar	1	-3.34	-2982.33	1	0	2	3.05	7

PMCMC (2013)

Advantages

- Generic method for CP and MS models
- Inference on multiple breaks by marginal likelihood
- Very good mixing properties

Drawbacks

- Model selection based on many estimations
- Very computationally demanding
- Difficult to calibrate the number of particles
- Difficult to implement

IHMM-GARCH

CP- and MS-GARCH models

$$
\begin{aligned}
y_t &= \sigma_t \epsilon_t \\
\sigma_t^2 &= \omega_{s_t} + \alpha_{s_t} y_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2 \\
\epsilon_t &\sim \text{i.i.d.} N(0,1) \\
s_t | s_{t-1}, P &\sim p_{s_{t-1}, s_t}
\end{aligned}
$$

Change-point

$$
P = \begin{pmatrix}
p_{1,1} & 1-p_{1,1} & 0 & \dots & 0 \\
0 & p_{2,2} & 1-p_{2,2} & \dots & 0 \\
\dots & \dots & \dots & \dots & \dots \\
0 & 0 & 0 & \dots & 1
\end{pmatrix}
$$

Markov-switching

$$
P = \begin{pmatrix}
p_{1,1} & p_{1,2} & p_{1,3} & \dots & p_{1,K+1} \\
p_{2,1} & p_{2,2} & p_{2,3} & \dots & p_{2,K+1} \\
\dots & \dots & \dots & \dots & \dots \\
p_{K+1,1} & p_{K+1,2} & p_{K+1,3} & \dots & p_{K+1,K+1}
\end{pmatrix}
$$

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Sets of parameters :

Continuous $\begin{cases} \Theta = (\theta_1, \theta_2, ..., \theta_{K+1})' \\ \theta_k = (\omega_k, \alpha_k, \beta_k) \\ P \end{cases}$

State var. $S_{1:T} = \{s_1, ..., s_T\}$

MCMC scheme :

1) $\Theta | Y_{1:T}, P, S_{1:T} \sim \text{Metropolis-Hastings}$

2) $P | Y_{1:T}, \Theta, S_{1:T} \sim \prod_{i=1}^{K+1} \text{Dir}(\eta_1 + n_{i,1}, ..., \eta_1 + n_{i,K+1})$

3) $S_{1:T} | Y_{1:T}, P, \Theta \sim \text{M-H based on approximate models}$

IHMM-GARCH

3) $S_{1:T}|Y_{1:T}, P, \Theta \sim \text{M-H based on approximate models}$

Sampling a full state vector is infeasible
due to the path dependence issue

⬇

Sampling a full state vector from an approximate model
Klaassen or Haas, Mittnik and Paolela

⬇

Accept/reject according to the Metropolis-hastings ratio

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Moreover, **Hierarchical dirichlet processes** are used

- To infer the number of regime in one estimation
- To include both CP and MS specification in one model

$$P = \begin{pmatrix} p_{1,1} & p_{1,2} & p_{1,3} & \cdots & \cdots \\ p_{2,1} & p_{2,2} & p_{2,3} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ p_{K+1,1} & p_{K+1,2} & p_{K+1,3} & \cdots & \cdots \end{pmatrix}$$

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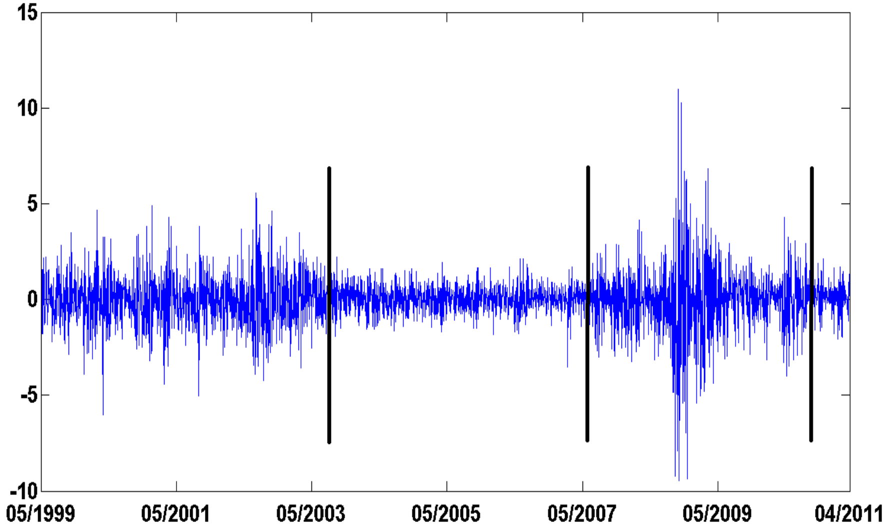
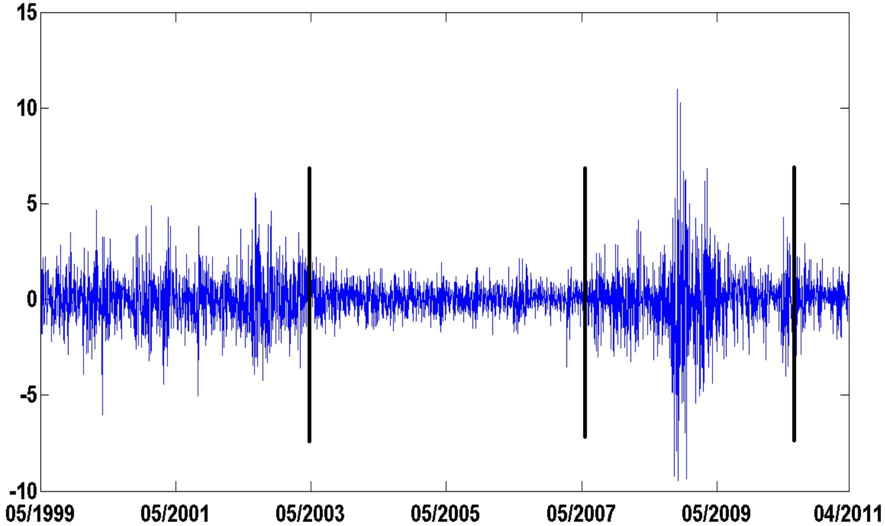
S&P 500 daily percentage returns from May 20,1999 to April 25, 2011

PMCMC



IHMM-GARCH



	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6	Regime 7
Prob.	0	**0.6046**	0.2075	0.1455	0.0224	0.0196	0.0004

Table: Posterior probabilities of the number of regimes for the *S&P*500 daily index

IHMM-GARCH (2014)

Advantages

- Generic method for CP and MS models
- Self-determination of the number of breaks
- Self-determination of the specification (CP and/or MS)
- Predictions of breaks
- Very good mixing properties
- Fast MCMC estimation

Drawbacks

- Difficult to implement

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