Uses of particle filtering in finance

L. C. G. Rogers

Statistical Laboratory, University of Cambridge

Overview

- The potential approach (Tino Kluge)
- The equity premium puzzle (Arnaud Jobert, Alessandro Platania)
- Dynamic Engine for Bayesian Inference (DEBI) (Elie Bassouls, Simon Godsill)

The potential approach

The potential approach.

The potential approach.

- Time-t price Y_t of a contingent claim Y_T to be paid at time $T > t$ is

$$Y_t = E[\,\zeta_T Y_T \,|\, \mathcal{F}_t\,]/\zeta_t$$

where ζ is the so-called *state-price density process*.

The potential approach.

- Time-t price Y_t of a contingent claim Y_T to be paid at time $T > t$ is

$$Y_t = E[\,\zeta_T Y_T \,|\, \mathcal{F}_t\,]/\zeta_t$$

where ζ is the so-called *state-price density process*.

- SPD commonly interpreted as

$$\zeta_t = \exp\left\{-\int_0^t r_s \; ds\right\} Z_t \equiv e^{-\int_0^t r_s \; ds} \; \frac{dP^*}{dP}\bigg|_{\mathcal{F}_t}$$

where r is the riskless interest rate, P^* is pricing measure.

The potential approach.

- Time-t price Y_t of a contingent claim Y_T to be paid at time $T > t$ is

$$Y_t = E[\,\zeta_T Y_T \,|\, \mathcal{F}_t\,]/\zeta_t$$

where ζ is the so-called *state-price density process*.

- SPD commonly interpreted as

$$\zeta_t = \exp\Big\{ -\int_0^t r_s \; ds \Big\} \; Z_t \equiv e^{-\int_0^t r_s \; ds} \; \frac{dP^*}{dP}\Big|_{\mathcal{F}_t}$$

where r is the riskless interest rate, P^* is pricing measure.

- SPD is a positive supermartingale (if $r \geq 0$).

The potential approach.

- Time-t price Y_t of a contingent claim Y_T to be paid at time $T > t$ is

$$Y_t = E[\,\zeta_T Y_T \,|\, \mathcal{F}_t\,]/\zeta_t$$

where ζ is the so-called *state-price density process*.

- SPD commonly interpreted as

$$\zeta_t = \exp\left\{-\int_0^t r_s\,ds\right\} Z_t \equiv e^{-\int_0^t r_s\,ds}\,\left.\frac{dP^*}{dP}\right|_{\mathcal{F}_t}$$

where r is the riskless interest rate, P^* is pricing measure.

- SPD is a positive supermartingale (if $r \geq 0$).
- Potential approach models SPD directly.

The potential approach.

- Time-t price Y_t of a contingent claim Y_T to be paid at time $T > t$ is

$$Y_t = E[\,\zeta_T Y_T \,|\, \mathcal{F}_t\,]/\zeta_t$$

where ζ is the so-called *state-price density process*.

- SPD commonly interpreted as

$$\zeta_t = \exp\left\{-\int_0^t r_s\, ds\right\} Z_t \equiv e^{-\int_0^t r_s\, ds}\; \frac{dP^*}{dP}\bigg|_{\mathcal{F}_t}$$

where r is the riskless interest rate, P^* is pricing measure.

- SPD is a positive supermartingale (if $r \geq 0$).
- Potential approach models SPD directly.
- Markov process X with generator $\mathcal{G}$:

$$\zeta_t = f(X_t)\exp(-\int_0^t \alpha(X_s)\, ds)$$

for some positive functions $\alpha, f : I \to (0, \infty)$.

The potential approach.

- Time-t price Y_t of a contingent claim Y_T to be paid at time $T > t$ is

$$Y_t = E[\,\zeta_T Y_T \,|\, \mathcal{F}_t\,]/\zeta_t$$

where ζ is the so-called *state-price density process*.

- SPD commonly interpreted as

$$\zeta_t = \exp\left\{-\int_0^t r_s\, ds\right\} Z_t \equiv e^{-\int_0^t r_s\, ds}\, \frac{dP^*}{dP}\bigg|_{\mathcal{F}_t}$$

where r is the riskless interest rate, P^* is pricing measure.

- SPD is a positive supermartingale (if $r \geq 0$).
- Potential approach models SPD directly.
- Markov process X with generator $\mathcal{G}$:

$$\zeta_t = f(X_t)\exp(-\int_0^t \alpha(X_s)\, ds)$$

for some positive functions $\alpha, f : I \to (0, \infty)$.

- Supermartingale iff

$$(\alpha - \mathcal{G})f \equiv g \geq 0.$$

Markov chains.

Markov chains.

- Assume statespace I is finite; generator is an $I \times I$ matrix, Q

Markov chains.

- Assume statespace I is finite; generator is an $I \times I$ matrix, Q
- Pricing model specified by

$$\Theta \equiv (Q, \alpha, g).$$

for some non-negative α, g.

Markov chains.

- Assume statespace I is finite; generator is an $I \times I$ matrix, Q
- Pricing model specified by

$$\Theta \equiv (Q, \alpha, g).$$

for some non-negative α, g.

- Row-sums of Q are zero, off-diagonal entries non-negative, scaling of g makes no difference, so $g(1) = 1$ and

$$\theta \equiv ((\log q_{ij})_{i \neq j}, \log \alpha, (\log g_i)_{i>1}).$$

Markov chains.

- Assume statespace I is finite; generator is an $I \times I$ matrix, Q
- Pricing model specified by

$$\Theta \equiv (Q, \alpha, g).$$

for some non-negative α, g.

- Row-sums of Q are zero, off-diagonal entries non-negative, scaling of g makes no difference, so $g(1) = 1$ and

$$\theta \equiv ((\log q_{ij})_{i \neq j}, \log \alpha, (\log g_i)_{i>1}).$$

- Derivative pricing is a finite sum!

Markov chains.

- Assume statespace I is finite; generator is an $I \times I$ matrix, Q
- Pricing model specified by

$$\Theta \equiv (Q, \alpha, g).$$

for some non-negative α, g.

- Row-sums of Q are zero, off-diagonal entries non-negative, scaling of g makes no difference, so $g(1) = 1$ and

$$\theta \equiv ((\log q_{ij})_{i \neq j}, \log \alpha, (\log g_i)_{i>1}).$$

- Derivative pricing is a finite sum!
- A new country is a new (α, g), not a new model!

Markov chains.

- Assume statespace I is finite; generator is an $I \times I$ matrix, Q
- Pricing model specified by

$$\Theta \equiv (Q, \alpha, g).$$

for some non-negative α, g.

- Row-sums of Q are zero, off-diagonal entries non-negative, scaling of g makes no difference, so $g(1) = 1$ and

$$\theta \equiv ((\log q_{ij})_{i \neq j}, \log \alpha, (\log g_i)_{i>1}).$$

- Derivative pricing is a finite sum!
- A new country is a new (α, g), not a new model!
- Dimension is large: 5 states, 3 currencies $\Rightarrow$ dimension = 47.

Markov chains.

- Assume statespace I is finite; generator is an $I \times I$ matrix, Q
- Pricing model specified by

$$\Theta \equiv (Q, \alpha, g).$$

for some non-negative α, g.

- Row-sums of Q are zero, off-diagonal entries non-negative, scaling of g makes no difference, so $g(1) = 1$ and

$$\theta \equiv ((\log q_{ij})_{i \neq j}, \log \alpha, (\log g_i)_{i>1}).$$

- Derivative pricing is a finite sum!
- A new country is a new (α, g), not a new model!
- Dimension is large: 5 states, 3 currencies $\Rightarrow$ dimension = 47.
- Price is a function of state of the chain - so only a few possible prices for any given instrument??

Particle filtering

Particle filtering

- hidden (discrete-time) Markov process (x_t), transition density $p(x'|x)$

Particle filtering

- hidden (discrete-time) Markov process (x_t), transition density $p(x'|x)$
- Observations (Y_t), likelihood of the observation y given the (hidden) state x is $f(y|x)$

Particle filtering

- hidden (discrete-time) Markov process (x_t), transition density $p(x'|x)$
- Observations (Y_t), likelihood of the observation y given the (hidden) state x is $f(y|x)$
- Posterior likelihood π_t at time t, is approximated by

$$(*) \qquad \pi_t \simeq \sum_{i=1}^{N} w_t^i \delta_{x_t^i}.$$

Particle filtering

- hidden (discrete-time) Markov process (x_t), transition density $p(x'|x)$
- Observations (Y_t), likelihood of the observation y given the (hidden) state x is $f(y|x)$
- Posterior likelihood π_t at time t, is approximated by

$$(*) \qquad \pi_t \simeq \sum_{i=1}^{N} w_t^i \delta_{x_t^i}.$$

- Move x_t^i to x_{t+1}^i according to a density $q(\cdot|x_t^i, y_{t+1})$

Particle filtering

- hidden (discrete-time) Markov process (x_t), transition density $p(x'|x)$
- Observations (Y_t), likelihood of the observation y given the (hidden) state x is $f(y|x)$
- Posterior likelihood π_t at time t, is approximated by

$$(*) \qquad \pi_t \simeq \sum_{i=1}^{N} w_t^i \delta_{x_t^i}.$$

- Move x_t^i to x_{t+1}^i according to a density $q(\cdot|x_t^i, y_{t+1})$
- Reweight as

$$w_{t+1}^i \propto \frac{w_t^i \, p(x_{t+1}^i|x_t^i)}{q(x_{t+1}^i|x_t^i, y_{t+1})} f(y_{t+1}|x_{t+1}^i)$$

Particle filtering

- hidden (discrete-time) Markov process (x_t), transition density $p(x'|x)$
- Observations (Y_t), likelihood of the observation y given the (hidden) state x is $f(y|x)$
- Posterior likelihood π_t at time t, is approximated by

$$(*) \qquad \pi_t \simeq \sum_{i=1}^{N} w_t^i \delta_{x_t^i}.$$

- Move x_t^i to x_{t+1}^i according to a density $q(\cdot|x_t^i, y_{t+1})$
- Reweight as

$$w_{t+1}^i \propto \frac{w_t^i \, p(x_{t+1}^i|x_t^i)}{q(x_{t+1}^i|x_t^i, y_{t+1})} f(y_{t+1}|x_{t+1}^i)$$

- PF interpretation resolves conceptual difficulty about finitely many possible prices: *The model price is the population average of the individual particle prices.*

Observations.

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain.

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain. Have to 'shake' parameters θ at each step, according to transition density $\kappa(\theta, \theta')$.

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain. Have to 'shake' parameters θ at each step, according to transition density $\kappa(\theta, \theta')$. In terms of the theory, this corresponds to approximating the posterior π_t not by (*) but by

$$\pi_t \simeq \sum_{i=1}^{N} w_t^i \, \delta_{\xi_t^i} \otimes \kappa(\theta_t^i, \cdot).$$

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain. Have to `shake' parameters θ at each step, according to transition density $\kappa(\theta, \theta')$.
In terms of the theory, this corresponds to approximating the posterior π_t not by (*) but by

$$\pi_t \simeq \sum_{i=1}^{N} w_t^i \, \delta_{\xi_t^i} \otimes \kappa(\theta_t^i, \cdot).$$

- Operationally, this is a simulated annealing step

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain. Have to 'shake' parameters θ at each step, according to transition density $\kappa(\theta, \theta')$. In terms of the theory, this corresponds to approximating the posterior π_t not by (*) but by

$$\pi_t \simeq \sum_{i=1}^{N} w_t^i \; \delta_{\xi_t^i} \otimes \kappa(\theta_t^i, \cdot).$$

- Operationally, this is a simulated annealing step
- Tried various forms of κ - gaussian, mutivariate-t, or Laplace

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain. Have to 'shake' parameters θ at each step, according to transition density $\kappa(\theta, \theta')$. In terms of the theory, this corresponds to approximating the posterior π_t not by (*) but by

$$\pi_t \simeq \sum_{i=1}^{N} w_t^i \, \delta_{\xi_t^i} \otimes \kappa(\theta_t^i, \cdot).$$

- Operationally, this is a simulated annealing step
- Tried various forms of κ - gaussian, mutivariate-t, or Laplace
- Observation y is a vector of market prices, which the model prices as $\eta(\xi, \theta)$. We suppose that the likelihood of y_t given x is of the form

$$f(y|x) = \varphi_Y(\log y - \log \eta(x))$$

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain. Have to 'shake' parameters θ at each step, according to transition density $\kappa(\theta, \theta')$. In terms of the theory, this corresponds to approximating the posterior π_t not by (*) but by

$$\pi_t \simeq \sum_{i=1}^{N} w_t^i \; \delta_{\xi_t^i} \otimes \kappa(\theta_t^i, \cdot).$$

- Operationally, this is a simulated annealing step
- Tried various forms of κ - gaussian, mutivariate-t, or Laplace
- Observation y is a vector of market prices, which the model prices as $\eta(\xi, \theta)$. We suppose that the likelihood of y_t given x is of the form

$$f(y|x) = \varphi_Y(\log y - \log \eta(x))$$

- Problem is essentially one of estimation, not filtering - is PF really a suitable technology??

Observations.

- The Markovian state is $x = (\xi, \theta)$, where ξ is a finite-state Markov chain. Have to 'shake' parameters θ at each step, according to transition density $\kappa(\theta, \theta')$. In terms of the theory, this corresponds to approximating the posterior π_t not by (*) but by

$$\pi_t \simeq \sum_{i=1}^{N} w_t^i \, \delta_{\xi_t^i} \otimes \kappa(\theta_t^i, \cdot).$$

- Operationally, this is a simulated annealing step
- Tried various forms of κ - gaussian, mutivariate-t, or Laplace
- Observation y is a vector of market prices, which the model prices as $\eta(\xi, \theta)$. We suppose that the likelihood of y_t given x is of the form

$$f(y|x) = \varphi_Y(\log y - \log \eta(x))$$

- Problem is essentially one of estimation, not filtering - is PF really a suitable technology??
- Particle-filtering approach gives us posterior for the price of *any* derivative, and could be used provide confidence intervals for the price.

Main technical issue:

Main technical issue:

- Importance-sampling appears indispensable:

Main technical issue:

- Importance-sampling appears indispensable: *find MLE of θ:*

$$\theta^* = \text{arg max } f(y_t|(1,\theta)).$$

use the MLE θ^* to generate proposed values of θ in a plausible region, and then we reweight them accordingly.

Main technical issue:

- Importance-sampling appears indispensable: *find MLE of θ:*

$$\theta^* = \text{arg max } f(y_t|(1,\theta)).$$

use the MLE θ^* to generate proposed values of θ in a plausible region, and then we reweight them accordingly.

- Restrict possible transitions - nearest-neighbour?

Main technical issue:

- Importance-sampling appears indispensable: *find MLE of θ:*

$$\theta^* = \text{arg max } f(y_t|(1, \theta)).$$

use the MLE θ^* to generate proposed values of θ in a plausible region, and then we reweight them accordingly.

- Restrict possible transitions - nearest-neighbour?

- Keep number of states small - 2 states, 3 countries requires 11 dimensions, 3 states, 3 countries requires 21 dimensions.

Main technical issue:

- Importance-sampling appears indispensable: *find MLE of θ:*

$$\theta^* = \text{arg max } f(y_t|(1, \theta)).$$

use the MLE θ^* to generate proposed values of θ in a plausible region, and then we reweight them accordingly.

- Restrict possible transitions - nearest-neighbour?
- Keep number of states small - 2 states, 3 countries requires 11 dimensions, 3 states, 3 countries requires 21 dimensions.
- Statesplit ....

Statesplit.

Statesplit.

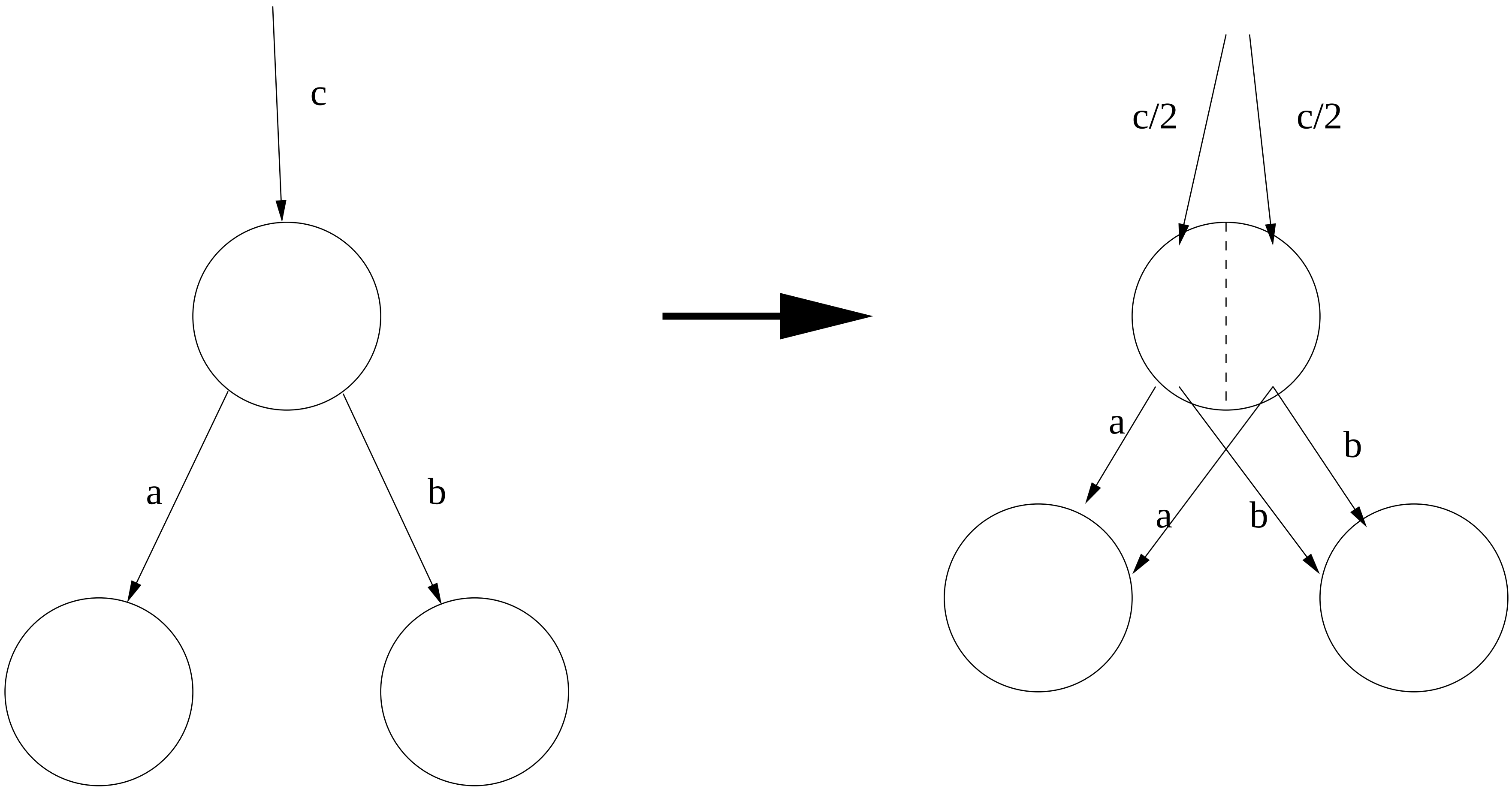

Figure 2: Replacing a state with an equivalent pair of states.

Statesplit.

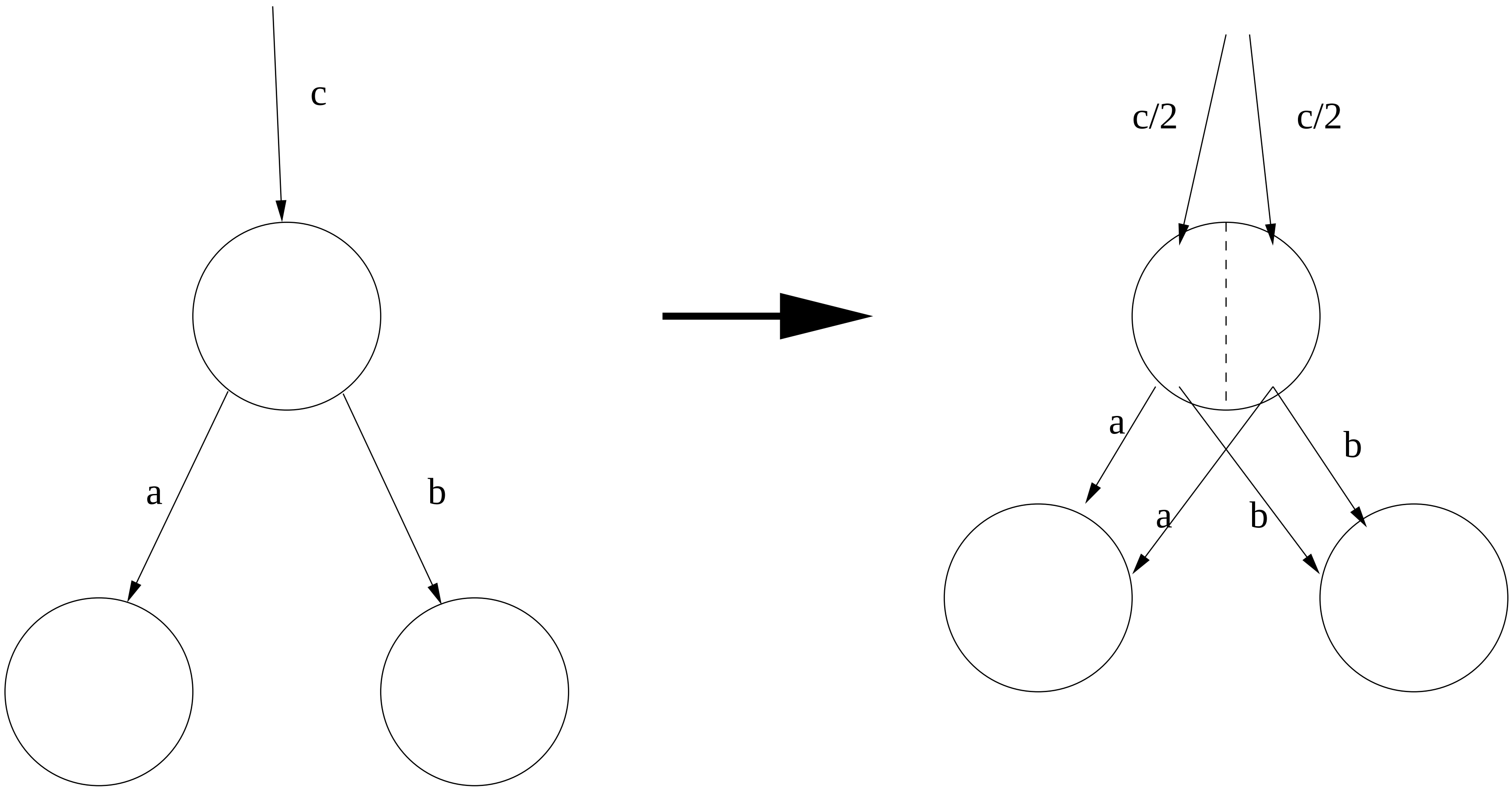

Figure 3: Replacing a state with an equivalent pair of states.

- Allow population to contain models with different numbers of states?

Some results.

Some results.

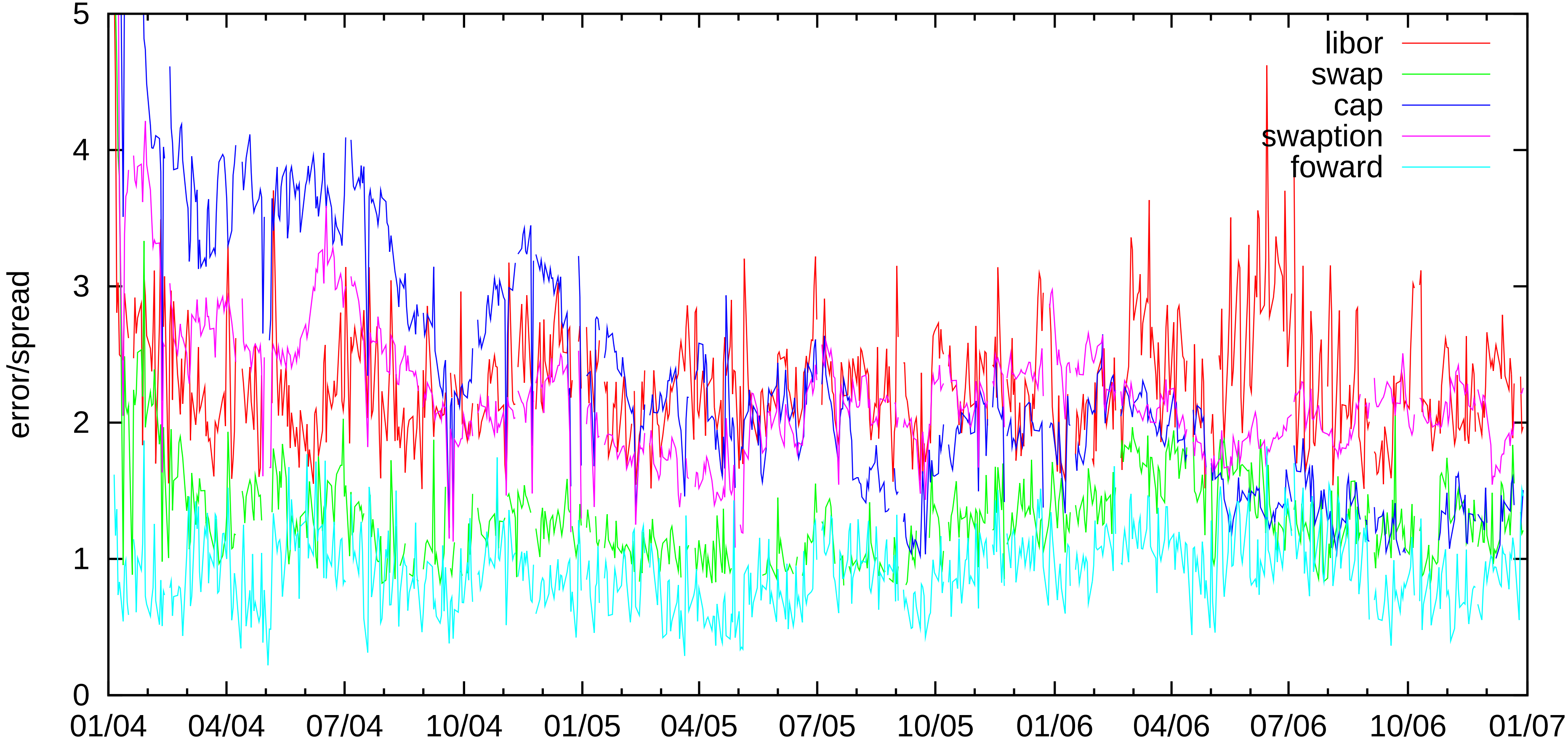

Figure 5: Mean errors (in spreads) for different classes

Some results.

Some results.

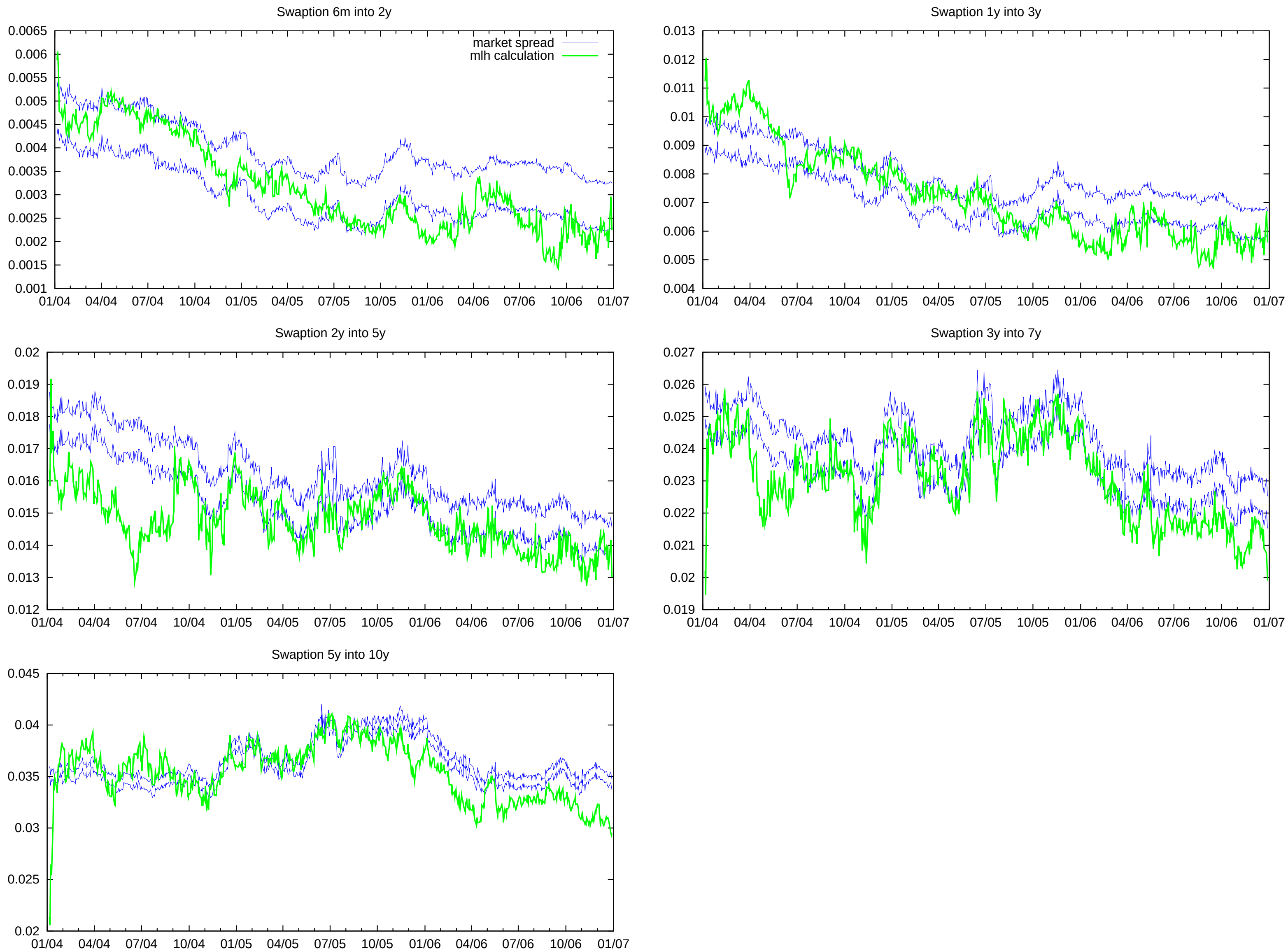

Figure 7: Euro swaption prices

Some results.

Some results.

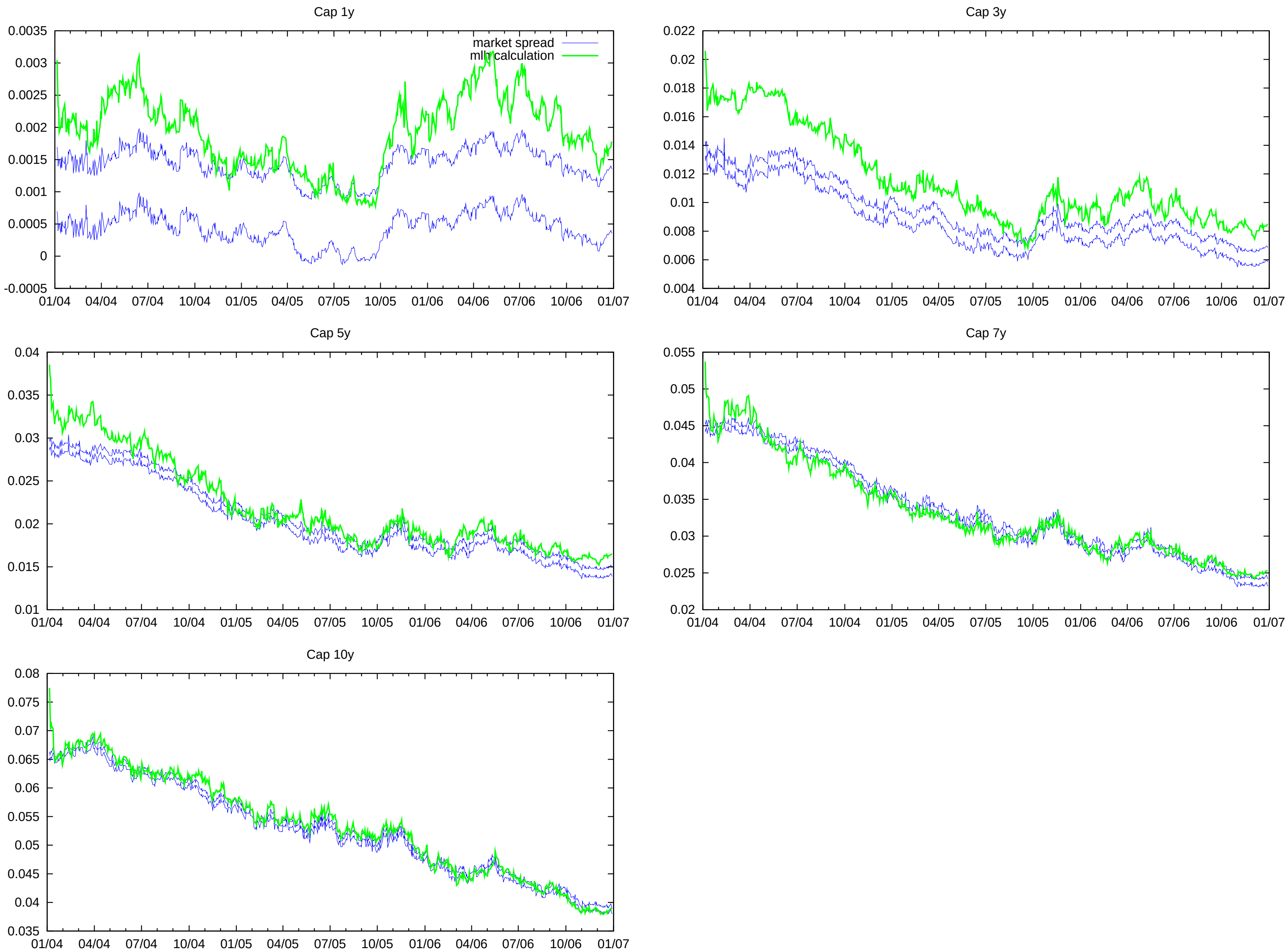

Figure 9: Euro cap prices

The equity premium puzzle

The equity premium puzzle.

The equity premium puzzle.

Representative agent's preferences:

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t U(c_t)\right],$$

$0 < \beta < 1$, and $U(c) = c^{1-R}/(1-R)$.

The equity premium puzzle.

Representative agent's preferences:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(c_t) \right],$$

$0 < \beta < 1$, and $U(c) = c^{1-R}/(1-R)$. Period-t output y_t = Period-t consumption c_t;

The equity premium puzzle.

Representative agent's preferences:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(c_t) \right],$$

$0 < \beta < 1$, and $U(c) = c^{1-R}/(1-R)$. Period-t output y_t = Period-t consumption c_t; Pricing of stock, one-period bond:

$$S_t = \zeta_t^{-1} E_t \Big[\sum_{s>t} \zeta_s y_s \Big], \quad B_t = \zeta_t^{-1} E_t \big[\zeta_{t+1} \big],$$

where

$$\zeta_t = \beta^t U'(y_t).$$

The equity premium puzzle.

Representative agent's preferences:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(c_t) \right],$$

$0 < \beta < 1$, and $U(c) = c^{1-R}/(1-R)$. Period-t output y_t = Period-t consumption c_t; Pricing of stock, one-period bond:

$$S_t = \zeta_t^{-1} E_t \Big[\sum_{s>t} \zeta_s y_s \Big], \quad B_t = \zeta_t^{-1} E_t \big[\zeta_{t+1} \big],$$

where

$$\zeta_t = \beta^t U'(y_t).$$

Assuming $\log y_t$ is a Gaussian random walk with known parameters, best-fitted value of R is way too high

The equity premium puzzle.

Representative agent's preferences:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(c_t) \right],$$

$0 < \beta < 1$, and $U(c) = c^{1-R}/(1-R)$. Period-t output y_t = Period-t consumption c_t; Pricing of stock, one-period bond:

$$S_t = \zeta_t^{-1} E_t \big[\sum_{s>t} \zeta_s y_s \big], \quad B_t = \zeta_t^{-1} E_t \big[\zeta_{t+1} \big],$$

where

$$\zeta_t = \beta^t U'(y_t).$$

Assuming $\log y_t$ is a Gaussian random walk with known parameters, best-fitted value of R is way too high ... but if we did not assume the parameters known...?

The equity premium puzzle.

Representative agent's preferences:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(c_t) \right],$$

$0 < \beta < 1$, and $U(c) = c^{1-R}/(1-R)$.   Period-t output y_t = Period-t consumption c_t;   Pricing of stock, one-period bond:

$$S_t = \zeta_t^{-1} E_t \big[\sum_{s>t} \zeta_s y_s \big], \quad B_t = \zeta_t^{-1} E_t \big[\zeta_{t+1} \big],$$

where

$$\zeta_t = \beta^t U'(y_t).$$

Assuming $\log y_t$ is a Gaussian random walk with known parameters, best-fitted value of R is way too high   ... but if we did not assume the parameters known...?

Assume mean (and precision) of the Gaussian steps unknown, assume some observational noise in the reported data.

Data .....

Data .....

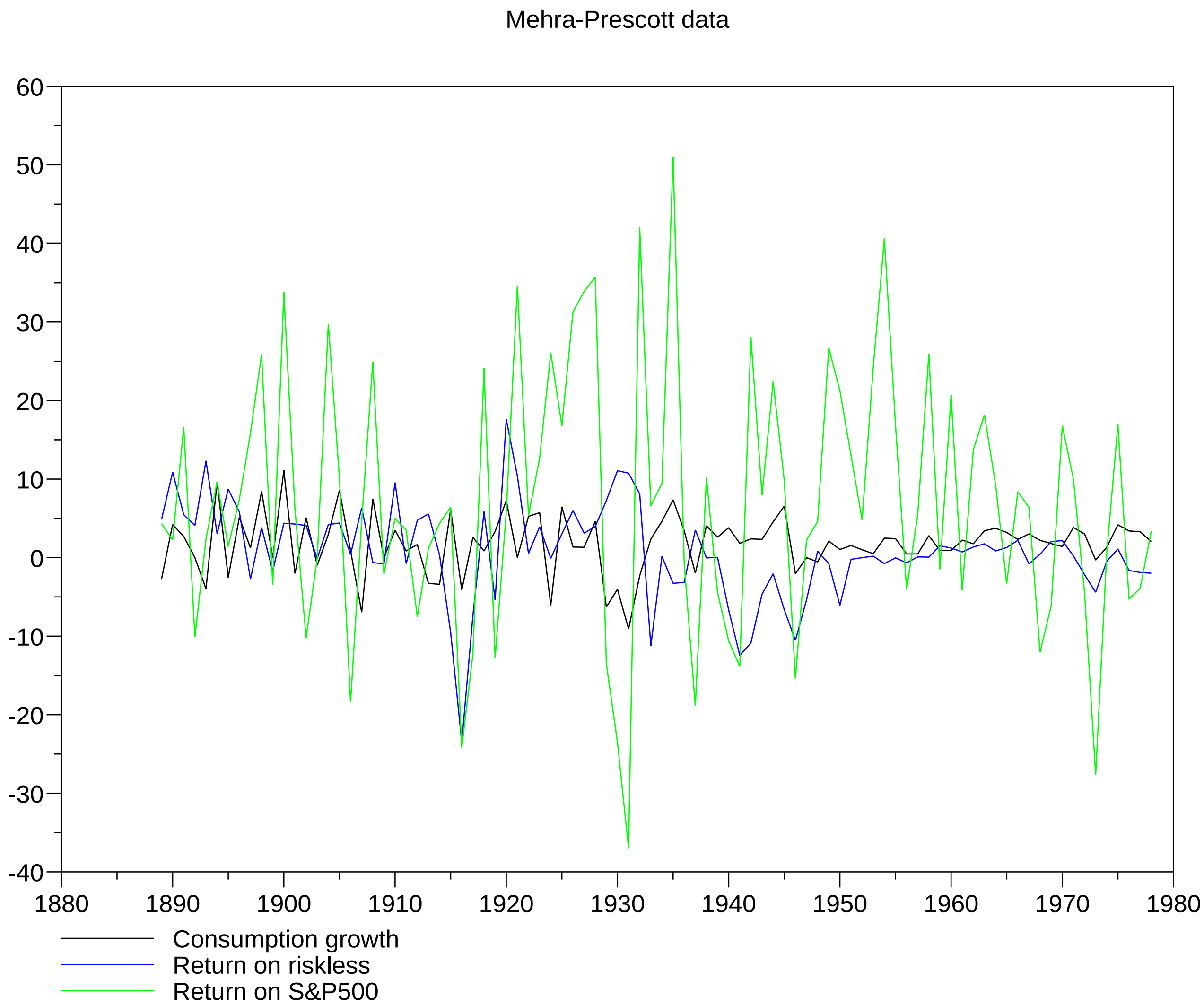

Figure 11: Mehra-Prescott data

... what data?

... what data?

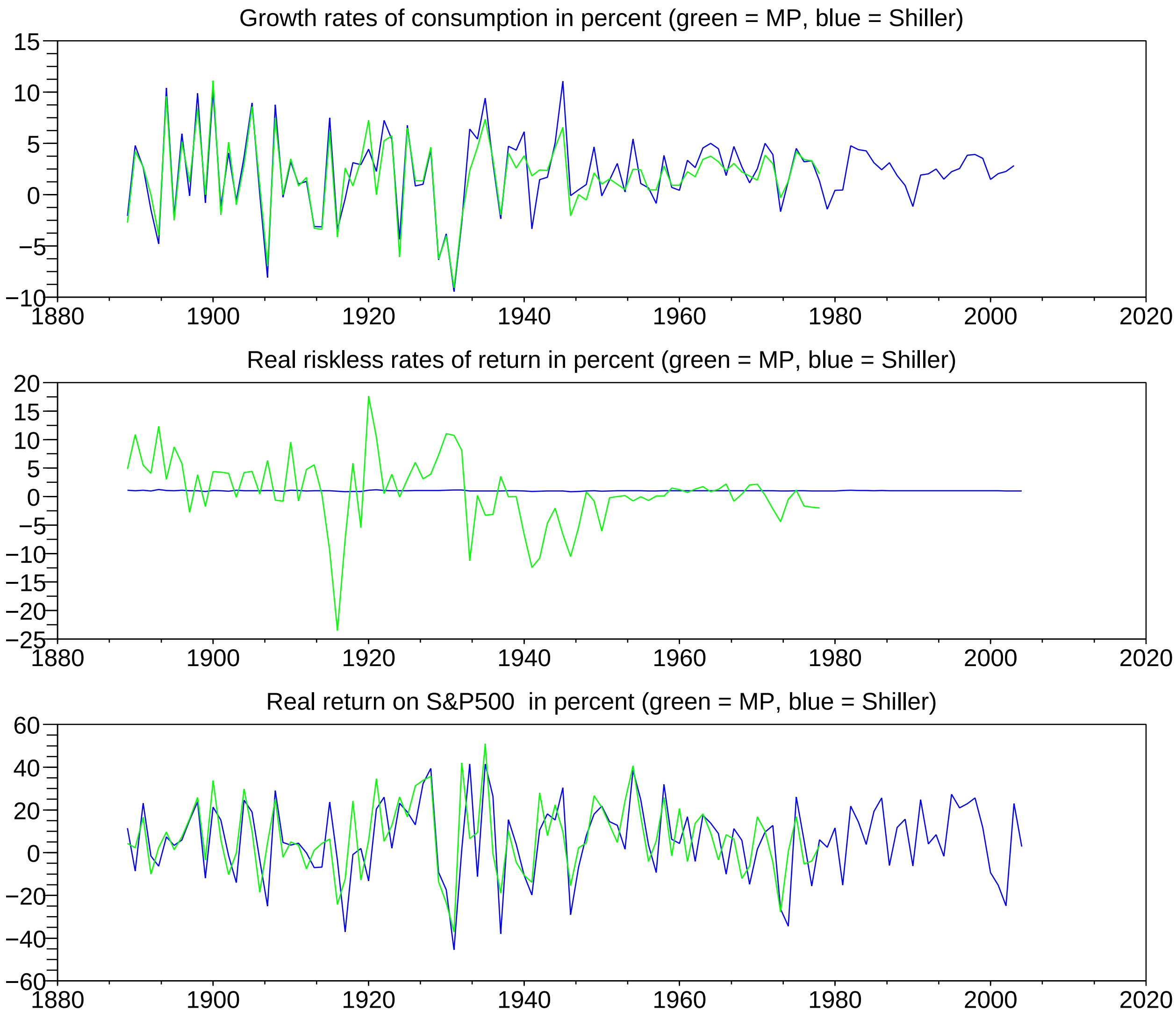

Figure 13: Mehra-Prescott's data, and Shiller's data

Data issues ...

Data issues ...

M& P report the annual rate of riskless nominal return, and the year-t value of a 1972 USD...

Data issues ...

M& P report the annual rate of riskless nominal return, and the year-t value of a 1972 USD... but only to the nearest percent ...

Data issues ...

M& P report the annual rate of riskless nominal return, and the year-t value of a 1972 USD... but only to the nearest percent ...

t	Year-t value of 1972 dollar
1911	0.21
1912	0.22

Data issues ...

M& P report the annual rate of riskless nominal return, and the year-t value of a 1972 USD... but only to the nearest percent ...

t	Year-t value of 1972 dollar
1911	0.21
1912	0.22

Thus we have a built-in change from 1911 to 1912 of about 5% !

Particle filtering?

Particle filtering?

- Posteriors for β and R are numerically sensible

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight ... but not in the same place next time

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight ... but not in the same place next time ... over-resampling?

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight ... but not in the same place next time ... over-resampling?
- Posteriors for observational noise quite high ..

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight ... but not in the same place next time ... over-resampling?
- Posteriors for observational noise quite high ..
- How stable do we think the data-generating process is?

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight ... but not in the same place next time ... over-resampling?
- Posteriors for observational noise quite high ..
- How stable do we think the data-generating process is?
- If the data is changing, PF will kill off alternative models which later look better

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight ... but not in the same place next time ... over-resampling?
- Posteriors for observational noise quite high ..
- How stable do we think the data-generating process is?
- If the data is changing, PF will kill off alternative models which later look better
- Perhaps do some regular input of random new particles?

Particle filtering?

- Posteriors for β and R are numerically sensible ... most of the time.
- Posterior for R usually quite tight ... but not in the same place next time ... over-resampling?
- Posteriors for observational noise quite high ..
- How stable do we think the data-generating process is?
- If the data is changing, PF will kill off alternative models which later look better
- Perhaps do some regular input of random new particles?

- The assumption that the data-generating process is unchanged over the kinds of timescales needed to reliably estimate the parameter is untenable.

How good was the model anyway?

How good was the model anyway?

Plot the fitted values (from ML):

How good was the model anyway?

Plot the fitted values (from ML):

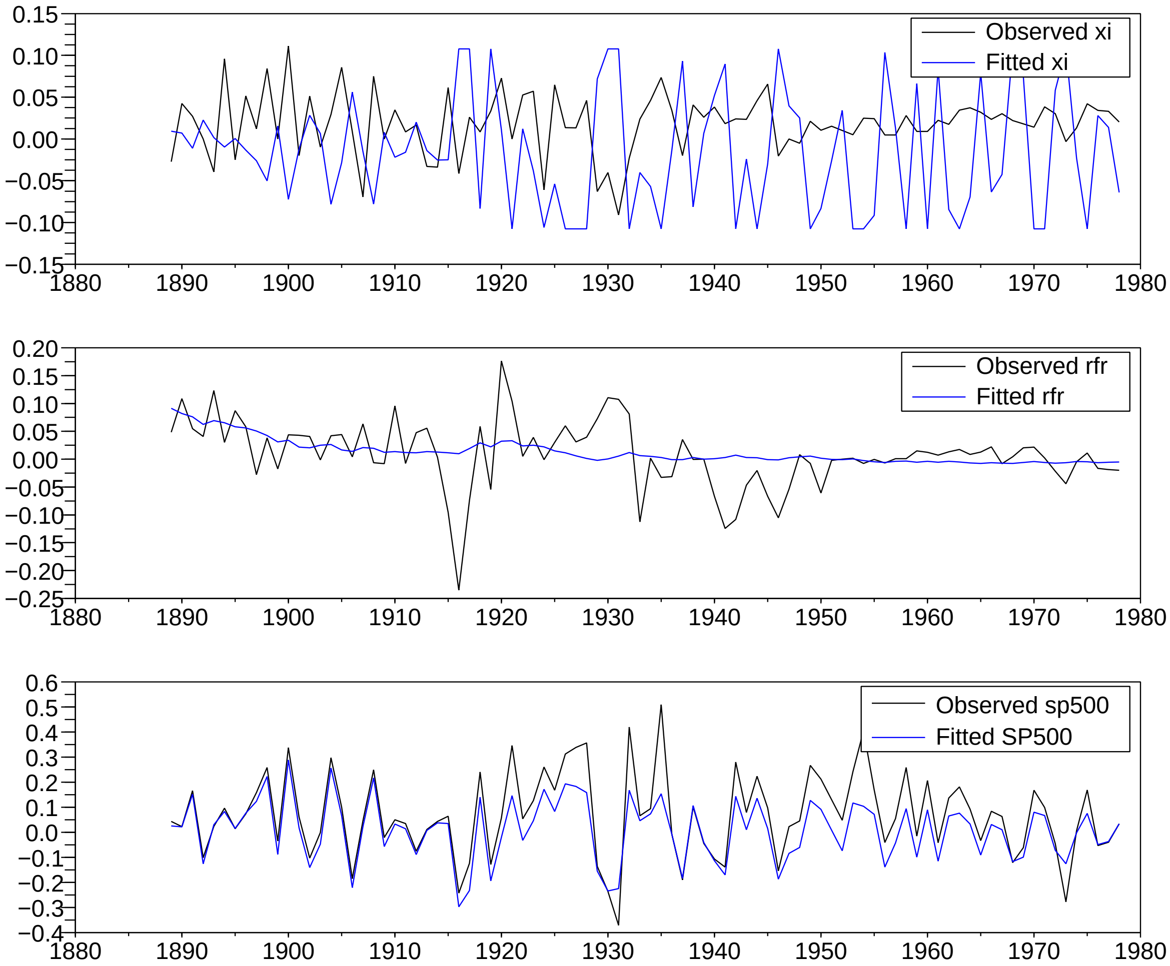

Figure 16: ML values with original MP data

How good was the model anyway?

How good was the model anyway?

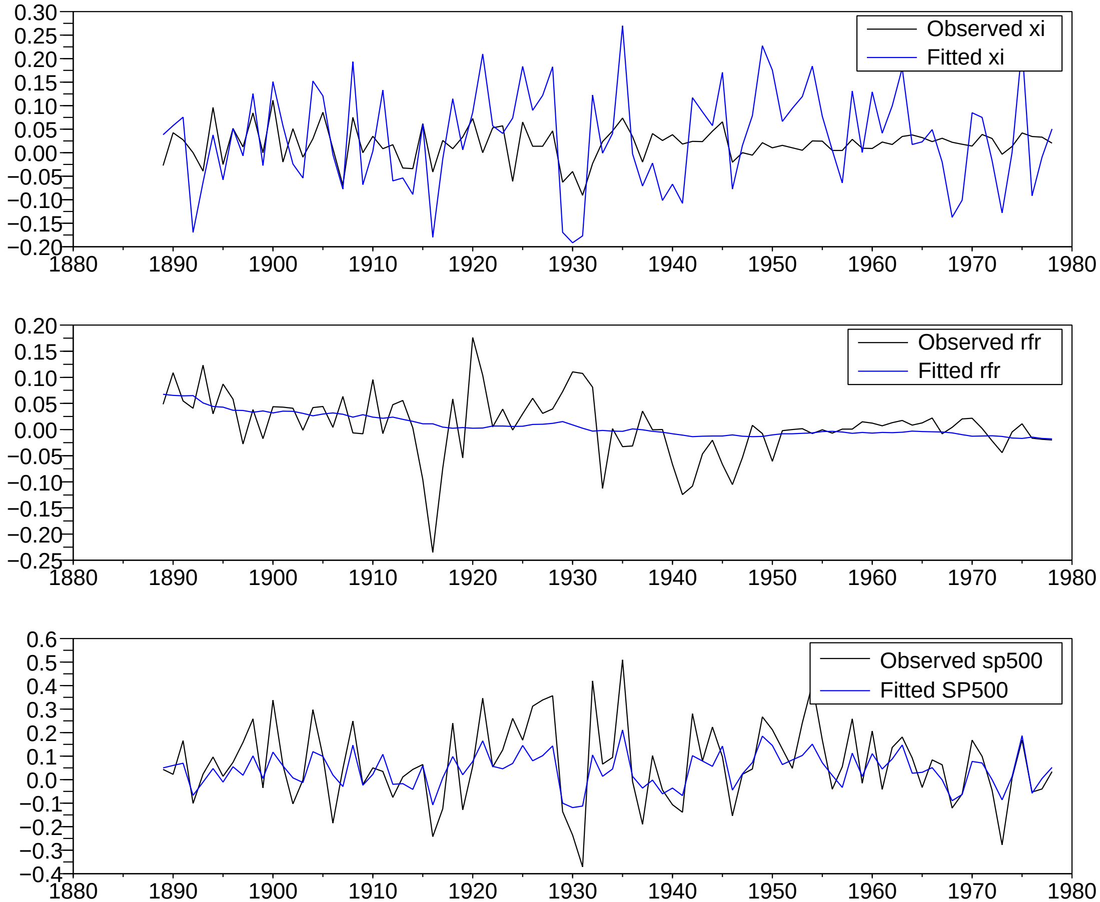

Figure 18: MCMC median values for MP data

How good was the model anyway?

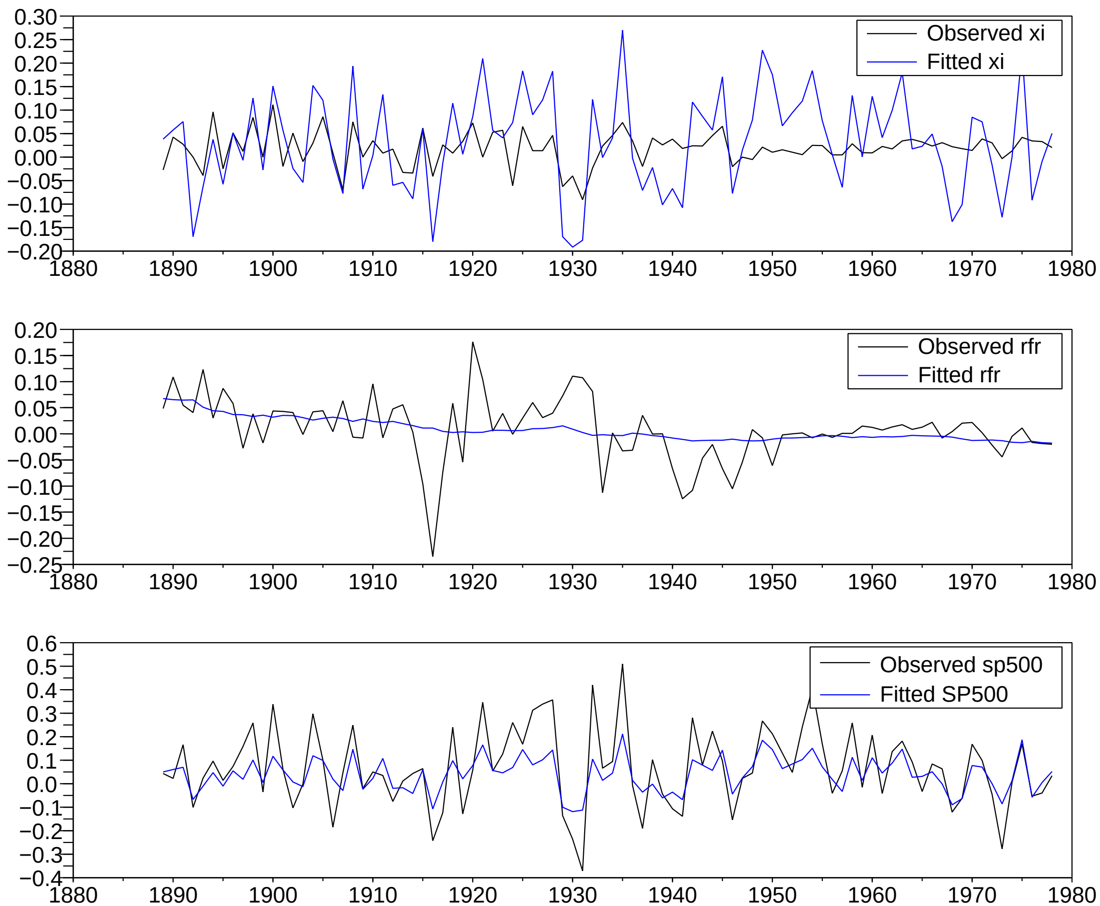

Figure 19: MCMC median values for MP data

Median for posterior of $R = 10.4$

What can we do?

What can we do?

- Perhaps a different U?

What can we do?

- Perhaps a different U?
- Perhaps recorded consumption data is too smoothed?

What can we do?

- Perhaps a different U?
- Perhaps recorded consumption data is too smoothed?
- Perhaps allow for government tax take?

What can we do?

- Perhaps a different U?
- Perhaps recorded consumption data is too smoothed?
- Perhaps allow for government tax take?
- It took 90 years to gather the MP data ... and in 25 years we are no nearer a satisfying explanation of this data.

What can we do?

- Perhaps a different U?
- Perhaps recorded consumption data is too smoothed?
- Perhaps allow for government tax take?
- It took 90 years to gather the MP data ... and in 25 years we are no nearer a satisfying explanation of this data.
- Recognise that there are only about 300 numbers in this dataset ...

What can we do?

- Perhaps a different U?
- Perhaps recorded consumption data is too smoothed?
- Perhaps allow for government tax take?
- It took 90 years to gather the MP data ... and in 25 years we are no nearer a satisfying explanation of this data.
- Recognise that there are only about 300 numbers in this dataset ... ... and leave this small bone for the dogs to fight over!

Dynamic Engine for Bayesian Inference

- general structure of all PF computations quite similar

- general structure of all PF computations quite similar
- same elements keep getting used in our models

- general structure of all PF computations quite similar
- same elements keep getting used in our models ... but modifying code to deal with a new example is time consuming and fiddly ...

- general structure of all PF computations quite similar
- same elements keep getting used in our models ... but modifying code to deal with a new example is time consuming and fiddly ...

- user-friendly GPL code to build PF code?!

- general structure of all PF computations quite similar
- same elements keep getting used in our models ... but modifying code to deal with a new example is time consuming and fiddly ...

- user-friendly GPL code to build PF code?!

- something like WinBUGS?

- general structure of all PF computations quite similar
- same elements keep getting used in our models ... but modifying code to deal with a new example is time consuming and fiddly ...

- user-friendly GPL code to build PF code?!

- something like WinBUGS?
- currently have basic lexer/parser, reading in simple models and constructing Java objects from them

- general structure of all PF computations quite similar
- same elements keep getting used in our models ... but modifying code to deal with a new example is time consuming and fiddly ...

- user-friendly GPL code to build PF code?!

- something like WinBUGS?
- currently have basic lexer/parser, reading in simple models and constructing Java objects from them
- next build Java interface to Scilab, then start with some simple PF examples

Summary

Summary

- Potential approach emphasises the need for high-dimensional methods

Summary

- Potential approach emphasises the need for high-dimensional methods
- Applications in finance will rarely be time-homogeneous, so need to understand how to deal with such examples

Summary

- Potential approach emphasises the need for high-dimensional methods
- Applications in finance will rarely be time-homogeneous, so need to understand how to deal with such examples
- Need a way to take the labour out of building/running models - DEBI?

Summary

- Potential approach emphasises the need for high-dimensional methods
- Applications in finance will rarely be time-homogeneous, so need to understand how to deal with such examples
- Need a way to take the labour out of building/running models - DEBI?
- Don't be unrealistic in what you expect SMC to be able to do