Package ‘ASV’

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Type Package

Title Stochastic Volatility Models with or without Leverage

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Description The efficient Markov chain Monte Carlo estimation of stochastic volatility models with and without leverage (asymmetric and symmetric stochastic volatility models). Further, it computes the logarithm of the likelihood given parameters using particle filters.

URL https://sites.google.com/view/omori-stat/english/software/asv-r

License GPL (>= 2)

Imports Rcpp (>= 1.0.7), freqdom, stats, graphics

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NeedsCompilation yes

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ASV-package — *Stochastic Volatility Models with or without Leverage*

Description

This function estimates model parameters and latent log volatilities for stochastic volatility models:

y(t) = eps(t)*exp(h(t)/2), h(t+1) = mu + phi*(h(t)-mu) + eta(t)

eps(t)~i.i.d. N(0,1), eta(t)~i.i.d. N(0,sigma_eta^2)

where we assume the correlation between eps(t) and eta(t) equals to rho.

Details

The highly efficient Markov chain Monte Carlo algorithm is based on the mixture sampler by Omori, Chib, Shephard and Nakajima (2007), but it further corrects the approximation error within the sampling algorithm. See Takahashi, Omori and Watanabe (2022+) for more details.

References

Omori, Y., Chib, S., Shephard, N., and J. Nakajima (2007), "Stochastic volatility model with leverage: fast and efficient likelihood inference," Journal of Econometrics, 140-2, 425-449.

Takahashi, M., Omori, Y. and T. Watanabe (2022+), Stochastic volatility and realized stochastic volatility models. JSS Research Series in Statistics, in press. Springer, Singapore.

See Also

`sv_mcmc`, `asv_mcmc`, `sv_pf`, `asv_pf`, `sv_apf`, `asv_apf`

asv_apf — *Auxiliary particle filter for stochastic volatility models with leverage*

Description

The function computes the log likelihood given (mu, phi, sigma_eta, rho) for stochastic volatility models with leverage (asymmetric stochastic volatility models).

Usage

```
asv_apf(mu, phi, sigma_eta, rho, Y, I)
```

Arguments

mu	parameter value such as the posterior mean of mu
phi	parameter value such as the posterior mean of phi
sigma_eta	parameter value such as the posterior mean of sigma_eta
rho	parameter value such as the posterior mean of rho
Y	T x 1 vector (y(1),...,y(T))' of returns where T is a sample size.
I	Number of particles to approximate the filtering density.

Value

Logarithm of the likelihood of Y given parameters (mu, phi, sigma_eta, rho) using the auxiliary particle filter by Pitt and Shephard (1999).

Author(s)

Yasuhiro Omori, Ryuji Hashimoto

References

Pitt, M. K., and N. Shephard (1999), "Filtering via simulation: Auxiliary particle filters." Journal of the American statistical association 94, 590-599.

Omori, Y., Chib, S., Shephard, N., and J. Nakajima (2007), "Stochastic volatility model with leverage: fast and efficient likelihood inference," Journal of Econometrics, 140-2, 425-449.

Takahashi, M., Omori, Y. and T. Watanabe (2022+), Stochastic volatility and realized stochastic volatility models. JSS Research Series in Statistics, in press. Springer, Singapore.

Examples

```
set.seed(111)
nobs = 80; # n is often larger than 1000 in practice.
mu = 0; phi = 0.97; sigma_eta = 0.3; rho = -0.3;
h  = 0;   Y = c();
for(i in 1:nobs){
  eps = rnorm(1, 0, 1)
  eta = rho*sigma_eta*eps + sigma_eta*sqrt(1-rho^2)*rnorm(1, 0, 1)
  y   = eps * exp(0.5*h)
  h   = mu + phi * (h-mu) + eta
  Y   = append(Y, y)
}
npart = 5000
asv_apf(mu, phi, sigma_eta, rho, Y, npart)
```

asv_mcmc *MCMC estimation for stochastic volatility models with leverage*

Description

This function estimates model parameters and latent log volatilities for stochastic volatility models with leverage (asymmetric stochastic volatility models):

y(t) = eps(t)*exp(h(t)/2), h(t+1) = mu + phi*(h(t)-mu) + eta(t)

eps(t)~i.i.d. N(0,1), eta(t)~i.i.d. N(0,sigma_eta^2)

where we assume the correlation between eps(t) and eta(t) equals to rho. Prior distributions are

mu~N(mu_0,sigma_0^2), (phi+1)/2~Beta(a_0,b_0), sigma_eta^2~IG(n_0/2,S_0/2),

(rho+1)/2~Beta(a_1,b_1),

where N, Beta and IG denote normal, beta and inverse gaussian distributions respectively. Note that the probability density function of x ~ IG(a,b) is proportional to (1/x)^(a+1)*exp(-b/x).

The highly efficient Markov chain Monte Carlo algorithm is based on the mixture sampler by Omori, Chib, Shephard and Nakajima (2007), but it further corrects the approximation error within the sampling algorithm. See Takahashi, Omori and Watanabe (2022+) for more details.

Usage

```
asv_mcmc(return_vector, nSim = NULL, nBurn = NULL, vHyper = NULL)
```

Arguments

`return_vector`	T x 1 vector (y(1),...,y(T))' of returns where T is a sample size.
`nSim`	Number of iterations for the MCMC estimation. Default value is 5000.
`nBurn`	Number of iterations for the burn-in period. Default value is the maximum integer less than or equal to 2*sqrt(nSim)+1.
`vHyper`	8 x 1 vector of hyperparameters. (mu_0,sigma_0^2,a_0,b_0,a_1,b_1,n_0,S_0). Default values are (0,1000, 1,1,1,1,0.01,0.01).

Value

A list with components:

`vmu`	nSim x 1 vector of MCMC samples of mu
`vphi`	nSim x 1 vector of MCMC samples of phi
`vsigma_eta`	nSim x 1 vector of MCMC samples of sigma_eta
`vrho`	nSim x 1 vector of MCMC samples of rho
`mh`	nSim x T matrix of latent log volatilities (h(1),...,h(T)). For example, the first column is a vector of MCMC samples for h(1).

Further, the acceptance rates of MH algorithms will be shown for h and (mu,phi,sigma_eta, rho).

Author(s)

Yasuhiro Omori, Ryuji Hashimoto

References

Omori, Y., Chib, S., Shephard, N., and J. Nakajima (2007), "Stochastic volatility model with leverage: fast and efficient likelihood inference," Journal of Econometrics, 140-2, 425-449.

Takahashi, M., Omori, Y. and T. Watanabe (2022+), Stochastic volatility and realized stochastic volatility models. JSS Research Series in Statistics, in press. Springer, Singapore.

See Also

See also ReportMCMC, asv_pf

Examples

```
set.seed(111)
nobs = 80; # n is often larger than 1000 in practice.
mu = 0; phi = 0.97; sigma_eta = 0.3; rho = -0.3;
h  = 0;   Y = c();
for(i in 1:nobs){
  eps = rnorm(1, 0, 1)
  eta = rho*sigma_eta*eps + sigma_eta*sqrt(1-rho^2)*rnorm(1, 0, 1)
  y   = eps * exp(0.5*h)
  h   = mu + phi * (h-mu) + eta
  Y   = append(Y, y)
}

# This is a toy example. Increase nsim and nburn
# until the convergence of MCMC in practice.

nsim = 500; nburn = 100;
vhyper = c(0.0,1000,1.0,1.0,1.0,1.0,0.01,0.01)
out  = asv_mcmc(Y, nsim, nburn, vhyper)
vmu = out[[1]]; vphi = out[[2]]; vsigma_eta = out[[3]]; vrho = out[[4]];
mh  = out[[5]];
```

---

asv_pf — *Particle filter for stochastic volatility models with leverage*

Description

The function computes the log likelihood given (mu, phi, sigma_eta, rho) for stochastic volatility models with leverage (asymmetric stochastic volatility models).

Usage

```
asv_pf(mu, phi, sigma_eta, rho, Y, I)
```

Arguments

mu	parameter value such as the posterior mean of mu
phi	parameter value such as the posterior mean of phi
sigma_eta	parameter value such as the posterior mean of sigma_eta
rho	parameter value such as the posterior mean of rho
Y	T x 1 vector (y(1),...,y(T))' of returns where T is a sample size.
I	Number of particles to approximate the filtering density.

Value

Logarithm of the likelihood of Y given parameters (mu, phi, sigma_eta, rho)

Author(s)

Yasuhiro Omori, Ryuji Hashimoto

References

Omori, Y., Chib, S., Shephard, N., and J. Nakajima (2007), "Stochastic volatility model with leverage: fast and efficient likelihood inference," Journal of Econometrics, 140-2, 425-449.

Takahashi, M., Omori, Y. and T. Watanabe (2022+), Stochastic volatility and realized stochastic volatility models. JSS Research Series in Statistics, in press. Springer, Singapore.

Examples

```
set.seed(111)
nobs = 80; # n is often larger than 1000 in practice.
mu = 0; phi = 0.97; sigma_eta = 0.3; rho = -0.3;
h  = 0;   Y = c();
for(i in 1:nobs){
  eps = rnorm(1, 0, 1)
  eta = rho*sigma_eta*eps + sigma_eta*sqrt(1-rho^2)*rnorm(1, 0, 1)
  y   = eps * exp(0.5*h)
  h   = mu + phi * (h-mu) + eta
  Y   = append(Y, y)
}
npart = 5000
asv_pf(mu, phi, sigma_eta, rho, Y, npart)
```

`ReportMCMC` *Summary statistics, diagnostic statistics and plots.*

Description

This function reports summary statistics of the MCMC samples such as the posterior mean, the posterior standard deviation, the 95% credible interval, the expected sample size, the inefficiency factor, the posterior probability that the parameter is positive. Further it plots the sample path, the sample autocorrelation function and the estimated posterior density.

Usage

```
ReportMCMC(mx, dBm = NULL, vname = NULL)
```

Arguments

`mx`	nSim x m matrix where nSim is the MCMC sample size and m is the number of parameters.
`dBm`	The bandwidth to compute the inefficient factor. Default value is the maximum integer less than or equal to 2*sqrt(nSim)+1.
`vname`	The vector of variable names. Default names are Param1, Param2 and so forth.

Value

`Mean`	The posterior mean of the parameter
`Std Dev`	The posterior standard deviation of the parameter
`95%L`	The lower limit of the 95% credible interval of the parameter
`Median`	The posterior median of the parameter
`95%U`	The upper limit of the 95% credible interval of the parameter
`ESS`	Expected sample size defined as the MCMC sample size divided by IF
`IF`	Inefficiency factor. See, for example, Kim, Shephard and Chib (1998).
`CD`	p-value of convergence diagnostics test by Geweke (1992). H_0:mean of the first 10% of MCMC samples is equal to mean of the last 50% of MCMC samples vs. H_1:not H_0.
`Pr(+)`	The posterior probability that the parameter is positive.

Further, it plots the sample path, the sample autocorrelation function and the posterior density for each parameter.

Note

‘freqdom’ package needs to be pre-installed.

Author(s)

Yasuhiro Omori

References

Kim, S., Shephard, N. and S. Chib (1998) "Stochastic volatility: likelihood inference and comparison with ARCH models", The Review of Economic Studies, 65(3), 361-393.

Geweke, J. (1992), "Evaluating the accuracy of sampling-based approaches to calculating posterior moments,"" in Bayesian Statistics 4 (ed J.M. Bernardo, J.O. Berger, A.P. Dawid and A.F.M. Smith), Oxford, UK.

Examples

```
nobs = 80; # n is often larger than 1000 in practice.
mu = 0; phi = 0.97; sigma_eta = 0.3; rho = 0.0;
h  = 0;   Y = c();

for(i in 1:nobs){
  eps = rnorm(1, 0, 1)
  eta = rho*sigma_eta*eps + sigma_eta*sqrt(1-rho^2)*rnorm(1, 0, 1)
  y   = eps * exp(0.5*h)
  h   = mu + phi * (h-mu) + eta
  Y   = append(Y, y)
}

# This is a toy example. Increase nsim and nburn
# until the convergence of MCMC in practice.

nsim = 500; nburn = 100;
vhyper = c(0.0,1000,1.0,1.0,0.01,0.01)
out  = sv_mcmc(Y, nsim, nburn, vhyper)
vmu = out[[1]]; vphi = out[[2]]; vsigma_eta = out[[3]]; mh  = out[[4]];
myname = c(expression(mu), expression(phi),expression(sigma[eta]))
ReportMCMC(cbind(vmu,vphi,vsigma_eta), vname=myname)
```

---

sv_apf — *Auxiliary particle filter for stochastic volatility models without leverage*

Description

The function computes the log likelihood given (mu, phi, sigma_eta) for stochastic volatility models without leverage (symmetric stochastic volatility models).

Usage

```
sv_apf(mu, phi, sigma_eta, Y, I)
```

Arguments

mu	parameter value such as the posterior mean of mu
phi	parameter value such as the posterior mean of phi
sigma_eta	parameter value such as the posterior mean of sigma_eta
Y	T x 1 vector (y(1),...,y(T))' of returns where T is a sample size.
I	Number of particles to approximate the filtering density.

Value

Logarithm of the likelihood of Y given parameters (mu, phi, sigma_eta) using the auxiliary particle filter by Pitt and Shephard (1999).

Author(s)

Yasuhiro Omori, Ryuji Hashimoto

References

Pitt, M. K., and N. Shephard (1999), "Filtering via simulation: Auxiliary particle filters." Journal of the American statistical association 94, 590-599.

Omori, Y., Chib, S., Shephard, N., and J. Nakajima (2007), "Stochastic volatility model with leverage: fast and efficient likelihood inference," Journal of Econometrics, 140-2, 425-449.

Takahashi, M., Omori, Y. and T. Watanabe (2022+), Stochastic volatility and realized stochastic volatility models. JSS Research Series in Statistics, in press. Springer, Singapore.

Examples

```
set.seed(111)
nobs = 80; # n is often larger than 1000 in practice.
mu = 0; phi = 0.97; sigma_eta = 0.3;
h  = 0;   Y = c();
for(i in 1:nobs){
  eps = rnorm(1, 0, 1)
  eta = rnorm(1, 0, sigma_eta)
  y   = eps * exp(0.5*h)
  h   = mu + phi * (h-mu) + eta
  Y   = append(Y, y)
}
npart = 5000
sv_pf(mu, phi, sigma_eta, Y, npart)
```

`sv_mcmc` *MCMC estimation for stochastic volatility models without leverage*

Description

This function estimates model parameters and latent log volatilities for stochastic volatility models without leverage (symmetric stochastic volatility models):

y(t) = eps(t)*exp(h(t)/2), h(t+1) = mu + phi*(h(t)-mu) + eta(t)

eps(t)~i.i.d. N(0,1), eta(t)~i.i.d. N(0,sigma_eta^2)

where we assume the correlation between eps(t) and eta(t) equals to zero. Prior distributions are

mu~N(mu_0,sigma_0^2), (phi+1)/2~Beta(a_0,b_0), sigma_eta^2~IG(n_0/2,S_0/2)

where N, Beta and IG denote normal, beta and inverse gaussian distributions respectively. Note that the probability density function of x ~ IG(a,b) is proportional to (1/x)^(a+1)*exp(-b/x).

The highly efficient Markov chain Monte Carlo algorithm is based on the mixture sampler by Omori, Chib, Shephard and Nakajima (2007), but it further corrects the approximation error within the sampling algorithm. See Takahashi, Omori and Watanabe (2022+) for more details.

Usage

```
sv_mcmc(return_vector, nSim = NULL, nBurn = NULL, vHyper = NULL)
```

Arguments

`return_vector`	T x 1 vector (y(1),...,y(T))' of returns where T is a sample size.
`nSim`	Number of iterations for the MCMC estimation. Default value is 5000.
`nBurn`	Number of iterations for the burn-in period. Default value is the maximum integer less than or equal to 2*sqrt(nSim)+1.
`vHyper`	6 x 1 vector of hyperparameters. (mu_0,sigma_0^2,a_0,b_0,n_0,S_0). Default values are (0,1000, 1,1,0.01,0.01).

Value

A list with components:

`vmu`	nSim x 1 vector of MCMC samples of mu
`vphi`	nSim x 1 vector of MCMC samples of phi
`vsigma_eta`	nSim x 1 vector of MCMC samples of sigma_eta
`vmh`	nSim x T matrix of latent log volatilities (h(1),...,h(T)). For example, the first column is a vector of MCMC samples for h(1).

Further, the acceptance rates of MH algorithms will be shown for h and (mu,phi,sigma_eta).

Author(s)

Yasuhiro Omori, Ryuji Hashimoto

References

Omori, Y., Chib, S., Shephard, N., and J. Nakajima (2007), "Stochastic volatility model with leverage: fast and efficient likelihood inference," Journal of Econometrics, 140-2, 425-449.

Takahashi, M., Omori, Y. and T. Watanabe (2022+), Stochastic volatility and realized stochastic volatility models. JSS Research Series in Statistics, in press. Springer, Singapore.

See Also

See also ReportMCMC, sv_pf

Examples

```
set.seed(111)
nobs = 80; # n is often larger than 1000 in practice.
mu = 0; phi = 0.97; sigma_eta = 0.3;
h  = 0;   Y = c();
for(i in 1:nobs){
  eps = rnorm(1, 0, 1)
  eta = rnorm(1, 0, sigma_eta)
  y   = eps * exp(0.5*h)
  h   = mu + phi * (h-mu) + eta
  Y   = append(Y, y)
}

# This is a toy example. Increase nsim and nburn
# until the convergence of MCMC in practice.

nsim = 500; nburn = 100;
vhyper = c(0.0,1000,1.0,1.0,0.01,0.01)
out  = sv_mcmc(Y, nsim, nburn, vhyper)
vmu = out[[1]]; vphi = out[[2]]; vsigma_eta = out[[3]]; mh  = out[[4]];
```

---

sv_pf *Particle filter for stochastic volatility models without leverage*

Description

This function computes the log likelihood given (mu, phi, sigma_eta) for stochastic volatility models without leverage (symmetric stochastic volatility models).

Usage

```
sv_pf(mu, phi, sigma_eta, Y, I)
```

Arguments

mu	parameter value such as the posterior mean of mu
phi	parameter value such as the posterior mean of phi
sigma_eta	parameter value such as the posterior mean of sigma_eta
Y	T x 1 vector (y(1),...,y(T))' of returns where T is a sample size.
I	Number of particles to approximate the filtering density.

Value

Logarithm of the likelihood of Y given parameters (mu, phi, sigma_eta)

Author(s)

Yasuhiro Omori, Ryuji Hashimoto

References

Omori, Y., Chib, S., Shephard, N., and J. Nakajima (2007), "Stochastic volatility model with leverage: fast and efficient likelihood inference," Journal of Econometrics, 140-2, 425-449.

Takahashi, M., Omori, Y. and T. Watanabe (2022+), Stochastic volatility and realized stochastic volatility models. JSS Research Series in Statistics, in press. Springer, Singapore.

Examples

```
set.seed(111)
nobs = 80; # n is often larger than 1000 in practice.
mu = 0; phi = 0.97; sigma_eta = 0.3;
h  = 0;   Y = c();
for(i in 1:nobs){
  eps = rnorm(1, 0, 1)
  eta = rnorm(1, 0, sigma_eta)
  y   = eps * exp(0.5*h)
  h   = mu + phi * (h-mu) + eta
  Y   = append(Y, y)
}
npart = 5000
sv_pf(mu, phi, sigma_eta, Y, npart)
```

Index