

# Chapter 14. Case study: POMP modeling to investigate financial volatility

## Objectives

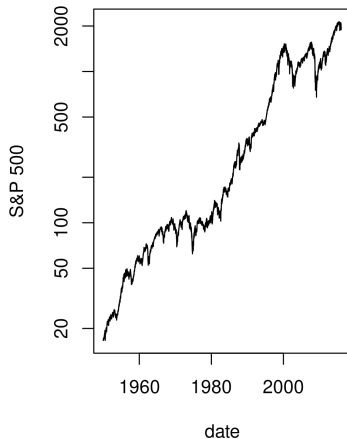
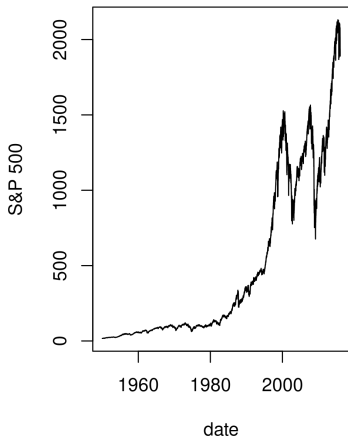
- 1 Introduce financial volatility and some models used to study it: ARCH, GARCH, and stochastic volatility models.
- 2 Provide a case study in using pomp to study a stochastic volatility model.
- 3 Discuss this case study as an example of a broader class of nonlinear POMP models, derived from adding stochastically time varying parameters to a linear or nonlinear time series model.
- 4 Discuss this case study as an example of an extension of the POMP framework which allows feedback from the observation process to the state process.

# Introduction

- Returns on investments in stock market indices or large companies are often found to be approximately uncorrelated.
- If investment returns are substantially correlated, investors can study their time series behavior and make money.
- If the investment is non-liquid (i.e., not reliably tradeable), or expensive to trade, then it might be hard to make money even if you can statistically predict a positive expected return.
- Otherwise, the market may notice a favorable investment opportunity. More buyers will lead to higher prices, and the opportunity will disappear.
- Consequently, most readily traded investments (e.g., stock market indices, or stock of large companies) have close to uncorrelated returns.
- The variability of the returns (called the volatility) can fluctuate considerably. Understanding this volatility is important for quantifying and managing the risk of investments.

- Recall the daily S&P 500 data that we saw earlier, in Chapter 3.

```
dat <- read.table("sp500.csv", sep=",", header=TRUE)
plot(as.Date(dat$Date), dat$Close,
     xlab="date", ylab="S&P 500", type="l")
plot(as.Date(dat$Date), dat$Close, log="y",
     xlab="date", ylab="S&P 500", type="l")
```



# Returns, absolute returns, and autocorrelation

- We write  $\{z_n, n = 1, \dots, N\}$  for the data.
- We write the return on the S&P 500 index, i.e., the difference of the log of the index, as

$$y_n = \log(z_n) - \log(z_{n-1}).$$

\* We saw in Chapter 3 that  $y_{2:N}$  has negligible sample autocorrelation.

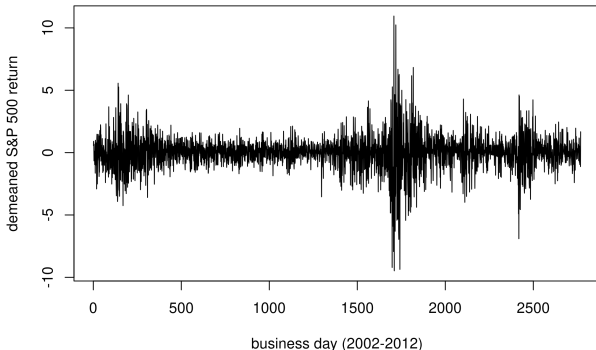
- However, the absolute deviations from average,

$$a_n = \left| y_n - \frac{1}{N-1} \sum_{k=2}^N y_k \right|$$

have considerable sample autocorrelation.

- We fit models to the demeaned daily returns for the S&P 500 index for 2002-2012, to compare with Bretó (2014).

```
load(file="sp500-2002-2012.rda")  
plot(sp500.ret.demeaned, type="l",  
     xlab="business day (2002-2012)", ylab="demeaned S&P 500 return")
```



**Question 14.1.** Is it appropriate to fit a stationary model to this series, or do we have evidence for violation of stationarity? Explain.

# The ARCH model

- The ARCH and GARCH models have become widely used for financial time series modeling. Here, we follow Cowpertwait and Metcalfe (2009) to introduce these models; see also Section 5.4 of Shumway and Stoffer (3rd edition).
- An order  $p$  **autoregressive conditional heteroskedasticity** model, known as ARCH( $p$ ), has the form

$$Y_n = \epsilon_n \sqrt{V_n},$$

where  $\epsilon_{1:N}$  is white noise and

$$V_n = \alpha_0 + \sum_{j=1}^p \alpha_j Y_{n-j}^2.$$

- If  $\epsilon_{1:N}$  is Gaussian, then  $Y_{1:N}$  is called a Gaussian ARCH( $p$ ). Note, however, that a Gaussian ARCH model is not a Gaussian process, just a process driven by Gaussian noise.
- If  $Y_{1:N}$  is a Gaussian ARCH( $p$ ), then  $Y_{1:N}^2$  is AR( $p$ ), but not Gaussian AR( $p$ ).

# The GARCH model

- The **generalized ARCH** model, known as GARCH(p,q), has the form

$$Y_n = \epsilon_n \sqrt{V_n},$$

where

$$V_n = \alpha_0 + \sum_{j=1}^p \alpha_j Y_{n-j}^2 + \sum_{k=1}^q \beta_k V_{n-k}$$

and  $\epsilon_{1:N}$  is white noise.

- The GARCH(1.1) model is a popular choice (Carpenter and Metcalfe; 2009) which can be fitted using `garch()` in the `tseries` R package.

# Fitting a GARCH model

```
require(tseries)
fit.garch <- garch(sp500.ret.demeaned, grad = "numerical", trace = F)
L.garch <- tseries::logLik.garch(fit.garch)
```

- This 3-parameter model has a maximized log likelihood of  $-4019.7$ .
- It appears that a bug in this version of `tseries` means that simply `logLik(fit.garch)` does not work.
- From `?garch` we learn this is actually a conditional log likelihood given the first  $\max(p, q)$  values.

**Question 14.2.** It is usually inappropriate to present numerical results to five significant figures. Is this appropriate for reporting the log likelihood here? Why?



- We are now in a position to employ the framework of likelihood-based inference for GARCH models. In particular, profile likelihood, likelihood ratio tests, and AIC are available.
- We can readily simulate from a fitted GARCH model, if we want to investigate properties of a fitted model that we don't know how to compute analytically.
- However, GARCH is a black-box model, in the sense that the parameters don't have clear interpretation. We can develop an appropriate GARCH( $p,q$ ) model, and that may be useful for forecasting, but it won't help us understand more about how financial markets work.
- To develop and test a hypothesis that goes beyond the class of GARCH models, it is useful to have the POMP framework available.

# Financial leverage

- It is a fairly well established empirical observation that negative shocks to a stockmarket index are associated with a subsequent increase in volatility.
- This phenomenon is called **leverage**.
- Here, we formally define leverage,  $R_n$  on day  $n$  as the correlation between index return on day  $n - 1$  and the increase in the log volatility from day  $n - 1$  to day  $n$ .
- Models have been proposed which incorporate leverage into the dynamics (Bretó; 2014).
- We present a pomp implementation of @breto14, which models  $R_n$  as a random walk on a transformed scale,

$$R_n = \frac{\exp\{2G_n\} - 1}{\exp\{2G_n\} + 1},$$

where  $\{G_n\}$  is the usual, Gaussian random walk.

# Time-varying parameters

- A special case of this model, with the Gaussian random walk having standard deviation zero, is a fixed leverage model.
- The POMP framework provides a general approach to time-varying parameters. Considering a parameter as a latent, unobserved random process that can progressively change its value over time (following a random walk, or some other stochastic process) leads to a POMP model. The resulting POMP model is usually nonlinear.
- Many real-world systems are non-stationary and could be investigated using models with time-varying parameters.
- Some of the midterm projects discovered examples of this.
- This is one possible thing to explore in your final project.

- Following the notation and model representation in equation (4) of Bretó (2014), we propose a model,

$$Y_n = \exp\{H_n/2\}\epsilon_n, \quad (1)$$

$$H_n = \mu_h(1 - \phi) + \phi H_{n-1} + \beta_{n-1} R_n \exp\{-H_{n-1}/2\} + \omega_n, \quad (2)$$

$$G_n = G_{n-1} + \nu_n, \quad (3)$$

where  $\beta_n = Y_n \sigma_\eta \sqrt{1 - \phi^2}$ ,  $\{\epsilon_n\}$  is an iid  $N(0, 1)$  sequence,  $\{\nu_n\}$  is an iid  $N(0, \sigma_\nu^2)$  sequence, and  $\{\omega_n\}$  is an iid  $N(0, \sigma_\omega^2)$  sequence.

- Here,  $H_n$  is the log volatility.

# Building a POMP model

- A complication is that transitions of the latent variables from  $(G_n, H_n)$  to  $(G_{n+1}, H_{n+1})$  depends on the observable variable  $Y_n$ .
- Formally, therefore, we use the state variable  $X_n = (G_n, H_n, Y_n)$  and model the measurement process as a perfect observation of the  $Y_n$  component of the state space.
- To define a recursive particle filter, we write the filtered particle  $j$  at time  $n - 1$  as

$$X_{n-1,j}^F = (G_{n-1,j}^F, H_{n-1,j}^F, y_{n-1}).$$

- Now we can construct prediction particles at time  $n$ ,

$$(G_{n,j}^P, H_{n,j}^P) \sim f_{G_n, H_n | G_{n-1}, H_{n-1}, Y_{n-1}}(g_n | G_{n-1,j}^F, H_{n-1,j}^F, y_{n-1})$$

with corresponding weight

$$w_{n,j} = f_{Y_n | G_n, H_n}(y_n | G_{n,j}^P, H_{n,j}^P).$$

- Resampling with probability proportional to these weights gives an SMC representation of the filtering distribution at time  $n$ .
- A derivation of this is given as an Appendix.

- We can coerce the basic sequential Monte Carlo algorithm, implemented as `pfilter` in `pomp`, into carrying out this calculation by building two different `pomp` objects, one to do filtering and another to do simulation.
- For the implementation in `pomp`, we proceed to write Csnippet code for the two versions of `rprocess`.

```
sp500_statenames <- c("H", "G", "Y_state")
sp500_rp_names <- c("sigma_nu", "mu_h", "phi", "sigma_eta")
sp500_ivp_names <- c("G_0", "H_0")
sp500_paramnames <- c(sp500_rp_names, sp500_ivp_names)
```

```

rproc1 <- "
  double beta,omega,nu;
  omega = rnorm(0,sigma_eta * sqrt( 1- phi*phi ) * sqrt(1-tanh(G)*t
  nu = rnorm(0, sigma_nu);
  G += nu;
  beta = Y_state * sigma_eta * sqrt( 1- phi*phi );
  H = mu_h*(1 - phi) + phi*H + beta * tanh( G ) * exp(-H/2) + omega
"

rproc2.sim <- "
  Y_state = rnorm( 0,exp(H/2) );
"

rproc2.filt <- "
  Y_state = covaryt;
"

sp500_rproc.sim <- paste(rproc1,rproc2.sim)
sp500_rproc.filt <- paste(rproc1,rproc2.filt)

```

```
sp500_rinit <- "  
  G = G_0;  
  H = H_0;  
  Y_state = rnorm( 0,exp(H/2) );  
"
```

```
sp500_rmeasure <- "  
  y=Y_state;  
"
```

```
sp500_dmeasure <- "  
  lik=dnorm(y,0,exp(H/2),give_log);  
"
```



# Parameter transformations

- For optimization procedures such as iterated filtering, it is convenient to transform parameters to be defined on the whole real line.
- We therefore write transformation functions for  $\sigma_\eta$ ,  $\sigma_\nu$  and  $\phi$ ,

```
sp500_partrans <- parameter_trans(  
  log=c("sigma_eta","sigma_nu"),  
  logit="phi"  
)
```

- We can now build a `pomp` object suitable for filtering, and parameter estimation by iterated filtering or particle MCMC.
- Note that the data are also placed in a covariate slot.
- This is a device to allow the state process evolution to depend on the data. In a POMP model, the latent process evolution depends only on the current latent state. In `pomp`, the consequence of this structure is that `rprocess` doesn't have access to the observation process.
- However, a POMP model does allow for the possibility for the basic elements to depend on arbitrary covariates. In `pomp`, this means `rprocess` has access to a covariate slot.
- The code below gives an example of how to fill the covariate slot and how to use it in `rprocess`.

```

sp500.filt <- pomp(data=data.frame(
  y=sp500.ret.demeaned,time=1:length(sp500.ret.demeaned)),
  statenames=sp500_statenames,
  paramnames=sp500_paramnames,
  times="time",
  t0=0,
  covar=covariate_table(
    time=0:length(sp500.ret.demeaned),
    covaryt=c(0,sp500.ret.demeaned),
    times="time"),
  rmeasure=Csnippet(sp500_rmeasure),
  dmeasure=Csnippet(sp500_dmeasure),
  rprocess=discrete_time(step.fun=Csnippet(sp500_rproc.filt),delta.t=1),
  rinit=Csnippet(sp500_rinit),
  partrans=sp500_partrans
)

```

- Simulating from the model is convenient for developing and testing the code, as well as to investigate a fitted model:

```
params_test <- c(
  sigma_nu = exp(-4.5),
  mu_h = -0.25,
  phi = expit(4),
  sigma_eta = exp(-0.07),
  G_0 = 0,
  H_0=0
)

sim1.sim <- pomp(sp500.filt,
  statenames=sp500_statenames,
  paramnames=sp500_paramnames,
  rprocess=discrete_time(
    step.fun=Csnippet(sp500_rproc.sim),delta.t=1)
)

sim1.sim <- simulate(sim1.sim,seed=1,params=params_test)
```

- Now. to build the filtering object from `sim1.sim`, we need to copy the new simulated data into the covariate slot, and put back the appropriate version of `rprocess`.

```
sim1.filt <- pomp(sim1.sim,  
  covar=covariate_table(  
    time=c(timezero(sim1.sim),time(sim1.sim)),  
    covaryt=c(obs(sim1.sim),NA),  
    times="time"),  
  statenames=sp500_statenames,  
  paramnames=sp500_paramnames,  
  rprocess=discrete_time(  
    step.fun=Csnippet(sp500_rproc.filt),delta.t=1)  
)
```

# Filtering on simulated data

- We check that we can indeed filter and re-estimate parameters successfully for this simulated data.
- As in previous case studies, we set up different run levels:

```
run_level <- 3
sp500_Np <- switch(run_level, 100, 1e3, 2e3)
sp500_Nmif <- switch(run_level, 10, 100, 200)
sp500_Nreps_eval <- switch(run_level, 4, 10, 20)
sp500_Nreps_local <- switch(run_level, 10, 20, 20)
sp500_Nreps_global <- switch(run_level, 10, 20, 100)
```

- We carry out replications in parallel to assess Monte Carlo error.

```
library(doParallel)
registerDoParallel()
library(doRNG)
registerDoRNG(34118892)
```

```
stew(file=sprintf("pf1-%d.rda",run_level),{
  t.pf1 <- system.time(
    pf1 <- foreach(i=1:sp500_Nreps_eval,
      .packages='pomp') %dopar% pfilter(sim1.filt,Np=sp500_Np))
  },seed=493536993,kind="L'Ecuyer")
(L.pf1 <- logmeanexp(sapply(pf1,logLik),se=TRUE))

##                                se
## -3658.4583078      0.1434091
```

- In 4.7 seconds, we obtain a log likelihood estimate of -3658.46 with a Monte standard error of 0.14. Notice that the replications are averaged using the `logmeanexp` function, since the likelihood estimate is unbiased on the natural scale but not the log scale.
- We could test the numerical performance of an iterated filtering likelihood maximization algorithm on simulated data.
- We could also study the statistical performance of maximum likelihood estimators and profile likelihood confidence intervals on simulated data.
- However, here we are going to cut to the chase and start fitting models to data.



# Fitting the stochastic leverage model to S&P500 data

- We are now ready to try out iterated filtering on the S&P500 data. We will use the IF2 algorithm of @ionides15, implemented by `mif2`.

```
sp500_rw.sd_rp <- 0.02
sp500_rw.sd_ivp <- 0.1
sp500_cooling.fraction.50 <- 0.5
sp500_rw.sd <- rw.sd(
  sigma_nu = sp500_rw.sd_rp,
  mu_h     = sp500_rw.sd_rp,
  phi      = sp500_rw.sd_rp,
  sigma_eta = sp500_rw.sd_rp,
  G_0      = ivp(sp500_rw.sd_ivp),
  H_0      = ivp(sp500_rw.sd_ivp)
)
```

```

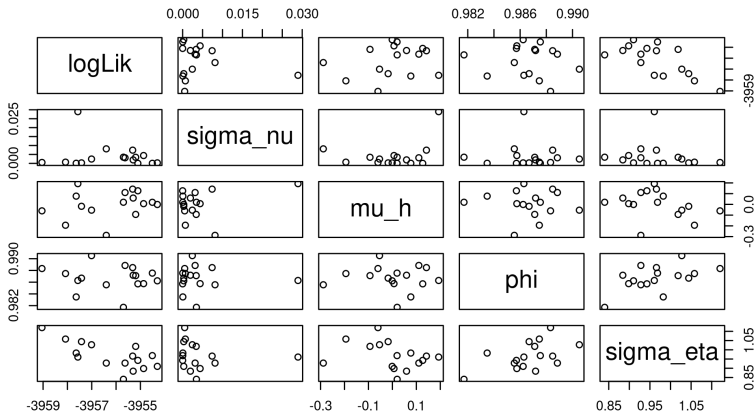
stew(file=sprintf("mif1-%d.rda",run_level),{
  t.if1 <- system.time({
    if1 <- foreach(i=1:sp500_Nreps_local,
      .packages='pomp', .combine=c) %dopar% mif2(sp500.filt,
        params=params_test,
        Np=sp500_Np,
        Nmif=sp500_Nmif,
        cooling.fraction.50=sp500_cooling.fraction.50,
        rw.sd = sp500_rw.sd)
    L.if1 <- foreach(i=1:sp500_Nreps_local,
      .packages='pomp', .combine=rbind) %dopar% logmeanexp(
        replicate(sp500_Nreps_eval, logLik(pfilter(sp500.filt,
          params=coef(if1[[i]]),Np=sp500_Np))), se=TRUE)
  })
},seed=318817883,kind="L'Ecuyer")

r.if1 <- data.frame(logLik=L.if1[,1],logLik_se=L.if1[,2],t(sapply(i
if (run_level>1) write.table(r.if1,file="sp500_params.csv",
  append=TRUE,col.names=FALSE,row.names=FALSE))

```

- This investigation took 25.9 minutes.
- The repeated stochastic maximizations can also show us the geometry of the likelihood surface in a neighborhood of this point estimate:

```
pairs(~logLik+sigma_nu+mu_h+phi+sigma_eta,  
      data=subset(r.if1,logLik>max(logLik)-20))
```



# Likelihood maximization using randomized starting values

- As for our other case studies, carrying out searches starting randomly throughout a large box can lead to reasonable evidence for successful global maximization.
- For our volatility model, a box containing plausible parameter values might be

```
sp500_box <- rbind(  
  sigma_nu=c(0.005,0.05),  
  mu_h      =c(-1,0),  
  phi = c(0.95,0.99),  
  sigma_eta = c(0.5,1),  
  G_0 = c(-2,2),  
  H_0 = c(-1,1)  
)
```

```

stew(file=sprintf("box_eval-%d.rda",run_level),{
  t.box <- system.time({
    if.box <- foreach(i=1:sp500_Nreps_global,
      .packages='pomp',.combine=c) %dopar% mif2(if1[[1]],
        params=apply(sp500_box,1,function(x)runif(1,x)))
    L.box <- foreach(i=1:sp500_Nreps_global,
      .packages='pomp',.combine=rbind) %dopar% {
      logmeanexp(replicate(sp500_Nreps_eval, logLik(pfilter(
        sp500.filt,params=coef(if.box[[i]]),Np=sp500_Np))),
        se=TRUE)
    }
  })
},seed=290860873,kind="L'Ecuyer")

r.box <- data.frame(logLik=L.box[,1],logLik_se=L.box[,2],
  t(sapply(if.box,coef)))
if(run_level>1) write.table(r.box,file="sp500_params.csv",
  append=TRUE,col.names=FALSE,row.names=FALSE)
summary(r.box$logLik,digits=5)

```

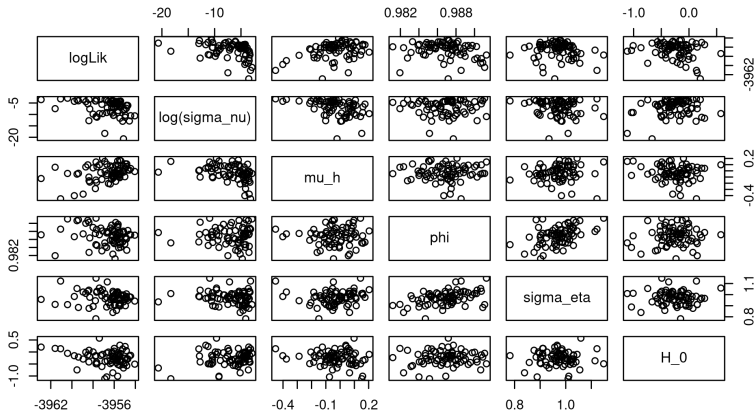
```

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -4009   -3968   -3957   -3965   -3956   -3954

```

- This search took 127.4 minutes.
- The best likelihood found was -3954.1 with a standard error of 0.2.
- We see that optimization attempts from diverse remote starting points can approach our MLE, but do not exceed it. This gives us some reasonable confidence in our MLE.
- Plotting these diverse parameter estimates can help to give a feel for the global geometry of the likelihood surface

```
pairs(~logLik+log(sigma_nu)+mu_h+phi+sigma_eta+H_0,  
data=subset(r.box,logLik>max(logLik)-10))
```



- This preliminary analysis does not show clear evidence for the hypothesis that  $\sigma_\nu > 0$ .
- That is likely because we are studying only a subset of the 1988 to 2012 dataset analyzed by Bretó (2014).
- Also, it might help to refine our inference by computing a likelihood profile over  $\sigma_\nu$ .



# Benchmark likelihoods for alternative models

- To assess the overall success of the model, it is helpful to put the log likelihoods in the context of simpler models, called **benchmarks**.
- Benchmarks provide a complementary approach to residual analysis and the investigation of simulations from the fitted model.
- The GARCH(1,1) model for this dataset has a maximized likelihood of -4019.7 with 3 fitted parameters.
- Our stochastic volatility model, with time-varying leverage, model has a maximized log likelihood of -3954.1 with 6 fitted parameters. AIC favors the stochastic volatility model.
- A model which both fits better and has meaningful interpretation has clear advantages over a simple statistical model.
- The disadvantage of the sophisticated modeling and inference is the extra effort required.

# Can a mechanistic model be helpful if it loses to a non-mechanistic alternative?

- Sometimes, the mechanistic model does not beat simple benchmark models. That does not necessarily mean the mechanistic model is entirely useless.
- We may be able to learn about the system under investigation from what a scientifically interpretable model fails to explain.
- We may be able to use preliminary results to improve the model, and subsequently beat the benchmarks.
- If the mechanistic model fits disastrously compared to the benchmark, our model is probably missing something important. We must reconsider the model, based on clues we might obtain by carrying out residual analysis and looking at simulations from the fitted model.

## Appendix: Proper weighting for a partially plug-and-play algorithm with a perfectly observed state space component

- Suppose a POMP model with latent variable  $X_n = (U_n, V_n)$  and observed variable  $Y_n$  has conditional density  $f_{Y_n|V_n}(y_n|v_n)$  depending only on  $V_n$ .
- The proper weight for an SMC proposal density  $q_n(x_n|x_{n-1})$  is

$$w_n(x_n|x_{n-1}) = \frac{f_{Y_n|X_n}(y_n|x_n)f_{X_n|X_{n-1}}(x_n|x_{n-1})}{q_n(x_n|x_{n-1})}.$$

- Consider the proposal  $q_n(u_n, v_n|x_{n-1}) = f_{U_n|X_{n-1}}(u_n|x_{n-1})g_n(v_n)$ . This is partially plug-and-play, in the sense that the  $U_n$  part of the proposal is drawn from a simulator of the dynamic system.
- Computing the weights, we see that the transition density for the  $U_n$  component cancels out and does not have to be computed, i.e.,

$$\begin{aligned} w_n(x_n|x_{n-1}) &= \frac{f_{Y_n|V_n}(y_n|v_n)f_{U_n|X_{n-1}}(u_n|x_{n-1})f_{V_n|U_n, X_{n-1}}(v_n|u_n, x_{n-1})}{f_{U_n|X_{n-1}}(u_n|x_{n-1})g_n(v_n)} \\ &= \frac{f_{Y_n|V_n}(y_n|v_n)f_{V_n|U_n, X_{n-1}}(v_n|u_n, x_{n-1})}{g_n(v_n)}. \end{aligned}$$

- Now consider the case where the  $V_n$  component of the state space is perfectly observed, i.e.,  $Y_n = V_n$ . In this case,

$$f_{Y_n|V_n}(y_n|v_n) = \delta(y_n - v_n),$$

interpreted as a point mass at  $v_n$  in the discrete case and a singular density at  $v_n$  in the continuous case.

- We can choose  $g_n(v_n)$  to depend on the data, and a natural choice is

$$g_n(v_n) = \delta(y_n - v_n),$$

for which the proper weight is

$$w_n(x_n|x_{n-1}) = f_{Y_n|U_n, X_{n-1}}(y_n|u_n, x_{n-1}).$$

- This is the situation in the context of our case study, with  $U_n = (G_n, H_n)$  and  $V_n = Y_n$ .

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- Produced with R version 3.6.1 and pomp version 2.7.0.1.
- These notes build on previous versions at `ionides.github.io/531w16` and `ionides.github.io/531w18`.
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- Bretó, C. (2014). On idiosyncratic stochasticity of financial leverage effects, *Statistics & Probability Letters* **91**: 20–26.
- Cowpertwait, P. S. and Metcalfe, A. V. (2009). *Introductory time series with R*, Springer Science & Business Media.