



# Stochastic Volatility

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## Agenda

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- Model Introduction
- Foreign Exchange Rates Introduction
- Simulated Example
- Fitting The Model To Data
- Conclusion
- Q/A





$$y_t|h_t \sim \mathcal{N}(0, \exp h_t),$$

$$h_t|h_{t-1}, \mu, \phi, \sigma_\eta \sim \mathcal{N}\left(\mu + \phi(h_{t-1} - \mu), \sigma_\eta^2\right),$$

$$h_0|\mu, \phi, \sigma_\eta \sim \mathcal{N}\left(\mu, \sigma_\eta^2/(1 - \phi^2)\right),$$

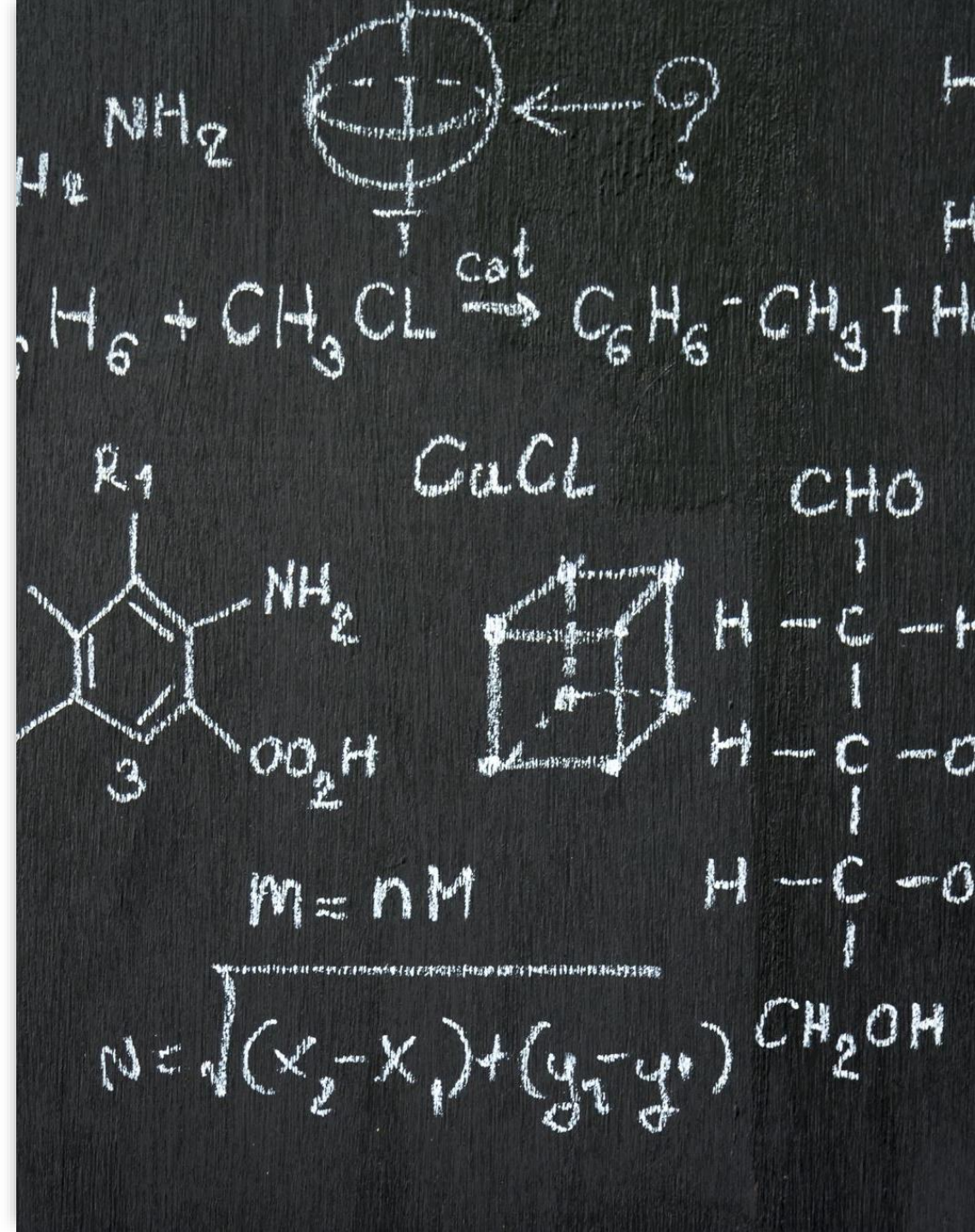
## Model Introduction: Equation

- Random Vector of Returns with Mean Zero:  $y = (y_1, y_2, \dots, y_n)^T$
- Each Observation Has Its Own Variance:  $e^{h_t}$
- Centered Parameterization:
  - $\mathcal{N}(\mu, \sigma_\eta^2)$  denotes the normal distribution with mean  $\mu$  and variance  $\sigma_\eta^2$ .
  - $\theta$  is referred to as the vector of parameters ( $\theta = (\mu, \phi, \sigma_\eta)^T$ )
  - The process  $h = (h_0, h_1, \dots, h_n)$  is an unobserved and interpreted as the log-variance process or time-varying volatility process.



# Model Introduction: Prior Distribution

- The model specifies a prior distribution for the parameter vector  $\theta$  where each component can be independent and follow a different distribution such that  $p(\theta) = p(\mu)p(\phi)p(\sigma\eta)$ .
  - $p(\mu)$  = level of log-variance
  - $p(\phi)$  = persistence of log-variance
  - $p(\sigma\eta)$  = volatility of log-variance
- Each parameter has it's set of hyperparameters:
  - $\mu \sim N(b\mu, B\mu)$
  - $(\phi + 1)/2 \sim B(a0, b0)$
  - $\sigma^2 \eta \sim B\sigma\eta \times \chi^2_{1^2} = G(\frac{1}{2}, 1/2B\sigma\eta)$





# Model Introduction: stochvol

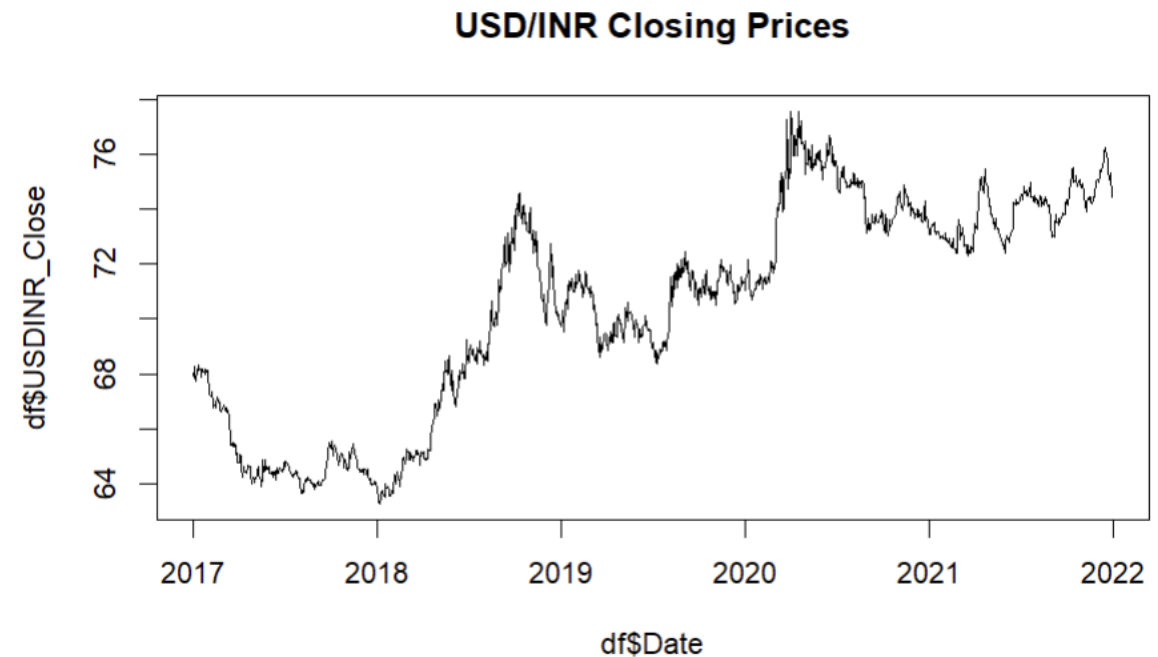
- stochvol is the R package used to forecast future volatilities.
- Key Functions:
  - `svsim(len, mu, phi, sigma)`
  - `svsample(y, priormu, priorphi, priorsigma)`
  - `volplot(x, forecast, dates)`

# Foreign Exchange Rates (daily updates) – Yahoo!

- Daily time series of FX rates from Kaggle for Stochvol
- Focused on USDINR\_Close for univariate time series forecasting

## EDA

- No Null Values
- Duplicates handling by imputing with mean
- Filtered for 2017-2021 data



## Simulated Example

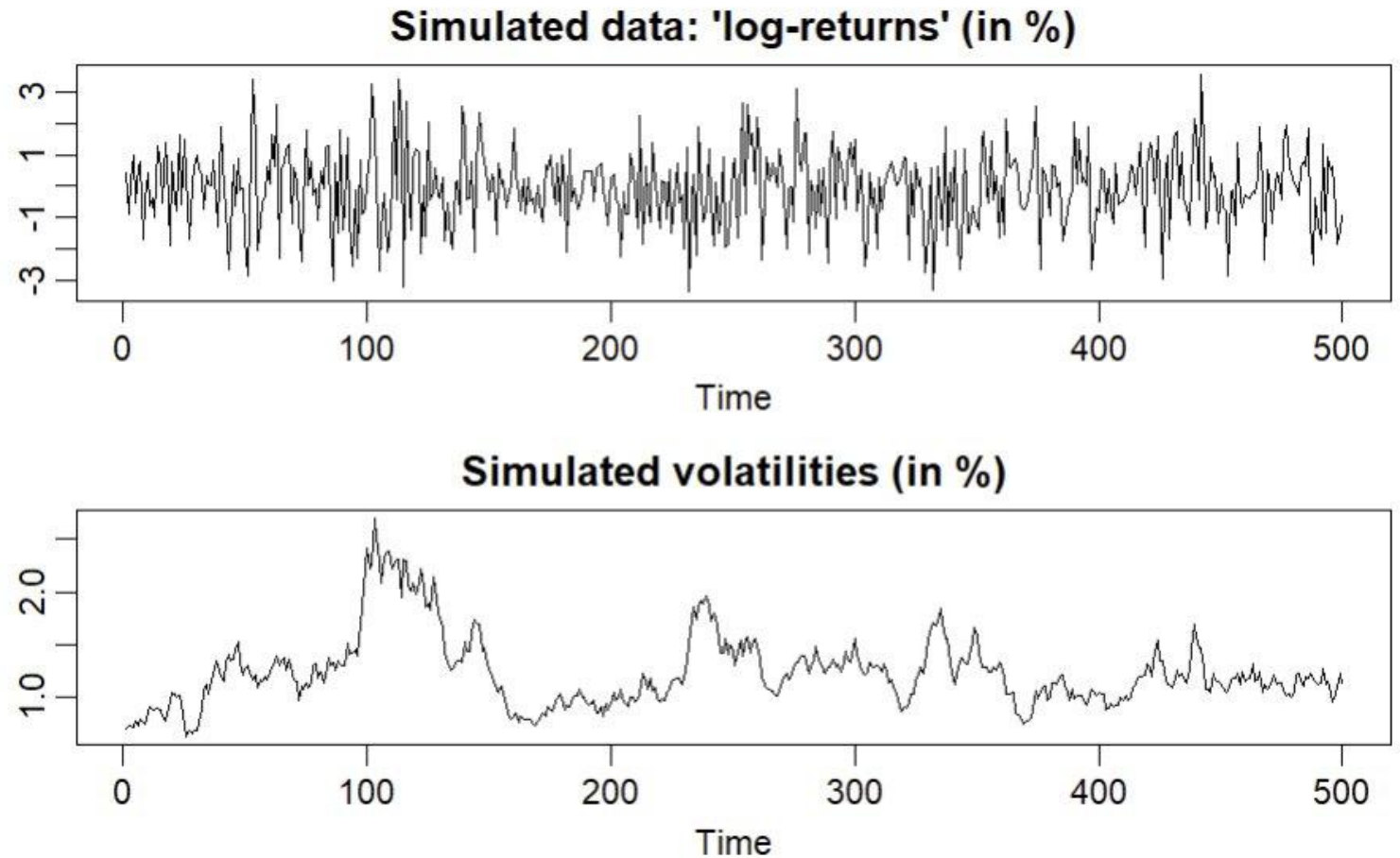
- First, we have simulated a time series data with 500 observations and arbitrary values of mean, phi and sigma using `svsim()` function from `stochvol` package in R.

```
#### {r}
sim <- svsim(500, mu = -9, phi = 0.95, sigma = 0.15)
par(mfrow = c(2, 1))
plot(sim)
####
```



# Simulated Data log returns and volatilities

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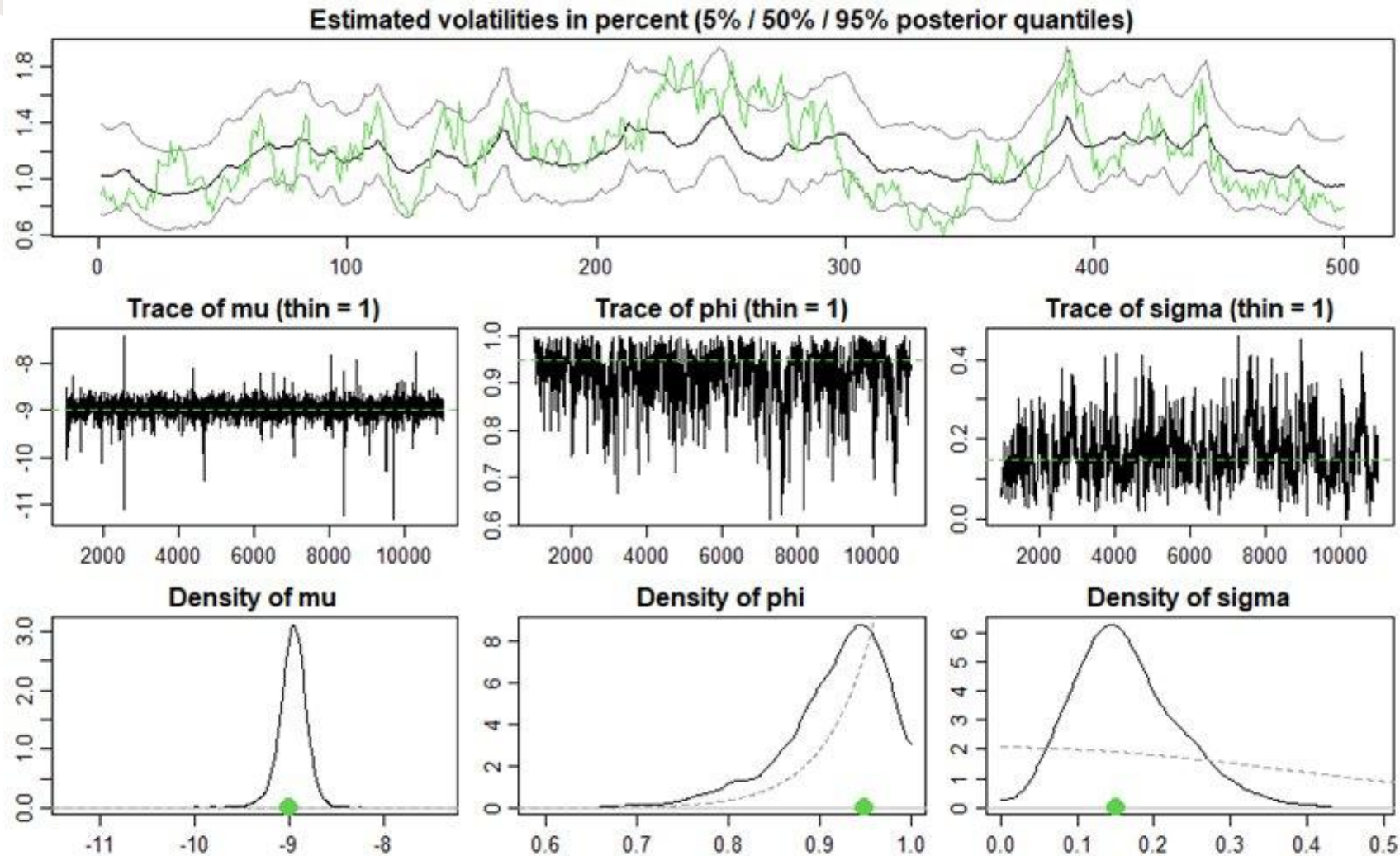


## Simulated Example Contd..

- And then with simulated data, we proceeded to infer the model parameters with the `svsample()` function. We applied a Bayesian approach, incorporating prior beliefs to get posterior draws.

```
```{r}
res1 <- svsample(sim, priormu = c(0, 100), priorphi = c(39, 1),
                 priorsigma = .15)
plot(res1, showobs = FALSE)
```
```

# Trace Plot of Simulated Data





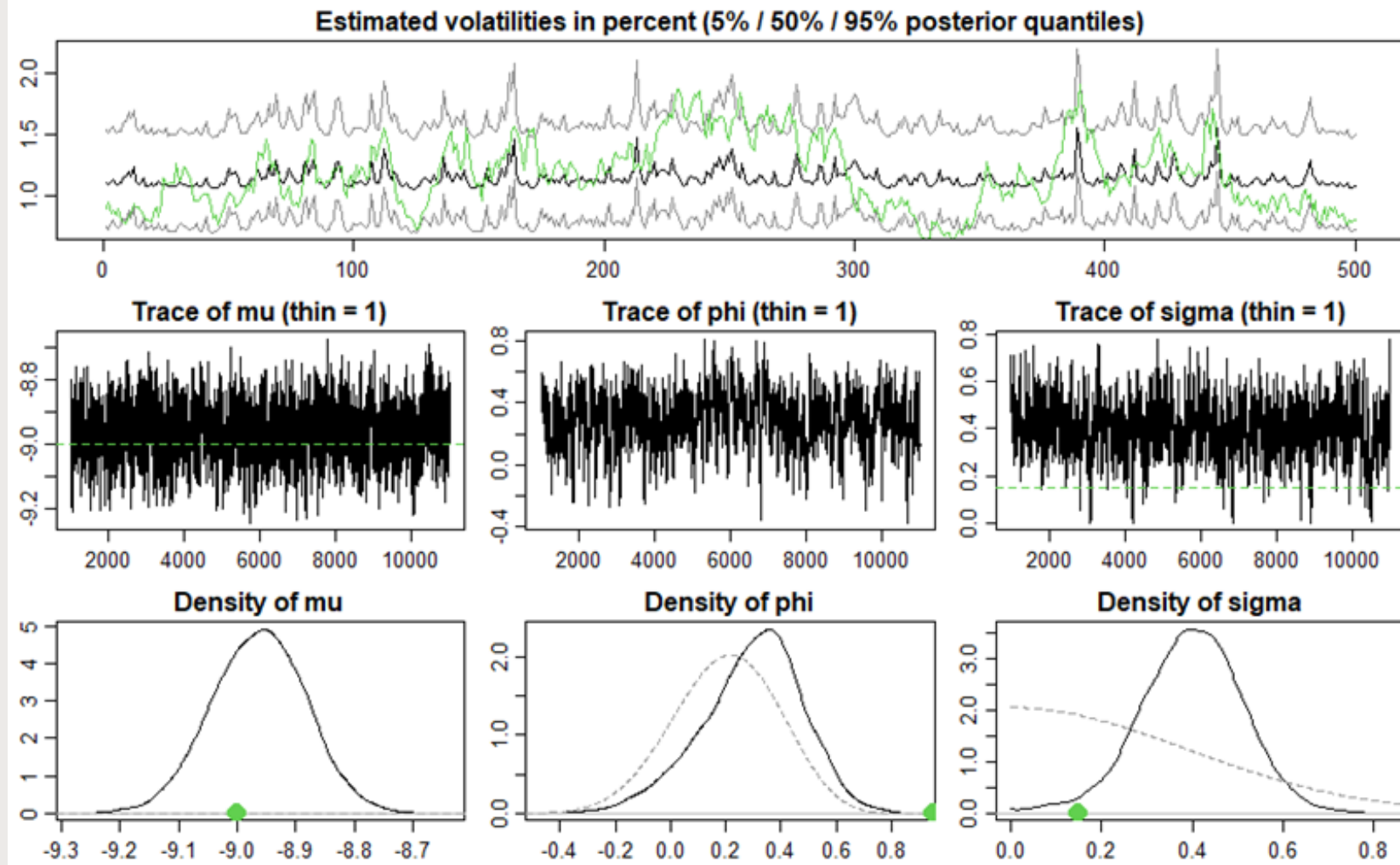
```
```{r}
res2 <- svsample(sim, priormu = c(0, 100), priorphi = c(15, 10),
                priorsigma = .15)
```
```

Simulated  
Example Contd..

- So, we repeated the same plot with the different priorphi now.



# Trace Plot of Simulated Data



```
```{r}
ret = logret(na.omit(df$USDINR_Close), demean = T)
res2 <- svsample(ret, priormu = c(0, 100), priorphi = c(10, 2), priorsigma = .1)
volplot(res2, forecast = 180, dates = df$Date[-1])
```
```

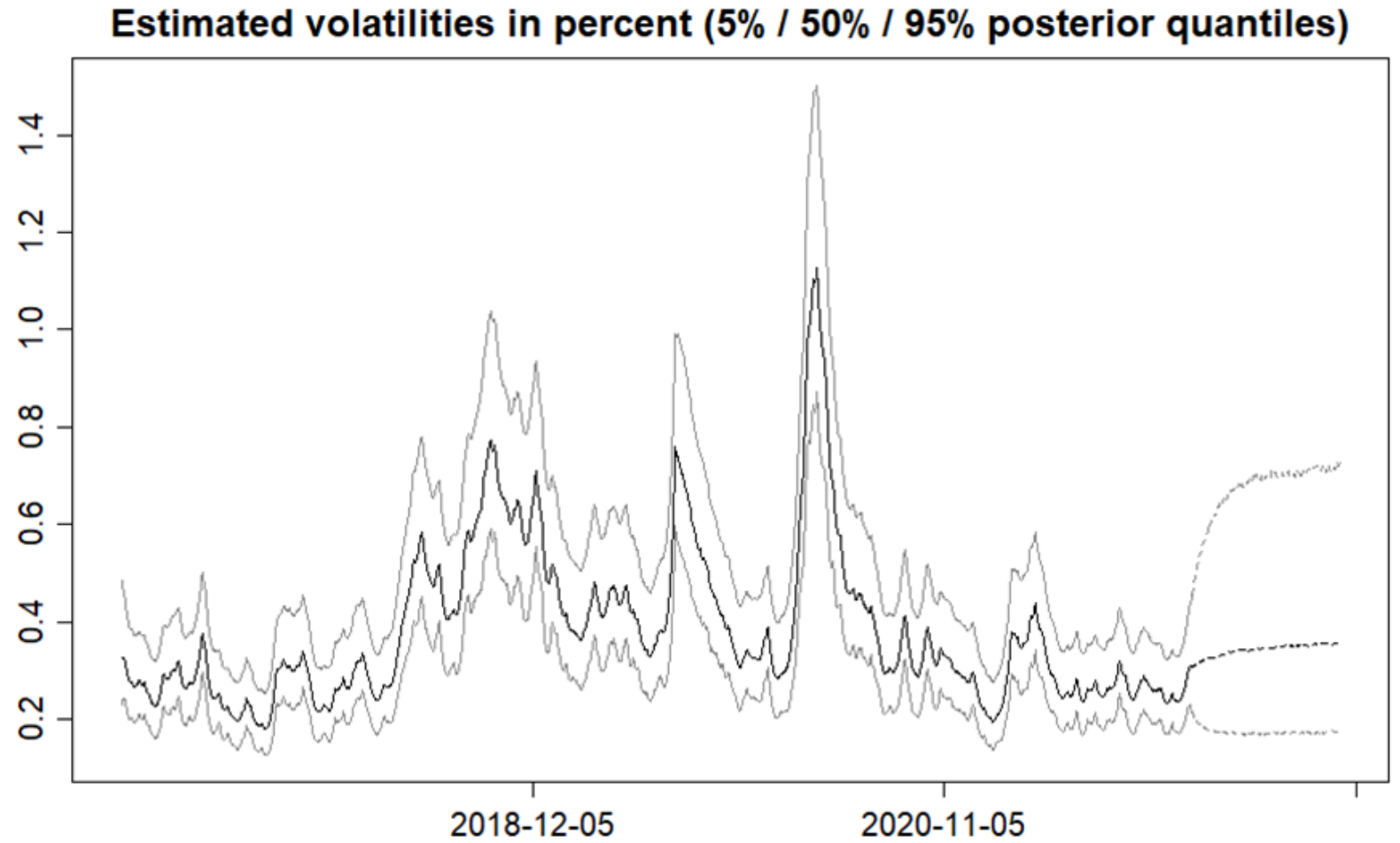
Fitting the  
model to data

- So after careful observation from Bayesian Inference with simulated data, we fitted the model with our original foreign exchange data with high priorPhi and tuning other prior beliefs.



# Volatility Forecast

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## PROS

- Capacity to build model that captures randomness.
- Bayesian Inference for posterior draws using prior knowledge.
- UniVariate and MultiVariate

## CONS

- Requires domain knowledge on priors and model specifications for modelling expertise.
- High significance of hyperparameters on the model.

Conclusion



Thanks



Any Questions