

Draft_Application_Stochastic_Volatility

1 SV models + Literary Review

In section (*fill with the number of the section*) a simple specification of a Stochastic Volatility model was presented and used as the data generating process of a simulated dataset. Denoting by y_t the log returns at time t and by x_t the latent volatility stochastic process, such state-space model was presented as follows,

$$\begin{aligned}y_t|x_t &\sim N(0, e^{x_t}) \\x_t|x_{t-1}, \alpha, \beta, \tau^2 &\sim N(\alpha + \beta x_{t-1}, \tau^2)\end{aligned}$$

This specification - which we will employ in this section on a real dataset - can be deemed as the standard version of the SV model. Throughout the recent decades, several extensions have been proposed, mostly (but not exclusively) in the field of financial econometrics. On the one hand, for simplicity we will stick to the standard version, one that will suffice for the scope of this work on Sequential Monte Carlo methods. On the other hand, it is worth mentioning some of these extensions: indeed, one can rather safely assume that, through their higher degree of sophistication, such extensions might well improve on the performance of our standard SV model in the analyses that will follow.

Stochastic Volatility Models, whose early formulation is commonly attributed to Taylor (1982, 1986), allow to account for time-varying and autoregressive volatility in financial returns, posing themselves as a valid alternative to ARCH (Engle 1982) or GARCH (Bollerslev 1986) models in dealing with non-constant volatility. Kim, Shephard and Chib (1998) define the canonical model for regularly spaced data as

$$\begin{aligned}y_t &= \psi e^{\frac{x_t}{2}} \epsilon_t \\x_{t+1} &= \mu + \beta(x_t - \mu) + \tau \eta_t \\x_1|\sigma, \beta &\sim N\left(\mu, \frac{\sigma^2}{1 - \beta^2}\right) \\\epsilon_t &\sim N(0, 1) \\\eta_t &\sim N(0, 1)\end{aligned}$$

where the log volatility x_t is assumed to follow a stationary process ($|\beta| < 1$), ψ is a constant scaling factor, β is the persistence in the volatility and τ is the

volatility of the log-volatility.¹ Most importantly, ϵ_t and η_t , the Gaussian white noise processes that drive the canonical model, are assumed to be uncorrelated. This latter assumption justifies another definition of this specification, namely “discrete SV model without leverage”.²

In order to accommodate for leverage effects, namely capture the increase in volatility that follows a drop in the returns, the model can be extended as in Omori et al. (2007),

$$\begin{aligned} y_t &= e^{\frac{x_t}{2}} \epsilon_t \\ x_{t+1} &= \mu + \beta(x_t - \mu) + \eta_t \\ \begin{pmatrix} \epsilon_t \\ \eta_t \end{pmatrix} \Big| \rho, \tau &\stackrel{i.i.d.}{\sim} N_2(\mathbf{0}, \Sigma), \quad \Sigma = \begin{pmatrix} 1 & \rho\tau \\ \rho\tau & \tau^2 \end{pmatrix} \end{aligned}$$

where $\rho < 0$ captures the negative correlation. Such specification, which can be referred to as “discrete SV model with leverage”, captures the asymmetric response of volatility to returns of different signs, so that similar specifications are sometimes also deemed as “asymmetric SV models” (e.g. Harvey and Shephard 1996, Mao et al. 2020).

Note that so far the assumptions on ϵ_t and η_t implied that the returns are conditionally normally distributed. The discrete time SV models can also be extended to allow for heavy-tailed or asymmetric conditional returns distributions: symmetric or skewed Student- t , Generalised Hyperbolic (GH) distribution, Generalised Error Distribution (GED) and scale mixtures of normals feature as popular choices (Kim and Stoffer 2008, Nakajima and Omori 2012, Mao et al. 2020). In fact, SV with heavy tailed return distributions were shown to better meet empirical regularities like the leptokurtic distribution of the returns and slowly decaying autocorrelation functions of the squared returns (Liesenfeld and Jung 2000).

Assuming that ϵ_t follows a Student- t distribution, and exploiting the fact that ϵ_t can then be written as $\lambda_t^{-1/2} \zeta_t$, where $\zeta_t \sim N(0, 1)$ and $v\lambda_t \sim \chi_v^2$ (Harvey et al. 1994, Chib et al. 2002), we have the following SV model with both fat tails

¹For identifiability reasons, either $\psi = 1$ or $\mu = 0$. Kim, Shephard and Chib (1998) prefer $\psi = 1$.

²Note that in this review we do not focus on continuous time SV models. In fact, such models have attracted a considerable amount of research in financial econometrics and mathematical finance, especially after Hull and White (1987) considered stochastic volatility for option pricing. Arguably, the most influential model was then proposed for option pricing by Heston (1993), a SV model with leverage effects and square root diffusion driving volatility. Diffusion-based SV models enjoyed increasing popularity, see for example Barndorff-Nielsen and Shephard (2001), or Christoffersen et al. (2010), who investigate alternatives to the entrenched affine square root SV model. Eraker (2004) proposed a SV model with correlated jumps in prices and volatility, extending Heston’s model, while Comte and Renault (1998) extended Hull and White’s model as to feature long memory properties. More recently, Gatheral et al. (2018) further built on Comte and Renault’s fractional SV model to propose the popular “rough volatility models” (see also Friz et al., 2021).

and leverage effect (Jacquier et al., 2004),

$$\begin{aligned}
y_t &= e^{\frac{x_t}{2}} \lambda_t^{-1/2} \zeta_t \\
x_{t+1} &= \alpha + \beta x_t + \eta_t \\
\begin{pmatrix} \zeta_t \\ \eta_t \end{pmatrix} \Big| \rho, \tau &\stackrel{i.i.d.}{\sim} N_2(\mathbf{0}, \begin{pmatrix} 1 & \rho\tau \\ \rho\tau & \tau^2 \end{pmatrix}) \\
v\lambda_t &\sim \chi_v^2
\end{aligned}$$

To capture other elements of the behaviour of financial data, several other extensions have been proposed. For example, SV models have been extended to include conditional heteroskedasticity in the mean returns (Koopman and Hol Uspensky 2002) to capture potential volatility feedback effects, or to feature autoregressive moving average innovations (Chan 2013, Zhang et al. 2020), allowing better goodness of fit and out-of-sample forecasts.^{3 4} The model proposed by Koopman and Hol Uspensky is specified as

$$\begin{aligned}
y_t &= \nu_t + \psi e^{\frac{x_t}{2}} \epsilon_t \\
\nu_t &= a + b y_{t-1} + d \psi^2 e^{x_t} \\
x_t &= \beta x_{t-1} + \tau \eta_t \\
\begin{pmatrix} \epsilon_t \\ \eta_t \end{pmatrix} &\stackrel{i.i.d.}{\sim} N_2\left(\mathbf{0}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right)
\end{aligned}$$

while the state space representation of the ARMA(p,q)-SV framework, as in Zhang et al. (2020), reads

$$\begin{aligned}
y_t &= \nu_t + \gamma_t \\
\gamma_t &= \phi_1 \gamma_{t-1} + \dots + \phi_p \gamma_{t-p} + u_t + \varphi_1 u_{t-1} + \dots + \varphi_q u_{t-q} \\
u_t | x_t &\sim N(0, e^{x_t}) \\
x_t &= x_{t-1} + \eta_t \\
\eta_t | \tau &\sim N(0, \tau^2)
\end{aligned}$$

where the error terms u_t and η_t are independent across all leads and lags, while ν_t follows an unspecified time-varying process.

³Dimitrakopoulos and Kolossiatis (2020) note that "the moving average component, the leverage effect and the conditional heteroscedasticity in mean have been considered separately in the stochastic volatility literature" and provide two specifications, one featuring an MA component and leverage effects, the other an MA component and conditional heteroskedasticity in mean.

⁴Other extensions, though ones for which we do not report the specifications, feature modelling the latent volatility process x_t as an ARFIMA process (Long Memory Stochastic Volatility model, Breidt et al. 1998) or as governed by a first-order Markov process (Markov Switching Stochastic Volatility model, So et al. 1998). Recently, Luo et al. (2018) incorporated neural networks in the stochastic volatility model (Neural Stochastic Volatility Model), while Xu and Chen (2021) employ deep learning models (Deep Stochastic Volatility Model).

Interestingly enough, the path along which the SV models evolved coincides with that suggested by optimal portfolio findings. Johannes, Korteweg and Polson (2014) found that, in order to generate statistically significant portfolio improvements in a Bayesian learning problem, the model employed by the investor should incorporate both time-varying expected returns and stochastic volatility: indeed, either of these features alone did not lead to statistically significant gains with respect to employing models with time-constant expected returns and volatility.⁵

Finally, before moving to the application of Sequential Monte Carlo techniques to a SV model, we conclude by going through some references for the Bayesian analysis proposed for such models. Starting from the seminal work of Jacquier et al. (1994), the use of MCMC methods has become increasingly popular for parameter estimation and smoothing exercises in SV models (e.g. Kastner 2019, presenting the R package *stochvol* for Bayesian parameter estimation, and Chopin and Papaspiliopoulos 2020, who use MCMC to sample from the smoothing distribution of a SV model). As regards filtering exercises, the adoption of particle filters was rather rapid:⁶ indeed, latent volatilities in Kim et al. (1998) were already filtered by employing the particle filter suggested in Pitt and Shephard (1999), paving the way for subsequent applications (*inter alia*) in Chib et al. (2006), Omori et al. (2007), Kim and Stoffer (2008) and Nakajima and Omori (2012).

2 Data

As previously mentioned, we will analyze the behaviour of the described filtering tools associated to a simple stochastic volatility model. In particular, we are evaluating the performance of such model on real data. For the observable process, namely financial returns in the SV model, we consider the continuously compounded daily returns (also called logarithmic returns) of three indices, S&P500, DOW JONES and STOXX50, in a time interval from June 1st, 2017 to May 30th, 2021. From these, we estimate the daily volatility, as computed by the model.

The indices have been selected as representatives of the global economic trends in the US and EU markets. Specifically, the S&P500 is a market-capitalization-weighted stock-price index tracing the performance of the 500

⁵One could then argue that caution is needed when employing basic specifications of stochastic volatility models. For instance, Poon and Granger (2005) found that historical volatility and ARCH models both achieved better volatility forecasting performance than SV models. Similarly, Allen and McAleer (2020, see also Allen, 2020) found that, using realised volatility as benchmark, neither the canonical SV model or a GARCH(1,1) specification could forecast better than a simple form of historical volatility model.

⁶Actually, SV models are now often used as straightforward applications of particle filters on non-linear state space models, see for example Andrieu et al. (2010), Douc et al. (2014) or Chopin and Papaspiliopoulos (2020).

largest companies listed on US stock exchanges (NYSE and Nasdaq Exchange). The DOW JONES, instead, is a price-weighted stock-market index and accounts for the 30 major companies listed on US stock exchanges, characterized for being “blue-chip”. Also the EURO STOXX 50 follows blue-chip stocks representing leading firms in regions of the Eurozone.

The three plots below represent the time series of the log returns calculated for the three indices during our period of interest. In particular, each series is a sequence of daily observations representing the logarithm of the ratio between the closing price of the index for a given day and the closing price of the day before.

At a first visual inspection, we can see a common behaviour in the volatility of all three indices. Especially, it is worth pointing out the similarity between the pattern of DJI and that of S&P500 (especially in terms of peaks), which both differ from the STOXX50E, presumably because the first two describe the US stock market, while the last index describes the European one. For example, a difference that can be seen by having a glance at the plots is that the US indices log returns displays differences in fluctuation magnitude across different periods that are more marked than for the EU index, for which log returns display, in general, wider fluctuations. Anyways, what stands out the most in all three plots is the very wide fluctuations present from February - March 2020 to around September 2020, which, very intuitively, are connected with the Covid-19 Pandemic Crisis.

As regards the series that we will employ in section (*fill with the number of the section*), namely the series of realised volatilities which we will employ as a proxy for the true latent volatilities, the data were retrieved from the Oxford-Man Institute’s Realized Library, which provides several different daily non-parametric measures of past volatility. We consider a proper rescaling of the *rv5* series, *i.e.* model-free daily volatility estimates based on 5 min intraday return intervals. Also in this case, the chosen interval spanned from June 1st, 2017 to May 30th, 2021.

Bibliography

Allen, D. E., & McAleer, M. (2020). Do we need stochastic volatility and generalised autoregressive conditional heteroscedasticity? Comparing squared end-of-day returns on FTSE. *Risks*, 8(1), 12.

Allen, D. E. (2020). Stochastic Volatility and GARCH: Do Squared End-of-Day Returns Provide Similar Information?. *Journal of Risk and Financial Management*, 13(9), 202.

Andrieu, C., Doucet, A., & Holenstein, R. (2010). Particle markov chain monte

carlo methods. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 72(3), 269-342.

Barndorff-Nielsen, O. E., & Shephard, N. (2001). Non-Gaussian Ornstein–Uhlenbeck-based models and some of their uses in financial economics. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 63(2), 167-241.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3), 307-327.

Breidt, F. J., Crato, N., & De Lima, P. (1998). The detection and estimation of long memory in stochastic volatility. *Journal of econometrics*, 83(1-2), 325-348.

Chan, J. C. (2013). Moving average stochastic volatility models with application to inflation forecast. *Journal of Econometrics*, 176(2), 162-172.

Chib, S., Nardari, F., & Shephard, N. (2002). Markov chain Monte Carlo methods for stochastic volatility models. *Journal of Econometrics*, 108(2), 281-316.

Chib, S., Nardari, F., & Shephard, N. (2006). Analysis of high dimensional multivariate stochastic volatility models. *Journal of Econometrics*, 134(2), 341-371.

Chopin, N., & Papaspiliopoulos, O. (2020). *An introduction to sequential Monte Carlo* (Vol. 4). Springer.

Comte, F., & Renault, E. (1998). Long memory in continuous-time stochastic volatility models. *Mathematical finance*, 8(4), 291-323.

Christoffersen, P., Jacobs, K., & Mimouni, K. (2010). Volatility dynamics for the S&P500: Evidence from realized volatility, daily returns, and option prices. *The Review of Financial Studies*, 23(8), 3141-3189.

Dimitrakopoulos, S., & Kolossiatis, M. (2020). Bayesian analysis of moving average stochastic volatility models: modeling in-mean effects and leverage for financial time series. *Econometric Reviews*, 39(4), 319-343.

Douc, R., Moulines, E., & Stoffer, D. (2014). *Nonlinear time series: Theory,*

methods and applications with R examples. CRC press.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the econometric society*, 987-1007.

Eraker, B. (2004). Do stock prices and volatility jump? Reconciling evidence from spot and option prices. *The Journal of Finance*, 59(3), 1367-1403.

Friz, P. K., Gassiat, P., & Pigato, P. (2021). Precise asymptotics: robust stochastic volatility models. *The Annals of Applied Probability*, 31(2), 896-940.

Gatheral, J., Jaisson, T., & Rosenbaum, M. (2018). Volatility is rough. *Quantitative finance*, 18(6), 933-949.

Harvey, A. C., & Shephard, N. (1996). Estimation of an asymmetric stochastic volatility model for asset returns. *Journal of Business & Economic Statistics*, 14(4), 429-434.

Harvey, A., Ruiz, E., & Shephard, N. (1994). Multivariate stochastic variance models. *The Review of Economic Studies*, 61(2), 247-264.

Heber, Gerd, Asger Lunde, Neil Shephard and Kevin Sheppard (2009). Oxford-Man Institute's realized library. Oxford-Man Institute, University of Oxford, version 0.3. Available at: <https://realized.oxford-man.ox.ac.uk/>.

Heston, S. L. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *The review of financial studies*, 6(2), 327-343.

Hull, J., & White, A. (1987). The pricing of options on assets with stochastic volatilities. *The journal of finance*, 42(2), 281-300.

Jacquier, E., Polson, N. G., & Rossi, P. (1994). Bayesian analysis of stochastic volatility models. *Journal of Business and Economic Statistics*, 12(4), 371-389.

Jacquier, E., Polson, N. G., & Rossi, P. E. (2004). Bayesian analysis of stochastic volatility models with fat-tails and correlated errors. *Journal of Econometrics*, 122(1), 185-212.

- Johannes, M., Korteweg, A., & Polson, N. (2014). Sequential learning, predictability, and optimal portfolio returns. *The Journal of Finance*, 69(2), 611-644.
- Kastner, G. (2019). Dealing with stochastic volatility in time series using the R package stochvol. arXiv preprint arXiv:1906.12134.
- Kim, S., Shephard, N., & Chib, S. (1998). Stochastic volatility: likelihood inference and comparison with ARCH models. *The review of economic studies*, 65(3), 361-393.
- Kim, J., & Stoffer, D. S. (2008). Fitting stochastic volatility models in the presence of irregular sampling via particle methods and the EM algorithm. *Journal of time series analysis*, 29(5), 811-833.
- Koopman, S. J., & Hol Uspensky, E. (2002). The stochastic volatility in mean model: empirical evidence from international stock markets. *Journal of applied Econometrics*, 17(6), 667-689.
- Liesenfeld, R., & Jung, R. C. (2000). Stochastic volatility models: conditional normality versus heavy-tailed distributions. *Journal of applied Econometrics*, 15(2), 137-160.
- Luo, R., Zhang, W., Xu, X., & Wang, J. (2018, April). A neural stochastic volatility model. In *Thirty-second AAAI conference on artificial intelligence*.
- Mao, X., Czellar, V., Ruiz, E., & Veiga, H. (2020). Asymmetric stochastic volatility models: Properties and particle filter-based simulated maximum likelihood estimation. *Econometrics and Statistics*, 13, 84-105.
- Nakajima, J., & Omori, Y. (2012). Stochastic volatility model with leverage and asymmetrically heavy-tailed error using GH skew Student's t-distribution. *Computational Statistics & Data Analysis*, 56(11), 3690-3704.
- Omori, Y., Chib, S., Shephard, N., & Nakajima, J. (2007). Stochastic volatility with leverage: Fast and efficient likelihood inference. *Journal of Econometrics*, 140(2), 425-449.
- Pitt, M. K., & Shephard, N. (1999). Filtering via simulation: Auxiliary particle filters. *Journal of the American statistical association*, 94(446), 590-599.

Poon, S. H., & Granger, C. (2005). Practical issues in forecasting volatility. *Financial analysts journal*, 61(1), 45-56.

So, M. E. P., Lam, K., & Li, W. K. (1998). A stochastic volatility model with Markov switching. *Journal of Business & Economic Statistics*, 16(2), 244-253.

Xu, X., & Chen, Y. (2021). Deep Stochastic Volatility Model. arXiv preprint arXiv:2102.12658.

Zhang, B., Chan, J. C., & Cross, J. L. (2020). Stochastic volatility models with ARMA innovations: An application to G7 inflation forecasts. *International Journal of Forecasting*, 36(4), 1318-1328.