Inference and Computation for Stochastic Volatility Models related to Option Pricing

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Abstract
This paper reviews the Black-Scholes theory and studies a number of extensions. In particular, we focus on logarithmic stochastic volatility (SV) models and square-root SV models with jumps. Inference on those models, using Markov chain Monte Carlo methods, is summarized. Generalized Black-Scholes (GBS) pricing formulas are presented as an important step in calibration of SV models using both return and option data. A Gaussian approximation scheme is proposed to significantly reduce the dimensionality of certain stochastic integrals involved in the GBS formulas, which shows a great promise in improving computational efficiency.

1 Introduction

The celebrated Black-Scholes (BS) theory [2] in financial economics lays a foundation for three important aspects: a probability model, an option pricing formula and a statistical inference procedure for volatilities. Although the past few decades have seen a great deal of progress in various extensions of the BS theory, a brief recap still provides a clear theme for our review and ongoing research.

• The geometric Brownian motion [BS Stochastic Differential Equation (SDE)]:

\[ \frac{dS_t}{S_t} = \mu \, dt + \sigma \, dW_t, \quad (1.1) \]

where \( S_t \) represents a stock price at time \( t \), the constants \( \mu \) and \( \sigma \) represent the expected rate of return and volatility respectively,
and \( \{ W_t \} \) is a standard Wiener process. The BS model consists of only two primary assets, i.e. the stock \( \{ S_t \} \) and a bank account \( \{ B_t \} \) with constant interest rate \( r \):

\[
B_t = B_0 e^{rt}. 
\]  

(1.2)

- **Pricing formulas for derivative securities**

Let \( t \leq T \). A contingent claim \( g(S_T) \) written on the stock price \( S_T \) can be given a time \( t \) “fair” price \( P(t, S_t) \) in two equivalent ways. The analytical approach yields \( P(t, s), t \in [0, T], s \geq 0 \) as the solution to the boundary value problem

\[
\frac{\partial P(t, s)}{\partial t} + r s \frac{\partial P(t, s)}{\partial s} + \frac{1}{2} s^2 \sigma^2 \frac{\partial^2 P(t, s)}{\partial s^2} - r P(t, s) = 0
\]

with \( P(T, s) = g(s) \).  

(1.3)

The probabilistic approach expresses \( P(t, S_t) \) as a conditional expectation given \( F_t \) under a risk-neutral probability measure \( Q \):

\[
P(t, S_t) = E^Q \left[ e^{-r(T-t)} g(S_T) | F_t \right],
\]

(1.4)

where \( Q \) is defined through its Radon-Nikodym derivative with respect to the real-world probability measure \( P \) (also referred to as the physical measure or objective measure) that governs the BS SDE (1.1)

\[
\frac{dQ}{dP} \big|_{F_t} = \exp \left[ -\frac{\mu - r}{\sigma} W_t - \frac{1}{2} \left( \frac{\mu - r}{\sigma} \right)^2 \right];
\]

(1.5)

and \( \{ F_t, t \geq 0 \} \) is the filtration generated by the Wiener process \( \{ W_t \} \). Note in this case, the information up to time \( t \), i.e. \( F_t \), is summarized by the current state \( S_t \). In the special case of an European call option, we have \( g(S_T) = \max\{ S_T - K, 0 \} \), where the positive constant \( K \) is called the strike price at the maturity time \( T \). The time \( t \) price \( P(t, S_t) \), denoted by a function \( C^{BS}(S_t, \sigma^2, r, K, T - t) \), enjoys a closed form solution by using either approach:

\[
C^{BS}(S_t, \sigma^2, r, K, T - t) = S_t \Phi(d_1) - e^{-r(T-t)} K \Phi(d_2),
\]

(1.6)

where \( \Phi(\cdot) \) is the cdf of \( N(0,1) \) distribution, and

\[
d_1 = \frac{1}{\sigma \sqrt{T - t}} \left[ \log \frac{S_t}{K} + (r + \sigma^2/2)(T - t) \right],
\]

(1.7)

\[
d_2 = d_1 - \sigma \sqrt{T - t}.
\]

(1.8)
Remarks:

(i) The equivalence between (1.3) and (1.4) was established via the Feynman-Kac formula (cf. [46], [56]). In what follows, we will follow the probabilistic approach and refer to [23] for the analytical approach.

(ii) The fundamental risk-neutral valuation principle for pricing derivatives originated from the seminal papers of [2], [53]. A rigorous probability framework was due to [35] and [36]. Several excellent books were written in mathematical finance at different levels, such as [38], [1], [13], [15], to name a few. For a systematic treatment of stochastic calculus, including the Girsanov theorem, see [46] and [56].

• Estimation of volatilities

To put the pricing formula (1.6) in action, numerical values of \( t, T, S_t, K, r, \sigma \) need to be specified. Among them, \( t, T, S_t, K \) are known or observable; while \( r \) and \( \sigma \) require more attention. In a simple case, it may not be hard to estimate \( r \). However, some other situations go beyond the scope of this work, in which \( r \) is not only changing over time, but also considered to be stochastic. This is a rich research area of interest rate modeling. We refer to [44] and [58] for more detailed accounts.

Focusing on estimation of volatility \( \sigma \), there are two substantially different methods:

(i) Historical volatility

This is just to estimate a population variance by a sample variance. Suppose we observe \( S_{t_0}, S_{t_1}, ..., S_{t_n} \) at \( t_0 < t_1 < \cdots < t_n \). Let

\[
R_i = \log S_{t_i} - \log S_{t_{i-1}}
\]

be the return incurred in \((t_{i-1}, t_i)\). Assume \( t_i - t_{i-1} = \Delta, \forall i = 1, ..., n \). Then \( R_1, ..., R_n \) are iid normal random variables with mean \((\mu - \sigma^2/2)\Delta\) and variance \(\sigma^2\Delta\). Naturally, a historical volatility estimate for \( \sigma \) is given by

\[
\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{n} (R_i - \bar{R})^2}{(n-1)\Delta}} \quad \text{with} \quad \bar{R} = \frac{1}{n} \sum_{i=1}^{n} R_i.
\]

Note that a common sense expression of return \( R_i \), given by \( (S_{t_i} - S_{t_{i-1}})/S_{t_{i-1}} \), is a first-order approximation of the definition in (1.9) with small \( \Delta \).
(ii) **Implied volatility**

An argument against the use of historical volatility is based on (a) volatility is not constant, but changes over time; (b) historical volatility only gives an estimate for the volatility over a past time period, but what is more relevant concerns the *market expectation* of the volatility in the near future. More specifically, if we want to determine the time $t$ price of an option with maturity time $T$, then the market expectation of the volatility in the life time $(t, T]$ of the option should be incorporated consistently in the volatility estimation. One way to realize the market expectation is the following: Note that $C^{BS}(\cdot)$ in (1.6) is an invertible map of $\sigma$ with other variables held fixed. Get a market price $c_0$ from a “benchmark” call option written on the same stock $\{S_t\}$. Then find $\sigma$ by inverting $C^{BS}(\cdot)$ from $c_0$. Such a value of $\sigma$ is called the implied volatility.

Mathematically, implied volatility does not follow a traditional statistical inference guideline as historical volatility does. It is similar to a dynamical programming strategy where at each step a conditional expectation of future reward given the current state is compared to the instantaneous reward, in order to determine an optimal strategy. The idea is far reaching. We will revisit it in later sections when studying calibration of stochastic volatility (SV) models using both return and option data.

## 2 SV Models and Markov Chain Monte Carlo (MCMC) Calibration

### 2.1 ARCH/GARCH models

Several drawbacks of the BS model were widely recognized, particularly the constant volatility $\sigma$. Since then, many efforts have been made to model volatility as a time-varying stochastic quantity. Along this line, the ARCH/GARCH (*autoregressive conditional heteroscedasticity/ generalized ~*) family is an important development in modeling volatility.

**ARCH($p$):**

$$X_t = \sigma_t \epsilon_t,$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i X_{t-i}^2,$$

where $\epsilon_1, \epsilon_2, \ldots$ are iid $N(0,1)$ random variables, and $\alpha_0 > 0, \alpha_i \geq 0$, $i = 1, \ldots, p$ are parameters. Note that $X_t$ is considered to be the return
in \((t-1, t]\), thus \(\sigma_{t}^{2} = E(X_{t}^{2}|\mathcal{F}_{t-1}) = Var(X_{t}|\mathcal{F}_{t-1})\) is the conditional variance or second moment of \(X_{t}\). In particular, \(\alpha_{0}\) represents the long-run volatility.

**GARCH\((p, q)\):**

\[
X_{t} = \sigma_{t} \epsilon_{t},
\]

\[
\sigma_{t}^{2} = \alpha_{0} + \sum_{i=1}^{p} \alpha_{i} X_{t-i}^{2} + \sum_{j=1}^{q} \beta_{j} \sigma_{t-j}^{2}
\]

(2.4)

with the additional parameters \(\beta_{j} \geq 0, j = 1, \ldots, q\). Apparently, \(ARCH(p)\) is a special case of \(GARCH(p, q)\) with \(q = 0\).

Since the original works of [18] and [3], ARCH/GARCH models have enjoyed great popularity. The likelihood functions have simple forms which make inference and prediction very convenient. There are many extended versions in the ARCH/GARCH family, among which [55] is noteworthy in relating GARCH and SV models. The books [22] and [65] also devote a couple of chapters to ARCH/GARCH models.

In ARCH/GARCH models, the sequence \(\{\sigma_{t}^{2}\}\) represents time-varying volatilities, and they are stochastic. However, the term “stochastic volatility” usually is not meant to include ARCH/GARCH models, but reserved for a different model class we are to discuss. The main distinction is that there is a single source of uncertainty from asset returns, and each \(\sigma_{t}^{2}\) is defined as a deterministic function of returns. In contrast, volatility in a SV model is defined as a stochastic process generated from an uncertainty source (often termed “factor”) in addition to that for asset returns. Sometimes more than one factors are introduced. The necessity for SV models lies in the modeling flexibility. Certain interesting behaviors in financial markets, such as the famous “volatility smile”, can be modeled by SV models, but not by ARCH/GARCH models. Here is a brief account: A call option is said to be “in the money” (ITM) at time \(t\) if \(S_{t} > K\) and “out of the money” (OTM) if \(S_{t} < K\). For put option with the contingent claim \(g(S_{T}) = \max\{K - S_{T}, 0\}\), the inequalities are reversed. If \(S_{t} = K\), the option is said to be “at the money” (ATM). Having observed the market prices of a number of European call options with the same maturity date \(T\) on the same underlying stock, the plot of implied volatility as a function of strike price \(K\) should be a horizontal straight line, if the assumption of constant volatility \(\sigma\) in the BS model is correct. Contrary to this, empirical evidences show that options far OTM or deep ITM are traded at higher implied volatilities than ATM options. The graph of the observed implied volatility function often looks like a smile shape, which gives rise to the term “volatility smile".

stochastic volatility models
2.2 SV models

Let $S = \{S_t\}$ denote a continuous-time process for an asset price under a physical measure $P$. The following SV model was considered in [6]:

\begin{align*}
    y_t &= \log S_t, \quad (2.5) \\
    dy_t &= \mu \, dt + e^{h_t/2} \left( \sqrt{1 - \rho^2} \, dW_{1t} + \rho \, dW_{2t} \right), \quad (2.6) \\
    dh_t &= (\alpha + \beta h_t) \, dt + \sigma \, dW_{2t}, \quad (2.7)
\end{align*}

where $W = \{W_t\} = \{(W_{1t}, W_{2t})\}$ is a standard 2D Wiener process defined on a probability space $(\Omega, \mathcal{F}, P)$. Let $\{\mathcal{F}_t : 0 \leq t \leq T\}$ denote the filtration generated by $W$. The parameter $\rho$ is the correlation between the asset return and the volatility factor.

This model consists of an observation equation (2.6) and a state evolution equation (2.7). It can be viewed as an example in state-space models or in filtering problems. The logarithmic volatility formulation guarantees that the resulting volatility $e^{h_t/2}$ is always positive. Although other forms of volatility evolution are available, log-SV models were introduced earlier and considered in [10], [64], [62], [51], [25], [41], [14], [31], [60], [61], [47], [23], [30], [9], [42], and [8].

To price an option on $S$, a standard approach is to assume no arbitrage and specify two risk premia processes. See [57] and [20]. In doing so, the SDEs describing the returns process have the same functional form under the physical measure $P$ and the risk neutral measure $Q$.

These two risk premia processes are

\begin{align*}
    \tilde{\nu}_t &= \nu_1 + \nu_2 \, h_t, \quad (2.8) \\
    \lambda_t &= \frac{1}{\sqrt{1 - \rho^2}} \left\{ e^{-h_t/2} \left[ (\mu - r) + e^{h_t/2} \right] - \rho \, \tilde{\nu}_t \right\}, \quad (2.9)
\end{align*}

where $r$ is the short rate, presumed constant. Assume the $L_2$ norms of the risk premia are bounded and $E \left[ \exp \left( \int_0^T (\lambda_u^2 + \tilde{\nu}_u^2) \, du \right) \right] < \infty$. As shown in [35] and [36], there exists an equivalent martingale measure $Q$ such that the time $t$ price of a contingent claim $g(S_{t'})$ (with $t' > t$) can be expressed as the conditional expectation $E^Q[e^{-r(t'-t)}g(S_{t'}) | \mathcal{F}_t]$. For the purpose of computing the expectation, the measure $Q$ can be expressed either as a Radon-Nikodým derivative with respect to the measure $P$,

\[
\left. \frac{dQ}{dP} \right|_{\mathcal{F}_t} = \exp \left( -\int_0^t \lambda_u \, dW_{1u} - \int_0^t \tilde{\nu}_u \, dW_{2u} - \frac{1}{2} \int_0^t \lambda_u^2 \, du - \frac{1}{2} \int_0^t \tilde{\nu}_u^2 \, du \right), \quad (2.10)
\]
or as a system of SDEs in terms of the Wiener processes

\[ W^Q_{1t} = W^Q_{1t} + \int_0^t \lambda u \, du, \]  
\[ W^Q_{2t} = W^Q_{2t} + \int_0^t \tilde{\nu}_u \, du, \]

which is

\[ \frac{dS_t}{S_t} = r \, dt + e^{h_t/2} \left[ \sqrt{1 - \rho^2} \, dW^Q_{1t} + \rho \, dW^Q_{2t} \right], \]
\[ dh_t = (\alpha - \nu_1 \sigma + (\beta - \nu_2 \sigma) h_t) \, dt + \sigma \, dW^Q_{2t}. \]

SV models enjoy tremendous modeling flexibility. They can model various important market behaviors, such as the volatility smile. A key idea, termed generalized BS (GBS) pricing formulas, was hinted in [39] but advocated explicitly in [60], [61], [59], [27] and [29]. Here is the GBS formula for the log-SV model (2.6)-(2.7) and (2.13)-(2.14):

\[ P(S_t, h_t, \theta, \nu) = E^Q \left[ C^{BS} \left( S_te^{Z_{t,T^*}}, \bar{V}_{t,T^*}, r, K, T^* - t \right) | \mathcal{F}_t \right], \]

\[ Z_{t,T^*} = \rho \int_t^{T^*} e^{h_u/2} \, dW^Q_{2u} - \frac{\rho^2}{2} \int_t^{T^*} e^{h_u} \, du, \]
\[ \bar{V}_{t,T^*} = \frac{1 - \rho^2}{T^* - t} \int_t^{T^*} e^{h_u} \, du, \]

where \( \theta = \{ \mu, \alpha, \beta, \sigma, \rho \} \) and \( \nu = \{ \nu_1, \nu_2 \} \) denote the parameters in (2.6)-(2.7) and (2.13)-(2.14); \( Q \) is a risk-neutral measure [Note: \( Q \) is not unique, which is specified by the choice of risk premia (2.8) and (2.9)]; \( C^{BS}() \) is the BS call option pricing formula given by (1.6) with life span \((t, T^*)\). Hence the GBS pricing formula is interpreted as a conditional expectation of the original BS option price with certain adjusted parameters, taken over the unobservable log-volatilities \( h_u, t < u \leq T^* \) in the life time of the option. The special case with constant volatility and \( \rho = 0 \) will turn (2.15) to the original BS call option price. A put option can be priced using the parity relation between a put \((P_t)\) and a call \((C_t)\), which is \( P_t = C_t - S_t + K \exp \left[ - r (T^* - t) \right] \). Other derivatives can also be priced in a similar way.

Later we will elaborate on how to compute GBS formulas efficiently by using certain probability approximations.

### 2.3 MCMC calibration

(i) **Estimation based on return data only**
Statistical inference for the SV model (2.6)-(2.7) concerns the model parameter \( \theta \) (parameter estimation) and latent volatilities \( h = \{ h_{t+i\Delta}, \ i = 0, 1, ..., n_y - 1 \} \) (state estimation), based on a time series of return data \( Y = \{ y_{t+i\Delta}, \ i = 0, 1, ..., n_y - 1 \} \) generated from a physical measure \( P \). Note that \( \Delta \) is the sampling window of observations; the initial time \( t \) is arbitrary to maintain flexibility; the risk-neutral measure \( Q \), risk premia parameter \( \nu \) are irrelevant because no option data are used for the time being (inference with option data to be studied later).

Discretization of the diffusion model (2.6)-(2.7) via an Euler scheme (see [48]) yields a likelihood. The presence of latent volatility sequence \( h \) poses an indirect inference problem, which can be tackled by several methods: EM algorithms, generalized method of moments (GMM), efficient method of moments (EMM), MCMC, etc. As for references, see [52] for EM algorithms, [33] and [5] for GMM, [24] for EMM, and [50] for MCMC. When applying to calibration of SV models, each method has its own pros and cons. No attempts are made in this paper for comparisons among different methods. Here we only mention [26] and [8] as examples of using GMM or EMM, and [41] as the earliest contribution to MCMC calibration of SV models. More references will be given when discussing inference on SV models using both return and option data in case (ii).

In the current context, MCMC methods generate a discrete-time Markov chain whose stationary distribution is the joint posterior distribution of model parameter \( \theta \) and latent variables \( h \), hence samples from the posterior distribution of any marginal are easy to obtain by selecting elements from the joint series.

Discretization can introduce bias. This bias may be eliminated by using any one of the fill-in methods proposed by [19] or [17]. But as verified by [20], for the type of data and class of models considered here, accuracy is adequate for a \( \Delta \) of one day so there is no need to use fill-in methods if data sampled at a daily frequency are available.

The MCMC method we adopt is a type of “Metropolis within Gibbs”. In the spirit of Gibbs, the unknowns \( \theta \) and \( h \) are classified in several blocks. Each block is sampled conditioning on the rest and one cycles through different blocks. Because the normalizing factors for the conditional distributions involved are not known, a Metropolis sampler is used to generate runs within each block. Implementation of a Metropolis step consists of generating a candidate move from a proposal density and deciding whether to accept the proposed move based on a Metropolis ratio. The art is that the proposal density is usually specified in a problem-dependent manner. In other words, a few guidelines are available, but no rigid rules.

Denote the posterior distribution for parameters and latent variables by \( P(h, \theta | Y) \). Holding \( Y \) fixed, this density is proportional to the like-
likelihood times the prior

\[ P(h, \theta \mid Y) \propto P(Y, h \mid \theta) P(\theta) = P(Y \mid h, \theta) P(h \mid \theta) P(\theta) \quad (2.18) \]

with

\[ P(Y \mid h, \theta) P(h \mid \theta) = \prod_{i=0}^{n-1} p(y_{t+(i+1)\Delta} \mid y_{t+i\Delta}, h_{t+i\Delta}, \theta) p(h_{t+(i+1)\Delta} \mid h_{t+i\Delta}, \theta), \quad (2.19) \]

where \( p(y_{t+(i+1)\Delta} \mid y_{t+i\Delta}, h_{t+i\Delta}, \theta) \) is the normal density of \( y_{t+(i+1)\Delta} \) with the conditional mean \( \mu_{t+(i+1)\Delta} = y_{t+i\Delta} + \alpha_{2} \Delta \) and conditional variance \( \sigma^{2}_{t+i\Delta} \), and \( p(h_{t+(i+1)\Delta} \mid h_{t+i\Delta}, \theta) \) is the normal density of \( h_{t+(i+1)\Delta} \) with the conditional mean \( \alpha \Delta + (1 + \beta_{2}\Delta) h_{t+i\Delta} \) and conditional variance \( \sigma^{2}_{t+i\Delta} \), following the discretization of (2.6)–(2.7).

The Gibbs blocking is as follows. The elements within the block of \( h \) are moved one at a time. The coordinate variable \( h_{t+i\Delta} \) at each \( i \) is generated from the conditional density

\[ p(h_{t+i\Delta} \mid h_{t+(i-1)\Delta}, h_{t+(i+1)\Delta}; y_{t+(i-1)\Delta}, y_{t+(i+1)\Delta}; \theta) \]

due to the Markovian structure in the dynamics of (2.6)–(2.7). The drift parameters \( \mu \) and \( \{\alpha, \beta\} \) are moved as two separate blocks and the diffusion parameters \( \{\sigma, \rho\} \) as another. The priors are uniform on their supports with the exception for \( \mu \) which has a conjugate normal prior, allowing \( \mu \) to be updated directly without Metropolis-Hastings acceptance/rejection intermediation. All priors are proper with boundary parameters set in the experiments to be effectively noninformative.

The single-move Gibbs sampler is not as efficient as some other Bayesian MCMC inference methods for calibrating SV models when using only returns data \( Y \). In particular, the multi-move Gibbs sampler with Kalman filters introduced in [63], [47] and [9] is more efficient computationally. Note in case (ii) we still use the single-move Gibbs sampler for calibrating SV models based on both return and option data because, to the best of our knowledge, no multi-move MCMC methods are available for that task. Given that we must use it for that purpose, we also use it for returns alone to reduce our coding and debugging burden.

(ii) Estimation based on both return and option data

The MCMC (Bayesian) inference on SV models is essentially an extension of the (frequentist) BS historic volatility approach in a broad sense that it only uses return data. Many financial econometricians argue that option data are at least as relevant as return data, if not more, in volatility calibration. Technically, the idea of BS implied volatility cannot be extended to SV models naively because the pricing formula,
as a map from latent volatilities to an option price, is not invertible, i.e. it is an ill-posed inverse problem due to the high dimensionality of $h$. Nevertheless, we could and should still incorporate observed option data in volatility estimation by checking the discrepancy (called a pricing error) between an observed option price and one calculated via a GBS formula.

Consider the additional information provided by options written on $Y$. The option prices $C$ we consider are on homogeneous instruments sampled at the same time as $y_{t+\Delta}$ so that $C$ has elements $c_{t+j\Delta}$ for $j = 0, 1, \ldots, n_c - 1$, where $c_{t+j\Delta}$ is the logarithm of the observed option price. (Note: Usually $n_c < n_y$ and the time $t$ where $C$ begins is larger than that of $Y$. But we do not consider those complications here.)

As is common in derivative pricing applications (cf. [20]), the distribution of $C$ is determined by both an option pricing formula, which is (2.15) in our case, and an assumption of pricing errors. Pricing errors are not only required to permit application of Bayesian and similar likelihood based methods but are also plausible reflections of bid-ask bounce and similar micro structure considerations (cf. [59], [43]). We assume that errors are additive in log-scale,

$$c_{t+j\Delta} = f_{t+j\Delta} + \delta \bar{\epsilon}_j, \quad j = 0, 1, \ldots, n_c - 1, \quad (2.20)$$

where, from (2.15),

$$f_{t+j\Delta} = \log \left[ P \left( S_{t+j\Delta}, h_{t+j\Delta}, \theta, \nu \right) \right], \quad (2.21)$$

and the errors $\bar{\epsilon}_j$, $j = 0, 1, \ldots, n_c - 1$ are iid $N(0, 1)$ random variables, independent of the processes $S$ and $h$. Note that (2.20) treats observed option data as a noisy version of the option prices predicted based on a GBS pricing formula. In [45], a different but somewhat equivalent approach is taken by using the implied volatility data (VIX) to be a noisy version of the latent volatility variables.

There are several unknowns now, including $\theta = \{\mu, \alpha, \beta, \rho, \sigma\}$ and $h$ that appear in the returns dynamics (2.6)-(2.7), the risk premia parameters $\nu = \{\nu_1, \nu_2\}$ that appear in the risk-neutral dynamics (2.13)-(2.14), and the pricing error standard deviation $\delta$ from (2.20).

We assume the three blocks $\{ Y, h, \theta \}$, $\nu$, and $\delta$ are mutually independent under the prior distribution. Under this assumption, the joint posterior distribution of interest becomes

$$P \left( h, \theta, \nu, \delta | C, Y \right) \propto P \left( C | Y, h, \theta, \nu, \delta \right) P \left( Y | h, \theta \right) P \left( h | \theta \right) P \left( \theta \right) P \left( \nu \right) P \left( \delta \right). \quad (2.22)$$

We have expressions for $P \left( Y | h, \theta \right)$ and $P \left( h | \theta \right)$ from case (i). Following
stochastic volatility models

The likelihood of the option prices is

\[ P(C|Y, h, \theta, \nu, \delta) \propto \prod_{j=0}^{n-1} \delta^{-1} \exp \left( -\frac{(c_{t+j\Delta} - f_{t+j\Delta})^2}{2\delta^2} \right). \]  

The Gibbs blocking is as follows. As in case (i) of this subsection, the elements \( h_{t+i\Delta} \) of \( h \) are moved one at a time, the drift parameters \( \mu \) and \( \{\alpha, \beta\} \) are moved as two separate blocks, and the diffusion parameters \( \{\sigma, \rho\} \) as another. The risk premium parameters \( \nu \) and the pricing error parameter \( \delta \) are moved as two separate blocks. The prior on \( \nu \) is uniform. The prior for \( \delta \) is the conjugate, so that \( \delta \) can be directly sampled from a product of inverse Gamma distributions without Metropolis-Hastings acceptance/rejection intermediation. All priors are proper with parameters set to be effectively noninformative.

3 GBS Formulas and Probability Approximations for Numerical Integration

A price that comes with the modeling capability by using SV models is the computational intensity required for calibrating SV models using financial data from two sources: underlying asset returns and option prices. Adding option data to this task creates a significant challenge for the following reason. In a SV model, a volatility time series consists of latent variables \( h_t, t = 0, 1, \ldots, T \). Calibration of parameter \( \theta \) (including the risk-neutral parameter \( \nu \) as some components) and volatilities \( \{h_t\} \) is an indirect inference problem, inviting certain Monte Carlo based algorithms, such as EMM or MCMC. There is an extensive literature in calibration of SV models using both return and option data. Here we only mention a few. See [7], [57] for EMM, and [30], [45], [20], [6] for MCMC. Those algorithms yield updated values \( \theta^{(m)} \) and \( h_t^{(m)}, t = 0, 1, \ldots, T \) in the \( m \)th iteration, \( m = 1, \ldots, M \). In particular, as an important part of the \( m \)th iteration in fitting a SV model, an option price \( f_t^{(m)} \) is calculated by using a pricing formula based on the SV model with the current parameter value \( \theta^{(m-1)} \) and volatility value \( h_t^{(m-1)} \), and compared to the observed option price \( C_t \). The comparison will lead to an adjustment of \( h_t^{(m-1)} \) to \( h_t^{(m)} \), and also updating of \( \theta^{(m-1)} \) to \( \theta^{(m)} \) based on \( h_t^{(m)} \), \( t = 0, 1, \ldots, T \). Notice that a general method of computing \( f_t^{(m)} \) is to perform high-dimensional numerical integration — treated as a conditional expectation over the space of sample paths of future volatilities, and this has to be done for every \( t \) and every \( m \) in the algorithm. The required computational time quickly adds up with large values of \( T \) (several hundred days) and \( M \) (typically more than 100,000 iterations). So
far, there have been basically two ways to handle the computation in practice. A basic strategy is to use “brute force” simulation, i.e. to generate a large number of “additional” sample paths of future volatilities based on which the Monte Carlo integration yields an approximation to \( f_t^{(m)} \). An alternative approach relies on the availability of closed-form option pricing formulas which can avoid the aforementioned brute force numerical integration. However, Heston’s model (cf. [37]) appears to be the only case beyond the original BS setting that enjoys a closed-form solution (still, certain low-dimensional numerical integration needed for a Fourier inversion strategy). The intractability of the brute force calculation and the limitation with closed-form pricing formulas present an urgent need for developing new efficient computational methodology.

In this section, we present a Gaussian approximation scheme for numerical computation of the option price and summarize the related work. The proposed Gaussian approximations promote a significant dimension reduction for numerical integration, from the space of volatility sample paths (with dimensionality of several hundreds) to the sample space of bivariate Gaussian vectors. See [6] (http://www.stat.unc.edu/faculty/cji/research.html) for detailed analytical arguments and numerical results. We will also include some ongoing work in [66] for Gaussian approximations applied to a SV model with jumps.

### 3.1 Gaussian approximations for logarithmic SV models

The obvious (and usual) approach to computing the integrals in (2.15)–(2.17) is to discretize (2.13)–(2.14), generate sample paths according to the recursions implied by the discretization, evaluate (2.15)–(2.17) over each sample path, and take an average. Indeed, this is how we check the accuracy of our proposed Gaussian approximations by creating a benchmark value of the option price. A number of useful tips with solid theoretical justifications are given in [48], [16], [32] regarding Monte Carlo simulation of SDEs. For the purpose of calibrating SV models via MCMC considered in this work, the brute force simulation is too computationally intensive to be practicable. Our proposal is as follows.

With a small time increment \( \Delta \), the Euler discretization of the volatility process under the risk-neutral measure \( Q \), i.e. (2.14) yields the recursion

\[
  h_{t+\Delta} = a + b \, h_t + c \, \epsilon_{t+\Delta},
\]

where \( \epsilon_{t+\Delta} \) is a \( N(0,1) \) random variable, which is independent of the past, i.e. independent of the spot volatility \( h_t \), of the drift terms \( a = (\alpha - \nu_1 \sigma) \Delta \) and \( b = 1 + (\beta - \nu_2 \sigma) \Delta \), and of the diffusion term
c = \sqrt{\Delta \sigma}$. Notice that our notation departs from convention because we have incorporated $\Delta$ into the expressions for $a$, $b$, and $c$ in order to simplify later formulas. Let $n = (T^* - t)/\Delta$. Our task is to derive the asymptotic distribution of the two sums

$$U_n = \sum_{j=0}^{n-1} e^{h_t+j\Delta}, \quad \text{(3.2)}$$

$$V_n = \sum_{j=0}^{n-1} e^{h_t+j\Delta/2} \epsilon_{t+(j+1)\Delta}, \quad \text{(3.3)}$$

which appear in the discretization of (2.16)–(2.17) using (3.1), i.e.

$$U_n \Delta \approx \int_t^{T^*} e^{h_u} \, du \quad \text{(3.4)}$$

$$V_n \sqrt{\Delta} \approx \int_t^{T^*} e^{h_u/2} \, dW^Q_u. \quad \text{(3.5)}$$

For fixed $t$, let $E_t(\cdot)$, $\text{Var}_t(\cdot)$ and $\text{Cov}_t(\cdot)$ denote the conditional expectation, variance and covariance operators respectively, given $h_t$.

**Theorem 3.1.** Assume $|b| < 1$. Fix $t$, $\Delta$ and an initial state $h_t$. As $n \to \infty$, the limiting distribution of $n^{-1/2}(U_n - E_t U_n, V_n - E_t V_n)$ conditioning on $h_t$ is a bivariate normal distribution with mean $(0, 0)$ and covariance matrix $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$ provided $a_{11} a_{22} > a_{12}^2$, with

$$a_{11} = \lim_{n \to \infty} n^{-1} \text{Var}_t(U_n),$$

$$a_{12} = a_{21} = \lim_{n \to \infty} n^{-1} \text{Cov}_t(U_n, V_n),$$

$$a_{22} = \lim_{n \to \infty} n^{-1} \text{Var}_t(V_n);$$

where

$$E_t U_n = \sum_{i=0}^{n-1} \exp \left[ \frac{a(1-b^i)}{1-b} + b^i h_t + \frac{c^2(1-b^{2i})}{2(1-b^2)} \right]; \quad \text{(3.6)}$$

$$E_t V_n = 0; \quad \text{(3.7)}$$
\[ Var_t(U_n) = \sum_{i=0}^{n-1} Var_t(e^{b_{i+1}\Delta}) + 2 \sum_{i=0}^{n-2} \sum_{j=i+1}^{n-1} Cov_t(e^{b_{i+1}\Delta}, e^{b_{j+1}\Delta}), \] 
(3.8)

\[ Cov_t(U_n, V_n) = \sum_{i=1}^{n-1} \sum_{j=0}^{i-1} c b^{i-j-1} \exp \left[ (b^i + b^j/2) h_t + a \left( \frac{3/2 - b^i - b^j/2}{1 - b} \right) + \frac{c^2 \left( 5/4 - b^{2i} - b^{2j}/4 + b^{i-j} - b^{i+j} \right)}{2(1 - b^2)} \right], \] 
(3.9)

\[ Var_t(V_n) = E_t U_n; \] 
(3.10)

with

\[ Var_t(e^{b_{i+1}\Delta}) = \exp \left( 2b^i h_t + \frac{2a(1 - b^i)}{1 - b} + \frac{c^2(1 - b^{2i})}{1 - b^2} \right) \left[ \exp \left( \frac{c^2(1 - b^{2i})}{1 - b^2} \right) - 1 \right], \]

\[ Cov_t(e^{b_{i+1}\Delta}, e^{b_{j+1}\Delta}) = \exp \left( (b^i b^j) h_t + \frac{a(2 - b^i - b^j)}{1 - b} + \frac{c^2(2 - b^{2i} - b^{2j})}{2(1 - b^2)} \right) \times \left[ \exp \left( \frac{c^2(b^{i-j} - b^{i+j})}{1 - b^2} \right) - 1 \right]. \]

Theorem 3.1 follows from a CLT for mixing sequences (cf. [40], [4]). The detailed proof, implementation of MCMC, and numerical results in simulation studies and an application to real foreign exchange data can be found in [6]. In particular, the assessment of computational efficiency (speed/accuracy) shows great promises of the proposed Gaussian approximations.

### 3.2 Gaussian approximations for SV models with jumps

Among several important recent contributions to calibration of SV models in recent years, SV models with jumps (simply denoted by SVJ in what follows) have received much attention. See [57], [21], [20], [8]. Jumps and SV are two ways to incorporate additional sources for risk and uncertainty into a model (SDE) for asset returns. Each of them has its own risk premium. Merton was the first one to introduce a jump-diffusion model for stock returns in [54]. An encyclopedic treatment of financial models with jumps is given in the excellent book [12]. Here
we present a SVJ model, a GBS pricing formula, and related Gaussian approximations. The notation in this subsection, following [66], is kept “local” and need not be consistent with those used in previous sections.

(i) SVJ models

Consider the SVJ model

\[ d(\log S_t) = \left( r_t + \eta_s V_t - \frac{V_t}{2} \right) dt + \sqrt{V_t} dW^s_t + U_s \, dN_t - \mu_1 \lambda V_t dt, \]  
\[ dV_t = \kappa (\theta - V_t) dt + \sigma_v \sqrt{V_t} dW^v_t, \]  

(3.11)

(3.12)

where for \( t \geq 0 \), \( S = \{S_t\} \) and \( V = \{V_t\} \) represent continuous-time asset price and SV processes respectively. \( r_t \) is the interest rate at time \( t \) (assumed to be known). Both \( \{W^s_t\} \) and \( \{W^v_t\} \) are standard 1D Wiener processes, which satisfy \( \text{Cov}(W^s_t, W^v_t) = \rho t \) with the correlation coefficient \( \rho \) to incorporate the leverage effect. The SV dynamic (3.12) corresponds to a square-root diffusion with a mean-reversion level \( \theta \) and a reversion rate \( \kappa \).

Price jumps are captured via a pure jump process that contains two components: a jump time process and a jump size process. Successive jumps at \( 0 < \tau_1 < \tau_2 < \cdots \) form a point process with a state-dependent intensity function \( \{\lambda V_t : t \geq 0\} \) for some constant \( \lambda > 0 \), which allows jumps to occur more frequently in high volatility regimes. Given the arrival of the \( i \)th jump, the price jumps from \( S_{\tau_i} \) to \( S_{\tau_i} \exp(U^s_i) \), where \( U^s_i, i = 1, 2, \ldots \) are iid normal random variables with mean \( \mu_J \) and variance \( \sigma^2_J \). Assume \( \{U^s_t\} \) is independent of processes \( \{\tau_i\} \), \( \{W^s_t\} \) and \( \{W^v_t\} \). Denote the mean relative jump size, conditioning on a jump event, by \( \mu_1 = E(\exp(U^s_1) - 1) = \exp(\mu_J + \sigma^2_J/2)/\exp(\mu_J + \sigma^2_J/2) - 1 \). It follows that the last term in (3.11) compensates the instantaneous price increment introduced by the pure jump process. The model parameters are \( \eta_s, \kappa, \theta, \sigma_v, \lambda, \mu_J, \sigma_J \).

(ii) Candidate pricing kernels

A pricing kernel, introduced in [34], is basically the Radon-Nikodym derivative \( \frac{dP}{dQ} \) of a risk-neutral measure \( Q \) with respect to a physical measure \( P \).

The unhedgeable risk factors introduced by the SV and jump processes make an incomplete market in our study. Consequently, a pricing kernel is not unique. To price those risk factors (the diffusive price shocks, the price jumps, and the diffusive volatility shocks), we define a candidate pricing kernel \( \pi_t \) by

\[ d(\log \pi_t) = h(V_t) \, dt + a(V_t) \, dW^v_t + b(V_t) \, dW^\perp_t + (\log \pi_t - \log \pi_{t-}) \, dN_t, \]  

(3.13)
where $W = (W^v, W^v\perp)$ is a standard 2D Wiener process. $N_t$ represents the number of price jumps up to time $t$, i.e. we assume that $\{\tau_t\}$ and $\{S_t\}$ share the same jump time process. Let $\log \pi_t - \log \pi_{t-} = U_t^\pi$ if $\tau_i = t$. Assume $U_t^\pi, i = 1, 2, \ldots$ are iid normal random variables with mean $\mu_\pi$ and variance $\sigma_\pi^2$, and $\{U_t^\pi\}$ is independent of $W$ and $\{N_t\}$. However, we allow the correlation $\text{Corr}(U_t^\pi, U_1^\pi) = \rho_\pi$.

The assumption of no arbitrage requires that the pricing kernel defined in (3.13) satisfies the following constraints:

\begin{equation}
\begin{aligned}
r_t + h(V_t) + \frac{1}{2} a^2(V_t) + \frac{1}{2} b^2(V_t) + \mu_2 \lambda V_t = 0, \\
\eta_s V_t - V_t/2 + \sqrt{V_t} [\rho a(V_t) + \sqrt{1 - \rho^2} b(V_t)] = -(\mu_3 - \mu_2 - \mu_1) \lambda V_t,
\end{aligned}
\end{equation}

where

\begin{align*}
\mu_2 &= E[\exp(U_1^\pi) - 1] = \exp(\mu_\pi + \sigma_\pi^2/2) - 1, \\
\mu_3 &= E[\exp(U_1^\pi + U_1^\sigma) - 1] = \exp(\mu_\pi + \sigma_\pi^2/2 + \rho_\sigma \sigma_\sigma + \mu_\sigma + \sigma_\sigma^2/2) - 1.
\end{align*}

(iii) **GBS pricing formulas**

Having introduced a pricing kernel $\{\pi_t\}$, all conditional expectations in what follows are taken under the physical measure $P$, and no risk-neutral measure $Q$ is necessary. Let $F_{t,T}^*$ denote the $\sigma$-field generated by $\{V_u, N_u : t < u \leq T\}$. Define

\begin{equation}
B^*(t, T^*) = E_t\left( \frac{\pi_{T^*}}{\pi_t} \bigg| F_{t,T^*} \right),
\end{equation}

\begin{equation}
\xi_t, T^* = E_t\left( \frac{\pi_{T^*}}{\pi_t} \frac{S_{T^*}}{S_t} \bigg| F_{t,T^*} \right).
\end{equation}

The time $t$ price $P(S_t, V_t, t, T^*)$ of an European call option with maturity time $T^*$ follows the GBS pricing formula:

\begin{equation}
P(S_t, V_t, t, T^*) = E_t \left[ \frac{\pi_{T^*}}{\pi_t} (S_{T^*} - K)^+ \right]
= E_t \left[ C^{BS} \left( \xi_t, T^*, {\pi_{T^*}}^2, \{r_u, \ t \leq u \leq T^*\}, K, T^* - t \right) \right]
= E_t \left[ S_t \xi_t, T^* \Phi(d_1) - K B^*(t, T^*) \Phi(d_2) \right],
\end{equation}

where

\begin{align*}
d_1 &= \frac{1}{\sqrt{T^* - t}} \sigma_{t,T^*} \left[ \log \left( \frac{S_t \xi_t, T^*}{KB^*(t, T^*)} \right) + \frac{1}{2} \left( \sigma_{t,T^*} \right)^2 (T^* - t) \right], \\
d_2 &= d_1 - \sigma_{t,T^*} \sqrt{T^* - t},
\end{align*}
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\[
(\sigma_{t,T^*})^2 = \frac{(1 - \rho^2) \int_t^{T^*} V_u \, du + \sigma_J^2 (N_{T^*} - N_t)}{T^* - t}, \tag{3.19}
\]

\[
B^*(t, T^*) = \left\{ \exp \left[ \int_t^{T^*} \left( -r_u - \frac{1}{2} a^2(V_u) - \mu_2 \lambda V_u \right) \, du \right.ight.
\]
\[+ \int_t^{T^*} a(V_u) \, dW_u \bigg]\} (\mu_2 + 1)^{N_{T^*} - N_t}, \tag{3.20}
\]

\[
\xi_{t,T^*} = \left[ \exp \left( -\int_t^{T^*} \mu_3 \lambda V_u \, du \right) \right] \left\{ \exp \left[ \int_t^{T^*} \left( a(V_u) + \rho \sqrt{V_u} \right) \, dW_u \right. \right.
\]
\[\left. - \frac{1}{2} \int_t^{T^*} \left( a(V_u) + \rho \sqrt{V_u} \right)^2 \, du \right] \} (\mu_3 + 1)^{N_{T^*} - N_t}. \tag{3.21}
\]

(3.18) clearly demonstrates the idea of GBS. The BS option price in this case is a function measurable on \(F_{t,T^*}\), i.e. a function of unobserved latent variables \(\{V_u, N_u, t < u \leq T^*\}\). Taking another conditional expectation over \(\{V_u, N_u, t < u \leq T^*\}\) then yields the option price \(P(S_t, V_t, t, T^*)\) for the SVJ model. Note that in this GBS formula, \(B^*(t, T^*), \xi_{t,T^*}\) and \(\sigma_{t,T^*}\) are interpreted as the bond price (or the discount factor), the stock price and the (integrated) volatility respectively in a virtual world where the information about future volatilities and jumps in \(F_{t,T^*}\) were known at time \(t\).

(iv) Gaussian approximations in computation of \(P(S_t, V_t, t, T^*)\)

To compute \(P(S_t, V_t, t, T^*)\) numerically, we propose a similar Gaussian approximation scheme. There are a number of integrals in (3.19)-(3.21): \(\int_t^{T^*} V_u \, du, \int_t^{T^*} a^2(V_u) \, du, \int_t^{T^*} \sqrt{V_u} a(V_u) \, du, \int_t^{T^*} \sqrt{V_u} \, dW_u^v, \int_t^{T^*} a(V_u) \, dW_u^v\). The specification \(a(V_u) = \text{constant} \sqrt{V_u}\) will enables us to focus on the joint distribution of two integrals: \(\int_t^{T^*} V_u \, du\) and \(\int_t^{T^*} \sqrt{V_u} \, dW_u^v\). Once again, let \(n = (T^* - t)/\Delta\) and define

\[
U_{1n} = \sum_{j=0}^{n-1} V_{t+j\Delta} \approx \Delta^{-1} \int_t^{T^*} V_u \, du,
\]

\[
U_{2n} = \sum_{j=0}^{n-1} \sqrt{V_{t+j\Delta}} \approx \Delta^{-1/2} \int_t^{T^*} \sqrt{V_u} \, dW_u^v,
\]

where \(\epsilon_{t+\Delta}, \epsilon_{t+2\Delta}, \ldots\) are iid \(N(0,1)\) random variables. For fixed \(\Delta\) and large \(n\), a Gaussian approximation scheme is proposed for the joint
distribution of \((U_{1n}, U_{2n})\). The theoretical justification will be provided by a CLT. Here we present the first and second moments of \((U_{1n}, U_{2n})\).

An Euler discretization scheme yields the SV dynamics

\[V_{t+\Delta} = a + b V_t + c \sqrt{V_t} \epsilon_{t+\Delta}, \quad (3.22)\]

where

\[a = \kappa \theta \Delta, \quad b = 1 - \kappa \Delta, \quad c = \sigma_v \sqrt{\Delta}\]

are transformations of the original parameters \(\kappa, \theta\) and \(\sigma_v\).

For fixed \(t\), let \(E_t(\cdot), \text{Var}_t(\cdot)\) and \(\text{Cov}_t(\cdot)\) denote the conditional expectation, variance and covariance operators respectively, given \(V_t\).

**Theorem 3.2.**

\[E_t U_{1n} = a + b (n - 1 - b) \frac{n - 1 - b^n}{1 - b} + \frac{n - 1 - b^n}{1 - b} V_t, \quad (3.23)\]

\[E_t U_{2n} = 0 \quad (3.24)\]

\[\text{Var}_t U_{1n} = B_0 + B_1 V_t + B_2 V_t^2 \quad (3.25)\]

\[\text{Var}_t U_{2n} = E_t U_{1n} \quad (3.26)\]

\[\text{Cov}_t(U_{1n}, U_{2n}) = \frac{ac}{(1-b)^3} \left[ n - 2 - nb + nb^{n-1} - (n-2)b^n \right] + c \frac{[1 - nb^{n-1} + (n-1)b^n]}{(1-b)^2} V_t \quad (3.27)\]

where the coefficients \(B_0, B_1\) and \(B_2\) in (3.25) enjoy the closed-form expressions

\[B_0 = \frac{ac^2(n - 2)}{(1-b)^2(1+b)} - \frac{abc^2(1-b^{n-2})(1 + 2b - b^n)}{(1-b)^3(1+b)^2} \quad (3.28)\]

\[+ \frac{2abc^2}{(1-b)^3(1+b)} \left[ (n-3)(1 + b^{n-2} + b^{n-1}) \right] \quad (3.29)\]

\[B_1 = \frac{1 - b^{n-1}}{(1-b)^3} \left[ c^2(1+b^n) + 2ab^n(1-b^2) \right] - \frac{2(n-1) b^{n-1} c^2}{(1-b)^2} \quad (3.30)\]

\[B_2 = 0 \quad (3.30)\]

4 Conclusion

Following the spirit of the Black-Scholes theory, several SV models are studied along with the related GBS pricing formulas and MCMC infer-
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ence methods. As a new contribution, a proposed Gaussian approximation scheme significantly reduces the dimensionality of certain stochastic integrals involved in the GBS formulas, which makes the computation on Monte Carlo based inference much more efficiently.

There are several related areas not presented in this paper, including the PDE approach for option pricing (cf. [23]), realized volatilities and high frequency data (cf. [12]), and the utility-based approach for option pricing with equilibrium models (cf. [49], [11], [28]). The cited references will provide more detailed information and treatments.

References


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