

Online Appendix to: Simulating Lévy Processes from Their Characteristic Functions and Financial Applications

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A. PROOF OF THEOREM 4.1

PROOF. The bias is given by

$$\begin{aligned} E[f(X)] - E[f(\hat{X})] &= \int_{\mathbb{R}} f(x)p(x)dx - \int_{\mathbb{R}} f(x)\hat{p}(x)dx \\ &= \int_{\mathbb{R}} f(x)p(x)dx - \int_{x_0}^{x_K} f(x)\hat{p}(x)dx - f(x_0)\hat{F}_0 - f(x_K)(1 - \hat{F}_K) \\ &= \sum_{k=1}^K \int_{x_{k-1}}^{x_k} f(x)(p(x) - \hat{p}(x))dx + \left(\int_{-\infty}^{x_0} + \int_{x_K}^{\infty} \right) f(x)p(x)dx \\ &\quad - f(x_0)\hat{F}_0 - f(x_K)(1 - \hat{F}_K). \end{aligned} \quad (22)$$

If $f(x)$ is differentiable in (x_{k-1}, x_k) , then for any $x \in (x_{k-1}, x_k)$, by the mean value theorem, there exists $\xi_k(x) \in (x_{k-1}, x)$ such that

$$\begin{aligned} \left| \int_{x_{k-1}}^{x_k} f(x)(p(x) - \hat{p}(x))dx \right| &= \left| \int_{x_{k-1}}^{x_k} (f(x_{k-1}+) + f'(\xi_k(x))(x - x_{k-1}))(p(x) - \hat{p}(x))dx \right| \\ &\leq \|f\|_{\mathcal{X}} \cdot |F_k - \hat{F}_k - (F_{k-1} - \hat{F}_{k-1})| + \|f'\|_{\mathcal{X}} \cdot \eta \cdot \int_{x_{k-1}}^{x_k} |p(x) - \hat{p}(x)|dx \\ &\leq 2 \cdot \|f\|_{\mathcal{X}} \cdot E_{\mathcal{X}} + \|f'\|_{\mathcal{X}} \cdot \eta \cdot \int_{x_{k-1}}^{x_k} |p(x) - \hat{p}(x)|dx. \end{aligned}$$

Here $f(x_{k-1}+)$ is the right limit of f at x_{k-1} , which is finite by the assumptions. In general, if $f(x)$ is not differentiable at n_k^f points in (x_{k-1}, x_k) , where $\sum_{k=1}^K n_k^f = n^f$, it can be shown in the same way as before that

$$\left| \int_{x_{k-1}}^{x_k} f(x)(p(x) - \hat{p}(x))dx \right| \leq 2(n_k^f + 1) \cdot \|f\|_{\mathcal{X}} \cdot E_{\mathcal{X}} + \|f'\|_{\mathcal{X}} \cdot \eta \cdot \int_{x_{k-1}}^{x_k} |p(x) - \hat{p}(x)|dx.$$

Note that

$$\begin{aligned} \int_{x_{k-1}}^{x_k} |p(x) - \hat{p}(x)|dx &= \int_{x_{k-1}}^{x_k} \left| p(x) - \frac{F_k - F_{k-1}}{\eta} + \frac{F_k - F_{k-1}}{\eta} - \frac{\hat{F}_k - \hat{F}_{k-1}}{\eta} \right| dx \\ &\leq \left| F_k - \hat{F}_k - (F_{k-1} - \hat{F}_{k-1}) \right| + \int_{x_{k-1}}^{x_k} \left| p(x) - \frac{F_k - F_{k-1}}{\eta} \right| dx \\ &\leq 2E_{\mathcal{X}} + \int_{x_{k-1}}^{x_k} \left| p(x) - \frac{F_k - F_{k-1}}{\eta} \right| dx. \end{aligned}$$

However, we have the following:

$$\int_{x_{k-1}}^{x_k} \left| p(x) - \frac{F_k - F_{k-1}}{\eta} \right| dx = \frac{1}{\eta} \int_{x_{k-1}}^{x_k} \left| \int_{x_{k-1}}^{x_k} (p(x) - p(y)) dy \right| dx.$$

Since $p(x)$ is differentiable in (x_{k-1}, x_k) , using the mean value theorem again, for any $x \neq y$ in (x_{k-1}, x_k) , there exists $\xi_k(x, y) \in (x, y)$ such that

$$p(y) = p(x) + p'(\xi_k(x, y))(y - x).$$

Therefore,

$$\int_{x_{k-1}}^{x_k} |p(x) - \hat{p}(x)| dx \leq 2E_{\mathcal{X}} + \|p'\|_{\mathcal{X}} \cdot \eta^2.$$

Consequently,

$$\left| \sum_{k=1}^K \int_{x_{k-1}}^{x_k} f(x)(p(x) - \hat{p}(x)) dx \right| \leq 2E_{\mathcal{X}} ((K + n^f) \|f\|_{\mathcal{X}} + \|f'\|_{\mathcal{X}} (x_K - x_0)) + \|f'\|_{\mathcal{X}} \|p'\|_{\mathcal{X}} (x_K - x_0) \eta^2.$$

As for the last two terms in (22), we have

$$|f(x_0)\hat{F}_0| \leq |f(x_0)|(E_{\mathcal{X}} + F_0), \quad |f(x_K)(1 - \hat{F}_K)| \leq |f(x_K)|(E_{\mathcal{X}} + 1 - F_K).$$

Combining the preceding, we obtain (15). \square

B. PROOF OF THEOREM 4.3

PROOF. Let F be the cdf of X . According to Theorem 4.1, the bias is bounded by (15). If $\phi \in H(\mathcal{D}_{(d_-, d_+)})$, from (7), for any $a \in (0, d_+)$, we have

$$f(x_0)F(x_0) = f(x_0) \int_{\mathbb{R}} \frac{e^{-ix_0(\xi + ia)} \phi(\xi + ia)}{-2\pi i(\xi + ia)} d\xi = f(x_0) \int_{-\infty + ia}^{+\infty + ia} \frac{e^{-ix_0 z} \phi(z)}{-2\pi iz} dz.$$

Since the integrand is analytic in $\{z \in \mathbb{C} : \Im(z) \in (0, d_+)\}$, using the condition (1) and Cauchy's integral theorem, for any $\epsilon > 0$ such that $d_+ - \epsilon > a$, we have

$$f(x_0)F(x_0) = f(x_0) \int_{-\infty + i(d_+ - \epsilon)}^{+\infty + i(d_+ - \epsilon)} \frac{e^{-ix_0 z} \phi(z)}{-2\pi iz} dz = f(x_0) e^{(d_+ - \epsilon)x_0} \int_{\mathbb{R}} \frac{e^{-ix_0 \xi} \phi(\xi + i(d_+ - \epsilon))}{-2\pi i(\xi + i(d_+ - \epsilon))} d\xi.$$

Let $\epsilon \downarrow 0$, we obtain

$$|f(x_0)F(x_0)| \leq \frac{\|\phi\|_+}{2\pi d_+} |f(x_0)| e^{x_0 d_+}.$$

Note that the probability density $p(x)$ admits the following inverse Fourier transform representation:

$$p(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-izx} \phi(z) dz.$$

By Cauchy's integral theorem and the condition (1), for any $\epsilon > 0$ such that $d_+ - \epsilon > 0$, we have

$$p(x) = \frac{1}{2\pi} \int_{-\infty + i(d_+ - \epsilon)}^{+\infty + i(d_+ - \epsilon)} e^{-izx} \phi(z) dz = e^{(d_+ - \epsilon)x} \int_{\mathbb{R}} \frac{1}{2\pi} e^{-ix\xi} \phi(\xi + i(d_+ - \epsilon)) d\xi.$$

Consequently,

$$\int_{-\infty}^{x_0} |f(x)| p(x) dx \leq \frac{\|\phi\|_+}{2\pi} \int_{-\infty}^{x_0} |f(x)| e^{x d_+} dx.$$

Similarly, using the representation (6), we have the following:

$$|f(x_K)|(1 - F(x_K)) \leq \frac{\|\phi\|^-}{2\pi|d_-|} |f(x_K)|e^{x_K d_-},$$

$$\int_{x_K}^{\infty} |f(x)|p(x)dx \leq \frac{\|\phi\|^-}{2\pi} \int_{x_K}^{\infty} |f(x)|e^{x d_-} dx.$$

Since $\xi\phi(\xi)$ is absolutely integrable on \mathbb{R} by the assumptions on ϕ ,

$$p'(x) = \frac{1}{2\pi} \frac{d}{dx} \int_{\mathbb{R}} e^{-i\xi x} \phi(\xi) d\xi = \frac{1}{2\pi i} \int_{\mathbb{R}} e^{-i\xi x} \xi \phi(\xi) d\xi,$$

where the interchange of the integration and differentiation is valid due to the dominated convergence theorem. Therefore,

$$\|p'\|_{\mathcal{X}} \leq \frac{1}{2\pi} \int_{\mathbb{R}} |\xi \phi(\xi)| d\xi.$$

Combining the preceding, we obtain the bound for the bias in (16). \square

C. PROOF OF THEOREM 4.5

PROOF. Denote the density of $\hat{F}^{(i)}$ by \hat{p}_i . From Theorem 4.1, we have the following for any $1 \leq i \leq d$:

$$\int_{\mathbb{R}} g_i(x) \hat{p}_i(x) dx \leq \|p_i g_i\|_1 + B_i,$$

$$\left| \int_{\mathbb{R}} f(x_1, \dots, x_d) (p_i(x_i) - \hat{p}_i(x_i)) dx_i \right| \leq B_i \prod_{j=1, j \neq i}^d g_j(x_j).$$

Following Glasserman and Liu [2010], $|\mathbb{E}[f(X_1, \dots, X_d)] - \mathbb{E}[f(\hat{X}_1, \dots, \hat{X}_d)]|$ is bounded by the following:

$$\begin{aligned} & \left| \mathbb{E}[f(X_1, X_2, \dots, X_{d-1}, X_d)] - \mathbb{E}[f(X_1, X_2, \dots, X_{d-1}, \hat{X}_d)] \right| \\ & + \left| \mathbb{E}[f(X_1, X_2, \dots, X_{d-1}, \hat{X}_d)] - \mathbb{E}[f(X_1, X_2, \dots, \hat{X}_{d-1}, \hat{X}_d)] \right| + \\ & \quad \vdots \\ & + \left| \mathbb{E}[f(X_1, \hat{X}_2, \dots, \hat{X}_{d-1}, \hat{X}_d)] - \mathbb{E}[f(\hat{X}_1, \hat{X}_2, \dots, \hat{X}_{d-1}, \hat{X}_d)] \right| \\ & \leq B_d \prod_{j=1}^{d-1} \|p_j g_j\|_1 + B_{d-1} \prod_{j=1}^{d-2} \|p_j g_j\|_1 \|\hat{p}_d g_d\|_1 + \dots + B_1 \prod_{j=2}^d \|\hat{p}_j g_j\|_1 \\ & \leq B \left(\prod_{j=1}^{d-1} \|p_j g_j\|_1 + \prod_{j=1}^{d-2} \|p_j g_j\|_1 (\|p_d g_d\|_1 + B) + \dots + \prod_{j=2}^d (\|p_j g_j\|_1 + B) \right), \end{aligned}$$

where $\|\hat{p}_i g_i\|_1 = \int_{\mathbb{R}} \hat{p}_i(x) g_i(x) dx$, $1 \leq i \leq d$. The conclusion then follows immediately. \square

D. ALGORITHM 3

ALGORITHM 3: Simulating Kou's double exponential jump diffusion

For $t > 0$, simulate $X_t = \mu t + \sigma B_t + \sum_{i=1}^{N_t} Z_i$

- (1) Generate a standard normal random variable G .
 - (2) Generate the Poisson process N_t using the inverse transform method described on p.128 of Glasserman [2004].
 - (3) Generate Z_i , $1 \leq i \leq N_t$, in the following way: generate U_i that is uniform in $(0, 1)$; if $U_i < p$, generate Z_i from an $\exp(\eta_1)$ distribution; otherwise, generate Z_i from the negative of an $\exp(\eta_2)$ distribution.
 - (4) Let $X_t = \mu t + \sigma \sqrt{t}G + Z_1 + \dots + Z_{N_t}$.
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