

# Small-time expansions for local jump-diffusions models with infinite jump activity

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# Outline

- 1 The local-jump diffusion model
  - Definition
  - Properties
- 2 The problem
  - Overview
  - Applications
  - Earlier literature
- 3 The main results
  - Expansions for the transition distributions
  - Expansions for the transition densities
- 4 Outline of Proof

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# Setup

- 1  $(\Omega, \mathcal{F}, \mathbb{P})$ : complete probability space;
- 2  $(W_t)$ : Wiener process (i.e. continuous process with independent and stationary increments such that  $W_t \sim \mathcal{N}(0, t)$ );
- 3  $(Z_t)$ : Lévy process (i.e. càdlàg independent and stationary increments s.t.  $Z_0 = 0$ ) without “Gaussian component” and with “Lévy density”  $h : \mathbb{R} \setminus \{0\} \rightarrow \mathbb{R}_+$ :

$$\mathbb{E} \exp(iuZ_t) = \exp \left\{ t \left( iub + \int_{\mathbb{R} \setminus \{0\}} (e^{iuz} - 1 - iuz \mathbf{1}_{\{|z| \leq 1\}}) h(z) dz \right) \right\}.$$

- 4  $W$  and  $Z$  are independent;

## Local jump-diffusion model

- 1 Assume  $Z$  to be of *bounded variation* without drift (i.e.  $Z_t = \sum_{s \leq t} \Delta Z_s$ );
- 2 Fix deterministic functions:

$$b(x) : \mathbb{R} \rightarrow \mathbb{R}, \quad \sigma(x) : \mathbb{R} \rightarrow \mathbb{R}, \quad \gamma(x, z) : \mathbb{R} \times \mathbb{R} \setminus \{0\} \rightarrow \mathbb{R}, \quad \text{s.t.} \quad \gamma(x, 0) = 0;$$

- 3 **The Model:**

$$X_t^x = x + \int_0^t b(X_s^x) ds + \int_0^t \sigma(X_s^x) dW_s + \sum_{s \leq t} \gamma(X_{s-}^x, \Delta Z_s).$$

- 4 Existence and uniqueness of  $(X_t^x)$  are guaranteed under standard linear growth and Lipschitz conditions on the coefficients  $b$ ,  $\sigma$ , and  $\gamma$ ;
- 5 **More general process:**

$$X_t^x = x + \int_0^t b(X_s^x) ds + \int_0^t \sigma(X_s^x) dW_s + \int_0^t \int_{|z| \leq 1} \gamma(X_{s-}^x, z) \bar{\mu}_z(ds, dz),$$

where  $\bar{\mu}_z := \mu_z - \mathbb{E}\mu_z$  is the compensated jump measure of  $Z$ :

$$\mu_z((u, v] \times [c, d]) := \# \{t \in (u, v] : \Delta Z_t \in [c, d]\}, \quad (0 < u < v, c < d).$$

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# Properties

- 1  $\Delta X_t^x := X_t^x - X_{t-}^x = \gamma(X_{t-}^x, \Delta Z_t)$ ;
- 2  $(X_t^x)$  is a **Homogeneous Markov Process**:

$$\mathbb{P}(X_T^x \in [c, d] | X_s^x, s \leq t) = \mathbb{P}(X_T^x \in [c, d] | X_t^x), \quad (t \leq T);$$

$$\mathbb{P}(X_T^x \in [c, d] | X_t^x = y) = \mathbb{P}(X_{T+h}^x \in [c, d] | X_{t+h}^x = y), \quad (t \leq T; h > 0).$$

- 3 **Dynkin's Formula**:

$$\mathbb{E}[f(X_t^x)] = f(x) + \int_0^t \mathbb{E}[Lf(X_s^x)] ds,$$

for  $f \in C_b^2$ , where  $L$  is the so-called **Generator Operator of  $X$** :

$$(Lf)(y) = b(y)f'(y) + \frac{\sigma^2(y)}{2}f''(y) + \int_{\mathbb{R} \setminus \{0\}} (f(y + \gamma(y, z)) - f(y))h(z) dz.$$

- 4 In particular,  $Lf(x) = \lim_{t \rightarrow 0} \frac{\mathbb{E}[f(X_t^x)] - f(x)}{t} \iff \mathbb{E}[f(X_t^x)] = f(x) + tLf(x) + o(t)$ ;
- 5 If  $f, Lf, \dots, L^n f := L(L^{n-1}f)$  are  $C_b^2$ , then

$$\mathbb{E}[f(X_t^x)] = f(x) + \sum_{k=1}^n \frac{t^k}{k!} L^k f(x) + \frac{t^{n+1}}{n!} \int_0^1 (1-\alpha)^n \mathbb{E}[L^{n+1} f(X_{\alpha t}^x)] d\alpha.$$

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# Short-time asymptotics for the transition distributions

## 1 Objective 1

Fix  $x \in \mathbb{R}$  and  $y > 0$ . Study the rate of convergence of  $\mathbb{P}(X_t^x \geq x + y)$  to 0 as  $t \rightarrow 0$ :

$$\mathbb{P}(X_t^x \geq x + y) = A_1(y; x)t + A_2(y; x)\frac{t^2}{2} + \cdots + A_n(y; x)\frac{t^n}{n!} + o(t^{n+1}).$$

## 2 Objective 2

Study the asymptotic behavior of transition density  $p_t(z; x) = \frac{d}{dz}\mathbb{P}(X_t^x \leq z)$  (when it exists) in short-time;

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# Applications

- ① Non-parametric estimation methods for  $\sigma$ ,  $\gamma$ ,  $b$  based on high-frequency observations  $X_\Delta, X_{2\Delta}, \dots, X_{n\Delta}$  of  $X$  (i.e. when time-span  $\Delta$ );

$$\frac{1}{\#\{X_{k\Delta} \in (x - \delta, x + \delta)\}} \sum_{X_{k\Delta} \in (x - \delta, x + \delta)} \mathbf{1}_{\{X_{(k+1)\Delta} \geq y + x\}} \longrightarrow A_1(y; x | \gamma, h) \Delta + o(\Delta).$$

- ② Numerical valuation of moments  $\mathbb{E}[\Phi(X_T^x)]$ :

Let  $F_t(x; \Phi) := \mathbb{E}[\Phi(X_t^x)]$  and  $\tilde{F}_t(x; \Phi)$  be an “explicit” approximation in short-time;  
Then, for  $m \in \mathbb{N}$  and  $\Delta := T/m$ ,

$$F_T(x; \Phi) = \mathbb{E}[\mathbb{E}[\Phi(X_T^x) | X_\Delta^x]] = \mathbb{E}[F_{T-\Delta}(X_\Delta^x; \Phi)] \approx \tilde{F}_\Delta(x; \tilde{\Phi}),$$

where  $\tilde{\Phi}(y) := F_{T-\Delta}(y; \Phi)$ , which in turn is approximated as before, replacing  $T$  by  $T - \Delta$ . **Convergence is attained whenever  $\tilde{F}_t$  is a second-order approximation.**

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Then, for  $m \in \mathbb{N}$  and  $\Delta := T/m$ ,

$$F_T(x; \Phi) = \mathbb{E}[\mathbb{E}[\Phi(X_T^x) | X_\Delta^x]] = \mathbb{E}[F_{T-\Delta}(X_\Delta^x; \Phi)] \approx \tilde{F}_\Delta(x; \tilde{\Phi}),$$

where  $\tilde{\Phi}(y) := F_{T-\Delta}(y; \Phi)$ , which in turn is approximated as before, replacing  $T$  by  $T - \Delta$ . **Convergence is attained whenever  $\tilde{F}_t$  is a second-order approximation.**

## Literature

- Léandre (1987):

For  $z \neq x$  and  $\sigma \equiv 0$  (Pure-jump case),

$$\lim_{t \rightarrow 0} \frac{1}{t} p_t(z; x) = -\frac{d}{dz} \int_{\{\zeta: \gamma(x, \zeta) \geq z\}} h(\zeta) d\zeta =: g(z - x; x) \quad (\text{"Lévy density" of } (X_t^x))$$

In particular, we expect, for  $y > 0$ ,

$$\lim_{t \rightarrow 0} \frac{1}{t} \mathbb{P}(X_t^x \geq x + y) = \lim_{t \rightarrow 0} \frac{1}{t} \int_{x+y}^{\infty} p_t(z; x) dz = \int_y^{\infty} g(u; x) du.$$

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Let  $z > x$ . Note that

$$\text{supp}(h) \cap \{\zeta : \gamma(x, \zeta) \geq z\} = \emptyset \quad \implies \quad \lim_{t \rightarrow 0} \frac{1}{t} p_t(z; x) = 0.$$

In that case,  $p_t(z; x) \sim t^{\kappa} g_{\kappa}(z; x)$ , where  $\kappa$  is the minimal number of jumps needed to reach  $z$  from  $x$  and  $g_{\kappa}(z; x) \neq 0$ .

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- 1 Provide a formal proof of expansions (1)-(2);
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- 1 **Key Assumption:** For all  $\varepsilon > 0$  and  $k \geq 0$ , the Lévy density  $h$  of  $X$  is smooth s.t.

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# Outline

- 1 The local-jump diffusion model
  - Definition
  - Properties
- 2 The problem
  - Overview
  - Applications
  - Earlier literature
- 3 The main results**
  - Expansions for the transition distributions
  - Expansions for the transition densities
- 4 Outline of Proof

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### Theorem (F-L & Ouyang, 2011)

For any  $x \in \mathbb{R}$  and  $y > 0$ ,

$$\mathbb{P}(X_t^x \geq x + y) = tA_1(x; y) + \frac{t^2}{2}A_2(x; y) + o(t^2), \quad \text{as } t \rightarrow 0,$$

where  $A_1(x; y)$  admits the representation:

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### Remarks:

- 1 Leading term depends only on the jump component;
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## Second-order expansion for the transition densities

### Theorem (F-L & Ouyang, 2011)

In addition to the previous conditions assume that  $b(x), \sigma^2(x) \in C_b^\infty$  and  $\sigma(x) \geq \delta$  for some  $\delta > 0$ . Then,

$$p_t(x+y; x) = ta_1(x; y) + \frac{t^2}{2}a_2(x; y) + O(t^3), \quad \text{as } t \rightarrow 0. \quad (3)$$

There exists a  $\varepsilon_0 > 0$  small-enough such that for all  $0 < \varepsilon < \varepsilon_0$ ,  $A_1$  and  $A_2$  admit the following representations:

$$a_1(x; y) := -\frac{\partial}{\partial y}A_1(x; y), \quad a_2(x; y) := -\frac{\partial}{\partial y}A_2(x; y).$$



# Outline

- 1 The local-jump diffusion model
  - Definition
  - Properties
- 2 The problem
  - Overview
  - Applications
  - Earlier literature
- 3 The main results
  - Expansions for the transition distributions
  - Expansions for the transition densities
- 4 Outline of Proof**

## Some needed notation

- $Z_t(\varepsilon) = \sum_{s \leq t} \phi_\varepsilon(\Delta Z_s) \Delta Z_s$  ("big" jumps) and  $Z'_t(\varepsilon) = \sum_{s \leq t} (1 - \phi_\varepsilon(\Delta Z_s)) \Delta Z_s$  ("small jumps").
- $Z_t(\varepsilon) = \sum_{i=1}^{N_t^\varepsilon} J_i^\varepsilon$ , with  $(N_t^\varepsilon)$  Poisson with intensity  $\lambda_\varepsilon := \int \phi_\varepsilon(z) h(z) dz$  and  $J_i^\varepsilon \stackrel{\text{i.i.d.}}{\sim} h_\varepsilon(z) / \lambda_\varepsilon$ .
- Define the following processes for a set  $\pi := \{s_1, \dots, s_n\} \subset \mathbb{R}_+$ :

$$X_t(\varepsilon, \emptyset, x) := x + \int_0^t b(X_u(\varepsilon, \emptyset, x)) du + \int_0^t \sigma(X_u(\varepsilon, \emptyset, x)) dW_u \\ + \sum_{0 < u \leq t} \gamma(X_{u-}(\varepsilon, \emptyset, x), \Delta Z'_u(\varepsilon));$$

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## For Further Reading I



Figueroa-López & Ouyang.

Small-time expansions for local jump-diffusions models with infinite jump activity  
Preprint, 2011. Available at [www.stat.purdue.edu/~figueroa](http://www.stat.purdue.edu/~figueroa).



Figueroa-Lopez & Houdré.

Small-time expansions for the transition distributions of Lévy processes.  
*Stochastic Processes and Their Applications*, 119:3862-3889, 2009.

# Rüschendorf & Woerner's Approach

- 1 Consider the Lévy-Itô decomposition:

$$X_t = \underbrace{X_t^{cp,\varepsilon}}_{\text{Comp. Poiss. of jumps } > \varepsilon} + \underbrace{b_\varepsilon t + \sigma B_t + \lim_{\delta \searrow 0} (X_t^{(\delta,\varepsilon)} - \mathbb{E}X_t^{(\delta,\varepsilon)})}_{\bar{X}_t^{(\varepsilon)} := \text{Drift} + \text{Brownian} + \text{Small-jumps}}.$$

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$$\mathbb{P}(X_t \geq x) = e^{-\lambda_\varepsilon t} \sum_{k=0}^n \frac{(\lambda_\varepsilon t)^k}{k!} + O(t^{n+1});$$

- 3 Using estimates by Léandre (1987), argue that for fixed  $n$ ,  $x_0 > 0$ , and  $\delta > 0$ , there exists  $t_0 := t_0(\delta) > 0$  and  $\varepsilon$  small enough s.t., for all  $k \geq 0$  and  $x \geq x_0$ ,

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