

Exercises

1. Suppose we have

$$dX_t = \alpha dt + \sigma dB_t + \int_{|x|<1} h(x) \tilde{N}(dt, dx) + \int_{|x|\geq 1} k(x) N(dt, dx),$$

$$X_0 = x_0,$$

where α, σ are constants and h and k are given functions from $\mathbb{R} \rightarrow \mathbb{R}$.

- (a) Use Itô's formula to find dY_t when $Y_t = \exp(X_t)$.
 (b) How do we choose α, σ, h and k if we want Y_t to solve the SDE

$$dY_t = Y_{t-} \left(\beta dt + \theta dB_t + \lambda \int_{|x|<1} x \tilde{N}(dt, dx) + \rho \int_{|x|\geq 1} x N(dt, dx) \right),$$

for given constants β, θ, λ and ρ .

2. Solve the following Lévy SDEs:

- (a) Let m, σ, λ be constants and

$$dX_t = (m - X_t) dt + \sigma dB_t + \lambda \int_{|x|<1} x \tilde{N}(dt, dx) + \rho \int_{|x|\geq 1} x N(dt, dx),$$

$$X_0 = x_0.$$

- (b) Let

$$dX_t = \alpha dt + \gamma X_{t-} \left(\int_{|x|<1} x \tilde{N}(dt, dx) + \int_{|x|\geq 1} x N(dt, dx) \right),$$

$$X_0 = x_0.$$

3. Let $h \in L^2(\mathbb{R})$ be deterministic and define

$$Y_t = \exp \left\{ \int_0^t \int_{\mathbb{R}_0} h(s) x \tilde{N}(ds, dx) - \int_0^t \int_{\mathbb{R}_0} (e^{h(s)x} - 1 - h(s)x) \nu(dx) ds \right\}.$$

Show that

$$dY_t = Y_{t-} \int_{\mathbb{R}_0} (e^{h(t)x} - 1) \tilde{N}(dt, dx).$$

4. Show that, under some conditions on $\gamma(s, x)$ (assumed to be deterministic) we have

$$\mathbb{E} \left[\exp \left(\int_0^t \int_{\mathbb{R}_0} \gamma(s, x) \tilde{N}(ds, dx) \right) \right] = \exp \left(\int_0^t \int_{\mathbb{R}_0} \{ e^{\gamma(s,x)} - 1 - \gamma(s, x) \} \nu(dx) ds \right).$$

5. Let

$$dX_t^i = \int_{\mathbb{R}_0} \gamma_i(t, x) \tilde{N}(dt, dx), \quad i = 1, 2,$$

be two one-dimensional Itô-Lévy processes. Prove that

$$X_t^1 X_t^2 = X_0^1 X_0^2 + \int_0^t X_{s-}^1 dX_s^2 + \int_0^t X_{s-}^2 dX_s^1 + \int_0^t \int_{\mathbb{R}_0} \gamma_1(s, x) \gamma_2(s, x) N(ds, dx).$$

6. Define, with suitable conditions on $\theta(s, x)$,

$$Z_t(\theta) = \exp \left(\int_0^t \int_{\mathbb{R}_0} \log(1 - \theta(s, x)) \tilde{N}(ds, dx) + \int_0^t \int_{\mathbb{R}_0} \{\log(1 - \theta(s, x)) + \theta(s, x)\} \nu(dx) ds \right).$$

Show that

$$dZ_t(\theta) = -Z_{t-}(\theta) \int_{\mathbb{R}_0} \theta(t, x) \tilde{N}(dt, dx).$$

7. Let $N = \{N_t\}_{t \geq 0}$ be a Poisson process with intensity parameter λ . Compute $\int_0^t N_{s-} dN_s$ and $\int_0^t N_s dN_s$.

8. Decide whether or not the following markets have arbitrages. If the market has an arbitrage find one.

(a) Consider

$$\begin{aligned} dS_t^0 &= 0, \quad S_0^0 = 1, \\ dS_t^1 &= S_{t-}^1 \left(\alpha dt + \int_{\mathbb{R}_0} x \tilde{N}(dt, dx) \right), \quad S_0^1 > 0, \end{aligned}$$

where ν is supported in $(-1, +\infty)$, $\alpha \in \mathbb{R}$ is a constant and $\int_{\mathbb{R}} |z| \nu(dz) > |\alpha|$.

(b) Consider

$$\begin{aligned} dS_t^0 &= 0, \quad S_0^0 = 1, \\ dS_t^1 &= S_{t-}^1 \left(-dt - 1dB_t + 3 \int_{\mathbb{R}_0} x \tilde{N}(dt, dx) \right), \quad S_0^1 > 0, \\ dS_t^2 &= S_{t-}^2 \left(4dt + 2dB_t - 6 \int_{\mathbb{R}_0} x \tilde{N}(dt, dx) \right), \quad S_0^2 > 0. \end{aligned}$$

9. Consider the following market

$$\begin{aligned} dS_t^0 &= 0, \quad S_0^0 = 1, \\ dS_t^1 &= S_{t-}^1 (\mu_1 dt + \gamma_1^1 d\eta_t^1 + \gamma_2^1 d\eta_t^2), \quad S_0^1 > 0, \\ dS_t^2 &= S_{t-}^2 (\mu_2 dt + \gamma_1^2 d\eta_t^1 + \gamma_2^2 d\eta_t^2), \quad S_0^2 > 0, \end{aligned}$$

where μ_i and $\gamma_j^i, i, j = 1, 2$, are constants and η^1 and η^2 are independent Lévy martingales of the form

$$d\eta_t^i = \int_{\mathbb{R}_0} x \tilde{N}^i(dt, dx), \quad i = 1, 2.$$

Assume that the matrix $\gamma = (\gamma_j^i)_{1 \leq i, j \leq 2}$ is invertible, with inverse $\gamma^{-1} = \lambda = (\lambda_j^i)_{1 \leq i, j \leq 2}$ and assume that

$$\int_{\mathbb{R}_0} |x| \nu^i(dx) > |\lambda_1^i \mu_1 + \lambda_2^i \mu_2|, \quad i = 1, 2.$$

Show that this market is arbitrage free.

$$\textcircled{1} \quad dY_t = \alpha dt + \sigma dB_t + \int_{|x| < 1} h(x) \tilde{N}(dt, dx) + \int_{|x| \geq 1} \kappa(x) N(dt, dx)$$

where α, σ are constants, h, κ functions

a) Use Itô's formula to find dY_t when $Y_t = \exp(X_t)$

b) How do we choose α, σ, h and κ if we want to solve the SDE.

$$dY_t = Y_{t-} \left(\beta dt + \theta dB_t + \lambda \int_{|x| < 1} x \tilde{N}(dt, dx) + \rho \int_{|x| \geq 1} x N(dt, dx) \right)$$

for given constants β, θ, λ and ρ .

a) Using Theorem 11.5 (Itô's formula 2) we get

$$f(x) = f'(x) = f''(x) = e^x$$

$$dY_t = d(\exp(X_t)) = \exp(X_{t-}) \left\{ \alpha dt + \sigma dB_t \right\} + \frac{1}{2} \exp(X_{t-}) \sigma^2 dt$$

$$+ \int_{|x| \geq 1} \left\{ \exp(X_{t-} + \kappa(x)) - \exp(X_{t-}) \right\} N(dt, dx)$$

$$+ \int_{|x| < 1} \left\{ \exp(X_{t-} + h(x)) - \exp(X_{t-}) \right\} \tilde{N}(dt, dx)$$

$$+ \int_{|x| < 1} \left\{ \exp(X_{t-} + h(x)) - \exp(X_{t-}) - h(x) \exp(X_{t-}) \right\} \nu(dx) dt$$

$$= Y_{t-} \left\{ \alpha + \frac{1}{2} \sigma^2 + \int_{|x| < 1} \left\{ e^{h(x)} - 1 - h(x) \right\} \nu(dx) \right\} dt$$

$$+ Y_{t-} \sigma dB_t + Y_{t-} \int_{|x| \geq L} \{e^{k(x)} - 1\} N(dt, dx)$$

$$+ Y_{t-} \int_{|x| < L} \{e^{h(x)} - 1\} \tilde{N}(dt, dx)$$

b) Clearly, we match the terms and get

$$\beta = \alpha + \frac{1}{2} \sigma^2 + \int_{|x| \geq L} \{e^{k(x)} - 1 - h(x)\} \nu(dx)$$

$$\theta = \sigma$$

$$\lambda x = e^{h(x)} - 1 \Rightarrow h(x) = \log(L + \lambda x)$$

$$\rho x = e^{k(x)} - 1 \Rightarrow k(x) = \log(L + \rho x)$$

In order for these to make sense we need $L + \lambda x > 0$ ν -a.e. and $L + \rho x > 0$ ν -a.e.

$\Rightarrow \nu$ must be supported in $(\max(-1/\lambda, -1/\rho), +\infty)$

2) Solve

a) m, σ + constants and

$$dX_t = (m - X_t) dt + \sigma dB_t + \int_{|x| < 1} X_t \tilde{N}(dt, dx) + \int_{|x| \geq 1} X_t N(dt, dx)$$

$$X_0 = x_0$$

b) let α, γ be constants and

$$dY_t = \alpha dt + \gamma X_t \left(\int_{|x| < 1} \tilde{N}(dt, dx) + \int_{|x| \geq 1} N(dt, dx) \right)$$

$$X_0 = x_0$$

Recall the integration by parts formula (or product rule)

$$d(X_t^1 X_t^2) = X_t^1 dX_t^2 + X_t^2 dX_t^1 + d[X^1, X^2]_t$$

To solve the SDE, we use the previous formula and the variation of constants techniques from O.D.E.

a) We compute

$$d(e^t \cdot X_t) = e^t dX_t + X_t e^t dt + [e^t, X]_{t=(\cdot)}$$

But $[e^t, X] \equiv 0$ because e^t has continuous path of finite variation. (Section 9.3 in the notes)

$$\begin{aligned} (\cdot) &= e^t m dt - \cancel{X_t e^t dt} + e^t \sigma dB_t + \cancel{\lambda e^t \int_{|x| < 1} \tilde{N}(dt, dx)} \\ &+ e \int_{|x| \geq 1} X_t N(dt, dx) + \cancel{X_t e^t dt} \end{aligned}$$

Since the r.h.s. of the previous equation does NOT depend explicitly on X we can integrate

$$e^t X_t = X_0 + \int_0^t m e^s ds + \int_0^t \sigma e^s dB_s + \int_0^t \int_{|x| < 1} \lambda e^s \tilde{N}(ds, dx) + \int_0^t \int_{|x| > 1} e^s x N(ds, dx)$$

=>

$$X_t = \underbrace{e^{-t} X_0 + m e^{-t} (e^t - 1)}_{= m + (X_0 - m) e^{-t}} + \int_0^t \sigma e^{-(t-s)} dB_s + \int_0^t \int_{|x| < 1} \lambda e^{-(t-s)} x \tilde{N}(ds, dx) + \int_0^t \int_{|x| > 1} e^{-(t-s)} x N(ds, dx)$$

b) Consider the process $G = \{G_t\}_{t \geq 0}$ given by

$$G_t = \exp \left(\int_0^t \int_{|x| < 1} \theta(z) \tilde{N}(dz, dx) + \int_0^t \int_{|x| > 1} \theta(z) N(ds, dx) - t \int_{|x| < 1} \{ e^{\theta(z)} - 1 - \theta(z) \} \nu(dx) \right)$$

For $\theta(z)$ a deterministic function (to choose). By Itô's formula

$$dG_t = G_t \left\{ \int_{|x| < 1} (e^{\theta(x)} - 1) \tilde{N}(dt, dx) + \int_{|x| > 1} (e^{\theta(x)} - 1) N(dt, dx) \right.$$

$$\begin{aligned}
 & + \left(\int_{|x| \leq L} (e^{\theta(x)} - 1 - \theta(x)) V(dx) \right) dt \\
 & - \left(\int_{|x| > L} (e^{\theta(x)} - 1 - \theta(x)) V(dx) \right) dt \\
 & = G_{t-} \left\{ \int_{|x| \leq L} (e^{\theta(x)} - 1) \tilde{N}(dt, dx) + \int_{|x| > L} (e^{\theta(x)} - 1) N(dt, dx) \right\}
 \end{aligned}$$

Next we consider the process

$$\tilde{X}_t = X_0 G_t + \alpha G_t \int_0^t G_s^{-1} ds$$

We will show that this process solves the SDE (by choosing an appropriate θ)

$$d\tilde{X}_t = X_0 dG_t + \alpha G_t \cdot G_t^{-1} dt + \alpha \left(\int_0^t G_s^{-1} ds \right) dG_t$$

$$\begin{aligned}
 & + \underbrace{d \left[\alpha G_t \int_0^t G_s^{-1} ds \right]}_G \quad \left\{ \begin{array}{l} \text{continuous and of finite variation.} \\ \text{G} \end{array} \right. \\
 & = \alpha dt + \left(X_0 + \alpha \left(\int_0^t G_s^{-1} ds \right) \right) dG_t
 \end{aligned}$$

$$= \alpha dt + \left(X_0 + \alpha \left(\int_0^t G_s^{-1} ds \right) \right) G_{t-} *$$

$$* \left(\int_{|x| \leq L} (e^{\theta(x)} - 1) \tilde{N}(dt, dx) + \int_{|x| > L} (e^{\theta(x)} - 1) N(dt, dx) \right)$$

$$= \alpha dt + \tilde{X}_{t-} \left(\int_{|x| \leq L} (e^{\theta(x)} - 1) \tilde{N}(dt, dx) + \int_{|x| > L} (e^{\theta(x)} - 1) N(dt, dx) \right)$$

Hence \tilde{X}_+ solves our equation if we choose θ

such that

$$e^{\theta(x)-1} = \gamma x \quad (\Rightarrow) \quad \theta(x) = \log(1 + \gamma x)$$

and γ is supported in $(-\frac{1}{x}, +\infty)$.

3) $h \in L^2(\mathbb{R})$ be deterministic and define

$$Y_t = \exp\left(\int_0^t \int_{\mathbb{R}_0} h(s) \times \tilde{N}(ds, dx) - \int_0^t \int_{\mathbb{R}_0} (e^{h(s)x} - 1 - h(s)x) v(dx) ds\right)$$

show that

$$dY_t = Y_{t-} \int_{\mathbb{R}_0} (e^{h(t)x} - 1) \tilde{N}(dt, dx)$$



Itô's formula. $Y_t = \exp(X_t)$ with

$$\begin{aligned} dX_t &= \int_{\mathbb{R}_0} h(t) \times \tilde{N}(dt, dx) - \int_{\mathbb{R}_0} (e^{h(t)x} - 1 - h(t)x) v(dx) dt \\ &= \int_{|x| < \varepsilon} h(t) \times \tilde{N}(dt, dx) + \int_{|x| \geq \varepsilon} h(t) \times N(dt, dx) \\ &\quad - \int_{\mathbb{R}_0} (e^{h(t)x} - 1 - h(t)x \mathbb{1}_{\hat{B}_\varepsilon(0)}(x)) v(dx) dt \end{aligned}$$

$$e^x = f(x) = f'(x) = f''(x).$$

$$\begin{aligned} dY_t &= d(\exp(X_t)) = \exp(X_{t-}) \int_{\mathbb{R}_0} (e^{h(t)x} - 1 - h(t)x \mathbb{1}_{\hat{B}_\varepsilon(0)}(x)) v(dx) dt \\ &\quad + \int_{|x| < \varepsilon} (e^{X_{t-} + h(t)x} - e^{X_{t-}} - h(t)x e^{X_{t-}}) v(dx) dt \\ &\quad + \int_{|x| < \varepsilon} (e^{X_{t-} + h(t)x} - e^{X_{t-}}) \tilde{N}(dt, dx) \\ &\quad + \int_{|x| \geq \varepsilon} (e^{X_{t-} + h(t)x} - e^{X_{t-}}) N(dt, dx) \end{aligned}$$

$$\begin{aligned}
&= Y_{t-} \left\{ - \int_{|x| > L} (e^{h(x)x} - 1) \cdot V(dx) dt \right. \\
&\quad + \int_{|x| < L} (e^{h(x)x} - 1) \tilde{N}(dt, dx) \\
&\quad \left. + \int_{|x| > L} (e^{h(x)x} - 1) N(dt, dx) \right\} \\
&= Y_{t-} \int_{\mathbb{R}_0} (e^{h(x)x} - 1) \tilde{N}(dt, dx)
\end{aligned}$$

Hidden assumption $\int_{|x| > L} x^2 V(dx) < +\infty$.

The Lévy process associated to N has finite second moment.

⑤ Under some conditions on $\gamma(s, x)$ deterministic we have

$$E \left[\exp \left(\int_0^t \int_{\mathbb{R}_0} \gamma(s, x) \tilde{N}(ds, dx) \right) \right] = \exp \left(\int_0^t \int_{\mathbb{R}_0} (e^{\gamma(s, x)} - 1 - \gamma(s, x)) \nu(dx) ds \right)$$

I identify an exponential martingale. You can use Proposition 10.5 (linking ordinary exponentials and stochastic exponentials) or using Theorem 12.10. combined with Novikov's condition for H^2 -Lévy processes.

For instance, using Theo. 12.10. Assuming that

$$E \left[\int_0^t \int_{|x| \geq 1} |e^{\gamma(s, x)} - 1| \nu(dx) ds \right] = \int_0^t \int_{|x| \geq 1} |e^{\gamma(s, x)} - 1| \nu(dx) ds < \infty$$

is deterministic.

$$Y_t = \int_0^t \int_{\mathbb{R}_0} \gamma(s, x) \tilde{N}(ds, dx) = - \int_0^t \int_{|x| \geq 1} \gamma(s, x) \nu(dx) ds + \int_0^t \int_{|x| \leq 1} \gamma(s, x) \tilde{N}(ds, dx) + \int_0^t \int_{|x| \leq 1} \gamma(s, x) \nu(dx) ds$$

Then $e^{Y_t + \int_0^t G_s ds}$ is a local martingale \Leftrightarrow

$$0 = G_t - \int_0^t \int_{|x| \geq 1} \gamma(s, x) \nu(dx) ds + \int_0^t \int_{|x| \leq 1} (e^{\gamma(s, x)} - 1 - \gamma(s, x)) \nu(dx) ds + \int_0^t \int_{|x| \leq 1} (e^{\gamma(s, x)} - 1) \nu(dx) ds$$

$$\Leftrightarrow - \int_{\mathbb{R}_0} (e^{\gamma(s, x)} - 1 - \gamma(s, x)) \nu(dx) = G_t$$

Hence

$$Y_t = \exp\left(\int_0^t \int_{\mathbb{R}_0} \gamma(s,x) \tilde{N}(ds, dx) - \int_0^t \int_{\mathbb{R}_0} (e^{\gamma(s,x)} - 1 - \gamma(s,x)) v(dx) ds\right) \text{ is}$$

a local martingale.

We need to find conditions on $\gamma(s,x)$ so that we have

Let Y is a martingale. Note that, then, we can claim that

$$1 = Y_0 = E[Y_t] = E\left[\exp\left(\int_0^t \int_{\mathbb{R}_0} \gamma(s,x) \tilde{N}(ds, dx)\right) \exp\left(-\int_0^t \int_{\mathbb{R}_0} (e^{\gamma(s,x)} - 1 - \gamma(s,x)) v(dx) ds\right)\right]$$

↑ because γ is deterministic

and we get the result.

Define $\lambda(s,x)$ such that $\gamma(s,x) = \log(L - \lambda(s,x))$,
 ($\lambda(s,x) = L - e^{\gamma(s,x)}$)

then,

$$Y_t = \exp\left(\int_0^t \int_{\mathbb{R}_0} \log(L - \lambda(s,x)) \tilde{N}(ds, dx) + \int_0^t \int_{\mathbb{R}_0} \left\{ \log(L - \lambda(s,x)) + \lambda(s,x) \right\} v(dx) ds\right)$$

Now we can apply Theorem 12.23 (Perikami.)

$$E\left[\exp\left(\int_0^T \int_{\mathbb{R}_0} \left\{ (L - \lambda(s,x)) \log(L - \lambda(s,x)) + \lambda(s,x) \right\} v(dx) ds\right)\right] < +\infty$$

⇔ $\lambda(s,x)$ is deterministic.

$$\int_0^T \int_{\mathbb{R}_0} \left\{ (L - \lambda(s,x)) \log(L - \lambda(s,x)) + \lambda(s,x) \right\} v(dx) ds < +\infty$$

⇔

$$\int_0^T \int_{\mathbb{R}_0} \left\{ e^{\gamma(s,x)} \gamma(s,x) + 1 - e^{\gamma(s,x)} \right\} v(dx) ds < +\infty$$

$$\textcircled{S} \quad dX_t^i = \int_{\mathbb{R}_0} \gamma_i(t, x) \tilde{N}(dt, dx) \quad i=1, 2$$

be two one-dimensional Itô-Lévy processes.

Prove that

$$\begin{aligned} X_t^1 X_t^2 &= X_0^1 X_0^2 + \int_0^t X_s^1 dX_s^2 + \int_0^t X_s^2 dX_s^1 \\ &+ \int_0^t \int_{\mathbb{R}_0} \gamma_1(s, x) \gamma_2(s, x) N(ds, dx) \end{aligned}$$

(Alternative Itô's formula)

By Theorem 11.11. we just have to show that

$$[X^1, X^2]_t = \int_0^t \int_{\mathbb{R}_0} \gamma_1(s, x) \gamma_2(s, x) N(ds, dx).$$

The processes X^1 and X^2 can be rewritten as

$$\begin{aligned} X_t^i &= - \int_0^t \int_{|x| \geq 1} \gamma_i(s, x) v(dx) ds + \int_0^t \int_{|x| < 1} \gamma_i(s, x) \tilde{N}(ds, dx) \\ &+ \int_0^t \int_{|x| \geq 1} \gamma_i(s, x) N(ds, dx) \end{aligned}$$

And using the formula for the quadratic variation of Itô-Lévy processes we get

$$\begin{aligned} [X^1, X^2]_t &= \int_0^t \int_{|x| < 1} \gamma_1(s, x) \gamma_2(s, x) N(ds, dx) + \int_0^t \int_{|x| \geq 1} \gamma_1(s, x) \gamma_2(s, x) N(ds, dx) \\ &= \int_0^t \int_{\mathbb{R}_0} \gamma_1(s, x) \gamma_2(s, x) N(ds, dx) \end{aligned}$$

6 Define Z_t with suitable conditions on $\theta(s, x)$,

$$Z_t(\theta) = \exp\left(\int_0^t \int_{\mathbb{R}_0} \log(L - \theta(s, x)) \hat{N}(ds, dx) \right. \\ \left. + \int_0^t \int_{\mathbb{R}_0} \{ \log(L - \theta(s, x)) + \theta(s, x) \} v(dx) ds \right)$$

Show that

$$dZ_t(\theta) = -Z_t(\theta) \int_{\mathbb{R}_0} \theta(t, x) \hat{N}(dt, dx)$$

$$\begin{cases} \theta(s, x) < L & P \otimes \lambda \otimes \nu - a.e. \\ \log(L - \theta(s, x)) \in \mathcal{F}_2([0, t]) \end{cases}$$

$Z_t(\theta) = \exp(Y_t)$, where Y_t can be written as

$$Y_t = \int_0^t \int_{|x| < L} \log(L - \theta(s, x)) \hat{N}(ds, dx) + \int_0^t \int_{|x| \geq L} \log(L - \theta(s, x)) N(ds, dx) \\ + \int_0^t \int_{\mathbb{R}_0} \{ \log(L - \theta(s, x)) \mathbb{1}_{\{|x| < L\}} + \theta(s, x) \} v(dx) ds$$

By Itô's formula with $f(x) = e^x = f'(x)$

$$dZ_t(\theta) = \exp(Y_{t-}) \int_{\mathbb{R}_0} \{ \log(L - \theta(t, x)) \mathbb{1}_{\{|x| < L\}} + \theta(t, x) \} v(dx) dt \\ + \int_{|x| \geq L} \{ \exp(Y_{t-} + \log(L - \theta(t, x))) - \exp(Y_{t-}) \} \hat{N}(dt, dx)$$

$$\begin{aligned}
 & + \int_{|x| \geq 1} \{ \exp(Y_{t-} + \log(L - \theta(t, x))) - \exp(Y_{t-}) \} N(dt, dx) \\
 & + \int_{|x| < 1} \{ \exp(Y_{t-} + \log(L - \theta(t, x))) - \exp(Y_{t-}) - \exp(Y_{t-}) \log(L - \theta(t, x)) \} \nu(dx) dt \\
 = & \exp(Y_{t-}) \left[\int_{\mathbb{R}_0} \{ \log(L - \theta(t, x)) \} \nu(dx) + \theta(t, x) \right] \\
 & + \int_{|x| \geq 1} \{ 1 - \theta(t, x) - 1 \} \hat{N}(dt, dx) \\
 & + \int_{|x| \geq 1} \{ L - \theta(t, x) - 1 \} N(dt, dx) \\
 & + \int_{|x| < 1} \{ 1 - \theta(t, x) - 1 - \log(L - \theta(t, x)) \} \nu(dx) dt] \\
 = & -Z_{t-}(\theta) \int_{\mathbb{R}_0} \theta(t, x) \hat{N}(dt, dx)
 \end{aligned}$$

If you set $\lambda(t, x) = -\theta(t, x)$ then $\left(\begin{array}{l} \lambda(s, x) > -1 \\ \log(1 + \lambda(s, x)) \in \mathcal{P}_2([0, \infty)) \end{array} \right)$

$$\begin{aligned}
 \tilde{Z}_t(\lambda) := & \exp \left(\int_0^t \int_{\mathbb{R}_0} \log(1 + \lambda(s, x)) \hat{N}(ds, dx) \right. \\
 & \left. + \int_0^t \int_{\mathbb{R}_0} \{ \log(1 + \lambda(s, x)) - \lambda(s, x) \} \nu(dx) ds \right)
 \end{aligned}$$

Solve the SDE.

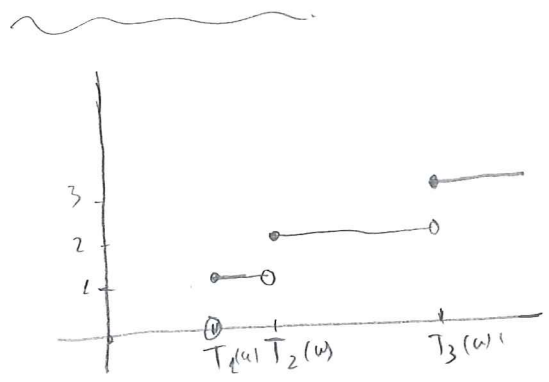
$$dY_t = Y_{t-} \int_{\mathbb{R}_0} \lambda(t, x) \hat{N}(dt, dx)$$

that is

$$\tilde{Z}_t(\lambda) = \sum_t \left(\int_0^t \int_{\mathbb{R}_0} \lambda(s, x) \hat{N}(ds, dx) \right)$$

(17) Let $N = \{N_t\}_{t \geq 0}$ be a Poisson process with intensity parameter λ .

Compute $\int_0^t N_{s-} dN_s$ and $\int_0^t N_s dN_s$.



let $T_0 \equiv 0$ and $\{T_n\}_{n \geq 1}$ the sequence of jump times of N .

Note that,

For $n \geq 0$, $N_t = n$ if $t \in [T_n, T_{n+1})$ and is càdlàg. But,

$N_{t-} = n$ if $t \in (T_n, T_{n+1}]$ for $n \geq 0$.

and hence it is càdlàg (left continuous with right limits). Since the filtration is the one generated by N , we have left continuous + adapted \Rightarrow predictable. The integral is pathwise.

$$\int_0^t N_{s-} dN_s = \sum_{k \geq 1} (k-1) (N_{t \wedge T_k} - N_{t \wedge T_{k-1}})$$

$$\begin{aligned} \left(\text{if } t \in [T_{n-1}, T_n) \right) &= \sum_{k \neq 1}^{n-1} (k-1) (N_{T_k} - N_{T_{k-1}}) = \sum_{k=1}^{n-1} (k-1) \\ &= \frac{(n-1)(n-2)}{2} \end{aligned}$$

But note that if $t \in [T_{m-1}, T_m)$, $N_t = m-1$
and we can conclude

$$\int_0^t N_{s-} dN_s = \frac{N_t (N_t - 1)}{2} \quad t \geq 0.$$

On the other hand, we have

$$\int_0^t N_s dN_s = \sum_{k \geq L} K (N_{t \wedge T_k} - N_{t \wedge T_{k-1}})$$

$$\left(\text{if } t \in [T_{m-1}, T_m) \right) = \sum_{k=L}^{m-1} K (N_{T_k} - N_{T_{k-1}}) = \sum_{k=L}^{m-1} K = \frac{(m-1)m}{2}$$

and we get that

$$\int_0^t N_s dN_s = \frac{N_t (N_t + 1)}{2}$$

Another approach to compute $\int_0^t N_{s-} dN_s$ is to use the Lévy-Itô decomposition of N (which is a Lévy process)

$$N_t = \int_{|x| \geq 1} x N(t, dx) \quad \text{where } \nu(dx) = \int_{\mathbb{Z}} \delta_x(x)$$

Using Itô's formula with $f(x) = x^2$, we get

$$N_t^2 = \int_0^t \int_{|x| \geq 1} \{ (N_{s-} + x)^2 - N_{s-}^2 \} N(ds, dx)$$

$$= \int_0^t \int_{|x| \geq 1} \left\{ \cancel{N_{s-}^2} + 2 N_{s-} x + x^2 - \cancel{N_{s-}^2} \right\} N(ds, dx)$$

$$= 2 \int_0^t \underbrace{N_{s-} \int_{|x| \geq 1} x N(ds, dx)}_{dN_s} + \int_0^t \int_{|x| \geq 1} x^2 N(ds, dx)$$

$$= 2 \int_0^t N_{s-} dN_s + \sum_{0 \leq u \leq t} \Delta N_u \mathbb{1}_{\{|x| \geq 1\}} (\Delta N_u)$$

(finite variation) = $2 \int_0^t N_{s-} dN_s + N_t$

Hence, we have

$$N_t^2 = 2 \int_0^t N_{s-} dN_s + N_t \quad (\Leftrightarrow) \quad \int_0^t N_{s-} dN_s = \frac{N_t^2 - N_t}{2} = \frac{N_t(N_t - 1)}{2}$$



8) Decide whether or not the following markets have arbitrages. If the market has an arbitrage find one.

a) Consider

$$dS_t^0 = 0, \quad S_0^0 = 1.$$

$$dS_t^1 = S_t^1 \left(\alpha dt + \int_{\mathbb{R}_0} \gamma \tilde{N}(dt, dx) \right), \quad S_0^1 > 0$$

where γ is supported in $(-1, +\infty)$, $\alpha \in \mathbb{R}$ and $\int_{\mathbb{R}} |\gamma| V(dx) > |\alpha|$ and is absolutely continuous with respect to λ .

b) Consider

$$dS_t^0 = 0, \quad S_0^0 = 1$$

$$dS_t^1 = S_t^1 \left(-dt - 1 dB_t + 3 \int_{\mathbb{R}_0} \gamma \tilde{N}(dt, dx) \right), \quad S_0^1 > 0$$

$$dS_t^2 = S_t^2 \left(4dt + 2 dB_t - 6 \int_{\mathbb{R}_0} \gamma \tilde{N}(dt, dx) \right), \quad S_0^2 > 0$$

a) We apply Theorem 13.14. We need to find

$$\theta_1 < 1 \quad \text{such that}$$

$$S_t \int_{\mathbb{R}_0} \gamma \theta(x) V(dx) = S_t \alpha$$



$$\int_{\mathbb{R}_0} \gamma \theta(x) V(dx) = \alpha \quad \left(\begin{array}{l} \text{We can choose } \theta \text{ to} \\ \text{not depend on } t \end{array} \right)$$

If $\int_{\mathbb{R}} |\gamma| V(dx) > |\alpha|$ we can choose $A \subset \mathbb{R}_0$ and bounded below

such that you still have $\int_A |x| V(dx) =: K < +\infty$
and then choose

$$\theta(x) = \frac{\alpha}{K} \mathbb{1}_A(x) \text{sign}(x)$$

Note that $|\theta(x)| \leq \frac{|\alpha|}{K} < 1$ and

$$\begin{aligned} \int_{\mathbb{R}_0} x \theta(x) V(dx) &= \frac{\alpha}{K} \int_{\mathbb{R}_0} x \mathbb{1}_A(x) \text{sign}(x) V(dx) \\ &= \frac{\alpha}{K} \int_A |x| V(dx) = \alpha \end{aligned}$$

2) Novikov's condition is

$$E \left[\exp \left(\int_0^T \int_{\mathbb{R}_0} \{ (1 - \theta(x)) \log(1 - \theta(x)) + \theta(x) \} V(dx) dt \right) \right] < +\infty$$

$\iff \theta$ is deterministic and does not depend on t

$$\int_{\mathbb{R}_0} \{ (1 - \theta(x)) \log(1 - \theta(x)) + \theta(x) \} V(dx) < +\infty$$

\iff the integrand is 0 if $x \notin A$.

$$\int_A \{ (1 - \theta(x)) \log(1 - \theta(x)) + \theta(x) \} V(dx) < +\infty$$

which holds because $\theta(x)$ can be chosen such that it is bounded away (from below) from 1.

Then we can use θ in Theorem 13.14 and conclude that there are no arbitrage in this market.

b) In this case the equation 13.2.2 in
Theorem 13.14 reads

$$\begin{pmatrix} -1 & S_{t-}^1 \\ 2 & S_{t-}^2 \end{pmatrix} \theta_0(t) + \begin{pmatrix} 3 & S_{t-}^1 \\ -6 & S_{t-}^2 \end{pmatrix}_{\mathbb{R}_0} \times \theta_c(t, x) V(dx) = \begin{pmatrix} (-1-0) S_{t-}^1 \\ (4-0) S_{t-}^2 \end{pmatrix}$$

where $\theta_0(t), \theta_c(t, x) \in \mathbb{R}$

Define $\tilde{\theta}_c(t) := \int_{\mathbb{R}_0} \theta_c(t, x) V(dx)$ and simplify the previous
system of equations.

$$\begin{aligned} -1 \theta_0(t) + 3 \tilde{\theta}_c(t) &= -1 \\ 2 \theta_0(t) - 6 \tilde{\theta}_c(t) &= 4 \end{aligned}$$

which is inconsistent (adding to the second equation
two times the first equation you get $0 = 2$).

By Theorem 13.4 (last addition) we know that
there exists an arbitrage. In this case it is easy
to find.

In this market the portfolios are predictable processes

$$\xi = (\xi_0(t), \xi_1(t), \xi_2(t))_{0 \leq t \leq T} \in \mathbb{R}^3$$

By Lemma 13.7, $\xi_1(t), \xi_2(t)$ we can choose

$\varphi_0(t)$ such that \mathcal{E} is self-financing and

we have freedom to choose $X_0^{\mathcal{E}}$.

Take $X_0^{\mathcal{E}} \equiv 0$ and $\varphi_1(t) = \frac{2}{S_{u-}^1}$, $\varphi_2(t) = \frac{1}{S_{u-}^2}$

and $\varphi_0(t)$ such that \mathcal{E} is self-financing.

$$\begin{aligned} X_t^{\mathcal{E}} &= \underbrace{X_0^{\mathcal{E}}}_{=0} + \int_0^t \underbrace{\varphi_0(s)}_{=0} dS_s^0 + \int_0^t \varphi_1(s) dS_s^1 + \int_0^t \varphi_2(s) dS_s^2 \\ &= \int_0^t \varphi_1(s) dS_s^1 + \int_0^t \varphi_2(s) dS_s^2 \\ &= \int_0^t \frac{2}{S_{u-}^1} (-du - dBu + 3) \Big|_{\mathbb{R}_0} \times \tilde{N}(du, dx) \\ &\quad + \int_0^t \frac{1}{S_{u-}^2} S_{u-}^2 (4du + 2dBu - 6) \Big|_{\mathbb{R}_0} \times \tilde{N}(du, dx) \\ &= \int_0^t 2 du > 0 \end{aligned}$$

The value of this portfolio is lower-bounded \Rightarrow it is admissible.

Clearly it is an arbitrage since

$$X_0^{\mathcal{E}} = 0 \quad \text{and} \quad X_T^{\mathcal{E}} = 2T > 0 \quad \text{a.s.}$$

9) Consider

$$dS_t^0 = 0, \quad S_0^0 = L$$

$$dS_t^1 = S_{t-}^1 (\mu_1 dt + \gamma_1^1 d\tilde{p}_t^1 + \gamma_2^1 d\tilde{p}_t^2), \quad S_0^1 > 0$$

$$dS_t^2 = S_{t-}^2 (\mu_2 dt + \gamma_1^2 d\tilde{p}_t^1 + \gamma_2^2 d\tilde{p}_t^2), \quad S_0^2 > 0$$

μ_j, γ_j^i constants, and \tilde{p}^1 and \tilde{p}^2 are independent

Lévy martingales of the form

$$d\tilde{p}_t^i = \int_{\mathbb{R}_0} x \tilde{V}^i(dt, dx), \quad i=1,2$$

Assume the matrix γ is invertible with inverse

$$\gamma^{-1} = \Lambda = (\lambda_{ij})_{1 \leq i,j \leq 2} \text{ and assume that}$$

$$\int_{\mathbb{R}_0} |x| v^i(dx) > |\lambda_{12}^i \mu_2 + \lambda_{22}^i \mu_2|, \quad i=1,2.$$

Show that this market is arbitrage free.

We apply Theorem 13.14. In this case equation (11.2.2) in Theorem 13.14 is

$$(1) \int_{\mathbb{R}_0} \left(\gamma_1^1 \right) \times \theta_2^1(t,x) \tilde{V}^1(dx) + \gamma_2^1 \int_{\mathbb{R}_0} \theta_2^2(t,x) \tilde{V}^2(dx) = (\mu_2 - 0) S_{t-}^1$$

$$(2) \int_{\mathbb{R}_0} \left(\gamma_1^2 \right) \times \theta_2^1(t,x) \tilde{V}^1(dx) + \gamma_2^2 \int_{\mathbb{R}_0} \theta_2^2(t,x) \tilde{V}^2(dx) = (\mu_2 - 0) S_{t-}^2$$

and with $\theta_1^i(x) = \lambda_i^{-1} \theta_i^i(x)$. We can take θ_i indep.
of λ_i , i.e., $\theta_i = (\theta_i^1(x), \theta_i^2(x))$.

Call $\hat{\theta}_i^i = \int_{\mathbb{R}_0} x \theta_i^i(x) \nu^i(dx)$ $i=1,2$.

Then the previous system can be written as

$$\gamma \begin{matrix} \hat{\theta}_1 \\ \hat{\theta}_2 \end{matrix} = \mu \quad (\Leftrightarrow) \quad \hat{\theta}_i = \gamma^{-1} \mu = \lambda_i \mu$$

$\mathbb{R}^{2 \times 2} \quad \mathbb{R}^{2 \times 1} \quad - \quad \mathbb{R}^{2 \times 1}$

Then the previous system is equivalent to

$$(3) \quad \int_{\mathbb{R}_0} x \theta_1^1(x) \nu^1(dx) = \lambda_1^2 \mu_1 + \lambda_1^1 \mu_2$$

$$(4) \quad \int_{\mathbb{R}_0} x \theta_2^2(x) \nu^2(dx) = \lambda_2^2 \mu_1 + \lambda_2^1 \mu_2$$

By assumption

$$\int_{\mathbb{R}_0} |x| \nu^i(dx) > |\lambda_1^i \mu_1 + \lambda_2^i \mu_2| \quad i=1,2$$

(assuming $\nu^i \ll \lambda$ (Lebesgue measure)), by absolute continuity of the integrals we can find $A_i \subset \mathbb{R}_0$ with

$$|\lambda_1^i \mu_1 + \lambda_2^i \mu_2| < \int_{A_i} |x| \nu^i(dx) = K_i < +\infty$$

and, then, the functions

$$\theta_2^i(x) = \text{sign}(x) \frac{\lambda_2^i \mu_1 + \lambda_2^i \mu_2}{\kappa_i} \mathbb{1}_{A_i}(x) \quad i=1,2.$$

solve (3) and (4). For $i=1,2$.

$$\int_{\mathbb{R}_0} x \theta_2^i(x) V^i(dx) = \int_{A_i} x \text{sign}(x) \frac{(\lambda_2^i \mu_1 + \lambda_2^i \mu_2)}{\kappa_i} V^i(dx)$$

$$= (\lambda_2^i \mu_1 + \lambda_2^i \mu_2) \underbrace{\int_{A_i} |x| V^i(dx)}_{\frac{1}{\kappa_i}}$$

By construction

$$|\theta_2^i(x)| = \left| \text{sign}(x) \frac{\lambda_2^i \mu_1 + \lambda_2^i \mu_2}{\kappa_i} \mathbb{1}_{A_i}(x) \right|$$

$$\leq \frac{|\lambda_2^i \mu_1 + \lambda_2^i \mu_2|}{\kappa_i} < 1.$$

Then, if we define

$$Z_T = \exp \left\{ \sum_{i=1}^2 \int_0^T \int_{\mathbb{R}_0} \log(1 - \theta_2^i(x)) \tilde{N}^i(ds, dx) \right.$$

$$\left. + \int_0^T \int_{\mathbb{R}_0} \{ \log(1 - \theta_2^i(x)) + \theta_2^i(x) \} V^i(dx) \right\}$$

then we put $dQ = Z_T dP$, we get that

Q is a EMM for (S^1, S^2) and there is no arbitrage.

see theorem 13.14.

To check that Z_T defines a probability measure, we need to check that Z is a martingale.

By Theorem 12.23 (Navitkar's) it is sufficient to check

$$E^T \exp \left(\sum_{i=1}^2 \int_0^T \left\{ (1 - \theta_i^i(x)) \log(1 - \theta_i^i(x)) + \theta_i^i(x) \right\} V^i(dx) \right) < +\infty$$

Since θ is deterministic and does not depend on t , the last condition is equivalent to

$$\int_{\mathbb{R}_0} \left\{ (1 - \theta_i^i(x)) \log(1 - \theta_i^i(x)) + \theta_i^i(x) \right\} V^i(dx) < +\infty$$

which holds because we can choose $\theta_i^i(x) \leq 1 - \delta$ for some $\delta > 0$.