

# A stochastic McKean–Vlasov equation arising in finance

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# The financial motivation

- Credit risk is the risk of default on a payment by an obligor.
- Portfolio credit derivatives, such as CDOs, were constructed to repackage default risk of many obligors for sale to those with different risk appetites.
- A portfolio consists of  $N \geq 1$  defaultable assets with random default times  $\{\tau^i\}_{1 \leq i \leq N}$ ,
- Options on the proportional loss process are

$$L_t^N = \frac{1}{N} \sum_{i=1}^N \mathbf{1}_{\tau^i \leq t}, \quad \text{payoff} = \Psi\left((L^N)_{t \in [0, T]}\right)$$

For CDO tranches the payoff  $\Psi$  is piecewise linear.

- Correlations matter: defaults tend to cluster.

# Model framework

- Want a model for generating  $\tau^i$
- Structural model: assign *distance-to-default* process,  $X^i$
- When  $X^i$  hits zero, default is triggered:

$$\tau^i := \inf\{t > 0 : X_t^i \leq 0\}.$$

## A Simple model

$$dX_t^i = \mu dt + \rho dW_t + \sqrt{1 - \rho^2} dW_t^i$$

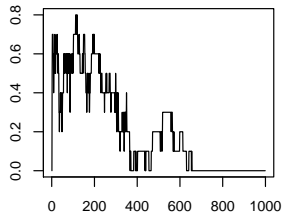
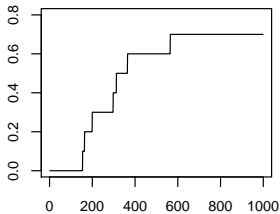
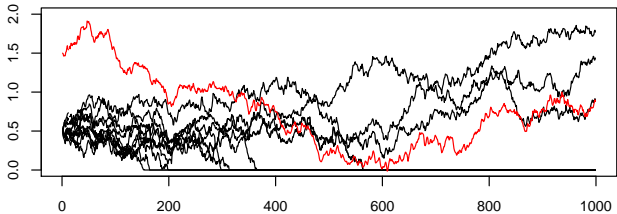
$$X_0^i \sim \nu_0$$

- Take a limit as  $N \rightarrow \infty$ ,
- Study the empirical processes

$$\nu_t^N = \frac{1}{N} \sum_{i=1}^N \mathbf{1}_{t < \tau^i} \delta_{X_t^i} \in \mathcal{M}$$

- $L_t^N = 1 - \nu_t^N((0, \infty))$ .

# Basic model



- $\nu_t^N(S) = \frac{1}{N} \sum_{i=1}^N \mathbf{1}_{X_t^i \in S; t < \tau^i} \rightarrow \mathbb{P}(X_t^1 \in S; t < \tau^1 | W)$ ,
- If we write  $\nu_t(\phi) = \int \phi d\nu_t$

## The SPDE in weak form

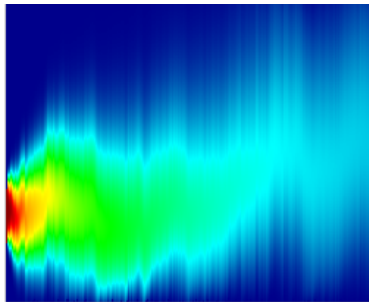
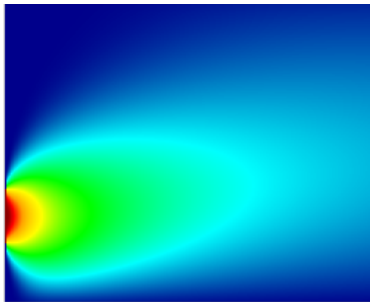
$$\begin{aligned} d\nu_t(\phi) &= \mu\nu_t(\partial_x\phi)dt + \frac{1}{2}\nu_t(\partial_{xx}\phi)dt + \rho\nu_t(\partial_x\phi)dW_t \\ \phi(0) &= 0. \end{aligned}$$

- If  $\nu$  has a density  $V$  it will satisfy

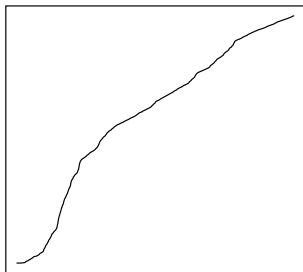
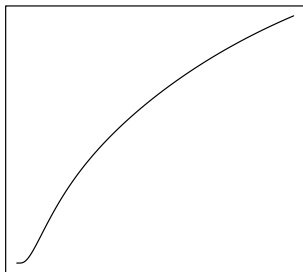
## The SPDE

$$\begin{aligned} dV_t &= -\mu\partial_x V_t dt + \frac{1}{2}\partial_{xx} V_t dt - \rho\partial_x V_t dW_t \\ V_t(0) &= 0. \end{aligned}$$

The heat map for the evolution started from a dirac mass when  $\rho = 0$  and  $\rho > 0$ .

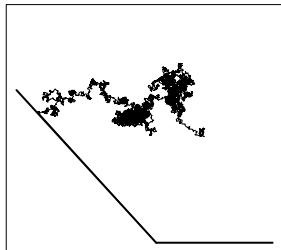
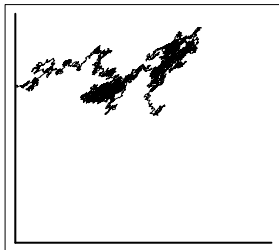


The loss function in the two cases



If  $\nu_0$  has an  $L^2$  density, then  $\nu_t$  has an  $H^1$  density  $V$  but  $xV_{xx} \in L^2$  (first observed by Krylov).

- Convergence of the particle system to the  $L^2$  density using kernel smoothing methods needs estimates on  $\mathbb{E}[\nu_t(0, \varepsilon)^2]$ .
- Need asymptotics for 2d Brownian motion near the apex of a cone.



- Ledger (2014) - the regularity of the SPDE at 0 is a function of  $\rho$ .



# Regularity

Let  $w_c(x) = x^c \exp(-x)$  for  $x > 0$  be a weight function.

Let  $\alpha = \pi/2 + \arcsin \rho$ .

## Theorem (Ledger)

*If  $V_0$  is bounded there exists a unique solution to the SPDE in the class of finite measure valued processes. For almost all  $(\omega, t) \in \Omega \times [0, T]$ ,  $\nu_t$  has a density  $V_t$  on  $(0, \infty)$ .*

*Furthermore, suppose  $V_0$  is  $n$  times weakly differentiable in  $(0, \infty)$  and that for  $k = 0, 1, \dots, n$  we have*

$$\|w_{k-\beta/2} V_0\|_2 < \infty, \quad \forall \beta \in (-\infty, \pi/\alpha - 1).$$

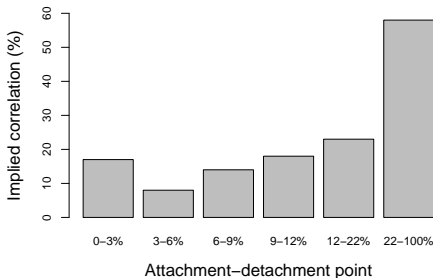
*Then, for almost all  $(\omega, t) \in \Omega \times [0, T]$  we have  $V_t$  is  $n + 1$  times weakly differentiable and for  $k = 0, 1, \dots, n + 1$*

$$\mathbf{E} \int_0^T \|w_{k-\beta/2} V_t\|_2^2 dt < \infty, \quad \forall \beta \in (-\infty, \pi/\alpha - 1).$$

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- More general coefficients,
- *Jump processes*, Bujok and Reisinger (2012)
- *Stochastic volatility*, H. and Kollipoulos (2017)
- *Numerical problems* (MLMC): Giles and Reisinger (2012); Reisinger and Wang (2016)
- *Mortgage-backed securities model*, Ahmad, H and Ledger (2016)
- *CLT/Fluctuations*, Giesecke, Spiliopoulos, Sirignano (2014)
- Our interest will be incorporating loss-dependent correlation and contagion effects in such structural models.

- The model is too simple as we cannot choose one  $\rho$  to match all traded tranche spreads, there is *correlation skew* or *smile*,

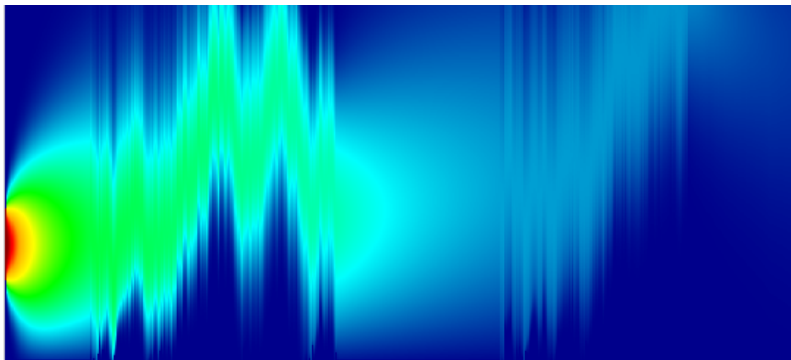


- A practitioner approach is to make  $\rho$  a function of the loss in the system.

## Loss-dependent model

$$dX_t^{i,N} = \rho(L_t^N) dW_t + \sqrt{1 - \rho^2(L_t^N)} dW_t^i$$

# Loss dependent example



Here we have an exaggerated loss dependent correlation

$$\rho(\ell) = \begin{cases} 0 & \text{if } \ell \in [0, \frac{1}{5}) \cup [\frac{2}{5}, \frac{3}{5}) \cup [\frac{4}{5}, 1] \\ \frac{9}{10} & \text{if } \ell \in [\frac{1}{5}, \frac{2}{5}) \cup [\frac{3}{5}, \frac{4}{5}). \end{cases}$$

- We can consider general case

$$X_t^{i,N} = X_0^i + \int_0^t \mu(s, X_s^{i,N}, L_s^N) ds + \int_0^t \sigma(s, X_s^{i,N}) \rho(s, L_s^N) dW_s + \int_0^t \sigma(s, X_s^{i,N}) (1 - \rho(s, L_s^N)^2)^{\frac{1}{2}} dW_s^i. \quad (1)$$

- Piecewise constant  $\rho$  across tranches desirable.
- Allow finitely many discontinuities: piecewise Lipschitz  $\rho$
- Need  $0 \leq \rho(\ell) \leq \rho_{\max} < 1$ , to prevent degeneracy
- Challenges: need to deal with boundary effects but correlation too complicated to do explicit calculations.
- For convergence, discontinuous  $\rho$  is bad. The key is to show limit points must have strictly increasing loss process.

# Coefficient assumptions

Let  $\mu : [0, T] \times \mathbb{R} \times [0, 1] \rightarrow \mathbb{R}$ ,  $\sigma : [0, T] \times \mathbb{R} \rightarrow [0, \infty)$  and  $\rho : [0, T] \times [0, 1] \rightarrow [0, 1)$  be the coefficients in (1) and  $\nu_0$  be the common law of the initial values of the distance-to-default processes. We assume that we have a sufficiently large constant,  $C \in (1, \infty)$ , such that all the following hold:

- (i) (Initial condition) The probability measure  $\nu_0$  is supported on  $(0, \infty)$ , has a density  $V_0 \in L^2(0, \infty)$  and satisfies for every  $\alpha > 0$ ,

$$\nu_0(\lambda, \infty) = o(\exp\{-\alpha\lambda\}), \quad \text{as } \lambda \rightarrow +\infty.$$

- (ii) (Spatial regularity) For all fixed  $t \in [0, T]$  and  $\ell \in [0, 1]$ ,  $\mu(t, \cdot, \ell), \sigma(t, \cdot) \in C^2(\mathbb{R})$  with

$$|\partial_x^n \mu(t, x, \ell)|, |\partial_x^n \sigma(t, x)| \leq C$$

for all  $t \in [0, T]$ ,  $x \in \mathbb{R}$ ,  $\ell \in [0, 1]$  and  $n = 0, 1, 2$ ,

(iii) (Non-degenerate) For all  $t \in [0, T]$ ,  $x \in \mathbb{R}$ ,  $\ell \in [0, 1]$

$$\sigma(t, x) \geq C^{-1} > 0, \quad 0 \leq \rho(t, \ell) \leq 1 - C^{-1} < 1,$$

(iv) (Piecewise Lipschitz in loss) There exists

$0 = \theta_0 < \theta_1 < \dots < \theta_k = 1$  such that

$$|\mu(t, x, \ell) - \mu(t, x, \bar{\ell})|, |\rho(t, \ell) - \rho(t, \bar{\ell})| \leq C|\ell - \bar{\ell}|,$$

whenever  $t \in [0, T]$ ,  $x \in \mathbb{R}$  and both  $\ell, \bar{\ell} \in [\theta_{i-1}, \theta_i]$  for some  $i \in \{1, 2, \dots, k\}$ ,

(v) (Integral constraint)  $\sup_{s \in [0, T]} \int_0^\infty |\partial_t \sigma(s, y)| dy < \infty$ .



# Regularity conditions

Let  $\nu$  be a càdlàg process taking values in the space of sub-probability measures on  $\mathbb{R}$ . The regularity conditions on  $\nu$  are

- (i) (Loss function) The loss  $L_t := 1 - \nu_t(0, \infty)$  is non-decreasing at all times and is strictly increasing when  $L_t < 1$ ,
- (ii) (Support) For every  $t \in [0, T]$ ,  $\nu_t$  is supported on  $[0, \infty)$ ,
- (iii) (Exponential tails) For every  $\alpha > 0$

$$\mathbf{E} \int_0^T \nu_t(\lambda, +\infty) dt = o(e^{-\alpha\lambda}), \quad \text{as } \lambda \rightarrow \infty,$$

- (iv) (Boundary decay) There exists  $\beta > 0$  such that

$$\mathbf{E} \int_0^T \nu_t(0, \varepsilon) dt = O(\varepsilon^{1+\beta}), \quad \text{as } \varepsilon \rightarrow 0,$$

- (v) (Spatial concentration) There exists  $C > 0$  and  $\delta > 0$  such that

$$\mathbf{E} \int_0^T |\nu_t(a, b)|^2 dt \leq C|b - a|^\delta, \quad \text{for all } a < b.$$

We state these for the simple case of  $\mu = 0, \sigma = 1$ .

## Theorem (Tightness/Weak existence)

*The sequence of triples  $(\nu^N, L^N, W)_{N \geq 1}$  are tight (with suitable topology). If  $(\nu^*, L^*, W)$  realises a limiting law, then*

$$d\nu_t^*(\phi) = \frac{1}{2}\nu_t^*(\partial_{xx}\phi)dt + \rho(L_t)\nu_t^*(\partial_x\phi)dW_t$$

$$L_t^* = 1 - \nu_t^*(0, \infty),$$

*[+ regularity conditions.] where  $\phi \in C^{\text{test}} = \{f \in C^2 : f(0) = 0\}$ .*

## Theorem (Pathwise uniqueness/LLN)

*Under the assumptions on regularity, for a given  $W$ , the SPDE has at most one solution  $\nu$  in  $(D_{S'}, M1)$ . The limit for the associated loss process  $L$  is unique in  $(D_{\mathbb{R}}, M1)$ . Hence there is a unique law of a solution  $(\nu, L, W)$  and we have the sequence  $(\nu^N, L^N, W)$  converges to  $(\nu, L, W)$  as  $N \rightarrow \infty$ .*

## Corollary

*With probability 1, for every  $t \in [0, T]$ , there exists  $V_t \in L^2([0, \infty))$  such that*

$$\nu_t(\phi) = \int_0^\infty \phi(x) V_t(x) dx, \quad \phi \in L^2(0, \infty).$$

The result can be expressed as a stochastic M–V problem.

## M–V problem

For any independent B.M.  $W^\perp$  there exists a process  $X$  satisfying

$$dX_t = \rho(L_t)dW_t + \sqrt{1 - \rho(L_t)^2} dW_t^\perp$$

$$\tau := \inf\{t > 0 : X_t \leq 0\}$$

$$\nu_t(\phi) = \mathbb{E}[\phi(X_t)\mathbf{1}_{t < \tau} | W], \quad L_t = \mathbb{P}(\tau \leq t | W).$$

The law of  $(X, W)$  is unique.

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- *Uniqueness*: Work in a weaker Sobolev space,  $H^{-1}$ , so that only first moment estimates are needed. There is no need for correlations.
- Additional stopping and regularity arguments are needed for discontinuous coefficients.

# Contagion model

- If a default occurs, each particle receives a kick of  $\frac{\alpha}{N}$  towards the boundary,  $\alpha > 0$  interesting case — positive feedback
- We drop the common noise term for simplicity

## Discrete model

$$X_t^i = X_0^i + B_t^i - \alpha L_t^N, \quad L_t^N = \frac{1}{N} \sum_{i=1}^N \mathbf{1}_{\tau^i \leq t}$$

- Ambiguity for jump size, smallest allows system to be càdlàg



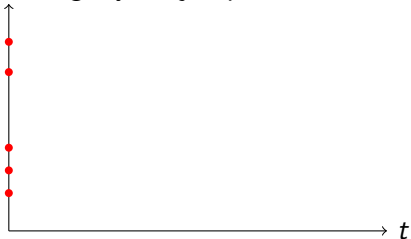
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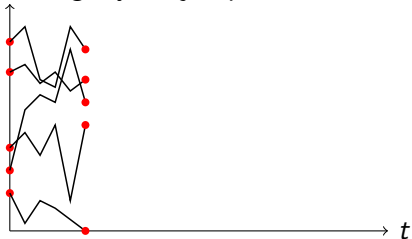
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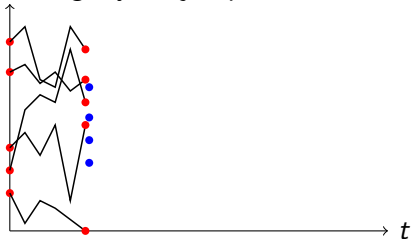
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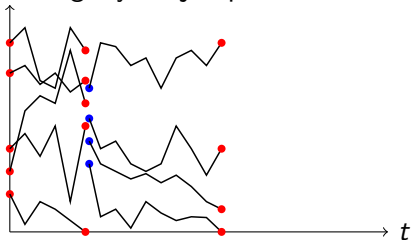
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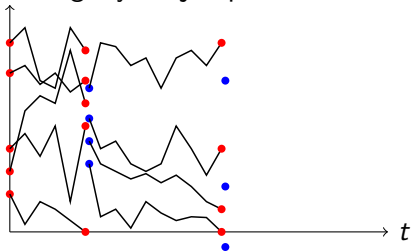
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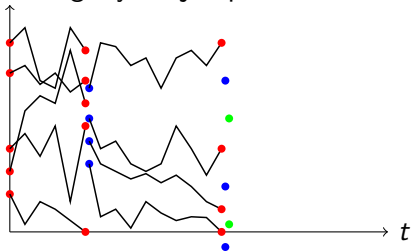
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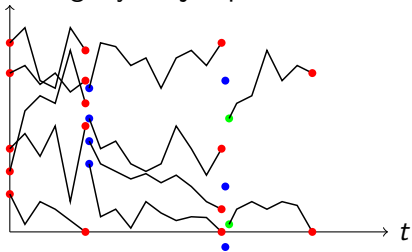
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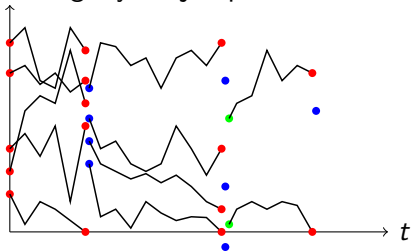
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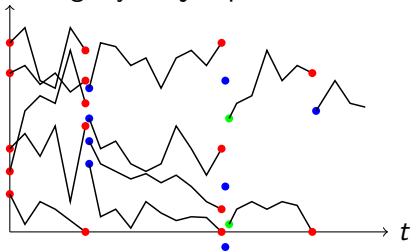
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## McKean–Vlasov problem (MV)

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$$d\nu_t(\phi) = \frac{1}{2}\nu_t(\partial_{xx}\phi)dt - \alpha\nu_t(\partial_x\phi)dL_t$$

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## Fixed-point problem

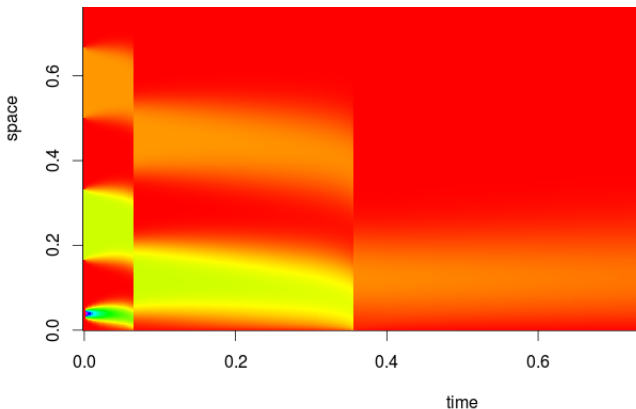
Let  $\Gamma : L. \rightarrow P(\tau^L < .)$  be the map taking the input loss function to its output. The fixed point satisfies

$$\int_0^\infty \Phi\left(-\frac{x - \alpha \ell_t}{t^{1/2}}\right) \nu_0(dx) = \int_0^t \Phi\left(\alpha \frac{\ell_t - \ell_s}{(t-s)^{1/2}}\right) d\Gamma[\ell]_t.$$

- Model in neuroscience: Delarue, Inglis, Rubenthaler, Tanré, 2015
- Essential difficulties are the same
- Show unique  $C^1$  solution for small enough  $\alpha$ ,  $\nu_0 = \delta_x$   $x > 0$
- In another paper, Delarue, Inglis, Rubenthaler, Tanré, 2015, also give existence for all  $\alpha$ , as limit points of particle system, with *physical jump condition*
- Initial  $\nu_0$  zero near zero
- Related financial model: Nadtochiy, Shkolnikov, 2017.  
Uniqueness up to a blow-up where  $L^2$  norm of derivative blows-up,  $\nu_0$  has  $H^1$  density  $V_0$  with  $V_0(0) = 0$ , so  $V_0(x) = O(x^{1/2})$

# Blow-ups

- If  $\alpha$  is large enough, no solution can be continuous for all times, Cáceres, Carrillo, Perthame (2011)
- Jump in loss must occur



- *Claim:* If  $\alpha > 2m_0$  where  $\nu_0 = \delta_{m_0}$ , then  $L$  cannot be continuous for all time.

- *Claim:* If  $\alpha > 2m_0$  where  $\nu_0 = \delta_{m_0}$ , then  $L$  cannot be continuous for all time.
- *Proof:*

$$0 \leq X_{t \wedge \tau} = X_0 + B_{t \wedge \tau} - \alpha L_{t \wedge \tau}$$

- Take expectation

$$m_0 \geq \alpha \mathbb{E}[L_{t \wedge \tau}].$$

- By comparison with B.M.  $\tau < \infty$  a.s.  $L_\infty = 1$

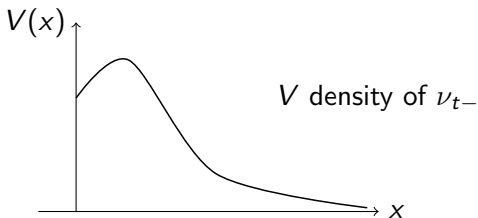
$$m_0 \geq \alpha \mathbb{E}[L_\tau] = \alpha \int_0^\infty L_s dL_s = \frac{\alpha}{2} (L_\infty^2 - L_0^2) = \frac{\alpha}{2}.$$





# What is happening at jumps?

- Before jump  $\nu_{t-}$
- If jump in loss is  $\Delta L_t$ , then push-down by  $-\alpha\Delta L_t$



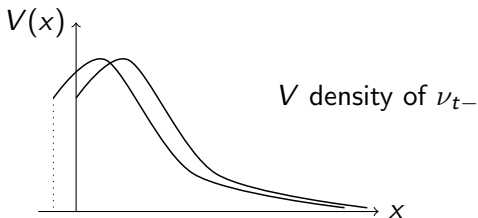
- Mass lost must equal  $\Delta L_t$ , so

$$\nu_{t-}(0, \alpha\Delta L_t) = \Delta L_t.$$

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- $\Delta L_t = \inf\{x > 0 : \nu_{t-}(0, \alpha x) < x\}$

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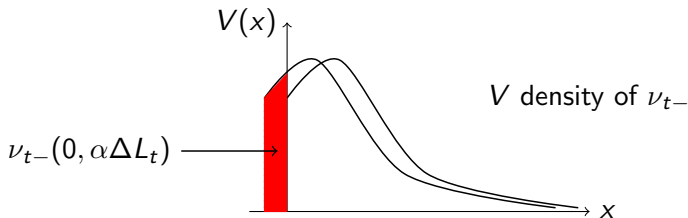
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# Global uniqueness?

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# Global uniqueness?

## Conjecture

There exists a unique solution to (MV) satisfying the natural-jump/minimal-jump condition. Jumps according to rule, between jumps  $C^1$  with  $\sqrt{t}$  singularities.

- Obstruction: after a jump the solution is  $\asymp 1$  near the boundary
- $\Rightarrow L_t$  grows at least as fast as  $\sqrt{t}$  near  $t = 0$
- $L'_t \asymp t^{-1/2}$ , Girsanov tricks just fail in this case

## Main problem

Show small time uniqueness for (MV) started from initial law  $\nu_0$  satisfying only  $\inf\{\nu_0(0, \alpha x) < x\} = 0$ .

- Cannot yet attack problem started from density  $V_0$  with  $V_0(x) \geq \delta > 0$  near zero, for  $\delta$  as small as you like.

- With S. Ledger, A. Søjmark, we can start with density  $O(x^\beta)$ , for  $\beta > 0$ , and we can add in the coefficients
- $O(x^\beta)$  implies  $L'_t = O(t^{-\frac{1-\beta}{2}})$
- Uniqueness in small time for  $\beta > 0$ , uniqueness in small  $\alpha$  for  $\beta = 0$ , but don't know solution lives there
- Would like to add a common noise term

$$X_t = X_0 + B_t + \beta(t) - \alpha L_t$$

with  $\beta$  a Brownian sample path, for example.

- For any fixed  $\alpha$ ,  $\beta$  can be bad enough to cause a blow-up.
- Methods relying on differentiability of the loss function are really broken!
- H, Søjmark: In the case where we mollify  $L$ , we can add loss-dependent coefficients and common noise

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