

Dynamical modelling of successive defaults

N. El Karoui M. Jeanblanc Y. Jiao

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Motivation and Introduction

- Rapid development of credit portfolio products : k^{th} -to-default swap, CDOs
- A practical question proposed by the practitioners: possibility of a recursive procedure to study the successive defaults?
- Calculation of conditional expectations $\mathbb{E}[Y_T|\mathcal{G}_t]$ when $(\mathcal{G}_t)_{t \geq 0}$ is some large filtration including default informations
- Study of the “after-default case” by using the density process approach

An illustrative example

An illustrative example

- A simple deterministic model of two credits, denote by $\tau = \min(\tau_1, \tau_2)$.
- Observable information : whether the **first default occurs**.
- The basic hypothesis is based on a stationary point of view of the practitioners

$$\mathbb{P}(\tau_i > T \mid \tau > t) = e^{-\mu^i(t) \cdot (T-t)}, \quad (i = 1, 2)$$

where $\mu^i(t)$ characterizes the individual default and it can be renewed with market information at t .

- The marginal distributions remain in the exponential family.

The joint probability

- Let $\mathbb{P}(\tau_1 > t_1, \tau_2 > t_2) = \mathbb{P}(\tau_1 > t_1)\mathbb{P}(\tau_2 > t_2)\rho(t_1, t_2)$.
Consider the **survival copula function** $\tilde{C}(u, v)$ such that $\tilde{C}(\mathbb{P}(\tau_1 > t_1), \mathbb{P}(\tau_2 > t_2)) = \mathbb{P}(\tau_1 > t_1, \tau_2 > t_2)$, then

$$\tilde{C}(u, v) = \begin{cases} uv\rho\left(\frac{\ln u}{\mu^1(0)}, \frac{\ln v}{\mu^2(0)}\right), & \text{if } u, v > 0; \\ 0, & \text{if } u = 0 \text{ or } v = 0. \end{cases}$$

- Joint probability : If $\rho(t_1, t_2) \in C^{1,1}$, then the joint survival probability is given by

$$\mathbb{P}(\tau_1 > t_1, \tau_2 > t_2) = \exp\left(-\int_0^{t_1} \mu^1(s \wedge t_2) ds - \int_0^{t_2} \mu^2(s \wedge t_1) ds\right).$$

- First observation:** The joint probability function depends on all the dynamics of the marginal distributions and the copula can not be chosen independently with marginal distributions.

The joint probability

- **Proposition:** If $\rho(t_1, t_2) \in C^2$ and if $\mu^1(t), \mu^2(t) \in C^1$, then

$$\begin{aligned} & \mathbb{P}(\tau_1 > t_1, \tau_2 > t_2) \\ &= \exp\left(-\mu^1(0)t_1 - \mu^2(0)t_2 + \int_0^{t_1 \wedge t_2} \varphi(s)(t_1 + t_2 - 2s)ds\right). \end{aligned}$$

where $\varphi(t) = \left. \frac{\partial^2}{\partial t_1 \partial t_2} \ln \rho(t_1, t_2) \right|_{t_1=t_2=t}$. In addition, we have

$$\mu^i(t) = \mu^i(0) - \int_0^t \varphi(s)ds.$$

- μ^1 and μ^2 follow the same dynamics apart from their initial values due to the symmetric information flow and the stationary property.

First default and contagious jumps

- The distribution of the first default is given by

$$\mathbb{P}(\tau > t) = \exp\left(-\int_0^t \mu^1(s) + \mu^2(s) ds\right);$$

- For the **surviving credit**, it becomes complicated. Let $\mathcal{D}_t = \mathcal{D}_t^1 \vee \mathcal{D}_t^2$ where $\mathcal{D}_t^i = \sigma(\mathbb{1}_{\{\tau_i \leq s\}}, s \leq t)$ ($i = 1, 2$). Then

$$\begin{aligned} \mathbb{E}[\mathbb{1}_{\{\tau_i > T\}} | \mathcal{D}_t] &= \mathbb{1}_{\{\tau > t\}} \exp\left(-(\mu^i(0) - \int_0^t \varphi(s) ds)(T - t)\right) \\ &+ \mathbb{1}_{\{\tau_i > t, \tau_j \leq t\}} \exp\left(-(\mu^i(0) - \int_0^T \varphi(s) ds)(T - t)\right) \\ &\cdot \frac{\mu^j(0) - \varphi(\tau)(T - \tau) - \int_0^T \varphi(s) ds}{\mu^j(0) - \varphi(\tau)(t - \tau) - \int_0^T \varphi(s) ds}. \end{aligned}$$

- We observe the contagious jump phenomenon

The second default time

- **Second observation** on $\sigma = \max(\tau_1, \tau_2)$: the conditional distribution $\mathbb{E}[\mathbf{1}_{\{\sigma > T\}} | \mathcal{D}_t^T]$ can not remain in the exponential family neither on $\{\tau > t\}$ nor on $\{\tau \leq t\}$, except when τ_1 and τ_2 are independent and identically distributed.
- Remark: conditioned on the first default, there exists no longer the stationary property, as expected by some market practitioners!
- We need to study the successive defaults in an abstract way.

The General Case

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the density process framework

Before-default case and Minimal assumption

- Let $(\Omega, \mathcal{G}, \mathbb{G}, \mathbb{P})$ be a filtered probability space representing the market. The filtration $\mathbb{G} = (\mathcal{G}_t)_{t \geq 0}$ represents the global information on the market.
- Let τ be a finite \mathbb{G} -stopping time.
- Consider a subfiltration \mathbb{F} of \mathbb{G} satisfying the following condition presented by Jeulin and Yor (1978), Jacod (1982).
- **(Minimal Assumption):** We say $(\mathbb{F}, \mathbb{G}, \tau)$ satisfy the Minimal Assumption (MA) if for any $t \geq 0$ and any $U \in \mathcal{G}_t$, there exists $V \in \mathcal{F}_t$ such that $U \cap \{\tau > t\} = V \cap \{\tau > t\}$.

Before-default case and Minimal assumption

Two examples of $(\mathbb{F}, \mathbb{G}, \tau)$ satisfying MA:

- In the single credit case, τ represents **one default time** and let $\mathbb{D} = (\mathcal{D}_t)_{t \geq 0}$ where $\mathcal{D}_t = \sigma(\mathbb{1}_{\{\tau \leq s\}}, s \leq t)$. \mathbb{F} satisfies $\mathbb{G} = \mathbb{D} \vee \mathbb{F}$.
- In the multi-credits case, τ represents the **first default time** $\tau = \min(\tau_1, \dots, \tau_n)$ and \mathbb{F} satisfies $\mathbb{G} = \mathbb{F} \vee \mathbb{D}^1 \dots \vee \mathbb{D}^n$.

A direct consequence: Assume that $(\mathbb{F}, \mathbb{G}, \tau)$ satisfy MA. For any \mathcal{G} -measurable random variable Y , if $\mathbb{P}(\tau > t | \mathcal{F}_t) > 0$, a.s. then

$$\mathbb{E}[\mathbb{1}_{\{\tau > t\}} Y | \mathcal{G}_t] = \mathbb{1}_{\{\tau > t\}} \frac{\mathbb{E}[\mathbb{1}_{\{\tau > t\}} Y | \mathcal{F}_t]}{\mathbb{E}[\mathbb{1}_{\{\tau > t\}} | \mathcal{F}_t]}.$$

After-default case and Density process

(H_J Hypothesis, Jacod (82)) For any $t, \theta \geq 0$, we assume that there exists a family of \mathbb{F} -adapted processes, called the **density process** $(\alpha_t(u), t \geq 0)$, such that

$$S_t(\theta) = \mathbb{P}(\tau > \theta | \mathcal{F}_t) = \int_{\theta}^{\infty} \alpha_t(u) du.$$

Proposition

For any $t, u \geq 0$, let $Y(t, u)$ be a random variable such that $Y(t, u) \in \mathcal{F}_t \otimes \mathcal{B}(\mathbb{R})$. If $\mathbb{G} = \mathbb{F} \vee \mathbb{D}$ and if $\alpha_t(u) > 0$, then for any $0 \leq t \leq T$,

$$E[Y(T, \tau) | \mathcal{G}_t] \mathbb{1}_{\{\tau \leq t\}} = \frac{E[Y(T, s) \alpha_T(s) | \mathcal{F}_t]}{\alpha_t(s)} \Big|_{s=\tau} \mathbb{1}_{\{\tau \leq t\}}.$$

Density and intensity processes

- The \mathbb{G} -compensator process Λ of τ is a predictable process such that $(N_t = \mathbb{1}_{\{\tau \leq t\}} - \Lambda_t, t \geq 0)$ is a \mathbb{G} -martingale. If $\Lambda_t = \int_0^t \lambda_s^{\mathbb{G}} ds$, then $\lambda^{\mathbb{G}}$ is called the \mathbb{G} -intensity process.
- **Proposition:** Assume that $(\mathbb{F}, \mathbb{G}, \tau)$ satisfy minimal assumption. If the survival density $\alpha_t(u)$ exists, then the \mathbb{G} -compensator process Λ of τ is given by

$$d\Lambda_t = \mathbb{1}_{]0, \tau]}(t) \frac{\alpha_t(t)}{\int_t^\infty \alpha_t(u) du} dt.$$

Density and intensity processes

- The intensity process can be deduced from the density process. However, the reverse is not true in general.
- **Proposition** : Assume that $(\mathbb{F}, \mathbb{G}, \tau)$ satisfy minimal assumption. If the \mathbb{G} -intensity process $(\lambda_t^{\mathbb{G}}, t \geq 0)$ of τ exists. Then, for any $u \geq t$, the density of the conditional survival law of τ is given by

$$\alpha_t(u) = \mathbb{E}[\lambda_u^{\mathbb{G}} | \mathcal{F}_t].$$

- The after-default case requires us to know $\alpha_t(u)$ for $u < t$, which can not be obtained from the intensity process.

Successive defaults

Two ordered default times - the first default

- Consider τ_1 and τ_2 with associated filtrations \mathbb{D}^1 and \mathbb{D}^2 . Let \mathbb{F} such that $\mathbb{G} = \mathbb{F} \vee \mathbb{D}^1 \vee \mathbb{D}^2$.
- Let $\tau = \min(\tau_1, \tau_2)$ and $\sigma = \max(\tau_1, \tau_2)$ with $\mathbb{D}^{(1)}$ and $\mathbb{D}^{(2)}$.
- $(\mathbb{F}, \mathbb{G}, \tau)$ satisfy the minimal assumption. Hence the first default can be treated in the same way as for a single credit.
- **Proposition:** Assume that the joint density process of (τ_1, τ_2) exists, i.e.

$$\mathbb{P}(\tau_1 > t_1, \tau_2 > t_2 | \mathcal{F}_t) = \int_{t_1}^{\infty} du_1 \int_{t_2}^{\infty} du_2 p_t(u_1, u_2).$$

Then the density process $(\alpha_t^\tau(\theta), t \geq 0)$ of τ is given by

$$\alpha_t^\tau(\theta) = \int_{\theta}^{\infty} du (p_t(\theta, u) + p_t(u, \theta)).$$

Two ordered default times - between two defaults

- The period between two defaults corresponds to before-default case of σ and after-default case of τ .
- Let $\mathbb{G}^{(1)} = \mathbb{F} \vee \mathbb{D}^{(1)}$ and $\mathbb{G}^{(2)} = \mathbb{G}^{(1)} \vee \mathbb{D}^{(2)}$. We calculate $\mathbb{G}^{(2)}$ -conditional expectations by a recursive way.
- **Corollary** : Assume that the conditional density process of $S_t^{(2|1)}(\theta) := \mathbb{P}(\sigma > \theta | \mathcal{G}_t^{(1)}) = \int_{\theta}^{\infty} \alpha_t^{(2|1)}(u) du$ exists for all $t, \theta \geq 0$. Let $Y(T, t_1, t_2)$ be an \mathcal{F}_T -measurable r.v. such that $Y(\cdot, t_1, t_2)$ is a Borel function. Then

$$\mathbb{E}[Y(T, \tau, \sigma) | \mathcal{G}_t^{(2)}] \mathbb{1}_{\{\tau \leq t < \sigma\}} = \frac{\mathbb{E}\left[\int_t^{\infty} du_2 Y(T, \tau, u_2) \alpha_T^{(2|1)}(u_2) | \mathcal{G}_t^{(1)}\right]}{\int_t^{\infty} du_2 \alpha_t^{(2|1)}(u_2)} \mathbb{1}_{\{\tau \leq t < \sigma\}}$$

Two ordered default times - between two defaults

- Furthermore, we can bring all calculations to \mathbb{F} -conditional expectations.
- Proposition**: Assume that the joint density process $(\alpha_t(t_1, t_2), t \geq 0)$ of (τ, σ) exists for all $t_1, t_2 \geq 0$. Then

$$\alpha_t^{(2|1)}(\theta) = \mathbb{1}_{\{\tau > t\}} \frac{\int_t^\infty du_1 \alpha_t(u_1, \theta)}{\int_t^\infty du_1 \int_{u_1}^\infty du_2 \alpha_t(u_1, u_2)} + \mathbb{1}_{\{\tau \leq t\}} \frac{\alpha_t(\tau, \theta)}{\int_\tau^\infty du_2 \alpha_t(\tau, u_2)}.$$

Moreover,

$$\mathbb{E}[Y(T, \tau, \sigma) | \mathcal{G}_t^{(2)}] \mathbb{1}_{\{\tau \leq t < \sigma\}} = \mathbb{1}_{\{\tau \leq t < \sigma\}} \mathbb{E} \left[\frac{\int_t^\infty dv Y(T, u, v) \alpha_T(u, v)}{\int_t^\infty dv \alpha_t(u, v)} \middle| \mathcal{F}_t \right] \bigg|_{u=\tau}.$$

Intensity process of τ and σ

- Denote by Λ^i the \mathbb{G} -compensator process of τ_i
- For the first default : If $\mathbb{P}(\tau_1 = \tau_2) = 0$, then

$$\Lambda_{t \wedge \tau}^\tau = \Lambda_{t \wedge \tau}^1 + \Lambda_{t \wedge \tau}^2.$$

- For the second default: by the recursive method, we have

$$d\Lambda_t^\sigma = \mathbb{1}_{[\tau, \sigma]}(t) \frac{\alpha_t(\tau, t)}{\int_t^\infty du_2 \alpha_t(\tau, u_2)} dt$$

Joint density processes

- Calculations are determined by the \mathbb{F} -adapted process $(\alpha_t(t_1, t_2), t \geq 0)$.
- Similar results exist for τ_1 and τ_2 following 4 possible default scenarios, using the non-ordered density process $(p_t(t_1, t_2), t \geq 0)$.

- **Proposition** : For any $t, t_1, t_2 \geq 0$,

$$\alpha_t(t_1, t_2) = \mathbb{1}_{\{t_1 \leq t_2\}} (p_t(t_1, t_2) + p_t(t_2, t_1)).$$

- **Modelling of $(p_t(t_1, t_2), t \geq 0)$!**

Generalization and application

- Consider ordered \mathbb{G} -stopping times $\sigma_1 \leq \dots \leq \sigma_n$,

$$\mathbb{E}[Y(T, \sigma_1, \dots, \sigma_n) | \mathcal{G}_t^{(1, \dots, n)}] = \sum_{i=1}^n \mathbb{1}_{\{\sigma_i \leq t, \sigma_{i+1} > t\}}.$$

$$\frac{\mathbb{E}\left[\int_{t \vee u_i}^{\infty} du_{i+1} \int_{u_{i+1}}^{\infty} \dots \int_{u_{n-1}}^{\infty} du_n Y(T, u_1, \dots, u_n) \alpha_T(u_1, \dots, u_n) | \mathcal{F}_t\right]}{\int_{t \vee u_i}^{\infty} du_{i+1} \int_{u_{i+1}}^{\infty} \dots \int_{u_{n-1}}^{\infty} du_n \alpha_t(u_1, \dots, u_n)} \Bigg|_{\substack{u_1 = \sigma_1 \\ \dots \\ u_i = \sigma_i}}$$

When $i = n$, we use convention $\sigma_{n+1} = \infty$.

Application

- Pour les CDOs, let $I_T = \sum_{i=1}^n \mathbb{1}_{\{\tau_i \leq T\}}$, then

$$\begin{aligned} \mathbb{E}[(K - I_T)^+ | \mathcal{G}_t^{(1, \dots, n)}] &= \int_{-\infty}^K \mathbb{E}[\mathbb{1}_{\{I_T \leq K\}} | \mathcal{G}_t^{(1, \dots, n)}] dK \\ &= \int_{-\infty}^K \mathbb{E}[\mathbb{1}_{\{\sigma_{[K]+1} > T\}} | \mathcal{G}_t^{(1, \dots, n)}] dK \end{aligned}$$

- For any $m \geq 0$,

$$\begin{aligned} \mathbb{E}[\mathbb{1}_{\{\sigma_m > T\}} | \mathcal{G}_t^{(1, \dots, n)}] &= \sum_{j=1}^{m-1} \mathbb{1}_{\{\sigma_j \leq t < \sigma_{j+1}\}} \cdot \\ &= \frac{\mathbb{E}\left[\int_{t \vee u_j}^{\infty} du_{j+1} \int_{u_{j+1}}^{\infty} \cdots \int_{u_{n-1}}^{\infty} du_n \mathbb{1}_{\{u_m > T\}} \alpha_T(u_1, \dots, u_n) | \mathcal{F}_t\right]}{\int_{t \vee u_j}^{\infty} du_{j+1} \cdots \int_{u_{n-1}}^{\infty} du_n \alpha_t(u_1, \dots, u_n)} \Bigg|_{\substack{u_1 = \sigma_1 \\ \dots \\ u_j = \sigma_j}} \end{aligned}$$