

# Credit Risk

MF 731 Corporate Risk Management

# Outline

Credit risk basics.

Bond pricing with deterministic hazard rates.

Credit default swaps.

Sampling default times.

Treating multiple defaults: copulas.

(these notes complement MF772 (Credit Risk))

# Credit Risk Basics

Recall the definition of credit risk:

“The risk of not receiving promised payments of outstanding debts due to the default of the borrower.”

Two main types of default.

Issuer: of a security or bond. *Issuer cannot pay you back the principle or interest.*

Counterparty: in an over the counter derivative contract.

This week: issuer default.

Next week: counterparty default.

# Hazard Rate Models

A bond is issued by a company which might default.

We do not know exactly when default may occur, though.

Let  $\tau$  denote the (random) default time.

$(\Omega, \mathcal{F}, \mathbb{Q})$ : probability space.  $\mathbb{Q}$ : risk-neutral measure.

$\tau : \Omega \mapsto [0, \infty]$  a random variable.

$\tau = \infty$  : no default.

# Hazard Rate Models

We will assume:

$\tau$  is a continuous r.v..

- 1) Hence  $\mathbb{Q}[\tau = 0] = 0$ : no default at 0. *no chance of immediate default*
- 2)  $\mathbb{Q}[\tau = \infty] = 0$ .

Company will default before the end of time.

Assumption not necessary, but makes the formulas nicer.

- 3)  $\mathbb{Q}[\tau > t] > 0$  for all  $t \geq 0$ .

Some chance of not defaulting over any horizon  $[0, t]$ .

As such  $F(t) = \mathbb{Q}[\tau \leq t] = 1 - e^{-\int_0^t \gamma(u)du}$ . *exp dist*

$\gamma$ : the hazard function of  $\tau$ .

$$\gamma(t) \equiv \gamma > 0 \quad \forall t > 0$$

$$F(t) = 1 - e^{-\gamma t} \Rightarrow T \sim \text{Exp}(\gamma)$$

$$F(t) = 1 - e^{-\int_0^t \gamma(u) du}$$

$\mathbb{Q}(\tau \leq t+h)$

$$\text{Since } \gamma(t) = \frac{d}{dt} (-\log(1 - F(t))):$$

$$= \frac{1}{h} \frac{\mathbb{Q}(\tau > t)}{1 - e^{-\int_0^{t+h} \gamma(u) du}} - \frac{(1 - e^{-\int_0^t \gamma(u) du})}{1 - e^{-\int_0^t \gamma(u) du}}$$

$$\lim_{h \downarrow 0} \frac{1}{h} \mathbb{Q} [\tau \leq t + h \mid \tau > t] = \lim_{h \downarrow 0} \frac{F(t + h) - F(t)}{h(1 - F(t))},$$

instantaneous  
likelihood rate of default  
(slope)

$$= \frac{1}{1 - F(t)} \frac{d}{dt} F(t);$$

$$= \frac{d}{dt} (-\log(1 - F(t)));$$

$$= \gamma(t).$$

$-\log(1 - F(t)) = \int_t^{\infty} \gamma(u) du$

$\mathbb{Q}[\tau \leq t+h \mid \tau > t] = \gamma(t)h$

$\gamma(t)$ : rate of default at  $t$ , given no default up to  $t$ .

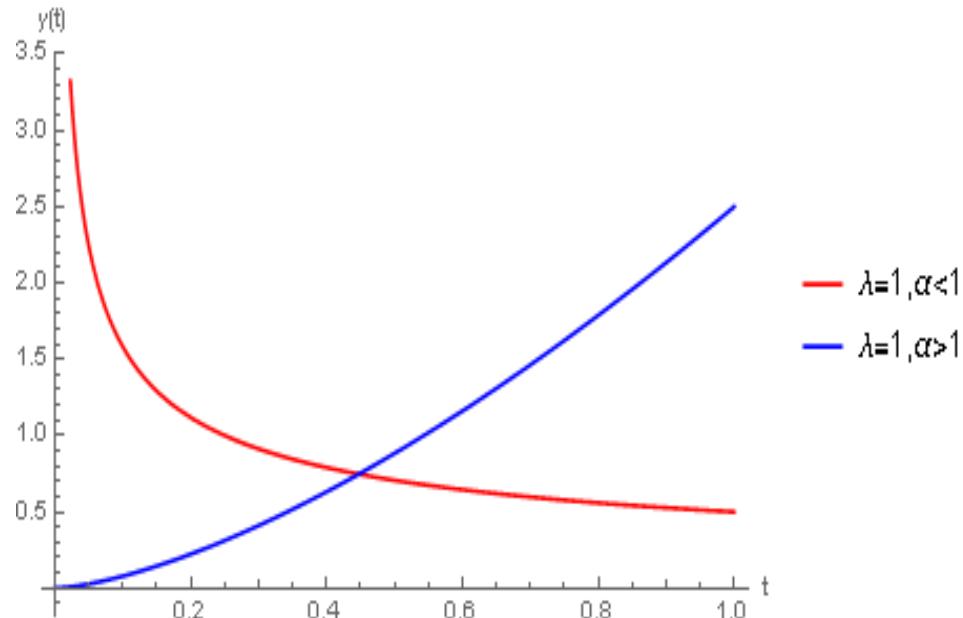
Typically, we start with  $\gamma$  and then produce  $\tau$ .

## Example: Weibull Distribution

$$F(t) = 1 - e^{-\lambda t^\alpha} \text{ for } \lambda, \alpha > 0.$$

$\lambda=1$ , exponential dist.

$$\gamma(t) = \lambda \alpha t^{\alpha-1}.$$



# Information Flow

At  $t$ , our information  $\mathcal{F}_t$  consists only of knowing the answer to

“Has the company defaulted by time  $t$ ?”

No other randomness to add to our information set.

$$\{\omega \mid \tau(\omega) \leq t\} \in \mathcal{F}_t - \forall t \geq 0$$

The event  $\{\tau \leq t\}$  is  $\mathcal{F}_t$  measurable for all  $t \geq 0$ .

$\tau$  is a  $\mathbb{F} = \{\mathcal{F}_t\}_{t \geq 0}$  stopping time.

# Conditional Expectations w.r.t. $\mathbb{F}$

unconditional

$$F(t) = 1 - e^{-\int_0^t \gamma(u) du} \Rightarrow \tau \text{ has p.d.f. } \gamma(t) e^{-\int_0^t \gamma(u) du} = f(t)$$

$$\mathbb{Q}[t < \tau \leq \ell \mid \tau > t] = \int_t^\ell \gamma(u) e^{-\int_t^u \gamma(v) dv} du.$$

$$\mathbb{Q}[t < \tau \leq \ell] = \int_t^\ell \gamma(u) e^{-\int_0^u \gamma(v) dv} du.$$

$$\mathbb{Q}[\tau > t] = e^{-\int_0^t \gamma(v) dv}.$$

$$\begin{aligned}\mathbb{Q}(t < \tau \leq \ell \mid \tau > t) &= \frac{\mathbb{Q}(t < \tau \leq \ell)}{\mathbb{Q}(\tau > t)} \\ &= \frac{\int_t^\ell \gamma(u) e^{-\int_u^\ell \gamma(v) dv} du}{1 - (1 - e^{-\int_0^t \gamma(v) dv})} = \int_t^\ell \gamma(u) e^{-\int_u^\ell \gamma(v) dv} du \\ &\quad \text{cond. cdf}\end{aligned}$$

Given  $\tau > t$ ,  $\tau$  has p.d.f.  $\gamma(u) e^{-\int_t^u \gamma(v) dv}$ .  $\leftarrow$  cond. pdf

Using this, one can show for all  $g$  that

$$\begin{aligned}E^{\mathbb{Q}}[1_{\tau > t} g(\tau) \mid \mathcal{F}_t] &= 1_{\tau > t} \underbrace{\int_t^\infty g(u) \gamma(u) e^{-\int_t^u \gamma(v) dv} du}_{= \mathbb{E}[g(\tau) \mid \tau > t] \text{ by def}} \\ &\quad \text{Given } \tau > t.\end{aligned}$$

# Risk Neutral Bond Pricing

As default is the only source of uncertainty, the money market rate  $r = \{r(t)\}_{t \geq 0}$  is deterministic.

We consider two securities:

Default-free zero coupon bond (ZCB): pays \$1 at maturity  $T$  with certainty.

Defaultable ZCB: pays \$1 at  $T$  if the firm has not defaulted.

For now, no recovery of principal.

# Risk Neutral Bond Pricing

$p_0(t, T)$ : default-free ZCB price at  $t$ .

$$p_0(t, T) = E^{\mathbb{Q}} \left[ e^{-\int_t^T r(u) du} \mid \mathcal{F}_t \right] = e^{-\int_t^T r(u) du}.$$

$r$  is not random.

$p_1(t, T)$ : defaultable ZCB price at  $t$ .

$$p_1(t, T) = E^{\mathbb{Q}} \left[ \underbrace{1_{\tau > T}}_{\text{if no default}} e^{-\int_t^T r(u) du} \mid \mathcal{F}_t \right] = 1_{\tau > t} e^{-\int_t^T (r(u) + \gamma(u)) du}.$$

Conditional expectation result for  $g(y) = 1_{y > T}$ . g(u) = 1\_{u > T}

Effect of default on pricing:

We discount at the higher rate  $r + \gamma$ .

$$(G(\tau=\infty)=0 = e^{-\int_0^\infty \gamma(u) du})$$

$$\begin{aligned} p_1(t, T) &= e^{-\int_t^T r(u) du} 1_{\tau > t} \times \int_t^\infty g(u) \delta(u) e^{-\int_u^\infty r(v) dv} du \\ &= e^{-\int_t^T r(u) du} 1_{\tau > t} \int_T^\infty \gamma(u) e^{-\int_u^\infty r(v) dv} du, \quad u=0 \\ &= e^{-\int_t^T r(u) du} 1_{\tau > t} \left( -e^{-\int_t^u r(v) dv} \Big|_{u=t}^{u=\infty} \right) \\ &= 1_{\tau > t} e^{-\int_t^T (r(u) + \gamma(u)) du} \end{aligned}$$

# Recovery

In practice, when a bond defaults, there is some recovery of principal.

Result of a complicated legal process.

We consider the easiest recovery model.

Upon default the bond holder receives  $(1 - \delta)$  in cash.

$\delta$ : loss given default.

“Recovery at Face” (RF) methodology.

## Bond Pricing with Recovery

$$\begin{aligned}
 p_1^{RF} &= \mathbb{E}^{\mathbb{Q}} \left[ 1_{\tau > t} (1_{\tau \leq T} e^{-\int_t^{\tau} r(u) du} + (1-\delta) 1_{t < \tau \leq T} e^{-\int_t^{\tau} r(u) du}) \mid \mathcal{F}_t \right] \\
 \text{RF payoffs} &= p_1(t, T) + 1_{\tau > t} \mathbb{E}^{\mathbb{Q}} \left[ (1-\delta) 1_{t < \tau \leq T} e^{-\int_t^{\tau} r(u) du} \mid \mathcal{F}_t \right] \\
 &= p_1(t, T) + 1_{\tau > t} \int_t^{\tau} (1-\delta) e^{-\int_t^u r(v) dv} r(u) e^{-\int_t^u r(v) dv} du \\
 &\quad 1_{\tau > T} \text{ at } T \text{ (no default).} \\
 &\quad (1-\delta) 1_{\tau \leq T} \text{ at } \tau \text{ (default at } \tau).
 \end{aligned}$$

Price at  $t$  given  $\tau > t$ :

$$\begin{aligned}
 p_1^{RF}(t, T) &= E^{\mathbb{Q}} \left[ 1_{\tau > T} e^{-\int_t^T r(u) du} + (1-\delta) 1_{t < \tau \leq T} e^{-\int_t^{\tau} r(u) du} \mid \mathcal{F}_t \right] ; \\
 &= p_1(t, T) + (1-\delta) 1_{\tau > t} \int_t^T \gamma(s) e^{-\int_t^s (r(u) + \gamma(u)) du} ds. \\
 &\quad (\text{cond. expect. result for } g(y) = 1_{y \leq T} e^{-\int_t^y r(u) du}).
 \end{aligned}$$

# Summary of Bond Prices

Default free ZCB:

$$p_0(t, T) = e^{-\int_t^T r(u)du}.$$

Defaultable ZCB with 0 recovery:

$$p_1(t, T) = 1_{\tau > t} e^{-\int_t^T (r(u) + \gamma(u))du}.$$

Defaultable ZCB with RF recovery:

$$p_1^{RF}(t, T) = p_1(t, T) + (1 - \delta) 1_{\tau > t} \int_t^T \gamma(s) e^{-\int_t^s (r(u) + \gamma(u))du} ds.$$

# Credit Default Swaps

A credit default swap (CDS) is a contract between two parties regarding the default of an underlying reference entity (R).

The protection buyer (B) pays the protection seller (S) a fixed premium to ensure against default of R.

There are many technical details regarding the CDS contract. Basic mechanics:

Today =  $t$ . Maturity =  $t + N$ .  $N$  year swap.

# CDS Mechanics

Premium payments occur at  $t_n = t + n/\Delta$ ,  
 $n = 1, \dots, N\Delta$ .

$\Delta$ : payment frequency. Typically:  $\Delta = 4$  (quarterly).

At  $t_n$ , if default has not occurred ( $\tau > t_n$ ), B pays  
 $x/\Delta$  to S.

$x$ : annualized CDS spread.

E.g.:  $x = 200bp$ ,  $\Delta = 4$ . Quarterly payment of 50bp.

After default, no further payments are made.

# CDS Mechanics

If R defaults at  $\tau \in (t_{n-1}, t_n]$ :

*Warning: many notions of default. E.g. bankruptcy, failure to pay a coupon, corporate restructuring.*

S pays the loss given default  $\delta$  to B. Payment is either in cash (cash settlement) or bond buy-back (physical delivery).

→ Idea: if B owns the bond, B will get  $(1 - \delta)$  from R upon default.  
Thus, B needs a residual protection of  $\delta$ .

B pays accrued interest  $x(\tau - t_{n-1})$  to S

For simplicity we will ignore this.

# Pricing CDS: Premium Side

Value of the premium side (ignoring accrued interest).

$$\begin{aligned} \text{B}\rightarrow\text{S} \quad V_t^{\text{prem}}(x) &= E^{\mathbb{Q}} \left[ \sum_{n=1}^{N\Delta} \frac{x}{\Delta} \mathbf{1}_{t_n < \tau} e^{-\int_t^{t_n} r(u) du} \mid \mathcal{F}_t \right]; \\ &= \frac{x}{\Delta} \sum_{n=1}^{N\Delta} p_1(t, t_n); \\ &= \frac{x}{\Delta} \mathbf{1}_{\tau > t} \sum_{n=1}^{N\Delta} e^{-\int_t^{t_n} (r(u) + \gamma(u)) du}. \end{aligned}$$

# Pricing CDS: Default Side

Value of the default side.

$$\begin{aligned} S \rightarrow B \quad V_t^{def} &= E^{\mathbb{Q}} \left[ \delta \mathbf{1}_{t < \tau \leq t+N} e^{- \int_t^\tau r(u) du} \mid \mathcal{F}_t \right]; \\ &= \delta \mathbf{1}_{\tau > t} \int_t^{t+N} \gamma(s) e^{- \int_t^s (r(u) + \gamma(u)) du} ds. \end{aligned}$$

The CDS spread equates the two sides.

$$x = x_t \text{ so that } V_t^{prem}(x_t) = V_t^{def}.$$

No payment at contract initiation.

$$x_t = \delta \frac{\int_t^{t+N} \gamma(s) e^{- \int_t^s (r(u) + \gamma(u)) du} ds}{\frac{1}{\Delta} \sum_{n=1}^{N\Delta} e^{- \int_t^{t_n} (r(u) + \gamma(u)) du}}.$$

# A Note on Calibration

$$x_t = \delta \frac{\int_t^{t+N} \gamma(s) e^{-\int_t^s (r(u)+\gamma(u)) du} ds}{\frac{1}{\Delta} \sum_{n=1}^{N\Delta} e^{-\int_t^{t_n} (r(u)+\gamma(u)) du}}.$$

We can use observed CDS spreads to approximate the default intensity  $\gamma$  under  $\mathbb{Q}$ .

Assume  $r, \gamma$  are small and constant.

$$e^{-\int_t^{t_n} (r(u)+\gamma(u)) du} \approx 1.$$

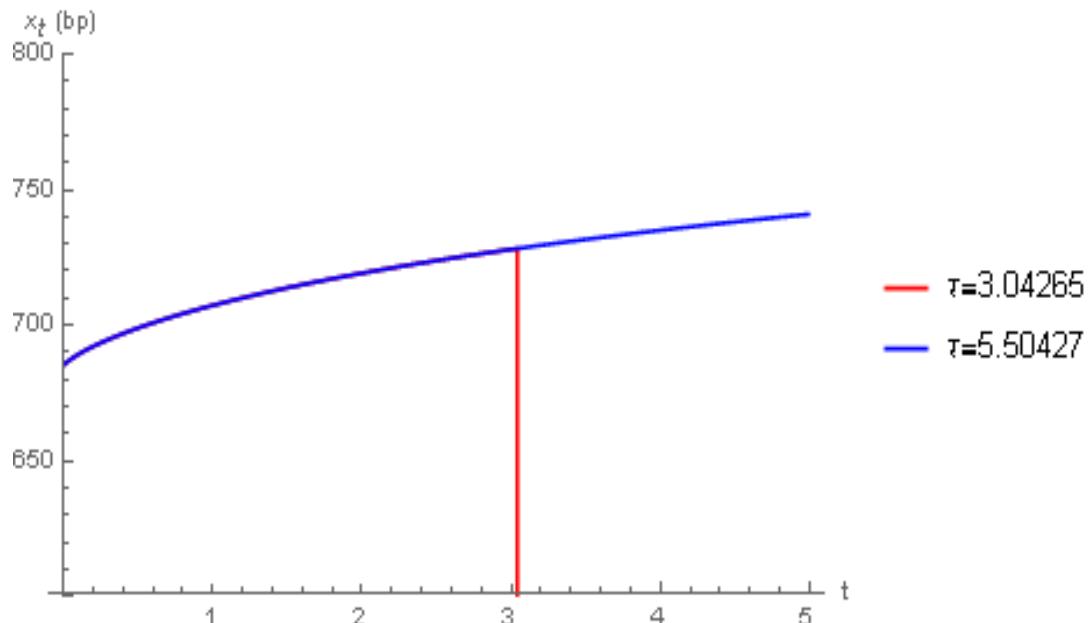
This yields the approximation

$$x_t \approx \delta \gamma \implies \gamma \approx x_t / \delta. \quad \text{— useful if simple approx to the hazard rate}$$
$$= \frac{\delta \gamma r}{N} = \delta r$$

Example: Weibull intensity  $\gamma(t) = \lambda\alpha t^{\alpha-1}$

$$x_t = \delta \frac{\int_t^{t+N} \gamma(s) e^{-\int_t^s (r(u)+\gamma(u)) du} ds}{\frac{1}{\Delta} \sum_{n=1}^{N\Delta} e^{-\int_t^{t_n} (r(u)+\gamma(u)) du}}.$$

$\lambda = 0.125$ ,  $\alpha = 1.05$ ,  $r \equiv 5\%$ ,  $\delta = 0.5$ ,  $N = 5$ ,  $\Delta = 4$ .



## Sampling $\tau$

How did we obtain  $\tau$  in the last picture?

Recall: if  $X \sim F$  then  $F(X) \sim U(0, 1)$ .

Proof (for continuous  $F$ ).

$$\mathbb{P}[F(X) \leq t] = \mathbb{P}[X \leq F^{-1}(t)] = F(F^{-1}(t)) = t.$$

Thus,  $X \sim F^{-1}(U)$  where  $U \sim U(0, 1)$ .

To sample  $X$ , we sample  $U \sim U(0, 1)$  and set  $X = F^{-1}(U)$ .

Provided we can invert  $F$ .

$$\text{Sampling } \tau \text{ with } F(t) = 1 - e^{-\int_0^t \gamma(v)dv}$$

$$Q(T=\infty) = \lim_{t \rightarrow \infty} Q(T=t) = \lim_{t \rightarrow \infty} 1 - F(t)$$

$$= \lim_{t \rightarrow \infty} 1 - (1 - e^{-\int_0^t \gamma(u)du})$$

$$= e^{-\int_0^\infty \gamma(u)du} = 0$$

$$F(t) = u \iff \int_0^t \gamma(v)dv = -\log(1-u).$$

Recall:  $\tau$  continuous with  $F(\infty) = \mathbb{Q}[\tau < \infty] = 1$

This implies  $\gamma(v) > 0$  and  $\int_0^\infty \gamma(v)dv = \infty$ .

For any  $u \in (0, 1)$  there is a unique  $t$  such that  
 $\int_0^t \gamma(v)dv = -\log(1-u)$ .

Thus, to simulate  $\tau$ , we let  $U \sim (0, 1)$  and set

$$\tau = \min \left\{ t \geq 0 \mid \int_0^t \gamma(v)dv = -\log(U) \right\}.$$

$U \sim U(0, 1)$  implies  $\underbrace{1 - U}_{\sim} \sim U(0, 1)$ .

## Sampling $\tau$ : examples

Constant  $\gamma(v) = \gamma > 0$ .

$$F(t) = 1 - e^{-\gamma t} \text{ so } \tau \sim \text{Exp}(\gamma).$$

$$\tau = \min \{t \mid \gamma t = -\log(U)\} = -\frac{1}{\gamma} \log(U). \text{ Sample exp dist}$$

Weibull  $\gamma(v) = \lambda \alpha t^{\alpha-1}$  so  $\int_0^t \gamma(v) dv = \lambda t^\alpha$ .

$$\tau = \min \{t \mid \lambda t^\alpha = -\log(U)\} = \left(-\frac{1}{\lambda} \log(U)\right)^{1/\alpha}.$$

# Multiple Defaults

What if we own a security whose payoff depends on the default of two reference entities?

$\tau_1$ : default time of first company.

$\tau_2$ : default time of second company.

Information  $\mathcal{F}_t$ : we know if defaults have occurred or not by  $t$ , but nothing else.

E.g.: ZCB which pays if neither company defaults.

Time 0 price:  $E^{\mathbb{Q}} \left[ 1_{\min\{\tau_1, \tau_2\} > T} e^{-\int_0^T r(v) dv} \right]$ . 都不违约

# Multiple Defaults

How can we price in this situation?

Easy way: assume  $\tau_1, \tau_2$  independent! E.g.  $\text{price} = e^{-\int_0^T r + n + \alpha du}$

$$\mathbb{Q}[\min\{\tau_1, \tau_2\} > T] = \mathbb{Q}[\tau_1 > T] \mathbb{Q}[\tau_2 > T] = e^{-\int_0^T (\gamma_1(v) + \gamma_2(v)) dv}.$$

Independence implies  $\min\{\tau_1, \tau_2\}$  has intensity  $\gamma_1 + \gamma_2$ .

But, assuming independence ignores contagion: not good

Default of one company increases the default likelihood for the other.

Akin to ignoring correlations of equity log returns.

# Multiple Defaults and Dependence

How can we model dependence?

Recall how we sample  $\tau_1, \tau_2$ .

$$\tau_1 = \min \left\{ t \mid \int_0^t \gamma_1(v) dv = -\log(U_1) \right\}.$$

$$U_1, U_2 \stackrel{\text{Q}}{\sim} U(0,1)$$

$$\tau_2 = \min \left\{ t \mid \int_0^t \gamma_2(v) dv = -\log(U_2) \right\}.$$

Idea: introduce dependence for  $\tau_1, \tau_2$  by assuming  $U_1, U_2$  are **DEPENDENT  $U(0,1)$  r.v..**

# Joint Distributions and Copulas

How can we sample dependent  $(U_1, U_2)$ ? *Copula*

A copula  $c$  is any map on  $[0, 1]^2$  such that

$c$  is a joint cdf.

$$c(u_1, u_2) = \tilde{\mathbb{P}}[U_1 \leq u_1, U_2 \leq u_2] \text{ for some } \tilde{\mathbb{P}} \text{ and } U_1, U_2.$$

$c$  gives rise to  $U(0, 1)$  marginals.

$$c(u_1, 1) = \tilde{\mathbb{P}}[U_1 \leq u_1] = u_1, \quad c(1, u_2) = \tilde{\mathbb{P}}[U_2 \leq u_2] = u_2.$$

Definition extends to  $d$  r.v.  $U_1, \dots, U_d$ .

# Copula Examples

Independence copula:  $c(u_1, u_2) = u_1 u_2.$

Corresponds to  $U_1 \perp\!\!\!\perp U_2.$

$$= \bar{P}(u_1 < u, u_2 < u_2)$$

Minimum copula:  $c(u_1, u_2) = \min \{u_1, u_2\}.$

Corresponds to  $U_1 = U_2.$

Perfectly positive dependence structure.

$$\bar{P}(1 - U_1 \leq u_1, U_2 \leq u_2) : \bar{P}(1 - U_1 \leq u_1 \wedge U_2 \leq u_2)$$

Maximum copula:  $c(u_1, u_2) = \max \{u_1 + u_2 - 1, 0\}. = (u_1 + u_2 - 1)^+$

Corresponds to  $U_1 = 1 - U_2.$

Perfectly negative dependence structure.

## Sklar's Theorem ( $\Rightarrow$ )

Let  $F$  be a joint cdf with marginals  $F_1, F_2$ . There exists a copula  $c$  such that  $F(x_1, x_2) = c(F_1(x_1), F_2(x_2))$ .  
(proof for cont. r.v.)

Set  $c(u_1, u_2) = F(F_1^{-1}(u_1), F_2^{-1}(u_2))$  so identity holds.

$$\begin{aligned} \text{Then } c(u_1, u_2) &= \tilde{\mathbb{P}}[X_1 \leq F_1^{-1}(u_1), X_2 \leq F_2^{-1}(u_2)] = \\ &\tilde{\mathbb{P}}[F_1(X_1) \leq u_1, F_2(X_2) \leq u_2] = \tilde{\mathbb{P}}[U_1 \leq u_1, U_2 \leq u_2]. \end{aligned}$$

$\underbrace{\phantom{0}}_{\sim U(0,1)}$        $\underbrace{\phantom{0}}_{\sim U(0,1)}$

This allows us to easily simulate  $(U_1, U_2)$ .

(1) Sample  $(X_1, X_2) \sim F$ .

$$c(u_{1,1}) := F(F^{-1}(u_{1,1}), \infty)$$

(2) Set  $U_1 = F_1(X_1), U_2 = F_2(X_2)$ .

$$\begin{aligned} &= F(F^{-1}(u_{1,1})) \\ &= u_{1,1} \end{aligned}$$

## Sklar's Theorem ( $\Leftarrow$ )

For any copula  $c$  and cdf  $(F_1, F_2)$ , the function  $c(F_1(x_1), F_2(x_2))$  is a joint cdf with marginals  $F_1, F_2$ .

(proof for cont. r.v.)

$$(x_1, x_2) \mapsto c(F_1(x_1), F_2(x_2))$$

$$\begin{aligned} c(F_1(x_1), F_2(x_2)) &= \tilde{\mathbb{P}}[U_1 \leq F_1(x_1), U_2 \leq F_2(x_2)] = \\ \tilde{\mathbb{P}}[F_1^{-1}(U_1) &\leq x_1, F_2^{-1}(U_2) \leq x_2] = \tilde{\mathbb{P}}[X_1 \leq x_1, X_2 \leq x_2] \end{aligned}$$

$$F(x_1, 1) = \tilde{\mathbb{P}}[U_1 \leq F_1(x_1)] = F_1(x_1) \quad (\text{same for } F(1, x_2)).$$

This allows us to build joint distributions using

Pre-specified marginal distributions.

Pre-specified copula.

A very flexible framework.

# Copulas: General Bounds

Theorem:  $\max \{u_1 + u_2 - 1, 0\} \leq c(u_1, u_2) \leq \min \{u_1, u_2\}$ .

$$U_1 = 1 - U_2$$

$$U_1 = U_2$$

Holds for any copula.

Proof:  $c(u_1, u_2) = \tilde{\mathbb{P}}[U_1 \leq u_1, U_2 \leq u_2]$  and

$$\begin{aligned}\tilde{\mathbb{P}}[U_1 \leq u_1, U_2 \leq u_2] &\leq \min \left\{ \tilde{\mathbb{P}}[U_1 \leq u_1], \tilde{\mathbb{P}}[U_2 \leq u_2] \right\} = \\ &\min \{u_1, u_2\}.\end{aligned}$$

$$\begin{aligned}\tilde{\mathbb{P}}[U_1 \leq u_1, U_2 \leq u_2] &= 1 - \tilde{\mathbb{P}}[U_1 > u_1 \cup U_2 > u_2] \geq \\ &1 - \tilde{\mathbb{P}}[U_1 > u_1] - \tilde{\mathbb{P}}[U_2 > u_2] = u_1 + u_2 - 1.\end{aligned}$$

All copulas lie in between those associated with  $(U, 1 - U)$  and  $(U, U)$ .

# Gauss Copula

Let  $X \sim N(0, \Sigma)$  for  $\Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$ .

$X$  has standard normal marginals (with cdf  $N$ ).

$$F_1 = F_2 \sim N(0, 1)$$

Gauss copula:

$$\begin{aligned} c_{\rho}^{Ga}(u_1, u_2) &= \tilde{\mathbb{P}} [X_1 \leq N^{-1}(u_1), X_2 \leq N^{-1}(u_2)] ; \\ &= \int_{-\infty}^{N^{-1}(u_1)} \int_{-\infty}^{N^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} e^{-\frac{x^2-2\rho xy+y^2}{2(1-\rho^2)}} dx dy \end{aligned}$$

# Archimedean Copulas

We can generate a large class of copulas as follows:

Let  $\psi : [0, \infty) \rightarrow [0, 1]$  be continuous, decreasing, with  $\psi(0) = 1, \lim_{t \uparrow \infty} \psi(t) = 0$ .

Archimedean copula:  $c(u_1, u_2) = \psi(\psi^{-1}(u_1) + \psi^{-1}(u_2))$ .

E.g.: Gumbel.  $\psi(t) = e^{-t^{1/\theta}}$  for  $\theta \geq 1$ .

$$c_\theta^{G_u}(u_1, u_2) = e^{-((-\log(u_1))^\theta + (-\log(u_2))^\theta)^{1/\theta}}.$$

$\lim_{\theta \uparrow \infty} e^{(-\log(u_1))(1 + (\frac{-\log(u_2)}{-\log(u_1)})^\theta)^{1/\theta}} = \min\{u_1, u_2\}$

At  $\theta = 1$  we obtain  $u_1 u_2$ . As  $\theta \uparrow \infty$  we obtain  $\min\{u_1, u_2\}$ .

$\theta$  allows us to span from independence to minimum copulas.

# Archimedean Copulas

E.g.: Clayton.  $\psi(t) = (1 + \theta t)^{-1/\theta}$  for  $\theta > 0$ .

$$c_{\theta}^{CL}(u_1, u_2) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$$

As  $\theta \downarrow 0$  we obtain  $u_1 u_2$ . As  $\theta \uparrow \infty$  we obtain  $\min \{u_1, u_2\}$ .

As before,  $\theta$  allows us to span from independence to minimum copulas.

# Pricing with Copulas

Let's come back to our application:

Pricing securities with dependence on multiple defaults.

## Examples

No default ZCB: payoff of 1 only if  $\tau_1 > T, \tau_2 > T$ .

At most one default ZCB: payoff of 1 if  $\tau_1 > T$  or  $\tau_2 > T$ .

How can we use copulas to price these bonds?

# Pricing with Copulas

$$\text{Price at } 0 = \mathbb{E}^Q [e^{-\int_t^T r(u) du} \mathbf{1}_{U_1 > T, U_2 > T}]$$

Abstractly, we have the formulas

$$p_{0d}(0, T) = e^{-\int_0^T r(v) dv} E^Q [\mathbf{1}_{\min\{\tau_1, \tau_2\} > T}].$$

$$p_{1d}(0, T) = e^{-\int_0^T r(v) dv} E^Q [\mathbf{1}_{\max\{\tau_1, \tau_2\} > T}].$$

To simplify things, assume constant  $\gamma_1, \gamma_2$ :

$$\tau_1 = -\frac{1}{\gamma_1} \log(U_1), \quad \tau_2 = -\frac{1}{\gamma_2} \log(U_2), \quad (U_1, U_2) \sim c.$$

$$\text{price at } 0 = e^{-\int_t^T r(u) du} Q(\bar{\tau}_1 > T, \bar{\tau}_2 > T)$$

This implies

$$\{\min\{\tau_1, \tau_2\} > T\} = \{U_1 < e^{-\gamma_1 T}, U_2 < e^{-\gamma_2 T}\} = e^{-\int_t^T r(u) du} Q(U_1 < e^{-\gamma_1 T}, U_2 < e^{-\gamma_2 T})$$

$$\{\max\{\tau_1, \tau_2\} > T\} = \{U_1 < e^{-\gamma_1 T}, U_2 < e^{-\gamma_2 T}\} \cup$$

$$\{U_1 < e^{-\gamma_1 T}, U_2 \geq e^{-\gamma_2 T}\} \cup \{U_1 \geq e^{-\gamma_1 T}, U_2 < e^{-\gamma_2 T}\}.$$

# Pricing with Copulas

For  $p_{0d}(0, T)$  we have the formula

$$p_{0d}(0, T) = e^{-\int_0^T r(v)dv} c(e^{-\gamma_1 T}, e^{-\gamma_2 T}).$$

The formula for  $p_{1d}(0, T)$  is more involved, but

We can always price  $p_{1d}(0, T)$  using simulation.

For  $m = 1, \dots, M$  sample  $(U_1^m, U_2^m) \sim c$ , and set  
 $\tau_1^m = -(1/\gamma_1) \log(U_1^m)$ ,  $\tau_2^m = -(1/\gamma_2) \log(U_2^m)$ .

$$\text{Output } p_{1d}(0, T) = e^{-\int_0^T r(v)dv} \frac{1}{M} \sum_{m=1}^M \mathbf{1}_{\max\{\tau_1^m, \tau_2^m\} > T}.$$

Note: we can price options with generic time  $T$  payoffs  $g(\tau_1, \tau_2)$  this way.

# Pricing with Copulas

We have many copulas from which to choose.

Independent, Minimum, Maximum, Gauss ( $\rho$ ), Clayton ( $\theta$ ), Gumbel ( $\theta$ ).

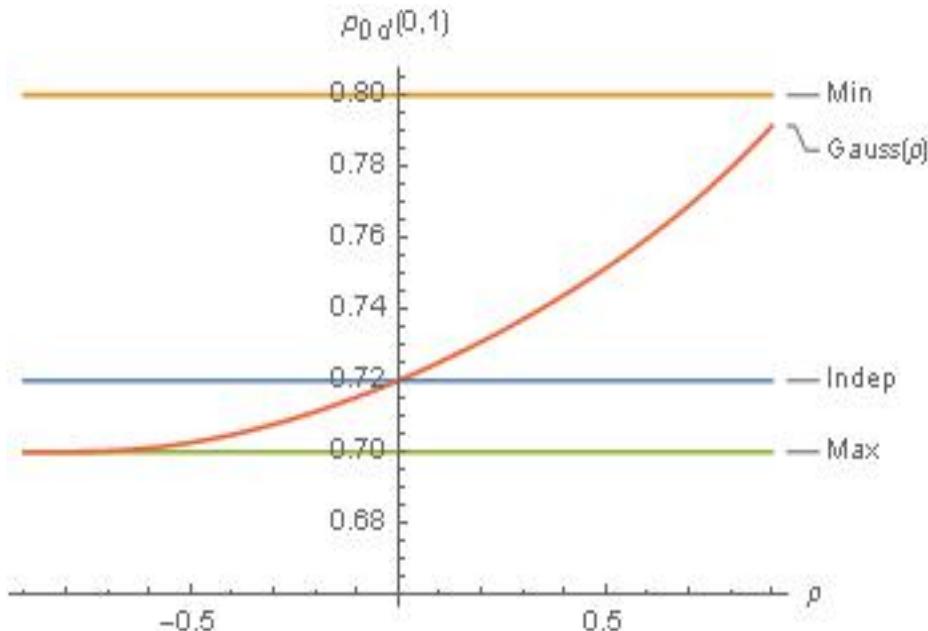
General archimedean ( $\psi$ ).

Generic  $c(u_1, u_2) = F(F_1^{-1}(u_1), F_2^{-1}(u_2))$ .

How do we choose? What are these copulas doing?  
What are the parameters doing?

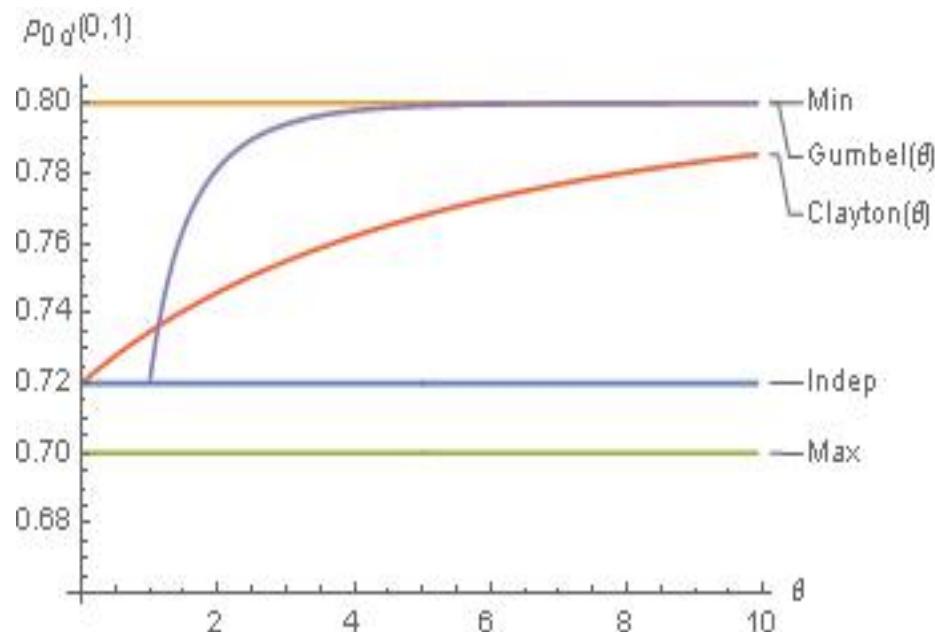
We will focus on  $p_{0d}(0, T) = c(e^{-\gamma_1 T}, e^{-\gamma_2 T})$  (set  $r \equiv 0$ ).

# $p_{0d}(0, T)$ for the Gauss Copula



$T = 1$ ,  $\gamma_1$ : 10% one-year default prob.  $\gamma_2$ : 20% one-year default prob.

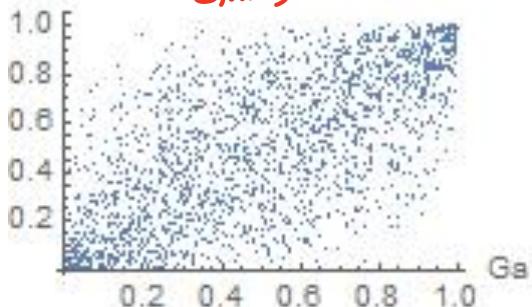
# $p_{0d}(0, T)$ for the Gumbel, Clayton Copulas



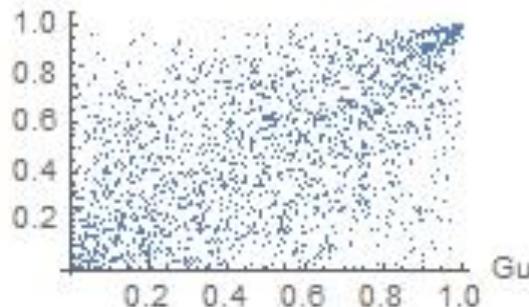
$T = 1$ ,  $\gamma_1$ : 10% one-year default prob.  $\gamma_2$ : 20% one-year default prob.

# 5000 $(U_1, U_2)$ Samples

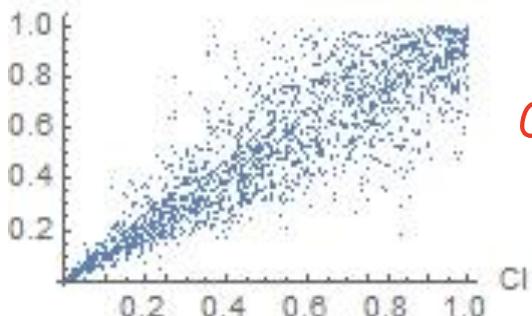
Gauss



Gumbel



Clayton



Gauss (0.7); Gumbel (1.61); Clayton (5.2).

Gumbel: upper tail dep., Clayton: lower tail dep..

Tail dependence: alignment of extreme values.