

Assignment 2

Ki Hyun

FINM 36702: Portfolio Credit Risk: Modeling and Estimation

Due: 18:00 (CT) April 6th 2023

1: Std. Dev. of Defaults

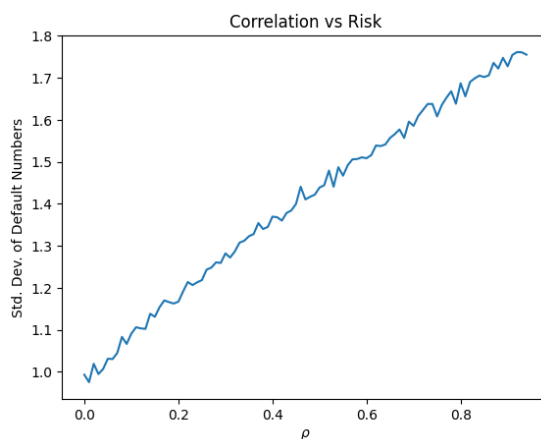
Correlation Matrix	Std. Dev
Original	1.2
Identity Matrix*	0.98

Table 1: Correlation and Std. Dev. of Defaults

* The identity matrix mentioned above would be in the form:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

2: ρ vs Risk

Figure 1: Std. Dev. of Defaults as a function of ρ

3: Exposures in Loan

(i: $\mathbb{P}[D_4 = 1, D_5 = 1]$)

$\mathbb{P}[D_4 = 1, D_5 = 1]$ can be calculated analytically using the multivariate normal distribution of the latent variables of all the 5 firms.

If the latent variable for firm i is d_i , the distribution can be represented as:

$$\mathbf{d} = \begin{pmatrix} d_1 \\ d_2 \\ d_3 \\ d_4 \\ d_5 \end{pmatrix} \sim MVN(\mu, \Sigma)$$

Here,

$$\mu = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \quad \Sigma = \begin{bmatrix} 1 & 0.15 & 0.2 & 0.25 & 0.3 \\ 0.15 & 1 & 0.25 & 0.3 & 0.35 \\ 0.2 & 0.25 & 1 & 0.35 & 0.4 \\ 0.25 & 0.3 & 0.35 & 1 & 0.45 \\ 0.3 & 0.35 & 0.4 & 0.45 & 1 \end{bmatrix}$$

Now the mathematical form for $\mathbb{P}[D_4 = 1, D_5 = 1]$ can be expressed as:

$$\begin{aligned} & \mathbb{P}[D_4 = 1, D_5 = 1] \\ &= \int_{-\infty}^{\Phi^{-1}(PD_5)} \int_{-\infty}^{\Phi^{-1}(PD_4)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) \\ & \quad dd_1 dd_2 dd_3 dd_4 dd_5 \\ &= \int_{-\infty}^{\Phi^{-1}(0.5)} \int_{-\infty}^{\Phi^{-1}(0.4)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) \\ & \quad dd_1 dd_2 dd_3 dd_4 dd_5 \\ & \quad (\because PD_4 = 0.4, PD_5 = 0.5) \\ & \approx 0.27 \end{aligned}$$

$$\therefore \mathbb{P}[D_4 = 1, D_5 = 1] \approx 0.27$$

(ii: $\mathbb{P}[D_4 = 1, D_5 = 1 \mid D_3 = 1]$)

Using the definition of conditional probability:

$$\mathbb{P}[D_4 = 1, D_5 = 1 \mid D_3 = 1] = \frac{\mathbb{P}[D_4 = 1, D_5 = 1, D_3 = 1]}{\mathbb{P}[D_3 = 1]}$$

Here,

$$\begin{aligned}
& \mathbb{P}[D_4 = 1, D_5 = 1, D_3 = 1] \\
&= \int_{-\infty}^{\Phi^{-1}(PD_5)} \int_{-\infty}^{\Phi^{-1}(PD_4)} \int_{-\infty}^{\Phi^{-1}(PD_3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) \\
& \quad dd_1 dd_2 dd_3 dd_4 dd_5 \\
&= \int_{-\infty}^{\Phi^{-1}(0.5)} \int_{-\infty}^{\Phi^{-1}(0.4)} \int_{-\infty}^{\Phi^{-1}(0.3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) \\
& \quad dd_1 dd_2 dd_3 dd_4 dd_5 \\
& \quad (\because PD_4 = 0.4, PD_5 = 0.5, PD_3 = 0.3)
\end{aligned}$$

Moreover,

$$\begin{aligned}
& \mathbb{P}[D_3 = 1] \\
&= \int_{-\infty}^{\Phi^{-1}(PD_3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) dd_1 dd_2 dd_4 dd_5 dd_3 \\
&= \int_{-\infty}^{\Phi^{-1}(0.3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) dd_1 dd_2 dd_4 dd_5 dd_3 \\
& \quad (\because PD_3 = 0.3)
\end{aligned}$$

Therefore,

$$\begin{aligned}
& \mathbb{P}[D_4 = 1, D_5 = 1 \mid D_3 = 1] \\
&= \frac{\mathbb{P}[D_4 = 1, D_5 = 1, D_3 = 1]}{\mathbb{P}[D_3 = 1]} \\
&= \frac{\int_{-\infty}^{\Phi^{-1}(0.5)} \int_{-\infty}^{\Phi^{-1}(0.4)} \int_{-\infty}^{\Phi^{-1}(0.3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) dd_1 dd_2 dd_3 dd_4 dd_5}{\int_{-\infty}^{\Phi^{-1}(0.3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) dd_1 dd_2 dd_4 dd_5 dd_3} \\
&\approx 0.44
\end{aligned}$$

$$\therefore \mathbb{P}[D_4 = 1, D_5 = 1 \mid D_3 = 1] \approx 0.44$$

(iii: Portfolio Expected Loss Rate)

Given the ELGD and Exposure of the portfolio across the 7 loans, the expected loss at default for each firm could be summarized to:

Firm	Expected Loss at Default
Firm 1	70
Firm 2	120
Firm 3	150
Firm 4	280
Firm 5	220

Now using 1,000,000 simulations from the $MVN(\mu, \Sigma)$ and comparing each result with the Probabilities of Default (PD_1, \dots, PD_5) to get 1,000,000 vectors in the form:

$$\mathbf{D}_{sim=j} = \begin{pmatrix} D_{1,sim=j} \\ D_{2,sim=j} \\ D_{3,sim=j} \\ D_{4,sim=j} \\ D_{5,sim=j} \end{pmatrix}$$

Here, $D_{i,sim=j}$ will represent if firm i has defaulted in the j^{th} simulation:

$$D_{i,sim=j} = \begin{cases} 1 & \text{Firm } i \text{ Defaulted in the } j\text{th simulation} \\ 0 & \text{Otherwise in the } j\text{th simulation} \end{cases}$$

Now, if we let $\mathbb{E}[\text{Loss}]$ be the vector:

$$\mathbb{E}[\text{Loss}] = \begin{pmatrix} 70 \\ 120 \\ 150 \\ 280 \\ 220 \end{pmatrix}$$

Our expected **portfolio** loss from the simulation will be:

$$\sum_{j=1}^{1,000,000} \mathbf{D}_{sim=j} \cdot \mathbb{E}[\text{Loss}]$$

Moreover, the expected loss rate can be estimated as:

$$\mathbb{E}[\text{Loss Rate}] = \frac{2800}{\sum_{j=1}^{1,000,000} \mathbf{D}_{sim=j} \cdot \mathbb{E}[\text{Loss}]} \approx 0.11$$

(iv: Dcorr)

First, similar to (part i), we can get $PDJ_{3,4}$ as:

$$\begin{aligned} & \mathbb{P}[D_3 = 1, D_4 = 1] \\ &= \int_{-\infty}^{\Phi^{-1}(PD_4)} \int_{-\infty}^{\Phi^{-1}(PD_3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) \\ & \quad dd_1 dd_2 dd_5 dd_3 dd_4 \\ &= \int_{-\infty}^{\Phi^{-1}(0.4)} \int_{-\infty}^{\Phi^{-1}(0.3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp \left(-\frac{1}{2} (\mathbf{d} - \mu)^T \Sigma^{-1} (\mathbf{d} - \mu) \right) \\ & \quad dd_1 dd_2 dd_5 dd_3 dd_4 \\ & \quad (\because PD_3 = 0.3, PD_4 = 0.4) \end{aligned}$$

Now using the properties of a Bernoulli distribution:

$$\begin{aligned}
& Dcorr_{3,4} \\
&= \frac{PDJ_{3,4} - PD_3 \cdot PD_4}{\sqrt{PD_3(1 - PD_3)}\sqrt{PD_4(1 - PD_4)}} \\
&= \frac{\int_{-\infty}^{\Phi^{-1}(0.4)} \int_{-\infty}^{\Phi^{-1}(0.3)} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{5/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{d} - \mu)^T \Sigma^{-1}(\mathbf{d} - \mu)\right) dd_1 dd_2 dd_3 dd_4}{\sqrt{0.3(1 - 0.3)} \cdot \sqrt{0.4(1 - 0.4)}} \\
&\quad - \frac{0.3 \cdot 0.4}{\sqrt{0.3(1 - 0.3)} \cdot \sqrt{0.4(1 - 0.4)}} \\
&\approx 0.22
\end{aligned}$$

$$\therefore Dcorr_{3,4} \approx 0.22$$

4: 36702 Distribution

The joint probability density of x and y was given as:

$$f_{x,y}[x, y] = \frac{1 + 3x - y}{2} \quad (4 - 0)$$

From this, we can derive the marginal density as:

$$f_x[x] = \int_0^1 \frac{1 + 3x - y}{2} dy = \frac{3}{2}x + \frac{1}{4}$$

and

$$f_y[y] = \int_0^1 \frac{1 + 3x - y}{2} dx = -\frac{1}{2}y + \frac{5}{4}$$

The marginal density now gives way to marginal CDF:

$$F_x[z] = \int_0^z \left(\frac{3}{2}x + \frac{1}{4}\right) dx = \frac{3}{4}z^2 + \frac{1}{4}z$$

and

$$F_y[z] = \int_0^z \left(-\frac{1}{2}y + \frac{5}{4}\right) dy = -\frac{1}{4}z^2 + \frac{5}{4}z$$

Now from the marginal CDF, we get the inverse CDF (quantile function) as:

$$F_x^{-1}[p] : p = \frac{3}{4}z^2 + \frac{1}{4}z, \quad 0 \leq p, z \leq 1$$

$$\Leftrightarrow F_x^{-1}[p] = \frac{-1 + \sqrt{1 + 48p}}{6} \quad (4 - 1)$$

Moreover,

$$\begin{aligned}
 F_y^{-1}[p] : p &= -\frac{1}{4}z^2 + \frac{5}{4}z, \quad 0 \leq p, z \leq 1 \\
 \Leftrightarrow F_y^{-1}[p] &= \frac{5 - \sqrt{25 - 16p}}{2} \quad (4 - 2)
 \end{aligned}$$

(i: PDJ)

The probability of default for x and y were given as $PD_x = 0.1$ and $PD_y = 0.2$.

Using this knowledge and the above, we can express the PDJ as:

$$\begin{aligned}
 &PDJ_{x,y} \\
 &= \int_0^{F_y^{-1}[0.2]} \int_0^{F_x^{-1}[0.1]} f_{x,y}[x, y] dx dy \\
 &= \int_0^{F_y^{-1}[0.2]} \int_0^{F_x^{-1}[0.1]} \frac{1 + 3x - y}{2} dx dy \\
 &(\because (4 - 0)) \\
 &= \int_0^{\frac{5 - \sqrt{25 - 16 \cdot 0.2}}{2}} \int_0^{\frac{-1 + \sqrt{1 + 48 \cdot 0.1}}{6}} \frac{1 + 3x - y}{2} dx dy \\
 &(\because (4 - 1), (4 - 2)) \\
 &\approx 0.025
 \end{aligned}$$

(ii: Dcorr)

Using the PDJ above, the Dcorr can be calculated using the characteristics of a Bernoulli distribution as:

$$\begin{aligned}
 &Dcorr_{x,y} \\
 &= \frac{PDJ_{x,y} - PD_x \cdot PD_y}{\sqrt{PD_x(1 - PD_x)} \sqrt{PD_y(1 - PD_y)}} \\
 &\approx 0.039
 \end{aligned}$$

(iii: ρ)

In order to find the ρ we need to declare another set of latent variables that are Gaussian copula.

If we let those latent variables be n_x and n_y :

$$\mathbf{n} = \begin{pmatrix} n_x \\ n_y \end{pmatrix} \sim MVN(\mu, \Sigma)$$

where

$$\mu = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

$PDJ_{x,y}$ can be expressed using the above Gaussian distribution as:

$$PDJ_{x,y} = \int_{-\infty}^{\Phi^{-1}[PD_y]} \int_{-\infty}^{\Phi^{-1}[PD_x]} \frac{1}{(2\pi)|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{n} - \mu)^T \Sigma^{-1}(\mathbf{n} - \mu)\right) dx dy$$

Now using the calculated $PDJ_{x,y}$ value and the given PD_x and PD_y values, the equation above becomes:

$$0.025 = \int_{-\infty}^{\Phi^{-1}[0.2]} \int_{-\infty}^{\Phi^{-1}[0.1]} \frac{1}{(2\pi)|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{n} - \mu)^T \Sigma^{-1}(\mathbf{n} - \mu)\right) dx dy$$

Using python, the ρ that satisfies the above equation turns out to be approximately 0.090.

$$\therefore \rho \approx 0.090$$