Default dependence in Thailand’s housing and automobile loan portfolio: A copula approach

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Motivation

- According to the Bank of Thailand, loan growth contracted 0.9% in 2023 quarter 3. NPL increased to 2.7%
- Thailand has high household debt about 90.7% to GDP
- Housing and automobile loans are top 2 loans KKP Bank, my ex-company.
- KKP Bank forecasted an upward trend in NPL.

Source: https://www.bot.or.th/en/news-and-media/news/news-20231120.html
https://kkp.listedcompany.com/misc/PRESN/20231025-kkp-am3q2023.pdf

Introduction and literature

- Traditional credit risk model employed linear correlation which assumes normally distributed. However, some studies shows normality was not met.
- In 2011, Crook and Moreira claimed that they first studied empirically applying copulas to consumer loan credit analyses.
- A study (Chan and Kroese, 2010) shows that Gaussian copulas failed to properly detect loan default correlation during period of high financial distress.
- Archimedean copula is more efficient to explain loan default than Gaussian copula (Fenesh, Vosgha, and Shafik 2015)

Methodology

- Normal copula

$$C_\alpha(u_1,u_2)=\frac{1}{2\pi\sqrt{1-\alpha^2}}\int_{-\infty}^{\Phi^{-1}(u_1)}\int_{-\infty}^{\Phi^{-1}(u_2)}exp(\frac{-(v_1^2-2\alpha v_1v_2+v_2^2)}{2(1-\alpha^2)})dv_1dv_2,\ \alpha\in(-1,1)$$

where Φ is the distribution function of $N(0,1)$

- Clayton copula

$$C_\alpha(u_1,u_2)=(u_1^{-\alpha}+u_2^{-\alpha}-1)^{-\frac{1}{\alpha}},\ \alpha>0$$

- Frank copula

$$C_\alpha(u_1,u_2)=-\frac{1}{\alpha}ln(1+\frac{(e^{-\alpha u_1}-1)(e^{-\alpha u_2}-1)}{e^{-\alpha}-1}),\ \alpha\neq 0$$

- Gumbel copula

$$C_\alpha(u_1,u_2)=e^{-((-lnu_1)^\alpha+(-lnu_2)^\alpha)^{\frac{1}{\alpha}}},\ \alpha\in[1\infty)$$

Copula feature

Based on Sklar's theorem, for all (x1, x2) ∈ R^2 and joint distribution function F, there exists a unique copula C such that F (x1, x2) = C(F1(x1), F2(x2))

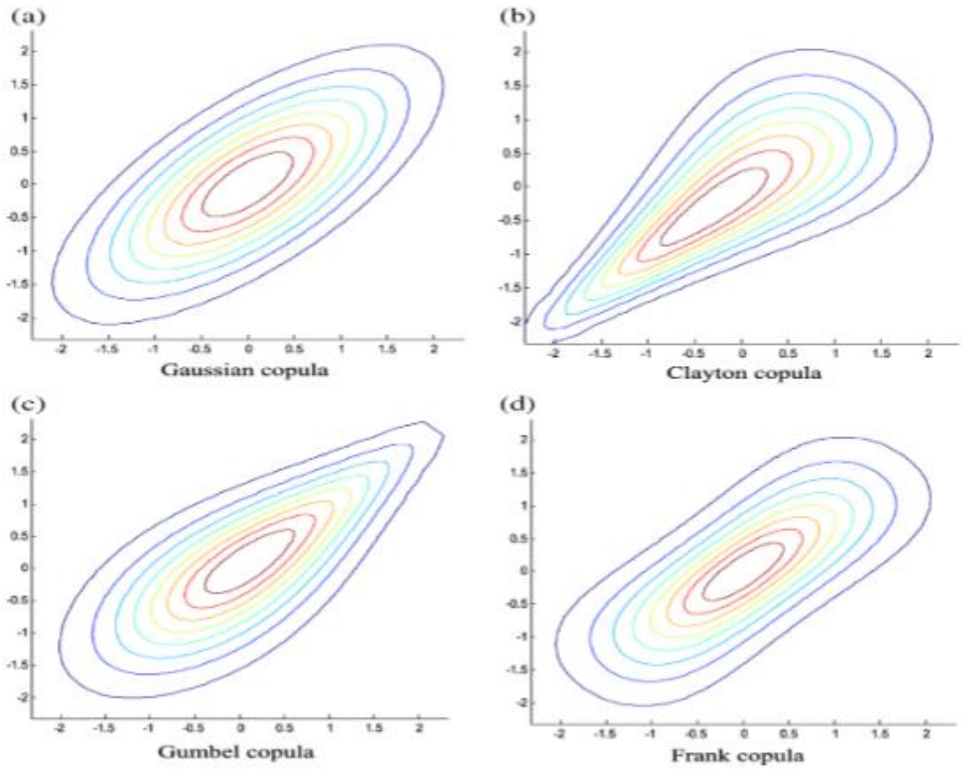
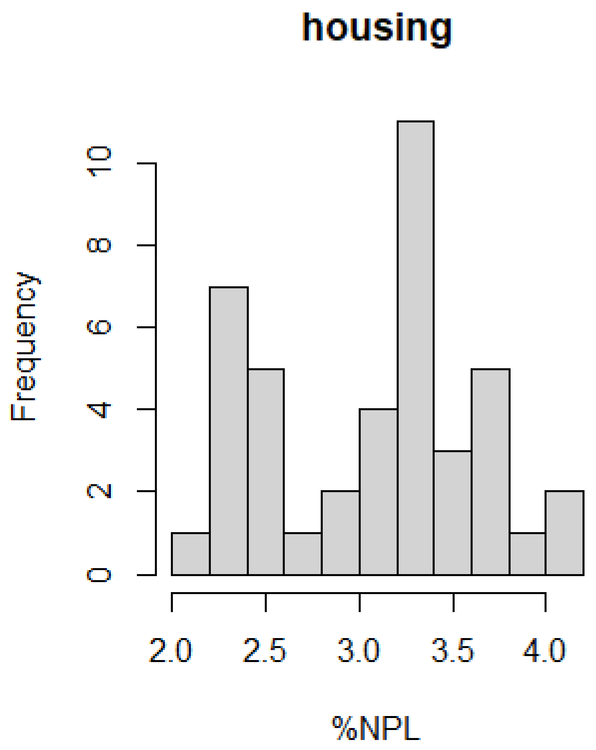


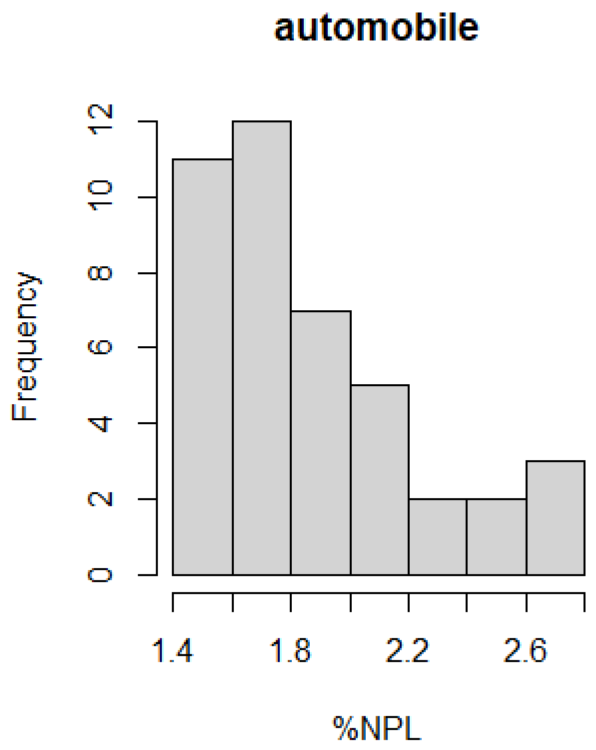
Figure 1: Copula Plots
Source: Park, C. , Kim, N. and Haftka, R. (2015). *The effect of ignoring dependence between failure modes on evaluating system reliability.* Structural and Multidisciplinary Optimization. 52. 10.1007/s00158-015-1239-7.

Copula	Dependence structure
Normal	Symmetric dependence without tail dependence
Clayton	Left (lower) tail dependence
Frank	Symmetric dependence without tail dependence
Gumbel	Right (upper) tail dependence

Data

- BoT provides a data set called "FI_NP_003_S2 Gross NPLs Outstanding Classified by Business Sector_ISIC Rev.4.0 1/"
- It contains NPL outstanding and %NPL from Q1/2013 to Q2/2023 (42 observations)
- I selected only housing and automobile loan for this study.





Source: https://app.bot.or.th/BTWS_STAT/statistics/BOTWEBSTAT.aspx?reportID=794&language=ENG

Normality test and data transformation

Variable	Jarque-Bera statistic	p-value
housing	2.5858	0.2745
automobile	6.6873	0.03531

Table 1: Jarque-Bera test

- Housing follows normal distribution with mean 3.007 and S.D. 0.548
- Automobile was transformed by Pseudo-Observation

Given n realizations $x_i = (x_{i1}, ..., x_{id})^T, i \in \{1, ..., n\}$ of a random vector X, the pseudo-observation are defined via $u_{ij} = r_{ij}/(n+1)$ for $i \in \{1, ..., n\}$ and $j \in \{1, ..., d\}$, where r_{ij} denotes the rank of x_{ij} among all $x_{kj}, k \in \{1, ..., n\}$

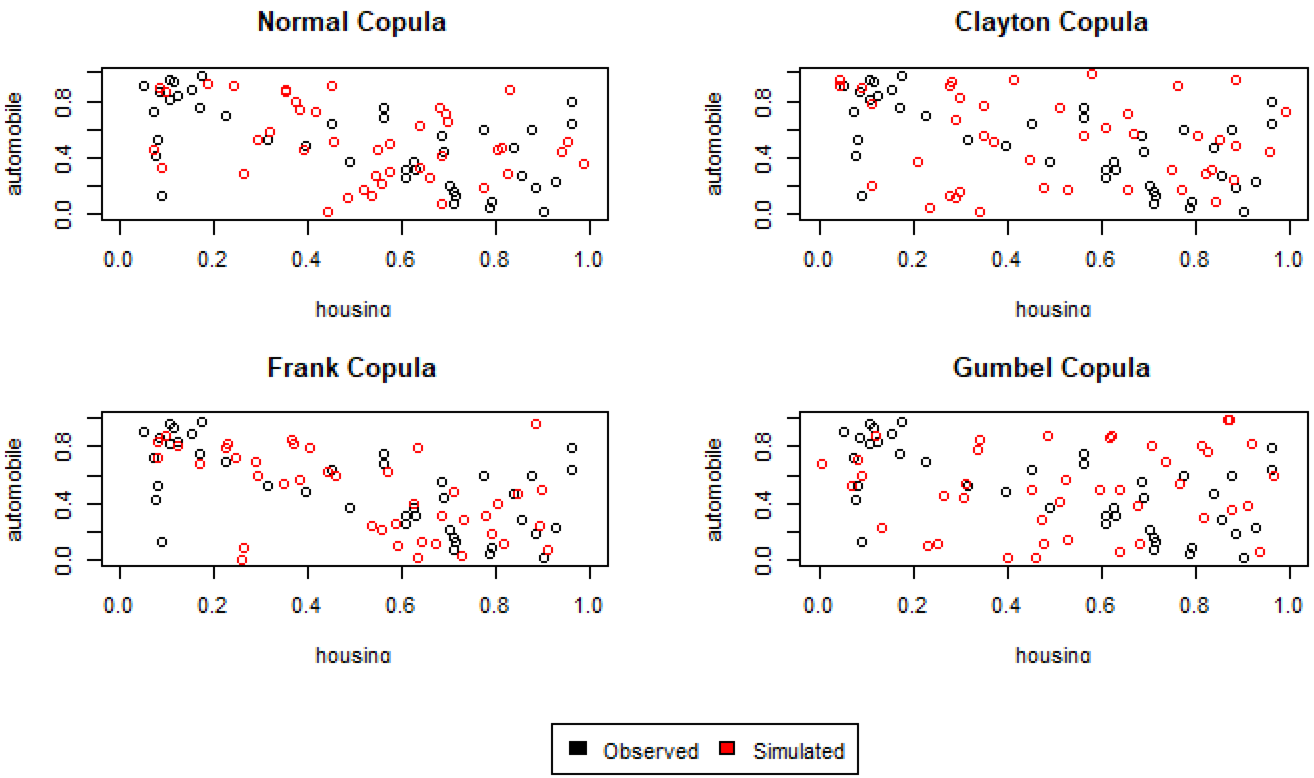
Result

Family	α	AIC	BIC
Normal	-0.5542	-10.45036	-8.712686
Clayton	-0.1861	-2.914093	-1.176423
Frank	-4.552	-16.40813	-14.67046
Gumbel	1	2.000001	3.73767

Table 2: Copula coefficient and information criteria

- Clayton copula performed best based on AIC and BIC

Result


Normal Copula
Clayton Copula
Frank Copula
Gumbel Copula
automobile
housing
0.0
0.4
0.8
0.2
0.6
1.0
Observed
Simulated

Limitation and future research

- Customer level data
- Goodness-of-fit test
- Marginal distribution fitting
- Additional copulas such as Student t and Galambos