Analyzing Nintendo and Sony stock using dependence studies and copulas

ACTSC445 A4 Q1

Introduction

Nintendo

Nintendo is a Japanese multinational consumer electronics and video game company that specializes in manufacturing video game consoles and video game distribution. Nintendo is one of the leading manufacturer and distributor in the video game industry and is valued at over $95 billion USD (The Small Business, 2021).

For our data, we will use the log-returns of the Nintendo stock (NASDAQ: NTDOY) from November 29, 2010 to November 26, 2021. So X will contain the log-returns of Nintendo.

Sony Corporation

Sony is a Japanese multinational conglomerate that specializes in manufacturing consumer electronics including video game consoles as well as video game distribution. Sony is ranked as the largest video game console manufacturers and video game distributor, and also is valued at over $137.3 billion USD (Forbes, n.d.a).

For our data, we will use the log-returns of the Sony stock (NYSE: SONY) from November 29, 2010 to November 26, 2021. So Y will contain the log-returns of Sony.

Basic Statistics of the log-return data

Nintendo

Mean: 0.0001841255

Median: -0.0003782528

1st quartile: -0.01242509

3rd quartile: 0.01215132

Standard Dev: 0.02490919

Sony

Mean: 0.000448942

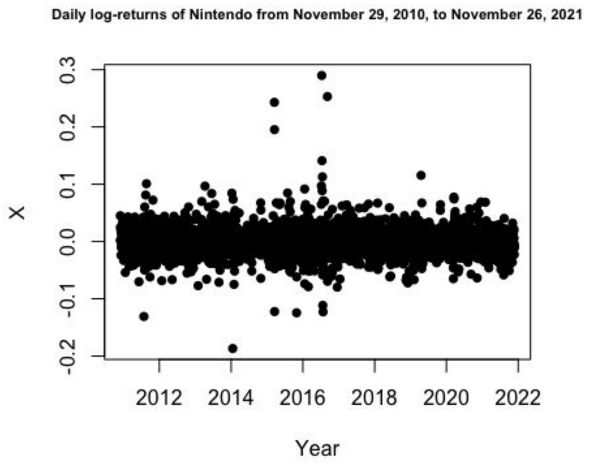
Median: 0.0005649002

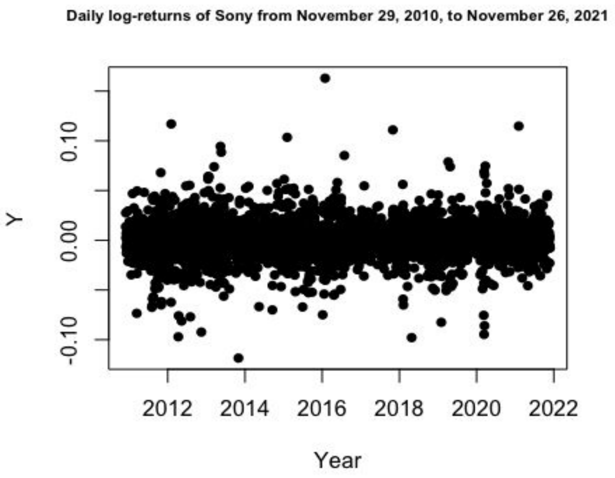
1st quartile: -0.01028899

3rd quartile: 0.01104981

Standard Dev: 0.02036412

Graph of log-returns over dates



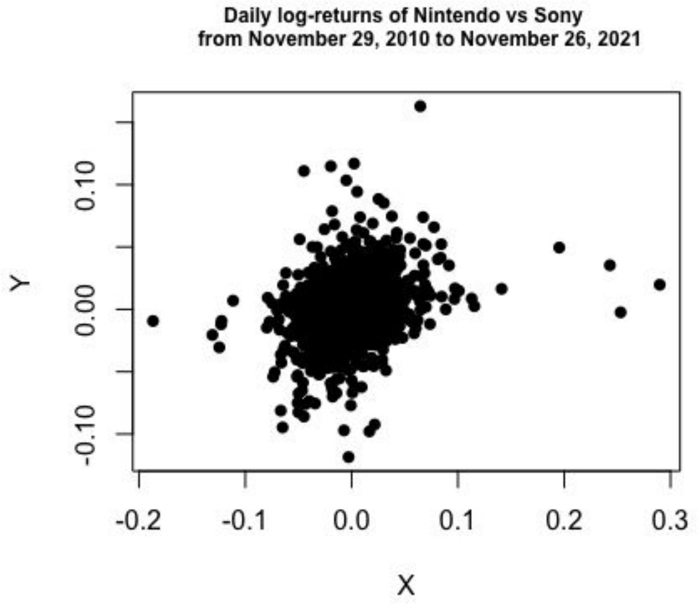


Based on the graphs, both data of log-returns looks to be bounded between two points most of the time. Both Nintendo and Sony also have similar log-return values as it looks the values are bounded between [-0.1, 0.1] most of the time.

Why stock of Nintendo and Sony may behave similarly

Nintendo and Sony might behave in a similar way since both companies are in the industry of manufacturing video game consoles and distributing video games. Also, both companies sell a variety of video games in their respective distribution network, but there are similar video games offered in both networks such as Overwatch, Resident Evil, etc. which makes them both similar in terms of the video games they distribute.

Scatterplot of pairs of log-returns



Based on the scatter plot, X and Y looks to have a positive correlation along with a fairly high correlation as there are a few outliers.

Correlation Coefficients

Pearson's r = 0.3279843

Spearman's p = 0.3643317

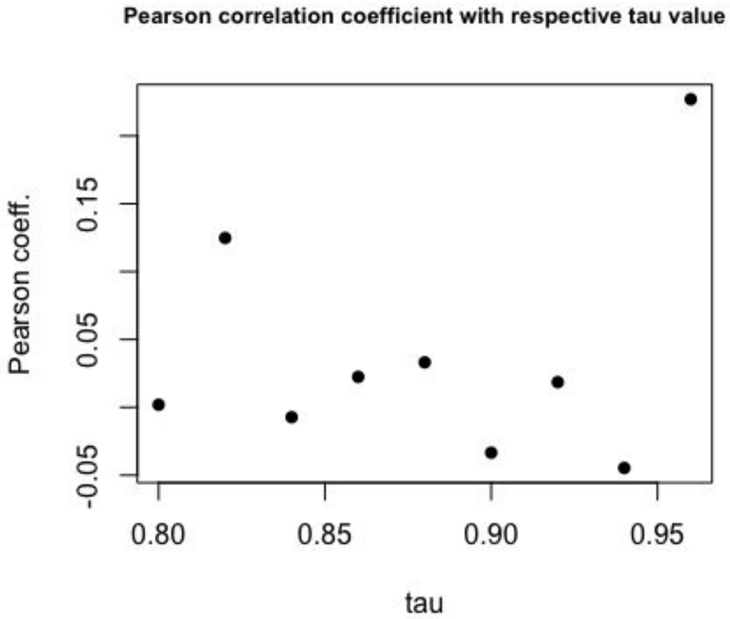
Kendall's tau = 0.2518681

Analyzing the asymmetry of dependence

Analyzing asymmetry of dependence

We consider tau = 0.8, 0.82, …, 0.96 and compute the corresponding 100tau% quantiles for both X and Y, respectively denoted as Ex, and Ey. Then we will compute the Pearson's r correlation coefficient of the subset of their pairs (X, Y) where X > Ex and Y > Ey.

Analyzing asymmetry of dependence

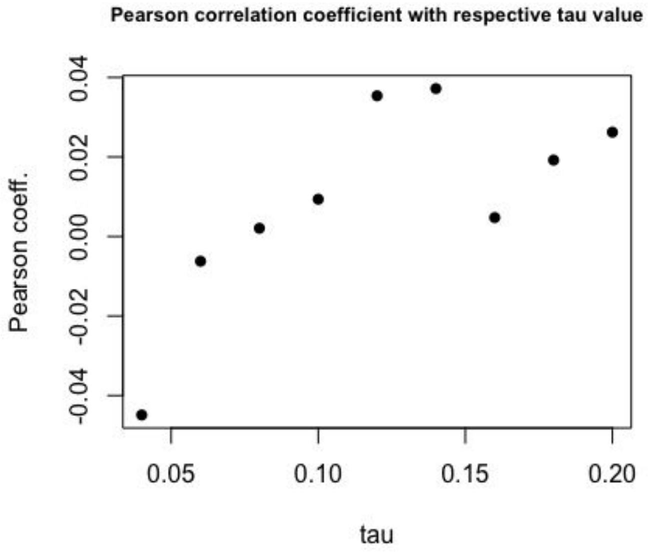


It looks that there is no clear pattern between the correlation coefficient vs tau value

Analyzing asymmetry of dependence

Now we consider tau = 0.2, 0.18, … , 0.04 and compute the corresponding 100tau% quantiles for both X and Y, respectively denoted as Ex, and Ey. Then we will compute the Pearson's r correlation coefficient of the subset of their pairs (X, Y) where X <= Ex and Y <= Ey.

Analyzing asymmetry of dependence



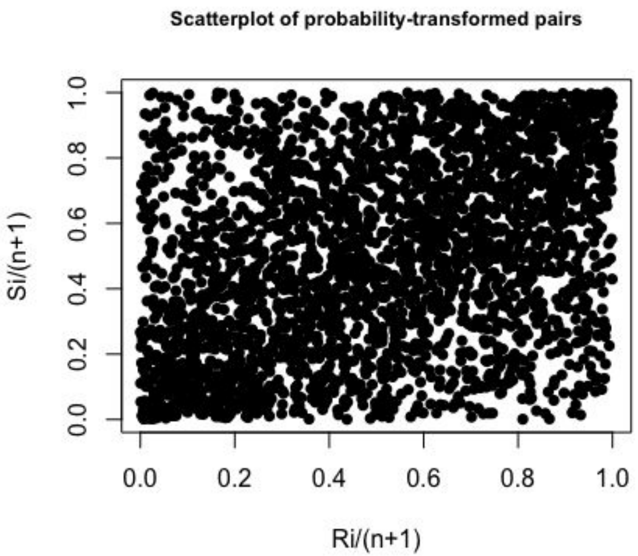
It looks that on average, as the tau value increases, the pearson correlation coefficient will increase

Analyzing asymmetry of dependence

Based on the graphs obtained, the Pearson's r correlation coefficients are relatively small as most of them are bounded between [-0.05, 0.04] while there are two values between [0.1, 0.2]. This suggests that there is weak correlation between X and Y.

Tail dependence study

Tail dependence study



Consider the scatterplot of the probability-transformed pairs of X and Y i.e: (Ri / (n+1), Si / (n+1)) where Ri and Si the rank of Xi and Yi respectively and n is the length of the data.

Based on the scatterplot, the data looks clustered but it looks the data has a very low positive correlation

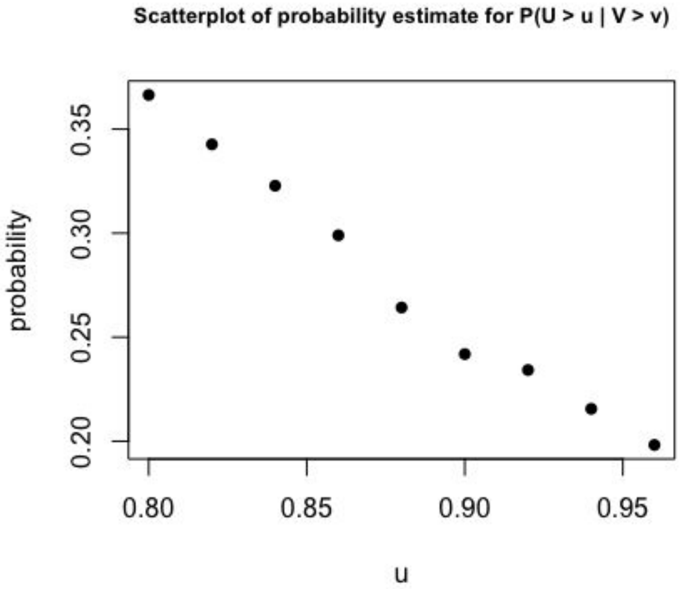
Tail dependence study

First we will take a look at the upper index of tail dependence.

Let F1 and F2 respectively denote the empirical distribution functions for log-returns X and Y respectively. Set Ui = F1(Xi) and Vi = F2(Yi).

We then develop an estimate of $Pr(U > u|V > u)$ for $u = 0.8, 0.82, \dots, 0.96$

Tail dependence study



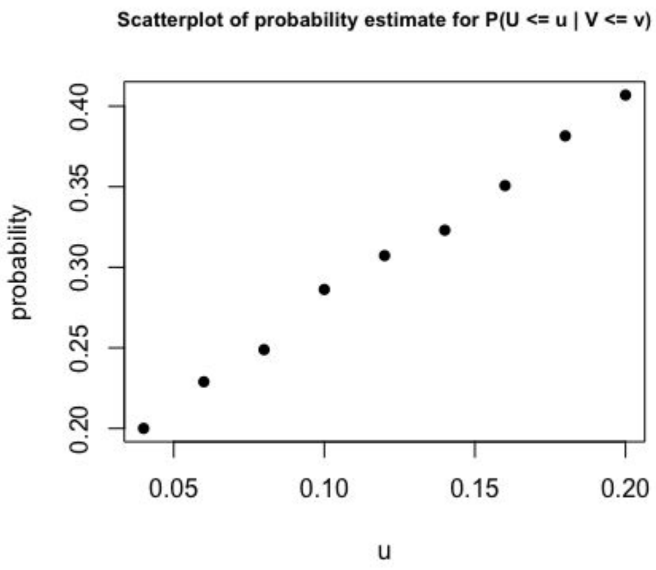
Based on the graph, as u increases, the conditional probability decreases. So it suggests that upper tail dependence index converges somewhere near 0.2.

Tail dependence study

Next we will take a look at the lower index of tail dependence.

This time we estimate $\Pr(U <= u|V <= u)$ for $u = 0.2, 0.18, \ldots, 0.04$

Tail dependence study



Based on the graph, as u increases, the conditional probability increases. Also it suggests that lower tail dependence index converges somewhere near 0.2.

Multivariate-distribution-function based model analysis

Multivariate-Distribution model analysis

We will use a bivariate normal distribution for the log-returns data set X and Y

The mean vector is: (0.0001841255 0.0004489420)

The covariance matrix is:

	[,1]	[,2]
[1,]	0.0006204680	0.0001663713
[2,]	0.0001663713	0.0004146972

We use these two to fit the log-returns data set into bivariate normal distribution model

Multivariate-Distribution model analysis

Now consider a portfolio with payoff: $10,000e^{X} + 10,000e^{Y},$

Using the mean vector and covariance matrix from the previous slide, we generate 2000 samples under a bivariate normal distribution to estimate the 95% VaR of the portfolio's loss variable using the empirical method.

We get the 95% VaR loss variable = -19418.72

Copula-based model method

Copula-based model method

We will use a univariate normal distribution for log-returns dataset X and Y

We can do this by using the following data to fit into a normal distribution:

Nintendo:

Mean: 0.0001841255

Standard Dev: 0.02490919

Sony:

Mean: 0.000448942

Standard Dev: 0.02036412

Copula-based model method

Let F_x and F_y respectively denote the fitted normal distributions for X and Y. Consider sequences $\{U_i = F_x(X_i), i = 1, \dots, n\}$ and $\{V_i = F_y(Y_i), i = 1, \dots, n\}$

We will fit the Gumbel, Frank, and Joe copulas for (U, V) and calculate their BIC values to select the best fitting copula.

Copula-based model method

Gumbel BIC = 5.432712

Frank BIC = 5.220447

Joe BIC = 6.162154

We choose the Frank copula as the best fitting since it has the lowest BIC value. Next we will use the Frank copula to develop an estimate for the 95% VaR for the same loss variable we considered in the multivariate-distribution model analysis.

Copula-based model method

We use the Frank copula and generate 2000 simulations of the loss variable. We will then use the empirical method to estimate the 95% VaR of the loss variable

We get the 95% VaR of the loss variable = -22709.55

References

https://thesmallbusinessblog.net/nintendo-net-worth/

https://www.forbes.com/companies/sony/?sh=778719f26f42

ACTSC445 Ch04_ShortTermPortfolioRisk

ACTSC445 Ch06_DependenceModellingWithCopula

ACTSC445 Ch07_SimulationAndInferenceOfCopulaMethods