VIET NAM NATIONAL UNIVERSITY HO CHI MINH CITY

UNIVERSITY OF ECONOMICS AND LAW

FINAL-TERM REPORT

PROGRAM PACKAGE IN FINANCE 2

THE FACTORS THAT AFFECT THE DEBT MATURITY STRUCTURE OF DEVELOPMENT INVESTMENT CONSTRUCTION JOINT STOCK COMPANY (DIG)

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TOPIC:

THE FACTORS THAT AFFECT THE DEBT MATURITY STRUCTURE OF DEVELOPMENT INVESTMENT CONSTRUCTION JOINT STOCK COMPANY (DIG)

DECLARATION

I hereby declare that the report "The factors that affect the debt maturity structure of Development Investment Construction Joint Stock Company (DIG)" is the result of my work under the guidance of Dr. Nguyen Thanh Liem within the framework of Program package in finance 2 module.

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Abstract

The maturity structure of corporate debt is one of the significant financing choices that a firm must make simultaneously while deciding how to finance its operational and investment decisions. The choice of a suitable debt maturity structure is exceptionally relevant for firms because it can enable them to avoid mismatch by aligning assets in line with liabilities, addressing agency-related problems, sidestepping the ill effects of the cost of capital, and signaling the firms' earning quality and value. The study investigates the firm-specific determinants and COVID-19 determinants significant for the debt maturity structure of Development Investment Construction Joint Stock Company with data from the company's financial statements collected on finance.vietstock.com from the first quarter of 2010 to the fourth quarter of 2021. The results of the regression model indicate that liquidity, leverage, asset intensity, and the dividend policy significantly determine the debt maturity structure. This study also explores the impact of COVID-19 on firm-specific determinants of debt maturity structure.

1. Introduction

Debt is an important aspect of finance and a tool to control disadvantages and increase advantages when choosing between short-term and long-term debt. Debt maturity is the maturity of short-term and long-term debt. Deciding to choose an optimal debt term will help businesses have many opportunities, reduce risks from funding sources, increase transparency, and exploit opportunities from tax deductions due to debt. Short-term debt plays an important role in reducing the costs of enterprises. However, borrowing in the short term causes enterprises to face many risks in terms of liquidity, refinancing, and reinvesting. This leads businesses, especially construction enterprises such as Development Investment Construction Joint Stock Corporation (DIG Corp.), to face a dilemma in choosing between short-term debt and long-term debt to bring the greatest benefit.

This study focuses on factors affecting the debt maturity structure of Development Investment Construction Joint Stock Corporation, analyzing the impact of internal factors of the company and the impact of COVID-19 on firm-specific determinants of debt maturity structure.

2. Literature review

There are research papers on debt maturity structure in both Vietnam and abroad, such as:

Mohammed (2020) researched the factors affecting debt maturity structure among the listed non-financial firms in Nigeria. The results indicate that the non-debt tax-shield, liquidity, asset intensity, diversification, growth opportunity, firm size, and dividend policy significantly determine the debt maturity structure among the listed non-financial firms in Nigeria. However, the evidence is not enough to conclude that profitability and investors' confidence determine the debt maturity structure among the non-financial firms in Nigeria. Firm diversification and liquidity appeared to have the most profound negative effect on the debt maturity structure, in line with predictions of the special use of debt hypothesis and the pecking order theory. Overall, it is concluded that firm-specific factors determine the choice of debt maturity structure among Nigerian listed non-financial firms.

Lemma and Negash (2012) show that internal factors impact a firm's debt maturity structure. Their findings confirm that asset maturity, income volatility, and debt ratio positively affect the debt maturity structure. Besides examining company-specific characteristics, they explore the effect of the industry sector and characteristics of the economy on the decisions about the debt maturity structure of firms in African countries. Their studies have shown that the size of the economy has a positive effect on debt maturity structure; thus, firms in low-income countries tend to use less long-term debt, whereas taxes and economic growth rate (GDP) have the opposite effect.

Acording Méndez (2013), the empirical determinants of a firm's debt maturity structure are examined for a sample of 38,993 non-financial Spanish firms over the period 1995-2006. The results show the relevance of growth opportunities, size, asymmetric information, and asset maturity in explaining debt maturity.

Correia et al. (2014) explore the factors affecting the debt maturity structure in European countries. Research results show that internal factors, including firm size, asset maturity, and leverage ratio, positively correlate with long-term debt, whereas profitability is negatively correlated with long-term debt. Their findings are in line with Lemma and Negash (2012); specifically, the larger the size of the banking system, the more these firms use short-term debt.

In Vietnam, Nguyen (2018) shows that the debt maturity structure of companies in Vietnam is dynamic. The author examines the internal and external factors that influence the debt maturity structure of Vietnamese enterprises. Internal characteristics, such as earnings volatility, liquidity, tangible assets, and firm size, positively affect debt maturity structure. In Vietnam, physical assets are the most important intrinsic factor affecting long-term debt. External circumstances impact a firm's debt term structure. In contrast, institutional quality and economic growth had no effect, and interest rate term structure, inflation, and the level of financial development, which included the intermediary financial system and financial markets, were all positively connected.

Pham (2018) studies the debt maturity structure of real estate companies listed on the Vietnamese stock market. The research results show that financial leverage, company size, asset structure, solvency, profit fluctuations are the factors affecting the debt maturity structure of enterprises, other factors such as growth opportunities, corporate income tax is not statistically significant.

Pham (2020) conducts another study regarding the capital structure and debt maturity structures of Vietnamese real estate investment and business firms. The findings of the study suggest that institutions hurt debt term structure decisions. Liquidity, business risk, firm size, financial development, and inflation affect debt maturity structure choice.

The Ngo and Le (2021) study investigates the firm-specific and macroeconomic determinants significant for the debt maturity structure of Vietnamese corporate firms. A sample of 722 non-financial firms listed on the Ho Chi Minh and Hanoi Stock Exchange in Vietnam from 2007 to 2018 was taken to test the hypothesis. The study's methods of fixed effects panel data analysis provide empirical evidence that firm size, firms' quality, liquidity, leverage, asset maturity, tax impact, and macro variables are significantly related to the debt maturity structure. Their study measures debt maturity based on the balance sheet approach and define debt maturity as the proportion of long-term debt to total debt.

Nguyen (2022) used the GMM method to find the factors that are significant predictors of debt maturity structure in Vietnamese listed firms from 2010 to 2019, namely the lagged debt maturity structure, leverage ratio, profitability, firm size, growth opportunities, GDP, and inflation. Research shows that debt maturity structure is positively correlated with lagged debt maturity structure, firm size, growth opportunities, and GDP under agency cost theory, while signaling theory creates the ground for the negative effects of profitability and leverage on debt maturity structure.

Based on the literature review, the way to measure the variables and the expectation of the sign of the estimator coefficients βi in the model are presented and explained in Table 1.

Table 1: Variable, definition, measure, and sources of the variables

	Variable	Measure	Sources
Dependent variable	Debt maturity structure	Long term debt/ Total debt	Ngo and Le (2021), Nguyen (2022)
Independent variable	Liquidity	Current assets/current liabilities	Kalsie and Nagpal (2018), Hussain et al. (2018), Mohammed (2020), Pham (2018), Pham (2020)
	Leverage	Total debt/ Total assets	Pham (2020), Nguyen (2022)
	Profitability	Earnings before interest and tax/ Total assets	Correia et al. (2014), Pham (2018), Nguyen (2022)
	Asset intensity	Fixed asset/Total assets	Lemma and Negash (2012), Mohammed (2020)
	Covid	0: Before Covid-19 period, 1: Covid-19 period	

3. Create Dataset

First, read the data, check for missing values, and handle it to make sure the dataset is clear. Then calculate the necessary variables, including debt maturity structure, liquidity, leverage, profitability, and asset intensity. In addition, the data included a dummy variable, COVID-19.

CODE:

```
#required packages
library(tidyverse)
library(readxl)
library(ggplot2)
library(lmtest)
library(forecast)
library(xts)
library(tseries)
```

```
#load data
data <- read_excel("D://học tập//NĂM 3//hk 6//gói ứng dụng trong tài chính//cuối kỳ//K204141927.xlsx", sheet = 1)
#all variable names
colnames(data)
```

RESULT:

```
[1] "Time"                 "long_term_debt"       "short_term_debt"
[4] "total_current_assets" "fixed_assets"         "total_assets"
[7] "interest_expense"     "EBT"                  "covid"
```

CODE:

```
#checking Na values
sum(is.na(data))
```

RESULT:

```
[1] 0
```

The data has no missing values. So we will proceed to calculate the variables.

CODE:

```
#create variables
data <- data %>%
  mutate(DMS= round((long_term_debt/(long_term_debt + short_term_debt)),4),
         liquidity = round((total_current_assets/short_term_debt),4),
         profitability = round((EBT + interest_expense)/total_assets,4), # +
interest_expense
         leverage =
round(((long_term_debt+short_term_debt)/total_assets),4),
         asset_intensity = round((fixed_assets/total_assets),4)
  )
df <- data %>%
  select(Time, DMS, liquidity, profitability, leverage, asset_intensity)
head(df)
#checking Na values
sum(is.na(data))
```

RESULT:

Table 2: Head of data

Time	DMS	liquidity	profitability	leverage	asset_intensity
31/03/2010	0.335	2.54	0.0202	0.376	0.0767
30/06/2010	0.346	2.76	0.0265	0.358	0.0748
30/09/2010	0.343	2.75	0.0824	0.364	0.0751
31/12/2010	0.257	2.38	0.0481	0.369	0.058
31/03/2011	0.368	2.43	0.0076	0.412	0.0742
30/06/2011	0.466	2.82	0.0069	0.424	0.0726

CODE:

```
#checking Na values
sum(is.na(df))
```

RESULT:

```
[1] 0
```

4. Descriptive statistics

CODE:

```
#entire period
entire_period <- df %>%
summarise(variables                                                   =
c('DMS','liquidity','profitability','leverage','asset_intensity'),
          obs = nrow(df),
          min    =    c(min(DMS),    min(liquidity),    min(profitability),
min(leverage), min(asset_intensity)),
          mean    =   c(mean(DMS),   mean(liquidity),   mean(profitability),
mean(leverage), mean(asset_intensity)),
          median  = c(median(DMS), median(liquidity), median(profitability),
median(leverage), median(asset_intensity)),
          std  = c(sd(DMS), sd(liquidity), sd(profitability), sd(leverage),
sd(asset_intensity)),
           max    =    c(max(DMS),    max(liquidity),    max(profitability),
max(leverage), max(asset_intensity))
           )
entire_period = data.frame(entire_period)
entire_period
```

RESULT:

Table 3: Descriptive statistics of all the variables for the entire period

Variables	Obs	Min	Mean	Median	Std	Max
DMS	48	0.1467	0.43899375	0.47920	0.16144022	0.6798
liquidity	48	1.2172	2.70494792	2.68900	0.68744383	4.0971
profitability	48	-0.0044	0.01278125	0.00660	0.01846407	0.0824
leverage	48	0.3575	0.50190000	0.50715	0.05709864	0.6340
asset_intensity	48	0.0361	0.06423542	0.05555	0.02677784	0.1182

From Table 3, it can be seen that there were 48 observations for the entire period from quarter 1 of 2010 to quarter 4 of 2021. The mean value of the debt maturity structure is 0.439, which means that DIC Joint Stock Company used average long-term debts of 0.439 during the period 2010–2021. Compared to the average long-term debt ratio of enterprises in the real estate industry of 0.308 (Pham, 2020), DIC Joint Stock Company uses more long-term debt. However, the company still uses short-term debt more than long-term debt in its debt structure. The financial market in Vietnam is still underdeveloped, the funding sources of companies are limited, most of these sources depend mainly on bank loans. Although banks have many types of loans from short term to long term. However, short-term loans are always preferred, and the conditions for making loans are also lighter than proving that the company has enough requirements for medium and long-term loan procedures. The minimum and maximum values of the debt maturity structure are 0.1467 and 0.6798, respectively. The minimum values of the liquidity and profitability variables are 1.2172 and -0.0044, respectively. However, their maximum values are 4.0971 and 0.0824. Leverage ratio has a mean value of 0.5019, and its minimum and maximum values are 0.3575 and 0.6340, respectively. The mean value of asset intensity is 0.0642. Simultaneously, the minimum and maximum values of asset intensity are 0.0361 and 0.1182, respectively.

CODE:

```
#before Covid-19 pandemic
before_covid <- df[1:40, ]
before_covid_period <- before_covid %>%
  summarise(variables   =   c('DMS','liquidity',   'profitability','leverage',
'asset_intensity'),
            obs = nrow(before_covid),
            min    =    c(min(DMS),    min(liquidity),    min(profitability),
min(leverage), min(asset_intensity)),
            mean    =   c(mean(DMS),   mean(liquidity),   mean(profitability),
mean(leverage), mean(asset_intensity)),
```

```
            median = c(median(DMS), median(liquidity), median(profitability),
median(leverage), median(asset_intensity)),
            std = c(sd(DMS), sd(liquidity), sd(profitability), sd(leverage),
sd(asset_intensity)),
            max    =    c(max(DMS),    max(liquidity),    max(profitability),
max(leverage), max(asset_intensity))
           )
before_covid_period = data.frame(before_covid_period)
before_covid_period
```

RESULT:

Table 4: Descriptive statistics of all the variables from quarter 1 of 2010 to quarter 4 of 2019

Variables	Obs	Min	Mean	Median	Std	Max
DMS	40	0.1653	0.4757550	0.50500	0.14375338	0.6798
liquidity	40	1.8681	2.8874075	2.75480	0.56334075	4.0971
profitability	40	-0.0044	0.0112800	0.00615	0.01687874	0.0824
leverage	40	0.3575	0.4903425	0.50170	0.05070914	0.5455
asset_intensity	40	0.0361	0.0642650	0.05395	0.02794183	0.1182

Table 4 shows that there are 40 observations for the period from quarter 1 of 2010 to quarter 4 of 2019. The mean value of the debt maturity structure is 0.4758, which means that DIC Joint Stock Company used average long-term debts of 0.4758 during the period 2010–2019. The minimum and maximum values of the debt maturity structure are 0.1653 and 0.6798, respectively. The minimum values of the liquidity and profitability variables are 1.8681 and -0.0044, respectively. However, their maximum values are 4.0971 and 0.0824. Leverage ratio has a mean value of 0.5019, and its minimum and maximum values are 0.3575 and 0.5455, respectively. The mean value of asset intensity is 0.0643. Simultaneously, the minimum and maximum values of asset intensity are 0.0361 and 0.1182, respectively.

CODE:

```
#during Covid-19 pandemic
on_covid <- df[41:48, ]
on_covid_period <- on_covid %>%
  summarise(variables   =   c('DMS','liquidity',   'profitability','leverage',
'asset_intensity'),
            obs = nrow(on_covid),
            min    =    c(min(DMS),    min(liquidity),    min(profitability),
```

```
min(leverage), min(asset_intensity)),
            mean   =   c(mean(DMS),   mean(liquidity),   mean(profitability),
mean(leverage), mean(asset_intensity)),
            median = c(median(DMS), median(liquidity), median(profitability),
median(leverage), median(asset_intensity)),
            std = c(sd(DMS), sd(liquidity), sd(profitability), sd(leverage),
sd(asses_intensity)),
            max    =    c(max(DMS),    max(liquidity),    max(profitability),
max(leverage), max(asset_intensity))
  )
on_covid_period = data.frame(on_covid_period)
on_covid_period
```

RESULT:

Table 5: Descriptive statistics of all the variables from quarter 1 of 2020 to quarter 4 of 2021

variables	**obs**	**min**	**mean**	**median**	**std**	**max**
DMS	8	0.1467	0.2551875	0.23705	0.11630539	0.4913
liquidity	8	1.2172	1.7926500	1.84140	0.51332173	2.4033
profitability	8	0.0023	0.0202875	0.00835	0.02499042	0.0648
leverage	8	0.4869	0.5596875	0.56920	0.05462667	0.6340
asset_intensity	8	0.0407	0.0640875	0.06025	0.02155448	0.0963

Table 5 shows that there are 8 observations for the period from quarter 1 of 2020 to quarter 4 of 2021. The mean value of the debt maturity structure is 0.2552, which means that DIC Joint Stock Company used average long-term debts of 0.2552 during the period 2020–2021. That is down more than 22% the debt maturity structure during the period 2010–2019. The minimum and maximum values of the debt maturity structure are 0.1467 and 0.4913, respectively. The minimum values of the liquidity and profitability variables are 1.2172 and 0.0023, respectively. However, their maximum values are 2.4033 and 0.0648. The mean value of liquidity decreased from 2.8874 to 1.7927. However, the mean value of profitability increased from 0.0113 to 0.0203. Leverage ratio has a mean value increased from 0.5019 to 0.560, and its minimum and maximum values are 0.4869 and 0.6340, respectively. The mean value of asset intensity is 0.0641, unchanged so much from the previous period. Simultaneously, the minimum and maximum values of asset intensity are 0.0407 and 0.0963, respectively. Thus, we can conclude that the COVID-19 pandemic has had an effect on the debt maturity structure of the company. The company's debt maturity structure has declined since the COVID-19 pandemic emerged. This shows that the majority of enterprises' loans are short-term loans and are mainly from financial sources such as bank financing.

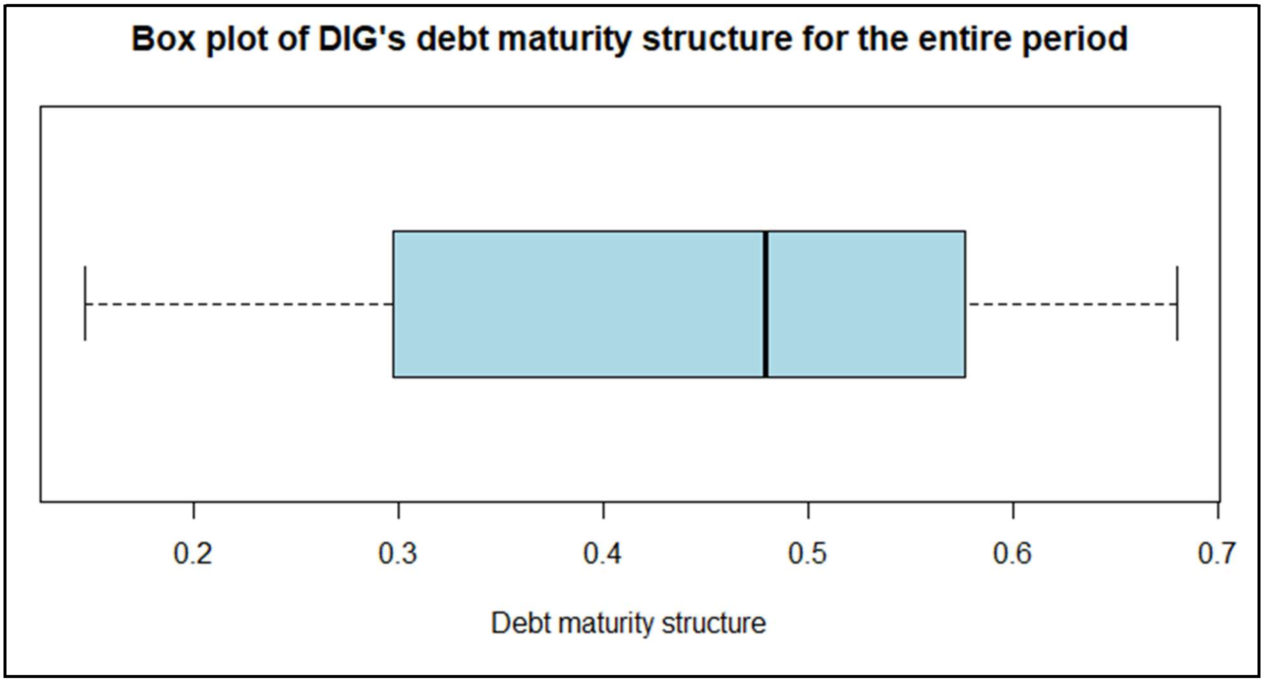
5. Data visualization

CODE:

```
#box plot
boxplot(df$DMS,
        main = "Box plot of DIG's debt maturity structure",
        col = "lightblue",
        xlab= "Debt maturity structure",
        horizontal = TRUE)
```

RESULT:

Figure 1: Box plot of DIG's debt maturity structure for the entire period

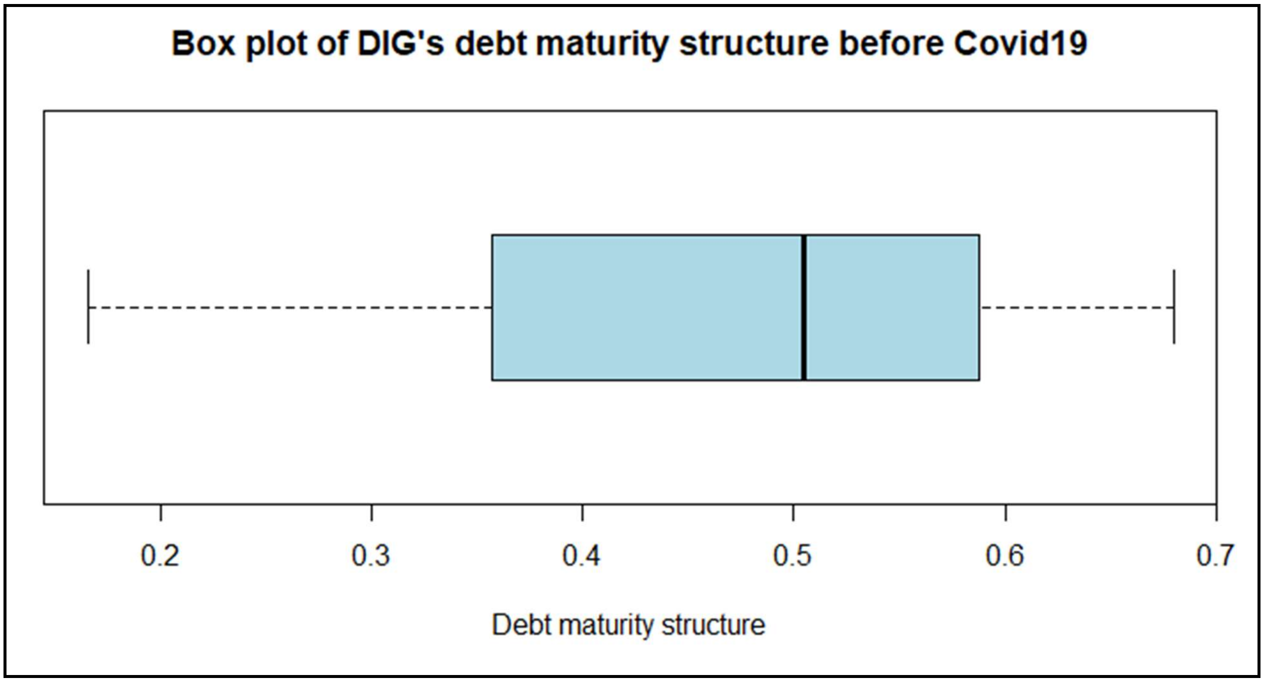


CODE:

```
#before covid
boxplot(before_covid$DMS,
        main = "Box plot of DIG's debt maturity structure before Covid19",
        col = "lightblue",
        xlab= "Debt maturity structure",
        horizontal = TRUE)
```

RESULT:

Figure 2: Box plot of DIG's debt maturity structure before COVID-19

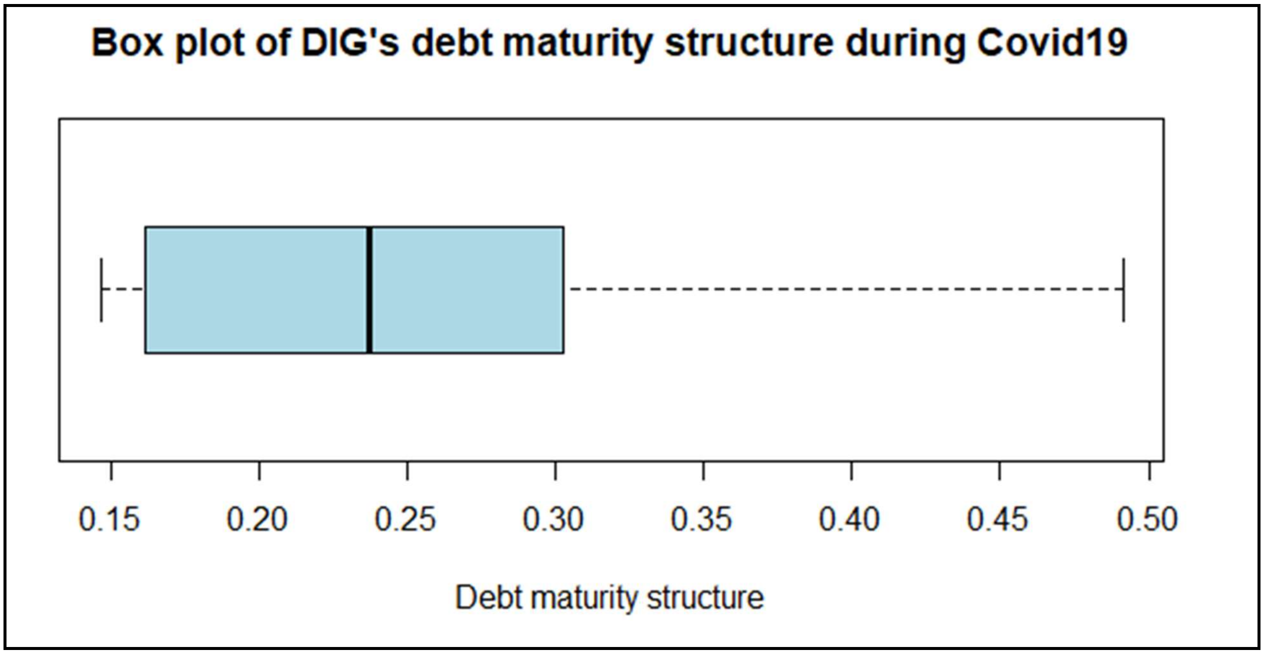


CODE:

```
#during covid
boxplot(on_covid$DMS,
        main = "Box plot of DIG's debt maturity structure during Covid19",
        col = "lightblue",
        xlab= "Debt maturity structure",
        horizontal = TRUE)
```

RESULT:

Figure 3: Box plot of DIG's debt maturity structure during COVID-19

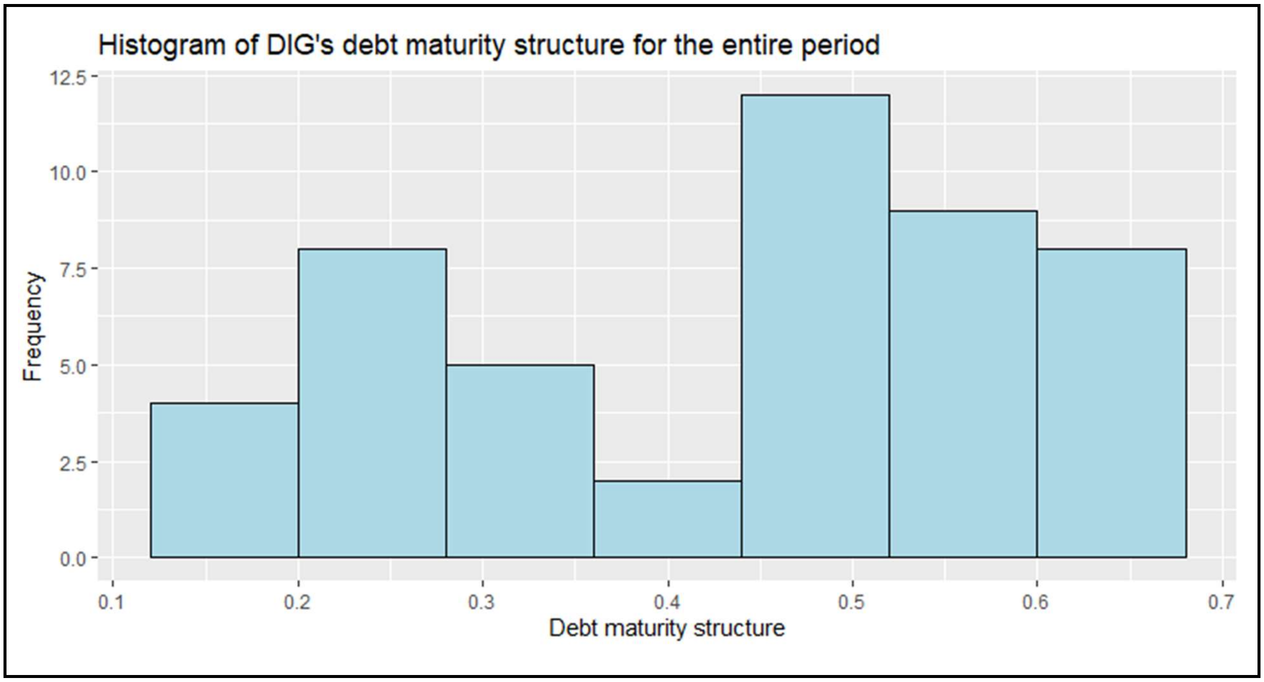


CODE:

```
# histogram
ggplot(df, aes(x = DMS)) +
  geom_histogram(binwidth = 0.08, fill = "lightblue", color = "black") +
  labs(title = "Histogram of DIG's debt maturity structure for the entire
period",
       x = "Debt maturity structure",
       y = "Frequency")
```

RESULT:

Figure 4: Histogram of DIG's debt maturity structure for the entire period

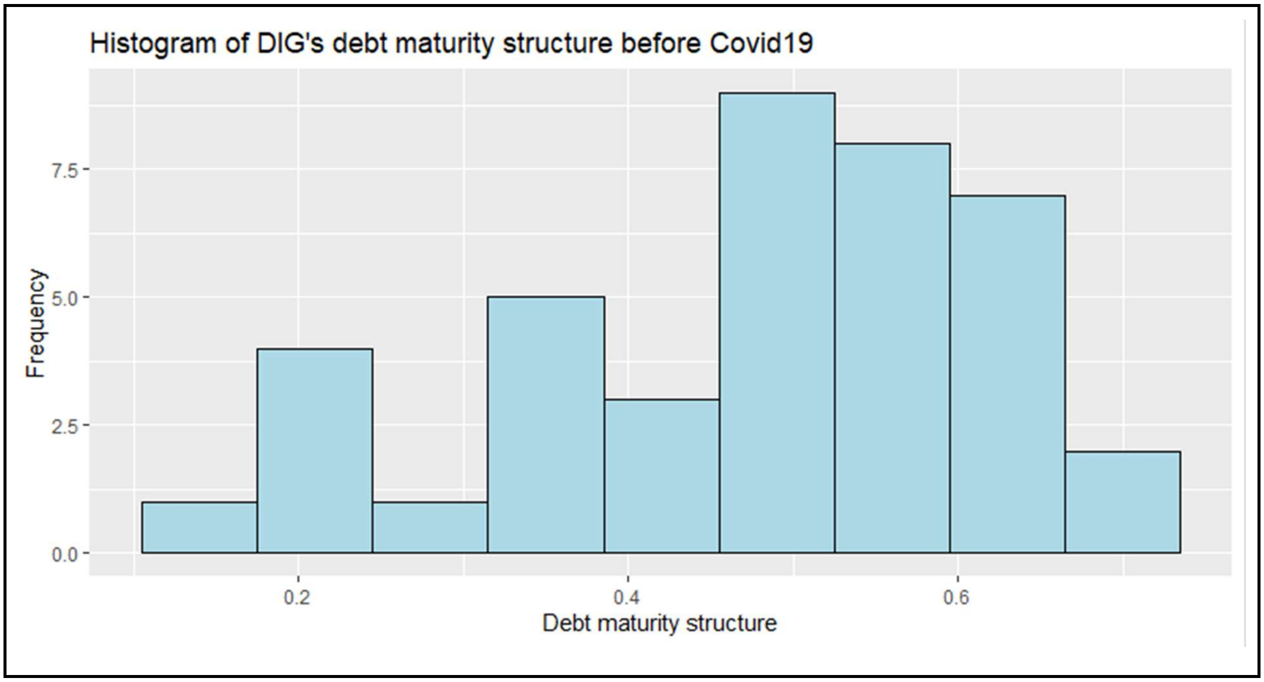


CODE:

```
# before covid
ggplot(before_covid, aes(x = DMS)) +
  geom_histogram(binwidth = 0.07, fill = "lightblue", color = "black") +
  labs(title = "Histogram of DIG's debt maturity structure before Covid19",
       x = "Debt maturity structure",
       y = "Frequency")
```

RESULT:

Figure 5: Histogram of DIG's debt maturity structure before COVID-19

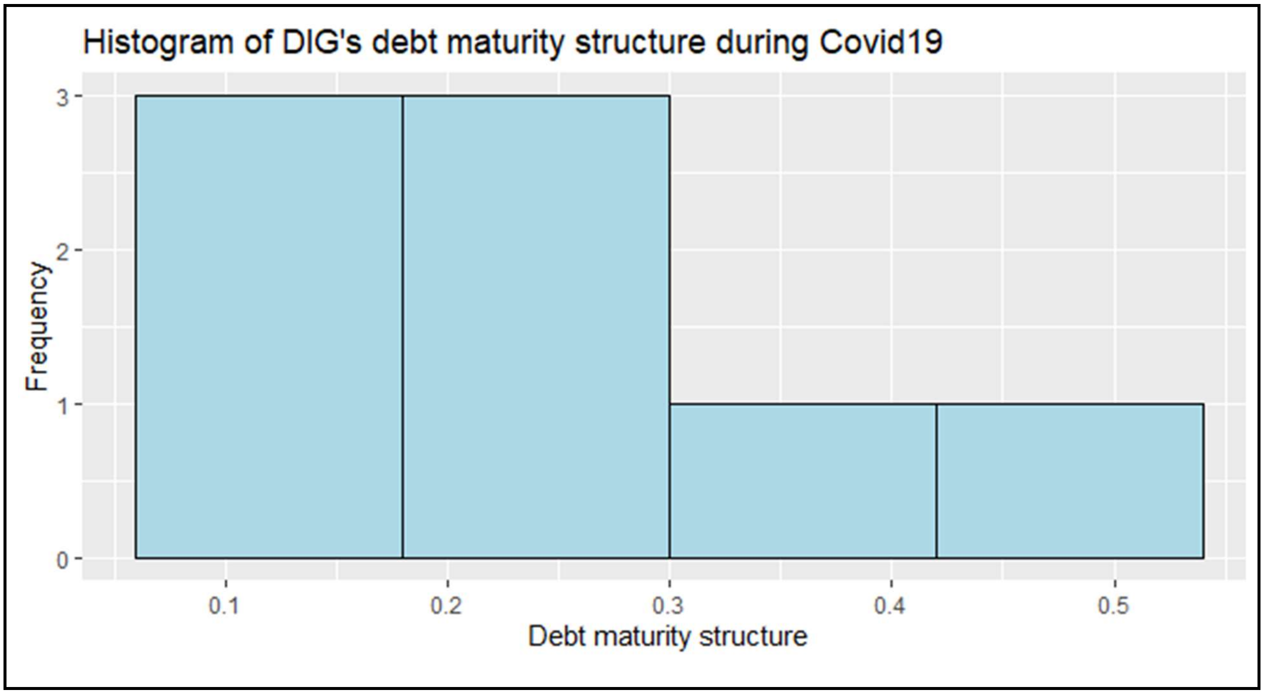


CODE:

```
#during covid
ggplot(on_covid, aes(x = DMS)) +
  geom_histogram(binwidth = 0.12, fill = "lightblue", color = "black") +
  labs(title = "Histogram of DIG's debt maturity structure during Covid19",
       x = "Debt maturity structure",
       y = "Frequency")
```

RESULT:

Figure 6: Histogram of DIG's debt maturity structure during COVID-19



Both the histogram plot and the box plot of the debt maturity structure of the DIC company for the entire period show that the debt maturity structure distribution of DIC is right skewed and mostly ranges from the lowest of 0.15 to the highest of around 0.68. However, the DIC company regularly maintains a debt maturity structure ranging from 0.3 to 0.58, of which the most frequent rate is 0.47.

During the period before Q1 2020, the debt term structure of the DIC company is right skewed and mostly ranges from the lowest of 0.15 to the highest of around 0.68. However, the DIC company regularly maintains a debt maturity structure ranging from 0.36 to 0.59, of which the most frequent rate is 0.51.

During the period from Q1 2020 to Q4 2021, the debt term structure of the DIC company is left skewed and mostly ranges from the lowest of 0.15 to the highest of around 0.49. However, the DIC company regularly maintains a debt maturity structure ranging from 0.17 to 0.31, of which the most frequent rate is 0.23.

6. Multiple regression

a. With all the individual variables (model 1)

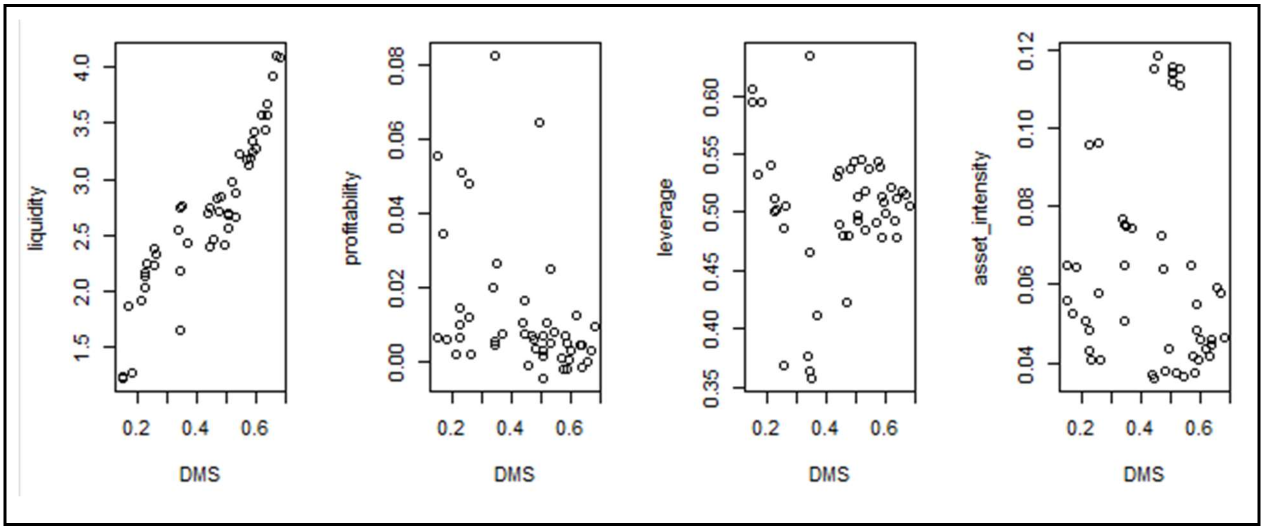
The relationship between the independent and dependent variables should be linear. We can check this visually through scatterplot.

CODE:

```
#Check linearity & multicollinearity
par(mfrow=c(1,4))
plot(liquidity ~ DMS, data = df)
plot(profitability ~ DMS, data = df)
plot(leverage ~ DMS, data = df)
plot(asset_intensity ~ DMS, data = df)
```

RESULT:

Figure 7: The relationship between the independent and dependent variables



The relationship between DMS and liquidity seems clear. But the relationships between DMS and profitability, DMS and leverage, DMS and asset intensity are a bit less clear.

CODE:

```
#multiple regression
dms.lm<-lm(DMS ~ liquidity + profitability + leverage + asset_intensity, data
= df)
summary(dms.lm)
```

RESULT:

Figure 8: Result of regression model 1

```
Call:
lm(formula = DMS ~ liquidity + profitability + leverage + asset_intensity,
    data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-0.10708 -0.01211  0.01064  0.02955  0.12934

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     -0.64434    0.11691  -5.511 1.87e-06 ***
liquidity        0.23704    0.01332  17.798  < 2e-16 ***
profitability   -0.19011    0.48180  -0.395 0.695097
leverage         0.72214    0.16194   4.459 5.81e-05 ***
asset_intensity  1.27888    0.32260   3.964 0.000273 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05238 on 43 degrees of freedom
Multiple R-squared:  0.9037,    Adjusted R-squared:  0.8947
F-statistic: 100.9 on 4 and 43 DF,  p-value: < 2.2e-16
```

The research results show that except for profitability, there is no impact on the debt maturity of the companies; the remaining variables all have a statistically significant impact on debt maturity. Specifically, as follows: liquidity, combined leverage, and asset intensity are positively correlated with debt maturity. All other things being unchanged, a company's liquidity increases by 1%, the DIC's debt maturity structure increases by 0,237%, the DIC's leverage increases by 1%, the DIC's debt maturity structure increases by 0,722%, the DIC's asset intensity increases by 1%, and the debt maturity structure increases by 1.279%. In this model, independent variables have explanatory significance at the significance level of 10%, and these independent variables explained 89.47% of the variation of DIC's debt maturity structure through the adjusted R-squared index.

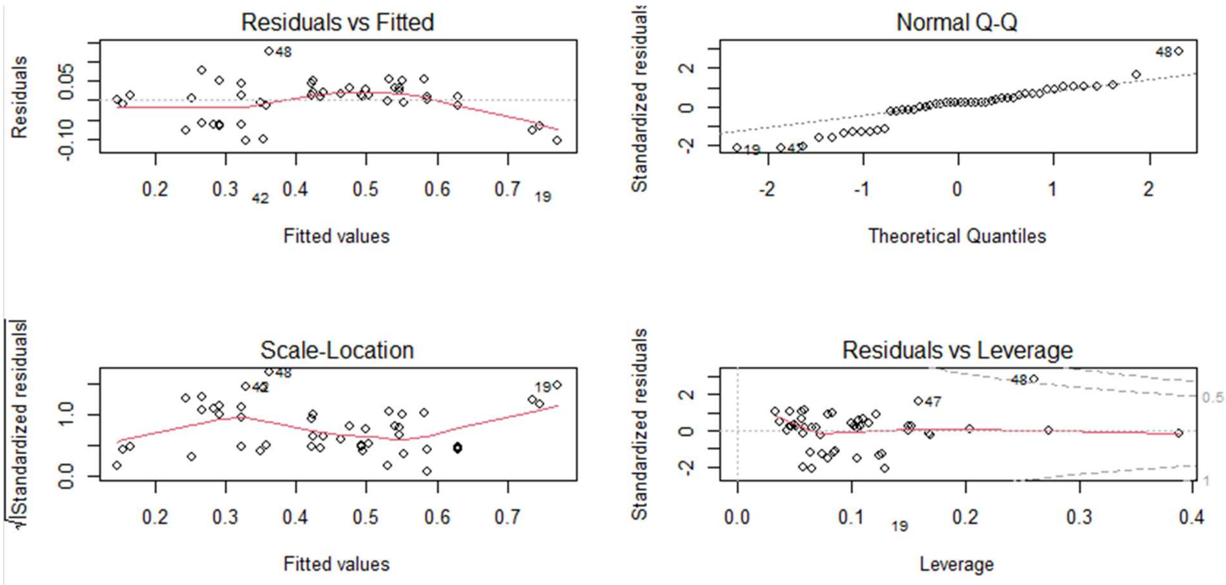
CODE:

```
#Check multicollinearity
car::vif(dms.lm)

#check important assumptions for linear regression
par(mfrow=c(2,2))
plot(dms.lm)
```

RESULT:

Figure 9: Result of checking important assumptions for linear regression

```
> car::vif(dms.lm)
      liquidity    profitability          leverage asset_intensity
       1.435991         1.355786          1.464662        1.278439
```



Test results for multicollinearity (VIF) among independent variables in the model show that all values are less than 10, so there is no multicollinearity between the variables.

CODE:

```
#check normality
shapiro.test(resid(dms.lm)) # Null hypothesis is normality

# Check homoscedasticity
bptest(dms.lm) #Null hypothesis is homoscedasticity
```

RESULT:

```
      Shapiro-Wilk normality test

data:  resid(dms.lm)
W = 0.93117, p-value = 0.007535

        studentized Breusch-Pagan test

data:  dms.lm
BP = 4.1371, df = 4, p-value = 0.3878
```

A Shapiro-Wilk test of the normality of the model residual indicated that the residuals are normal with p-value = 0.6909 > α = 0.1 (accepting H0). At the same time, this data set does not have homoscedasticity with p-value = 0.0005093 < α = 0.1 (reject H0) in the Breusch-Pagan test. That indicates that the OLS is a good estimator of the sampled data.

b. With the usual individual variables and the interaction between Covid-19 dummy variable and the independent variables (model 2)

Since the profitability variable is not statistically significant, we will leave it out of the model.

CODE:

```
#convert data
data <- data %>%
  mutate(covid = ifelse(covid == 'covid_period',1,0)
)
data$covid = factor(data$covid)
df2 <- data %>%
  select(Time, DMS, liquidity, profitability, leverage, asset_intensity,
covid)
#multiple regression
dms2.lm<-lm(DMS ~ liquidity + leverage + asset_intensity + liquidity*covid + leverage*covid
+ asset_intensity*covid, data = df2) #liquidity*covid +  + leverage*covid
summary(dms2.lm)
```

RESULT:

Figure 10: Result of regression model 2

```
Call:
lm(formula = DMS ~ liquidity + leverage + asset_intensity + liquidity *
    covid + leverage * covid + asset_intensity * covid, data = df2)

Residuals:
      Min        1Q    Median        3Q       Max
-0.106834 -0.022781  0.007021  0.026065  0.058917

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           -0.63307    0.08456  -7.487 3.98e-09 ***
liquidity              0.24202    0.01311  18.457  < 2e-16 ***
leverage               0.63225    0.14522   4.354 9.03e-05 ***
asset_intensity        1.55624    0.27058   5.752 1.06e-06 ***
covid1                -1.24016    0.54240  -2.286   0.0276 *
liquidity:covid1       0.13015    0.06682   1.948   0.0585 .
leverage:covid1        1.91954    0.69902   2.746   0.0090 **
asset_intensity:covid1 -1.04055   1.07929  -0.964   0.3408
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.04378 on 40 degrees of freedom
Multiple R-squared:  0.9374,	Adjusted R-squared:  0.9264
F-statistic: 85.57 on 7 and 40 DF,  p-value: < 2.2e-16
```

The research results show that except for asset_intensity*covid, there is no impact on the debt maturity of the companies; the remaining variables all have a statistically significant impact on debt maturity. Specifically, as follows: liquidity, leverage, asset intensity, liquidity*covid1, and leverage*covid1 are positively correlated with debt maturity while covid1 is negatively correlated with debt maturity. All other things being unchanged, a company's liquidity increases by 1%, the DIC's debt maturity structure increases by 0,24202%, the DIC's leverage increases by 1%, the DIC's debt maturity structure increases by 0,63225%, the DIC's asset intensity increases by 1%, and the debt maturity structure increases by 1.55624%, the DIC's liquidity*covid1 increases by 1%, and the debt maturity structure increases by 0.13015%, the DIC's leverage*covid1 increases by 1%, and the debt maturity structure increases by 1.91954%. The impact of COVID-19 causes the debt maturity structure to decrease by 1.24016%. In this model, independent variables have explanatory significance at the significance level of 10%, and these independent variables explained 92.64% of the variation of DIC's debt maturity structure through the adjusted R-squared index.

CODE:

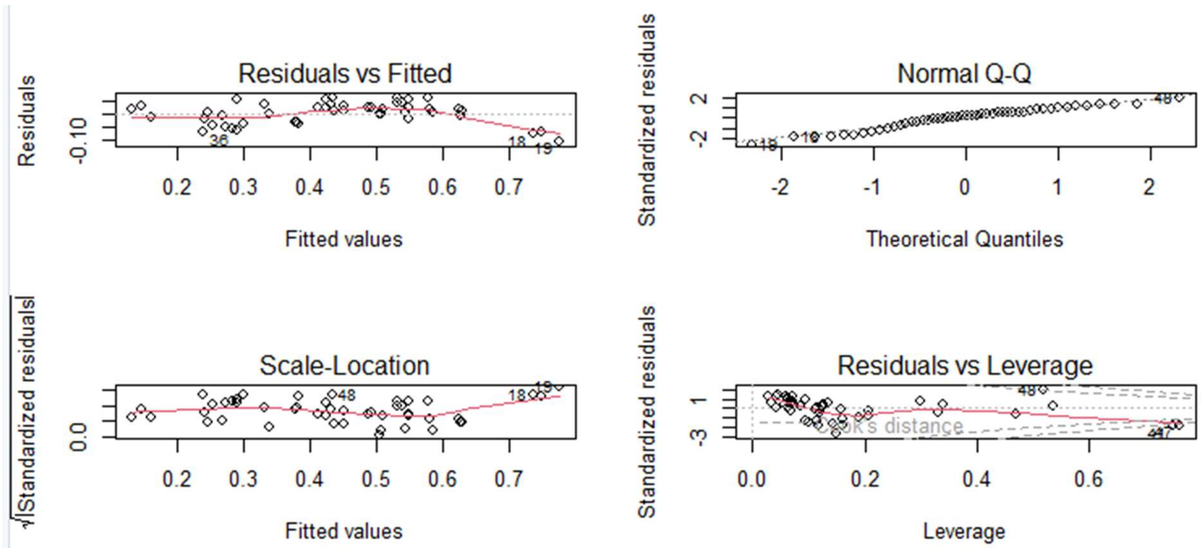
```
#Check multicollinearity
car::vif(dms2.lm)
```

```
#check important assumptions for linear regression
par(mfrow=c(2,2))
plot(dms2.lm)
```

RESULT:

Figure 11: Result of checking important assumptions for linear regression

```
             liquidity              leverage       asset_intensity 
              1.991930              1.685618              1.287007 
                 covid       liquidity:covid        leverage:covid 
           1023.068306             54.197181            537.598126 
asset_intensity:covid 
             18.613400 
```



Test results for multicollinearity (VIF) among independent variables in the model show that covid, liquidity*covid, leverage*covid, and asset_intensity*covid are higher than 10, so there is multicollinearity between the variables.

CODE:

```
# Check normality
shapiro.test(resid(dms2.lm)) # Null hypothesis is normality

# Check homoscedasticity
bptest(dms2.lm) #Null hypothesis is homoscedasticity
```

RESULT:

```
        Shapiro-Wilk normality test

data:  resid(dms2.lm)
```

```
W = 0.95576, p-value = 0.06805

        studentized Breusch-Pagan test

data:  dms2.lm
BP = 8.0146, df = 7, p-value = 0.3313
```

A Shapiro-Wilk test of the normality of the model residual indicated that the residuals are not normal with p-value = 0.06805 < α = 0.1 (reject H0). At the same time, this data set has homoscedasticity with p-value = 0.3313 > α = 0.1 (accepting H0) in the Breusch-Pagan test. This make the estimated regression coefficients ineffective.

To obtain reliable estimates in the presence of heteroscedasticity, there are several corrective measures that can be taken, including:

- Transform the variables in the model to reduce the impact of heteroscedasticity. For example, taking the logarithm or square root of a variable may help to reduce heteroscedasticity.
- Use a different modeling technique that can handle heteroscedasticity, such as weighted least squares. This type of regression assigns a weight to each data point based on the variance of its fitted value. Essentially, this gives small weights to data points that have higher variances, which shrinks their squared residuals. When the proper weights are used, this can eliminate the problem of heteroscedasticity.

c. Predict the value of the variable of assigned topic for all the quarters of the sample using Model 1

CODE:

```
#use model 1 to predict the response value for all the quarters of the sample
pred_model = predict(dms.lm, data = df[,3:6])

pred_table =data.frame(Time = df$Time,
                       Actual_DMS = df$DMS,
                       Predicted_DMS = round(pred_model,4))
pred_table$Difference = abs(pred_table$Actual_DMS - pred_table$Predicted_DMS)
pred_table

summary(pred_table$Difference)
```

RESULT:

Table 6: Result of predicting the response value for all the quarters of the sample

Time	**Actual_DMS**	**Dredicted_DMS**	**Difference**
31/03/2010	0.3348	0.3233	0.0115

30/06/2010	0.3464	0.3586	0.0122
30/09/2010	0.3432	0.3505	0.0073
31/12/2010	0.2568	0.2518	0.0050
31/03/2011	0.3678	0.3228	0.0450
30/06/2011	0.4657	0.4217	0.0440
...	…	…	…
30/09/2020	0.2522	0.3549	0.1027
31/12/2020	0.1475	0.1462	0.0013
31/03/2021	0.1765	0.1652	0.0113
30/06/2021	0.1467	0.1556	0.0089
30/09/2021	0.3460	0.2678	0.0782
31/12/2021	0.4913	0.3620	0.1293

```
> summary(pred_table$Difference)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
0.00040 0.01123 0.02630 0.03750 0.05903 0.12930 
```

The regression model predicts quite well the debt maturity structure for all the quarters of the sample. The difference between the actual debt maturity structure and the predicted debt maturity structure is not large, in the range of 0.00040 to 0.12930.

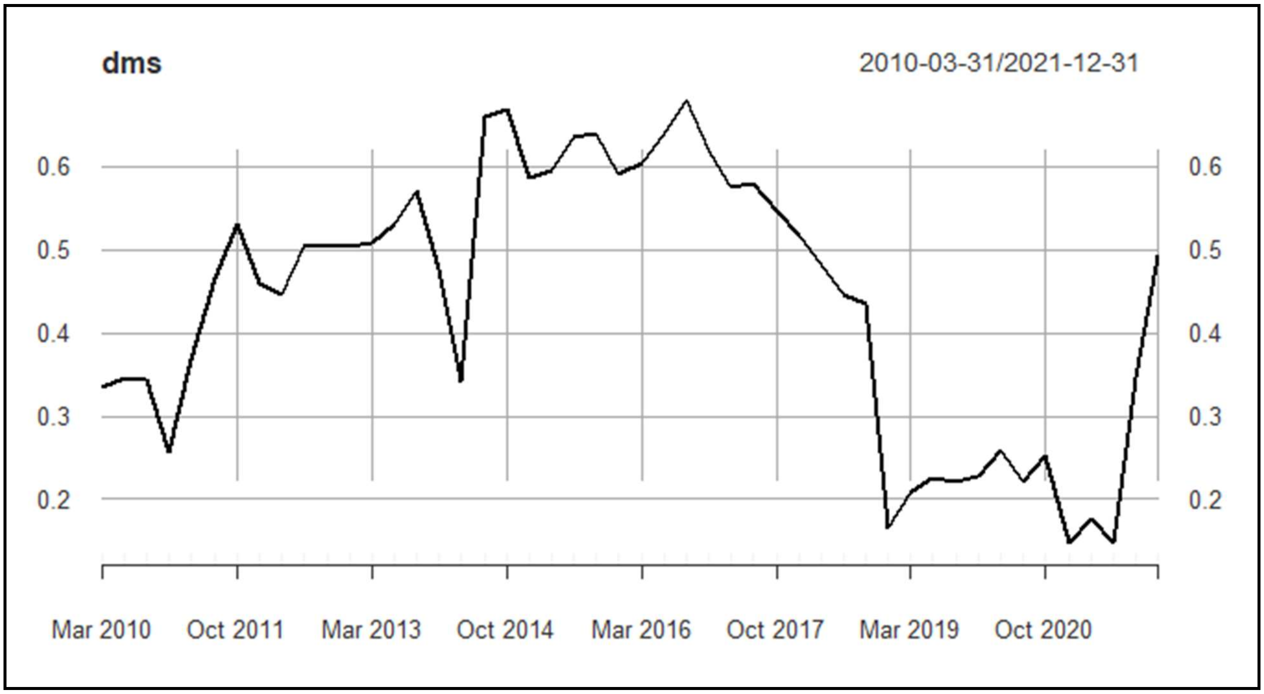
7. ARIMA model

CODE:

```
class(df$Time)
date.time = seq(as.Date("2010/03/31"), by = "quarter", length.out = nrow(df))
date.time

# Create a xts Dataframe
dms = xts(df[,2],date.time)
class(dms)

#plot the data - look at the debt maturity structure of DIG
par(mfrow=c(1,1))
plot(dms)
```

RESULT:

Figure 12: The debt maturity structure of DIG from 2010 to 2021



CODE:

```
#stationary check
par(mfrow=c(1,2))
print(adf.test(dms))
```

RESULT:

```
        Augmented Dickey-Fuller Test

data:  dms
Dickey-Fuller = -2.2378, Lag order = 3, p-value = 0.4792
alternative hypothesis: stationary
```

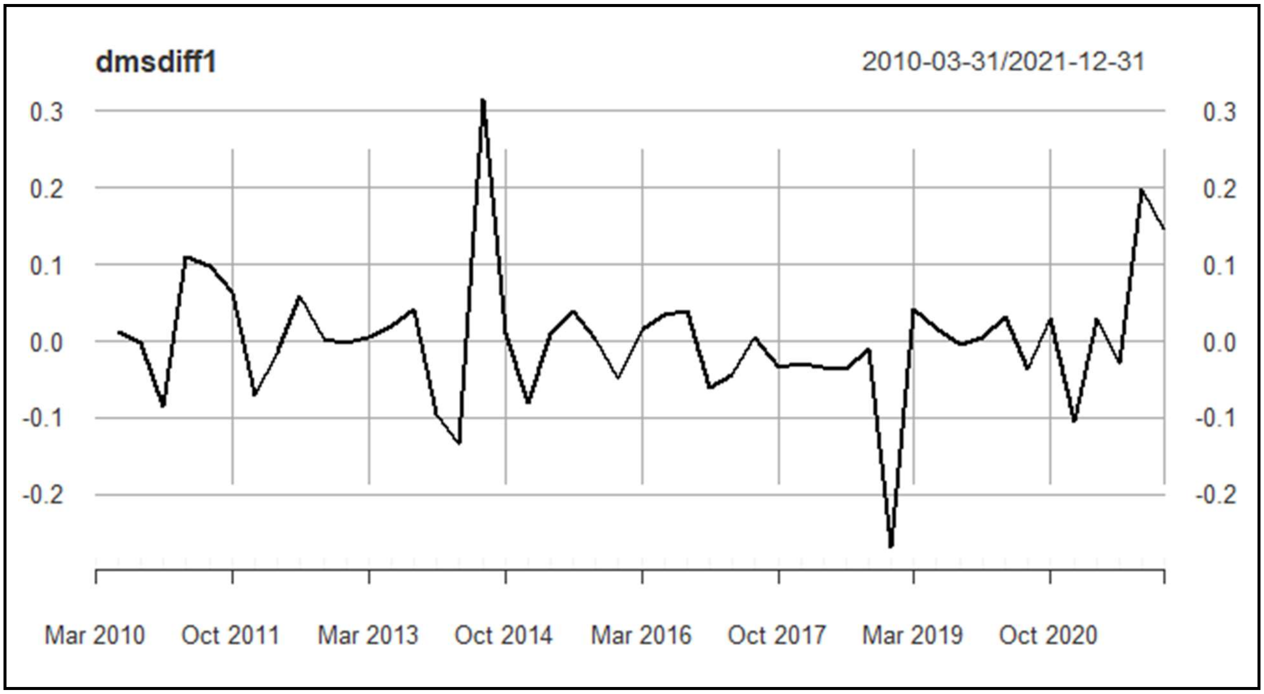
P value is 0.4792 > 0.05. So, the debt maturity structure series is not stationary. Therefore, we take the first hierarchical error in the series and check for stationarity.

CODE:

```
dmsdiff1 <- diff(dms, differences = 1)
par(mfrow=c(1,1))
plot(dmsdiff1)
dmsdiff1 = na.omit(dmsdiff1)
print(adf.test(dmsdiff1))
```

RESULT:

Figure 13: The debt maturity structure series at the first hierarchical error




```
        Augmented Dickey-Fuller Test

data:  dmsdiff1
Dickey-Fuller = -2.5208, Lag order = 3, p-value = 0.3665
alternative hypothesis: stationary
```

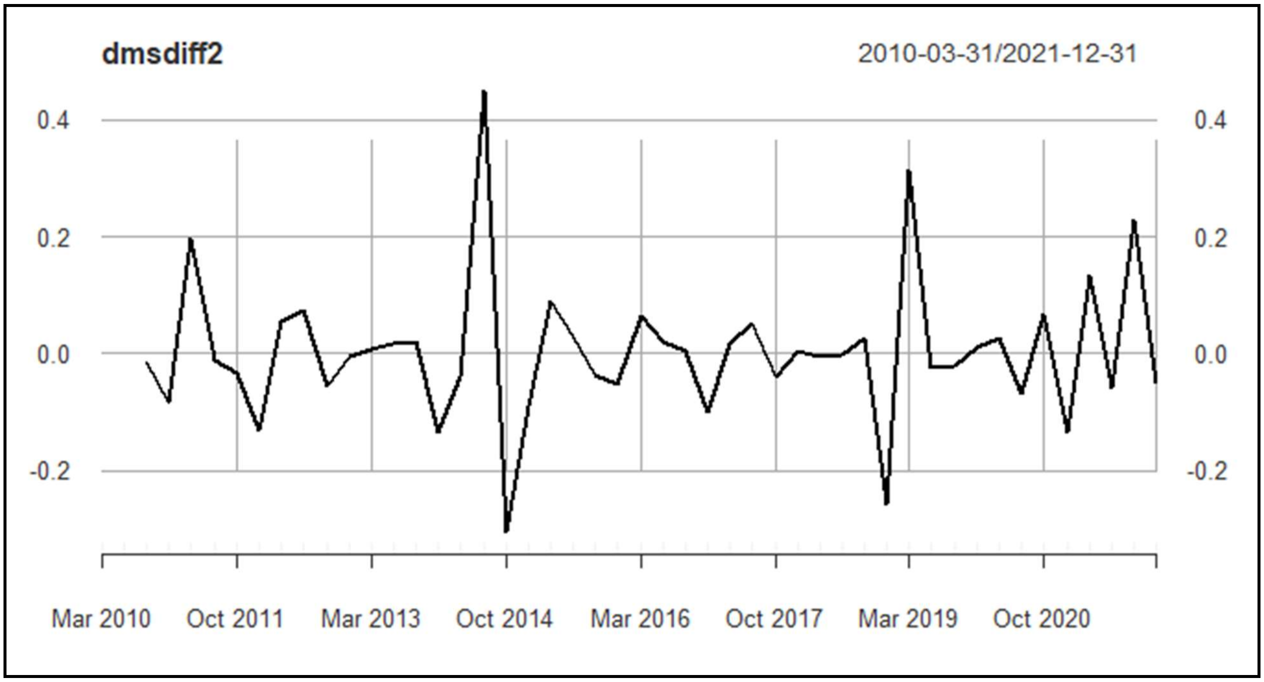
P value is 0.3665 > 0.05. So, the 1st hierarchy of the debt maturity structure series is not stationary. Therefore, we take the second hierarchical error in the series and check for stationarity.

CODE:

```
dmsdiff2 <- diff(dms, differences = 2)
par(mfrow=c(1,1))
plot(dmsdiff2)
dmsdiff2 = na.omit(dmsdiff2)
print(adf.test(dmsdiff2))
```

RESULT:

Figure 14: The debt maturity structure series at the second hierarchical error




```
        Augmented Dickey-Fuller Test

data:  dmsdiff2
Dickey-Fuller = -5.6808, Lag order = 3, p-value = 0.01
alternative hypothesis: stationar
```

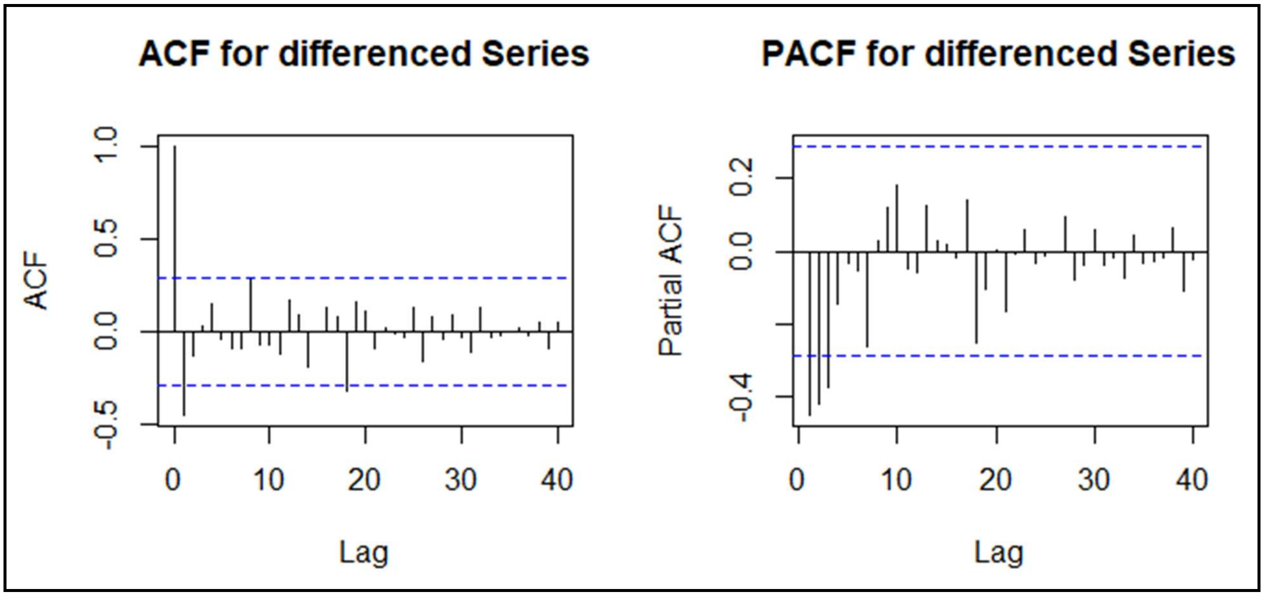
P value is 0.01 < 0.05. The ADF test results also show that the 2nd hierarchy of the debt maturity structure series is stationary, so d = 2.

CODE:

```
#graph the ACF and PACF looking for identifiable lags PACF -> p ACF -> q
par(mfrow=c(1,2))
acf(dmsdiff2, main = 'ACF for differenced Series', lag.max = 40)
pacf(dmsdiff2, main = 'PACF for differenced Series', lag.max = 40)
acf(dmsdiff2, lag.max = 40, plot = FALSE)
pacf(dmsdiff2, lag.max = 40, plot=FALSE)
```

RESULT:

Figure 15: ACF and PACF schemes of the debt maturity structure series at the second hierarchical error



Based on the PACF and ACF schemes in Figure 15, we have:

PACF: The order of AR(p) can be selected as: 1, 2, 3

ACF: The order of MA(q) can be selected as: 1, 2, 18

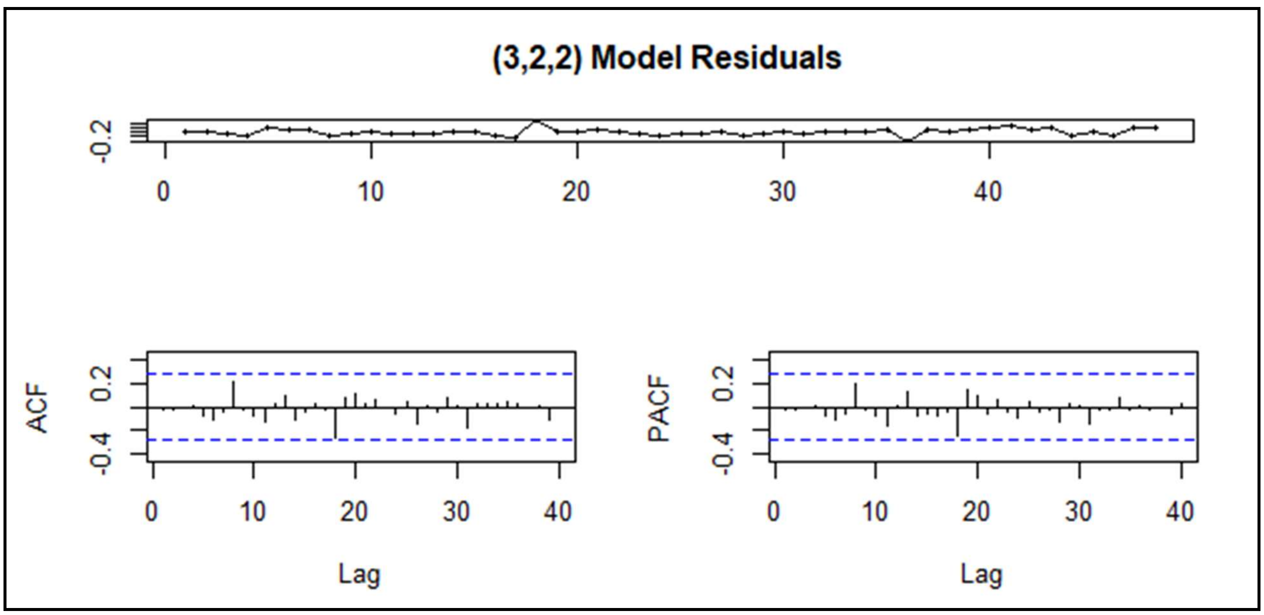
Therefore, we consider the following 9 ARIMA models: ARIMA(1,2,1), ARIMA(1,2,2), ARIMA(1,1,18), ARIMA(2,2,1), ARIMA(2,2,2), ARIMA(2,2,18), ARIMA(3,2,1), ARIMA(3,2,2), ARIMA(3,2,18). If the model has the smallest AIC, SigmaSQ, and maximum likelihood, it will be the chosen model.

CODE:

```
#building ARIMA model
a = auto.arima(dms,seasonal=F) #ARIMA(0,1,0)
a
b = arima(dms, order = c(1,2,1)) #sigma^2 estimated as 0.007535:  log
likelihood = 45.2,  aic = -84.4
b
arima(dms, order = c(1,2,2)) #sigma^2 estimated as 0.007544:  log likelihood
= 45.2,  aic = -82.4
arima(dms, order = c(1,2,18)) #sigma^2 estimated as 0.003476:  log
likelihood = 54.93,  aic = -69.85
c = arima(dms, order = c(2,2,1)) #sigma^2 estimated as 0.007131:  log
likelihood = 46.2,  aic = -84.4
c
arima(dms, order = c(2,2,2)) #sigma^2 estimated as 0.007129:  log likelihood
= 46.21,  aic = -82.41
arima(dms, order = c(2,2,18)) #sigma^2 estimated as 0.002872:  log
likelihood = 56.69,  aic = -71.38
arima(dms, order = c(3,2,1)) #sigma^2 estimated as 0.007434:  log likelihood
= 46.43,  aic = -82.86
d = arima(dms, order = c(3,2,2)) #sigma^2 estimated as 0.006222:  log
likelihood = 48.29,  aic = -84.59
d
tsdisplay(residuals(d), lag.max = 40 ,main = '(3,2,2) Model Residuals')
arima(dms, order = c(3,2,18)) #sigma^2 estimated as 0.00287:  log likelihood
= 56.71,  aic = -69.41
```

RESULT:

Figure 16: ARIMA(3,2,2) model Residuals



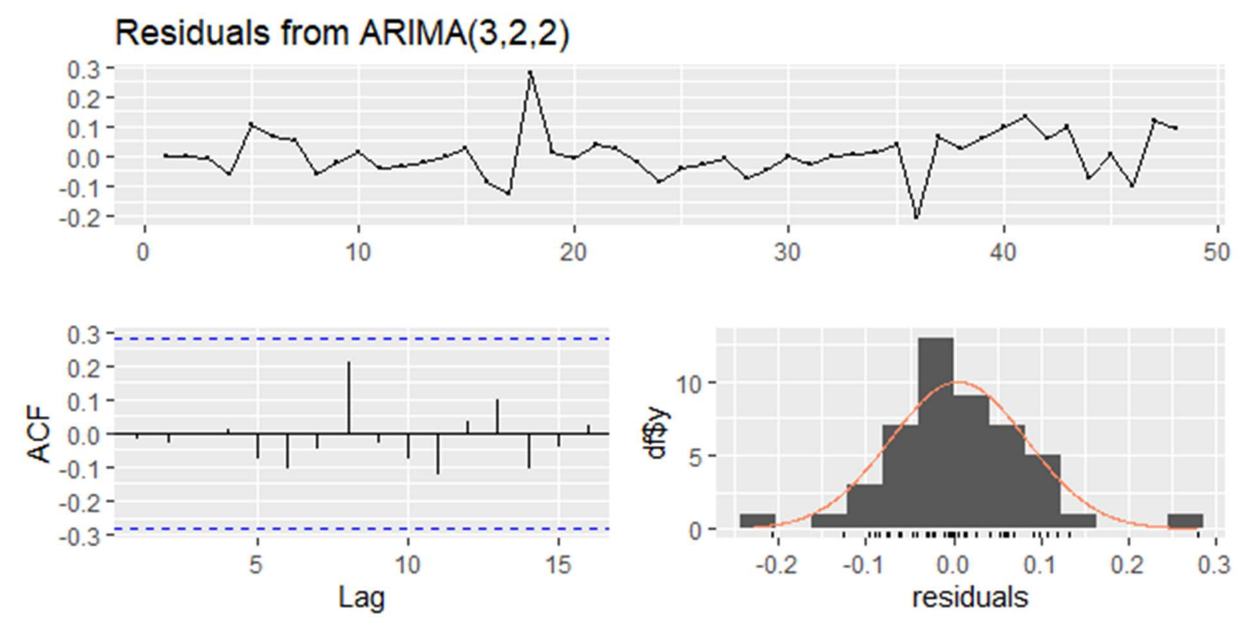
Choose model ARIMA(3,2,2) with sigma^2 estimated as 0.006222, log likelihood = 48.29, aic = -84.59. To see if the model is effective in predicting, we need to test whether the residual series et is white noise or not. To test the hypothesis that et is a white noise, we need to check the stationarity of the residual series et and check whether et follows the normal distribution.

CODE:

```
#perform the portmanteau test
checkresiduals(d, lag = 40)
summary(d$residuals)
```

RESULT:

Figure 17: Residuals from ARIMA(3,2,2)



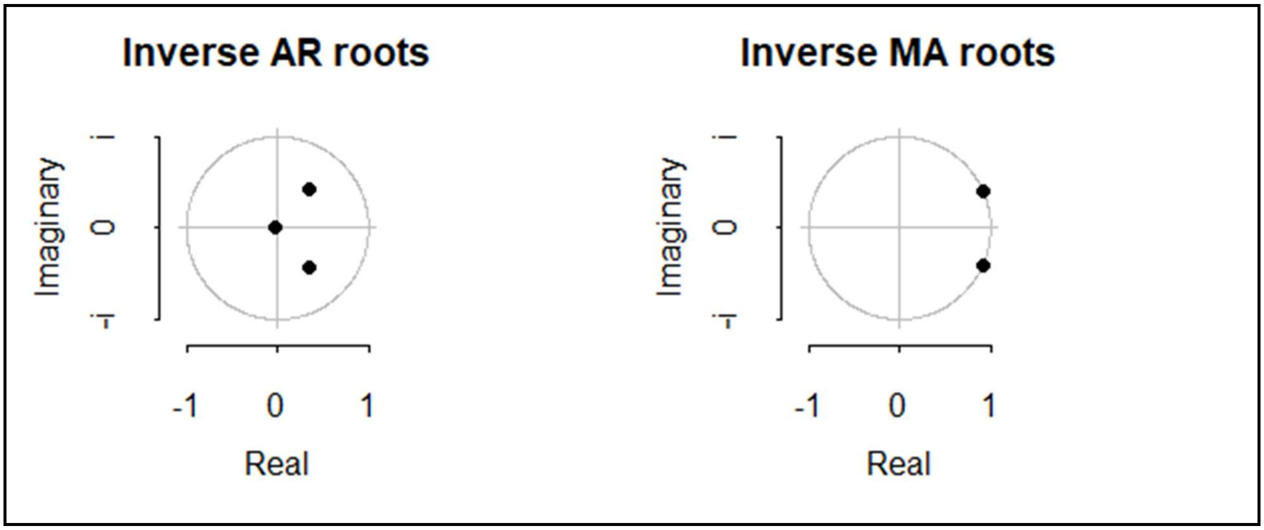

```
        Ljung-Box test

data:  Residuals from ARIMA(3,2,2)
Q* = 27.302, df = 35, p-value = 0.8203

Model df: 5.   Total lags used: 40

> summary(d$residuals)
      Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
-0.2082700 -0.0339960 -0.0003034  0.0051902  0.0449494  0.2797717
```

Since the ACF histogram shows that no autocorrelation in the first 16 lags exceeds the limit of statistical significance and the p-value of the Ljung-Box test is 0.8203. Therefore, we can conclude that there is little evidence for non-zero autocorrelation in the forecast errors at the first 16 lags. The forecast errors are normally distributed with zero mean and constant variance.

CODE:

```
#ARMA roots table
plot(d)
```

RESULT:



Both AR and MA roots are inside the circle. The estimated model is covariance stationary and the estimated process is invertible.

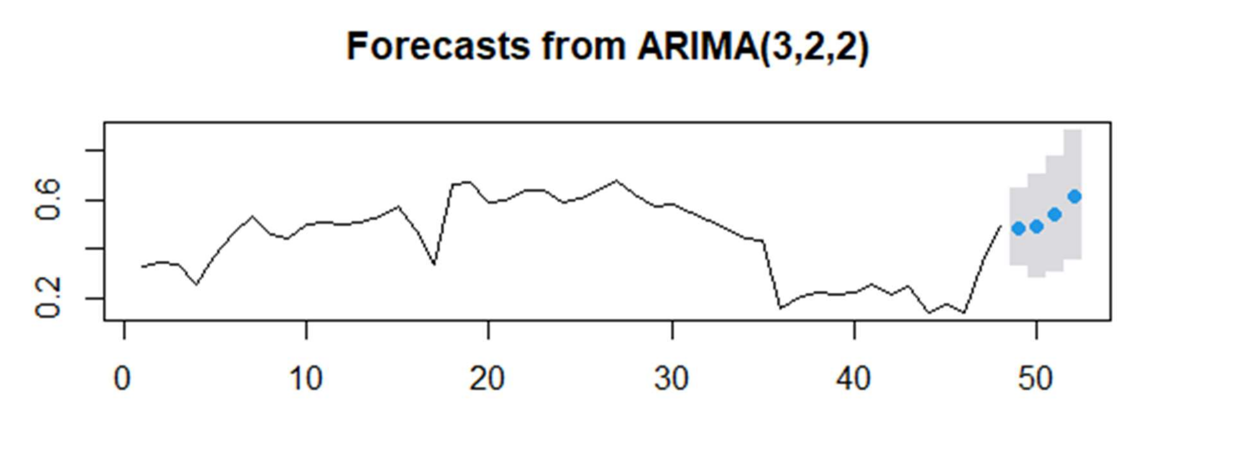
CODE:

```
#predict the DMS for the 4 quarters in 2022
dmsforecast = forecast(b,h = 4, level = c(95))
dmsforecast
par(mfrow=c(1,1))
plot(dmsforecast)
```

RESULT:

Table 7: Predict the debt maturity structure for the four quarters in 2022

	Point Forecast	**Lo 95**	**Hi 95**
49	0.4879297	0.3300959	0.6457636
50	0.4908107	0.2819825	0.6996390
51	0.5390058	0.3042845	0.7737270
52	0.6164303	0.3529888	0.8798718



CODE:

```
#comparison of actual DMS and forecasted DMS
actual_dms2022 <- read_excel("D://học tập//NĂM 3//hk 6//gói ứng dụng trong
tài chính//cuối kỳ//K204141927.xlsx",
                             sheet = 2)
actual_dms <- actual_dms2022 %>% select(Time, DMS)

dmsforecast_ = data.frame(forecast(b,h = 4, level = c(95)))
forecast_table = data.frame(Time = actual_dms$Time,
                            Actual_DMS = round((actual_dms$DMS),4),
                            Predicted_DMS = dmsforecast_$Point.Forecast)
forecast_table$Difference = abs(forecast_table$Actual_DMS -
forecast_table$Predicted_DMS)
forecast_table
```

RESULT:

Table 8: Comparison of actual DMS and forecasted DMS

Time	Actual_DMS	Predicted_DMS	Difference
31/03/2022	0.5304	0.4879297	0.04247027
30/06/2022	0.5567	0.4908107	0.06588926
30/09/2022	0.5673	0.5390058	0.02829424
31/12/2022	0.4366	0.6164303	0.17983030

The forecasted debt maturity structure is not much different from reality, about 0.03% to 0.18%.

8. How Decision Tree algorithm can be used to make prediction whether the firm will increase/decrease the debt maturity structure?

The Decision Tree algorithm can be used to make predictions about whether a firm will increase or decrease its debt maturity structure. The Decision Tree model can be used as follows:

First, prepare the data: obtain the data from the company's financial statements, clean the data, handle missing values, and encode categorical variables if necessary. Divide the dataset into two parts: a training set and a test set.

Second, identify the features from the dataset that are most likely to influence the change in debt maturity structure.

Label encoding: Assign labels to the target variable that represents the change in debt maturity structure. For example, you can encode "increase" as 1 and "decrease" as 0.

Decision Tree training: Use the training set to train a Decision Tree classifier. The decision tree algorithm will use historical data to create a tree-like model that captures the relationships between the input features and the target.

Model evaluation: Using the test set, evaluate the trained decision tree model. Use appropriate evaluation metrics such as accuracy, precision, recall, or F1 score to assess its performance.

Prediction: Once the model has been trained and evaluated, it can be used to make predictions on new, previously unseen data. Provide the trained decision tree with the relevant features of a firm, and it will predict whether the firm's debt maturity structure is likely to increase or decrease.

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APPENDIX

```
#1/ required packages
library(tidyverse)
library(readxl)
library(ggplot2)
library(lmtest)
library(forecast)
library(xts)
library(tseries)

#2/ create dataset
#load data
data <- read_excel("D://học tập//NĂM 3//hk 6//gói ứng dụng trong tài chính//cuối
kỳ//K204141927.xlsx", sheet = 1)
#all variable names
colnames(data)
#checking Na values
sum(is.na(data))
#create variables
data <- data %>%
  mutate(DMS= round((long_term_debt/(long_term_debt + short_term_debt)),4),
         liquidity = round((total_current_assets/short_term_debt),4),
         profitability = round((EBT + interest_expense)/total_assets,4), # + interest_expense
         leverage = round(((long_term_debt+short_term_debt)/total_assets),4),
         asset_intensity = round((fixed_assets/total_assets),4)
  )
df <- data %>%
```

```
  select(Time, DMS, liquidity, profitability, leverage, asset_intensity)

head(df)

#checking Na values

sum(is.na(df))


#3/descriptive statistics

#entire period

entire_period <- df %>%

  summarise(variables = c('DMS','liquidity', 'profitability','leverage', 'asset_intensity'),

            obs = nrow(df),

            min = c(min(DMS), min(liquidity), min(profitability), min(leverage),
min(asset_intensity)),

            mean = c(mean(DMS), mean(liquidity), mean(profitability), mean(leverage),
mean(asset_intensity)),

            median = c(median(DMS), median(liquidity), median(profitability), median(leverage),
median(asset_intensity)),

            std = c(sd(DMS), sd(liquidity), sd(profitability), sd(leverage), sd(asset_intensity)),

            max = c(max(DMS), max(liquidity), max(profitability), max(leverage),
max(asset_intensity))

)

entire_period = data.frame(entire_period)

entire_period

#before Covid-19 pandemic

before_covid <- df[1:40, ]

before_covid_period <- before_covid %>%

  summarise(variables = c('DMS','liquidity', 'profitability','leverage', 'asset_intensity'),

            obs = nrow(before_covid),
```

```
      min = c(min(DMS), min(liquidity), min(profitability), min(leverage),
min(asset_intensity)),

      mean = c(mean(DMS), mean(liquidity), mean(profitability), mean(leverage),
mean(asset_intensity)),

      median = c(median(DMS), median(liquidity), median(profitability), median(leverage),
median(asset_intensity)),

      std = c(sd(DMS), sd(liquidity), sd(profitability), sd(leverage), sd(asset_intensity)),

      max = c(max(DMS), max(liquidity), max(profitability), max(leverage),
max(asset_intensity))

  )

before_covid_period = data.frame(before_covid_period)

before_covid_period

#during Covid-19 pandemic

during_covid <- df[41:48, ]

during_covid_period <- during_covid %>%

  summarise(variables = c('DMS','liquidity', 'profitability','leverage', 'asset_intensity'),

      obs = nrow(during_covid),

      min = c(min(DMS), min(liquidity), min(profitability), min(leverage),
min(asset_intensity)),

      mean = c(mean(DMS), mean(liquidity), mean(profitability), mean(leverage),
mean(asset_intensity)),

      median = c(median(DMS), median(liquidity), median(profitability), median(leverage),
median(asset_intensity)),

      std = c(sd(DMS), sd(liquidity), sd(profitability), sd(leverage), sd(asset_intensity)),

      max = c(max(DMS), max(liquidity), max(profitability), max(leverage),
max(asset_intensity))

  )

during_covid_period = data.frame(during_covid_period)

during_covid_period
```

```
#4/box & whisker plot and histogram
#box plot
boxplot(df$DMS,
        main = "Box plot of DIG's debt maturity structure for the entire period",
        col = "lightblue",
        xlab= "Debt maturity structure",
        horizontal = TRUE)
#before covid
boxplot(before_covid$DMS,
        main = "Box plot of DIG's debt maturity structure before Covid19",
        col = "lightblue",
        xlab= "Debt maturity structure",
        horizontal = TRUE)
#during covid
boxplot(during_covid$DMS,
        main = "Box plot of DIG's debt maturity structure during Covid19",
        col = "lightblue",
        xlab= "Debt maturity structure",
        horizontal = TRUE)
#histogram
ggplot(df, aes(x = DMS)) +
  geom_histogram(binwidth = 0.08, fill = "lightblue", color = "black") +
  labs(title = "Histogram of DIG's debt maturity structure for the entire period",
       x = "Debt maturity structure",
       y = "Frequency")
```

```
#before covid
ggplot(before_covid, aes(x = DMS)) +
  geom_histogram(binwidth = 0.07, fill = "lightblue", color = "black") +
  labs(title = "Histogram of DIG's debt maturity structure before Covid19",
       x = "Debt maturity structure",
       y = "Frequency")
#during covid
ggplot(during_covid, aes(x = DMS)) +
  geom_histogram(binwidth = 0.12, fill = "lightblue", color = "black") +
  labs(title = "Histogram of DIG's debt maturity structure during Covid19",
       x = "Debt maturity structure",
       y = "Frequency")

#5/ multiple regression
#5.1 regression with all the individual variables
#Check linearity & multicollinearity
par(mfrow=c(1,4))
plot(liquidity ~ DMS, data = df)
plot(profitability ~ DMS, data = df)
plot(leverage ~ DMS, data = df)
plot(asset_intensity ~ DMS, data = df)
#Multiple regression
dms.lm<-lm(DMS ~ liquidity + profitability + leverage + asset_intensity, data = df)
summary(dms.lm)
#Check multicollinearity
car::vif(dms.lm) #VIF >10 thì đa cộng tuyến
```

```
#check important assumptions for linear regression

par(mfrow=c(2,2))

plot(dms.lm)

#check normality

shapiro.test(resid(dms.lm))# Null hypothesis is normality

# Check homoscedasticity

bptest(dms.lm) #Null hypothesis is homoscedasticity #p.value >5%, lúc đó phương sai đồng nhất, phương sai không đổi


#5.2 regression with the usual individual variables

#and the interaction between Covid-19 dummy variable and the independent variables

#convert data

data <- data %>%

  mutate(covid = ifelse(covid == 'covid_period',1,0)

)

data$covid = factor(data$covid)

df2 <- data %>%

  select(Time, DMS, liquidity, profitability, leverage, asset_intensity, covid)

dms2.lm<-lm(DMS ~ liquidity + leverage + asset_intensity + liquidity*covid + leverage*covid + asset_intensity*covid, data = df2) #liquidity*covid +  + leverage*covid

summary(dms2.lm)

#Check multicollinearity

car::vif(dms2.lm)

#check important assumptions for linear regression

par(mfrow=c(2,2))

plot(dms2.lm)

# Check normality
```

```
shapiro.test(resid(dms2.lm))# Null hypothesis is normality
# Check homoscedasticity
bptest(dms2.lm) #Null hypothesis is homoscedasticity

#5.3 Prediction
#use model 1 to predict the response value for all the quarters of the sample
pred_model = predict(dms.lm, data = df[,3:6])
pred_table =data.frame(Time = df$Time,
                    Actual_DMS = df$DMS,
                    Predicted_DMS = round(pred_model,4))
pred_table$Difference = abs(pred_table$Actual_DMS - pred_table$Predicted_DMS)
pred_table
summary(pred_table$Difference)

#6/ ARIMA model
class(df$Time)
date.time = seq(as.Date("2010/03/31"), by = "quarter", length.out = nrow(df))
date.time
# Create a xts Dataframe
dms = xts(df[,2],date.time)
class(dms)
#plot the data - look at the debt maturity structure of DIG
par(mfrow=c(1,1))
plot(dms)
#stationary check
par(mfrow=c(1,2))
print(adf.test(dms))
```

```
dmsdiff1 <- diff(dms, differences = 1)

par(mfrow=c(1,1))

plot(dmsdiff1)

dmsdiff1 = na.omit(dmsdiff1)

print(adf.test(dmsdiff1))

dmsdiff2 <- diff(dms, differences = 2)

par(mfrow=c(1,1))

plot(dmsdiff2)

dmsdiff2 = na.omit(dmsdiff2)

print(adf.test(dmsdiff2))

#graph the ACF and PACF looking for identifiable lags PACF -> p ACF -> q

par(mfrow=c(1,2))

acf(dmsdiff2, main = 'ACF for differenced Series', lag.max = 40)

pacf(dmsdiff2, main = 'PACF for differenced Series', lag.max = 40)

acf(dmsdiff2, lag.max = 40, plot = FALSE)

pacf(dmsdiff2, lag.max = 40, plot=FALSE)

# p = 1,2,3 ; q = 1,2,18

#building ARIMA model

a = auto.arima(dms,seasonal=F) #ARIMA(0,1,0)

a

b = arima(dms, order = c(1,2,1)) #sigma^2 estimated as 0.007535:  log likelihood = 45.2,  aic = -
84.4

b

arima(dms, order = c(1,2,2))#sigma^2 estimated as 0.007544:  log likelihood = 45.2,  aic = -82.4

arima(dms, order = c(1,2,18)) #sigma^2 estimated as 0.003476:  log likelihood = 54.93,  aic = -
69.85
```

```
c = arima(dms, order = c(2,2,1)) #sigma^2 estimated as 0.007131:  log likelihood = 46.2,  aic = -84.4

c

arima(dms, order = c(2,2,2)) #sigma^2 estimated as 0.007129:  log likelihood = 46.21,  aic = -82.41

arima(dms, order = c(2,2,18)) #sigma^2 estimated as 0.002872:  log likelihood = 56.69,  aic = -71.38

arima(dms, order = c(3,2,1)) #sigma^2 estimated as 0.007434:  log likelihood = 46.43,  aic = -82.86

d = arima(dms, order = c(3,2,2)) #sigma^2 estimated as 0.006222:  log likelihood = 48.29,  aic = -84.59

d

tsdisplay(residuals(d), lag.max = 40 ,main = '(3,2,2) Model Residuals')

arima(dms, order = c(3,2,18)) #sigma^2 estimated as 0.00287:  log likelihood = 56.71,  aic = -69.41

#perform the portmanteau test

checkresiduals(d, lag = 40)

summary(d$residuals)

#ARMA roots table

plot(d)

#predict the DMS for the 4 quarters in 2022

dmsforecast = forecast(d,h = 4, level = c(95))

dmsforecast

par(mfrow=c(1,1))

plot(dmsforecast)

#comparison of actual DMS and forecasted DMS

actual_dms2022 <- read_excel("D://học tập//NĂM 3//hk 6//gói ứng dụng trong tài chính//cuối kỳ//K204141927.xlsx",

                     sheet = 2)
```

```
actual_dms <- actual_dms2022 %>% select(Time, DMS)
dmsforecast_ = data.frame(forecast(d,h = 4, level = c(95)))
forecast_table = data.frame(Time = actual_dms$Time,
                            Actual_DMS = round((actual_dms$DMS),4),
                            Predicted_DMS = dmsforecast_$Point.Forecast)
forecast_table$Difference = abs(forecast_table$Actual_DMS - forecast_table$Predicted_DMS)
forecast_table
```