VIET NAM NATIONAL UNIVERSITY HO CHI MINH CITY

**UNIVERSITY OF ECONOMICS AND LAW**

**MID-TERM REPORT**

**PROGRAM PACKAGE IN FINANCE 2**

**THE FACTORS THAT AFFECT THE TRADE CREDIT (RECEIVABLE) OF LISTED FIRMS ON HNX**

|  |  |
| --- | --- |
| **Study program** | **: K20414C\_ Fintech** |
| **Course** | **: Program package in finance2** |
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**THE FACTORS THAT AFFECT THE TRADE CREDIT (RECEIVABLE) OF LISTED FIRMS ON HNX**

# DECLARATION

I hereby declare that the report "The factors that affect the trade credit (receivable) of listed firms on HNX" 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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## Perform literature review

The theory of trade credit was first mentioned by Le Goff (1957). He argues that the form of trade credit has been used since the Middle Ages; it was formed when the seller did not require the buyer to pay immediately upon receipt of the product (Le Gof, 1957). Since then, topics related to trade credit have always been of interest to many scientists around the world.

Nadiri's research (1969) analyzes the factors affecting receivables from customers and payables to suppliers for all US manufacturing enterprises with quarterly data for the period 1949–1964. The results show that size (sales) has a positive effect and liquidity has a negative effect on accounts receivable.

Research by Petersen & Rajan (1997) on 3,404 small businesses in the United States in the period 1988–1989 shows that size (assets), bank loans, and sales growth all have a positive impact on accounts receivable. Net profit (profit after tax to sales) has a negative impact; besides, the number of years of operation and gross profit margin (gross profit/ sales) have a nonlinear impact on accounts receivable.

Vaidya (2011) used the GMM method to study the factors affecting trade credit based on a dataset of 1,522 firms in India during the period 1993-2006. Research shows that fixed assets (fixed assets to total assets), liquidity (cash and marketable securities to sales) and size (assets) positively affect AR (receivables to sales). Negative factors: inventory (inventory/sales), profitability (profit before depreciation and tax/sales), short-term bank loans (bank loan/sales). Furthermore, the regression results also show that finished good inventories (finished good inventories/sales) have a negative impact on accounts receivable, while raw material inventories (raw material inventories/sales) have a positive impact.

Research on the determinants of trade credit: the case of developing economies (Ahmed, Xiaofeng, and Khalid, 2014), with data from 2005 to 2011 from non-financial firms in Pakistan, has applied three models for estimation: the pooled ordinary least squares method, the fixed effects method, and the random effects method. They conclude that inventory, product quality, size (revenue), and liquidity have a negative impact on trade credit supply, whereas sales growth and GDP have a positive impact.

Akinlo (2012) analyzes panel data from 66 non-financial companies listed on the Nigerian stock market for the period 1999–2007 to study the factors affecting trade credit. The results of the pooled OLS analysis show that many factors have a significant influence on A/R. Bank loans (short-term loans to assets) and liquidity (money and negotiable securities to assets) have a positive impact, and return on assets (ROA), size (sales), and inventory (value of inventory and assets) have a negative effect. On the other hand, through the Hausman test, the study shows that the FEM method gives better results than the REM method. The results of the FEM analysis only confirm two factors that determine A/R: size has a negative impact and liquidity has a positive impact.

In Vietnam, the study by Phan Dinh Nguyen and Truong Thi Hong Nhung (2014) on the factors affecting the commercial credit of listed companies in Vietnam by using quantitative methods for panel data for the period 2007-2012. Research results show that receivables have a negative relationship with inventory, firm’s size, collateral, liquidity, and revenue growth but a positive relationship with the short-term debt ratio.

Tran Ai Ket (2017) conducted a study on the factors affecting the trade credit of the listed transportation industry with a sample of 34 enterprises from 2015–2016 and used the FEM estimation method. Except the positive effect of the years of operation; liquidity (current assets to total current liabilities), inventory and fixed assets (fixed assets to total assets) had a negative impact on A/R.

Pham Xuan Quynh and Tran Duc Tuan (2020) used data from the financial statements of 16 food companies during the period from 2013 to 2017. Their study analyzes the factors affecting enterprises's trade credit. By using the REM model, the result shows that the proportion of customer receivables is affected by factors such as size (total assets), changes in revenue, and the liquidity abilities of companies. Size, liquidity had a negative impact, and the changes in revenue had a positive impact on the proportion of customer receivables.

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: Measure the variables and the expectation of the sign of the estimator coefficients βi

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Variable | Measure | Symbol | Sign expectation |
| Dependent variable | Accounts Receivable | Accounts Receiable/ Total assets | AR |  |
| Independent | Type of firm | 0: Total equity < 100000000000 (VND)  1: Total equity > 100000000000 (VND) | Type\_firm | +/- |
| variable | Short term debt | Current liabilities/ Total assets | debt | + |
|  | Fixed assets | Fixed assets/ Total assets | FA | +/- |

Type of firm: firms in the dataset belong to the trade and services sector, the industry and construction sector. According to Article 5 of Decree 80/2021/ND-CP, which stipulates the criteria for identifying small and medium-sized enterprises, classifying enterprises according to the size of the year's total capital of no more than 100 billion VND will be small and medium enterprises. medium, denoted 0. Enterprises with total capital of over 100 billion dong for the year will be large enterprises, denoted by 1.

## Create Dataset

|  |
| --- |
| **CODE:**  **#required packages**  library(tidyverse)  library(readxl)  library(ggplot2)  library(lmtest) |

|  |
| --- |
| **CODE:**  **#load data**  data <- read\_excel("C:/Users/ASUS/Downloads/040522 Data Mid-term test Final.xlsx")  head(data) |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#rows and columns**  dim(data) |

|  |
| --- |
| **RESULT:**  [1] 753 26 |

|  |
| --- |
| **CODE:**  **#all variable names**  colnames(data) |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#select firms listed on HNX**  df <- data %>%  filter(exchangename=='HANOI STOCK EXCHANGE')  dim(df) |

|  |
| --- |
| **RESULT:**  [1] 345 26 |

|  |
| --- |
| **CODE:**  **#select features**  df <- df %>%  select(firmcode, firmname, receivable, cash, totalasset,  currentliabilities, ppe, totalequity, industry)  **#create a random sample**  set.seed(927)  df <-  df[sample(1:nrow(df), 100), ]  dim(df)  head(df) |

|  |
| --- |
| **RESULT:**  [1] 100 8 |

|  |
| --- |
| **CODE:**  **#identify number of NAs in data frame**  colSums(is.na(df)) |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#replace missing values with the median value of the corresponding variable**  df$receivable[is.na(df$receivable)]=median(df$receivable,na.rm=T)  df$totalasset[is.na(df$totalasset)]=median(df$totalasset,na.rm=T)  df$currentliabilities[is.na(df$currentliabilities)]=median(df$currentliabilities,na.rm=T)  df$ppe[is.na(df$ppe)]=median(df$ppe,na.rm=T)  df$totalequity[is.na(df$totalequity)]=median(df$totalequity,na.rm=T)  **#check number of NAs again**  colSums(is.na(df)) |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#create discrete variable from continuous variables**  df$type\_firm <- ifelse(df$totalequity <= 100000000000, 0, 1)  **#create continuous variables**  df <- df %>%  mutate(debt=currentliabilities/totalasset,  FA=ppe/totalasset)  **#create dependent variable**  df <- df %>%  mutate(AR=receivable/totalasset)  head(df) |

## Report

|  |
| --- |
| **CODE:**  **#5 firms with highest trade credit**  top5\_highest <- df %>%  select(firmcode, firmname, AR, industry) %>%  arrange(desc(AR)) %>%  head(5)  top5\_highest |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#5 firms with lowest trade credit**  top5\_lowest <- df %>%  select(firmcode, firmname, AR, industry) %>%  arrange(AR) %>%  head(5)  top5\_lowest |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#descriptive statistics of AR**  **#different categories of the discrete variable**  discrete\_variable <- df %>%  group\_by(type\_firm) %>%  summarize(mean\_AR = mean(AR),  median\_AR = median(AR),  min\_AR = min(AR),  max\_AR = max(AR),  sd\_AR = sd(AR))  discrete\_variable |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#groups of above/below median of the continuous variable**  continuous\_variable <- df %>%  group\_by(debt>median(debt)) %>%  summarize(mean\_AR = mean(AR),  median\_AR = median(AR),  min\_AR = min(AR),  max\_AR = max(AR),  sd\_AR = sd(AR))  continuous\_variable |

|  |
| --- |
| **RESULT:** |

Small and medium-sized firms have, on average, larger AR (accounts receivable/total assets) than large firms.

The group of firms with a higher ratio of short-term debt will have a higher AR.

## Data visualization

|  |
| --- |
| **CODE:**  **#histogram of trade credit**  ggplot(df, aes(x = AR)) +  geom\_histogram(fill = "lightblue", color = "black") +  labs(title = "Histogram of AR", x = "AR", y = "Frequency") |

|  |
| --- |
| **RESULT:** |

Most firms have AR (Accounts Receiable/ Total assets) between 0.1 and 0.2.

|  |
| --- |
| **CODE:**  **#scatter plot of trade credit with the continuous variable**  plot(AR ~ debt, data=df) |

|  |
| --- |
| **RESULT:** |

The relationship between debt and AR seems to be linear.

|  |
| --- |
| **CODE:**  **#plot that allow the combination of continuous, discrete variables and trade credit**  plot(AR ~ FA, data=df) |

|  |
| --- |
| **RESULT:** |

The relationship between FA and AR seems to be linear too.

|  |
| --- |
| **CODE:**  **#boxplot of trade credit with the discrete variable**  df %>%  ggplot(aes(x = type\_firm,  y = AR,  fill = as.factor(type\_firm))) +  geom\_boxplot() |

|  |
| --- |
| **RESULT:** |

Small and medium-sized firrms have a larger AR (receivables/total assets) than large firms.

|  |
| --- |
| **CODE:**  **#plot that allow the combination of continuous, discrete variables and trade credit**  ggplot(df, aes(x = debt, y = AR, color = as.factor(type\_firm))) +  geom\_jitter(width = .1) |

|  |
| --- |
| **RESULT:** |

Small and medium-sized firms have a larger ratio of short-term debt to total assets than large firms.

## Regression

|  |
| --- |
| **CODE:**  **#plot that allow the combination of continuous, discrete variables and trade credit**  ggplot(df, aes(x = debt, y = AR, color = as.factor(type\_firm))) +  geom\_jitter(width = .1) |

|  |
| --- |
| **RESULT:** |

Estimation results of the research model show that all coefficients have a significance level of at least 0.05. That indicates that all 3 factors affect AR and are statistically significant, including: debt, FA, type of firm. Specifically:

The short term debt has a positive effect on AR. When the short term debt increases, the business tends to ỉncrease the accounts receivable. This result is similar to the study of Phan Dinh Nguyen and Truong Thi Hong Nhung (2014).

The fixed assets have a negative effect on AR. This result is similar to the study of Tran Ai Ket (2017), but contrary to many previous studies such as Vaidya (2011).

The type of firm or size of equity has a negative effect on AR. When the size of equity increases, the business tends to reduce the accounts receivable. This result is similar to the study of Akinlo (2012) and Pham Xuan Quynh and Tran Duc Tuan (2020), but contrary to many previous studies here, such as Nadiri (1969), Petersen & Rajan (1997) and Vaidya (2011).

The "Residual standard error" is an estimate of the standard deviation of the errors or residuals, and it is 0.1447. The "Multiple R-squared" and "Adjusted R-squared" are measures of how well the model fits the data, and they are 0.3626 and 0.3427, respectively. The F-statistic is 18.21, with a corresponding p-value of 1.969e-09, indicating that the model is statistically significant overall.

|  |
| --- |
| **CODE:**  **#check important assumptions for linear regression**  par(mfrow=c(2,2))  plot(trade\_receivable.lm) |

|  |
| --- |
| **RESULT:** |

|  |
| --- |
| **CODE:**  **#test of multicollinearity**  cor(df$debt, df$FA)  cor(df$debt, df$type\_firm)  cor(df$type\_firm, df$FA) |

|  |
| --- |
| **RESULT:** |

The correlation between debt and FA (-0.17 correlation), debt and type\_firm (-0.21 correlation), type\_firm and FA (-0.03 correlation) is small, so I can include these variables in the same model.

|  |
| --- |
| **CODE:**  **#test of heteroskedasticity**  bptest(trade\_receivable.lm) |

|  |
| --- |
| **RESULT:** |

The test statistic is 11.094 and the corresponding p-value is 0.01123. Since the p-value is less than 0.05, we reject the null hypothesis. We have sufficient evidence to say that heteroscedasticity is present in the regression model.

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. However, it's important to keep in mind that this approach may also affect the interpretation of the coefficients.
* 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.

## Loop

|  |
| --- |
| **CODE:**  **#count the number of firms in an industry**  c = unique(df$industry)  industry\_name <- "Industrials"  count <- 0  for (i in df$industry) {  if (i == industry\_name) {  count <- count + 1}}  cat("Number of firms in", industry\_name, "is", count, "firms") |

|  |
| --- |
| **RESULT:**  Number of firms in Industrials is 37 firms |

|  |
| --- |
| **CODE:**  **#count the number of firms in an industry and with AR above median of AR**  industry\_name <- "Industrials"  median(df$AR)  count <- 0  for (i in 1:length(df$industry)) {  if (df$industry[i] == industry\_name && df$AR[i] > median(df$AR)) {  count <- count + 1  }}  cat("Number of firms in", industry\_name, "with trade credit above median of AR is", count, "firms") |

|  |
| --- |
| **RESULT:**  [1] 0.1359398  Number of firms in Industrials with AR above median of AR is 25 firms |

# APPENDIX

#required packages

library(tidyverse)

library(readxl)

library(ggplot2)

library(lmtest)

#load data

data <- read\_excel("D:/học tập/NĂM 3/hk 6/gói ứng dụng trong tài chính/040522 Data Mid-term test Final.xlsx")

head(data)

#rows and columns

dim(data)

#all variable names

colnames(data)

#select firms listed on HNX

df <- data %>%

filter(exchangename=='HANOI STOCK EXCHANGE')

dim(df)

#select features

df <- df %>%

select(firmcode, firmname, receivable, totalasset,

currentliabilities, ppe, totalequity, industry)

#create a random sample

set.seed(927)

df <-

df[sample(1:nrow(df), 100), ]

dim(df)

head(df)

#identify number of NAs in data frame

colSums(is.na(df))

#replace missing values with the median value of the corresponding variable

df$receivable[is.na(df$receivable)]=median(df$receivable,na.rm=T)

df$totalasset[is.na(df$totalasset)]=median(df$totalasset,na.rm=T)

df$currentliabilities[is.na(df$currentliabilities)]=median(df$currentliabilities,na.rm=T)

df$ppe[is.na(df$ppe)]=median(df$ppe,na.rm=T)

df$totalequity[is.na(df$totalequity)]=median(df$totalequity,na.rm=T)

#check number of NAs again

colSums(is.na(df))

#create discrete variable from continuous variables

df$type\_firm <- ifelse(df$totalequity <= 100000000000, 0, 1)

#create continuous variables

df <- df %>%

mutate(debt=currentliabilities/totalasset,

FA=ppe/totalasset)

#create dependent variable

df <- df %>%

mutate(AR=receivable/totalasset)

head(df)

#5 firms with highest trade credit

top5\_highest <- df %>%

select(firmcode, firmname, AR, industry) %>%

arrange(desc(AR)) %>%

head(5)

top5\_highest

#5 firms with lowest trade credit

top5\_lowest <- df %>%

select(firmcode, firmname, AR, industry) %>%

arrange(AR) %>%

head(5)

top5\_lowest

#descriptive statistics of AR

#different categories of the discrete variable

discrete\_variable <- df %>%

group\_by(type\_firm) %>%

summarize(mean\_AR = mean(AR),

median\_AR = median(AR),

min\_AR = min(AR),

max\_AR = max(AR),

sd\_AR = sd(AR))

discrete\_variable

#groups of above/below median of the continuous variable

continuous\_variable <- df %>%

group\_by(debt>median(debt)) %>%

summarize(mean\_AR = mean(AR),

median\_AR = median(AR),

min\_AR = min(AR),

max\_AR = max(AR),

sd\_AR = sd(AR))

continuous\_variable

#data visualization

#histogram of trade credit

ggplot(df, aes(x = AR)) +

geom\_histogram(fill = "lightblue", color = "black") +

labs(title = "Histogram of AR", x = "AR", y = "Frequency")

#scatter plot of trade credit with the continuous variable

plot(AR ~ debt, data=df)

plot(AR ~ FA, data=df)

#boxplot of trade credit with the discrete variable

df %>%

ggplot(aes(x = type\_firm,

y = AR,

fill = as.factor(type\_firm))) +

geom\_boxplot()

#plot that allow the combination of continuous, discrete variables and trade credit

ggplot(df, aes(x = debt, y = AR, color = as.factor(type\_firm))) +

geom\_jitter(width = .1)

#regression

trade\_receivable.lm<-lm(AR ~ debt + FA + type\_firm, data = df) #+ liquidity 0.388 + FA

summary(trade\_receivable.lm)

#check important assumptions for linear regression

par(mfrow=c(2,2))

plot(trade\_receivable.lm)

#test of multicollinearity

cor(df$debt, df$FA)

cor(df$debt, df$type\_firm)

cor(df$type\_firm, df$FA)

#test of heteroskedasticity

bptest(trade\_receivable.lm)

#count the number of firms in an industry

c = unique(df$industry)

industry\_name <- "Industrials"

count <- 0

for (i in df$industry) {

if (i == industry\_name) {

count <- count + 1}}

cat("Number of firms in", industry\_name, "is", count, "firms")

#count the number of firms in an industry and with AR above median of AR

industry\_name <- "Industrials"

median(df$AR)

count <- 0

for (i in 1:length(df$industry)) {

if (df$industry[i] == industry\_name && df$AR[i] > median(df$AR)) {

count <- count + 1

}}

cat("Number of firms in", industry\_name, "with AR above median of AR is", count, "firms")

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