Modeling SMEs Credit Default Risk: The Case of Saudi Arabia

Nermean Senan[1], Tahar Tayachi[2,3] and Ahmed BenSaïda[1,*]

[1]College of Business, Effat University, Jeddah, Saudi Arabia

[2]College of Business Administration, American University in the Emirates, UAE

[3]FSEG Mahdia, University of Monastir, Mahdia, Tunisia

Abstract: This study assesses the credit risk of small and medium-sized enterprises (SMEs) to minimize unexpected risk events. We construct a hybrid statistical model based on factor analysis and logistic regression to predict enterprise default on loans and determine the factors predicting SMEs default. We assess the credit risk of SMEs listed on the Saudi stock market. The results indicate that the SMEs acid-test ratios are the most influential factors in predicting SMEs credit risk. Therefore, the designed logistic model can be used by financial institutions during the decision-making process of granting loans to SMEs. This study sheds light on challenging access to bank credits due to the lack of financial transparency of most Saudi SMEs.

Keywords: Credit risk, SME, Probability of default, Risk assessment.

1. INTRODUCTION

Small and medium-sized enterprises (SMEs) have crucial role in the dynamic economy, as they are the main source of job creation in both developed and developing countries. In modern economy, SMEs sector proved that it is the most innovative system through its vital contribution to economic growth. For OECD members, SMEs account for 97% of the total firms. In the U.S., SMEs are responsible for approximately 75% of the net jobs.[1] Despite the recognized role SMEs take in the economy, they have less access to finance comparing to large enterprises due to higher risk. Studies form UN and OECD have been encouraging governments to promote financial lending to overcome obstacles facing lenders when dealing with SMEs. The high risk associated with SMEs lending made banks reluctant to fund them. The perceived risk stems from limited information disclosure to banks, lack of credit information, and inadequate financial statements in most SMEs. As a result, banks or financial institutions find it difficult to assess the risk of the loan, so they either charge large premiums or deny lending.

Among the goals of vision 2030, Saudi Arabia is primarily supporting its SMEs via specialized funded vehicles like the Kafalah program. This step comes to increase SMEs financing to raise the level of their contributions in the GDP above the actual share of 33%, which is considered the highest among GCC (Tripathi, 2019), yet lower than other developing countries. However, the economic reforms have impacted SMEs lending. Saudi banks, such as Alrajhi bank, has limited the lending ahead of Saudi economic reforms. The Saudi government is in crucial stage of economic transformation. Hence, in order to support these small ambitions, a strong formal of borrowing is required to grant worthy SMEs access to finance. It is important to assess small business entities credit risk to price the associated level of risk (Altman & Sabato, 2007).

Banks and other financial institutions must have a robust approach to managing credit risk if they want to achieve long-term success (Witzany, 2017). Lending institutions have done this for many years in the past. Credit risk management involves identifying or measuring the uncertainties associated with lending (Vaidyanathan, 2013). This helps financial institutions to make sound decisions to protect their businesses from bankruptcy and closure due to continued loss-making. The primary purpose of measuring uncertainties in financial lending is to assist in quantifying the credit risk level presented to the lender by the borrower (Witzany, 2017). Lenders can achieve this through the assignment of measurable numbers to the expected default probability of the client. Financial institutions use these numbers to assess the ability of potential borrowers to satisfy the obligations of the debt (Bouteille & Coogan-Pushner, 2012). Therefore, a credit analysis primarily aims at determining or assessing potential borrower's creditworthiness, as well as their ability to meet the obligations of the debt.

Lenders identify lending risks to assess the likelihood of the borrower defaulting the loan. Banks often use the credit rating of customers to ascertain the degree of financial risk. If a high risk is anticipated, the lender will reject the borrower's credit application. By doing this, financial institutions can minimize the loss of revenue due to uncertainties in lending (Witzany, 2017). The monitoring of the uncertainties enables banks to understand potential clients with a high credit risk that

*Address correspondence to this author at the College of Business, Effat University, Jeddah, Saudi Arabia; Tel: +966 12137812;
E-mail: ahmedbensaida@yahoo.com

JEL codes: G21, G32.

[1]Source: www.sba.gov (U.S. Small Business Administration).

exceeds the pre-determined risk tolerance level. Credit applications of borrowers who present a significantly acceptable default risk are often approved at the agreed conditions or terms of payment (Bouteille & Coogan-Pushner, 2012).

Measuring the uncertainties in financial lending also enables banks and other institutions to set an appropriate cost that the borrower should pay in addition to the borrowed sum to compensate for the associated risk. The extra money paid by borrowers for credit advancement is referred to as interest or finance cost (Bouteille & Coogan-Pushner, 2012). If the potential borrower has low creditworthiness or high risk of default, the bank will charge higher finance costs (interest rate). This interest will be used to compensate the lender for the uncertainty should the client fail to repay the principal within the agreed maturity. Customers with high creditworthiness, or positive credit rating, usually receive a tremendous amount of credit with a low interest rate due to the low default risk and uncertainty (Ross, Westerfield & Jordan, 2013).

The measuring of uncertainty in financial lending is related to credit risk modeling. It refers to the due diligence carried out by a financial institution to evaluate the risk of the borrower individually, as well as collectively from the time application to full repayment (Bandyopadhyay, 2016). The modeling of credit risk is a forward-looking process that helps a bank to forecast the extent of the loan portfolio's fluctuation in value in the underlying credit of the borrower. To some extent, credit risk modeling involves identifying and measuring the uncertainty in financial lending. Credit managers usually assess the creditworthiness of a potential borrower to ascertain the default risk before approving the credit (Witzany, 2017).

Small businesses are essential in today's corporate world. They are volatile due to a lack of financial transparency, low capital, and small asset bases. Many international banks have designed credit-risk models for large companies with limited consideration for SMEs. This is a similar scenario in Saudi Arabia, as SMEs credit risk assessment is considered a new venture posing difficulties in its management. SME's credit risk modeling is essential in assessing risks in all facets of a business and setting pricing for different risk levels. Therefore, it is essential to assess the credit risk of SMEs to minimize unexpected risk events. According to the literature, most credit-risk models apply to large enterprises, while limited models apply to SMEs (Altman & Sabato, 2007).

In view of the abovementioned problems, the objective of this study is threefold. (1) First, constructs a statistical model underlying a logistic regression principle to predict SMEs default on loans. (2) Second, determines the factors predicting SMEs default. (3) Finally, employs the designed model to make decisions about granting SMEs fair credits when lending. The empirical analysis employs a panel data of 61 Saudi companies with revenues less than 200 million Saudi riyals (SAR) over the period from 2017 to 2019 to determine the factors that most affect a company's credit worthiness.

The contribution of this study, relative to the existing literature on credit-risk assessment, is to employ data of all Saudi listed SMEs on the stock exchange market (Tadawul). Furthermore, the paper develops a default prediction model using logistic regression. We investigate only internal factors of a company's performance including profitability, liquidity, solvency, activity, and other ratios to derive the most affecting factors on credit risk. Furthermore, the methodology of this research – the use of a hybrid model that includes both factor analysis and logistic regression – can be used by financial institutions and other specialized agencies to create more accurate default-prediction model, since they have access to more reliable data, especially default status.

The remainder of this paper is organized as follows. Section 0 is a review of the relevant literature on credit default and its measures. Section 0 demonstrates variable selection criteria and develops a specific model to predict SMEs default status. Section 0 summarizes the findings and emphasizes the most predictive variables affecting the model. Section 0 concludes.

2. LITERATURE REVIEW

There is no solid definition of small businesses; different organizations or institutions have their definitions. Most private and public firms define small businesses as annual revenues generated by a business entity. Other definitions consider the number of staff as a discerning entity, whereas others consider the balance-sheet size. However, small businesses also have their own internationally recognized definitions, as quoted by international public institutions, summarized in Table **1**.

The Small and Medium Enterprise Authority (SMEA) in Saudi Arabia – or Monshaat – defines a SME according to the number of staffs or annual sales as listed below (Monshaat's classification for SMEs):[2]

[2] "Monshaat" refers to the Small and Medium Enterprises Authority, it was established in 2016. The objectives of Monshaat are to organize, support, develop and sponsor the SME sector to increase the productivity of these enterprises and increase their contribution to the GDP from 20% to 35% by 2030.

Table 1: Definition of SMEs by International Institutions

Institution	Maximum number of employees	Maximum turnover or revenues ($)	Maximum assets ($)
World Bank	300	15,000,000	15,000,000
MIF-IADB	100	3,000,000	None
UNDP	200	None	None
African Development Bank	50	None	None

Note: this table summarizes the SMEs definitions according to selected international institutions (Source: Gibson & Van der Vaart, 2008).

1. Micro entities are those having less than or equal to five full-time staff members, or the annual sales is up to 3 million SAR.

2. Small size entities are those with six to forty-nine full-time staff members, or annual sales of up to 3-40 million SAR.

3. Medium size entities are those with 50-249 full-time staff members, or annual sales of 4-200 million SAR.

4. Large-sized entities are those whose full-time staff members exceed 250, or the annual sales is more than 200 million SAR.

The definition based on the number of full-time employees and annual sales is interdependent; if one is absent, it is substituted with the other.

SMEs are increasingly deemed to be the pillar of most countries' economies. For members of OECD, SMEs account for more than 97% of the total number of firms. In the U.S., for instance, SMEs create 75% of the country's additional annual employment opportunities and employ nearly 50% of the private labor force, signifying 99.7% of total employers (Grigorescu & Ion, 2019). The success of SMEs is highly attributed to its simple arrangement, their speedy reaction to economic conditions and their ability to satisfy the needs of local clients, sometimes expanding to large and influential companies or failing within a short span from its commencement. From the outlook of credit risk, SMEs vary from large companies in numerous ways. For instance, a study by Dietsch & Petey (2004) on a group of French and German SMEs determines that they bear more risk but possess a lower asset connection with each other compared to large companies. Certainly, we theorize that employing a default expectation model, established on a huge corporate data to SMEs, will culminate in reduced prediction power and probably an inferior corporate portfolio performance compared to a different portfolio containing distinct prototypes for large corporates and SMEs.

One key objective is to examine a full set of financial ratios associated with Saudi SMEs and to detect the most predictive factors influencing a firm's credit worthiness. One impetus is to depict the significance for banks of modelling SMEs credit risk distinctly from huge corporations. The only documented research that focused on modeling credit risk explicitly for SMEs is a somewhat distant study by Edmister (1972), which investigated 19 financial ratios and, by employing multivariate discriminant analysis, formulated a model to forecast small business problems. The study assessed a sample of small and medium-sized companies between 1954 and 1969. Our study will use Edmister (1972)'s approach by employing the definition of SME as enshrined in the new SMEA (sales from 4 to 200 million SAR) and employing a logit regression investigation to establish the model. The study will also entail a thorough analysis of a host of financial metrics to come up with the most predictive ones. Apart from an all-encompassing investigation of SME financial features, the eventual result will also include a model to forecast their default probability (PD).

Abouzeedan & Busler (2004) focus on analyzing the performance models of small and medium-sized enterprises. The research states that the theoretical models of SMEs can be divided into either firm dynamic models or performance prediction models. The study revealed that both Z-scores and ZETA-scores models are critical and they are used to look at a company's failures in times of financial distress, such as the bankruptcy of a company. Managers working on the basic financial ratios of the company will find the Z-scores and ZETA-scores models useful. However, general managers, such as those working on strategic levels, will not find the models effective.

Nam (2013) developed a new credit risk model covering the small and medium-sized enterprises based on the DSW model of stochastic defaulting intensity. The model recognizes the default probability and the probability of the initial public offering (IPO) based on a stopping time model. The research suggested that the proposed model might be used as an early warning system to predict a possible sudden collapse of the economic fundamental, leading to financial losses. Altman & Sabato (2007) also developed a distress prediction model for SMEs. The research investigated whether banks should separate SMEs from large corporation when developing credit risk systems and strategies. The study found that banks, which intend to manage SMEs credit risks, should use models and procedures based on SME segments. The study advised that banks should not use different strategies and conditions to manage SMEs and large companies. Instead, banks should consider using tools, such as scoring and rating systems, that focus on the SME portfolio.

A recent study by Kanapickiene & Spicas (2019) focused on assessing the enterprise financial performance using the enterprise trade credit risk assessment (ETCRA) model to determine the default probability. The research concluded that both the financial and non-financial variables should be part of the statistical ETCRA models. Moreover, the ETCRA models are simple to use, with high accuracy and interpretability.

Saudi Arabia's new energy industry consists of a wide development outlook and is deemed to be a plan emerging industry. According to Shalaby (2004), the growth of the new energy industry is dependent on the progression of the emerging energy firms that, in turn, require huge capital investments to achieve the thrust-forward advancement, which surpasses the sphere of their private funds and government outlay. Hence, there is a tremendous need for exogenous financing. Nevertheless, new energy firms normally consist of individually owned SMEs. Numerous new energy firms have suffered from growth bottlenecks. Financing challenges normally deter the growth of enterprises. Precisely, the new energy firms operate within an intricate internal and external environment coupled with variations in the global environment and domestic regulations, changes in the macroeconomic environment, as well as financial malpractice (Zamberi-Ahmad, 2012). All the mentioned variables influence the financial atmosphere as well as functional costs and risks, directly or indirectly. In this regard, the development of new energy enterprises highly relies on the ability to diminish financing challenges and to mitigate against their financial risks.

The emerging energy industry is both a skill and capital-intensive industry, needing huge capital investments due to the large scope of research and development (R&D) activities. Therefore, it is critical for any organization to select the proper financing scheme with the capacity to efficiently deal with the challenges of escalated financing costs and a long financing sequence. Currently, there exist numerous SME-based financing approaches and networks innovations. A higher percentage of high-tech SMEs are skewed towards bank loan and equity financing, as opposed to bond financing.

There is substantial literature on default prediction procedures. In the last fifty years, numerous scholars have investigated several likely realistic options to forecast default by clients or business failure. Amongst the earliest works are those by Beaver (1966) and Altman (1968), who established univariate and multivariate models to forecast business letdowns by employing a host of financial ratios. Beaver (1966) applied a dichotomous classification test to establish the fault rates of a latent creditor, if companies were categorized based on specific financial ratios, as failed or non-failed. The author used an equal sample of 158 companies (half failed and half non-failed) and evaluated 14 accounting ratios. On the other hand, Altman (1968) employed a multiple discriminant analysis methodology (MDA) to correct the discrepancy issue associated with Beaver (1966)'s univariate analysis, as well as to evaluate a more comprehensive financial summary of companies. Altman (1968)'s analysis was based on an equal sample of 66 manufacturing companies (half failed and half non-failed) that filed an insolvency plea over the 1946-65 period. The author further assessed 22 likely useful financial ratios, finally choosing five as offering collaboratively the best general forecast of corporate insolvency. The variables were grouped into five typical ratio classes: profitability, solvency and liquidity, leverage, and activity ratios.

Lately, the fresh Basel Accord for bank capital adequacy (Basel II) has motivated numerous scholars, such as Altman & Sabato (2005), Jacobson *et al*. (2005), and Berger (2006), to focus on the SME segment. Essentially, numerous criticisms, posted by SME associations and governments, inflated capital charges on SMEs. These critics culminate in credit limiting of small companies and, considering the relevance of these companies in the economy, could deter economic expansion. The abovementioned researches have addressed the issue of the likely consequences of Basel II on capital requirements of banks. However, the issue of modeling credit risk, explicitly for SMEs, has either not been mentioned in totality, or only momentarily deliberated upon.

Other scholars emphasized on the challenges and the capabilities of small commercial lending, assessing the main factors of SME riskiness and profitability for banks in the U.S. (Kolari & Shin, 2004), or the lending facilities and plans (Berger & Udell, 2006). Lately, Berger & Frame (2007) investigated the likely effects of the small business ranking on the accessibility of credit. The findings of the study reveal that banking firms, that adopt automated decision structures (e.g., scoring systems), bolster small business credit accessibility. They concentrate on micro firm credits (reaching a maximum of $250,000) that were administered using credit scoring towards the close of the 20th century in the U.S., and using individual credit history of the main owner accessed from one or several consumer credit bureaus, such as Experian, FICO, or Equifax.

Nonetheless, modern banks should bear the capacity to manage retail SME customers with a minimal of 1 million Euro yearly turnover (if they are to adhere to the Basel II requirements) to gain competitive advantage in the business of issuing credit. With the exception of sole entrepreneurship and self-employed micro business, the intricacies associated with the other larger corporations cannot be managed solely with bureau information, but rather a detailed financial analysis.

Based on relevant literature including Kolari & Shin (2004) and Berger (2004), we conclude that lending to SMEs largely impacts on bank profitability. Nonetheless, we also derive that there is a large inherent risk associated with lending to SMEs compared to lending to large companies, as proven by Dietsch & Petey (2004) and Saurina & Trucharte (2004). As a result, it is recommended that Saudi banks develop credit risk models explicitly tailored to fit the needs of SMEs, to curtail their projected and unforeseen losses. Numerous banks and consulting firms already employ this technique of differentiating large companies from SMEs in the process of modelling credit risk. Nevertheless, previous academic works lack a decisive investigation that portrays the noteworthy advantages of such a move. Edmister (1972) only concentrated on the choice of financial ratios important in forecasting SME failure, but failed to explain the reasoning behind separating SMEs from large corporations. Indeed, the focus on SME credits in the contemporary business environment is very critical, and modelling tailor-made credit risk systems is highly probable, under specific situations, to culminate in reduced capital requirements for Saudi's SMEs.

3. METHODOLOGY AND DATA

This study assesses the credit risk of SMEs in Saudi Arabia, using a logistic regression model based on factor analysis. Therefore, the variable explained by the model is the credit risk of SMEs, which includes both non-defaulters and defaulters. According to Kanapickiene & Spicas (2019), including both good debtors and bad debtors is important to measure the accuracy of credit risk modeling. Three fundamental principles will be followed to evaluate the credit risk of SMEs in Saudi Arabia. First, financial factors will be identified to determine the independent variables selected for the model. Second, dimension reduction using factor analysis will be adopted to reduce the number of factors. Finally, a model for assessing credit risk for SMEs will be developed using logistic regression methods. This will make the extracted principal components, using factor analysis, the predictor variables while the credit risk of SMEs will be the dependent variable. Furthermore, the extracted principal components will be the model's explanatory variables. In other words, the data of the original influencing factors will be reflected upon, and the likely relationship between the independent variables eliminated. Moreover, the principal components will help reduce the explanatory variables, thus, improving the model's prediction accuracy.

To determine the influential factors to SME's credit risk, SMEs will be considered as enterprises. Relative financial ratios, which are computed from an enterprise's financial statements, are frequently the most analyzed financial variables. Because financial reports have to obey specific standards. It would be suitable to identify likely financial ratios through the analysis of various ratios applied in the professional and scientific literature. It is necessary for the final financial ratios included in the model to be representative of distinct areas of SMEs activities. In previous studies, Spicas *et al*. (2015) analyzed 101 distinct models of predicting bankruptcy and credit risk, while Spicas *et al*. (2018) identified over 168 distinct financial ratios. Furthermore, Kanapickiene & Spicas (2019) accessed the credit risk of SMEs in Lithuania and abridged 52 distinct financial ratios applicable to the market.

Our study derives the 52 distinct financial ratios from Kanapickiene & Spicas (2019) as Table **2** illustrates. However, only variables without a significant amount (> 20%) of missing values will be included in the analysis. The data is collected from the Saudi stock exchange market.[3] The identified financial ratios are grouped into profitability ratios, liquidity ratios, solvency ratios, activity ratios, structure ratios, and other ratios. Furthermore, as indicated by Li (2016), it is important to include many time-variant and firm size factors as control variables to mitigate endogeneity problems, such as simultaneity, omitted variables, and measurement error. Different control variables have been used in the literature, such as firm size, R&D expenses, leverage, advertising expense, and return on assets (ROA) (Cho *et al*., 2019). According to Dang *et al*. (2018), the size of an enterprise is a crucial control variable, which could be measured using total assets, market capitalization, and total sales.

[3] Security exchange and depository centre in Saudi Arabia: https://www.tadawul.com.sa/.

Table 2: Selected Dimensions

Dimension	Financial ratio variable (represented by the calculation formula)	Source
1. Profitability ratios	Gross profit/sales	Financial Statements
	EBIT/sales	
	EBT/sales	
	Net profit/sales	
	Gross profit/total assets	
	EBIT/total assets	
	EBIT/current liabilities	
	EBT/total asset	
	EBT/equity	
	EBT/(equity − current liabilities	
	Net profit/total assets	
	Net profit/equity	
	Current assets/current liabilities	
2. Liquidity ratios	(Current assets − inventories)/current liabilities	Financial Statements
	Inventories/current liabilities	
	Accounts receivable/total liabilities	
	Accounts receivable/(total liabilities − cash)	
	Cash/current liabilities	
	(Cash – inventories)/current liabilities	
	Cash/total liabilities	
	Cash/equity	
	Working capital/total assets	
	Working capital/equity	
	(Current liabilities − cash)/total assets	
3. Solvency Ratios	Total liabilities/total assets	Financial Statements
	Equity/total assets	
	Equity/(equity + long term liabilities)	
	Equity/total liabilities	
	Fixed assets/equity	
	Current assets/(total liabilities – cash)	
4. Activity ratios	Inventories/sales	Financial Statements
	Accounts receivable/sales	
	Sales/fixed assets	
	Sales/current assets	
	Sales/total assets	
	Sales/cash	
	Equity/sale	
	Cost of sales/sales	
	Current liabilities/sales	
	Working capital/sales	
	Working capital/operating expenses	
	EBIT/interest expenses	
5. Structure ratios	Current assets/total asset	Financial Statements
	Accounts receivable/inventories	
	Inventories/total assets	
	Cash/total assets	
	Retained earnings/total assets	
	Current liabilities/(total liabilities − cash)	
6. Other ratios	The logarithm of total assets	Financial Statements
	The logarithm of total sales	
	Sales/capital stock	
7. Credit Status	Financial strength reports	Financial statements and SME credit reports

Note: This table reports the financial ratio variables (represented by calculation formula), symbol, and sources.

Furthermore, Herrador-Alcaide & Hernández-Solís (2019) and Kanapickiene & Spicas (2019) highlighted that the number of employees can be used to measure the size of an enterprise. Because financial data, such as cash flows from operation, R&D, and advertising expenses are hardly published in the financial statements of Saudi Arabian SMEs.

Most of the SMEs in Saudi Arabia do not provide financial statements or annual reports. The purposive sampling was used to include only the SMEs whose financial data are available for the considered period. Therefore, 61 SMEs in Saudi Arabia with available financial data from 2017 to 2019 are included in the model.

According to Iacobucci (2018), dimension reduction is a technique used to reduce many factors to just a few components. Factor analysis enables the reduction of factors via the construction of the rotated factor matrix. Moreover, factor rotation is the replacement of the original variables while maintaining the variable's original data to the maximum. Factor analysis changes the original variables with given correlations to jointly independent major components. The number of the explanatory variables is significantly reduced, reflecting the variable's key interactions, but excluding the variable's relationships (Liu *et al*., 2018). Our data contains potential significant correlations between 52 variables within the seven groups of profitability ratios, liquidity ratios, solvency ratios, activity ratios, structure ratios, credit status, and other ratios. The tests for the factor analysis included Kaiser-Meyer-Olkin (KMO) and Bartlett's test and the rotation, as well as extraction of factors, are done using the principal component analysis using VARIMAX model with Kaiser normalization.

The logistic regression is one of the most used statistical analysis of assessing and describing the correlation between a dependent variable and a set of independent variables. We employ it to assess the credit risk of SMEs. Logistic regression models predict the probability of the explained variable occurrence using a set of independent variables (Zhu *et al*., 2016). Hence, the projected resultant Y variable is non-default (0) or default (1).

$$\Pr\left(Y = \frac{1}{X} = x\right) \tag{1}$$

where $\Pr$ is a conditional probability highlighted as the function of x. When the correlation of $\Pr\left(Y = \frac{1}{X} = x\right)$ and x is linear, a challenge arises where any increase in x would either increase or decrease the probability value (Wu, 2017). The probability should only exist between 0 and 1 because linear models are limitless. However, the probability value can fall outside the 0 and 1 limits. The regression model overcomes this restriction with linear regression, which entails the explained variables to follow a normal distribution.

Specifically, in the assessment of credit risk of SMEs, the likely values are either non-default or default. Indeed, the variable has only two likely values: 1 and 0, which is discrete and categorical. This is a strong indication, that in the proposed study, the logistic regression analysis is more appropriate. Furthermore, some independent variables can influence the outcome, represented as $X_1, X_2, \ldots, X_k$. The correlation between the outcome and the independent variables (IVs) is represented by the conditional probability distribution of Y considering $X_1, X_2, \ldots, X_k$.

The logistic regression is widely applied for predicting the odds of something occurring (Liu *et al*., 2018). The credit risk occurrence of default is, therefore, a dichotomous variable, with two possible odds: default occurred, or default did not occur. The coding of a default in the incidence variables will be done using 1, 0 for instance,

- $Y_i = 1 \iff$ SME *i* defaulted.
- $Y_i = 0 \iff$ SME *i* did not default.

Whereas many methods have been formulated to assess the probability of a specific occurrence, our study uses the logistic model because of its popularity for predicting default risk. The model is written as:

$$PD = \Pr(y = 1) = \frac{1}{1 + e^{-z}},$$
$$Z = \beta_0 + \beta_1 X_1 \ldots \beta_k X_k \tag{2}$$

where PD stands for the probability of default, which is the dependent variable (DV) in the model. In the logistic regression, PD is the credit status of SMEs. In other words, PD will record value 1 $(Y = 1)$ if a SME has defaulted during the observed period and 0 $(Y = 0)$ otherwise (Kanapickiene & Spicas, 2019). In the linear combination of k IVs $(i = 1, \ldots, k)$, the particular coefficient is represented by β_i. The IVs X_i are all relevant parameters, which might influence credit risk (Kanapickiene & Spicas, 2019). The IVs included in the logistic model are represented by X_i and are all financial variables, as well as the control variables.

Additionally, the forward regression method is applied. First, the constant is concluded, and the IVs strongly correlated with the DV are gradually added to the model. As proposed by Kanapickiene & Spicas (2019), each of the 7 financial ratio groups are analyzed. Consequently, the insignificant ratios are eliminated from the model. Finally, the model is considered suitable after complying with the following requirements. We expect a chi-square criterion with a *p*-value less than 0.05, the Cox and Snell's and Nagelkerke's R^2 should range from 0 to a maximum of 1 (Field, 2013). Only the variables with statistically significant values (Wald's *p*-value < 0.05) are included in the model (Kanapickiene & Spicas, 2019).

4. RESULTS

Before performing principal component analysis (PCA) for the aforementioned independent variables, it is necessary to perform an applicability test. The basic reason is to examine the associations between initial variables. To this end, if the correlation between the initial variables is statistically insignificant, then factor analysis is considered unsuitable. Two tests are frequently used, as suggested by Tobias & Carlson (1969). KMO test and Bartlett's test of sphericity. When the value of KMO is higher than 0.5 and Bartlett's test probability value is below the 0.05 threshold, factor analysis technique is considered suitable (Tobias & Carlson, 1969).

In this study, many variables contain negative values, and most variables have cross-loadings. To

Table 3: Variables Included in the PCA

Variable (represented by the calculation formula)	Symbol
EBIT/sales	X_1
EBT/sales	X_2
Net profit/sales	X_3
EBT/equity	X_4
EBT/(equity – current liabilities)	X_5
Net profit/equity	X_6
Current assets/current liabilities	X_7
(Current assets – inventories)/current liabilities	X_8
Accounts receivable/total liabilities	X_9
Accounts receivable/(total liabilities – cash)	X_{10}
Cash/current liabilities	X_{11}
Cash/total liabilities	X_{12}
Working capital/total assets	X_{13}
Working capital/equity	X_{14}
(Current liabilities – cash)/total assets	X_{15}
Equity/total liabilities	X_{16}
Fixed assets/equity	X_{17}
Current assets/(total liabilities – cash)	X_{18}
Accounts receivable/sales	X_{19}
Sales/current assets	X_{20}
Sales/total assets	X_{21}
Cost of sales/sales	X_{22}
Working capital/operating expenses	X_{23}
Current assets/total asset	X_{24}
Accounts receivable/inventories	X_{25}
Inventories/total assets	X_{26}
Cash/total assets	X_{27}
Retained earnings/total assets	X_{28}
Current liabilities/(total liabilities – cash)	X_{29}
The logarithm of total sales	X_{30}
Sales/capital stock	X_{31}

Note: This table defines the variables employed in the model with the calculation formula.

Table 4: KMO and Bartlett Tests

Test		Measure
Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy		0.613
Bartlett's test of sphericity	Approx. Chi-Square	13258.3
	Degrees-of-freedom	465
	p-value	0.000

solve this issue, the variable's values are initially suppressed at 0.3 as suggested by Field (2013), while variables with cross-loadings are excluded from PCA. Consequently, the independent variables are reduced to 31 variables highlighted in Table **3**.

Table **4** presents the findings of the KMO and Bartlett tests. From the results, the KMO test value is 0.613, which is higher than the 0.5 thresholds. The Bartlett's test suggests a strong association between the variables. Therefore, it is appropriate to extract principal components using dimension reduction.

According to Field (2013), besides passing the KMO and Bartlett tests, the diagonal coefficients of the anti-image correlation matrix should be examined. The values for these coefficients should be greater than 0.5. The PCA establishes that most of the diagonal

Table 5: Communalities

Symbol	Variable	Initial	Extraction
X_1	EBIT/sales	1.000	0.949
X_2	EBT/sales	1.000	0.921
X_3	Net profit/sales	1.000	0.345
X_4	EBT/equity	1.000	0.841
X_5	EBT/(equity – current liabilities)	1.000	0.860
X_6	Net profit/equity	1.000	0.950
X_7	Current assets/current liabilities	1.000	0.907
X_8	(Current assets – inventories)/current liabilities	1.000	0.945
X_9	Accounts receivable/total liabilities	1.000	0.896
X_{10}	Accounts receivable/(total liabilities – cash)	1.000	0.881
X_{11}	Cash/current liabilities	1.000	0.908
X_{12}	Cash/total liabilities	1.000	0.856
X_{13}	Working capital/total assets	1.000	0.864
X_{14}	Working capital/equity	1.000	0.799
X_{15}	(Current liabilities – cash)/total assets	1.000	0.959
X_{16}	Equity/total liabilities	1.000	0.946
X_{17}	Fixed assets/equity	1.000	0.923
X_{18}	Current assets/(total liabilities – cash)	1.000	0.793
X_{19}	Accounts receivable/sales	1.000	0.582
X_{20}	Sales/current assets	1.000	0.855
X_{21}	Sales/total assets	1.000	0.854
X_{22}	Cost of sales/sales	1.000	0.915
X_{23}	Working capital/operating expenses	1.000	0.930
X_{24}	Current assets/total asset	1.000	0.936
X_{25}	Accounts receivable/inventories	1.000	0.873
X_{26}	Inventories/total assets	1.000	0.876
X_{27}	Cash/total assets	1.000	0.470
X_{28}	Retained earnings/total assets	1.000	0.858
X_{29}	Current liabilities/(total liabilities – cash)	1.000	0.819
X_{30}	The logarithm of total sales	1.000	0.763
X_{31}	Sales/capital stock	1.000	0.612

Note: Extraction method: Principal Component Analysis.

coefficients had values > 0.5 as deduced from Table **10** in the Appendix. The PCA determines that the off-diagonal coefficients are small, as pointed out by Field (2013). Overall, the KMO test, the anti-image correlation matrix, and Bartlett's test indicate that the data is suitable for PCA.

4.1. Extraction of Components

The communalities of the variables are illustrated in Table **5**, which highlights the factor variance of the factor analysis, a common measure of assessing the effectiveness of the PCA. Overall, higher levels of communalities indicate high efficiency of the performed test. As represented in Table **5**, the extent of communalities of the majority of variables is over 70%, suggesting that the extracted components relatively held superior explanatory power, while containing complete unique information concerning the examined variables.

The PCA method is applied to reduce the dimensions. To that end, the cumulative variance percentage of contribution is the reference value, while the initial eigenvalue is the auxiliary criterion. Overall, when the eigenvalue is equal to or greater than one, and the percentage cumulative variance is equal to or greater than 75%, then the common factors extracted from the model are considered as representative for the initial information contained in the variables (Field, 2013). As Table **11** in the Appendix highlights, seven principal components are extracted with eigenvalues greater than one. In addition, the cumulative variance percentage of contribution of the first seven components is over 83.5%. This suggests that less than 17% of the initial variable information is lost. Hence, the principal components extracted from the analysis would represent much information concerning the variables. The scree plots reflect the original variables and the principal factor's cumulative effect, which helps identify how many principal components to extract. As Figure **1** illustrates, eigenvalue changes stop dropping significantly from the eighth principal component, highlighting the sense of including seven principal factors. In summary, the extent of communality of variables and scree plot, using the analysis of the cumulative variance percentage, verify that the extraction of seven principal components is sensible.

4.2. VARIMAX with Kaiser Normalization

The extraction of seven principal components from the initial variables reflects most of the initial data and reduces their correlations. However, it is impossible to determine the key factors using the initial extracted component matrix. Consequently, the VARIMAX model

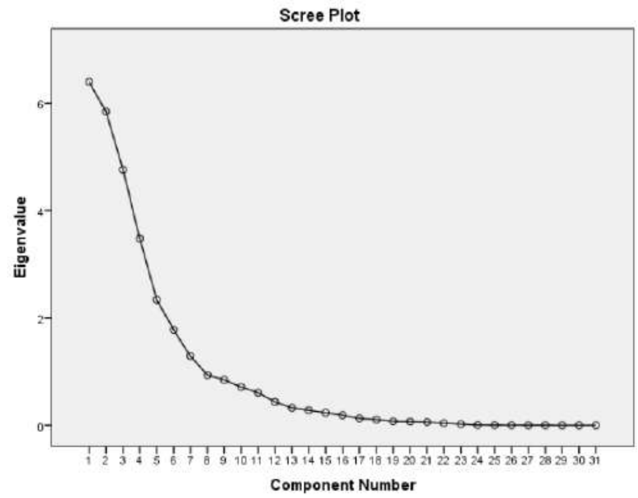

Figure 1: Scree plot shows the extracted components.

is applied to carry out an orthogonal rotation. This helps make the correlation with each initial factor clearer. The correlation between the initial variable and the extracted principal is stronger for variables loading higher on the principal component.

As illustrated in Table **12** in the Appendix, the first component (1) is more suitable in representing the initial information contained by seven variables: EBIT/sales, EBT/sales, Net profit/sales, EBT/equity, EBT/(equity – current liabilities), Net profit/equity, and Accounts receivable/total liabilities. The factors load to an extent of 97.3%, -89.7, 57.2%, 90.5%, 91.4%, 97.3%, and 93.9%, respectively. Most of the factors in the first component represent the profitability ratios of SMEs, hence, component 1 is labelled "SMEs profitability ratios (PC_1)".

The second principal component (2) represents: Accounts receivable/(total liabilities – cash), Cash/current liabilities, Cash/total liabilities, Working capital/total assets, Retained earnings/total assets, and Current liabilities/(total liabilities – cash). The variables load 90.5%, 93.1%, 92.4%, 92.8%, 92.4%, and 87.5%, respectively. These variables reflect the liquidity ratios of SMEs, and therefore, component 2 is labelled "SMEs liquidity ratios (PC_2)".

Component three (3) represents: Working capital/equity, (Current liabilities – cash)/total assets, Equity/total liabilities, Fixed assets/equity, Current assets/(total liabilities – cash), Accounts receivable/sales, and Sales/current assets. The variables load 88%, 97.6%, 96.9%, -84.3%, 83.2%, 58.4%, and 91.6%, respectively. Most of the variables load high on component 3, which represents SMEs solvency ratios labeled "SMEs solvency ratios (PC_3)".

The fourth component (4) represents the Sales/total assets (91.9%), Cost of sales/sales (94.5%), and

Working capital/operating (93.4%). These variables represent the activity ratios of SMEs, thus, the principal component 4 is labelled “SMEs activity ratios (PC_4)”.

The fifth component (5) loads with Current assets/total asset (95.1%), Accounts receivable/inventories (92.4%), Inventories/total assets (89%), and Cash/total assets (-52%). The variables load high on component five that represents structure ratios, thus, component 5 is labelled the “SMEs structure ratios (PC_5)”.

The sixth component (6) has two highly loading variables (Current assets – inventories)/current liabilities (96.6%) and Current assets/current liabilities (93.4%). Both variables represent the ability of SMEs to use their quick assets to extinguish their current liabilities, hence, the component is labelled “SMEs acid-test ratio (PC_6)”.

The final seventh component (7) has two highly loading variables: The logarithm of total sales (82.9%) and Sales/capital stock (61%). Both variables represent other financial ratios, and the component is labelled “SMEs extra financial ratios (PC_7)”.

Based on the component matrix provided Table **13** in the Appendix, the equations for the seven principal components are presented as follows.

$$PC_1 = 0.184X_1 + 0.055X_2 + 0.096X_3 + 0.192X_4 + 0.25X_5 + 0.168X_6 + 0.052X_7 - 0.006X_8 + 0.263X_9 - 0.812X_{10} - 0.798X_{11} - 0.662X_{12} - 0.652X_{13} + 0.592X_{14} + 0.681X_{15} + 0.676X_{16} - 0.901X_{17} + 0.57X_{18} + 0.419X_{19} + 0.633X_{20} + 0.014X_{21} + 0.023X_{22} + 0.037X_{23} + 0.013X_{24} + 0.004X_{25} + 0.025X_{26} + 0.011X_{27} - 0.654X_{28} - 0.65X_{29} - 0.13X_{30} + 0.365X_{31}$$

$$PC_2 = 0.938X_1 - 0.937X_2 + 0.562X_3 + 0.877X_4 + 0.879X_5 + 0.943X_6 + 0.222X_7 + 0.146X_8 + 0.881X_9 + 0.099X_{10} + 0.092X_{11} + 0.044X_{12} + 0.043X_{13} - 0.241X_{14} - 0.177X_{15} - 0.172X_{16} + 0.175X_{17} - 0.221X_{18} - 0.197X_{19} - 0.168X_{20} + 0.173X_{21} + 0.184X_{22} + 0.178X_{23} + 0.049X_{24} + 0.043X_{25} + 0.055X_{26} + 0.247X_{27} + 0.042X_{28} - 0.193X_{29} + 0.029X_{30} - 0.036X_{31}$$

$$PC_3 = 0.081X_1 + 0.155X_2 + 0.064X_3 + 0.159X_4 + 0.131X_5 + 0.066X_6 + 0.116X_7 + 0.111X_8 + 0.142X_9 + 0.457X_{10} + 0.508X_{11} + 0.635X_{12} + 0.653X_{13} + 0.59X_{14} + 0.664X_{15} + 0.66X_{16} - 0.27X_{17} + 0.558X_{18} + 0.433X_{19} + 0.629X_{20} + 0.217X_{21} + 0.219X_{22} + 0.214X_{23} + 0.079X_{24} + 0.057X_{25} + 0.088X_{26} + 0.334X_{27} + 0.646X_{28} + 0.589X_{29} + 0.114X_{30} - 0.315X_{31}$$

$$PC_4 = -0.111X_1 + 0.055X_2 - 0.016X_3 - 0.041X_4 - 0.044X_5 - 0.109X_6 - 0.042X_7 + 0.062X_8 - 0.112X_9 - 0.04X_{10} - 0.045X_{11} - 0.076X_{12} - 0.069X_{13} - 0.112X_{14} - 0.115X_{15} - 0.111X_{16} + 0.074X_{17} - 0.106X_{18} + 0.297X_{19} - 0.094X_{20} + 0.611X_{21} + 0.696X_{22} + 0.743X_{23} + 0.751X_{24} + 0.706X_{25} + 0.778X_{26} - 0.31X_{27} - 0.064X_{28} - 0.046X_{29} - 0.29X_{30} + 0.043X_{31}$$

$$PC_5 = -0.112X_1 + 0.063X_2 - 0.05X_3 - 0.065X_4 - 0.04X_5 - 0.11X_6 + 0.415X_7 + 0.39X_8 - 0.121X_9 - 0.031X_{10} - 0.037X_{11} - 0.067X_{12} - 0.064X_{13} - 0.122X_{14} - 0.067X_{15} - 0.065X_{16} + 0.037X_{17} - 0.088X_{18} + 0.184X_{19} - 0.052X_{20} + 0.56X_{21} + 0.54X_{22} + 0.513X_{23} - 0.582X_{24} - 0.538X_{25} - 0.488X_{26} + 0.352X_{27} - 0.062X_{28} - 0.092X_{29} - 0.108X_{30} - 0.002X_{31}$$

$$PC_6 = -0.066X_1 + 0.071X_2 + 0.062X_3 + 0.057X_4 - 0.037X_5 - 0.066X_6 + 0.809X_7 + 0.857X_8 - 0.044X_9 - 0.015X_{10} - 0.014X_{11} + 0.001X_{12} - 0.003X_{13} - 0.065X_{14} + 0.022X_{15} + 0.015X_{16} - 0.025X_{17} + 0.06X_{18} - 0.133X_{19} + 0.008X_{20} - 0.189X_{21} - 0.144X_{22} - 0.188X_{23} + 0.143X_{24} + 0.27X_{25} + 0.059X_{26} - 0.272X_{27} + 0.006X_{28} + 0.036X_{29} + 0.251X_{30} + 0.107X_{31}$$

$$PC_7 = 0.011X_1 + 0.062X_2 - 0.098X_3 + 0.007X_4 + 0.053X_5 + 0.018X_6 - 0.111X_7 - 0.147X_8 - 0.025X_9 - 0.022X_{10} - 0.023X_{11} + 0.042X_{12} + 0.042X_{13} + 0.104X_{14} - 0.071X_{15} - 0.089X_{16} + 0.027X_{17} + 0.29X_{18} - 0.203X_{19} - 0.134X_{20} + 0.234X_{21} + 0.186X_{22} + 0.019X_{23} + 0.071X_{24} + 0.08X_{25} - 0.132X_{26} + 0.067X_{27} + 0.057X_{28} - 0.001X_{29} + 0.757X_{30} + 0.604X_{31}$$

4.3. Logistic Regression Model

In order to establish which principal components should be included in the logistic regression model in eq. (2), we derive the scores in Table **6**. The variables removed from the model are PC_1, PC_2, PC_3, PC_4, PC_5, and PC_7. Based on the sample data obtained from Saudi Arabian SMEs, these factors have *p*-values greater than 0.05, indicating that they do not influence the defaulting of Saudi Arabian SMEs. Consequently, only PC_6 will be considered in the logistic regression.

The estimation results of the logistic model are illustrated in Table **7**. The first factor added in step one is PC_6 (SMEs acid-test ratio). Hence, only one model is significant with one independent variable, PC_6. The component is statistically significant at 5% confidence level. The pseudo-R^2 for step 1 is 0.117. Overall, the pseudo-R^2 should increase with every step and might be concluded that model 1 shows good variation in the dependent variable.

To test the suitability of using the logistic regression, particularly for risk estimation models, we apply the Hosmer-Lemeshow (HL) test. A suitable goodness fit indicates how well the data suits the model. Table **8**

Table 6: Variables Removed from the Model

	Variable	Score	*dof*	*p*-value
Step 1	PC_1	0.003	1	0.959
	PC_2	1.956	1	0.162
	PC_3	3.096	1	0.078
	PC_4	2.024	1	0.155
	PC_5	1.327	1	0.249
	PC_7	0.433	1	0.511
	Overall Statistics	8.739	6	0.189

Note: This table reports the variables excluded from the regression. *dof* stands for the degrees-of-freedom.

Table 7: Logistic Model Estimation Results

Variable			Standard error	*p*-value	Log-likelihood	Cox & Snell R^2	Pseudo-R^2
Step 1	PC_6	-2.085	0.581	0.000	226.97	0.086	0.117
	Constant	0.672	0.174	0.000			

Note: This table reports the estimation results for the logistic model. Estimation terminated at iteration 6 because parameter estimates changed by less than 0.001.

Table 8: Hosmer-Lemeshow Test

Step	Chi-square	Degrees-of-freedom	*p*-value
1	14.740	8	0.064

presents the HL test results and the model is fitting the data with significance level > 0.05.

The classification of the data in Table **9** highlights the percentage step 1 that explains the data. The overall rating for step 1 is 70.5%.

Using the output data in Table **7**, the final equation predicting SMEs risk of defaulting is:

$$\text{Probability of default} = \frac{1}{1 + e^{-(0.672 - 2.085\, PC_6)}} \qquad (3)$$

In summary, the analysis establishes that the most influential factors, based on the PCA and logistic regression model, are the SMEs acid-test ratios. This includes both “(Current assets – inventories)/current liabilities” and “Current assets/current liabilities”. The acid-test ratios represent the ability of SMEs to immediately settle their current liabilities by using their quick assets.

4.4. Policy Implication

The SME sector in emerging countries in general, and in Saudi Arabia in particular, is informationally opaque, which leads to bias in assessing the credit risk. The proposed model in eq. (3) that evaluates the probability of default of a SME based on its acid-test ratios brings a great deal of information to governments and financial institutions. Furthermore, the usually employed default prediction models by financial institutions are mainly designed for large corporations, hence, applying these models to SMEs will likely result in poor performance. However, the crucial question is whether policy makers should use variants of the proposed model to identify troubled companies in the SME sector.

Researchers agreed that credit risk evaluation for large companies differs from SMEs. Therefore, financial institutions should employ appropriate tools to accommodate for the peculiarities of SMEs. Consequently, they should employ specific risk

Table 9: Classification Table

		Observed		Predicted credit rating	
				Defaulted	Correct (%)
Step 1	Credit rating	No default	26	44	37.1%
		Defaulted	10	103	91.2%
	Overall rating				70.5%

Note: The cut value is 0.5.

assessment models, which consider the scarce financial information provided by SMEs managers in order to avoid bias in the probability of default. A policy implication that seems reasonable is to urge financial institutions to separate the credit risk assessment for large companies and SMEs, and to employ a version of the proposed model that accounts for the features of small and medium-sized enterprises depending on the country's regulations.

5. CONCLUSION AND RECOMMENDATIONS

This study aims to construct a statistical model using both factor analysis with the principal component method, and logistic regression to predict SMEs default on loans. The model's outcome is a score, which represents the probability of default of the SME. Application is conducted on a sample of 61 Saudi Arabian SMEs. The financial data of the SMEs from 2017 to 2019 is collected from Saudi stock exchange market, Tadawul. The study includes 51 independent variables and one dependent variable. The principal component analysis (PCA) reduces the 51 independent variables to seven major variables: SMEs profitability ratios (PC_1), SMEs liquidity ratios (PC_2), SMEs solvency ratios (PC_3), SMEs activity ratios (PC_4), SMEs structure ratios (PC_5), SMEs acid-test ratio (PC_6), and SMEs extra financial ratios (PC_7). The seven variables are added to a logistic regression model. Based on the results, the most influential factor in predicting SMEs credit risk is PC_6 or the SMEs acid-test ratios calculated as: (current assets – inventories)/current liabilities, and Current assets/current liabilities. The designed logistic model can be used by banks during the decision-making process of granting loans to small and medium-sized enterprises.

The derived model is simple and requires little interpretation even for individuals without prior statistical or information technology knowledge. Hence, creditors can use this study's model to evaluate the trade credit risk of SMEs of other emerging and frontier markets. In addition, collecting the required data is not a complicated procedure. Since most SMEs submit financial statements every year and banks have access to their financial data. Financial ratios and their trends (calculated for different periods) should provide crucial information about the credit health status of SMEs. In addition, SMEs acid-test ratios should help predict the future solvency of SMEs.

This research is limited by applying a non-random procedure of sampling due of the sensitivity of the topic. However, the research took steps to mitigate the possibility of sampling bias or errors by approaching different SMEs across different sectors and industries in Saudi Arabia. It is recommended that future studies examine credit risk by including nonfinancial ratios. This would give creditors the option to complement the financial ratios used in this study, since some SMEs may not have readily available financial data. Future research can extend the derived model to other markets, to determine whether the same financial ratios can be used to determine the credit risk of SMEs. This would help confirm the validity of the developed PCA and logistic model as well as proving the model goodness of fit.

APPENDIX

Table 10: Anti-Image Correlation Matrix

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	X25	X26	X27	X28	X29	X30	X31
X1	0.7	0.8	0.0	0.0	0.1	0.7	0.0	0.1	0.0	0.0	0.1	0.1	0.2	-0.1	0.0	0.3	0.0	-0.7	0.1	-0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.1	-0.2	-0.1	0.0	0.7
X2	0.8	0.5	0.0	-0.1	0.0	1.0	0.0	0.1	-0.1	0.0	0.2	0.1	0.2	-0.2	0.0	0.4	0.0	-1.0	0.1	-0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.2	-0.2	-0.1	0.0	0.9
X3	0.0	0.0	0.8	-0.1	0.0	0.0	0.0	-0.3	0.3	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.1	0.0	0.0	0.0	0.1	0.0	0.1	0.1	0.0
X4	0.0	-0.1	-0.1	0.9	-0.4	-0.2	0.0	-0.3	0.3	0.0	-0.1	0.1	0.1	0.1	-0.1	-0.1	0.0	0.1	-0.1	0.1	0.0	-0.1	0.1	0.0	0.2	0.0	-0.2	-0.1	-0.2	-0.1	-0.1
X5	0.1	0.0	0.0	-0.4	0.9	0.0	0.2	0.0	-0.1	0.1	0.1	0.1	-0.1	-0.1	0.0	-0.2	-0.2	-0.1	0.3	0.2	0.3	-0.1	0.0	0.0	-0.1	0.0	-0.1	0.1	0.2	0.1	0.1
X6	0.7	1.0	0.0	-0.2	0.0	0.5	0.0	0.2	-0.1	0.0	0.2	0.0	0.1	-0.2	0.0	0.4	0.0	-1.0	0.1	-0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.2	-0.2	0.0	0.0	0.9
X7	0.0	0.0	0.0	0.0	0.2	0.0	0.9	-0.1	0.0	0.1	0.2	-0.1	-0.2	0.0	0.1	0.0	0.0	0.0	0.3	0.0	-0.1	-0.2	0.2	0.2	0.2	-0.3	0.2	0.2	0.1	0.0	0.1
X8	0.1	0.1	-0.3	-0.3	0.0	0.2	-0.1	0.4	-0.8	0.0	0.1	-0.1	0.0	0.0	0.1	0.1	0.0	-0.1	0.0	-0.1	-0.2	0.1	-0.1	0.0	-0.2	0.1	0.2	0.0	-0.1	0.0	0.1
X9	0.0	-0.1	0.3	0.3	-0.1	-0.1	0.0	-0.8	0.5	0.0	-0.1	0.0	0.1	0.3	-0.1	0.0	0.0	0.1	-0.1	0.0	0.2	-0.1	0.0	0.0	0.1	0.0	-0.2	-0.1	0.1	0.0	-0.1
X10	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	1.0	-0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	-0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0
X11	0.1	0.2	0.0	-0.1	0.1	0.2	0.2	0.1	-0.1	-0.4	0.6	-0.5	-0.8	0.3	0.0	0.0	-0.2	-0.2	0.3	0.0	-0.2	0.0	0.0	0.3	0.1	-0.3	0.2	0.8	0.5	-0.2	0.4
X12	0.1	0.1	0.0	0.1	0.1	0.0	-0.1	-0.1	0.0	0.0	-0.5	0.6	0.7	-0.2	-0.1	-0.6	-0.6	-0.1	-0.1	0.6	0.3	0.0	0.0	-0.1	-0.1	0.2	-0.1	-0.7	-0.3	0.1	0.0
X13	0.2	0.2	0.0	0.1	-0.1	0.1	-0.2	0.0	0.1	0.0	-0.8	0.7	0.6	-0.3	0.0	0.0	0.1	-0.1	-0.4	0.0	0.3	0.0	0.0	-0.2	-0.1	0.2	-0.2	-1.0	-0.5	0.2	-0.1
X14	-0.1	-0.2	0.1	0.1	-0.1	-0.2	0.0	0.0	0.3	0.0	0.3	-0.2	-0.3	0.8	0.0	-0.2	-0.1	0.0	-0.2	0.2	0.0	0.0	0.0	0.0	0.2	0.0	-0.1	0.3	0.2	0.1	0.0
X15	0.0	0.0	0.0	-0.1	0.0	0.0	0.1	0.1	-0.1	0.0	0.0	-0.1	0.0	0.0	1.0	-0.1	0.1	0.0	0.1	0.0	-0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	-0.2	0.0
X16	0.3	0.4	0.0	-0.1	-0.2	0.4	0.0	0.1	0.0	0.0	0.0	-0.6	0.0	-0.2	-0.1	0.6	0.9	-0.3	-0.2	-1.0	-0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	-0.1	0.1	0.3
X17	0.0	0.0	0.0	0.0	-0.2	0.0	0.0	0.0	0.0	0.0	-0.2	-0.6	0.1	-0.1	0.1	0.9	0.7	0.1	-0.3	-0.9	-0.1	0.0	0.0	-0.1	0.1	0.0	-0.1	-0.1	-0.2	0.1	-0.2
X18	-0.7	-1.0	0.0	0.1	-0.1	-1.0	0.0	-0.1	0.1	0.0	-0.2	-0.1	-0.1	0.0	0.0	-0.3	0.1	0.5	-0.1	0.3	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	0.1	0.0	0.0	-1.0
X19	0.1	0.1	0.0	-0.1	0.3	0.1	0.3	0.0	-0.1	0.1	0.3	-0.1	-0.4	-0.2	0.1	-0.2	-0.3	-0.1	0.7	0.2	-0.2	0.0	0.0	0.1	0.0	-0.1	0.2	0.4	0.1	0.1	0.1
X20	-0.3	-0.4	0.0	0.1	0.2	-0.4	0.0	-0.1	0.0	0.0	0.0	0.6	0.0	0.2	0.0	-1.0	-0.9	0.3	0.2	0.6	0.1	0.0	0.0	0.0	-0.1	0.0	0.0	0.0	0.1	0.0	-0.3
X21	0.0	0.0	0.0	0.0	0.3	0.0	-0.1	-0.2	0.2	0.0	-0.2	0.3	0.3	0.0	-0.1	-0.1	-0.1	0.0	-0.2	0.1	0.7	-0.1	-0.1	-0.1	-0.1	0.1	-0.3	-0.3	0.1	0.0	-0.1
X22	0.0	0.0	-0.1	-0.1	-0.1	0.0	-0.2	0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.4	-1.0	-0.8	0.0	0.9	0.1	0.0	0.0	0.0	0.0
X23	0.0	0.0	0.1	0.1	0.0	0.0	0.2	-0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	-1.0	0.4	0.8	0.0	-0.9	0.0	0.0	0.0	0.0	0.0

X24	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	-0.1	0.3	-0.1	-0.2	0.0	0.1	0.0	-0.1	0.0	0.1	0.0	-0.1	-0.8	0.8	0.4	-0.2	-1.0	0.1	0.2	0.1	-0.3	0.1
X25	0.0	0.0	0.0	0.2	-0.1	0.0	0.2	-0.2	0.1	0.0	0.1	-0.1	-0.1	0.2	0.0	0.1	0.1	0.0	0.0	-0.1	-0.1	0.0	0.0	-0.2	0.9	0.0	0.1	0.1	0.1	0.0	0.1
X26	0.0	0.0	0.0	0.0	0.0	0.0	-0.3	0.1	0.0	0.1	-0.3	0.2	0.2	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	0.1	0.9	-0.9	-1.0	0.0	0.4	0.0	-0.2	-0.1	0.3	-0.1
X27	0.1	0.2	0.1	-0.2	-0.1	0.2	0.2	0.2	-0.2	0.0	0.2	-0.1	-0.2	-0.1	0.1	0.0	-0.1	-0.2	0.2	0.0	-0.3	0.1	0.0	0.1	0.1	0.0	0.6	0.1	0.5	0.0	0.2
X28	-0.2	-0.2	0.0	-0.1	0.1	-0.2	0.2	0.0	-0.1	0.0	0.8	-0.7	-1.0	0.3	0.0	0.0	-0.1	0.1	0.4	0.0	-0.3	0.0	0.0	0.2	0.1	-0.2	0.1	0.6	0.4	-0.2	0.1
X29	-0.1	-0.1	0.1	-0.2	0.2	0.0	0.1	-0.1	0.1	0.0	0.5	-0.3	-0.5	0.2	0.0	-0.1	-0.2	0.0	0.1	0.1	0.1	0.0	0.0	0.1	0.1	-0.1	0.5	0.4	0.7	0.0	0.1
X30	0.0	0.0	0.1	-0.1	0.1	0.0	0.0	0.0	0.0	0.1	-0.2	0.1	0.2	0.1	-0.2	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0	-0.3	0.0	0.3	0.0	-0.2	0.0	0.6	-0.1
X31	0.7	0.9	0.0	-0.1	0.1	0.9	0.1	0.1	-0.1	0.0	0.4	0.0	-0.1	0.0	0.0	0.3	-0.2	-1.0	0.1	-0.3	-0.1	0.0	0.0	0.1	0.1	-0.1	0.2	0.1	0.1	-0.1	0.2

Table 11: Total Variables Explained

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.394	20.627	20.627	6.394	20.627	20.627	5.749	18.545	18.545
2	5.843	18.849	39.476	5.843	18.849	39.476	5.573	17.978	36.523
3	4.761	15.359	54.835	4.761	15.359	54.835	5.520	17.805	54.328
4	3.482	11.231	66.066	3.482	11.231	66.066	2.909	9.384	63.712
5	2.339	7.546	73.612	2.339	7.546	73.612	2.886	9.310	73.022
6	1.779	5.740	79.351	1.779	5.740	79.351	1.886	6.085	79.107
7	1.289	4.158	83.510	1.289	4.158	83.510	1.365	4.403	83.510
8	0.937	3.023	86.533						
9	0.850	2.741	89.274						
10	0.714	2.303	91.577						
11	0.608	1.962	93.539						
12	0.436	1.407	94.945						
13	0.328	1.059	96.005						
14	0.282	0.909	96.914						
15	0.237	0.764	97.678						
16	0.191	0.616	98.294						
17	0.133	0.428	98.722						
18	0.110	0.353	99.075						
19	0.076	0.245	99.321						
20	0.071	0.229	99.550						
21	0.062	0.201	99.751						
22	0.041	0.132	99.884						
23	0.022	0.070	99.953						
24	0.006	0.018	99.972						
25	0.003	0.010	99.982						
26	0.003	0.009	99.990						
27	0.002	0.005	99.996						
28	0.001	0.004	99.999						
29	0.000	0.001	100.000						
30	0.000	0.000	100.000						
31	0.000	0.000	100.000						

Table 12: Rotated Component Matrix

Variable	Component						
	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7
EBIT/sales (X_1)	0.973	-0.025	-0.003	0.011	-0.026	-0.016	0.030
EBT/sales (X_2)	-0.897	0.025	0.336	-0.014	0.022	0.008	0.053
Net profit/sales (X_3)	0.572	0.000	-0.005	0.006	0.037	0.108	-0.069
EBT/equity (X_4)	0.905	0.010	0.058	0.063	0.027	0.114	0.038
EBT/(equity - current liabilities) (X_5)	0.914	-0.053	0.075	0.107	-0.016	0.029	0.062
Net profit/equity (X_6)	0.973	-0.024	-0.026	0.013	-0.025	-0.017	0.037
Current assets/current liabilities (X_7)	0.146	0.009	0.033	0.060	-0.086	0.934	0.042
(Current assets - inventories)/current liabilities (X_8)	0.053	0.038	0.000	0.081	0.017	0.966	0.004
Accounts receivable/total liabilities (X_9)	0.939	-0.041	0.107	-0.001	-0.013	0.007	0.001
Accounts receivable/(total liabilities - cash) (X_{10})	0.011	0.905	-0.244	0.028	-0.016	0.009	-0.037

Cash/current liabilities (X_{11})	0.014	0.931	-0.197	0.029	-0.015	0.010	-0.036
Cash/total liabilities (X_{12})	0.009	0.924	-0.003	0.022	-0.013	0.007	0.036
Working capital/total assets (X_{13})	0.010	0.928	0.016	0.033	-0.011	0.006	0.033
Working capital/equity (X_{14})	-0.042	-0.008	0.880	-0.014	-0.008	-0.098	0.111
(Current liabilities - cash)/total assets (X_{15})	0.036	-0.025	0.976	-0.013	-0.021	0.043	-0.043
Equity/total liabilities (X_{16})	0.039	-0.025	0.969	-0.012	-0.021	0.040	-0.062
Fixed assets/equity (X_{17})	-0.025	0.458	-0.843	0.027	0.012	-0.025	-0.003
Current assets/(total liabilities - cash) (X_{18})	-0.045	-0.017	0.832	0.016	0.005	-0.005	0.313
Accounts receivable/sales (X_{19})	-0.117	-0.054	0.584	0.375	0.067	0.001	-0.282
Sales/current assets (X_{20})	0.031	-0.018	0.916	-0.007	-0.020	0.044	-0.110
Sales/total assets (X_{21})	0.059	0.043	0.008	0.919	0.024	0.030	0.052
Cost of sales/sales (X_{22})	0.064	0.032	0.007	0.945	0.110	0.073	0.006
Working capital/operating expenses (X_{23})	0.065	0.017	0.016	0.934	0.151	0.052	-0.169
Current assets/total asset (X_{24})	0.051	0.040	0.031	0.132	0.951	-0.086	0.040
Accounts receivable/inventories (X_{25})	0.034	0.030	0.011	0.095	0.924	0.041	0.079
Inventories/total assets (X_{26})	0.053	0.026	0.037	0.191	0.890	-0.091	-0.186
Cash/total assets (X_{27})	0.270	0.222	0.183	0.192	-0.520	-0.085	0.018
Retained earnings/total assets (X_{28})	0.007	0.924	0.009	0.037	-0.006	0.012	0.049
Current liabilities/(total liabilities - cash) (X_{29})	-0.222	0.875	0.025	-0.029	0.035	0.013	0.000
The logarithm of total sales (X_{30})	0.030	0.208	0.007	-0.146	-0.078	0.064	0.829
Sales/capital stock (X_{31})	-0.028	-0.480	0.019	0.073	0.057	-0.028	0.610

Note: Extraction method: principal component analysis. Rotation method: VARIMAX with Kaiser normalization. Rotation converged after 5 iterations.

Table 13: Component Matrix

Variable	Component						
	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7
EBIT/sales (X_1)	0.184	0.938	0.081	-0.111	-0.112	-0.066	0.011
EBT/sales (X_2)	0.055	-0.937	0.155	0.055	0.063	0.071	0.062
Net profit/sales (X_3)	0.096	0.562	0.064	-0.016	-0.050	0.062	-0.098
EBT/equity (X_4)	0.192	0.877	0.159	-0.041	-0.065	0.057	0.007
EBT/(equity - current liabilities) (X_5)	0.250	0.879	0.131	-0.044	-0.040	-0.037	0.053
Net profit/equity (X_6)	0.168	0.943	0.066	-0.109	-0.110	-0.066	0.018
Current assets/current liabilities (X_7)	0.052	0.222	0.116	-0.042	0.415	0.809	-0.111
(Current assets - inventories)/current liabilities (X_8)	-0.006	0.146	0.111	0.062	0.390	0.857	-0.147
Accounts receivable/total liabilities (X_9)	0.263	0.881	0.142	-0.112	-0.121	-0.044	-0.025
Accounts receivable/(total liabilities - cash) (X_{10})	-0.812	0.099	0.457	-0.040	-0.031	-0.015	-0.022
Cash/current liabilities (X_{11})	-0.798	0.092	0.508	-0.045	-0.037	-0.014	-0.023
Cash/total liabilities (X_{12})	-0.662	0.044	0.635	-0.076	-0.067	0.001	0.042
Working capital/total assets (X_{13})	-0.652	0.043	0.653	-0.069	-0.064	-0.003	0.042
Working capital/equity (X_{14})	0.592	-0.241	0.590	-0.112	-0.122	-0.065	0.104
(Current liabilities - cash)/total assets (X_{15})	0.681	-0.177	0.664	-0.115	-0.067	0.022	-0.071
Equity/total liabilities (X_{16})	0.676	-0.172	0.660	-0.111	-0.065	0.015	-0.089
Fixed assets/equity (X_{17})	-0.901	0.175	-0.270	0.074	0.037	-0.025	0.027
Current assets/(total liabilities - cash) (X_{18})	0.570	-0.221	0.558	-0.106	-0.088	0.060	0.290
Accounts receivable/sales (X_{19})	0.419	-0.197	0.433	0.297	0.184	-0.133	-0.203
Sales/current assets (X_{20})	-0.168	0.633	0.629	-0.094	-0.052	0.008	-0.134
Sales/total assets (X_{21})	0.173	0.014	0.217	0.611	0.560	-0.189	0.234
Cost of sales/sales (X_{22})	0.184	0.023	0.219	0.696	0.540	-0.144	0.186
Working capital/operating expenses (X_{23})	0.178	0.037	0.214	0.743	0.513	-0.188	0.019
Current assets/total asset (X_{24})	0.049	0.013	0.079	0.751	-0.582	0.143	0.071
Accounts receivable/inventories (X_{25})	0.043	0.004	0.057	0.706	-0.538	0.270	0.080
Inventories/total assets (X_{26})	0.055	0.025	0.088	0.778	-0.488	0.059	-0.132
Cash/total assets (X_{27})	0.247	0.011	0.334	-0.310	0.352	-0.272	0.067
Retained earnings/total assets (X_{28})	0.042	-0.654	0.646	-0.064	-0.062	0.006	0.057
Current liabilities/(total liabilities - cash) (X_{29})	-0.193	-0.650	0.589	-0.046	-0.092	0.036	0.000
The logarithm of total sales (X_{30})	0.029	-0.130	0.114	-0.290	-0.108	0.251	0.757
Sales/capital stock (X_{31})	-0.036	0.365	-0.315	0.043	-0.002	0.107	0.604

Note: Extraction method: principal component analysis. Seven components are extracted.

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Received on 23-05-2022 Accepted on 16-11-2022 Published on 21-11-2022

https://doi.org/10.6000/1929-7092.2022.11.04