

Research paper

The application of Principal Component Analysis in the Selection of Industry Specific Financial Ratios

Ben Chin-Fook Yap, Zulkifflee Mohamad and K-Rine Chong^{1*}

¹*Bank Rakyat School of Business & Entrepreneur, Universiti Tun Abdul Razak, Kuala Lumpur, Malaysia.*

ABSTRACT

Aims: This paper investigates the application of principal component analysis in the selection of financial ratios that are significant and representative for two industry sectors in Malaysia. Companies in different industries, even in the same country, have different operational, market and capital structures. Therefore, to use ratios that are found to be useful for one industry sector may not be valid for companies in another industry sector.

Study design: Research Paper.

Place and Duration of Study: Malaysia. Secondary data from 2006 to 2010.

Methodology: 70 and 40 companies from the consumer and trading and services sector respectively are randomly selected and analyzed over a period of five years. An initial set of 28 financial ratios were factor analysed to obtain a smaller set of significant and useful ratios.

Results: The results showed that only seven ratios out of 28, for each sector were identified as representative ratios. It is found that three ratios, earnings before interest and tax, total debts to total assets and current asset turnover, are the only ratios that were selected for both industries indicating that these three ratios are considered equally useful for these two industries while the others are more specific to their industry sector.

Conclusion: This study showed that it is not necessary to use the many ratios that are found in the literature for assessing financial performances or the financial conditions of companies and a smaller set of representative ratios are sufficient and that financial ratios are industry specific and cannot be applied across industries.

Keywords: *Financial ratios; Factor analysis; Principal Component Analysis.*

1. INTRODUCTION

Financial ratios are used extensively for various purposes including assessment of company financial performance, credit and bond ratings, prediction of failures, evaluations of company efficiency and management's success in steering a company's operating and financials in the right direction. Financial analysts and accountants have often used ratios to forecast future profits and liquidity and solvency positions. Researchers use ratios for predicting possible company failures and assessment of risks [see 1,2,3]. Single ratios or a group of ratios are often used in both univariate and multivariate studies. Chen and Shimerda [4]

found that there were 65 accounting ratios that have been used in 26 past studies. Their study found that out of the seven most popularly used ratios, three ratios measure profitability and liquidity respectively while only one ratios measure solvency. In another study by Hossari and Rahman [5], they identified 48 ratios used in 53 studies and found that out of the ten most commonly used ratios, four each measure profitability and liquidity respectively and two measure solvency. Courtis [6] said that financial ratios have become an accepted evaluative technique of financial analysts. His examination of 12 studies found 28 ratios as useful in assessing corporate distress. Eidleman [7] states that different ratio information can address different issues and concerns to different stakeholders. According to Gibson [8], of particular interest to analysts are financial ratios that pertain to various important parts of the financial statements.

There are so many financial ratios that can be computed from the financial data found in a set of financial statements. Different researchers in different studies would have used different ratios and they would naturally have found varying usefulness in the specific ratios they have selected. It would not be necessary nor would it be beneficial to use all the ratios as many of the ratios overlap in terms of the meaning and interpretation of the ratios. Taffler [9] found that it is not necessary to used so many ratios as a smaller number of dominant ratios are sufficient to achieve the objectives of his study.

Companies in different industries, even in the same country, have different operational, market and capital structures. Therefore, to use ratios that are found to be useful for one industry sector may not be valid for companies in another industry sector. Furthermore, ratios that are found to be significant at a point in time may not show similar explanatory results when used over a period of time due to changes in the economic environment, market conditions and government regulatory changes. Furthermore, ratios found to be significant in company failure studies may not be useful in ratings of bonds and equities or credit and loan evaluation.

Factor analysis was described by Hair et al. [10] as a statistical tool that is used to analyze the interrelationships among a large number of variables and to explain these variables in terms of their common underlying factors with a minimum loss of information.

Factor analysis on financial ratios was first used by Pinches et al. [11] to try to develop an empirically-based classification of financial ratios as well as trying to measure the stability these classifications. According to Ali and Charbaji [12], since the Pinches study mentioned above, research on the use of factor analysis with financial ratios have developed in two main directions namely using factor analysis to test and develop theoretical ratio structures and as another multivariate method to reduce the number of ratios used in studies for predicting bond ratings, corporate failures, market crashes, and corporate acquisitions. Their study used 42 financial ratios and after applying factor analysis, five factors were found to be significant as they explain 72% of the ratio variances. Tan et al. [13] used the factor analysis on 29 financial ratios in a Singapore study and found 8 underlying factors. Öcal et al. [14] applied factor analysis on 25 financial ratios on Turkish construction companies and found 5 underlying factors.

In Malaysia, studies and researches using a carefully selected set of financial ratios through factor analysis for analysis of financial statements are very limited not to mention the selection of significant ratios specific to different industry sectors. The objective of this paper is to investigates the application of principal component analysis in the selection of financial ratios that are specific and significant for the consumer products and trading and services sector in Malaysia. 28 ratios representing different measures are proposed and then factor analyzed to obtain a more parsimonious and more useful set of ratios for companies from two different industries sectors namely, the consumer products sector and the trading and

services sector. The former is associated with manufacturing consumer products while the latter is involved in retailing and provision of services. Factor analysis and more specifically, principal component analysis is used to select the financial ratios that are most useful for companies in each of the two industry sectors.

2. METHODOLOGY

2.1 Sample Size

In this study, financial statements from the annual reports of companies from the Consumer Products and the Trading and Services sectors as listed in the Bursa Saham Malaysia (Malaysian Stock Exchange) are used in this study. 70 companies from the Consumer Products and 40 companies from the Trading and Services sector would be randomly selected and analyzed over a period of five years from 2006 to 2010.

2.2 Selection of Variables

Twenty eight ratios are initially selected and classified into five groups. The ratios are chosen because they are commonly used in company financial performance forecasts. They are mainly taken from the studies by Hossari and Rahman [5], Tan et al. [13] and Pinches et al. [11]. The ratios are grouped under five main categories. The Categories they represent, the ratio variables and the codes used are:

A) <u>Short Term Liquidity</u>	<u>Codes</u>
A1. Working Capital Ratio	WCR
A2. Quick Ratio	QR
A3. Interest Cover	IC
A4. Working Capital/Sales	WCS
A5. Cash Flow/Sales	CFS
A6. Cash Flow/Total Assets	CFTA
A7. Cash Flow/Total Debts	CFTD
B) <u>Cash Position</u>	
B1. Cash/Sales	CS
B2. Cash/Total Assets	CTA
B3. Cash/Current Liabilities	CCL
B4. Cash/Total Debts	CTD
C) <u>Profitability</u>	
C1. Earnings Before Interest and Tax/Sales	EBITS
C2. Earnings Before Interest and Tax/Total Assets	EBITTA
C3. Net Profit Margin	NP
C4. Net Income/Total Assets	NITA
C5. Net Income/Shareholders Fund	NISF
C6. Net Income/Total Debts	NITD
C7. Retained Profit/Total Assets	RPTA
D) <u>Solvency and Financial Leverage</u>	
D1. Total Debts/Shareholders Fund	TDSF
D2. Total Debts/Total Assets	TDTA
D3. Long Term Debts/Total Assets	LTDTA
D4. Long Term Debt/Shareholders Fund	LTDSF

136		
137		
138	E) <u>Operating Asset Efficiency and</u>	
139	E1. Debtors Turnover	DT
140	E2. Debtors Collection Days	DD
141	E3. Inventory Turnover	IT
142	E4. Inventory Average Days	ID
143	E5. Total Assets Turnover	TAT
144	E6. Current Assets Turnover	CAT
145		

146 2.3 Analysis Techniques

147 *Factor Analysis and Principal Component Analysis*

148 Jolliffe [15] pointed out that “the central idea of principal component analysis is to reduce the
149 dimensionality of a data set in which there are a large number of interrelated variables, while
150 retaining as much as possible of the variation present in the data set”.

151 The reduction will result in a new set of variables called the principal components which are
152 not correlated and where the first few components retain most of the variation that was
153 present in all the original variables.

154 Principal components in a set of data can be explained as follows:

155 Assumed that the random vector $Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_p \end{bmatrix}$ has the covariance matrix Σ . Since we will be
156 interested only in the variance-covariance structure, we assume that the mean vector is 0.
157 Let l be a p -component column vector such that $l^t l = 1$. The variance of $l^t Y$ is $E(l^t Y Y^t l) = l^t \Sigma l$.

158 The i 'th Principal Component, usually denoted by PC_1 , can be defined inductively. The first
159 principal component PC_1 is the linear combination where $l_1^t Y$ where l_1 is the vector which
160 maximizes $\text{Var}(l_1^t Y)$ subject to $l_1^t l_1 = 1$.

161 The second principal component PC_2 is the linear combination $l_2^t Y$ where l_2 maximizes
162 $\text{Var}(l_2^t Y)$ subject to $l_2^t l_2 = 1$ and $\text{Cov}(l_2^t Y, l_1^t Y) = 0$. Similarly, the i 'th principal component $PC_i =$
163 $l_i^t Y$ where l_i maximizes $\text{Var}(l_i^t Y)$ subject to $l_i^t l_i = 1$ and $\text{Cov}(l_i^t Y, l_k^t Y) = 0$ for $k < i$.

164 Thus, the first principal component has the largest variance among all standardized linear
165 combinations of Y . Similarly, the second principal component has the largest variance
166 among all standardized linear combinations of Y uncorrelated with the first principal
167 component, and so on.

168 Using principal component analysis is most appropriate in this study as the objective is to
169 obtain the minimum number of factors to explain a maximum proportion of the variance
170 found in the original variables. Only factors with an eigenvalue of more than 1 will be
171 considered as significant and will be extracted. Tests of appropriateness will be undertaken
172 with the test of sphericity and well as tests to measure of sampling adequacy (MSA) will be
173 utilized. A minimum requirement of 0.5 is necessary for the adequacy of the sampling
174 adequacy. The measure of sampling adequacy is measured by the Kaiser-Meyer-Olkin
175 (KMO) statistic. Principal component analysis requires that the probability associated with
176 Bartlett's Test of Sphericity be less than the level of significance.

177 When evaluating measures of sampling adequacy, communalities, or factor loadings, we
178 ignore the sign of the numeric value and base our decision on the size or magnitude of the

value. The sign of the number indicates the direction of the relationship. The minus sign indicates an inverse or negative relationship; the absence of a sign is meant to imply a plus sign indicating a direct or positive relationship. Communalities represent the proportion of the variance in the original variables that is accounted for by the factor solution. The factor solution should explain at least half of each original variable's variance, so the communality value for each variable should be 0.50 or higher.

Principal component analysis (PCA) will be applied to the 28 ratios to reduce the number of interrelated variables and to obtain only the more significant variables which are uncorrelated. The significant variables obtained are linear combinations of the original variables and are called principal components. The values given to these new variables are called factor scores or factor loadings. Factor scores are the scores of each case on each factor. In PCA this is also known as the component score. The factor score for a case is the multiplication of the case's score on each variable and the corresponding factor loading of the variable. A benefit of calculating the factor scores is that they may be used to find factor outliers.

To assist in the interpretation of the analysis, rotation of the factors is undertaken. Factor rotation will not affect the amount of variance extracted nor the number of factors extracted. There are two types of factor rotation methods, namely the orthogonal and the oblique rotation methods. The orthogonal methods are more popular and are the preferred method when the objective is data reduction and the outcome is a structure matrix which is a matrix of the factor loadings. The objective of the oblique rotation methods is to obtain several theoretically meaningful factors. The outcomes of the oblique rotation are a structure matrix as in the orthogonal methods as well as a pattern matrix.

This study will use the orthogonal methods of factor rotation as the main objective of using factor analysis is data reduction. There are several orthogonal methods such as Quatimax, Varimax and Equimax. The most popular and common method is the Varimax method and this method from SPSS will be used in this study. It maximizes the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix. Each of the factors obtained will have either large or small loadings of any particular variable. Examining the Varimax results will help the analyst to identify easily each variable with a single factor.

3. RESULTS AND DISCUSSION

3.1 Consumer Products

The sample consists of 70 companies over a period of 5 years giving a total of 350 cases. Seven variables were selected and the variable for each of the factor with the highest factor loadings are highlighted in bold. The seven variables are:

<u>Variables</u>	<u>Category</u>	<u>Factor Loadings</u>
(i) CTD	Cash Position	0.952
(ii) EBITTA	Profitability	0.923
(iii) CAT	Asset Efficiency	0.845
(iv) CFTA	Short-term Liquidity	0.888
(v) LTDSF	Solvency	0.915
(vi) TDTA	Solvency	-0.732
(vii) DT	Asset Efficiency	0.799

It is significant that two ratios that measure solvency (LTDSF and TDTA) and two ratios that measure efficiency (CAT and DT) are selected. The sampling adequacy was good with the

240 Kaiser-Meyer-Olkin (KMO) measure showing a P -value of 0.744. The P -value for the KMO
 241 measure should be greater than 0.05. The Bartlett's test of sphericity is significant at 0.000.
 242 The variables chosen all have eigenvalues of above 1. Table 1 below shows the factor
 243 loadings for the 28 ratios used in the factor analysis.

244
 245 **Table 1: Rotated Component Matrix for the Consumer Product sector**

Factors	1	2	3	4	5	6	7
CR	.831	.056	-.196	.020	-.053	.317	.035
QR	.873	.072	-.049	.056	-.044	.272	-.131
WCS	.457	.461	-.250	-.060	-.018	.496	.092
CFS	.241	.106	-.154	.858	.045	.158	-.094
CFTA	.212	.173	.146	.888	-.096	.101	.063
CFTD	.634	.127	.032	.648	-.109	.164	.035
IC	.682	.284	.077	.300	-.201	.152	.027
CS	.869	.108	-.168	.110	-1.493E-5	.055	-.060
CTA	.802	.168	.113	.203	-.166	.006	.107
CCL	.948	.036	-.065	.080	-.025	.076	.015
CTD	.952	.083	-.012	.134	-.107	.025	.041
EBITS	.058	.825	-.006	-.075	.102	.062	.010
EBBITA	.286	.923	.074	.306	-.192	.077	.107
NI	.043	.918	-.004	-.086	.108	.055	.004
NITA	.246	.868	.053	.280	-.169	.073	.073
NISF	.074	.821	.016	.171	-.255	.088	-.003
NITD	.625	.530	.026	.360	-.146	.070	.054
RPTA	.046	.463	-.045	.173	-.144	.583	.122
TDSF	-.206	-.035	.076	-.130	.328	-.679	.003
TDTA	-.468	-.068	.120	-.206	-.043	-.732	-.029
LTDSF	-.117	-.099	.066	-.039	.915	-.220	.031
LTDTA	-.183	-.102	.002	-.043	.907	-.049	.039
DT	-.034	.006	-.213	-.064	-.012	-.035	.799
DD	-.076	-.130	-.286	-.087	-.098	-.145	-.772
IT	.013	-.021	.731	-.085	.052	.053	-.111
ID	.038	.020	-.696	-.116	-.028	.242	.333
TAT	-.032	.183	.772	.001	-.283	-.091	.310
CAT	-.209	-.032	.845	.038	.177	-.083	.179

247 248 3.2 Trading and Services

249
 250 The sample consists of 40 companies over a period of 5 years giving a total of 200 cases.
 251 Seven variables were selected and the variable for each of the factor with the highest factor
 252 loadings are highlighted in bold and is shown in Table 2 below. The seven variables are:

Variables	Category	Factor loadings
(i) CCL	Cash Position	0.934
(ii) EBITTA	Profitability	0.887
(iii) CAT	Asset Efficiency	0.866
(iv) CFS	Short-term Liquidity	0.905
(v) TDTA	Solvency	0.904
(vi) TDSF	Solvency	-0.880
(vii) LTDTA	Solvency	0.913

It is significant that three ratios that measure solvency (TDTA, TDSF and LTDTA) are selected. The Kaiser-Meyer-Olkin measure of sampling adequacy is 0.630 which is acceptable. A value greater than 0.5 is considered the minimum value for Factor Analysis to proceed. The Bartlett's Test of Sphericity is significant with a *P*-value of 0.00. A significant *P*-value is necessary as it would mean that the correlation matrix is not an identity matrix. The first variable, CCL has an eigenvalue of 7.119 while the last variable, LTDTA has an eigenvalue of 1.661. The cut-off eigenvalue is set at 1.000 and above.

Table 2: Rotated Component Matrix for the Trading & Services sector

Factors	1	2	3	4	5	6	7
CR	.831	.056	-.196	.020	-.053	.317	.035
QR	.873	.072	-.049	.056	-.044	.272	-.131
WCS	.457	.461	-.250	-.060	-.018	.496	.092
CFS	.241	.106	-.154	.858	.045	.158	-.094
CFTA	.212	.173	.146	.888	-.096	.101	.063
CFTD	.634	.127	.032	.648	-.109	.164	.035
IC	.682	.284	.077	.300	-.201	.152	.027
CS	.869	.108	-.168	.110	-1.493E-5	.055	-.060
CTA	.802	.168	.113	.203	-.166	.006	.107
CCL	.948	.036	-.065	.080	-.025	.076	.015
CTD	.952	.083	-.012	.134	-.107	.025	.041
EBITS	.058	.825	-.006	-.075	.102	.062	.010
EBBITA	.286	.923	.074	.306	-.192	.077	.107
NI	.043	.918	-.004	-.086	.108	.055	.004
NITA	.246	.868	.053	.280	-.169	.073	.073
NISF	.074	.821	.016	.171	-.255	.088	-.003
NITD	.625	.530	.026	.360	-.146	.070	.054
RPTA	.046	.463	-.045	.173	-.144	.583	.122
TDSF	-.206	-.035	.076	-.130	.328	-.679	.003
TDTA	-.468	-.068	.120	-.206	-.043	-.732	-.029
LTDSF	-.117	-.099	.066	-.039	.915	-.220	.031
LTDTA	-.183	-.102	.002	-.043	.907	-.049	.039
DT	-.034	.006	-.213	-.064	-.012	-.035	.799
DD	-.076	-.130	-.286	-.087	-.098	-.145	-.772
IT	.013	-.021	.731	-.085	.052	.053	-.111
ID	.038	.020	-.696	-.116	-.028	.242	.333
TAT	-.032	.183	.772	.001	-.283	-.091	.310
CAT	-.209	-.032	.845	.038	.177	-.083	.179

3.3 Summary of the Findings

Table 3 below present a summary of the variables selected after factor analysis for all the three sectors. Of the initial 28 ratios that were factor analysed, seven ratios each were selected for the two industry sectors. EBITTA, CAT and TDTA are found in both sectors, while CCL, CFTA, LTDTA, TDSF, LTDSF, CFS, DT and CTD are found in one of the two sectors. To examine these ratios according to what they measure, **The table also show the breakdown of the selected ratios according to their ratio groupings.** From the table, the ratios measuring solvency and leverage seem to be significant with two ratios found in the consumer product sector and three in the trading and services sector. EBITTA that measures profitability, TDTA that measures solvency and CAT that measures efficiency are

the only ratios that are found in both the sectors. Ratios that measure the cash position and short term liquidity have one ratio in each of the sector.

Table 3: Summary of Financial Ratios as selected through Factor Analysis

FINANCIAL RATIOS	CATEGORY	CONSUMER PRODUCTS	TRADING & SERVICES	TOTAL
EBITTA	PROFITABILITY	X	X	2
CAT	ASSET EFFICIENCY	X	X	2
DT	ASSET EFFICIENCY	X		1
CFTA	SHORT-TERM LIQUIDITY	X		1
CFS	SHORT-TERM LIQUIDITY		X	1
CTD	CASH POSITION	X		1
CCL	CASH POSITION		X	1
TDTA	SOLVENCY	X	X	2
TDSF	SOLVENCY		X	1
LTDTA	SOLVENCY		X	1
LTDSF	SOLVENCY	X		1
TOTAL		7	7	14

4. CONCLUSION

There are so many financial ratios that can be computed from the financial data found in a set of financial statements. Different researchers in different studies would have used different ratios and they would naturally have found varying usefulness in the specific ratios they have selected. Companies in different industries, even in the same country, have different operational, market and capital structures. Therefore, to use ratios that are found to be useful for one industry sector may not be valid for companies in another industry sector. The purpose of this paper is to use a method of factor analysis, principal component analysis, to obtain a more parsimonious and useful smaller set of financial ratios from the many available ratios that are found in the literature. An initial set of 28 ratios from 70 companies in the consumer products sector and 40 companies in the trading and services sector over the period of five years from 2006 to 2010 are factor analysed. The aim is to analyse the interrelationships among this large number of ratios and to explain these ratios in terms of their common underlying factors with a minimum loss of information. The results showed that different ratios are found to be more significant than others for the two different industries used in this study. For the consumer product sector and the trading and services sector, the solvency and leverage ratios seem to be prominent with two and three ratios respectively being selected. For measures of short-term liquidity, cash position, profitability and operating assets efficiency, one ratio for each sector was selected. Three ratios, earnings before interest and tax, total debts to total assets and current asset turnover, are the only ratios that were selected for both industries indicating that these three ratios are considered useful for these two industries while the other ratios are useful only for their particular industry. This study will contribute to the very limited research studies in Malaysia on selecting and utilising the most significant and useful ratios when analyzing the financial statements of listed companies from two industry sectors.

The study is limited to two industry sectors namely, consumer products and the trading and services sectors. Not included in the study are companies in the industrial products, finance, property and construction, mining, plantations and others. Future research could expand the number of companies in the analysis as only about 50% and 23% of the total number of companies listed in the consumer and trading and services sector respectively are used.

Study of companies in the other sectors may show material differences in the choice of financial ratios that are useful compared to this study as companies in the other sectors have different capital structures, trading policies and processes as well as governed by different government and statutory regulations. It is recommended that special focus should be given to the significant ratios that are specific and effective for each industry sector and not apply the same ratios across different industries.

331

COMPETING INTERESTS

332

Authors have declared that no competing interests exist.

335

REFERENCES

336

1. Beaver WH. Financial ratios as predictors of failure. *Journal of Accounting Research*. 1966;4:71-111.
2. Altman EI. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*. 1968;23(4):589-609.
3. Merton R. On the pricing of corporate debt: The risk structure of Interest rates. *Journal of Finance*. 1974;29:449-470.
4. Chen KH, Shimerda TA. An empirical analysis of useful financial ratios. *Financial Management*. 1981;10(1):51-60.
5. Hossari G, Rahman S. A comprehensive formal ranking of the popularity of financial ratios in multivariate modeling of corporate collapse. *Journal of American Academy of Business*. 2005;6(1):321-327.
6. Courtis JK. Modelling a financial ratios categoric framework. *Journal of Business Finance & Accounting*. 1978;5(4):371-386.
7. Eidleman GJ. Z scores—A guide to failure prediction. *The CPA Journal*. 1995;65(2):52-55.
8. Gibson C. How Chartered Financial Analysts View Financial Ratios. *Financial Analysis Journal*. 1987;May/June:74-76.
9. Taffler RJ. The assessment of company solvency and performance using a statistical model. *Accounting and Business Research*. 1983;13(52):295-307.
10. Hair JF, Tatham RL, Anderson RE, Black W. *Multivariate data analysis*. 7th ed. Prentice Hall; 2009.
11. Pinches GE, Mingo KA, Caruthers JK. The stability of financial patterns in industrial organizations. *Journal of Finance*. 1973;28(3):389-396.
12. Ali HF, Charbaji A. Applying Factor Analysis to Financial Ratios of International Commercial Airlines. *International Journal of Commerce and Management*. 1994;4(1&2): 25.
13. Tan PMS, Koh HC, Low LC. Stability of Financial ratios: A study of listed companies in Singapore. *Asian Review of Accounting*. 1997;5(1):9-39.
14. Ocal ME, Oral EL, Erdis E, Vera G. Industry financial ratios—application of factor analysis in Turkish construction industry. *Building and Environment*. 2007;42:385–392.
15. Jolliffe T. *Principal component analysis*. New York: Springer;2002.