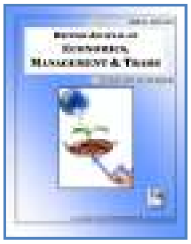

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The Application of Principal Component Analysis in the Selection of Industry Specific Financial Ratios

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Authors' contributions

This work was carried out in collaboration between all authors. Author BCFY designed the study, performed the statistical analysis, wrote the protocol, managed the analysis of the study and wrote the first draft of the manuscript. Authors ZM and KRC managed the literature searches. All authors read and approved the final manuscript.

Research Article

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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 companies each from the consumer and trading and services sector respectively are randomly selected and analysed 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 and nine ratios out of 28 for each sector respectively were identified as representative ratios. It is found that three ratios, cash flow to total assets, long-term debts to shareholders' funds and current assets 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.

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Conclusion: This study showed that, for the present data, for the sample period taken and for an emerging economy like Malaysia, 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 [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 ratio measures 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 use 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 analyse 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 of 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 investigate 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 industry 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. METHODOLOGIES

2.1 Sample Size

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 70 companies from the Trading and Services sector would be randomly selected and analysed 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) Short Term Liquidity	Codes
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) Cash Position	
B1. Cash/Sales	CS
B2. Cash/Total Assets	CTA
B3. Cash/Current Liabilities	CCL
B4. Cash/Total Debts	CTD
C) Profitability	
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) Solvency and Financial Leverage	
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
E) Operating Asset Efficiency	
E1. Debtors Turnover	DT
E2. Debtors Collection Days	DD
E3. Inventory Turnover	IT
E4. Inventory Average Days	ID
E5. Total Assets Turnover	TAT
E6. Current Assets Turnover	CAT

2.3 Analysis Techniques

2.3.1 Factor analysis and principal component analysis

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

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

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

Assume that the random vector $Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_p \end{bmatrix}$ has the covariance matrix $\sum$. Since we will be interested only in the variance-covariance structure, we assume that the mean vector is 0. The variance of l^tY is $E(l^tYY^tl) = l^t\,\Sigma l$.

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

The second principal component PC_2 is the linear combination $l_2^t Y$ where l_2 maximizes Var($l_2^t Y$) subject to $l_2^t l_2$ = 1 and *Cov*($l_1^t Y, l_2^t$) = 0. Similarly, the *i*'th principal component PC_1= $l_i^t Y$ where l_i maximizes *Var*($l_i^t Y$) subject to $l_i^t l_i$= 1 and *Cov*($l_k^t Y$. ($l_i^t Y$) = 0 for k < i.

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

Using principal component analysis is most appropriate in this study as the objective is to obtain the minimum number of factors to explain a maximum proportion of the variance found in the original variables. Only factors with an eigenvalue of more than 1 will be considered as significant and will be extracted. The value of 1 is the SPSS default setting Kaiser stopping criterion for deciding how many factors to extract. A more conservative stopping criterion can be set by requiring a higher eigenvalue. Tests of appropriateness will be undertaken with the test of sphericity as well as tests to measure of sampling adequacy (MSA) will be utilised. A minimum requirement of 0.5 is necessary for the adequacy of the sampling adequacy. The measure of sampling adequacy is measured by the Kaiser-Meyer-Olkin (KMO) statistic. Principal component analysis requires that the probability associated with Bartlett's Test of Sphericity be less than the level of significance.

When evaluating measures of sampling adequacy, communalities, or factor loadings, we 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 maximises 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 of 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 five 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:

	Variables	Category	Factor Loadings	Communalities
1.	CTD	Cash Position	0.952	94.5%
2.	EBITTA	Profitability	0.923	87.5%
3.	CAT	Asset Efficiency	0.845	83.0%
4.	CFTA	Short-term Liquidity	0.888	90.8%
5.	LTDSF	Solvency	0.915	91.5%
6.	TDTA	Solvency	-0.732	81.9%
7.	DT	Asset Efficiency	0.799	69.0%

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 Kaiser-Meyer-Olkin (KMO) measure showing a *P*-value of 0.744. The *P*-value for the KMO measure should be greater than 0.05. The Bartlett's test of sphericity is significant at 0.000. The variables chosen all have eigenvalues of above 1. The first factor CTD has an eigen-value of 10.003 while the last factor has an eigenvalue of 1.075. The communalities showed the percentage of variance in that particular factor that has been accounted for. For example, 94.5% of the variance in CTD is accounted for by this particular extracted factor. The seven factors together explained 80.8% of the ratio variances. Table 1 below shows the factor loadings for the 28 ratios used in the factor analysis.

Table 1. Rotated component matrix for the consumer product sector

Factors	1	2	3	4	5	6	7
WCR	.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	-1.49E	.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

3.2 Trading and Services

The sample consists of 70 companies covering a period of five years giving a total of 350 cases. Nine variables were selected and the variable for each of the factor with the highest factor loadings are highlighted in bold and is shown in Table 2 below. The nine variables are:

	Variables	Category	Factor loadings	Communalities
1.	CCL	Cash Position	0.947	94.1%
2.	EBITS	Profitability	0.860	89.4%
3.	CAT	Asset Efficiency	0.797	76.4%
4.	RPTA	Profitability	0.845	79.4%
5.	CFTA	Short-Term Liquidity	0,836	89.1%
6.	NISF	Solvency	0.787	83.0%
7.	LTDSF	Solvency	0.868	83.2%
8.	ID	Asset Efficiency	-0.785	65.5%
9.	CFTD	Short-Term Liquidity	0.726	81.9%

It is significant that two ratios that measure solvency (NISF and LTDSF) and two ratios that measure asset efficiency (CAT and ID) are selected in each of the two sectors. The Kaiser-

Meyer-Olkin measure of sampling adequacy is 0.603 which is acceptable. It is necessary to have a minimum value greater than 0.5 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 6.983 while the last variable, CFTD has an eigenvalue of 1.063. The cut-off eigenvalue is set at 1.000 and above as in the consumer products sector. The communalities showed the percentage of variance in that particular factor that has been accounted for. For example, 94.1% of the variance in CCL is accounted for by this particular extracted factor. The nine factors explained 77.4% of the ratio variances.

Table 2. Rotated component matrix for the trading & services sector

Factors	1	2	3	4	5	6	7	8	9
WCR	.883	.111	-.011	-.233	.074	.081	-.085	.014	.118
QR	.922	.093	-.043	-.165	.062	.050	-.032	-.021	.118
WCS	.574	.123	-.296	-.062	-.082	.230	.015	-.137	-.359
CFS	-.078	-.136	.018	-.136	.827	.004	.076	-.087	.073
CFTA	.025	-.019	.050	.419	**.836**	.035	.009	.094	-.058
IC	.069	.442	-.094	-.232	.335	-.125	-.276	.004	.081
CFTD	.517	.074	.083	.036	.065	.009	.027	-.078	**.726**
CS	.659	.245	-.267	.245	-.317	-.020	.049	-.173	-.364
CTA	.646	.121	-.067	.230	.002	.061	.003	.426	-.382
CCL	**.947**	.098	.021	-.067	-.009	.005	-.027	-.017	.168
CTD	.905	.124	.029	-.004	-.098	.005	-.153	.114	.022
EBITS	.303	**.860**	.104	.106	-.137	.078	.057	-.083	-.082
EBBITA	-.074	.693	-.037	-.085	.066	.024	-.117	.187	.107
NI	.352	.768	.131	.105	-.205	.125	.105	-.120	-.175
NITA	.165	.774	-.100	-.267	-.070	.239	.020	.171	-.028
NISF	.059	.368	.032	-.123	.047	**.787**	.211	.033	-.094
NITD	.588	.554	-.057	-.070	-.093	.055	-.080	.015	.355
RPTA	.056	.099	-.075	**-.845**	.059	.065	-.033	.219	.063
TDSF	-.156	-.159	-.134	.331	-.142	-.650	.215	.229	.279
TDTA	-.264	-.085	-.094	.783	.233	-.075	.016	.330	.107
LTDSF	-.076	-.043	-.109	.067	-.062	-.120	**.868**	.159	.107
LTDTA	-.124	-.010	-.109	-.027	.142	.008	.810	-.234	-.098
DT	-.012	-.101	.604	.150	-.127	.068	-.063	-.084	.104
DD	-.032	-.196	-.747	.150	-.116	.093	-.004	.020	-.042
IT	-.045	.052	.202	-.117	.092	-.701	.188	-.042	-.183
ID	-.071	-.124	-.061	.096	.058	.052	.010	**-.785**	-.007
TAT	-.078	.005	.574	.283	.168	.093	-.118	.595	-.080
CAT	-.158	-.070	**.797**	-.064	.028	-.114	-.128	.245	-.067

3.3 Summary of the Findings

Table 3 below presents a summary of the variables selected after factor analysis for the two sectors. Of the initial 28 ratios that were factor analysed, seven ratios were selected for the consumer sector while nine ratios were selected for the Trading and Services sector. To examine these ratios according to what they measure, the table shows the breakdown of the selected ratios according to their ratio groupings. The only ratios that are found to be relevant for the two sectors are CAT, CFTA and LTDSF (highlighted in bold). Finally, another significant conclusion was the high percentage of variances that were explained by each of the extracted factors with values of above 80% for most of the ratios and for the two sectors.

Table 3. Summary of financial ratios as selected through factor analysis

Financial Ratios	Category	Consumer Products	Trading & Services	Total
EBITTA	Profitability	X		1
EBITS	Profitability		x	1
Rpta	Profitability		x	1
CAT	Asset efficiency	**X**	**X**	**2**
DT	Asset efficiency	X		1
ID	Asset efficiency		x	1
CFTA	Short-term liquidity	**X**	**x**	**2**
Cftd	Short-term liquidity		x	1
CTD	Cash position	X		1
CCL	Cash position		x	1
TDTA	Solvency	X		1
LTDSF	Solvency	**x**	**x**	**2**
NISF	Solvency		x	1
Total		**7**	**9**	**16**

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 70 companies in the trading and services sector over the period of five years from 2006 to 2010 were 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. Three ratios, cash flow to total assets, long-term debts to shareholders' funds 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 showed that, for the present data, for the sample period taken and for an emerging economy like Malaysia, 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. Finally, this paper will contribute to the very limited research studies in Malaysia on selecting and utilising the most significant and useful ratios when analysing 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 well as 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.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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