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Measuring the Systematic Risk Factors in Malaysia Stock Market Returns: A Principal Component Analysis Approach

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ABSTRACT

Stock market return was used as a leading indicator that measures the strength of the economy. The performance of stock market can be measured by stock market returns. However, the uncertainty in the stock market will cause systematic risk for investors. The aim of the paper to measures the systematic risk factors in Malaysia stock market. The study makes used of principal components analysis to construct a Kuala Lumpur Composite Index (KLCI) that serves a proxy variable of Malaysia stock market return and macroeconomic variables as sources of systematic risk factors. This paper used Malaysian time series data covering a period from January 2009 to December 2019. The study gives insight for understanding the components in the principal component analysis of the correlation matrix of a group of risks may contain useful financial information by identifying highly correlated pair or larger groups of risks. The results of the study can be a benefit to investor's applies to manage their portfolio.

INTRODUCTION

Stock market provided an important channel to raise capital for the economy and also to stimulate the economy. The stock market was used as a leading indicator that measures the strength of the economy (Nordin, Nordin, & Ismail, 2014). The performance of stock market can be measured by stock market returns. The increase in stock market return has a tendency to be related to increase in business investment and vice versa. The principal component analysis is a standard method in statistics for extracting an ordered set of uncorrelated sources of variation in the multivariate system (Jolliffe, 1990). The theoretical underpinning the effect between macroeconomic variables and the stock market is explained by Arbitrage pricing theory (APT) model (Ross, 1976). The APT was known as multi factors model which can compare more than one factor to analyze the explanatory power of the variables to stock market returns. APT hypothesizes the relationship between stock market return and certain macroeconomic variables. APT models clarify how the fluctuations in macroeconomic variables can influence stock market returns. Macroeconomic variables were the primary source of risk known as systematic risk factors. Systematic risk is unpredictable and impossible to avoid completely, thus systematic risk always exist in the markets. In addition, there always a chance to encounter with economic downturn either the whole industry or a particular industry segment and systematic risk cannot be avoided or reduced through diversification, but only through hedging or by using the right asset allocation strategy can minimize or limit of the systematic risk. Unlike the normal logic argument that the higher returns bear more the risk. The simpler logic or reasoning will be the sensitivity of the expected returns on the factor movements. Two assets considered close substitute can have the same price and offer the same returns because they have the same sensitivity to each of systematic risk factors. In effect, they only differ marginally in unsystematic or residual risk that they might bear. This can be explained mathematically,

$$R = E + \beta F + e \tag{1.1}$$

where: R = the actual return, E = the expected return on the asset, β = measures the sensitivity, F = the actual return on systematic risk factor, e = measures return on unsystematic risk factor

Thus, actual returns equals to expect returns add factor sensitivity multiply by factor movement plus residual risk. Actually there is more than one factor, and then the equation (1.1) is expanded to:

$$R = E + \beta_1 F_1 + \beta_2 F_2 + \beta_3 F_3 + \beta_4 F_4 + \beta_5 F_5 + \beta_6 F_6 + \beta_7 F_7 + e \tag{1.2}$$

where: F_1, F_2, F_3, F_4, F_5, F_6, F_7 are the economic forces.

The factors that create these risks are usually macroeconomic factors. Sources of systematic risk can be macroeconomic factors such as inflation rate, interest rates, exchange rate, foreign direct investment, recessions, natural disasters, wars and government regulations (Tripathi & Neerza, 2015; Zahiri, Mehrara, & Falahati, 2014). Macroeconomic factors that affect the direction and instability of the whole market will be systematic risk. Based on the scenario mentioned above, the risk of money supply, interest rate, inflation rate, exchange rate, financial development, crude oil price and industrial production index were suitable variables to represent systematic risk in Malaysia context. Since in this study all observes is unanticipated variables, therefore all the variables except financial development (FD) will be converted into unanticipated variables. All the macroeconomic variables will be regressed with the lagged two of its own variable to obtain the residuals. The residuals will be powered by two to obtain the variance which represents the risk of each variable. This study suggested the unanticipated money supply (UMS), unanticipated interest rate (UIR), unanticipated inflation rate (UCPI), unanticipated exchange rate (UEXR), financial development rate (FD), unanticipated crude oil price (UOP) and unanticipated industrial production index (UIPI). The parameter is the factor sensitivity. If the has a higher value, it was considered a steeper liner line with the assumption that all other factors were zero. The asset of the is considered highly sensitive. If the value of is low then it can be considered the factor with that will be less sensitive to the factor where belongs. The can also be positive or negative indicating the direction and magnitude of the sensitivity.

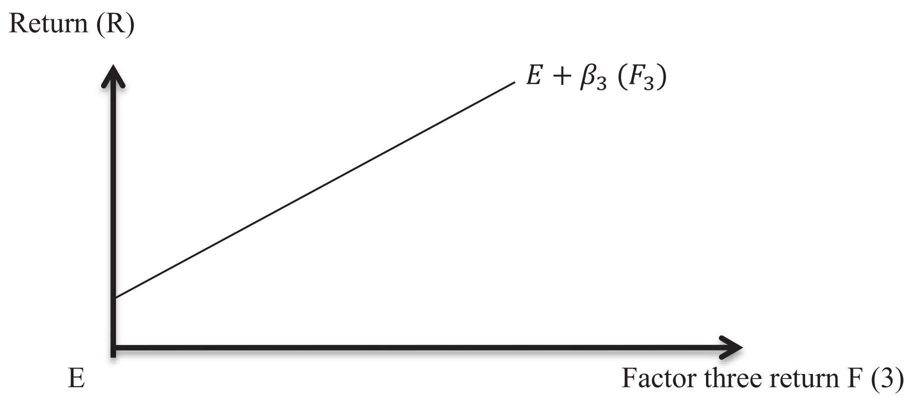

Figure 1 Actual return

Assume that if factor one to seven has a return of zero, except factor three, this does not mean actual return is zero. The actual return will be equal to an expected return (E). represents the unanticipated changes in each systematic risk factors. Thus, is the deviation from the actual return to the expected returns.

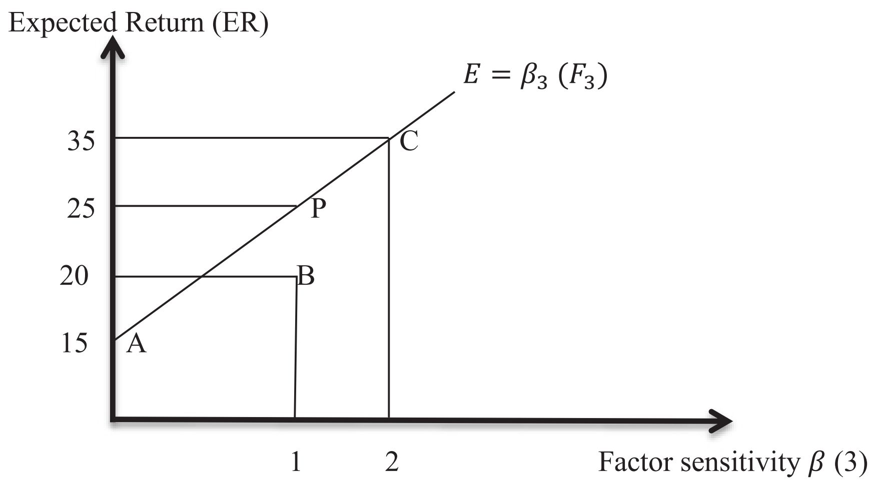

Figure 2 Expected return

Stock A is the risks less portfolio, the expected return is ER. Stocks B and C have an expected return of 20 per cent and 35 per cent respectively. Stocks B and P have the same factor sensitivity but stock P has higher returns (25 per cent) compared to stock B (20 per cent). Arbitrage opportunity takes place. No doubt the sensitivity of the factors can be the same but at the end of the day, the outcome makes the difference. When the investor reduces the stock B and replaces with stock P, the price of stock B falls but the price P increases. At lower price stock B might look attractive compared to stock P. This process goes on until actual return equals to expected returns in all the stocks. Then all the stocks will be on the same linear line, arbitrage will not exist anymore.

Scholars (Connor & Korajczyk, 1993; McGowan & Francis, 1991) emphasized that factor analysis need to conduct to identify the appropriate systematic risk factors to be included to measure stock market return. Factor analysis is used to estimate a model which explains variance or covariance between a set of observed variables (in a population) by a set of (fewer) unobserved factor and weightings.

ESTIMATION APPROACH

Therefore, a model needs to be constructed to explain the covariance between the systematic risk factors. The covariance between the systematic risk factors can exist because of some unobserved factors like political scandal, corruption and others. These factors can cause variance and covariance (causality effects). The unobserved factors each have different weightage (w). There is a set of weight and a set of unobserved factors. The analysis will measure the weightage of observed factors. The unobserved factors can also be correlated.

Assume there is a set of the unobserved factor for each systematic risk factor. the unobserved factors for money supply, the unobserved factors for interest rate, the unobserved factors for inflation rate, the unobserved factors for exchange rate, the unobserved factors for financial development, the unobserved factors for crude oil price and the unobserved factors for industrial production index. If the unobserved factors like and were correlated to each other than will have a set of covariance. Each systematic risk factor is represented by a vector (and).

Each vector (Y_i) is a representation of all the vectors of (Y_i) at different time period.

$$Y_1 = \begin{bmatrix} Y_1^t \\ Y_1^{t+1} \\ . \\ . \\ Y_1^{t+2} \\ Y_1^N \end{bmatrix} \quad . \quad . \quad . \quad . \quad . \quad Y_7 = \begin{bmatrix} Y_7^t \\ Y_7^{t+1} \\ . \\ . \\ Y_7^{t+2} \\ Y_7^N \end{bmatrix} \tag{2.1}$$

This is similar for all the vectors
Vector of equations:

$$\square_1 = \text{unobserved factor}_1$$
$$\square_2 = \text{unobserved factor}_2$$

Thus,

$$\begin{aligned}
Y_1 &= \square_{11}\square_1 + \lambda_{1\,2}\square_2 + \varepsilon_1 \\
Y_2 &= \square_{21}\square_1 + \lambda_{2\,2}\square_2 + \varepsilon_2 \\
Y_3 &= \square_{31}\square_1 + \lambda_{3\,2}\square_2 + \varepsilon_3 \\
Y_4 &= \square_{41}\square_1 + \lambda_{4\,2}\square_2 + \varepsilon_4 \\
Y_5 &= \square_{51}\square_1 + \lambda_{5\,2}\square_2 + \varepsilon_5 \\
Y_6 &= \square_{61}\square_1 + \lambda_{6\,2}\square_2 + \varepsilon_6 \\
Y_7 &= \square_{71}\square_1 + \lambda_{7\,2}\square_2 + \varepsilon_7
\end{aligned} \tag{2.2}$$

where:
vectors for all the variables communality
$\mathcal{E}$ = unique variables

Each equations has fixed weightage for each vectors represented by λ and there were parts that varies on each equation shown by ι (actual scores of the hidden individuals)

$$\iota_1 = \begin{bmatrix} \iota_{i\,1}^{1} \\ \iota_{i\,1}^{2} \\ \iota_{i\,1}^{3} \end{bmatrix} \tag{2.3}$$

Stack each equation one on top the other, we can obtain a matrix.

$$\begin{bmatrix} Y_{i\,1} \\ Y_{i\,2} \\ Y_{i\,3} \\ Y_{i\,4} \\ Y_{i\,5} \\ Y_{i\,6} \\ Y_{i\,7} \end{bmatrix} \begin{matrix} = \\ = \\ = \\ = \\ = \\ = \\ = \end{matrix} \begin{bmatrix} \lambda_{1\,1} & \lambda_{1\,2} \\ \lambda_{2\,1} & \lambda_{2\,2} \\ \lambda_{3\,1} & \lambda_{3\,2} \\ \lambda_{4\,1} & \lambda_{4\,2} \\ \lambda_{5\,1} & \lambda_{5\,2} \\ \lambda_{6\,1} & \lambda_{6\,2} \\ \lambda_{7\,1} & \lambda_{7\,2} \end{bmatrix} \begin{bmatrix} \iota_{i\,1} \\ \iota_{i\,2} \\ \iota_{i\,3} \\ \iota_{i\,4} \\ \iota_{i\,5} \\ \iota_{i\,6} \\ \iota_{i\,7} \end{bmatrix} \begin{matrix} + \\ + \\ + \\ + \\ + \\ + \\ + \end{matrix} \begin{bmatrix} \varepsilon_{i\,1} \\ \varepsilon_{i\,2} \\ \varepsilon_{i\,3} \\ \varepsilon_{i\,4} \\ \varepsilon_{i\,5} \\ \varepsilon_{i\,6} \\ \varepsilon_{i\,7} \end{bmatrix} \tag{2.4}$$

Weightage unobserved factor
This can also be written the equation in another from as:

$$\underline{Y} = \underset{\sim}{\lambda}\,\iota + \varepsilon$$
$$Y_{ij} = \lambda_{j\,i}\,\iota_{i\,1} + \lambda_{j\,i}\,\iota_{i\,2} + \varepsilon_{i\,j} \tag{2.5}$$

where:
i = 1, ...N (time)
j = 1,2,3,4,5,6,7 (no of systematic risk factor)

$$\begin{bmatrix} Y_{1\,1} & Y_{1\,2} \\ Y_{2\,1} & Y_{2\,2} \\ . & . \\ . & . \\ Y_{N\,1} & Y_{N\,2} \end{bmatrix} = \begin{bmatrix} \iota_{1\,1} & \iota_{1\,2} \\ \iota_{2\,1} & \iota_{2\,2} \\ . & . \\ . & . \\ \iota_{N\,1} & \iota_{N\,2} \end{bmatrix} \begin{bmatrix} \lambda_{1\,1} & \lambda_{1\,2} \\ \lambda_{2\,1} & \lambda_{2\,2} \\ . & . \\ . & . \\ \lambda_{N\,1} & \lambda_{N\,2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1\,1} & \varepsilon_{1\,2} \\ \varepsilon_{2\,1} & \varepsilon_{2\,2} \\ . & . \\ . & . \\ \varepsilon_{N\,1} & \varepsilon_{N\,2} \end{bmatrix} \tag{2.6}$$

where:
N = row (years)
f = number of factors
V = observed characteristics
2 = Unobserved factor
7 = Observed factor

$$\underset{\sim}{Y}\ N\ \mathrm{v} = \underset{\sim}{\mathrm{F}}\ N\ \mathrm{f}\ \underset{\sim}{P^1}\ N\ \mathrm{v} + \underset{\sim}{\varepsilon}\ N\ \mathrm{v} \tag{2.7}$$

where:
N = dimension
V = vector f

$$\underset{\sim}{\varepsilon}\ N_1\mathrm{v} = \underset{\sim}{U}\ N\ \mathrm{v}\quad \underset{\sim}{D^1}\ \mathrm{v}\ \mathrm{v}$$

$$\underset{\sim}{D^1}\ \mathrm{v}\ \mathrm{v} = \begin{bmatrix} \lambda_{U1} & 0 \\ & \\ 0 & \lambda_{UV} \end{bmatrix} \tag{2.8}$$

Equation for factor analysis written in complete form:

$$\underset{\sim}{Y}\ N_1\ \mathrm{v} = \underset{\sim}{\mathrm{F}}\ N\ \mathrm{f}\ \underset{\sim}{P^1}\ \mathrm{f}\ \mathrm{v} + \underset{\sim}{U}\ N\ \mathrm{v}\ \underset{\sim}{D^1}\ \mathrm{v}\ \mathrm{v} \tag{2.9}$$

DESCRIPTION OF VARIABLES AND DATA SOURCES

Stock Market Return

The stock market return is a return from the stock investment. Stock market returns indicate a combination of expected returns (risk factors) and residual returns that were correlated with industry specific news. Monthly composite market indexed in Bursa Malaysia.

Money Supply

Money supply is volume of money available in the market. Based on portfolio theory, an increase in the money supply can results in a portfolio change from non-interest bearing money assets to financial assets like stock. When a surplus of liquidity condition available in market will allow investors to buy more stock and arise the prices of stock were raising due to the demand for a stock increase. The monthly money circulation in Malaysia market of category 2 (broad money M_2) was used in this study.

Interest Rate

Interest rate risk is the cost of payment the borrower requires to pay or the payment need paid by the bank to depositors as a value of money depends on the time period. Interest rate is used as an important variable because interest rate can determine the price of the financial assets. The monthly overnight interest rate in Malaysia was used in this study.

Inflation rate

The increase of commodity price named as inflation rate. The inflation rate fluctuation represents percentage of risk related with increase uncertainty in the activity of stock market. The consumer price index (CPI) represent inflation rate in this study. The monthly consumer price index in Malaysia was used in this study to represent the rate of inflation.

Exchange Rate

The price of one currency used to exchange for other currency called as exchange rate. Exchange rate is related through the changes in the value of domestic currency relative to foreign currencies and it takes into consideration of inflation rate. Monthly currency exchange rate between Ringgit Malaysia (MYR)/ US Dollar (USD).

Financial Development

Financial development can be defined in two parts, firstly increasing a total of financial institutions and services available in a nation and second, an increase of financial institutions per capita and financial services or an increase in the ratio of financial assets to income. Financial development plays an important role in decreasing the cost of investment which contributed to the performance of the stock market. Particularly, strong financial development will have a positive effect on the country economy as well as on the stock market. The monthly ratio of M_2 over GDP of Malaysia was used to represent the financial development in the study.

Crude Oil Price

An increase in crude oil prices will cause expected earning to decrease due to the operation and production costs. Crude oil prices have a significant role in determine the country economic. The monthly oil price of one barrel in Malaysia was used as the crude oil price.

Industrial Production Index

Industrial production index is used to forecasting future gross domestic product (GDP) and economic performance. Increase in industrial production index will raise the corporate earnings and the impact of increment will improve the present value of the company. Hence, it will lead to increase the investment in the stock market which eventually improves the stock market returns. The monthly change in output in Malaysian manufacturing, mining, construction, and electricity, gas and water was used to represent the industrial production index in this study.

DATA AND EMPIRICAL RESULTS

The research is based on the Kuala Lumpur Composite Index (KLCI) stock market as dependent variables and independent variables the set of systematic risk factors chosen in this study is based on the macroeconomic variables affected by the Economic Transformation Programme (ETP) during the study period. The economic factors were unanticipated money supply (UMS), unanticipated interest rate (UIR), unanticipated inflation rate (UCPI), unanticipated exchange rate (UEXR), financial development (FD), unanticipated crude oil price (UOP) and unanticipated industrial production index (UIPI). Since the observation is only from January 2009 to December 2016, the study only focuses on the era of the New Economic Model (NEM). Thus, in this sample time frame, there is a degree of variance and covariance between the economic or systematic risk factor chosen. All these observed variables were analyzed using principal components analysis. The results were presented in Table 1.

Table 1 Principal component analysis of systematic risk factor results

Table 1(a) Eigenvalues explained by principal components

1	2	3	4	5	6	7
1.709	1.241	1.085	0.968	0.731	0.657	0.608

Table 1(b) Per cent of total variance explained

1	2	3	4	5	6	7
24.41	17.73	15.51	13.83	10.45	9.38	8.69

Table 1(c) Eigenvectors (Loadings)

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
UMS	0.352	0.498	–0.193	–0.336	0.552	0.225	0.350
UIR	–0.120	0.455	0.273	0.760	0.046	–0.089	0.339
UCPI	0.511	–0.273	–0.121	0.195	0.303	–0.721	–0.211
UEXR	0.390	–0.343	–0.305	0.490	0.062	0.619	–0.099
FD	0.512	–0.100	0.313	–0.163	–0.574	0.047	0.520
UOP	0.424	0.530	0.129	0.019	–0.261	–0.007	–0.674
UIPI	0.082	–0.249	0.815	–0.063	0.446	0.191	–0.164

The summary of the eigenvalues in Table 1 (a) showed the value and the percentage of total variance explained and the principal components on a correlation matrix for the 7 variables is to 7. Kaiser (1960) stated that the components with on eigenvalues of less than one should be eliminated so that only the components that have eigenvalues greater than one were retained for interpretation (Chatfield & Collins, 1980). The first three components were extracted and others components were eliminated. The first principal component accounts for 24.41 per cent of the total variance (1.709/7 = 0.2441), while the second account for 17.73 per cent (1.241/7 = 0.1773) of the total and the third principal component account for 15.51 per cent (1.085/7 = 0.1551) of the total. When the percentage of the total variance of three extracted components were accumulated (Table 1(b)), it can be seen that these three principal components account for 57.65 per cent of the total variance of the original data. Since the first three components account for over 55 per cent of the total variation, this means that the majority of the variance of the original data has been accounted for by these extracted components. However, since this study also performed other analysis on the data, therefore it needed at least 90 per cent of the variance explained by the principal components. Alternatively, many scholars agree that it is problematic and inefficient when it comes to determining the number of factors to extract or eliminate components (Hayton, Allen, & Scarpello, 2004; Fabrigar, Wegener, MacCallum, & Strahan, 1999). This was supported by Zwick and Velicer (1986) that this method can lead to arbitrary decisions; for instance, it does not make such sense to regard a factor with an eigenvalue of 1.01 as major and one with an eigenvalue of 0.99 as trivial.

Table 1(c) section describes the linear combination coefficients. The first principal component (PC1) is a roughly equal linear combination of all 7 of the systematic risk factor, it might reasonably be interpreted as a general systematic risk factors. All the variables have positive loadings except for unanticipated interest rate (UIR) variables which had negative loadings (–0.120). In these results, the first principal component (PAC1) has a large positive association with financial development (FD) (0.512) and unanticipated inflation (UCPI) (0.511). Thus, this component primarily measured long run economic growth. The second principal component (PC2) has negative loadings for four systematic risk factors which is financial development (FD) (–0.100), unanticipated inflation rate (UCPI) (–0.273), unanticipated exchange rate (UEXR) (–0.343) and unanticipated industrial production index (UIPI) (–0.250) and the positive loadings for three variables which is unanticipated interest rate (UIR) (0.455), unanticipated money supply (UMS) (0.498) and unanticipated oil price (UOP) (0.530). The second principal component (PAC2) has a large positive association with unanticipated oil price (UOP) (0.530). Therefore, this component primarily measures the stability of oil price in markets.

Meanwhile, the third principal component (PC3) has negative loadings for three systematic risk factors which were unanticipated inflation rate (UCPI) (–0.121), unanticipated exchange rate (UEXR) (–0.305) and unanticipated money supply (UMS) (–0.193). In contrast, four variables has positive loadings for third principal component (PC3) which is financial development (FD) (0.313), unanticipated industrial production index (UIPI) (0.815), unanticipated interest rate (UIR) (0.274), and unanticipated oil price (UOP) (0.129). The third principal component (PAC3) has large positive association with unanticipated industrial production index (UIPI) (0.815). Therefore, this component primarily measured change in output at Malaysian manufacturing, mining, construction, and electricity, gas and water. However, the other four principal components (PC4, PC5, PC6 and PC7) has to be eliminated even though the fourth principal component (PC4) has large positive association with unanticipated interest rate (UIR) (0.761), fifth principal component (PC5) has large positive association with unanticipated money supply (UMS) (0.552) and sixth principal component (PC6) also has large positive association with unanticipated exchange rate (UEXR) (0.619). Therefore, problematic and inefficient do exists when using this method that used eigenvalues of the correlation matrix with unities at the diagonal. In addition, this method also has demonstrated a tendency to substantially overestimate the number of factors in some cases and even underestimate them in some cases (Zwick & Velicer, 1986).

Table 1(d) Ordinary correlation

	UMS	UIR	UCPI	UEXR	FD	UOP	UIPI
UMS	1						
UIR	–0.018	1					
UCPI	0.112	–0.104	1				
UEXR	0.023	–0.058	0.311	1			
FD	0.119	–0.104	0.252	0.164	1		
UOP	0.299	0.117	0.131	0.049	0.242	1	
UIPI	–0.082	0.008	0.048	–0.031	0.157	–0.010	1

Table 1(d) showed the ordinary correlations matrix obtained from the principal component analysis. The table aimed to show the correlation values between each systematic risk factor. The results showed that 7 variables were seen all hang together in one distinct group only which is a weak group below 0.4 (Evans, 1996). First, the correlation relationship between UCPI and UEXR (0.311), UMS and UOP (0.299), FD and UCPI (0.252), FD and UOP (0.242), FD and UEXR (0.164), FD and UIPI (0.157), UCPI and UOP (0.131), FD and UMS (0.119), UIR and UOP (0.117), UCPI and UMS (0.112) has a positive but weak correlation between them. In addition, UEXR and UOP (0.049), UCPI and UIPI (0.048), UEXR and UMS (0.023), UIPI and UIR (0.008) also have a positive but weak correlation between the variables. Moreover, FD and UIR (–0.104), UCPI and UIR (–0.104), UEXR and UIR (–0.058), UEXR and UIPI (–0.031), UIPI and UMS (–0.082), UIR and UMS (–0.018), UIPI and UOP (–0.010) has a negative and weak correlation between the variables. Therefore, as a result the correlation between the systematic risk factors showed relatively weak correlations among each other. These clearly indicate that each systematic risk variable does not have either a strong or even moderate correlation with each other. Therefore multicollinearity issue does not exist among the independent variables.

The correlations result totally differ from the expectation rational theory where the correlations between variables were strong with each other because when the inflation rate increases it will also increase the interest rate through contractionary monetary policy, which indirectly increases saving. The increase in saving caused the demand of MYR to increase and the increase in demand for MYR caused an increase in exchange rate. In addition, an increase in saving also affected the capital formation which increased investment and gross domestic product (GDP). Meanwhile, increase in saving also increased the financial development (FD) because financial development variables were measured using the ratio of money supply (M2) over the gross domestic product (GDP) and it also affected the money supply variables due to increase in others variables because the variables were correlated to each other. No doubt, in theory, the variables should be correlated but since this study employed unanticipated data to represent each independent variable as systematic risk factor expects for financial development the results differed.

Based on Table 1(d), it can be concluded that unanticipated inflation (UCPI), unanticipated exchange rate (UEXR) and financial development (FD) were the factors to be considered as independent variables to represent systematic risk factors. Other independent variables like unanticipated interest rate (UIR), unanticipated money supply (UMS), unanticipated oil price (UOP) and unanticipated industrial production index (UIPI) were found to have a low explanation in variance from the total variation. Scholars like Ledesma and Mora (2007) supported the study by Zwick and Velicer (1986) that principal component analysis narrowed the number of variances by using the total variance explained by those variables. However, this method is also found to be problematic and inefficient when it comes to determining the number of factor to extracted or eliminate components. Therefore, other variables deemed important that might not show high variation explained through principal component analysis, but it can be included in the analysis to prove the changes in these variables that can have given an impact to the stock market returns because of the new transformation policy introduced during the period of analysis. Therefore, no doubt principal component analysis suggests excluding unanticipated interest rate (UIR), unanticipated money supply (UMS), unanticipated oil price (UOP) and unanticipated industrial production index (UIPI) these variables were included in the study due to its significant contribution through the new economic transformation policy. Moreover, the correlation matrix for all the independent variables as systematic risk factors clearly indicated there were no multicollinearity problems among the variables. This finding was supported by Katchova (2013) that principal component analysis was undertaken in the case when there is a sufficient correlation among the original variables to warrant the factor or component representation. Moreover, when data is mostly uncorrelated with each other principal component analysis method should not be implementing to summaries using common factor or component but if the data have a very high degree of correlation among the variables then it's good to use principal component analysis.

CONCLUSION

The objectives of this paper were to measure the systematic risk factors of Malaysia stock market. The study proposes KLCI index as the observed variables for the stock market return (KLCI), unanticipated money supply (UMS), unanticipated interest rate (UIR), unanticipated inflation rate (UCPI), unanticipated exchange rate (UEXR), financial development (FD), unanticipated oil price (UOP) and unanticipated industrial production index (UIPI) were selected for the analysis. Through the principal components analysis method found that the problem related to factor analysis and not with the APT model. The scholars (Diacogiannis, 1986; Dhrymes, Friend, & Gultelcin, 1985; Dhrymes, 1984; Shanken, 1982; Reinganum, 1981) claimed the techniques of factor identification in the APT by applying factor analysis were quite unclear. Among the problem mentioned by the scholars like the factor analysis was incapable to examine specific hypotheses thoroughly. Certain studies practices factor analysis in measuring the APT however the statistical methods fail to show the effect of a specific factor in the model. In contrast, regression analysis is a statistical tool that can be applied to examine thoroughly the model specification and showed whether or not the data support the model being examined. The second problem which rises by the previous scholars about the sampling error can easily affect the outcomes. Dhrymes et al. (1984) claimed that the factor analysis applied to examine the APT was seriously inconsistent because the number of factors is subject to the number of assets included in the sample group and also whether a likely 'factor' is priced, cannot be examined directly. Besides that, the availability of large and heterogeneous data banks generates another problem. Additionally, many scholars claimed that the number of significant factors described in previous research was too small because the data selected were insufficient. Meanwhile, Kryzanowski and To (1983) supported and claimed that the larger is sample size, the simpler was the factor structure in term of the number of related factors. Meanwhile, the last problem mention by scholars related to factor analysis about the recognizing factors that were statistically categorized by factor analysis is crucial and difficult. Therefore, it can be concluded that all the variables were selected as a variables in measure the risk that will influence the stock market return in Malaysia.

REFERENCES

Chatfield, C., & Collins, A. J. (1980). Principal component analysis. In *Introduction to multivariate analysis* (pp. 57 – 81). Springer, Boston, MA.

Connor, G., & Korajczyk, R. A. (1993). A test for the number of factors in an approximate factor model. *The Journal of Finance*, *48* (4), 1263 – 1291.

Dhrymes, P. J. (1984). The empirical relevance of arbitrage pricing models. *The Journal of Portfolio Management*, *10* (4), 35 – 44.

Dhrymes, P. J., Friend, I., Gultekin, N. B., & Gultekin, M. N. (1985). An empirical examination of the implications of arbitrage pricing theory. *Journal of Banking & Finance*, *9* (1), 73 – 99.

Diacogiannis, G. P. (1986). Arbitrage pricing model: A critical examination of its empirical applicability for the London stock exchange. *Journal of Business Finance & Accounting*, *13* (4), 489 – 504.

Elton, E. J., Gruber, M. J., & Gultekin, M. N. (1984). Professional expectations: Accurary and diagonosis of errors. *Journal of Financial and Quantitative Analysis*, *19* (4), 351 – 363.

Evans, J. D. (1996). *Straightforward statistics for the behavioral sciences*. Thomson Brooks/Cole Publishing Co.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4* (3), 272.

Hayton, J. C., Allen, D. G., & Scarpello, V. (2004). Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. *Organizational Research Methods*, *7* (2), 191 – 205.

Jolliffe, I. T. (1990). Principal component analysis: a beginner's guide-I. Introduction and application. *Weather*, *45* (10), 375 – 382.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, *20* (1), 141 – 151.

Katchova, Ani. (2013). *Principal Component analysis and Factor Analysis*. Econometric Academy. Retieved from https://youtu.be/hnzW8UxQlvo.

Kryzanowski, L., & To, M. C. (1983). General factor models and the structure of security returns. *Journal of Financial and Quantitative Analysis*, *18* (1), 31 – 52.

Ledesma, R. D., & Valero-Mora, P. (2007). Determining the number of factors to retain in EFA: An easy-to-use computer program for carrying out parallel analysis. *Practical Assessment, Research & Evaluation*, *12* (2), 1 – 11.

McGowan, C. B., & Francis, J. C. (1991). Arbitrage pricing theory factors and their relationship to macroeconomic variables. *Advances in Quantitative Analysis of Finance and Accounting*, *1*, 25 – 43.

Nordin, S., Nordin, N., & Ismail, R. (2014). The impact of palm oil price on the Malaysian stock market performance. *Journal of Economics and Behavioral Studies*, *6* (1), 1 – 9.

Reinganum, M. R. (1981). The arbitrage pricing theory: Some empirical results. *The Journal of Finance*, *36* (2), 313 – 321.

Shanken, J. (1982). The arbitrage pricing theory: is it testable? *The Journal of Finance*, *37* (5), 1129 1140.

Tripathi, V., & Neerza, (2015).Sources of Systematic Risks in BRICS Stock Markets: A Survey of Investment Analysts and Market Experts. *International Journal of Marketing, Financial Services and Management Research*, *4* (5).

Zahiri, N. H., Mehrara, M., & Falahati, Z. (2014). The Relationship between systematic risk and stock returns in Tehran Stock Exchange using the capital asset pricing model (CAPM). *International Letters of Social and Humanistic Sciences*, *21*, 26 – 35.

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin*, *99* (3), 432.