

# APPLICATION OF PRINCIPAL COMPONENT ANALYSIS ON EQUITY VALUATION MULTIPLES: EVIDENCE FROM MALAYSIAN FIRMS

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## ABSTRACT

*Investment analysts often used equity valuation multiples to assess the performance of stocks in relation to likely future return to shareholders. Valuation multiples used by analysts are price to earnings, price to book value, price to cash flow and price to sales multiples. However, researchers have argued that correlation exists between the multiples hence assessing them individually and later merging them to one multiple results to reduplication. This study employed the principal component analysis (PCA) method to condense the four equity valuation multiples (EVM) of 223 randomly selected listed firms in Malaysia for the period of 2008-2013. The PCA result reveals that three (3) components explained 99% of the total variables variance. Suggesting that, the three components (price to earnings, price to book value and price to cash flow multiples) can satisfactorily explain all the EVMs. The implication is that strong correlation exists between EVMs of Malaysian firms. Therefore, the study recommends the application of principal component analysis methodology in the analysis of the equity valuation multiples because of correlation that exists between the valuation multiples. The study is limited to EVMs, entity valuations are not covered in the study. Applying PCA to equity valuation multiples ensures accuracy and reliability of result interpretation due to absence of multicollinearity in the decomposed principal component.*

**Keywords:** equity valuation multiples, price-earnings, price-book value, price-cash flow price-sales multiples, principal component analysis and Malaysia

## 1. INTRODUCTION

In conducting scientific research, researchers often encounter problem of correlated variables and interpretation made on these variables could be bias. One of the solutions to such problem is the use of factor models. Factor models are usually used as data reduction techniques in situation where a researcher has number of variables that are closely associated with one another. Factor models are applied to decompose the creation of a group of series to common factors to all series and a percentage that is explicit to each series known as idiosyncratic deviation (Brooks, 2008). In addition, Brooks (2008), categorized factor models into two; macroeconomic model, and mathematical model. In the macroeconomic model, all the factors are observable, whereas, in mathematical model all the factors are unobservable and principal component analysis (PCA) represents mathematical factor model. Principal component analysis is a tool that is useful in situation where variables are closely related. The PCA represent a factorial method where fresh variables are produced, as mixtures of the original displays, having no association between them with a maximum variance (Opris, Demeter, & Palade, 2014). In the Principal component total variance of variables is explained (Opris, et al 2014). Mathematically, PCA method creates unrelated components or files, where each component is a linear weighted mixture of the initial variable (Vyas &

Kumaranayake, 2006). Also, PCA converts variables that are initially associated to new unassociated variables with maximum depiction of the initial variables (Kim, 1986). Similarly, a statistical tool designed to condense inter-relationships among related variables is the principal component analysis (PCA) and one of its purposes is to cluster variables to a small factors sample that maintain full information that is contained in the initial variables (Chen & Shimerda, 1981).

Equally, PCA labels the difference inside the input data environment by determining the ways of greatest variation inside the data (Graham, Wagner, & Castner, 2006). Likewise, mathematically principal component analysis consists of one value decomposition of the difference-codifference matrix, yielding the distinctive vectors (eigenvectors) and distinctive roots (eigenvalues) of the difference- codifference matrix. Thus, the new variables generated (PC1, PC2, for example) formed by this transform are linear mixtures of the initial variables (Graham et al., 2006).

According to Passamani, Tamborini, and Tomaselli (2015), principal component analysis is a reasonably common technique in macroeconomic and finance with respect to standard econometric tests of models that is applied to reduce variables number in a data set through extracting important linear mixtures from the perceived variables that might concur to describe a given phenomenon. These mixtures are referred to as “common factors”. Previous studies have successfully applied the PCA technique to reduce number of correlated variables that contains maximum representation of the original variable for effective and efficient interpretation of results (Gherghina, 2015; Ittner & Larcker, 2001; Libby, 1975; Miller & Bromiley, 1990; Sajedinejad, et al 2015).

Equity valuation multiples on the other hand, are commonly used as investment appraisal techniques to value stock returns for investment decision making. Equity valuation multiples (EVM) represent the methods, which tell about the market’s view of a firm’s market valuation of ordinary holders benefit (Penman, 2006). Therefore, valuation of ordinary shareholders claim is an important aspect of investment decision for security analysts, investors, sellers and buyers of company stocks. Equity valuation multiples are the common approaches used in stock valuation as documented in the prior studies (Aras & Yilmaz, 2008; Fairfield, 1994; Jing Liu, Nissim & Thomas, 2002; Shahed, Barker, & Clubb, 2008; Liu, Nissim, & Thomas, 2007).

Equity valuation multiples includes, price to earnings (P/E), price to book value (P/B), price to cash flow (P/C) and price to sales (P/S) multiples (Schreiner, 2007). Using company market price of stock as the numerator distinguishes the equity valuation multiples from financial accounting ratios (FARs) (growth ratio, profitability ratio, liquidity ratio (Sehgal & Pandey 2010). As a result of using price to represent the numerator for the EVMs, researchers argued that correlations exist between them.

However, others researchers argued that multiples are entirely different and each of valuation multiple is independent. Hence, each of value multiple can be applied to predict stock price without recourse to the other multiples. The argument now is whether equity value multiples of Malaysian firms are correlated or uncorrelated and if they are correlated, to what extent is the correlation. In addition, several other studies in different field of knowledge applied PCA method to reduce variables number. For example, corporate governance variables (Gherghina, 2015), various financial index (Lenka, 2015), corporate social responsibility (Lys, Naughton, & Wang, 2015), out sourcing strategy (Isaksson & Lantz, 2015), maternal

mortality factors across countries (Sajedinejad, et al 2015), corporate institutional variables (Sajedinejad, et al 2015) and debt covenant indexes (Nikolaev, 2010). Notwithstanding the practical application of PCA as data reduction technique and the application of EVMs to predict stock price no existing study used PCA method to generate appropriate component that explained valuation multiples in Malaysia. This study therefore applied the PCA method to the four EVMs of Malaysian firms. The objective is to produce accurate principal component that explains EVM in Malaysia, thereby providing practical contribution to investment analysts and methodology. The subsequent part of the paper is divided in to the following format. Literature section presented previous studies that use PCA, the succeeding section discusses the methodology, and the next section presented and discusses the principal component results. Lastly, the paper presented a concluding remark for the entire research.

## **2.0 PRIOR STUDIES OF PCA AS A DATA REDUCTION TECHNIQUE**

This section extensively explored previous knowledge on the application of principal component analysis as a technique for data reduction while retaining the features of the initial variables. PCA is used in the natural sciences, social and human sciences and management sciences to reduced number correlated variables to new variables that are uncorrelated. The objective of PCA application is to remove dormant variables while retaining information of the original values. The principal component value generated from the PCA is free of multicollinearity, therefore making interpretation of such variable more robust and reliable.

The review will provide and insight on different researches that used the PCA method to reduce the number variables thereby justifying our study. Studies that used PCA to condense variables include the following. Bird and Casavecchia (2007) applied the PCA methodology in order to build a number of combined variables that greatly explain the deviation in earnings per share (EPS) across companies during the period, then combined variables were used as the independent variables in a regression model designed to predict the prospect of a specific stock. On their part, Ittner and Larcker (2001) employed Principal components to condense 12 factors of the corporate organizational strategy (COS) and firm environment that are usually used to quantify strategy and environmental uncertainty to three (3) factors models.

Likewise, Larcker and Richardson (2007) adopted the principal components analysis approach to condense 39 measures of corporate governance (CG) to 14 factors to see their influence on accounting outputs and organizational performance. Similarly, Dey (2008) applied investigative principal components analysis to 22 separate governance mechanisms and obtained seven (7) distinct corporate governance factors signifying the composition and operation of the firm board of directors, executive directors compensation, stock-based compensation for directors, auditor independence , structure and working of the firm audit committee, and control of financial reporting quality by the board.

Also, Ammann, Oesch, and Schmid (2011) Applied principal components to condense 64 corporate governance variables from seven developed countries to seven (7) components. likewise, Gherghina (2015) employed the PCA method to condense seven variables of corporate governance to three factors. The variables reduced are, shareholding agreeing to the first three stockholders, number of stockholders having capitals over 5%, firm board size, number of firm independent directors, number of firm non-executive directors, number of women serving on board, and duality of CEO. In the same vein, Boone, Casares, Karpoff, and Raheja (2007) used principal components (PC) to transform the set of alternative

variables for each of different corporate governance variables into a reduced number of features that have the same value. In similar study, Isaksson and Lantz (2015) used principal component analysis (PCA) to condense the 16 items of out sourcing strategy to generate a grouped of four principal components (back office activities, accounting activities, primary activities, and support activities), reflecting the four basic outsourcing strategies. In addition, Lys, Naughton, and Wang (2015), effectively used the principal component analysis to condensed ten (10) corporate social responsibility to three factors extracted from Thompson and Reuters data stream. The researchers then used the condensed principal components to predict the influences of the four principal components on the future financial performance of firms.

Moreover, Ayoola, Adeyemi, and Jabaru (2015), used principal component analysis tool to dimensionalized twenty-eight crime variables that are crime prone to eight principal components, retaining most of the information. The PCA result explained 94% of the total variables variation. Furthermore, Sheu and Lee (2012) adopted principal component analysis to build index from several managerial entrenchment to predict investment behaviour and excess cash holding among firms. To add, Kong (2011) applied principal components analysis technique to generate a different factor model from Social network, Social capital and Transaction costs, which is the direct function of the three factors mentioned.

Correspondingly, Ahuja and Medury (2010) considered principal components analysis (PCA) with Varimax rotation to regroup 27 variable's to represent corporate blog to four namely, organizational, promotional, relational and general. They collectively explained almost 99.84% of the variability in the initial variables. Therefore, the difficulty of the data arrangement was reduced significantly by using the four components. In related study, Passamani, Tamborini, and Tomaselli (2015), employed the principal components analysis in order to pool the inter-nation as well as time series lengths of data set of the nations. This according to the authors is a reasonably unusual technique in macroeconomic and finance with respect to standard econometric tests of models. However, it is particularly well suited to reduce variables number in a data set, through extracting important linear mixtures from the perceived variables, which might concur to describe a given phenomenon. These mixtures, named "common factors", could be understood as latent, non-observable variables. Principal component analysis was carried out on farmer's choice of market strategy in New Zealand. The component linking are strategic orientation, values, selling behaviour, and association status as main features of farm producers choice market strategy (Bensemam & Shadbolt, 2015).

Similarly, Elbadry, Gounopoulos, and Skinner (2015) conduct a principal component analysis (PCA) of spread, volatility, trade value and trade volume and discover that the first PC of the four variables explains about 94.5 per cent of the total variables variation of the data set. This submits that the first principal component could form a worthy summary of the four variables. Additionally, Sajedinejad, et al (2015), performed principal component analysis to extract 439 measures of maternal mortality across different countries to ten factors models with linear representation of the initial displayed variables.

In the same way, Nikolaev (2010), implemented principal component analysis (PCA) technique over the five separate debt covenant indices, that obviously finds one main factor model that represent all the three variables while retaining the initial variable representation. By the same token, Libby (1975) in his study from 60 sampled companies consisting of 30 nonfailed and 30 failed, used principal component analysis to reduce 14 accounting ratios to

5 ratios, while forecasting failure in relative to ratios. PCA method is performed to condense nine firm corporate governance mechanisms to three factors and those factors that account for almost half of the variance in the governance mechanisms to predict value-relevance of firms accounting information (Habib & Azim, 2008). For further support, Lenka (2015) used Principal components analysis approach to build Financial Depth Index (IFD) in India which serves as alternative variable for financial development situation of the nation. To conclude, Miller and Bromiley (1990) used a total of 493 companies that appeared in both sampling time periods, adopted PCA to reduce 9 corporate risk measures of management research to 3 variables.

From the above literature explorations, the principal component method has been applied in various field of knowledge to reduce number of correlated variables to new variables that are not correlated. The review has given us the idea of using the principal component analysis method in our study. Therefore, this study used the principal component analysis methodology to condense the four (4) equity valuation multiples (price to earnings, price to book value, price to cash flow, price to sales) to generate variables that represent other equity valuation multiples. This study provides literature insight by looking at Malaysian market because of its importance in the Asian market. Furthermore, deducting from Ashton, Cooke, Tippett and Wang (2003) aggregation theorem of market value and equity model is used in the study, thus;

$$EVM(\eta) = \beta_0 + \beta_1x(t) + \beta_2b_2(t) + \beta_3c_3(t) + \beta_4s_4(t) + \varepsilon(t) \quad (1)$$

Where EVM is the equity valuation multiple, x(t) is the price to earnings multiple, b(t) is price to book value multiple, c(t) price to cash flow multiple, s(t) is price to sales multiple, and  $\beta(s)$  are the constants of valuations associated with every element of condense valuation model, and  $\varepsilon$  denote error term in the model. The subsequent section presented the methodology applied in the research.

### 3.0 METHODOLOGY

This section discusses the methods, variables and model used in the research to achieve the set objective. The study utilized secondary data of published financial statements of sampled listed firms in Malaysia. The data are collected from Thompson and Reuter's data stream covering the period of six (6) years (2008-2013). The period is selected because it is considered as the period of post global financial crises that resulted in loss of large volume of money by stockholders across the world due to drastic decrease in the prices of equities. The loss affected local and the foreign investors in different countries of the world. Thus, the study of equities in the post financial period becomes important. The study population consists of publicly listed firms in Malaysia and 233 are drawn from different sectors to represent the population at random and availability of information. The principal component analysis technique is then employed to condense the valuation multiples and produce principal components for equity valuation multiples of Malaysian firms.

#### 3.1 Variable Meaning and Measurement

This subsection explained the equity valuation multiples and how they are computed before application of the PCA method. Table 3.1 below presents variables and their measurement.

Table 1  
Variable meaning of equity valuation multiples construct

EVM Variables	Measurements
Price to earnings (P/E)	Price per share divided by earnings per share
Price to book value (P/B)	Price per share divided by book value per share
Price to cash flow (P/C)	Price per share divided by cash flow from operation per share
Price to sales (p/s)	Price per share divided by gross revenue/sales per share

### 3.2 Model Specification

To achieve the objective of the study, the model 2 present variables in the regression equation.

$$PCAV_{it} = \beta_0 + \beta_1 PE_{it-1} + \beta_2 PB_{it} + \beta_3 PC_{it} + \beta_4 PS_{it} \dots \dots \dots 2$$

Thus, PCAV is the principal component analysis value generated from the equity valuation multiples,  $\beta$  is the parameters of the equity valuation multiples, PE is price-earnings multiple, PB is price-book value multiple, PC is price-cash flow multiple, PS price-sales multiple *it* refers to element of observation of firms over time. The next section present and discusses the results obtained from the principal component analysis.

### 4.0 PRINCIPAL COMPONENT ANALYSIS RESULT AND DISCUSSIONS

This section present and discusses the result from the principal component analysis of the equity valuation multiples (price to earnings, price to book value, price to cash flow and price to sales multiples), the interpretation of the results and the implication was also presented in this section. Table 4.1, presents the principal component/correlation of the equity valuation multiples. While, Table 4.2 reports the principal component (eigenvectors) computed form the principal component for all the equity valuation multiples.

Table 4.1  
Principal components/correlation

Component	Eigenvalues	Difference	Proportion	Cumulative
Comp1	1.96	0.60	0.49	0.49
Comp2	1.36	0.73	0.34	0.83
Comp3	0.65	0.59	0.16	0.99
Comp4	0.037	0.0	0.01	1.00
Number of observation	<b>1393</b>			
Number of components	<b>4</b>			
Trace	<b>4</b>			
Rho	<b>1.00</b>			

Table 4.1 above has presented eigenvalues variances of all the principal components (price to earnings, price to book value, price cash flow and price to sales) variable variance. For example, the first principal component (PC) has variance 1.96, explaining 49% of the total variation. The first principal component has eigenvalues variances of 1.96 and proportional

representation of 0.49 (1.96/4) of the total variable variance. This suggests that 49% variation of the equity value multiples is explained in the first component. This means that 49% of the EVMs will be represented in the first component. The subsequent principal component (PC) which is the second component has eigenvalues variance of 1.36 and proportionate variation of or 34 percent (1.36/4) of the total variable variance. This suggests that 34% of the variation in the equity valuation multiples is explained by the second principal component. The Principal components analysis values generated are uncorrelated with each other. This may provide evidence that, the first and the second principal components explained the amount of the variances of the each separate component 49 and 34, or  $49+34 = 83\%$  of the total variance. This therefore suggests that using the first and the second components, 83% of the total variance of the equity valuation multiples will be explained. The third principal component has an eigenvalues variance of 0.65 and proportion of 0.16. This also, suggests that, 16% of the variation is explained in the third principal component. This result is line previous findings of principal component analysis approach to data decomposition (Nikolaev, 2010; Sheu & Lee 2012).

Had it been the components been interrelated, they would have partially represented the same data, so the data contained in the mixture would not have remained equal to the summation of the data of the components. All the four principal components collectively explained all variance that exist in variables. Hence, the unexplained variances enumerated in the second panel result are all zero, and  $Rho = 1.00$  as presented above in the first panel result. More than 80% of the variance is contained within the first two principal components. While extending our components to three will contained 99% of variance in the principal components. The implication is that strong correlation exist between the equity valuation multiples and all of them if combined together can be reduce to three factors only explaining 99% of the total variation. This implied that three components can satisfactorily represent equity valuation multiples. The next subsection presents principal component eigenvectors

Table 4.2  
Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
PB	0.71	0.03	0.02	0.72	0
PC	-0.01	0.71	-0.71	0.00	0
PS	0.71	0.03	0.02	-0.72	0
PE	-0.05	0.71	0.71	-0.00	0
Number of observation		<b>1393</b>			

The principal components analysis in panel two Table 4.2 above presented the eigenvectors. These principal components (PC) have element distance; the column wise summation of the squares for loadings is 1 ( $-0.05^2 + 0.71^2 + -0.01^2 + 0.71^2 = 1$ ), thus, principal components analysis tend to show principal components (PC) normed to the related eigenvalues than to 1. The eigenvalues sum up to the summation of the differences of the variables in the analysis the “total difference” of the variables. The variables are consistent to have component variance, so our total variance in this circumstance is 4, price to earnings price to book value, price to cash flow and price to sales multiples. To verify the result of the principal component, Keiser-Meyer measure of selection adequacy is presented in Table 4.3 below

Table 4.3  
Keiser-Meyer measure of sampling adequacy

<b>Variable</b>	<b>KMO</b>
PB	0.5002
PC	0.4992
PS	0.5002
PE	0.5025
<b>Overall</b>	<b>0.5003</b>

From the Table 4.3 above, the principal component analysis is based on the equity valuation multiple. The data as used in the study presented the Kaiser-Meyer-Olkin (KMO) sampling adequacy measure for the equity valuation multiples. The overall KMO sampling adequacy for the four equity valuation multiples is 0.50 suggesting that principal component analysis can be reasonably applied to equity valuation multiples of Malaysian listed firms as data reduction method. This is because there is 50% correlation between the valuation multiples. Finally, deducting from Cooke et al (2003), the first principal component loads 0.49, x(t) on price to earnings multiple. The second component loads 0.34 b(t) on price to book value multiple. The third principal component loads 0.16 c(t) on to price to cash flow multiple. Thus, the three equity valuation multiples (price to earnings, price to book value and price to cash flow) can explain up to 99% of the equity valuation multiples of Malaysian firms. The equity value multiple (price to sales) is therefore not required because the principal component loading is only 0.01%.

#### **4.1 Concluding Remark**

As discussed above, the essential idea of the principal component analysis is to condense the dimensionality of a data set consisting correlated variables by removing the dormant factors among them. This research achieved the set objective by translating the original equity valuation multiples to a new set of uncorrelated predictors. The principal components, which are ordered in relations to those that, explained the largest percentage of the difference in the original variables. The four equity valuation multiples (price to earnings, price to book value, price to cash flow multiples and price to sales.) are reduced to three components with 99% explanation of the variation. The implication is that strong correlation exists between EVMs of Malaysian firms. The study is limited to EVMs, entity valuations are not covered in the study. Thus, the study concludes that correlation exist between the valuations multiples of Malaysian firms and the best way to explain the multiples collectively is through the application of principal component analysis. The study recommends the application of PCA in attempt to explain the equity valuation multiples collectively instead of looking at multiples individually and later aggregating them to one.

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