PRINCIPAL COMPONENT ANALYSIS OF MANUFACTURE AND SERVICE PARAMETERS IN SELECTED SHARE MARKET

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Abstract-This paper focuses on mergers and acquisitions of financial data. It analyses the post and premergers and acquisition services and manufacturing industry from 2008 - 2018. In this regard, the paper discussed step by step procedure for factor analysis. The factors were extracted by measuring the correlation matrix's Eigen values. Variance maximize the transformation matrix's rotation was made to promote the factor loading interpretation. The PC1 and PC2 percentage values and heat map to easy identify which ratio is most important role in Mergers and Acquisition.
Keywords: Mergers and Acquisition, Factor Analysis, Linear regression, Principal Component Analysis, MATLAB

1 INTRODUCTION

It was dissatisfied with the classical economic advantages to be established in the theoretical model of mergers and acquisitions to see if the flow of activities on the Indian market in the M&A sector between 1990 and 2010 fits and supports the theoretical assumptions of the M&A activity proposed in the various past analyses, both with regard to India and with reference to the problems [1]. This paper discussed 21 parameter values/ 21 items form the share market data [2]. It is calculated the Eigen values for pre and post data calculation from real life data. This works is very useful for share market industry such as great calculations when compare to real data in PCA approach [3].

Here lot of parameters are there in share market, but we selected only 21 items such as very important for solutions in senses, it is total variance and Eigen values properties used in a whole paper [4]. The diagrams with the help of MATLAB and data's from government recognised bodies [5]. The Eigen values are positive we conclude that the logic is PCA 2 or PCA 3 in position for statistical inference, it is concluded that calculated the parameter values and minimise the parameter estimation also [6]. But this paper we have taken one single data for absolute liquid ratio, and helps the statistical analysis in the programming [7]. Similarly remaining all parameters analysed. The same procedure we used in remaining parameters also.

2 RELATED WORKS

To Study is an attempt to understand how far the desired efficiency gains are actually achieved by consolidating firms in India, which experienced a large number of mergers and acquisitions, especially following the 1990's economic reforms [8].In recent years, technological developments at an unprecedented pace have driven dramatic increases in industrial productivity [9]. These advances are clearly started since the first technological revolution in 18th century with the invention of external-combustion engine, introduction of mechanical production facilities supported by water and steam power. 2nd technological revolution were started towards the top of the 19th century and its continued into the 20th century ended at the start of war I, by the mixing of the production line with the using electric power into manufacturing systems are the milestones of this era [10].

The 3rd technological revolution is additionally referred to as the knowledge technology period from the mid-20th century until the start of the 2000s, which started after the planet War II and increased its momentum after the 1970s [11]. The digitalization of production and therefore the computer aided manufacturing (CAM), computer aided design (CAD) systems has emerged during this period [12]. Lastly, much discussed term in nowadays, Industry 4.0 conceptwas first utilized in Germany at the Hannover Fair in 2011, the world's largest industry fair, are often defined because the whole of systems developed to extend the efficiency and productivity in production by means of the machines interacting with one another through the web and by using less manpower and producing more qualified and faster production with lower costs [13]-[16].

3 PROPOSED WORK FOR PCA

The following theoremsare the some preliminaries of PCA procedure [17]:

Theorem 3.1: If V is nonzero $m \times n$ real matrix which is symmetric, then V is orthogonally diagonalizable [19]. Let $\lambda_1, \lambda_2, \ldots, \lambda_n$ be the real eigenvalues of V and the eigenvectors are $\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_n$ then for each 1=1, 2,..,n:

$$V\vec{x}_i = \lambda_i \vec{x}_i .$$

Theorem 3.2: If V is nonzero $m \times n$ real matrix, then the matrix VV^T of order $m \times m$ and the matrix V^TV of order $n \times n$ both are symmetric.

Theorem 3.3: The same nonzero eigenvalues is shared between the two matricesVV^T and V^TV.

Proof: Let we take a nonzero eigenvector of V^TV be $\vec{x}$ and the eigenvalue $\lambda \neq o$. Which implies that,

$$\left(VV^T\right)\vec{x} = \lambda \vec{x}.$$

Multiply V on both sides we get,

(1) $\Rightarrow VV^T\left(V\vec{x}\right) = \lambda\left(V\vec{x}\right).$

$\Rightarrow V\vec{x}$ is an eigenvector of VV^T also λ is the eigenvalue of VV^T.

Since, $\lambda \neq o$ then $\vec{x} \neq \vec{0}$.

Therefore, $V\vec{x} \neq \vec{0}$.

So, the nonzero eigenvalue λ of V^TV is also an eigenvalue of VV^T.

Hence the proof

The main paper plays a vital role in the flowing theorem [18].

Theorem 3.3: The eigenvalues of VV^T and V^TV are positive.

Proof: Let $\vec{x}$ and λ are the eigenvector and eigenvalues of V^TV respectively.

By using the dot product formula for length of $V\vec{x}$,

$$\begin{aligned} V\vec{x}.V\vec{x} &= \left\|V\vec{x}\right\|^2 \\ &= \left(V\vec{x}\right)^T\left(V\vec{x}\right) \\ &= \vec{x}^T\left(V^TV\right)\vec{x} \\ &= \lambda\left\|\vec{x}\right\|^2 . \end{aligned}$$

Thus λ is positive as length does not negative.

Replace V by V^T in the above proof we get λ is positive for both V^TV and VV^T.

1st sample Principle component = linear combination $x_1^{'}v_j$ subject to $x_1^{'}x_1 = 1$.

2nd sample Principle component = linear combination $x_2^{'}v_j$ subject to $x_2^{'}x_2 = 1$ and zero sample covariance for the pairs $\left(x_1^{'}v_j, x_2^{'}v_j\right)$.

ithsample Principle component = linear combination $x_i^{'}v_j$ subject to $x_i^{'}x_i = 1$ and zero. sample covariance for the pairs $\left(x_i^{'}v_j, x_k^{'}v_j\right)$, $k < i$.

The first principle component maximizes $x_1^{'}Tx_1$. Equivalently,

$$\frac{x_1^{'}Tx_1}{x_1^{'}x_1}$$

The largest eigenvalue $\hat{\lambda}_1$, made for the choices of x_1 maximize subject to $0 = x_i^{'}T\hat{a}_k = x_i^{'}\hat{\lambda}_k\hat{a}_k$, or x_i perpendicular to $\hat{a}_k$.

If $T = \{t_{ik}\}$ is the $n \times n$ sample covariance matrix with $\left(\hat{\lambda}_1, \hat{a}_1\right), \left(\hat{\lambda}_2, \hat{a}_2\right), \ldots, \left(\hat{\lambda}_n, \hat{a}_n\right)$, the ithsample Principle component is $\hat{u}_i = \hat{a}_i v = \hat{a}_{i1}v_1 + \ldots + \hat{a}_{in}v_n$,

$$i = 1, 2, \ldots, n.$$

Where $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \ldots \geq \hat{\lambda}_p \geq o$. and v is arbitrary value on the variable $V_1, V_2, \ldots, V_n$. Also,

Sample variance $\left(\hat{u}_k\right) = \hat{\lambda}_k$,

$$k = 1, 2, \ldots, n.$$

Sample Covariance $\left(\hat{u}_i, \hat{u}_k\right) = 0$, $i \neq k$.

In addition,

Total sample variance = $\sum_{i=1}^{n} t_{ii} = \hat{\lambda}_1 + \hat{\lambda}_2 + \ldots + \hat{\lambda}_n$.

And $$c_{\hat{u}_i, v_k} = \frac{\hat{a}_{ik}\sqrt{\hat{\lambda}_i}}{\sqrt{s_{kk}}},$$

$$i, k = 1, 2, \ldots, n.$$

Let us denote $\hat{u}_1, \hat{u}_2, \ldots, \hat{u}_n$ as sample principle components either they get from T or C but they are not same. The ith principle component $\hat{u}_i = \hat{a}_i^{'}\left(v - \overline{v}\right)$,

$i = 1, 2, \ldots, n$ for arbitrary vector v. Suppose we assume the ithcomponent $\hat{u}_{ji} = \hat{a}_i^{'}\left(v_j - \overline{v}\right), j = 1, 2, \ldots, n.$ Then,

$$\overline{\hat{u}}_i = \frac{1}{p}\sum_{j=1}^{n} \hat{a}_i^{'}\left(v_j - \overline{v}\right) = \frac{1}{p}\hat{a}_i^{'}\left(\sum_{j=1}^{n}\left(v_j - \overline{v}\right)\right) = \frac{1}{p}\hat{a}_i^{'}0 = 0.$$

Standardization is constructing for sample is as follows,

$$A_j = Q^{-1/2}\left(v_j - \overline{m}\right) = \begin{bmatrix} \dfrac{v_{j1} - \overline{m}_1}{\sqrt{t_{11}}} \\ \dfrac{v_{j2} - \overline{m}_2}{\sqrt{t_{22}}} \\ \vdots \\ \dfrac{v_{jn} - \overline{m}_n}{\sqrt{t_{nn}}} \end{bmatrix},$$

$$j = 1, 2, \ldots, n.$$

The $p \times n$ data matrix of standardized observations,

$$A = \begin{bmatrix} A_1^{'} \\ A_2^{'} \\ \vdots \\ A_p^{'} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{p1} & A_{p2} & \cdots & A_{pn} \end{bmatrix}$$

$$= \begin{bmatrix} \dfrac{v_{11} - \overline{m}_1}{\sqrt{t_{11}}} & \dfrac{v_{12} - \overline{m}_2}{\sqrt{t_{22}}} & \ldots & \dfrac{v_{1n} - \overline{m}_n}{\sqrt{t_{nn}}} \\ \dfrac{v_{21} - \overline{m}_1}{\sqrt{t_{11}}} & \dfrac{v_{22} - \overline{m}_2}{\sqrt{t_{22}}} & \ldots & \dfrac{v_{2n} - \overline{m}_n}{\sqrt{t_{nn}}} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{v_{p1} - \overline{m}_1}{\sqrt{t_{11}}} & \dfrac{v_{p2} - \overline{m}_2}{\sqrt{t_{22}}} & \ldots & \dfrac{v_{pn} - \overline{m}_n}{\sqrt{t_{nn}}} \end{bmatrix}.$$

The yields the sample mean,

$$\overline{A} = \frac{1}{p}\left(1'A\right)' = \frac{1}{p}A_1^{'} = \frac{1}{p}\begin{bmatrix} \sum_{j=1}^{p} \dfrac{v_{j1} - \overline{m}_1}{\sqrt{t_{11}}} \\ \sum_{j=1}^{p} \dfrac{v_{j2} - \overline{m}_2}{\sqrt{t_{22}}} \\ \vdots \\ \sum_{j=1}^{p} \dfrac{v_{jn} - \overline{m}_n}{\sqrt{t_{nn}}} \end{bmatrix} = o.$$

And the sample covariance matrix,

$$T_A = \frac{1}{p-1}\left(A - \frac{1}{p}11'A\right)'\left(A - \frac{1}{p}11'A\right),$$

$$= \frac{1}{p-1}\left(A - 1\overline{A}'\right)'\left(A - 1\overline{A}'\right),$$

$$= \frac{1}{p-1}A'A,$$

$$= \frac{1}{p-1}\begin{bmatrix} \dfrac{(p-1)t_{11}}{t_{11}} & \dfrac{(p-1)t_{12}}{\sqrt{t_{11}}\sqrt{t_{22}}} & \ldots & \dfrac{(p-1)t_{1n}}{\sqrt{t_{11}}\sqrt{t_{nn}}} \\ \dfrac{(p-1)t_{21}}{\sqrt{t_{11}}\sqrt{t_{22}}} & \dfrac{(p-1)t_{22}}{t_{22}} & \ldots & \dfrac{(p-1)t_{2n}}{\sqrt{t_{22}}\sqrt{t_{nn}}} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{(p-1)t_{n1}}{\sqrt{t_{11}}\sqrt{t_{nn}}} & \dfrac{(p-1)t_{2n}}{\sqrt{t_{22}}\sqrt{t_{nn}}} & \ldots & \dfrac{(p-1)t_{nn}}{t_{nn}} \end{bmatrix}.$$

If A_1, A_2 be the standardized observations with ovariance matrix C, the ith sample principle component is,

$$\hat{u}_i = \hat{a}_i^{'}A = \hat{a}_{i1}^{'}A_1 + \hat{a}_{i2}^{'}A_2 + \ldots + \hat{a}_{in}^{'}A_n,$$

$$i = 1, 2, \ldots, n.$$

Where $\left(\hat{\lambda}_i, \hat{a}_i\right)$ is the ith eigenvalue-eigenvector pair of C with $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \ldots \geq \hat{\lambda}_n \geq o$. Also

Sample variance $\left(\hat{u}_i\right) = \hat{\lambda}_i$,

$$i = 1, 2, \ldots, n.$$

Sample Covariance$\left(\hat{u}_i, \hat{u}_k\right) = 0, \quad i \neq k$.

Total sample variance $= tr\left(C\right) = n = \hat{\lambda}_1 + \hat{\lambda}_2 + \ldots + \hat{\lambda}_n$ and $c_{\hat{u}_i, A_k} = \hat{a}_{ik}\sqrt{\hat{\lambda}_i}$, $i, k = 1, 2, \ldots, n.$

(proportion of sample variance due to

i[th] sample principal component) $= \frac{\hat{\lambda}_j}{n} \; i = 1, 2, \ldots, n.$

4 RESULTS AND DISCUSSION

The first eight components in table 1 have their own value greater than one, but the value of the ninth component is very close below one, and it explains 4.492 % of the overall variance [19]. Unless the first ninth element determines the total percentage of variance it counts just 86.793% [20]. The process used for identifying a factor is the Scree plot analysis. According to these criteria, the main factors are structured as a bend, with a large slope while the trivial factors are grouped at the bend base. For this fig 1, 11th factor the curve slope is very small and this factor could be removed from the model. In this fig 2 capital turnover ratio, the creator turnover ratio, the debtor turnover ratio, the stock return ratio, the gross profit ratio, the operating ratio and the cost ratio were not significant in mergers and acquisitions. In Fig 6 In figure 1 to 6 shows the pre-pca analysis for single parameter.

Table 1 Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	%of Variance
1	4.138	19.704	19.704	4.138	19.704
2	2.909	13.850	33.554	2.909	13.850
3	2.531	12.052	45.606		
4	2.056	9.790	55.396		
5	1.761	8.384	63.780		
6	1.468	6.990	70.770		
7	1.269	6.044	76.814		
8	1.152	5.487	82.301		
9	.943	4.492	86.793		
10	.834	3.973	90.766		
11	.467	2.225	92.991		
12	.402	1.913	94.904		
13	.347	1.652	96.556		
14	.318	1.513	98.069		
15	.210	.998	99.067		
16	.150	.713	99.780		
17	.035	.169	99.949		
18	.010	.050	99.999		
19	.000	.001	100.000		
20	3.147E-16	1.499E-15	100.000		
21	-2.211E16	-1.053E15	100.000		

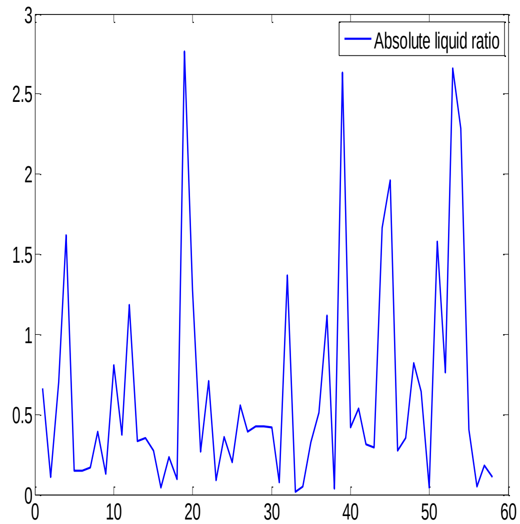

Figure 1 Pre- PCA analysis for absolute liquid ratio

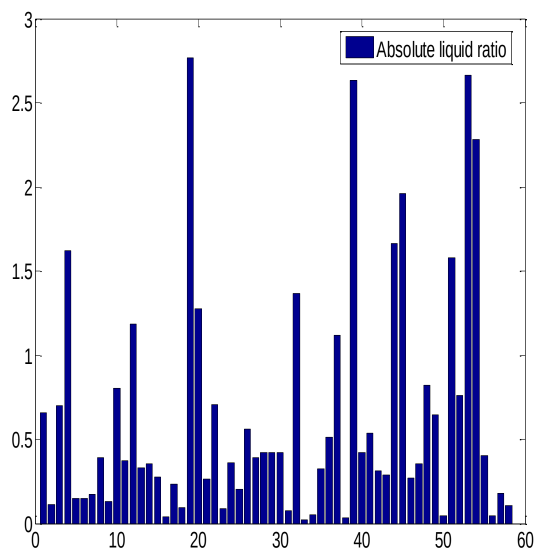

Figure 2 Pre- PCA analysis for absolute liquid ratio bar diagram

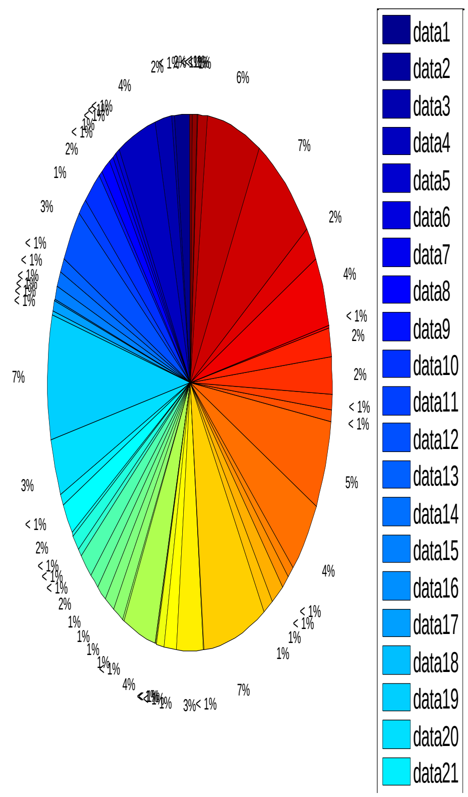

Figure 3 Pre- PCA analysis for 21 data

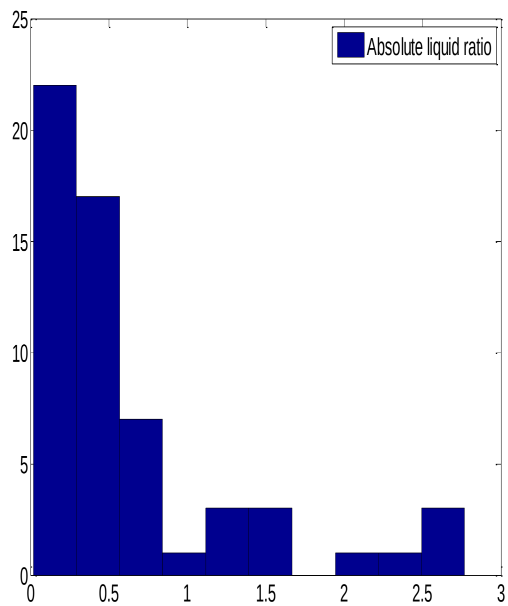

Figure 4 Pre- PCA analysis for absolute liquid ratio bar diagram

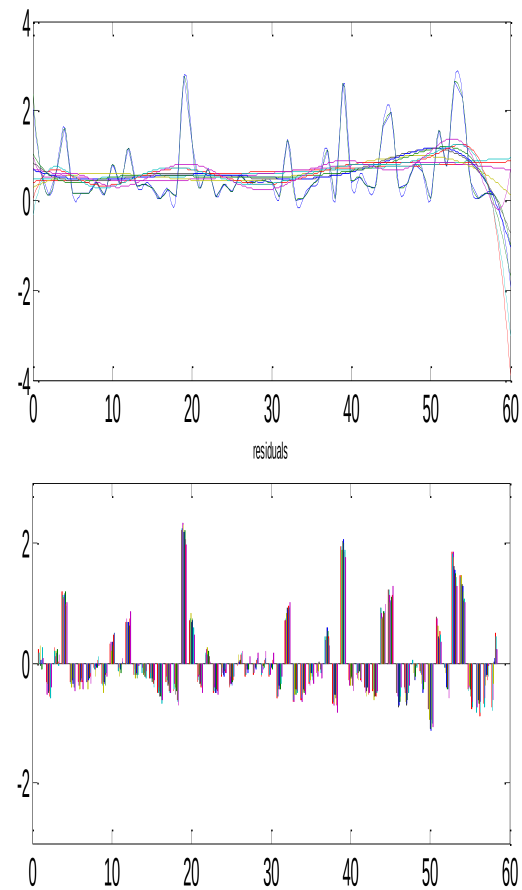

Figure 5 Pre- PCA analysis for maxima and minima

The first seven components in table 2 have their own value greater than one, but the value of the seven components are very close to one, and it explains 5.329 % of the overall variance [21]. Unless the first seven elements determine the total percentage of variance it counts just 82.538% [22]. The process used for identifying a factor is the Scree plot analysis [23]. According to these criteria, the main factors are structured as a bend, with a large slope while the trivial factors are grouped at the bend base. For this fig 3, 13th factor the curve slope is very small and this factor could be removed from the model. In figure 7 to 10 shows the post-pca analysis for single parameter

Table 2 Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings	
Component	Total	% of Variance	Cumulative %	Total	% of Variance
1	4.229	20.138	20.138	4.229	20.138
2	3.715	17.693	37.831	3.715	17.693
3	3.132	14.914	52.744		
4	2.625	12.501	65.245		
5	1.343	6.394	71.638		
6	1.170	5.570	77.208		
7	1.119	5.329	82.538		
8	.870	4.143	86.681		
9	.740	3.524	90.204		
10	.583	2.776	92.980		
11	.438	2.085	95.064		
12	.338	1.611	96.676		
13	.274	1.306	97.982		
14	.180	.859	98.841		
15	.138	.655	99.496		
16	.042	.199	99.695		
17	.041	.197	99.892		
18	.021	.100	99.992		
19	.002	.008	100.000		
20	3.914E-9	1.864E-8	100.000		
21	1.590E-9	7.569E-9	100.000		

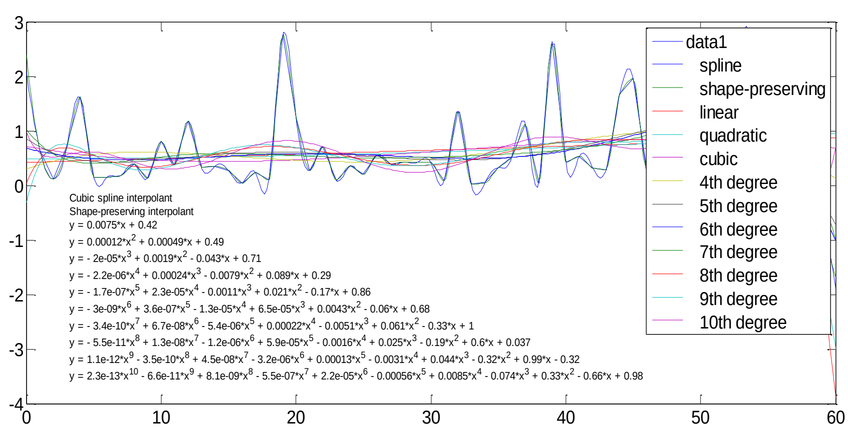

Figure 6 Pre- PCA analysis for finding the new equations

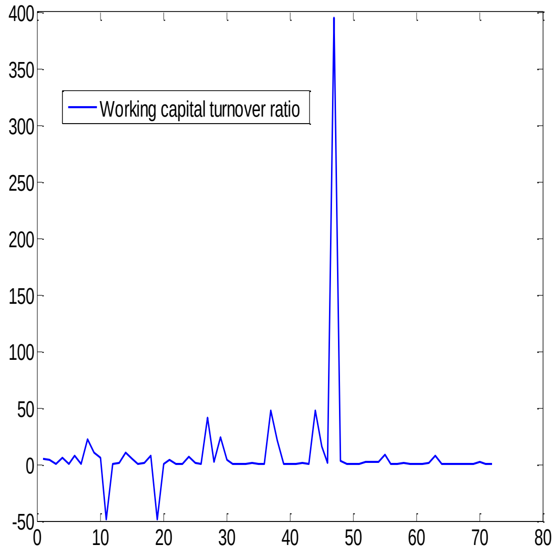

Figure 7 Post-PCA analysis for capital turnover ratio

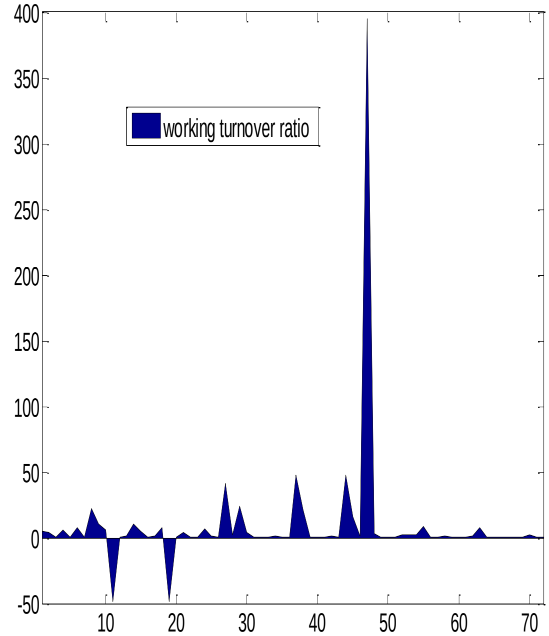

Figure 9 Post-PCA analysis for turnover ratio

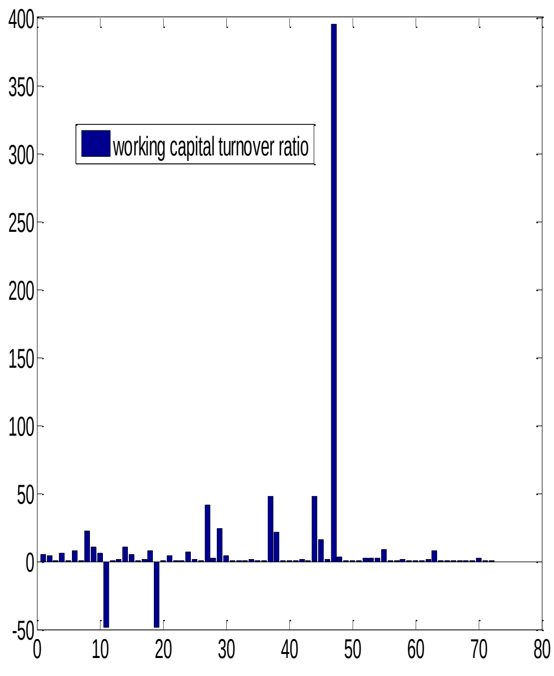

Figure 8 Post- PCA analysis for capital turnover ratio bar both sides

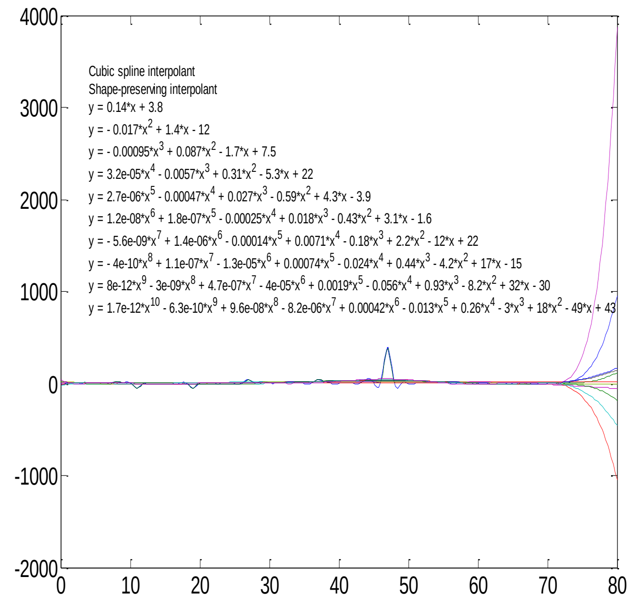

Figure 10 Post- PCA analysis for find the new equations

Using Factor analysis to reduce the Linear Equations are,

Pre Mergers and acquisition $Y= 0.873-0.11X_1-0.11X_2-0.66X_3-0.26X_4-0.30X_5$

Post Mergers and acquisition $Y= -0.144 +0.002X_1 -0.01X_2+0.007X_3-0.008X_4+0.005X_5$

5 CONCLUSIONS

The Principal component analysis can be used when the same construct is calculated by many variables. PCA consists of evaluating the suitability of the data for this technique, and select the best factors that identify the total variance of the initial variables. Heat map is very useful tools for analyse which ratio is most important role in Mergers and Acquisition.

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