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Application of Multivariate Statistical Methods in Analyzing Business Surveys in Central Bank of Nigeria

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Dissertation report presented as partial requirement for obtaining the Master's degree in Statistics and Information Management

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APPLICATION OF MULTIVARIATE STATISTICAL METHODS IN ANALYZING EXPECTATION SURVEYS IN CENTRAL BANK OF NIGERIA

by

Ogbuka Obinna Raymond

Dissertation proposal presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Information Analysis and Management.

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DEDICATION

I dedicate this project to GOD, my late father Engr. G.O.L Ogbuka and my late brother Mr. Godwin Ogbuka who greatly inspired me to carry out this work.

I also dedicate this project to my mother, Mrs L.A.R Ogbuka and all by siblings for their help and support financially and otherwise.

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ABSTRACT

In analyzing survey data, most researchers and analysts make use of statistical methods with straight forward statistical approaches. More common, is the use of one-way, two-way or multi-way tables, and graphical displays such as bar charts, line charts, etc. A brief overview of these approaches and a good discussion on aspects needing attention during the data analysis process can be found in Wilson & Stern (2001). In most cases however, analysis procedures that go beyond simple summaries are desirable. In this research work, data from 790 survey respondents who are purchasing managers in the manufacturing sector was analyzed using principal component analysis. The data spans Q32014 to Q22016.The result obtained enabled us to ascertain the factors that affect the manufacturing sector in Nigeria within quarterly period observations.

KEYWORDS

Principal components, Factor analysis, purchasing managers survey, eigen values

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LIST OF ABBREVIATIONS AND ACRONYMS

CBN	Central Bank of Nigeria
KMO	Kaiser Meyer Olkin
PCA	Principal Component Analysis
EFA	Exploratroy Factor Analysis
PMI	Purchasing Manager Index
IAS	Inflation Attitudes Survey
CES	Consumer Expectation Survey
BES	Business Expectation Survey

1. INTRODUCTION

The major role of a Central Bank is to formulate monetary policies that positively impact the economic and social growth of a country. In formulating these monetary policies, useful data must be collected and analyzed. Data is usually collected through surveys and compulsory data renditions by participating entities. Most times the data is too large and complex and the analysis of this data is both time consuming and difficult, hence the need for the use of more robust scientific and statistical methods and procedures.

The Central Bank of Nigeria (CBN) aside from its price and monetary stability mandate is also tasked with supporting the Government's policies on economic growth and unemployment reduction. This is done by using opinions and feedback from respondents to explore the general understanding of monetary policy issues. This is because good estimates and public understanding of what influences them are important parameters for successful monetary policy formulation.

This feedback is usually in the form of periodic surveys (monthly and quarterly) which are compared with other economic data in taking policy conditions. These surveys include Purchasing Managers Index survey (PMI) which is based on a survey of purchasing and supply executives of manufacturing and non-manufacturing organizations, The Business Expectation Survey (BES) which provides advance indication of change in overall business activity in the economy, The Inflation Attitudes Survey (IES) which samples the views of households on their perception of the price change of goods and services within a period, and the Consumer Expectation Survey (CES) aimed at capturing an overall consumer confidence index.

This thesis will focus on the use of multivariate statistical analysis method namely - factor analysis to extract useful information on the data realized from the conduct of the Purchasing Managers Index (PMI) survey in the manufacturing sector. The results of this analysis will facilitate knowledge of understanding the growth movement of the manufacturing sector in Nigeria and the factors that drive the growth in this sector and their impact on monetary policy formulation.

2. THEORETICAL FRAMEWORK

2.1 LITERATURE REVIEW

The use of multivariate statistical techniques for analysis in various fields has greatly increased over the years. One of the mostly used techniques in multivariate statistical analysis is the Factor Analysis. Factor Analysis is a method for modeling observed variables, and their covariance structure, in terms of a smaller number of underlying unobservable (latent) “factors". The factors typically are viewed as broad concepts or ideas that may describe an observed phenomenon. Factor analysis is generally an exploratory and descriptive method that requires many subjective judgments by the researcher. Factor analysis is somewhat similar to principal component analysis in that the former is an inversion of the later. In factor analysis, we model the observed variables as linear function of the “factors”, while in principal components we create new variables (components) that are linear combinations of the observed variables.

Factor analysis is a widely utilized and broadly applied statistical technique in the social sciences and surveys. It is also prominently used in marketing, biological, agricultural, and financial applications, to name a few. In recently published studies, it has been used for a variety of applications, including developing an instrument for the evaluation of school principals (Lovett, Zeiss, & Heinemann, 2002), assessing the motivation of Puerto Rican high school students (Morris, 2001), and determining what types of services should be offered to college students (Majors & Sedlacek, 2001).

A number of research work has been done using Factor analysis. Bork and Moller (2012) examined the US housing price forecastability using a common factor approach based on a large panel of 122 economic time series. They found that a simple three factor model generates an explanatory power of about 50% in one-quarter ahead in-sample forecasting regressions. The predictive power of the model stayed high at longer horizons. The estimated factors were strongly statistically significant according to a bootstrap resampling method which took into account that the factors are estimated regressors.

Hassan et all (2012) focused on using the statistical technique - factor analysis to construct the new factors affecting students' learning styles of the survey done among university students. Their results showed seven new factors were successfully constructed using factor analysis and assigned as the factors affecting the learning styles; which are 1) students' attitude before and after attending class, 2) strategies used to comprehend the lecture, 3) the importance of lecture, 4) class size and its condition, 5) efforts outside class, 6) classroom convenient and 7) importance on listening to lecture.

Reuben and Pedro (2007) concluded that Parallel Analysis (PA) is one of the most recommendable rules for factor selection in Factor Analysis and Principal Component Analysis. However they said that this method is not available as an analysis option in the most commonly used statistical software packages. In view of that, they described a new, interactive and easy-to-use computer program capable of carrying out PA – the ViSta-PARAN program.

Melanie Hof (2005) used two statistical methods namely Factor Analysis and Cronbach Alpha to evaluate a questionnaire used to determine Dutch seventh graders' pleasure in writing. She concluded that although a questionnaire is generally accepted as reliable when the Cronbach alpha is higher than 0.8, we cannot claim that the questionnaire is valid based on the factor analysis alone. However, to prove that it measures one's pleasure in writing, the results of other measures of one's pleasure in writing should be compared.

Diana D. Suhr (2005) examined the basic differences between Principal Component Analysis (PCA) and Exploratory Factor Analysis (EFA). In her work, she inferred that Principal Component Analysis and Exploratory Factor Analysis are powerful statistical techniques. The techniques have similarities and differences. A priori decisions on the type of analysis to answer research questions allow you to maximize your knowledge.

Jill (2005) developed a new method for constructing measures of gender and women's empowerment from cross-sectional survey data using factor analysis. He re-conceptualized gender and women's empowerment for measurement purposes and argued that gender and women's empowerment are best measured as a system of interrelated dimensions derived from context specific gender norms. The results of the confirmatory factor analysis were used to construct weighted measures of women's empowerment that are compared to simple scale measures

Rubén Daniel Ledesma (2007) described and illustrated how to determine the number of factors to retain in Principal Component Analysis (PCA) and Exploratory Factor Analysis (EFA). In his work, he applied the Monte Carlo simulation technique, Parallel Analysis, with an easy-to-use computer program called ViSta-PARAN, a user-friendly application that can compute and interpret Parallel Analysis.

Anna B. Costello and Jason W. Osborne (2005) looked at the best practices in Exploratory Factor Analysis. They aimed at collecting, in one article, information that will allow researchers and practitioners to understand the various choices available through popular software packages, and to make decisions about 'best practices' in exploratory factor analysis. They concluded that factor analysis, as well as other latent variable modeling techniques, can allow researchers to test hypotheses via inferential techniques, and can provide more informative analytic options.

Using the Regression model with many variables that are highly correlated with each other will not return the best estimators. The principal components that are to be taken into consideration are those factors that can explain the largest part of the information given by the initial variables. In this respect the number of factors which should be retained in the analysis is a decision matter for the researcher. For plotting purposes, two or three principal components deal with more variables that usually are correlated in order to reduce the dimension of the analysis to a small number of factors that are not correlated. Thus the negative effects of the multicollinearity are avoided. During factor extraction the total variance of a variable is split into two components; the shared variance between the variable and each factor and its unique variance (error variance). There are many extraction rules and approaches in the determination of the number of factors that are to be retained. One of the most popular is Kaiser's criteria which state that only those factors with eigenvalue higher than the mean will be retained in the model. Also the Scree plot test, the cumulative percent of variance extracted will be used. Furthermore, a logical judgment would be involved in this selection process in order to determine the meaning of every factor retained in the model. For a better interpretation of the results, we would implore a rotational method, which maximizes high item loadings and minimizes low item loadings. The rotation technique to be used is Orthogonal Varimax.

2.2 Objective

The clear objective of this work is to understand the pulse of the manufacturing sector and to empirically test and ascertain the factors that affect the growth of the manufacturing sector during the period Q32014-Q22016, by obtaining and using the factors in the data that best describes this growth.

3. STUDY RELEVANCE AND IMPORTANCE

The Central Bank of Nigeria (CBN) and indeed other central banks are tasked with administering monetary policies that will assist in maintaining price stability in an economy. One way this can be done is to check and regulate the amount of output in an economy. The central banks also establishes inflationary measures by tinkering the demand and supply of commodities. Through this study, knowledge of the degree of output from the manufacturing sector can give policy makers an idea of how to structure policies that affect general output.

Central banks also give monetary interventions to the real and manufacturing sector in order to boost output. This study can help to make these interventions more focused. For example, the relevant factors in this analysis of the survey explained the main factors responsible for the drive in the manufacturing sector. This can tell the area monetary interventions are needed.

This study is also important to the manufacturers in terms of knowledge of the level of employment and manpower in order to increase output.

4. METHODOLOGY

For the purpose of this study, in applying the PCA and Factor analysis, the variables used are metric ones (likert scale). These variables represent factors that affect the manufacturing output in the manufacturing sector in Nigeria. The variables are represented as x1 to x11 as outlined below:

4.1 Description of Variables

1. Production Level – x1
2. Level of new orders or customers or incoming business received – x2
3. Suppliers' delivery time – x3
4. Level of employment in organisation – x4
5. Raw materials inventory/work in progress – x5
6. New export order received – x6
7. Average price of outputs – x7
8. Average price of inputs – x8
9. Quantity of items purchased – x9
10. Level of outstanding business/Backlog of work in organization – x10
11. Stock of finished goods – x11

4.2 Measurment Scale

The variables will be measured using the likert scale with numbers form 1 – 3 assigned as outlined below:

1. Higher – 3
2. Same – 2
3. Lower – 1

Starting from the assumption that these variables are collinear, the purpose of the PCA is to reduce the number of variables that measure the factors affecting manufacturing output to a small number of factors that are not correlated.

4.3 Sample Size

The sample size is derived from monthly questionnaire feedback from purchasing managers in 560 manufacturing businesses in Nigeria. We would use the mean of the monthly returns of 3 consecutive months to get a quarterly series, ranging from 2014Q3 to 2016Q2. Thus for each quarter, we have 560 data points.

4.4 Definition of Methods

From our data let's assume we develop a population variance-covariance matrix similar to the one below;

1. VAR(X) $= \Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2p} \\ \Downarrow & & & \\ \sigma_{p1} & \sigma_{p2} & \cdots & \sigma_p^2 \end{pmatrix}$

- Considering the linear combinations,

$$
\begin{aligned}
Y_1 &= e_{11}X_1 + e_{12}X_2 + \ldots\ldots + e_{1p}X_p \\
Y_2 &= e_{21}X_1 + e_{22}X_2 + \ldots\ldots + e_{2p}X_p \\
&\vdots \\
Y_p &= e_{p1}X_1 + e_{p2}X_2 + \ldots\ldots + e_{pp}X_p
\end{aligned}
$$

- Each of these can be thought of as a linear regression predicting Y_J from $X_1, X_2, \ldots, X_p$
- There is no intercept, but $e_{j1}, e_{j2}, \ldots, e_{j2}$ can be viewed as regression coefficients.
- Y_j is a function of our random data, and so is also random.

- Therefore it has a population variance.

$$\text{var}(Y_j) = \sum_{K=1}^{p}\sum_{l=j}^{p} e_{jk}\, e_{jl}\sigma_{kl} = \mathbf{e'}_j\mathbf{\Sigma e}_j$$

- Hence, Y_j and Y_k will have a population covariance of

$$\text{cov}(Y_j, Y_k) = \sum_{K=1}^{p}\sum_{l=j}^{p} e_{jk}e_{jl}\sigma_{kl} = \mathbf{e'}_j\mathbf{\Sigma e}_k$$

- In this case the coefficients e_{jk} are collected into the vector

$$e_{jk} = \begin{pmatrix} e_{j1} \\ e_{j2} \\ e_{j3} \end{pmatrix}$$

2. FIRST PRINCIPAL COMPONENT (PC1) : Y_1

- The first principal component is the linear combination of x-variables that has maximum variance (among all linear combinations), so it accounts for as much variation in the data as possible.

- Specifically we will define coefficients $e_{11}, e_{12}, e_{13},\ldots, e_{1p}$ for that component in such a way that its variance is maximized, subject to the constraint that the sum of the squared coefficients is equal to one.

- We require this constraint so that a unique answer is obtained.

- Thus we formally select $e_{11}, e_{12}, e_{13},\ldots, e_{1p}$ that maximizes

$$\text{var}(Y_j) = \sum_{K=1}^{P}\sum_{l=1}^{P} e_{1k}\; e_{1l}\sigma_{kl} = \mathbf{e'}_1\mathbf{\Sigma e}_1$$

subject to the constraint that

$$e'_1 e_1 = \sum_{j=1} e^2_{1j} = 1$$

3. SECOND PRINCIPAL COMPONENT (PC2) : Y_2

- The second principal component is the linear combination of x-variables that accounts for as much of the remaining variation as possible, with the constraint that the correlation between the first and second component is 0.

- We select $e_{21}, e_{22}, e_{13}, \ldots, e_{2p}$ that maximizes the variance of the new component

$$var(Y_2) = \sum_{K=1}^{P} \sum_{l=i}^{P} e_{2k} e_{2l} \sigma_{kl} = \mathbf{e'}_2 \Sigma \mathbf{e}_2$$

subject to the constraint that the sums of squared coefficients add up to one,

$$e'_2 e_2 = \sum_{j=1}^{P} e^2_{2j} = 1$$

along with the additional constraint that these two components will be uncorrelated with one another.

$$cov(Y_1, Y_2) = \sum_{K=1}^{P} \sum_{l=i}^{P} e_{1k} e_{2l} \sigma_{kl} = \mathbf{e'}_1 \Sigma \mathbf{e}_2 = 0$$

4. j-th PRINCIPAL COMPONENT (PCj) : Y_j

- Subsequently all principal components are now linear combination that account for as much of the remaining variation as possible and they are not correlated with the other principal components.

- Hence generalizing, we have $e_{j1}, e_{j2}, e_{j3}, \ldots, e_{jp}$ that maximizes

$$var(Y_j) = \sum_{k=1}^{P} \sum_{l=j}^{P} e_{ik} e_{jl} \sigma_{kl} = \mathbf{e'}_j \Sigma \mathbf{e}_j$$

subject to the constraint that the sums of squared coefficients add up to one, along with the additional constraint that this new component will be uncorrelated with all the previously defined components.

$$e'_1 e_1 = \sum_{j=1} e^2_{1j} = 1$$

$$\text{cov}(Y_1, Y_j) = \sum_{k=1}^{P}\sum_{l=j}^{P} e_{1k} e_{jl} \sigma_{kl} = \mathbf{e'}_1 \boldsymbol{\Sigma} \mathbf{e}_j = 0$$

$$\text{cov}(Y_2, Y_2) = \sum_{k=1}^{P}\sum_{l=j}^{P} e_{2k} e_{jl} \sigma_{kl} = \mathbf{e'}_2 \boldsymbol{\Sigma} \mathbf{e}_j = 0$$

$$\text{cov}(Y_{j-1}, Y_2) = \sum_{k=1}^{P}\sum_{l=j}^{P} e_{j-i,k}\, e_{jl} \sigma_{kl} = \mathbf{e'}_{j-1} \boldsymbol{\Sigma} \mathbf{e}_j = 0$$

- Thus all principal components are uncorrelated with one another.

5. FACTOR ANALYSIS AND PRINCIPAL COMPONENTS RELATIONSHIP

Earlier on, Factor Analysis was defined as a method for modeling observed variables and their covariance structure, in terms of a smaller number of underlying unobservable (latent) “factors". It was also stated that Factor analysis is somewhat similar to principal component analysis in that the former is an inversion of the latter. In factor analysis, we model the observed variables as linear function of the “factors”, while in principal components we create new variables that are linear combinations of the observed variables.

The similarities between principal component analysis and factor analysis are outlined below:

- Recall that our previous definition of principal components let to the equation below:

$$
\begin{aligned}
Y_1 &= e_{11}X_1 + e_{12}X_2 + \ldots\ldots + e_{1p}X_p \\
Y_2 &= e_{21}X_1 + e_{22}X_2 + \ldots\ldots + e_{2p}X_p \\
&\vdots \qquad \vdots \qquad \vdots \qquad\qquad \vdots \\
&\vdots \qquad \vdots \qquad \vdots \qquad\qquad \vdots \\
Y_p &= e_{p1}X_1 + e_{p2}X_2 + \ldots\ldots + e_{pp}X_p
\end{aligned}
$$

- Let $\mathbf{e}'_k = (e_{k1}\ e_{k2}\ e_{k3}\ \ldots\ e_{kp})$ be the p x 1 *k*-eigenvector of the correlation matrix $\mathbf{R}$, with the associated eigenvalue λ_k.

- Therefore denoting $\mathbf{E} = (\mathbf{e}_1\ \mathbf{e}_2\ \ldots.\ \mathbf{e}_p)$ then the definition of the principal component is: $\mathbf{Y} = \mathbf{E'X}$

  Where $\mathbf{X'} = (X_1\ X_2\ \ldots.\ X_p)$ is the vector where we collected the observed variables, $\mathbf{Y'} = (Y_1\ Y_2\ \ldots.\ Y_p)$ is the principal components vector and $\mathbf{\Lambda} = diag(\lambda_1\ \lambda_2\ \ldots\ \lambda_p)$ is the diagonal matrix containing the eigenvalues.

- As a consequence of the definition of the principal components,

$$E(\mathbf{Y}) = \mathbf{0} \text{ and } Var(\mathbf{Y}) = \mathbf{\Lambda}$$

- In order to have standardized principal components (leading to standardized scores), we have to provide

$$\mathbf{Y^*} = \mathbf{\Lambda}^{-1/2}\ \mathbf{E'X},$$

  Where $\mathbf{Y^{*\prime}} = (Y^*_1\ Y^*_2\ \ldots.\ Y^*_p)$ is the vector of standardized principal components.

- Writing $\mathbf{X}$ as a function of $\mathbf{Y^*}$, we have:

$$\mathbf{Y^*} = \mathbf{\Lambda}^{-1/2}\ \mathbf{E'X}$$

$$\mathbf{\Lambda}^{1/2}\ \mathbf{Y} = \mathbf{E'X}$$

$$\mathbf{X} = \mathbf{E\Lambda}^{1/2}\ \mathbf{Y} \quad \text{(we will denote } \mathbf{E\Lambda}^{1/2} = \mathbf{L}\text{)}$$

- This means that the matrix of loadings of the factor model $\mathbf{L}$ is given by

$$\mathbf{L} = \begin{pmatrix} e_{11}\sqrt{\lambda_1} + e_{21}\sqrt{\lambda_2} + \ldots\ldots + e_{p1}\sqrt{\lambda_p} \\ e_{12}\sqrt{\lambda_1} + e_{22}\sqrt{\lambda_2} + \ldots\ldots + e_{p2}\sqrt{\lambda_p} \\ \vdots \quad\quad \vdots \quad\quad \vdots \\ \vdots \quad\quad \vdots \quad\quad \vdots \\ e_{1p}\sqrt{\lambda_1} + e_{2p}\sqrt{\lambda_2} + \ldots\ldots + e_{pp}\sqrt{\lambda_p} \end{pmatrix}$$

- The corresponding equations are:

$$X_1 = e_{11}\sqrt{\lambda_1}\, Y_1^* + e_{21}\sqrt{\lambda_2}\, Y_2^* + \ldots\ldots + e_{p1}\sqrt{\lambda_p}\, Y_P^*$$

$$X_2 = e_{12}\sqrt{\lambda_1}\, Y_1^* + e_{22}\sqrt{\lambda_2}\, Y_2^* + \ldots\ldots + e_{p2}\sqrt{\lambda_p}\, Y_P^*$$

$$\vdots$$

$$X_P = e_{1p}\sqrt{\lambda_1}\, Y_1^* + e_{2p}\sqrt{\lambda_2}\, Y_2^* + \ldots\ldots + e_{pp}\sqrt{\lambda_p}\, Y_P^*$$

Alternatively, $\mathbf{X} = \mathbf{LY^{*\prime}}$,

And each $e_{jk}\sqrt{\lambda_k}$ is the loading of the variable *j* on the principal component *k*, l_{jk}

- Using principal component to extract latent factors means we keep just the first m, leaving the remaining ones in a specific factor:

$$X_1 = e_{11}\sqrt{\lambda_1}\, Y_1^* + e_{21}\sqrt{\lambda_2}\, Y_2^* + \ldots\ldots + e_{m1}\sqrt{\lambda_m}\, Y_m^* + \underbrace{\sum_{K=m+1}^{P} e_{k1}\sqrt{\lambda_k} Y_k^*}_{\varepsilon_1}$$

$$X_2 = e_{12}\sqrt{\lambda_1}\, Y_1^* + e_{22}\sqrt{\lambda_2}\, Y_2^* + \ldots\ldots + e_{m2}\sqrt{\lambda_m}\, Y_m^* + \underbrace{\sum_{K=m+1}^{P} e_{k2}\sqrt{\lambda_k} Y_k^*}_{\varepsilon_2}$$

$$\vdots$$

$$X_P = e_{1p}\sqrt{\lambda_1}\, Y_1^* + e_{2p}\sqrt{\lambda_2}\, Y_2^* + \ldots\ldots + e_{mp}\sqrt{\lambda_m}\, Y_m^* + \underbrace{\sum_{K=m+1}^{P} e_{kp}\sqrt{\lambda_k} Y_k^*}_{\varepsilon_3}$$

- We call factors to the initial retained standardized principal components, $\mathbf{Y}^{*\prime} = (Y_1^*\ Y_2^* \ldots.\ Y_p^*) = \mathbf{f'} = (f_1\ f_2 \ldots.\ f_p)$

Furthermore, two main differences exist between principal component analysis and factor analysis. They include:

- First, principal components analysis places emphasis on the explaining the variance in the data; the objective of factor analysis is to explain the correlation among the indicators.

- Second, in principal components analysis the variables form an index. For example, in the following equation

$$Y_1 = e_{11}X_1 + e_{12}X_2 + ... + e_{1p}X_p$$

The variables are called formative indicators of the component and the index is formed by the variables.

- In factor analysis, on the other hand, the indicators reflect the presence of unobservable construct(s) or factor(s). For example, in the following equations:

$$X_1 - \mu_1 = \ell_{11}F_1 + \ell_{12}F_2 + ... + \ell_{1m}F_m + \mathcal{E}_1$$

$$X_2 - \mu_2 = \ell_{21}F_1 + \ell_{22}F_2 + ... + \ell_{2m}F_m + \mathcal{E}_2$$

$$\vdots \qquad\qquad\qquad\qquad \vdots$$

$$X_P - \mu_P = \ell_{P1}F_1 + \ell_{P2}F_2 + ... + \ell_{Pm}F_m + \mathcal{E}_P$$

- Where the variables (X1, X2, ... Xp) are functions of the latent construct(s) or factor(s), (f1, ,f2,....fm) and the specific factors (Ɛ1, Ɛ2, ... Ɛp).

In other words, they reflect the presence of the unobservable or latent constructs and hence the variables are called reflective indicators.

6. FACTOR ANALYSIS METHODOLOGY

Chua (2009) suggested that factor analysis is the procedure been used by researchers to organize, identify and minimize big items from the questionnaire to certain constructs under one dependent variable in a research. Kaiser Meyer Olkin KMO test was done to identify whether the data is suitable for factor analysis. The KMO test formula as stated by Norusis is:

$$\text{KMO} = \frac{\sum_{J=1}^{n} \sum_{i=1}^{n} r_i^2{}_j}{\left(\sum_{J=1}^{n} \sum_{i=1}^{n} r_i^2{}_j + \sum_{J=1}^{n} \sum_{i=1}^{n} a_i^2{}_j\right)}$$

Where:

$r_i^2{}_j$ = correlation coefficient

a_{ij}^2 = Partial correlation coefficient

Recall that the factor analysis model as stated by Johnson and Wichern is:

$$X_1 - \mu_1 = \ell_{11}F_1 + \ell_{12}F_2 + \ldots.. + \ell_{1m}F_m + \varepsilon_1$$

$$X_2 - \mu_2 = \ell_{21}F_1 + \ell_{22}F_2 + \ldots.. + \ell_{2m}F_m + \varepsilon_2$$

$$\vdots \qquad\qquad\qquad\qquad \vdots$$

$$X_P - \mu_P = \ell_{P1}F_1 + \ell_{P2}F_2 + \ldots.. + \ell_{Pm}F_m + \varepsilon_P$$

Johnson and Wichern stated the orthogonal factor model with m common factors as follows:

$$\underset{}{X} = \underset{(p \text{ X } 1)}{\mu} + \underset{(p \text{ X } 1)}{L} \quad \underset{(p \text{ X } m)}{F} + \underset{(m \text{ X } m)}{\varepsilon}$$

Where:

μ_i = mean of variable *i*

ε_i = *i*th specific factor

F_j = *j*th common factor

L_{ij} = loading of the *i*th variable on the *j*th factor

Johnson and Wichern (2002) also estimate the communalities as:

$$\tilde{h}_i^2 = \tilde{\ell}^2_{i1} + \tilde{\ell}^2_{i2} + \ldots\ldots + \tilde{\ell}^2_{im}$$

The principal component factor analysis of the sample covariance matrix S is specified in terms of its eigenvalue-eigenvector pairs $(\hat{\lambda}_1, \hat{e}_1)$, $(\hat{\lambda}_2, \hat{e}_2)$, ... ,$(\hat{\lambda}_3, \hat{e}_3)$ where $(\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq .. \hat{\lambda}_p)$. Let $m < p$ be the number of common factors. Then the matrix of estimated factor loadings $\{\tilde{\ell}\}$ is given by:

$$\tilde{L} = \left[\sqrt{(\hat{\lambda}_1 \hat{e}_1)} \ \vdots \ \sqrt{(\hat{\lambda}_2 \hat{e}_2)} \ \vdots \ \ldots.. \ \vdots \ \hat{\lambda}_m \hat{e}_m) \right]$$

Johnson and Wichern (2002) stated that the estimated specific variances are provided by the diagonal elements of the matrix $S - \tilde{L}\tilde{L}'$, so

$$\tilde{\Psi} = \begin{pmatrix} \tilde{\Psi}_1 & 0 & \cdots & 0 \\ 0 & \tilde{\Psi}_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \tilde{\Psi}_p \end{pmatrix}$$

with $\hat{\Psi}_i = S_{ii} - \sum_{J=1}^{m} \tilde{\ell}^2_{ij}$

4.5 Procedure/Steps

STEP 1: DESCRIPTIVE STATISTICS

McClave et al. (2005) defined descriptive statistics as an approach that utilizes numerical and graphical methods to look for patterns in a data set, to summarize the information revealed in a data set, and to present the information in a convenient form.

Altman et al. (2006) also stated that pilot study was a small experiment done to test the logic and to improve the information quality and efficiency collected from big study.

STEP 2: RELIABILITY ANALYSIS

Coakes and Ong (2011) suggested that reliability analysis was used to determine the internal consistency of the scales using Cronbach Alpha. The formula as stated by Fraenkel and Wallen (1996) is:

$$r_{Kk} = \left(\frac{k}{k-1} \right) . \left(1 - \frac{S_i^2}{S_x^2} \right)$$

where:

r_{Kk} = estimated Cronbach Alpha coefficient value

k = number of items in the questionnaire

S_i^2 = sum of item variances

S_x^2 = factor variances

STEP 3: INITIAL EXTRACTION OF THE COMPONENTS

In principal component analysis, the number of components extracted is equal to the number of variables being analyzed. Since eleven variables are analyzed in the present study, eleven components will be extracted. The first component can be expected to account for a fairly large amount of the total variance. Each succeeding component will account for progressively smaller amounts of variance. Although a large number of components may be extracted in this way, only the first few components will be important enough to be retained in order to determine the new factors.

STEP 4: DETERMINING THE NUMBER OF MEANINGFUL COMPONENTS TO RETAIN

Earlier it was stated that the number of components extracted is equal to the number of variables being analyzed, necessitating that there would be a decision of just how many of these components are truly meaningful and worthy of being retained for rotation and interpretation. In general, we expect that only the first few components will account for meaningful amounts of variance, and that the later components will tend to account for only trivial variance. The next step of the analysis, therefore, is to determine how many meaningful components should be retained for interpretation. The study will describe three main criteria that would be used in making this decision: the eigenvalue-one criterion, the scree test, the proportion of variance accounted for.

A: The Eigenvalue-One Criterion; In principal component analysis, one of the most commonly used criteria for solving the number-of-components problem is the eigenvalue-one criterion, also known as the Kaiser criterion (Kaiser, 1960). With this approach, we would retain and interpret any component with an eigenvalue greater than the mean of eigenvalues.

The rationale for this criterion is straightforward. Each observed variable contributes one unit of variance to the total variance in the data set. Any component that displays an eigenvalue greater than the mean is accounting for a greater amount of variance than had been contributed by one variable. Such a component is therefore accounting for a meaningful amount of variance, and is worthy of being retained.

On the other hand, a component with an eigenvalue less than the mean is accounting for less variance than had been contributed by one variable. The purpose of principal component analysis is to reduce a number of observed variables into a relatively smaller number of components; this cannot be effectively achieved if we retain components that account for less variance than had been contributed by individual variables. For this reason, components with eigenvalues less than 1.00 are viewed as trivial, will not be retained.

B: The Scree Test; With the scree test (Cattell, 1966), we would plot the eigenvalues associated with each component and look for a "break" between the components with relatively large eigenvalues and those with small eigenvalues. The components that appear before the break will be assumed to be meaningful and would be retained for rotation; those appearing after the break are assumed to be unimportant and are not retained.

Sometimes a scree plot will display several large breaks. When this is the case, we would look for the last big break before the eigenvalues begin to level off. Only the components that appear before this last large break should be retained.

C: Proportion of variance accounted for; A third criterion to be implored in this study to solve the number of factors problem involves retaining a component if it accounts for a specified proportion (or percentage) of variance in the data set. We will to retain any component that accounts for at least 50% to 60% of the total variance. This proportion can be calculated with a simple formula:

$$\text{Proportion} = \frac{\text{Eigenvalue for the component of interest}}{\text{Total eigenvalues of the correlation matrix}}$$

In principal component analysis, the "total eigenvalues of the correlation matrix" is equal to the total number of variables being analyzed (because each variable contributes one unit of variance to the analysis.

STEP 5: ROTATION

When more than one component has been retained in an analysis, the interpretation of an unrotated factor pattern is usually quite difficult. To make interpretation easier, we will perform an operation called a rotation. A rotation is a linear transformation that is performed on the factor solution for the purpose of making the solution easier to interpret. For software purposes, we would apply a varimax rotation which results in uncorrelated components. Compared to some other types of rotations, a varimax rotation tends to maximize the variance of a column of the factor pattern matrix (as opposed to arrow of the matrix).

STEP 6: INTERPRETING THE ROTATED SOLUTION

The rotated solution will be interpreted by determining what is measured by each of the retained components. Briefly, this would involve identifying the variables that demonstrate high loadings for a given component, and determining what these variables have in common. A name would be assigned to each retained component that describes its content.

The first decision to be made at this stage is to decide how large a factor loading must be to be considered “large.” Stevens (1986) discusses some of the issues relevant to this decision, and even provides guidelines for testing the statistical significance of factor loadings. For purpose of this study however, we would simply consider a loading to be “large” if its absolute value exceeds 0.5.

Finally we will carry out a reliablity anaysis of or internal consistency of the factors using Cronbach alpha. Based on the factor analysis, we want to use a subset of the items to assess the factors. This would enable us know how well the items from each factor hang together such that one can use a single composite score or further analysis. A useful rule states that a scale is reliable if it has a Cronchbach’s alpha of 0.70 or greater (Nunnally 1978). For the purpose of this project, we would use a Conchbach’s alpha of 0.70.

Furthermore, when performing reliability analysis, you might want to know which variables are the most and least useful in your scale. You can calculate alpha if item deleted by removing each variable in turn and computing alpha without that variable in the analysis. The higher the alpha if item deleted is, the less that target variable contributes to the internal consistency of the scale. Conversely, a small alpha if item deleted suggests that the item is important to the reliability of the scale.

5. RESULTS AND DISCUSSION

5.1 Q3 2014

We would consider the data from Q3 2014 to be suitable for Factor Analysis, because looking at the overall data quality measure – KMO (Table 9.1.2), the value obtained is approximetely 0.766 which is suitable.

The table displaying the correlations and relationship between each of the various variables in the data is also displayed in Table 9.1.3

Recall that from the eigenvalue-one criterion otherwise known as the kaiser criterion, we would retain and interprete any component with an eigenvalue greater than the mean (in this case greater thatn one).

Tabel 5.1.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.27817784	1.81756	0.29800	0.298
2	1.46061766	0.30427811	0.13280	0.43080
3	1.15633955	0.17757367	0.10510	0.53590
4	0.97876588	0.17480878	0.08900	0.62490
5	0.8039571	0.09451569	0.07310	0.69800
6	0.7094414	0.05511039	0.06450	0.76250
7	0.65433102	0.04353682	0.05950	0.82200
8	0.61079419	0.00561358	0.05550	0.87750
9	0.60518061	0.14232947	0.05500	0.93250
10	0.46285114	0.18330752	0.04210	0.97460
11	0.27954362		0.02540	1

From the table 5.1.1 and using the Kaiser criterion, we can evidently see that the first, second and third factors have eigenvalues greater than 1 and hence would be retained. These factors account for 53.6% of the total variability of all the variables.

Furthermore, the scree plot of the eigenvalues and factors shows that the number of factors to be retained is the data points that are above the break (i.e point of inflexion). To determine the break, we can draw an imaginary horizontal and vertical line from each end of the grap

The factor pattern matrix as shown in table 5.1.2 displays the loadings for the solution with three factors. For interpretation purposes, we would take into consideration the loadings with absolute value greater than 0.5

Tabel 5.1.2. Factor Pattern Matrix

	Factor1	Factor2	Factor3
x1	0.73599	-0.19750	-0.35499
x2	0.73108	-0.14725	-0.38324
x3	0.56163	0.006	-0.33489
x4	0.53514	0.07123	-0.19843
x5	0.62405	-0.05366	0.16444
x6	0.4054	0.16206	0.32069
x7	0.32966	0.78933	0.07770
x8	0.28121	0.78308	0.04620
x9	0.65677	-0.13014	0.11911
x10	0.41607	-0.16327	0.59865
x11	0.50419	-0.29296	0.47043

The initial factor extraction looks cleaner than the rotated factor patter as we don't have variables representing different dimensions in the same factor and we need the factors to include the 11 variables in the analysis. Hence it is easier to name the factors.

The first variable has a significant loading on factor 1. The other loadings on factor2 and factor3 are insignificant. Furthermore, the second variable has one significant loading on factor1 only and insignificant loadings on the other factors. The same pattern is evidenced in the third, fourth and fifth variable.

Hence the general interpretation for the factor pattern is given as:

Factor1: Loadings X1, X2, X3, X4, X5, X9 and X11.

Factor2: Loadings X7 and X8.

Factor3: Loadings X10.

From the factor extraction, and looking at the variable representations, we can assign unique characteristics to the factors as detailed below:

Factor1: Level of production.

Factor2: Pricing.

Factor3: Level of outstanding/unfinished work

In order to establish the reliability, quality and internal consistency of these factors, we would test them using the Cronbach alpha.

The output for factor1 is shown in table 5.1.8 below. Recall that the minimum Cronbach alpha value we previously prescribed was 0.7. The raw alpha (0.764) and standardized alpha (0.723) for Factor1 are acceptable.

Tabel 5.1.3. Cronbach Alpha

Factor 1		Factor 2	
Variables	**Alpha**	**Variables**	**Alpha**
Raw	0.764364	Raw	0.67414
Standardized	0.762532	Standardized	0.67472

Consequently, the table of alpha for items deleted (Table 9.1.11) shows the correlation of each item together with its scale, the estimate of alpha if the variable were deleted from the analysis, and standardized correlation and alpha if deleted.

Looking at the output, we see that no single variable stands out as helping the scale score more than other items. Notice that the alpha figures are all less than the overall Cronbach Alpha for Factor1. Hence Factor1 can be assumed to be reliable. The smallest value for alpha if deleted is for variable x1 (Production Level), which suggests that x1 contributes more to the overall alpha than other variables and without this variable, internal consistency would be reduced. This information is helpful in naming the factors. As stated earlier, factor 1 could be represented as ‘Level of Production’.

The output for factor2 as below depicts the Conbach’s Alpha value for factor2 as 0.674 for raw alpha and 0.675 for standardized alpha. We could accept these values as it is significant to 0.7, which is the prescribed Cronbach alpha value.

There is no Cronbach Alpha value for factor3 because the alpha option is not allowed with fewer than two variables.

5.2 Q4 2014

Just like the previous quarter, the data for Q4 2014 is suitable for Factor Analysis, because the overall data quality measure – KMO (see appendix) is approximetely 0.77 which is suitable.

From the eigenvalue-one criterion, we would retain and interprete any component with an eigenvalue greater than the mean (in this case greater than one).

Tabel 5.2.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.50914459	2.21756	0.31900	0.319
2	1.29158657	0.12461912	0.11740	0.43640
3	1.16696745	0.1881656	0.10610	0.54250
4	0.97880184	0.10889727	0.08900	0.63150
5	0.86990458	0.10822003	0.07910	0.71060
6	0.76168454	0.11031297	0.06920	0.77980
7	0.65137157	0.07717284	0.05920	0.83900
8	0.57419873	0.05046785	0.05220	0.89120
9	0.52373088	0.13104561	0.04760	0.93890
10	0.39268527	0.11276129	0.03570	0.97460
11	0.27992398		0.02540	1

From the table 5.2.1, it is evident that the first, second and third factors have eigenvalues greater than 1 and hence would be retained. These factors account for 54.3% of the total variability of all the variables.

The scree plot of the eigenvalues and factors also guides in suggesting the the number of factors to be retained are the data points that are above the break (i.e point of inflexion).

The factor pattern matrix in table 5.2.2 displays the loadings for the solution with three factors. For interpretation purposes, we would take into consideration the loadings with absolute value greater than 0.5.

The initial factor extraction looks clean and we need the factors to include the 11 variables in the analysis. Hence we can name the factors.

Tabel 5.2.2. Factor Pattern Matrix

	Factor1	Factor2	Factor3
X1	0.69201	-0.26519	-0.23283
X2	0.77926	-0.17701	-0.26872
X3	0.60586	-0.04152	-0.41723
X4	0.59303	-0.04918	-0.27918
X5	0.57687	0.00995	0.11250
X6	0.18958	0.06446	0.48847
X7	0.46154	0.74428	0.10259
X8	0.53837	0.66476	0.08845
X9	0.67265	-0.13879	0.15327
X10	0.40705	-0.29908	0.49431
X11	0.46317	-0.27742	0.50109

From the table above, the variables with significant loadings on thefactors are outlined below:

Factor1: Loadings X1, X2, X3, X4, X5 and X9.

Factor2: Loadings X7 and X8.

Factor3: Loadings X6, X10 and X11.

From the factor extraction, and looking at the variable representations, we can assign unique characteristics to the factors as detailed below. Note that this is a similar trend to the preceeding quarter in 2014.

Factor1: Level of production.

Factor2: Pricing.

Factor3: Level of outstanding business and goods

To establish reliability, quality and internal consistency of these factors, we would test them using the Cronbach Alpha.

The output for factor1 is shown in table 5.2.3 below. The raw alpha (0.7680) and standardized alpha (0.777) for Factor1 are acceptable, since the minimum prescribed Cronbach Alpha value is 0.7.

Tabel 5.2.3. Cronbach Alpha

Factor 1		Factor 2		Factor 3	
Variables	Alpha	Variables	Alpha	Variables	Alpha
Raw	0.780036	Raw	0.72591	Raw	0.38403
Standardized	0.777434	Standardized	0.72602	Standardized	0.37201

The correlation of each item together with its scale, the estimate of alpha if the variable were deleted from the analysis, and standardized correlation and alpha if deleted, is shown in Table 9.2.11 (see appendix)

From the table, no single variable stands out as helping the scale score more than other items. The alpha figures are all less than the overall Cronbach Alpha for Factor1 and Factor1 can be assumed to be reliable. The smallest value for alpha if deleted is for variable x2 (Level of new customers or new business received).

From Table 5.2.3, the Cronbach Alpha value for factor2 is 0.726 for raw alpha and 0.726 for standardized alpha, which is acceptable.

Factor 3 is not reliable or consistent.

5.3 Q1 2015

The data from Q1 2015 is suitable as the KMO test shows a value of approximately 0.76.

We are retaining and interpreting any component with an eigenvalue greater than the mean (in this case greater than one).

From the table 5.3.1, we are retaining the first, second and third factors with eigenvalues greater than 1. These factors account for 54.4% of the total variabilty of all the variables.

Tabel 5.3.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.43498146	2.10284	0.31230	0.3123
2	1.33213727	0.11532435	0.12110	0.43340
3	1.21681293	0.24682531	0.11060	0.54400
4	0.96998762	0.14500352	0.08820	0.63220
5	0.8249841	0.04830169	0.07500	0.70720
6	0.77668241	0.10372895	0.07060	0.77780
7	0.67295347	0.04557585	0.06120	0.83900
8	0.62737762	0.10059504	0.05700	0.89600
9	0.52678258	0.10541977	0.04790	0.94390
10	0.42136281	0.22542506	0.03830	0.98220
11	0.19593775		0.01780	1

Consequently, from the scree plot of the eigenvalues and factors. The number of factors to be retained is the data points that are above the break.

From the factor pattern matrix displayed in table 5.3.5, we see the loadings for the solution with three factors. As earlier stated, we would take into consideration the loadings with absolute value greater than 0.5.

The initial factor extraction looks clean and we can conclude on the factors to obtain.

Tabel 5.3.2. Factor Pattern Matrix

	Factor 1	Factor 2	Factor 3
X1	0.76322	-0.05847	-0.40952
X2	0.78889	-0.08577	-0.38495
X3	0.56021	0.04703	-0.28618
X4	0.49436	-0.22995	-0.05059
X5	0.5842	-0.20342	0.04639
X6	0.18442	-0.12344	0.62385
X7	0.34798	0.7937	0.09209
X8	0.45201	0.7075	0.18560
X9	0.68222	-0.10018	0.19262
X10	0.46798	-0.18738	0.45415
X11	0.53551	-0.18438	0.37260

From the table above, the variables with significant loadings on thefactors are outlined below:

Factor1: Loadings X1, X2, X3, X4, X5, X9 and X11

Factor2: Loadings X7 and X8.

Factor3: Loadings X6.

From the foregoing, we can assign unique characteristics to the factors as detailed below.

Factor1: Level of production.

Factor2: Pricing.

Factor3: Amount of new exports received.

We would test them using the Cronbach Alpha in order to establish reliability, quality and internal consistency of these factors,

The output for factor1 is shown in table 5.3.3 below. The raw alpha (0.780) and standardized alpha (0.776) for Factor1 are acceptable, since the minimum acceptable Cronbach Alpha value is 0.7.

The Cronbach Alpha value for factor2 is 0.672 for raw alpha and 0.673for standardized alpha, which could be accepted.

Tabel 5.3.3. Cronbach Alpha

Factor 1		Factor 2	
Variables	Alpha	Variables	Alpha
Raw	0.780211	Raw	0.67197
Standardized	0.773593	Standardized	0.67285

The correlation of each item together with its scale, the estimate of alpha if the variable were deleted from the analysis, and standardized correlation and alpha if deleted, is shown in Table 9.3.11 (see appendix)

From the table, no single variable stands out as helping the scale score more than other items. The alpha figures are all less than the overall Cronbach Alpha for Factor1, hence can be assumed to be reliable. The smallest value for alpha if deleted is for variable x2 (Level of new customers or new business received).

The Cronbach alpha value for factor3 is not suitable.

5.4 Q2 2015

The data from Q4 2014 is also suitable for Factor Analysis as the overall data quality measure – KMO is suitable.

Like previous quarters, we would retain and interprete any component with an eigenvalue greater than the mean (in this case greater than one), according to the eigenvalue-one criterion as shown in Table 5.4.1

Tabel 5.4.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.19215477	1.81012425	0.29020	0.2902
2	1.38203052	0.14137048	0.12560	0.41580
3	1.24066005	0.22527745	0.11280	0.52860
4	1.0153826	0.10566874	0.09230	0.62090
5	0.90971386	0.2300707	0.08270	0.70360
6	0.67964317	0.01560915	0.06180	0.76540
7	0.66403401	0.04029248	0.06040	0.82580
8	0.62374153	0.03851353	0.05670	0.88250
9	0.58522801	0.10631073	0.05320	0.93570
10	0.47891728	0.25042308	0.04350	0.97920
11	0.2284942		0.02080	1

The first, second, third and fourth factors have eigenvalues greater than 1 and hence would be retained. These factors account for 62.1% of the total variability of all the variables, the scree plot (see appendix) also explains this.

The factor pattern matrix shown in table 5.4.2 displays the loadings for the solution with three factors. For interpretation purposes, we would take into consideration the loadings with absolute value greater than 0.5.

The initial factor extraction looks clean and we need the factors to include the 11 variables in the analysis. Hence we can name the factors.

Tabel 5.4.2. Factor Pattern Matrix

	Factor1	Factor2	Factor3	Factor4
X1	0.72283	-0.32822	-0.30893	0.21712
X2	0.74851	-0.2888	-0.31793	0.2226
X3	0.57588	0.13936	-0.36704	-0.155
X4	0.53816	-0.0523	-0.07729	-0.1287
X5	0.5778	-0.1561	0.22003	0.08317
X6	0.21917	0.11162	0.62728	0.57223
X7	0.44601	0.70258	-0.03475	0.09094
X8	0.3719	0.73123	0.02427	0.03713
X9	0.66483	-0.0365	0.16329	-0.0435
X10	0.41589	0.06866	0.26875	-0.7076
X11	0.39249	-0.3123	0.60072	-0.1776

Looking at Table 5.4.2 above, the variables with significant loadings on thefactors are outlined below:

Factor1: Loadings X1, X2, X3, X4, X5 and X9.

Factor2: Loadings X7 and X8.

Factor3: Loadings X6 and X11.

Factor4: Loadings X10

From the factor extraction, and looking at the variable representations, we can also assign unique characteristics to the factors as detailed below.

Factor1: Level of production.

Factor2: Pricing.

Factor3: New orders and stock of finished goods

Factor4: Level of outstanding business and goods

To establish reliability, quality and internal consistency of these factors, we would test them using the Cronbach Alpha.

The output for factor1 is shown in table 5.2.3 below. The raw alpha (0.771) and standardized alpha (0.765) for Factor1 are acceptable.

Tabel 5.4.3. Cronbach Alpha

Factor 1		Factor 2		Factor 3	
Variables	**Alpha**	**Variables**	**Alpha**	**Variables**	**Alpha**
Raw	0.77074	Raw	0.65611	Raw	0.33591
Standardized	0.76474	Standardized	0.65644	Standardized	0.34178

The estimate of alpha if the variable were deleted from the analysis, and standardized correlation and alpha if deleted, is shown in Table 9.4.11 (see appendix).

No single variable stands out as helping the scale score more than other items. The alpha figures are all less than the overall Cronbach Alpha for Factor1 and can be assumed to be reliable. The smallest value for alpha if deleted is for variable x2 (Level of new customers or new business received).

Also, the Cronbach Alpha value for factor2 is approximately 0.656 for raw alpha and 0.656 for standardized alpha, which is also acceptable.

Factor 3 is incosistent since the cronbach alpha value is much lower than 0.7 as shown in Table 5.4.3. Cronbach alpha value for Factor 4 does not exist since it consists of one variable only.

5.5 Q3 2015

The data from Q3 2015 is suitable for Factor Analysis since the KMO is approximetely 0.800. (see appendix, table 9.5.2)

According to the eigenvalue-one criterion, we would retain and interprete any component with an eigenvalue greater than the mean.

Tabel 5.5.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.46265276	2.29910406	0.31480	0.3148
2	1.16354869	0.11577519	0.10580	0.42060
3	1.0477735	0.10681919	0.09530	0.51580
4	0.94095431	0.08962205	0.08550	0.60140
5	0.85133227	0.12073843	0.07740	0.67880
6	0.73059384	0.0218302	0.06640	0.74520
7	0.70876364	0.00468899	0.06440	0.80960
8	0.70407465	0.09492568	0.06400	0.87360
9	0.60914897	0.05064057	0.05540	0.92900
10	0.5585084	0.33585943	0.05080	0.97980
11	0.22264897		0.02020	1

The Eigen values matrix in the table above shows that the first, second and third factors have eigenvalues greater than 1 and hence would be retained. These factors account for 52% of the total variability of all the variables.

Furthermore, the factor pattern matrix below displays the loadings for the solution with three factors. For interpretation purposes, we would take into consideration the loadings with absolute value greater than 0.5.

Tabel 5.5.2. Factor Pattern Matrix

	Factor1	Factor2	Factor3
x1	0.74542	-0.01590	-0.49437
x2	0.75704	0.01653	-0.46990
x3	0.51088	-0.39929	-0.18567
x4	0.51593	-0.20976	0.11056
x5	0.51465	0.37172	0.13759
x6	0.31985	0.49373	0.33302
x7	0.51706	-0.45432	0.36055
x8	0.52969	-0.32305	0.49990
x9	0.63972	0.06338	0.05582
x10	0.49387	0.19485	0.13984
x11	0.05884	0.47423	0.49833

The general interpretation for the factor pattern is given as:

Factor1: Loadings X1, X2, X3, X4, X5, X7, X8, X9 and X10.

Factor2: Loadings X6.

Factor3: Loadings X11.

From the factor extraction, and looking at the variable representations, we can assign unique characteristics to the factors as detailed below:

Factor1: Level of production and pricing

Factor2: New export order received

Factor3: Stock of finished goods

Going forward, we would test them using the Cronbach Alpha for reliability

The output for factor1 is shown in table 5.5.6 below. The raw alpha (0.769) and standardized alpha (0.768) for Factor1 are acceptable.

Tabel 5.5.3. Cronbach Alpha

Factor 1	
Variables	**Alpha**
Raw	0.769481
Standardized	0.767803

From table 5.5.3, we see the 'alpha with deleted variable' figures in the raw and standardized variables column are all less than the overall Cronbach Alpha for Factor1. Hence Factor1 can be assumed to be reliable. The smallest value for alpha if deleted is for variable x2 (Level of new customers). See table 9.5.11 in appendix.

There are no alpha values for Factor 2 and Factor 3, as they comprise single variables.

5.6 Q4 2015

The KMO test shows a value of approximately 0.79 (see appendix), for the data from Q4 2015. Hence it is suitable for factor analysis

We would also retain and interprete any component with an eigenvalue greater than the mean (in this case greater than one).

Tabel 5.6.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.33705047	2.12794035	0.30340	0.3034
2	1.20911013	0.17583952	0.10990	0.41330
3	1.0332706	0.03779484	0.09390	0.50720
4	0.99547577	0.10527936	0.09050	0.59770
5	0.8901964	0.12086318	0.08090	0.67860
6	0.76933323	0.04623104	0.06990	0.74860
7	0.72310219	0.07458205	0.06570	0.81430
8	0.64852014	0.05989481	0.05900	0.87330
9	0.58862533	0.10351599	0.05350	0.92680
10	0.48510934	0.16490294	0.04410	0.97090
11	0.3202064		0.02910	1

Since we are retaining factors with eigenvalues greater than 1, the first, second and third factors from Table 5.6.1 would be used.. These factors account for 51% of the total variabilty of all the variables.

From the factor pattern matrix displayed in table 5.6.2, we see the loadings for the solution with three factors. We are taking into consideration the loadings with absolute value greater than 0.5.

The initial factor extraction looks clean and we can conclude on the factors to obtain.

Tabel 5.6.2. Factor Pattern Matrix

	Factor1	Factor2	Factor3
x1	0.6898	-0.21950	0.0919
x2	0.72805	-0.2488	0.05352
x3	0.56647	-0.0342	-0.28389
x4	0.57192	-0.2904	-0.14243
x5	0.57007	-0.0203	0.10738
x6	0.27251	-0.2133	0.82334
x7	0.43685	0.65895	0.26311
x8	0.42014	0.70462	0.04397
x9	0.68887	0.04599	-0.32585
x10	0.53779	0.06057	-0.21435
x11	0.50717	-0.1765	0.09151

From the table above, the variables with significant loadings on thefactors are outlined below:

Factor1: Loadings X1, X2, X3, X4, X5, X9 X10 and X11

Factor2: Loadings X7 and X8.

Factor3: Loadings X6.

From the foregoing, we can assign unique characteristics to the factors as detailed below.

Factor1: Level of production and outstanding business

Factor2: Pricing.

Factor3: Amount of new exports received.

We would test them using the Cronbach Alpha in order to establish reliability, quality and internal consistency of these factors,

The output for factor1 is shown in table 5.6.3 below. The raw alpha (0.765) and standardized alpha (0.762) for Factor1 are acceptable, since the minimum acceptable Cronbach Alpha value is 0.7.

Tabel 5.6.3. Factor Pattern Matrix

Factor 1		Factor 2	
Variables	**Alpha**	**Variables**	**Alpha**
Raw	0.76447	Raw	0.67682
Standardized	0.76173	Standardized	0.67696

The correlation of each item together with its scale, the estimate of alpha if the variable were deleted from the analysis, and standardized correlation and alpha if deleted, is shown in Table 9.6.11 (see appendix).

From the table, no single variable stands out as helping the scale score more than other items. The alpha figures are all less than the overall Cronbach Alpha for Factor1 and can be assumed to be reliable. The smallest value for alpha if deleted is for variable x2 (Level of new customers or new business received).

The Cronbach alpha value for factor2 is 0.677 for raw alpha and 0.677 respectively for raw and standardized alpha, which is acceptable.

There is no Cronbach Alpha value for factor3 since it has just one variable.

5.7 Q1 2016

Just like previous quarters, the data from Q1 2016 is suitable for Factor Analysis, because the overall data quality measure (KMO) is greater than 0.7. (See appendix).

Again, from the eigenvalue-one criterion, we would retain and interprete any component with an eigenvalue greater than the mean (in this case greater than one).

Tabel 5.7.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.37935185	1.97683998	0.30720	0.3072
2	1.40251187	0.19138027	0.12750	0.43470
3	1.2111316	0.28503367	0.11010	0.54480
4	0.92609793	0.12751568	0.08420	0.62900
5	0.79858225	0.06685205	0.07260	0.70160
6	0.7317302	0.01059105	0.06650	0.76810
7	0.72113915	0.08023523	0.06560	0.83370
8	0.64090392	0.09822131	0.05830	0.89190
9	0.54268261	0.10864735	0.04930	0.94130
10	0.43403526	0.22220188	0.03950	0.98070
11	0.21183338		0.01930	1

Using the Kaiser criterion, it is evident from table 5.7.1, the first, second and third factors have eigenvalues greater than 1 and hence would be retained. These factors account for 54.5% of the total variability of all the variables.

Also in table 8.7. (see appendix), the scree plot of the eigenvalues and factors shows that the number of factors to be retained is the data points that are above the break (i.e point of inflexion).

Tabel 5.7.3. Factor Pattern Matrix

	Factor1	Factor2	Factor3
x1	0.77567	-0.21943	-0.3237
x2	0.75006	-0.2293	-0.41274
x3	0.59846	-0.0076	-0.41896
x4	0.55229	-0.1455	0.27077
x5	0.62431	-0.2102	0.24150
x6	0.21719	-0.1217	0.44130
x7	0.39517	0.75914	-0.03466
x8	0.35681	0.79443	0.06161
x9	0.62077	0.08666	-0.02272
x10	0.42259	-0.0329	0.53548
x11	0.51728	-0.0746	0.37656

The factor pattern matrix shown in table 5.7.3 displays the loadings for the solution with three factors. For interpretation purposes, we would take into consideration the loadings with absolute value greater than 0.5.

The initial factor extraction is also clean therefore we can name the factors.

From the table above, the variables with significant loadings on thefactors are outlined below:

Factor1: Loadings X1, X2, X3, X4, X5, X9 and X11.

Factor2: Loadings X7 and X8.

Factor3: Loadings X10.

We can assign unique characteristics to the factors as detailed below.

Factor1: Level of production.

Factor2: Pricing.

Factor3: Level of outstanding business and goods

To establish reliability, quality and internal consistency of these factors, we would test them using the Cronbach Alpha.

The output for factor1 is shown in table 5.7.3 below. The raw alpha (0.768) and standardized alpha (0.776) for Factor1 are acceptable, since the minimum prescribed Cronbach Alpha value is 0.7.

Tabel 5.7.6. Cronbach Alpha

Factor 1		Factor 2	
Variables	**Alpha**	**Variables**	**Alpha**
Raw	0.76820	Raw	0.69468
Standardized	0.77636	Standardized	0.69488

The correlation of each item together with its scale, the estimate of alpha if the variable were deleted from the analysis, and standardized correlation and alpha if deleted, is shown in Table 9.7.11 (see appendix)

From the table, no single variable stands out as helping the scale score more than other items. The alpha figures are all less than the overall Cronbach Alpha for Factor1 and fFctor1 can be assumed to be reliable. The smallest value for alpha if deleted is for variable x1 (Production Level). Note that this is similar to the output in Q3 2014.

From Table 5.7.6 the Cronbach Alpha value for factor2 is 0.695 for raw alpha and 0.694 for standardized alpha, which could be accepted.

Factor 3 doesnt have any Cronchback alpha figure since it contains a single variable.

5.8 Q2 2016

The data from Q2 2016 is suitable as the KMO test shows a value of approximately 0.77 as shown in Table 9.8.2 (see appendix).

We would retain and interprete any component with an eigenvalue greater than the mean (in this case greater than one).

Tabel 5.8.1. Eigen values Matrix

	Eigenvalue	Difference	Proportion	Cumulative
1	3.25566803	1.720728	0.29600	0.296
2	1.53494003	0.45022595	0.13950	0.43550
3	1.08471408	0.14063356	0.09860	0.53410
4	0.94408053	0.10140934	0.08580	0.61990
5	0.84267119	0.09131236	0.07660	0.69660
6	0.75135883	0.05662177	0.06830	0.76490
7	0.69473706	0.02939231	0.06320	0.82800
8	0.66534475	0.15402265	0.06050	0.88850
9	0.5113221	0.10114608	0.04650	0.93500
10	0.41017601	0.10518862	0.03730	0.97230
11	0.3049874		0.02770	1

From the table above we are retaining the first, second and third factors with eigenvalues greater than 1. These factors account for 53.4% of the total variabilty of all the variables.

Furthermore, the factor pattern matrix displayed in table 5.3.5, shows the loadings for the solution with three factors for both the factor pattern matrix and the rotated factor pattern matrix.

The initial factor extraction looks clean. However factor extraction from the rotated factor pattern matrix has a representation of all the variables as compared to the initial factor pattern matrix. Hence we would adopt the rotated factor matrix for analysis. It can be observed that the trend in both matrices is similar.

Table 5.8.2. Factor Pattern Matrix

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
X1	0.76255	0.05858	-0.0205
X2	0.76523	0.11628	0.00349
X3	0.55914	0.33421	0.03233
X4	0.51036	0.02812	-0.11868
X5	0.61172	0.16236	0.08878
X6	0.46175	-0.0848	-0.57318
X7	0.09887	0.85935	0.03681
X8	0.0402	0.86123	-0.01747
X9	0.70635	0.04048	0.28371
X10	0.29995	-0.0045	0.78656
X11	0.50401	-0.1261	0.28583

Factor Pattern			
	Factor1	Factor2	Factor3
X1	0.73812	-0.14314	0.14149
X2	0.75985	-0.0899	0.11681
X3	0.53199	0.1985	0.03372
X4	0.47544	-0.0994	0.19852
X5	0.63897	-0.0109	0.00682
X6	0.33122	-0.1648	0.64193
X7	0.33214	0.79848	-0.04162
X8	0.26879	0.81939	0.00244
X9	0.72489	-0.1661	-0.16727
X10	0.40075	-0.1361	-0.72769
X11	0.48765	-0.2733	-0.19781

From the table above, the variables with significant loadings on the factors (rotated factor pattern) are outlined below:

Factor1: Loadings X1, X2, X3, X4, X5, X9 and X11

Factor2: Loadings X7 and X8

Factor3: Loadings X6 and X10

We can assign unique characteristics to the factors as detailed below.

Factor1: Level of production.

Factor2: Pricing.

Factor3: Amount of new exports received and outstanding work/business.

We would test them using the Cronbach Alpha in order to establish reliability, quality and internal consistency of these factors,

The output for factor1 is shown in table 5.8.3 below. The raw alpha (0.764) and standardized alpha (0.759) for Factor1 are acceptable, since the minimum acceptable Cronbach Alpha value is 0.7.

Tabel 5.8.3. Cronbach Alpha

Factor 1		Factor 2		Factor 3	
Variables	**Alpha**	**Variables**	**Alpha**	**Variables**	**Alpha**
Raw	0.76420	Raw	0.72208	Raw	-0.07541
Standardized	0.75905	Standardized	0.72343	Standardized	-0.07601

The correlation of each item together with its scale, the estimate of alpha if the variable were deleted from the analysis, and standardized correlation and alpha if deleted, is shown in Table 9.8.10. (See appendix)

From the table, no single variable stands out as helping the scale score more than other items because the alpha figures are all less than the overall Cronbach Alpha for Factor1. Hence Factor1 can be assumed to be reliable. The smallest value for alpha if deleted is for variable x2 (Level of new customers or new business received).

Furthermore, the Cronbach Alpha value for factor2 is 0.722 for raw alpha and 0.723 for standardized alpha, which is acceptable.

Factor3 is inconsistent from alpha values as shown in figure 5.8.3 above.

5.9 Factor Summary

Tabel 5.9.1. Factor Summary

QUARTERS	FACTORS	VARIABLES
Q3 2014	Factor 1 - Level of Production Factor 2 - Pricing Factor 3- Level of outstanding business/backlog of work	Factor 1 - X1, X2, X3, X4, X5, X9, X11 Factor 2 - X7, X8 Factor 3- X10
Q4 2014	Factor 1 - Level of Production Factor 2 - Pricing Factor 3- Level of outstanding business/goods	Factor 1 - X1, X2, X3, X4, X5, X9 Factor 2 - X7, X8 Factor 3- X6, X10, X11
Q1 2015	Factor 1 - Level of Production Factor 2 - Pricing Factor 3- New export orders received	Factor 1 - X1, X2, X3, X4, X5, X9, X11 Factor 2 - X7, X8 Factor 3- X6
Q2 2015	Factor 1 - Level of Production Factor 2 - Pricing Factor 3- New orders and stock of finished goods Factor 4 - Level of outstanding business/backlog of work	Factor 1 - X1, X2, X3, X4, X5, X9 Factor 2 - X7, X8 Factor 3- X6, X11 Factor4 - X10
Q3 2015	Factor 1 - Level of Production and Pricing Factor 2 - New export orders received Factor 3- Stock of finished goods	Factor 1 - X1, X2, X3, X4, X5, X7, X8, X9, X10 Factor 2 - X6 Factor 3- X11
Q4 2015	Factor 1 - Level of Production and outstanding business Factor 2 - Pricing Factor 3- New export orders received	Factor 1 - X1, X2, X3, X4, X5, X9, X10, X11 Factor 2 - X7, X8 Factor 3- X6
Q1 2016	Factor 1 - Level of Production Factor 2 - Pricing Factor 3- Level of outstanding business/backlog of work	Factor 1 - X1, X2, X3, X4, X5, X9 and X11 Factor 2 - X7, X8 Factor 3- X10
Q2 2016	Factor 1 - Level of Production Factor 2 - Pricing Factor 3-Amount of new exports received and outstanding work/business	Factor 1 - X1, X2, X3, X4, X5, X9, X11 Factor 2 - X7, X8 Factor 3- X6, X10

Table 5.9.1 presents a summary of the factors that represent the major drivers or constraints that has been affecting the manufacturing sector in Nigeria overtime (Q3 2014 – Q2 2016), and the variables that are contained in each of the factors.

If we study the table critically, one can easily observe that two broad factors; Level of production and Pricing were constant for all quarters. This means that these broad components affected the manufacturing sector constantly overtime. Although in Q3 2015, Level of production and Pricing were merged in one factor.

Also, apart from the level of production and pricing, there were other factors that were also evident throughout these periods, even though they were inconsistent over time. These include 'New export orders received' which occured in three out of the eight quarters; Q1 2015, Q3 2015 and Q4 2015 and 'level of outstanding business/backlog of work' which also occured in three different quarters namely Q3 2014, Q2 2015 and Q1 2016.

6. CONCLUSION

The factor summary table (Table 5.9.1) shows Level of Production and Pricing as two factors that consistently affect the manufacturing sector in Nigeria over the quarters under review. This means that from the view of purchasing managers in manufacturing companies, the pricing of raw materials needed for production and pricing of the finished goods plays a key role in determining growth of the manufactoring sector. Further more level of production (production level, level of employment level of new orders and raw materials inventory) and level of outstanding business also had a consistent effect on the manufactoruing growth in Nigeria, according to the purchasing managers.

On the other hand, 'New export orders received', and 'Level of outstanding business/backlog of work affected output in the manufacturing sector in three distinct quarters only respectively as earlier mentioned. The reason could be that the exchange rate volatility in the other five quarters was responsible for the reduced or absence of export orders for manufacturing companies, hence there was no impact on output. Further more, an increased working hours for company staff, increased workforce and reduced purchase order requests could have been the reason 'level of outstanding business/backlog or work' did not affect output in Q32014, Q12015, Q32015, Q42015 and Q22016.

Finally, the Central bank of Nigeria (CBN) is tasked with regulating the Nigerian economy by administering monetary policies that affect exchange rates and promote monetary and price stability. These directly and indirectly affect production level and output of the manufacturing sector. It is therefore important that the CBN takes into consideration the perceptions of purchasing managers in manufacturing companies, in order to understand the pulse of the manufacturing sector and administer policies to ensure its growth.

7. LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

7.1 Limitations

Although this thesis work reached its aims and objectives to a great extent, I am fully aware of the existence of some unavoidable limitations and shortcomings.

Firstly, not all manufacturing companies can easily be identified due to lack of efficient company records. Due to time constraints this thesis focus on a reasonable percentage of the manufacturing companies in Nigeria. Furthermore the work does not capture the non-manufactuing sector due to time constraints.

Secondly, this work focuses on purchasing manager perception of the factors that affect output in the manufacturing sector. Hence there were problems likened to empathy in filling out questionnaires due to heavy work load on the managers or unessecary bias in response.

7.2 Recommendations for Future Work

For future purposes, it would be appriopriate to also access the factors that also affect the non-manufactuing sector in Nigeria.

Also, another useful work would be to develop a purchasing manager perception quantitative index that can actually measure the value or degree of to which these factors affects production. With this one can now ascertain the direction of growth (i.e a positive or negative) between different periods (month, quarters or years) and also deduce the rate of this change between the periods.

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9. APPENDIX

9.1 Q3 2014

Tabel 9.1.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
Mean	2.02202	2.01726	1.99464	2.09435	2.00119	2.12321	1.88482	1.80952	2.01339	2.09821	2.07768
Std Dev	0.4131	0.42424	0.37748	0.36883	0.40715	0.35005	0.36721	0.3864	0.42585	0.40773	0.411

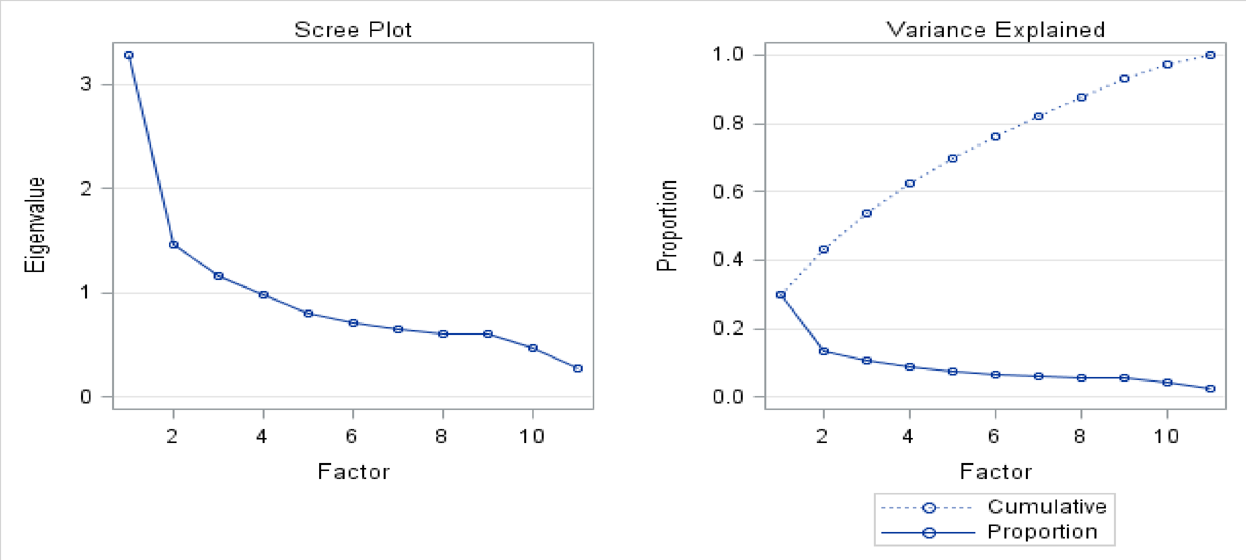
Tabel 9.1.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.76628430										
x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
0.72466	0.73107	0.89659	0.84878	0.83714	0.84997	0.59295	0.57803	0.87369	0.7678	0.80457

Tabel 9.1.3. Correlation Matrix

Correlations											
	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
x1	1	0.71121	0.37806	0.27986	0.30238	0.15439	0.09144	0.09233	0.4209	0.19837	0.25449
x2	0.71121	1	0.3779	0.29444	0.33705	0.18508	0.12634	0.10012	0.35409	0.1614	0.23283
x3	0.37806	0.3779	1	0.26919	0.21861	0.08924	0.15471	0.12518	0.26754	0.13903	0.17565
x4	0.27986	0.29444	0.26919	1	0.3434	0.2	0.14092	0.11795	0.26308	0.05062	0.15448
x5	0.30238	0.33705	0.21861	0.3434	1	0.25279	0.16577	0.0722	0.34842	0.19446	0.31541
x6	0.15439	0.18508	0.08924	0.2	0.25279	1	0.18096	0.10623	0.20025	0.15042	0.15095
x7	0.09144	0.12634	0.15471	0.14092	0.16577	0.18096	1	0.50912	0.10935	0.07702	0.01033
x8	0.09233	0.10012	0.12518	0.11795	0.0722	0.10623	0.50912	1	0.11459	0.05713	0.02199
x9	0.4209	0.35409	0.26754	0.26308	0.34842	0.20025	0.10935	0.11459	1	0.2786	0.30493
x10	0.19837	0.1614	0.13903	0.05062	0.19446	0.15042	0.07702	0.05713	0.2786	1	0.34107
x11	0.25449	0.23283	0.17565	0.15448	0.31541	0.15095	0.01033	0.02199	0.30493	0.34107	1

Figure 9.1.4. Scree Plot



Tabel 9.1.5. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.621172	0.704824	0.616028	0.703927	x1: PRODUCTION LEVEL
x2	0.605466	0.707757	0.604054	0.706605	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.42387	0.74713	0.423943	0.74528	x3: SUPPLIERS DELIVERY TIME
x4	0.400127	0.751486	0.401126	0.749969	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.473742	0.737353	0.474122	0.734802	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.502478	0.731249	0.500981	0.729101	x9:QUANTITY OF ITEMS PRODUCED
x11	0.358236	0.761368	0.355771	0.759154	x11: STOCK OF FINISHED GOODS

Figure 9.1.6a Factor Pattern

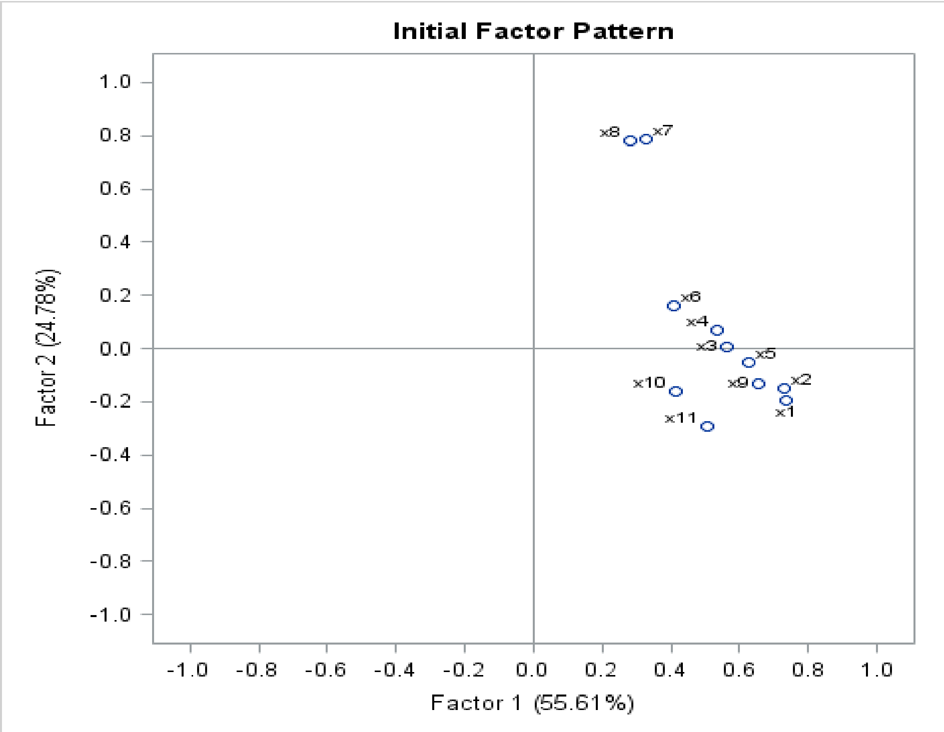


Figure 9.1.6b Factor Pattern

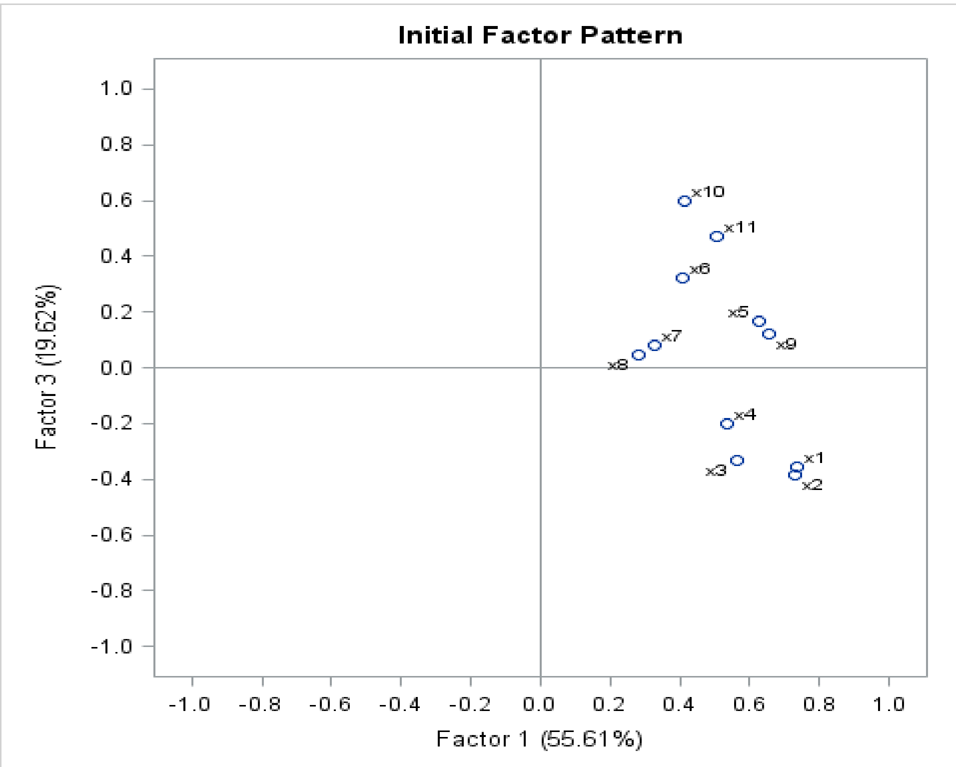
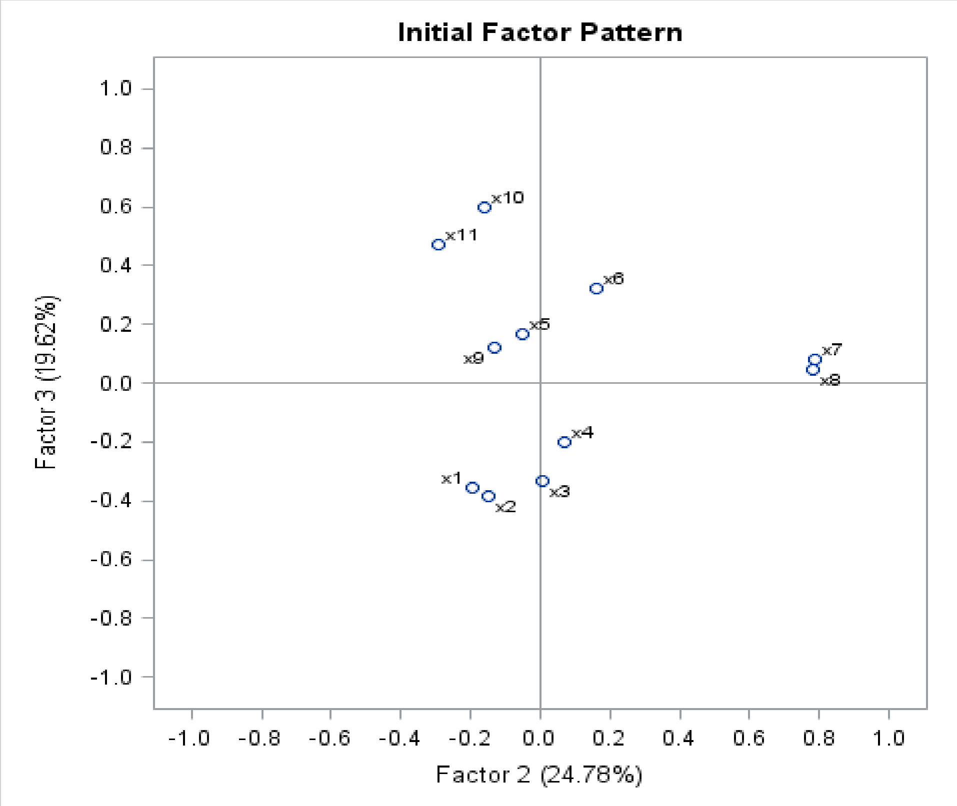


Figure 9.1.6c Factor Pattern



Tabel 9.1.7. Variance Explained

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.27818	1.46062	1.15634

Tabel 9.1.8. Rotated Factor Pattern

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
x1	0.82199	0.17198	-0.0383
x2	0.82752	0.13495	0.0058
x3	0.64231	0.04351	0.11475
x4	0.53075	0.12239	0.18481
x5	0.40385	0.49051	0.12515
x6	0.10647	0.4432	0.29275
x7	0.09897	0.06048	0.85106
x8	0.08028	0.00989	0.82938
x9	0.46786	0.49043	0.05531
x10	-0.0025	0.747	0.0116
x11	0.16235	0.72402	-0.1038

Tabel 9.1.9. Variance Explained

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
2.49062	1.82817	1.57634

Figure 9.1.10a Rotated Factor Pattern

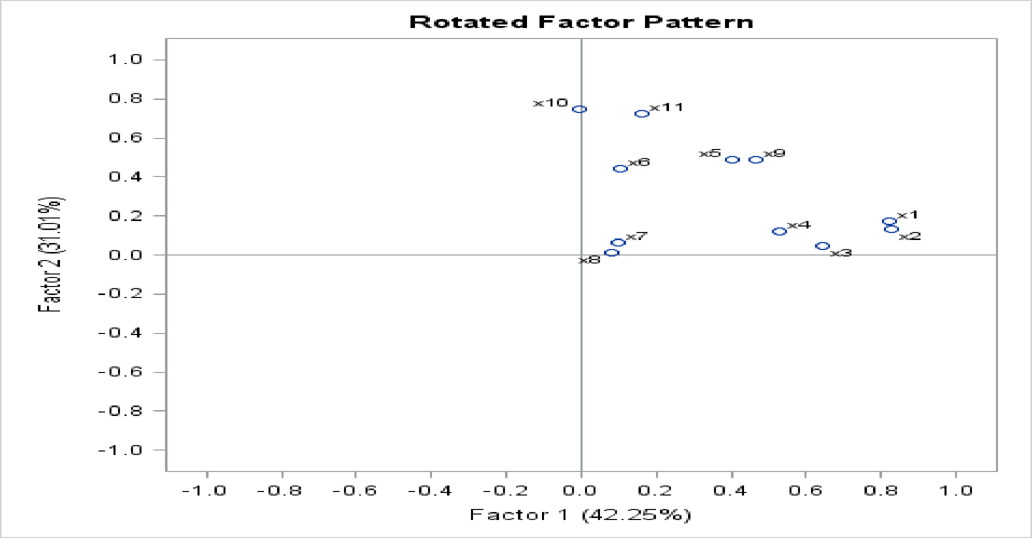
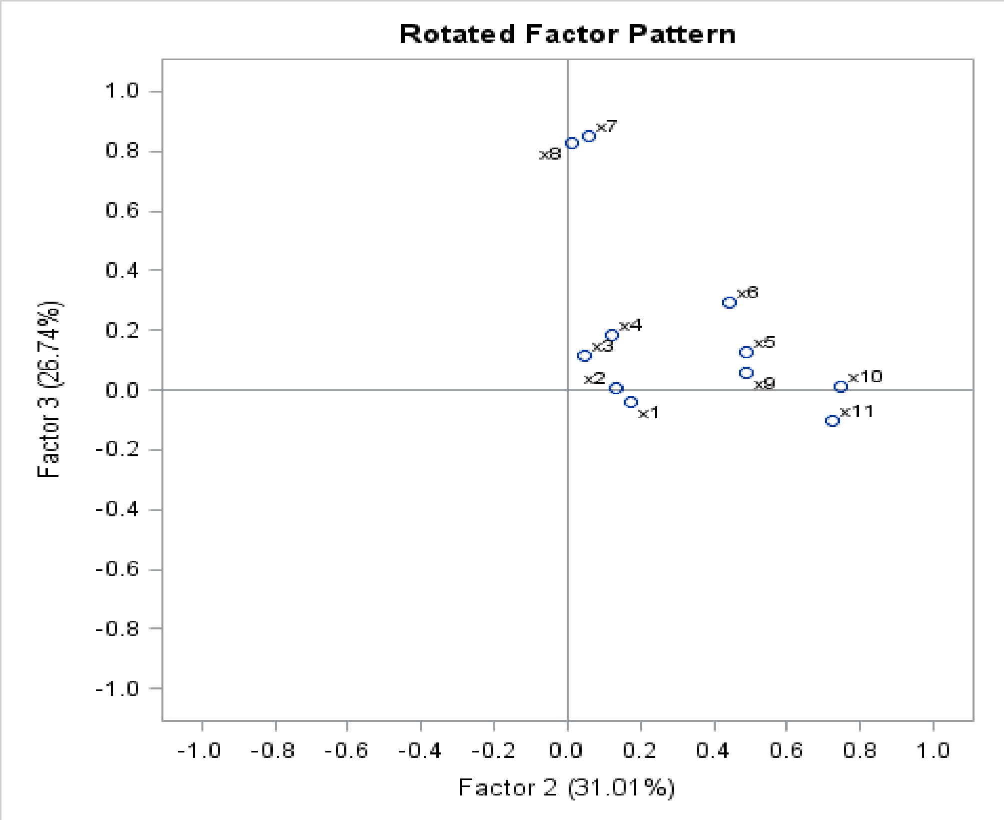


Figure 9.1.10b Rotated Factor Pattern

Figure 9.1.10c Rotated Factor Pattern



Tabel 9.1.11. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.621172	0.704824	0.616028	0.703927	x1: PRODUCTION LEVEL
x2	0.605466	0.707757	0.604054	0.706605	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.42387	0.74713	0.423943	0.74528	x3: SUPPLIERS DELIVERY TIME
x4	0.400127	0.751486	0.401126	0.749969	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.473742	0.737353	0.474122	0.734802	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.502478	0.731249	0.500981	0.729101	x9:QUANTITY OF ITEMS PRODUCED
x11	0.358236	0.761368	0.355771	0.759154	x11: STOCK OF FINISHED GOODS

Tabel 9.1.12. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x7	0.509118	.	0.509118	.	x7: AVERAGE PRICE OF OUTPUTS
x8	0.509118	.	0.509118	.	x8: AVERAGE PRICE OF INPUTS

9.2 Q4 2014

Tabel 9.2.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Mean	1.93095	1.91369	1.93631	2.05774	1.95476	2.03988	1.94167	1.83452	1.89583	2.0131	2.01429
Std Dev	0.44894	0.44168	0.36887	0.34597	0.39468	0.33924	0.37642	0.36818	0.41448	0.39905	0.39651

Tabel 9.2.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.77526398										
X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
0.76802	0.7532	0.82766	0.8427	0.85971	0.62183	0.65008	0.67994	0.85825	0.78098	0.80464

Tabel 9.2.3. Correlation Matrix

Correlations											
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
X1	1	0.68863	0.33708	0.31493	0.28747	0.08206	0.16079	0.18328	0.40351	0.18036	0.23669
X2	0.68863	1	0.45908	0.37347	0.35498	0.09332	0.23507	0.25548	0.49368	0.18912	0.21929
X3	0.33708	0.45908	1	0.43226	0.22593	-0.013	0.18649	0.24863	0.28934	0.13396	0.16387
X4	0.31493	0.37347	0.43226	1	0.33213	0.05994	0.18464	0.20934	0.25686	0.16152	0.16785
X5	0.28747	0.35498	0.22593	0.33213	1	0.12484	0.18958	0.27531	0.27004	0.16279	0.2823
X6	0.08206	0.09332	-0.013	0.05994	0.12484	1	0.13966	0.03224	0.13138	0.0578	0.11397
X7	0.16079	0.23507	0.18649	0.18464	0.18958	0.13966	1	0.56988	0.19412	0.07258	0.08283
X8	0.18328	0.25548	0.24863	0.20934	0.27531	0.03224	0.56988	1	0.29974	0.12436	0.15101
X9	0.40351	0.49368	0.28934	0.25686	0.27004	0.13138	0.19412	0.29974	1	0.32312	0.28724
X10	0.18036	0.18912	0.13396	0.16152	0.16279	0.0578	0.07258	0.12436	0.32312	1	0.32292
X11	0.23669	0.21929	0.16387	0.16785	0.2823	0.11397	0.08283	0.15101	0.28724	0.32292	1

Figure 9.2.4. Scree Plot

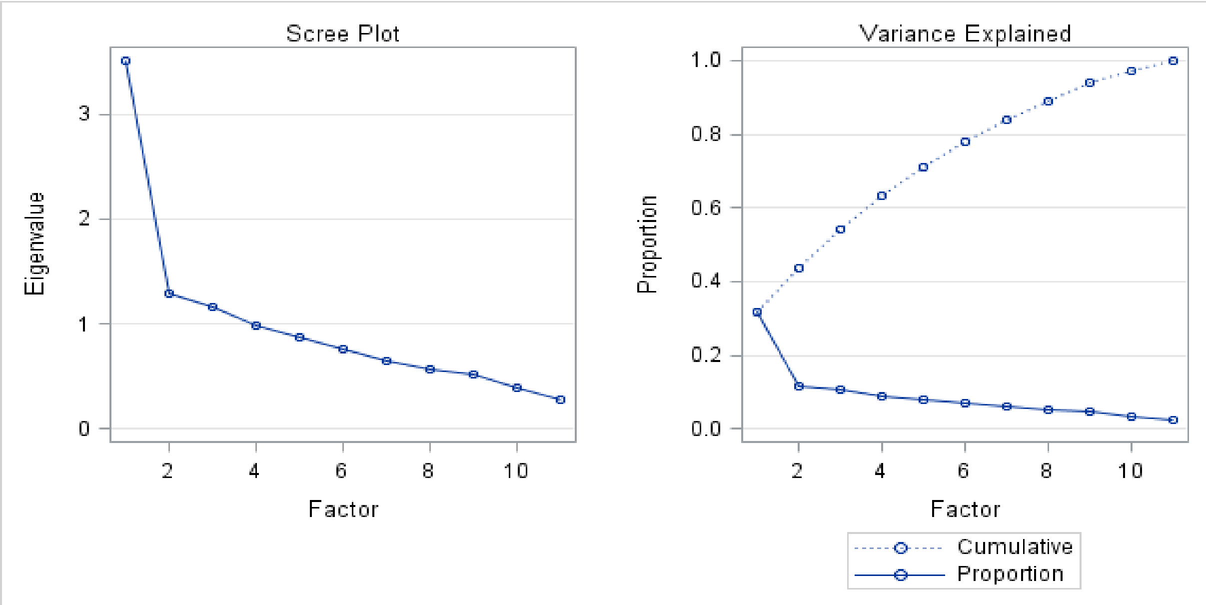


Figure 9.2.5a Factor Pattern

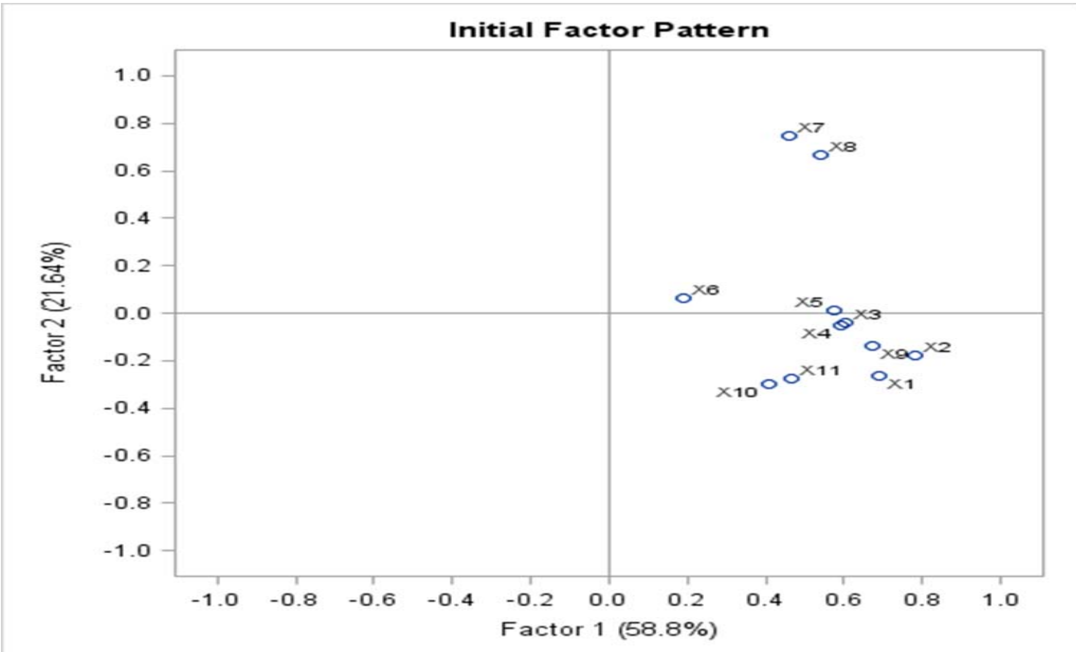


Figure 9.2.5b Factor Pattern

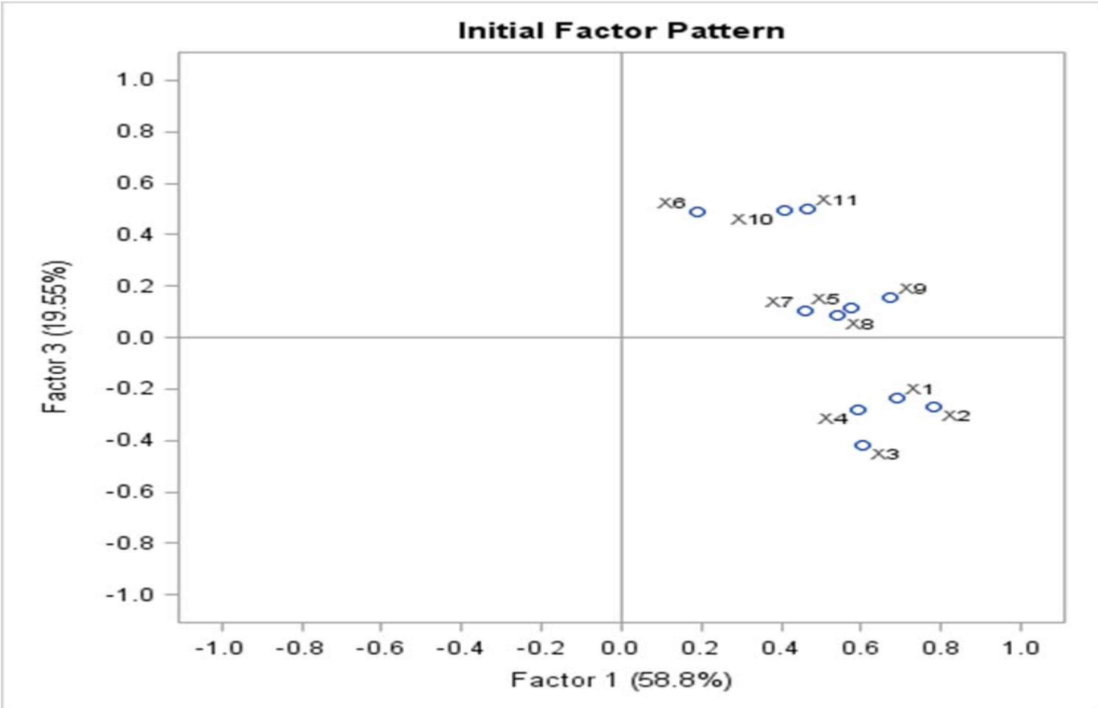
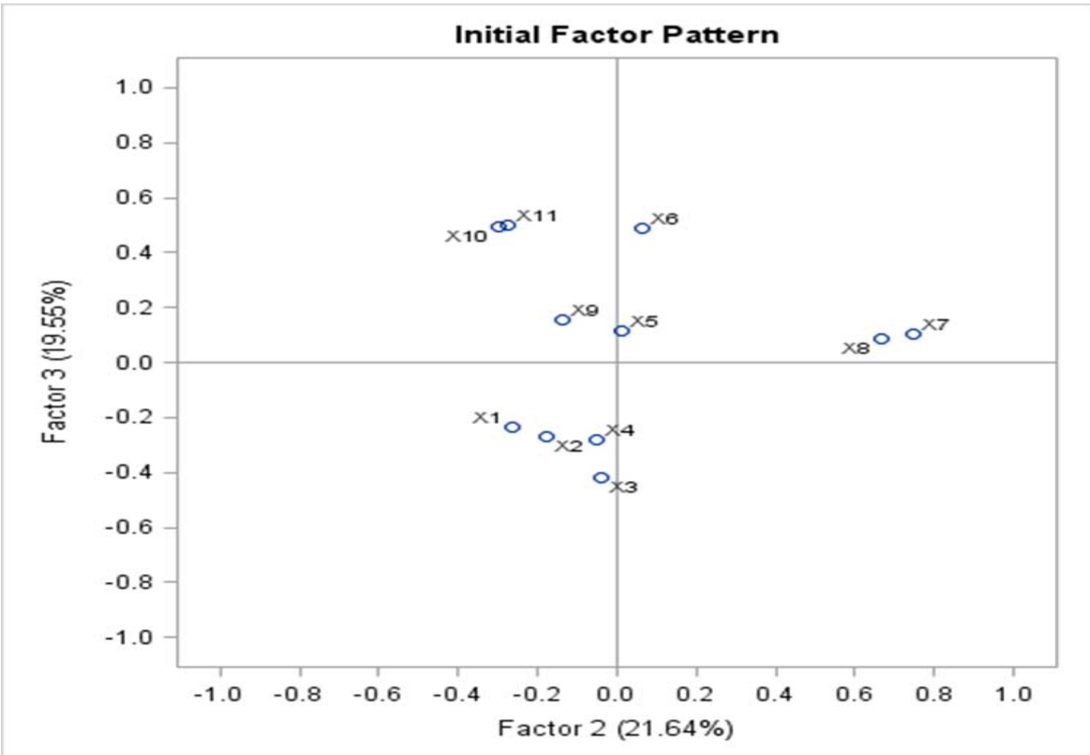


Figure 9.2.5c Factor Pattern



Tabel 9.2.6. Variance Explained by Factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.50914	1.2915866	1.16697

Tabel 9.2.7. Rotated Factor Pattern

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
X1	0.75238	0.19314	-0.0057
X2	0.8185	0.17361	0.1035
X3	0.72012	-0.0704	0.13911
X4	0.6394	0.04238	0.14633
X5	0.40539	0.34569	0.24836
X6	-0.11959	0.47367	0.2001
X7	0.12297	0.05473	0.87142
X8	0.21361	0.10181	0.82679
X9	0.50092	0.46913	0.15562
X10	0.14957	0.68919	-0.046
X11	0.18571	0.71279	-0.0036

Tabel 9.2.8. Variance Explained by rotated factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
2.7106	1.6345621	1.62254

Figure 9.2.9a Rotated Factor Pattern

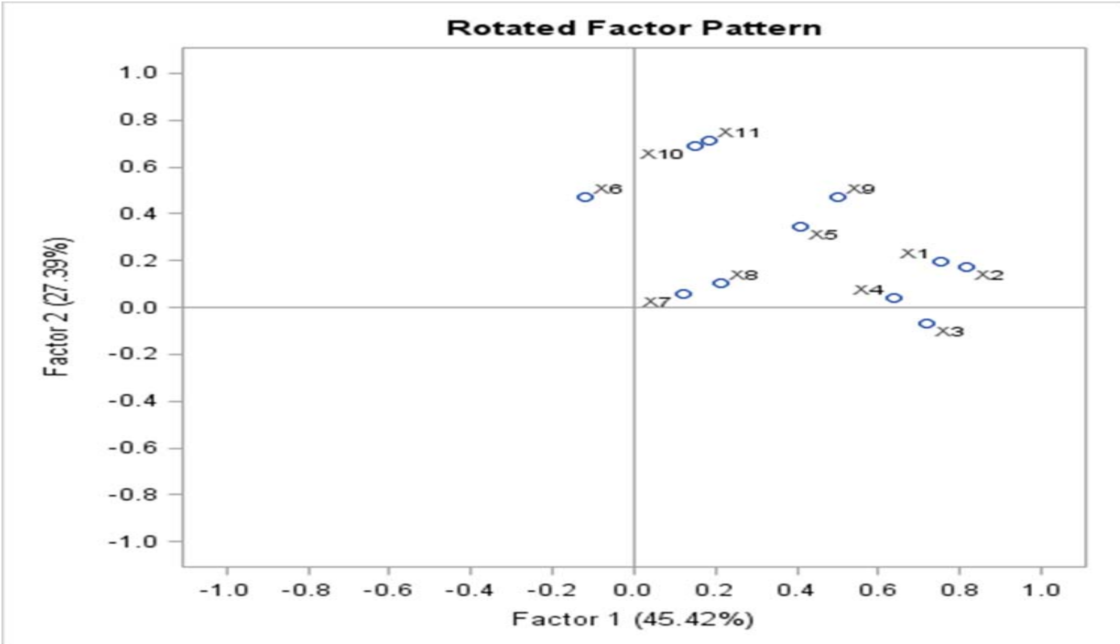


Figure 9.2.9b Rotated Factor Pattern

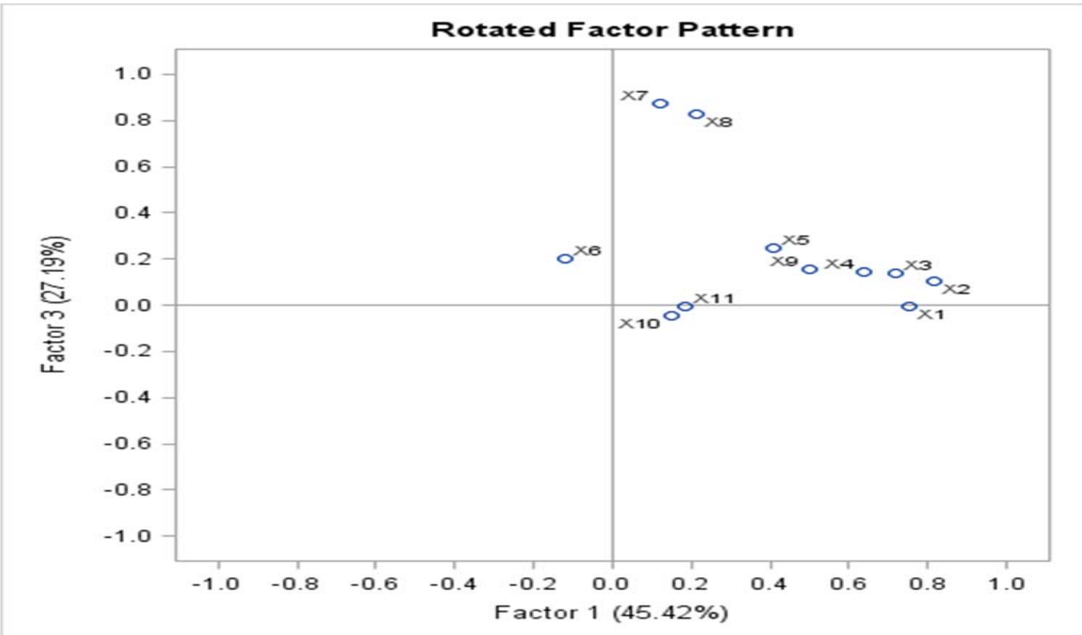
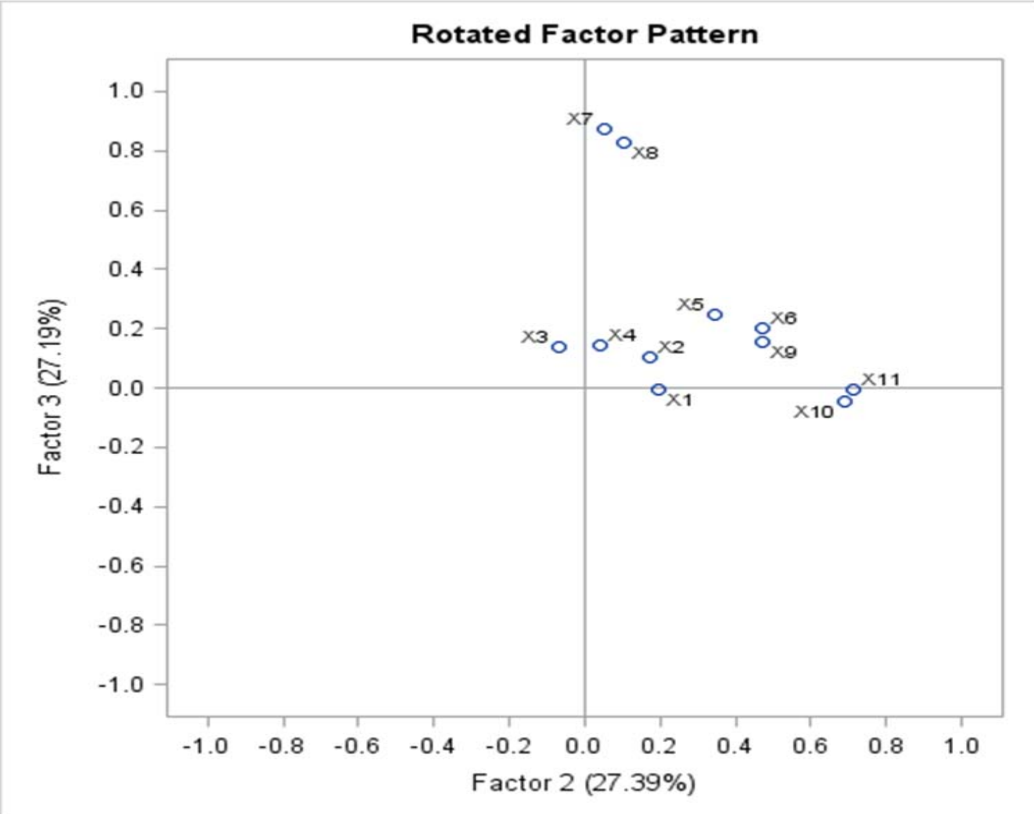


Figure 9.2.9c Rotated Factor Pattern



Tabel 9.2.10. Cronbach Alpha

6 Variables:	x1 x2 x3 x4 x5 x9

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.78004
Standardized	0.77743

Tabel 9.2.11. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.599265	0.727987	0.587079	0.728102	x1: PRODUCTION LEVEL
x2	0.717165	0.693729	0.70501	0.696859	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.487421	0.756665	0.492178	0.752048	x3: SUPPLIERS DELIVERY TIME
x4	0.474863	0.759823	0.481266	0.754734	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.404242	0.776084	0.406333	0.772816	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.490233	0.756473	0.482478	0.754436	x9:QUANTITY OF ITEMS PRODUCED

Tabel 9.2.12. Cronbach Alpa

2 Variables:	x7 x8

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.725905
Standardized	0.726018

Tabel 9.2.13. Cronbach Alpa

3 Variables:	x6 x10 x11

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.384025
Standardized	0.372009

Tabel 9.2.14. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x7	0.509118	.	0.509118	.	x7: AVERAGE PRICE OF OUTPUTS
x8	0.509118	.	0.509118	.	x8: AVERAGE PRICE OF INPUTS

9.3 Q1 2015

Tabel 9.3.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Mean	1.91548	1.9607143	1.935119	2.0119048	1.972619	1.91905	1.99702	1.86131	1.922619	2.02619	1.98095
Std Dev	0.46717	0.46422854	0.38138559	0.32003457	0.39228837	0.41512	0.35971	0.33779	0.41580326	0.40336	0.4008

Tabel 9.3.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.75931538										
X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
0.71021	0.72211	0.88755	0.80914	0.86481	0.71869	0.57789	0.64046	0.84292	0.81738	0.85264

Tabel 9.3.3. Correlation Matrix

Correlations											
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
X1	1	0.79578	0.38863	0.24472	0.36479	0.00463	0.19367	0.19135	0.43083	0.1932	0.26102
X2	0.79578	1	0.41331	0.3015	0.34772	0.01441	0.15166	0.22631	0.46511	0.2178	0.28548
X3	0.38863	0.41331	1	0.28644	0.20864	0.03707	0.18115	0.1846	0.20894	0.15578	0.20386
X4	0.24472	0.3015	0.28644	1	0.34933	0.109	0.04347	0.11826	0.24294	0.14694	0.17068
X5	0.36479	0.34772	0.20864	0.34933	1	0.12429	0.11634	0.13779	0.31113	0.2206	0.25963
X6	0.00463	0.01441	0.03707	0.109	0.12429	1	0.04231	0.05729	0.16977	0.11715	0.14124
X7	0.19367	0.15166	0.18115	0.04347	0.11634	0.04231	1	0.50699	0.10212	0.06904	0.09336
X8	0.19135	0.22631	0.1846	0.11826	0.13779	0.05729	0.50699	1	0.29564	0.13904	0.14929
X9	0.43083	0.46511	0.20894	0.24294	0.31113	0.16977	0.10212	0.29564	1	0.34157	0.34776
X10	0.1932	0.2178	0.15578	0.14694	0.2206	0.11715	0.06904	0.13904	0.34157	1	0.35473
X11	0.26102	0.28548	0.20386	0.17068	0.25963	0.14124	0.09336	0.14929	0.34776	0.35473	1

Figure 9.3.4. Scree Plot

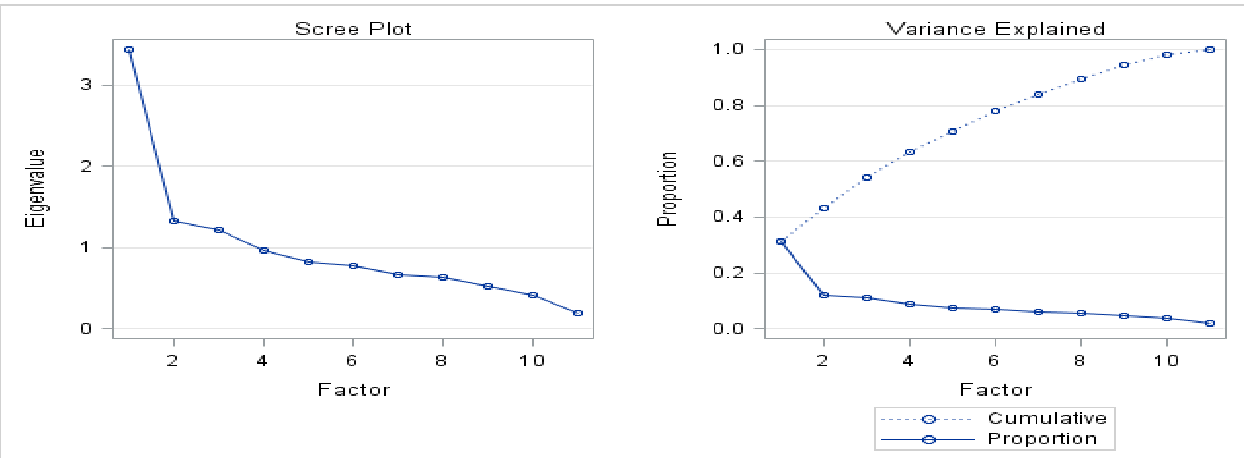


Figure 9.3.5a Factor Pattern

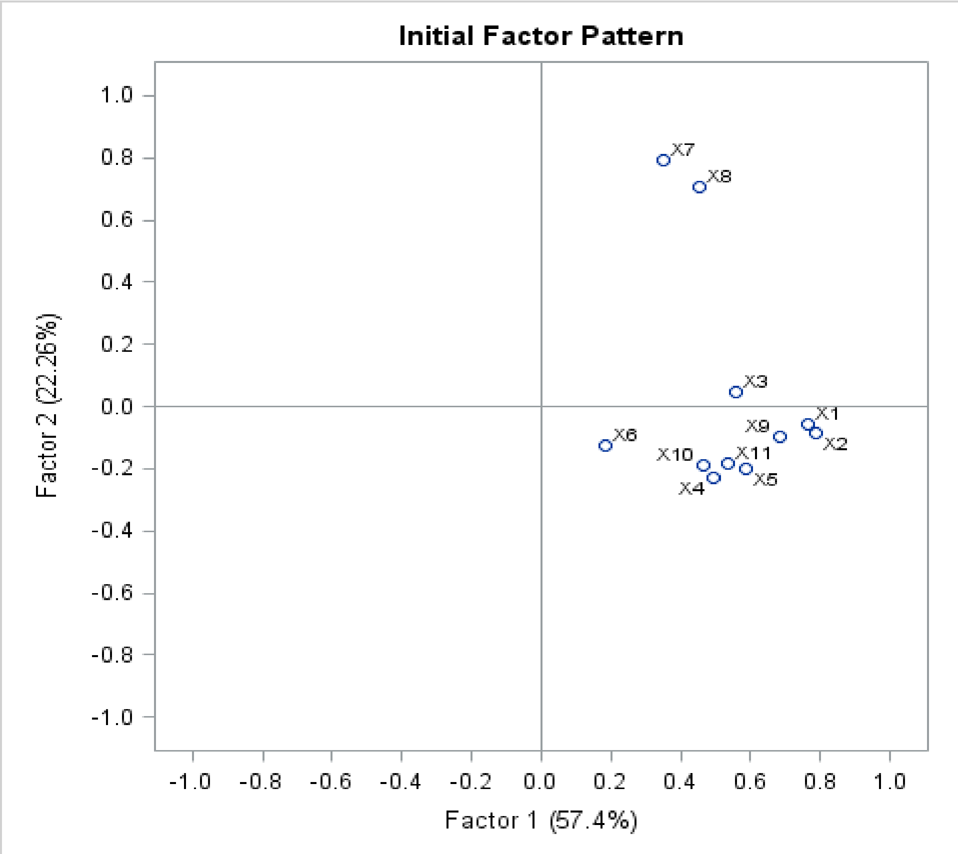


Figure 9.3.5b Factor Pattern

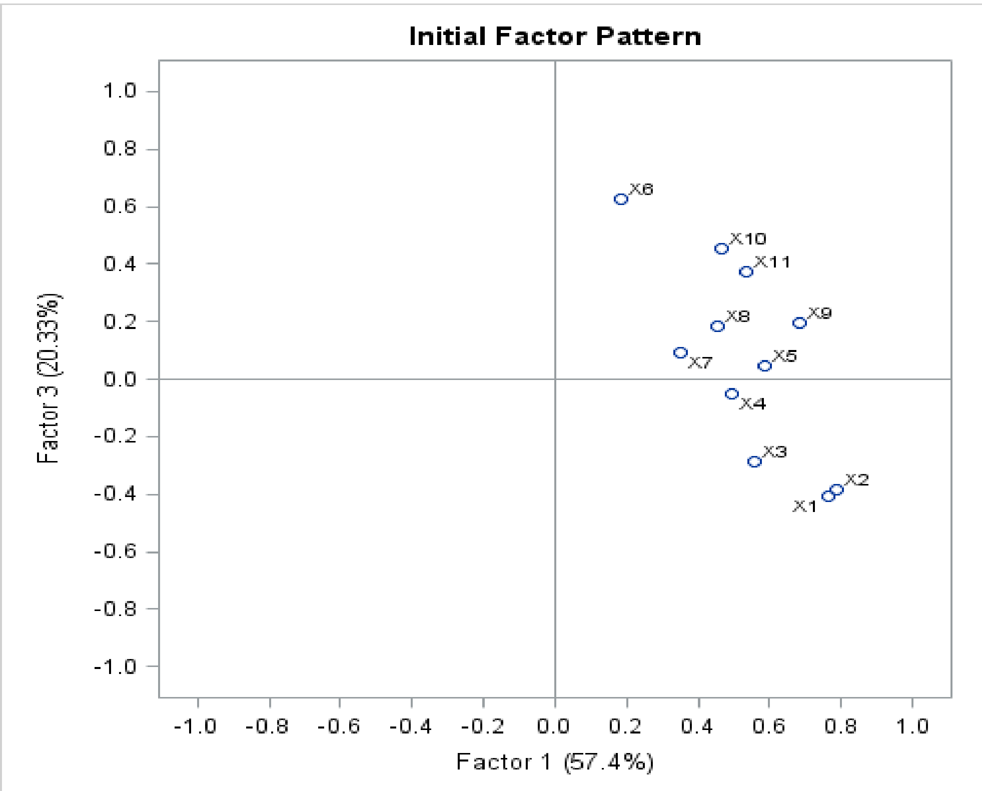
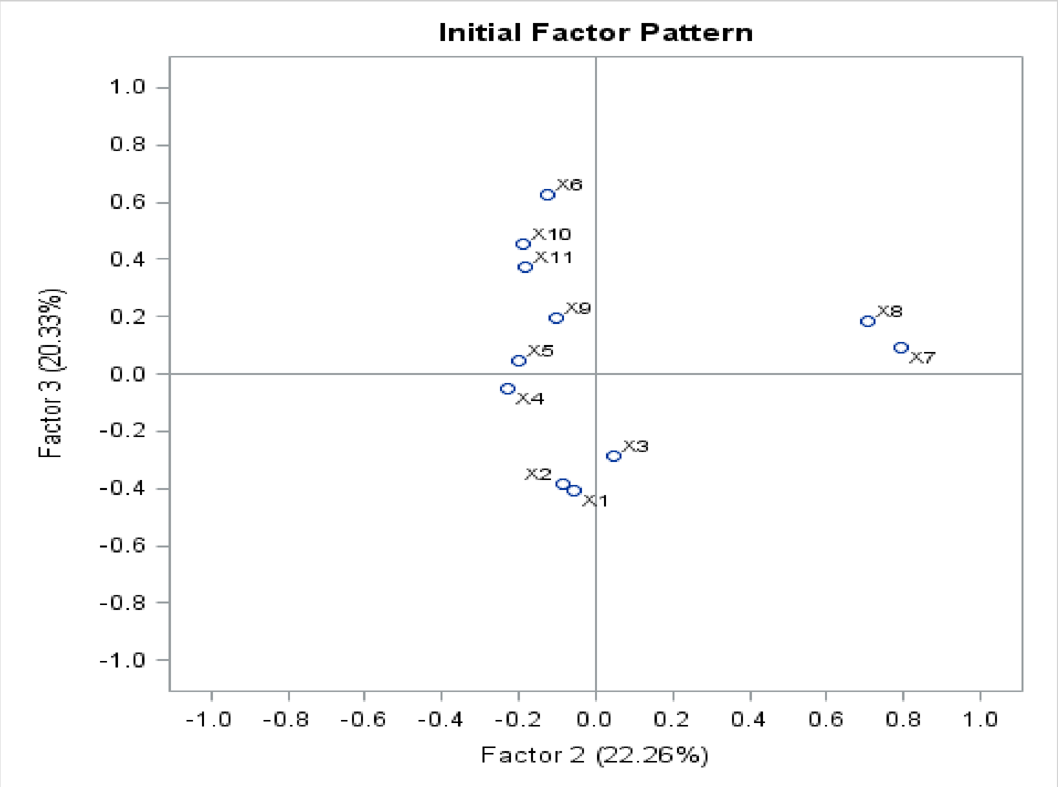


Figure 9.3.5c Factor Pattern



Tabel 9.3.6. Variance Explained by Factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.4349815	1.3321373	1.2168129

Tabel 9.3.7. Rotated Factor Pattern

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
X1	0.85835	0.0389	0.12395
X2	0.8714	0.0796	0.11048
X3	0.60524	0.01344	0.17732
X4	0.477	0.2608	-0.06541
X5	0.49368	0.37561	0.0033
X6	-0.1603	0.64109	0.04171
X7	0.08609	0.002	0.86724
X8	0.13765	0.15455	0.83456
X9	0.47609	0.51202	0.15407
X10	0.176	0.6537	0.04553
X11	0.27475	0.61714	0.05699

Tabel 9.3.8. Variance Explained by rotated factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
2.7188603	1.72237	1.5427

Figure 9.3.9a Rotated Factor Pattern

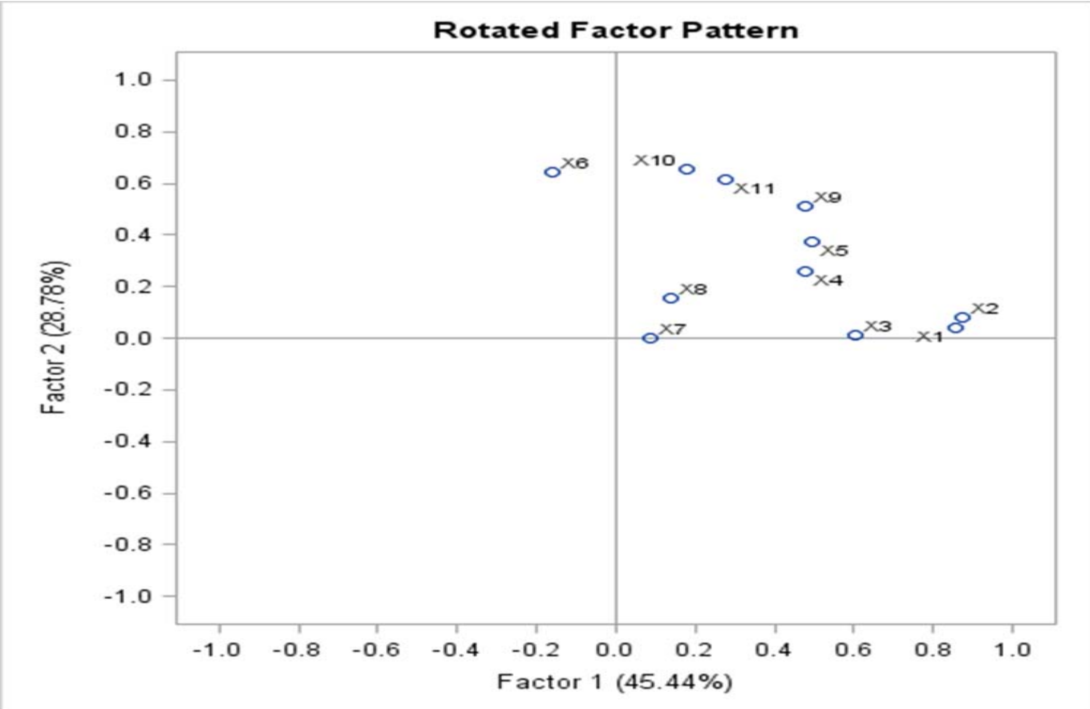


Figure 8.3.9b Rotated Factor Pattern

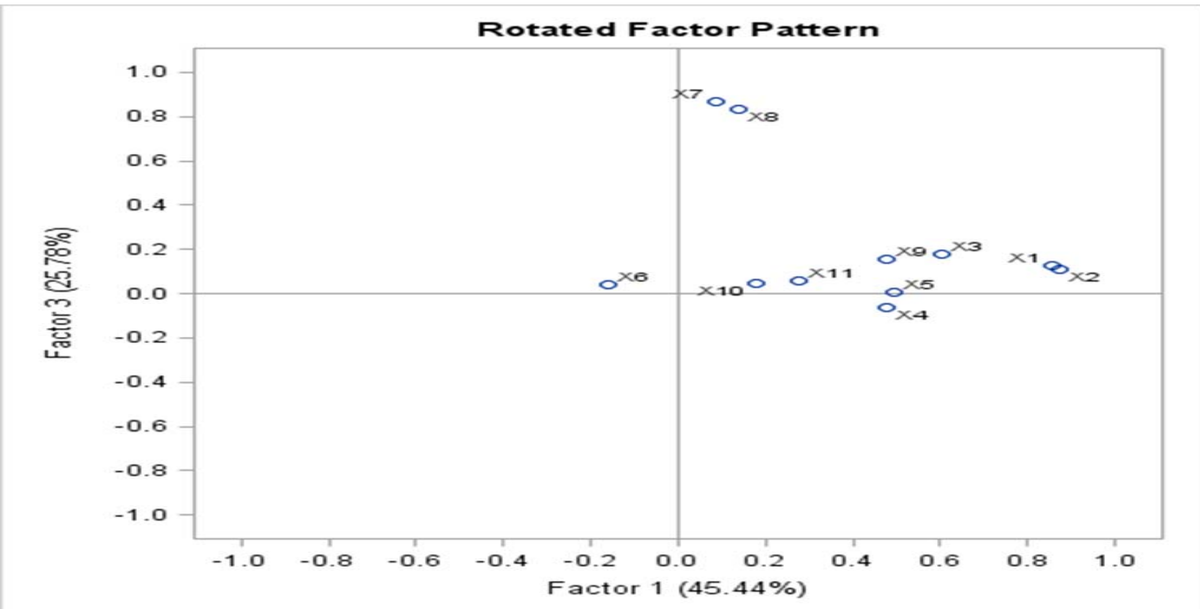
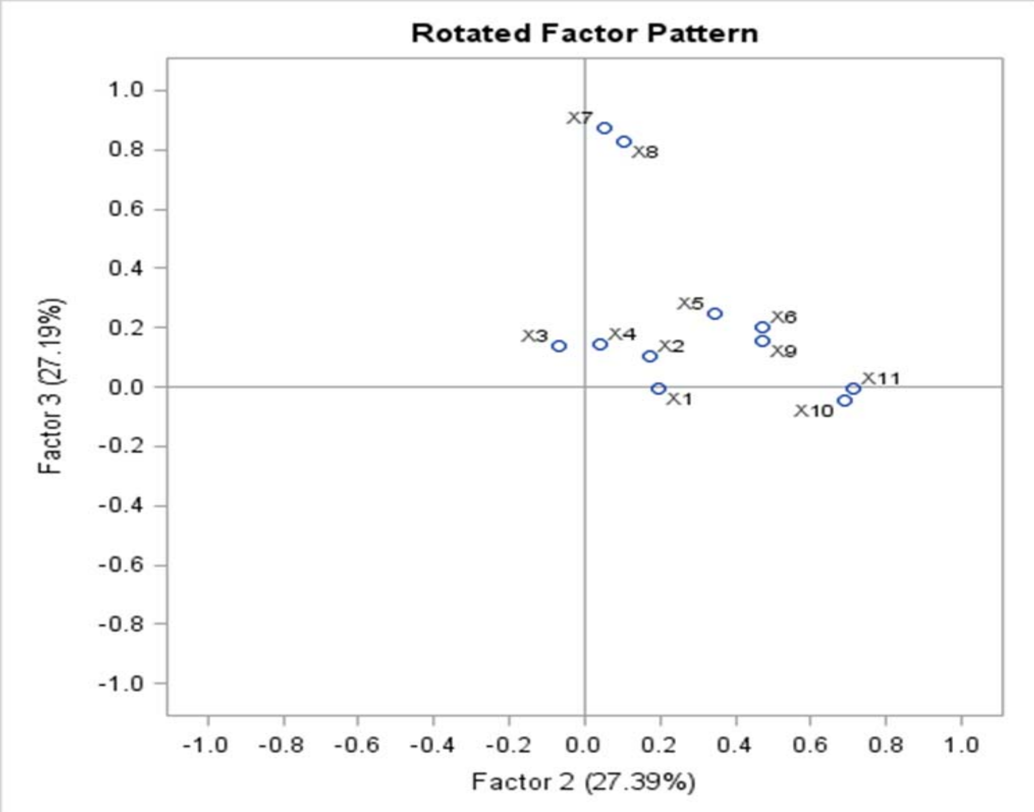


Figure 8.3.9c Rotated Factor Pattern



Tabel 9.3.10. Cronbach Alpa with deleted variable

7 Variables:	x1 x2 x3 x4 x5 x9 x11

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.78021
Standardized	0.77359

Tabel 9.3.11. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.666458	0.715582	0.64604	0.713675	x1: PRODUCTION LEVEL
x2	0.702529	0.706827	0.68375	0.705449	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.424738	0.767189	0.42277	0.759816	x3: SUPPLIERS DELIVERY TIME
x4	0.386951	0.77306	0.3918	0.765879	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.45366	0.76207	0.45896	0.752628	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.512514	0.750787	0.50543	0.743236	x9:QUANTITY OF ITEMS PRODUCED
x11	0.374409	0.777031	0.37379	0.769368	x11: STOCK OF FINISHED GOODS

Tabel 9.3.12. Cronbach Alpa

2 Variables:	x7 x8

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.67197
Standardized	0.67285

Tabel 9.3.13. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x7	0.506987	.	0.506987	.	x7: AVERAGE PRICE OF OUTPUTS
x8	0.506987	.	0.506987	.	x8: AVERAGE PRICE OF INPUTS

9.4 Q2 2015

Tabel 9.4.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Mean	1.91905	1.9684524	1.8785714	2.0315476	1.9633929	2.1369	2.00655	1.8744	1.96369	2.07262	2.047619
Std Dev	0.43248	0.43454121	0.40609688	0.34648587	0.41115822	0.37342	0.38372	0.36805	0.40035	0.41235	0.446852

Tabel 9.4.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.73951912										
X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
0.68551	0.68925	0.84403	0.84659	0.85435	0.56989	0.65925	0.65107	0.86602	0.75763	0.70441

Tabel 9.4.3. Correlation Matrix

Correlations											
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
X1	1	0.76484	0.32081	0.26512	0.32257	0.03429	0.16969	0.08087	0.37561	0.13557	0.20101
X2	0.76484	1	0.37023	0.2931	0.30336	0.06586	0.17886	0.10941	0.41729	0.1426	0.1787
X3	0.32081	0.37023	1	0.31969	0.2257	-0.0239	0.2717	0.19567	0.24669	0.18332	0.05602
X4	0.26512	0.2931	0.31969	1	0.31508	0.07256	0.13	0.12465	0.24041	0.1801	0.12123
X5	0.32257	0.30336	0.2257	0.31508	1	0.19	0.1464	0.09106	0.295	0.18571	0.23616
X6	0.03429	0.06586	-0.0239	0.07256	0.19	1	0.15187	0.09496	0.13702	-0.0001	0.19672
X7	0.16969	0.17886	0.2717	0.13	0.1464	0.15187	1	0.46606	0.20339	0.17914	-0.0157
X8	0.08087	0.10941	0.19567	0.12465	0.09106	0.09496	0.46606	1	0.23339	0.12045	0.02193
X9	0.37561	0.41729	0.24669	0.24041	0.295	0.13702	0.20339	0.23339	1	0.25922	0.29634
X10	0.13557	0.1426	0.18332	0.1801	0.18571	-0.0001	0.17914	0.12045	0.25922	1	0.2552
X11	0.20101	0.1787	0.05602	0.12123	0.23616	0.19672	-0.0157	0.02193	0.29634	0.2552	1

Figure 9.4.4. Scree Plot

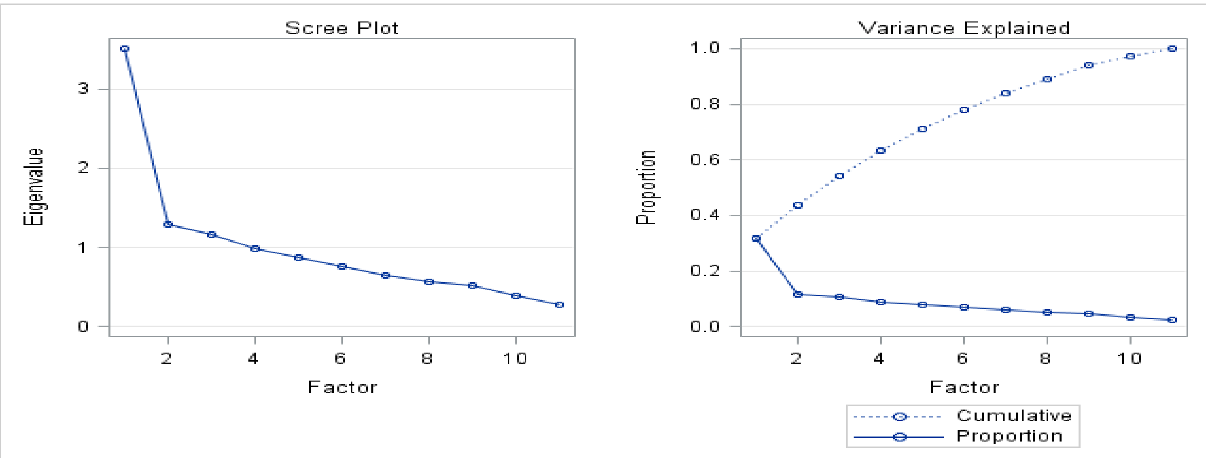


Figure 9.4.5a Factor Pattern

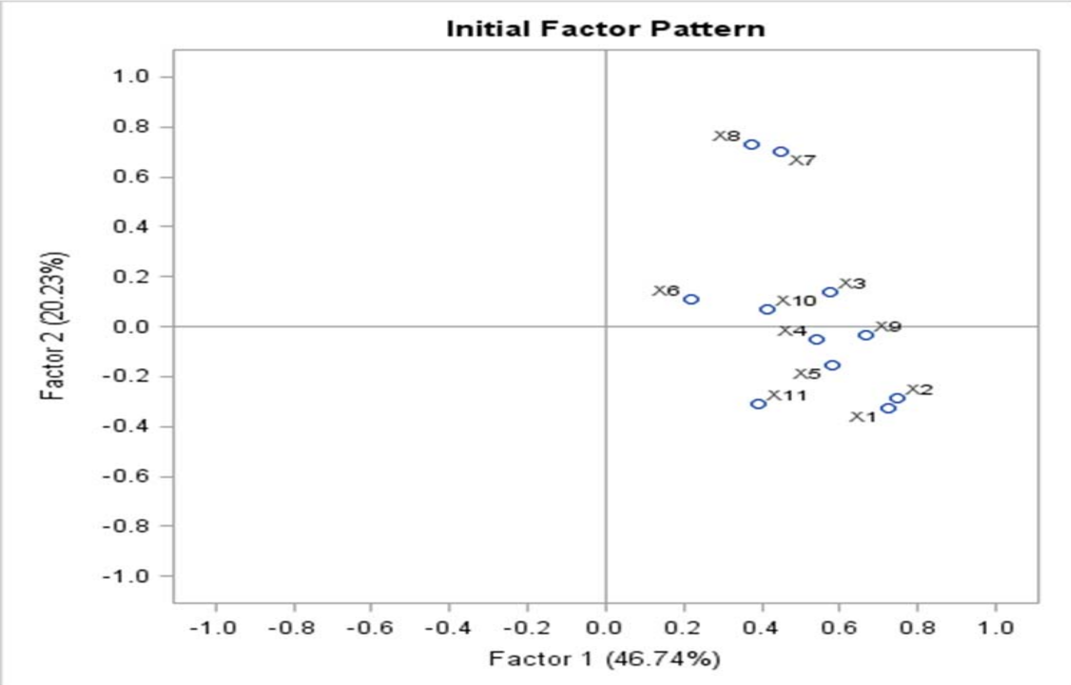


Figure 9.4.5b Factor Pattern

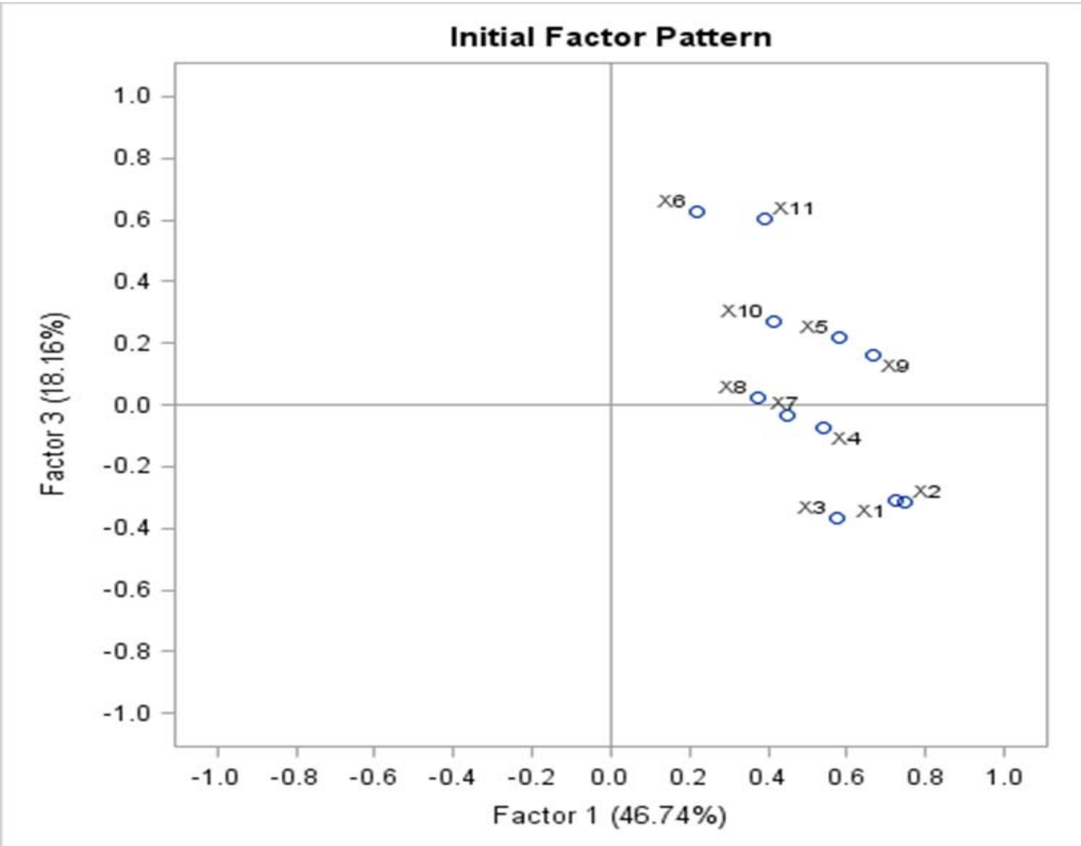
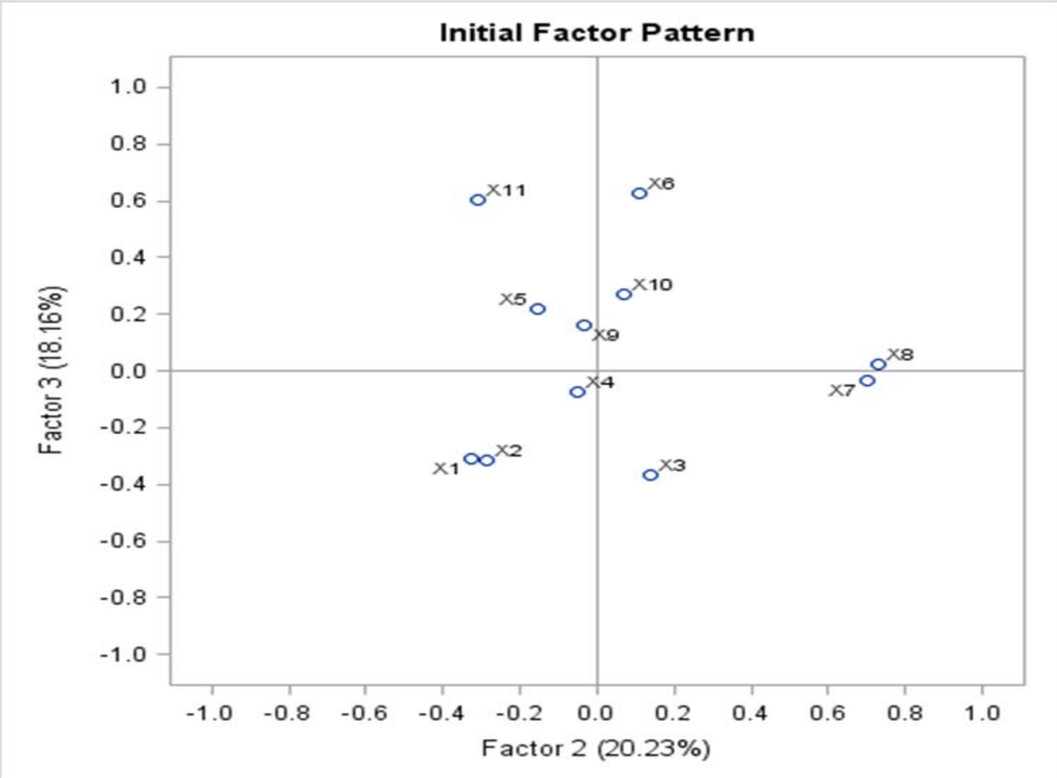


Figure 9.4.5c Factor Pattern



Tabel 9.4.6. Variance Explained by Factor

Variance Explained by Each Factor			
Factor1	Factor2	Factor3	Factor4
3.19215	1.38203	1.24066	1.01538

Tabel 9.4.7. Rotated Factor Pattern

Rotated Factor Pattern				
	Factor1	Factor2	Factor3	Factor4
X1	0.87722	-0.0136	-0.0001	0.0556
X2	0.8889	0.03315	-0.0022	0.05532
X3	0.5361	0.35722	0.14361	-0.2723
X4	0.46305	0.14762	0.27807	-0.0369
X5	0.45742	0.05405	0.30158	0.3323
X6	0.00703	0.16343	-0.0193	0.8685
X7	0.14682	0.8202	0.02973	0.0828
X8	0.04116	0.814	0.068	0.07783
X9	0.48232	0.19581	0.39036	0.22029
X10	0.06096	0.17159	0.82921	-0.1727
X11	0.15495	-0.1929	0.63424	0.4249

Tabel 9.4.8. Variance Explained by rotated factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
2.7188603	1.72237	1.5427

Figure 9.4.9a Rotated Factor Pattern

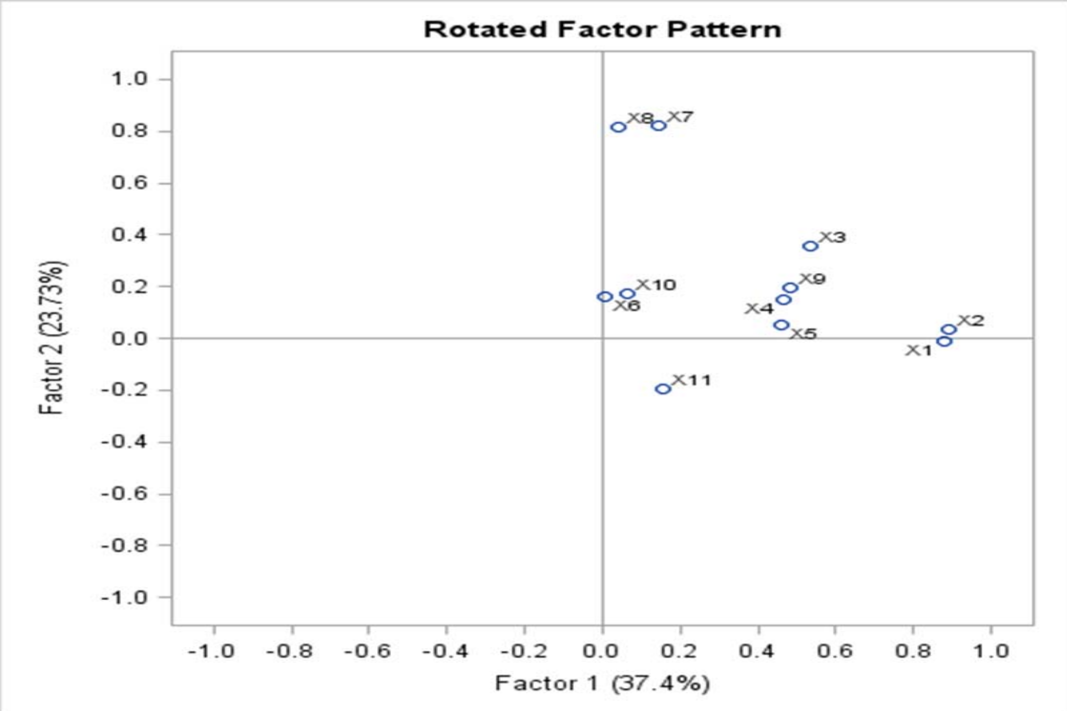


Figure 9.4.9b Rotated Factor Pattern

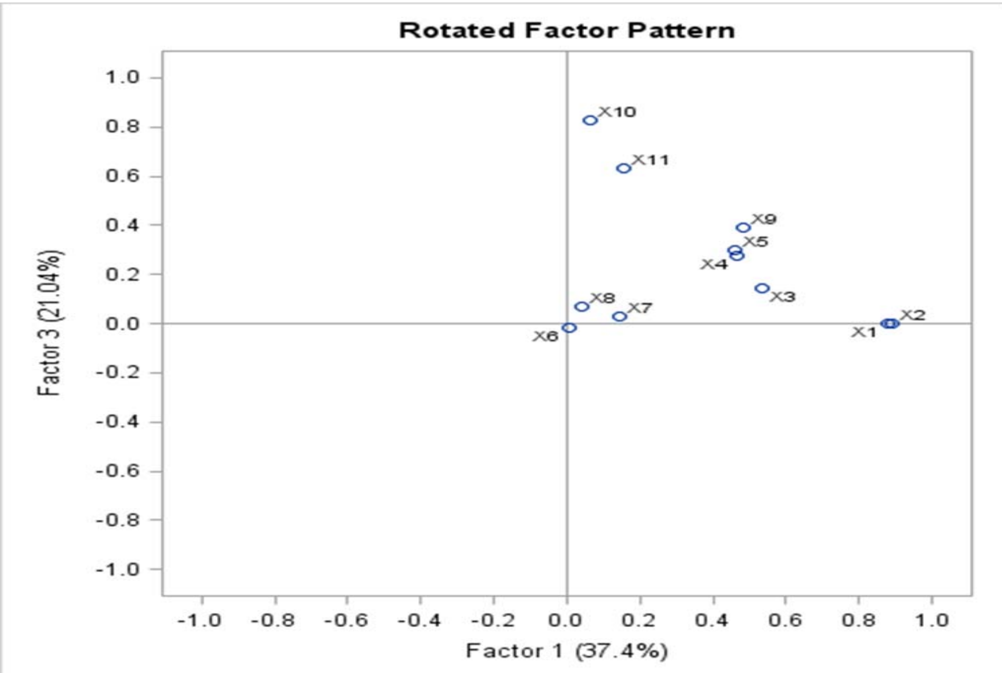
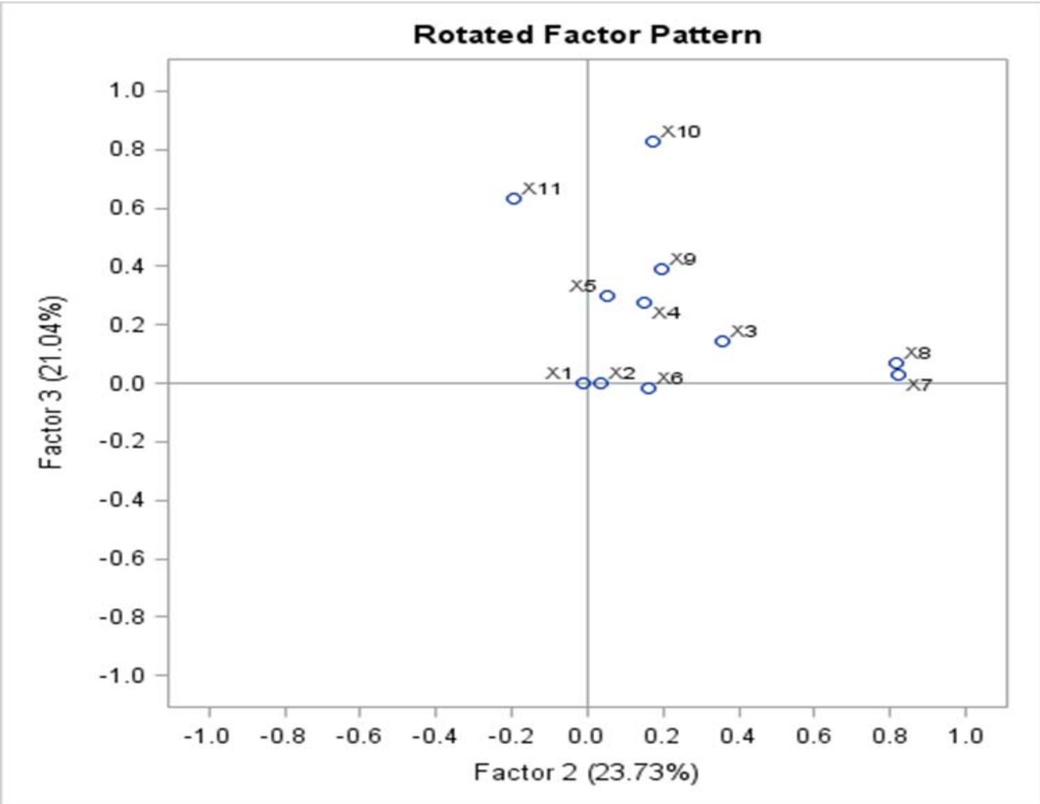


Figure 9.4.9c Rotated Factor Pattern



Tabel 9.4.10. Cronbach Alpha

6 Variables:	x1 x2 x3 x4 x5 x9

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.770744
Standardized	0.764736

Tabel 9.4.11. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
	Raw Variables		Standardized Variables		
Deleted Variable	Correlation with Total	Alpha	Correlation with Total	Alpha	Label
x1	0.660702	0.695151	0.645675	0.692799	x1: PRODUCTION LEVEL
x2	0.677144	0.690575	0.662108	0.688197	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.396041	0.765186	0.395989	0.758547	x3: SUPPLIERS DELIVERY TIME
x4	0.422412	0.758425	0.428015	0.750541	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.376812	0.76938	0.378352	0.762904	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.558048	0.725316	0.550866	0.718675	x9:QUANTITY OF ITEMS PRODUCED

Tabel 9.4.12. Cronbach Alpa

2 Variables:	x7 x8

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.656107
Standardized	0.656444

Tabel 9.4.13. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
	Raw Variables		Standardized Variables		
Deleted Variable	Correlation with Total	Alpha	Correlation with Total	Alpha	Label
x7	0.488587	.	0.488587	.	x7: AVERAGE PRICE OF OUTPUTS
x8	0.488587	.	0.488587	.	x8: AVERAGE PRICE OF INPUTS

Tabel 9.4.14. Cronbach Alpa

2 Variables:	x6 x11

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.335913
Standardized	0.341779

Tabel 9.4.15. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
	Raw Variables		Standardized Variables		
Deleted Variable	Correlation with Total	Alpha	Correlation with Total	Alpha	Label
x6	0.206112	.	0.206112	.	x6: NEW EXPORT ORDERS RECEIVED
x11	0.206112	.	0.206112	.	x11: STOCK OF FINISHED GOODS

9.5 Q3 2015

Tabel 9.5.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
Mean	1.963	2.010119	1.889881	2.0666667	1.960119	2.14464	2.04881	1.92857	1.98155	2.1255952	2.09643
Std Dev	0.464	0.47486703	0.40221112	0.33231807	0.41608103	0.36262	0.49001	0.38204	0.41663	0.41620385	0.4398

Tabel 9.5.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.79980982										
x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
0.71216	0.71765	0.87903	0.89414	0.85624	0.80928	0.81456	0.80451	0.87831	0.87649	0.86999

Tabel 9.5.3. Correlation Matrix

Correlations											
	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
x1	1	0.76986	0.31777	0.26776	0.24359	0.14106	0.26349	0.23168	0.40896	0.27264	0.25946
x2	0.76986	1	0.3399	0.27534	0.30485	0.18425	0.27379	0.23627	0.36765	0.23895	0.28465
x3	0.31777	0.3399	1	0.28403	0.16731	0.03036	0.27138	0.21002	0.19899	0.15282	0.13767
x4	0.26776	0.27534	0.28403	1	0.22914	0.11447	0.23998	0.23484	0.24291	0.16785	0.15585
x5	0.24359	0.30485	0.16731	0.22914	1	0.228	0.16945	0.15461	0.25947	0.22295	0.27196
x6	0.14106	0.18425	0.03036	0.11447	0.228	1	0.11792	0.11632	0.12558	0.10331	0.19904
x7	0.26349	0.27379	0.27138	0.23998	0.16945	0.11792	1	0.39559	0.23712	0.14727	0.09895
x8	0.23168	0.23627	0.21002	0.23484	0.15461	0.11632	0.39559	1	0.32638	0.22653	0.16883
x9	0.40896	0.36765	0.19899	0.24291	0.25947	0.12558	0.23712	0.32638	1	0.32174	0.28092
x10	0.27264	0.23895	0.15282	0.16785	0.22295	0.10331	0.14727	0.22653	0.32174	1	0.24102
x11	0.25946	0.28465	0.13767	0.15585	0.27196	0.19904	0.09895	0.16883	0.28092	0.24102	1

Figure 9.5.4. Scree Plot

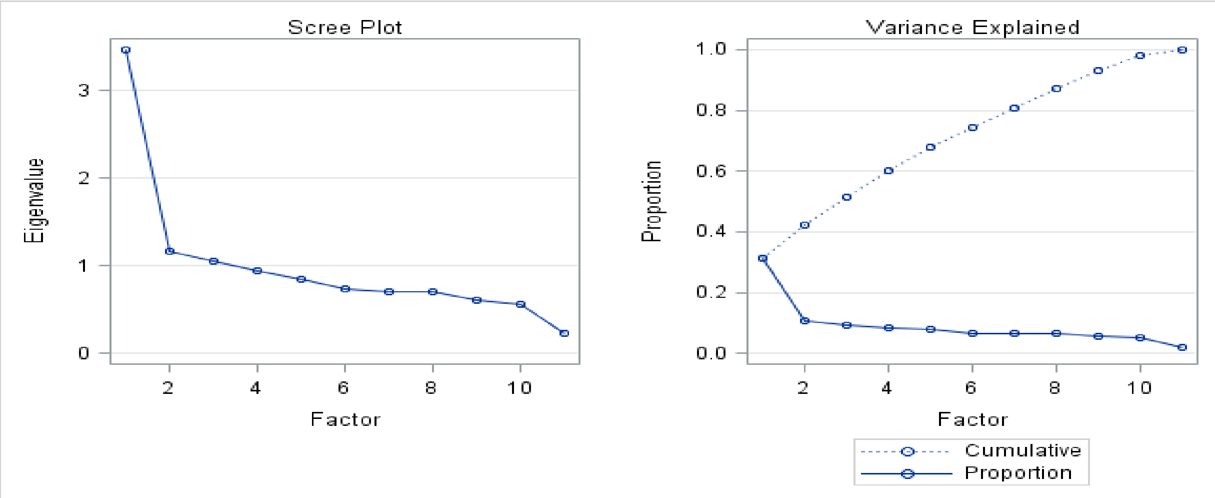


Figure 9.5.5a Factor Pattern

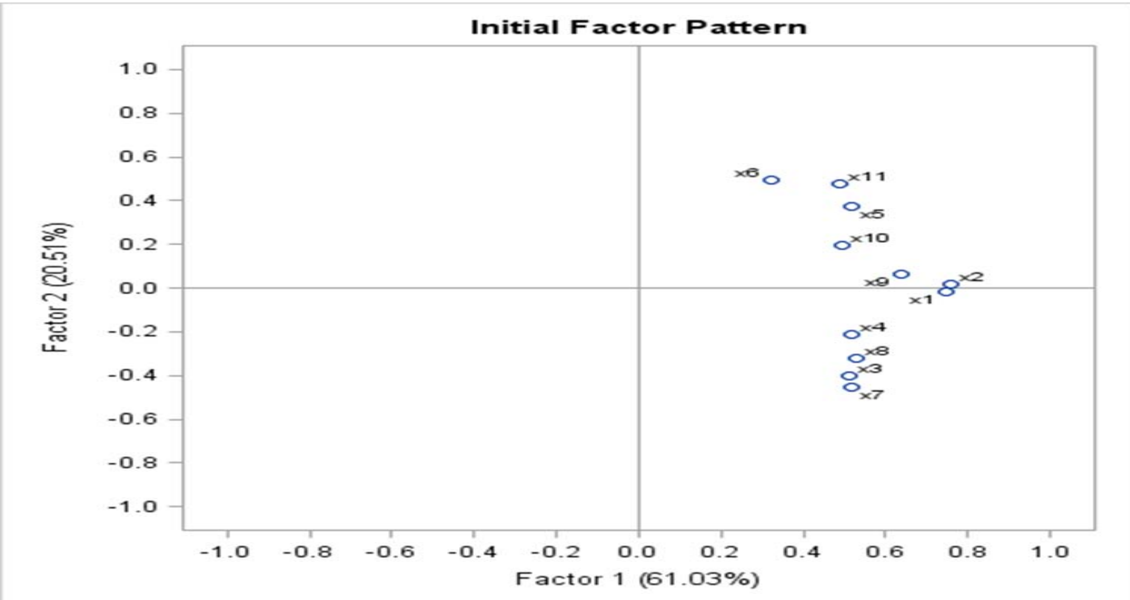


Figure 9.5.5b Factor Pattern

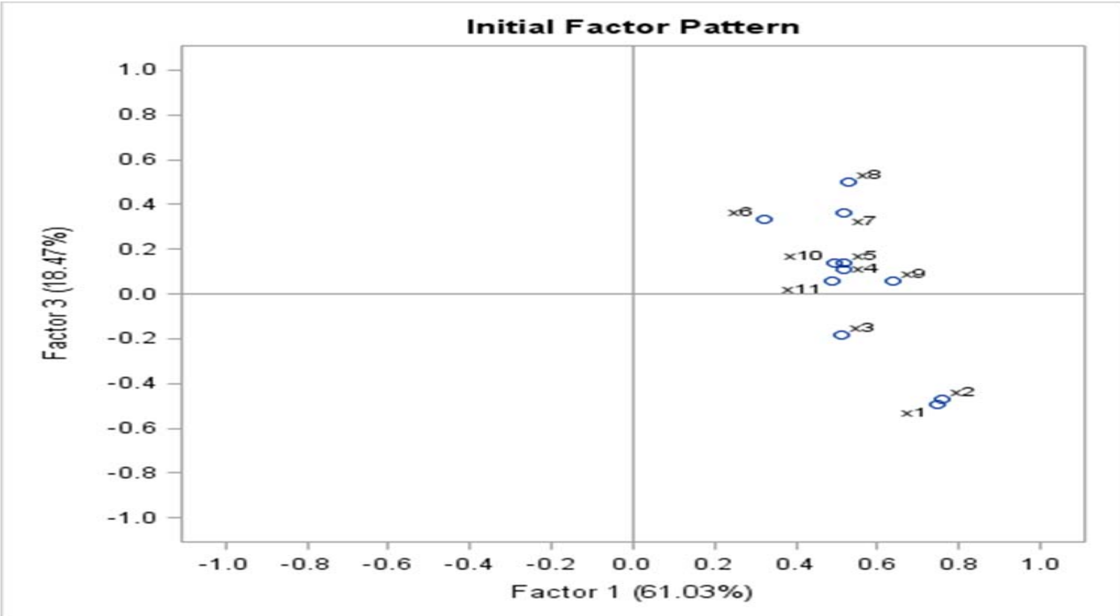
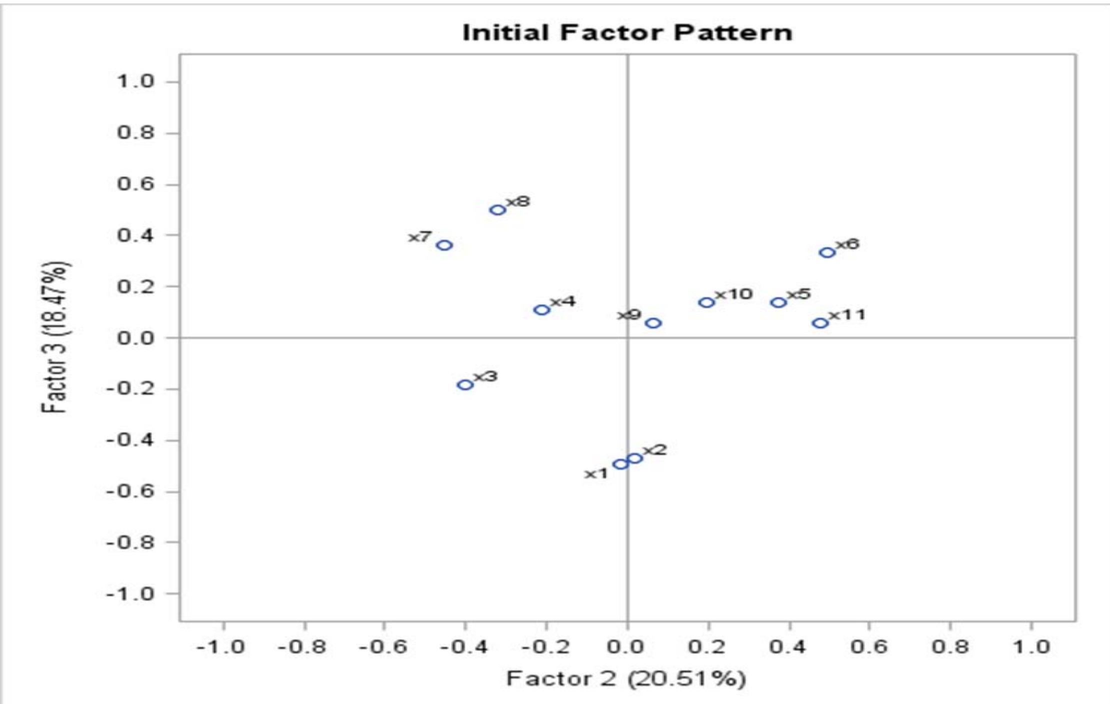


Figure 9.5.5c Factor Pattern



Tabel 9.5.6. Variance Explained by Factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.46265	1.16355	1.04777

Tabel 9.5.7. Rotated Factor Pattern

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
x1	0.85853	0.2246	0.11306
x2	0.84353	0.26411	0.11348
x3	0.52942	-0.096	0.4067
x4	0.28708	0.15201	0.46571
x5	0.18489	0.61064	0.12209
x6	-0.105	0.66523	0.05858
x7	0.13708	0.0463	0.76343
x8	0.02394	0.20109	0.7706
x9	0.37083	0.41198	0.33035
x10	0.1943	0.46322	0.22159
x11	0.2115	0.64968	-0.0011

Tabel 9.5.8. Variance Explained by rotated factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
2.0959	1.8169	1.76117

Figure 9.5.9a Rotated Factor Pattern

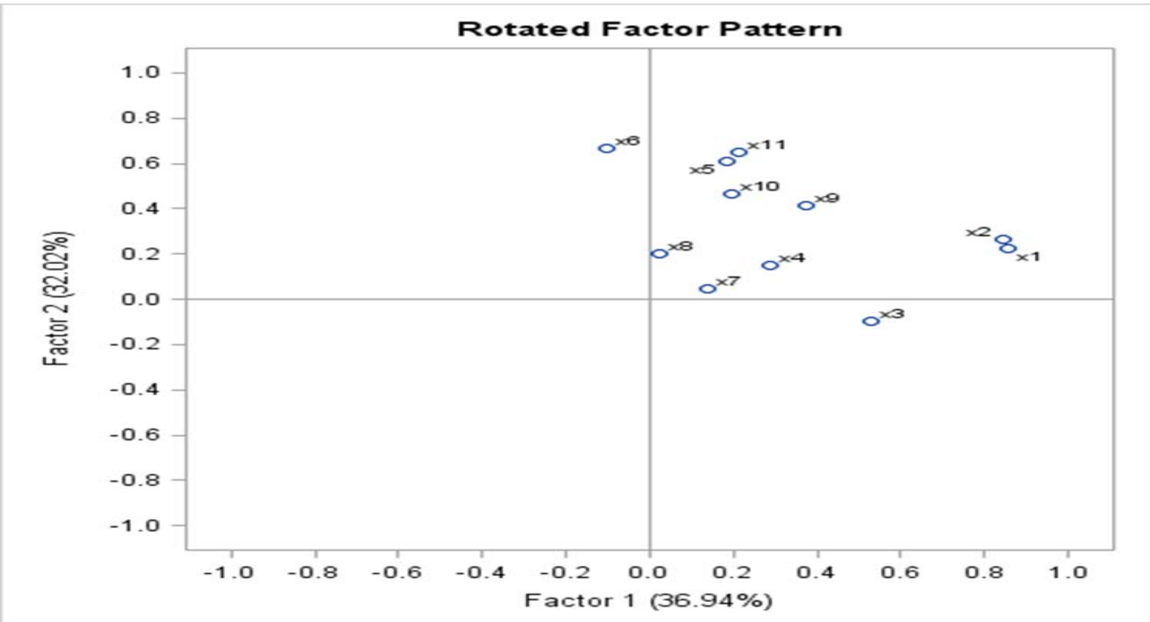


Figure 9.5.9b Rotated Factor Pattern

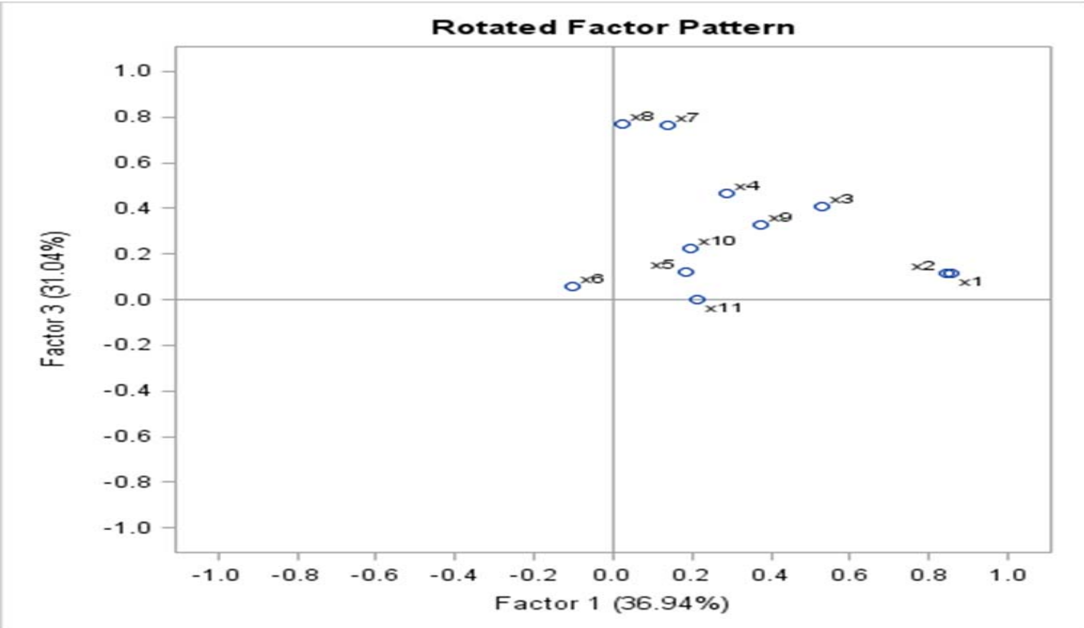
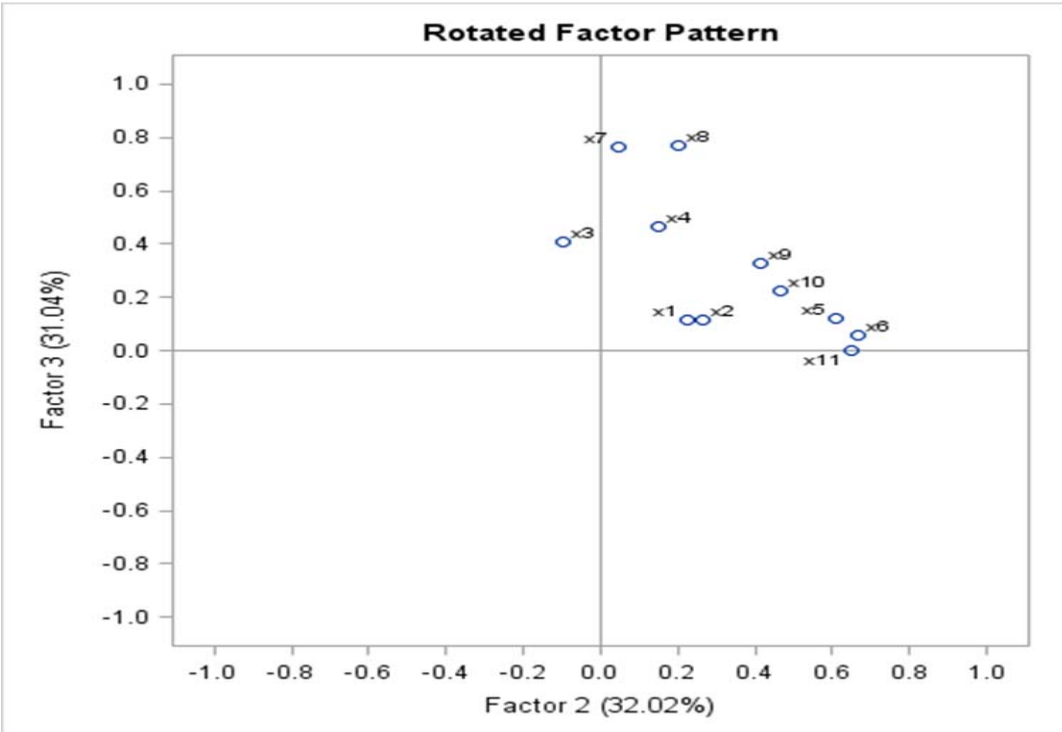


Figure 9.5.9c Rotated Factor Pattern



Tabel 9.5.10. Cronbach Alpha

9 Variables:	x1 x2 x3 x4 x5 x7 x8 x9 x10

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.769481
Standardized	0.767803

Tabel 9.5.11. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.607354	0.7216	0.594578	0.723349	x1: PRODUCTION LEVEL
x2	0.612625	0.7202	0.602041	0.722158	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.401892	0.7548	0.400982	0.753157	x3: SUPPLIERS DELIVERY TIME
x4	0.399486	0.7556	0.400899	0.753169	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.357622	0.7613	0.358672	0.759396	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x7	0.407564	0.7563	0.413493	0.751294	x7: AVERAGE PRICE OF OUTPUTS
x8	0.419287	0.7524	0.417509	0.750694	x8: AVERAGE PRICE OF INPUTS
x9	0.497136	0.7409	0.496891	0.738652	x9:QUANTITY OF ITEMS PRODUCED
x10	0.35686	0.7614	0.35853	0.759416	x10: LEVEL OFOUTSTADING BUSINESS/BACKLOG OF WORK

9.6 Q4 2015

Tabel 9.6.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
Mean	1.9184524	1.9625	1.9053571	2.052381	1.9482143	2.14048	2.03333	1.91667	1.98274	2.0660714	2.0506
Std Dev	0.5356472	0.45333029	0.37931388	0.35838244	0.4006266	0.37792	0.35845	0.36791	0.41668	0.40199221	0.39929

Tabel 9.6.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.79205562										
x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
0.74474	0.74003	0.86591	0.87073	0.86187	0.74466	0.7243	0.71429	0.83112	0.79932	0.88071

Tabel 9.6.3. Correlation Matrix

Correlations											
	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
x1	1	0.66597	0.28185	0.21799	0.28039	0.15783	0.20674	0.15911	0.37039	0.21615	0.26282
x2	0.66597	1	0.35269	0.29473	0.25633	0.18511	0.19486	0.17787	0.41221	0.22304	0.28173
x3	0.28185	0.35269	1	0.26317	0.29469	0.03883	0.18698	0.15845	0.33297	0.20142	0.16554
x4	0.21799	0.29473	0.26317	1	0.22935	0.10847	0.07149	0.08743	0.26562	0.15391	0.18702
x5	0.28039	0.25633	0.29469	0.22935	1	0.17942	0.21136	0.15677	0.28874	0.27183	0.24628
x6	0.15783	0.18511	0.03883	0.10847	0.17942	1	0.1121	0.02573	0.04698	0.08926	0.15303
x7	0.20674	0.19486	0.18698	0.07149	0.21136	0.1121	1	0.40544	0.1955	0.16677	0.10069
x8	0.15911	0.17787	0.15845	0.08743	0.15677	0.02573	0.40544	1	0.26936	0.15959	0.13158
x9	0.37039	0.41221	0.33297	0.26562	0.28874	0.04698	0.1955	0.26936	1	0.42808	0.26451
x10	0.21615	0.22304	0.20142	0.15391	0.27183	0.08926	0.16677	0.15959	0.42808	1	0.28501
x11	0.26282	0.28173	0.16554	0.18702	0.24628	0.15303	0.10069	0.13158	0.26451	0.28501	1

Figure 9.6.4. Scree Plot

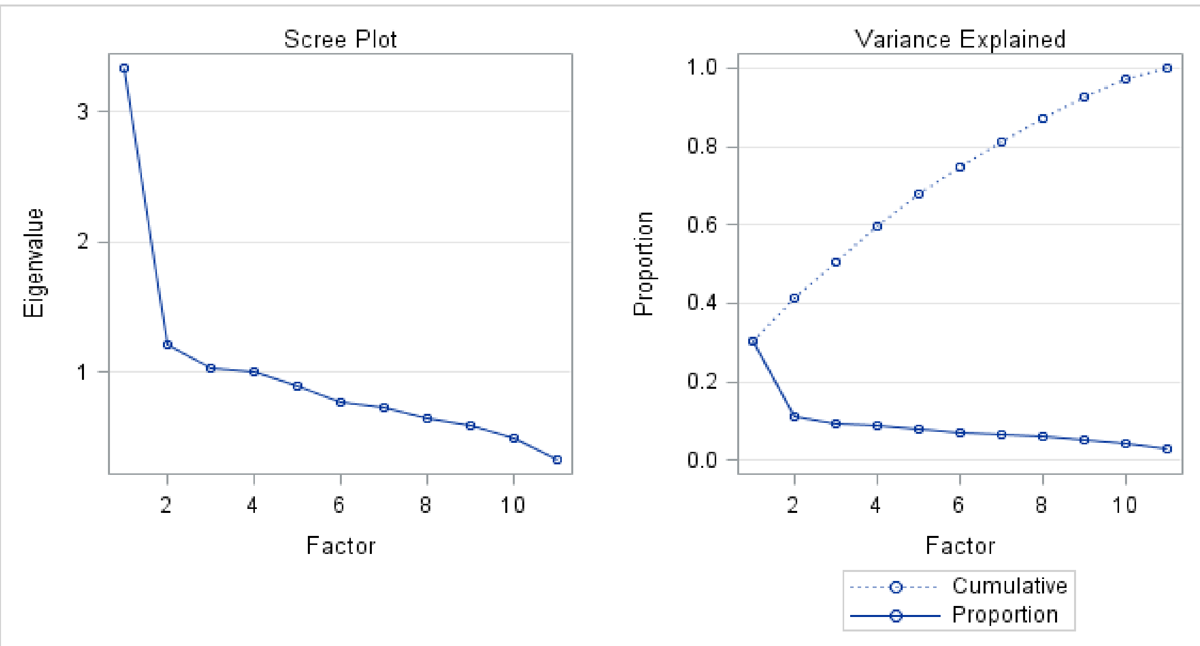


Figure 9.6.5a Factor Pattern

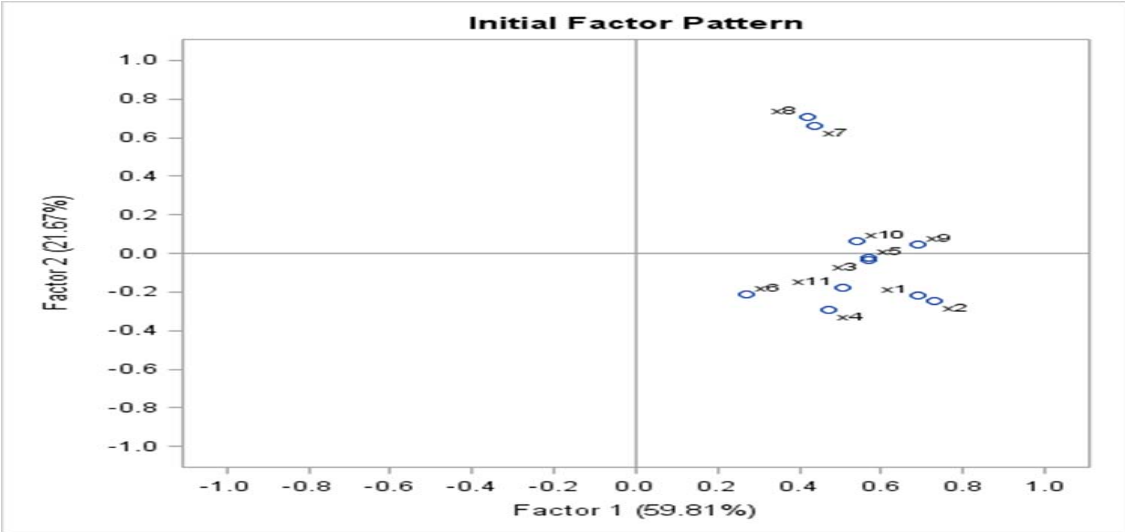


Figure 9.6.5b Factor Pattern

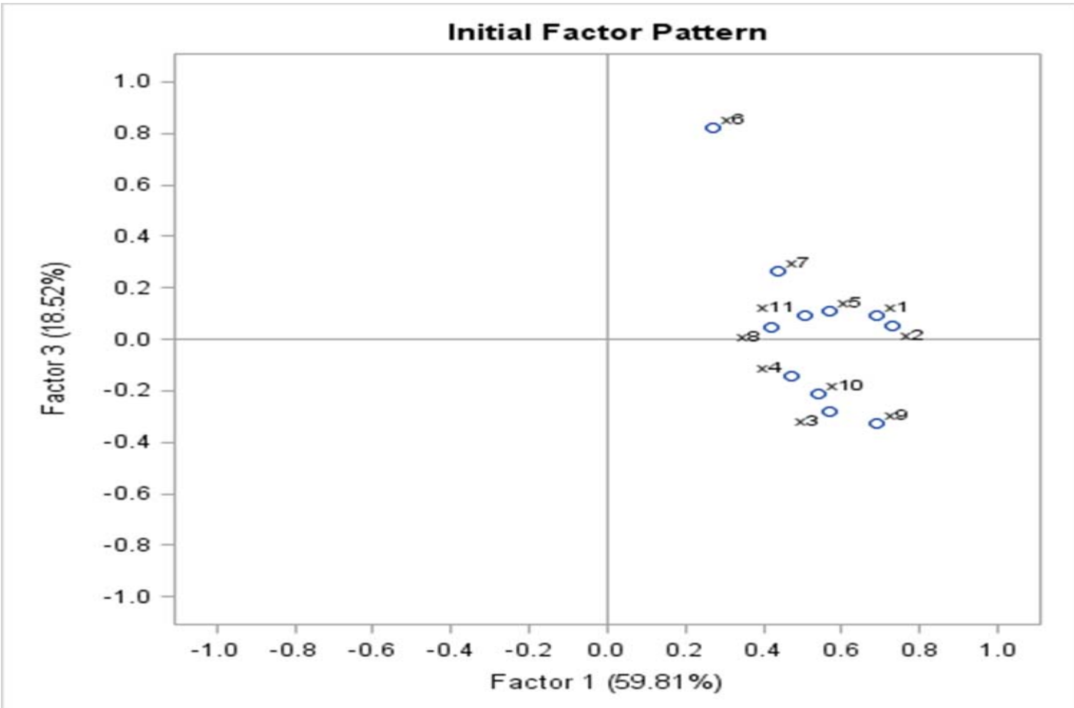
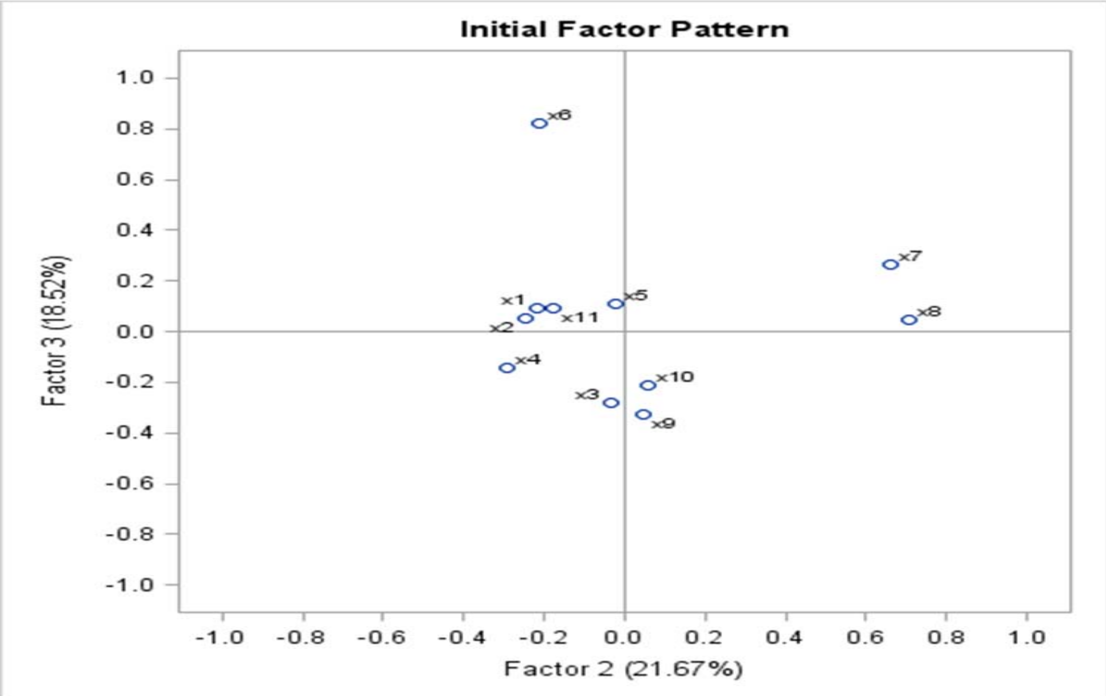


Figure 9.6.5c Factor Pattern



Tabel 9.6.6. Variance Explained by Factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.33705	1.20911	1.03327

Tabel 9.6.7. Rotated Factor Pattern

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
x1	0.65775	0.08279	0.3049
x2	0.71339	0.06438	0.28593
x3	0.60642	0.13861	-0.1253
x4	0.5595	-0.1058	0.0555
x5	0.48209	0.21986	0.23702
x6	0.05277	0.05331	0.88996
x7	0.09646	0.81103	0.16494
x8	0.13584	0.8083	-0.056
x9	0.70331	0.25125	-0.1583
x10	0.52857	0.22539	-0.093
x11	0.48091	0.05131	0.25067

Tabel 9.6.8. Variance Explained by rotated factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
2.8906	1.52025	1.16858

Figure 9.6.9a Rotated Factor Pattern

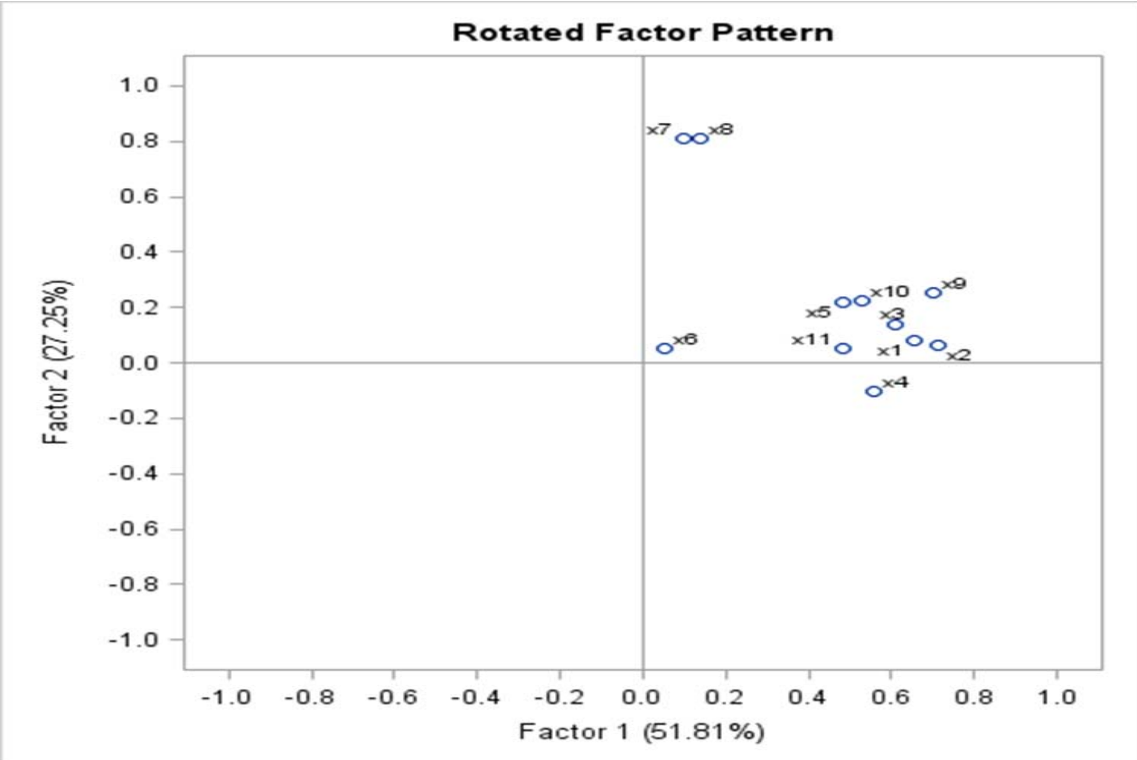


Figure 9.6.9b Rotated Factor Pattern

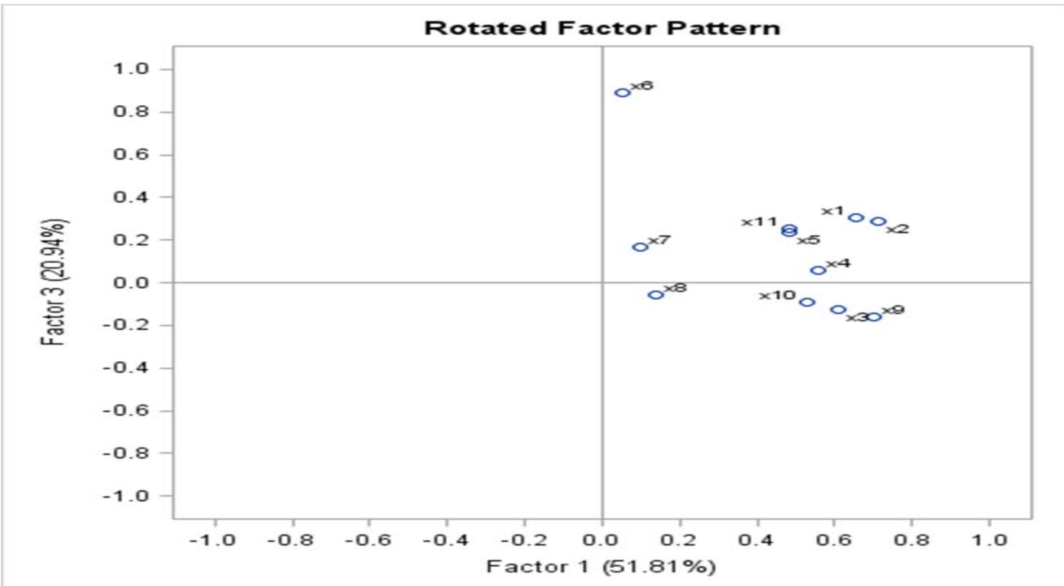
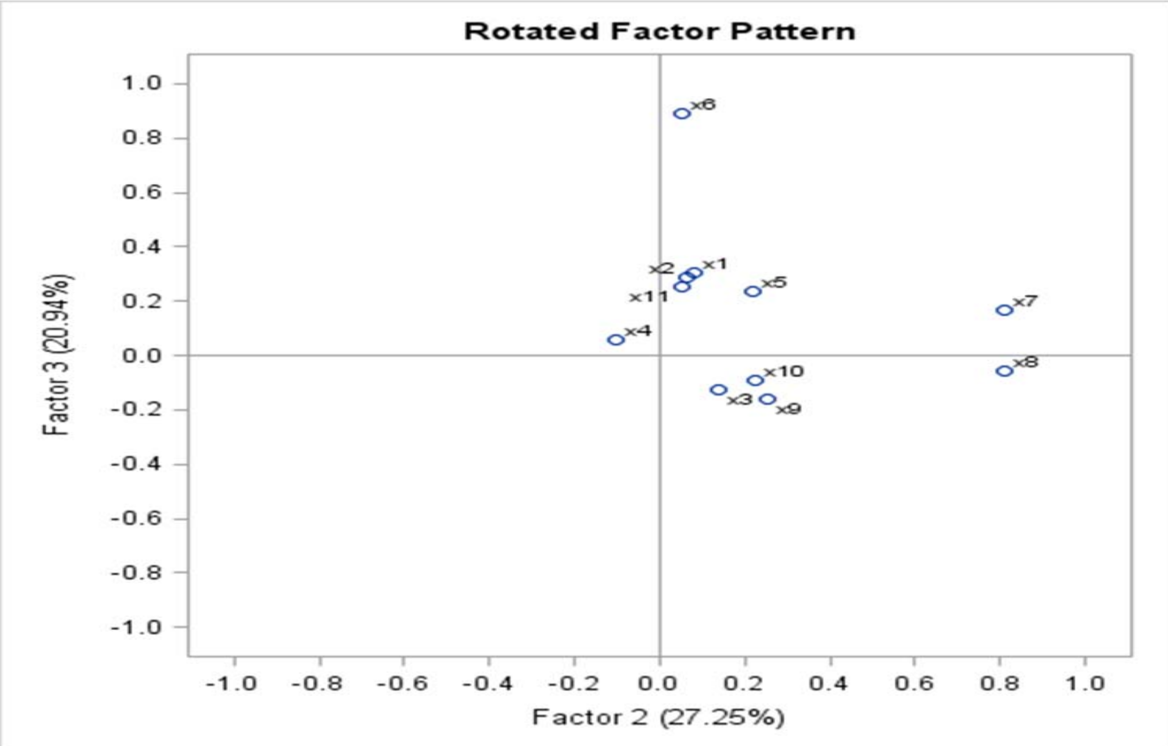


Figure 9.6.9c Rotated Factor Pattern



Tabel 9.6.10. Cronbach Alpha

8 Variables:	x1 x2 x3 x4 x5 x9 x10 x11

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.764471
Standardized	0.761728

Tabel 9.6.11. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.607354	0.721586	0.594578	0.723349	x1: PRODUCTION LEVEL
x2	0.612625	0.720221	0.602041	0.722158	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.401892	0.7548	0.400982	0.753157	x3: SUPPLIERS DELIVERY TIME
x4	0.399486	0.755638	0.400899	0.753169	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.357622	0.761297	0.358672	0.759396	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.497136	0.740911	0.496891	0.738652	x9:QUANTITY OF ITEMS PRODUCED
x10	0.35686	0.761408	0.35853	0.759416	x10: LEVEL OFOUTSTADING BUSINESS/BACKLOG OF WORK
x11	0.374409	0.777031	0.373794	0.769368	x11: STOCK OF FINISHED GOODS

Tabel 9.6.12. Cronbach Alpa

2 Variables:	x7 x8

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.67682
Standardized	0.676959

Tabel 9.6.13. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x7	0.405441	.	0.405441	.	x7: AVERAGE PRICE OF OUTPUTS
x8	0.405441	.	0.405441	.	x8: AVERAGE PRICE OF INPUTS

9.7 Q1 2015

Tabel 9.7.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
Mean	2.0654762	2.1208333	2.00476	2.0982143	2.0952381	2.160119	1.9095238	1.83333	2.09643	2.15179	2.08869
Std Dev	0.46554787	0.4430188	0.3788	0.33493471	0.41447802	0.3504218	0.38163539	0.39324	0.61923	0.4098	0.44836

Tabel 9.7.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.75688203										
x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
0.71584	0.70412	0.83655	0.83563	0.87032	0.81899	0.60576	0.58219	0.86886	0.82941	0.86096

Tabel 9.7.3. Correlation Matrix

Correlations											
	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
x1	1	0.77207	0.41189	0.271	0.41984	0.10498	0.19003	0.10097	0.40003	0.20515	0.26924
x2	0.77207	1	0.47864	0.28558	0.36913	0.09409	0.1506	0.11238	0.34219	0.13747	0.23315
x3	0.41189	0.47864	1	0.27517	0.206	0.02869	0.21748	0.13344	0.32344	0.09521	0.16253
x4	0.271	0.28558	0.27517	1	0.35345	0.12827	0.08364	0.13205	0.23122	0.22861	0.30191
x5	0.41984	0.36913	0.206	0.35345	1	0.15347	0.11112	0.11097	0.27316	0.27634	0.31171
x6	0.10498	0.09409	0.02869	0.12827	0.15347	1	0.05353	0.01515	0.07253	0.12805	0.10681
x7	0.19003	0.1506	0.21748	0.08364	0.11112	0.05353	1	0.53243	0.18922	0.09686	0.1434
x8	0.10097	0.11238	0.13344	0.13205	0.11097	0.01515	0.53243	1	0.23672	0.11903	0.10315
x9	0.40003	0.34219	0.32344	0.23122	0.27316	0.07253	0.18922	0.23672	1	0.24457	0.27054
x10	0.20515	0.13747	0.09521	0.22861	0.27634	0.12805	0.09686	0.11903	0.24457	1	0.24573
x11	0.26924	0.23315	0.16253	0.30191	0.31171	0.10681	0.1434	0.10315	0.27054	0.24573	1

Figure 9.7.4. Scree Plot

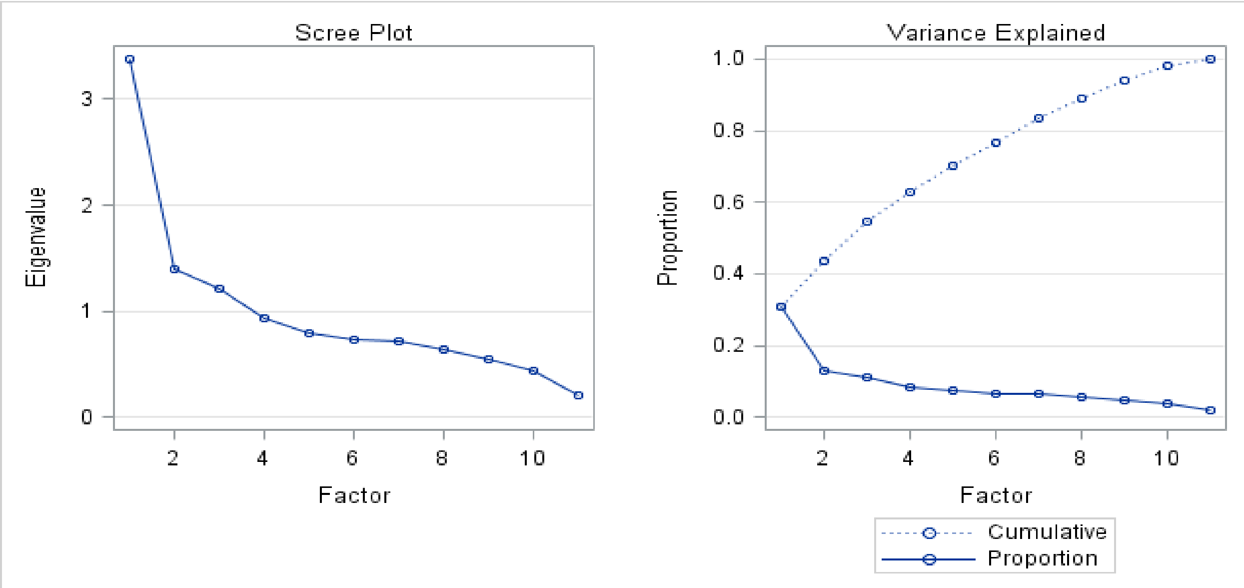


Figure 9.7.5a Factor Pattern

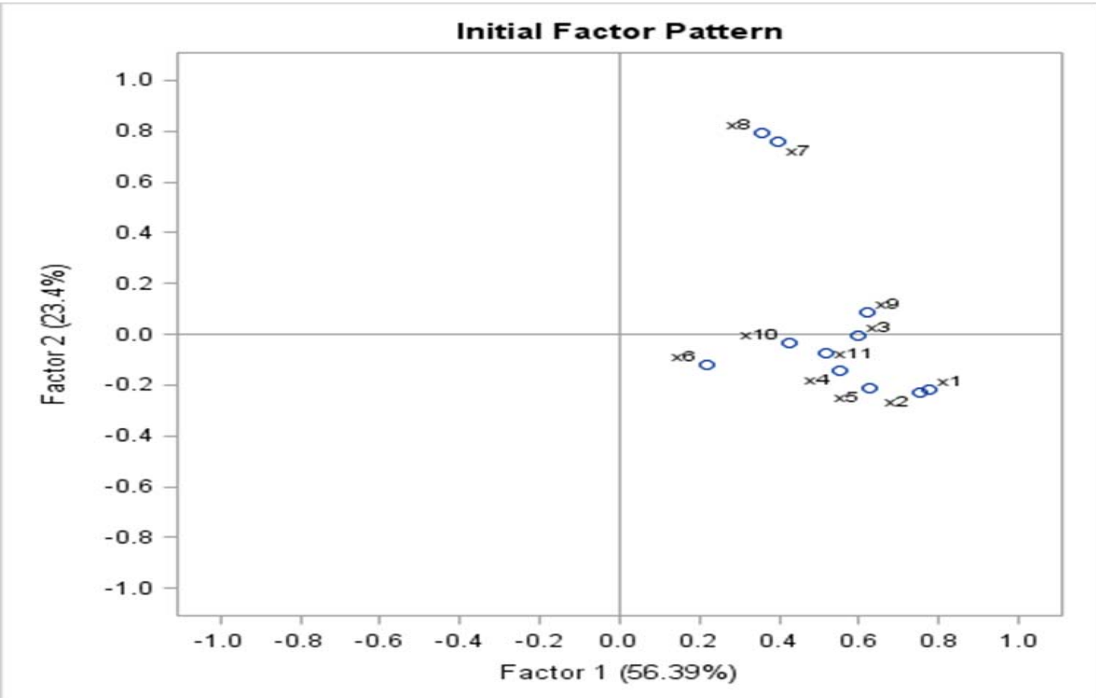


Figure 9.7.5b Factor Pattern

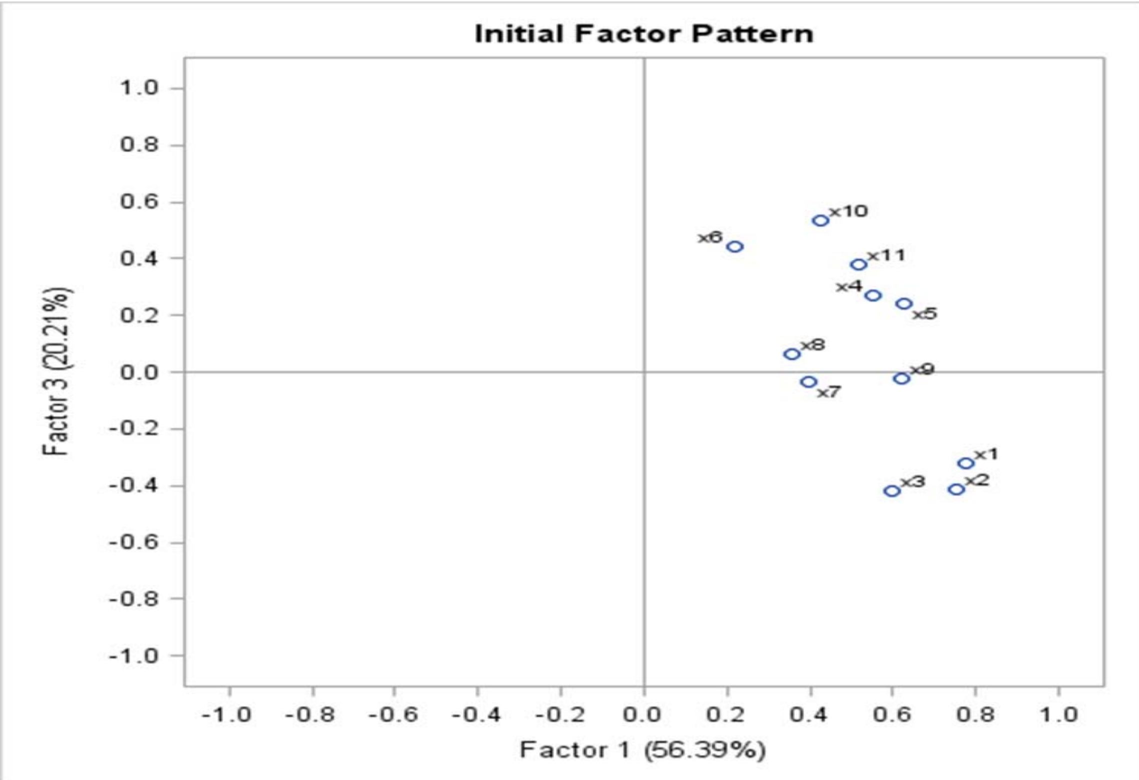
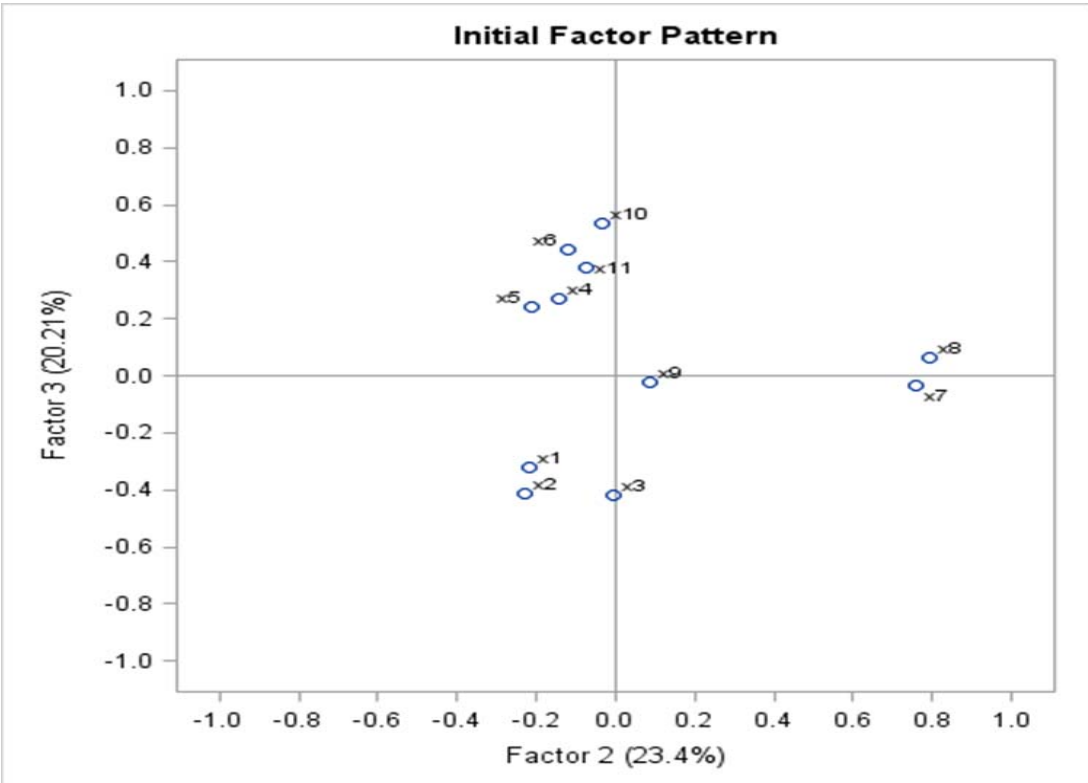


Figure 9.7.5c Factor Pattern



Tabel 9.7.6. Variance Explained by Factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.37935	1.40251	1.21113

Tabel 9.7.7. Rotated Factor Pattern

Rotated Factor Pattern			
	Factor1	Factor2	Factor3
x1	0.84242	0.21051	0.02516
x2	0.87722	0.12642	0.00532
x3	0.7109	-0.0076	0.16824
x4	0.30288	0.55318	0.04196
x5	0.39116	0.58244	0.00223
x6	-0.0622	0.50159	-0.03547
x7	0.14571	0.03418	0.84336
x8	0.0511	0.08369	0.86754
x9	0.47306	0.30594	0.27568
x10	0.02032	0.67277	0.11563
x11	0.19683	0.60495	0.1012

Tabel 9.7.8. Variance Explained by rotated factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
2.51995	1.87756	1.59548

Figure 9.7.9a Rotated Factor Pattern

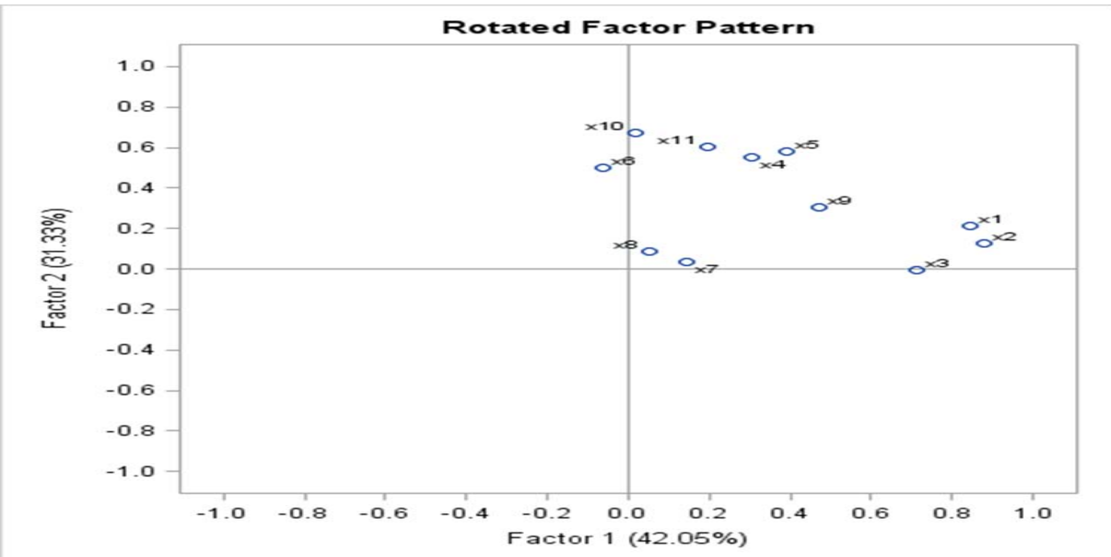


Figure 9.7.9b Rotated Factor Pattern

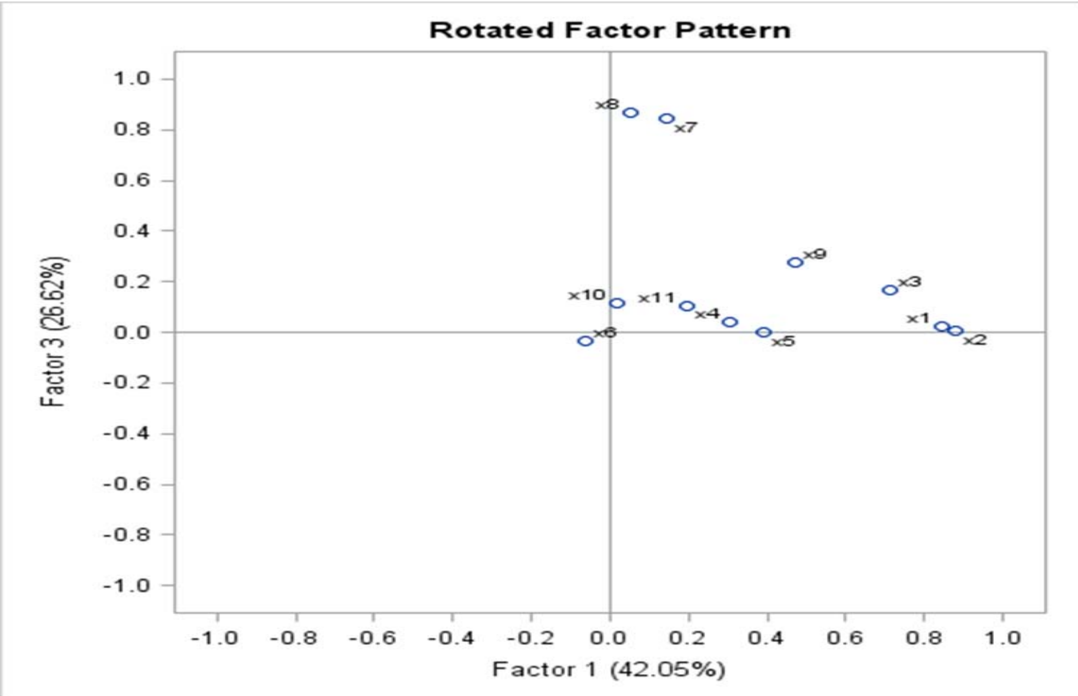
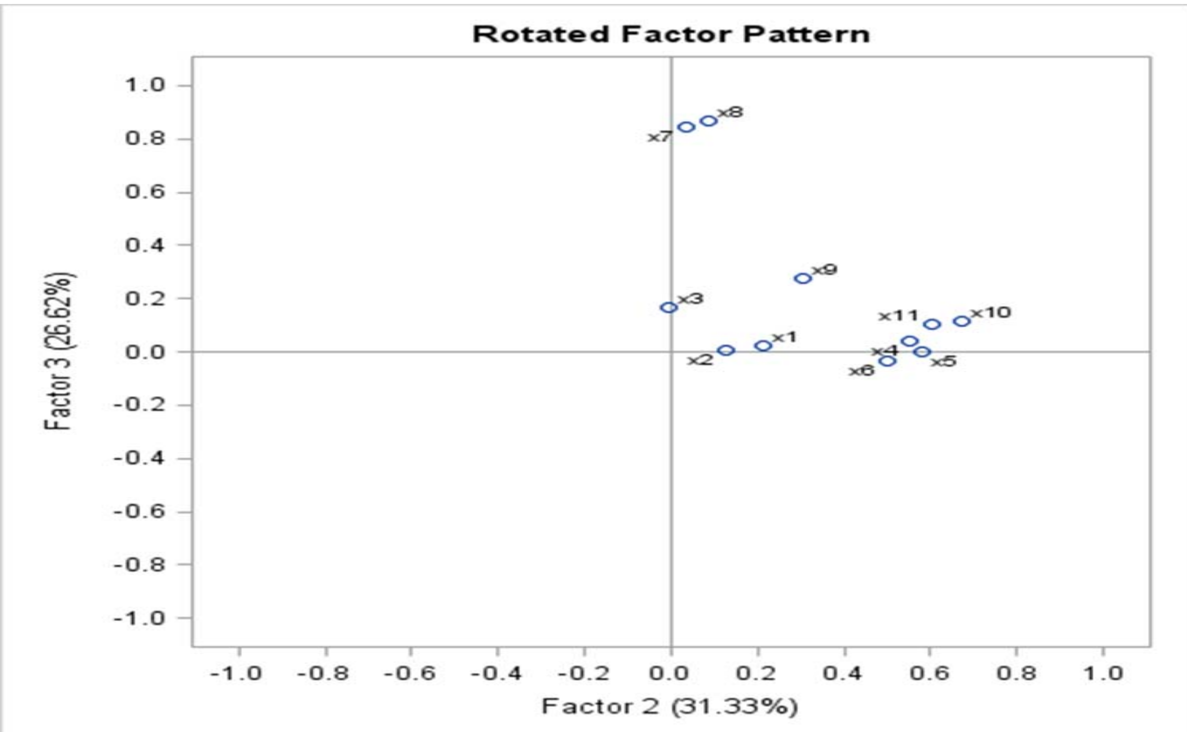


Figure 9.7.9c Rotated Factor Pattern



Tabel 9.7.10. Cronbach Alpha

7 Variables:	x1 x2 x3 x4 x5 x9 x11

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.768199
Standardized	0.776361

Tabel 9.7.11. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.664076	0.700398	0.660502	0.714682	x1: PRODUCTION LEVEL
x2	0.638871	0.707873	0.641335	0.718789	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.464704	0.745209	0.461419	0.755787	x3: SUPPLIERS DELIVERY TIME
x4	0.415838	0.754502	0.423191	0.763294	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.476959	0.742061	0.48246	0.751602	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.458918	0.758711	0.456695	0.756721	x9:QUANTITY OF ITEMS PRODUCED
x11	0.375693	0.762112	0.377649	0.77208	x11: STOCK OF FINISHED GOODS

Tabel 9.7.12. Cronbach Alpa

2 Variables:	x7 x8

Cronbach Coefficient Alpha	
Variables	**Alpha**
Raw	0.694678
Standardized	0.694881

Tabel 9.7.13. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x7	0.532427	.	0.532427	.	x7: AVERAGE PRICE OF OUTPUTS
x8	0.532427	.	0.532427	.	x8: AVERAGE PRICE OF INPUTS

9.8 Q2 2016

Tabel 9.8.1. Means and Standard Deviations Output

Means and Standard Deviations from 560 Observations											
Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Mean	1.969048	2.07917	2.00595	2.1006	2.10268	2.2744	1.76726	1.6321429	2.08571	2.16607	2.17381
Std Dev	0.430217	0.4075	0.351	0.31145	0.39125	0.36425	0.39223	0.42342295	0.42083	0.41249	0.40464

Tabel 9.8.2. KMO Test

Kaiser's Measure of Sampling Adequacy: Overall MSA = 0.76489919										
X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
0.74199	0.76398	0.90163	0.84521	0.88744	0.80443	0.57914	0.5458	0.83718	0.73342	0.85261

Tabel 9.8.3. Correlation Matrix

Correlations											
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
X1	1	0.68294	0.30923	0.21761	0.35311	0.21285	0.14923	0.03886	0.45712	0.17799	0.24448
X2	0.68294	1	0.32605	0.27856	0.34663	0.19218	0.17269	0.10457	0.44138	0.19717	0.27563
X3	0.30923	0.32605	1	0.17452	0.27996	0.08359	0.21221	0.17257	0.29258	0.12221	0.11586
X4	0.21761	0.27856	0.17452	1	0.2348	0.16624	0.04068	0.10175	0.3193	0.09407	0.18908
X5	0.35311	0.34663	0.27996	0.2348	1	0.18898	0.16507	0.13542	0.40399	0.19098	0.27377
X6	0.21285	0.19218	0.08359	0.16624	0.18898	1	0.02209	0.01514	0.16787	-0.0366	0.16671
X7	0.14923	0.17269	0.21221	0.04068	0.16507	0.02209	1	0.5667	0.09217	0.07716	0.02615
X8	0.03886	0.10457	0.17257	0.10175	0.13542	0.01514	0.5667	1	0.09472	0.01923	0.00376
X9	0.45712	0.44138	0.29258	0.3193	0.40399	0.16787	0.09217	0.09472	1	0.34496	0.30106
X10	0.17799	0.19717	0.12221	0.09407	0.19098	-0.0366	0.07716	0.01923	0.34496	1	0.25071
X11	0.24448	0.27563	0.11586	0.18908	0.27377	0.16671	0.02615	0.00376	0.30106	0.25071	1

Figure 9.8.4. Scree Plot

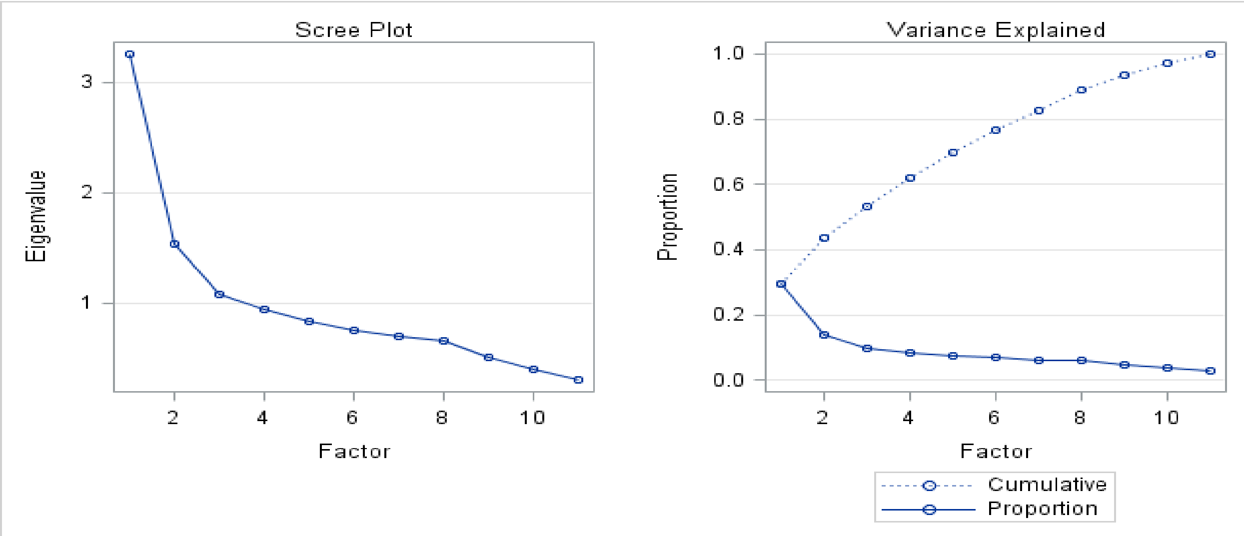


Figure 9.8.5a Factor Pattern

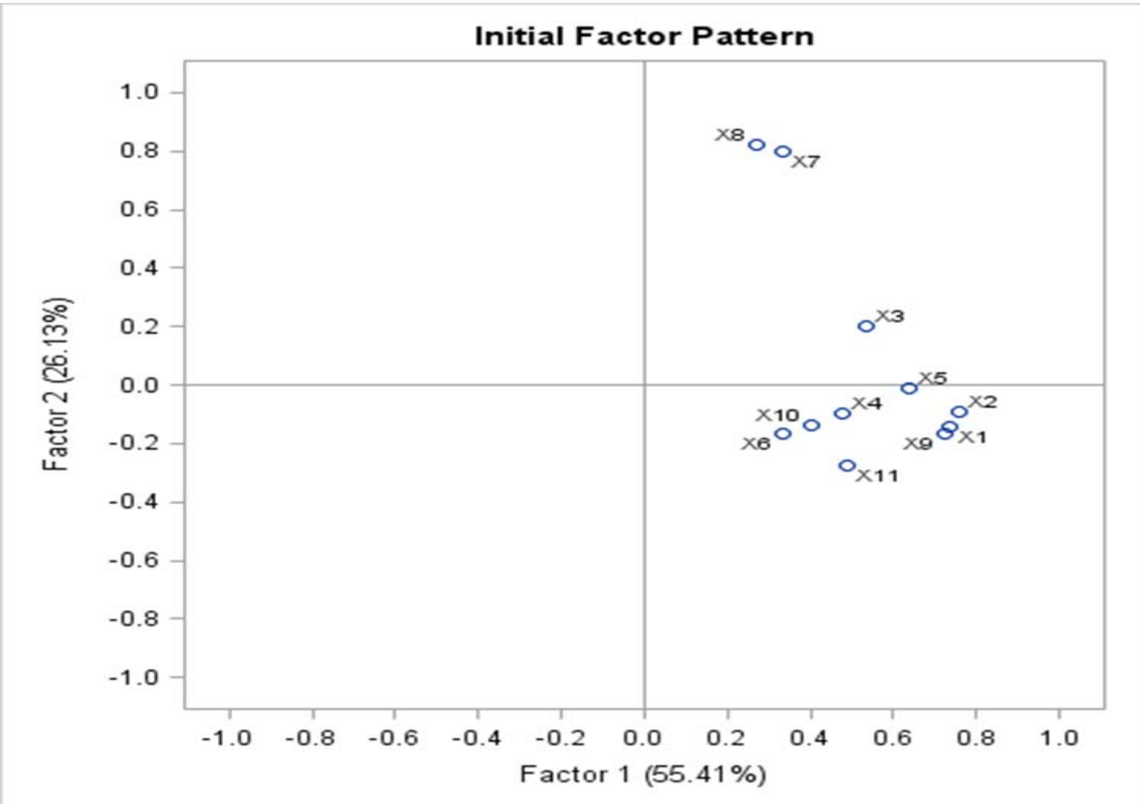


Figure 9.8.5b Factor Pattern

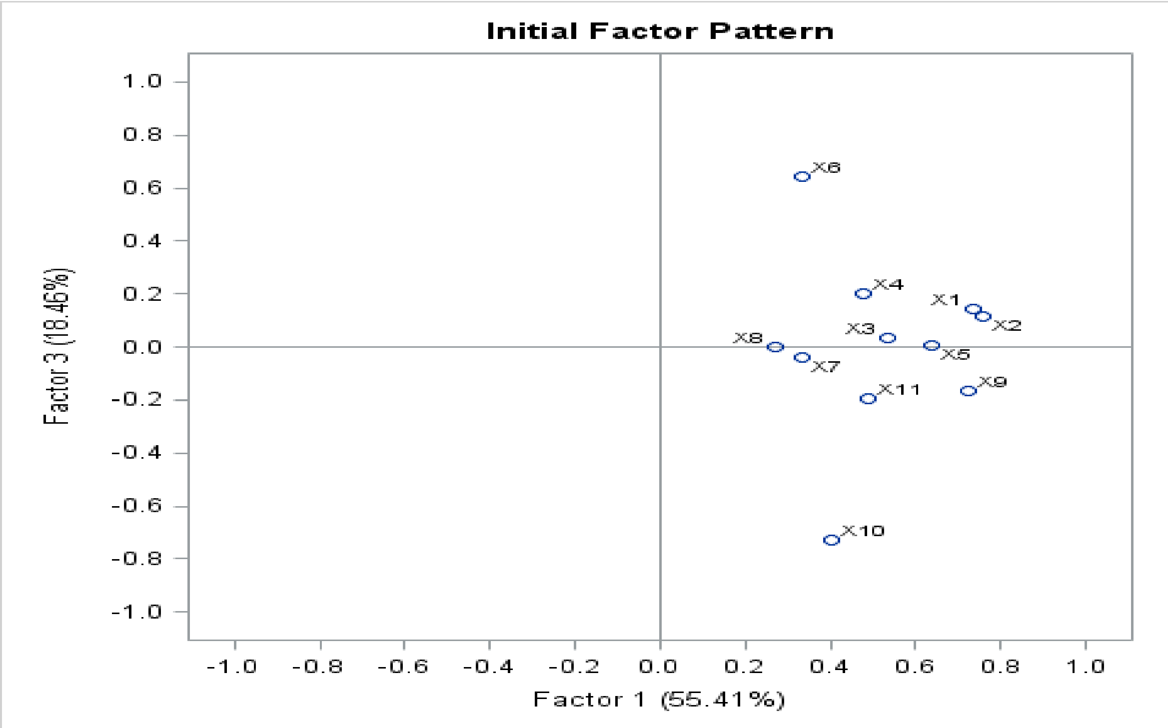
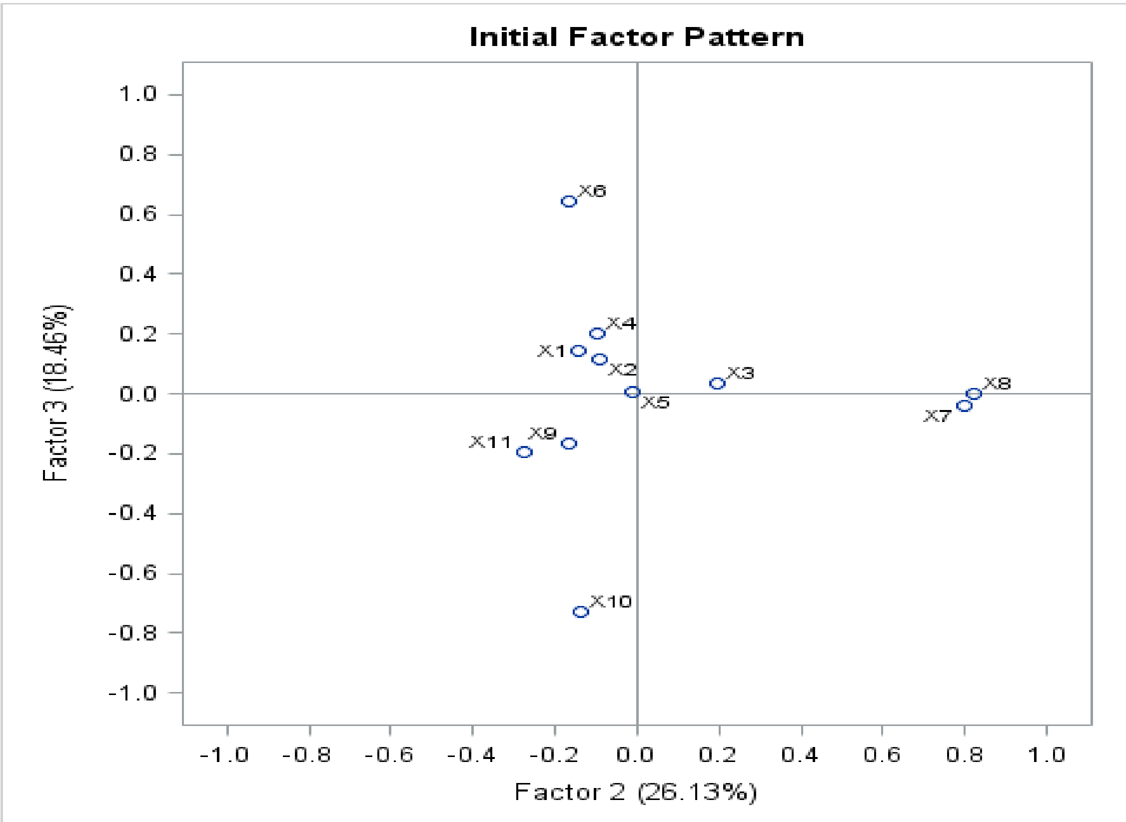


Figure 9.8.5c Factor Pattern



Tabel 9.8.6. Variance Explained by Factor

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.255668	1.53494	1.08471

Tabel 9.8.7. Rotated Factor Pattern

Variance Explained by Each Factor		
Factor1	Factor2	Factor3
3.0800451	1.66077	1.13451

Figure 9.8.8a Rotated Factor Pattern

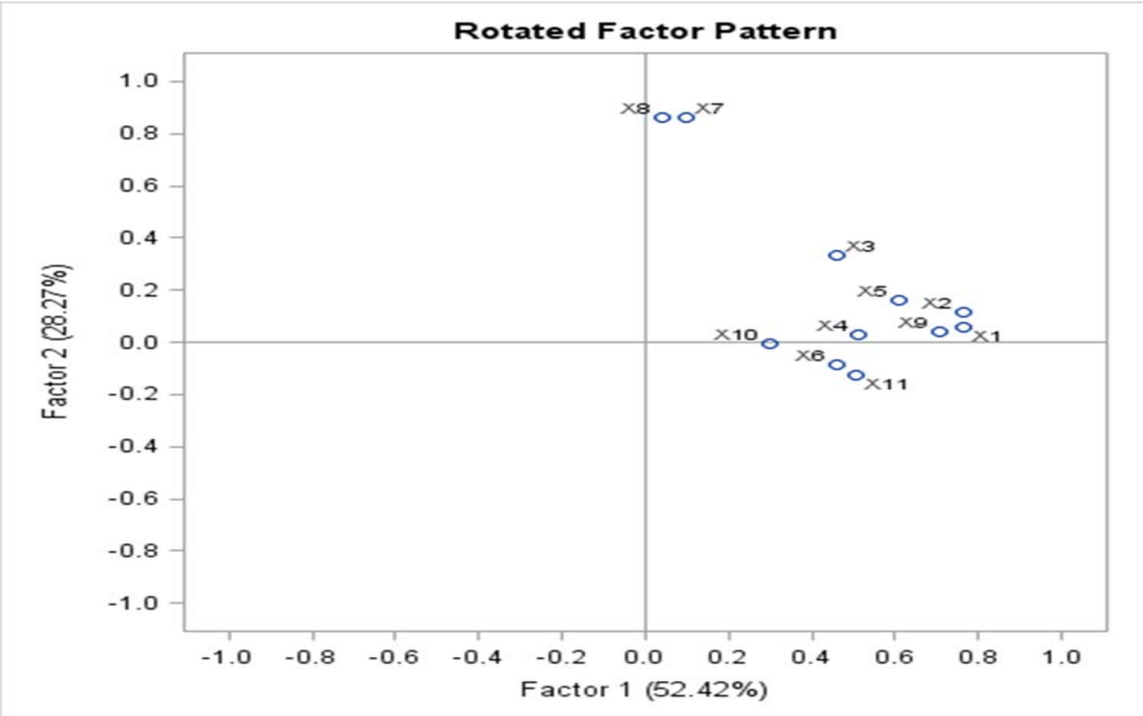


Figure 9.8.8b Rotated Factor Pattern

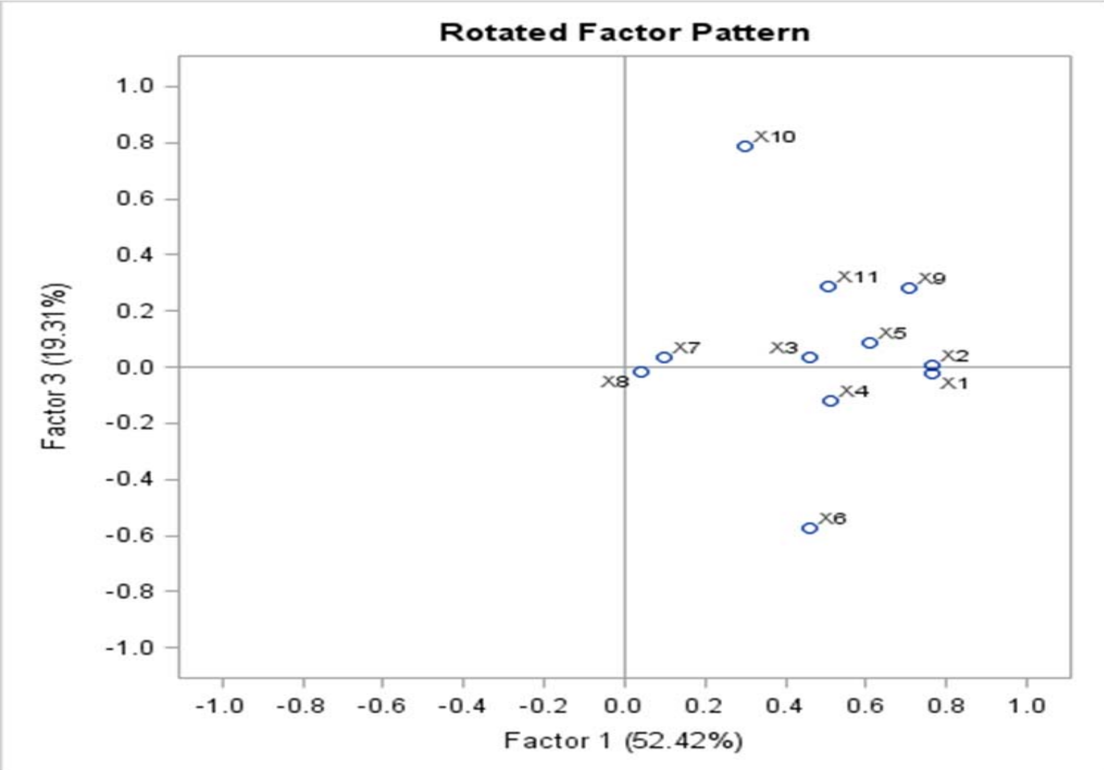
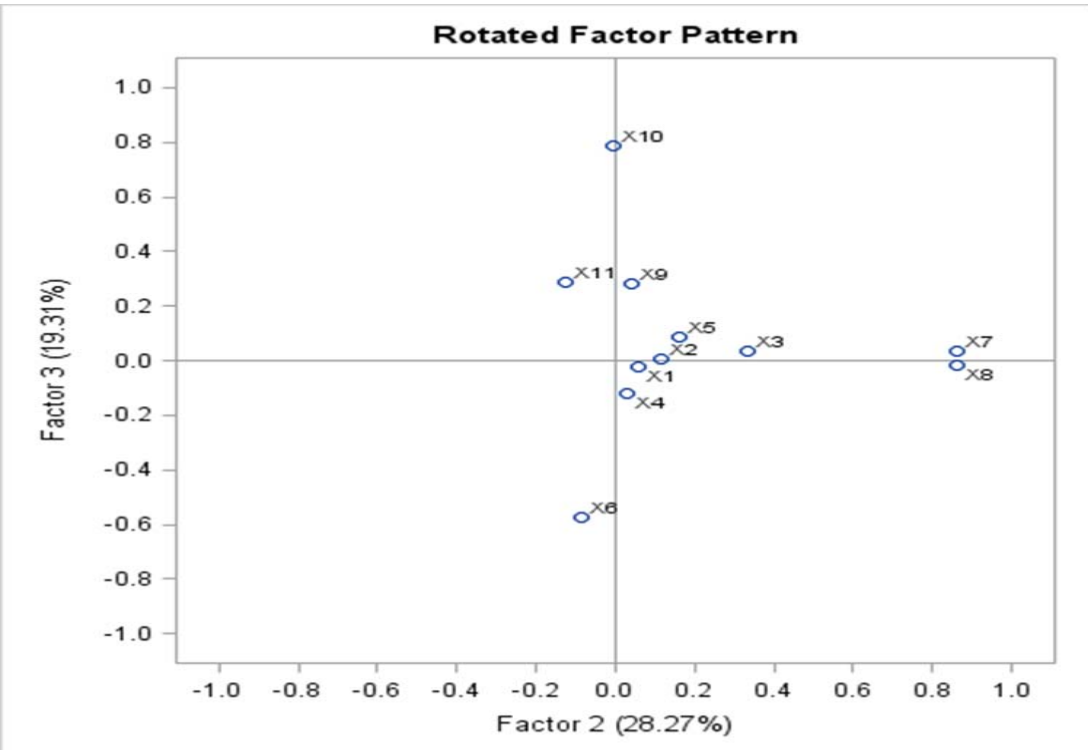


Figure 9.8.8c Rotated Factor Pattern



Tabel 9.8.9. Cronbach Alpha

7 Variables:	x1 x2 x3 x4 x5 x9 x11

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.7642
Standardized	0.759054

Tabel 9.8.10. Cronbach Alpha with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x1	0.604026	0.706951	0.594555	0.703666	x1: PRODUCTION LEVEL
x2	0.630542	0.701748	0.621044	0.697661	x2: LEVEL OF NEW CUSTOMERS OR INCOMING BUSINESS RECEIVED
x3	0.376076	0.755581	0.374097	0.751092	x3: SUPPLIERS DELIVERY TIME
x4	0.351832	0.759081	0.351198	0.755764	x4: LEVEL OF EMPLOYMENT IN ORGANISATION
x5	0.486042	0.734532	0.484544	0.727895	x5:RAW MATERIALS INVENTORY/WORK IN PROGRESS
x9	0.580387	0.712949	0.579718	0.707	x9:QUANTITY OF ITEMS PRODUCED
x11	0.349906	0.763502	0.347418	0.75653	x11: STOCK OF FINISHED GOODS

Tabel 9.8.11. Cronbach Alpa

2 Variables:	x7 x8

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.72208
Standardized	0.72343

Tabel 9.8.12. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x7	0.566698	.	0.566698	.	x7: AVERAGE PRICE OF OUTPUTS
x8	0.566698	.	0.566698	.	x8: AVERAGE PRICE OF INPUTS

Tabel 9.8.13. Cronbach Alpa

2 Variables:	x6 x10

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	-0.075406
Standardized	-0.076012

Tabel 9.8.14. Cronbach Alpa with deleted variable

Cronbach Coefficient Alpha with Deleted Variable					
Deleted Variable	Raw Variables		Standardized Variables		Label
	Correlation with Total	Alpha	Correlation with Total	Alpha	
x7	-0.036615	.	-0.036615	.	x7: AVERAGE PRICE OF OUTPUTS
x8	-0.036615	.	-0.036615	.	x8: AVERAGE PRICE OF INPUTS