Factors Affecting Money Demand in Sudan: Statistical and Analytical Study (1990-2019)

Elmogiera Fadlallah. Elsyed Elawad [(1)], Adel Ali Ahmed Mohamed [(2)]

(1): Associate Professor of Statistics - University of Gezira – Sudan

(2): Professor of Statistics - University of Gezira – Sudan

Abstract

The study aimed to know the most important factors affecting the demand for money in Sudan, and the study relied on secondary sources where data were obtained from the Bank of Sudan and the Central Statistical Organization, and statistical packages were used in the processing and analysis of data. The result shows the possibility of using the key components in the analysis method. - KMO test was used to measure the adequacy of the sample size and the result shows the lowest correlation was (0.780). Kaiser standard detected three factors with roots value higher than 1.0, these three factors explain 92.422% of the total variation, the first factor contribute to 60.115%, second factor contribute by 19.115% of the total variance, while the third factor contribute by 13.192% of the total variance. To explain these three factors the study used Varimax method of how the biggest disparity, where the result showed that factors had strong weights, and through the interpretation of factors most of the changes in the money demand during the study period attributable to the change in the monetary and economic indicators. - The study found that the first factor saturated with the following variables (Exchange Rate, GDP (Current prices), Money supply, Public budget, and the currency of the public, Funding, Index Number, Import, and Export). The second factor saturated with the following variables (Inflation, GDP (Fixed prices), and Funding Cost). The third factor saturated with the following variable (Velocity Circulation of Money). The most recommendations of this paper are**,** the necessity of existence of a sophisticated statistical system to reflect the actual status to planners and policy makers of monetary and economic sectors and Unification of data collection methods according to statistical methods and classification, which will facilitate researcher contributing in the research.

1. Background:

This paper is concerned with one of the important macroeconomic indicators, which represents the pillar of the economy in all countries and influenced by some factors, which is the demand for money, through the use of one of the multiple variables analysis models, which is the global analysis to extract the most important factors affecting the demand for money in Sudan, due to the difficulty of studying And the methods of analyzing the multiple variables to the need to understand and explain the interrelated relationships between the variables that affect the phenomenon under study and also the vastness of the data that must be analyzed, in addition to more advanced mathematical methods necessary to derive statistical methods that are used in statistical inference about multiple variables, and algebraic and statistical methods have been chosen in the interpretation of the results of this study.

Money is used in many of our daily transactions, and it can be many things, but the definition of money is very specific in economists, where economists define money (money supply) as anything that receives general public acceptance in trading for the purchase of goods and services as well as in the payment of debt. (Al-Rifai, 2002).

2. Study Questions:

In this paper, there are many financial and economic indicators related to the demand for money. Because of the difficulty in knowing the relationship between these variables, we would like in this study to apply one of the methods of analyzing multiple variables (factor analysis) to these variables and then reach the answer to the following questions:

- What is the relationship between financial and economic indicators for money demand in Sudan?

- What are the variables that have the greatest impact on the demand for money in Sudan?

3. Importance of the Study:

The importance of the study stems from the importance of the factors affecting the demand for money. By analyzing some of the macroeconomic variables and indicators that have to do with the demand for money, decision makers and monetary policy makers are helping to develop appropriate plans and programs to control the demand for money in Sudan.

4. Objectives:

- To measure the relationship between financial and economic indicators for money demand in Sudan.

- To estimate the variables that has the greatest impact on the demand for money in Sudan.

5. Study Methodology:

The study used an analytical descriptive approach to measure the relationship between financial and economic indicators for money demand in Sudan.

5.1. Data Source:

In this paper, secondary data was collected from the Bank of Sudan and the Central Statistical Organization in the period from (1990 - 2018).

5.2 Methods of Analysis:

In this study the researcher apply the statistical indicators and statistical models related to the data of the demand for money. In the research plan, the focusing will be on descriptive statistics, factors analysis, because it's suitable to the data collected.

Data were analyzed by using the Statistical Package for Social Science (SPSS) and stata10.

6. Statistical Model:

As for principal components analysis, factor analysis is a multivariate method used for data reduction purposes. Again, the basic idea is to represent a set of variables by a smaller number of variables. In this case they are called factors. These factors can be thought of as underlying constructs that cannot be measured by a single variable (Cornish, 2007).

6.1. Factor Analysis Model:

Multiple linear regression models:

$$x_1 = \lambda_{11}f_1 + \cdots + \lambda_{1k}f_k + u_1 \quad \ldots\ldots(1)$$

$$x_2 = \lambda_{21}f_1 + \cdots + \lambda_{2k}f_k + u_2 \ldots\ldots(2)$$

$$x_p = \lambda_{p1}f_1 + \cdots + \lambda_{pk}f_k + u_p \ldots\ldots(3)$$

Where:

$x = (x_1, \ldots, x_p)$ are the observed variables (random)

$f = (f_1, \ldots, f_k)$ are the common factors (random)

$u = (u_1, \ldots, u_p)$ are called specific factors (random)

$\lambda_{ij} = (\lambda_1, \ldots, \lambda_p)$ are called factor loadings (constants)

In short:

$$x = \Lambda f + u, \ldots\ldots(4)$$

where: Λ is the $p \times k$ matrix containing the λ_{ij}.

6.2 Assumptions of Factor Analysis Model:

Factor analysis is designed for interval data; although it can also be used for ordinal data (e.g. scores assigned to Likers scales). The variables used in factor analysis should be linearly related to each other. This can be checked by looking at scatter plots of pairs of variables. Obviously the variables must also be at least moderately correlated to each other; otherwise the number of factors will be almost the same as the number of original variables, which means that carrying out a factor analysis would be pointless (Cornish, 2007).

6.3 Analysis of Co-variances and Correlations:

Since factor analysis usually works with the variances and co-variances of the observed x variables, it is sometimes referred to as ''the analysis of covariance structures''. Some hint of this is apparent in equation (1), where the absence of an intercept term suggests that the means of the observed variables are either zero or of no direct interest. Indeed, this is typically the case in factor analysis, where the task is to learn about inter-relationships among variables rather than model level of each variable. Moreover, it is generally not possible to estimate both the factor loadings and intercept terms (Joreskog and Sorbom, 1979 cited in Child D, 2013). Also (Bollen 1989 cited in Cornish, 2007). Consequently, all the x variables and the unobserved n are presumed to have zero means, constraining any intercept term in equation (1) to zero. In addition, for the ordinal variables frequently encountered in surveys, the latent variable approach to generating a correlation matrix posits the variances of the latent variables to be 1, making the all co-variances between the latent variables interpretable as correlations.

6.4. The Steps in Factor Analysis:

The factor analysis model can be written algebraically as follows. If you have p variables$x_1, x_2, \dots, x_p$ measured on a sample of n subjects, then variable i can be written as a linear combination of m factors $f_1, f_2, \dots, f_m$ where, as explained above m < p. Thus,

$$x_i = \lambda_{i1}f_1 + \lambda_{i2}f_2 + \dots + \lambda_{im}f_m + e_i \quad \text{..........................(5)}$$

Where: the λ_{is} are the factor loadings (or scores) for variable i and e_i is the part of variable x_i that cannot be 'explained' by the factors.

There are three main steps in a factor analysis:

Step 1: Calculate Initial Factor Loadings: The factor loadings λ are parameters to be estimated that tap how the unobserved factors account for the observed variables: the larger the values of λ, the more a particular variable is said to ''load'' on the corresponding factor. Note that the factor loadings λ vary a cross survey items, but not across individuals. Put differently, items vary in the way they are explained by the underlying factors, but the relationships between underlying factors and observed responses is constant across individuals (hence the absence of an i subscript indexing λ). Note also that there are fewer underlying factors than there are variables (p < k), consistent with the notion that like any statistical procedure, factor analysis is a device for ''data reduction' taking a possibly rich though unwieldy set of survey responses and summarizing them with a simpler underlying structure.

Calculate initial factor loadings can be done by principal component method**:**

As the name suggests, this method uses the method used to carry out a principal components analysis. However, the factors obtained will not actually be the principal components (although the loadings for the k^{th} factor will be proportional to the coefficients of the k^{th} principal component) (Cornish, 2007).

Principal components method: found the linear combination explains the maximum variance from the X's. This is the first factor. Then find the next combination that explains the maximum proportion of the remaining variance and is orthogonal to the next factor, etc. (proceed until all variance is explained) (Child, 2013)**.**

Let $(\lambda_i\,;\, e_i)$ be the Eigen value – Eigen vector pairs of $\sum$, with $\lambda_1 \geq \lambda_2 \dots \lambda_p > 0$

From the spectral theorem:

$$\sum = \lambda_1 e_1 e'_1 + \lambda_2 e_2 e'_2 + \dots\dots \lambda_p e_p e'_p \qquad (6)$$

$$\text{Let } L = \sqrt{\lambda_1 e_1}\,,\ \sqrt{\lambda_2 e_2}\,, \dots\dots, \sqrt{\lambda_p e_p} \qquad (7)$$

Then

$$\Sigma = \lambda_1 e_1 e'_1 + \ldots\ldots + \lambda_p e_p e'_p = LL' = L\grave{L} + 0 \qquad (8)$$

Thus L is given by $\sqrt{\lambda_i}$ times the coefficient of principles components, $\psi = 0$

Now, if $\lambda_{m+1}, \lambda_{m+2}, \ldots\ldots\lambda p$ are small, then the first m principle components explain most Σ.

$$\text{Thus , with } L_m = \sqrt{\lambda_1 e_1} \quad , \ldots\ldots\ldots \sqrt{\lambda}_m \lambda e \qquad (9)$$

$$\Sigma \approx L_M L'_M$$

With specific factors this becomes

$$\Sigma \approx L_M L'_M + \psi \qquad (10)$$

Where:

$$\psi = \sigma_{ii} - \sum_{j=1}^{m} \lambda_{ij}^2 \qquad (11)$$

As estimator for the factor loadings and specific variances, we take:

$$\tilde{L} = \tilde{L}m = (\sqrt{\hat{\lambda}_1 \hat{e}_1} \quad \ldots\ldots\ldots\sqrt{\hat{\lambda}_m \hat{e}_m}) \qquad (12)$$

where $(\hat{\lambda}_i, \hat{e}_i)$ are the Eigen value -Eigen vector pairs of the sample covariance matrix S, and Where:

$$\psi = S_{ii} - \sum_{i=1}^{m} \lambda_{ij}^2 \qquad (13)$$

ψ : diagonal matrix

In many cases, the correlation matrix R (which is also the covariance matrix of the standardized data) is used instead of S, to avoid problems related to measurements being in different scales.

Step 2: Factor Rotation: Once the initial factor loadings have been calculated, the factors are rotated. This is done to find factors that are easier to interpret. If there are 'clusters' (groups) of variables - i.e. subgroups of variables that are strongly inter-related — then the rotation is done to try to make variables within a subgroup score as highly (positively or negatively) as possible on one particular factor while, at the same time, ensuring that the loadings for these variables on the remaining factors are as low as possible. In other words, the objective of the rotation is to try to ensure that all variables have high loadings only on one factor.

There are two types of rotation method: orthogonal and oblique rotation. In orthogonal rotation, the rotated factors will remain uncorrelated whereas in oblique rotation the resulting factors will be correlated. There are a number of different methods of rotation of each type.

1. Orthogonal rotate the factor axes to maximize the variance of the squared loadings of a factor on all the variables, keeping the factors independent of each other.
2. Oblique does the same thing, but allows the factors to be correlated. Thus the loadings now represent how each variable is weighted for each factor, but not correlations between variables and factors(Cornish, 2007).

Step 3: Calculation of Factor Scores: When calculating the final factor scores (the values of the m factors, f_1, f_2, . . . , f_m, for each observation), a decision needs to be made as to how many factors to include. This is usually done using one of the following methods:

1. Choose m such that the factors account for a particular percentage (e.g. 75%) of the total variability in the original variables.
2. Choose m to be equal to the number of Eigen values over 1 (if using the correlation matrix).
3. Use the Scree plot of the Eigen values. This will indicate whether there is an obvious cut-off between large and small Eigen values (Cornish, 2007).

7. Data Analysis and Discussion:

The study was based on economic and financial variables and indicators, and a specialist was used to choose these variables and indicators in order to find out the relationship between these indicators and the demand for money.

Descriptive Analysis: Table(1) shows the descriptive statistics of study variables, means and standard deviation SD of economic and monetary indicators, the researcher found that the mean GDP(Current prices) (188780) with a standard deviation (289344), the other indicators shown in table(1) bellow:

Table (1): Descriptive statistics of economic and monetary indicators

Variables	Mean	Std. Deviation	Sample (N)
Exchange Rate	4.18	8.56	29
Inflation	40.18	4.08	29
GDP(Current prices)	188780	289344	29
GDP(Fixed prices)	19818.62	9624.15	29
Money supply	43837	87411	29
Public budget	-4207.63	7567.82	29
The currency of the public	18634	28003	29
Funding	21505	36897	29
Funding Cost	18.98	9.31	29
Index Number	200.92	309.39	29
Import	30535	68981	29
Export	16657	30447	29
Velocity Circulation of Money	6.11	2.41	29

Source: Study output from central bank of Sudan, annual reports (1990-2018)

Examine the Correlation Matrix of Relationships: In order to make the matrix valid for factor analysis it must show at least some correlation to reach to (0.3) or higher, if the researcher do not find this result, the matrix judge as invalid for factor analysis and therefore overlook to use the main components. Given Table (2), the researcher found that the correlation matrix contained some variables with (0.3) and above which shows the possibility of using the method of the main components in the analysis. Also the result shows that there were positive and negative correlations between the thirteen – variables. Another way to determine the factorability of inter correlation matrix by Bartletts test of Sphericity.

.Table (2): Correlation Matrix

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13
Q1	1.000	-.006	.817	.536	.929	-.922	.662	.764	-.212	.865	.993	.972	-.248
Q2	-.006	1.000	-.129	-.500	-.031	.068	.311	-.103	.613	-.102	.002	-.063	-.372
Q3	.817	-.129	1.000	.829	.956	-.917	.684	.979	-.422	.989	.856	.822	-.368
Q4	.536	-.500	.829	1.000	.711	-.729	.354	.801	-.781	.792	.599	.627	-.296
Q5	.929	-.031	.956	.711	1.000	-.974	.738	.946	-.320	.983	.951	.926	-.386
Q6	-.922	.068	-.917	-.729	-.974	1.000	-.700	-.904	.381	-.943	-.948	-.947	.431
Q7	.662	.311	.684	.354	.738	-.700	1.000	.695	-.056	.702	.691	.645	-.576
Q8	.764	-.103	.979	.801	.946	-.904	.695	1.000	-.394	.978	.805	.777	-.399
Q9	-.212	.613	-.422	-.781	-.320	.381	-.056	-.394	1.000	-.382	-.267	-.347	.297
Q10	.865	-.102	.989	.792	.983	-.943	.702	.978	-.382	1.000	.896	.864	-.357
Q11	.993	.002	.856	.599	.951	-.948	.691	.805	-.267	.896	1.000	.983	-.338
Q12	.972	-.063	.822	.627	.926	-.947	.645	.777	-.347	.864	.983	1.000	-.361
Q13	-.248	-.372	-.368	-.296	-.386	.431	-.576	-.399	.297	-.357	-.338	-.361	1.000

Source: Study output from central bank of Sudan, annual reports (1990-2018) * Determinant = 1.80E-017

Table (3): KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.780
Bartlett's Test of Sphericity	Approx. Chi-Square	880.36
	Df	78
	Sig.	.000

Source: Study output from central bank of Sudan, annual reports (1990-2018)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO): This test is used to test the adequacy of the sample size the sufficient sample size must not be less than the 0.50 value, given the Table (3) we find that the KMO test value equal to (0.780) which indicates that the sample size was large enough to reliably extract factors

Bartlett's Test of Sphericity: Used test whether the original correlation matrix is unit matrix or not, if the correlation matrix is not a matrix unit indicates that the absence of relations between the variables and that is what is required when using the method of the main components method in factor analysis. Given Table (3), the researcher found that Bartlett test value equal to (880.36) and the level of significance (.000), and this shows that the test D. (moral) statistically significant at a moral level (0.01), also the significant value of the test p= 0.000 indicates that there was a correlation between the thirteen – variables.

Determine the number of key components: In this step the researcher extracts an initial solution

(Using the principal components method) to determine the appropriate number of factors.

Table (4) presents the total variance of the variables in initial solution. The results of initial solution extracted thirteen factors the same number as the number of variables factored. The factors extracted accounted for more than 1.0 units of variance, or have an Eigen value $\lambda > 1$. The initial solution extracted three factors accounting for more than 1.0 unit of variance. The values in this panel of the table represent the distribution of the variance after the varimax rotation. Varimax rotation tries to maximize the variance of each of the factors, so the total amount of variance accounted for is redistributed over the three extracted factors.
Factor 1: The 1stfactor has an Eigen value equals (7.815). Since this is greater than 1.0, it explains more variance than a single variable, in fact (7.815) times as much. The percent a variance explained: (7.815 / 13 units of variance)* (100) = (60.115%).
Factor 2: The 2nd factor has an Eigen value equals (2.485) it is also greater than 1.0, and therefore explains more variance than a single variable. The percent a variance explained: (2.485 / 13 units of variance)* (100) = (19.115%).
Factor 3: The 3rd factor has an Eigen value equals (1.715) it is greater than 1.0, and therefore explains more variance than a single variable. The percent a variance explained: (1.715 / 13 units of variance) * (100) = (13.192%).
The cumulative percentage of variance explained by the first three factors was (92.422%).

Table (4): Total Variance Explained

Component	Initial Eigen values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.850	68.078	68.078	8.850	68.078	68.078	7.815	60.115	60.113
2	2.066	15.890	83.967	2.066	15.890	83.967	2.485	19.115	79.230
3	1.098	8.449	92.417	1.098	8.449	92.417	1.715	13.192	92.422
4	.488	3.750	96.167						
5	.263	2.021	98.187						
6	.127	.974	99.161						
7	.051	.394	99.555						
8	.036	.280	99.835						
9	.012	.094	99.929						
10	.007	.052	99.981						
11	.001	.011	99.992						
12	.001	.005	99.997						
13	.000	.003	100.000						
Extraction Method: Principal Component Analysis.									

Source: Study output from central bank of Sudan, annual reports (1990-2018)

Communalities: The amount of contributions to the variables represents the percentage of variance that the factors extracted from these variables explain. If the amount of contributions is high, this indicates that the factors extracted explain a high percentage of the variability of the variables. Looking at Table (5), the extracted factors explain a high rate of variance of variables, as the lowest percentage is (0.795) for the variable of the inflation rate. Table (5) shows the communalities of the thirteen variables. The communality of the variable is simply the sum of its squared factor loading.

Table (5): Distinctive roots and aggregate variance after rotation

	Initial	Extraction
Exchange Rate	1.000	.942
Inflation	1.000	.899
GDP(Current prices)	1.000	.933
GDP(Fixed prices)	1.000	.940
Money supply	1.000	.992
Public budget	1.000	.964
The currency of the public	1.000	.795
Funding	1.000	.891
Funding Cost	1.000	.909
Index Number	1.000	.961
Import	1.000	.951
Export	1.000	.898
Velocity Circulation of Money	1.000	.940
Extraction Method: Principal Component Analysis		

Source: Study output from central bank of Sudan, annual reports (1990-2018)

Rotate the factor (method orthogonal rotation): Factors were rotated to find factors that easier to interpret and to ensure that all variables had high loading only on one factor. Table (5) shows the rotated component matrix. The table illustrates that rotated pattern improved three variables only. The improvement in the solution is presented in Table (5) below.

Table (6): Rotated Component Matrix

	Component		
	1	2	3
Exchange Rate	.970		
Inflation		.803	
GDP(Current prices)	.887		
GDP(Fixed prices)		-.765	
Money supply	.964		
Public budget	-.934		
The currency of the public	.702		
Funding	.856		
Funding Cost		.922	
Index Number	.926		
Import	.967		
Export	.930		
Velocity Circulation of Money			-.943

Source: Study output from central bank of Sudan, annual reports (1990-2018)

Computing factor scores: Factor scores are composite measures that can be computed for each subject on each factor. Table (7) shows the component score coefficient matrix. The result shows that not much change in factors and score pattern was not a substantial improvement over rotated pattern. Finally the thirteen variables were reduced to three factors. These three factors account for (92.422%) of the covariance among the variables.

Table (7): Component Score Coefficient Matrix

	Component		
	1	2	3
Exchange Rate	-.192	.131	.200
Inflation	.320	.354	.010
GDP(Current prices)	.008	-.057	.098
GDP(Fixed prices)	.070	-.316	-.017
Money supply	-.039	.036	.141
Public budget	.008	-.003	-.122
The currency of the public	.257	.125	.060
Funding	.050	-.058	.084
Funding Cost	-.216	.461	.141
Index Number	-.026	-.020	.120
Import	-.115	.095	.173
Export	-.093	.050	.153
Velocity Circulation of Money	-.715	.109	.166

Source: Study output from central bank of Sudan, annual reports (1990-2018)

Interpretation of factors :Finally the thirteen variables were reduced to three factors. These three factors account for (92.422%) of the covariance among the variables.

Table (8): Factor (1)

Saturation	Variable Name	**Variable**
.970	Exchange Rate	Q1
.887	GDP(Current prices)	Q3
.964	Money supply	Q5
-.934	Public budget	Q6
.702	The currency of the public	Q7
.856	Funding	Q8
.926	Index Number	Q10
.967	Import	Q11
.930	Export	Q12

Source: Study output from central bank of Sudan, annual reports (1990-2018)

$$P_{C1} = .970Q_1 + ..887Q_3 + .964Q_5 - .934Q_6 + .702Q_7 + .856Q_8 + .926Q_{10} + .967Q_{11} + .930Q_{12}$$

Table (9): Factor (2)

Saturation	Variable Name	**Variable**
.803	Inflation	Q2
-.765	GDP(Fixed prices)	Q4
.922	Funding Cost	Q9

Source: Study output from central bank of Sudan, annual reports (1990-2018)

$$P_{C2} = .803Q_2 - .765Q_4 + .922Q_9$$

Table (10): Factor (3)

Saturation	Variable Name	**Variable**
-.943	Velocity Circulation of Money	Q13

Source: Study output from central bank of Sudan, annual reports (1990-2018)

$$PC_3 = -.943Q12$$

8. Conclusion and Recommendations:

8.1 Conclusion:

This paper aims to use statistical methods to gain results that can contribute to the knowledge of the most important factors that affect Demand in Sudan (1990-2019), study variables were subjected to analysis according to component method using SPSS software, the most important findings of the study as follow: - Bartlett test has been applied, which revealed that the correlation relationship between variables, the result shows the possibility of using the key components in the analysis method. - KMO test was used to measure the adequacy of the sample size and the result shows the lowest correlation was (0.780).

Kaiser standard detected three factors with roots value higher than 1.0, these three factors explain 92.422% of the total variation, the first factor contribute to 60.115%, second factor contribute by 19.115% of the total variance, while the third factor contribute by 13.192% of the total variance. To explain these three factors the study used Varimax method of how the biggest disparity, where the result showed that factors had strong weights, and through the interpretation of factors most of the changes in the money demand during the study period attributable to the change in the monetary and economic indicators. - The study found that the first factor saturated with the following variables (Exchange Rate, GDP (Current prices), Money supply, Public budget, and the currency of the public, Funding, Index Number, Import, and Export). The second factor saturated with the following variables (Inflation, GDP (Fixed prices), and Funding Cost). The third factor saturated with the following variable (Velocity Circulation of Money).

8.2 Recommendations:

- The necessity of existence of a sophisticated statistical system to reflects the actual status to planners and policy makers of monetary and economic sectors.
- Unification of data collection methods according to statistical methods and classification, which will facilitate researcher contributing in the research.
- Take advantage to offering the data for researchers to develop statistical models contribute to solving economic problems.
- Further studies on this subject

References:

1. Bollen, K. A. (1989). “Structural equations with latent variables”. Wiley, New York: USA.
2. Cornish, R . (2007). “Factor analysis”. Mathematics Learning Support Centre, London: England [From http://mlsc.lboro.ac.uk/resources/statistics/3.2%20Principle%20Com.pdf.
3. Child, D. (2013). “The essentials of factor analysis. Holt Rinehart and Winston: US.
4. Ghalib Awad Al-Rifai,(2002): Money and Banking Economics (Fundamentals), First Edition,
5. Joreskog, K.G., Sorbom, D. and J. (1979). “Advances in factor analysis and structural equation models”. Abt Books, Cambridge: England.
6. Karl pearson, R.G. (1901). The comparative effects of multiple-choice versus short answer tests in retention J. of educ measurement