Factor Analysis on Economy Condition of Countries 2021

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1 Introduction

The economy of a country represents how the consumption, production, good and services are distributed (Chen, 2012). There are numerous factors that affect to the economy of a country which leads measuring economy is a complex task. Thus, using Factor Analysis that complexes can be reduced. It assists to identify underlying relationships between affecting variables as well. The major question of this study is to recognize the major factors effecting to the economic condition of country by reducing dimensions of the data set. For this study, the data is collected data from (PATIL, 2021).

2 Methodology

Data Cleaning and Preprocessing:

Only the data of year 2021 of countries was collected from (PATIL, 2021) and the column name was changes in to simplified names. There were 55 cells with NA values. And they were removed (data rows). The dimension of the data was 162 and 22. Since variables are on different scales and units of measurements, the data set was standardized.

Data Analysing:

Exploratory Factor Analysis:

Correlation and Correlation matrix of the dataset was drawn in order to have a over view of correlations between variables. Then cortest bartlett test with the Null hypothesis here are no correlations between variables, was carried out. Then scree plot, eigen values and and cumulative percentages of explained variance were calculated. After that, estimating the parameters of the factor model was done using Maximum likelihood Estimation Method (MLE) and principal component Method (PC) taking number of factors as 3. Then, factor rotation was conducted using Varimax Rotation. Then, estimation of factor scores was carried out using Ordinary Least Squares (OLS) and Regression Method (RM).

Confirmatory Factor Analysis (CFA): Then, Confirmatory Factor Analysis were conducted

considering the model as having 3 factors as f1,f2 and f3. Model: $f1 = \tilde{A}MA + IMF$ $f2 = \tilde{P}opulation + Agriculture + inventories + Manufacturing + Mining$ $f3 = \tilde{P}CGNI + Construction + Exports + FinalConsExpen + GeneralConsExpen + GCF + GFCF + Household + Imports + Other_Activities + TotalValueAdd + Transport + GNI + GDP$

3 Results and Discussion

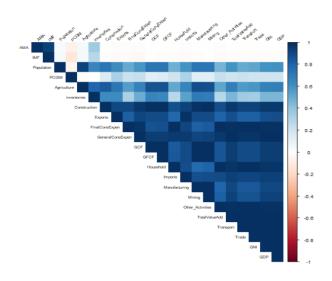


Figure 1: Correlation plot

Correlation plot and Correlation matrix are as above $\ref{eq:correlation}$ By examining plot, there are almost no negative correlation between variable. In contrast, there strong positive correlation between the variables in the latter part of the list. For instance, correlation between "other activities" and "Transport" and "Trade". The results of cortest bartlett test is as follows. chisq:20752.83, p.value:0, df:231. Since, P values is less than 0.05, reject null hypothesis at 0.05% significant level. Therefore, there are correlations between variable. Hence, factor analysis can be applied.

The Scree Plot is as above 2. (1): according to plot, the non-steep of the graph can be seen

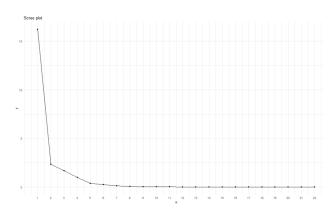


Figure 2: Scree Plot

after the 5th, therefore according to this, number of of Factors to Extract is 4.

- (2): according to method of eigenvalues at least one, considering above results, number of of Factors to Extract is 3. Also, 4th eigen value also close to 1.
- (3): by considering last column, cumulative proportion of at least 80% is explained by extracting 3 number of factors because by 1st two factors it already explains 91.88% of total variance.

Therefore, considering above (1),(2),(3) number of factors are 2. The residual matrix of MLE method is as follow 3. The residual matrix of PC method is as follows 4. Since, residuals under PC are much less than those under ML. Therefore, PC method is more appropriate. The factor loadings of PC method as follows.

For the first factor, except variables AMA and IMF all other variables have positive loading on F1. Among them, PCGNI variables has much lower values. In the second factor, PCGNI FinalConsExpen Household Other_Activities TotalValueAdd Transport Trade GNI and GDP have negative loadings while all others have positives. For the third factor, AMA and IMF have lager positive value while inventories smaller positive and Population Agriculture inventories GCF GFCF Manufacturing and Mining have negative values. Here for variable AMA IMF PCGNI and inventories they have loadings that are close to each other. To over come from that factor rotation was used. The loading matrix after factor rotation given above ??. This output clearly shows AMA, IMF are highly loaded on 3rd factor.

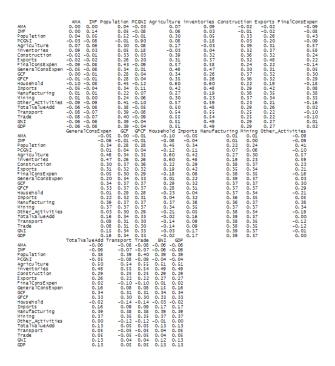


Figure 3: Residual matrix of MLE method

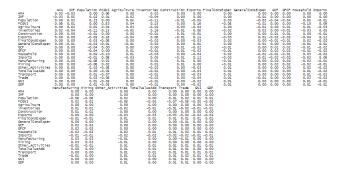


Figure 4: Residual matrix of PC method

PGCNI highly loaded on 1st factor while inventories on the 2nd factor. Considering the output of factor score estimation, in both methods almost all factor scores are negative values. As, shown in the figure below (only a part of output is given) in OLS method, positive values indicate higher levels of the corresponding common factor, while negative values indicate lower levels. For instance, for the 1st country has negative values on 1st and 3rd factor while positive on 2nd factor. As for the RM method (shown in figure 7 below), there were higher magnitude of scores than in OLS.

Loadings:			
	PC1	PC2	PC3
AMA		0.750	0.635
IMF		0.744	0.630
Population	0.680	0.383	-0.413
PCGNI	0.195	-0.324	0.165
Agriculture	0.774	0.417	-0.440
inventories	0.566	0.672	-0.269
Construction	0.990		
Exports	0.916		
FinalConsExpen	0.945	-0.208	0.222
GeneralConsExpen	0.985		
GCF	0.976	0.108	-0.133
GFCF	0.978		-0.129
Household	0.924	-0.235	0.257
Imports	0.948		
Manufacturing	0.951	0.154	-0.194
Mining	0.963	0.139	-0.165
Other_Activities	0.932	-0.237	0.248
TotalValueAdd	0.986	-0.103	0.104
Transport	0.955	-0.186	0.202
Trade	0.956	-0.182	0.196
GNI	0.986	-0.109	0.108
GDP	0.988	-0.102	0.102

Factor loadings of PC method

In CFA, the number of factors are needed at the beginning, that may depend on the research study (Huang, 2017). I have selected above 3 factors. The output of that as follows 8.

4 Conclusion and Recommendation

As a conclusion rotated loadings indicate that global currency exchanging factor (i.e AMA and IMF)highly loaded on 3rd factor and resource usage factor (i.e Population, Agriculture, inventories, Manufacturing and Mining) highly loaded of 2nd factor while development of economy factor (i.e other variables) highly loaded on 1st factor. And, those factors explains 91.88% of total variance of data. As for CFA, the output includes warning massages that may due to convergence issues because of that parameter estimates and in the output may not be reliable. The simplest model which having only one factor with all variables is also having same issues. Thus, I would recommend to use another model with using different

RC1	RC2	RC3
		0.981
		0.974
0.259	0.843	
0.350	-0.180	-0.123
0.314	0.932	
0.114	0.862	0.298
0.770	0.631	
0.729	0.559	
0.957	0.264	
0.892	0.436	
0.722	0.678	
0.731	0.669	
0.963	0.216	
0.839	0.449	
0.660	0.728	
0.687	0.709	
0.967	0.224	
0.905	0.419	
0.950	0.294	
0.946	0.301	
0.908	0.413	
0.905	0.421	
	0.259 0.350 0.314 0.114 0.770 0.729 0.957 0.892 0.722 0.731 0.963 0.660 0.687 0.967 0.905 0.950 0.946 0.908	0.259

Figure 5: Loading matrix after factor rotation

factors with different variables in the data set.

5 References

References

Chen, M. A. (2012). The informal economy: Definitions, theories and policies.

Huang, F. L. (2017). Conducting multilevel confirmatory factor analysis using r. Unpublished Manuscript). http://faculty. missouri. edu/huangf/data/mcfa/MCFA% 20in% 20R% 20HUANG. pdf.

PATIL, P. (2021). Global economy indicators. https://www.kaggle.com/datasets/prasad22/global-economy-indicators.

```
scores
                     0.097695275
      -0.273929223
                                  -0.15793371
      -0.097153236
                    -0.319260687
                                  -0.23483411
      -0.267977648
                    -0.018415896
                                  -0.08371996
      -0.234098700
                    -0.094416215
      -0.091600166
                    -0.006414508
                                  -0.18608700
                    -0.180084334
       0.647764576
       0.184622223
                    -0.294038464
      -0.156987900
                    -0.234975004
                    -0.184858298
      -0.165020880
                                  -0.20341849
[10,
      -0.238226146
                    -0.122593631
 11.
      -0.195166615
                     0.189742869
                    -0.127421400
       0.211461688
13
      -0.251970384
                    -0.115950764
 14
      -0.247345399
                    -0.087417760
                                  -0.18924344
      -0.236305558
                    -0.112560458
 16
      -0.231407419
                     -0.128717378
       0.244712420
                     0.315625739
18,
      -0.240098839
                    -0.131748742
19,
[20,
                    -0.113049959
      -0.254769289
      -0.085395959
                    -0.335939309
 21,
      -0.133805893
                    -0.260732778
      -0.211899413
                     0.077887761
      -0.277288834
                     0.004109155
      -0.250966653
                    -0.109968548
                                   0.15376138
      -0.224937136 -0.078202030
                                  -0.18773597
```

Figure 6: Factor Score - ML Method

6 Appendices

The dataset was collected from (PATIL, 2021) and taken only data of year 2021. The variables are AMA exchange rate (AMA), IMF based exchange rate (IMF), Population, Per capita GNI (PCG), Per capita Gross National Income(PCGNI), Agriculture, hunting, forestry, fishing (ISIC A-B) (Agriculture), Changes in inventories (inventories), Construction (ISIC F) (Construction), Exports of goods and services (Exports), Final consumption expenditure (FinalConsExpen), General government final consumption expenditure (GeneralCnsExpn), Gross capital formation (GCF), Gross fixed capital formation (GFCF), Household consumption expenditure (Household), Imports of goods and services (Imports), Manufacturing (ISIC D), Mining, Manufacturing, Utilities (ISIC C-E) (Mining), Other Activities (ISIC J-P), Total Value Added, Transport, storage and communication (ISIC I), Wholesale, retail trade, restaurants and hotels (ISIC G-H), Gross National Income(GNI) in USD and Gross Domestic Product (GDP). All are numerical variables. They were 162 observation after removing NA values. The R codes used in markdown are mentioned below. library(tidyverse) library(dplyr) library(corrplot) library(psych) library(GPArotation)

```
Factor1
       -2.8213308
                    -0.27399873
[2,
[3,
[4,
[5,
[6,
[7,
[8,
[9,
       -4.0902615
                    -0.61712837
                                  -0.572761626
       -3.7540397
                    -0.21246056
                                 -0.188220956
        -1.2549799
                    -0.39390439
                                  -0.100155898
                    -0.51689637
                                   0.001322837
                    -0.60782496
                                  -0.375067535
                    -0.55741527
                    -0.50368883
                                  -0.378491841
          . 2555625
                    -0.30916990
                                  -0.377203106
11,
                    -0.52749255
                                  -0.451045487
12,
        1.6969879
                    -0.38843580
                                   0.018587133
13,
                    -0.45298557
                                  -0.379830639
       -4.0590775
                    -0.46616769
                                  -0.322656891
                    -0.46382264
                                  -0.343994360
16,
17,
        4.2071038
                    -0.48255426
                                  -0.382620088
                    -0.42710974
                                  -0.394536422
18,
                    -0.48738748
19,
        4.3809411
                     -0.47385085
20,
21,
        -4.0799261
                    -0.62956168
                                  -0.589699839
       -4.0648940
                    -0.57891284
                                  -0.508840051
22,
                     -0.40803048
                                  -0.229071382
                     0.10020365
                                  -0.158395921
        -4.3457858
                     0.19170583
                                  -0.378356120
```

Figure 7: Factor Score - RM Method

```
DataSet = read.csv(file = ".../Data/GEI.csv")
DataSet = DataSet %; % drop_na()
DataSet = scale(DataSet) DataSet\_Cor = cor(DataSet)
corrplot(round(DataSet_Cor, digits = 2), method = "color", type = "upper", tl.col = "black",
tl.srt = 45, tl.cex = 0.7,
                                                                                                                         cortest.bartlett(DataSet_Cor, n= 162)
n = \dim(DataSet\_Cor)[1] DataSet\_Scree = tibble(x = 1:n, y = sort(eigen(DataSet\_Cor)$value,
decreasing = TRUE)
scree\_plot = DataSet\_Scree \%; \% ggplot(aes(x, y)) + geom\_point() + geom\_line() + ylab("Presentage") + geom\_line() + geo
of explanined variances") scale_x_continuous(breaks = 1:n) + ggtitle("Scree plot") eigenVal-
ues = eigen(DataSet_Cor) df=data.frame(eigenValuesvalues, eigenValuesvalues ;1,prpor-
tion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_of_variance_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_prportion_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eigenValuesvalues/sum(eigenValuesvalues)*100.Cumulative_explanined=eig
fa_by_ML =fa(DataSet_Cor,nfactors = 3, fm='ml') factor_loadings_ML = fa_by_ML$loadings
LL_ML = factor_loadings_ML %*% t(factor_loadings_ML) residual_matrix_ML = DataSet_Cor
- LL_ML round(residual_matrix_ML,digits = 2)
fa_by_PC= principal(DataSet, nfactors = 3, rotate = 'none') factor_loadings_PC = fa_by_PC$loadings
LL_PC = factor_loadings_PC %*% t(factor_loadings_PC) residual_matrix_PC = DataSet_Cor
```

Figure 8: CFA - Output

- LL_PC round(residual_matrix_PC,digits = 2)

fa_by_PC= principal(DataSet, nfactors = 3, rotate = "varimax")

 $Factor_Scores_OLS = factor.scores(DataSet,fa_by_PC\$loadings,method="regression")$

Factor_Scores_Reg = factanal(DataSet,3, rotation = "none") loadings ;- Factor_Scores_Reg\$loadings Factor_scores_regression ;- as.matrix(DataSet) Factor_scores_regression

GlobalEconomy_1 = 'f1 = AMA + IMF f2 = Population + Agriculture +inventories + Manufacturing + Mining f3 = PCGNI + Construction + Exports + FinalConsExpen + GeneralConsExpen + GCF + GFCF + Household + Imports + Other_Activities + Total-ValueAdd + Transport + GNI + GDP

AMA ~~ AMA IMF ~~ IMF Population ~~ Population Agriculture ~~ Agriculture inventories ~~ inventories Manufacturing ~~ Manufacturing Mining ~~ Mining PCGNI ~~ PCGNI Construction ~~ Construction Exports ~~ Exports FinalConsExpen ~~ FinalConsExpen GeneralConsExpen ~~ GeneralConsExpen GCF ~~ GCF GFCF ~~ GFCF Household ~~ Household Imports ~~ Imports Other_Activities ~~ Other_Activities TotalValueAdd ~~ TotalValueAdd Transport ~~ Transport GNI ~~ GNI GDP ~~ GDP result_1= cfa(GlobalEconomy_1, data = DataSet) summary(result_1, fit.measures=TRUE) '