COVID-19 spread between poverty clusters in Africa: Markov Chain modeling approach

Mintodê Nicodème Atchadé[a,b,c,], Gandonou Sèdjro Amos[a], Svetlana Vladimirovna Kurisheva[c]

[a] *National Higher School of Mathematics Genius and Modelization, National University of Sciences, Technologies, Engineering and Mathematics, Abomey, Benin Republic*
[b] *University of Abomey-Calavi / International Chair in Mathematical Physics and Applications (ICMPA : UNESCO-Chair), 072 BP 50 Cotonou, Rep. Benin*
[c] *Saint-Petersburg State University of Economics, Department of Statistcs and Econometrics, Russian Federation*

Abstract

The coronavirus disease 2019 (COVID-19) has been declared as a pandemic on 11^{th} march 2020 by the World Health Organization. Since that, countries around the world are taking measures to flatten its curve. In this work, a 2-steps analysis is developed. Firstly, we defined countries clusters according to their poverty level. Secondly, a Markov Chain model is used to understand the behavior of COVID-19 spread among poverty groups in Africa. For this purpose, we exploited data sets of new cases and poverty level from "Our World In Data" and "IndexMundi" data portals. The findings revealed that poorest countries present more risk in shifting from non severe state to middle or severe state of COVID-19 spread. Moreover, the forecasts of COVID-19 new cases in long run term among poverty clusters have been computed. The policy implication is that efforts should be strengthened to curb of poverty dynamics in the form of inclusive programs adapted to the pandemic situation.

Keywords: COVID-19, Markov chain, Africa, Poverty, Statistical modeling

*Corresponding author
Email address: nickpowerabc@gmail.com (Mintodê Nicodème Atchadé)

1. Introduction

The COVID-19 pandemic has been a challenge to the world health system and the number of new cases in the world has been increasing [1, 2, 3, 4]. COVID-19 transmission could be person to person [3]. In this context, many researchers have been working to help controlling the COVID-19 spread[5, 6, 7, 8, 9, 10]. Many restrictions such as quarantine and confinement [11], travel restrictions [12] have been taken to decrease the spread of the pandemic. The spread of the virus varies among countries in the world, especially in African countries. In these circumstances, poor countries may be more exposed to the pandemic and its consequences. Social living standards and hunger might be more severe in poorest countries [13]. The present work focuses on transition risks of COVID-19 in African countries among no severe, middle and severe states of the pandemic. Some researchers discovered that the drop in work-related mobility during the first lockdown period was significantly lower in high poverty regions in comparison with other regions [14, 15, 16, 17]. According to this paper [18], in South Africa lockdown measure in poor classes is with more challenge in terms of compliance with physical distancing rules. Moreover, this work [19] found that there is a partial adherence to social distancing and wearing of masks within public transportation during the COVID-19 pandemic in poor countries especially in Ghana. Considering the aforementioned points, we also notice that there is nobody of knowledge about the plausible transition risks between COVID-19 states spread among poverty classes in Africa using Markov Chain modeling. Besides, we also hypothesized in this study that the higher is the poverty level, the higher is the risk to shift from non severe state to middle or severe state of COVID-19 spread. The results of this work will be a baseline for authorities at regional and international levels to fight the pandemic. To reach those expectations, we presented the tools and methodology in Materials and methods, and finally presented the results, discussion and conclusion.

2. Materials and methods

2.1. Materials

For our purpose, we used COVID-19 new cases data from 2020-03-30 to 2021-04-30, and monetary poverty level 2021 in African countries. The poverty data were taken from "IndexMundi". We also referred to dataset entitled "Corona virus Pandemic (COVID-19)" from "Our World in Data".

The variable of interest is the count of daily confirmed new cases in African countries that we classified in 3 groups (low, middle and high) according to the poverty level. The data were accessed on 2021-02-25 and we will make the data sets available if requested.

The accuracy of COVID-19 new cases are related to daily verifications and changes. Actually in the context of this work, we classified African coutries in poverty groups and then studied the transitions between states (A- non severe, B- middle, and C-severe) to find out how poverty in Africa contributes to the spread of the virus.

2.2. Methods

The threshold classification and the Markov chain modeling have been implemented in this work. Besides, we defined the Markov Chain states using mean confidence interval.

2.2.1. Threshold classification

This classification consists to merge countries according to the defined intervals. In our case, we aim to obtain three groups:

- countries with poverty level less than 30% ;
- countries with poverty level between 30% and 60% ;
- countries with poverty level higher than 60%.

2.2.2. Markov chain modeling

Let Z_t be a random process having finite number of states. If the process is in state i at time t, then it will be in state j at time $t+1$ with the probability $p_{i,j}$ [9]. $(Z_t)_{t\geq 0}$ is a Markov chain if for any i, j , $i_0, ..., i_{t-1} \in S$; $\quad t \geq 0$.
The following probability depends only on i, j and t.

$$\begin{aligned} p_{i,j}^{t,t+1} &= P(Z_{t+1} = j \mid Z_t = i, Z_{t-1} = i_{t-1}, ..., Z_1 = i_1, Z_0 = i_0) \\ &= P(Z_{t+1} = j \mid Z_t = i) \end{aligned} \tag{1}$$

where $p_{i,j}^{t,t+1}$ is state transition probability from state i to j. We adopt the following assumptions:

- The probability $p_{i,j}^{t,t+1}$ does not depend on t, then the Markov Chain is homogeneous. For any $i, j \in S$; $0 \leq p_{i,j} \leq 1$; $\sum_{j\in S} p_{i,j} = 1$. The transition matrix is given by:

$$P = \begin{bmatrix} p_{0,0} & p_{0,1} & \cdots & p_{0,j} \\ p_{1,0} & p_{1,j} & \cdots & p_{1,j} \\ \vdots & \vdots & \ddots & \vdots \\ p_{i,0} & p_{i,1} & \cdots & p_{i,j} \end{bmatrix}$$

- Besides, we assume that being in a state at time t depends only on the state we were at time $t-1$.

Markov Chain states

In this study the states of the Markov Chain are defined as:

- A for $NC_k < \bar{NC} - 1.96\ sd(NC)/\sqrt{n}$;
- B for $NC_k \in \bar{NC} \pm 1.96\ sd(NC)/\sqrt{n}$;
- C for $NC_k > \bar{NC} + 1.96\ sd(NC)/\sqrt{n}$.

with NC_k the confirmed new cases in the country k, $\bar{NC}$ the mean of NC, $sd(NC)$ its standard deviation, and n the sample size.

2.3. Analysis process

We used R software for the whole work and the library "markovchain" with the functions **markovchainFit()** and **steadyStates()**. The analysis process is described in the following steps.

Step 1: Classification of the 54 African countries according to their monetary poverty level. We obtained:

- Group 1: 12 countries with poverty level less than 30% ;
- Group 2: 30 countries having poverty rate between 30% and 60% ;
- Group 3: 12 countries with poverty level higher than 30%.

Step 2: We estimated the total daily confirmed new cases for each of the three classes. The data are aggregated.

Step 3: According to the defined states A, B, C; we recoded the variable of interest NC.

Step 4: We constructed for each poverty class the Markov Chain and its stationary distribution.

3. Results

The classification results are as follows:

Group 1: African countries having their poverty level less than 30% Namibia, Egypt, Ghana, Djibouti, Algeria, United Republic of Tanzania, Uganda, Botswana, South Africa, Tunisia, Morocco, Mauritius.

Group 2: African countries where the poverty level is between 30% and 60% Lesotho, Togo, Zambia, Liberia, Malawi, Eritrea, Gambia, Guinea, Chad, Senegal, Sudan, Congo, Mozambique, Niger, Comoros, Equatorial Guinea, Burkina Faso, Seychelles, Rwanda, Angola, Benin, Kenya, Mali, Gabon, Mauritania, Cabo Verde, Cameroon, Ethiopia, Libya, Ivory Coast.

Group 3: African countries with a poverty level higher than 60% Burundi, Eswatini, Central African Republic, Democratic Republic of the Congo, Guinea-Bissau, Madagascar, Nigeria, Sao Tome and Principe, Sierra Leone, Zimbabwe, South Sudan, Somalia. The confidence interval at 5% error risk for the mean number of new COVID-19 cases in African countries is:

$$I = [3531.028 \quad 4087.889]$$

State summary for each category

	Group 3	Group 2	Group 1
A	395	273	83
B	1	21	19
C	1	103	295

Transition matrices for each poverty class

Group 1

	A	B	C
A	0.7952	0.0361	0.1687
B	0.2105	0.3158	0.4737
C	0.0408	0.0340	0.9252

Group 2

	A	B	C
A	0.9155	0.0478	0.0367
B	0.6190	0.0952	0.2858
C	0.0971	0.0583	0.8446

Group 3

	A	B	C
A	0.9950	0.0025	0.0025
B	1	0	0
C	1	0	0

Stationary distributions

$\pi_1 = (0.1993 \quad 0.0479 \quad 0.7528)$

$\pi_2 = (0.6869 \quad 0.0530 \quad 0.2601)$

$\pi_3 = (0.9950 \quad 0.0025 \quad 0.0025)$

4. Discussion

The main objective of this work is to evaluate the risk of COVID-19 srpead among poverty classes in Africa. From the WHO situation reports [2], we noticed that Africa has been less affected. The latter appears different when compared with all the other continents [20]. Among factors that contribute to COVID-19 spread, we can mention transportation that was quite important [21, 22, 23]. Transportation led to higher imported cases making African countries more exposed as travellers can speed the COVID-19 spread[24]. Another issue is related to how poverty reduction policies are implemented during the pandemic. The COVID-19 spread rate in Africa is relatively low but the risk is still present. This can be explained by the fact that an important part of the population has been doubting about the effectiveness of the vaccins[25, 26, 27]. The latter is related to the motivation of this work because public health stakeholders need to realize the probable further risk that every country might face in terms of hesitancy of the proposed solutions. And the results of this work show that even very poor countries are still at risk. Consequently, policies should continue taking into account this threat to control the pandemic spread. Furthermore, there is a limitation related to this study. We think that poverty threshold might be reviewed.

5. Conclusion

This study can be summarized in two points. Firstly, based on monetary poverty level, we classified African countries in three groups of 12, 30, 12 countries respectively. Secondly, we estimated the total daily confirmed new cases for each of the three groups. The data are aggregated. According to the defined

states A, B, C; the variable of interest has been recoded. We implemented for each poverty class the Markov Chain and its stationary distribution. The confidence interval at 5% error risk for the mean number of new COVID-19 cases in African countries is set from 3531.028 to 4087.889. From the stationary state, we can see that poor countries may be more exposed to the pandemic and its consequences as their populations are bigger than in less poor countries. As perspectives, we are planning to investigate the dynamics amoung populations over the world.

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Conflict of interest

The authors declare that they have no conflict of interest.

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