



# A Spatiotemporal Analysis of the COVID-19 Pandemic in North Africa

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**Special Section:**

The COVID-19 pandemic and environmental conditions in Africa

**Key Points:**

- Spatial panel models are formed to explain the prevalence of COVID-19 cases in the North African countries
- Spatial spillovers and a change in the travel restrictions policy are shown to have significant effects on the pandemic outbreak
- More socio-demographic and behavioral variables are needed for future research on the determinants of the spread of the disease

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**Abstract** Spatial panel-data models are estimated to identify the factors of the prevalence of the coronavirus outbreak in North Africa. Using daily data on the number of cases collected between March 2020 and December 2021, three types of general models are investigated, and they include spatial spillovers between the neighboring countries of the region. In one model the spatial dependence is accounted for by adding a spatial lag of the dependent variable (SAR model). In an alternative specification, spatially correlated error terms are considered in the model (SEM), and in the third model a spatial lag dependent variable and spatially correlated errors are both added (SAC). To deal with unobservable individual heterogeneity, random and fixed individual effects specification are investigated in each of these models. The results of the maximum likelihood and generalized method of moments' estimations show that the lift of travel restrictions had an important impact on the spike in the numbers of COVID-19 cases in North Africa and that the effects of endogenous interactions between the countries are strongly significant. It is found that spatial spillovers and a change in the travel policy are the main factors that can explain the mechanism of spread the coronavirus pandemic in North Africa. However, more data on socio-demographic and behavioral variables and on vaccination rates are needed to better understand what caused the recent surge in the number of infections in the region.

**Plain Language Summary** Previous studies on infectious diseases including the recent coronavirus pandemic in developing countries have had only limited interest to address the issue of spatial spillovers between neighboring countries in the search of identifying the main factors to explain the prevalence of the pandemic outbreak and therefore to implement travel restrictions and health protocols accordingly. This study uses spatial panel data models to address the geographical importance for the spread of a pandemic between neighboring countries and presents an empirical investigation of COVID 19 in North Africa.

## 1. Introduction

The region of North Africa includes five countries which are Morocco, Algeria, Tunisia, Libya, and Egypt as shown in Figure 1. The region has an important geographic location because it links the three continents of Africa, Europe, and Asia. It is known for its long history and common heritage despite its diverse economies with Algeria and Libya' economies dominated by oil and gas sectors, and Tunisia, Morocco and Egypt relying more on tourism, agriculture and some light industrial sectors. But as noted by Tiliouine and Estes (2016), many of these countries are going through an unprecedented state of political issues and economic volatility. With around 200 million people living in North Africa, the GDP (Gross Domestic Product) per capita does not exceed 3,500 dollars on average, in nominal terms. These countries have, in general, economic, and social issues related to high unemployment, low living standards, and their desperate need to reform their economies to achieve more stability and better social conditions. The countries of North Africa (except Egypt) looked for closer ties and free trade initiatives to foster economic growth, and so they formed the Arab Maghreb Union. A founding treaty was signed between its member states in February 1989. As noted by Chabrier et al. (1994), the purpose of this union was to find a mechanism that would result in a gradual movement toward free trade of goods, services, and production factors between these neighboring countries. However, there was no provision or agreement on inter-country migration.

In terms of the pandemic, official statistics showed that as of December 2021, the coronavirus disease has caused more than 2.64 million infections and took the lives of nearly 75 thousand people so far in North Africa even though initially these countries were spared from the worst of COVID-19. In epidemiology it is known that three major outbreaks of the coronavirus, a zoonotic virus known to cause respiratory disease, have been reported since 2002, including SARS-CoV, MERS-CoV and the most recent 2019-nCoV, or more recently known as

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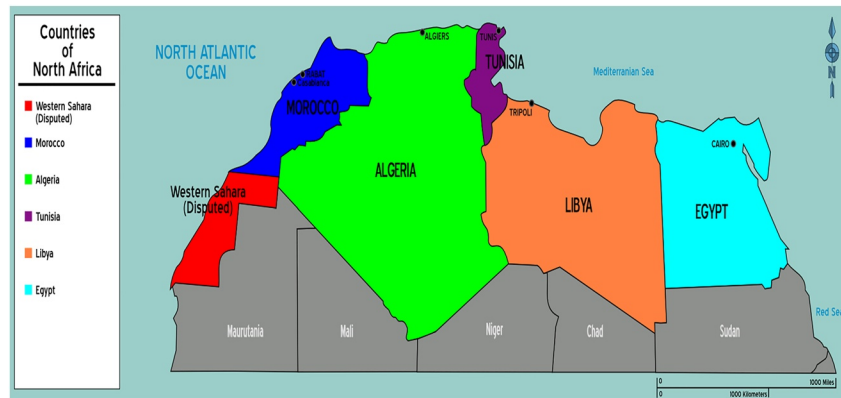


Figure 1. Map of North Africa (source: SpringerLink).

SARS-CoV-2. Bats are known to be the primary animal reservoir for coronaviruses. However, in the past few decades, the virus has been able to mutate and adapt to infect humans, resulting in an animal-to-human species barrier jump. The emergence of a novel coronavirus during the last 2 years posed a serious global public health threat and possibly carried the potential of causing a major pandemic outbreak in the naïve human population (Sharma et al., 2021). However, the North African governments reacted quickly and effectively with a combination of border closures, economic lockdowns, quarantines and social distancing (Beschel & Youssef, 2020). These measures were taken very seriously by health officials, and they were indeed implemented by law enforcement agents. The immediate result was a noticeable success in controlling the spread of the virus and in keeping its impact to a minimum during the first few months of the start of the pandemic. For example, in Tunisia (Figure 2) and Morocco (Figure 3), prior to summer 2020, the total number of infections was small, and the total number of deaths was less than 20 for both countries combined. The same can be said about the other North African countries since before early July 2020, statistics also indicate that daily COVID-19 cases (Figures 4–6) and also the rates of infection and fatalities per capita were well below those found in hard-hit regions in Europe, South Asia, the United States and Latin America.

But like other Arab countries in the region (Khedhiri, 2021a), the success to control the spread of the virus did not last long. The economic performance of these countries was not impressive and government officials feared that if the restrictive measures to control the pandemic like travel restrictions and lockdowns continue, the economic indicators would go from bad to worse, poverty would increase, and social challenges would rise even further. Tourism (The Economist Group, 2021) and transportation-strategic sectors for the North Africa economies-were

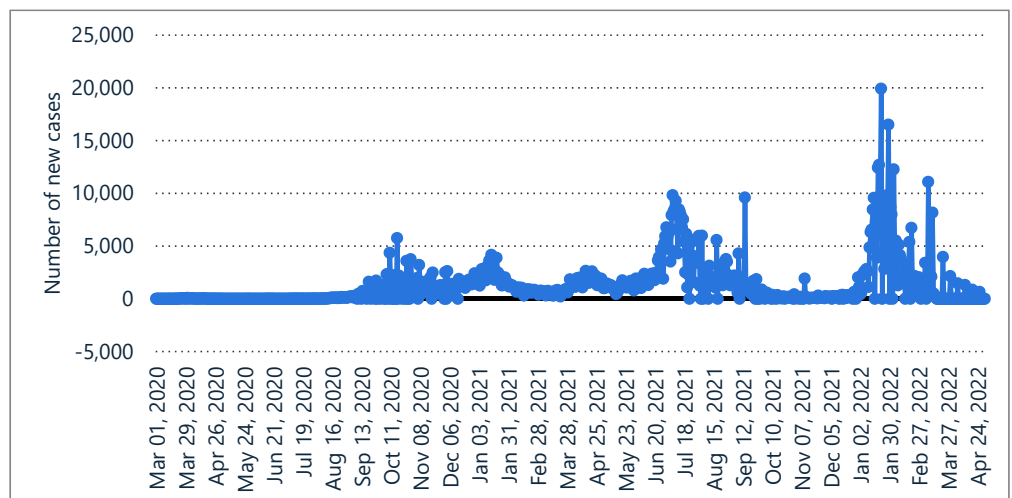
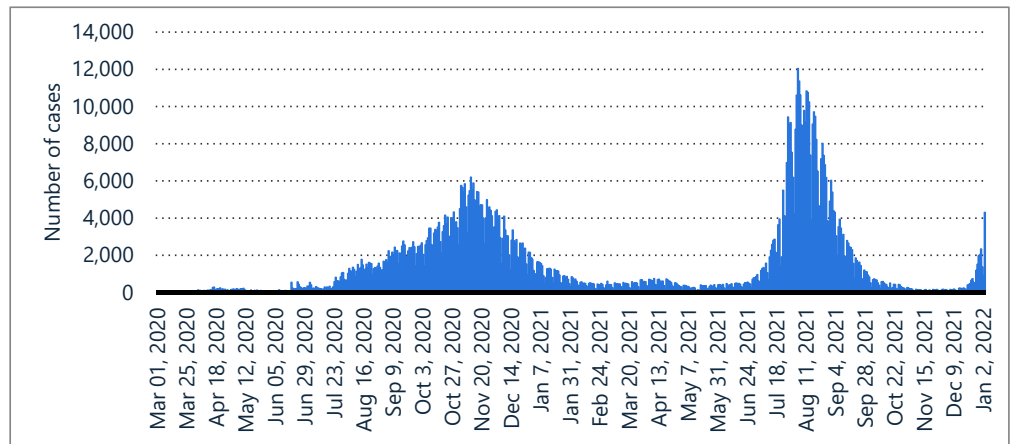


Figure 2. Number of new daily COVID-19 cases in Tunisia (Source: Statista. Information from Johns Hopkins University).

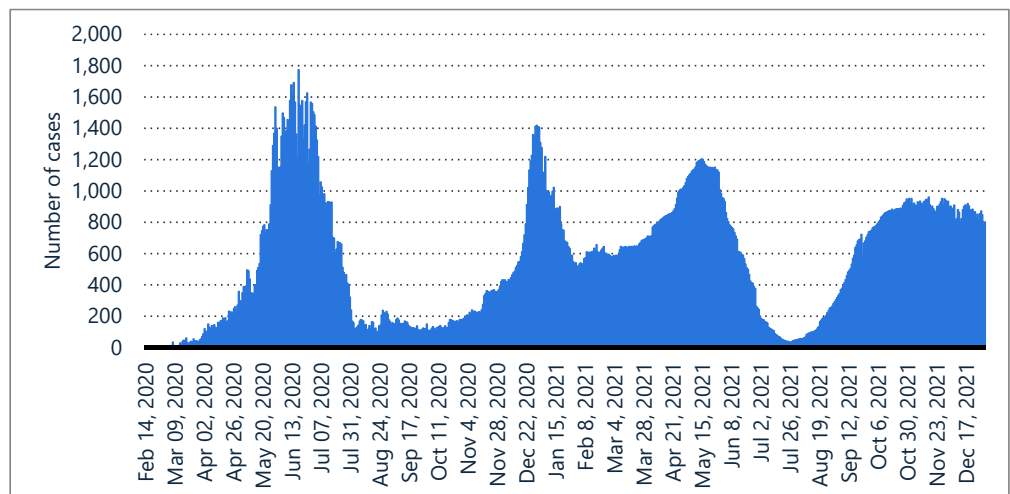


**Figure 3.** Number of new daily COVID-19 cases in Morocco (Source: Statista. Information from Johns Hopkins University).

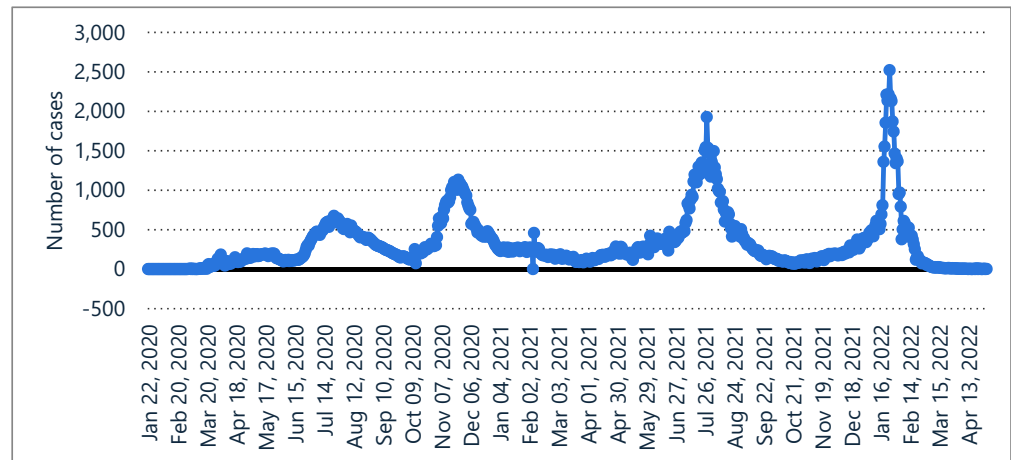
hit very hard by the pandemic and these sectors, unlike in the wealthy Gulf countries, will be less likely to recover easily according to a United Nations Economic Commission for Africa report (2020). Therefore, decision-makers in North Africa had to act, and they did, first by taken measures to reinforce the financing program in favor of micro and small and medium enterprises, and second by taking measures to stir the tourism sector. The latter action called for a policy to relax travel restrictions, but it was incautiously implemented since tourists especially from European countries and locals who are living abroad were allowed to enter the countries without proper COVID-19 testing and without scrupulous use of health protocols like mandatory self-isolation.

The consequence of this policy was a significant widespread of the coronavirus and a spike in the number of people infected, hospitalized, and dead due to the pandemic. To illustrate this fact, Khedhiri (2021b) used alternative statistical models based on zero inflation and generalized count time series models to show that the lift of travel restrictions in summer 2020 had a powerful impact on the pandemic spread and the staggering increase in death tolls in Tunisia. In addition, as of March 2021, official records show that the five North African countries have among the highest numbers of cases in the continent after South Africa and with the emerging new variants, it is expected that the pandemic will hit even harder and the North African health systems will continue experiencing strong challenges.

Other studies including Wehbe et al. (2021) showed the existence of a threefold increase in the number of deaths in the region especially between September and December 2020. This was followed by a staggering increase in the number of cases lately, mainly due to the highly contagious Omicron variant. In addition, it was argued that



**Figure 4.** Number of new daily COVID-19 cases in Egypt (Source: Statista. Information from Johns Hopkins University).



**Figure 5.** Number of new daily COVID-19 cases in Algeria (Source: Statista. Information from Johns Hopkins University).

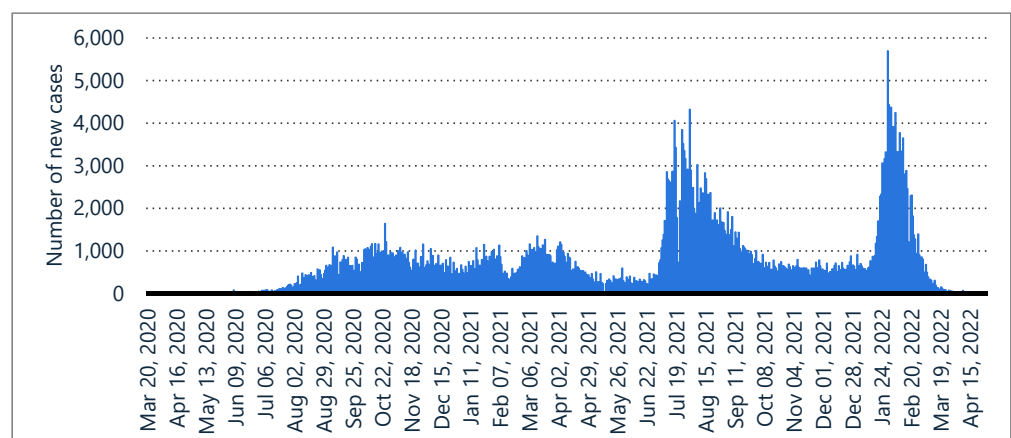
COVID-19 is projected to become among the major leading causes of death before a global vaccination rollout takes place effectively.

## 2. Methods

In this paper, a statistical analysis is performed to model the number of COVID-19 cases in the region of North Africa to understand the major determinants of its spread using spatial panel modeling. Research using spatial methods applied to the region has been done before and one can mention the spatial econometric analysis that was conducted by Daud and Podivinsky (2011) and which included the Middle East and North Africa. However, our study is among the first to use statistical methods to investigate the importance of the spatial structure in epidemiologic research in the region.

Spatial panel data models have the advantage of testing for the existence of spatial interaction and spatial spillover effects which are particularly important for research in epidemiology where scholars might be interested to understand the mechanism of the spread of an infectious disease within a country and between countries in the same region. This in fact is what motivates our current study, and a full spatial analysis is conducted to determine potential major factors for COVID-19 spread that are not possible to identify with panel-data methods that do not include the spatial and the geographic dimensions.

It is well known that spatial spillovers decrease as the distance between two countries increases and spatial panel-data models represent an insightful tool to measure these spillovers. In this paper we estimate these models



**Figure 6.** Number of new daily COVID-19 cases in Libya (Source: Statista. Information from Johns Hopkins University).

with maximum likelihood and generalized method of moments estimation with fixed effects and random effects specifications.

Let  $y_{it}$  denote the dependent variable which represents the number of COVID-19 cases and  $x_{kit}$  denotes some exogenous variables observed at time  $t = 1, \dots, T$ .

Let  $W$  be  $n$  by  $n$  matrix which describes the spatial weights associated to countries  $i$  and  $j$ , given by  $w_{ij}$  where  $i, j = 1, \dots, n$  and  $w_{ii} = 0$  to exclude self-neighboring. In this study  $n = 5$ .

Specify a linear spatial panel-data model augmented with spatial lag exogenous variable and given by,

$$y_{it} = \alpha + \lambda \sum_{j=1}^n w_{ij} y_{jt} + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 \sum_{j=1}^n w_{ij} x_{2jt} + \mu_i + \gamma_t + v_{it} \quad (1)$$

$$v_{it} = \rho \sum_{j=1}^n g_{ij} u_{jt} + \varepsilon_{it} \quad (2)$$

Equations 1 and 2 represent a spatial autoregressive combined model (SAC) where the spatial dependence at time  $t$  is accounted for by means of the spatial lag dependent variable  $\left(\sum_{j=1}^n w_{ij} y_{jt}\right)$ , the spatially correlated errors  $\left(\rho \sum_{j=1}^n g_{ij} u_{jt} + \varepsilon_{it}\right)$ , and the spatial lag explanatory variable  $\left(\sum_{j=1}^n w_{ij} x_{2jt}\right)$ . Without spatial lagged dependent variable ( $\lambda = 0$ ) the model is alluded to as a spatial error model (SEM), and in addition if  $\mu_i = \varphi \sum_{j=1}^5 w_{ij} \mu_j + \xi_i$  then the model is a spatial panel random effects model. The exogenous variables in the empirical analysis are represented by the lift of travel restrictions ( $x_1$ ) and population size ( $x_2$ ).

For a model with  $\rho = 0$ , we obtain a spatial autoregressive model (SAR). In fact, spatial interaction and common factors are two specifications explored in the literature where individuals' activities and outcomes are not independently distributed (Shi & Lee, 2017). In this paper, we investigate whether individuals in one North African country were exposed to COVID-19 infection because their neighbors are infected and directly transmitted the virus to them and this can be modeled by the SAR model specification. Alternatively, if more people are being infected in one country partly because of some unobserved common factors with their neighbors then an SEM model will be more suitable. The more general SAC model includes both specifications and, in our representation, it may also include spatial lag exogenous variables. This is like the spatial Durbin model that was investigated along with SDEM model by Elhorst (2014).

The estimation methods in this paper yield consistent estimators. We start with maximum likelihood estimation, and for a fixed effects specification a partial likelihood function is formed to estimate the model. Also, under the assumption of independence between country specific effects and model exogenous regressors, a model with random effects can be estimated where the likelihood function is decomposed into the product of a partial likelihood function and a between equation (Lee & Yu, 2010). Next, a spatial Hausman test is applied to show which specification is more consistent with the data. The second method of estimation is based on generalized method of moments. Thus, with random effects, three sets of GM estimators are introduced following Millo and Piras (2012). The first set includes initial estimators derived from moment conditions, followed by a second set of estimators which uses the moment conditions and an optimal weighting matrix defined by the inverse of the covariance matrix of sample moments evaluated at the true parameter values. The last set of estimators also uses all the moment conditions but with a simplified version of the weighting matrix computation. An extension of generalized moments (GMM) estimation for dynamic spatial models was introduced in Lee and Yu (2014) using exogenous and predetermined variables as instruments for the moments with neighboring variables and additional higher moment conditions.

To deal with the unobservable heterogeneity in the data we consider two conditions of the individual effects. Under the assumption that these effects are uncorrelated with the explanatory variables and thus they may be considered as a component of the error term, we estimate the models with random effects condition. Alternatively, if the country specific effects are correlated with the exogenous regressors then we estimate the model coefficients with maximum likelihood and generalized method of moments under a fixed effects specification. These effects are also estimated and interpreted as shown below.

We collect daily data on the number of cases for COVID-19 infection in Morocco, Algeria, Tunisia, Libya, and Egypt. The data covers the period from 06 March 2020, to 17 December 2021. Thus, the data includes 652 daily observations for each of the five countries and are freely obtained from the website of Statista (2002) (available at: <http://www.statista.com/statistics/1110995/coronavirus-cases-in-tunisia/>). Regarding the reliability of the data, it should be mentioned however that some records especially related to cases for Libya do not seem reliable as there were zero counts reported in days which were preceded and followed by high numbers of infection cases and deaths. But for the most part, the data looks fine except for these few irregular records.

### 3. Results and Discussion

Following the early spike in the number of infections reported after July 2020, most likely due to the lift of initial travel restrictions implemented by the governments, we add an indicator variable in the model which takes the values zero and one, before and after summer 2020, respectively.

Equations 1 and 2 are run to estimate a COVID-19 model, where the dependent variable is the number of cases in country  $i = 1 \dots, 5$  at time  $t = 1 \dots 652$ . The explanatory variables are represented by the travel restrictions lift ( $x_{1t}$ ) and the size of the population in each country ( $x_{2t}$ ). In addition, in the estimated models a spatial lag of population as an additional explanatory variable is included to measure the spillovers due to exogenous effects between neighboring countries, and in the SAC and SAR models we also add spatial lag of COVID-19 cases in order to assess the endogenous interactions. Each model is estimated with country specific fixed and random effects.

The spatial weight matrix was formed based on the distance between each pair of capitals of the North African countries. Therefore, based on this criterion we form the matrix  $W$ . There are several alternative suitable methods which are well studied in the literature regarding how to select the spatial weights (Anselin & Rey, 2014). For this study, the row-standardized matrix of weights is given by,

$$W = \begin{pmatrix} 0 & .439 & .276 & .167 & .118 \\ .272 & 0 & .427 & .198 & .103 \\ .163 & .389 & 0 & .336 & .112 \\ .111 & .214 & .397 & 0 & .278 \\ .131 & .183 & .229 & .457 & 0 \end{pmatrix}$$

We start the empirical analysis by checking if there is significant spatial correlation in the data and whether we need to use spatial modeling for this study. Following Pesaran (2021), a test for the null hypothesis of no cross-sectional dependence against the alternative of local cross-sectional dependence is computed. We also compute an alternative test (Millo, 2017) to check for the spatial dependence in the health data for the region. A review of these tests statistics and their  $R$  codes can be found in Croissant and Millo (2019).

Pesaran's test for the number of cases is applied and the result shows a statistically significant average correlation between cases reported in North African neighboring countries. This confirms that the data are correlated in the cross section. The following step is to investigate whether this correlation can be explained by the spatial structure. The answer to this question is given from the second test which is reported in Table 1 which shows a strong spatial dependence even after controlling for cross-sectional correlation. Furthermore, we apply the same testing procedure to the residuals from the regression of cases on population size and travel policy. The idea is to check for spatial error correlation and Table 1 results find that it is strongly significant.

Next, spatial panel data models are estimated with random effects. This requires the assumption that individual effects are independent of the model explanatory variables. The maximum likelihood estimations are performed with *spml*  $R$  package (Millo & Piras, 2012). The number of cases is transformed in logarithm plus one, and population data are also in log transform. The results are reported in Tables 3–5 for SAC, SEM, and SAR models, respectively. In addition to the spatial lagged dependent variable whose coefficient is ( $\lambda$ ) and which measures the endogenous spillovers, we also created a spatial lag of population in a panel setting with  $R$  code, denoted by *spop*. However, when included in the regression to measure the effect of spatial population on the number of cases, it turns out to be not consequential.

**Table 1**  
*Testing for Spatial Dependence in the Data*

COVID-19 cases	Pesaran's test for local cross-sectional dependence in panels	$z = 34.374$ , p-value $<2.2e-16$ alternative hypothesis: cross-sectional dependence.
	Randomized test for spatial correlation	p-value $<2.2e-16$ alternative hypothesis: spatial dependence
COVID-19 deaths	Pesaran's test for local cross-sectional dependence in panels	$z = 14.389$ , p-value $<2.2e-16$ alternative hypothesis: cross-sectional dependence.
	Randomized test for spatial correlation	p-value $<2.2e-16$ alternative hypothesis: spatial dependence

**Table 2**  
*Maximum Likelihood Estimation With Random Effects*

SAC model:							
Spatial error coefficient:							
	Estimate	Std. Error	t-value	Pr(> t )			
rho	0.552429	0.066272	8.3358	$<2e-16$ ***			
Spatial autoregressive coefficient:							
	Estimate	Std. Error	t-value	Pr(> t )			
lambda	0.587320	0.036533	16.077	$<2.2e-16$ ***			
Coefficients:							
	Estimate	Std.	Error	t-value	Pr(> t )	Estimate	Std.
(Intercept)	-48.508424		6.837099	-7.0949		1.295e-12	***
policy	0.653696		0.067166	9.7325		$<2.2e-16$	***
pop	15.297212		1.070662	14.2876		$<2.2e-16$	***
spop	-0.043442		0.139707	-0.3110		0.7558	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1							
SEM model							
Spatial error coefficient:							
	Estimate	Std. Error	t-value	Pr(> t )			
rho	0.229604	0.030172	7.6099	2.743e-14 ***			
Coefficients:							
	Estimate	Std. Error	t-value	Pr(> t )			
(Intercept)	-63.595801	8.986268	-7.0770	1.473e-12 ***			
policy	1.104582	0.090416	12.2167	$<2.2e-16$ ***			
pop	20.133238	1.309825	15.3709	$<2.2e-16$ ***			
spop	-0.048239	0.129356	-0.3729	0.7092			
SAR model							
Spatial autoregressive coefficient:							
	Estimate	Std. Error	t-value	Pr(> t )			
lambda	0.266535	0.027935	9.5413	$<2.2e-16$ ***			
Coefficients:							
	Estimate	Std. Error	t-value	Pr(> t )			
(Intercept)	-63.595801	8.986268	-7.0770	1.473e-12 ***			
policy	1.104582	0.090416	12.2167	$<2.2e-16$ ***			
pop	20.133238	1.309825	15.3709	$<2.2e-16$ ***			
spop	-0.048239	0.129356	-0.3729	0.7092			

Note. SAC, spatial autoregressive combined model; SEM, spatial error model; SAR, spatial autoregressive model.

**Table 3**  
*Maximum Likelihood Estimation With Fixed Effects*

SAC model					
Spatial error coefficient:					
	Estimate	Std. Error	t-value	Pr(> t )	
rho	0.48757	0.06967	6.9982	2.593e-12 ***	
Spatial autoregressive coefficient:					
	Estimate	Std. Error	t-value	Pr(> t )	
lambda	0.574567	0.038641	14.869	<2.2e-16 ***	
Coefficients:					
	Estimate	Std. Error	t-value	Pr(> t )	
policy	0.645752	0.091478	7.0591	1.676e-12 ***	
pop	15.876932	1.244214	12.7606	<2.2e-16 ***	
spop	-0.044198	0.139296	-0.3173	0.751	
SEM model					
Spatial error coefficient:					
	Estimate	Std. Error	t-value	Pr(> t )	
rho	0.230172	0.030418	7.5669	3.822e-14 ***	
Coefficients:					
	Estimate	Std. Error	t-value	Pr(> t )	
policy	1.521947	0.104024	14.6308	<2e-16 ***	
pop	22.343799	1.391588	16.0563	<2e-16 ***	
spop	-0.046462	0.121925	-0.3811	0.7031	
SAR model					
Spatial autoregressive coefficient:					
	Estimate	Std. Error	t-value	Pr(> t )	
lambda	0.26592	0.02777	9.5755	<2.2e-16 ***	
Coefficients:					
	Estimate	Std. Error	t-value	Pr(> t )	
policy	1.084655	0.103752	10.4543	<2e-16 ***	
pop	20.587213	1.339103	15.3739	<2e-16 ***	
spop	-0.048586	0.129185	-0.3761	0.7068	

*Note.* SAC, spatial autoregressive combined model; SEM, spatial error model; SAR, spatial autoregressive model.

On important interpretation from the results is that spatial dependence may be occurring through two channels; an endogenous interaction represented by a spatial lag of cases and an interaction by means of some unobserved spatial common factors represented by the model errors. The coefficients ( $\lambda$ ) and ( $\rho$ ) describe each interaction. This study shows that they are strongly significant in all the estimated models, a result that is not unexpected. Take the example of Tunisia. There were 9.43 million tourists in Tunisia in 2019, which means 0.81 tourist per resident. This small North African country generated around 2.68 billion US Dollars in the tourism sector alone which corresponds to 6.4% of its gross domestic product (WorldData, 2021) and approximately 10% of all international tourism receipts in Northern Africa. In that same year 2019, nearly 3 million tourists came from Algeria and 2 million from Libya. Thus, more than 53% of the total numbers of visitors to Tunisia were from its closest neighbors. Similarly, in Libya more than 100 thousand migrants are from Egypt representing more than 52% of all North African migrants and 15% of the total number of migrants in the country in 2019. These statistics obviously speak volumes about the potential spatial spillovers during a pandemic.



**Table 4**  
*Maximum Likelihood Estimation of Spatial Autoregressive Model (SAC) Model (3)*

Random effects:				
Spatial error coefficient:				
	Estimate	Std. Error	t-value	Pr(> t )
rho	0.504498	0.074622	6.7607	1.373e-11 ***
Spatial autoregressive coefficient:				
	Estimate	Std. Error	t-value	Pr(> t )
lambda	0.583370	0.041215	14.154	<2.2e-16 ***
Coefficients:				
	Estimate	Std. Error	t-value	Pr(> t )
(Intercept)	-48.642835	6.819461	-7.1329	9.824e-13 ***
policy	0.653550	0.067157	9.7316	<2.2e-16 ***
pop	15.291565	1.070508	14.2844	<2.2e-16 ***
Fixed effects:				
Spatial fixed effects:				
	Estimate	Std. Error	t-value	Pr(> t )
Morocco	-3.8199	4.4782	-0.8530	0.3936609
Algeria	-7.5451	4.6311	-1.6292	0.1032625
Tunisia	11.5793	3.0668	3.7757	0.0001596 ***
Libya	18.7591	2.5972	7.2227	5.095e-13 ***
Egypt	18.9734	5.6650	3.3492	0.0008104 ***

Also, it is conveyed that when governments relaxed travel restrictions this had a significant impact on the increased records of COVID-19 cases. It is noticed that population size has also a significant role overall, despite the relatively smaller number of cases for a populated country like Algeria compared to other less populated countries in the region. Following Kapoor et al. (2007), we proceed with the estimation of the same random effects model but without spatially lagged number of cases. The maximum likelihood estimation is summarized in Table 2 below.

Alternatively, a model that accounts for spatial auto regression of the dependent variable only is estimated and Table 2 casts its statistical results. Clearly the findings prove that travel restrictions lift policy and population size have a remarkable explanatory power in the model, spatially lagged number of cases is notably significant and so is the spatial correlation that drives the model errors. However, the spatial lag of population does not have a significant spatial spillover effect on the number of COVID-19 cases in North Africa.

When the assumption of independence between country specific effects and model regressors does not hold then the estimation of these models with fixed effects is more appropriate. To this end, we start with maximum likelihood estimation. The results listed in Table 3 for the SAC, SEM, and SAR models, respectively, also confirm the significance of model explanatory variables.

Notable impact of travel policy and population size and outstanding spatial dependence may be concluded from the statistical results. Thus, in addition to the lift of travel restrictions policy and population size being crucial factors in explaining the observed spike in COVID-19 cases in North Africa, the spatial structure also provides additional explanation. First, the surge of infection in one country can be spilled over to the neighboring country and thus tighter travel restrictions on the borders need to be rigorously re-implemented. Second, we refer to a study by Gesesew et al. (2021) in which the authors show evidence that the susceptibility to COVID-19 infection, being seriously ill and the risk of death are influenced by individual characteristics such as socio-demographic factors and behavioral traits and other pre-existing medical conditions. Our results confirm these findings in some sense, since it is shown that unobservable common factors for North Africans are spatially correlated.

**Table 5**  
*Fixed Effects Model Estimated Without Spatial Population Lag*

Spatial fixed effects:				
	Estimate	Std. Error	t-value	Pr(> t )
Morocco	-3.8199	4.4782	-0.8530	0.3936609
Algeria	-7.5451	4.6311	-1.6292	0.1032625
Tunisia	11.5793	3.0668	3.7757	0.0001596 ***
Libya	18.7591	2.5972	7.2227	5.095e-13 ***
Egypt	18.9734	5.6650	3.3492	0.0008104 ***

Next, we turn our attention to the effect specification in modeling the spread of infection. Therefore, in the next step we want to determine whether the data supports random or fixed effects. To answer this question, we start with maximum likelihood method to estimate a parsimonious model which includes only the significant regressors (policy, population, special lag of cases) for each alternative specification, random and fixed individual effects. The model is given by the following equation and excludes lagged explanatory variables:

$$y_{it} = \alpha + \lambda \sum_{j=1}^n w_{ij} y_{jt} + \beta_1 x_{1it} + \beta_2 x_{2it} + \mu_i + \gamma_t + v_{it} \quad (3)$$

The estimation results are displayed in Table 4.

The estimation results of the individual fixed effects of each country are exhibited in Table 5 and they show strong significance for Egypt, Tunisia and Libya, and less important country fixed effects for Algeria and Morocco.

Next, an alternative consistent estimation method is considered based on GMM to estimate a parsimonious model with individual effects specified alternatively as random and fixed. The GMM statistical results are unveiled in Table 6.

The estimation of the model with generalized method of moments did not change the significance of the variables found previously with maximum likelihood, although the t-statistics for *policy* are slightly lower but still show a clear weighty impact for relaxing travel restrictions on the number of cases.

Although both conditions, random and fixed effects, did not yield contradictory results in terms of the significance of the variables and the spatial correlation in the model and in the model errors, in the final step of our empirical analysis statistical tests are computed to determine which specification is more consistent with the data.

Therefore, in the last step of our empirical investigation we examine the test of Baltagi (Baltagi et al., 2007) to provide further evidence on the significance of the spatial correlation in the model. The results in Table 7 remove any doubt about the importance of spatial dependence in the data. In addition, spatial Hausman test is computed to verify if the data supports the assumption of random effects or fixed effects (Hausman, 1978). The results which are reported in the lower panels of Table 7 demonstrate that a spatial fixed effects specification is the more likely to be supported by the data for modeling COVID-19 infections in North Africa, although this conclusion is slightly more significant with maximum likelihood than with the generalized method of moments estimation.

**Table 6**  
*GMM Estimation Results*

Random effects model				
Coefficients:				
	Estimate	Std. Error	t-value	Pr(> t )
lambda	0.706496	0.068949	10.2467	<2e-16 ***
policy	0.196725	0.081768	2.4058	0.00816 **
pop	6.009870	0.655211	9.3080	<2e-16 ***
Fixed effects model				
Coefficients:				
	Estimate	Std. Error	t-value	Pr(> t )
lambda	0.556710	0.056216	9.9031	<2e-16 ***
policy	0.187476	0.098635	1.9007	0.02881 *
pop	5.919940	0.729731	8.1125	4.957e-16 ***

**Table 7**  
*Specification Tests for Country Effects and Spatial Correlation*

Baltagi et al. test for spatial correlation with possible RE:

LM = 6.1476, p-value = 7.866e-10

alternative hypothesis: Spatial autocorrelation

Hausman test for spatial models: ML estimation

chisq = 7.3376, df = 2, p-value = 0.02551

alternative hypothesis: one model is inconsistent

Hausman test for spatial models: GM estimation

chisq = 5.5312, df = 2, p-value = 0.06294

alternative hypothesis: one model is inconsistent

## 4. Conclusions

This paper presents a statistical analysis using spatial panel-data methodology to explain the factors for the spike of COVID-19 cases observed in North Africa after summer 2020, and then lately in the fall of 2021. We estimate alternative models to account for spatial spillovers between the countries. The results show that the lift of travel restrictions that were initially implemented and the population size are important factors that can explain the observed widespread of the virus. In addition, the spatial modeling allows us to identify significant spatial lag and spatial error dependences. The limitation of this study is mainly related to finding more reliable public health surveillance data in North Africa. Also, it would be insightful to include additional socio-demographic and behavioral variables and also data related to vaccination rates in the region in future related research.

## Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

## Data Availability Statement

COVID-19 incidence data for the North African countries are available from the website given with links in the references. These data can be freely downloaded from repository (<http://wwwstatista.com/statistics/1110995/coronavirus-cases-in-tunisia/>). Please change the country name accordingly to download the data for the other countries.

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## References

- Anselin, L., & Rey, S. (2014). *Modern spatial econometrics in practice: A guide to GeoDa, GeoDaSpace and PySal*. GeoDa Press.
- Baltagi, B. H., Song, S. H., Jung, B. C., & Koh, W. (2007). Testing for serial correlation, spatial autocorrelation and random effects using panel data. *Journal of Econometrics*, *140*(1), 5–51.
- Beschel, R., & Youssef, T. (2020). The Middle East and North Africa and COVID-19: Gearing up for the long haul. Paper Retrieved from <https://www.brookings.edu/opinions/the-middle-east-and-north-africa-and-covid-19-gearing-up-for-the-long-haul/>
- Chabrier, P., Finaish, M., & Bell, E. (1994). *The Arab Maghreb Union*. IMF eLibrary (ISBN: 9781451969122). Retrieved from <https://www.elibrary.imf.org/view/journals/001/1994/055/article-A001en.xml#:~:text=The%20Founding%20Treaty%20of%20the,factors%20of%20production%20among%20them>
- Croissant, Y., & Millo, G. (2019). *Panel data econometrics with R*. John Wiley & Sons Ltd.
- Daud, S., & Podivinsky, J. (2011). Debt-growth nexus: A spatial econometrics approach for developing countries. *Transition Studies Review*, *18*, 1–15. <https://doi.org/10.1007/s11300-011-0190-6>
- Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Springer.
- Gesesew, H. A., Koye, D. N., Fetene, D. M., Woldegiorgis, M., Kinfu, Y., Geleto, A. B., et al. (2021). Risk factors for COVID-19 infection, disease severity and related deaths in Africa: A systematic review. *BMJ Open*, *11*(2). <https://doi.org/10.1136/bmjopen-2020-044618>
- Hausman, J. (1978). Specification tests in econometrics. *Econometrica*, *46*(6), 1251–1271.
- Kapoor, M., Kelejian, H. H., & Prucha, I. R. (2007). Panel data model with spatially correlated error components. *Journal of Econometrics*, *140*(1), 97–130.
- Khedhiri, S. (2021a). Forecasting COVID-19 infections in the Arabian Gulf region. *Modeling Earth Systems and Environment*. <https://doi.org/10.1007/s40808-021-01332-z>
- Khedhiri, S. (2021b). Statistical modeling of COVID-19 deaths with excess zero counts. *Epidemiologic Methods*(s1). <https://doi.org/10.1515/em-2021-0007>
- Lee, L.-f., & Yu, J. (2010). Estimation of spatial panels. *Foundations and Trends in Econometrics*, *4*(1–2), 1–164.
- Lee, L.-f., & Yu, J. (2014). Efficient GMM estimation of spatial dynamic panel data models with fixed effects. *Journal of Econometrics*, *180*(2), 174–197.
- Millo, G. (2017). A simple randomization test for spatial correlation in the presence of common factors and serial correlation. *Regional Science and Urban Economics*, *66*, 28–38. <https://doi.org/10.1016/j.regsciurbeco.2017.05.004>
- Millo, G., & Piras, G. (2012). Splm: Spatial panel data models in R. *Journal of Statistical Software*, *47*(1), 2–39.
- Pesaran, H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, *60*, 13–21. <https://doi.org/10.1007/s00181-020-01875-7>
- Sharma, A., Farouk, I. A., & Lal, S. K. (2021). A review on the novel coronavirus disease evolution, transmission, detection, control, and prevention. *Viruses*, *13*(2). <https://doi.org/10.3390/v13020202>
- Shi, W., & Lee, L.-f. (2017). Spatial dynamic panel data models with interactive fixed effects. *Journal of Econometrics*, *197*, 323–347. <https://doi.org/10.1016/j.jeconom.2016.12.001>
- Statista (2022). <http://www.statista.com/statistics/1110995/coronavirus-cases-in-tunisia>

- The Economist Group. (2021). *Tunisian tourism receipts fell further in first half of 2021*. The Economist Intelligence Unit. Retrieved from [http://country.eiu.com/article.aspx?articleid=91181192&Country=Tunisia&topic=Economy&subtopic=For\\_4](http://country.eiu.com/article.aspx?articleid=91181192&Country=Tunisia&topic=Economy&subtopic=For_4)
- Tiliouine, H., & Estes, R. (2016). Social development in North African countries: Achievement and current challenges. In *The state of social progress of islamic societies*. [https://doi.org/10.1007/978-3-319-24774-8\\_5](https://doi.org/10.1007/978-3-319-24774-8_5)
- United Nations Economic Commission for Africa. (2020). COVID-19 crisis in North Africa: The impact and mitigation responses. Retrieved from <https://www.tralac.org/documents/resources/covid-19/regional/3942-covid-19-crisis-in-north-africa-the-impact-and-mitigation-responses-unece-june-2020/file.html>
- Wehbe, S., Fahmi, S., Rizk, A., Mumtaz, G. R., DeJong, J., & Sibai, A. M. (2021). COVID-19 in the Middle East and North Africa region: An urgent call for reliable, disaggregated and openly shared data. *BMJ Global Health*, *6*(2), 1–4.
- WorldData. (2021). Tourism in Tunisia. Retrieved from [www.worlddata.info/africa/tunisia/tourism.php](http://www.worlddata.info/africa/tunisia/tourism.php)