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A Dynamic Spatiotemporal Analysis of Growth Convergence, Natural Disasters and Climate Change in the MENA Region

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ECONOMIC RESEARCH FORUM

منتدى البحوث الاقتصادية

A Dynamic Spatiotemporal Analysis of Growth Convergence, Natural Disasters and Climate Change in The MENA Region

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Abstract: This study aims to investigate growth convergence using a spatial approach. The convergence process is affected by environmental factors, according to empirical findings. This process seems to be strongly influenced by both the country's idiosyncratic characteristics; the environmental neighboring countries' feedback loop effect; and ecological spillover intensity. These spillovers affect not only neighbors in close vicinity (neighbors of first order or contiguous neighbors), but also concern the neighbors of higher order, and might spread to the whole region.

Keywords: Growth Convergence, Spillover Effects; Spatial Models; Climate Change.

JEL classifications: O47, D62, C31, Q54.

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I. Introduction

Exploring the concept of economic growth and income convergence[1] in the context of climate change is a prominent and debated issue, especially for the MENA region which has been dramatically cursed by recurrent chaotic events, some of them are of extreme violence (internal and external conflicts, economic crisis, people displacement, natural disasters, etc.). Accordingly, the interconnection of the economies, combined with the chocs related to these events, appeal for a holistic and an ambitious analysis to understand the logic behind the chronic lethargy of the economic growth in the MENA region despite the abundance of human and natural resources.

Some chief queries arise, both from an environmental and economical point of view. Will the climate factors raise the convergence speed across the MENA region or contribute to more regional disparities? Do spatial locations impact the MENA development path? Do neighboring countries with similar environmental factors converge quickly? Are there any spillovers in the region? If any, what kind are they and how far they are spread geographically?

This exploratory spatial and ecological analysis evaluates the spatial correlation between the MENA economies in terms of economic convergence by including the questionable influence of the ecologic situation. The contribution of this study is twofold. First, we examine the impact of the environmental degradation and climate change alongside the economic growth to fill the MENA empirical analysis gap. Second, the implementation of different spatial models and techniques are designed to overcome the previous studies by considering the spatial interdependence as a source of externalities that could spill over to adjacent countries or remote ones. Hence a panel data of 18 MENA countries is set over the period 1996-2019 to examine the aforementioned questions.

[1] Broadly speaking the economic convergence theory postulates that all economies will eventually converge in terms of per-capita output. Accordingly, economic divergence occurs when we observe an income growth differential between a sample of countries and a list of benchmark countries. Baumol (1986); Barro and Sala-I Martin (1997); Lee et al. (1997); Bernard and Durlauf (1995); Luginbul and Koopman (2004), have meaningfully shaped the economic convergence analysis.

II. Economic Growth-Ecological Footprint Nexus: Why Spatial Analysis Matters?

Lesage (2010, p.20) states that "spatial econometrics is a field whose analytical techniques are designed to incorporate dependence among observations (regions or points in space) that are in close geographical proximity. Extending the standard linear regression model, spatial methods identify cohorts of « nearest neighbors » and allow for dependence between these regions/observations". Indeed, the spatial econometric framework would be a promising approach to deal with the importance of territorial interferences in the context of economic growth as well as the environmental issues. Actually, what happen in a country is likely to impact directly or indirectly the others (neighbors or remote locations) through several transmission channels.

The constraining OLS[2] hypothesis of the independence of the observational units[3] may lead to serious misspecification problems and as result the coefficient of the OLS estimators' risk to be biased and inaccurate. Another relevant point to be stated is the difficulty to detect and measure properly the spillover effects. These externalities are recognized and admitted in the OLS framework. However, they are rarely measured due to the OLS technical limits. The spatial econometric models are designed to deal with this shortcoming. Henceforward, in the presence of geographical interaction, spatial models propose a promising alternative to OLS or non-spatial regressions by taking into account the spatial autocorrelation impacting the dependent as well as the explanatory variables, (LeSage & Pace, 2009).

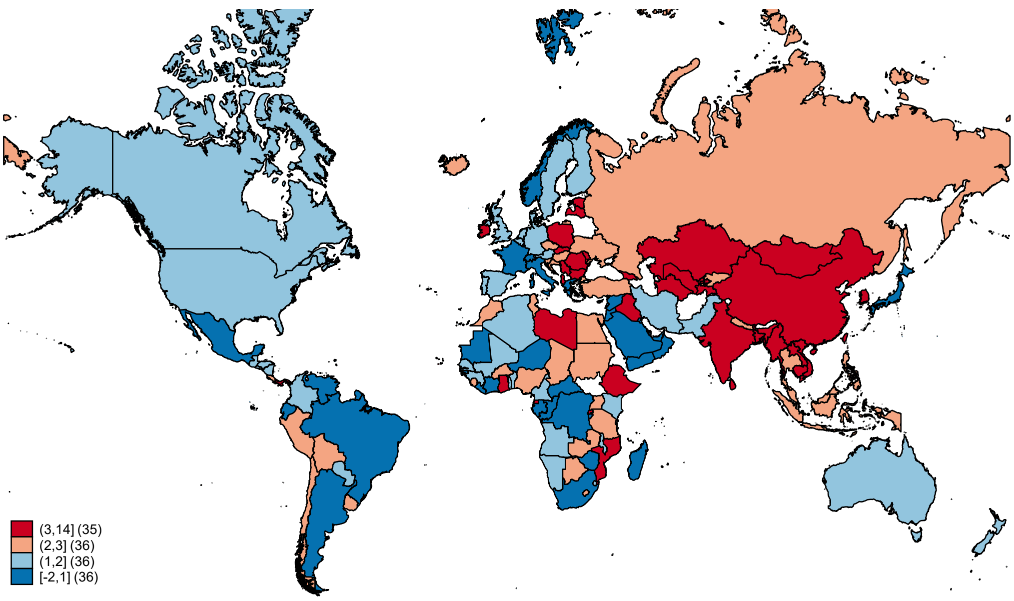
Over the few last years, spatial effect has been recognized as a key force in the process of economic convergence (Rey and Montouri, 1999). In fact, the geographic world income is not uniformly distributed across the world: rich countries and fast-growing economies are likely to be geographically clustered (i.e., located close to each other's). The concentration of the same colors' tones in certain regions (Asia, Europe, and America) observed on the map below (see figure 1) describing the distribution of the GDP per capita growth across the world presume the presence of positive spatial correlation (i.e., clusters of countries with respectively high values (dark tones) and low values (light tones) of GDP per capita growth. One of the advantages of

[2] Ordinary Least square.

[3] Formally this can be expressed by the following equation: $E\left[u_i\, u_j\right] = 0;\ \forall\, i \neq j$

spatial econometric is to confirm or not if there is a certain logic behind this phenomenon (the existence of a specific structure) or if this occurs randomly. Finding out whether there is a definite logic or a random coincidence behind such a phenomenon is one the benefits of using spatial econometrics. Accordingly, it is worthwhile to note that spatial interdependence in the economic growth context matters, (Tian and Chen, 2010). It seems that a shadow growth effect (growth spillover effects coming from the other countries) exists and should be taken into account when exploring the economic convergence between the countries. For instance, in the last decade, a stream of empirical work on the economic convergence process has shown that spatial dependence is worth being considered. It is meaningful to state that neglecting the spatial interactions would lead to serious misspecification. The income growth and economic convergence in one country will not depend exclusively on the conditions of that country but also will be influenced by those prevailing in a third country. Space, in fact, is not composed of units isolated from each other. What happens in each of them can influence others: there is spatial interaction, (Jayet, 1993). The economic growth disparities (as indicated by the figure1) contrast with the orthodox neoclassical approach of absolute convergence. Economic differences exist and poor countries didn't converge to the same steady growth and/or have not caught up the developed countries so far. As a matter of fact, it could be interesting to explore other approaches instead of the unrealistic absolute convergence hypothesis.

Fig.1: Panorama of the GDP/Capita Growth in the World
(Period average: 1996-2019, 143 countries)



Source: Author calculation using The World Bank Data

III. The Empirical Work

To estimate the convergence of GDP per capita determinants in the MENA region we use a dataset of 18 economies[4] over the period 1996-2019. The time frame and countries were selected to supply both balanced panel data and a quite large sample size dataset to properly run the spatial regressions. Data is collected from the Penn World Table database (PWT.10.01) from the University of California and the University of Groningen[5], The World Bank (World Development Indicators and The Worldwide Governance Indicator) and The International Monetary Fund.

III.1. The OLS Regression Results

In a first step, we estimate the basic version of the Solow model (see Eq.1) by ordinary least square (OLS) as a benchmark model of absolute convergence concept (see Table 1) before carrying out the spatial regressions of the Solow augmented equation by adding additional economic and environmental idiosyncratic covariates (to be on line with the conditional convergence spirit).

$$G_r = \beta_0 + \beta_1 Y_0 \qquad \text{[Eq.1]}$$

Hence, in the second we regress the growth of real GDP per capita $G_r = \frac{GDP/Cap_t - GDP/Cap1996}{T}$ on the initial real GDP per capita[6] (GDP/Cap_{1996}) (per capita GDP of the year 1996), the capital stock (*CapStock*) (proxy of physical capital accumulation), and the sum of population growth, technology growth rate and capital depreciation rate (*NGD*) [7]$[NGD = (n + g + \delta)]$[8], the natural resources endowment[9] (ResEndow) is approximated by total natural resources rents (% of GDP). The environmental regressors (retrieved) from the online IMF database[10]) include respectively; the carbon dioxide emissions (*CO2*) in kiloton (kt)

[4] Algeria, Bahrain, Egypt, Jordan, Kuwait, Iran, Libya, Oman, Mauritania, Morocco, Qatar, Saudi Arabia, Sudan, Syria, Tunisia, Turkey, and the United Arab Emirates.
[5] Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at: www.ggdc.net/pwt
[6] At constant 2017 national prices (in mil. 2017US$)
[7] Following the economic growth literature $g + \delta$ is supposed to be equal to 0.05.
[8] *GDP/cap, ck,* n, δ *are extracted* from PWT.10.01
[9] WDI
[10] https://climatedata.imf.org/

as a proxy of environmental pollution; and the annual sum of natural disaster climate related disasters frequency of drought, extreme temperature, flood, landslide, storm and wildfire (*NatDisaster*). Except the governanace variable (*Gov*[11]) and the natural disaster indicator (*NatDisaster*), all the other variables are expressed in logarithm.

Table 1. OLS estimates of the β-Convergence regression of per-capita income in the MENA region Period: 1996-2019

	(1)
VARIABLES	Gr
GDP/Cap1996	-0.371***
	(-2.579)
Constant	3.849***
	(2.836)
Observations	432
Number of id	18

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[11] The mean of five governance indicators [Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption ranging from -2.5 (weak) and 2.5 (strong) performance].

The OLS results[12] indicate that the coefficient of β-convergence for the whole period is highly significant with the expected negative sign, confirming the presence of convergence over the years 1996- 2019. The initial per capita GDP's negative sign is consistent with the research on growth convergence: poorer countries' per capita income will grow at faster rates then the richer countries. Its value (-0.371) implies an annual rate of convergence of 1.9% and a half-life of 38.48 years[13].

[12] Based on the absolute convergence hypothesis since the regression equation does not include explanatory variables measuring the countries characteristics.

[13] $Speed\ convergence$: $b = -\frac{ln(1+\beta)}{T} = 0.019$; $t_{half-life} = \frac{ln\ (2)}{b} = 38.48$

Table 2.: OLS Estimation of The Determinants of Conditional Convergence in MENA18 Period:1996-2019

VARIABLES	(1) Gr
GDP/Cap1996	-1.011***
	(-7.237)
CapStock	-0.125**
	(-2.255)
NGD	0.440**
	(2.175)
ResEndow	0.183***
	(5.311)
CO2	2.352***
	(4.002)
CO2sq	-0.0880***
	(-3.161)
NatDisaster	-0.0605**
	(-2.193)
GOV	0.656***
	(4.511)
Constant	-2.513
	(-0.749)
Observations	432
Number of id	18

statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The OLS conditional convergence results (see Table 2) including both economic and ecologic factors reveal that the convergence hypothesis (that poor countries tend to grow faster than wealthy nations) is supported by the negative coefficient of the initial GDP per capita. In addition, we denote a positive and significant impact (at a level of 1%) of resources endowment, the CO_2 emission, and governance. For the *NGD* variable, this is accurate, but only with a 5% statistical significance. In addition, we observe significant and negative consequences of *CO2sq*, the capital stock and natural disasters on the MENA growth convergence. Furthermore, we find that natural disasters, the capital stock, have a significant (at the level of 5%) and detrimental impact on the convergence of MENA growth. For *CO2sq*, the same perception holds true, but at the conventional level 1% level[14].

[14] Further information on this point is provided in the findings of the spatial regression later on.

III.2. The Spatial Econometric Regressions

Broadly speaking, there are four popular spatial models used in applied research specifically the Spatial Lag Model or Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), the SAC model (or SARAR, Cliff-Ord model) and the Spatial Durbin model (SDM). The Spatial Lag [Eq.4], Spatial Autoregressive (SAR) model postulates that levels of the dependent variable y depend on the levels of y in neighboring units apprehended by the weighted matrix W and represented by ρW_y. In the Spatial Error Model (SEM) [Eq.5], the spatial influence comes exclusively via the error terms $\mu = \lambda W_\mu + \varepsilon$ and is useless for spillovers detection. The SAC model [Eq.6] is a mixed or a combined spatial autoregressive model involving the endogenous interaction among the dependent variable Wy as well as the autoregressive disturbance λW_μ. If $\lambda = 0$, we obtain the Spatial Durbin Model (SDM) [Eq.7] which incorporates the lagged dependent variable y [ρW_y or simply Rho in the regression results tables) and the spatially related residuals. Compared to the SEM model, the SDM model just adds average-neighbor values of the independent variables to the specification through the expression $WX\theta$.

SAR:	$y = \rho W_y + \alpha + \beta X + \varepsilon$		[Eq.2]
SEM:	$y = \alpha + \beta X \mu \quad \mu = \lambda W_\mu + \varepsilon$		[Eq.3]
SAC:	$y = \rho W_y + \alpha + \beta X + WX\theta + \varepsilon$	$\mu = \lambda W_\mu + \varepsilon$	[Eq.4]
SDM:	$y = \rho W_y + \alpha + \beta X + WX\theta + \varepsilon$		[Eq.5]

III.2.1. The Space Configuration

In order to run spatial economic regressions, a weighted matrix should be implemented. This matrix aims to configurate the space and parameterizes the potential of interactions between observations of each country's pairs i, j. The positive and symmetric $n \times n$ spatial matrix[15] is composed by elements $W_{i,j}$ at location i, j. By convention $W_{i,j} = 0$ for the diagonal elements which means that a location cannot be a neighbor wit itself.

$$W = \begin{pmatrix} w_{1,1} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,n} \end{pmatrix}$$

[15] n is the number of spatial units.

There is a spectrum of techniques designed to specify the structure of the spatial weight matrix[16]. For example, the weight can be measured by contiguity[17]. Another alternative is to use an inverse distance or a threshold distance[18]. In this study we use an inverse distance $w_{i,j} = \frac{1}{e^{d_{ij}}} = e^{-d_{ij}} \quad \forall\, i \neq j; i,j = 1, \ldots\ldots, N$ describing a primitive and canonical principle of geographic law described concisely Tobler (1970, p.236)[19], "“Everything is related to everything else, but near things are more related than distant things”. Also, a contiguity matrix is applied on some regressions for check robustness purposes.

III.2.2. Completing The Growth Convergence Equation with The Spatial Model

To run the spatial regression models, we follow Tian et al. (2010), Fingleton, and Lopez-Bazo (2006), Arbia (2006), and Kubi and Schneider (2016) who accommodated and rearranged the Cobb-Douglas function to the spatial dependence concept. In line with Marshallian literature where two kinds of externalities are identified namely technological and pecuniary externalities; the authors stipulate that the main source of spatial effects is coming from externalities through regional interaction in terms of knowledge spillovers, factor mobility and trade.

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[16] It is recommended to experiment a variety of weighted spatial matrix W in the estimation process because results may be very sensitive to the structure of matrix W.
[17] i, j locations interact when they are contigus i.e sharing a common border. Then we obtain a binary matrix with value 0 (countries are not contigus) and 1 (countries are contigus).
[18] $(i, j$ locations interact when being within a critical distance band).
[19] Tobler, W. (1979). "Cellular Geography." In *Philo.oph"* in Geograph", edited by S. Gale and G. Olsson, pp. 579-86. Dordrecht: Reidel.Cited in (Anselin, 1988, p.8)

The Solow Cobb-Douglas equation proposed by the authors is a classical constant return to scale function taking the following form:

$$y_i(t) = A_i\,(t)K_i^{\propto}(t)L_i^{1-\propto}(t), 0 <\propto< 1 \qquad \text{[Eq.7]}$$

Where $y_i(t), A_i\,(t), K_i(t)\ and\ L_i(t)$ represent respectively the output, aggregated level of technology, capital and labor, in region i and time t while $\propto$ is a parameter representing the capital elasticity.

After rearrangement we obtain the Spatial Durbin Model of the augmented Solow function expressed by the following equation:

$$G_r = \beta_0 + \beta_i X_i + WX_i + \rho W G_r + \varepsilon \qquad \text{[Eq.8]}$$

Where, G_r X_i , WX_i and ρWG_r represent respectively: the dependent variable, the selected independent variables (GDP/Cap1996, $CapStock$, NGD, ResEndow, CO_2, $CO2sq$, NatDisaster), the spatially lagged independent variables (preceded by the weighted matrix W, and the spatially dependent variable ($\rho W G_r$)[20].

III.2.3. The Selection of The Spatial Model and The Regressions Results

We run different maximum likelihood spatial regression models. The maximum likelihood is supposed to adjust the OLS bias and inconsistency induced by endogeneity problems when we run a spatial lag model. However, in the case of spatial error model regression, OLS is unbiased but inefficient due to the error term's spatial autocorrelation. Contrary to the SEM, the SAR, SAC and SDM models allow spillovers to be detected and to manifest. This is one among the reasons to better emphasize on the SAR and SDM models.

[20] Formally this is can be expressed by the following equation:
$\mathrm{G_r} = \beta_0 + \beta_1\ \mathrm{GDP/Cap1996} + \beta_2\mathrm{CapStock} + \beta_3\mathrm{NGD} + \beta_4\mathrm{ResEndow} + \beta_5\mathrm{CO2} + \beta_6\mathrm{CO2sq} + \beta_7\mathrm{NatDisaster} + \beta_8\mathrm{GOV} + \theta_1\mathrm{GDP/Cap1996} + \theta_2\mathrm{WCapStock} + \theta_3\mathrm{WNGD} + \theta_4\mathrm{WResEndow} + \theta_5\mathrm{WCO2} + \theta_6\mathrm{WCO2sq} + +\theta_7\mathrm{WNatDisaster} + \theta_8\mathrm{WGOV} + \rho\mathrm{WG_r} + \varepsilon$

Given the existence of a plethora of spatial models we run some tests to detect the spatial model with the best goodness-of-fit. As proposed by Belotti et al. (2017), we start by regressing the most general specification of our model, namely the SDM. In the second step, to test the spatial autoregressive model (SAR) specification we check econometrically whether the parameters are $\rho \neq 0$ and $\theta = 0$. Then, we test the specification of a spatial error model (SEM) by examining if $\theta = -\beta\rho$. Next, we use the Akaike information criterion (AIC) to evaluate the specification of a SDM with autoregressive disturbance model (SAC)[21]. Based on the estimation tests, we found that the best model is the dynamic SDM (DSDM). Indeed, the tests of specification between SDM and SAR and between SDM and SEM reject the null hypothesis at the significance level of 1% favoring SDM in both cases. Following, we compare the information criteria of SAC and SDM, SDM has lower values of AIC[22]. Henceforward, we find that the best model is the dynamic SDM (DSDM) is the model with the best goodness-of-fit. Furthermore, the potential bias caused by omitted variables may be corrected using this model, (LeSage and Pace, 2010).

[21] Since the SAC and SDM are non-nested, we can rely on information criteria to test whether the most fitting model is the SDM or the SAC model. In this empirical work, the Akaike's information criterion favors the SDM compared to the SAC model (see Table 6 in the appendix).
[22] For more details see Table 5 and Table 6 in the Appendix.

Table 3: SAR Estimation of the Impact of Climate Change on Growth Convergence in MENA18 (*W*: Contiguity and Inverse Distance)
Period:1996-2019, (Blue color: spatial indicators, LR: Long-run spillovers)

	Model 1: Contiguity Weighted Matrix						Model 2: Inverse Distance Weighted Matrix					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Main	Spatial	Variance	LR_Direct	LR_Indirect	LR_Total	Main	Spatial	Variance	LR_Direct	LR_Indirect	LR_Total
GDP/Cap1996	-0.999***			-1.044***	-0.437***	-1.481***	-1.029***			-1.039***	-0.562**	-1.601***
	(-5.613)			(-5.398)	(-3.751)	(-5.057)	(-5.729)			(-5.519)	(-2.144)	(-4.109)
CapStock	-0.0805			-0.0869*	-0.0358	-0.123*	-0.130**			-0.135**	-0.0724*	-0.207**
	(-1.547)			(-1.650)	(-1.614)	(-1.658)	(-2.377)			(-2.506)	(-1.716)	(-2.360)
NGD	0.282			0.317*	0.131	0.449*	0.271			0.297	0.152	0.449
	(1.529)			(1.713)	(1.630)	(1.708)	(1.366)			(1.543)	(1.246)	(1.509)
ResEndow	0.194***			0.203***	0.0844***	0.287***	0.189***			0.191***	0.101**	0.292***
	(5.281)			(5.486)	(4.167)	(5.389)	(4.780)			(4.969)	(2.404)	(4.517)
CO2	2.348***			2.459***	1.028***	3.487***	2.079***			2.104***	1.111**	3.215***
	(4.139)			(4.307)	(3.441)	(4.186)	(3.425)			(3.578)	(2.159)	(3.375)
CO2sq	-0.0896***			-0.0936***	-0.0391***	-0.133***	-0.0715**			-0.0720**	-0.0376*	-0.110**
	(-3.334)			(-3.407)	(-2.911)	(-3.341)	(-2.483)			(-2.541)	(-1.872)	(-2.499)
NatDisaster	-0.0361			-0.0376	-0.0156	-0.0532	-0.0540**			-0.0545*	-0.0293	-0.0838*
	(-1.454)			(-1.391)	(-1.351)	(-1.391)	(-2.042)			(-1.958)	(-1.469)	(-1.870)
GOV	0.786***			0.815***	0.343***	1.158***	0.695***			0.695***	0.380*	1.076***
	(5.607)			(5.576)	(3.516)	(4.973)	(4.705)			(4.704)	(1.934)	(3.464)
Rho		0.326***						0.346***				
		(7.879)						(3.889)				
lgt_theta			-1.843***						-1.765***			
			(-8.353)						(-7.804)			
sigma2_e			0.265***						0.302***			
			(14.08)						(14.24)			
Constant	-3.397						-1.748					
	(-0.999)						(-0.489)					
Observations	432											
R-squared	0.258											
Number of id	18											

z-statistics in parentheses
**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table 4: The Effect of Climate Change on Growth Convergence in MENA18: A Dynamic SDM Model Estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Main	*Wx*	Spatial	Variance	SR_Direct	SR_Indirect	SR_Total	LR_Direct	LR_Indirect	LR_Total
L.Gr	0.881***									
	(44.91)									
L.WGr	-0.00123									
	(-0.00702)									
GDP/Cap1996	0	0			0.00341	-0.00196	0.00146	2.802	-2.799	0.00289
	(omitted)	(omitted)			(0.111)	(-0.0883)	(0.0520)	(0.0502)	(-0.0502)	(0.0487)
CapStock	-0.0195	0.365***			-0.0485	0.253***	0.205***	-9.809	10.24	0.431***
	(-0.643)	(7.483)			(-1.478)	(5.819)	(5.592)	(-0.0382)	(0.0399)	(3.833)
NGD	0.0528	0.597***			0.0106	0.365***	0.375***	-15.98	16.77	0.786***
	(0.653)	(3.679)			(0.138)	(3.587)	(3.150)	(-0.0360)	(0.0378)	(2.814)
ResEndow	0.0362**	-0.0357			0.0408**	-0.0391*	0.00164	1.936	-1.933	0.00311
	(1.978)	(-1.163)			(2.210)	(-1.802)	(0.0768)	(0.0367)	(-0.0366)	(0.0683)
CO2	5.330***	8.848***			4.849***	3.435***	8.284***	13.98	3.435	17.41***
	(15.29)	(17.46)			(14.43)	(4.583)	(10.05)	(0.0198)	(0.00487)	(4.941)
CO2sq	-0.256***	-0.461***			-0.230***	-0.189***	-0.419***	0.0925	-0.973	-0.881***
	(-14.42)	(-18.02)			(-13.94)	(-5.038)	(-10.11)	(0.00176)	(-0.0185)	(-4.959)
Natdisaster	0.00587	0.0104			0.00606	0.00474	0.0108	0.0669	-0.0443	0.0226
	(0.580)	(0.805)			(0.591)	(0.469)	(1.095)	(0.0335)	(-0.0222)	(1.046)
GOV	0.753***	1.322***			0.682***	0.533***	1.215***	-1.660	4.214	2.554***
	(9.964)	(11.87)			(9.238)	(4.312)	(8.801)	(-0.0116)	(0.0295)	(4.711)
rho			0.731***							
			(4.646)							
sigma2_e				0.0371***						
				(15.20)						
Observations	414									
R-squared	0.172									
Number of id	18									

Notes: Blue color: Spatial Indicators *L.Gr*: Tme-Lagged Dependent Variable, *L.WGr*: Spatial-Time-Lagged Dependent; *Wx*: Spatial lagged Independent Variable, LR: Long-Run spillovers, SR: Short-Run spillovers, z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

According to the econometric estimations the coefficient of the initial GDP per capita is negative and significant at statistical level of 1%. This is true for all the models that have been run and confirm the growth convergence hypothesis. In addition, the regression results show that the variable NGD (the sum of population growth, technology growth rate and capital depreciation rate) contribute positively and significantly (at the statistical level of 1%) to the growth convergence. This has not been confirmed by the SAR model (either by the SAR with contiguity weighted matrix or the inverse distance matrix). However, the spatial dynamic results show that this variable contributes strongly (at the statistical conventional level of 1%) and positively to the MENA growth convergence process. At the same significance level, the dynamic SDM results indicate that the physical capital accumulation favors the growth divergence (for the SAR this variable is not significant). The resources endowment and governance support the convergence process, and this is true for both the SAR and the dynamic SDM model. The environmental factors namely the air pollution impact significantly the MENA growth convergence path and this has been evidenced by the SAR as well as the DSDM regression results.

The indicator of natural disasters measured by the drought, extreme temperature, flood, landslide, storm and wildfire incidence, is negatively significant at 5% in the SAR (but insignificant in the DSDM). Hence, according to the SAR model the natural disasters when they happen increase the MENA countries' disparities. This might be explained by the diverse chocs' intensity and the specific capacity of each country to absorb and manage these chocs. This could create and/or amplify the gaps across the MENA region. For CO_2 emissions as a proxy of air pollution we find a nonlinear association inverted U-shaped relationship) between the degradation of air quality and economic growth. Indeed, the SAR and the DSDM regression results indicate that the CO_2 improves the growth convergence (as shown by the positive and significant CO_2 coefficient at the level of 1%) and this effect turns negative (still at 1%) when we consider the square of *CO2* emission. In fact, the relationship between economic growth is ambiguous and a two-sided kind involving multiple feedback and loop effects. The rise (decrease) of one drags the other. This has been underlined by several previous empirical studies who recognized an array of links which encompass N-shaped, U-shaped, and inverted U-shaped curves. One of the plausible reasons cited is the large diversity of covariates and tools that has been used in the econometric regressions.

As spatial regression models exploit the complex dependence structure between units (countries in this study), changes in an explanatory variable for a particular country will have an impact on that country directly as well as perhaps on all other countries. This suggests the presence of total marginal impacts as well as direct (or feedback effect) and indirect effects (spillovers). In other words, the direct effect records the impact on the dependent variable of a particular country from changes in the economic growth convergence covariates of that country, while the indirect effect shows the impact of changing growth convergence covariate of a particular country and how this affects growth convergence in surrounding countries. For the variable highlighting the spatial dependence namely (the Rho coefficient, Wx (the weighted explanatory variables or the effect of neighbors' covariates), the regression results of the SAR and DSDM pinpoint a positive feedback effect of economic growth in the MENA region which help the MENA economies to reach a growth steady state. The spatial durbin model (SDM) which nests the SAR contains (in addition to the spatially lagged dependent variable ($\rho \mathrm{W} G_r$ or Rho) the spatial lags of the explanatory variables (W_x). The novelty of the DSDM compared to the SAR and the other spatial models is its aptitude to disaggregate the marginal effects into direct and indirect effects. The DSM results highlight the presence of short-term positive spillovers in the MENA region through the physical capital accumulation (CapStock), the *NGD* variable, the CO_2 emission and the proxy of governance (*GOV*). However, the variables *CO2sq* and *ResEndow* specify the existence of short-term negative spillovers. Meanwhile, the DSDM did not record any long-term significant spillovers.

IV. Conclusion

The purpose of this study is to examine the growth convergence by adopting a spatial paradigm. Empirical results revealed that environment aspects matter for the convergence process. This process seems to be shaped directly via the idiosyncratic characteristic of a country as well as neighbor's feedback loop effect and substantive spillovers (both positive and negative). This is revealed by the spatially lagged variables ($\rho \mathrm{W} G_r$ and W_x). Also, the environmental aftermath is significant and it manifests directly and indirectly via different channels stated by the spatial mechanisms. These spillovers within the MENA region are global in nature. In other words, they don't concern only the neighbors of immediate proximity (neighbors of first order or contiguous neighbors) but spread to neighbors with higher order, and perhaps reach the whole region. Accordingly, policymakers should adopt a proactive approach to maximize the positive spillovers and minimize the negative ones. Since the geographic scope of spillovers extend to the whole region, the environment policy as well the growth process should also be treated in global and regional perspective. Cooperation and commitment to the protection of the environment is a win-win strategy and is the key word to boost an eco-friendly growth process.

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Table 5: Specification tests for the Spatial model selection

SAR Test	SEM Test
(1) [Wx]GDP/Cap1996 - [Wx]CapStock = 0	(1) [Wx]ln_cn = -[Spatial]rho*[Main]CapStock
(2) [Wx]GDP/Cap1996 - [Wx]NGD = 0	(2) [Wx]lnNGD = -[Spatial]rho*[Main]NGD
(3) [Wx]GDP/Cap1996 - [Wx]ResEndow = 0	(3) [Wx]ln_ResEndow = -[Spatial]rho*[Main]ResEndow
(4) [Wx]GDP/Cap1996 - [Wx] CO_2 = 0	(4) [Wx]ln_co2kt = -[Spatial]rho*[Main]CO_2
(5) [Wx]GDP/Cap1996 - [Wx]CO2sq = 0	(5) [Wx]ln_co2ktsq = -[Spatial]rho*[Main]CO2sq
(6) [Wx]GDP/Cap1996 - [Wx] Nat_Disaster = 0	(6) [Wx]disaster_total = -[Spatial]rho*[Main]Nat_Disaster
(7) [Wx]GDP/Cap1996 - [Wx] GOV = 0	(7) [Wx]gov = -[Spatial]rho*[Main] GOV
(8) [Wx]GDP/Cap1996 = 0	
Chi2(8) = 141.03 Prob > chi2 = 0.0000	Chi2(7) = 136.29 Prob > chi2 = 0.0000

Table 6: Akaike's information criterion

Model	Obs	ll(model)	df	AIC
SDM	432	-329.0055	20	7085.797
SAC	432	-340.9169	10	7094.223