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SPATIAL CONVERGENCE OF PER CAPITA CO_2 EMISSIONS AMONG MENA COUNTRIES

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Abstract

This paper investigates the spatial convergence hypothesis for per capita CO_2 emissions among Middle East and North Africa (MENA) countries during 1970–2010. Spatial econometric techniques bring us a powerful tool to model spatial spillover effects of pollutions. Also, according to the empirical studies, ignoring spatial autocorrelation and spatial heterogeneity will lead to biased statistical inference. By applying cross-section modeling and spatial dynamic panel data techniques, our results show: (1) per capita CO_2 emissions among MENA countries have weak absolute convergence, (2) considering spatial dimension increases conditional convergence speed, but not affects the steady state level of emissions, (3) in long-term steady state, level of per capita CO_2 emissions is determined by per capita GDP and degree of urbanization. The implications of these results for sustainable regional development policies are discussed.

Keywords: MENA, carbon dioxide emissions, convergence, spillover, spatial panel econometrics

JEL classifications: C23, O47, Q53, P48

1. Introduction

According to the new report of World Bank, Middle East and North Africa region (MENA)among other countries are vulnerable to the threats induced by Global Warming; threats such as food (and potable water) security and sea level rise. Therefore ,it is crucial to cut down the CO_2 emissions in order to reduce atmospheric concentration of greenhouse gases (GHGs) in MENA region. Coupled with, under the principles of international law, these states have neither right to use, nor permission to exploit their territories to damage the environment of other states. Spatial econometrics provides a powerful method to assess pollution-caused influence of neighboring countries on another country's pollution level. Spatial spillover effects play a significant role in assessing the determinants of environmental quality. Some environmental phenomena are inherently spatial; flowing polluted water, atmospheric pollution and the spread of epidemic phenomena causing spatial autocorrelation in Analysis of the spatial econometrics. Moreover, countries can interact strongly with each other through channels such as trade, technological diffusion, capital inflows, common politics, economic and environmental policies, which these are undergoing spatial heterogeneity of environmental variables. In the common econometric when it is said that two variables X and Y are directly correlated together, this means that high values of X are correlated with those of Y, and vice versa; also the average values of X have tendency towards the average values of Y. But, in the spatial econometric we are dealing with a variable Y, and if the spatial correlation becomes positive, meaning that the regions which own more Y are surrounded by the ones with more values of Y, as well as the regions with average Y have been surrounded through the regions with average Y. Conversely, the regions with less Y have been encompassed by the regions with less Y (Griffith and Paelinck, 2011, p. 26).According to the *Tobler's first law of geography that "Everything is related to everything else, but near things are more related than distant things"* (Tobler, 1970), when we apply the data with local component in the research, two issues are emerged, one relates to spatial dependency between the observations and the latter for the spatial heterogeneity in relationships intended to be modeling. This subject took later the attention of many researchers in the social sciences, economics, geography, and biological sciences. Calculating the inter-unit (inter-regional) interactions in economic sciences is achieved through the creation of spatial weight matrices and considering them in the classic econometric models.

On the other hand, the most empirical studies about convergence include two conclusions in topic, one of these conclusions is microeconomics and marketing perspective and another is growth and macroeconomics. In the first approach, convergence appears in the form of purchasing power parity (PPP) and law of one price (LOOP) generating from market performance. In the second approach, convergence is presented in the form of growth models and marginal diminishing return law as well as learning effects. According to the law of one price, if there are no costs of transportation and trading obstacles, common goods in calculating with one unit joint currency ought to have common price in diverse countries or in provinces of one country. From theoretical standpoint, profit searching and arbitrage operation equalize the price of common goods in different countries. Convergence in the literature of growth economy results from the concepts of neoclassical growth model. Neoclassical growth theory predicts a long-run tendency toward convergence of output and income per capita across the world economy, because: (a) Technology is a globally public good, thereby all countries should experience the same long-run rates of technical progress, (b) Diminishing returns imply that investment in rich countries should slow down as poor countries continue to accumulate, (c) International mobility of capital and labor, combined with commodity trade should reinforce the market forces driving convergence toward common worldwide wage rates and profit rates, as well as common living standards (Bertram, 2004: 343-344). In empirical studies, convergence concept becomes applicable for economical variants of per capita CO_2 emissions, Carbon Dioxide intensity, real per capita GDP, total factor productivity (TFP), consumer price index (CPI), inflation, retail price of energy sources and energy intensity (or energy productivity). Making decisions about establishing or breakup regional blocs, market segmentation and fair environmental policies are important applications of convergence concept for governmental decision-makers and international organizations (Hamidi Razi et al., 2014). In this vein, there are rich empirical literatures about testing convergence hypothesis of per capita CO_2 emissions (Jobert et al. 2010; Criado and Grether, 2011; Huang and Meng, 2013; Zhu et al. 2014; Pettersson et al. 2014; Hamidi Razi and Feshari, 2015; Oliveira and Mores, 2015; Timilsina, 2016; Lopez et al. 2016). In most of these studies the convergence of per capita CO_2 emissions depends on the methodology and group of countries. In addition, the empirical research conducted on the convergence of per capita CO_2emissions exhibits some evidence of convergence between developed (OECD) countries and among regional specimens, while at the global level there are pieces of evidence associated with divergence.

The MENA is an economically specific region that includes both the oil-rich economies in the Gulf and countries that are resource-scarce in relation to population, such as Egypt, Morocco, and Yemen. The region's economic fortunes over much of the past quarter century have been heavily influenced by two factors – the price of oil and the legacy of economic policies and structures – that had emphasized a leading role for the state (World Bank, 2015). Despite the large differences, there are also some similarities between the MENA countries; the MENA region has an arid-to-semiarid climate. The region is considered one of the most arid area in the world and a majority of countries in the region are in water-stressed or water scarce situation. The water scarcity index is generally larger than 1, which means that the water use is larger than the minimum water recharge levels. The major environmental challenges that the region faces are water scarcity, land degradation (incl. desertification), coastal and marine environment degradation, air pollution and climate change (Sida, 2010).Meanwhile climate change and global warming are particularly addressed. There are considerable evidence that global warming (and its consequences)poses one of the causes of the conflict in Syria (Gleick, 2014). With regard to the political tensions and acute disputes (e.g., violence) intra- and inter-countries in the region, regional cooperation in terms of climate change and regional sustainable development can be more effective. In this regard, studying of the convergence hypothesis of per capital carbon dioxide (CO_2) emissions and its long run dynamics in MENA can be effective. The aim of this paper is testing of the spatial convergence hypothesis of per capita CO_2 emissions among MENA countries during 1970-2010. To this end we test convergence hypothesis of per capita CO_2 emissions within the framework of spatial dynamic panel data. The main contribution of this study is in the use of dynamic spatial panel econometric techniques to estimate coefficients and thus to avoid the Omitted Variable Bias (OVB).

This paper is organized as follows: section 2 reviews theoretical framework and literature on convergence hypothesis. Methodology and model setup are explained in section 3. Section 4 contains descriptive statistics of per capita CO_2 emissions and its spatial statistics. Empirical results are discussed in section 5. Some concluding remarks and political suggestions are provided in the end of the paper.

2. Literature review

In the literature on economic growth, principles of growth models were founded first by Ramsey in 1928 and then developed by Solow and Swan in 1956. Exogenous growth model which has been knowing as a neoclassical growth model is now considered the basis for growth models. In neoclassical growth models with diminishing returns such as Solow and Swan model (1956) and Cass–Koopmans model (1965), the growth rate of a country's per capita income has inversely related to the initial level of per capita income. Therefore, without external shocks, per capita income of poor and rich countries will converge together and it can be expected that other variables associated with per capita income comply with this rule. On the other hand, if we assume several economies or areas with the same parameters of growth model such as saving rate, level of technology, depreciation rate and population growth rate but with different level of capital per unit of effective labor, in long term, these economies will get a same capital per unit of effective labor, per capita output; hence this convergence is called non-conditional or absolute beta convergence (β). However, these economies have a same production function but with the different population growth rate, depreciation rate, saving rate and level of capital per unit of effective labor; convergence occurred here is called conditional convergence beta (β). Here all levels of variables such as capital per unit of effective labor, per capita output will grow with the same rate. The mentioned beta convergence calculates the speed with which output of a given economy (region) converges over time to its steady-state value. Added to that, there is another type of convergence which represents a reduction of inequality among regions over time; this convergence is called sigma convergence (σ). In endogenous growth models, the phenomenon of convergence can be viewed as a technological spillover effect. The convergence of real per capita output among several economies or regions plays a determining role in regional integration and its sustainability (Heidari and Hamidi, 2012). Among various tests of convergence hypothesis (such as σ-convergence, β-convergence, stochastic convergence, and distribution dynamics) only the β-convergence can provide comprehensive information with the future distribution of per capita CO_2 emissions.

Specifically, the information includes the equilibrium emission level, the speed of CO_2 emissions returning to that equilibrium level and the relationship between per capita CO_2 emissions and other factors (control variables) like spatial spillover of pollution. Therefore, this paper would adopt the β-convergence test. “β-convergence seeks to determine whether a “catch-up” process happens, or not. The “catch-up” process means that, countries with initially lower levels of CO_2 emission per capita would experience higher growth in per capita CO_2 emissions, and eventually both the high- emission and low-emission countries just converge to the same emission level” (Li and Lin, 2013, p. 359). In this regard, Li and Lin (2013) investigated the global convergence in per capita CO_2 emissions over the period 1971–2008. Their results manifest an absolute convergence within subsamples grouped by income level, while provide little evidence of absolute convergence in the full sample containing 110 countries. Furthermore, they take the GDP per capita into consideration within the conditional convergence framework. Interestingly, the result reveals that, within different income groups, the relationships between GDP per capita and per capita CO_2 emission growth are different. Specially, per capita CO_2 emissions of high-income countries would maintain at the “steady state” as income rises. Jobert et al. (2010) investigated CO_2 emissions convergence hypothesis across 22 European countries over the 1971 to 2006 period. To this end, they employed the Bayesian shrinkage estimation method. The main results are followed as: first, the hypothesis of absolute convergence in per capita CO_2 emissions is supported and a slight upward convergence is observed; second, the fact that countries differ considerably in both their speed of convergence and volatility in emissions makes it possible to identify different groups of countries; third, the results connected with convergence do not vary much once the share of industry in GDP is accounted for in a conditional convergence analysis. However, a decreasing share of industry in GDP seems to contribute to a decline in per capita emissions.

Some studies have used (panel or time series) unit root test for searching convergence. Christidou et al. (2013) examined the Stationarity of carbon dioxide (CO_2) emissions per capita for a set of 36 countries covering the period 1870–2006. By applying unit root and stationarity tests that allow for the mean reverting process to be nonlinear and takencross sectional dependence into account, they confirmed convergence. As well as, Romero-Ávila (2008)inspected the existence of stochastic and deterministic convergence of carbon dioxide (CO_2) emissions in 23 countries over the period 1960–2002. By applying unit root test which assumes a highly flexible trend function by incorporating an unknown number of structural breaks, he confirmed stochastic and deterministic convergences in per capita CO2 emissions.

Empirical studies, besides, are being undertaken using spatial framework to investigate determinants of emissions. Kang et al. (2016) by using spatial STIRPAT model (stochastic impacts by regression on population, affluence and technology) studied the impact of energy-related factors on CO_2 emissions in China. Their results indicate that there exist obvious spatial correlation and spatial agglomeration features in spatial distribution of per capita CO_2 emissions china. Together with, spatial economic model is demonstrated to offer a greater explanatory power than the traditional non-spatial panel model. Moreover, GDP per capita, energy intensity, industrial structure and urbanization have positive and significant effects on CO_2 emissions, while the coefficient of population is not significant. Burentt et al. (2013) examined how economic activity affects U.S. state-level carbon dioxide emissions during 2001–2009 by using spatial econometric techniques. Their estimation results and rigorous diagnostic analysis suggest that: (1) economic distance plays a role in intra- and inter-state CO_2 emissions; and (2) there are statistically significant, positive economic spillovers and negative price spillovers to state-level emissions. Zhao et al. (2014) investigated the influential factors of energy-related, carbon dioxide emission intensity among a panel of 30 provinces in China covering the period 1991–2010. Their results suggest (1) emission intensities are negatively affected by per-capita, province-level GDP and population density; (2)

emission intensities are positively impressed by the structure of energy consumption and the transportation sector; and, (3) energy prices have no effect on emission intensities. In the same way, Dong and Liang (2014) confirmed the existence of cluster effect for the regional air pollutants and CO_2 emissions among China's 30 provinces. Building on their results, while emission amount increases from western regions to eastern ones, the emission per GDP takes an inverse trend.

Relying on the brief overview provided above, it is essential to take into account spatial dependence in testing of per capita CO_2 emissions convergence. The main contribution of this study refers to the use of dynamic spatial panel econometric techniques to estimate coefficients and thus to avoid the Omitted Variable Bias (OVB).

3. Variables and model setting

As noted there are three main approaches to test the convergence hypothesis in econometrics: sigma convergence, beta convergence and stochastic convergence. In this paper, we applied the concept of beta convergence. Technically beta convergence hypothesis is tested within the framework of cross-section data and dynamic panel data. Based on Li and Lin (2013), the absolute beta convergence is modeled as:

$$\frac{1}{T}\left[\ln\left(\frac{E_{i,t+T}}{E_{i,t}}\right)\right] = \alpha - \frac{1}{T}\left(1 - e^{-\beta T}\right)\ln E_{i,t} + \varepsilon_{i,t} \qquad (1)$$

Where i, means the *i*th economic entity; t denotes the time; T means the length of the period; $E_{i,t}$ represents the initial level of CO_2 emissions per capita; $E_{i,t+T}$ denotes the emission level at the end of the period; β is the convergence speed, a significant and positive β implies the absolute convergence in the tested region during period T; $\varepsilon_{i,t}$ is the stochastic error term. Because Model (1) only selects data of two time points, the initial and the final periods of the empirical study, the information between the two points is left out. Therefore, in order to make full use of the data information we construct Model (1) into a dynamic model:

$$\left[\ln\left(\frac{E_{i,t}}{E_{i,t-1}}\right)\right] = \alpha - \left(1 - e^{-\beta}\right)\ln E_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

According to Model (2), if β is significant and positive, the distribution of per capita CO_2 emissions can be assumed to follow the process as;

$$\ln E_{i,t} = \alpha + e^{-\beta}\ln E_{i,t-1} + \varepsilon_{i,t} \qquad (3)$$

Convergence empirical studies take non-overlapping five-year averages of all variables to smooth out short-term fluctuations and reduce the potential bias arising from having a large number of time observations in dynamic panel estimation (Islam, 2003). Therefore, we can rewrite Equation 3 as follows:

$$\ln \mathrm{E}_{\mathrm{i,t}} = \alpha + \mathrm{e}^{-\beta \mathrm{T}} \ln \mathrm{E}_{\mathrm{i,t-1}} + \varepsilon_{\mathrm{i,t}} \tag{4}$$

Where T is the length of each sub-period. Different from absolute convergence method, conditional convergence method accounts for the impacts of individual difference on per capita CO_2 emissions. Thus, it introduces control variables like per capita income, industry structure, and urbanization level into model (4). The existence of absolute convergence among countries also indicates that conditional convergence is present. The conditional convergence model is:

$$\ln \mathrm{E}_{\mathrm{i,t}} = \alpha + \mathrm{e}^{-\beta \mathrm{T}} \ln \mathrm{E}_{\mathrm{i,t-1}} + \vartheta \mathrm{X}_{\mathrm{i,t}} + \varepsilon_{\mathrm{i,t}} \tag{5}$$

Where X_{it} denotes the vector of control variables. One of the most recently used conditional variables is spatial spillover of pollution. General specification for the spatial panel data models is given as:

$$\begin{aligned} \mathrm{y}_{\mathrm{it}} &= \tau \mathrm{y}_{\mathrm{it-1}} + \rho \mathrm{W} \mathrm{y}_{\mathrm{it}} + \mathrm{X}_{\mathrm{it}} \beta + \theta \mathrm{D} \mathrm{X}_{\mathrm{it}} + \mathrm{a}_{\mathrm{i}} + \gamma_{\mathrm{t}} + \mathrm{v}_{\mathrm{it}} \\ \mathrm{v}_{\mathrm{it}} &= \lambda \mathrm{M} \mathrm{v}_{\mathrm{it}} + \mathrm{u}_{\mathrm{it}} \end{aligned} \tag{6}$$

Where u_{it} is a normally distributed error term, W is the spatial matrix for the autoregressive component, D is the spatial matrix for the spatially lagged of independent variables, M the spatial matrix for the idiosyncratic error component. a_i is the individual fixed or random effect and γ_t is the time effect. Depending on conditions the following nested models are:

- The Spatial Autoregressive Model (SAR) with lagged dependent variable (θ=λ=0)
- The Spatial Durbin Model (SDM) with lagged dependent variable (λ=0)
- The Spatial Autocorrelation (SAC) Model (θ=τ=0)
- The Spatial Error Model (SEM) (ρ=θ=τ=0)
- The Generalized Spatial Panel Random Effects (GSPRE) Model (ρ=θ=τ=0)

Where the standard SAR and SDM models are obtained by setting τ=0. The spatial panel Durbin model occupies an interesting position in spatial panel Econometrics. Spatial Durbin model allows simultaneously spatial interactions for a dependent variable as well as explanatory variables. In other words, the main feature of SDM compared with other spatial models (such as; SAR and SEM) is simultaneously entering of spatial lag of dependent variable and spatial lags of explanatory variables as new explanatory variables in the model (Elhorst, 2010; Belotti et al.2013). In this paper, we merge spatial models with convergence hypothesis. For this purpose, we test conditional β-convergence hypothesis with spatial lag control variable (in other words "spatial convergence hypothesis"). Therefore, with considering spatial dimension and control variables, we stipulated following two dynamic SAR and SDM models[1]:

[1]. Only two SAR and SDM models are consistent with dynamic panels

$$\ln E_{i,t} = \gamma \ln E_{i,t-1} + \rho \sum_{j=1}^{n} W_{ij} \ln E_{j,t} + \varphi_1 \ln Y_{it} + \varphi_2 \ln U_{it} + \delta_i + \mu_t + \varepsilon_{it} \qquad (7)$$

$$\ln E_{i,t} = \gamma \ln E_{i,t-1} + \rho \sum_{j=1}^{n} W_{ij} \ln E_{j,t} + \theta \sum_{j=1}^{n} D_{ij} \ln Y_j + \varphi_1 \ln Y_{it} + \varphi_2 \ln U_{it} + \delta_i + \mu_t + \varepsilon_{it} \qquad (8)$$

Where δ_i and μ_t are country and time (year) fixed effects, respectively.$\ln Y_{it}$is natural logarithm of real per capita GDP and $\ln U_{it}$ is natural logarithm degree of urbanization[2]. Note that, in this research spatial weight matrices (i.e. W& D) are the same. The spatial weight matrix reflects the geographic relationship among different regions (countries). There are two categories of spatial weight matrix: the binary contiguity matrix and the inverse-distance function matrix. In the binary contiguity matrix, if the two regions i and j are neighbors, then the matrix elements $w_{ij}=1$; if the two regions are non-neighbors, then $w_{ij}=0$. In the distance function matrix, the element is no longer binary but a distant function $w_{ij}=f(d_{ij})$. The distance d_{ij} refers to the distance between the geometric centers (centroids) or capitals of region i and region j. In inverse-distance based spatial weight matrix, the elements of the spatial weight matrix are defined as follows:

$$w_{ij} = \begin{cases} 0, & \text{if } i = j \\ 1/d_{ij}, & \text{if } i \neq j \end{cases} \qquad (9)$$

In which;

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (10)$$

Where x and y are longitude and latitude, respectively. In order to normalize the outside influence upon each region, the spatial weight matrix must be row-standardized. In current research, empirical model has been estimated by using *Stata / SE 12.0*. Also, in order to determine the latitude and longitude coordinates for inverse-distance spatial weighted matrix and contiguity matrix, Geographic Information System (GIS) has been used.

4. Preliminary data analysis and spatial statistics

4.1 Data sources and data processing

This paper uses the panel data of MENA's 27countries from 1970 to 2010. There is not a commonly accepted definition of the MENA area. The definitions of the League of Arab States

[2]. Urban population (% of total)

(LAS) and the Economic and Social Commission for Western Asia of the United Nations (UN-ESCWA) coincide and include 22 member states. The definition of the World Bank excludes the Comoros Islands, Mauritania, Somalia, and Sudan, but includes Iran, Israel and Malta, for a total of 21 countries. Other authors refer to more distinctly operational definitions. For instance, Nugent and Pesaran (2007) follow an enlarged definition, including 25 countries and excluding the Comoros Islands and Malta. The definition regarded here is operationally extended to include more observations (27 countries are listed in table 1). The data of per capita CO_2 emissions are derived from World Bank online database. Table 1 represents the most important individual descriptive statistics of per capita CO2 emissions for each country. Qatar possesses a high average (mean) of per capita CO_2 emissions (53.59 metric tons). The United Arab Emirates (UAE) has maximum of standard deviation of per capita CO_2 emissions.

Table 1. Individual Descriptive Statistics of per capita CO_2 emissions (in metric tons)

Countries	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Obs(N)
ALGERIA	2.79	3.47	1.03	0.6	-1.17	3.84	10.51	0.01	41
BAHRAIN	23.63	24.63	12.17	2.87	-3.08	11.32	183.01	0.00	41
COMOROS	0.15	0.2	0.07	0.03	-0.48	3.26	1.7	0.43	41
DJIBOUTI	0.74	1.08	0.52	0.15	0.58	2.21	3.39	0.18	41
EGYPT	1.5	2.62	0.6	0.61	0.35	2.15	2.09	0.35	41
ERITREA	0.13	0.17	0.05	0.04	-0.42	1.75	1.6	0.45	17
IRAN	4.7	7.85	2.79	1.48	0.82	2.52	4.98	0.08	41
IRAQ	3.24	4.29	2.12	0.57	0.02	2.38	0.66	0.72	41
ISRAEL	7.58	10.86	5.29	1.9	0.2	1.39	4.73	0.09	41
JORDAN	2.8	3.89	1.03	0.87	-0.9	2.34	6.25	0.04	41
KUWAIT	22.7	34.56	5.1	8.16	-0.19	1.73	3.02	0.22	41
LEBANON	3.48	5.26	1.7	1.04	0.19	1.66	3.32	0.19	41
LIBYA	8.78	15.58	3.84	1.76	0.5	8.49	53.12	0.00	41
MALTA	4.86	7.32	2.18	1.67	-0.4	1.55	4.69	0.10	41
MAURITANIA	0.71	1.76	0.21	0.44	1.08	2.6	8.21	0.02	41
MOROCCO	1.01	1.64	0.46	0.34	0.33	2.15	1.97	0.37	41
OMAN	8.04	20.41	0.32	4.28	0.96	3.73	7.25	0.03	41
PALESTINE	0.47	0.83	0.15	0.2	-0.07	1.94	0.66	0.72	14
QATAR	53.59	87.72	24.71	15.19	-0.09	2.54	0.41	0.81	41
SAUDI_ARABIA	14.1	17.67	7.8	2.22	-0.54	3.11	2.03	0.36	41
SOMALIA	0.08	0.17	0	0.05	0.16	2.28	1.06	0.59	41
SUDAN	0.22	0.36	0.1	0.07	0.62	2.21	3.7	0.16	41
SYRIA	2.64	3.48	1.04	0.71	-1.04	2.81	7.39	0.02	41
TUNISIA	1.68	2.45	0.73	0.48	-0.29	2.19	1.71	0.43	41
TURKEY	2.61	4.13	1.23	0.83	0.17	1.92	2.19	0.34	41
UAE	37.49	80.06	15.96	16.75	1.25	3.47	11.05	0.00	41
YEMEN	0.73	1.1	0.24	0.25	-0.54	1.94	3.9	0.14	41

4.2 Spatial diagnostic tests

To recognize spatial interdependence, global and local spatial diagnostic tests are used. These tests are: Moran's I, Geary's C and Getis and Ord's G (Table 2). Null hypothesis in these tests is zero spatial autocorrelation or in other words spatial independence.

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (E_i - \overline{E})(E_j - \overline{E})}{\sum_i (E_i - \overline{E})^2} \tag{11}$$

$$C = \frac{(N-1) \sum_i \sum_j w_{ij} \left(E_i - E_j\right)^2}{2W \sum_i (E_i - \overline{E})^2} \tag{12}$$

$$G = \frac{\sum_i^n \sum_j^n w_{ij} E_i E_j}{\sum_i^n \sum_j^n E_i E_j}, \qquad \forall\, j \neq i \tag{13}$$

Where, E_i and E_j represent the per capita CO_2 emission of country i and j at period t respectively. w_{ij} refers to the element in the spatial weight matrix, and W is the sum of all the elements of the weight matrix. The range of Global Moran's I index is [1 ,-1]. This index, with the variable greater than 0, presents the overall positive spatial correlation; with one less than 0, it indicates a negative correlation; and with 0, it means irrelevance. Also, the range of Geary's C index is [0, 2]. This index, with the variable greater than 1, gives the overall negative spatial correlation; with one less than 1, it indicates a positive correlation; and with 1, it means irrelevance. Getis and Ord's G measures the existence of High/Low Clustering. The null hypothesis for the High/Low Clustering (General G) statistic states that there is no spatial clustering of feature values. If the null hypothesis is rejected, then the sign of the z-score becomes important. If the z-score value is positive, the observed General G index is larger than the expected General G index, indicating high values for the attribute are clustered in the study area. If the z-score value is negative, the observed General G index is smaller than the expected index, indicating that low values are clustered in the study area (Getis and Ord, 1992).

Table 2. Global spatial diagnostic tests for per capita CO_2 emissions in metric tons

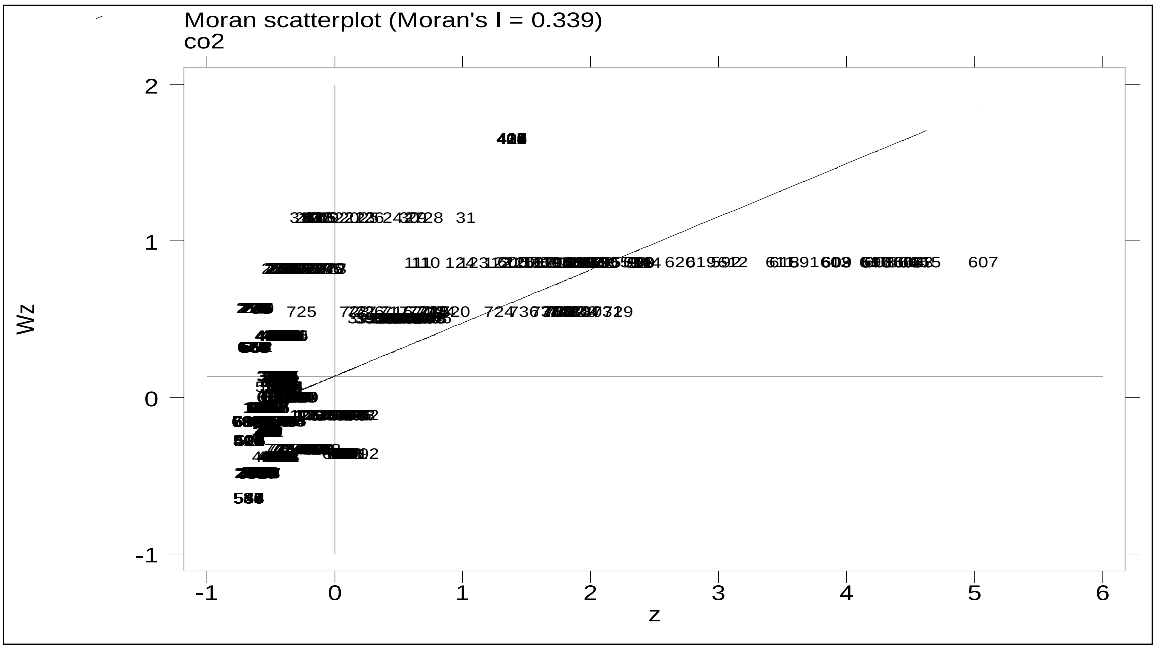
	statistics	**z**	**p-value**
Moran's, I	0.339	100.393	0.000***
Geary's C	0.786	-11.817	0.000***
Getis and Ord's G	0.646	13.275	0.000***

Note: in this paper, cross-sectional spatial diagnostic tests were consistent for panel data.

***Statistically significant at the 1% level.

According to the spatial diagnostic tests, per capita CO_2 emissions of MENA countries have positive spatial autocorrelation; therefore, the modeling of CO_2 emissions in MENA region should be carried out in the presence of spatial dimension.

Figure 1. Moran scatterplot of per capita CO_2 emissions in MENA countries (1970-2010)



5. Empirical results

5.1 Absolute convergence

Figure 2 depicts a graphical analysis of the initial level and average growth rate of per capita CO_2 emissions from 1970 to 2010, together with an estimated linear regression model ($R^2 = 0.25$). Based on the literature about convergence, the negative slope of the estimated trend line implies a convergence trend in per capita CO_2emissions among MENA countries. Additionally according to table 3,the level of steady state of per capita CO_2through which all countries converge, is 13.34 (ton) and time period required by countries with lower per capita CO_2 emissions to catch up with countries initially with higher per capita CO_2 emissions is 5.37(years). Figure 3 portrays cross-sections means and cross-section standard deviations during 1970-2010. We can see on average for all period, cross-sectional standard deviations have a decliningtrend. In other words, sigma convergence has occurred. On the other side, a low coefficient of determination (R-Squared) indicates that the concept of absolute convergence is not able to explain the long-run dynamics of per capita CO_2 well (Table 3). Therefore, it is required to run conditional convergence model. Conditional convergence method considers the impacts of individual difference and control variables on per capita CO2 emissions. According to Li and Lin (2013) the existence of absolute convergence among countries also indicates the existence of conditional convergence.

Figure 2. Average growth rate and primary level of per capita CO_2 emissions (Absolute Convergence)

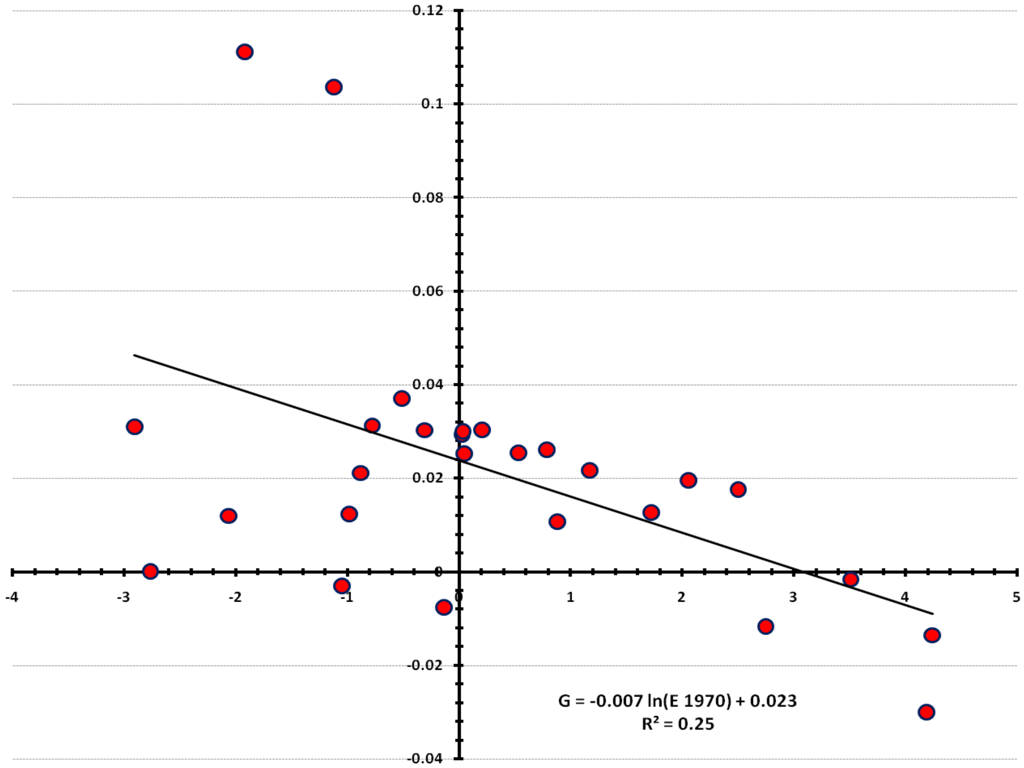
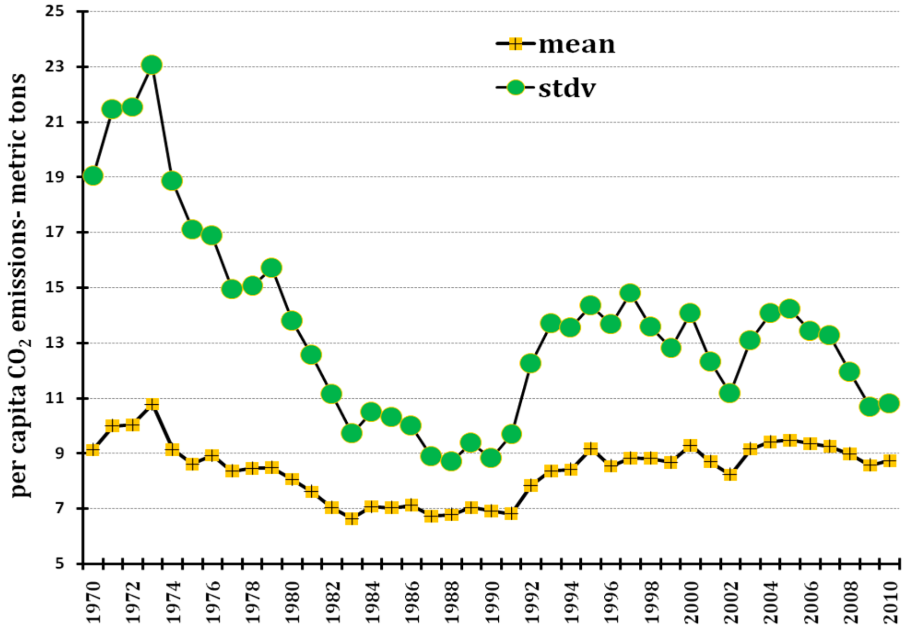


Table 3. Absolute Convergence Estimate

	Coef.	t-stat	P-value	remark
Ln E (1970)	-0.0077 **	2.42	0.023	weak absolute convergence
α	0.0237 ***	3.84	0.001	
β(convergence speed)	0.92 %	-	-	
E_0	13.34 ton	-	-	
T	5.37(year)	-	-	
R-squared	0.25	-		
F (1, 25)	5.87 **	-	0.0230	

Note: heteroskedasticity was removed and model is specified. * Statistically significant at the 10% level. ** Statistically significant at the 5% level.

Figure 3. Cross-section means and standard deviations of per capita CO_2 emissions in MENA countries during 1970-2010



5.2 Conditional Convergence

Due to the availability of data and significant spatial diagnostic tests, control variables for running conditional convergence are: per capita GDP, urbanization degree and space dimension. For estimating the conditional convergence, we applied three dynamic panel estimators: Arellano and Bond (1991), Spatial Autoregressive (SAR) and Spatial Durbin (SDM). Since the ordinary least square (OLS) method is inefficient and inconsistent in spatial econometrics, we applied bias-corrected Quasi-Maximum Likelihood Estimator (QMLE) to estimate spatial coefficients. The estimated results are shown in Table 4.

Table 4. Estimation results of conditional convergence in the framework of dynamic panel data

	GMM Arellano and Bond (1991)	**SAR**	**SDM**
LE_{t-1}	**0.5930** (0.000) ***	**0.1680** (0.026) **	**0.1667** (0.034) **
Ly	**0.0773** (0.030) **	**0.4476** (0.000) ***	**0.5014** (0.000) ***
Lu	**0.2471** (0.376)	**0.5042** (0.036) **	**0.4554** (0.056) *
Con.	**-1.1788** (0.244)	-	-
ρ	-	**-0.1194** (0.503)	**0.1007** (0.600)
W*Ly	-	-	**-0.2405** (0.059) *

Sargan test	**32.16** (0.187)	-	-
AR (1)	**-2.22** (0.025) **	-	-
AR (2)	**-0.713** (0.475)	-	-
Convergence speed (β)	**10.44 %**	**35.67 %**	**35.81 %**

Note: values in parentheses, (…), are p-values of t-test. Country (individual) and year (time) fixed effects are controlled for avoiding the Omitted Variable Bias (OVB) in spatial convergence model. *Statistically significant at the 10% level. **Statistically significant at the 5% level. ***Statistically significant at the 1% level. Also: $\gamma = e^{-\beta}, \beta(\text{convergence rate}) = -\frac{\ln\gamma}{5}$

According to the estimation results, convergence coefficients in all models are positive and statistically significant. Also, controlling impacts of per capita income, urbanization and spatial dimension led to an increase of convergence speed. In Arellano and Bond (1991) dynamic panel GMM estimator, only per capita GDP has a (positive) significant impact on per capita CO_2emissions. According to table 4,all diagnostic tests (Sargan and serial correlation) confirm the GMM results and present no evidence of model misspecification.

According to the results of dynamic SAR model both per capita GDP and degree of urbanization have significant effects on per capita CO_2 emissions, but spatial spillovers do not. In dynamic SDM results, the per capita GDP of country (i) is significantly positive versus spatial lag of per capita GDP of neighboring countries which have negative significant impacts on per capita CO_2emissions (overall per capita income has a positive impact; **0.5014-0.2405=0.2609**). Also in SDM, spatial spillover coefficient is positive but not significant. Therefore, despite the fact in terms of long-term period, considering space dimension increases the speed of convergence in the growth pass, but does not affect the steady-state level of per capita CO_2 emissions. According to the results, in the long-run the steady state of emissions was determined by per capita income (of own and neighboring countries) and degree of urbanization.

6. Conclusions

MENA region is majorly important in many respects. It includes some of the world’s largest reserves of oil and fossil gas, but is poor in water resources and arable land. The major environmental challenges that the region faces, are the water scarcity, desertification, coastal and marine environmental degradation, air pollution and climate change. In this research, spatial convergence hypothesis of per capita CO_2 emissions among selected MENA countries has been reviewed during 1970-2010.To this aim, we apply cross-section and dynamic spatial panel data econometric techniques. There are strong evidences that the atmospheric emissions have positive spatial dependence and econometric modeling must be implemented in the presence of spatial dimension. The main policy implications of this study are:

- It is recommended that in the per capita CO_2 emissions, determinants studies especially convergence researches among MENA countries and spatial spillover of pollution must be regarded as a control variable.
- Although in the short-term a part of the pollution in MENA countries results from spillover effects, the steady state level of per capita CO_2 emissions is determined by per capita GDP and degree of urbanization in the long-term. Therefore, in ordaining the environmental restrictions for MENA countries, per capita income and urbanization rate must be considered.
- According to our results, MENA countries must make regional treaty for cutting down per capita CO_2 emissions. Regional treaties have a high consistency and flexibility with climate and geographical features of each region. Also at a regional level, theoretical achievements of international arrangements (e.g.COP21, Copenhagen, Kyoto, etc.) are more practicable.

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