

Carbon Dioxide Emissions: A Dynamic Panel Analysis of Energy Intensive Industries in Egypt

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Abstract

Most energy intensive industries are high carbon dioxide (CO₂) emitters. As CO₂ emissions show large discrepancies between regions, it is important to test for spatial dependence when estimating emissions. The present study thus examines spatial dependence of CO₂ emissions for the twenty-seven governorates of Egypt over the period 2007-2016. Determinants of CO₂ emissions include road network density, investments in fixed assets, the structure of economic activity, the share of females, and the various levels of education in the regions' respective population. Incorporating the spatial dimension, as well as using female and educational levels amongst the determinants, are contributions to research done on CO₂ emissions in Egypt. Estimation results indicate that CO₂ emissions across governorates are spatially-random rather than spatially-dependent. The study therefore uses a generalized method of moments (GMM) dynamic panel model. The lag of CO₂ emissions per capita, net fixed capital formation, share of illiterates in the working age population, and the share of services in economic activity are significant and have positive effects (increasing emissions). The share of females in working age population, and the share of agriculture in economic activity are significant and have negative effects (diminishing emissions). Policy implications based on the study results are given.

Keywords: Spatial Analysis, Dynamic Panel Model, Carbon Dioxide Emissions, Energy Intensive Industries, Egypt

1. Introduction

Environmental degradation continues to be a threat to sustainability. Factors that contribute to environmental degradation include growth, trade, manufacturing, net fixed capital formation, environmental awareness and gender. The Environmental Performance Index showed that Egypt's rank was 66 in 2018 and slipped down to 94 in 2020 out of 180 countries (Environmental Performance Index in 2018, 2020). This movement may stress the extent to which Egypt continues to rely heavily on energy intensive industries, and has relatively low efficiency in utilising energy sources at the sectoral level (CAPMAS, 2018).

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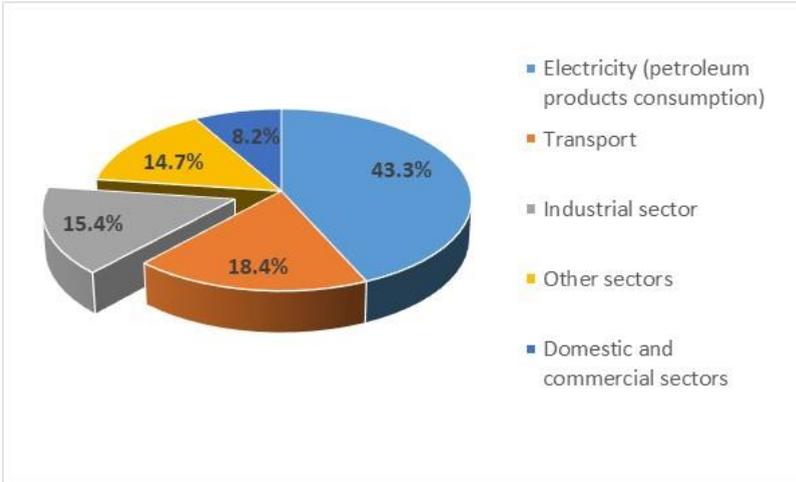


Figure 1 below gives the sources of CO₂ emissions by sector in Egypt for the year 2018.

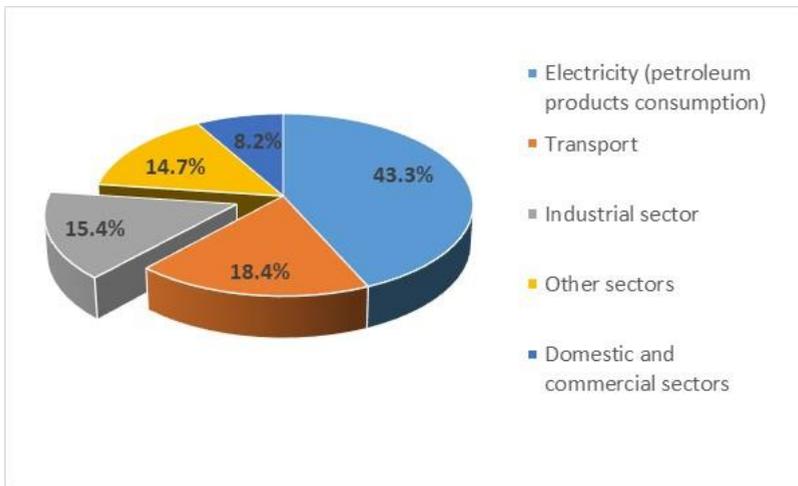


Figure 1: Sources of CO₂ Emissions by Sector in Egypt
 Source: (CAPMAS, 2018)

The industrial sector is evidently the third contributor of CO₂ emissions in Egypt. It poses as one of the major threats to environmental degradation. Hence, it is crucial to study the determinants of CO₂ in energy-intensive industries since they are the high CO₂ emitters among industries. This paper aims at analysing the determinants of CO₂ emission per capita from polluting- and energy-intensive industries across Egypt's governorates in a panel model which incorporates the spatial dimension over the period 2007-2016.¹ To the authors' knowledge, this is the first research that studies CO₂ emissions from polluting energy-intensive industries at the regional level in Egypt through spatial panel analysis. The

¹ For more information regarding Egypt's governorates, see table A1 in the appendix.

paper is organised as follows: section two provides the literature review; section three discusses the methodology used and variable description; section four discusses the results; and section five concludes and suggests policy implications.

2. Literature Review

The Environmental Kuznets Curve (EKC) hypothesis is commonly used to describe the relationship between economic growth and environmental quality (Cai, 2008; Friedl and Getzner, 2003; Grossman and Krueger, 1991; Lin and Jiang, 2009; LoreMBER *et al.*, 2020; Panayotou, 1993; Schmalensee *et al.*, 1998). The hypothesis states that the relationship between economic growth and environmental degradation is represented by an inverted U-shape curve (Özokcu and Özdemir, 2017). However, it is criticized for two reasons: first, for excluding other determinants of pollution emissions level; second, for not incorporating the spatial dimension in the analysis which may result in spurious results (Zheng *et al.*, 2014), biased or inconsistent estimators (Burnett and Bergstrom, 2010), and unreliable statistical inference (Zhao *et al.*, 2014).

Spatial dependence is defined as “the propensity for nearby locations to influence each other and to possess similar attributes” (Goodchild, 1992). In general, all spatial data tend to have spatial dependence (Anselin, 1991). Spatial dependence with respect to CO₂ emissions is likely to occur when there is degree of cooperation and strong integration between different regions. In addition, because of its gas nature, CO₂ can spread easily across regions depending on the wind speed and other weather conditions (Zheng *et al.*, 2014). On the other hand, spatial independence can be an alternative. This can be due to spatial *randomness* that occurs from having zero spatial autocorrelation. Such cases indicate identically distributed random data that do not vary by geographic location (Gangodagamage *et al.*, 2008). One possible reason for this could be the absence of cooperation and coordination between neighboring regions. Alternatively, CO₂ could be distributed homogenously across the whole land area (Goodchild, 1992).

Further important factors that ought to be considered when estimating CO₂ emissions is to include the persistence or correction of pollution emissions level. If there is persistence, static models would be misspecified, while dynamic models would be more fitting. Since dynamic models are used when historical values of the dependent variable matter, they would account for the *dynamic (intertemporal)* feature of sustainability in studying CO₂ emissions level. They would also account for the CO₂ accumulation in the atmosphere. However, an endogeneity problem arises when using dynamic panel models, as the strict exogeneity of the regressors is violated. Hence, it is essential to tackle the endogeneity problem in dynamic panel models.

In general, externalities, such as the pollution emissions level, tend to have both ‘spatial’ and ‘dynamic’ dimensions (Nicolaisen *et al.*, 1991). In addition, Elhorst (2012) stated that both spatial and dynamic effects must be taken into account to avoid biased estimators. In other words, if the spatial effects are considered, while the dynamic effects are omitted, estimators are biased. Likewise, if only dynamic effects are considered, and the spatial effects are omitted, estimators are biased. Hence, a spatial dynamic panel model framework is more suitable in studying CO₂ emissions level.

With respect to EKC, Balado-Naves *et al.* (2018) employ a panel data model on 173

countries for the period 1990–2014 to test the EKC hypothesis for neighbouring per capita income and energy intensity in Europe, Asia and the World. Empirical results support the standard EKC hypothesis in which neighbouring per capita income and national per capita emissions are exhibiting an inverted U-shaped relationship. A further study by Jeanty et al. (2013) tested the existence of spatial interdependence in the EKC in some European countries between 1961–2009 via panel data model methods. Results of the spatial dynamic panel study indicated the presence of a strong degree of interdependence in CO₂ emissions per capita in these European countries under the studied period.

Elliott & Clement (2014) also studied spatial inequality in CO₂ across the United States using a spatial panel regression model with two-way fixed effects. The study used integrated county-level environmental data, residential and industrial emissions along with demographic and economic data. Results revealed spatial segregation between carbon-intensive production and socio-environmental interactions within as well as across societies, as industrial combustion and urban cities grow. Furthermore, Fang et al. (2015) propose that determinants contributing to increasing CO₂ in the G-20 countries include population growth and economic growth, while increases in energy efficiency contribute to reducing carbon emissions level.

Liu & Zhao H (2012) analyse the regional distribution of CO₂ intensity in China, showing that emissions are unbalanced across regions, but increasing over time. Fan and Liu (2012) as cited in Zheng et al. (2014) propose that there is direct relationship between CO₂ intensity and the degree of industrialization and the provincial industrial composition. They used the Theil index and spatial autocorrelation to find that the CO₂ intensity across 8 economic zones in China between 1999 and 2007 are clustered in three zones that are related on the provincial level. Further studies applying spatial autocorrelation and multi regression methods include Dong and Liang, (2014) as cited in (Azimi & Yang, 2018), tested how technology upgrading constraints across 30 provinces in China may contribute to regional disparities in emission patterns. Three main air pollutants, namely, Sulphur dioxide (SO₂), Nitrogen oxide (NO) and CO₂ were used in the study to analyse environmental discrepancy and inequity across regions using the Lorenz curve and the Gini coefficient. Results showed cluster effects and regional discrepancies in air pollutants where the richer and the relatively more industrialised regions in the Eastern provinces of China, give lower emissions. On the other hand, higher emissions are found in less developed Central and Western regions. Poorer regions of China are shown to struggle while attaining the necessary funds for pollution control. (Azimi & Yang, 2018).

A study by Cole et al. (2013) calculated how Japanese firms are influenced by neighbouring firms' contribution to CO₂ emissions. The main determinants of firms' emissions used in the study are: the capital–labour ratio, firm size, expenditure on research and development, advertising expenditure, and exports as a share of output. Results showed that firm size is a critical determinant of CO₂ emissions, where large firms produce lower emissions per unit of output by using abatement activity. The study thus suggests that firms do not operate in isolation of each other, but they influence each other through imitation and demonstration effects, and through competitive pressures.

With reference to India, Paul and Bhattacharya (2004) determine the factors influencing changes in CO₂ emissions in India at the aggregated and the disaggregated levels. The study uses the decomposition technique developed by Sun (1998) to gauge changes in energy

consumption over time. The study considers four different factors: changes in carbon dioxide emissions; the pollution coefficient effect; the intensity effect; and the structural and activity effects (Paul and Bhattacharya, 2004). Results show that the pollution coefficient effect, the energy intensity effect, the structural effect and the economic activity effect are the major factors that cause an escalation in CO₂ emissions. The study further shows that economic growth is a key contributor to increasing CO₂ emissions in the agricultural, industrial and transport sectors in India (Paul and Bhattacharya, 2004).

Also using decomposition analysis, Akbostancı *et al.* (2011) study the CO₂ emissions in the Turkish manufacturing industry using fuel consumption data covering 57 industries between 1995 and 2001. The study uses a decomposition of the changes in the CO₂ emissions of manufacturing industry into 5 components. Their findings indicate that changes in CO₂ emissions are mainly driven by the changes in total industrial activity and energy intensity during the study period.

With reference to countries of the Far East, a study by Anwar, Younis and Ullah (2020) studies the main determinants of CO₂ emissions in Far East countries between 1980-2017, by adopting panel data fixed effects model. The study shows that urbanization level, economic growth and trade openness are the main determinants of CO₂ emissions in the selected countries.

Xiaoyan *et al.* (2013) use a dynamic spatial system-GMM panel approach on Chinese provincial data from 1995-2009 to study China's industrial transformation and CO₂ emissions. Results show that transformation of China's industrial structure led to a reduction in CO₂ emissions and that knowledge- and technology-intensive industries have lower CO₂ emissions due to their limited energy consumption. The study further shows that China's current technical progress was not the reason behind reducing CO₂ emissions, but that advancement and optimization of the industrial structure was the main determinants. A dynamic spatial panel model is also used by Zhao, Burnett, & Lacombe, (2015) to test the convergence of CO₂ intensities for 30 Chinese provinces between 1990-2010. Results show that CO₂ emissions are converging across Chinese provinces with a positive spatial correlation.

The following section discusses the methodology and results of testing for spatial dependence of CO₂ emissions for Egypt's industrial sector at the governorate level.

3. Methodology

Cross-sectional spatial econometric analysis relies on studying spill-over effects amongst neighbouring regions (i.e., spatial dependence). It is very important to test for spatial dependence in order to prevent bias (Nsiah and Wu, 2014) and inefficiencies in parameter estimates (Jeetoo, 2020). To account for spatial dependence, a binary 'contiguity weight matrix' uses the geographical attributes of region(s) to identify their neighbourhood. The diagonal zero element in the matrix are those of each region being its own self. The off-diagonal elements are 1 for those regions it neighbours. The weight matrix is then transformed by row-standardizing whereby each element in the row is divided by the sum of row elements².

² For example, in a system of four regions, and with region *i* neighbouring two out of three *j*'s, weights assigned are 0 for the region itself, 0 for regions with which it does not neighbour, and one for each neighbour,

As a start, an OLS spatial cross sectional model³ is estimated without considering spatial lag terms which control of spatial autocorrelation effects of the dependent variable. This estimation is followed by testing for spatial dependence. First, spatial correlation of the cross sectional regression residuals is tested using the Moran's I spatial statistic as per the following equation:

$$MI = \frac{(n-1) \sum_{i=1}^n \sum_{j=1}^n w_{ij} \varepsilon_i \varepsilon_j}{\sum_{i=1}^n \varepsilon_i^2} \quad (1)$$

Further, spatial correlation is tested using the Moran's I conducted for the dependent variable, as per the following equation:

$$MI = \frac{(n-1) \sum_i^N \sum_j^N w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_i^N \sum_j^N w_{ij} (y_i - \bar{y})^2} \quad (2)$$

Where w_{ij} is the element of the spatial weights matrix, $i=1,2,\dots,27, j=1,2,\dots,27$, and $m=n$ or $m \neq n$. The significance of the Moran's I of both the regression residuals and of the dependent variable is tested by the Z-score.

Upon establishing significance of the dependent variable's and residual spatial correlation, spatial models are estimated in a manner that controls for the spatial autocorrelation effects, and are estimated using maximum likelihood method. Specifications of spatial models vary. On the one hand, the spatial Durbin model (SDM) accounts for the spatial autocorrelation of the dependent variable by incorporating an average value of the independent variable (x) in neighbouring region(s). This is, in turn, associated with the weight matrix ($y_i = \beta x_i + \theta W x_j + \mu$), and μ is assumed to behave normally. On the other hand, the spatial autoregressive model (SAR) regresses levels of y in region i on levels of y in neighbouring region(s) j (thereby accounting for the dependent variable's spatial autocorrelation by incorporating values of the dependent variable in the regions which it neighbours). Thus, the model allows for spill-overs of y from j into i ($y_i = \beta x_i + \lambda W y_j + \mu$, and μ is assumed to behave normally. The spatial error model (SEM) incorporates the dependent variable's spatial autocorrelation through the error term, such that $y_i = \beta x_i + \mu$, $\mu = \lambda W \mu_i + v$, where v is assumed to behave normally. Finally, the general spatial model (usually denoted by SAC) combines the SAR and the SEM models.

If the significance of the dependent variable, and of the residuals, spatial correlation is not established, then the data for the regions would not show spatial dependence, but rather spatial randomness. In this case, a panel data model is estimated without considering spatial lag terms. In this case, a dynamic panel data model would be estimated using the

summing to 2. Row weights would be $\frac{1}{2}$ for each of the two regions that i neighbours, 0 for region i itself, and 0 for the non-neighbour region. There are four criteria for considering regions to be 'neighbours': 1) whether they share (part of) a common eastern or western border (Linear contiguity); 2) whether they share part of a common border on any side for a small distance (Rook contiguity); 3) whether they meet at a point (even less than the snapshot distance) (Bishop contiguity); 4) whether they share any part of common border (Queen contiguity - union of the Rook and the Bishop). Spatial weights matrices, testing for OLS residual spatial correlation, and estimation of cross sectional SAR, SEM and SAC models, are carried out using GeoDa open source software. GeoDa constructs the spatial weights matrix using geographical attributes given in ESRI shape files provided by a nation's Survey Authority. For Egypt, shape files are provided by The Central Agency for Public Mobilization and Statistics (CAPMAS).

³ Same method is applied for panel data models. Also in case of suspected endogeneity of dependent and one or more of the independent variables, estimation is conducted as a generalized method of moments (as in results shown in table 2)

generalized method of moments.

3.1 Data Description

Data for the dependent variable ***CO₂ emissions*** by governorate are not readily available for Egypt. A proxy variable was derived as the share of the nominal value of output (at selling price) of energy-intensive polluting activities of the governorate in the total nominal value of output of energy-intensive polluting industries nation-wide. Energy-intensive polluting industries are, namely, mining, and polluting manufacturing industries.⁴ Each governorate's share is multiplied by total nation-wide CO₂ (emissions resulting from the burning of fossil fuels in consumption or in gas flaring, measured in millions of metric tonnes) gives a proxy of CO₂ emissions by governorate.⁵ ***CO₂ emissions per capita*** is obtained as the CO₂ emissions by governorate divided by the governorate population.

Net fixed capital formation for industry (mining and manufacturing industries) is among the variables that commonly affect carbon dioxide emissions level at the regional level, (see Sodersten et al., 2017; and Wensong et al., 2018). Net fixed capital formation is defined as gross fixed capital formation minus depreciation of existing capital, hence, reflecting the net addition to capital. The expected sign is positive if investments are concentrated in polluting industries. However, when investors are using environmentally-friendly techniques of production, the expected sign is negative. It is measured in nominal value.

Population density also affects pollution emissions level. It is defined as the ratio of population of the governorate to its area, measured per squared km. The expected sign of this variable is indistinct. This is because, on the one hand, the sign is expected to be positive if we consider the scale effect in which the needs of a populous region are met through large scale production. Consequently, the more the production is, the higher the pollution emissions will be. This is definitely magnified if firms use traditional polluting techniques of production. On the other hand, the expected sign is negative if improvements in technology in urban areas that are usually highly populated result in a reduction in pollution emissions level (Wensong et al., 2018).

This variable ***is omitted*** from the set of independent variable in this model since the dependent variable is defined as ***CO₂ emissions per capita*** for high possibility of endogeneity.

Females in working age population is defined as the share of females in the working age population (15-64). This variable is added to test for the effect of the gender composition of population in Egypt's governorates on CO₂ emissions level. Indeed, contemporary literature such as Brough et al. (2016) suggest that females are more environmentally conscious than males⁶, in which case the expected sign is negative, and

⁴ Many studies show that there is a strong correlation between energy use and CO₂ emissions level. For more information, see Gao and Zhang (2014) and Hassaballa (2011).

⁵ Polluting industries as identified based on their actual emissions intensity per unit of output. Manufacturing industries ranked in order of pollution intensity are: ferrous and non-ferrous basic metals; industrial chemicals, refined petroleum products, nonmetallic mineral products, paper and pulp, rubber, leather, and fabricated metal products except machinery. Of the above industries, all *except leather products* are energy-intensive. Thus, almost all polluting industries are themselves energy-intensive.

⁶ For more information, see "Global Women's Issues: Women in the World Today, extended version", Chapter 11, 2012.

Sundström and McCright (2014).

In addition, the **educational level** can reflect the degree of environmental awareness per region.⁷ Three variables are used to assess whether higher education may be associated with greater environmental awareness, hence an expected positive effect on environmental quality: **illiterates in working age population**, **intermediate degree holders in working age population**, **university degree holders in working age population** which is defined as the share of illiterates, intermediate degree holders, university degree holders in the working age population (15-64), respectively. The expected sign is positive for illiterates, as perhaps illiterates are expected to lack awareness. The expected sign is negative for intermediates and university degree holders as individuals may become more aware of the hazards of environmental degradation with higher levels of education.

Furthermore, the type of activity that the region specializes in is believed to affect the level of CO₂ emissions (Wensong et al., 2018). For lack of data for value added of industrial, agricultural and service activities by region, three proxy variables are used to reflect the dominance of an economic activity in a region: **industry**, **agriculture**, and **services employed in total employed in each governorate**. These three variables are defined as the share of those employed in industry (mining and manufacturing), in agriculture and in services in the total number of employed labour force members in the governorate, respectively. The expected signs of the three variables are either positive if firms use polluting techniques in their production or negative if they adopt environmentally friendly techniques of production which could be due to stringent environmental regulations. For instance, if an emission standard is imposed, farmers may shift to planting less polluting crops instead of more polluting ones resulting in a decline in pollution emissions level (Some et al., 2017).

Finally, **Road network density** effect on carbon dioxide emissions level is also considered. Road network density is the ratio of total road length of the governorate to its geographical area in km². The expected sign is negative because a higher road network density will result in less congestion which in return leads to less environmental damages from car exhausts, holding other things constant (Wensong et al., 2018). A Summary of the study variables and their expected signs are shown in table 1.

Table 1: Model Variables

Variable	Name	Description	Sign
<i>PCCO2_emiss</i>	CO ₂ emissions per capita	is obtained as the CO ₂ emissions by governorate divided by the governorate population.	Dependent variable
<i>PCCO2_emiss_1</i>	Lagged CO ₂ emissions per capita	is obtained as the CO ₂ emissions by governorate divided by the governorate population in the previous period	Positive or negative
<i>NFKF</i>	Net fixed capital formation	is defined as gross fixed capital formation minus depreciation of existing capital, hence, reflecting the net addition to capital.	Positive or negative
<i>FWAge</i>	Females in working	is defined as the share of females in the	Negative

⁷ See Global Education Monitoring Report by the UNESCO at <https://gemreportunesco.wordpress.com/2015/12/08/education-increases-awareness-and-concern-for-the-environment/>

	age population	working age population (15-64	
<i>IllitWAge</i> <i>UniWAge</i>	illiterates in working age population; university degree holders in working age population	is defined as the share of illiterates, university degree holders in the working age population (15-64), respectively	Positive for illiterates Negative for university degree holders
<i>IndEmp</i> , <i>AgrEmp</i> <i>ServEmp</i>	industry, agriculture, and services employed in total employed in each governorate.	are defined as the share of those employed in industry (mining and manufacturing), in agriculture and in services in the total number of employed labour force members in the governorate, respectively.	Positive or negative
RdNetw	Road network density	is the ratio of total road length of the governorate to its geographical area in km ² .	Negative

Source: Designed by the authors

3.2 Data Sources

Data on CO₂ emissions are obtained from the World Development Indicators by the World Bank. Output and net fixed capital formation data, on the governorate level, are obtained from CAPMAS Annual Bulletin of Industrial Production Statistics (2007-2016), and population data are drawn from the statistical yearbook issued annually by CAPMAS (2007-2016). Data on the governorate level for females, illiterates, university degree holders, the working age population, industry employed, agriculture employed, and services employed are utilised from the Annual Statistical Bulletin of the Labour Force Survey in Egypt issued annually by CAPMAS (2007-2016). Road network density data are drawn from the Annual Bulletin of Statistics on Roads and Bridges issued annually by CAPMAS (2007-2016). *Stata* is the software used in the estimation.

4. Estimation results

An OLS spatial cross-section model is estimated for each of the years of study. Moran's I (error) tests are performed to assess the availability of spatial autocorrelation of the residuals from the estimated equations. Test results are given in Table 2 below:

Table 2: Moran's I (error) diagnostic test for weights matrix of the governorates of Egypt (row-standardized weights), 2007-2016

Summary of output		: Least squares estimation					
Data set		: egypt_admbnda_adm1_capmas_20170421					
Dependent Variable		: PCCO2_emiss		Number of Observations:		: 27	
Mean dependent variable		: 0.0171		Number of Variables		: 10	
S.D. dependent variable		: 0.0447		Degrees of Freedom		: 17	
Regression Year	Moran's I	Z-score	p-value > Z	Regression Year	Moran's I	Z-score	p-value > Z
2007	0.263	-1.027	0.30	2012	-0.191	-1.025	0.31
2008	-0.131	0.645	0.52	2013	-0.180	-0.940	0.35
2009	-0.058	-0.080	0.94	2014	0.097	1.308	0.19

2010	-0.196	-1.084	0.28	2015	0.086	-0.316	0.75
2011	-0.029	0.275	0.78	2016	-0.140	-0.834	0.40

Source: Authors' Computations

P-values indicate that the test statistics for all Moran I's are not statistically significant pointing to the absence of spatial autocorrelation of the residuals. Hence, there is no spatial dependence between neighbouring regions in CO₂ emissions per capita in Egypt, but spatial randomness instead. Upon further testing for spatial autocorrelation of the dependent variable (CO₂ emissions per capita), the Moran's I is also not significant for all the years of study, providing further evidence for spatial randomness. Test results are given Table 3:

Table 3: Moran's I (CO₂ emissions per capita) diagnostic test for weights matrix of the governorates of Egypt (row-standardized weights), 2007-2016

Year	Moran's I	Z-score (I)	p-value > Z	Year	Moran's I	Z-score (I)	p-value > Z
2007	-0.105	-0.590	0.32	2012	-0.042	0.092	0.38
2008	-0.048	0.054	0.42	2013	-0.049	0.049	0.40
2009	-0.028	0.260	0.37	2014	-0.027	0.157	0.35
2010	-0.046	0.089	0.35	2015	-0.102	-0.691	0.25
2011	-0.056	-0.020	0.43	2016	-0.069	-0.304	0.45

Source: Authors' Computations

The spatial randomness evident from both tests does not agree with most empirical findings for other countries which find that CO₂ emissions (level and per capita) are highly spatially dependent (see for example, Wensong et al. 2018; Yang et al. 2019; Zhao et al. 2014). It is therefore important to understand why such spatial randomness of CO₂ emissions per capita may exist in Egypt.

As a start, Figure 2 represents spatial randomness as the dispersed dark squares which have no pattern of clustering.

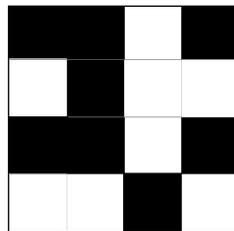


Figure 2: Representation of spatial randomness

Source: <https://www.statisticshowto.com/morans-i/>

The representation of spatial randomness in Figure 2 corresponds with the average 2007-2016 CO₂ emissions per capita for the governorates of Egypt shown in Figure 3. This is apparent for the four governorates which fall in the highest (darkest shaded) emissions per capita quantile (Matrouh, Suez, South Sinai and Red Sea). Relative to 2007-2016 average *nation-wide level* of CO₂ emissions, the share of the average CO₂ emissions in 2007-2016 is 12% in Matrouh; 11% in the Red Sea; 4% in South Sinai; and 5% in Suez (Source: authors' computations). Reasons underlying these shares include the existence of highly polluting activities in each of these governorates: Matrouh (extraction of crude petroleum); Red Sea (extraction of crude petroleum and quarrying of non-ferrous metals (e.g., phosphates));

South Sinai (extraction of oil and gas, and quarrying of stones, sand and clay); Suez (petroleum refining, non-metallic mineral products, basic metals, industrial chemicals, metal processing).

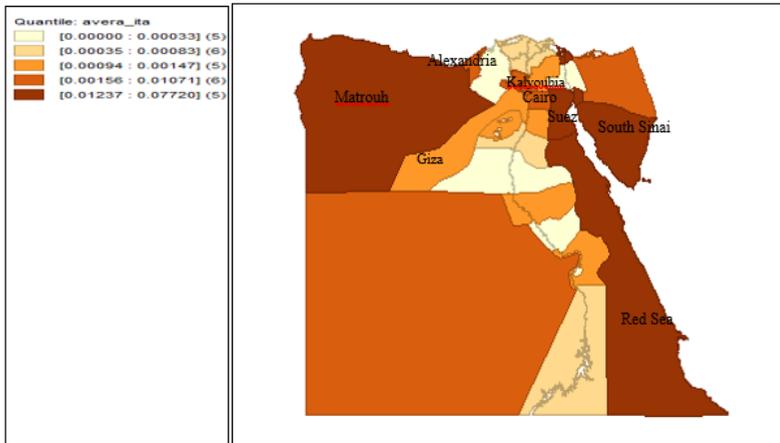


Figure 3: Map of 2007-2016 average CO₂ emissions per capita for the governorates of Egypt

Source: Authors' Computations

The aforementioned Moran's I test statistics for the residuals of the cross sectional regression equations for all the years of study (2007 through 2016), and for CO₂ emissions per capita are found to be insignificant. Also, spatial randomness in CO₂ emissions is evident from Figure 3. Therefore, using the spatial specification for estimating CO₂ emissions per capita equation for Egypt is not appropriate. A dynamic panel data model is estimated using the Arellano and Bond generalized method of moments. With all the explanatory variables are transformed by differencing, and estimation is done using the generalized method of moments, this method achieves greater efficiency in estimation compared to the simpler instrumental variable estimation (Roodman, 2009).

$$CO2/capita_{it} = \alpha CO2/capita_{i,t-1} + \beta x_{it} + \varepsilon_{it} \quad (3)$$

where $i=1,2,\dots,27$, $t=1,2,\dots,10$, and x_{it} denotes the independent variables of governorate i at time t , and ε_{it} is assumed to behave normally.

Because there is an expected perfect collinearity between the three variables used as proxies for the economic activity (employment in industry, agriculture and services), two models are estimated. Model (1) includes industry and services, and model (2) includes industry and agriculture. Results of model (1) and model (2) estimations are given in 4.

Table 4: Arellano and Bond Difference GMM

Dependent Variable: PCCO2_emiss				
Variables	Model (1)		Model (2)	
	Coefficient	t-statistic	Coefficient	t-statistic
PCCO2_emiss_1	1.701***	27.95	1.696***	28.43
NFKF	1.19e-09*	1.90	1.23e-09*	2.01
RdNetw	-0.001	-0.71	-0.001	-0.71
FWAge	-0.657*	-1.99	-0.689**	-2.14
IlltWAge	0.598*	2.03	0.625**	2.17

UniWAge	-0.003	-0.15	0.015	1.13
IndEmp	0.0363	1.20	0.018	0.59
ServEmp	0.020**	2.14		
AgrEmp			-0.019**	-2.12
	Number of observations	216	Number of observations:	216
	Observations per group:		Observations per group:	
	min, average, max	8	min, average, max	8
	F statistic (8, 27):	20585.35	F statistic (8, 27)	21076.56
	Prob>F	0.00	Prob> F	0.00
	Groups/instruments	27/14	Groups/instruments	27/14
	Arellano-Bond test for	0.421	Arellano-Bond test for	0.421
	AR(2) in first differences		AR(2) in first differences	
	Hansen test of over-	0.437	Hansen test of over-	0.441
	identified restrictions chi2(6)		identified restrictions chi2(6)	

Notes: ***, **, * are statistically significant at 1%, 5%, and 10%, respectively; p-values reported for AR (2) and Hansen Statistic.

Source: Authors' Computations.

The AR(2) is found to be statistically insignificant indicating that the model is not suffering from second order serial correlation. In other words, the second lags used as instruments are not correlated with the error term. Further, the insignificant Hansen statistic indicates that the instruments used in the model are valid, and thereby the model does not suffer from over-identification of instruments.

The coefficients obtained from GMM estimates are the short run coefficients. In model (1), a one percent increase in CO₂ emissions per capita in previous period is associated with a 1.7% increase in present period CO₂ emissions per capita in the *short run* at a 1% level of significance, *ceteris paribus*. Thus, the deterioration of environmental quality is highly associated with previous period CO₂ emissions per capita. This also indicates that there is *persistence* in CO₂ emissions.

A one percent increase in net fixed capital formation is associated with 1.2 e-09 % increase in CO₂ emissions per capita in the *short run* at a 10% level of significance, *ceteris paribus*. This effect of net fixed capital formation is indeed of an extremely small magnitude. However, the statistical significance indicates that investments in Egypt were, as may be expected, heavily and primarily concentrated in polluting (energy intensive) economic activities.

A one percent increase in the share of females in working age population is associated with a 0.66% decrease in CO₂ emissions per capita in the *short run* at a 10% level of significance. This result is in line with literature, indicating a relatively high environmental awareness among females as suggested by Sundström and McCright (2014) and Brough et al. (2016).⁸ However, illiterates share in the working age population's effect is opposite to that of females. A one percent increase in the share of illiterates in the working age population is associated with a 0.59% increase in CO₂ emissions per capita in the *short run* at a 10% level of significance.

⁸ See "Global Women's Issues: Women in the World Today, extended version", Chapter 11, 2012, for more information.

It is worth noting that the result for university degree holders in model (1), though not statistically significant, but does show a negative effect on CO₂ emissions per capita. As such, one may conclude that illiterates, as may be expected, lack environmental awareness, while university degree holders may be more environmentally conscious.

The effect of services' shares in total employed is significant and positive in model (1). A one percent increase in the share of services employed is associated with a 0.02% increase in CO₂ emissions per capita in the *short run* at a 5% level of significance *ceteris paribus*. Meanwhile, in model (2) agriculture share of the total employed is found to decrease CO₂ emissions per capita, such that a one percent increase in the share of agriculture employed is associated with a 0.02% decrease in CO₂ emissions per capita in the *short run* at a 5% level of significance. Thus, services and agriculture are found to have opposing effects on CO₂ emissions per capita.

Finally, though not statistically significant in either model (1) or (model (2)), the coefficient of industry employed is positive. This may indicate that industrial firms (both of mining and manufacturing activities) are using polluting techniques in their production (Hassaballa, 2011; Mercian *et al.* 2007).

As for the road network density, the negative sign on coefficient would be in line with the literature suggesting that a higher road network density reduces congestion which, in turn, may reduce environmental damages from car exhausts, holding other things constant (Wensong *et al.*,2018; Liu, 2019). For a discussion of long run coefficients, see table A2 in the appendix.

5. Conclusion and Policy Implications

The current research tested for the existence of spatial dependence of CO₂ emissions for the twenty-seven governorates of Egypt over the period 2007-2016 utilising a generalized method of moments dynamic panel model. Results revealed that CO₂ emissions are not spatially dependent and are spatially random. The lag of CO₂ emissions per capita, net fixed capital formation, share of illiterates in the working age population, and the share of services in economic activity are found to be statistically significant and positively affects CO₂ emissions. In contrast, the share of females in working age population, and the share of agriculture in economic activity are statistically significant and of a negative effect.

Reducing CO₂ emissions level should be top priority for policy makers in Egypt, particularly in the light of the current results that show multiple factors contributing to its rise. The contribution of these factors is magnified due to the persistence of CO₂ emissions level. Persistent CO₂ emissions are an indication of little serious effort being made towards pollution reduction. Hence, shifting to a green economy pathway is advisable to achieve this target. For instance, it has been estimated by the UNEP (2015) that more than US\$1.3 billion will be saved in the agriculture sector in addition to saving of US\$1.1 billion in the water sector per year if Egypt shifts to a green economy. Furthermore, most importantly, there will also be a decline in CO₂ emissions level by 13% (UNEP (2015)).

In addition, the positive contribution of net fixed capital formation indicates that investments result in further environmental degradation. To tackle this problem, the Egyptian government should enforce stringent environmental regulations. At the same

time, it should provide financial and technical assistance to motivate polluting firms to abide by the legal standards. The government should further incorporate the environmental dimension in its decisions at the macro level. Likewise, firms should adopt a holistic environmental management system. In such system, firms can easily achieve their environmental objective and improve their environmental performance through regular review and evaluation (Hassaballa, 2011).

Moreover, the results highlighted that illiterates contribute positively to the rise of CO₂ emissions level, making it imperative to fight illiteracy. For illiteracy among children, the government should use all the possible channels such as public and social media to *raise awareness about the importance of educating children*. In addition, it should *enforce strict penalties on child labour*. A review of the educational curricula is essential to avoid high drop-out rates. Aiming to enable families and to prevent their heavy reliance on child labour, the government is well-advised to *ease credit availability to the poor*.

As for adult illiteracy, *identifying the number of illiterates in each district, and each sub-district*, is much needed. In doing so, it would be possible to target their illiteracy eradication over a given time line. *Rewarding and incentivizing adults* who succeed in attaining “read and write” status at old age is highly recommended.

It may be counterintuitive that the services sector increases environmental degradation. However, this could, in fact, be the effect of the type of dominant service activities. For instance, the services sector can be polluting if it is dominated by tourism, and healthcare sectors. If environmental regulations in tourism are lax, environmental degradation may result. Also, if healthcare sector is disposing of wastes through open burning and incineration, this would be of further environmental damage.

Finally, the results showed positive contribution of female and the agricultural sector to environmental quality. Thus, it is very important to transfer this environmentally friendly attitude of females to their children, husbands and the rest of the population at large. As for the agricultural sector, this sector should be studied in depth to identify the causes of this environmentally friendly result. This is to evaluate whether it could be replicated in other sectors or not.

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Appendix

Table A1: Area, population, population density of the governorates of Egypt, 2019

Governorate	Area (sq km)	Population	Population Density
Cairo	3085.12	978,8739	3172.89
Alexandria	2300	5,299,718	2304.23
Port Said	1344.96	764,499	568.42
Suez	9002.21	749,657	83.27
Damietta	910.26	1,539,075	1690.81
Dakahlia	3538.23	6,679,368	1887.77
Sharkia	4911	7,401,700	1507.17
Kalyoubia	1124.28	5,792,066	5151.80
Kafr El-Sheikh	3466.69	3,478,267	1003.34

Gharbia	1942.34	5,146,411	2649.59
Menoufia	2499	4,441,717	1777.40
Beheira	9826	6,404,210	651.76
Ismailia	5066.97	1,352,548	266.93
Giza	13184	8,915,164	676.21
Beni Suef	10954	3,288,219	300.18
Fayoum	6068	3,747,942	617.66
Menia	32279	5,745,212	177.99
Asyout	25926	4,587,577	176.95
Sohag	11022	5,193,052	471.15
Qena	10798	3,302,894	305.88
Aswan	62726	1,532,400	24.43
Luxor	2409.68	1,296,540	538.05
Matrouh	166563	461,847	2.77
North Sinai	28992	463,975	16.00
South Sinai	31272	105,953	3.39
Red Sea	119099.13	372,862	3.13
El-Wadi El-Gedeed	440098	249,399	0.57

Source: Authors' computation based on data from *Statistical Yearbook, CAPMAS, 2019*.

Long run relations:

As a further step, it is customary to generate long run coefficients for those variables found to be statistically significant in the short run (as per results in Table). The long run coefficient δ_k is the long run effect, and is computed as $\delta_k = \beta_k / (1 - \theta)$, where, β_k is the estimated short run coefficient of variable k , while θ is the coefficient of the lagged dependent variable (PCCO2_emiss_1). The significance of θ (tested by a Z-score) would reflect whether the variable is significant in the long run and has the direction of the effect (positive or negative) as it does in the short run. The results are as follows:

Table A2: Long run effects of statistically significant variables on CO₂ emissions per capita

Dependent Variable: PCCO2_emiss				
	Model (1)		Model (2)	
Variables with significant short run relation	Coefficient	Z-statistic	Coefficient	Z-statistic
NFKF	-1.70e-09*	-1.90	-1.77e-09**	-2.01
FWAge	0.938*	1.81	0.990*	1.94
IlltWAge	-0.854*	2.17	-0.898**	-1.97
ServEmp	-0.028***	-2.61		
AgrEmp			0.028***	2.58

Source: Authors' Computations.

All the variable coefficients are found to be statistically significant in the long run, *ceteris paribus*. In magnitude, *Net fixed capital formation* has about the same effect in long run as in the short run, but females, *illiterate, services and agriculture* have a larger long run than short run

effect. *In terms of direction of the effect, all coefficient changed signs*, whereby net fixed capital formation has negative effect, females have a positive effect, illiterates have a negative effect, and services have a negative effect, while agriculture has a positive effect. The change in the direction of the effect is intriguing because it results from the coefficient of the dependent variable lagged being greater than one. In other words, for every per cent increase in the previous year's per capita CO₂ emissions, the present year's per capita CO₂ emissions increase by more than one percent. This effect is, in fact, reversing the effect of each of these variables in the long run compared to the short run.