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Assessing the Impacts of Technological Innovation on Carbon Emissions in MENA Countries: Application of the Innovation Curve Theory

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Abstract: This study investigates the relationship between technological innovation, renewable energy, economic growth, and carbon dioxide (CO_2) emissions in a group of six specific Middle East and North Africa (MENA) countries from 1990 to 2019. The study utilizes the modified innovation environmental Kuznets curve model (ICC) theory to examine the potential existence of an inverted U-shaped curve between innovation and environmental quality in these selected MENA countries. Various econometric methods are employed to analyse the data. The results show a positive and significant impact of patents for residents on CO_2 emissions, affirming the influence of patents on environmental quality. Additionally, the square of patents demonstrates a significant negative relationship with carbon emissions, providing evidence for the inverted U shape of Claudia's theory. These findings imply that the ICC is relevant to the selected countries, with the quadratic patent variable suggesting that the use of innovative technology initially increases emissions but reaches a turning point after a certain threshold.

Keywords: innovation Claudia curve theory (ICC); CO_2 emission; renewable energy; technological innovation; MENA countries; panel data

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1. Introduction

Recently, there has been extensive discourse surrounding the impact of environmental degradation on a global scale, particularly in relation to issues like global warming and climate change. As a result, the environmental Kuznets curve (EKC) hypothesis, initially posited by [1] to address the repercussions of economic growth on environmental damage, has garnered significant attention as a research subject. In addition, the notion of technological innovation, credited to [2], is widely acknowledged as a crucial factor in understanding and tackling critical environmental concerns. Technological innovation can be defined as advancements in the methods, equipment, or expertise utilized in the development of a product or the rendering of a service, ultimately leading to patenting. The primary motivation behind patenting is to safeguard inventions and technologies. According to [3], patenting takes on two forms: patent applications and patent grants, with patents being prevalent in various fields, including those pertaining to environmental technologies. Notably, many researchers in both environmental and economic literature have utilized patents as indicators of innovation [4]. In 2021, the International Energy Agency published a report indicating that energy-related carbon dioxide (CO_2) emissions increased to 36.6 Gt because of rapid economic growth in the post-COVID-19 period and because of slow progress in improving energy intensity [5]. This rise in emissions contradicts what is required internationally from countries by 2050 to reach net zero emissions.

The importance of the Middle East and North Africa (MENA) region is attributed to its enormous resources in the global oil and gas markets. The region plays a significant role in meeting the global growth in energy demand. In the past few decades, the environmental situation in the region has deteriorated rapidly because of the increased demand for energy, which is driven by population growth and economic progress [6]. In addition, low energy costs have played a major role in the growth of energy demand, as the MENA region recorded the second-highest average growth (exceeding 500%) in CO_2 emissions in the world between 1970 and 2019 [7]. In comparison to global income, this represents 48% of global energy subsidies and inexpensive energy costs, which has resulted in a rise in the inefficient use of fuel [8]. According to BP Energy Outlook 2030, the Middle East will be more energy intensive than it was in the 1970s, when the region's energy intensity was less than half the level of that of other non-Organisation for Economic Co-operation and Development (OECD) countries [9].

Figure 1 above shows the annual share of each MENA country in the global CO_2 emissions for 1990–2021, with Iran having the highest rate (2.02%), followed by Saudi Arabia (1.81%), Egypt (0.67%), Algeria (0.47%), Morocco (0.19%) and Tunisia (0.09%). Moreover, according to statistical data on the annual percentage change in CO_2 emissions, Tunisia recorded the highest rate of change at 14%, followed by Morocco (9.05%), Egypt (5.85%), Iran (2.59%), Algeria (2.18%) and Saudi Arabia (1.06%).

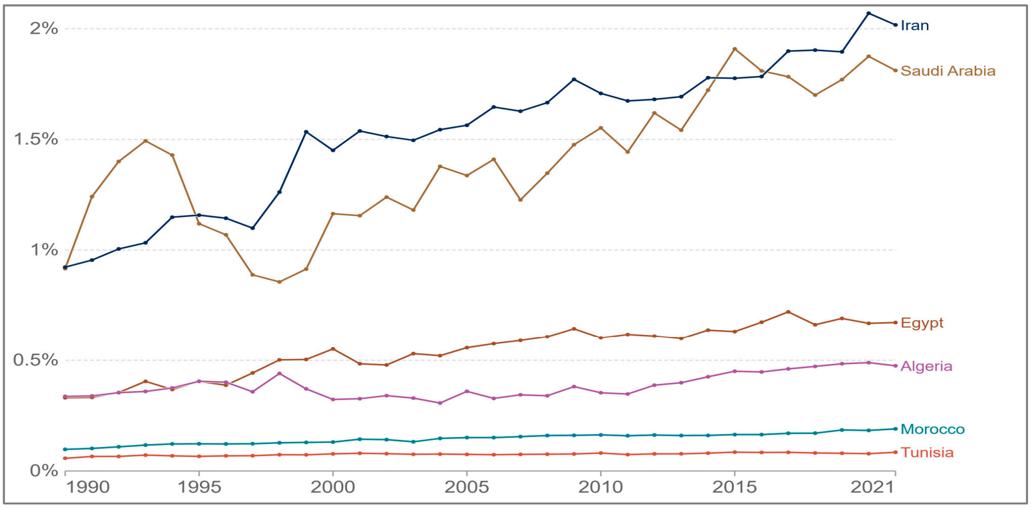

Figure 1. Annual share of global CO_2 emissions. Source: Our World in Data based on the Global Carbon Project (2022).

Figure 2 illustrates the evolution of per capita CO_2 emissions in our sample of six countries in the MENA region from 1990 to 2021. In 2021, Saudi Arabia recorded the highest emissions at 18.7 tonnes per capita, followed by Iran (8.52 t per capita), Algeria (3.99 t per capita), Tunisia (2.58 t per capita), Egypt (2.28 t per capita), and Morocco (1.9 t per capita). Additionally, Figure 3 compares the CO_2 emissions per capita in the countries concerned to the global average and shows that Saudi Arabia and Iran have per capita CO_2 emissions that are higher than the global average. Tunisia, Algeria, Morocco and Egypt have per capita CO_2 emissions below the global average.

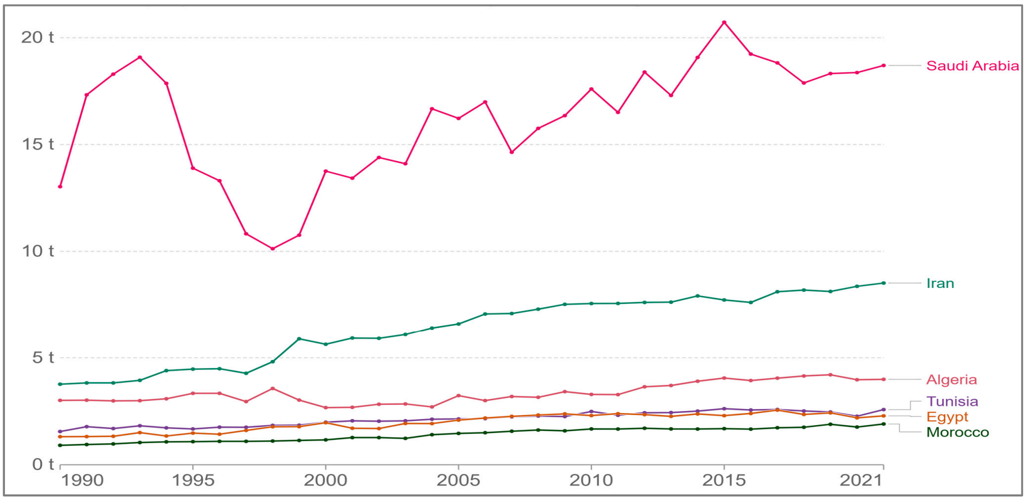

Figure 2. Per capita CO_2 emissions. Source: Our World in Data based on the Global Carbon Project (2022).

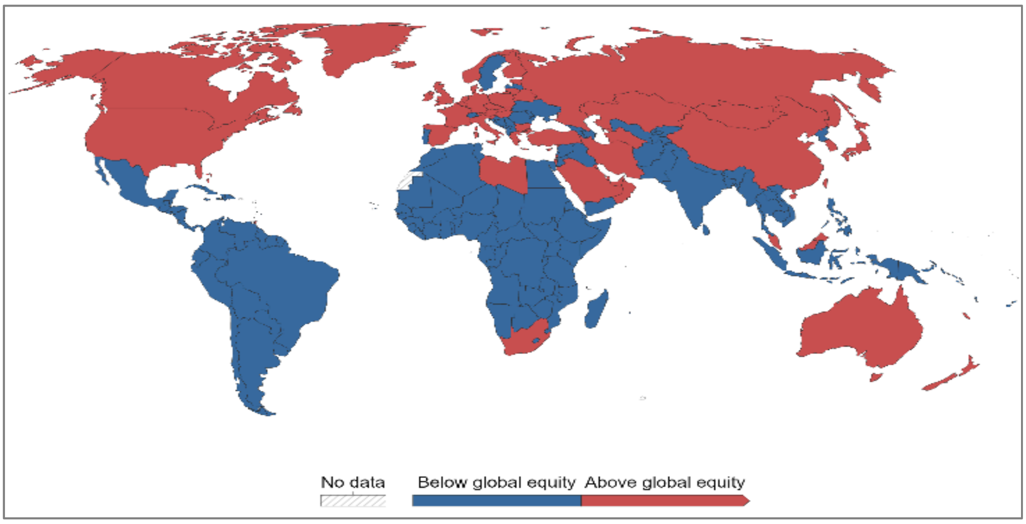

Figure 3. Comparing the CO_2 emissions per capita with the global average Source: Our World in Data based on the Global Carbon Project (2022).

This research utilizes a revised EKC theory to analyse how technological innovation affects CO_2 emissions in certain MENA countries, as well as the influence of other environmental and economic factors on CO_2 emissions. Familiarity with the background information and existing studies enhances comprehension of the relationship between CO_2 emissions and technological innovation, providing valuable insights for policymakers and contributing to environmental improvement efforts. This understanding not only aids in reducing CO_2 emissions, but also supports the growth of the technological innovation industry and the national economy. However, this study stands out from existing research in three key ways, addressing gaps in the current literature. Firstly, this study adds to the small body of literature by focusing on different environmental factors in selected countries from the MENA region [10–12]. Utilizing panel data from the World Bank database, the study evaluates the impact of technological innovation and other related variables such as renewable energy, economic growth, trade, and population on CO_2 emissions at the regional level, with the aim of informing effective policies for technological innovation.

Secondly, while previous studies have reported opposite relationships [10,11], this study explores the links between CO_2 emissions and technological innovation and other environmental and economic factors. Thirdly, the study allows for a more robust analysis of the impact of technological innovation and other control variables on CO_2 emissions in the MENA region. The study contributes fresh insights to the existing literature on the role of technological innovation, renewable energy, trade, and economic and population growth in achieving environmental sustainability. Even though all those factors have been separately utilized in different studies, this study merged all these factors in a single econometrics model. The remaining parts of this paper are organised as follows. The Section 2 presents studies related to the topic, followed by the Section 3. The Sections 4 and 5 present the findings of the study and discuss the main results. The Section 6 concludes the paper and proposes recommendations for policymakers.

2. Literature Review

2.1. Economic and Environmental Factors

Numerous empirical studies have been carried out in a variety of countries to investigate the factors that impact the environment. Of particular interest is the research on the correlation between CO_2 emissions, gross domestic product (GDP), and the use of renewable energy. For example, Vo and Vo [13] emphasised the importance of utilizing renewable energy to achieve sustainable economic growth in the Association of Southeast Asian Nations region by moderating population growth. The use of renewable energy not only addresses population growth but also reduces CO_2 emissions. Additionally, various studies have identified a causal relationship between economic growth, energy consumption, and CO_2 emissions [13,14]. Nathaniel, Adeleye [15] examined the correlation between carbon emissions, population, economic growth, and renewable energy in East African countries. Their results, obtained using the Autoregressive Distributed Lag (ARDL) approach, revealed that CO_2 emissions are positively influenced by economic and population growth, while the impact of renewable energy consumption on CO_2 emissions is negative.

Kahia, Omri [16] utilized the generalised method of moments (GMM) to analyse the correlation between economic growth, green energy, and environmental quality in Saudi Arabia from 1990 to 2016. The results indicated that initially, economic growth led to an increase in CO_2 emissions, but eventually contributed to lowering emission levels, thus supporting the validity of the EKC hypothesis. Similarly, Gierałtowska, Asyngier employed a two-step system GMM to study 163 countries from 2000 to 2016, confirming the EKC theory. This suggests that urbanization, GDP, and innovation, as represented by resident patents, have an inverted U-shaped relationship with CO_2 emissions, while renewable energy consumption diminishes CO_2 emissions. In contrast, [17] study on MENA countries from 1975 to 2014 found differing results, indicating no significant relationship between economic growth and CO_2 emissions, as well as no negative impact of energy conservation policies on economic growth.

In terms of MENA countries, Multiple research studies have explored the significance of reducing CO_2 emissions by analysing a range of factors. For example, [18] determined that economic growth harms the environment, while renewable energy decreases carbon emissions. This outcome aligns with the findings of [19] who investigated a group of 12 countries in the MENA region from 1980 to 2012 using the Panel Vector Autoregression (PAVR) model. Their research revealed that economic growth contributes to environmental damage, while renewable energy, international trade, and foreign direct investment help to decrease CO_2 emissions. Ekwueme and Zoaka [20] also confirmed this result, discovering a negative association between trade openness, financial development, and CO_2 emissions in MENA countries using the econometrics method. Additionally, Al-Mulali, Fereidouni [21] utilized time-series data from 1980 to 2009, finding a positive correlation between urbanization, energy consumption, and CO_2 emissions in MENA countries. Moreover, Nathaniel, Adeleye [15] tested the EKC theory in the MENA region and pointed out that there is a bidirectional causal connection in both the short and long terms between energy consumption and economic growth.

The EKC theory was examined in the MENA region, revealing a two-way causal relationship between energy consumption and economic growth in both the short and long term. Research by Kahia, Kadria [22] indicated that renewable energy policies have a significant and positive impact on economic growth. Similarly, [23] advocated for policies that enhance the capacity of renewable energy and promote environmental sustainability. Their study, conducted from 2006–2016 using ARDL approach, concluded that increasing the use of renewable energy improves efficiency, while increasing the use of conventional energy has negative effects on environmental quality, efficiency, and long-term sustainability in MENA countries.

Investigating the complex correlation between trade and carbon dioxide (CO_2) emissions has been the subject of extensive scholarly inquiry. The literature reveals diverse findings regarding the relationship between trade and CO_2 emissions, warranting a closer examination. [24] highlight the nuanced influence of trade policies on CO_2 emissions, demonstrating both positive and negative effects depending on the specific policies implemented within an economy. On one hand, studies by Schmalensee, Stoker, Taylor and Copeland and Ansari, Haider [25–27] provide evidence supporting the assertion that trade liberalization, through the removal of barriers to global commerce, may lead to increased CO_2 emissions due to heightened transportation and production activities. However, contrasting findings suggest an alternative perspective. Shahbaz, Lean [28] propose that trade openness can also result in a reduction of CO_2 emissions by allowing nations access to global markets and increasing their market shares. This competition among nations fosters an incentive to import cleaner technologies, subsequently reducing carbon dioxide emissions and optimizing resource utilization [29]. Overall, the literature presents contradictory perspectives, highlighting the need for a comprehensive analysis of the mechanisms and contextual factors at play in the relationship between trade and CO_2 emissions.

The Impact Population Affluence Technology (IPAT) framework has been widely utilized in various studies to contribute to an ongoing discourse on the factors that drive environmental change [30,31]. This framework incorporates essential aspects of human influence on environmental change within a model that encompasses environmental impact, population, and economic activity. These factors are considered to be the primary anthropogenic driving forces affecting environmental quality, even in more advanced frameworks [32]. The focus of most studies was on estimating the effects of CO_2 emissions due to their significant role in radiative forcing and the availability of reliable data on CO_2 emissions for numerous nations. Population growth is identified as a major driver for CO_2 emissions, and multiple studies highlight its impact on CO_2 emissions [32,33].

2.2. Technological Innovation

It is widely acknowledged that technological innovation plays a crucial role in the global efforts to reduce CO_2 emissions. Various research studies have investigated the impact of innovation on carbon emissions, yielding significant insights. For example, Wang, Yang [34] demonstrated that patents for carbon-free energy technologies contributed to a reduction in CO_2 emissions in eastern China between 1997 and 2008. Additionally, Wang, Li [35] utilized an ARDL approach to analyse the relationship between technological innovation and CO_2 emissions in China from 1970 to 2017, revealing that technological innovation effectively mitigates CO_2 emissions. Furthermore, Adebayo, Adedoyin [36] applied wavelet techniques to examine the dynamic impact of trade openness, technological innovation, economic growth, and renewable energy use on environmental degradation in the Portuguese economy from 1980 to 2019. Their findings indicated that renewable energy consumption helps to control CO_2 emissions, whereas trade openness, technological innovation, and economic growth contribute to an increase in CO_2 emissions. Similarly, Destek and Manga [37] focused on the effects of technological innovation on CO_2 emissions and the ecological footprint of major emerging markets from 1995 to 2016, revealing that while technological innovation effectively reduces CO_2 emissions, it does not have a significant impact on the environmental footprint.

Finally, Kihombo, Ahmed [38] assessed the influence of technological innovation on the ecological footprints of West Asian and Middle Eastern nations from 1990 to 2017, demonstrating that technological innovation plays a role in decreasing CO_2 emissions. Fethi and Rahuma [39] used investment in research and development (R&D) as a proxy for environmental innovation in the 20 largest oil-exporting economies. The research indicates that investment in research and development has a negative impact on CO_2 emissions in the long term. Furthermore, Mensah, Long [40] conducted a study on 28 OECD countries from 1990 to 2014, investigating the role of innovation in reducing emissions. Their findings suggest that innovation plays a crucial role in decreasing CO_2 emissions in most of the countries studied. Similarly, Rafique, Li [41] that technological innovation helps reduce emissions in BRICS countries. Additionally, Wang, You [42] research on carbon emissions from 1990 to 2017 using data from N-11 economies showed that renewable energy, the technological impact of renewable energy consumption, globalization, and innovation all contribute to mitigating CO_2. The studies also show that technological innovation and renewable energy significantly decrease CO_2 emissions and improve environmental quality, particularly in Brazil [7,43,44].

The majority of the literature in the eco-innovation field is centred on the role of innovation in reducing CO_2 emissions. In contrast, Adebayo and Kirikkaleli [45] introduced a fresh perspective on the correlation between CO_2 emissions and GDP growth, renewable energy, technological innovation, and globalisation in Japan by employing wavelet statistical tools. Their empirical findings demonstrate that globalisation, GDP growth, and technological innovation contribute to increased CO_2 emissions in Japan, while the use of renewable energy helps to mitigate emissions in the short and medium terms. In a separate study, Wang, Li [35] examined the relationship between CO_2 emissions and environmental innovation in 30 provinces in China from 2004 to 2016, with results indicating that higher CO_2 emissions stimulate environmental innovation. Furthermore, Weina, Gilli [46] conducted a study on the connection between eco-innovation and CO_2 emissions in 95 Italian provinces from 1990 to 2010, revealing that eco-innovation does not have a significant impact on reducing CO_2 emissions.

The correlation between technological innovation and carbon emissions can differ based on the varying countries and economic circumstances. In a study of seven MENA countries, Dauda, Long [10] found that innovation increased CO_2 emissions in the region when using dynamic ordinary least squares. Otherwise, Bilal, Li and Albaker, Abbasi [11,12] conducted research that supported the idea of innovation having a negative impact on CO_2 emissions. As a result, the relationship between innovation and CO_2 emissions in the MENA region remains inconclusive due to the limited sample of countries considered in the literature. There is a gap in the MENA literature regarding the identification of the relationship between innovation and CO_2 emissions, especially in consideration of other economic and environmental factors.

3. Materials and Methods

The study utilises the adapted innovation EKC model, known as the innovation Claudia curve theory, to assess the impact of innovative technology on CO_2 emissions and to investigate the presence of a U-shaped relationship between innovation and environmental quality in specific MENA countries. The initial phase of the empirical analysis involved conducting initial tests to identify the most suitable estimator for the empirical models. Given the significant global integration, panel data methods that neglect cross-sectional dependence could yield unreliable results. Consequently, it is crucial to assess the interdependence among the selected countries when employing panel data techniques, specifically to determine if cross-sectional dependencies exist. The model is shown as follows:

$$CO2_{it} = \alpha_0 + \beta_1 GDP_{it} + \beta_2 PAT_{it} + \beta_3 PAT^2{}_{it} + \beta_4\ Rec_{it} + \beta_5\ Pop + \beta_6\ TRADE_{it} + \varepsilon_{it} \quad (1)$$

This study will focus on six MENA countries only because of data availability issues, namely, Algeria, Egypt, Morocco, Saudi Arabia, Tunisia, and Iran, from 1990 to 2019. Data from these countries were used to test whether the modified EKC hypothesis existed and applied to such data. In addition, the empirical analysis conducted in this study depends on theoretical considerations, the structure of the dataset and any potential econometric issues that need to be dealt with. Thus, this study used panel data methods to deal with some problems in MENA countries.

The dependent variable is the CO_2 emission and PAT measures of patent application by residents as the main explanatory variable. This proxy for innovation was employed by Khan, Han [31], Chuzhi and Xianjin [34] who arrived at the same conclusions, proving that patents have beneficial effects on CO_2 emissions. The current study also adds the following explanatory variables: PAT^2, which refers to the quadratic of patent application by residents. To show the existence of an inverted U shape, the quadratic of PAT2 is used. The variable GDP refers to the gross domestic product per capita (constant 2015 USD), REC refers to renewable energy consumption (renewable energy consumption, % of the total final energy consumption), and trade variable serves as a control variable represent the trade as a percentage of GDP. The total population also included as a significant control variable and ε is the error term. Table 1 shows the brief description of the variables included in the model.

Table 1. Description of variables.

Variables	Description	Symbols	Data Source
CO_2 emission	intensity (kg per kg of oil equivalent energy use)	CO_2	World Bank Indicators
Gross domestic product	Gross domestic product per capita (constant 2015 USD)	GDP	World Bank Indicators
Renewable energy consumption	Renewable energy consumption % of total final energy consumption	REC	World Bank Indicators
Patent application by resident	A measure of innovation technology	PAT	World Bank Indicators
Trade	Trade as % of GDP	TRADE	World Bank Indicators
Population	Total population	POP	World Bank Indicators

4. Results

Panel data models are employed to address the issue of heterogeneity or individual effects that may or may not be present. These models consider group (individual-specific) effects, time effects, or a combination of both. These effects can be either fixed or random. In a random effect model, the focus is on examining variations in error variance components across individuals or time periods. On the other hand, a fixed effect model assesses whether intercepts vary across groups or time periods [47]. And because the panel data has the same number of the observation in each cross-sectional entity, it is balanced panel data. The analyses start with the descriptive data which in Table 2 shows the means and standard deviations of the variables considered in the analysis. The descriptive statistics provide an overview of the panel data sample and observations.

Table 2. Descriptive statistics.

Variable	Observation	Mean	Std. Dev.	Min	Max
CO_2	180	184,545.2	175,437.8	14,671.90	637,433.7
GDP	180	5871.828	5875.806	1521.217	20,627.92
PAT	180	1190.428	3241.189	6	15,403
REC	180	5.118605	6.844913	0.009032	23.000
TRADE	180	62.88441	18.60216	29.22822	114.3437
POP	180	41,528,348	26,095,556	8,440,023	106,000

In the first step of empirical analysis, the study employed some preliminary tests, for instance, unit root, and cointegration to determine the most appropriate estimator for our empirical models. Due to the high level of integration around the world, panel data methods do not consider cross-sectional dependence, which may lead to unreliable results. Accordingly, when using panel data techniques, it is most likely necessary to test the interdependence between the selected countries, in other words, if the selected countries have cross-sectional dependencies. Breusch and Pagan came up with the Lagrange multiplier test in 1980 to check the cross-sectional dependence in the panel series, which can be shown by the LM test using the following equation:

$$Y_{it} = a_i + \beta_i X_{it} + \varepsilon_{it},\ where\ i = 1, \ldots .N, t = 1, \ldots ..T, \tag{2}$$

where i and t show the size of the cross-section and time, respectively. The null hypothesis, H0: Cov (ε_{it}, ε_{it}) = 0, means that the cross-sections do not depend on each other. While the alternative hypothesis, H1: Cov (ε_{it}, ε_{it}) $\neq$ 0, shows that at least one pair of cross-sections depends on each other. Therefore, we can find the LM test from the following:

$$\mathrm{LM} = \mathrm{T} \sum_{i=1}^{N-1} \sum_{j=j+1}^{N} \hat{\rho}_{ij}^2 X^2_{N(N-1)/2} \tag{3}$$

where ($\hat{\rho}_{ij}^2$) is a sample of the cross-sectional correlation between the residuals estimated using OLS in Equation (2). A Lagrange multiplier statistic for cross-sectional dependency (CDL, Hereafter) developed by [48] is an excellent alternative to the LM test in cases where T is small, and N is large. However, the potential CSD among MENA nations is analysed with the CD test. In cases of zero population average pair-wise correlations, the CD test is ineffectual and inconsistent, so the bias-adjusted LM test [49] is used to explore the existence of CD in the panel series, which can be shown in the following equation:

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{(T-K)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \mathrm{N}(0,1) \tag{4}$$

where k, μ_{Tij}, v_{Tij}^2 represent the number of regressors, actual mean, and the variance pf $(T-K)\,\hat{\rho_{ij}}$ [49].

Table 3 displays the results of the cross-section dependency test obtained using the [48] method. The result demonstrates the rejection of the null hypothesis because there is clearly no cross-sectional dependency. Thus, the necessity of evaluating the impact of globalization on the study's metrics is emphasized.

Table 3. CD cross sectional dependence test.

(p-Value) Variables	**CO_2**	**GDP**	**REC**	**PAT**	**PAT2**	**Trade**	**POP**
Breusch-Pagan LM	426.86 (0.00)	341.29 (0.00)	111.38 (0.00)	300.62 (0.00)	239.93 (0.00)	124.29 (0.00)	446.48 (0.00)
Pesaran scaled LM	75.19 (0.00)	59.57 (0.00)	17.59 (0.00)	52.14 (0.00)	41.06 (0.00)	19.95 (0.00)	78.77 (0.00)
Bias-corrected scaled LM	75.09 (0.00)	59.47 (0.00)	17.49 (0.00)	52.04 (0.00)	40.96 (0.00)	19.85 (0.00)	78.67 (0.00)
Pesaran CD	20.65 (0.00)	18.15 (0.00)	6.713 (0.00)	17.25 (0.00)	15.19 (0.00)	10.25 (0.00)	21.13 (0.00)

In our quest to account for cross-sectional dependence (CD), we employed the well-known and widely utilised unit root test developed by [50], which is the cross-sectional augmented Dickey–Fuller (CADF). The CADF is calculated as follows:

$$\Delta Y_{it} = a_i + \rho Y_{it-1} + \beta_i \overline{Y}_{t-1} + \sum_{j=0}^{k} \gamma_{ij} \Delta \overline{Y}_{it-1} + \sum_{j=0}^{k} \delta_{ijY_{it-1}} + \varepsilon_{it} \tag{5}$$

If a_i is a deterministic term, k_i is the lag order and Y_t is time's cross-sectional mean. Following the previous equation, t-statistics are derived by computing individual ADF statistics. Additionally, the CIPS is calculated from the average of the CADF-statistics for each i, as shown in the following:

$$\text{CIPS} = (\frac{1}{N})\sum_{i=1}^{N} t_i(N,T) \tag{6}$$

As a result, the stationarity of the series can be approximated one by one for the entire panel and for each cross-section. In T > N and N > cases, the CADF test is used to hypothesise that each country is influenced differently by time effects, and it considers spatial autocorrelation. The stationarity is tested for each country by comparing the statistical values with critical Peseran's CADF table values. If the CADF critical value is greater than the CADF statistics value, the null hypothesis is rejected, and the country's series is determined to be stationary. The CADF test statistics are assessed as follows:

$$\Delta Y_{i,t} = (1-\phi_i)\mu_i + \phi_i Y_{i,t-1} + u_{i,t} \quad i = 1,2,\ldots N \text{ and } t = 1,2,\ldots\ldots..T \tag{7}$$

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \tag{8}$$

$\mathrm{f_t}$: unabsorved comment factor for each country

$\varepsilon_{it} : individual\ -\ specific\ errod$

From Equations (7) and (8) the unit root test hypothesis is:

$$\Delta Y_{i,t} = (1-\Phi_i)\mu_i + \Phi_i Y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \quad i = 1,2,\ldots N \text{ and } t = 1,2,\ldots\ldots..T \tag{9}$$

$H_0 : \beta_i = 0\ for\ all\ i$

$H_1 : \beta_i < 0\ i = 1,2,\ldots..,\ldots N_1\beta_i = 0.\ \ i = N_1+1,\ N_1+2,\ldots,N$

Table 4 presents the critical values for each country and exhibits the CD and unit root test results. The results of the unit root illustrate that CO_2, GDP, PAT, PAT^2, trade, and Pop are non-stationary at the levels but become stationary at the first differences; they are considered to be integrated at first difference, I (1). REC is stationary at the level, so it is cointegrated at level I(0). The study applies Pesaran's CIPS unit root test based on the CSD confirmation, as the stationarity process of variables must be examined using a unit root test that permits CSD [50]. The results in Table 5 indicate that the unit root process cannot be rejected when variables are in level form, except in REC, PoP Nonetheless, in the first-differenced form, all variables have become stationary. Therefore, the findings of the CIPS panel unit root tests indicate that CO_2, GDP, PAT, PAT^2, and trade are non-stationary at the levels but become stationary at the first differences, while REC and pop are stationary at the level.

Table 4. Second generation (CIPS unit root test).

Variables	Level	First Different	Critical Value
CO_2	−2.52	−4.48 *	−3.1
GDP	−1.281	−4.138 *	−3.1
PAT	−1.859	−5.772 *	−3.1
PAT2	−1.442	−5.459 *	−3.1
REC	−3.267 *	_	−3.1
Trade	−1.49	−5.40 *	−3.1
POP	−3.85 *	_	−3.1

* Critical values for the CIPS test of Pesaran (2007) [50] are −2.73, −2.86, and −3.1 at 10%, 5%, and 1% level, respectively.

Table 5. Model estimation.

Variables	POL Model		FE Model		RE Model	
	Coefficient	***p*-Value**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**
Constant	1276.7	0.9678	63461.0	0.1768	1276.7	0.96W
GDP	17.24	0	16.801	0	17.23	0
PAT	73.28	0	73.487	0	73.28	0
PAT2	−0.0033	0	−0.003	0	−0.003	0
Rec	−1533.0	0.1165	−1835.0	0.0819	−1533.0	0.14
Trade	−443.29	0.1851	−1045.2	0.037	−443.29	0.21
POP	0.0016	0	0.001	0.0029	0.0016	0
Model fit	N = 180	R^2 = 0.90	N = 180	R^2 = 0.90	N = 180	R^2 = 0.90
Husman test					6.87	0
Breusch-Pagan	138.70	0				0

Panel data analysis requires a careful selection between the random effects model and the fixed effects model to ensure the validity of the results [51]. The initial step involves evaluating whether the observations constitute a random sample from the population of interest, representing a randomly selected subset of individuals. If the observations meet the criteria of a random sample, further analysis is conducted; otherwise, the fixed effects model is chosen as the final approach. When a random sample is employed, the next step involves estimating both the fixed effects and random effects models.

The Hausman test is then performed to compare these models, with the null hypothesis being that the random effects model is preferred over the fixed effects model. The Hausman test primarily examines the correlation between the unique errors and regressors. If the coefficients show significant differences, indicating a correlation, the fixed effects model is selected as the appropriate choice [52]. Subsequently, the Lagrange multiplier test is employed to determine the suitability of the random effects model or the pooled OLS model for the research. The null hypothesis of this test asserts that there are zero variances across entities, signifying no significant differences across countries. To determine the optimal model, the Hausman test is employed to assess whether the model exhibits common effects or fixed effects [53]. The obtained result of the Hausman test, with a chi-square value of 6.87 and a *p*-value of 0.33, fails to reject the null hypothesis, suggesting that the random effects model is preferable over the fixed effects model.

Moreover, to compare the pooled model with the random effects model, the Lagrange multiplier test is conducted. The random effects model assumes that the variation among entities is stochastic and uncorrelated with the independent variables, thereby allowing time-invariant variables to function as independent variables. This characteristic facilitates the inclusion of variables such as the superficialities of providence, which would otherwise be absorbed by the intercept in the fixed effects model. However, the random effects model necessitates the specification of specific attributes that may impact the independent variables, although the omission of certain variables could introduce omitted variable bias into the model. The equation for the random effects model can be represented as follows:

$$y_{it} = \propto + \beta_k X_{k,it} + u_{it} + \varepsilon_{it} \tag{10}$$

In the present empirical research, the Lagrange multiplier test is employed with various Pagan–LaGrange multipliers to examine the presence of random effects. The test's null hypothesis assumes zero variances between entities, indicating no significant differences across units. The significant result obtained from this test indicates the presence of random effects, thereby providing evidence of substantial variations across MENA countries. Consequently, the results derived from the random effects model are deemed valid for evaluating the relationship between CO_2 emissions and technological innovation.

The empirical findings in Table 4 above highlight the significant impacts of two independent variables, patents, and GDP, as well as one control variable, on environmental quality. Notably, the random effects estimation reveals that an increase of one unit in patents leads to a 73.23 kg rise in CO_2 emission intensity. Additionally, GDP exhibits a positive and significant effect on carbon emissions, with a one-unit increase resulting in a 17.2 kg rise in CO_2 intensity. Conversely, the analysis indicates that renewable energy consumption and trade have statistically insignificant effects on CO_2 emissions. However, population size demonstrates a positive and significant relationship with environmental quality, suggesting its influence on environmental outcomes.

Furthermore, the inclusion of the patent squared term displays a significant negative association with carbon emissions, corroborating Claudia's theory regarding an inverted U-shaped relationship. According to Claudia's theory, an initial surge in CO_2-mitigating patent innovation leads to higher emissions due to limited accessibility, but further increases gradually reduce emissions. These findings imply that the protection of patented technologies can contribute to reducing carbon dioxide emissions when multiple technologies are involved. Finally, the trade variable is found to be statistically insignificant, and the consumption of renewable energy does not exhibit a significant impact. However, it is essential to note that this study primarily emphasizes the significant effects of patents, GDP, population, and the quadratic term of patents on CO_2 emissions. Taken together, these results signify the influential roles of technological innovation, economic growth, and population size in shaping environmental outcomes.

To assess the robustness of random effect models in panel data, researchers have proposed various approaches. Herwartz [54] introduced a bootstrap scheme to generate critical values for the Breusch–Pagan (BP) statistic, commonly used to distinguish between pooled regression and random effects models. This method allows for a more reliable comparison between the two. In the present study, the Breusch–Pagan test yielded a statistic value of 138.70 with a p-value less than 0.05, indicating that the random effect model is more appropriate than the pooled model. Furthermore, the Hausman test provides additional support for the validity of the random effect model over the fixed effect model. The Hausman test examines the correlation between the unique errors and regressors, with the null hypothesis suggesting that the random effects model is preferred. Considering the results of the Hausman test, we can conclude that the random effect model is the more suitable choice.

5. Discussion

The output of this study is consistent with the findings of [55] regarding the relationship between patents, patent square, and co Studies conducted in China [56], a cross-country analysis [57], and in the MENA countries context [10] provide substantial evidence that technological innovation has an impact on CO_2 emissions reduction. This is particularly true for high-income economies, as research has shown that advancements in green technology significantly contribute to the reduction of CO_2 emissions [58]. However, the effectiveness of these advancements may vary depending on the specific economic context and income level. Therefore, technological advancement plays a critical role in reducing CO_2 emissions.

Several studies have found a positive correlation between GDP and CO_2 emissions. Souza Mendonça, Barni and Namahoro, Wu [59,60] support this correlation, with Mendonca emphasizing the significance of population expansion. Islami, Prasetyanto [61] adds further evidence by stating that CO_2 emissions are influenced by GDP per capita, while their reduction can be facilitated through the use of renewable energy. Additionally, Mirza, Sinha [62] highlights the importance of energy efficiency, fuel mixtures, and industrial structure in this correlation. Consistently, population growth has a positive influence on CO_2 emissions, as shown by research conducted by [63,64]. Economic expansion and increased energy consumption accompanying population growth contribute to this effect. However, the influence of population size on carbon dioxide emissions varies among countries and income brackets [65]. Therefore, while population growth is a significant contributor to rising CO_2 emissions, other factors such as industrial structure and technology must be considered when developing CO_2 abatement strategies.

Our findings indicate that the impact of renewable energy consumption on CO_2 emissions is insignificant. This aligns with previous studies that highlight the presence of various factors influencing the effectiveness of renewable energy consumption in improving environmental quality. The relationship between renewable energy usage and CO_2 emissions reduction is complex and depends on multiple factors. Dong, Hochman [64] discovered that while renewable energy usage does contribute to CO_2 emissions, its impact is relatively minor compared to the overall growth of the economy and the increased use of non-renewable energy sources. Coiante and Barra [66] discussed technical challenges associated with renewable energy sources, which can limit their effectiveness in environmental improvement. On the other hand, Paramati, Sinha and Jia, Lei [67,68] both emphasized the potential of renewable energy consumption to benefit the economy and reduce CO_2 emissions, particularly in developing and underdeveloped countries. However, the widespread adoption of renewable energy faces various barriers at present, hindering its full potential in mitigating CO_2 emissions.

The finding suggests that the impact of trade on environmental quality is not significant, primarily due to weak policies that promote the use of renewable energy. As mentioned in other studies [69,70], the impact of trade on environmental quality depends on the policies implemented by countries. Given that most of the selected countries in our data are developing countries, they lack policies to improve environmental quality or enhance the use of renewable energy. In this case, we observe no impact of trade due to the low level of policies implemented in these countries to improve environmental quality.

Although more stringent environmental regulations in importing countries may result in increased CO_2 emissions from domestic production, they can effectively decrease emissions from exporting and importing countries [71]. CO_2 emissions exhibit a positive correlation with energy consumption, income, and trade openness; however, trade openness has the potential to mitigate emissions over an extended period of time [72]. The impact of international trade on domestic carbon dioxide (CO_2) emissions is substantial, demanding its inclusion in discussions regarding climate change [73]. The potential increase in CO_2 emissions in developing countries resulting from trade with high-income partners is contingent upon the level of development and the direction of trade [74].

6. Conclusions

The objective of this study was to evaluate the adjusted EKC model for innovation and analyse the impact of innovation technology on CO_2 emissions. Additionally, it sought to investigate the presence of a U-shaped curve between innovation and environmental quality in a group of MENA countries from 1990 to 2019 using the panel REM estimation method. The findings from the empirical econometric analysis demonstrated that the integrated EKC model is applicable to the chosen countries, and the quadratic patent variable suggested that the utilization of innovation technology initially increases emissions but reaches a turning point after a certain threshold; it was also revealed that patents have a substantial influence on environmental quality. Consequently, the outcomes provided evidence supporting the notion that as more patents are filed and utilized, the environment's quality improves and the amount of environmental degradation diminishes [75,76].

Based on the study's findings, the following recommendations are proposed. Countries in the MENA region must improve their environmental quality by effectively enhancing technological innovation indicators and their use of renewable energy. Moreover, the countries studied in this work may continue to use energy that does not come from natural resources to help their economies grow; however, from the recommendations, it is shown that promoting innovation significantly helps in converting non-renewable energy to renewable forms because if innovation increases, energy intensity improves as well. Prioritising and investing in sustainable and clean technologies can mitigate the potential negative impacts of technological innovations on CO_2 emissions.

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