Ousama BEN-SALHA • Mourad ZMAMI

THE IMPACT OF HUMAN CAPITAL ON THE LOAD CAPACITY FACTOR IN THE MIDDLE EAST AND NORTH AFRICA

Ousama **Ben-Salha** (ORCID: 0000-0002-0253-313X) – Humanities and Social Research Center, Northern Border University

Mourad **Zmami** (ORCID: 0000-0002-8838-6512) – Department of Finance and Insurance, College of Business Administration, Northern Border University

Correspondence address: Humanities and Social Research Center, Northern Border University P.O. Box 1321, Arar 91431, Saudi Arabia e-mail: ousama.bensalha@nbu.edu.sa

ABSTRACT: Although there has been a substantial body of research analysing the factors influencing environmental sustainability, the role of human capital has been relatively understudied. The objective of this research is to fill this gap by examining the impact of human capital on load capacity factor (LCF) across 14 MENA countries from 1990 to 2019. The empirical investigation employs the Method of Moments Quantile Regression (MMQR) alongside a variety of second-generation panel data techniques. The empirical analysis confirms the presence of a long-term linkage between human capital and environmental sustainability. Furthermore, the MMQR suggests a negative impact of human capital on LCF across all quantile orders, indicating that enhanced human capital reduces LCF and deteriorates environmental quality. Although the detrimental effects of human capital on the environment is observed in all countries, they are more pronounced in countries with good environmental performance. Additionally, the MMQR indicates the validity of the Load Capacity Curve hypothesis within MENA countries. Finally, economic globalisation and population have detrimental impacts on the environment, whereas clean energy consumption has a positive effect. This study emphasises the necessity of increasing public awareness of environmental challenges, as well as the implementation of strategies for mitigating climate change in the MENA region.

KEYWORDS: human capital, load capacity factor, MMQR, MENA region

Introduction

Human capital (HC) is critical for the achievement of Sustainable Development Goals (SDGs). Indeed, HC can affect all pillars of sustainable development. First, HC has been considered in the economic literature as a crucial determinant of economic development (Mincer, 1984). Furthermore, the investment in HC is important for skill development, job creation, poverty reduction, and improved quality of life. Finally, HC can contribute to SDGs by lessening the ecological footprint (EF) and promoting environmental sustainability. The prior literature highlighted the contribution of HC in fostering environmental awareness and shaping individual behaviours toward the use of clean energy. Countries with a strong emphasis on HC are concerned with policies that support environmental protection, including carbon taxes, renewable energy projects, and eco-friendly goods, which may improve environmental quality (Li & Ouyang, 2019; Yao et al., 2020; Li & Ullah, 2022). A review of the existing literature suggests that studies on factors affecting environmental sustainability have concentrated on the impact of economic activity, energy demand, urbanisation, financial development and energy prices, among others (Fatima et al., 2021; Aller et al., 2021; Meo et al., 2023; Ben-Ahmed & Ben-Salha, 2024). Nonetheless, the role of HC has been relatively understudied. This suggests a substantial gap in the current understanding of the multifaceted association between HC and environmental quality.

The objective of this paper is to address this gap in the literature on environmental sustainability by investigating the significant yet often overlooked role of HC. Specifically, this research empirically assesses the effects of HC on environmental conditions in 14 Middle East and North African (MENA) countries from 1990 to 2022. This study extends upon previous research in many ways. To start, this study represents the first attempt to evaluate the environmental repercussions of HC in the MENA region. The selection of MENA countries has not been made arbitrarily but driven, at least, by two reasons. On the one hand, the MENA region is confronted with substantial climatic and environmental challenges, such as air pollution, extreme weather events, droughts, and increasing temperatures. According to Arkeh and Hamzawy (2024), MENA countries are among the most vulnerable to the physical risks of climate change. Furthermore, temperature in the MENA region is 20% higher than the global average (United Nations, 2023). On the other hand, some MENA countries, such as Egypt, have experienced a boom in population during the last decades, whereas others, particularly in the Middle East, have witnessed improvements in HC during the same period. Consequently, an in-depth understanding of the interplay between HC and environmental quality is important to formulate effective policies for climate change mitigation in MENA countries. Second, the present study employs the load capacity factor (LCF) as a proxy for environmental quality. Indeed, LCF has significant advantages over conventional environmental measures. On the one hand, LCF not only assesses air pollution but also the impacts on soil, land, and water, among others. On the other hand, unlike the EF, LCF considers both the demand and supply of natural capital, offering a more comprehensive understanding of the environmental situation. The LCF has been recently employed in environmental research, such as Pata and Tanriover (2023), Alharbey and Ben-Salha (2024), and Djedaiet et al. (2024). However, scarce studies, including Pata and Isik (2021) for China, Çamkaya and Karaaslan (2024) for the United States and Dai et al. (2024) for ASEAN countries, assessed the effects of HC on LCF. Nonetheless, no prior research examined the impact of HC on LCF in the MENA region. Another advantage of utilising the LCF is that it enables assessing the validity of the Load Capacity Curve (LCC) hypothesis in the MENA region, a task that has not been explored in the previous literature. Third, the present research adds to the literature by employing the Method of Moments Quantile Regression (MMQR) developed by Machado and Santos Silva (2019) to estimate the environmental implications of HC in MENA countries. Indeed, quantile regression represents a robust estimation technique that addresses many econometric issues, including nonnormal distribution of the data, heteroscedasticity and outliers (Wang et al., 2024). Moreover, it allows for the estimation of the effects of the interest variable (HC) on the different quantiles of the dependent variables (LCF), i.e., the effects of HC on the LCF under different environmental conditions. In addition, the MMQR is a nonparametric technique that does not require any strict parametric assumption about the error distribution. By doing so, the MMQR allows the formulation of more accurate and specific policy recommendations. Many recent studies, including Afshan et al. (2023), Guloglu et al. (2023), Ali and Meo (2024) and Raggad et al. (2024), revealed the suitability of quantile-based approaches in analysing the factors contributing to

environmental degradation and providing more accurate findings compared to conventional estimation techniques.

The rest of this research is structured as follows. Section 2 summarizes the previous literature, while Section 3 describes the data and empirical methodology. Section 4 is reserved for the discussion of the empirical findings. Finally, Section 5 summarizes the key findings, provides policy recommendations, and discusses the limitations.

An overview of the literature

Abundant research has focused on identifying the factors influencing environmental quality, driven mainly by the rising global concerns about environmental challenges. The examination of the impact of HC on environmental quality is a relatively recent area of academic inquiry.

Theoretical considerations

In theory, different mechanisms can be identified to explain how HC influences environmental quality. The first line of research concentrates on the environmental behaviour of economic agents. Chankrajang and Muttarak (2017) underscored that increased years of schooling increase the likelihood of individuals engaging in environmentally friendly practices. In addition, corporations with high levels of HC often adopt stricter pollution control measures and are less likely to violate environmental regulations. In addition, investing in HC via education and training can lead to better behaviour vis-à-vis the environment and improved environmental quality, as many environmental problems are induced by human activities (Ahmed & Wang, 2019). In this context, earlier studies have examined the relationship between HC and energy consumption, which in turn influences environmental quality. According to Churchill et al. (2023), HC and energy consumption are interconnected via the income effect, technology effect and HC-energy linkage. The income effect suggests that an enhancement in HC leads to increased financial resources and greater energy consumption, resulting in heightened/reduced environmental degradation. The environmental impact is contingent upon whether there has been an increase in the demand for nonrenewable or renewable energy sources. The technology effect suggests that improvements in HC lead to a rise in national income, subsequently fostering investment in R&D, promoting green technological innovation, accelerating the energy transition process and enhancing environmental quality. Finally, the authors claimed the importance of the linkage between HC and energy as production factors. They argued that HC can either increase or decrease energy consumption, depending on whether it is complementary or substitute with energy.

Some studies revealed a negative association between HC and energy use. For example, Akram et al. (2019) concluded that HC affects the long-run demand for petroleum in India, which could deteriorate environmental indicators. However, other studies confirmed a positive association between HC and energy consumption. For instance, Zen et al. (2014) concluded that education has positive effects on circular economy activities, which is important for environmental preservation. They highlight that economies with higher levels of HC tend to prioritise energy conservation, waste reduction, and renewable energy sources. Similarly, Yao et al. (2019) found that HC is associated with lower energy consumption in OECD countries. The study suggests that improved HC can lead to a shift from fossil fuels to renewable energy sources, thereby enhancing environmental quality. Churchill et al. (2023) concentrated on the influence of HC on energy consumption in the United Kingdom between 1500 and 2018 and concluded that higher levels of HC are associated with lower energy demand in the long term. More specifically, an extra year of education reduces energy demand between 4% and 9%.

Empirical studies

A growing body of literature has debated the repercussions of HC on the environment. Bano et al. (2018) examined the effects of HC on CO₂ emissions in Pakistan between 1971 and 2014. The results showed that improving HC through education reduces long-run emissions. Additionally, Ahmed and Wang (2019) investigated the effects of HC on EF in India from 1971 to 2014. The authors concluded that improved HC reduces EF and enhances environmental conditions. Furthermore, Li and Ouyang

(2019) explored the consequences of HC on CO₂ emissions in China from 1978 to 2018. They determined that enhanced HC has been associated with reduced long-term CO₂ emissions while shortterm emissions increased. Moreover, Li and Ullah (2022) estimated the response of CO₂ emissions to education in BRICS countries from 1991 to 2019. The findings suggest mixed findings regarding the impacts of environmental quality on education. Recently, Feng et al. (2024) examined the repercussions of HC on the EF in BRICS using the CS-ARDL model and revealed that higher levels of HC contribute to environmental preservation.

Some recent studies have rather investigated the impacts of HC on LCF. For instance, Pata et al. (2023) examined the implications of HC on LCF in the US using the Augmented ARDL model. The authors concluded that HC increases LCF and improves long-run environmental quality. In addition, Pata and Ertugrul (2023) analysed the effects of HC on LCF in India during the period 1988-2018. The findings confirm the presence of positive impacts of HC on environmental quality. Furthermore, Guloglu et al. (2023) explored the repercussions of HC on LCF in 16 OECD countries over the period 1980-2018. The analysis revealed that HC has positive effects on environmental quality. Recently, Dai et al. (2024) analysed the effects of clean energy and HC on LCF in ASEAN economies between 1986 and 2018. The empirical analysis indicates that HC plays a significant role in improving environmental quality. Finally, Ali et al. (2024) analysed the impact of the Human Development Index on LCF in G20 countries between 1994 and 2018. The MMQR suggests a positive association between HC and environmental quality.

Research gap

The literature review highlights mixed findings regarding the effects of HC on environmental quality, which is partly attributable to the implementation of different methodologies, environmental indicators, and samples. Nevertheless, no previous studies have analysed the contribution of HC to environmental sustainability in the MENA region. Moreover, most previous studies on MENA countries have mainly relied on conventional environmental measures, mainly CO₂ emissions and EF, which are recognised for their limited accuracy in accounting for all environmental aspects. This research is, therefore, an attempt to fill these gaps by providing fresh evidence on the repercussions of HC on LCF in MENA countries using the recently developed MMQR technique.

Data and methodology

Data

This research examines the implications of human capital on LCF in 14 MENA countries, namely Algeria, Bahrain, Egypt, Iraq, Jordan, Kuwait, Malta, Morocco, Qatar, Saudi Arabia, Syria, Tunisia, the United Arab Emirates and Yemen, over the period 1990-2019. Unlike the existing literature on the drivers of environmental sustainability in the MENA region, we utilise LCF, defined as the ratio of biocapacity to EF, as a measure of environmental quality. It is important to note that, unlike CO2 emissions and EF, a rise in LCF designates improved environmental conditions, while a decline implies more environmental degradation. HC is quantified by the Human Capital Index, which incorporates years of schooling and returns to education. Based on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model developed by Dietz and Rosa (1994), three factors have been included as control variables, namely Population (P), Affluence (A), and Technology (T). By incorporating population, affluence, and technology as control variables, one can better isolate the specific impact of HC on LCF while controlling for the impacts of other factors that may affect environmental outcomes. In line with the previous literature, total population size serves as a proxy for P, whereas GDP per capita is utilised as a proxy for affluence. Finally, technology is measured by renewable energy consumption, reflecting the adoption of cleaner technologies in the economy. Furthermore, GDP per capita squared is introduced to check the LCC hypothesis in the MENA region. As in Hassan et al. (2020), we introduce the economic globalisation index to check the contribution of openness to environmental sustainability. All variables were subjected to a natural logarithmic transformation. Table 1 provides detailed information on the variables used in the empirical investigation, along with their definitions, units and sources.

Acronym	Variable	Definition	Unit	Source	
LCF	Load capacity factor	Biocapacity to ecological footprint	Index	Global Footprint Network (2024)	
HC	Human capital	Human capital index which accounts for years of schooling and returns to education	Index	Feenstra et al. (2015)	
GDP	GDP per capita	Gross domestic product to total population	Constant 2015 US\$		
GDPSQ	GDP per capita squared	Square of GDP per capita	-	World Bank (2024)	
POP	Total population	Total population	Persons		
REN	Renewable energy consumption	Renewable energy consumption to total final energy consumption	%	-	
KOF	Economic globalization	Economic integration, including trade and capital flows	Index	Dreher (2006), Gygli et al. (2019)	

Table 1. Definitions and sources of variables

Empirical methodology

As shown in Figure 1, the empirical methodology involves a multi-step process. Given that the quantile-based techniques are well-suited for non-normally distributed data, we begin the investigation by conducting a normality analysis. To do this, we implement the Jarque-Bera, Shapiro-Wilk W, and Shapiro-Francia W' tests, along with a visual inspection of quantile-quantile (Q-Q) plots. Then, we check the existence of cross-section dependence (CSD) for all series using the CDw test developed by Juodis and Reese (2022) and the CDw+ test proposed by Fan et al. (2015).

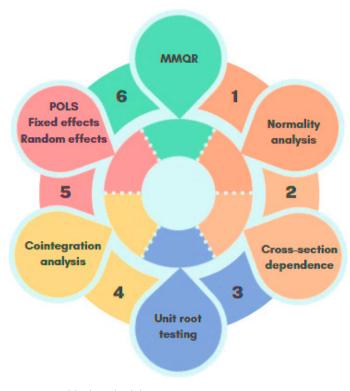


Figure 1. Empirical methodology

These tests allow for identifying CSD and deciding whether first- or second-generation unit root and cointegration tests should be utilised. As a unit root test, we employ the PP-Fisher Chi-square test by removing cross-sectional means to account for CSD. After that, we implement the Westerlund bootstrapped panel cointegration and the demeaned Kao residual-based panel cointegration tests to assess the existence of long-run connections between LCF, HC and the set of explanatory variables. The impact of HC on LCF is then estimated using conventional estimation techniques, i.e., techniques that do not account for non-normally distributed data, namely the pooled OLS, FE and RE. These findings provide a baseline for comparison with subsequent findings obtained using the MMQR. Finally, the MMQR is implemented to estimate the conditional effects of HC on LCF. The use of quantile regression allows for estimating the effects of HC on the different quantiles of LCF and assessing how HC affects LCF in countries with different levels of environmental performance (poor, normal, and good). One advantage of the MMQR is it accounts for individual-specific fixed effects across the conditional distribution, which allows for capturing both location and scale effects (Alhassan et al., 2020). Furthermore, the MMQR is a nonparametric technique that does not require any assumptions about the error distribution (Halidu et al., 2023).

Empirical findings

Normality analysis

As mentioned previously, the first stage of the empirical investigation consists of checking whether the dependent variable, LCF, follows the normal distribution or not. To assess the normality of the dependent variable, we conducted the Jarque-Bera, Shapiro-Wilk and Shapiro-Francia tests. The findings are reported in Table 2.

Table 2.	Normality	/ test results
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Variable: LCF	statistics	p-value	
Jarque-Bera test	27.689***	0.000	
Shapiro-Wilk W test	0.954***	0.000	
Shapiro-Francia W' test	0.956***	0.000	

*** denotes the rejection of the null hypothesis at 1% level.

The three tests suggest the rejection of normality at the 1% level, which confirms that LCF does not follow a normal distribution. This finding is confirmed in Figure 2, depicting the quantile-quantile plots. As shown, the blue points deviate from the straight red diagonal line for almost all variables, which confirms the nonnormal distribution of the data. Therefore, it can be concluded that all variables, particularly LCF, exhibit a non-normal distribution. This outcome provides strong justification for the implementation of the MMQR to estimate the effects of HC on LCF.

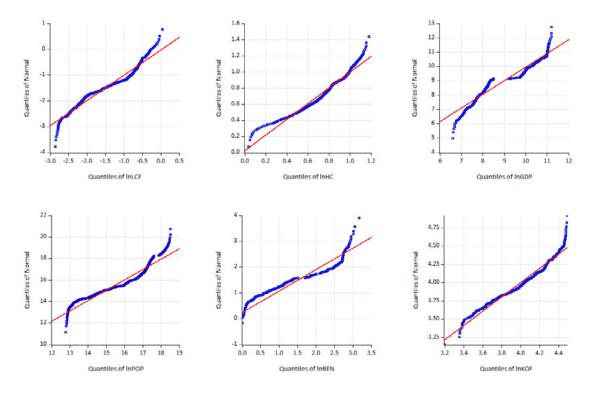


Figure 2. Quantile-quantile plots

CSD analysis

To assess the presence of CSD, we employ the CDw CDw+ tests. The CDw+ test results reported in Table 3 suggest the rejection of the null hypothesis of no CSD for all variables. The CDw test also indicates the existence of CSD for most variables, except LCF, squared GDP and population. Consequently, the findings confirm the existence of significant CSD among the cross-sectional units.

Maria Maria	CDw	test	CDw+ test		
Variables	statistics	p-value	statistics	p-value	
LCF	-1.660*	0.096	230.710***	0.000	
HC	17.630***	0.000	472.910***	0.000	
GDP	-2.040**	0.041	312.770***	0.000	
GDPSQ	0.980	0.326	316.280***	0.000	
POP	0.290	0.769	501.990***	0.000	
REN	-2.120**	0.034	173.240***	0.000	
KOF	-1.420	0.156	247.290***	0.000	

Table 3. CSD test results

***, ** and * denote the rejection of the null hypothesis at 1, 5 and 10% level, respectively.

Unit root testing

This research employs the PP-Fisher Chi-square test, which is commonly applied to check stationarity in panel data. The test is based on four statistics: the inverse chi-square statistics (P), the inverse normal statistics (Z), the inverse logit statistics (L*), and the modified inverse chi-squared statistics (Pm). It is worth mentioning that the PP-Fisher Chi-square test is a first-generation panel unit root test. However, the test in implemented after removing cross-sectional means to account for CSD. The findings reported in Table 4 reveal that the null hypothesis cannot be rejected for most variables at levels, regardless of the specific statistics employed within the PP-Fisher Chi-square unit root test. An exception is population size, for which there is only weak evidence of stationarity. However, when taking the variables at first differences, the findings suggest the rejection of the null hypothesis at 1% for all variables. Therefore, it can be concluded that all series are integrated of order one.

Variables	Inverse chi-square stat. (P)	Inverse normal stat. (Z)	Inverse logit stat. (L*)	Modified inv. chi-squared stat. (Pm)				
Level								
LCF	17.272 (0.943)	1.570 (0.941)	1.516 (0.933)	-1.433 (0.924)				
НС	34.149 (0.196)	-0.604 (0.272)	-0.455 (0.325)	0.821 (0.205)				
GDP	16.640 (0.955)	1.560 (0.940)	1.602 (0.943)	-1.518 (0.935)				
GDPSQ	16.943 (0.949)	1.369 (0.914)	1.364 (0.911)	-1.477 (0.930)				
РОР	42.722** (0.037)	-1.123 (0.130)	-1.119 (0.133)	1.967** (0.024)				
REN	10.567 (0.998)	3.930 (1.000)	4.125 (1.000)	-2.329 (0.990)				
KOF	37.417 (0.109)	-1.210 (0.113)	-1.263 (0.105)	1.258 (0.104)				
First-difference								
LCF	220.364*** (0.000)	-12.498*** (0.000)	-16.345*** (0.000)	25.705*** (0.000)				
НС	80.765*** (0.000)	-5.835*** (0.000)	-5.831*** (0.000)	7.051*** (0.000)				
GDP	159.087*** (0.000)	-10.021*** (0.000)	-11.786*** (0.000)	17.517*** (0.000)				
GDPSQ	162.588*** (0.000)	-10.165*** (0.000)	-12.047*** (0.000)	17.985*** (0.000)				
POP	133.432*** (0.000)	-8.664*** (0.000)	-9.838*** (0.000)	14.089*** (0.000)				
REN	162.436*** (0.000)	-10.023*** (0.000)	-12.027*** (0.000)	17.964*** (0.000)				
KOF	192.832*** (0.000)	-11.407*** (0.000)	-14.299*** (0.000)	22.026*** (0.000)				

Table 4. PP-Fisher Chi-square unit root test results

*** and ** denote the rejection of the null hypothesis at 1 and 5%, respectively. Numbers under parentheses are p-values.

Cointegration analysis

The cointegration analysis is conducted using the Westerlund bootstrapped panel cointegration and the Kao panel cointegration tests. The Westerlund test is a second-generation cointegration test that takes into account CSD, while the Kao test is a first-generation cointegration test that may be less reliable in the presence of CSD. Therefore, to address the issue of CSD, we removed cross-sectional means prior to conducting the Kao cointegration test. The outcomes in Table 5 suggest that three of the four statistics associated with the Westerlund test are statistically significant, indicating the existence of cointegration. Additionally, the different variants of the Kao cointegration test suggest rejecting the hypothesis of no cointegration. Consequently, the empirical evidence suggests the existence of long-run connections between the variables under investigation. These results suggest that there are long-term associations between HC, environmental quality, and other economic and demographic variables.

Table 5. Cointegration test results

Westerlund bootstraped panel cointegration test							
Statistics	Z-value	Bootstrapped p-value					
G _t -3.822***		-5.119	0.000				
G _a	-7.882	2.680	0.180				
P_t	-13.422***	-4.582	0.000				
P _a	0.673	0.080					
Demeaned Kao residual-based panel cointegration test							
Statistics p-value							
Modified Dickey-Fuller t	-2.827***	0.002					
Dickey-Fuller t	-2.820***	0.002					
Augmented Dickey-Fuller t	-1.634*	0.051					
Unadjusted modified Dickey-Fuller t	-4.524***	0.000					
Unadjusted Dickey-Fuller t	-3.502***	0.000					

Critical values are obtained based on 10,000 bootstrap replications. *** and * denote the rejection of the null hypothesis at 1 and 10%, respectively.

Pooled OLS, FE and RE estimation results

Prior to the implementation of the MMQR, we employed traditional panel data techniques, namely pooled OLS, FE and RE models. These techniques yield the mean effect of the explanatory variables while not taking into account the distribution of the dependent variable. The outcomes are reported in Table 6. First, the different estimation techniques yield heterogeneous findings regarding the significance, sign and magnitude of coefficients. For example, GDP per capita is found to increase LCF using the FE and RE estimators, while the pooled OLS suggests no significant impact on GDP per capita. Similarly, the findings for squared GDP per capita differ across estimation techniques. The FE and RE indicate negative and significant coefficients of -0.057 and -0.059, respectively, which suggests an adverse marginal impact of affluence on environmental quality. However, the pooled OLS estimator fails to detect a significant relationship. Therefore, the combined investigation of GDP per capita and its square reveals an inverted U-shaped relationship between GDP per capita and LCF. This indicates that as economies expand, they experience better environmental conditions. However, as they progress, they adopt less sustainable practices, resulting in a decline in environmental quality. Therefore, the FE and RE findings contradict the predictions of the LCC hypothesis, suggesting that the hypothesis is not supported in the MENA region.

Mariah la a	Pooled OLS		Fixed	effects	Random effects		
Variables	coeff.	p-value	coeff.	p-value	coeff.	p-value	
GDP	-0.429	0.132	1.048***	0.002	0.880**	0.016	
GDPSQ	0.022	0.131	-0.057***	0.001	-0.059***	0.005	
POP	-0.010	0.511	-0.826***	0.000	-0.528***	0.000	
REN	0.235***	0.000	0.270***	0.000	0.274***	0.000	
KOF	-1.014***	0.000	-0.062	0.489	-0.312***	0.002	
НС	-1.388***	0.000	0.057	0.641	-0.451***	0.000	
constant	5.571***	0.000	7.830***	0.000	5.211***	0.001	

 Table 6. Standard panel data estimation techniques results

The Hausman test statistic is equal to 97.74 with a p-value of 0.000.

Furthermore, both FE and RE estimators yield negative and statistically significant coefficients for the total population, which indicate that a rise in population size is associated with a decline in LCF and increased environmental degradation. More specifically, a 1% increase in the total population leads to a decline in LCF ranging from 0.528% to 0.826%. These results corroborate those of Haouas et al. (2023), who found that total population, urban population, and population density negatively impact environmental quality in MENA countries. Additionally, Abdallh and Abugamos (2017) employed a semi-parametric panel fixed effects technique to confirm a positive association between population growth and CO2 emissions in MENA countries. The table also shows that economic globalisation has a detrimental impact on environmental conditions in the region. However, these results are only supported by the pooled OLS and RE models. Indeed, economic globalisation can reduce barriers and facilitate the coming of polluting investments from abroad, as well as environmentally harmful foreign projects, particularly in countries with weak environmental regulations (Zmami & Ben-Salha, 2020). Finally, the table reveals some heterogeneity regarding the impact of HC on LCF. The coefficients estimated using both the pooled OLS and RE models are negative and statistically

barriers and facilitate the coming of polluting investments from abroad, as well as environmentally harmful foreign projects, particularly in countries with weak environmental regulations (Zmami & Ben-Salha, 2020). Finally, the table reveals some heterogeneity regarding the impact of HC on LCF. The coefficients estimated using both the pooled OLS and RE models are negative and statistically significant. However, a notable difference exists in the magnitude of coefficients between the pooled OLS and RE models. The coefficient obtained from the FE model is not statistically significant. The Hausman test was employed to identify the most appropriate estimation technique. The results reported in Table 6 suggest the suitability of the FE estimator for the analysis. Therefore, the results suggest that HC does not significantly influence LCF in MENA countries. These outcomes are not in line with the conclusions of earlier studies estimating the repercussions of HC on environmental conditions in developing countries. For example, Pata and Ertugrul (2023) and Rehman et al. (2023) identified a positive linkage between HC and environmental quality in India and selected emerging countries, respectively. In addition, Dai et al. (2024) concluded that HC improves environmental conditions in ASEAN countries. The insignificant environmental effect of HC in MENA countries could be attributable to the fact that the traditional estimation techniques assume normal distribution of the data, which is not the case in our study, as illustrated in Table 2 and Figure 2. To address this limitation, employing the MMQR could provide more robust and reliable outcomes on the impact of HC on environmental quality.

MMQR estimation results

At this stage, we employ the MMQR to assess the effects of HC and other explanatory factors on LCF across various quantile orders of LCF. Specifically, we consider five quantile orders, Q10 and Q25 as low quantiles, Q50 as medium quantiles and Q75 and Q90 as high quantiles. The results are summarised in Table 7, while Figure 3 illustrates the coefficients obtained from the pooled OLS and MMQR. First, the MMQR yields different results regarding the impact of GDP and GDP squared when compared to pooled OLS, FE and RE estimators. Indeed, the coefficient of GDP is negative and statistically significant at 1% for low quantiles and 10% for medium quantiles, whereas GDP squared shows significant coefficients only for low quantiles. This finding suggests a U-shaped relationship between income and LCF in MENA countries, providing evidence for the validity of the LCC hypothesis in MENA countries only for lower quantiles of LCF. In other words, the LCC hypothesis appears to be more applicable to countries characterised by low LCF values, i.e., with relatively low environmental quality. However, the LCC hypothesis may not be confirmed in countries with good environmental conditions. These results contradict those obtained using the pooled OLS, FE and RE estimators. Additionally, these results underscore the superiority of the MMQR over traditional estimators, as the validity of the LCC hypothesis is not observed across all environmental conditions. This also suggests that considering the distribution of the dependent variable provides valuable insights into the economic development-environmental quality nexus in MENA countries.

Variables	Location Scale		Low quantiles		Medium quantile	High quantiles	
			Q10	Q25	Q50	Q75	Q90
GDP	-0.429	0.276	-0.848***	-0.686***	-0.437*	-0.220	0.034
	(0.109)	(0.141)	(0.003)	(0.005)	(0.100)	(0.535)	(0.944)
GDPSQ	0.022	-0.013	0.043***	0.035***	0.023	0.012	-0.0002
	(0.112)	(0.171)	(0.005)	(0.007)	(0.102)	(0.514)	(0.991)
POP	-0.010	0.017	-0.037*	-0.027	-0.011	0.002	0.018
	(0.551)	(0.164)	(0.055)	(0.102)	(0.527)	(0.915)	(0.574)
REN	0.235***	-0.010	0.251***	0.244***	0.235***	0.227***	0.217***
	(0.000)	(0.595)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
KOF	-1.014***	0.119	-1.195***	-1.125***	-1.018***	-0.924***	-0.814***
	(0.000)	(0.206)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
НС	-1.388***	-0.265***	-0.986***	-1.141***	-1.380***	-1.589***	-1.834***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	5.571***	-1.619**	8.027***	7.077***	5.619***	4.344***	2.850
	(0.000)	(0.033)	(0.000)	(0.000)	(0.000)	(0.002)	(0.156)

Table 7. MMQR estimation results

***, ** and * denote the statistical significance at the 1%, 5% and 10% levels, respectively

Table 7 further confirms the findings of Shaari et al. (2021) by showing a weak impact of population on the environment. Specifically, the coefficient of population is negative and significant at 10% only for Q10. This indicates that the population adversely affects LCF in countries with poor environmental quality; in other words, the population exacerbates the already poor environmental conditions in those countries. These results may be due to many factors, including the lack of public awareness of environmental challenges in countries with poor environmental conditions. This could also be attributed to the adoption of harmful environmental behaviours and prioritisation of short-term needs over long-term sustainability. Indeed, individuals in countries with poor environmental conditions may exacerbate environmental degradation by excessive resource depletion, deforestation, overexploitation of groundwater, etc. Such practices may worsen environmental problems and impede efforts focused on enhancing environmental quality. The coefficients associated with renewable energy consumption are positive and statistically significant at all quantile orders. The findings revealed that irrespective of the environmental condition, renewable energy consumption increases LCF and improves environmental conditions. The table also indicates that the associated coefficients decrease when moving from low to high quantiles, suggesting that renewable energy consumption has a more pronounced environmental impact in countries with poor environmental quality. Specifically, a 1% increase in renewable energy use results in a 0.251% enhancement in environmental quality in countries with poor environmental conditions and a 0.217% enhancement in those with good environmental quality. This could be due to the fact that policymakers in countries with poor environmental conditions generally demonstrate a higher degree of concern for environmental issues and adopt measures to mitigate environmental degradation through energy transition.

The coefficients associated with economic globalisation are negative and significant at the 1% level. This finding points out that economic globalisation shrinks LCF in MENA countries and contributes to heightened environmental degradation. These results corroborate those of Hassan et al. (2020), who confirmed that economic globalisation, as measured by the KOF Index, led to increased long-term CO₂ emissions in developed and developing economies. In addition, the authors showed that the adverse environmental implications of economic globalisation are more pronounced in developing countries. From an economic perspective, these results indicate that free trade and capital flows in MENA countries have been linked to greater environmental degradation. The existing literature suggests that international trade and capital flows can have either positive or negative impacts on environmental quality. The outcome may depend on institutional quality and the stringency of environmental laws in host countries. The findings in Table 7 show that environmental con-

ditions in MENA countries have been adversely affected by economic globalisation. Developing countries, including those in the MENA region, often rely on exports of goods and services that are harmful to the environment. This is largely due to factors like the overexploitation of natural resources, the heavy reliance on fossil fuels for the production process, and the use of outdated production methods. Foreign capital is also detrimental to the environment, as many investors relocate pollution-intensive industries from developed to developing countries, including those in the MENA region. This may be particularly observed in countries with poor environmental regulations, such as many MENA countries.

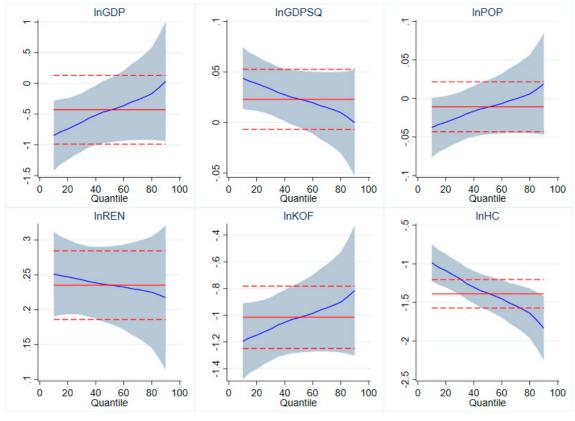


Figure 3. Plot of the MMQR quantile process and OLS regression

Finally, the MMQR results indicate that the coefficient of HC is negative and statistically significant across all quantiles of the LCF distribution. These outcomes align with those from the pooled OLS, FE, and RE models, indicating that increased HC in MENA countries has been associated with a decline in LCF and deterioration in environmental quality. The existing body of literature offers a nuanced viewpoint on the connection between HC and environmental conditions. Although HC may drive technological progress and promote sustainable practices, it may also result in higher resource depletion, which could induce environmental degradation. The MMQR results indicate a detrimental effect of HC on environmental quality in the MENA region, which can be attributed to the fact that as HC improves, income and well-being increase. Consequently, there will be a rise in the demand for goods and services, resulting in heightened energy consumption and resource depletion during the production process. In addition, improved HC leads to increased energy consumption, as pointed out by Churchill et al. (2023), which negatively affects the environment. Furthermore, the table shows that the adverse effects of HC on the environment differ when moving from low to high quantiles. The most pronounced adverse repercussions of HC on environmental quality are observed in countries with good environmental performance. This suggests that HC affects the environment more seriously as environmental quality improves. Even in countries with poor environmental quality, HC still has a detrimental impact, albeit to a lesser extent. These outcomes reveal that improvements in environmental quality are associated with a fall in environmental awareness and a less proactive attitude toward environmental sustainability. This could lead to more significant adverse effects of HC on the environment in countries with good environmental conditions.

Conclusion, policy recommendations and limitations

The objective of this study was to explore empirically the effects of HC on LCF in 14 MENA countries from 1990 to 2019. The Method of Moments Quantile Regression was utilised to account for the specific distributional properties of the dependent variable, providing a more robust and accurate analysis. The findings of the empirical investigation may be summarised as follows. First, the different normality tests confirmed the nonnormality of the dependent variable, justifying the use of the MMQR. Second, there is evidence of a long-term association between HC and environmental quality in MENA countries. Third, standard panel data techniques, i.e., pooled OLS, FE and RE, yield mixed findings on the effects of HC on environmental quality. Fourth, the MMQR indicates the validity of the LCC hypothesis in MENA countries, particularly those with poor environmental quality. Furthermore, environmental quality is enhanced by renewable energy consumption and deteriorated by economic globalisation. Additionally, the adverse environmental effects of the population are contingent upon the quantile order. Most importantly, the MMQR indicate that increased HC is associated with a decline in LCF and deterioration of environmental quality. In addition, although the detrimental effects of HC on the environmental effects of HC is associated with good environmental performance.

The insights from this study may be valuable in shaping effective policies for the MENA region. The findings show that human capital has an adverse effect on environmental quality. Policymakers in the MENA region should, therefore, design and implement strategies that align human capital development with environmental sustainability. This can be accomplished by improving individuals' awareness of the risks and perils of climate change and environmental degradation. To effectively mitigate the adverse impacts of human capital on environmental quality, a multifaceted approach that includes both public awareness campaigns and educational programs should be implemented. First, public awareness campaigns involving both traditional and social media may significantly impact the public perception of environmental issues. Such campaigns can significantly influence individuals to adopt sustainable practices and protect the environment. Second, integrating environmental education into curricula can result in a generation of citizens committed to environmental preservation. The incorporation of environmental sustainability principles into educational programs also enables students to gain a deeper understanding and awareness of environmental challenges, which could drive them to take action to safeguard the environment. Furthermore, policymakers should take proactive steps to encourage corporations to adopt Environmental, Social, and Governance (ESG) principles and promote sustainable practices within their workforce. Given the environmental benefits associated with renewable energy sources, it is imperative to raise awareness of the importance of renewable energy in the reduction of fossil fuels, the promotion of energy transition, and the protection of the environment. It is also important to combine financial incentives and tax reductions with increased public awareness in order to encourage the adoption of renewable energy. These measures could reduce the initial investment costs associated with renewable energy technologies, thereby increasing the accessibility and affordability of these technologies for both individuals and corporations.

The findings of the current study provided new insights into the impact of human capital on environmental quality in the MENA region. Nevertheless, the study only focuses on selected MENA countries. The empirical analysis could be extended to include more countries or regions, allowing for a broader generalisation of the findings and the design of country-specific policy recommendations. Furthermore, examining the role of particular aspects of human capital, including education, health, and skills, in shaping environmental conditions may provide important insights for policymakers.

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The contribution of the authors

Conceptualization, O.B.-S. and M.Z.; methodology, O.B.-S.; software, O.B.-S.; data curation, O.B.-S.; writing – original draft preparation, O.B.-S. and M.Z.; writing – review and editing, O.B.-S.

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