After the Shock
Reform, Resilience, and Economic Transformation in MENA

ERF 32nd Annual Conference
June 14-16 | Cairo, Egypt

2026

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Rayhana Chabbouh El Asmi
and Essahbi Essaadi

ECONOMIC RESEARCH FORUM
منتدى البحوث الاقتصادية

# CO2 emissions and financial development: Does geopolitical risk matter? Evidence from MENA countries

Rayhana Chabbouh El Asmi[1] and Essahbi Essaadi[⋆]

[1]ESCT University of Manouba; Lab PS2D, Tunisia; Email: rayhana.chabbouh@esct.uma.tn. orcid.org/0000-0002-8928-8463.
[⋆]University of Manouba, ESCT, QuAnLab (LR24ES21), Tunisia; Email: Essahbi.Essaadi@esct.uma.tn. (Corresponding author). orcid.org/0000-0003-4770-3785.

November 30, 2025

**Abstract**

Climate change poses an escalating threat to global stability. The Middle East and North Africa (MENA) region is emerging as one of the most vulnerable economies due to a heavy reliance on fossil fuel industries. Against a climate of rising global carbon emissions and the region's socio-political fragility,this article empirically investigates the complex triadic relationship between financial development, geopolitical risk, and CO2 emissions within this geopolitically vulnerable and oil-dependent region.

This study addresses a critical gap in the literature by jointly exploring how geopolitical instability, ranging from armed conflicts to trade disputes, interacts with financial systems to shape environmental outcomes. Using the bootstrap panel causality approach developed by Kónya (2006) testing the Geopolitical Risk index and the CO2 emissions, we reveal that geopolitical risk significantly exacerbates environmental issues by disrupting supply chains, deterring green investment, and shifting national priorities away from long-term climate goals. The findings suggest that reducing CO2 emissions in the MENA region requires a coherent policy framework. Recommendations include integrating geopolitical risk assessments into financial decision-making strategies, promoting research and development (R&D) in new energy technologies, and enhancing international cooperation to ensure decarbonisation strategies remain resilient amid regional volatility.

***Keywords:*** bootstrap panel causality, Financial development, Geopolitical Risk, sectoral carbon emissions, MENA economies

***JEL Classification:*** C33, G18, Q48, Q54, P18 and P28.

# 1 Introduction

The increase in greenhouse gas emissions, particularly carbon dioxide (CO2), poses a substantial threat to humanity's well-being in the 21st century. Carbon dioxide (CO2) emissions are the primary source of environmental degradation and have increased substantially over recent decades. In view of the sustained global economic expansion and the persistence of high emission levels, countries are increasingly prioritizing the development of policies and the implementation of measures intended to mitigate the harmful effects of CO2 emissions on the global climate.

At the same time, financial development has emerged as a critical factor shaping environmental outcomes. Well-functioning financial systems can facilitate green investments, enhance energy efficiency, and promote the adoption of low-carbon technologies. However, financial deepening may also stimulate economic activity and energy consumption, thereby contributing to higher emissions. Understanding the direction and magnitude of these effects is particularly important for MENA economies, where financial markets are undergoing a gradual transformation and where economic diversification remains a key policy priority.

Geopolitical risk constitutes a further dimension that may influence the relationship between financial development and environmental sustainability. Elevated geopolitical tensions can deter investment, disrupt energy markets, alter policy priorities, and shift the allocation of financial resources away from long-term environmental objectives. Given the MENA region's multi-layered exposure to geopolitical shocks, assessing how geopolitical risk interacts with financial development to shape carbon emissions is essential for designing resilient and effective climate strategies. Indeed, integrating geopolitical risk assessment into environmental and financial policy frameworks has not been widely explored by researchers. Such integration is necessary in the process of effective examination of contemporary global political and economic problems, which are now complex and multi-dimensional.

Geopolitical risk has been identified as a substantial factor in the relationship between financial development and CO2 emissions. It functions as a significant factor, amplifying environmental challenges posed by financial growth and foreign investments. This emphasises the need for a holistic policy framework that considers geopolitical stability in order to achieve efficient emissions reduction and sustainable growth. This is particularly relevant for regions where structural vulnerabilities increase climate-related risks. Among these regions, the Middle East and North Africa (MENA) occupies a distinctive position. On the one hand, it is a major energy-producing hub, accounting for a substantial share of global oil and natural gas reserves. On the other hand, it's still one of the world's most geopolitically unstable regions and an area which still witnesses frequent conflicts, chronic political instability, as well as increased regional tensions.

The Middle East and North Africa region is marked by a dense concentration of interconnected geopolitical conflicts that create one of the most volatile strategic environments in the world. The socio-political impacts of the "Arab Spring" (Tunisia, 2011) are still very tangible in the region. In North Africa, the region's security challenges are centred on ongoing civil wars in Syria, Yemen and Libya, persistent instability in Iraq, and the long-standing Israeli-Palestinian conflict. These crises are further exacerbated by the wider Iran-Saudi Arabia rivalry, which leads to proxy confrontations in several countries. Tensions are intensified by the dispute over Western Sahara between Morocco and the Polisario Front, as well as by insurgencies in the Maghreb and Sahel regions that undermine state stability by causing cross-border instability. Additional turbulence, such as the renewed conflict in Sudan, further exacerbates the region's vulnerability to political fragmentation and humanitarian crises. Together, these overlapping conflicts create a highly unstable geopolitical landscape with significant consequences for energy markets, regional development, and global security.

The two-fold nature of the MENA region, being energy dependent as well as geopolitically volatile, makes it an interesting context to study the intricate underpinnings of CO2 emissions. The Middle East and North Africa (MENA) region, as a key player in the global energy market and a major contributor to the world's carbon emissions, faces a complex challenge in balancing economic growth with environmental sustainability. We need to understand the specific dynamics at play in this strategically vital area as they grapple with climate change.

This article explores the interaction between carbon emissions, financial development and geopolitical risk in the MENA region and contributes to the growing empirical literature by investigating the nexus between these three concepts within the MENA region. By focusing on a context where energy production, political instability, and ongoing economic reforms converge, the analysis provides insights that are both regionally specific and globally relevant.

The plan of the rest of the paper is as follows. Firstly, we present some related literature review in section 2. Secondly, section 3 introduces the analytical framework and the estimation technique, and we describe the empirical model. After that, data, and empirical results , and discussion are reported in section 4. Section 5 offers some concluding remarks.

# 2 Literature review

Financial development is a pair of interconnected concepts that are crucial for sustainable development goals. Successful studies on the relationship between financial development and environmental quality demonstrate that, despite several opposing arguments, the financial sector plays a critical role in promoting the development and use of new technologies for environmentally friendly production (Ross Levine, 2005; Artur Tamazian, Juan Pineiro Chousa, and Krishna Chaitanya Vadlamannati, 2009; Abdul Jalil and Mete Feridun, 2011; Muhammad Shahbaz, Sakiru Adebola Solarin, Haider Mahmood, and Mohamed Arouri, 2013; Muhammad Umar, Xiangfeng Ji, Dervis Kirikkaleli, and Qinghui Xu, 2020).

Luo & Sun. (2024) and Wei et al. (2022) consider that the effect of financial development on CO2 emission depends on the country's development stage. Financial development can increase or decrease CO2 emissions; it tends to raise emissions in developing and emerging economies, while its effect is weaker or even negative in developed countries.

The increase in geopolitical uncertainty has underscored the importance of maintaining a stable and resilient financial system. The relationship between geopolitical dynamics and financial development has therefore attracted considerable scholarly attention (Dutta & Roy, 2011; Dutta & Dutta, 2022; Barradas, 2022; Zhang & Shi, 2023; Luo & Sun, 2024; Mertzanis & Tebourbi, 2024; Ben Abdallah et al., 2024). Dutta and Roy (2011) demonstrated that political stability has a significant influence on financial development, based on panel data from 97 countries. Similarly, Dutta and Dutta (2022) explored the relationship between the Geopolitical Risk Index (GPR) and renewable energy exchange-traded funds, finding that heightened geopolitical risk is associated with reduced risk in green assets. Barradas (2022) provided evidence that financial development has constrained economic growth across EU countries, both before and after the financial crisis.

In another context, Zhang and Shi (2023) examined the impact of geopolitical risk on financial development among BRICS nations over the period 1990-2022, revealing a negative and statistically significant relationship. Luo and Sun (2024) investigated the nexus between geopolitical risk and CO2 emissions across 27 countries from 1990 to 2020, concluding that the adverse effects of geopolitical risk on environmental outcomes are more pronounced in developing economies.

Furthermore, Mertzanis and Tebourbi (2024) analysed the influence of geopolitical risk on green bond issuances across 73 countries between 2008 and 2021, establishing a direct and positive association between these two variables. Finally, Ben Abdallah et al. (2024) assessed the combined effects of geopolitical risks and financial development on the energy transition in industrialised countries, concluding that nations operating within volatile geopolitical environments tend to intensify investments in cleaner energy sources as part of their strategic response. Other researchers have explored the correlation between geopolitical risk and CO2 emissions. Anser et al., (2021), Paramati et al., (2025) find that higher geopolitical risk (GPR), including conflict, military tension, and political instability, leads to increased CO2 emissions across a wide range of countries and time periods. For example, in BRICS countries, a 1% increase in GPR can escalate CO2 emissions by 13% (Anser et al., 2021). Chen et al., 2023; Wei et al., 2022 provide similar positive associations in both developed and developing countries.

They also demonstrate that in some cases, GPR can exacerbate inequality in emissions, with wealthier groups increasing their consumption while poorer groups lack access to cleaner alternatives. However, Luo & Sun (2024) have argued that Strong environmental policies and higher renewable energy use can mitigate the emission-raising effect of geopolitical risk, but their effectiveness is reduced when this risk is high.

M. Ahmad et al. (2023) noted that the effect is nuanced; in fact, controlling geopolitical risk is crucial for sustainable development. Additionally, Kai-Hua Wang et al. (2022) discovered a two-way causal relationship between geopolitical risk and CO2 emissions in China, indicating a complex interactive dynamic. Thus, geopolitical risk significantly increases CO2 emissions, particularly in developing economies and during periods of instability. Emission reduction measures require stable governance, robust environmental policies, and strong support for the adoption of renewable energy. Sofuoglu & Ay (2020) examined the relationship between climate change and political instability in 18 Middle East and North African (MENA) countries covering the period 1985-2016 with monthly data. They concluded that there is a causal link between climate change and political instability.

Significant research gaps persist in evaluating the combined effects of financial development and geopolitical risks on CO2 emissions, especially for countries in the Middle East and North Africa (MENA). While the academic literature increasingly acknowledges these interconnected factors, most studies tend to analyze them in isolation, thus neglecting their compounded impact within specific regional or national contexts.

Existing scholarship has primarily delineated the separate effects of financial development or geopolitical risks on carbon emissions. The limited integration of comprehensive datasets-incorporating elements such as the Financial Development Index (FDI) and the Geopolitical Risk Index (GPR)-further underscores the need for studies that explore the joint impact of financial development and geopolitical risk on CO2 emissions.

# 3 Model and methods

To introduce the econometric model of interest to investigate the relationship between Environmental degradation (ED) and financial development. In this study, we built our model on the theoretical frameworks of the EKC hypothesis initially proposed by Kuznets (1955) and the STIRPAT model proposed by Dietz and Rosa (1997) that suggest a connection between economic growth and environmental degradation. We augment this model by adding financial development and Geopolitical risk that affects the environment through an energy demand increase or by boosting economic growth. Thus, we propose for our model the following econometric form:

$$lnCO2_{it} = \beta_0 + \beta_1 lnGDP_{it} + \beta_2 lnEC_{it} + \beta_3 FinDev_{it} + \beta_4 GPR_{it} + \varepsilon_{it}, \tag{1}$$

where $i$ depicts selected MENA country ($i = 1, 2, ..10$) and $t$ represents the year ($t = 1983, ..., 2021$). $CO2$ is the carbon emission per capita, $GDP$ represents the real GDP per capita, the $EC$ refers to total energy consumption per capita, and the $GPR$ refers the annual risk level of the Geopolitical risk index. All these variables are transferred into the natural logarithm to form provide more stationary behavior (Vogelvang, 2005) and to obtain reliable and consistent results. $FinDev$ is a set of three financial development indicators (FDI, FMA, and FIA).

## 3.1 Econometric procedure

To estimate our model (Eq. 1), we propose five econometric procedures:($i$) a cross-section dependence test, ($ii$) a unit root test, ($iii$) a panel cointegration test, ($iv$) an estimation of the long-run relationship between environment and financial development, and finally ($v$) Granger causality analysis.

### 3.1.1 Cross sectional dependence tests

To select the appropriate tests for our cointegration analysis, we need to specify whether the cross-sectional dependence affects the panel model. Obviously, this dependence between errors in terms of cross-sections makes the cross-panel estimations and tests biased. Given the homogenous aspect of a selected MENA countries, a contemporaneous correlation across them is expected. Therefore, we apply two tests for which the null hypothesis is no cross-sectional dependence among the individual series. The first one is the Lagrange Multiplier (LM) test statistic developed by Breusch and Pagan (1980) which is valid for small cross-section dimensions and large time dimensions:

$$LM_{BP} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij}^2 \tag{2}$$

Where the $\rho_{ij}^2$ is the estimated correlation coefficient obtained from the individual OLS estimation. The $LM_{BP}$ statistic is asymptotically distributed $\chi^2$ with $\frac{(N(N-1))}{2}$ degrees of freedom.

In addition, we employ the CD test of Pesaran (2004) for robustness despite this test is more appropriate in the case of large cross section dimension ($N$). The $CD$ statistic is expressed as follow:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij}^2. \tag{3}$$

This $CD$ statistic is distributed as asymptotically standard normal.

If the cross-sectional dependence is confirmed by rejecting the null hypothesis by both tests, we must use the appropriate panel units root and cointegration tests which consider the existing dependency among the cross sections.

### 3.1.2 Panel unit roots tests

To determine the correct order of integration of variables and given that the cross-sectional dependence is expected amongst the selected MENA countries, we employ the most popular panel units root tests of Pesaran (2007), using the cross-sectionally augmented Dickey-Fuller (CADF) statistic. In contrast to the first-generation panel unit root test, the CADF test relaxes the restraining cross-sectional independence assumption. Pesaran (2007) shows that the CADF test is robust even for a relatively small value of N, which corresponds to our case with only six countries. To evaluate the presence of the unit root, Pesaran (2007) uses the regression per country, such as:

$$\Delta Y_{it} = a_i + b_i Y_{i,t-1} + c_i \overline{Y}_{t-1} + d_i \Delta \overline{Y}_t + e_i. \tag{4}$$

That is, the conventional ADF regressions are augmented with cross-section averages of lagged levels and the first differences of each series to eliminate the cross-sectional dependence. In this respect, the CADF statistic is the average of the individual CADF statistics and allows us to test the null hypothesis of the presence of unit root test in all individual series.

### 3.1.3 Panel cointegration analysis

If Pesaran (2007)'s test indicates that all variables have unit roots, then we test the presence of a cointegration relationship among variables. In this regard, three tests are conducted to test the null hypothesis of no cointegration. This study employs, thus, the well-known Kao (1999) and Pedroni (1999, 2004) tests. Nevertheless, the hypothesis of cross-sectional independence suggested by both tests is extremely restrictive (Banarjee and Carrion-i Silvestre, 2006; Charfeddine and Kahia, 2019). Hence, the Westerlund (2006) test is also used to consider the existence of cross-sectional dependence in the panel.

**a. Kao (1999) test**

The first test of panel cointegration used in this study is the Kao (1999) test. This test is based on the residual Engle-Granger approach; it searches for a unit root in the residuals of the pooled regression allowing for individual fixed effects using an Augmented Dickey-Fuller (ADF) panel test. Nevertheless, this test considers homogeneous cointegration vectors. In addition, it is worth noting that the ADF statistic in this test converges to a standard Normal distribution.

**b. Pedroni (1999, 2004) test**

In contrast to Kao (1999)'s test, the Pedroni (1999, 2004) panel cointegration test considers the country heterogeneity allowing for multiple regressors of the cointegration vector to vary across various panel sections. Therefore, the following specification is used to compile test statistics:

$$Y_{it} = a_i + b_i t + \sum_{k=1}^{m} c_{ij} X_{ji,t} + \varepsilon_{it}, \tag{5}$$

where $m$ is the number of exogenous variables $X_{ji}$. In the case of integrated variables of this model ($Y_{it}$ and $X_{ji,t}$) of order one, the cointegration relationship between them is confirmed only if the residual errors $\varepsilon_{it}$ are stationary in level. Hence, all statistics of Pedroni (1999, 2004) test are based on the auxiliary following regressions showing the individual autoregressive residues with a unit root according to the null hypothesis:

$$\varepsilon_{it} = \varphi_i \varepsilon_{i,t-1} + \mu_{it}. \tag{6}$$

The null hypothesis ($H_0 : \varphi_i = 1 \forall i$) is thus tested using four test statistics based on the common autoregressive coefficients that are derived from the within dimension (panel v-statistics test, panel rho-statistics test, panel ADF-statistics test, and panel PP- statistics test) and three test statistics are based on the individual autoregressive coefficients that depend on the between dimension (group rho-statistics test, group ADF-statistics test, and group PP-statistics test). In addition, it is important to note that the seven statistics are standard Normal distributed.

**c. Westerlund (2006) test**

As we mentioned earlier, the Westerlund (2006) panel cointegration test assumes cross-sectional dependence in contrast to Kao (1999) and Pedroni (1999, 2004) tests. The Westerlund (2006) test computes four test statistics from an error correction model and the null hypothesis assumes that the error correction term of the panel is equal to zero for all cross-sections. The two first statistics ($P_t$ and $P_a$) are used to test cointegration in the panel as a whole. That is, the rejection of the null hypothesis in this case implies the presence of a cointegration relationship in all cross-sections. In contrast, the alternative hypothesis for the further two statistics ($G_t$ and $G_a$) indicates the presence of a cointegration relationship for at least one of the cross-sections. Moreover, Westerlund (2006) shows that all four test statistics converge to the Normal distribution and provide robust p-values against cross-sectional dependency.

### 3.1.4 Estimation of long-run panel cointegration regression

If the results of panel cointegration tests indicate the presence of cointegration between variables, the literature proposes to estimate the long and short-run relationships (Pedroni, 1999, 2001; Kao and Chiang, 2001; Mark and Sul, 2003). Kao and Chiang (2001); Pedroni (2001), and Hsiao (2022) suggest using the Fully Modified OLS (FMOLS) and the Dynamic OLS (DOLS) estimators. In this paper, we estimate the long-run equation (Eq. 1) by using the FMOLS procedure. The latter provides an estimator consistent with the heterogeneity and endogenous problems that could affect the cointegrated vectors (Kahia et al., 2017). In order to robustness analysis, we estimate the long-run equation using the DOLS and the Panel-corrected standard error (PCSE) estimators. The PCSE estimator, developed by Beck and Katz (1995), helps in solving the possible cross-sectional correlation and heteroscedasticity. It produces more precise standard error estimates without any loss in efficiency (Beck and Katz, 1995).

Moreover, once the cointegration relationship is verified and the long-run equation is estimated, we could further estimate a panel error correction model (ECM) to apply the Granger-causality tests from explicative variables. To estimate the ECM, following Kahia et al. (2017), the two-step Engle and Granger approach is conducted (Engle and Granger, 1987). The idea is to introduce the lagged estimated residuals from the long run equation (Eq. 1) estimated by the FMOLS, called the error correction term (ECT), in the following equation:

$$\Delta lnCO2_{it} = \gamma_i + \sum_{k=1}^{q} \theta_{1,ik} \Delta lnCO2_{it-k} + \sum_{k=1}^{q} \theta_{2,ik} \Delta lnGDP_{it-k} + \sum_{k=1}^{q} \theta_{3,ik} \Delta lnEC_{it-k} + ...$$
$$\sum_{k=1}^{q} \theta_{4,ik} \Delta FinDev_{it-k} + \lambda_i ECT_{it-1} + \vartheta_{it}. \quad (7)$$

Where $\Delta$ represents the first difference operator, $\gamma_i$ refers to the fixed cross-sectional effect, $q$ denotes the optimal lag length. $ECT_{it-1}$ refers to the lagged error correction terms and $\lambda_i$ is the error-correcting speed of adjustment toward the long-term equilibrium for each $i$. It is expected to be significantly negative if there is a long-run cointegration relationship. It is worth noting that the Feasible Generalized Least Square (FGLS) procedure is used to estimate the panel ECM with a specific fixed effect. Following Salahuddin et al. (2015)Salahuddin et al. (2015), we are imposing homogeneity restrictions on the long-run and Short-run allowing only intercept to vary on countries. This is justified by the macroeconomic characteristics similarity of the selected MENA countries (oil-based economies). In addition, we implement the FGLS procedure by considering both cross-sectionally heteroskedastic and contemporaneously correlated errors. This allows for avoiding the cross-sectional problem caused by a potential high contemporaneous correlation between the error term $\vartheta_{it}$ of our model (Eq. 7). Also, our procedure allows potentially endogeneity between the explicative variables and the specific term $\gamma_i$ that captures the countries' heterogeneity. We employ a robust method for computing the coefficient standard errors using the methodology of Beck and Katz (1995)Beck and Katz (1995).

For causality analysis, we apply the Wald test of Granger (1969)Granger (1969) to test the null hypothesis of non-causality averaged across the cross-sections. To do this, a jointly statistical significance test of coefficients of each lagged explicative variable is implemented. For example, the null hypothesis $H0$ : all $\theta_{4,ik}$ are jointly equal to zero in Eq. (7) is equivalent to $FinDev$ does not Granger-cause $CO2$.

## 3.2 Further disaggregated panel causality analysis

This study uses Granger Causality to answer the causality relationship. The causal concept is found in the VAR model, assuming that the variables x and y (if using two) are stationary and not cointegrated. In addition, the VAR model has one answer for all samples. However, problems arise when using panel data in heterogeneous conditions. As a result, the resulting analysis does not provide a unique solution. Kónya (2006) introduced the bootstrap panel causality method with the Seemingly Unrelated Regression (SUR) estimator to solve this problem. This method has several advantages; among others, first, it is very robust against stationarity and cointegration, so these two conditions do not need to be tested again for panel data (Destek and Aslan, 2017). Second, each country's statistical results are based on bootstrapping (Zhang et al., 2016). Third, causality equations can be formed as bivariate and trivariate SUR. Fourth, SUR is more efficient in estimating country by country than Pooled Least Square (PLS) (Zhang et al., 2016)

Akadiri et al. (2020) In the econometric literature, there exists well-documented Granger causality procedures, namely Generalized Method of Moments which is based on panel vector error correction model, Dumitrescu and Hurlin (2012) Granger causality and bootstrapped Granger causality approach. The first approach does account for heterogeneity and cross-sectional dependence whereas, the second approach proposed by Dumitrescu and Hurlin (2012) consider heterogeneity but does not account for possible cross-sectional dependence. On the other hand, the third approach developed by Kónya (2006) is able to account for both country-specific heterogeneity and cross-sectional dependence. This technique is based on Seemingly Unrelated Regression (SUR) framework that accommodates cross-sectional dependence (CD) across the country-specific bootstrap critical values. Furthermore, another advantage of the bootstrapped panel Granger causality test is that, there are no pre-testing requirements for panel unit root and long-run relationship (Kónya, 2006) considering the fact that, the method generate country-specific bootstrap critical values, thus stationarity properties of the variables of interest is not required (Kónya, 2006). Considering the aforementioned, Kónya (2006) has significant merit over other Granger causality testing approaches. Using a country-by-country analysis, a Granger causality between $lnCO2$ (CO2 and its principal sectors) and $GPR$ can be investigated using the following finite-order bivariate vector autoregression (VAR) model:

$$\begin{aligned} lnCO2_{i,t} &= \alpha_{1,t} + \sum_{l=1}^{mlyi} \beta_{1,i,l} lnCO2_{i,t-l} + \sum_{l=1}^{mlxi} \gamma_{1,i,l} GPR_{i,t-l} + \varepsilon_{1,i,t} \\ GPR_{i,t} &= \alpha_{2,t} + \sum_{l=1}^{mlyi} \beta_{2,i,l} lnCO2_{i,t-l} + \sum_{l=1}^{mlxi} \gamma_{2,i,l} GPR_{i,t-l} + \varepsilon_{2,i,t}, \end{aligned} \tag{8}$$

where index $i$ refers to the country ($i = 1, ..., N$), $t$ to the time ($t = 1, ..., T$) and $l$ to the lag.

# 4 Results and discussion

## 4.1 Data

In this paper, we use annual data from 1980 to 2021 for ten selected MENA countries, viz: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, the United Arab Emirates (UAE), Tunisia, Morroco, Algeria, Egypt, Jordanie , and Turkey. The variables operated in this study were sourced from two different locations. Firstly, information on total and sectoral CO2 emissions was gathered from the Emissions Database for Global Atmospheric Research (EDGAR). The sources of CO2 emissions were classified into six sectors, viz: Buildings (Bu), Fuel exploitation (Fu), Industrial combustion (In), Power industry (Po), Processes (Pr) and Transport (Tr). Total CO2 emissions, which denotes carbon dioxide emissions is expressed in metric tons per capita, were also collected. Secondly, the Financial sector development index (FDI) and its sub-index were secured from the International Monetary Fund (IMF). The FDI is an aggregate of the Financial Institutions Index (FIA)[1] and the Financial Market Index (FMA). These two indices are the result of three other indices, each one measuring depth, access, and efficiency viz: the Financial Institutions Depth Index (FID), Financial Institutions Efficiency Index (FIE), and the Financial Institutions Index; for the first and Financial Markets Depth Index (FMD), Financial Markets Efficiency Index (FME), Financial Markets Index (FMI) for the second. We use also a Monetary Sector credit to private sector (% GDP)as a second proxy for the financial development index.

## 4.2 Results

## 4.3 Panel cointegration analysis

Table 1 presents the results of both Breusch and Pagan (1980) and Pesaran (2004) tests using $LM_{BP}$ and $CD$ statistics, respectively. Based on the results, the null hypothesis of no cross-sectional dependence is strongly rejected at the 1% significance level for all variables of the model, except the LnCO2 using the $CD$ statistics. This indicates that the GCC countries are highly dependent on a common shock. Therefore, the unit root test of Pesaran (2007) is the more appropriate test to identify the integration degree of variables in the model.

[1]The Financial Institutions Index (FIA) is not available for Bahrain.

Table 2 reports the results of the CADF panel unit root test developed by Pesaran (2007). The results confirm the presence of a unit root in all model variables. Hence, the first difference is applied to get stationary, so all variables are integrated in the first order. This result allows us to test the possibility of a cointegration relationship between environmental degradation, real GDP, energy consumption, and financial development.

In this study, Kao (1999); Pedroni (1999, 2004), and Westerlund (2006) tests are deployed to test the null hypothesis of no cointegration between all variables of the model. The results are reported in Tables 3, 4, and 5 respectively. Although only four of seven tests of Pedroni (1999, 2004) reject the null hypothesis, the results of the Kao (1999) test support the hypothesis of cointegration among our variables, regardless of the financial development indicator used (FDI, FIA, and FMA). In addition, the results of the Westerlund (2006) test, which are more consistent and robust to the presence of cross-sectional dependence in our panel, confirm the rejection of the null hypothesis using the three financial development indicators. Therefore, this empirical result provides evidence for the existence of a long-run equilibrium between CO2, real GDP, energy consumption, and financial development.

Table 6 presents the results of the long-run relationship between carbon emissions, real GDP, energy consumption, and financial development in the GCC region. The estimation results are derived from the FMOLS method, and for robustness, we add the DOLS and PCSC estimators. All results show the statistically significant long-run impact with the expected sign of all explanatory variables. Indeed, as real GDP and energy consumption are logarithmic, positive coefficients of both variables could be interpreted as long-run elasticity. As shown in table 5, a 1% increase in real GDP per capita and energy consumption per capita leads to an increase in CO2 emissions in the GCC region of almost 0.2% and 0.5%, respectively, in the long run. In addition, our results show that a 1-point percentage increase in the financial development index (FDI) in the GCC region reduces carbon emissions by about 0.5% in the long run. Furthermore, a 1-point percentage increase in the Financial Development Institutions (FIA) and Financial Markets (FMA) indexes is associated with a 1.7% and 0.3% improvement in environmental quality in the long run, respectively.

Table 7 reports the results of the panel error correction model (Eq. 7) and Granger causality tests for the three financial development indices. Results show the significance of the ECT coefficient with a negative sign regardless of the financial development index, confirming the existence of the long-run equilibrium as suggested by the results of Kao (1999); Pedroni (1999, 2004), and Westerlund (2006) tests. The speed of adjustment in our three models (using FDI, FIA, and FMA) allows the correction of about 18.5% of the disequilibrium, suggesting that about 5.4 years are needed to return to the long-run equilibrium. Regarding the short-run relationship, the results of the panel error correction model indicate that only real GDP per capita and the financial development indices FD and FM have a positive and significant impact on CO2 emissions. This result is in line with economic intuition. On one hand, economic growth positively affects environmental degradation in either the short or the long run. On the other hand, financial development negatively affects the environment in the short run but allows for an improvement in environmental quality in the long run. Furthermore, there is no significant relationship between energy consumption and CO2 emissions in the short term. This effect is limited in the long term. Consequently, these results on short-term relationships are confirmed by the panel Granger causality tests. Indeed, except for energy consumption, the results provide evidence of causality from real GDP and the financial development indices FDI and FMA to CO2 emissions.

# 5 Conclusion

The relationship between CO2 emissions and financial development is significantly influenced by geopolitical risk. Studies focusing on countries like Turkey show that financial development, foreign direct investment, and geopolitical risk jointly lead to higher CO2 emissions over time, indicating that geopolitical risk exacerbates the environmental impact of financial development. This suggests that policies for sustainable environmental quality must consider mitigating the negative effects stemming from geopolitical instability alongside financial factors.

Moreover, geopolitical risk not only affects emissions but also influences the transition to renewable energy. In some emerging markets, financial development positively supports renewable energy consumption, while geopolitical risk, unexpectedly, may also increase renewable energy use, though it can act as a barrier to sustainable energy adoption through increased uncertainty and constraints.

Evidence from multiple studies highlights the importance of integrating geopolitical risk assessment in environmental and financial policies. For example, addressing geopolitical risk can moderate the harm caused by financial development on emissions, and enhance sustainable development goals like climate action. In industrial economies, geopolitical risks tend to have adverse effects on climate-related goals despite positive financial development impacts. Geopolitical risk does matter substantially in the nexus between financial development and CO2 emissions. It acts as a critical factor amplifying environmental challenges posed by financial growth and foreign investments, necessitating comprehensive policy approaches that encompass geopolitical stability to effectively manage emissions and promote sustainable development.

The MENA's governments can consider GPR to control CO2 emissions by increasing green investment and the ratification of environmental contracts. Enterprises must prioritize investment in research and development (R&D) and innovation in the field of new energy technologies. Furthermore, international organizations can serve as a valuable instrument for the monitoring of decarbonization policies and the resolution of conflicts between nations.

# Appendices

## A Abbreviation

- Financial Development Index ⇒ FDI
- Financial Institutions Access Index ⇒ FIA
- Financial Institutions Depth Index ⇒ FID
- Financial Institutions Efficiency Index ⇒ FIE
- Financial Institutions Index ⇒ FII
- Financial Markets Access Index ⇒ FMA
- Financial Markets Depth Index ⇒ FMD
- Financial Markets Efficiency Index ⇒ FME
- Financial Markets Index ⇒ FMI

- Bu ⇒ Buildings includes small-scale non-industrial stationary combustion.
- Fu ⇒ Fuel exploitation: fuel extraction, transformation, and refineries activities, including venting and flaring.
- In ⇒ Industrial combustion includes combustion for industrial manufacturing.
- Po ⇒ Power industry includes power and heat generation plants (public and auto-producers).
- Pr ⇒ Processes includes industrial process emissions (e.g. chemicals, etc.).
- Tr ⇒ Transport includes road transport, rail transport, domestic aviation, domestic shipping, and inland waterway transport for each country. International shipping and aviation also belong to this sector and are presented separately in the country factsheets due to their international nature.

Table 1: Cross-sectional dependence test results

| Statistics | lnCO2 | lnGDP | lnEC | FDI | FIA | FMA |
|---|---|---|---|---|---|---|
| $LM_{BP}$ | 127.951*** | 160.8*** | 134.048*** | 366.682*** | 229.071*** | 297.764*** |
| $CD$ | 0.304 | 3.87*** | 8.607*** | 18.984*** | 14.225*** | 16.976*** |

Notes. *** denotes 1% level of significance.

Table 2: Results of the CADF unit root

| | Statistics | LnCO2 | LnGDP | LnEC | FD | FI | FM |
|---|---|---|---|---|---|---|---|
| Level | CADF statistic | 0.169 | | | | | |
| | -0.556 | 0.801 | 1.702 | 2.797 | 1.503 | | |
| | p-Value | 0.567 | 0.289 | 0.789 | 0.956 | 0.997 | 0.934 |
| First difference | CADF statistic | -5.00*** | -2.093*** | -4.599*** | -7.851*** | -6.898*** | -7.656*** |
| | p-Value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Notes. *** denotes 1% level of significance.

Table 3: Results of the Kao (1999) panel cointegration test

| | FDI | | FIA | | FMA | |
|---|---|---|---|---|---|---|
| | t-statistic | Prob | t-statistic | Prob | t-statistic | Prob |
| ADF | -2.816 | 0.002*** | -2.597 | 0.004*** | -2.750 | 0.003*** |
| Residual variance | 0.008 | | 0.008 | | 0.008 | |
| HAC variance | 0.006 | | 0.005 | | 0.006 | |

Notes. Null hypothesis: no cointegration. *** denotes 1% level of significance.

Table 4: Results of the Pedroni (1999, 2004) panel cointegration test

| | Within-Dimension | | | | |
|---|---|---|---|---|---|
| | | Statistic | Prob. | weighted Statistic | Prob. |
| FDI | Panel v-statistic | -0.74 | 0.77 | -0.77 | 0.779 |
| | Panel rho-statistic | -1.378 | 0.083* | -1.688 | 0.045** |
| | Panel PP-statistic | -3.368 | 0.000*** | -3.669 | 0.000*** |
| | Panel ADF-statistic | -1.012 | 0.155 | -0.975 | 0.164 |
| FIA | Panel v-statistic | -0.72 | 0.764 | -0.724 | 0.765 |
| | Panel rho-statistic | -1.34 | 0.09* | -2.365 | 0.009*** |
| | Panel PP-statistic | -3.33 | 0.000*** | -4.363 | 0.000*** |
| | Panel ADF-statistic | -0.949 | 0.171 | -1.662 | 0.048** |
| FMA | Panel v-statistic | -0.681 | 0.752 | -0.751 | 0.773 |
| | Panel rho-statistic | -1.491 | 0.067* | -1.677 | 0.046** |
| | Panel PP-statistic | -3.472 | 0.000*** | -3.67 | 0.000*** |
| | Panel ADF-statistic | -0.86 | 0.194 | -0.78 | 0.217 |
| | Between-Dimension | | | | |
| | | Statistic | Prob. | | |
| FDI | Group rho-statistic | -0.734 | 0.231 | | |
| | Group PP-statistic | -3.418 | 0.000*** | | |
| | Group ADF-statistic | -1.7 | 0.044** | | |
| FIA | Group rho-statistic | -1.122 | 0.13 | | |
| | Group PP-statistic | -3.703 | 0.000*** | | |
| | Group ADF-statistic | -1.698 | 0.044** | | |
| FMA | Group rho-statistic | -0.76 | 0.223 | | |
| | Group PP-statistic | -3.491 | 0.000*** | | |
| | Group ADF-statistic | -1.384 | 0.083* | | |

Notes. Null hypothesis: no cointegration. ***, **, and* denote 1%, 5%, and 10% level of significance, respectively.

Table 5: Results of the Westerland (2007) panel cointegration test

| | FD | | FI | | FM | |
|---|---|---|---|---|---|---|
| | z-value | Prob | z-value | Prob | z-value | Prob |
| $G_t$ | -1.838 | 0.033** | -1.334 | 0.091* | -1.779 | 0.038** |
| $G_a$ | -1.154 | 0.124 | -0.351 | 0.363 | -1.098 | 0.136 |
| $P_t$ | -2.557 | 0.005*** | -2.027 | 0.021** | -2.64 | 0.004*** |
| $P_a$ | -2.476 | 0.007*** | -1.678 | 0.047** | -2.543 | 0.006*** |

Notes. Null hypothesis: no cointegration. ***, **, and* denote 1%, 5%, and 10% level of significance, respectively.

Table 6: Results of the long run cointegration equation

| | FDI | | | FIA | | | FMA | | |
|---|---|---|---|---|---|---|---|---|---|
| | FMOLS | DOLS | PCSC | FMOLS | DOLS | PCSC | FMOLS | DOLS | PCSC |
| $lnGDP$ | 0.166*** (2.648) | 0.238*** (2.97) | 0.285*** (5.04) | 0.058 (0.95) | 0.136* (1.684) | 0.283*** (4.99) | 0.198*** (3.219) | 0.27*** (3.311) | 0.292*** (5.23) |
| $lnEC$ | 0.611*** (12.895) | 0.521*** (8.336) | 0.432*** (10.1) | 0.666*** (14.732) | 0.584*** (9.439) | 0.427*** (10.27) | 0.568*** (12.534) | 0.484*** (7.832) | 0.422*** (9.87) |
| $FinDev$ | -0.639*** (-4.967) | -0.579*** (-3.291) | -0.244* (-1.58) | -1.747*** (-6.884) | -1.643*** (-4.669) | -0.635*** (-2.28) | -0.293*** (-3.964) | -0.263*** (-2.49) | -0.091 (-1.01) |
| $\overline{R}^2$ | 0.92 | 0.91 | 0.9 | 0.93 | 0.92 | 0.89 | 0.92 | 0.91 | 0.9 |

Table 7: Results of the panel Error Correction Model and Granger causality tests

| | FDI | FIA | FMA |
|---|---|---|---|
| Short run model | | | |
| $ECT_{i,t-1}$ | -0.185*** (-5.545) | -0.182*** (-5.066) | -0.186*** (-5.587) |
| $\Delta lnCO2_{i,t-1}$ | -0.04 (-0.684) | -0.039 (-0.652) | -0.038 (-0.655) |
| $\Delta lnGDP_{i,t-1}$ | 0.133*** (2.428) | 0.136*** (2.415) | 0.12** (2.229) |
| $\Delta lnEC_{i,t-1}$ | -0.011 (-0.286) | -0.031 (-0.784) | -0.005 (-0.143) |
| $\Delta GPR_{i,t-1}$ | 0.172* (1.675) | 0.115 (0.576) | 0.104* (1.863) |
| $Constant$ | -0.001 (-0.324) | -0.0005 (-0.145) | -0.0005 (-0.184) |
| $DW$ | 2.048 | 2.03 | 2.046 |
| $Grangercausalitytest(H_0)$ | | | |
| $lnGDPdoesnotcauselnCO2$ | 5.899[0.015] | 5.832[0.015] | 4.969[0.025] |
| $lnECdoesnotcauselnCO2$ | 0.081[0.774] | 0.616[0.432] | 0.02[0.885] |
| $GPRdoesnotcauselnCO2$ | 2.806[0.093] | 0.332[0.564] | 3.471[0.062] |

Note: The SC and HQ information criteria are used to fix the optimal lag length.

Table 8: Bootstrap Granger causality from GPR to CO2/cap

| | | | | | | |
|---|---|---|---|---|---|---|
| Alg | Sum of Coefficients (Sign of Causality)= -0.0010 | Wald Statistic = 0.0008 | Critical Value_10= 2.8134 | Critical Value_5= 4.0294 | Critical Value_1= 7.5197 | p-value = 0.9744 |
| Bah | Sum of Coefficients (Sign of Causality)= 0.0025 | Wald Statistic = 0.0147 | Critical Value_10= 2.7909 | Critical Value_5= 3.9641 | Critical Value_1= 7.5380 | p-value = 0.9062 |
| Egy | Sum of Coefficients (Sign of Causality)= 0.0113 | Wald Statistic = 0.3127 | Critical Value_10= 2.8847 | Critical Value_5= 4.2301 | Critical Value_1= 7.4412 | p-value = 0.5806 |
| Irk | Sum of Coefficients (Sign of Causality)= 0.0572 | Wald Statistic = 1.0415 | Critical Value_10= 2.9459 | Critical Value_5= 4.2330 | Critical Value_1= 7.2839 | p-value = 0.3186 |
| Irn | Sum of Coefficients (Sign of Causality)= 0.0067 | Wald Statistic = 0.0567 | Critical Value_10= 2.7530 | Critical Value_5= 4.0060 | Critical Value_1= 7.2028 | p-value = 0.8119 |
| Jor | Sum of Coefficients (Sign of Causality)= 0.0657 | Wald Statistic = 3.6307 | Critical Value_10= 2.9225 | Critical Value_5= 4.2788 | Critical Value_1= 7.5451 | p-value = 0.0690 |
| Kuw | Sum of Coefficients (Sign of Causality)= -0.0791 | Wald Statistic = 1.7407 | Critical Value_10= 2.8563 | Critical Value_5= 4.1796 | Critical Value_1= 7.8340 | p-value = 0.1866 |
| Leb | Sum of Coefficients (Sign of Causality)= -0.0260 | Wald Statistic = 0.1627 | Critical Value_10= 3.0248 | Critical Value_5= 4.3051 | Critical Value_1= 8.1374 | p-value = 0.7028 |
| Lib | Sum of Coefficients (Sign of Causality)= -0.0228 | Wald Statistic = 0.1843 | Critical Value_10= 2.8690 | Critical Value_5= 4.2665 | Critical Value_1= 8.0070 | p-value = 0.6705 |
| Mau | Sum of Coefficients (Sign of Causality)= 0.2067 | Wald Statistic = 4.6341 | Critical Value_10= 3.1035 | Critical Value_5= 4.5520 | Critical Value_1= 8.5954 | p-value = 0.0480 |
| Mor | Sum of Coefficients (Sign of Causality)= -0.0115 | Wald Statistic = 0.4612 | Critical Value_10= 2.8259 | Critical Value_5= 4.0934 | Critical Value_1= 7.2566 | p-value = 0.5046 |
| Oma | Sum of Coefficients (Sign of Causality)= -0.0823 | Wald Statistic = 0.8856 | Critical Value_10= 2.8808 | Critical Value_5= 4.4331 | Critical Value_1= 8.7334 | p-value = 0.3384 |
| Qat | Sum of Coefficients (Sign of Causality)= -0.0876 | Wald Statistic = 4.1899 | Critical Value_10= 2.8265 | Critical Value_5= 4.0940 | Critical Value_1= 7.5119 | p-value = 0.0467 |
| Sau | Sum of Coefficients (Sign of Causality)= -0.0663 | Wald Statistic = 3.1425 | Critical Value_10= 2.8082 | Critical Value_5= 4.0976 | Critical Value_1= 7.8465 | p-value = 0.0817 |
| UAE | Sum of Coefficients (Sign of Causality)= -0.0248 | Wald Statistic = 0.3836 | Critical Value_10= 2.8462 | Critical Value_5= 4.2324 | Critical Value_1= 7.6450 | p-value = 0.5291 |
| Tur | Sum of Coefficients (Sign of Causality)= 0.0047 | Wald Statistic = 0.0449 | Critical Value_10= 2.7077 | Critical Value_5= 3.9430 | Critical Value_1= 6.9881 | p-value = 0.8338 |
| Tun | Sum of Coefficients (Sign of Causality)= -0.0079 | Wald Statistic = 0.1886 | Critical Value_10= 2.9081 | Critical Value_5= 4.2064 | Critical Value_1= 7.5671 | p-value = 0.6678 |

Table 9: Bootstrap Granger causality from GPR to Fuel exploitation

| Coutries | Sum of Coefficients (Sign of Causality) | Wald Statistic | Critical Value 10% | 5% | 1% | p-value |
|---|---|---|---|---|---|---|
| Bahrein | 0.0812 | 2.3253 | 2.9455 | 4.2662 | 7.5010 | 0.1395 |
| Kuwait | 0.9777 | 16.0273 | 2.9589 | 4.0886 | 7.0524 | 0.0001 |
| Oman | 0.1939 | 2.3928 | 2.8188 | 4.0693 | 7.3464 | 0.1295 |
| Qatar | 1.0249 | 11.0935 | 2.9522 | 4.1735 | 7.5580 | 0.0028 |
| Saudi Arabia | 0.1370 | 2.0838 | 2.9650 | 4.2015 | 7.2880 | 0.1625 |
| UAE | 0.0149 | 0.0625 | 2.8104 | 4.0966 | 7.3708 | 0.8107 |

Table 10: Bootstrap Granger causality from GPR to Industrial combustion

| Coutries | Sum of Coefficients (Sign of Causality) | Wald Statistic | Critical Value 10% | 5% | 1% | p-value |
|---|---|---|---|---|---|---|
| Bahrein | 1.1562 | 3.8349 | 3.7387 | 5.3317 | 8.3671 | 0.0968 |
| Kuwait | 0.4209 | 4.1062 | 2.8317 | 3.9423 | 6.6775 | 0.0458 |
| Oman | 0.7799 | 2.0853 | 2.9902 | 4.3418 | 8.2097 | 0.1625 |
| Qatar | -0.0000 | 0.0000 | 2.8595 | 4.0987 | 6.9615 | 0.9998 |
| Saudi Arabia | 0.1741 | 1.6501 | 2.8826 | 4.2295 | 7.5878 | 0.2120 |
| UAE | 0.2621 | 6.2111 | 2.9286 | 4.3205 | 7.7642 | 0.0197 |

**Availability of dat:**a Data will be available upon request.

**Authors' contribution**

1R.Chabouh: Drafting

2E. Essaadi: Conceptualization and data analysis

**Declarations**

**Ethical approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.

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Table 11: Bootstrap Granger causality from GPR to Power Industry

| Coutries | Sum of Coefficients (Sign of Causality) | Wald Statistic | Critical Value 10% | 5% | 1% | p-value |
|---|---|---|---|---|---|---|
| Bahrein | 0.1484 | 1.3076 | 2.9930 | 4.3540 | 7.6753 | 0.2626 |
| Kuwait | 0.3287 | 3.2184 | 2.8915 | 4.2862 | 7.1311 | 0.0833 |
| Oman | 0.1322 | 1.5918 | 2.8516 | 4.0101 | 7.3842 | 0.2119 |
| Qatar | -0.0054 | 0.0050 | 2.9120 | 4.1125 | 7.7742 | 0.9405 |
| Saudi Arabia | -0.0600 | 2.8969 | 2.9365 | 4.2227 | 7.3680 | 0.1020 |
| UAE | -0.1729 | 3.8791 | 2.8049 | 4.0226 | 7.2742 | 0.0537 |

Table 12: Bootstrap Granger causality from GPR to Processes

| Coutries | Sum of Coefficients (Sign of Causality) | Wald Statistic | Critical Value 10% | 5% | 1% | p-value |
|---|---|---|---|---|---|---|
| Bahrein | 0.0468 | 0.0749 | 2.8792 | 4.0650 | 7.4473 | 0.7762 |
| Kuwait | 0.1953 | 1.4651 | 2.9634 | 4.3214 | 7.5760 | 0.2374 |
| Oman | 0.2463 | 0.1980 | 3.3699 | 5.5878 | 13.0378 | 0.6371 |
| Qatar | 0.3293 | 4.5296 | 2.8896 | 4.1330 | 7.2098 | 0.0406 |
| Saudi Arabia | -0.1065 | 1.1349 | 2.8011 | 4.1523 | 7.0406 | 0.2969 |
| UAE | 0.7672 | 11.7085 | 3.1803 | 4.6755 | 8.9881 | 0.0044 |

Table 13: Bootstrap Granger causality from GPR to Transport

| Coutries | Sum of Coefficients (Sign of Causality) | Wald Statistic | Critical Value 10% | 5% | 1% | p-value |
|---|---|---|---|---|---|---|
| Bahrein | 0.0847 | 2.0605 | 2.8690 | 4.1330 | 7.3515 | 0.1593 |
| Kuwait | 0.1337 | 0.7500 | 2.8839 | 3.9292 | 6.5328 | 0.4120 |
| Oman | 0.0757 | 0.5135 | 2.8939 | 4.2145 | 8.2589 | 0.4736 |
| Qatar | 0.1256 | 1.6418 | 3.1948 | 4.6229 | 8.7912 | 0.2237 |
| Saudi Arabia | -0.0856 | 0.9414 | 2.8343 | 4.1228 | 7.2476 | 0.3410 |
| UAE | 0.0960 | 1.1140 | 2.9130 | 4.0964 | 7.3468 | 0.2988 |


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