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Government Effectiveness, Renewable Energy and Economic Complexity: Evidence from Morocco and Emerging Economies

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Abstract

Does the energy transition foster productive sophistication, or does it merely replace fossil fuels within an unchanged industrial structure? This study examines the relationship between renewable electricity and economic complexity in Morocco and 29 emerging and frontier economies. It combines an autoregressive distributed lag (ARDL) model for Morocco (1996–2021), using bootstrap critical values, with a panel Pooled Mean Group (PMG) estimator for 29 economies (2011–2023). Robustness checks address common shocks, parameter heterogeneity, and country sensitivity. For Morocco, the results suggest a fast-adjusting long-run relationship, although sensitivity to lag selection and individual years, together with residual autocorrelation, limits the evidence. At the panel level, renewable electricity shows no statistically significant common long-run association with economic complexity. Government effectiveness is positively associated with complexity in the PMG estimates, but its magnitude declines after controlling for common year effects, and its significance weakens under alternative estimators. An interaction specification suggests that renewable electricity is more strongly associated with complexity where government effectiveness is higher. These conditional associations do not establish causality but challenge the assumption that renewable capacity automatically drives industrial upgrading. The findings identify institutional capacity as a potential enabling condition and motivate three policy hypotheses for future testing.

Keywords: Energy transition; Economic complexity; ARDL bounds testing; Pooled Mean Group estimator; Emerging economies; Morocco.

JEL Classification: O33; O55; Q42; Q43; C33.

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1. Introduction

Governments increasingly treat the energy transition as an industrial strategy, not only a climate policy. Renewable electricity capacity has grown faster in emerging economies over the past decade than at any point before (International Renewable Energy Agency [IRENA], 2023). A separate body of work shows that long-run growth depends on the accumulation of productive capabilities. These capabilities are measured through the diversity and sophistication of a country's export structure (Hidalgo and Hausmann, 2009; Hausmann et al., 2014). Whether these two processes reinforce each other is a question of first-order importance for policy design.

Two views compete in the literature. One view holds that building solar, wind, storage, and grid infrastructure requires engineering and manufacturing capabilities. Once developed locally, these capabilities spill over into other sectors and raise the sophistication of the whole economy (Balland et al., 2022). The other view holds that renewable capacity deployed through imported equipment and turnkey contracts improves the energy mix without any matching accumulation of local capability. Creti and Ftiti (2024) call this pattern a transition without transformation. Which pattern dominates likely depends on the capabilities a country already has. This is an empirical question, not a theoretical one.

This paper answers it with a two-stage design. The first stage draws on the deepest annual record available for a single country: Morocco. Morocco has pursued one of the most ambitious renewable electricity programs among emerging economies since its National Energy Strategy of 2009. Twenty-six years of annual data allow ARDL bounds testing (Pesaran et al., 2001). They are not enough for methods that need many more observations, such as quantile regression or spectral decomposition, and they call for small-sample critical values. The second stage asks whether Morocco's experience generalizes. We assemble a panel of 29 emerging and frontier economies observed annually from 2011 to 2023. We estimate a common long-run relationship with the Pooled Mean Group estimator (Pesaran et al., 1999), which pools the long-run coefficients across countries while letting each country adjust at its own speed. Because the panel is short and its series are exposed to common global shocks, we then compare PMG with estimators that relax its two main restrictions, a common long-run vector and the absence of common factors, and we test whether the results depend on individual countries. A complementary dynamic-panel and

System GMM analysis checks whether either variable leads the other. This addresses the causal-direction question that a battery of prior single-equation studies leaves open.

One method runs through both main stages, which keeps the analysis coherent. It is an error-correction model that treats economic complexity as moving toward a long-run equilibrium level, and asks how fast, and toward what, it corrects. The paper makes four contributions. First, it applies bounds testing to Morocco's annual history with bootstrap critical values, rather than relying on aggregation or interpolation of the outcome and the main regressor to manufacture a longer sample. Second, it tests whether the country result generalizes through a Pooled Mean Group panel model, a combination rarely found in the energy-complexity literature. Third, it documents how far the panel conclusions depend on the estimator: we report the PMG baseline alongside Mean Group, year-demeaned PMG, common correlated effects, interaction, sample-split, and leave-one-country-out estimates, and we state which results are stable and which are not. Fourth, it isolates a policy-relevant asymmetry: renewable electricity shows no common long-run association with complexity at the panel level, whereas government effectiveness is positively associated with complexity in the PMG baseline and in several alternative estimators, although its magnitude and statistical significance depend on how common shocks are handled. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and sets out the two-stage empirical strategy, with equations for every test used. Section 4 reports the results, including robustness checks. Section 5 discusses them against the literature and draws out policy hypotheses. Section 6 concludes.

2. Literature Review and Research Hypotheses

2.1. The Energy Transition as a Driver of Structural Transformation

The energy transition was first understood as a substitution of fossil fuels by low-carbon sources, centered on security and emissions (Geels, 2002; Sovacool, 2016). More recent work treats it as a systemic transition that arises from the co-evolution of technology, industry, and institutions (Geels and Schot, 2007; Markard et al., 2012; Köhler et al., 2019). Investment in renewables, storage, and smart grids no longer serves climate policy alone. It can redraw comparative advantage and open paths to industrial diversification (Markard and Rosenbloom, 2023).

This connects to older theories of structural transformation (Hirschman, 1958; Lewis, 1954; Rodrik, 2013), in which growth comes from reallocating resources toward more technology-intensive activities. Green industrial policy, and mission-oriented approaches in particular (Mazzucato, 2021), reflect this logic: the state coordinates investment and innovation around decarbonization rather than simply correcting market failures. The benefits are uneven, however. Countries with a diversified industrial base and capable institutions capture more value from low-carbon technologies. Economies dependent on imported equipment risk a transition without a matching industrial upgrade (Creti and Ftiti, 2024). This risk is well documented in emerging economies, where abundant renewable potential does not automatically translate into local manufacturing or research and development (Caldarola et al., 2024).

2.2. Theoretical Foundations of Economic Complexity

Economic complexity theory (Hidalgo and Hausmann, 2009; Hausmann and Hidalgo, 2011) explains development gaps through the accumulation of productive capabilities, such as knowledge, skills, technology, and institutions, rather than factor endowments alone. This theory gives rise to the Economic Complexity Index (ECI), built from the diversity and rarity of a country's exports. Its predictive power over future growth often exceeds conventional macroeconomic indicators (Hausmann et al., 2014).

Diversification follows a path-dependent logic. Countries move more easily into activities technologically close to what they already do than into wholly unrelated ones (Hidalgo et al., 2007; Balland et al., 2019). Balland et al. (2022) describe economic complexity as a new paradigm for development analysis that links knowledge networks, innovation, and structural transformation in one framework. Applied to the energy transition, the implication is direct. Designing and manufacturing solar panels, batteries, or smart grids draws on a dense set of scientific and industrial capabilities. A country's success in the transition should depend less on the sheer abundance of its renewable resources than on its capacity to build the capabilities needed to design, manufacture, and maintain these technologies (Balland et al., 2022).

2.3. Mechanisms Linking the Energy Transition to Economic Complexity

Four mechanisms connect the two phenomena, and they are largely interdependent. Green innovation is the most direct channel. Designing photovoltaic, wind, storage, or hydrogen

technologies mobilizes engineering, materials science, and software skills that add directly to a country's stock of productive knowledge. Caldarola et al. (2024) show that countries with a more complex productive base file more green patents and occupy stronger positions in low-carbon value chains. Human capital and technological learning matter too. Hidalgo and Hausmann (2009) treat human capital as a reservoir of productive capability rather than a simple factor of production, and learning by doing in photovoltaics or batteries strengthens this reservoir as firms accumulate experience.

Global value chains are a third channel. Producing panels, turbines, or batteries relies on internationalized production networks (Gereffi et al., 2005), but the learning gained depends on the segment occupied: design and component manufacturing teach far more than assembly (Humphrey and Schmitz, 2002). Economies confined to assembly convert energy investment into complexity less efficiently. Institutions and green industrial policy are the fourth channel, and they determine whether any of this happens at all. Renewable resources alone do not generate technological upgrading without institutions capable of coordinating investment, financing innovation, and building skills (Mazzucato, 2021; Rodrik, 2024). These effects reduce coordination costs and ease entry into higher value-added segments of global value chains (Hausmann et al., 2014; Balland et al., 2022).

2.4. Conceptual Framework

Taken together, this literature does not support treating the energy transition as an automatic, positive driver of complexity (Hidalgo and Hausmann, 2009; Balland et al., 2022; Caldarola et al., 2024). It supports a conditional relationship instead. Whether renewable investment builds complexity depends on the productive, technological, and institutional base already in place (Lall, 1992; Hausmann et al., 2014). Where this base is strong, the mechanisms in Section 2.3 combine into cumulative learning and diversification. Where it is weak, the same investment risks becoming technological dependence on imported equipment: a transition without transformation (Creti and Ftiti, 2024).

The framework also leaves the direction of causality open. The mechanisms above run from the transition to complexity, but complexity may also condition a country's capacity to deploy renewables in the first place (Sarsar and Echaoui, 2024; Viglioni et al., 2025). Figure 1 sets out

this framework. The energy transition and economic complexity are connected through a base of pre-existing capabilities, with a feedback channel running back from complexity to the transition. The whole relationship is an equilibrium that a country moves toward and corrects around, rather than a one-off, one-directional effect.

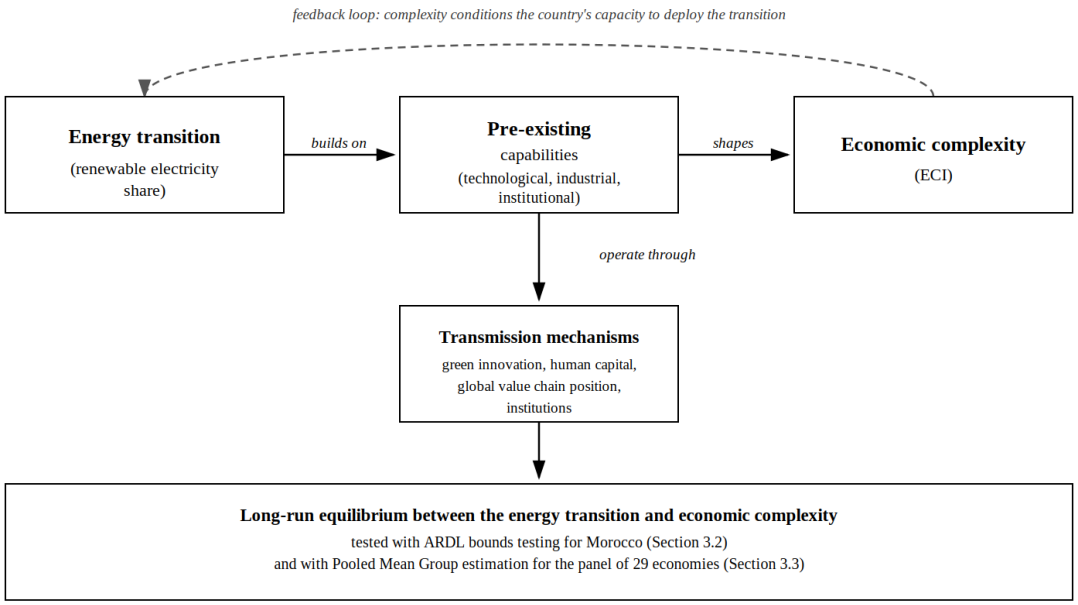


Figure 1. Conceptual framework linking the energy transition, pre-existing capabilities, and economic complexity

Source: authors' elaboration.

2.5. Development of Research Hypotheses

The framework above translates into four testable hypotheses. Each is developed below from the literature that motivates it, together with the methodological gap that our two-stage ARDL design is built to close.

2.5.1. A Long-Run Relationship in a Single, Data-Constrained Economy

A recurring feature of the energy-growth literature is its reliance on dynamic ARDL and panel ARDL methods to establish long-run relationships from short annual records. These methods remain valid with a limited number of time-series observations, unlike quantile regression or spectral methods. Ashfaq et al. (2024) apply a simulated dynamic ARDL to the renewable energy and green growth nexus, and they recover a stable long-run relationship from annual data spanning

little more than two decades. Hazmi et al. (2024) use panel ARDL on GCC economies to link clean energy, pollution, and growth, and Belabbas et al. (2025) do the same for Arab MENA economies, linking renewable energy to environmental performance. In both cases, the authors treat ARDL bounds testing as the appropriate tool precisely because the available annual series are too short for methods that require many observations.

None of these studies examines whether this kind of long-run relationship holds between the energy transition and economic complexity specifically, in a single emerging economy observed at annual frequency, without interpolating the outcome or the main regressor to lengthen the sample artificially. Morocco is a natural test case, given the scale of its renewable electricity program since 2009 and the availability of a continuous annual complexity series since 1996. This motivates:

Hypothesis 1. Renewable electricity and economic complexity share a long-run equilibrium relationship in Morocco, with deviations from that equilibrium corrected over time.

2.5.2. From One Country to a Population: Testing Generalizability Rather Than Assuming It

A single-country result, however credible, only informs policy elsewhere if it is representative rather than idiosyncratic. Here the literature offers a caution rather than a reassurance. Caldarola et al.'s (2024) systematic review of economic complexity and the sustainability transition argues that the effect of the energy transition on productive sophistication is unlikely to be uniform across countries, because it depends on capabilities, such as human capital, innovation systems, and industrial policy coherence, that vary widely across economies. Using a Method-of-Moments Quantile Regression on 31 OECD countries, Labidi (2025) shows that the joint benefit of economic complexity and renewable energy for growth is markedly stronger in the upper quantiles of the country distribution. Writing in Applied Energy, Hossain et al. (2024) reach a parallel conclusion using the same method on a different OECD panel. Both results imply that a coefficient estimated on one country, at one point in its own distribution, need not describe the population of emerging and frontier economies as a whole.

Reproducing this quantile-based evidence for our own sample is not feasible. Quantile methods, panel or otherwise, require substantially more than the thirteen annual waves available for the 29-country panel assembled here. The Pooled Mean Group estimator offers the closest available

substitute for testing generalizability under this data constraint. It estimates one long-run relationship common to the whole panel, rather than assuming Morocco's own coefficient applies elsewhere. This motivates:

Hypothesis 2. The long-run relationship identified for Morocco generalizes, in sign and significance, to a broader panel of emerging and frontier economies.

2.5.3. Institutions as an Independent, Non-Energy-Specific Capability

The mechanisms reviewed in Section 2.3 converge on one point. Institutional capacity to coordinate investment, finance innovation, and build skills is itself a productive capability, not merely a facilitating condition for others. Mazzucato (2021) frames the state as an active coordinator of technological development, and Rodrik (2024) argues that institutional quality increasingly determines which economies can absorb new technologies at all, independently of their specific sector of application. Hausmann et al. (2014) and Balland et al. (2022) make the same point from the complexity side: institutional quality conditions how effectively any investment, energy-related or not, is converted into productive diversification. If this institutional channel operates as these authors describe, it should show up as a stable association between government effectiveness and complexity, one that does not depend on a country's specific energy mix, and one that is precisely estimated when tested across a heterogeneous cross-country panel, even if a single country's short annual record is too noisy to pin the sign down reliably on its own. This motivates:

Hypothesis 3. Government effectiveness is positively associated with economic complexity in the long run, independently of the energy transition, and this association keeps its sign across alternative estimators.

The framework in Section 2.4 also implies that the two channels interact. If institutional capacity determines whether renewable investment is converted into local capabilities, the association between renewable electricity and complexity should be stronger where government effectiveness is higher, and a pooled estimate that averages over countries with very different institutions may hide it. This motivates:

Hypothesis 4. The long-run association between renewable electricity and economic complexity increases with government effectiveness.

3. Data and Empirical Strategy

The strategy has two stages, and both rest on the same idea: economic complexity moves toward a long-run equilibrium level that depends on renewable electricity, FDI, income, and institutional quality, and it corrects deviations from that equilibrium over time. The first stage tests this idea on Morocco alone, using its full annual record. The second stage tests it again, and generalizes it, on a panel of 29 emerging and frontier economies. One method runs through both stages: the autoregressive distributed lag (ARDL) error-correction model.

3.1. Data and Variables

Table 1 defines the five variables used at both stages, together with their role in the model and their source. The Morocco sample covers 1996 to 2021 (26 annual observations). The panel sample covers 2011 to 2023 for 29 countries (377 country-year observations, balanced, with no missing values).

Table 1. Variable definitions

Variable	Role	Definition	Source
ECI	Dependent	Economic Complexity Index (SITC classification), measuring the diversity and ubiquity of a country's export structure	The Observatory of Economic Complexity (OEC)
Renewable electricity share	Independent	Share of renewable sources in total electricity generation (%), log-transformed (natural log of one plus the share in the panel, because four panel observations equal zero)	IRENA
FDI	Independent	Net foreign direct investment inflows (% of GDP); log-transformed for Morocco, inverse hyperbolic sine transformed for the panel to accommodate negative values	WDI
GDP per capita	Control	GDP per capita (US dollars), log-transformed	WDI
Government effectiveness	Control	Composite governance indicator capturing the quality of public services, policy formulation and implementation, and the credibility of government commitment	WGI

Source: authors' compilation.

Government effectiveness and ECI already take positive and negative values by construction and enter in levels. The other three variables enter as described in Table 1. Renewable electricity enters the panel as ln(1 + share), because four observations (Kuwait 2011-2013 and Saudi Arabia 2011) record a zero share. Thirteen panel observations of net FDI inflows are negative (mainly Qatar), which is why the inverse hyperbolic sine is used. Morocco's government-effectiveness series is observed for 23 of the 26 years: the World Governance Indicators were not published for 1997, 1999, and 2001, and these three values are linearly interpolated. Section 4.7.1 tests whether this affects the results.

The panel covers 29 economies and 377 country-year observations from 2011 to 2023, with no missing values. It comprises 22 economies classified as emerging markets, six labelled frontier candidates (Bangladesh, Kazakhstan, Kenya, Pakistan, Ukraine, and Vietnam), and Morocco, which anchors the first stage. The classification follows the MSCI market classification recorded when the dataset was assembled. Economies were retained when annual data on all five variables were available for the whole period, so the sample reflects data availability and is not a random draw from the population of emerging economies. Table A2 in the Appendix lists every country with its group, initial ECI, average renewable electricity share, average GDP per capita, and a hydrocarbon-exporter indicator. The indicator identifies Kazakhstan, Kuwait, Qatar, Saudi Arabia, and the United Arab Emirates, and it is used in the heterogeneity tests of Section 4.7.3.

3.2. Country-Level Model: Morocco, 1996-2021

For Morocco, twenty-six annual observations are available (twenty-five after differencing and lagging). This is too few for methods built for long or high-frequency series, and it rules out quantile regression or spectral decomposition. The ARDL bounds-testing approach of Pesaran et al. (2001) is built for this situation: it handles a small number of annual observations, and it does not require every variable to be integrated of the same order. Its asymptotic critical values are, however, unreliable in samples this small (Narayan, 2005), so we also report bootstrap critical values and a set of sensitivity checks.

The starting point is the general ARDL(p, q1, q2, q3, q4) representation of the relationship, before any error-correction transformation:

$$ECI_t = c + \sum_{i=1}^{p} \alpha_i \, ECI_{t-i} + \sum_{j=0}^{q} \beta_j' X_{t-j} + \varepsilon_t \tag{1}$$

where X collects renewable electricity, FDI, GDP per capita, and government effectiveness, each in logarithms or levels as described in Table 1. Given the short sample, one lag is retained for the dependent variable and for each regressor (p = q = 1). This keeps the number of estimated parameters well below the number of observations. Equation (1) is then rewritten in unrestricted error-correction form, which isolates the long-run relationship as the coefficient on the lagged levels:

$$\begin{aligned} \Delta ECI_t = {} & c + \varphi \, ECI_{t-1} + \beta_1 \ln(RE)_{t-1} + \beta_2 \ln(FDI)_{t-1} \\ & + \beta_3 \ln(GDP)_{t-1} + \beta_4 \, GovE_{t-1} + \gamma \, \Delta ECI_{t-1} + \sum_{j} \delta_j' \Delta X_{t-j} + \varepsilon_t \end{aligned} \tag{2}$$

The null hypothesis of no long-run relationship, φ = β1 = β2 = β3 = β4 = 0, is tested with an F-statistic, whose significance we assess against bootstrap critical values for our sample size and number of regressors (case III: unrestricted intercept, no trend). If the F-statistic exceeds the critical value generated with integrated variables (the upper bound), the null is rejected regardless of whether the underlying regressors are I(0) or I(1). This is what makes bounds testing suitable here, given the mixed order of integration reported in Section 4.2. Once cointegration is established, the long-run coefficient on each variable is recovered from equation (2) as:

$$\theta_i = -\frac{\beta_i}{\varphi} \tag{3}$$

Its standard error is obtained by the delta method, since θi is a ratio of two estimated coefficients. Standard errors throughout this stage are Newey-West corrected for residual autocorrelation with one lag. Four post-estimation diagnostics accompany the model: the Breusch-Godfrey test for residual serial correlation (Breusch, 1978; Godfrey, 1978), the Breusch-Pagan test for heteroskedasticity (Breusch and Pagan, 1979), the Jarque-Bera test for residual normality (Jarque and Bera, 1987), and the Ramsey RESET test for functional-form misspecification (Ramsey, 1969). Newey-West standard errors correct inference but do not show that the dynamic specification is adequate, so we also examine how the results change under alternative lag structures.

Four further checks address the small sample. First, bootstrap critical values for the F-statistic are obtained from 3,000 residual-bootstrap replications generated under the null of no long-run relationship, with the regressors modelled as a first-order vector autoregression in differences. Second, we assess parameter stability with the CUSUM and CUSUMSQ tests. Third, we re-estimate the model with a dummy for the post-2009 period and with an impulse dummy for 2009, the year of the National Energy Strategy, as a simple test for a policy-regime break, and with a dummy for the three interpolated values of government effectiveness. Fourth, we re-estimate the model dropping one year at a time, and we compute Cook's distances to identify influential observations.

3.3. Panel Model: 29 Countries, 2011-2023

For the panel, a single common long-run relationship is imposed across countries, while each country is left free to adjust toward it at its own speed and through its own short-run dynamics. This is the Pooled Mean Group (PMG) estimator of Pesaran et al. (1999). It is the natural panel counterpart to the Morocco model: the same error-correction logic, now estimated jointly across 29 economies. For country i in year t:

$$\Delta ECI_{it} = \varphi_i \left(ECI_{i,t-1} - \theta' X_{i,t-1} \right) + \delta_i' \Delta X_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

The long-run vector θ is restricted to be the same for every country. The speed of adjustment φi, the short-run coefficients δi, and the country intercept μi are all free to differ. This is what makes PMG suitable for a panel with a moderate number of years: the long-run relationship, the part hardest to pin down with limited data, borrows strength from the full panel, while genuine cross-country differences in short-run dynamics are not forced into a common mould.

Estimation follows Pesaran et al. (1999). For any candidate θ, each country's equation is linear and can be estimated by ordinary least squares. This delivers φi, δi, μi, and a residual variance σi² as functions of θ. Concentrating these out of the likelihood leaves a function of θ alone:

$$\ln L(\theta) = -\frac{1}{2} \sum_i T_i \left[\ln(2\pi) + \ln \sigma_i^2(\theta) + 1 \right] \tag{5}$$

which is maximized numerically over θ. Because this function can have more than one local maximum in short panels, the optimization is started from several initial values, and the maximum

with the highest likelihood is retained. Standard errors are obtained from the curvature of this concentrated likelihood at its maximum, and they should be read as approximate with only twelve differenced observations per country. We average the estimated φi across countries to summarize the typical speed of adjustment, and we compare PMG to the unrestricted Mean Group (MG) estimator, which estimates every parameter, long-run included, separately for each country before averaging. We compare the two with a Hausman-type test (Hausman, 1978):

$$H = (\theta_{PMG} - \theta_{MG})' \left[\mathrm{Var}(\theta_{MG}) - \mathrm{Var}(\theta_{PMG})\right]^{-1} (\theta_{PMG} - \theta_{MG}) \sim \chi^2(k) \tag{6}$$

A test that does not reject is compatible with pooling, but it is not proof of homogeneity. With only thirteen annual observations per country, the individual Mean Group estimates are noisy and the Hausman test has low power to detect economically meaningful heterogeneity. PMG is more efficient than Mean Group only if the pooling restriction is valid, so we treat the Hausman result as one piece of evidence and examine heterogeneity directly in Section 3.6.

3.4. Panel Diagnostics

Two diagnostics precede panel estimation. First, a Fisher-type panel unit root test (Maddala and Wu, 1999) combines the augmented Dickey-Fuller (Dickey and Fuller, 1979, 1981) p-values obtained separately for each of the 29 countries:

$$P = -2 \sum_{i=1}^{N} \ln(p_i) \sim \chi^2(2N) \tag{7}$$

where pi is the ADF p-value for country i. ARDL and PMG remain valid whether the underlying series are integrated of order zero or one, provided none is integrated of order two. This test is used to confirm that condition. It assumes cross-sectional independence, so we complement it with the CIPS test of Pesaran (2007) described in Section 3.6. Second, a cross-sectional dependence test (Pesaran, 2021) checks whether the panel is exposed to common shocks. This is likely, given that all 29 countries share the same global trends in renewable-energy costs and were jointly exposed to the 2020 pandemic:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{8}$$

where ρ̃ij is the pairwise correlation of OLS residuals between countries i and j. Under the null of cross-sectional independence, CD is asymptotically standard normal. Where dependence is detected, we do not rely on corrected standard errors alone, because common factors that are correlated with the regressors can bias the coefficients themselves. Section 3.6 describes the estimators used to address this.

3.5. Complementary Analysis: Direction of the Relationship

The two-stage ARDL design establishes whether a long-run relationship exists and whether it generalizes, but it does not by itself establish which variable leads the other. Thirteen annual waves are too few to run the individual country-by-country regressions that a formal Dumitrescu and Hurlin (2012) panel Granger-causality test requires. As a complementary check, we instead estimate a pooled dynamic panel with country and year fixed effects in both directions:

$$ECI_{it} = \rho\, ECI_{i,t-1} + \psi \ln(RE)_{i,t-1} + \lambda' Z_{i,t-1} + \mu_i + \tau_t + \varepsilon_{it} \tag{9}$$

estimated once with ECI as the dependent variable and lagged renewable electricity as a predictor, and once in reverse, with renewable electricity as the dependent variable and lagged ECI as a predictor. Z collects the remaining lagged controls, and μi and τt are country and year fixed effects. A lagged dependent variable together with fixed effects is known to bias the estimated persistence downward in short panels (Nickell, 1981). We therefore cross-check equation (9) with a two-step System GMM estimator (Arellano and Bond, 1991; Blundell and Bond, 1998). We collapse the instrument set to keep the instrument count below the number of countries (the Hansen test has two degrees of freedom, so the system is overidentified by two restrictions), and we report the Hansen test of overidentifying restrictions alongside the AR(2) test for residual autocorrelation.

3.6. Robustness: Common Factors, Heterogeneity, and Influential Countries

The cross-sectional dependence documented in Section 4.3 is not only a matter of standard errors. If common factors, such as global renewable-technology costs, commodity prices, or the 2020 shock, are correlated with the regressors, the PMG coefficients can themselves be inconsistent. We therefore take three steps. First, we apply the cross-sectionally augmented panel unit-root test of Pesaran (2007), CIPS, which is robust to cross-sectional dependence. Tabulated critical values do not exist for N = 29 and T = 13 in our specification, so we obtain them by Monte Carlo

simulation under a single-factor unit-root process. Second, we re-estimate PMG on data from which the cross-section mean of each variable has been removed in every year, which absorbs common factors with homogeneous loadings. Third, we estimate the long-run relationship in levels with the common correlated effects estimators of Pesaran (2006), in their mean group version (CCE-MG) and pooled version (CCE-P). These augment each country's regression with the cross-section averages of the dependent variable and the regressors, which allows country-specific factor loadings. With thirteen annual observations and ten parameters per country, they leave three degrees of freedom per country, so we use them as a check on sign and order of magnitude, not as precise estimates. The dynamic extensions, DCCE and CS-ARDL (Chudik and Pesaran, 2015), require lags of the cross-section averages and are not feasible in a panel this short.

To examine heterogeneity, we add to the long-run vector the interaction between renewable electricity and government effectiveness, with both variables centered, which tests the conditional-capability proposition behind Hypothesis 4. We also add the interaction between log GDP per capita and an indicator for hydrocarbon exporters, and we estimate PMG separately for economies with initial (2011) ECI above and below the sample median. Finally, we re-estimate PMG dropping one country at a time to identify countries that drive the result.

4. Results

4.1. Descriptive Statistics and Correlations (Panel)

Table 2 reports descriptive statistics for the 377 country-year observations in the panel. ECI ranges from -0.826 to 1.717, so the sample spans both below-average and highly sophisticated economies. Renewable electricity has the widest relative spread among the explanatory variables, reflecting how differently the 29 countries have progressed through the energy transition. Jarque-Bera tests reject normality for four of the five variables. This is expected in a panel pooling very different economies, and it does not affect the validity of ARDL or PMG, neither of which assumes normally distributed levels.

Table 2. Descriptive statistics, panel sample (N = 377)

Variable	Mean	Std. dev.	Min	Max	Skew.	Kurt.	J-B (p)
ECI	0.374	0.623	-0.826	1.717	0.194	2.323	0.008

Variable	Mean	Std. dev.	Min	Max	Skew.	Kurt.	J-B (p)
ln(Renewable electricity)	2.612	1.263	0.000	4.527	-0.639	2.550	<0.001
FDI (asinh)	1.376	0.740	-1.293	3.224	-0.524	3.377	<0.001
ln(GDP per capita)	9.001	1.075	6.730	11.594	0.127	2.333	0.018
Government effectiveness	0.211	0.561	-0.837	1.628	0.455	2.514	<0.001

Source: authors' calculations.

Table 3 gives the pairwise correlations. Government effectiveness and GDP per capita move closely together (r = 0.73), which is unsurprising since richer countries tend to have stronger institutions. ECI correlates most strongly with government effectiveness (r = 0.52) and only weakly with renewable electricity (r = -0.02) at the bivariate level. This near-zero raw correlation does not rule out a meaningful relationship once fixed effects and other covariates are taken into account, as Section 4.5 shows. Variance Inflation Factors, reported in the same table, stay below 3 for every regressor, so multicollinearity is not a concern for the panel estimates.

Table 3. Correlation matrix and variance inflation factors, panel sample

	ECI	ln(RE)	FDI (asinh)	ln(GDPpc)	GovE	VIF
ECI	1.000	-0.017	0.160	0.279	0.515	-
ln(RE)		1.000	0.441	-0.469	-0.252	1.65
FDI (asinh)			1.000	-0.064	0.074	1.30
ln(GDPpc)				1.000	0.733	2.66
GovE					1.000	2.25

Note: VIF not applicable to the dependent variable (ECI). Source: authors' calculations.

4.2. Unit Root Tests

Morocco. Table 4 reports Augmented Dickey-Fuller (Dickey and Fuller, 1979, 1981), Phillips-Perron (Phillips and Perron, 1988), and KPSS (Kwiatkowski et al., 1992) tests on the annual Morocco series. The results are mixed. ECI, renewable electricity, and government effectiveness reject a unit root in levels under the ADF test, while FDI and GDP per capita do not. KPSS results are borderline for several series, which is common with only 26 annual observations. No series requires second differencing. This mixed, and on some tests ambiguous, order of integration is exactly the condition bounds testing is designed for: it remains valid whether the regressors are I(0), I(1), or a mixture of the two.

Table 4. Unit root tests, Morocco, 1996-2021 (p-values in parentheses)

Variable	ADF, level	ADF, first diff.	Phillips-Perron, level	KPSS, level	KPSS, first diff.
ECI	-4.472 (0.002)	-5.444 (0.000)	-4.460 (0.002)	0.141 (0.059)	0.433 (0.063)
ln(Renewable electricity)	-4.001 (0.009)	-4.031 (0.001)	-3.589 (0.031)	0.131 (0.078)	0.268 (0.100)
ln(FDI)	0.117 (0.995)	-2.658 (0.082)	-6.605 (0.000)	0.150 (0.046)	0.241 (0.100)
ln(GDP per capita)	-1.123 (0.925)	-0.570 (0.878)	-1.672 (0.763)	0.173 (0.027)	0.207 (0.100)
Government effectiveness	-4.603 (0.001)	-3.243 (0.018)	-1.333 (0.880)	0.122 (0.094)	0.107 (0.100)

Source: authors' calculations.

Panel. Table 5 reports the Fisher-type combination of country-level ADF tests. FDI rejects the unit-root null decisively ($p < 0.001$), consistent with net capital flows being comparatively volatile and mean-reverting, while the other four series do not reject at conventional levels with a single lag, suggesting they are typically I(1) at the country level. As with Morocco, no series shows evidence of I(2) behavior, which is what makes PMG estimation valid here. This first-generation test assumes cross-sectional independence, which Table 6 rejects, so Section 4.7.2 also reports the CIPS test.

Table 5. Fisher-type panel unit root test (Maddala and Wu, 1999)

Variable	Fisher P-statistic	Degrees of freedom	p-value
ECI	57.13	58	0.508
ln(Renewable electricity)	71.25	58	0.113
FDI (asinh)	101.95	58	<0.001
ln(GDP per capita)	50.53	58	0.746
Government effectiveness	51.74	58	0.706

Source: authors' calculations.

4.3. Cross-Sectional Dependence (Panel)

Table 6 reports the Pesaran (2021) CD test. Renewable electricity, FDI, GDP per capita, and government effectiveness all show significant cross-sectional dependence, while ECI does not. This is consistent with shared global trends in renewable-energy costs and the synchronized 2020 pandemic shock. Correcting standard errors would not be enough if these common factors are correlated with the regressors, because the PMG coefficients themselves could then be

inconsistent. Section 4.7.2 therefore compares PMG with estimators that explicitly handle common factors.

Table 6. Pesaran (2021) test of cross-sectional dependence

Variable	CD statistic	p-value
ECI	-0.002	0.998
ln(Renewable electricity)	28.742	<0.001
FDI (asinh)	2.477	0.013
ln(GDP per capita)	22.787	<0.001
Government effectiveness	3.982	<0.001

Source: authors' calculations.

4.4. Morocco: Evidence of a Long-Run Relationship

Table 7 reports the bounds test. The F-statistic is 5.70. It exceeds the 5 percent critical value of 5.05 obtained by bootstrap for our sample ($p = 0.034$), so the null of no long-run relationship is rejected at 5 percent, but not at 1 percent (critical value 7.88). The result is consistent with a long-run relationship between economic complexity and renewable electricity, FDI, GDP per capita, and institutional quality under the maintained specification. This supports Hypothesis 1, with the caveats discussed below and in Section 4.7.1.

Table 7. ARDL bounds test and adjustment coefficient, Morocco

Statistic	Value	Bootstrap 5% critical value	Bootstrap p-value
F-statistic	5.70	5.05	0.034
Adjustment coefficient (φ)	-1.109*** ($p < 0.001$)	-	-

*Note: *** $p < 0.01$. Critical values from 3,000 residual-bootstrap replications under the null of no long-run relationship (case III: unrestricted intercept, no trend); the 1 percent critical value is 7.88 and the 10 percent value is 4.12. Source: authors' calculations.*

The adjustment coefficient is -1.109 and statistically significant. A value beyond -1 means the model overshoots and corrects with a one-year oscillation rather than a smooth glide. It still converges, since the implied autoregressive root, one plus the coefficient, equals -0.109 and lies well inside the unit circle. In practical terms, a shock to the long-run relationship is almost fully absorbed within a year. This is a very fast adjustment for a slow-moving structural indicator such as economic complexity. It may partly reflect measurement noise in the annual ECI, which

produces apparent mean reversion, so it should be read as a feature of the reduced-form model rather than as a literal speed of structural change.

Table 8. Long-run and short-run coefficients, Morocco

Variable	Long-run coeff.	p-value	Short-run coeff. (Δ)	p-value
Renewable electricity	-0.097	0.004	-0.066	0.105
FDI	-0.097	0.025	-0.048**	0.006
GDP per capita	0.368	<0.001	-0.076	0.743
Government effectiveness	-0.187	0.013	0.008	0.944

*Note: ** p < 0.05. Newey-West standard errors (one lag). Source: authors' calculations.*

Renewable electricity carries a small negative long-run coefficient in Morocco, with no significant short-run counterpart. FDI is the only variable significant at both horizons, negative in the short run and negative in the long run alike. GDP per capita is, as expected, the strongest driver of complexity in the long run, though not in the short run. Government effectiveness enters with a negative long-run sign, which differs from the panel result reported in Section 4.5. With 25 usable observations for a single country, all coefficients should be read with caution. The sensitivity checks in Section 4.7.1 show, however, that the sign of the government-effectiveness coefficient and its size, between -0.13 and -0.24, are stable across the alternatives we tried, so the contrast with the panel is not a fragile feature of one specification. It signals that the country-specific relationship differs from the pooled one.

Table 9. Diagnostic tests, Morocco ARDL model

Test	Statistic	p-value	Conclusion
Jarque-Bera (normality)	0.592	0.744	Residuals normal
Breusch-Godfrey (serial correlation, 1 lag)	4.649	0.031	Autocorrelation detected at 5%; addressed by Newey-West standard errors
Breusch-Pagan (heteroskedasticity)	14.305	0.112	No heteroskedasticity
Ramsey RESET (functional form)	0.365	0.555	No misspecification

Note: Model $R^2 = 0.732$, adjusted $R^2 = 0.571$, N = 25 (first-differenced sample). Source: authors' calculations.

The one diagnostic concern is residual autocorrelation, detected at the 5 percent level by the Breusch-Godfrey test (p = 0.031 with one lag and p = 0.007 with two lags). This is unsurprising

given only 25 usable observations after differencing and lagging, but it persists under every alternative lag structure in Table 14 (p between 0.01 and 0.04), so the dynamic specification is not fully adequate. Newey-West standard errors, used for the coefficients above, correct inference for this form of misspecification but do not remove it, and the Morocco results should be read in that light. The other three diagnostics are clean: residuals are normal, homoskedastic, and the functional form is not rejected.

4.5. Panel: A Common Long-Run Relationship Across 29 Economies

Table 10 reports the PMG long-run and average short-run coefficients, testing whether Morocco's relationship generalizes (Hypothesis 2). The estimates are the global maximum of the concentrated likelihood found from multiple starting values. Section 4.7.2 shows that a second, lower local maximum exists and that the choice between the two depends on a few countries.

Table 10. Pooled Mean Group estimates, panel of 29 economies

Variable	Long-run coeff.	Std. error	p-value	Mean short-run coeff.	p-value
Renewable electricity	-0.004	0.012	0.772	0.211	0.104
FDI (asinh)	0.026***	0.007	<0.001	-0.013	0.555
GDP per capita	-0.161***	0.021	<0.001	0.020	0.845
Government effectiveness	0.133***	0.014	<0.001	0.040	0.485

*Note: *** $p < 0.01$. Standard errors from the curvature of the concentrated likelihood. Source: authors' calculations.*

Renewable electricity has no significant long-run relationship with complexity once the coefficient is pooled across 29 economies. This does not support Hypothesis 2 for this variable: Morocco's own negative coefficient does not generalize to the pooled estimate. Its average short-run coefficient is positive but not significant at conventional levels ($p = 0.104$), and it is a cross-country average masking wide dispersion, not a precisely estimated effect. At the panel level, and over this period, the energy transition shows no common long-run association with complexity, on average. This is the paper's central negative result, with one qualification: it describes the pooled PMG estimate, and Section 4.7.3 shows that an average of zero may combine very different country-level relationships.

FDI and government effectiveness both carry positive long-run coefficients in the PMG baseline, with small standard errors, and the government-effectiveness result is consistent with Hypothesis 3. The FDI result is not robust (Section 4.7.2). GDP per capita is negative in the long run. None of the short-run coefficients is individually significant, which is typical of PMG estimates given the limited within-country variation available over 13 years.

4.5.1. Sign Reversals Between Morocco and the Panel

Two of these panel coefficients change sign relative to the Morocco-only regression in Table 8. FDI is negative in Morocco and positive in the PMG baseline. Part of this contrast is mechanical: Morocco's FDI series is log-transformed, while the panel series uses the inverse hyperbolic sine transformation needed to accommodate the negative net inflows recorded in several panel countries, so the two coefficients are not measured on strictly comparable scales. The panel sign is also not robust: it turns negative in the second PMG solution and in the PMG estimated on year-demeaned data (Table 16), so we do not interpret it substantively.

GDP per capita shows the opposite reversal: strongly positive in Morocco, negative in the PMG baseline. Because GDP per capita enters as a log in both samples, this is unlikely to be a scale artifact. We first considered a composition explanation, in which high-income resource exporters with narrow export structures pull the pooled coefficient negative. A direct test does not support it: the interaction of GDP per capita with a hydrocarbon-exporter indicator is not significant, and the baseline GDP coefficient is essentially unchanged (Table 17). The sign also turns positive in the second PMG solution and in the year-demeaned PMG (Table 16). The negative coefficient is therefore specific to the baseline PMG solution and should not be given a substantive interpretation.

Table 11. Hausman test, Pooled Mean Group versus Mean Group

Variable	θ (PMG)	θ (MG)	$\chi^2(1)$	p-value
Renewable electricity	-0.004	0.178	1.226	0.268
FDI (asinh)	0.026	-0.008	0.448	0.503
GDP per capita	-0.161	-0.051	0.219	0.640
Government effectiveness	0.133	0.135	0.000	0.994
Joint test (4 d.f.)	-	-	1.89	0.756

Source: authors' calculations.

The Hausman test does not reject the pooling restriction for any variable individually, nor jointly (chi-squared = 1.89, 4 degrees of freedom). This is compatible with pooling but is weak evidence of homogeneity: with only 12 to 13 usable annual observations per country, the individual Mean Group estimates are very noisy, so the test has little power to detect heterogeneity. The wide dispersion of the unrestricted estimates, most visibly for renewable electricity, where the MG average (0.178) is far from the PMG estimate (-0.004), shows the cost of estimating each country separately, but it also shows that the pooled estimate hides substantial country differences. PMG is more efficient than MG only if the common long-run vector is valid, and the heterogeneity tests of Section 4.7.3 suggest that it is not valid for all variables.

Government effectiveness is the variable whose long-run coefficient is most stable in the PMG framework: it is close to 0.13 in the baseline and in the MG average (0.135), 0.12 in the second PMG solution, and positive in the year-demeaned PMG. It is negative in Morocco alone, and it is not statistically significant in most of the static common correlated effects estimates (Table 16). We therefore read it as a positive conditional association whose size depends on how common shocks are treated, which supports Hypothesis 3 with these qualifications.

4.6. Complementary Analysis: Direction of the Relationship

Table 12 reports the dynamic fixed-effects panel estimates of equation (9) in both directions, and Table 13 reports the System GMM robustness check, addressing the causal-direction question left open by the ARDL and PMG results above.

Table 12. Dynamic panel estimates, both directions (country and year fixed effects)

Direction tested	Lagged own variable	Lagged other variable	p-value (other variable)
Renewable electricity → ECI	0.510*** (ECI, t-1)	-0.033 (ln RE, t-1)	0.416
ECI → Renewable electricity	0.899*** (ln RE, t-1)	0.054 (ECI, t-1)	0.387

*Note: *** $p < 0.01$. Both models control for FDI, GDP per capita, and government effectiveness (lagged), plus country and year fixed effects. Source: authors' calculations.*

Table 13. System GMM estimates (two-step, Windmeijer-corrected standard errors)

Variable	Coefficient	Std. error	p-value
ECI, t-1	-0.117	0.238	0.625
Renewable electricity	-0.041	0.044	0.358
FDI (asinh)	0.000	0.014	0.999
GDP per capita	-0.076	0.079	0.336
Government effectiveness	0.049	0.059	0.406

Note: Hansen test of overidentifying restrictions, $\chi^2(2) = 4.30$, $p = 0.117$ (instruments valid). AR(2) test, $z = -1.00$, $p = 0.318$ (no second-order autocorrelation, GMM specification valid). Source: authors' calculations.

Neither variable predicts the other once its own past value is taken into account. The fixed-effects estimates, which cover both directions, and the System GMM estimate for the ECI equation agree on this point. Complexity and renewable electricity are each highly persistent from one year to the next, but they do not lead one another in a statistical sense. This is a modest complementary result, and with N = 29 and T = 13 the dynamic-panel estimators have limited power. It does not overturn the long-run relationships discussed in Sections 4.4 and 4.5, but it clarifies that they should be read as associations within an equilibrium-correction framework, not as a one-way causal channel running from the energy transition to complexity or back. None of the estimates in this paper identifies a causal effect.

4.7. Robustness and Heterogeneity

This section reports the checks designed to test how far the main results depend on the specification, the estimator, and individual observations. Throughout, the estimates are conditional associations.

4.7.1. Morocco: Small-Sample, Stability, and Influence Checks

Table 14 summarizes the sensitivity of the Morocco results. Across eight alternative sets of short-run terms, the adjustment coefficient stays between -1.10 and -1.13 and the long-run coefficient of government effectiveness between -0.17 and -0.19, so these two are stable. The long-run coefficient of renewable electricity is not: it ranges from -0.03, when no differenced regressors are included, to -0.10 in the baseline, and the F-statistic ranges from 3.44 to 8.53. Adding the lagged difference of ECI lowers the F-statistic to 3.44, below the 10 percent bootstrap critical value of 4.12, so the evidence of a long-run relationship depends on the lag structure. A post-2009 dummy (coefficient 0.04, p = 0.59) and an impulse dummy for 2009 (p = 0.85) are not significant, and the

long-run coefficients change little when they are included. We therefore find no evidence of a structural break around the National Energy Strategy, although a test with 25 observations has little power. The dummy for the three interpolated values of government effectiveness is also insignificant (p = 0.74), and the long-run coefficient of government effectiveness is -0.18 when it is included.

Table 14. Morocco: sensitivity of the bounds test and long-run coefficients

Specification	F-statistic	φ	θ (RE)	θ (GE)
Baseline (Δ of all four regressors)	5.70	-1.109	-0.097	-0.187
No differenced regressors	7.25	-1.127	-0.026	-0.174
Δ ln RE only	7.05	-1.105	-0.051	-0.185
Δ ln RE and Δ ln FDI	8.53	-1.125	-0.096	-0.187
Δ ln RE and Δ GE	6.81	-1.121	-0.059	-0.172
Δ GE only	6.86	-1.132	-0.028	-0.170
Baseline + lagged Δ ECI	3.44	-1.103	-0.092	-0.190
Baseline + lagged Δ ln RE	4.95	-1.114	-0.104	-0.182
Baseline + post-2009 dummy	5.46	-1.076	-0.106	-0.215
Baseline + interpolation dummy	5.39	-1.124	-0.090	-0.176
Baseline + both dummies	5.13	-1.091	-0.098	-0.204
Leave-one-year-out (range)	3.39 to 6.80	-1.18 to -0.89	-0.13 to -0.06	-0.24 to -0.13

Note: F-statistic of the bounds test, adjustment coefficient (φ), and long-run coefficients of ln renewable electricity (θ RE) and government effectiveness (θ GE). The 5 and 1 percent bootstrap critical values of the baseline model are 5.05 and 7.88, and the 10 percent value is 4.12. Source: authors' calculations.

The CUSUM test does not signal instability (p = 1.00), and the CUSUMSQ statistic stays inside the approximate 5 percent band, but both tests have low power in a sample this small. Dropping one year at a time, the F-statistic ranges from 3.39 to 6.80, the adjustment coefficient from -1.18 to -0.89, the long-run coefficient of renewable electricity from -0.13 to -0.06, and that of government effectiveness from -0.24 to -0.13. No sign changes. The F-statistic falls below 4 only when 2013 is dropped, and Cook's distance flags 2012 (0.40, against a threshold of 4/n = 0.16) as the most influential observation. In short, the Morocco coefficients are stable in sign, but the evidence for cointegration is marginal and sensitive to the specification and to individual years.

4.7.2. Panel: Common Factors and Estimator Dependence

Table 15 reports the CIPS test. At the 5 percent level (simulated critical value -2.21), it rejects the unit-root null for ECI and FDI but not for renewable electricity, GDP per capita, or government effectiveness. The panel therefore mixes stationary and non-stationary series. This is compatible with the error-correction framework, but it means that the long-run coefficients should not be read as cointegrating vectors in the strict sense.

Table 15. CIPS panel unit-root test (Pesaran, 2007)

Variable	CIPS statistic	Decision
ECI	-2.652	Rejects unit root at 5%
ln(Renewable electricity)	-1.689	Does not reject
FDI (asinh)	-2.416	Rejects unit root at 5%
ln(GDP per capita)	-1.304	Does not reject
Government effectiveness	-1.885	Does not reject

Note: Intercept only, no augmentation lags. Simulated critical values for N = 29 and T = 13: -2.41 (1%), -2.21 (5%), -2.09 (10%). Source: authors' calculations.

The PMG likelihood has two local maxima. The one reported in Table 10 has the higher likelihood, but a second maximum yields a renewable-electricity coefficient of 0.095, an FDI coefficient of -0.068, a GDP coefficient of 0.145, and a government-effectiveness coefficient of 0.121 (Table 16). Dropping any one of Czechia, Indonesia, Kenya, or Mexico moves the global maximum to this second solution, and so does dropping Indonesia, Brazil, and Ukraine together, the three countries with unstable adjustment coefficients in Table A1. The estimates for renewable electricity, FDI, and GDP per capita are therefore not stable. Government effectiveness is: it stays between 0.12 and 0.14 in both solutions and in all leave-one-country-out estimates.

Removing the cross-section mean of each variable in every year changes the picture. In the year-demeaned PMG, the coefficient of renewable electricity is 0.010 and not significant, FDI turns negative (-0.094), GDP per capita turns positive (0.124), and the government-effectiveness coefficient falls to 0.063, about half the baseline, though it remains significant at 5 percent. The static common correlated effects estimates are noisier. The government-effectiveness coefficient is 0.268 (standard error 0.164) in CCE-MG and 0.008 (0.119) in CCE-P, neither significant. Excluding the five hydrocarbon exporters, it is 0.188 (0.082) in CCE-MG, significant at 5 percent, and 0.032 (0.060) in CCE-P, not significant. A static two-way fixed-effects benchmark gives 0.159. The sign of the government-effectiveness coefficient is therefore positive in every panel

estimator we ran, but the evidence that it differs from zero once common factors with country-specific loadings are allowed for is weak, a conclusion limited by the three degrees of freedom available per country.

Table 16. Long-run coefficients across panel estimators

Estimator	ln RE	FDI (asinh)	ln GDP	Government effectiveness
PMG baseline (Table 10)	-0.004 (0.012)	0.026*** (0.007)	-0.161*** (0.021)	0.133*** (0.014)
PMG, second local maximum	0.095*** (0.014)	-0.068*** (0.011)	0.145*** (0.020)	0.121*** (0.016)
Mean Group (average of country estimates)	0.178	-0.008	-0.051	0.135
PMG, year-demeaned data	0.010 (0.028)	-0.094*** (0.020)	0.124*** (0.041)	0.063** (0.028)
CCE-MG, static	0.491 (0.329)	-0.026 (0.033)	0.135 (0.135)	0.268 (0.164)
CCE-P, static	-0.109 (0.230)	-0.012 (0.029)	0.119 (0.113)	0.008 (0.119)
CCE-MG, excl. hydrocarbon exporters (N = 24)	-0.001 (0.115)	-0.010 (0.038)	-0.069 (0.114)	0.188** (0.082)
CCE-P, excl. hydrocarbon exporters (N = 24)	-0.034 (0.035)	-0.005 (0.010)	0.087 (0.067)	0.032 (0.060)

*Note: Standard errors in parentheses. ** p < 0.05, *** p < 0.01. PMG standard errors come from the concentrated likelihood and are likely understated with twelve differenced observations per country. CCE estimators are static, in levels, with cross-section averages of all variables (three degrees of freedom per country); CCE-MG standard errors use the dispersion of country estimates and CCE-P standard errors the non-parametric variance of Pesaran (2006). The Mean Group row repeats the averages of Table 11. Hydrocarbon exporters: Kazakhstan, Kuwait, Qatar, Saudi Arabia, United Arab Emirates. Source: authors' calculations.*

4.7.3. Panel: Heterogeneity

Table 17 reports the heterogeneity tests. The interaction between renewable electricity and government effectiveness, both centered, has a positive and significant long-run coefficient in the PMG (0.082, standard error 0.026), while the main effects of both variables are close to zero at the sample means (-0.010 for renewable electricity and -0.002 for government effectiveness). This pattern supports Hypothesis 4: renewable electricity is associated with higher complexity where government effectiveness is above average and with lower complexity where it is below. It also means that the positive baseline association of government effectiveness operates partly through this interaction. The same specification estimated with common correlated effects is too imprecise to be informative, so this finding rests on the PMG alone and should be treated as suggestive. The interaction of GDP per capita with the hydrocarbon-exporter indicator is not significant (-0.314, standard error 0.328). Splitting the sample by initial ECI gives a clear contrast for government

effectiveness: its coefficient is positive in economies with initial ECI above the median (0.150, N = 15) and negative in those below it (-0.282, N = 14), and the FDI and GDP coefficients also differ markedly between the two groups. This is the kind of heterogeneity that the PMG restriction rules out, although PMG standard errors in subsamples this small are likely understated. Excluding the five hydrocarbon exporters produces a PMG solution that is numerically unstable, with implausibly small standard errors, and we do not report it.

Table 17. PMG long-run coefficients, heterogeneity tests

Specification	ln RE	FDI (asinh)	ln GDP	GE	Additional term
Interaction RE × GE (centered)	-0.010 (0.028)	-0.119*** (0.018)	-0.194*** (0.033)	-0.002 (0.028)	RE × GE: 0.082*** (0.026)
Interaction GDP × hydrocarbon exporter	-0.007 (0.012)	0.026*** (0.007)	-0.157*** (0.021)	0.131*** (0.014)	GDP × hydrocarbon: -0.314 (0.328)
Initial ECI above median (N = 15)	0.000 (0.012)	0.027*** (0.008)	-0.158*** (0.027)	0.150*** (0.021)	-
Initial ECI below median (N = 14)	0.007 (0.057)	0.182*** (0.019)	0.344*** (0.032)	-0.282*** (0.080)	-

*Note: Standard errors in parentheses. *** $p < 0.01$. Interaction variables are centered at the sample mean, so the main effects are evaluated at the mean of the other variable. Initial ECI is the 2011 value. Source: authors' calculations.*

5. Discussion

Five results deserve discussion against the wider literature: the fast adjustment found in Morocco, the null result on renewable electricity at the panel level, the sign reversals in FDI and GDP per capita, the conditional association between government effectiveness and complexity, and the absence of detectable causality in either direction.

5.1. Fast Adjustment and Equilibrium Correction

An error-correction coefficient beyond unity, as found for Morocco, is unusual but not unprecedented. It indicates a system that overshoots and corrects rather than converging smoothly, while still being stable. This fits the broader finding in the ARDL literature applied to emerging economies that structural indicators can adjust quickly to energy-sector shocks (Ashfaq et al., 2024, in a dynamic ARDL study of renewable energy and green growth; Hazmi et al., 2024, using panel ARDL for GCC economies). Belabbas et al. (2025), working with panel ARDL on Arab MENA economies, similarly report a fast-adjusting long-run relationship between renewable

energy and environmental performance. Morocco's result sits within this range. Two cautions apply. A coefficient of -1.109 implies almost complete correction within a year, which is striking for an indicator that changes as slowly as economic complexity. And our checks show that the evidence for cointegration is marginal at the 5 percent level, sensitive to the lag structure, and accompanied by residual autocorrelation (Table 9; Table 14). The result is therefore best read as evidence consistent with a long-run relationship under the maintained specification, not as a firmly established equilibrium.

5.2. Why the Panel Result on Renewable Electricity Differs from Morocco

The absence of a significant panel-level relationship between renewable electricity and complexity contrasts with Morocco's own negative coefficient, and this contrast is itself informative. Caldarola et al.'s (2024) systematic review argues that the effect of the energy transition on complexity is unlikely to be uniform across countries, because it depends on capabilities that vary widely across the sample. A null average effect is consistent with this heterogeneity if positive and negative country-specific effects offset one another once pooled, a pattern directly visible in Table 11, where the unrestricted Mean Group estimate for renewable electricity (0.178) sits far from, and much less precisely than, the pooled PMG estimate (-0.004). The results of Section 4.7 reinforce this reading: the pooled estimate depends on a few countries, and renewable electricity is suggestively associated with higher complexity only where government effectiveness is high. Sarsar and Echaoui (2024) and Viglioni et al. (2025) make a related point from the other causal direction: economic complexity itself conditions a country's capacity to deploy renewable technologies, which means the raw relationship observed in any one country reflects both directions of influence at once. The causality tests in Section 4.6 are consistent with this reading. Neither direction is statistically detectable once persistence is controlled for, which is compatible with a slow-moving, mutually reinforcing relationship that a simple lead-lag test is not powered to isolate over only thirteen annual waves.

This reading also qualifies the more optimistic literature, in which economic complexity and renewable-energy consumption reinforce each other most strongly in the highest quantiles of a country distribution, a pattern documented by Hossain et al. (2024) for OECD economies and by Labidi (2025) using the same method-of-moments quantile approach. Both studies rely on samples large enough, and long enough, for genuine quantile estimation. The present panel, with only 13

years, is not, and this is precisely why we replaced quantile methods with PMG rather than force them onto data too short to support them. The two literatures are not in conflict. They describe different samples, at different levels of aggregation, using methods matched to the data each had available.

5.3. Sign Reversals in FDI and GDP per Capita: An Interpretation

Two further coefficients change sign between Morocco and the panel. FDI carries a negative long-run coefficient in Morocco (Table 8) and a positive coefficient in the PMG baseline (Table 10). Part of this contrast is mechanical: Morocco's FDI series is log-transformed, while the panel series uses the inverse hyperbolic sine transformation to accommodate negative net inflows recorded in several panel countries, so the two coefficients are not measured on strictly comparable scales. Substantively, the panel coefficient is not robust. It turns negative in the second PMG solution (-0.068) and in the year-demeaned PMG (-0.094), and it is not significant in the CCE estimates (Table 16). The panel sign of FDI therefore depends on the estimator, and it offers a weak basis for any conclusion about the role of FDI.

GDP per capita shows the same pattern in reverse. It is the strongest driver of complexity in Morocco (Table 8, positive) and negative in the PMG baseline (Table 10). This is unlikely to be a scale artifact, since GDP per capita enters as a log in both samples. We considered a composition explanation, in which high-income resource exporters with narrow export structures pull the pooled coefficient negative. The direct test does not support it: the interaction of GDP per capita with a hydrocarbon-exporter indicator is not significant (Table 17), and the sign turns positive in the second PMG solution and in the year-demeaned PMG (Table 16). A more likely reading is that the baseline sign reflects the particular PMG solution and the way common trends in income and complexity are absorbed, so we do not interpret it substantively. A fuller test of the composition hypothesis would need a broader definition of resource dependence than the five hydrocarbon exporters used here.

5.4. Institutions as a Candidate Channel

The most stable result at the panel level is the positive association between government effectiveness and complexity. Its sign is the same in the PMG baseline, the second PMG solution, the Mean Group average, the year-demeaned PMG, and the fixed-effects benchmark, and its size

stays between 0.12 and 0.14 in all leave-one-country-out PMG estimates. This is consistent with the institutional mechanism discussed by Mazzucato (2021) and Rodrik (2024): coordinating investment, financing innovation, and building skills is itself a capability, and one that does not depend on a country's specific energy mix. It also echoes Hausmann et al. (2014) and Balland et al. (2022), who treat institutional quality as a precondition for converting any form of investment into productive diversification. Three qualifications limit the conclusion. First, the coefficient is negative in the Morocco-only regression (Table 8) and in economies with low initial complexity (Table 17), so the association is not uniform. Second, its magnitude halves once year effects are removed (0.063), and it is not statistically distinguishable from zero in most static CCE estimates, so we cannot rule out that part of the baseline association reflects common trends. Third, in the interaction specification the coefficient at the mean renewable share is close to zero, which suggests that government effectiveness matters mainly in combination with renewable investment, as Hypothesis 4 proposes. None of these estimates identifies a causal effect. The evidence supports the view that institutional capacity is a plausible condition for upgrading, and a more dependable correlate of complexity than renewable capacity in this sample, but not that raising it would raise complexity.

5.5. On the Absence of Detectable Causality

The absence of significant Granger-type causality in either direction (Section 4.6) does not contradict the cointegration evidence in Sections 4.4 and 4.5. The two describe different things. Cointegration establishes that the variables move together toward a shared equilibrium over time. A lead-lag causality test asks whether last year's value of one variable improves the prediction of this year's value of the other, once each series' own persistence is already accounted for. A relationship can satisfy the first without satisfying the second, particularly when, as here, the error-correction mechanism itself operates quickly (Section 4.4). If most of the adjustment happens within a single year, a one-period-lag causality test has little contemporaneous asymmetry left to detect. We report this null result because it is informative, not despite that: it counsels against over-interpreting the country-level negative coefficient in Morocco as evidence of a mechanical, one-way causal channel from renewable electricity to complexity.

5.6. Policy Hypotheses

The regressions do not measure local content, domestic manufacturing, technology transfer, green innovation, skills, or participation in higher-value segments of renewable-energy value chains. The three policy ideas below are therefore hypotheses, motivated by the conditional-capability argument and by the literature, that follow from the patterns reported above. They are not interventions whose effects the regressions demonstrate.

5.6.1. Local-Content and Technology-Transfer Clauses in Renewable Procurement

Pattern: renewable electricity share carries no significant common long-run coefficient in the panel (Table 10: coefficient = -0.004, p = 0.772) and shows no detectable lead-lag relationship with complexity in either direction (Table 12; Table 13). Hypothesis: if capacity addition without capability accumulation explains this pattern, procurement contracts for solar, wind, and storage capacity that carry a minimum local-content share and a technology-transfer clause, requiring domestic engineering firms to participate in design or component manufacturing and not only in installation and assembly, would strengthen the association between renewable deployment and complexity. This follows the assembly-versus-design distinction documented by Humphrey and Schmitz (2002). Our data cannot test it, because local content is not measured; a test would need project-level or sector-level data.

5.6.2. Technology-Oriented Screening of Renewable-Sector FDI

Pattern: the FDI coefficient is positive in the PMG baseline (Table 10: coefficient = 0.026, $p < 0.001$) but changes sign across estimators (Table 16), so it gives little support for promoting FDI in general. Hypothesis: if what matters is the technological content of foreign investment, investment promotion agencies that score incoming renewable-sector FDI on technology content, similar to local-content scoring used in other sectors, and that prioritize projects committing to local research and development, joint ventures, or component manufacturing over turnkey, fully imported installations, would improve the link between FDI and complexity. The present evidence does not test this.

5.6.3. Public-Sector Effectiveness Reform Alongside Capacity Targets

Pattern: government effectiveness is positively associated with complexity in the PMG baseline (Table 10: coefficient = 0.133, $p < 0.001$), keeps its sign across the alternative estimators (Table 16), and interacts positively with renewable electricity (Table 17), although its magnitude is

sensitive to common shocks. Hypothesis: if institutional capacity conditions whether renewable investment builds capabilities, reforms that reduce renewable-project permitting time, standardize grid-connection procedures, and strengthen procurement oversight, undertaken alongside and not after capacity targets, would raise the complexity gains from the transition. This is a hypothesis about a conditional association, and the regressions do not show that such reforms would raise complexity.

If the adjustment found in Morocco is as fast as Table 7 suggests, any such measure could be reviewed annually against export-complexity data, rather than left in place for a five-year cycle before the first evaluation. Given the sensitivity of that adjustment estimate (Section 4.7.1), this is a practical suggestion for monitoring, not an empirical result.

6. Conclusion

This paper asked whether the energy transition builds productive sophistication, using a two-stage ARDL design that moves from a single, deeply observed country to a panel that tests whether the country result generalizes, and that subjects both stages to unit-root, cross-sectional-dependence, Hausman, common-factor, heterogeneity, and influence diagnostics. Morocco shows evidence consistent with a fast-adjusting, mildly negative long-run relationship between renewable electricity and economic complexity under the maintained specification. The evidence is marginal at the 5 percent level, sensitive to the lag structure and to individual years, and accompanied by residual autocorrelation. This relationship does not carry over to the pooled panel estimate: renewable electricity shows no significant common long-run association with complexity across 29 emerging and frontier economies, and a complementary dynamic-panel and System GMM analysis finds no significant lead-lag relationship in either direction. A zero average may hide different country relationships: in a PMG interaction specification, renewable electricity is associated with higher complexity mainly where government effectiveness is high. Government effectiveness is the most stable variable in the panel. It is positively associated with complexity in the PMG baseline and keeps its sign in the alternative panel estimators. Its magnitude is halved once common year effects are removed, it is not clearly distinguishable from zero in static common correlated effects estimates, and it is negative in Morocco alone. The estimates for FDI and GDP

per capita depend on the estimator and on a few countries. All results are conditional associations, and none identifies a causal effect.

Four limitations bound these conclusions. First, thirteen years is short for a panel ARDL. The PMG likelihood has more than one local maximum and the choice between them depends on a few countries, the common correlated effects estimators leave only three degrees of freedom per country, and dynamic common-factor estimators (DCCE, CS-ARDL) are not feasible. Longer panels would sharpen the long-run estimates and allow these tests. Second, the 29-country sample was built for data availability across emerging and frontier markets, a reasonable but not the only possible sampling frame, and the results describe this population, not a universal law of the energy transition. Third, the Morocco analysis rests on 25 usable observations, with three interpolated values of government effectiveness and unresolved residual autocorrelation. Fourth, the regressions do not measure local content, technology transfer, or participation in renewable value chains, so the policy statements in Section 5.6 are hypotheses.

Future work could extend the panel as more years accumulate, estimate dynamic common correlated effects models once the time dimension allows them, apply a formal Dumitrescu and Hurlin panel causality test once country-by-country regressions become reliable, use a broader and externally defined measure of resource dependence, measure local content and technology transfer directly, and test whether the institutional channel operates through specific sub-components of government effectiveness, such as regulatory quality, rule of law, and control of corruption.

A. Appendix

Table A1 reports the country-specific adjustment speed, φi, recovered from the Mean Group step that underlies the Hausman comparison in Table 11. Twenty-six of the 29 countries show a stable adjustment coefficient between -2 and 0. Indonesia's coefficient (-2.161) falls just outside this band, and Brazil and Ukraine show small positive values, which is why the baseline long-run relationship is estimated with PMG rather than by simply averaging the 29 individual country regressions. Section 4.7.2 shows, however, that the PMG solution is sensitive to these three countries.

Table A1. Country-specific adjustment speed (φi), Mean Group estimation

Country (ISO3)	φi	Country (ISO3)	φi
IDN	-2.161	GRC	-0.815
CZE	-1.823	PHL	-0.658
MEX	-1.801	BGD	-0.542
KEN	-1.346	KOR	-0.506
PAK	-1.170	MAR (Morocco)	-0.479
ARE	-1.165	MYS	-0.439
POL	-1.034	CHL	-0.369
KAZ	-0.919	COL	-0.326
TUR	-0.898	QAT	-0.307
KWT	-0.887	IND	-0.302
SAU	-0.222	EGY	-0.218
ZAF	-0.145	THA	-0.141
VNM	-0.098	CHN	-0.078
PER	-0.054	BRA	0.041
UKR	0.043		

Source: authors' calculations.

Table A2. Panel sample: classification and descriptive information

Country	ISO3	Group	Initial ECI (2011)	Mean RE share (%)	Mean GDP per capita (US$)	Hydrocarbon exporter
Bangladesh	BGD	FC	-0.789	1.9	1,733	No
Brazil	BRA	EM	0.527	80.7	10,119	No
Chile	CHL	EM	0.057	45.5	14,914	No
China	CHN	EM	1.291	24.6	9,409	No
Colombia	COL	EM	0.125	72.8	6,862	No
Czechia	CZE	EM	1.532	11.3	22,996	No
Egypt	EGY	EM	-0.043	9.7	3,169	No

Country	ISO3	Group	Initial ECI (2011)	Mean RE share (%)	Mean GDP per capita (US$)	Hydrocarbon exporter
Greece	GRC	EM	0.325	30.2	20,514	No
India	IND	EM	0.407	16.8	1,844	No
Indonesia	IDN	EM	0.154	16.5	3,888	No
Kazakhstan	KAZ	FC	-0.599	10.5	10,589	Yes
Kenya	KEN	FC	-0.314	81.6	1,676	No
Kuwait	KWT	EM	0.043	0.1	36,823	Yes
Malaysia	MYS	EM	0.854	14.4	10,566	No
Mexico	MEX	EM	1.154	17.5	10,587	No
Morocco	MAR	BL	-0.229	15.8	3,400	No
Pakistan	PAK	FC	-0.490	31.1	1,365	No
Peru	PER	EM	-0.567	56.3	6,710	No
Philippines	PHL	EM	0.485	23.6	3,093	No
Poland	POL	EM	1.146	15.0	15,478	No
Qatar	QAT	EM	-0.488	0.6	79,616	Yes
Saudi Arabia	SAU	EM	0.199	0.2	28,526	Yes
South Africa	ZAF	EM	0.360	3.0	6,748	No
South Korea	KOR	EM	1.612	3.8	32,080	No
Thailand	THA	EM	0.838	14.9	6,440	No
Turkiye	TUR	EM	0.586	33.4	10,995	No
Ukraine	UKR	FC	0.731	8.9	3,550	No
United Arab Emirates	ARE	EM	0.507	2.0	47,554	Yes
Vietnam	VNM	FC	0.235	42.1	3,053	No

Note: Group follows the MSCI classification recorded in the dataset (EM = emerging, FC = frontier candidate, BL = baseline country, Morocco). Initial ECI is the 2011 value; the renewable electricity share and GDP per capita are 2011-2023 averages. Hydrocarbon exporters are the five economies used in Section 4.7.3. Source: authors' calculations.

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