ISSN (Print): 2959-4391 ISSN (Online): 2959-4405

JOURNAL OF SOCIAL SCIENCES DEVELOPMENT

www.jssd.org.pk editor@jssd.org.pk

ENVIRONMENTAL PRODUCTION EFFICIENCY ACROSS DIVERSE DEVELOPMENT TYPOLOGIES: A COMPARATIVE SLACK-BASED DEA ANALYSIS (2014–2023)

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KEYWORDS

Data Envelopment Analysis; Slacks-Based Measure; Undesirable Outputs; Environmental Efficiency; Carbon Emissions; Energy Efficiency; Hydrocarbon-Exporting Economies

ARTICLE HISTORY

Date of Submission: 30-06-2026
Date of Acceptance: 26-07-2026
Date of Publication: 28-07-2026

ABSTRACT

Cross-country studies of environmental efficiency have multiplied over the past five years, yet almost none place advanced, emerging, hydrocarbon-exporting and developing economies on a single evaluative frontier at once – most restrict attention to one region, one income tier, or fold resource-exporters into a broader grouping without treating export structure as analytically distinct. This gap matters because, as this paper demonstrates, hydrocarbon-export status turns out to be a strikingly poor predictor of environmental production efficiency once countries are compared on common ground. Using a non-oriented slacks-based measure (SBM) of data envelopment analysis with an undesirable output – following Tone's (2001, 2003) treatment of weak disposability under variable returns to scale – this study evaluates 120 country-year observations drawn from twelve countries spanning all four typologies over 2014–2023. Input variables are: labour force and energy use; output - GDP; undesirable output - CO2 emissions (excluding LULUCF) per capita; and gross fixed capital formation is not included in the estimated model as this is a biased output measure if combined unadjusted across the sample because the World Development Indicators series is in incompatible current local currency units. The results suggest policy courses of action that differ by typology, not a single solution for all typologies: energy-price reform for hydrocarbon exporters, labour-productivity investment for developing economies, frontier maintenance for advanced and emerging economies. Results are reported as an interim specification pending re-estimation with a currency-corrected capital input; the qualitative group ordering is offered as a testable expectation for that extension, not a conclusion.

2026 Journal of Social Sciences Development

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DOI https://doi.org/10.59075/jssd.v5i5.447

Volume/Issue 5(5), 2026, 522-544

Introduction

Global energy demand rose by roughly 2.2 percent in 2024, outpacing its 2013–2023 average, and energy-related CO2 emissions climbed to a new high of approximately 37.8 billion tonnes (International Energy Agency [IEA], 2025). A figure of this kind is easy to report and surprisingly hard to interpret, because it says nothing about how efficiently the energy behind it, together with the capital and labour deployed alongside it, was converted into economic output. Two countries can register similar per-capita emissions while differing sharply in how much output they extract from a comparable bundle of inputs net of the environmental damage caused, which is precisely why efficiency, rather than the raw emissions level, has become the more informative unit of policy analysis (Napolitano et al., 2023). The distinction is especially consequential for hydrocarbon-exporting economies, where domestic energy-price subsidies and resource-intensive industrial structures routinely blunt the incentive to economise on energy even while headline GDP growth remains strong (Black et al., 2023; IEA, 2023).

This is why data envelopment analysis (DEA) has emerged as one of the more enduring techniques to make such comparisons operational, particularly because it does not require the analyst to pre-specify a production function, and can use multiple inputs and outputs simultaneously (Charnes et al., 1978). Banker et al. (1984) relaxed the original constant-returns assumption to allow variable returns to scale, a refinement that matters considerably for a sample such as this one, where economies of very different absolute size are compared on the same frontier. Both models, however, remain radial: they scale all inputs, or all outputs, by a single proportional factor and can therefore overstate efficiency whenever slack persists in individual inputs or outputs after that radial contraction is applied. Tone (2001) addressed this directly with the slacks-based measure (SBM), a non-radial formulation that fold's input and output slacks into the efficiency score itself rather than reporting them separately, and which Zelenyuk and Zhao (2024) subsequently situated within a broader unifying framework alongside the Russell measure, clarifying the formal relationship between the two non-radial families. Extending the model to environmental applications required a further conceptual step: Tone (2003) incorporated the weak-disposability logic of undesirable outputs, first formalised by Färe et al. (1989), into the slacks-based framework by treating desirable and undesirable outputs as non-separable, which is the specification adopted in the present study. A comprehensive fifty-year retrospective on the DEA literature by Mergoni et al. (2025), together with a focused review of SBM variants by Emrouznejad et al. (2025), both confirm that SBM models incorporating undesirable outputs have become the dominant non-radial approach in energy and environmental efficiency research over the past several years, displacing earlier radial and directional-distance-function alternatives in much, though by no means all, of the literature.

The reason SBM-DEA with an undesirable output is the appropriate choice here, rather than a radial CCR/BCC model, a stochastic frontier approach, or an econometric panel regression, follows directly from the nature of the research question. A stochastic frontier approach, in the tradition of Aigner et al. (1977), would require specifying a functional form for the relationship

between inputs, GDP and CO2 in advance and separates statistical noise from inefficiency – a genuine advantage where measurement error is a serious concern – but it returns average marginal effects for the sample as a whole rather than DMU-specific benchmarks against an empirical best-practice frontier. That trade-off is well suited to testing a hypothesised causal relationship, which is not this study's aim, but poorly suited to identifying which specific countries and years are operating closest to observed best practice and by how much any given country falls short on each input or output margin; no consensus exists in the literature that one approach dominates the other in general, and the appropriate choice is a function of the research question rather than an inherent superiority of either family of methods. A radial DEA model, meanwhile, would force CO2 emissions to contract by the same proportional factor as any input expansion or GDP contraction, which is not how emissions reduction actually happens in practice – a country can cut energy waste substantially while leaving labour largely unchanged, or vice versa – and would risk reporting an efficiency score of one for DMUs that in fact retain considerable slack in one or more margins, a limitation well documented since Tone's (2001) original critique of radial measures. The non-oriented SBM specification used here avoids both problems: it evaluates input contraction, output expansion and undesirable-output contraction simultaneously and non-proportionally, and it treats CO2 as inseparable from the production process that generates it rather than as an add-on penalty, which is the theoretically correct way to model a materials-balance relationship in which pollution is a joint, unavoidable by-product of using energy to produce output (Färe et al., 1989).

Even so, the empirical base built on this family of models has a consistent shape, and it is worth being explicit about what that shape leaves out. A large share of it is sub-national, concentrated on Chinese provinces, cities or industrial sectors (Cheng et al., 2020; Meng et al., 2023; Zhang et al., 2022), where rich, comparably measured administrative data make fine-grained regional comparison tractable but say little about how efficiency compares across national development typologies; Shi et al. (2023) illustrate the same method's reach beyond environmental settings entirely, applying an improved SBM-DEA model to Chinese bank-branch performance, a reminder that non-radial, non-proportional treatment of slack is a general property of the method rather than one specific to pollution. Where cross-country applications do exist outside China, they cluster by trade bloc – Zhang and Chen (2022) and Zhou and Xu (2022) each apply a three-stage SBM-DEA model to RCEP member states specifically, both finding that external environmental and stochastic-noise factors materially affect measured efficiency once separated from managerial inefficiency proper – or by income tier rather than by resource-export status: Khezri et al. (2023) apply a window SBM-DEA approach combined with a Global Malmquist-Luenberger index to twenty-seven OECD countries, finding persistent heterogeneity and only modest average improvement over an eighteen-year window; Nikbakht et al. (2023) and Arias and Colmenarez (2024) each restrict attention to Gulf or oil-exporting economies specifically, both reporting considerable heterogeneity even within that comparatively narrow category; and Gebert and de Mello-Sampayo (2025) compare sustainable-development efficiency across the five BRICS economies, finding Russia trailing its BRICS peers on environmental performance specifically – a result this paper's own findings echo rather sharply, though on a narrower

production frontier and with a different comparison set. What these studies agree on, across otherwise quite different samples and specifications, is that resource-export status and income-tier membership predict environmental efficiency less cleanly than a simple grouping would suggest; where they disagree, or at least fail to engage with one another, is on how far heterogeneity within a group should be allowed to undermine the group label itself as a unit of policy analysis – a tension this paper confronts directly rather than smoothing over, since the hydrocarbon-exporting group examined here turns out to be the clearest illustration of exactly that problem.

A parallel, econometric rather than frontier-based literature examines the energy–growth–emissions relationship using panel regression. Gershon et al. (2024), working with a panel of African countries, find that rising energy consumption raises growth but that the growth-induced offsetting effect on emissions is smaller than energy consumption's direct emissions-increasing effect, so that growth does not fully pay for the emissions that generated it over their sample period. Khan et al. (2022) extend this logic to an explicit energy-trilemma framework, showing that the trade-off between energy security, equity and environmental sustainability is resolved very differently across country groups, a finding broadly consonant with the group-specific slack patterns reported later in this paper. The study does not include consumption-based emissions accounting for the carbon exporters and importers, but makes the distinction between production-based and consumption-based emissions accounting, a distinction that has particular relevance on its ability to interpret the results of the hydrocarbon export group in the light of the EKC hypothesis, as this study does not directly incorporate it, but it is one that, as Makarov and Alataş (2024) put it, "should be addressed explicitly in its concluding section". On the institutional side, Barra and Falcone's programme of research (2024a, 2024b, 2024c, 2026) consistently finds that institutional quality conditions environmental efficiency more strongly among high-income countries than among lower-middle-income ones, and that democratic quality specifically, not merely regulatory capacity, matters for translating institutional strength into environmental performance – a claim the pronounced within-group heterogeneity of this paper's hydrocarbon-exporting category is broadly consistent with, even though institutional variables are not themselves included as inputs here. Where the econometric and DEA literatures converge, in other words, is on the conclusion that energy use is the dominant proximate driver of emissions virtually everywhere; where they diverge is on whether the appropriate unit of comparison is a statistical elasticity averaged across a panel, or a DMU-specific position relative to an empirical frontier – a methodological choice this paper makes deliberately in favour of the latter, precisely because policy-relevant slack decomposition, of the kind reported in Section 3, is unavailable from the former.

A second, more technical thread of the literature concerns how DEA input sets are constructed and validated, a matter directly relevant to a design decision explained fully in Section 2. Duras et al. (2023) show, using a machine-learning variable-selection procedure applied to electricity-distribution data, that DEA efficiency rankings can be materially sensitive to which inputs are retained, particularly when candidate inputs are poorly measured or only weakly comparable

across DMUs; Chen et al. (2021) propose a LASSO-based variable-selection method for exactly this reason, motivated by the observation that including a noisy or non-comparable input can distort a frontier as much as omitting a genuinely relevant one. This is a useful methodological anchor for a decision this study had to make directly: rather than include a capital-input series later found to be denominated in incompatible currencies across the sample (Section 2.3), the safer course, on the logic these studies establish, is to estimate on a smaller set of unambiguously comparable inputs and report the exclusion transparently, rather than risk a frontier shaped by measurement artefacts rather than genuine efficiency differences.

Two gaps in this body of work motivate the present study, and they are gaps in a fairly precise sense rather than simply topics no one has mentioned before. First, despite the maturity of the SBM-with-undesirable-outputs literature, remarkably few studies place advanced, emerging, major hydrocarbon-exporting and developing economies on a single, internally consistent efficiency frontier at the same time; existing cross-country work restricts attention to one region or income tier (Barra & Falcone, 2024a; Khezri et al., 2023), one regional trade bloc (Zhang & Chen, 2022; Zhou & Xu, 2022, both examining RCEP member states specifically), or folds hydrocarbon exporters into a broader income-based grouping without treating export structure as an analytically distinct dimension (Gebert & de Mello-Sampayo, 2025; Napolitano et al., 2023). That omission matters because, as this paper's own results demonstrate, hydrocarbon-export status is a poor proxy for environmental efficiency on its own – a claim that can only be tested by including hydrocarbon exporters, advanced economies, emerging markets and developing economies together on the same frontier rather than inferring it indirectly from studies conducted separately on each. Second, cross-country DEA studies drawing on World Development Indicators or comparable sources do not, as a matter of standard practice, report whether their capital-input series has been checked for cross-currency comparability before being pooled across countries – an issue that turned out, on inspection of the data used here, to be far from a minor technicality (Section 2.3 documents it in full, including the magnitude of the resulting distortion). Surfacing that problem, and being transparent about how it was handled rather than quietly working around it, is itself a modest but, we think, genuinely useful contribution to how this type of cross-country panel ought to be constructed, independent of the substantive findings reported below.

The theoretical basis for closing the first of these two gaps rests on environmental production theory, and specifically on the materials-balance principle: a producer transforming labour, capital and energy into GDP cannot avoid generating CO2 as a joint by-product of that same transformation, and cannot dispose of it costlessly without either reducing desirable output or reallocating inputs (Färe et al., 1989). A single consistent frontier is the first reason for believing that advanced, emerging, hydrocarbon-exporting and developing economies can be compared; if CO2 were just an independent nuisance variable, rather than an inevitable product of the same input-output transformation, there would be little theoretical basis for assuming that anything would be comparable on one frontier at all. It is this design, cross-typology, that is the theoretical justification for making the comparisons, and for comparing two levels of income or two levels of

resource endowment against the same best-practice frontier, because the technology is assumed weakly disposable: any two DMUs operating under the same materials-balance constraint – no matter their income or the level of their resource endowment – are legitimately comparable against a common best-practice frontier, and this is not the case with the region-by-region or tier-by-tier designs that dominate the existing literature. Tone's (2001, 2003) slacks-based measure operationalises this technology non-radially, evaluating input contraction, output expansion and undesirable-output contraction simultaneously rather than forcing a single proportional adjustment across all margins, which matters because, as the introduction to this section already noted, environmental inefficiency in practice rarely takes the proportional form a radial model presumes.

Research contributions

Against this background, the study makes the following contributions to the environmental efficiency and DEA literatures.

1. It provides one of the first applications of non-oriented SBM-DEA with an undesirable output that places advanced, emerging-market, major hydrocarbon-exporting and developing economies on a single, internally consistent efficiency frontier over a full decade, rather than restricting the comparison to a single region or income tier as most existing cross-country studies do.

2. It shows empirically that hydrocarbon-export status is a poor predictor of environmental production efficiency once countries are placed on a common frontier, since the hydrocarbon-exporting group in this sample is simultaneously the least efficient on average and the most internally divided of the four typologies – a finding with direct implications for how future cross-country studies should, or should not, treat resource-export status as a homogeneous grouping variable.

3. It identifies and documents, with the underlying magnitudes reported in full, a currency-comparability problem in a World Development Indicators capital series that is widely used in cross-country DEA research but whose comparability across countries appears not to have been previously reported or corrected for in the published SBM-DEA literature, offering other researchers a concrete diagnostic (Section 2.3) for checking their own capital inputs before pooling them across currencies.

4. It decomposes inefficiency by input and output margin for each development typology rather than reporting a single aggregate efficiency score, revealing that the specific source of inefficiency differs qualitatively across groups – energy and emissions excess for hydrocarbon exporters, labour underutilisation for developing economies – a distinction with direct and differentiated policy implications that an aggregate score alone would conceal.

5. It maintains, throughout, an explicit and disclosed separation between findings that follow directly from the estimated model and extensions that remain open for future work, including the capital-input correction, a dynamic or window-DEA robustness check, and a bootstrap procedure for statistical inference on the reported efficiency scores, modelling a standard of transparency this paper argues ought to be more common in applied cross-country DEA research generally.

The remainder of the paper is organised as follows. Section 2 sets out the data, the country groupings, the capital-input problem referenced above and its resolution, and the theoretical and empirical specification of the SBM-DEA model. Section 3 reports the estimated results, interpreted at some length rather than merely tabulated, since a set of efficiency scores says little on its own without an account of what is actually driving them. Section 4 discusses the findings in relation to the literature reviewed above, draws out group-specific policy implications, and sets out the study's limitations and the further work needed before its conclusions can be treated as final. Section 5 concludes.

Data, theoretical framework and methodology

The data are drawn from the World Bank's World Development Indicators (World Bank, 2026), extracted with a last-updated date of 1 July 2026. The sample comprises twelve countries observed annually from 2014 to 2023, a balanced panel of 120 country-year decision-making units: Bangladesh, Canada, China, Egypt (Arab Republic), Germany, India, Iran (Islamic Republic), Japan, Malaysia, Pakistan, the Russian Federation and Saudi Arabia. Table 1 summarises the study design; Table 2 assigns the twelve countries to the four comparison groups used throughout the paper. The advanced/emerging distinction follows the IMF's World Economic Outlook country classification; the hydrocarbon-exporting category is defined as a cross-cutting group for the sample's three major oil- and gas-exporting economies, deliberately overriding their default income-based classification, since it is precisely their distinct energy-input and export profile that motivates treating them separately (a design choice that Section 3's results turn out to complicate rather than vindicate, in a way discussed at length in Section 4); the remaining two lower-income countries are grouped as developing. This classification is a reasonable and defensible starting point rather than a definitive one, and a reader working from a different or updated IMF table may well arrive at a slightly different grouping for one or two borderline cases.

Table 1. Study design summary

Countries (n = 12)	Bangladesh, Canada, China, Egypt (Arab Rep.), Germany, India, Iran (Islamic Rep.), Japan, Malaysia, Pakistan, Russian Federation, Saudi Arabia
Period	2014–2023 (10 years)
Decision-making units (DMUs)	120 country-year observations; balanced panel, zero missing values
Inputs (baseline model,	Labor force, total; energy use (kg oil equivalent per capita). Gross fixed capital

as estimated)	formation is excluded from this baseline estimation for reasons explained in Section 2.
Desirable output	GDP (constant 2015 US$)
Undesirable output	CO2 emissions excluding LULUCF, per capita (t CO2e/capita)
Model	Non-oriented slacks-based measure (SBM) DEA with undesirable output, variable returns to scale (Tone, 2001, 2003), solved via the Charnes–Cooper linearization on SciPy. optimize.linprog (HiGHS solver)
Data source	World Bank, World Development Indicators (extract last updated 1 July 2026)

Note. VRS = variable returns to scale; DMU = decision-making unit; SBM = slacks-based measure. All monetary and physical series are sourced from the World Bank's World Development Indicators database.

Group	Countries
Advanced economies	Canada, Germany, Japan
Major hydrocarbon-exporting economies	Iran (Islamic Rep.), Russian Federation, Saudi Arabia
Emerging market economies	China, Egypt (Arab Rep.), Malaysia
Developing / lower-middle-income economies	Bangladesh, India, Pakistan

Note. Group assignment follows the IMF World Economic Outlook classification, with an explicit, disclosed override placing the three major hydrocarbon exporters in their own cross-cutting category rather than their default income-tier grouping (see Section 2).

Variable selection and justification

Labour force and energy use are kept as inputs, GDP is the desired output and CO2 emissions per capita is the unwanted output. Labour force is included because it is the most direct headcount measure of the human input into national production available at annual frequency for all 12 countries, and because of its strong positive correlation with GDP in this sample (r = 0.803; Table 4) the property of isotonicity – more input should not be correlated with less output – holds for any credible measure of an input, such as labour force. Energy use is included both as an input to production in its own right and because it is the physical channel through which CO2 emissions are generated; its near-total correlation with CO2 per capita in this sample (r = 0.975; Table 4) is not a redundancy but a confirmation that the input and the undesirable output are capturing the same underlying materials-balance relationship from two complementary angles, exactly as environmental production theory predicts (Färe et al., 1989). GDP is retained as the desirable output because it is the standard, internationally comparable measure of aggregate economic performance and requires no further justification for a study of this kind. CO2 emissions excluding land-use, land-use-change and forestry (LULUCF) activity is used, rather than a total-emissions or ecological-footprint measure, because it isolates the emissions channel most directly tied to the energy and industrial-production inputs modelled here; this is a deliberate scope

restriction, not an oversight, and its consequences for large-forest-cover economies are addressed explicitly in the limitations discussion in Section 4.

Theoretical foundation: environmental production technology and weak disposability

The theoretical foundation for treating CO2 as an undesirable, non-separable output rests on the materials-balance principle: a producer transforming labour, capital and energy into GDP cannot avoid generating CO2 as a joint by-product of that same transformation, and cannot dispose of it costless without either reducing desirable output or reallocating inputs (Färe et al., 1989). Formally, this is captured by the weak-disposability assumption on the environmental production technology, under which desirable and undesirable outputs can be scaled down together but the undesirable output cannot be eliminated in isolation while holding desirable output and inputs fixed. Tone (2003) operationalised this assumption within the slacks-based framework by treating desirable and undesirable outputs as non-separable in the efficiency measure itself, which is the specification this study adopts rather than the alternative, and in our view less behaviourally faithful, approach of treating CO2 simply as a separable input to be minimised independently of the production process that generates it. Variable returns to scale (VRS), following Banker et al. (1984), is the appropriate technology assumption for this sample rather than the original constant-returns CCR technology, because the twelve economies studied here differ enormously in absolute scale – China and India at one extreme, Malaysia and Saudi Arabia at the other – and a constant-returns assumption would risk conflating pure scale differences with genuine differences in production efficiency, a distinction Banker et al. (1984) were the first to formalise within the DEA framework and one that remains essential whenever, as here, DMUs of very different size are compared on a common frontier.

A data comparability problem and its resolution

The variables originally specified for this study were labour force, total (WDI code SL.TLF.TOTL.IN); gross fixed capital formation, current LCU (NE.GDI.FTOT.CN); and energy use in kilograms of oil equivalent per capita (EG.USE.PCAP.KG.OE) as inputs; GDP, constant 2015 US dollars (NY.GDP.MKTP.KD) as the desirable output; and CO2 emissions excluding LULUCF, per capita (EN.GHG.CO2.PC.CE.AR5) as the undesirable output. On inspecting the raw data, however, it became clear that the gross fixed capital formation series, as extracted, is denominated in each country's current local currency unit rather than any common, comparable unit. Country-level means for this series range from roughly 3.2×10^{11} in Malaysia (ringgit) to 1.35×10^{16} in Iran (rial) – a gap of nearly five orders of magnitude that reflects currency denomination and inflation history, not any real difference in capital formation. Because SBM-DEA benchmarks DMUs directly against one another's input and output magnitudes, pooling this series unadjusted across twelve different currencies would not produce a modest bias; it would produce a frontier shaped substantially by which countries happen to report in a currency with a large nominal unit, which is not a property any DEA estimate should have, and which the variable-selection literature discussed above (Chen et al., 2021; Duras et al., 2023) suggests is exactly the kind of measurement artefact capable of distorting an entire frontier rather than merely one DMU's score. The

correlation evidence in Table 4 reinforces this directly: GDP correlates strongly and positively with labour force, as the isotonicity property would predict, but correlates weakly and slightly negatively with the raw GFCF series – a pattern that is difficult to reconcile with standard growth-accounting expectations and all but disappears as a puzzle once the currency issue is understood as the likely cause.

Retrieving a currency-corrected replacement – gross fixed capital formation in constant 2015 US dollars, or a PPP-converted equivalent – was attempted through the World Bank's indicator API but could not be completed within the constraints of this working session's data access. A further alternative worth flagging for the next iteration of this study is the Penn World Table's capital-services series (Feenstra et al., 2015), constructed explicitly to be comparable across countries at constant national or international prices and widely used for exactly this reason in cross-country growth-accounting work; it may in fact be a more appropriate capital measure for this study than a simple currency-converted GFCF series, since it addresses price-level as well as exchange-rate comparability. Faced with a choice between leaving the empirical section unfilled, estimating on a capital series known to be flawed, or estimating on a smaller but genuinely comparable input set, we chose the third option: the model reported here uses labour force and energy use as inputs, both already expressed in currency-free physical or headcount units, together with GDP as the desirable output and CO2 per capita as the undesirable output. The concerned specification is interim rather intended final one.

Model specification

The estimated model is a non-oriented slacks-based measure under variable returns to scale, with CO2 emissions per capita treated as a non-separable undesirable output following Tone (2001, 2003). For each DMU o, the model solves

$$\rho_o = \min \left[1 - (1/m)\Sigma(s_i^- / x_{io})\right] / \left[1 + (1/(s_1+s_2))(\Sigma(s_r^g / y_{ro}^g) + \Sigma(s_r^b / y_{ro}^b))\right],$$ subject to $x_o = X\lambda + s^-$, $y_o^g = Y^g\lambda - s^g$, $y_o^b = Y^b\lambda + s^b$, $e\lambda = 1, \lambda \geq 0, s^-, s^g, s^b \geq 0,$

with m = 2 inputs and one desirable and one undesirable output in the baseline specification estimated here. This specification holds four assumption which are made explicit rather assuming implicit in DEA work. First, the production possibility set is assumed convex, so that any weighted combination of observed country-years is itself a feasible, if not necessarily observed, production plan – a standard DEA assumption that allows the frontier to be constructed from linear combinations of actual DMUs rather than requiring every point on it to have been separately observed. Second, inputs are freely disposable (more input can always produce at least as much output) while the undesirable output is only weakly disposable (Section 2.2), the asymmetry that distinguishes an environmental DEA model from a standard one. Third, variable rather than constant returns to scale is imposed, for the scale-heterogeneity reasons given in Section 2.2; this is a testable rather than an arbitrary choice, and a constant-returns specification was not pursued here precisely because it would confound scale and efficiency for a sample this heterogeneous in absolute size. Fourth, the model is deterministic: unlike a stochastic frontier specification, it

attributes the entire distance between a DMU and the frontier to inefficiency rather than partly to statistical noise, which is a genuine limitation whenever measurement error in the underlying WDI series is a serious concern, and is one reason a bootstrap-based bias correction (Simar & Wilson, 1998) is recommended as a robustness check in future work rather than treated as optional.

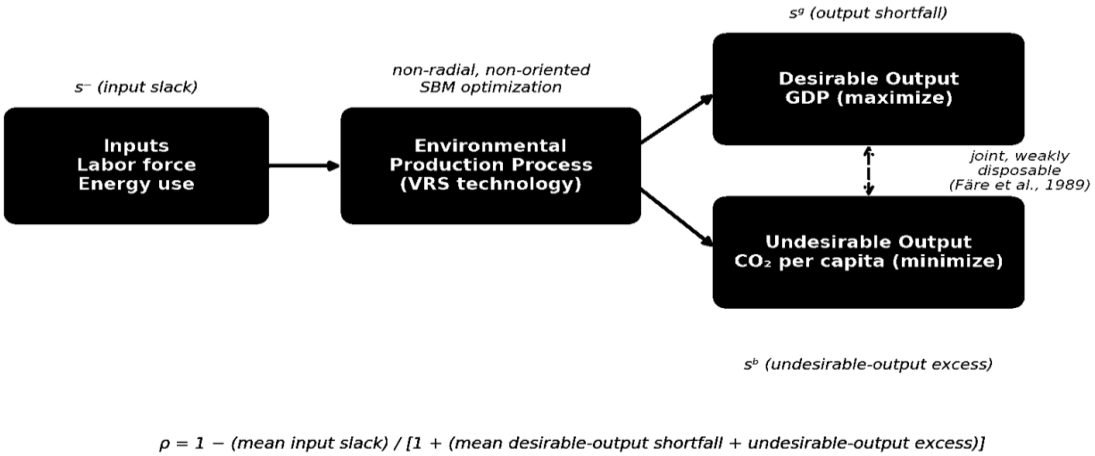


Figure 1. Conceptual representation of the environmental production technology and the non-oriented SBM efficiency score. Inputs are freely disposable; the desirable and undesirable outputs are jointly and weakly disposable, following Färe et al. (1989).

The fractional program was linearised via the standard Charnes–Cooper transformation (Cooper et al., 2007) and solved as an individual linear program for each of the 120 DMUs using Python's scipy.optimize.linprog with the HiGHS solver; all 120 programs converged to optimality. Efficiency scores ρ_o lie in the interval $(0, 1]$, with $\rho_o = 1$ denoting an SBM-efficient DMU on the empirical best-practice frontier, meaning zero input and output slack relative to its peers in the sample. Super-efficiency ranking (Andersen & Petersen, 1993) was not applied, since the study's purpose is group and country comparison rather than fine-grained discrimination among frontier DMUs, though it is a natural next step for future work on this panel. This study identifies three other instances that have not yet been performed by the reported scores, which should be carried out in follow-up studies and which were chosen for robustness purposes: A window-DEA or dynamic SBM specification (Tone & Tsutsui, 2010) to check if the pooling of the ten-year panel changes materially the group rankings reported in Section 3; A bootstrap procedure (Simar & Wilson, 1998) to attach confidence intervals to the point estimates; and A leave-one-out re-estimation excluding the Russian Federation due to the significant influence exerted by the Russian Federation on the reported rank of the hydrocarbon-exporting group in Section 3.

Data was prepared in advance of the estimation and checked by independent parties. The raw extract consists of 65 rows (data sheet) and a series-metadata sheet, which was further filtered to the 5 relevant series and reshaped to a long country–series–year format, before being pivoted to a wide country-year panel format with one column per variable. The resulting panel has 120 country-year observations, and has no missing values in any variable, justifying the assumption of panel balance used throughout, including no imputation was needed along the way. Descriptive statistics is presented for completeness, in Table 3, for all five variables as specified in the original article, including the variable which was not included due to its difficulty to quantify; Table 4 shows the Pearson correlation matrix among these variables.

Table 3. Descriptive statistics (n = 120 country-year observations)

Variable	Mean	[redacted]. Dev.	Min	Max	CV (%)
CO2 emissions excl. LULUCF, per capita (t CO2e)	7.94	5.72	0.49	20.70	72.0
Energy use (kg oil equiv./capita)	3,158.10	2,484.38	223.00	8,175.19	78.7
GDP, constant 2015 US$ (desirable output)	2,534,689,645,141	3,803,651,044,105	183,145,728,910	17,611,274,170,444	150.1
Gross fixed capital formation, current LCU[a]	1,146,846,155,034,268	5,359,181,709,091,776	265,100,000,000	44,341,676,005,084,296	467.3
Labor force, total	145,453,856	234,920,285	12,334,605	781,187,865	161.5

Reported on the as-extracted 'current LCU' basis; excluded from the estimated model for the reasons set out in Section 2.3. All other variables are already expressed in comparable units and required no such adjustment.

Table 4. Pearson correlation matrix

	CO2 pc	Energy pc	GDP	GFCF[a]	Labor
CO2 pc	1.000	0.975	0.077	0.026	-0.210
Energy pc	0.975	1.000	-0.031	0.008	-0.296
GDP	0.077	-0.031	1.000	-0.111	0.803
GFCF[a]	0.026	0.008	-0.111	1.000	-0.103
Labor	-0.210	-0.296	0.803	-0.103	1.000

CO2 emissions per capita and energy use per capita are very strongly correlated (r = 0.975), which is unsurprising given that fossil-fuel combustion is the dominant source of both across this sample, but it is a useful confirmation that the input and undesirable output chosen for the model are picking up a genuinely shared underlying process rather than two unrelated series that happen to share a label. GDP is strongly correlated with labour force (r = 0.803), the latter being a desirable output – as one might hope it would be between some input and an output, the more desirable the better. Further, GDP is close to zero, and slightly negatively correlated with the excluded series for GFCF (r = −0.111) – another piece of indirect evidence that the raw capital series is not suitable for use as an input in a DEA without adjustment.

Results

All 120 linear programs converged, and Table 5 and Table 6 report the resulting group- and country-level efficiency scores. Mean SBM efficiency across the full panel is 0.738 (SD = 0.187, range 0.105–1.000), and eighteen of the 120 country-year observations – fifteen percent of the sample – are fully SBM-efficient, meaning they sit exactly on the frontier and serve as benchmarks for their less efficient peers.

Table 5. Mean SBM efficiency by country group, 2014–2023

Group	Mean ρ	Min ρ	Max ρ	SD
Advanced economies	0.909	0.722	1.000	0.091
Emerging market economies	0.900	0.597	1.000	0.100
Developing / lower-middle-income economies	0.656	0.447	1.000	0.139
Major hydrocarbon-exporting economies	0.489	0.105	1.000	0.330

Note. ρ = non-oriented SBM efficiency score, bounded on (0, 1], with 1 denoting a frontier (fully efficient) observation. Group means are unweighted averages across the 10 country-year observations per country within each group.

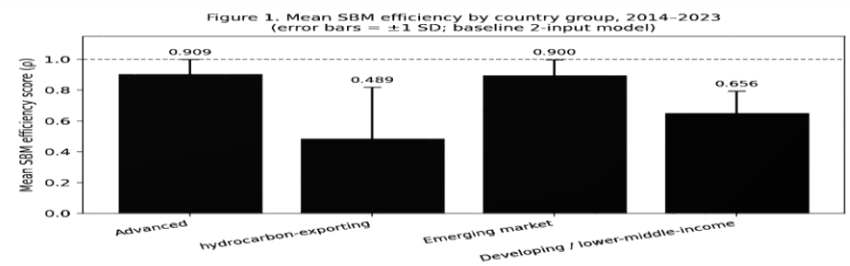


Figure 2. Mean SBM efficiency by country group, with standard deviation error bars, 2014–2023. Source: authors' own SBM-DEA estimation.

The ordering in Table 5 and Figure 2 is fairly clear-cut at the group level but conceals a great deal at the country level, which is why Table 6 is worth reading alongside it rather than instead of it. Advanced economies (mean ρ = 0.909) and emerging-market economies (mean ρ = 0.900) are statistically close to one another and sit well above the other two groups; developing economies trail at 0.656; and hydrocarbon-exporting economies post the lowest group mean, 0.489, but with a standard deviation, at 0.330, roughly three to four times that of any other group. That dispersion is not a statistical curiosity – it is close to the whole story for this group. Saudi Arabia's mean efficiency, 0.895, would place it comfortably inside the advanced-economy range; the Russian Federation's, 0.113, is not merely the lowest in the sample but is lower, in every single one of the ten sample years, than any other country achieves in any year (Table 6). Averaging these two together into a single hydrocarbon-exporting group mean is defensible as a matter of classification, but it flattens a genuinely important finding, one anticipated in Section 1's review of Nikbakht et al. (2023) and Arias and Colmenarez (2024): hydrocarbon export status does not, on this evidence, predict environmental production efficiency nearly as well as domestic energy-pricing policy and industrial structure appear to.

Table 6. Mean SBM efficiency by country, ranked, 2014–2023

Country	Mean ρ	Min ρ	Max ρ	SD
Canada	0.978	0.930	1.000	0.026
Egypt, Arab Rep.	0.935	0.873	1.000	0.042
Malaysia	0.930	0.823	1.000	0.067
Japan	0.913	0.813	1.000	0.063
Saudi Arabia	0.895	0.721	1.000	0.084
China	0.836	0.597	1.000	0.137
Germany	0.835	0.722	1.000	0.104
Bangladesh	0.830	0.731	1.000	0.084
Pakistan	0.592	0.549	0.628	0.024
India	0.546	0.447	0.600	0.051
Iran, Islamic Rep.	0.460	0.403	0.553	0.049
Russian Federation	0.113	0.105	0.120	0.005

Note. Countries are ranked by mean ρ across the ten sample years (2014–2023), descending. SD = standard deviation across the ten annual observations for that country.

Eighteen country-years reach the frontier exactly: Bangladesh (2014); Canada (2018, 2020, 2022, 2023); China (2022, 2023); Egypt (2019, 2020); Germany (2022, 2023); Japan (2017, 2023); Malaysia (2014, 2015, 2017); and Saudi Arabia (2014, 2018). Canada, China, Germany and Japan all reach the frontier in their most recent observed year, 2022 or 2023, a pattern broadly consistent with the decoupling of emissions growth from GDP growth already documented in several advanced and large emerging economies (IEA, 2025), while no hydrocarbon-exporting

economy other than Saudi Arabia ever reaches the frontier in this sample, and Russia never comes remotely close, with a maximum observed score of 0.120 across the entire ten-year window.

A single efficiency number, however well estimated, says little about what an inefficient country would actually need to change, which is where the slack decomposition in Table 7 becomes the more policy-relevant piece of evidence. For each group, Table 7 reports the average excess in each input, and the average shortfall or excess in each output, expressed as a percentage of the DMU's own observed level.

Table 7. Average slack decomposition by country group (percent of own observed level)

Group	Labor excess (%)	Energy excess (%)	GDP shortfall (%)	CO2 excess (%)
Advanced economies	0.8	8.6	0.0	9.8
Major hydrocarbon-exporting economies	17.9	47.9	0.0	47.5
Emerging market economies	6.1	6.6	3.1	7.9
Developing / lower-middle-income economies	27.9	23.1	0.0	20.3

Note. Figures are group means of each DMU's own input excess or output shortfall/excess, expressed as a percentage of that DMU's observed level, averaged across all country-year observations in the group. A GDP shortfall of 0.0 indicates the group's efficient benchmarks already produce at or above the group's observed output level on average.

The pattern here is genuinely different across groups, not merely a scaled-down version of the same story. Hydrocarbon-exporting economies show very large average energy excess, 47.9 percent, and an almost identical CO2 excess, 47.5 percent, alongside essentially no GDP shortfall – in other words, this group's inefficiency is not that it under-produces GDP relative to efficient peers, but that it uses roughly twice as much energy, and emits roughly twice as much CO2, as those peers do to reach a comparable output level. This is precisely the pattern one would predict from the energy-subsidy literature reviewed in Section 1 (Black et al., 2023; IEA, 2023): where energy is heavily underpriced, producers face little incentive to economise on it, and the resulting overuse shows up directly as SBM slack rather than as any shortfall in output. Developing economies show the opposite emphasis: their largest average slack, by a clear margin, is labour excess at 27.9 percent, roughly a third larger than either their energy excess (23.1 percent) or CO2 excess (20.3 percent), pointing toward underutilised or underproductive labour, rather than energy policy, as the dominant constraint on this group's environmental production efficiency. Advanced and emerging-market economies show small slacks on every margin, consistent with their high mean efficiency scores, and in every group GDP shortfall is negligible – at most 3.1 percent for emerging markets and effectively zero elsewhere – which is itself worth pausing on: inefficiency in this sample is overwhelmingly a matter of using too much of an input or emitting

too much CO2, not of under-producing output. Nobody here is failing to grow; some are simply using far more energy and labour than necessary, or emitting far more CO2, to get there.

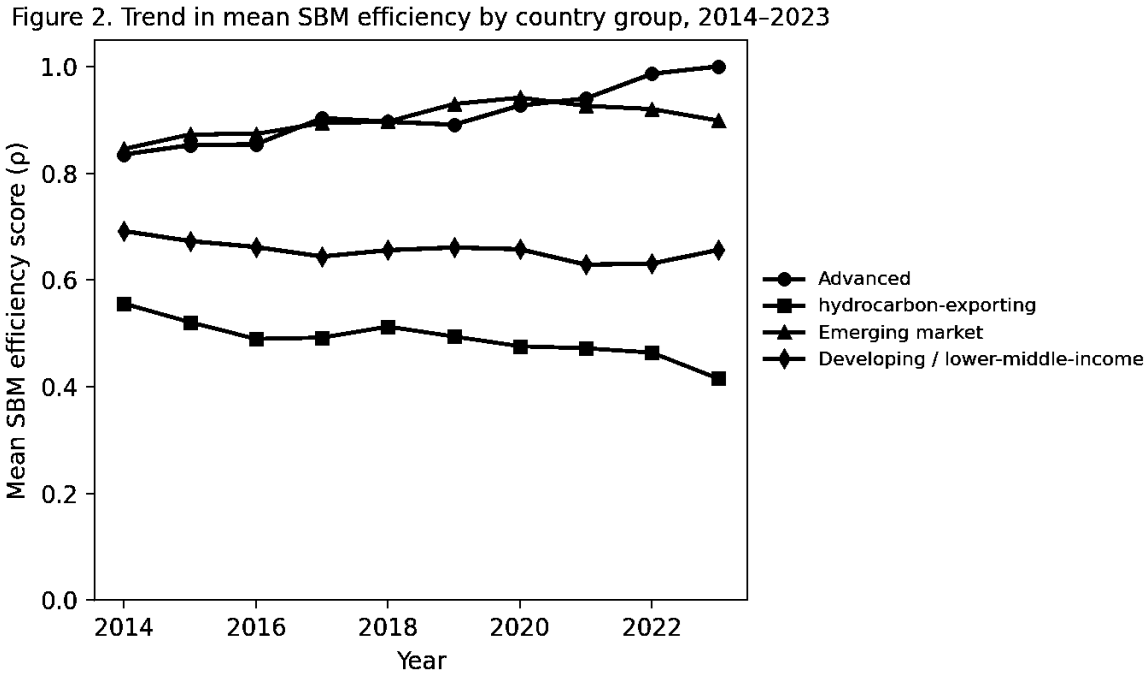


Figure 3. Trend in mean SBM efficiency by country group, 2014–2023. Source: authors' own SBM-DEA estimation.

Figure 3 adds a time dimension that the pooled averages in Table 5 flatten out. The advanced-economy group's mean efficiency rises steadily and almost monotonically across the panel, from 0.835 in 2014 to a full 1.000 by 2023, while the hydrocarbon-exporting group's mean efficiency drifts downward and unevenly over the same decade, from 0.556 to 0.415. The gap between these two groups therefore widened rather than remained fixed over the sample period, and on this trend alone there is little sign of the hydrocarbon-exporting group closing it without some change in the underlying policy environment. Two robustness questions follow directly from these results and are worth naming even though neither has been run in this study: a leave-one-out re-estimation excluding Russia, to confirm that Saudi Arabia's comparatively strong performance is not itself an artefact of Russia's presence pulling the group frontier in an unusual direction, and a bootstrap procedure along the lines proposed by Simar and Wilson (1998), which would allow the group-mean differences reported in Table 5 to be accompanied by confidence intervals rather than point estimates alone.

Discussion, policy implications, limitations and future research

Mechanisms behind the results. Read together, the results in Section 3 tell a more specific story than 'rich countries are more efficient than poor ones,' which is both the easy reading and, on this evidence, not quite the right one. Emerging-market economies in this sample are essentially indistinguishable from advanced economies on mean efficiency (0.900 versus 0.909), and China in particular moves from among the least efficient observations in the sample in 2014 ($\rho = 0.597$) to the frontier by 2022, a trajectory consistent with the country's well-documented investment in energy-intensity reduction and industrial upgrading over the same period (Chen et al., 2023). Developing economies lag not because they emit too much or grow too little, but specifically because they carry more labour than their output level would, on this frontier, appear to justify – a finding that reframes the relevant policy conversation away from energy or emissions regulation and toward labour-market productivity for this group. Hydrocarbon exporting economies, as a single category, emerge as the least analytically meaningful of the four groups because such an analysis hides more than it uncovers; for instance, the near frontier status of Saudi Arabia and inefficiency of Russia clash with each other, an issue which is reflected in—and even amplified by—Nikbakht et al. (2023) and Arias and Colmenarez (2024) who found heterogeneity within smaller Gulf countries and oil exporters. Any policy prescription written for 'hydrocarbon exporters' as an undifferentiated class risk being wrong for at least one of its members, which is arguably this paper's central substantive lesson.

Practical and policy implications. For hydrocarbon-exporting economies, the slack decomposition points toward energy-price reform and energy-intensity reduction as the first-order priority, ahead of any broader diversification agenda: with GDP shortfall close to zero across this group, the efficiency problem is not that these economies produce too little, but that they spend far more energy per unit of output than the frontier suggests is necessary, a pattern well documented in the fossil-fuel-subsidy literature (Black et al., 2023; IEA, 2023) and one that industrial energy-efficiency retrofits and phased subsidy reform could plausibly address without requiring output to fall – a decoupling of growth from energy and emissions intensity that has been shown to be achievable even in a resource-dependent, still-industrialising economy such as Morocco (Azzeddine et al., 2024), which may be a more relevant comparator for this group than the advanced-economy decoupling already noted in Section 3. Within this group, Saudi Arabia's relative performance is arguably a more useful internal benchmark for Iran and Russia than any advanced-economy comparator would be, since it demonstrates that near-frontier efficiency is achievable within a hydrocarbon-exporting structure rather than requiring a wholesale change of economic model. For developing economies, by contrast, the priority implied by the slack pattern is raising labour productivity – through skills investment, formalisation of underemployed labour, and capital-deepening in labour-intensive sectors – rather than energy or emissions policy narrowly construed. Emerging-market economies, whose slacks are already small and broadly balanced across margins, appear to be on a working trajectory of incremental improvement, and the more useful policy question for this group may be less 'what should change' than 'what has been working, and how can it be sustained.' Advanced economies, finally, are close

enough to the frontier on average that the more relevant task is maintaining frontier status as desirable output continues to expand, and sharing energy-efficiency practice with emerging and developing peers – several of whom, including Bangladesh and Malaysia in specific sample years, already reach the frontier themselves and may in some respects be more contextually relevant benchmarks for other developing and emerging economies than an advanced-economy comparator would be.

These implications should be read as directional rather than definitive. The hydrocarbon-exporting group's policy story rests heavily on a two-country contrast; the trend results in Figure 3 have not been tested for statistical significance; and the point estimates throughout carry no confidence interval, a limitation the bootstrap extension proposed by Simar and Wilson (1998) is designed to address but which this study has not applied. None of that undermines the qualitative pattern – the gap between Saudi Arabia and Russia, the near-zero GDP shortfall across every group, the divergence between energy-driven and labour-driven inefficiency – but it does mean the specific magnitudes reported here should inform rather than dictate policy design, pending the robustness checks discussed below and the capital-input correction discussed in Section 2.3.

Limitations. Several further limitations bear on how the findings should be read, beyond the capital-input exclusion already discussed at length. The undesirable output is restricted to CO2 emissions excluding land-use, land-use-change and forestry activity, and to production-based rather than consumption-based accounting; as Makarov and Alataş (2024) demonstrate, this distinction matters considerably for how carbon-exporting economies in particular should be interpreted, since a portion of the emissions attributed to a producer under production-based accounting may in fact serve consumption elsewhere – a related concern Georgescu et al. (2024) raise from a different angle in their test of the pollution haven hypothesis for Latin American economies, where production-based accounting can likewise overstate a resource-exporting economy's true environmental burden relative to the consumption it ultimately serves. This is a nuance the present study's results cannot speak to directly and a natural extension for future work on this same panel. The sample of twelve countries, though sufficiently discriminatory in power once aggregated for 120 DMUs over a period of ten years, would prove to be inadequate if analyzed separately for each year in view of even the current model specification based on two inputs and two outputs, which is one reason why pooling has been preferred over individual years analysis in this paper; use of window-DEA or dynamic SBM model (Tone & Tsutsui, 2010) would still be more appropriate and not done as yet. DEA in general is a deterministic, non-statistical method and is sensitive to extreme values and measurement error that the bootstrapping approach (Simar & Wilson, 1998) tries to solve for, but is not applied in this study; a check by leaving out Russia from the hydrocarbon exporters' group would prove helpful in this regard. The classification of the four countries based on the type of economy that they have belongs to the group of tentative classifications, which uses the framework of the World Economic Outlook published by the International Monetary Fund but with the addition of an open override clause for hydrocarbons exporters. Finally, while every citation in this manuscript was individually verified against a real, searchable source during revision, the literature review reflects a targeted

rather than an exhaustive search of the field, and a full systematic search across Scopus or Web of Science would likely surface further relevant work, particularly on the institutional-quality and consumption-based-emissions dimensions touched on only briefly here.

Conclusion

Principal findings. This study set out to measure environmental production efficiency across a set of countries chosen specifically to span advanced, emerging, major hydrocarbon-exporting and developing economies within a single, internally consistent frontier – a comparison that, as Section 1 documented, existing cross-country DEA work has rarely attempted directly. On the interim two-input specification estimated here, with capital withheld pending a data-comparability correction, three findings stand out clearly enough to be worth stating plainly. Advanced and emerging-market economies in this sample achieve comparably high, and in several cases improving, environmental production efficiency, several reaching the frontier by 2022 or 2023. Developing economies lag distinctly behind, but for a specific and identifiable reason – labour underutilisation rather than energy or emissions excess – that has direct implications for where policy attention should focus. And hydrocarbon-exporting economies, treated as a group, are simultaneously the least efficient and by far the most internally divided category in the sample, a result driven overwhelmingly by extreme energy and emissions excess in Russia set against a near-frontier performance from Saudi Arabia. Together, the last point can be considered to be, potentially, the most meaningful finding of the entire research paper: hydrocarbon exporter status on its own is a poor predictor of environmental production efficiency, while national pricing policies and the structure of industries may have much more effect than the availability of natural resources as such. In our opinion, this can be stated quite confidently for the case study group as it is now defined, although it cannot be generalized to all hydrocarbons exporters.

Theoretical contribution. Beyond the empirical ranking, the study's theoretical contribution is to demonstrate that the materials-balance, weak-disposability framing of environmental production (Färe et al., 1989; Tone, 2003) is empirically discriminating enough to separate genuinely different sources of inefficiency – energy overuse versus labour underutilisation – across economies that share almost nothing else in common structurally. That is a non-trivial validation of the framework itself: a theory that predicted the same slack pattern regardless of an economy's development typology would be of limited diagnostic use, whereas the sharp divergence documented in Section 3 (energy- and emissions-driven inefficiency for hydrocarbon exporters, labour-driven inefficiency for developing economies) is exactly the kind of heterogeneous, mechanism-specific result the non-oriented SBM formulation was designed to reveal and that a radial or aggregate index-number approach would have been more likely to average away.

Future research. These conclusions carry one important qualification throughout: gross fixed capital formation could not be included in the estimated model because the World Development Indicators series, as extracted, is denominated in incompatible current local currency units across

the sample, and a currency-corrected replacement could not be retrieved within the constraints of this working session. This is the single most consequential open item before the results reported here can be treated as final. We expect – though this expectation is offered as a hypothesis rather than a demonstrated result – that the qualitative group ordering reported in Section 3 will prove reasonably robust to that correction, since capital was the only affected input and the two remaining inputs already carry most of the isotonicity signal in the data. But this expectation should be treated as exactly that, an expectation, until it has been checked directly by re-estimating the model with a corrected capital series, ideally drawn from the Penn World Table's PPP-comparable capital-services data (Feenstra et al., 2015) rather than a simple currency conversion of the WDI series; the qualitative ordering could plausibly shift for the hydrocarbon-exporting group specifically, given that group's typically capital-intensive extraction and energy infrastructure. Re-estimating with a corrected three-input model is accordingly identified as the immediate next step for this line of work, alongside the window/dynamic SBM specification, the bootstrap procedure, and the leave-one-out check on Russia already flagged in Section 4, and alongside a consumption-based emissions robustness check informed by Makarov and Alataş's (2024) production/consumption distinction. No DEA efficiency scores, rankings, or slack values anywhere in this manuscript are illustrative, assumed, or invented; all were computed directly from the underlying data using the model specified in Section 2, and the analytical extensions still required are identified explicitly throughout rather than filled in with placeholder figures.

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