

Gravina, Antonio Francesco; Lanzafranco, Matteo

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"What's your shape?": A data-driven approach to estimating the environmental Kuznets Curve

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“WHAT’S YOUR SHAPE?”

A DATA-DRIVEN APPROACH TO ESTIMATING
THE ENVIRONMENTAL KUZNETS CURVE

Antonio Francesco Gravina and Matteo Lanzafame

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Antonio Francesco Gravina (antoniofrancesco.gravina@unipa.it) is an assistant professor of economics at the University of Palermo. Matteo Lanzafame (mlanzafame@adb.org) is a principal economist at the Economic Research and Development Impact Department, Asian Development Bank.



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6 ADB Avenue, Mandaluyong City, 1550 Metro Manila, Philippines
Tel +63 2 8632 4444; Fax +63 2 8636 2444
www.adb.org

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ABSTRACT

The substantial literature on the existence of an inverted U-shaped relationship between environmental degradation and economic growth—known as the Environmental Kuznets Curve (EKC)—has produced very mixed evidence. This largely depends on model and variable selection uncertainty. We address these issues relying on Bayesian Model Averaging techniques. Our results indicate that the EKC has an inverted-N shape, with almost all emerging economies analyzed on the upward segment of the curve displaying a positive association between per capita gross domestic product and carbon dioxide emissions, and most advanced economies analyzed on the second downward segment of the curve. These findings are robust to the use of different measures of environmental pollution and (non-Bayesian) Least Absolute Shrinkage and Selection Operator (LASSO) regression techniques.

Keywords: Environmental Kuznets Curve, economic growth, model uncertainty

JEL codes: C52, O13, Q56

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1. Introduction

With climate change emerging as a paramount concern on the global stage, the relationship between economic growth and environmental sustainability has returned to the center of economic and policy debates. Rising global average temperatures, increasingly frequent and severe extreme weather events, and other negative impacts of climate change have created new challenges for growth and development strategies. Designing appropriate policy responses requires a comprehensive understanding of the links between economic activities and the environment. Unsurprisingly, efforts to dissect the main causes and consequences of environmental deterioration have intensified (e.g., Gurjar et al. 2010, Jiang and Guan 2016).

One of the central paradigms in this context is the Environmental Kuznets Curve (EKC) hypothesis. Originally proposed by Grossman and Krueger (1991), the EKC posits the existence of an inverted U-shaped relationship between ecological degradation and economic development, with the latter typically proxied by per capita gross domestic product (GDP). The intuition is as follows. In the initial phases of economic development, increased industrialization boosts growth but also produces polluting emissions. As a result, environmental conditions deteriorate alongside rising per capita GDP. Once a certain threshold of per capita income is reached, the sign of this relationship turns negative. This threshold may vary depending on the specific environmental indicator, but the same pattern holds: at higher income levels, economic growth becomes associated with increasingly lower emissions. Among others, possible explanations for this include the reduced role of industry in favor of less-polluting services activities, the development of greener technologies, and the implementation of environmental protection measures.

Despite nearly 3 decades of research and thousands of contributions on the topic, a consensus has yet to be reached on some critical aspects of the EKC, including whether such

a relationship exists at all.¹ This leaves open significant gaps in the empirical literature, the most challenging of which can be related to model uncertainty and variable selection—i.e., the choice of control variables.

Model uncertainty questions arise from the inconclusive evidence on the shape of the functional form “truly” characterizing the interplay between economic growth and polluting emissions (e.g., Shahbaz et al. 2023, Leal and Marques 2022). A substantial body of empirical research indicates that the standard inverted U-shaped EKC is not consistently reflected in the data. Indeed, evidence has emerged for other non-standard EKC patterns, including a monotonically increasing or decreasing (linear) relationship; a quadratic U-shaped relation; and a cubic pattern, either N-shaped or inverted N-shaped. Additionally, in some cases, empirical findings indicate that no statistically significant relationship exists between economic growth and environmental degradation (e.g., Pata et al. 2021, Arminen and Menegaki 2019). This mixed evidence underpins and, at the same time, reinforces a certain arbitrariness in empirical studies regarding the assumed functional form of the EKC.²

Additionally, variable selection in models aimed at investigating the determinants of environmental decay remains a challenge (e.g., Stern 2004). Beyond economic growth, the empirical literature has identified a large array of potential causes of polluting emissions (e.g., Dinda 2004, Leal and Marques 2022). A non-exhaustive list includes the use of fossil fuels, international tourism, the sectoral composition of an economy, financial development, urbanization, technological progress, and the quality of political institutions. Empirically, this abundance of potential regressors complicates the trade-off between the selection of an appropriately parsimonious model specification and avoidance of omitted variable bias.

¹ As of 29 September 2023, a Scopus search for articles, book chapters, reviews, conference papers, and letters focusing on “Environmental Kuznets Curve” within the areas of Environmental Science; Economics, Econometrics and Finance; Energy, and Social Science produced 3,685 documents published between 1994 and 2023, available in the English language.

² On this point, see Sinha et al. (2019).

This paper contributes to the empirical literature on the EKC by directly addressing model uncertainty and variable selection issues relying on the Bayesian Model Averaging (BMA) approach.³ BMA estimation is a purely data-driven technique that minimizes arbitrariness in model specification and selection of control variables (e.g., Hasan et al. 2018, Cazachevici et al. 2020, Balima and Sokolova 2021). In our case, use of the BMA approach serves at least two purposes. First, it ensures that the estimated EKC relationship is not overly dependent on a subjectively determined modelling choice. Second, variable selection performed via the BMA approach results in statistically robust identification of the key determinants of the underlying EKC dynamics.

To the best of our knowledge, Aller et al. (2021) is the most relevant contribution relying on the BMA approach to investigate the determinants of polluting emissions.⁴ These authors' findings reject the EKC hypothesis in favor of a linear, positive relationship between economic growth and carbon dioxide (CO₂) emissions. While the research questions are similar, we extend the work in Aller et al. (2021) in several directions. First, we address misspecification concerns considering all possible EKC shapes suggested in the empirical literature, as opposed to focusing only on the classic quadratic EKC pattern. Second, going beyond the conventional reliance on CO₂ emissions, we also investigate the existence, functional form, and robust regressors of the EKC for several other polluting indicators. Relatedly, a greater number of potential factors affecting polluting emissions are included in our study. Third, we assess the robustness of the BMA results using a large array of model priors and model parameter priors, as well as employing specific estimation techniques to deal with endogeneity concerns.

³ Far from being specific to EKC studies, model uncertainty and variable selection issues are common in the empirical literature—including in the field of economic growth (e.g., Steel 2020, Sala-i-Martin 1997, Barro 2003, Moral-Benito 2012).

⁴ Another related contribution is Lamla (2009), who employs Bayesian Averaging of Classic Estimates (BACE) on a panel of 47 countries and long-term averages over the years 1980–2000. This study's findings confirm the classic EKC for water pollution, while the evidence is less conclusive for sulfur dioxide. As for CO₂, given that the estimated maximum exceeds the range of per-capita GDP values in his sample, Lamla (2009) concludes that the relationship with economic growth is concave—that is, there is no well-defined maximum point for the inverted U-shaped EKC.

Our analysis is based on a panel of 84 advanced and emerging economies with annual data for 1995–2015.⁵ We consider both anthropogenic measures and biological indicators, including ozone precursors or greenhouse and acidifying gases, primary particulates, and ecological footprints. To complement the estimates based on Bayesian statistical principles, we also assess the robustness of our main results to the use of a frequentist approach. Specifically, we rely on a version of the Least Absolute Shrinkage and Selection Operator (LASSO) estimation framework (Tibshirani 1996), the Double-Selection LASSO (DSL). Proposed by Belloni et al. (2014), DSL is a two-step procedure that uses LASSO regressions for variable selection and ordinary least squares (OLS) regression to obtain coefficient estimates, along with standard errors and test statistics, for a specified subset of variables of interest.

The key finding in this paper is that the relationship between economic growth and CO₂ emissions follows an inverted N-shaped pattern. This suggests the presence of two distinct turning points. The first is a minimum point, beyond which the relationship changes from negative to positive—i.e., increasing per capita GDP is associated with rising pollutant emissions. The second represents a maximum point, where the relationship transitions from positive to negative. That is, as economies continue to grow, rising per capita GDP is associated with increasingly smaller pollutant emissions. Notably, the estimated minimum and maximum points of the curve produce a clearcut distinction between emerging and advanced economies. In particular, almost all emerging economies in our panel are located on the upward segment of the EKC, while for most advanced economies, the association between per capita GDP and CO₂ emissions is negative. The finding of an inverted N-shaped EKC is robust to the use of other pollution measures and environmental indicators, such as nitrogen oxides, primary particulates, and ecological footprint. Furthermore, the evidence gathered indicates that—together with per capita GDP—the use of fossil fuels, international tourism, the shares of GDP attributed to industrial and service

⁵ Economies included in the advanced and emerging economies groups are reported in Table A2.1 in the Appendix. The Appendix is available at <http://dx.doi.org/10.22617/WPS240334-2>.

activities, financial development, political polarization, and urbanization are among the most important factors explaining CO₂ emission dynamics.

The remainder of the paper is structured as follows. Section 2 provides an overview of the literature on the EKC. Section 3 describes the data employed in the empirical analysis. Section 4 illustrates the BMA methodology. Section 5 presents and discusses the main findings. Section 6 deals with a set of robustness checks. Section 7 reports the DSL estimates. Section 8 concludes.

2. Overview of the Literature

Three recent literature surveys by Özcan and Ozturk (2019), Shahbaz and Sinha (2019), and Purcel (2020) document extensive empirical work on the EKC hypothesis, but also mixed evidence. A considerable number of multi-country panel analyses, typically focusing on CO₂ emissions, provide support for the standard EKC hypothesis (e.g., Apergis et al. 2017, Jebli et al. 2016). In other cases, however, estimates indicate that there is no significant association between CO₂ emissions and per capita GDP (e.g., Arminen and Menegaki 2019, Destek and Sinha 2020). In other studies, still, the evidence points to the existence of non-EKC type relationships—including U-shaped, monotonically increasing or decreasing, as well as (inverted) N-shaped patterns (e.g., Liu et al. 2019, Tamazian and Rao 2010, López-Menéndez et al. 2014, Dijkgraaf and Vollebergh 2005, Álvarez-Herránz et al. 2017a).

Model uncertainty issues are reinforced by the contrasting findings obtained with different EKC specifications. Standard quadratic EKC formulations typically reject the hypothesis of a nonlinear relationship in favor of a monotonically increasing or decreasing linear relationship (e.g., Richmond and Kaufmann 2006, Oshin and Ogundipe 2014)—regardless of sample features, estimation techniques, and/or additional controls included. In contrast, when a cubic model specification is assumed (i.e., including a cubed per capita GDP term), the estimates often suggest that the EKC hypothesis is consistent with the data only in quadratic (or linear) formulations (e.g., Galeotti et al. 2006, Farzin and Bond 2006).

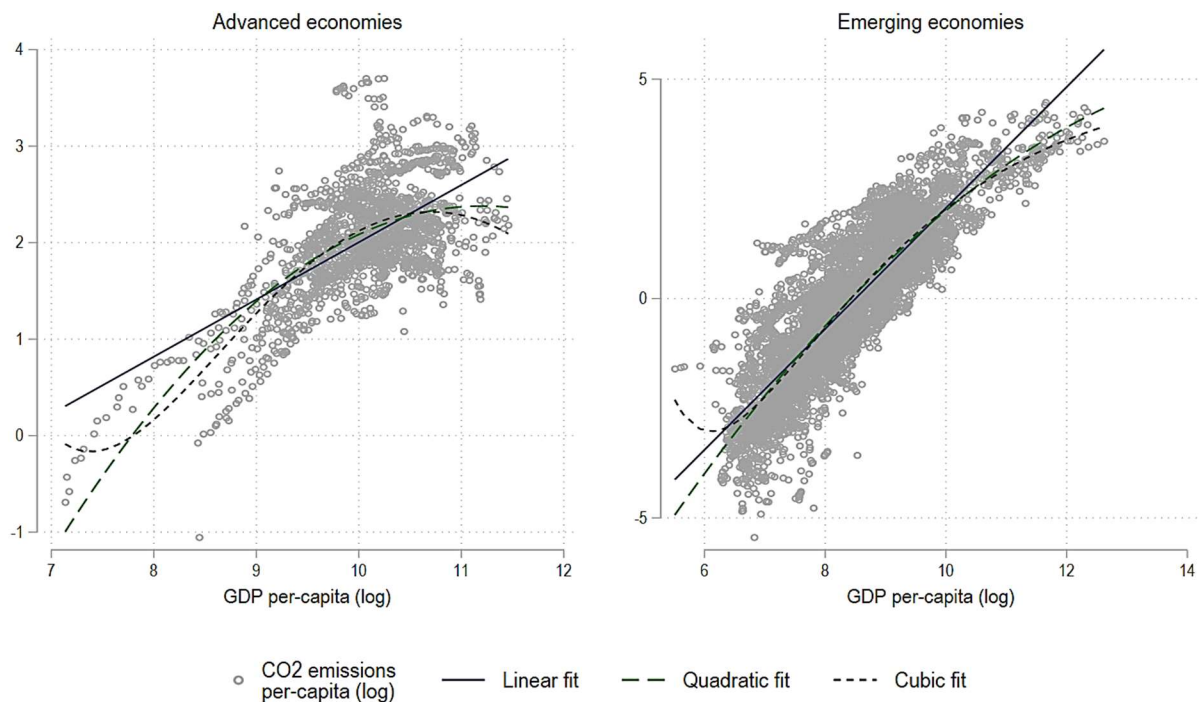
Conflicting evidence emerges even in recent studies conducted through meta-analyses or systematic literature reviews. Saqib and Benhmad (2021) examine 101 research papers published between 2006 and 2019 and reached conclusions in favor of the overall validity of the EKC in its classic inverted U-shaped formulation. However, findings are highly sensitive to the selection of the environmental indicators. Anthropogenic measurements (e.g., CO₂, nitrous oxide) are more likely to support the existence of the EKC, while the use of chemical and biological indicators (e.g., sulfur dioxide, industrial waste, deforestation) points in the opposite direction. In the same vein, performing a content analysis of the 100 most influential articles on the EKC classified according to their average annual citations, Naveed et al. (2022) find that 62% of the studies provide evidence of an inverted U-shaped relationship between environmental pollution indicators and per capita GDP, 29% highlight different patterns (e.g., U-shaped, N-shaped, etc....), while the remaining 9% do not find any evidence in support of the EKC. Overall, their extended analysis of 1,654 scientific articles, books, and book chapters published from 1992 to 2022 confirms the validity of the inverted U-shaped EKC hypothesis, with the maximum point identified at an average income level of \$9,260 per capita. This estimate is also in line with evidence from the meta-analysis performed by Sarkodie and Stretzov (2019), which indicates that studies supporting the existence of the classic EKC identify the critical threshold at a per capita GDP level of approximately \$8,910. Based on purchasing power parity (PPP)-adjusted 2017 international dollars, such a threshold value would suggest that in 2019, 56% of emerging economies covered in the Penn World Table 10.1 (PWT) (Feenstra et al. 2015)—as well as all advanced economies—were already experiencing increasingly smaller emissions as per capita GDP rises.⁶ Preliminary evidence suggests this is an implausibly large share.

⁶ One additional problem in the empirical literature on the EKC is that studies are often unclear on how per-capita GDP is measured, which complicates comparisons of the estimated EKC turning points across different analyses. In this paper, per-capita GDP is expressed in PPP-adjusted 2017 international dollars, which allows for consistent comparisons both across countries and time.

Figure 1 displays scatterplots of all available annual data matches between CO₂ emissions and per capita GDP for advanced and emerging economies, along with linear, quadratic, and cubic regression fit lines. Graphical inspection indicates that the data are consistent with a non-linear (either quadratic or cubic) relationship for advanced countries, with a maximum point located at around 35,000 international dollars (dashed black line). Conversely, a mostly linear and positive relationship is observed for emerging economies, although the onset of a trend reversal is noticeable for the quadratic and cubic fit lines beyond the 35,000 international dollars threshold.

Overall, therefore, this descriptive evidence indicates that the threshold per capita income beyond which polluting emissions start to grow increasingly smaller may be substantially higher than \$9,000 dollars. In what follows, we formally investigate this hypothesis in the context of a comprehensive empirical analysis of the EKC.

Figure 1: Carbon Dioxide Emissions vs. Per capita Gross Domestic Product in Advanced and Emerging Economies



CO₂ = carbon dioxide, GDP = gross domestic product.
Source: Authors' calculations.

3. Data and Variables

Building on the existing literature on the determinants of environmental degradation, our empirical analysis considers a large set of indicators. Annual data are collected from various sources and used to construct an unbalanced panel, with the aim of ensuring the broadest possible country–year coverage. The outcomes and predictors (covariates or regressors) included in the panel dataset, along with the corresponding data sources, are classified as follows:⁷

- **Environmental indicators and polluting emissions.** We consider a sizable array of measures as dependent variables throughout the empirical analysis.
 - CO₂, expressed in logs of metric tons per capita, from the World Development Indicators database (WDI 2023). This is our primary environmental indicator.
 - Ozone precursors/greenhouse gases (i.e., carbon monoxide [CO], nitrogen oxides [NO_x], non-methane volatile organic compounds [NMVOC], methane [CH₄], and nitrous oxide [N₂O]); acidifying gases (i.e., ammonia [NH₃] and sulfur dioxide [SO₂]); and primary particulates (i.e., particulate matter with a diameter of 10 micrometers or less [PM₁₀], particulate matter with a diameter of 2.5 micrometers or less [PM_{2.5}], black carbon [BC], and organic carbon [OC]). These are from the Emissions Database for Global Atmospheric Research (EDGAR 2020), expressed in logs of kilotons per capita.
 - Carbon footprint of consumption and carbon footprint of production, expressed in logs of global hectares (gha) per capita and retrieved from the

⁷ For reasons of space, further details and the related literature on the determinants of environmental degradation considered in our empirical analysis are reported and discussed in Section A1 of the Appendix.

Global Footprint Network (2019).⁸

- Ecological footprint of consumption and ecological footprint of production, expressed in logs of gha per capita and collected from the Global Footprint Network (2019).
- **Economic growth.**
 - (logs of linear, squared and cubed terms of) Per capita GDP, expressed in PPP-adjusted 2017 international dollars, drawing from data sourced from PWT 10.1 (Feenstra et al. 2015).
- **Sectoral composition.**
 - Agriculture, industry, and services values added (expressed as percentages of GDP), from WDI (2023).
- **Energy variables.**
 - Fossil fuel energy consumption (percentage of total), from WDI (2023).
 - Alternative and nuclear energy (percentage of total energy use), from WDI (2023).
 - Energy imports (net, percentage of energy use), from WDI (2023).
- **Sociodemographic variables.**
 - Urban population (percentage of total population), from WDI (2023).
 - Population density (people per sq. km of land area), from WDI (2023).
 - KOF Globalization Index (Gygli et al. 2019).
- **Technology and total factor productivity.**
 - Investment-specific technological progress (PWT).
 - Total factor productivity (TFP) level at current PPPs, from PWT.

⁸ In ecological footprint accounts, the global hectare represents the area of biologically productive land and water required to absorb all fossil fuel carbon emissions generated within a specific country or region.

- **Environmental institutions and policies.**
 - Environmental ministry establishment, from Aklin and Urpelainen (2014).
 - The (log of) number of international environmental agreements (IEAs) ratified per year, from Mitchell (2020) and Mitchell et al. (2020).
- **Natural characteristics.**
 - Forest land (percentage of land area), from the Food and Agriculture Organization of the United Nations (FAO 2020).
- **Economic variables.**
 - Tertiary education (percentage of the population aged 15–64), from Barro and Lee (2013).
 - Foreign direct investment (FDI) net inflows (as a percentage of GDP), from WDI (2023).
 - Gini index before taxes (log), from the Standardized World Income Inequality Database (SWIID) (Solt 2020).
 - International tourism, number of arrivals as a ratio of destination country population (log), from WDI (2023).
 - Labor productivity (log), from PWT.
 - Inflation, consumer prices (annual percentage), from WDI (2023).
 - Imports, exports, and overall trade of goods and services (expressed as percentages of GDP), from WDI (2023).
 - Private credit (percentage of GDP, log), from Beck et al. (2010).
- **Institutional quality variables.**
 - Corruption index, from PRS Group (2021).
 - Polity score index, from Marshall and Gurr (2020).
 - Political Polarization index, from Cruz et al. (2021).

Including all these indicators in our empirical analysis entails a trade-off in terms of country–year coverage. As a result of the merging process, we obtain a panel of 84 advanced and emerging economies—including 12 Asian Development Bank (ADB) regional members—with annual data over 1995–2015, for a total of 1215 observations.⁹ Descriptive statistics for the main variables included in the empirical analysis in the paper are reported in Table 1.¹⁰

Table 1: Main Variables' Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
CO ₂ emissions (metric tons per capita) (log)	1,215	1.245	1.201	-2.641	3.212
Real GDP per capita at chained PPPs (in mil. 2017 US\$) (log)	1,215	9.558	1.008	6.828	11.458
Fossil fuel energy consumption (% of total)	1,215	72.031	23.296	5.542	99.997
Environmental ministry establishment	1,215	0.871	0.336	0	1
TFP level at current PPPs	1,215	0.715	0.24	0.15	1.491
Agriculture, value added (% of GDP)	1,215	7.644	7.629	0.033	45.042
Energy imports, net (% of energy use)	1,215	9.436	115.227	-843.482	99.085
Foreign direct investment (% of GDP)	1,215	4.709	7.928	-57.532	86.479
Industry, value added (% of GDP)	1,215	27.515	7.365	10.162	66.429
Overall trade (% of GDP)	1,215	82.592	55.971	14.772	437.327
Inflation, consumer prices (annual %)	1,215	7.52	31.991	-4.478	1,058.374
Urban population (% of total population)	1,215	65.427	18.335	16.216	100
Alternative and nuclear energy (% of total energy use)	1,215	8.295	9.951	0	49.59
Services, value added (% of GDP)	1,215	56.591	9.632	10.876	92.562
KOF Globalization Index	1,215	67.022	13.605	29.479	91.07
Corruption Index	1,215	3.184	1.287	0.5	6
Polity Score Index	1,215	6.281	5.404	-10	10
Political Polarization Index	1,215	0.758	0.903	0	2
Tertiary Education (% of total population aged 15–64)	1,215	18.026	12.111	0.014	64.398
Investment specific technological progress	1,215	1.085	0.873	0.549	30.11
Gini Index (log)	1,215	3.857	0.124	3.481	4.281
International tourism (log)	1,215	-1.192	1.705	-6.703	2.495
Labor productivity (log)	1,215	10.454	0.919	7.628	12.162
Private credit to GDP (%) (log)	1,215	3.784	0.841	0.251	5.356

Continued of the next page

⁹ The ADB members included in the sample are Armenia, India, Indonesia, Kazakhstan, Malaysia, Mongolia, the Philippines, the People's Republic of China (PRC), the Republic of Korea, Singapore, Sri Lanka, and Thailand.

¹⁰ For the sake of readability, descriptive statistics for the other dependent variables are presented in Table A2.2 in the Appendix.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Number of IEAs ratified per year (log)	1,215	1.095	0.665	0	3.219
Forest land (% of land area)	1,215	33.628	20.222	0.05	91.88
Population density (people per sq. km of land area)	1,215	213.644	823.67	1.506	7,714.703
Imports of goods and services (% of GDP)	1,215	41.717	26.413	7.574	208.333
Exports of goods and services (% of GDP)	1,215	40.875	30.274	4.969	228.994

CO₂ = carbon dioxide, GDP = gross domestic product, IEA = international environmental agreement, PPP = purchasing power parity, TFP = total factor productivity.

Source: Authors' calculations.

4. Methodology

A standard EKC-type empirical specification to investigate the determinants of environmental degradation can be expressed as follows:

$$E_{i,t} = \alpha + \beta_1 y_{i,t} + \beta_2 y_{i,t}^2 + \beta_3 y_{i,t}^3 + \sum_{k=1}^K \gamma_k X_{k,i,t} + \sum_{j=1}^J \delta_j F_{j,i,t} + \varepsilon_{i,t} \quad (1)$$

where $E_{i,t}$ is the natural log of an environmental indicator (e.g., CO₂ emissions, ecological footprint, etc.), in country i and year t (with $i = 1, 2, \dots, N$; $t = 1, 2, \dots, T$); y is the natural log of per capita GDP, X is a vector encompassing a set of potential factors influencing environmental degradation; F is a vector including a time trend, country and year fixed effects; $\varepsilon_{i,t}$ represents a well-behaved error term.

According to the empirical literature, the inclusion of the linear, quadratic, and cubic components of y accounts for all the possible shapes that can characterize the relationship between economic growth and polluting emissions (Özcan and Öztürk 2019, Leal and Marques 2022). In particular, estimates of Equation (1) can yield the following functional forms:

1. $\beta_1 = \beta_2 = \beta_3 = 0 \rightarrow$ no association.
2. $\beta_1 > 0, \beta_2 = \beta_3 = 0 \rightarrow$ linearly increasing.
3. $\beta_1 < 0, \beta_2 = \beta_3 = 0 \rightarrow$ linearly decreasing.

4. $\beta_1 < 0, \beta_2 > 0, \beta_3 = 0 \rightarrow$ U-shaped.
5. $\beta_1 > 0, \beta_2 < 0, \beta_3 = 0 \rightarrow$ inverted U-shaped (i.e., classic EKC).
6. $\beta_1 > 0, \beta_2 < 0, \beta_3 > 0 \rightarrow$ N-shaped.
7. $\beta_1 < 0, \beta_2 > 0, \beta_3 < 0 \rightarrow$ inverted N-shaped.

Considering this variety of possible alternative EKC shapes, concerns relating to model uncertainty and variable selection become clear. These emerge due to the multifaceted nature of the interplay between the many potential influencing factors.

Model uncertainty reflects the complexity of identifying the most appropriate specification to fit the relationship between economic growth and environmental decay. In our context, the uncertainty surrounding the appropriate functional form (i.e., linear, quadratic, or cubic) can be considered one of the main challenges (Aller et al. 2021). Variable selection involves the critical decision of which specific predictors (e.g., energy consumption, population, and institutional factors) should be included in the analysis. EKC predictors typically vary substantially across different studies in the literature (e.g., Hamilton and Turton 2002, Friedl and Getzner 2003, Sharma 2011, Dong et al. 2019, Naves et al. 2020), thus impacting results and comparability. To address these concerns, we rely on BMA techniques (Draper 1995, Raftery et al. 1997, George 2004, Steel 2020).

To illustrate how BMA works, we express Equation (1) in matrix form:

$$E_{i,t} = X'_{i,t}\beta + \varepsilon_{i,t} \quad (2)$$

where X' is a $k \times 1$ vector encompassing all potential factors influencing environmental degradation. In the model averaging framework, each group of included regressors in X represents a separate statistical model. BMA handles model uncertainty by estimating Equation (2) for every potential combination of regressors. It subsequently computes a weighted average across all these candidate models, using Bayes' rule to determine the weights. Given a prior

model probability, the probability that model j (M_j) accurately represents the data (D)—that is, that M_j is the “true model” through the posterior model distribution— is defined as:

$$P(M_j|D) = \frac{P(D|M_j)P(M_j)}{\sum_{M^*} P(D|M^*)P(M^*)} \quad (3)$$

where $P(D|M_j)$ denotes the marginal likelihood of M_j ; $P(M_j)$ indicates the prior model probability, while $\sum_{M^*} P(D|M^*)P(M^*)$ is the integrated likelihood of M_j over the model space, M^* .

In our context, model uncertainty arises from the uncertainty around which predictors should be included in the model. If E is our outcome variable, with p potential predictors (or covariates/regressors) $x = (X_1, X_2, \dots, X_p)$, and $D = \{e_i, x_{1i}, x_{2i}, \dots, x_{pi}\}_{i=1}^n$ is a sample of observations on E and x , it is unknown which covariates properly explain E . Thus, we can consider any subset of x as a potential candidate set, denoting x_j as the j th subset, and M_j defined as the model associated with x_j , and belonging to the discrete model space $\{M_j\}_{j=1}^{2^p}$.¹¹

BMA applications allow to estimate regression coefficients. Let $\hat{\beta}_{M_j}$ represent an estimate of a $p \times 1$ regression coefficient vector β with respect to model M_j , wherein the coefficients for predictors not included the model are constrained to zero. Then, the BMA estimate of β can be written as follows:

$$\hat{\beta}_{BMA} = \sum_{j=1}^{2^p} P(M_j|D) \hat{\beta}_{M_j} \quad (4)$$

To sum up, the BMA procedure involves the estimation of model specifications including all possible combinations of explanatory variables and assigns weights to their coefficients based on various measures of model fit. BMA can evaluate a wide range of potential regressors,

¹¹ In case of predictors always included, p_a , the model space consists of 2^{p-p_a} models. For additional methodological details, see Hasan et al. (2018).

providing insights into their posterior inclusion probability (PIP)—i.e., the likelihood of their relevance in explaining the dependent variable—and calculates the weighted mean and standard deviation of their respective coefficients. Predictors with PIP exceeding 0.5 are typically regarded in the literature as those having a “robust” relationship with the dependent variable (e.g., Barbieri and Berger 2004, Eicher et al. 2011).¹² As argued by Hasan et al. (2018), by considering many possible regressors, BMA also effectively addresses omitted variable bias, which often leads to inconsistently estimated coefficients. In our case, this greatly reduces concerns related to endogeneity issues, which are typically associated with model uncertainty. Specifically, since per capita GDP does not directly influence emissions but only through other variables—e.g., industrial production, fossil fuel energy consumption, tourism—controlling for these and other regressors in a BMA setup minimizes omitted variable bias concerns.

4.1. Priors for Models and Model Parameters

In the context of BMA analysis, model priors and parameter model priors play essential roles in estimating and selecting models. Model priors represent the prior probabilities assigned to different models in the model space.¹³ BMA deals with multiple candidate models, each with a different combination of predictors or regressors. In other words, model priors can be thought of as the prior knowledge about the likelihood of each model being the “true” or most appropriate model before observing the data. The literature offers various options for model priors and priors for model parameters, including informative and non-informative ones, as well as data-agnostic and data-driven approaches (Steel 2020).

¹² Specifically, Eicher et al. (2011) introduced a PIP classification scheme for assessing the strength of evidence, which consists of four categories: weak (50-75% PIP), substantial (75-95%), strong (95-99%), and decisive (99%+) evidence. In contrast, Barbieri and Berger (2004) emphasize the predictive capabilities of the median model, which includes those regressors with PIP values exceeding 0.5.

¹³ Moral-Benito (2015), Fragoso et al. (2018), and Steel (2020) have details on various model priors.

In our empirical analysis, we rely on the uniform model prior on the model space, which assigns the same probability (i.e., $1/2^p$) of being the “true” one for each model. The uniform prior is typically considered a weak model prior in Bayesian statistics for at least two reasons (Box and Tiao 2011, Jaynes 2003, among others). First, it is non-informative in nature, reflecting a lack of prior information or the assumption that all possible models are equally likely before observing the data. Second, the uniform prior has a minimal impact on posterior distributions, as it gives more weight to the likelihood function. These features make it a suitable choice when we aim to avoid strong assumptions and let the data-driven likelihood guide the inference process. Nonetheless, we also assess the sensitivity of our findings to the use of different model priors and find that they remain robust when using beta-binomial and binomial model priors.¹⁴

In BMA regressions, parameter model priors (also known as hyperparameters, shrinkage parameters or *g*-priors) underpin the specification of prior distributions for model parameters (Zellner, 1986). These are associated with the model’s parameters (i.e., coefficients) within each candidate model and help control the shape and characteristics of the prior distribution which, in turn, influence the BMA results. Essentially, *g*-priors help determine how much information from the data should be used to inform the prior beliefs about the coefficients (i.e., to express uncertainty about the values of model parameters before observing the data). By incorporating parameter model priors, BMA accounts for the possibility of certain parameters being (more or less) influential or uncertain in different models.

Frequently employed priors, like Zellner’s prior with a fixed *g* parameter for regression coefficients (Fernández et al. 2001), offer precise calculations of marginal likelihoods. While these priors are computationally efficient, they may not consistently yield the most accurate predictive performance. On the other hand, using *g*-priors with random *g* parameters (Ley and Steel 2012) provides greater flexibility in BMA analysis, but introduces complexity in model

¹⁴ To save space, these additional results are not presented in the paper, but they are available upon request.

specification and simulation. In the absence of strong information about the data generating process and model parameters, BMA results can be sensitive to the choice of priors. To assess the robustness of our results, we make use of both fixed and random g -priors.

Denoting with p the number of predictors and n the sample size, for the fixed priors case we consider the benchmark prior (Fernandez et al. 2001) with $g = \max(n, p^2)$; the unit information prior (UIP) (Kass and Raftery 1995) with $g = n$; the risk inflation criterion (RIC) (Foster and George 1994) with $g = p^2$; and the empirical Bayes local (EBL) (Liang et al. 2008) estimate for g . As for the random priors case, we make use of the hyper- g ; hyper- gn (Liang et al. 2008); inverse-gamma (ZSIOW) (Zellner and Siow 1980); and robust g -priors (Bayarri et al. 2012).

4.2. Estimation: Markov Chain Monte Carlo Sampling

Markov chain Monte Carlo (MCMC) sampling, rather than model enumeration, is employed to enhance the efficiency of exploring the model space. This is achieved by focusing on models that are deemed more probable based on the observed data. For instance, one method to attain this is through MCMC Model Composition (MC3) sampling, as introduced by Madigan and York (1995). When employing this type of sampling, it is crucial to assess the convergence of the MCMC process. For models containing a large number of predictors, achieving convergence can be challenging, if not infeasible, without constraining the model space using a strong model prior.¹⁵ To assess the MCMC convergence of a BMA model, we check for the sampling correlation, as suggested by Fernández et al. (2001). This measures the conformity between the expected and observed Posterior Model Probabilities (PMPs). Non-convergence is suspected when the sampling correlation exhibits either negative or low positive (less than 10%) values. In any case, sampling correlation can be only considered as an informal measure of MCMC convergence in

¹⁵ An example of a strong model prior is the independent Bernoulli prior, in which a select group of predictors is assigned a high probability of inclusion, while the remainder receive a low probability of inclusion.

BMA. In particular, the use of a random g -prior lacks a reliable method for estimating sampling correlation, due to the absence of an analytical formula for PMPs. In such instances, sampling correlation is calculated by means of the harmonic-mean approximation of the analytical PMP distribution, introducing potential imprecisions related to the approximation itself, as well as to the inherent sampling variability. Additional tools that can be employed to assess convergence include graphical diagnostics.¹⁶

5. Bayesian Model Averaging Regression Results: Carbon Dioxide Emissions

Table 2 reports the BMA regression results based on a uniform model prior, assigning equal prior probabilities to all possible models. In performing these estimates, the time trend, the country-, and year-fixed effects are treated as “always-included” predictors—i.e., they are included in every model within the model space. The other potential determinants of CO₂ emissions are considered as “in-out” predictors, meaning that they may be either included or excluded from a model during the estimation. The UIP fixed g -prior results are in panel (1) of Table 2, while the robust random g -prior estimates are in panel (2). In both cases, the sampling correlation value is consistently high, providing a partial indication of estimation convergence (subsection 5.1).

The PIP values for the linear, squared, and cubed terms of per capita GDP are all equal to 1, providing a strong indication that all three are robust predictors of CO₂ emissions. The three terms enter with, respectively, a negative, positive, and negative sign. This outcome is consistent with an inverted N-shaped relationship between per capita GDP and CO₂ emissions, indicating that there exist three different phases (Figure A2.1 in the Appendix). In the early stages of economic development emissions decline alongside rising per capita GDP. One possible explanation for this result is that least-developed countries are typically largely agricultural and

¹⁶ All the BMA estimates, using the model and parameter priors discussed, as well as the convergence checks and other tests reported in this paper, are performed by means of the STATA suite *bmaregress*.

rely on low-productivity and environmentally inefficient techniques for food production (e.g., Sadowski et al. 2024, Salman et al. 2022), so their emissions are initially high. As more productive agricultural techniques are gradually adopted, emissions fall as incomes rise. In the next two phases, the process traces that of the classic EKC. Higher productivity in agriculture frees up surplus labor in the sector and rising incomes boost demand for industrial goods, setting the stage for a first reversal in the relationship between emissions and per capita GDP. As industrialization sets in and boosts growth, emissions start to rise with increasing incomes and consumption levels. As incomes increase further and the economy matures, a new (maximum) turning point is reached. Beyond this threshold, emissions become progressively smaller for further increases in per capita GDP. This may occur because wealthier societies can invest in cleaner technologies, implement stricter environmental regulations, and shift towards less carbon-intensive production.

The estimated (cubic) inverted N-shaped relationship is consistent with the presence of two distinct turning points—the first is a minimum and the second a maximum. According to Sinha et al. (2019), however, this finding is not sufficient to draw definitive conclusions on the EKC functional form. This is because, for Equation (1) to have well-defined minima and maxima, the following condition must be satisfied:

$$\beta_2^2 - 3\beta_1\beta_3 > 0 \quad (5)$$

When (5) holds, minima and maxima can be found based on $y = e^{\left(-\beta_2 \pm \sqrt{\beta_2^2 - 3\beta_1\beta_3}\right)/3\beta_3}$. For the estimates in Table 2, the condition in (5) is always satisfied. The estimated minimum, beyond which the relationship transitions from negative to positive, is located at about 1,270 international dollars. The maximum, where the relationship changes from positive to negative, is identified at approximately 41,500 international dollars. Such values are consistent with the abovementioned possible mechanisms underlying an inverted N-shaped EKC relationship. Specifically, taking the year 2015 as a reference, out of all the economies in our panel only Niger—a low-income and

largely agricultural developing economy—is located below the estimated per capita GDP minimum. In contrast, only high-income economies in our panel are found to be beyond the maximum.¹⁷ The remaining countries—including all emerging economies and a small number of advanced economies—are on the upward-sloping part of the inverted N-shaped EKC, experiencing rising CO₂ emissions as per capita GDP increases.

Table 2: Bayesian Model Averaging Regression Results

Dependent Variable: CO ₂ emissions per capita (log)						
Predictor	(1) Fixed <i>g</i> -prior			(2) Random <i>g</i> -prior		
	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.
Real GDP per capita (log)	1	-7.302	1.389	1	-7.300	1.398
Real GDP per capita squared (log)	1	0.854	0.153	1	0.854	0.155
Real GDP per capita cubed (log)	1	-0.032	0.006	1	-0.032	0.006
Fossil fuel energy consumption (% of total)	1	0.015	0.001	1	0.015	0.001
International tourism, number of arrivals per population (log)	1	0.094	0.014	1	0.094	0.014
Private credit to GDP (%) (log)	1	0.068	0.014	1	0.069	0.014
Industry, value added (% of GDP)	0.997	0.010	0.003	0.995	0.010	0.003
Alternative and nuclear energy (% of total energy use)	0.998	-0.010	0.002	0.996	-0.010	0.002
Forest Land (% of Land Area)	0.998	-0.014	0.003	0.983	-0.014	0.003
Political Polarization Index	0.990	-0.022	0.006	0.983	-0.022	0.006
Gini Index (log)	0.993	0.553	0.143	0.988	0.550	0.149
Urban population (% of total population)	0.983	0.007	0.002	0.981	0.007	0.002
Exports of Goods and Services (% of GDP)	0.815	-0.003	0.002	0.834	-0.004	0.002
Services, value added (% of GDP)	0.889	-0.005	0.002	0.878	-0.005	0.002
Agriculture, value added (% of GDP)	0.737	-0.005	0.004	0.729	-0.005	0.003
Year fixed effects		Y			Y	
Country fixed effects		Y			Y	
Time trend		Y			Y	
Model prior		Uniform			Uniform	
<i>g</i> -prior		UIP			Robust	

Continued of the next page

¹⁷ These include Bahrain; Saudi Arabia; and 14 OECD economies—Australia, Austria, Belgium, Canada, Denmark, Finland, Ireland, Luxembourg, the Netherlands, Norway, Singapore, Sweden, the United Kingdom, and the United States. It is worth noting that in 1995 only two high-income economies were already located beyond the maximum: Luxembourg and the United States.

Dependent Variable: CO ₂ emissions per capita (log)						
Predictor	(1) Fixed <i>g</i> -prior			(2) Random <i>g</i> -prior		
	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.
Sampling correlation		0.993			0.970	
Number of observations		1215			1215	
Number of predictors		134			134	
Number of models		4,758			4,453	
Mean model size		120.684			121.579	
Existence condition of min & max		0.028			0.028	
Min (PPP adjusted 2017 international \$)		1273.43			1268.63	
Max (PPP adjusted 2017 international \$)		41509.15			41527.69	

BMA = Bayesian Model Averaging, CO₂ = carbon dioxide, GDP = gross domestic product, MC3 = MCMC Model Composition, MCMC = Markov chain Monte Carlo, PIP = posterior inclusion probability, PPP = purchasing power parity, Std. Dev. = standard deviation, UIP = unit information prior.

Notes: BMA estimates using MC3 sampling algorithm with 2,500 burn-in iterations and MCMC sample size of 200,000. Source: Authors' calculations.

It is also worth noting that our estimated maximum point is more than four times higher than the average \$9,000 of per capita GDP identified in the meta-analyses by Sarkodie and Stretzov (2019) and Naveed et al. (2022). Based on Penn World Table's data, in 2015 real per capita GDP exceeded 9,000 international dollars in 119 out of 183 economies. Findings in Sarkodie and Stretzov (2019) and Naveed et al. (2022) would thus imply that an implausibly high 65% of the world's economies were already on the downward-sloping segment of the EKC—compared to 17% according to our estimates.¹⁸

According to our BMA estimates, as well as the per capita GDP terms, 12 out 30 additional predictors are associated with PIP values higher than 0.5.¹⁹ As mentioned, this indicates that these factors are more likely to belong in the “true” model. Predictors entering with a positive sign, thus contributing to increasing CO₂ emissions, are fossil fuel energy consumption; the share of GDP attributed to industrial activities; international tourism; private

¹⁸ As mentioned in footnote 6, empirical studies on the EKC are often unclear on how per-capita GDP is measured. As such, the estimated per-capita GDP thresholds in this paper are not immediately comparable to those reported in Sarkodie and Stretzov (2019) and Naveed et al. (2022). If, rather than PPP-adjusted 2017 international dollars, one uses nominal (real) per-capita GDP in US dollars, the same comparison implies that 82 (66) percent of the world's economies were on the downward-sloping segment of the EKC in 2015.

¹⁹ The complete set of estimates is available upon request.

credit to GDP; Gini index; and urban population. By contrast, the use of alternative and nuclear energy; forest land; the exports of goods and services; the shares of GDP attributed to agriculture and service activities; and political polarization are correlated with lower levels of CO₂ emissions.

5.1 *Other Pollutants and Environmental Indicators*

The empirical evidence gathered so far provides robust evidence in favor of a cubic specification for the EKC, consistent with an inverted N-shaped relationship between CO₂ emissions and economic growth. This prompts the question of whether such an outcome may be specific to CO₂ emissions. To explore this issue, we carry out a series of BMA regressions using the alternative environmental indicators and the same potential predictors listed in Section 3. The results are presented in Tables 3 to 5, where details regarding predictors other than the linear, quadratic, and cubic components of per capita GDP have been omitted for the sake of readability.

The BMA estimates confirm the existence of an inverted N-shaped relationship with economic growth for 11 out of the 15 alternative outcome variables.²⁰ As in the case of CO₂ emissions, the minimum point is always identified at a low value of per capita GDP. This ranges from 368 international dollars per capita for NMVOC emissions, to approximately 461 for NO_x emissions, 616 for the carbon footprint of production, and 3,278 for N₂O emissions (Table 3). As for the maximum point, the threshold varies from about 15,179 international dollars per capita for N₂O emissions to 47,448 for NMVOC emissions (Table 3).

In sum, extending the analysis to indicators other than CO₂ emissions produces three main results. First, the finding of a cubic functional form for the EKC is robust to the use of alternative environmental degradation indexes. Second, given the low or very low estimated minimum points, going forward the implications from the uncovered inverted N-shaped relationship are in most

²⁰ The detailed estimates are available upon request. In the case of SO₂, NH₃ and CH₄ emissions, as well as the carbon footprint of consumption, the BMA estimations produce inconclusive evidence regarding the relationship with per-capita GDP. Therefore, these estimates are excluded from the main text.

cases virtually equivalent to those from the classic inverted U-shaped EKC, as very few or no economies in our sample are now located on the first downward-sloping segment of the inverted-N. Third, while the estimated maximum points vary somewhat across different emission indicators, they are almost always close to the per capita GDP thresholds associated with CO₂ emissions. As a result, based on 2015 per capita GDP levels, emerging economies are still almost always located on the upward-sloping part of the EKC even when indicators other than CO₂ emissions are considered.

Table 3: Bayesian Model Averaging Regression Results on Alternative Pollutants (Part 1)

Dependent Variable:	BC emissions per capita (log)			N ₂ O emissions per capita (log)			CO emissions per capita (log)			NMVOC emissions per capita (log)		
Predictor	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.
Real GDP per capita (log)	1	-9.693	1.899	1	-11.220	1.394	1	-14.347	2.189	0.988	-4.829	1.407
Real GDP per capita squared (log)	1	1.176	0.211	1	1.276	0.153	1	1.693	0.242	1	0.633	0.155
Real GDP per capita cubed (log)	1	-0.045	0.008	1	-0.048	0.006	1	-0.064	0.009	0.999	-0.025	0.006
Year fixed effects		Y			Y			Y			Y	
Country fixed effects		Y			Y			Y			Y	
Time trend		Y			Y			Y			Y	
Model prior		Uniform			Uniform			Uniform			Uniform	
g-prior		Robust (random)			Robust (random)			Robust (random)			Robust (random)	
Sampling correlation		0.967			0.974			0.961			0.901	
Number of observations		1,216			1,216			1,216			1,216	
Number of predictors		134			134			134			134	
Number of models		4,149			12,339			13,491			4,770	
Mean model size		118.94			114.735			117.976			119.23	
Existence condition of min & max		0.063			0.012			0.095			0.034	
Min (PPP adjusted 2017 international \$)		886.51			3,277.84			1,299.02			367.79	
Max (PPP adjusted 2017 international \$)		35,830.95			15,178.89			31,627.42			47,447.87	

BC = black carbon, BMA = Bayesian Model Averaging, CO = carbon monoxide, GDP = gross domestic product, MC3 = MCMC Model Composition, MCMC = Markov chain Monte Carlo, N₂O = nitrous oxide, NMVOC = non-methane volatile organic compounds, PIP = posterior inclusion probability, PPP = purchasing power parity, Std. Dev. = standard deviation.

Notes: BMA estimates using MC3 sampling algorithm with 2500 burn-in iterations and MCMC sample size of 200,000.

Source: Authors' calculations.

Table 4: Bayesian Model Averaging Regression Results on Alternative Pollutants (Part 2)

Dependent Variable:	NO _x emissions per capita (log)			OC emissions per capita (log)			PM ₁₀ emissions per capita (log)			PM _{2.5} emissions per capita (log)		
Predictor	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.
Real GDP per capita (log)	0.974	-5.177	1.740	1	-9.820	1.963	1	-7.850	1.552	1	-8.673	1.623
Real GDP per capita squared (log)	0.998	0.666	0.192	1	1.159	0.217	1	0.951	0.171	1	1.048	0.179
Real GDP per capita cubed (log)	0.999	-0.027	0.007	1	-0.044	0.008	1	-0.037	0.006	1	-0.041	0.007
Year fixed effects		Y			Y			Y			Y	
Country fixed effects		Y			Y			Y			Y	
Time trend		Y			Y			Y			Y	
Model prior		Uniform			Uniform			Uniform			Uniform	
g-prior		Robust (random)			Robust (random)			Robust (random)			Robust (random)	
Sampling correlation		0.972			0.971			0.980			0.990	
Number of observations		1,216			1,216			1,216			1,216	
Number of predictors		134			134			134			134	
Number of models		6,814			6,977			10,104			5,380	
Mean model size		118.724			118.319			118.865			118.997	
Existence condition of min & max		0.032			0.046			0.036			0.042	
Min (PPP adjusted 2017 international \$)		460.64			1,262.43			977.03			1,007.89	
Max (PPP adjusted 2017 international \$)		40,466.58			33,067.61			30,162.90			29,607.71	

BMA = Bayesian Model Averaging, GDP = gross domestic product, MC3 = MCMC Model Composition, MCMC = Markov chain Monte Carlo, NO_x = nitrogen oxides, OC = organic carbon, PIP = posterior inclusion probability, PM₁₀ = particulate matter with a diameter of 10 micrometers or less, PM_{2.5} = particulate matter with a diameter of 2.5 micrometers or less, PPP = purchasing power parity, Std. Dev. = standard deviation.

Notes: BMA estimates using MC3 sampling algorithm with 2500 burn-in iterations and MCMC sample size of 200,000.

Source: Authors' calculations.

Table 5: Bayesian Model Averaging Regression Results on Other Environmental Indicators (Part 3)

Dependent Variable:	Ecological footprint of consumption, gha per capita (log)			Ecological footprint of production, gha per capita (log)			Carbon footprint of production, gha per capita (log)		
Predictor	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.
Real GDP per capita (log)	1	-5.161	0.824	1	-9.872	0.830	1	-6.6638	0.691
Real GDP per capita squared (log)	1	0.574	0.092	1	1.113	0.092	1	0.743	0.077
Real GDP per capita cubed (log)	1	-0.020	0.003	1	-0.041	0.003	1	-0.027	0.003
Year fixed effects		Y			Y			Y	
Country fixed effects		Y			Y			Y	
Time trend		Y			Y			Y	
Model prior		Uniform			Uniform			Uniform	
<i>g</i> -prior		Robust (random)			Robust (random)			Robust (random)	
Sampling correlation		0.953			0.966			0.977	
Number of observations		1,203			1,203			899	
Number of predictors		133			133			114	
Number of models		10,079			9,777			5,527	
Mean model size		112.445			114.416			96.191	
Existence condition of min & max		0.016			0.033			0.023	
Min (PPP adjusted 2017 international \$)		573.17			2,045.09			616.35	
Max (PPP adjusted 2017 international \$)		38,346.89			40,128.28			27,680.87	

BMA = Bayesian Model Averaging, GDP = gross domestic product, MC3 = MCMC Model Composition, MCMC = Markov chain Monte Carlo, PIP = posterior inclusion probability, PPP = purchasing power parity, Std. Dev. = standard deviation.

Notes: BMA estimates using MC3 sampling algorithm with 2500 burn-in iterations and MCMC sample size of 200,000.

Source: Authors' calculations.

6. Robustness of Bayesian Model Averaging-based Results: Carbon Dioxide Emissions

In this section, we assess the robustness and reliability of the results presented in Table 2. First, we conduct a series of statistical checks on the BMA regressions (subsection 6.1). Next, we carry out additional regressions considering potential endogeneity concerns (subsection 6.2).

6.1 g-priors, Markov Chain Monte Carlo-sample Coefficient Densities, Jointness Measures, and Model Sampling Convergence

To assess the robustness of our findings, we perform BMA estimations using different fixed or random g -priors.²¹ The model goodness of fit of such BMA regressions can be examined relying on the log predictive-score (LPS), which is defined as the negative of the log of the posterior predictive density evaluated at an observation. The smaller LPS is, the better the model fit. Table 6 presents the LPS associated with each utilized g -prior.²² This reveals that the robust (random) g -prior provides the better model fit, with a mean of -0.013. In what follows, we will consider estimates based on BMA regressions with a uniform model prior and a robust (random) g -prior as our benchmark, to which we will apply tests and convergence checks.

Table 6: Log Predictive-Scores (LPS)

LPS	Mean	Minimum	Maximum
Benchmark (fixed)	0.307	-1.397	35.624
UIP (fixed)	0.626	-1.346	33.315
RIC (fixed)	0.307	-1.397	35.624
EBL (fixed)	0.694	-1.355	33.668
Hyper-g (random)	-0.012	-1.355	29.474
Hyper- g_n (random)	-0.001	-1.355	29.620
ZSIOW (random)	-0.013	-1.355	29.505
Robust (random)	-0.013	-1.355	29.468

EBL = empirical Bayes local, LPS = log predictive-scores, RIC = risk inflation criterion, UIP = unit information prior, ZSIOW = inverse-gamma.

Source: Authors' calculations.

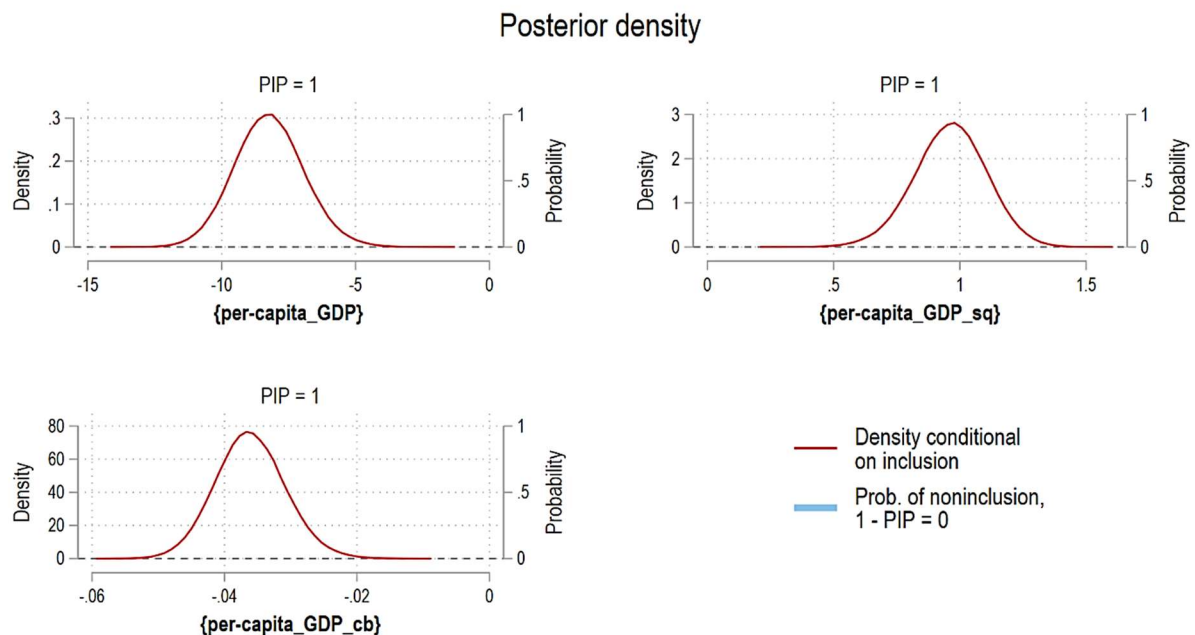
²¹ To save space, the results of these additional BMA regressions are not reported here but are available upon request.

²² The LPS is obtained using the uniform model prior.

Based on the BMA benchmark estimation with a uniform model prior and a robust (random) g -prior, it is possible to compute and plot MCMC-sample posterior densities of regression coefficients. These comprise both discrete and continuous components. The discrete part corresponds to the posterior probability of non-inclusion, meaning the probability that the respective predictor is not part of the model after observing the data. This is the probability that the coefficient is exactly zero. The continuous component represents the density that is conditional on the predictor being included in the model—that is, the probability that the coefficient is not equal to zero.

Computing and plotting MCMC-sample posterior densities for our BMA benchmark estimates results in Figure 2. As can be seen, only the continuous component is plotted. This implies that for the linear, quadratic, and cubic components of per capita GDP, the PIP consistently equals 1. In other words, the “true” model should contain these three predictors.

Figure 2: Posterior Inclusion Probability for the per capita Gross Domestic Product Terms



GDP = gross domestic product, PIP = posterior inclusion probability.
Source: Authors' calculations.

PIP values can be used to evaluate the importance of a single predictor in explaining the outcome variable, while accounting for model uncertainty. However, in the case of the EKC's functional form, it is of particular interest to understand whether the three per capita GDP terms tend to be present across all models, consequently increasing the explanatory power for the outcome variable. For this purpose, we rely on jointness measures which account for the joint posterior distribution for the inclusion of predictors over the model space. Specifically, we consider the Ley–Steel type 1 (LS1) (Ley and Steel 2007) and Modified Yule's Q (YQM) (Hofmarcher et al. 2018) jointness indicators. Both measures assess the probability that a pair of predictors are jointly included in the “true” model. The LS1 ranges from 0 to 1, the YQM from -1 to 1. A value of 1 indicates decisive jointness.

The test results for LS1 and YQM are reported in Table 7. The probability of the linear term (GDPpc) being jointly included with the quadratic and cubic terms (GDPpc squared and GDPpc cubed, respectively) of per capita GDP is 1 for both the LS1 and YQM jointness measures. The same applies to the other possible combinations of predictor pairs. Overall, the outcomes of the jointness tests confirm and reinforce the view that the cubic (inverted N-shaped) relationship represents the correct model specification for the EKC.

Table 7: Jointness Inclusion of per capita Gross Domestic Product Variables

	Ley–Steel type 1 jointness			Modified Yule's Q jointness		
	GDPpc	GDPpc squared	GDPpc cubed	GDPpc	GDPpc squared	GDPpc cubed
GDPpc	-	1	1	-	1	1
GDPpc squared	1	-	1	1	-	1
GDPpc cubed	1	1	-	1	1	-

GDPpc = Gross Domestic Product per capita linear term, GDPpc squared = Gross Domestic Product per capita squared term, GDPpc cubed = Gross Domestic Product per capita cubed term.

Source: Authors' calculations.

Since the BMA estimation with the robust random g -prior has emerged as the best-fitting model according to the LPS (Table 6), the value taken by the sampling correlation is not sufficient to draw a conclusion regarding the convergence of the estimate. To do that, we rely on graphical

convergence diagnostics. Figure A3.1 in the Appendix displays the harmonic and MCMC sampling probabilities for the top 500 visited models, arranged in decreasing order of their PMPs. The close alignment of the two curves indicates that there are no signs of non-convergence. We also perform a convergence control for the parameter g . As depicted in Figure A3.2 in the Appendix, the graphical inspection reveals that convergence has been achieved, particularly when examining the autocorrelation plot.

6.2 *Addressing Endogeneity Concerns: Two-Stage Least Squares Bayesian Model Averaging*

Although the BMA approach is capable of substantially mitigating omitted variable bias issues, we cannot rule out the possibility that other endogeneity concerns—including simultaneity and reverse causality between CO₂ emissions and per capita GDP—may affect the results in Section 5. We now address these concerns via the two-stage least squares (2SLS) BMA methodology proposed by Durlauf *et al.* (2008).

The 2SLS-BMA approach consists of two steps. The first involves regressing the potentially endogenous variables on a set of instruments. In the second stage, the first-stage fitted values are included in a BMA estimation. Within our 2SLS-BMA setup, the three terms of per capita GDP are instrumented with the linear, quadratic, and cubic terms of the lagged values of per capita GDP and the age-dependency ratio. Lagged GDP values are widely used as credible instruments in the empirical literature on the determinants of economic growth (e.g., Temple 1999, Mirestean and Tsangarides 2016, Jetter and Parmeter 2018). As for the age-dependency ratio—defined as the sum of people younger than 15 or older than 64 as a percentage of working-age

population—Lin and Liscow (2013) argue that this measure is directly correlated with per capita GDP but has no direct effect on CO₂ emissions.²³

The 2SLS-BMA estimates are reported in Table 8.²⁴ Two noteworthy results emerge. First, the PIPs of the three (instrumented) terms of per capita GDP are only marginally lower than 1 and the signs of their respective coefficients are confirmed. This implies that the inverted N-shaped relationship between per capita GDP and CO₂ emissions is confirmed by the data even when dealing with endogeneity concerns through the 2SLS-BMA approach. Relatedly, at approximately 1,000 (42,300) international dollars of per capita GDP, the estimated minimum (maximum) is only slightly lower (higher) than those reported in Table 2. Second, with respect to the benchmark BMA estimates (Table 2), the 2SLS-BMA regressions (Table 8) lead to the inclusion of three robust additional predictors in the “true” model—albeit with PIP values close to the 0.5 threshold cutoff. Specifically, the KOF index of globalization index enters as positively correlated with CO₂ emissions in both the fixed and random *g*-prior results, while the GDP shares of imports and trade are selected only by the fixed *g*-prior estimation and enter with, respectively, a positive and negative sign.

Overall, therefore, the 2SLS-BMA estimates provide qualified support to the benchmark BMA results.

²³ For example, a higher age-dependency ratio, reflecting a larger proportion of elderly individuals, may lead to a decline in the working-age population. This shift can impact labor market dynamics, potentially resulting in a reduced labor force participation rate and slower economic growth (e.g., Cruz and Ahmed 2018, Maestas et al. 2023).

²⁴ As further checks to mitigate simultaneity and endogeneity bias concerns, we also performed BMA and 2SLS-BMA regressions using lagged covariates. The main findings do not change. In the first case, results are consistent with the same inverted N-shaped relationship between economic growth and CO₂ emissions. The estimated minima and maxima are only slightly different compared to those reported in Tables 2 and 8. The minimum point is estimated at around 1,050 international dollars, while the maximum point is at around 43,600 international dollars. These estimates, not shown here for reasons of space, are available from the authors upon request. As for the 2SLS-BMA regressions with lagged predictors, the core findings remain unchanged, with low values for the estimated minima and maxima slightly above 47,000 international dollars per-capita. For the sake of completeness, the corresponding results are reported in Table A4.1 of the Appendix.

Table 8: Two-Stage Least Squares Bayesian Model Averaging Regression Results

Dependent Variable: CO ₂ emissions per capita (log)						
Predictor	(1) Fixed <i>g</i> -prior			(2) Random <i>g</i> -prior		
	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.
Real GDP per capita (log) *	0.967	-5.793	2.089	0.963	-5.673	2.223
Real GDP per capita squared (log) *	0.987	0.689	0.231	0.977	0.676	0.247
Real GDP per capita cubed (log) *	0.993	-0.026	0.008	0.987	-0.026	0.009
Fossil fuel energy consumption (% of total)	1	0.015	0.001	1	0.015	0.001
International tourism, number of arrivals per population (log)	1	0.938	0.014	1	0.094	0.014
Private credit to GDP (%) (log)	1	0.061	0.014	0.998	0.061	0.014
Industry, value added (% of GDP)	0.998	0.011	0.003	0.998	0.011	0.003
Political Polarization Index	0.996	-0.023	0.006	0.992	-0.023	0.006
Alternative and nuclear energy (% of total energy use)	0.995	-0.010	0.003	0.988	-0.010	0.003
Urban population (% of total population)	0.982	0.007	0.002	0.975	0.007	0.002
Forest Land (% of Land Area)	0.947	-0.012	0.004	0.936	-0.012	0.004
Gini Index (log)	0.923	0.480	0.192	0.903	0.468	0.203
Services, value added (% of GDP)	0.914	-0.005	0.002	0.900	-0.005	0.002
Agriculture, value added (% of GDP)	0.750	-0.005	0.004	0.728	-0.005	0.004
Exports of Goods and Services (% of GDP)	0.707	-0.004	0.003	0.829	-0.005	0.003
Imports of Goods and Services (% of GDP)	0.553	0.003	0.003			
Trade (% of GDP)	0.551	-0.001	0.003			
KOF Globalization Index	0.501	0.003	0.003	0.516	0.003	0.003
Year fixed effects		Y			Y	
Country fixed effects		Y			Y	
Time trend		Y			Y	
Model prior		Uniform			Uniform	
<i>g</i> -prior		UIP			Robust	
Sampling correlation		0.678			0.908	
Number of observations		1,215			1,215	
Number of predictors		134			134	
Number of models		5,239			5,611	
Mean model size		120.728			120.715	
Existence condition of min & max		0.021			0.021	
Min (PPP adjusted 2017 international \$)		1,022.25			1,000.37	
Max (PPP adjusted 2017 international \$)		42,989.74			43,162.17	

2SLS = Two-Stage Least Squares, BMA = Bayesian Model Averaging, CO₂ = carbon dioxide, GDP = gross domestic product, MC3 = MCMC Model Composition, MCMC = Markov chain Monte Carlo, OLS = ordinary least squares, PIP = posterior inclusion probability, PPP = purchasing power parity, UIP = unit information prior.

Notes: 2SLS-BMA estimates using MC3 sampling algorithm with 2,500 burn-in iterations and MCMC sample size of 200,000. Predictors marked with * represent the fitted values obtained from a first stage OLS regression on our set of instruments.

Source: Authors' calculations.

7. A Frequentist Perspective: Double-Selection Least Absolute Shrinkage and Selection Operator

The empirical analysis in this paper relies on the use of Bayesian statistical principles, which underpin the BMA approach. In this section, we assess the robustness of our main results to the use of an estimator rooted in frequentist statistical principles: the Double-Selection LASSO (DSL) (Belloni et al. 2014).

DSL is a method that combines two approaches: two steps of LASSO regressions to select relevant predictors among potential control variables; an intermediate OLS regression to estimate coefficients, standard errors, and confidence intervals for variables of interest—i.e., the target variables. Variable selection in DSL is performed by shrinking some coefficients to exactly zero by means of a penalty parameter (λ^*), effectively excluding variables from the model. As such, DSL is computationally less intensive compared to BMA estimation and does not require specifying prior distributions, since it does not involve Bayesian statistical principles. However, contrary to the BMA approach, DSL does not provide a full probabilistic representation of model uncertainty.

We use the DSL procedure to estimate the effects of our variables of interest—the linear, squared, and cubed per capita GDP components—on CO₂ emissions, our primary dependent variable. The additional predictors to be included in the model out of all potential regressors in Table 1 are selected via LASSO linear regressions.

Table 9 reports the results of DSL estimations. We consider the following alternative selection methods for an optimal value of the LASSO penalty parameter λ^* for each LASSO (or square-root LASSO) estimation: “plugin” iterative formula dependent on the data; cross validation (CV); adaptive; Bayesian information criterion (BIC); and square-root LASSO. These different selection methods produce very similar results which, in turn, are consistent with the BMA-based

findings.²⁵ Specifically, the inverted N-shaped relationship between economic growth and CO₂ emissions is always confirmed by the DSL estimates. Most importantly, the identified turning points closely align with those retrieved from the BMA estimates in Table 2, with maxima ranging from about 35,750 to 40,570 international dollars.²⁶

**Table 9: Double-Selection Least Absolute Shrinkage and Selection Operator
Regression Results**

Dependent Variable: CO ₂ emissions per capita (log)					
Predictor	Selection				
	Plugin	CV	Adaptive	BIC	Sqrt LASSO
Real GDP per capita (log)	-6.919*** (2.306)	-7.335*** (2.104)	-4.864** (2.013)	-7.335*** (2.104)	-5.722** (2.477)
Real GDP per capita squared (log)	0.877*** (0.245)	0.865*** (0.224)	0.587*** (0.212)	0.865*** (0.224)	0.771*** (0.265)
Real GDP per capita cubed (log)	-0.035*** (0.009)	-0.033*** (0.008)	-0.023*** (0.008)	-0.033*** (0.008)	-0.031*** (0.009)
Year fixed effects	Y	Y	Y	Y	Y
Country fixed effects	Y	Y	Y	Y	Y
Time trend	Y	Y	Y	Y	Y
Number of observations	1,215	1,215	1,215	1,215	1,215
Number of selected controls	108	132	126	132	107
Existence condition of min & max	0.047	0.030	0.016	0.030	0.053

Continued of the next page

²⁵ As discussed in subsection 6.2, the classic BMA estimates may suffer from endogeneity problems, which can be addressed via the 2SLS-BMA procedure. In a similar vein, we also carry out a two-stage estimation to address endogeneity in the DSL setup. As with 2SLS-BMA, in the first stage the potentially endogenous per-capita GDP terms are regressed on our set of instruments. The fitted values obtained are used in the DSL estimation in the second stage. These additional estimates confirm the main findings in this paper and are reported in Table A4.2 of the Appendix. For completeness, we also carried out the same two-stage DLS regression with predictors lagged one period: the key results did not change and are presented in Table A4.3 of the Appendix.

²⁶ Unlike the BMA estimates, the additional predictors selected by the DSL regressions—that is, covariates other than three per-capita GDP terms—are not informative from an econometric and/or economic standpoint, as these techniques do not produce estimates of the associated coefficients and standard errors. Nevertheless, in terms of explanatory power, the control variables selected by the DSL procedure largely overlap with those reported in Table 2. For example, in the case of the adaptive selection method, the identified predictors include the KOF globalization index, tertiary education, TFP, political polarization index, private credit to GDP, polity score index, alternative and nuclear energy use, fossil fuel energy consumption, the shares of GDP in the industrial and service sectors, international tourism, trade, and urbanization.

Dependent Variable: CO ₂ emissions per capita (log)					
Predictor	Selection				
	Plugin	CV	Adaptive	BIC	Sqrt LASSO
Min (PPP adjusted 2017 international \$)	555.69	1,158.99	914.64	1,158.99	302.11
Max (PPP adjusted 2017 international \$)	35,743.16	40,573.27	38,058.40	40,573.27	39,339.36

BIC = Bayesian information criterion, CO₂ = carbon dioxide, CV = cross validation, GDP = gross domestic product, LASSO = Least Absolute Shrinkage and Selection Operator, PPP = purchasing power parity.

Notes: ***, ** and * denote statistical significance at 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

Source: Authors' calculations.

To sum up, two estimation methods based on different—Bayesian and frequentist—statistical principles yield highly comparable results. Together with the robustness tests conducted on the BMA estimations, this outcome provides strong support for at least five conclusions. First, our findings confirm that there exists a statistically significant EKC relationship. Second, the EKC is an inverted N-shaped curve. Third, the estimated inverted N-shaped EKC is closely related to the classic inverted U-shaped EKC. This is because, given the very low minimum estimated, only a single low-income (and largely agricultural) economy was located on the first downward-sloping part of the inverted N-shaped curve in 2015. Fourth, these results are robust to the inclusion of a large set of additional regressors. Fifth, to obtain reliable estimates of the relationship between economic growth and polluting emissions, it is crucial to address both variable selection and model uncertainty.

8. Conclusions

This study takes an agnostic approach to the investigation of the relation between environmental degradation and economic growth. We provide an empirical investigation of the EKC hypothesis relying on purely data-driven methods, applied to a panel dataset of annual data for 84 advanced and emerging economies over 1995–2015. The use of BMA estimation techniques allows us to tackle head on concerns related to model uncertainty and variable selection, which permeate much of the literature on the EKC. Our primary focus is on the following three objectives: first,

ascertaining empirically the validity of the EKC hypothesis; second, detecting the correct functional form (i.e., the shape) of the curve; third, identifying robust determinants of polluting emissions other than per capita GDP.

Using CO₂ emissions as a benchmark measure of environmental degradation, the central finding of our study points to the existence of an inverted N-shaped association with per capita GDP. This functional form marks the presence of two distinct thresholds. The minimum point, where the relationship shifts from negative to positive is located at approximately 1,300 international dollars. The maximum point, beyond which economic growth is associated with increasingly lower CO₂ emissions, is identified at around 40,000 international dollars. These threshold values have important implications. Given the very low minimum estimated, at the end of the period under consideration only one low-income economy was located on the first downward-sloping part of the curve. As such, the uncovered inverted N-shaped relationship is closely related to the classic inverted U-shaped EKC. Additionally, only high-income economies are located on the downward-sloping part of the EKC beyond the estimated maximum point. As a result, almost all emerging economies turn out to be located on the upward-sloping segment of the curve, where economic growth is linked to increasing CO₂ emissions. These findings are confirmed when we extend the analysis to consider different environmental degradation indicators, including BC, N₂O, and ecological footprint.

Among the many potential explanatory variables for CO₂ emissions different from economic growth, the BMA estimates select fossil fuel energy consumption; industrial activity; international tourism; financial development; the use of nuclear and alternative energy; income inequality; trade; labor productivity; political polarization; and urbanization as robust determinants.

To assess the reliability of the BMA-based results, we conduct extensive robustness checks. These include relying on the 2SLS-BMA approach to address endogeneity concerns and implementing a frequentist (rather than Bayesian) estimation method. The main findings of the benchmark BMA estimates are confirmed. All additional regressions indicate that the EKC, using

CO₂ emissions as primary polluting measure, is inverted N-shaped, and the estimates are consistent with very similar threshold values for the minimum and maximum of the curve.

Our results carry significant policy implications. The strong support for a significant EKC relationship confirms that the process of economic development cannot be easily separated from environmental degradation and, all else constant, beyond very low per capita GDP levels economies can be expected to move along the classic inverted U-shaped EKC as they grow wealthier. All else, however, need not remain constant. Among others, policy measures addressing income inequality; promoting sustainable international tourism and agricultural activities; increasing investment in nuclear and alternative energy sources; and incentivizing reforestation can all lead to reductions in CO₂ emissions—shifting downward the EKC, so that the same per capita GDP level is associated with lower environmental damages. With the right policies in place, economic growth need not entail significant trade-offs with environmental sustainability as a whole.

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“What’s Your Shape?”

A Data-Driven Approach to Estimating the Environmental Kuznets Curve

Studies on the inverted U-shaped relationship between environmental degradation and economic growth—known as the Environmental Kuznets Curve—have produced very mixed evidence. This largely depends on model and variable selection uncertainty. This paper addresses these issues relying on Bayesian Model Averaging techniques. The results indicate that the Environmental Kuznets Curve has an inverted-N shape. Almost all of the emerging economies analyzed display a positive association between per capita gross domestic product and carbon dioxide emissions, whereas most advanced economies analyzed are on the second downward segment of the curve.

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ASIAN DEVELOPMENT BANK

6 ADB Avenue, Mandaluyong City

1550 Metro Manila, Philippines

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