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

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APPENDIX

“What’s Your Shape?” A Data-Driven Approach to Estimating the Environmental Kuznets Curve

Antonio Francesco Gravina and Matteo Lanzafame

ADB Economics Working Paper No. 731

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A1. Environmental Indicators and Determinants of Ecological Degradation: Related Literature

- *Environmental Indicators*
 - **Carbon footprint of consumption and carbon footprint of production.**

The carbon footprint of consumption measures the total carbon emissions associated with the consumption of goods and services within a country, accounting for all emissions generated throughout the lifecycle of products—including their production, transportation, and disposal. In contrast, the carbon footprint of production focuses exclusively on the direct emissions produced within a specific geographical area during the production of goods and services. It comprises the carbon emissions generated by industries, factories, and businesses within that region, and does not consider the emissions resulting from the consumption of these products.
 - **Ecological footprint of consumption and ecological footprint of production.**

The ecological footprint of consumption measures the environmental impact linked to the consumption patterns of communities within an economy. Specifically, it quantifies the biologically productive land and sea areas necessary for resources consumed and waste generated during the life cycle of goods and services. On the other hand, the ecological footprint of production assesses the environmental impact associated with the production of goods and services, thus reflecting the biologically productive land and sea areas required for raw materials, energy, waste, and emissions throughout the production process.
- *Economic Growth*
 - **Per-capita gross domestic product.**

Since the early contributions that explored the determinants of environmental degradation, considerable attention has been devoted to understanding the role played by the process of economic growth and development. The studies in this context commonly employ per-capita gross domestic product (GDP) as a measure of development, to address the so-called “scale” effect. This suggests that increased economic activity tends to lead to higher pollution levels, as industries and consumption patterns associated with economic growth are typically pollution-intensive. However, as countries become wealthier and

social awareness of environmental issues increases, they tend to progressively switch to more environmentally friendly production techniques and goods. The combination of these two opposing trends is consistent with the well-known classic Environmental Kuznets Curve (EKC), depicting an inverted U-shaped relationship between economic growth and environmental decay (e.g., Grossman and Krueger 1991, Harbaugh et al. 2002). Meanwhile, recent literature has conjectured the existence of even more complex, cubic interplays between environmental degradation and economic growth—resulting in either N-shaped or inverted N-shaped EKCs. These are consistent with the presence of two turning points and three different phases. Our estimations account for these potential EKC functional forms by including the (logs of) linear, squared, and cubed terms of per-capita GDP.

- *Sectoral Composition*

- **Agriculture, industry, and services values added.** The sectoral composition of an economy, represented by the GDP shares of agriculture, industry, and services, can significantly affect pollution emissions. This is because environmental impacts vary across sectors, owing to different production processes, type and intensity of energy and other resource use, etc. Typically, industry-biased structural transformation boosts pollutant emissions, as agriculture and service activities are generally characterized by lower emissions (e.g., Panayotou 1997, Suh 2006, Wang et al. 2017, Khan et al. 2020, Lin and Li 2020).

- *Energy Variables*

Energy sources play a fundamental role in shaping environmental outcomes. The choices made regarding energy production, consumption, and demand can significantly impact pollution levels and environmental sustainability. Based on the empirical literature, we consider the following indicators:

- **Fossil fuel energy consumption.** The burning of fossil fuels, such as coal, oil, and natural gas, is a primary source of greenhouse gas (GHG) emissions (Huijbregts et al. 2006, Baek 2016, Henriques and Borowiecki 2017). When these fuels are combusted for energy, they release carbon dioxide (CO₂) and other pollutants into the atmosphere. For this reason, we expect a positive sign for the associated coefficient, especially for GHG emissions.

- **Alternative and nuclear energy.** These sources—including wind, solar, hydropower, and nuclear energy—are considered low-carbon alternatives, as they produce minimal or no direct CO₂ emissions during energy generation. Therefore, these are typically associated with lower levels of emissions per unit of output (e.g., Dong et al. 2018, Piłatowska et al. 2020).
- **Energy imports.** Evidence suggests that whether a country is a net energy importer or exporter matters for its emissions profile. Specifically, big energy importers tend to have higher emissions, particularly if the imported energy comes from non-renewable sources (e.g., Álvarez-Herránz et al. 2017b).
- *Sociodemographic Variables*
 - **Urban population.** Higher urbanization can influence pollutant emissions due to several factors. Urban areas often exhibit more concentrated economic activities, transportation networks, and higher per-capita energy consumption. Additionally, increased urbanization can lead to greater energy demands for heating and cooling, often matched by relying on fossil fuels. Therefore, higher urbanization typically correlates with increased emissions, making it a key factor in understanding pollution dynamics (e.g., Liddle 2013, Sadorsky 2014).
 - **Population density.** Similar to urbanization, high population density can intensify pollutant emissions due to increased human activities and resource consumption. In fact, dense urban areas often experience elevated energy demand, leading to higher industrial output, transportation-related emissions, and increased waste generation. Additionally, concentrated populations may exert pressure on land use, potentially contributing to deforestation and changes in land cover (e.g., Zarco-Perinan et al. 2021)
 - **KOF Globalization Index.** Globalization can influence pollutant emissions in several ways. Increased trade and production often lead to greater energy consumption, potentially resulting in higher emissions (e.g., Wang 2018, Destek 2019). On the other hand, by laying bare the need for environmental improvements and the fight against climate change, globalization can help create the political conditions for the approval of more stringent environmental regulations (e.g., Chen et al., 2020). At the same time, globalized lifestyles may encourage resource-intensive behaviors and

increased consumption, which can contribute to worsening environmental conditions (Destek 2019, Wang et al. 2019). Therefore, globalization's multifaceted nature can affect pollutant emissions through different channels, working in opposite directions. The KOF Globalization Index synthesizes economic, political, and social aspects of globalization and is included in our empirical analysis to capture the overall magnitude and sign of the impact of globalization.

- *Technology and Total Factor Productivity*
 - **Investment-specific technological progress.** According to the literature, technological progress, particularly when embedded in investments, can influence pollution emissions through two main mechanisms. On one hand, it can lead to emissions reduction by promoting cleaner and more efficient production processes and energy sources (e.g., Greaker and Hagem 2014, Li and Wang 2017). Conversely, technological innovation may result in emissions increases if it fuels higher industrial activity and energy demand (Wang et al. 2019, Li et al. 2021). Thus, the direction of impact depends on the nature and adoption of these technologies within the economic system. We assess the contribution of this factor in shaping emissions dynamics using a proxy of investment-specific technological progress, constructed as the ratio of the price level of capital formation to the price level of household consumption (Gravina and Lanzafame 2021).¹
 - **Total factor productivity level.** Total factor productivity (TFP) can affect pollutant emissions through various mechanisms. An increase in TFP often results in a more efficient use of resources, reducing emissions per unit of output and leading to lower pollution levels (e.g., Cole et al. 2005, Marin 2013). But rapid TFP growth, especially in developing economies, can stimulate economic activity, potentially increasing overall emissions (Yao and Tang 2020). Thus, the net effect of TFP on emissions depends on the relative strength of these mechanisms.

¹ The relative price of investment goods can be considered as a good proxy for investment-specific technological progress, as it captures changes in technology that affect the cost and productivity of capital goods. As this relative price decreases, it suggests improvements in investment-specific technology, leading to increased investment and, ultimately, contributing to economic growth (e.g., Greenwood et al. 1997, 2000).

- *Environmental Institutions and Policies*

Environmental institutions and policies can contribute to reducing polluting emissions associated with economic activity (e.g., Tang et al. 2014, Khan et al. 2021, Puertas and Marti 2021). These usually set regulatory frameworks, provide incentives for cleaner technologies, determine penalties for environmental violations, and create a conducive environment for sustainable practices. We use two indicators to measure the impact of such institutions and policies:

- **Environmental ministry establishment.** It is represented by a dummy variable, equal to 1 from the year a country introduced the dicastery and 0 otherwise.²
- **The number of international environmental agreements ratified per year.** International environmental agreements (IEAs) establish stringent environmental regulations, encouraging member states to adopt measures that reduce emissions and enhance pollution control. In addition, participation in IEAs facilitates the exchange of cleaner technologies among member states, promoting innovation and the adoption of more sustainable practices. Relatedly, ratifying IEAs can stimulate market demand for eco-friendly products and services, incentivizing investment in cleaner technologies and practices (e.g., Vollenweider 2013, Oikonomou et al. 2021).

- *Natural Characteristics*

Forest land (percentage of land area). Forest land, through mechanisms like CO₂ absorption, soil conservation, support for biodiversity, and sustainable management practices, significantly influences pollutant emissions. This impact extends to reducing GHG emissions, preventing deforestation-related carbon release, maintaining healthy ecosystems, fostering sustainable industrial practices, and contributing to air quality through the release of volatile organic compounds (Pan et al. 2011).

- *Economic Variables*

- **Tertiary education.** The literature typically suggests that individuals with

² To harmonize it with other variables considered in our analysis, we followed Aklın and Urpelainen's (2014) procedure to extend the time-series coverage of this indicator from 2010 to 2015.

more education tend to be more environmentally conscious and aware of the consequences of pollution. They are more likely to support and adopt sustainable practices, both in their personal lives and through their influence on policy decisions (e.g., Goetz et al. 1998, Graff Zivin and Neidell 2013). Moreover, education can lead to innovation and the development of cleaner technologies, further contributing to emission reduction (Blackman and Kildegaard 2010).

- **Foreign direct investment net inflows.** Foreign direct investment (FDI) inflows can have contrasting effects on polluting emissions, depending on several factors. In fact, the empirical literature typically suggests that FDI can influence emissions in both directions. FDI may lead to an increase in emissions when foreign investors introduce polluting industries or technologies in the host country, prioritizing economic gains over environmental concerns (e.g., De Pascale et al. 2020, Opoku and Boachie 2020). Conversely, FDI can contribute to reducing emissions if associated with the adoption of cleaner technologies, managerial practices, and environmental standards. Foreign investors tend to promote energy efficiency, cleaner production processes, and sustainable practices if incentivized to meet international standards and to enhance their corporate image (e.g., Solarin and Al-Mulali 2018, Rafique et al. 2020).
- **Gini index before taxes.** Income inequality can impact polluting emissions through various transmission mechanisms—Berthe and Elie (2015) have a full review. In economies with significant income inequality, the wealthiest individuals often exhibit higher consumption patterns, which can drive up emissions. These individuals may prefer energy-intensive products and lifestyles, all of which contribute to greater carbon footprints (e.g., Boyce 1994, Pickett and Wilkinson 2010). Additionally, they might possess greater political influence, potentially advocating for pro-business policies that prioritize economic growth over environmental concerns, possibly resulting in higher emissions (e.g., Borghesi 2006). On the flip side, income inequality can spur shifts in economic structures. In some cases, societies with high income inequality might transition toward cleaner, service-oriented economies as rich individuals may be more inclined to adopt sustainable behaviors. This shift may result from a desire to reduce pollution levels in

urban areas, where the wealth gap is most noticeable. This could involve investing in renewable energy sources, adopting energy-efficient technologies, and advocating for eco-friendly policies (Scruggs 1998, Heenrik et al. 2001).

- **International tourism.** International tourism can impact pollution emissions via various channels. Firstly, it often involves long-haul flights and extensive use of transportation, especially by air. These modes of travel are associated with significant carbon emissions, contributing to pollution (Lenzen et al. 2018). Secondly, the hospitality industry, including hotels and resorts, consumes substantial energy and resources, leading to increased emissions. Furthermore, large-scale tourist accommodations, particularly in environmentally sensitive areas, can strain local ecosystems and exacerbate pollution problems (Koçak et al. 2020).
- **Labor productivity.** Labor productivity, measured as the amount of output produced per unit of labor input, can also influence emissions in various ways. When labor productivity increases, firms can produce more goods or services with the same amount of labor, boosting economic growth. Increased economic activity, if not accompanied by improvements in environmental efficiency, can potentially result in higher emissions due to higher energy consumption (e.g., Simionescu et al. 2021). On the other hand, higher labor productivity can also drive technological advancements and process innovations. Firms may invest in cleaner and more efficient technologies to maximize their productivity gains. These cleaner technologies often require less energy and generate fewer emissions per unit of output, which can contribute to reduced emissions (Mazzanti and Zoboli 2009).
- **Inflation.** Inflation can affect energy consumption patterns. When prices rise, individuals and businesses may reduce their energy use to control costs, which can lead to lower emissions if energy production is carbon-intensive (e.g., Setyadharma et al. 2021). The level of inflation also matters. Low inflation may provide more stable economic conditions, facilitating investment in cleaner technologies. Conversely, due to uncertainty and higher costs, high inflation may lead firms to delay or reduce investments in environmental innovations and cleaner technologies, thus prioritizing short-

term economic performance over long-term environmental concerns (Ahmad et al. 2021).

- **Imports, exports, and overall trade of goods and services.** Trade can influence emissions through various channels. Increased trade can lead to higher production and transportation activities, which can result in higher emissions. When countries engage in more trade, they often produce more goods for export and transport more raw materials and finished products, potentially increasing their carbon footprint (Wang and Ang 2018). The types of goods a country imports and exports can also influence emissions. If a country specializes in producing and exporting goods with a low carbon footprint (e.g., technology or services) while importing carbon-intensive goods (e.g., heavy machinery), its net emissions may decrease (Felbermayr et al. 2020, Misch and Wingender 2021). Trade can also facilitate the transfer of cleaner and more efficient technologies across borders. When countries import advanced technologies or cleaner production methods, it can lead to reduced emissions per unit of output (e.g., Herrerias et al. 2013). Economies with stricter environmental regulations might “outsource” more emissions by importing carbon-intensive goods produced in countries with lax regulations (Cole 2004). Conversely, countries with stringent regulations may reduce emissions by exporting cleaner products (Peters and Hertwich 2008). To assess whether, and to what extent, the different dimensions of international trade may impact polluting emissions, the analysis separately considers imports and exports as shares of GDP, as well as a total trade measure, given by the sum of the first two.
- **Private credit.** Financial development, typically measured as the ratio of banking sector credit to GDP, can also impact environmental emissions. A well-developed financial sector can allocate capital more efficiently, directing funds toward investments in cleaner and more sustainable technologies. This can lead to reduced emissions, as industries adopt environmentally friendly practices (e.g., Lv and Li 2021). Additionally, financial institutions can encourage compliance with environmental regulations by incorporating environmental, social, and governance criteria into lending and investment decisions. This can incentivize companies to

reduce their emissions to maintain access to capital (Li et al. 2020, Shi et al. 2022). On the other hand, by providing easier access to credit and investment capital, a more developed financial sector can also boost high-emitting industrial activities, particularly in the early stages of development (e.g., Sadorsky 2011).

- *Institutional Quality Variables*

Institutions play a pivotal role in shaping a nation's approach to environmental sustainability and, consequently, its impact on emissions. Government bodies, regulatory agencies, legal frameworks, and governance structures collectively influence environmental policy and enforcement. Strong and capable institutions often contribute positively to environmental preservation by formulating and enforcing regulations, promoting sustainable practices, and fostering innovation in cleaner technologies (e.g., Adams and Klobodu 2017, Bhattacharya et al. 2017). Conversely, weaker or corrupt institutions may struggle to enforce regulations, creating an environment where businesses can evade environmental standards, consequently leading to higher emissions (Arminen and Menegaki 2019). In our empirical analysis, we consider the following indicators of institutional quality:

- **Corruption index.** The index ranges from 0 to 6, where 0 represents the highest level of corruption. Corruption within institutions can have significant implications for polluting emissions. For instance, corrupt practices can undermine the enforcement of environmental regulations. When businesses can bribe officials or evade penalties, they are less motivated to reduce emissions. As a result, pollution levels may increase in regions where corruption is prevalent (e.g., Balsalobre-Lorente et al. 2019). Corruption can lead to the misallocation of resources, including environmental funds. Instead of investments in emission-reduction technologies or sustainable practices, funds may be diverted for personal gain. This misallocation can hinder progress in emissions reduction (Hao et al. 2020). Corrupt practices can enable industries to capture the policymaking process. This means that policies may be formulated in favor of polluting industries rather than in the interest of environmental protection. Consequently, emissions may rise due to lax regulations (Fredriksson and Svensson 2003). More generally, as pointed out by Welsch (2004) and Cole

(2007), corruption can influence pollutant emissions through direct and indirect effects. Typically, the direct effects of corruption are associated with higher emissions. Indirect effects, working through a reduction in per-capita income, may lead to lower pollutant emissions. The net effect remains ambiguous a priori and represents an empirical question.

- **Polity score index.** This indicator quantifies the spectrum of regime authority on a 21-point scale that spans from –10 (representing hereditary monarchies) to +10 (denoting consolidated democracies). Countries with more democratic institutions are usually associated with reduced pollutant emissions. Democratic societies tend to have greater transparency and accountability in government decision-making, which can lead to more stringent environmental regulations and better enforcement of existing laws (e.g., Li and Reuveny 2006). Furthermore, democratic governments are often responsive to public concerns on environmental issues and may enact policies to address them, such as promoting renewable energy sources and regulating emissions (Bernauer 2013). Finally, democratic institutions can foster a greater sense of environmental stewardship among citizens, leading to voluntary efforts to reduce emissions (Neumayer 2002). Conversely, authoritarian regimes may be associated with higher emissions due to a focus on economic growth, limited environmental regulations, reduced accountability, and restricted public engagement in environmental matters. These factors can hinder efforts to mitigate emissions effectively (Shultz and Stone 1994).
- **Political polarization index.** This index ranges from 0 to 2, where 0 represents the absence of polarization, indicating that the chief executive's party government holds an absolute political majority in the legislature. Political polarization, characterized by stark ideological divisions among political parties and the electorate, can have mixed effects on polluting emissions. For instance, political polarization can lead to increased economic uncertainty, which may result in lower long-term investments—including those with potential environmental impacts. In turn, this may lead to lower levels of emissions (Azzimonti 2011). In cases where political polarization coexists with heightened public awareness and sustained pressure from environmental advocacy groups, political parties may be

compelled to enact more stringent environmental policies. The fear of losing electoral support can drive parties to promote robust environmental regulations (Fisher et al. 2013). International pressure and global climate agreements can compel political parties to collaborate in addressing pollution emissions. In these cases, political polarization may be superseded by the urgent need to adhere to international commitments (Garmann 2014). On the other hand, high levels of political polarization often result in policy gridlock, making it difficult to reach consensus on robust and consistent environmental policies. This can hinder progress in addressing pollution emissions (Coffey and Joseph 2013). Polarized political environments can foster a focus on short-term gains and immediate economic concerns over long-term environmental considerations. This could lead to policies that prioritize economic growth at the expense of emissions reduction (Di Bartolomeo et al. 2020).

A2. Additional Tables and Figures

Table A2.1: Economies Included in the Analysis

Advanced economies
Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Greece, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Republic of Korea, Singapore, Slovak Republic, Slovenia, Spain, Sweden, United Kingdom, United States
Emerging economies
Armenia, Bahrain, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Egypt, Gabon, Guatemala, Honduras, Hungary, India, Indonesia, Iran, Jamaica, Jordan, Kazakhstan, Kenya, Malaysia, Mexico, Mongolia, Morocco, Mozambique, Namibia, Nicaragua, Niger, Panama, Paraguay, People's Republic of China (PRC), Peru, Philippines, Poland, Russian Federation, Saudi Arabia, Senegal, South Africa, Sri Lanka, Sudan, Tanzania, Thailand, Togo, Tunisia, Türkiye, Ukraine, Uruguay, Venezuela, Zambia

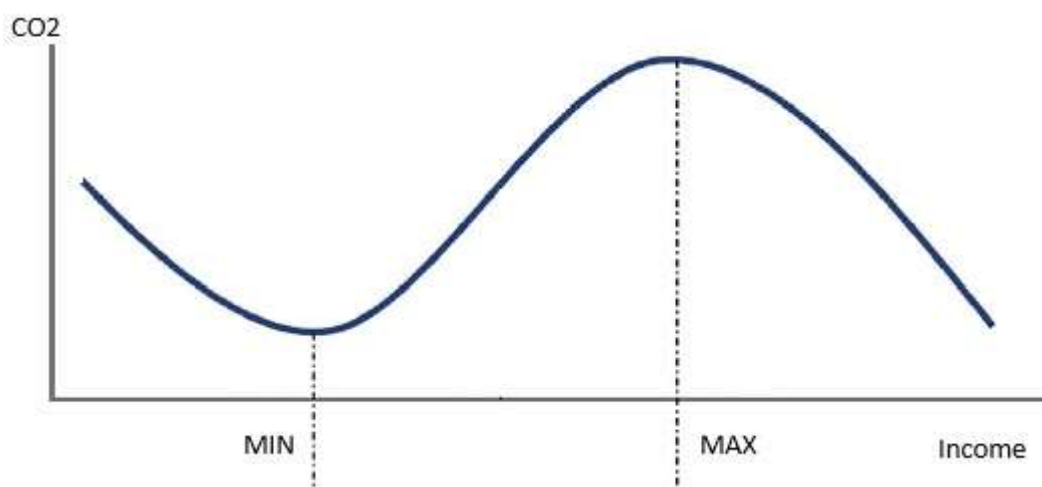
Notes: Economy groups are defined following the International Monetary Fund's World Economic Outlook (WEO) classification (<https://www.imf.org/en/Publications/WEO/weo-database/2023/April/groups-and-aggregates>). The "Emerging economies" group includes economies in the WEO's "Emerging Market and Developing Economies" group.
Source: Authors.

Table A2.2: Alternative Dependent Variables' Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
BC emissions, kilo tons per-capita (log)	1216	-14.418	0.567	-17.417	-12.977
N ₂ O emissions, kilo tons per-capita (log)	1216	-13.355	0.744	-15.221	-11.51
CH ₄ emissions, kilo tons per-capita (log)	1216	-9.762	0.784	-11.277	-6.66
NH ₃ emissions, kilo tons per-capita (log)	1216	-11.743	0.723	-14.348	-9.914
CO emissions, kilo tons per-capita (log)	1216	-9.417	0.622	-11.731	-7.972
NMVOC emissions, kilo tons per-capita (log)	1216	-10.745	0.467	-12.058	-9.207
NO _x emissions, kilo tons per-capita (log)	1216	-11.01	0.786	-13.309	-9.095
OC emissions, kilo tons per-capita (log)	1216	-13.779	0.802	-16.731	-12.216
PM ₁₀ emissions, kilo tons per-capita (log)	1216	-12.023	0.633	-14.299	-10.283
PM ₂₅ emissions, kilo tons per-capita (log)	1216	-12.518	0.604	-14.902	-10.92
SO ₂ emissions, kilo tons per-capita (log)	1216	-11.367	1.072	-14.931	-9.018
Ecological footprint of consumption, gha per-capita (log)	1203	1.216	0.637	-0.242	2.875
Ecological footprint of production, gha per-capita (log)	1203	1.157	0.728	-0.376	2.669
Carbon footprint of consumption, gha per-capita (log)	899	0.436	1.144	-2.966	2.567
Carbon footprint of production, gha per-capita (log)	899	0.208	1.292	-3.67	2.228

BC = black carbon, CH₄ = methane, CO = carbon monoxide, gha = global hectare, N₂O = nitrous oxide, NH₃ = ammonia, NMVOC = non-methane volatile organic compounds, NO_x = nitrogen oxides, OC = organic carbon, 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, SO₂ = sulfur dioxide.

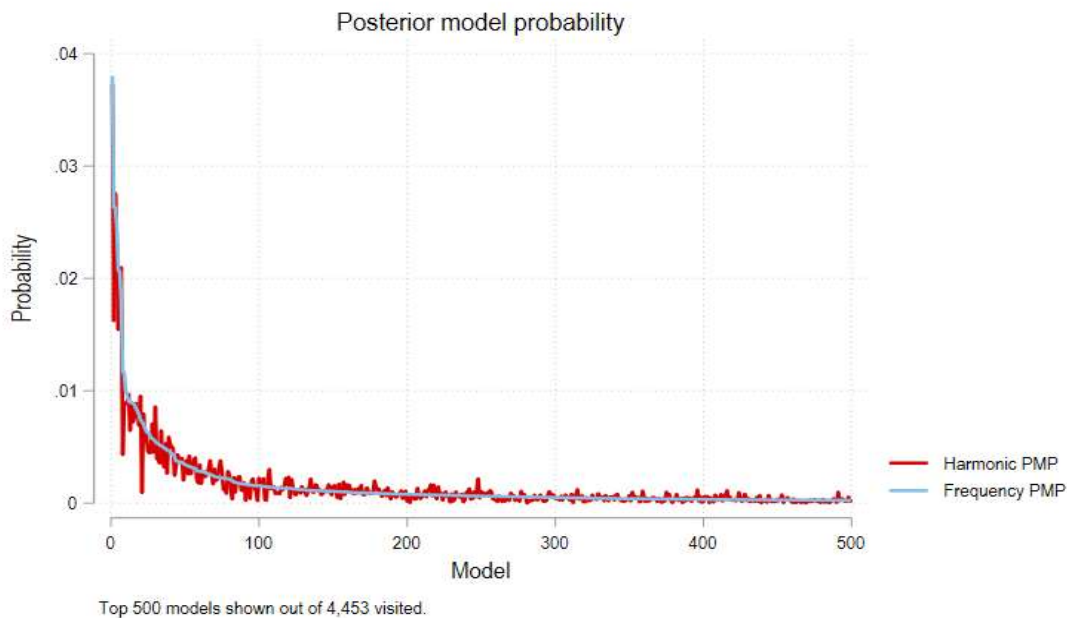
Source: Authors' calculations.

Figure A2.1: Inverted N-shaped Environmental Kuznets Curve

Source: Authors.

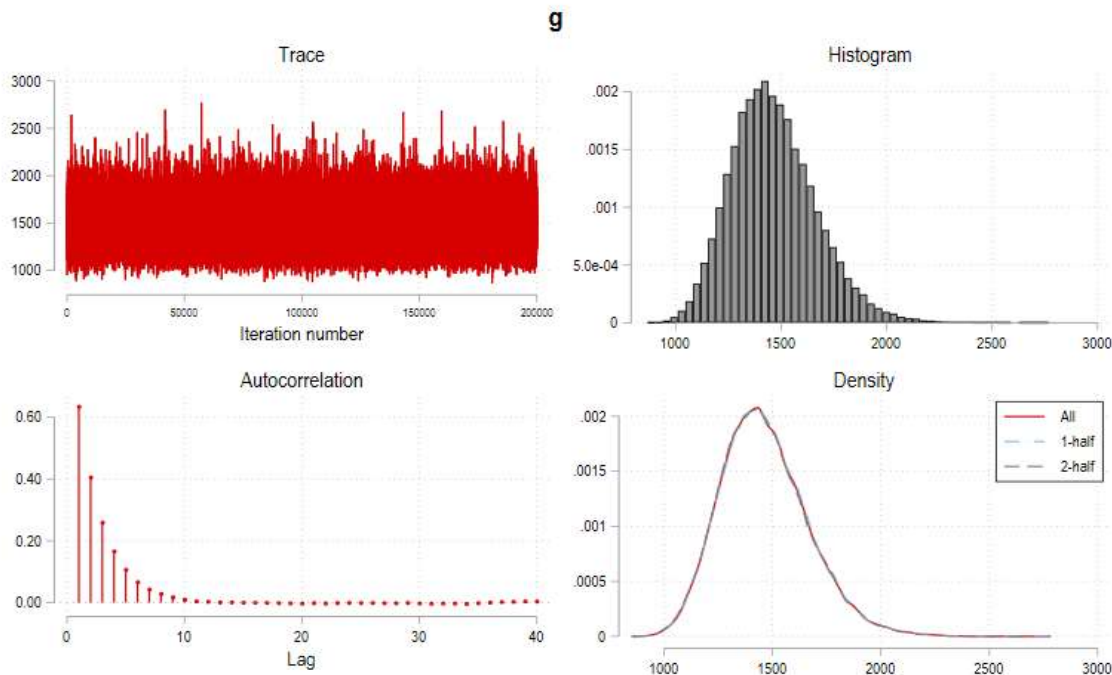
A3. Diagnostics

Figure A3.1: Check for Model Sampling Convergence



PMP = Posterior model probability.
Source: Authors' calculations.

Figure A3.2: Diagnostic Plot for the g Parameter



Source: Authors' calculations.

A4. Sensitivity Analysis

Table A4.1: Robustness Checks—Two-Stage Least Squares—Bayesian Model Averaging Regression Results

Dependent Variable:	CO ₂ emissions per-capita (log)					
	(1) Fixed <i>g</i> -prior			(2) Random <i>g</i> -prior		
Predictor	PIP	Mean	Std. Dev.	PIP	Mean	Std. Dev.
Real GDP per-capita (log) *	1	-6.787	1.499	1	-6.761	1.474
Real GDP per-capita squared (log) *	1	0.799	0.165	1	0.796	0.163
Real GDP per-capita cubed (log) *	1	-0.030	0.006	1	-0.299	0.006
Fossil fuel energy consumption (% of total)	1	0.013	0.001	1	0.013	0.001
International tourism, number of arrivals per population (log)	1	0.090	0.013	1	0.090	0.012
Urban population (% of total population)	1	0.011	0.002	1	0.011	0.002
Forest Land (% of Land Area)	1	-0.015	0.001	1	-0.015	0.003
Services, value added (% of GDP)	1	-0.009	0.001	1	-0.009	0.001
KOF Globalization Index	0.999	0.009	0.002	0.998	0.009	0.002
Agriculture, value added (% of GDP)	0.997	-0.009	0.002	0.997	-0.009	0.002
Political Polarization Index	0.996	-0.023	0.006	0.994	-0.023	0.006
Corruption Index	0.855	0.018	0.009	0.853	0.018	0.009
Gini Index (log)	0.546	0.191	0.198	0.535	0.179	0.197
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		0.999			0.991	
Number of observations		1,190			1,190	
Number of predictors		133			133	
Number of models		2273			1900	
Mean model size		116.466			116.411	
Existence condition of min & max		0.028			0.028	
Min (PPP adjusted 2017 international \$)		1,110.96			1,107.78	
Max (PPP adjusted 2017 international \$)		47,387.59			47,516.59	

2SLS = two-stage least squares, BMA = Bayesian Model Averaging, CO₂ = carbon dioxide, GDP = gross domestic product, IEA = international environmental agreement, MC3 = MCMC Model Composition, MCMC = Markov chain Monte Carlo, OLS = ordinary least squares, PPP = purchasing power parity, Std. Dev. = standard deviation, 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, while the remaining predictors are lagged one period.

Source: Authors' calculations.

Table A4.2: Two-Stage 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) ^	-4.584* (2.540)	-6.201*** (2.149)	-6.237** (2.147)	-6.201*** (2.149)	-4.584* (2.540)
Real GDP per-capita squared (log) ^	0.656** (0.272)	0.744*** (0.235)	0.746*** (0.235)	0.744*** (0.235)	0.656** (0.272)
Real GDP per-capita cubed (log) ^	-0.028*** (0.009)	-0.028*** (0.009)	-0.023*** (0.009)	-0.028*** (0.009)	-0.028*** (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	107	132	128	132	107
Existence condition of min & max	0.049	0.026	0.026	0.026	0.049
Min (PPP adjusted 2017 international \$)	185.62	940.55	973.46	940.55	185.62
Max (PPP adjusted 2017 international \$)	38,159.62	41,797.82	41,885.73	41,797.82	38,159.62

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

Notes: ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively. Robust standard errors in parentheses. Variables marked with ^ represent the fitted values obtained from a first stage OLS regression on our set of instruments.

Source: Authors' calculations.

Table A4.3: Robustness Checks: Two-Stage 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) ^	-7.275*** (2.460)	-8.283*** (2.270)	-5.569** (2.365)	-8.283*** (2.270)	-7.275*** (2.460)
Real GDP per-capita squared (log) ^	0.947*** (0.258)	0.972*** (0.237)	0.685*** (0.244)	0.972*** (0.237)	0.947*** (0.258)
Real GDP per-capita cubed (log) ^	-0.038*** (0.009)	-0.036*** (0.009)	-0.026*** (0.009)	-0.036*** (0.009)	-0.038*** (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	1,190	1,190	1,190	1,190	1,190
Number of selected controls	106	129	117	129	106
Existence condition of min & max	0.069	0.039	0.028	0.039	0.069
Min (PPP adjusted 2017 international \$)	409.50	1,200.24	682.17	1,200.24	409.50
Max (PPP adjusted 2017 international \$)	40,617.19	43,141.42	47,720.58	43,141.42	40,617.19

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

Notes: ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively. Robust standard errors in parentheses. Variables marked with ^ represent the fitted values obtained from a first stage OLS regression on our set of instruments, while the remaining predictors are lagged one period.

Source: Authors' calculations.