

Article

The Relationship Between Economic Activity and CO₂ Emissions: Is There a GDP Growth Consistent with No Growth in CO₂ Emissions?

Jaime Marquez *, Jiayi Ding and Soobin Lee

School of Advanced International Studies, Johns Hopkins University, 1740 Massachusetts Ave. N.W., Washington, DC 20036, USA; jding19@jhu.edu (J.D.); slee507@jhu.edu (S.L.)

* Correspondence: jmarque1@jhu.edu

Abstract

This paper offers estimates of the per-capita GDP growth trajectories consistent with zero growth in per-capita CO₂ emissions using Ordinary Least Squares (OLS) and Instrumental Variables (IVs). The focus is on six developed economies (Canada, Germany, Italy, Japan, Singapore, and the United States) and six emerging economies (China, India, Indonesia, Malaysia, Mexico, and South Korea). To this end, we postulate a model linking the growth of per-capita CO₂ emissions to per-capita GDP growth and technology. Given the parameter estimates, we use the model to estimate the growth rate of per-capita GDP that is consistent with zero growth in CO₂ emissions.

Keywords: CO₂ emissions; environmental kuznets curve; China; sustainable growth path; cross-country analysis; decarbonization

1. Introduction

Over the past four decades, global economic expansion has been accompanied by a sustained rise in CO₂ emissions, intensifying concerns about the long-term compatibility of growth and environmental sustainability. The accumulation of atmospheric CO₂ has accelerated global warming and generated substantial economic losses. [Kahn et al. \(2021\)](#) estimate that unmitigated climate change could reduce global GDP by up to 23 percent by 2100 relative to a no-warming baseline. Against this backdrop, a simple question has received insufficient direct empirical attention: what rate of per-capita GDP growth is consistent with zero growth in per-capita CO₂ emissions? This paper offers a country-specific, time-varying empirical answer for twelve selected economies.

The question is related to two well-established lines of theories: the Environmental Kuznets Curve (EKC) literature, which asks whether emissions eventually decline as income rises ([Grossman & Krueger, 1991](#)), and the decoupling literature, which documents whether absolute reductions in aggregate emissions have been achieved alongside positive growth ([International Energy Agency, 2024](#)). Our contribution reframes the question in terms of a GDP growth rate compatible with zero growth in per-capita CO₂ emissions, that is, the stability of emissions per capita. Rather than asking whether emissions have fallen, we examine at what speed an economy can grow while keeping per-capita CO₂ emissions constant, that is, zero growth in per-capita emissions.

We examine six advanced economies (Canada, Germany, Italy, Japan, Singapore, and the United States) and six emerging economies (China, India, Indonesia, Malaysia, Mexico,



Academic Editor: Luis Alberiko Gil-Alana

Received: 12 March 2026

Revised: 4 June 2026

Accepted: 22 June 2026

Published: 2 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](#) license.

and South Korea), together representing approximately 62 percent of the world's GDP ([International Monetary Fund, 2025b](#)). The analysis uses annual per-capita data from 1981 to 2022: a span that encompasses the acceleration of globalization, large-scale industrialization in Asia, the post-2008 recovery, and the emergence of explicit decarbonization commitments. Country-specific time series regressions are estimated, and, in the end, we complement the country-level results with a fixed-effects panel specification that imposes common slope coefficients to compare the selected countries with world development.

The empirical model relates per-capita CO₂ emissions growth to per-capita GDP growth and a linear time trend, which proxies for the autonomous, country-specific pace of technological progress. We caution that this reduced-form trend cannot uniquely identify specific mechanisms. We estimate the model using Ordinary Least Squares (OLS) and Instrumental Variables (IVs), using the growth rate of trade as a share of GDP as the instrument for GDP growth. The IV strategy follows a tradition established by [Basu and McLeod \(1991\)](#) and formalized in the trade-and-environment literature by [Antweiler et al. \(2001\)](#), who decomposed the trade–environment nexus into scale, composition, and technique effects. The instrument is motivated by the insight that trade-induced demand shocks affect domestic output through channels, export demand, import competition, and terms-of-trade movements, which are plausibly orthogonal to domestic carbon policy. We acknowledge the limitations of this instrument, report first-stage F-statistics to assess relevance, where the instrument is weak (first-stage $F < 10$; [Staiger & Stock, 1997](#)), and interpret IV results as indicative rather than causal.

Given the parameter estimates, we define the sustainable per-capita GDP growth rate (Y_s) as the growth rate at which the growth of CO₂ emissions per capita equals zero. Because the time trend enters the model with a country-specific coefficient, Y_s varies across countries and over time. The 95% confidence intervals for Y_s are computed via the delta method¹ to quantify estimation uncertainty. The sustainable growth gap is then defined as the difference between actual and sustainable per-capita GDP growth; a positive gap indicates growth in excess of the zero emissions growth benchmark.

This paper makes five contributions. First, we derive and quantify a time-varying, country-specific sustainable growth rate, translating estimated emissions output elasticities into a concrete policy benchmark. Second, we apply IV estimation with a trade-based instrument across a heterogeneous twelve-country panel, explicitly reporting the first-stage diagnostics called for by the literature ([Acheampong, 2018](#); [Wang et al., 2022](#)). Third, we provide 95% confidence intervals for all derived quantities, addressing the uncertainty-quantification gap. Fourth, we document that the choice of estimation method matters substantially for emerging economies but not for advanced ones, suggesting that the endogeneity of trade-led growth is a relevant concern for carbon accounting in industrializing nations. Fifth, we use panel-data estimation for these countries to recognize that CO₂ is a global phenomenon with implications for global growth.

The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature organized around four thematic blocks. Section 3 describes the data and variable construction. Section 4 outlines the empirical strategy, including econometric diagnostics and robustness checks. Section 5 presents the results. Section 6 discusses policy implications and limitations.

2. Literature Review

2.1. The EKC and the Decoupling Debate

The relationship between income and environmental quality has been studied intensively since [Grossman and Krueger \(1991\)](#) documented an inverted U pattern between per-capita income and several air pollutants across a cross-section of countries; a pattern

later termed the Environmental Kuznets Curve (EKC) by [Panayotou \(1993\)](#). The EKC hypothesis posits that pollution rises with income at low development levels, peaks at an intermediate income threshold, and subsequently declines as countries grow wealthier and shift toward cleaner technologies and service-oriented economic structures. [Stern \(2004\)](#) provides a comprehensive survey and critique, noting that the evidence for the EKC is sensitive to functional form, sample composition, and the pollutant considered: results are more robust for local pollutants such as sulfur dioxide than for global pollutants such as CO₂, where the turning point, if it exists, typically lies at income levels far above those observed in most developing countries.

A related but distinct question concerns absolute decoupling: whether aggregate CO₂ emissions can decline alongside positive GDP growth. The [International Energy Agency \(2024\)](#) documents that the statistical relationship between GDP growth and CO₂ has weakened appreciably in advanced economies over recent decades, with several recording emissions reductions during periods of positive growth. However, these aggregate patterns mask substantial heterogeneity: emissions gains in developed economies have been partly offset by continued emissions growth in industrializing nations, where energy-intensive manufacturing remains the dominant growth driver. Our paper contributes to this debate by deriving, for each country individually, the GDP growth rate at which per-capita CO₂ growth equals zero.

2.2. Theoretical Foundations: Growth Models with Emissions

The literature offers two canonical frameworks. In models of exogenous growth (e.g., the Solow–Swan model, augmented with pollution as a byproduct of output), emissions are proportional to GDP through a fixed emissions intensity, which declines exogenously over time as cleaner technologies diffuse. In models of endogenous growth with emissions and abatement, pioneered by [Acemoglu et al. \(2012\)](#) and extended by [Aghion et al. \(2016\)](#), the technological progress is itself influenced by the direction of innovation, which depends on the relative profitability of each type of R&D and on the stringency of carbon pricing policy. In these frameworks, the long-term emissions–growth relationship is an equilibrium outcome of innovation incentives rather than a structural constant, and the sustainable growth rate is endogenously determined by the tax-and-subsidy regime for clean technology adoption. Our empirical specification is consistent with the reduced form of both frameworks: CO₂ emissions growth is linearly related to GDP growth, and a time trend captures the combined effect of exogenous technological progress and slow-moving structural change in the energy mix, among other considerations that are not explicitly controlled empirically.

The Kaya identity ([Kaya, 1990](#)) provides a useful accounting framework for decomposing changes in CO₂ emissions into four multiplicative components: population, per-capita income, energy intensity of output (energy / GDP), and carbon intensity of energy (CO₂ / energy). This identity implies that the elasticity of emissions with respect to GDP growth is not a structural parameter but the outcome of the interplay between scale effects (rising output) and technique effects (improving energy and carbon intensity). Emissions decline only if improvements in energy or carbon intensity outpace the scale effect of growth.

The empirical literature largely applies the Kaya decomposition to explain historical emissions trends. [Ang \(2004\)](#) surveys index decomposition methods and finds that energy intensity improvements have been the dominant source of emissions reductions in most OECD countries, while carbon intensity has declined more slowly and unevenly. [Su and Ang \(2012\)](#) extend the analysis to developing countries and find that the scale effect of rapid GDP growth has dominated technical effects in emerging Asian economies, consistent with our finding of significantly positive sustainable growth gaps in China, India, Indonesia,

Malaysia, and South Korea. Our regression-based approach complements the Kaya decomposition: rather than attributing observed emissions changes to their sources *ex post*, we estimate that the GDP growth rate is prospectively compatible with emissions stability, given the estimated pace of technological improvement captured by the time trend.

2.3. Endogeneity, Trade, and Instrumental Variable Strategies

A central methodological challenge in the emissions–growth literature is the potential endogeneity of GDP growth with respect to CO₂ emissions. [Acheampong \(2018\)](#) provides panel Granger-causality evidence that the causal relationship between emissions, economic growth, and energy consumption runs in multiple directions: higher emissions impose costs on health, agricultural productivity, and infrastructure that feed back into lower growth, while faster growth stimulates energy demand and emissions. This bidirectional causality implies that OLS estimates of the emissions–income elasticity are generally biased, most likely downward if emissions impose negative productivity externalities, and that any sustainability benchmark derived from OLS estimates may be misleading.

To isolate exogenous variation in per-capita GDP growth, we follow a tradition of using trade exposure as an instrument. [Basu and McLeod \(1991\)](#) established that terms-of-trade fluctuations generate income shocks in developing economies through export revenue channels that are largely independent of domestic environmental policy. [Frankel and Romer \(1999\)](#) used a geography-based instrument for trade openness to identify the causal effect of trade on income, establishing the methodological precedent for trade-based IV in growth regressions. [Antweiler et al. \(2001\)](#) formalized the decomposition of trade effects on emissions into scale effects (more output and more emissions), composition effects (where trade changes the sectoral mix of production), and technique effects (where trade imports cleaner technologies and management practices). Their analysis implies that the net effect of trade on emissions is theoretically ambiguous and depends on whether trade expands carbon-intensive or clean sectors—a source of heterogeneity we document across our sample.

The exclusion restriction requires that trade growth affects CO₂ emissions only through its effect on GDP growth. In the first-stage regressions, we report the F-statistic for instrument relevance following [Staiger and Stock \(1997\)](#), who establish the conventional threshold of $F > 10$ for a strong instrument. Countries for which the first-stage F-statistic falls below 10 are identified in the results as having weak instruments, and we interpret IV estimates for these countries as indicative rather than causal. [Wang et al. \(2022\)](#) applied a comparable IV strategy to study the effect of growth targets on Chinese emissions, confirming that OLS estimates of the emissions–growth relationship are systematically biased and that causal estimates require an instrument that generates exogenous variation in output.

2.4. Panel Data, Country Heterogeneity, and Estimation

Pooled OLS imposes common slope coefficients across countries, which is efficient under homogeneity but inconsistent if slopes differ ([Pesaran & Smith, 1995](#)). The fixed-effects (within) estimator allows country-specific intercepts but still imposes slope homogeneity. The mean group (MG) estimator of [Pesaran and Smith \(1995\)](#) averages country-specific coefficients and is consistent even under slope heterogeneity, at the cost of efficiency. The pooled mean group (PMG) estimator of [Pesaran et al. \(1999\)](#) imposes long-term slope homogeneity while allowing short-run dynamics to vary, providing a middle ground.

Given the small number of time periods per country (approximately 42 years) and the substantial *a priori* heterogeneity in industrial structure and development stage, we estimate country-specific regressions as our primary specification. This approach is consistent with the mean group estimator and allows us to derive country-specific sustainable

growth rates and growth gaps without imposing cross-country restrictions that the data may not support. We complement this with a fixed-effects panel regression that imposes slope homogeneity and provides an efficiency comparison. The country-specific time series regressions rely on asymptotic approximations in T , which are standard in the macro-panels literature, while the panel estimator relies on both N and T asymptotics.

Our paper addresses a different, more operationally specific question: given the estimated structural relationship between emissions and growth, what is the maximum GDP growth rate consistent with emissions stability, and how far has actual growth deviated from that threshold? This reframing turns an econometric estimate into a forward-looking policy benchmark and allows a formal, country-by-country assessment of the gap between actual and sustainable growth trajectories. Our work is also distinguished by its explicit comparison of OLS and IV estimates of the sustainable gap. The finding that IV estimates of the gap are systematically larger than OLS estimates for emerging economies is consistent with, though not definitive evidence for, the possibility that trade-driven growth carries a higher carbon intensity than average growth. The differences between OLS and IV estimates may also reflect weak instrument bias or exclusion restriction violations, and these mechanisms cannot be cleanly disentangled within the current framework. This result is consistent with the composition-effect mechanism of Antweiler et al. (2001): in emerging economies, trade expansion tends to shift production toward energy-intensive manufacturing for export, raising the carbon content of growth above what OLS, with all sources of income variation, would suggest.

3. Data

3.1. Variable Construction

The dataset comprises annual observations for 12 countries over the period 1980 to 2022 (Figure 1). Three variables are used at the per-capita level to ensure cross-country comparability. Per-capita GDP is measured in constant purchasing-power-parity (PPP) US dollars and is sourced from the IMF World Economic Outlook database (International Monetary Fund, 2025a). Per-capita CO₂ emissions (metric tons per person) are drawn from Our World in Data (n.d.-a), which aggregates production-based CO₂ estimates from the Global Carbon Project. Trade openness, the instrument for GDP growth, is measured as trade as a share of GDP (exports plus imports divided by GDP), sourced from Our World in Data (n.d.-b). All three series are converted to annual growth rates: $[(x_t/x_{t-1}) - 1] \times 100$ to produce GDP_G, CO₂_G, and Trade_G respectively.

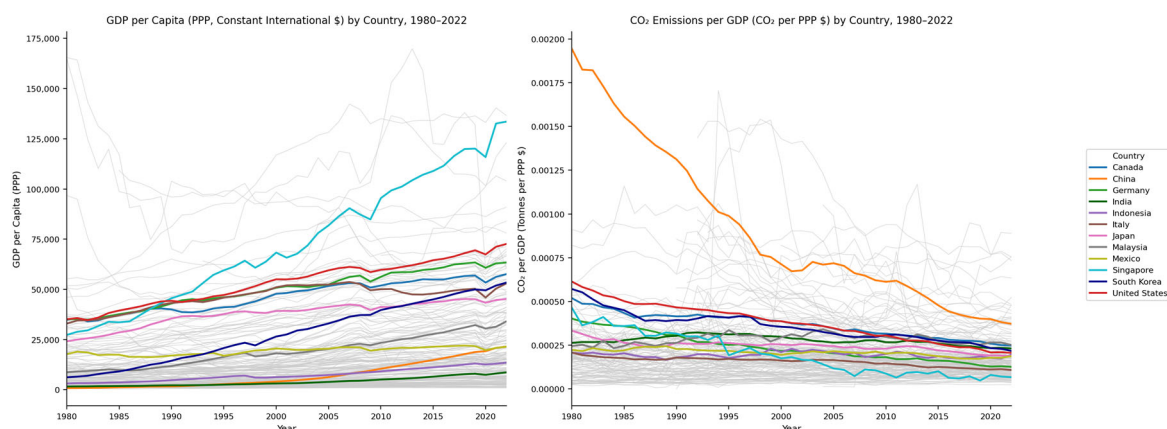


Figure 1. GDP per capita, ppp (constant\$) and CO₂ emissions per GDP by country in time series.

3.2. Descriptive Statistics

Table 1 reports summary statistics for the level and growth-rate variables. The twelve countries span a wide range of income levels: GDP per capita ranges from a mean of USD 3951 (India) to USD 73,267 (Singapore), with a total sample mean of USD 32,717 masking substantial within-sample heterogeneity. CO₂ emissions per capita similarly range from 1.06 tons (India) to 18.78 tons (United States), reflecting large differences in energy mix and industrial structure.

Table 1. Summary Statistics. 12 Countries GDP per Capita and CO₂ per Capita Data for 1980 to 2022 Period.

Country	GDP per Capita (USD)		CO ₂ per Capita (Tons)		GDP Growth (%)		CO ₂ Growth (%)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Canada	46,570.1300	7608.8000	16.4976	1.1169	1.2342	2.3638	−0.5384	3.0585
China	7160.5200	6450.2800	4.2158	2.2955	8.2455	2.9001	4.1840	4.2541
Germany	50,074.4000	9119.1200	11.1075	1.6400	1.4305	1.9639	−1.3005	3.0923
India	3951.4170	2141.8950	1.0611	0.4811	4.1455	2.7267	3.7893	3.1030
Indonesia	7397.6480	3152.5960	1.4225	0.5810	3.6215	3.4371	3.7609	7.1933
Italy	46,220.3600	5904.4330	7.0758	0.9953	1.1774	2.8831	−0.3427	4.3147
Japan	37,880.7300	6072.7880	9.1301	0.9175	1.5317	2.2387	0.1331	3.7698
Korea	28,234.8200	14,872.7700	8.9234	3.2425	5.3330	3.6356	3.0275	5.0758
Malaysia	19,157.0800	7523.3690	5.4026	2.0768	3.3840	3.6756	3.4882	7.8184
Mexico	19,338.4600	1787.2850	3.9599	0.2391	0.5176	3.6018	−0.2196	3.6001
Singapore	73,266.7900	31,647.6200	10.8222	2.3650	3.9332	4.1817	−0.3082	10.1305
United States	53,352.6500	10,977.7600	18.7779	2.0354	1.7626	1.9366	−0.7273	3.2870

In terms of growth rates, China (8.25%), South Korea (5.33%), Malaysia (3.38%), and Singapore (3.93%) record the highest average per-capita GDP growth rates, while Mexico (0.52%), Canada (1.23%), and Italy (1.18%) record the lowest. On the emissions side, average per-capita CO₂ growth is negative for Canada (−0.54%), Germany (−1.30%), Italy (−0.34%), Mexico (−0.22%), Singapore (−0.31%), and the United States (−0.73%), indicating that these economies have, on average, been decarbonizing in per-capita terms over the sample period. By contrast, China (4.18%), India (3.79%), Indonesia (3.76%), Malaysia (3.49%), and South Korea (3.03%) have experienced positive average CO₂ growth, consistent with emission-intensive industrialization. These unconditional averages motivate the regression-based analysis that follows, which controls for the simultaneous evolution of GDP growth and technological progress (Figure 2).

3.3. Time-Series Properties

Given the annual time series structure of the data, we test for stationarity using the Augmented Dickey–Fuller (ADF) test for each country and each variable. Table 2 reports the ADF statistics and *p*-values. All three growth-rate variables (CO₂_G, GDP_G, Trade_G) are stationary at the 5% significance level for all countries, with two minor exceptions: China’s CO₂ growth (*p* = 0.052) and South Korea’s GDP growth (*p* = 0.057) are stationary at the 10% level. Stationarity of all regression variables removes the risk of spurious correlations from integrated series, supporting the use of OLS and IV regression in growth rates without differencing. We note that stationarity alone does not validate causal identification, exogenous assumptions, or model specification; these issues are addressed separately in Section 4 through diagnostic tests and IVs.

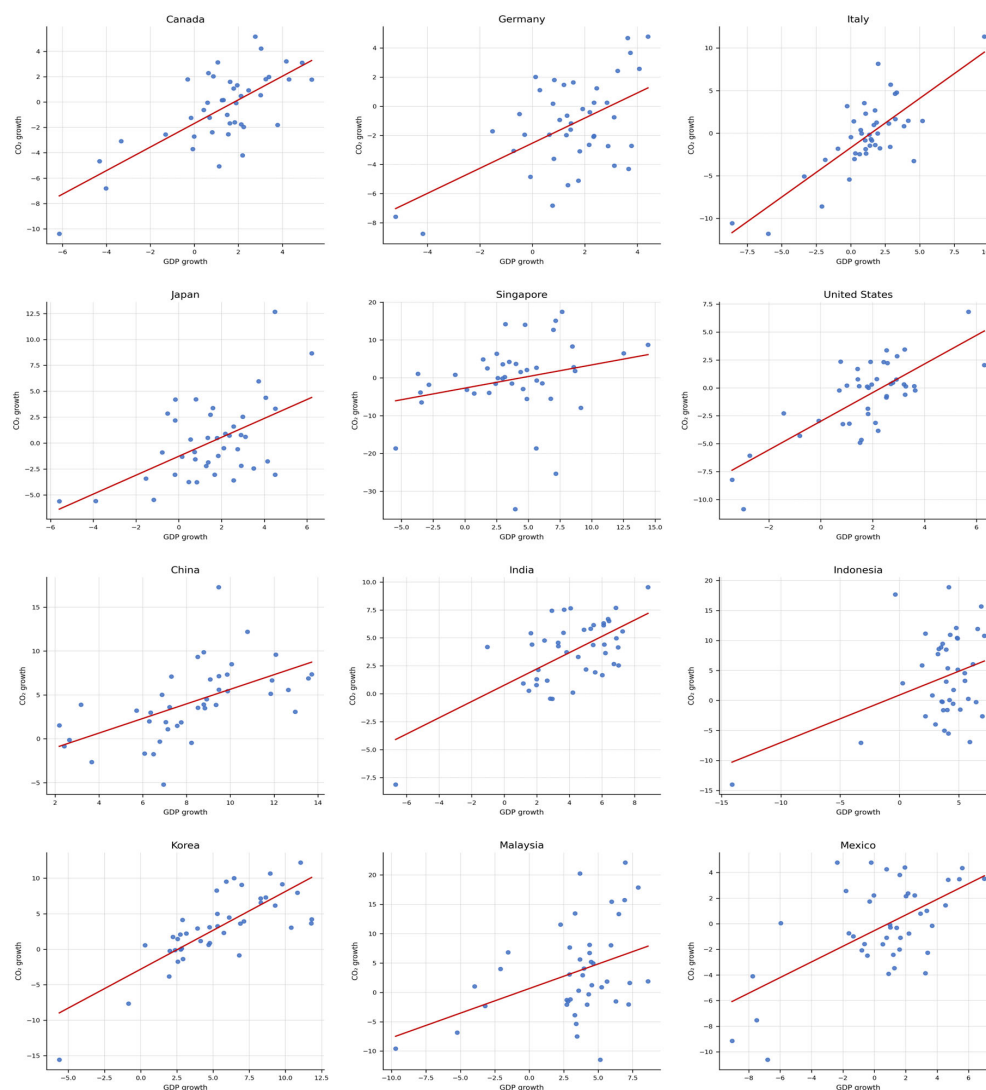


Figure 2. Plot of developed economies for country-level per-capita GDP growth vs. per-capita CO₂ emissions growth scatterplots (1981–2022). Red line represents the OLS fitted regression line. (Top 3 rows: developed economies; bottom 3 rows: emerging economies).

Table 2. ADF Test for Stationarity.

Country	CO ₂ _G		GDP_G		Trade_G	
	ADF Stat	<i>p</i> -Value	ADF Stat	<i>p</i> -Value	ADF Stat	<i>p</i> -Value
Canada	−5.8954	0.0000	−4.8351	0.0000	−4.1295	0.0009
China	−2.8448	0.0522	−3.1799	0.0212	−4.8130	0.0001
Germany	−4.5273	0.0002	−5.4918	0.0000	−5.1092	0.0000
India	−4.6047	0.0001	−4.5679	0.0001	−3.3027	0.0148
Indonesia	−5.2746	0.0000	−4.0520	0.0012	−5.6926	0.0000
Italy	−3.5182	0.0075	−3.7135	0.0039	−5.1820	0.0000
Japan	−3.5942	0.0059	−3.1475	0.0232	−4.5622	0.0002
Korea	−3.4511	0.0093	−2.8102	0.0568	−4.2520	0.0005
Malaysia	−4.2882	0.0005	−4.8835	0.0000	−3.5622	0.0065
Mexico	−5.5636	0.0000	−5.1346	0.0000	−5.5936	0.0000
Singapore	−6.5880	0.0000	−5.8911	0.0000	−4.3556	0.0004
United States	−5.5192	0.0000	−4.6549	0.0001	−5.4794	0.0000

Notes: The table reports the results of stationarity tests for all regression variables. The estimation sample covers annual growth rates of GDP, CO₂ emissions, and trade from 1981 to 2022. A variable is considered stationary if the *p*-value < 0.05.

4. Methodology

4.1. Baseline Model

The baseline empirical model relates per-capita CO₂ emissions growth to per-capita GDP growth with a linear time trend for each country *i*:

$$\text{CO}_2\text{-G}_{it} = \beta_{0i} + \beta_{1i} \cdot \text{GDP_G}_{it} + \beta_{2i} \cdot \text{Trend}_t + \varepsilon_{it} \quad (1)$$

where CO₂_G_{it} is the annual growth rate of per-capita CO₂ emissions for country *i* in year *t*; GDP_G_{it} is the annual growth rate of per-capita GDP; Trend_t is the linear time trend (=1 in 1981, 2 in 1982, ..., 42 in 2022); and ε_{it} is the regression error. The coefficient β_{1i} is the country-specific elasticity of emissions growth with respect to GDP growth, and β_{2i} captures the net annual change in CO₂ growth attributable to technological progress and structural change, holding GDP growth constant.² The model is estimated separately for each country, allowing all coefficients to vary across countries (Pesaran & Smith, 1995).

Table 3 reports the OLS estimates of Equation (1) for all twelve countries. Several patterns emerge. First, the coefficient of GDP_G (β₁) is positive and statistically significant at the 1% level for all twelve countries, confirming a robust positive association between per-capita GDP growth and per-capita CO₂ emissions growth across the full sample period. The magnitude of the elasticity ranges from 0.61 (Singapore and South Korea) to 1.27 (United States), with a cross-country mean of approximately 0.90. This implies that, on average, a one percentage point increase in per-capita GDP growth is associated with a 0.90 percentage point increase in per-capita CO₂ emissions, holding technological progress constant.

Table 3. OLS Output Table.

	(1) Canada	(2) China	(3) Germany	(4) India	(5) Indonesia	(6) Italy	(7) Japan	(8) Korea	(9) Malaysia	(10) Mexico	(11) Singapore	(12) United States
GDP_G	0.9276 (0.1307)	0.8781 (0.1484)	0.8602 (0.2033)	0.8124 (0.1340)	0.8068 (0.2589)	1.1564 (0.1334)	0.9125 (0.2213)	0.6145 (0.2786)	1.2417 (0.2397)	0.8118 (0.2137)	0.6147 (0.1377)	1.2700 (0.1947)
Trend	−0.0046 (0.0302)	0.0396 (0.0339)	−0.0002 (0.0345)	−0.0731 (0.0275)	0.0359 (0.0785)	−0.0032 (0.0374)	0.0000 (0.0420)	0.0014 (0.1075)	0.0662 (0.0578)	−0.1126 (0.0929)	−0.0433 (0.0394)	−0.0144 (0.0329)

Notes: Each column reports OLS estimates for an individual country regression of CO₂ growth on GDP growth and a time trend. The estimation sample covers annual growth rates from 1981 to 2022. Standard errors in parentheses.

We conducted a full suite of econometric diagnostics for each country regression (Table 4). Heteroskedasticity was tested using the White test; Canada (*p* = 0.021) and Mexico (*p* = 0.037) showed evidence of non-constant error variance at the 5% level, while the remaining ten countries did not.

Table 4. White Test for Heteroskedasticity.

Country	Chi2	df	p-Value
Canada	13.3232	5.0000	0.0205
China	3.5213	5.0000	0.6202
Germany	5.5791	5.0000	0.3494
India	4.0269	5.0000	0.5455
Indonesia	2.8629	5.0000	0.7211
Italy	3.5545	5.0000	0.6152
Japan	7.6081	5.0000	0.1792
Korea	9.7776	5.0000	0.0818
Malaysia	10.2928	5.0000	0.0674
Mexico	11.8445	5.0000	0.0370
Singapore	4.2469	5.0000	0.5144
United States	8.4744	5.0000	0.1320

Notes: The table reports the White Test results for heteroskedasticity across all countries. The test examines whether the variance of the regression error terms is constant (homoskedasticity). The null hypothesis (H₀) states that errors are homoscedastic. H₀ is rejected when the *p*-value < 0.05, indicating the presence of heteroskedasticity. A *p*-value ≥ 0.05 suggests no strong evidence of heteroskedasticity.

Serial correlation was tested using the Breusch–Godfrey LM test (Table 5); China ($p = 0.031$), Indonesia ($p = 0.049$), Malaysia ($p = 0.010$), Singapore ($p = 0.016$), and South Korea ($p = 0.002$) rejected the null of no autocorrelation at the 5% level. In response, all country-level regressions were estimated with the Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, which remain valid under both heteroskedasticity and serial correlation.

Table 5. Breusch-Godfrey LM Test for Serial Correlation.

Country	Chi2	df	p-Value
Canada	0.0310	1.0000	0.8608
China **	4.6780	1.0000	0.0305
Germany	1.5950	1.0000	0.2067
India	0.1000	1.0000	0.7516
Indonesia **	3.8830	1.0000	0.0488
Italy	0.0020	1.0000	0.9618
Japan	0.4150	1.0000	0.5195
Malaysia **	6.5920	1.0000	0.0102
Mexico	2.0920	1.0000	0.1480
Singapore **	5.6780	1.0000	0.0163
South Korea ***	9.4270	1.0000	0.0021
United States	0.2850	1.0000	0.5936

Notes: The table reports the Breusch-Godfrey LM test results for serial correlation in the residuals of each country regression. The null hypothesis (H_0) is that there is no serial correlation. H_0 is rejected when p -value < 0.05 , indicating the presence of autocorrelation which may bias standard errors. *** $p < 0.01$, ** $p < 0.05$.

4.2. Instrumental Variables Estimation

Equation (1) estimated by OLS may yield biased estimates of β_{1i} if GDP growth is endogenous with respect to per-capita increases in CO₂ emissions, which is when higher emissions impose productivity costs that feed back into lower GDP growth (Acheampong, 2018). To address this, we used the instruments GDP_G_{it} with Trade_G_{it}, with the annual growth rate of trade as a share of GDP. The first-stage regression is given as follows:

$$\text{GDP_G}_{it} = \gamma_{0i} + \gamma_{1i} \cdot \text{Trade_G}_{it} + \gamma_{2i} \cdot \text{Trend}_t + \nu_{it} \quad (2)$$

Instrument relevance is assessed via the first-stage F-statistic, using a threshold of $F > 10$ (Staiger & Stock, 1997). Instrument exogeneity requires that Trade_G_{it} affects CO₂_G_{it} only through its effect on GDP_G_{it}. We acknowledge this is a strong assumption; trade can directly affect emissions through composition and technique effects (Antweiler et al., 2001), and IV results should be interpreted cautiously where this assumption may be violated.

Table 6 reports the IV estimates for countries where the instrument is sufficiently strong to support causal interpretation. For advanced economies with strong instruments, IV coefficients are modestly larger than their OLS counterparts: Canada (IV: 1.067 vs. OLS: 0.928), Germany (1.000 vs. 0.860), Italy (1.293 vs. 1.156), Japan (1.249 vs. 0.913), and the United States (2.098 vs. 1.270). The upward revision from OLS to IV is consistent with a mild downward bias in OLS arising from the negative feedback from growth in per-capita emissions to per-capita GDP growth: OLS underestimates the true structural effect of income growth on emissions because emissions impose productivity costs that attenuate the observable income–emissions correlation.

We conducted a first-stage test to examine the strength of the instrument variable. Table 7 reports the first-stage F-statistics. The instrument is strong ($F > 10$) for Canada (17.6), Germany (14.6), Italy (12.2), Japan (11.9), and the United States (11.6). It is borderline for China (6.7) and Singapore (4.9). It is weak for India (0.41), Indonesia (1.28), South Korea (0.13), Mexico (3.5), and Malaysia (0.65). For countries with weak instruments, IV estimates

are presented for completeness but are not interpreted as causal; OLS estimates are the primary specification for these countries.

Table 6. IV Output Table.

	(1) Canada	(2) China	(3) Germany	(4) India	(5) Indonesia	(6) Italy	(7) Japan	(8) Korea	(9) Malaysia	(10) Mexico	(11) Singapore	(12) United States
GDP_G	1.0670 (0.1867)	1.6151 (0.7963)	1.0000 (0.2535)	1.9679 (2.0239)	1.7856 (1.3175)	1.2931 (0.2690)	1.2485 (0.3213)	−2.2395 (1.9719)	1.6667 (2.1289)	1.0194 (1.4316)	0.9051 (0.3282)	2.0975 (0.3914)
trend	−0.0021 (0.0309)	0.0866 (0.0757)	0.0039 (0.0319)	−0.1387 (0.1449)	0.0664 (0.0844)	0.0052 (0.0398)	0.0291 (0.0498)	−0.1810 (0.2200)	0.1491 (0.4204)	−0.1083 (0.1009)	−0.0456 (0.0393)	0.0050 (0.0382)

Notes: Each column reports IV estimates for an individual country regression of CO₂ growth on GDP growth and a time trend, using trade growth and trend as instrument variables. The estimation sample covers annual growth rates from 1981 to 2022. Standard errors in parentheses.

Table 7. First-Stage Test (F-Statistic).

Country	F-Stat	p-Value
Canada	17.6020	0.0002
China	6.6957	0.0135
Germany	14.6496	0.0005
India	0.4067	0.5274
Indonesia	1.2765	0.2655
Italy	12.2338	0.0012
Japan	11.8819	0.0014
Korea	0.1297	0.7207
Malaysia	0.6513	0.4245
Mexico	3.5123	0.0684
Singapore	4.9125	0.0326
United States	11.5658	0.0016

Notes: The table reports the first-stage F-statistics from the instrumental variable (IV) estimation, where trade growth (Trade_G) serves as the instrument for GDP growth (GDP_G). The estimation sample covers annual growth rates from 1981 to 2022. A country's instrument is considered strong when F-stat > 10.

4.3. Sustainable Growth Rate and Sustainable Growth Gap

Setting $\text{CO}_2\text{-G}_i^t = 0$ in Equation (1) and solving for GDP_G yields the sustainable per-capita GDP growth rate for country i at time t :

$$Y_{it}^s = -(\beta_{0i} + \beta_{2i} \cdot \text{Trend}^t) / \beta_{1i} \quad (3)$$

Because $\beta_{2i} \neq 0$ in general, Y_{it}^s evolves over time as technology improves, generating a time-varying sustainability threshold. Confidence intervals for Y_{it}^s are computed via the delta method, which linearizes the nonlinear function of estimated coefficients and propagates estimation uncertainty from the variance-covariance matrix of $(\hat{\beta}_{0i}, \hat{\beta}_{1i}, \hat{\beta}_{2i})$ to the derived quantity Y_{it}^s . The sustainable growth gap is then defined as follows:

$$\text{Gap}_{it} = \text{GDP_G}_{it} - Y_{it}^s \quad (4)$$

A positive Gap_{it} indicates that actual per-capita GDP growth in country i at time t exceeds the compatible threshold for the per-capita emissions growth rate, implying upward pressure on CO₂ emissions. A negative gap implies that growth could accelerate without increasing emissions. Statistical significance of the mean gap is assessed using a t -test of $H_0: E[\text{Gap}_{it}] = 0$, with the standard error of the mean computed over the time dimension T for each country. The standard error of the mean may understate true sampling uncertainty, and the t -statistics should be interpreted with appropriate caution where serial correlation in the gap series is present.

4.4. Panel Fixed-Effects Specification

To complement the country-specific regressions, we estimate a pooled fixed-effects (within) regression that imposes common slope coefficients while allowing country-specific intercepts:

$$\text{CO}_2_G_{it} = \alpha_i + \beta_1 \cdot \text{GDP_G}_{it} + \beta_2 \cdot \text{Trend}^t + \varepsilon_{it} \quad (5)$$

where α_i is the country fixed effect. Standard errors are clustered at the country level to account for within-country serial correlation and heteroskedasticity (12 clusters). The panel IV specification instruments GDP_G_{it} with Trade_G_{it} were used alongside the time trend. The panel results serve as a pooled benchmark and efficiency comparison; country-specific regressions remain the primary specification, given the documented heterogeneity in slope coefficients.

5. Results and Discussion

5.1. OLS Estimates vs. IV Estimates

For countries with weak instruments are India (F-stat: 0.41), Indonesia (1.28), South Korea (0.13), and Malaysia (0.65). For these, IV estimates are highly imprecise. The South Korea IV coefficient is -2.24 (SE: 1.97); sign reversal could be a symptom of weak instrument bias, which can push IV estimates arbitrarily far from the true parameter (Staiger & Stock, 1997). These estimates may not be interpreted causally. The panel IV estimate of the common GDP_G coefficient is 0.271 (SE: 1.896, z-stat: 0.14, $p = 0.887$), which is statistically indistinguishable from zero, reflecting the averaging of the weak-instrument problem across the full panel.

5.2. Sustainable Growth Paths

Figure 3 displays the time paths of actual per-capita GDP growth alongside the OLS- and IV-estimated sustainable growth rates with 95% confidence intervals for the six advanced economies and the six emerging economies. Several features are notable.

Among advanced economies, the sustainable growth paths for Germany, Canada, Italy, and Japan are positive and relatively stable over time, reflecting positive but modest trend coefficients. For Germany, both the OLS and IV sustainable paths lie near or slightly above zero and exhibit gentle upward slopes, consistent with ongoing technological decarbonization. The pattern for Italy is similar. For the United States, the OLS sustainable path is approximately 2.5% per year, substantially above zero. Average U.S. per-capita GDP growth over the full sample is approximately 1.76%, which falls below this threshold. The positive OLS sustainable growth gap in Table 8 reflects a cancellation of the high growth experienced during the 1980s, with lower growth since the post-2008 financial crisis, when U.S. growth remained largely below the emissions-compatible threshold. Singapore's sustainable path rises over time as its negative trend coefficient suggests an improving carbon efficiency, while actual growth has been volatile and frequently exceeded the sustainable threshold in earlier decades.

Among emerging economies, the sustainable paths under OLS and IV diverge more substantially, particularly for China, Indonesia, and Malaysia. For China, the positive trend coefficient suggests a declining sustainable growth rate over time; as China's industrial structure became more carbon-intensive during rapid growth, the pace of GDP growth compatible with stable per-capita emissions fell. By contrast, Malaysia's sustainable path rose sharply over time under both OLS and IV estimates, as the negative trend coefficient is consistent with the idea of an accelerating pace of decarbonization. Despite this improvement, actual Malaysian growth has consistently exceeded the sustainable threshold, producing a persistently positive gap. India and Indonesia show broadly similar patterns:

sustainable paths that have improved modestly over time but remain well below the pace of actual economic growth, generating large and statistically significant gaps throughout the sample.

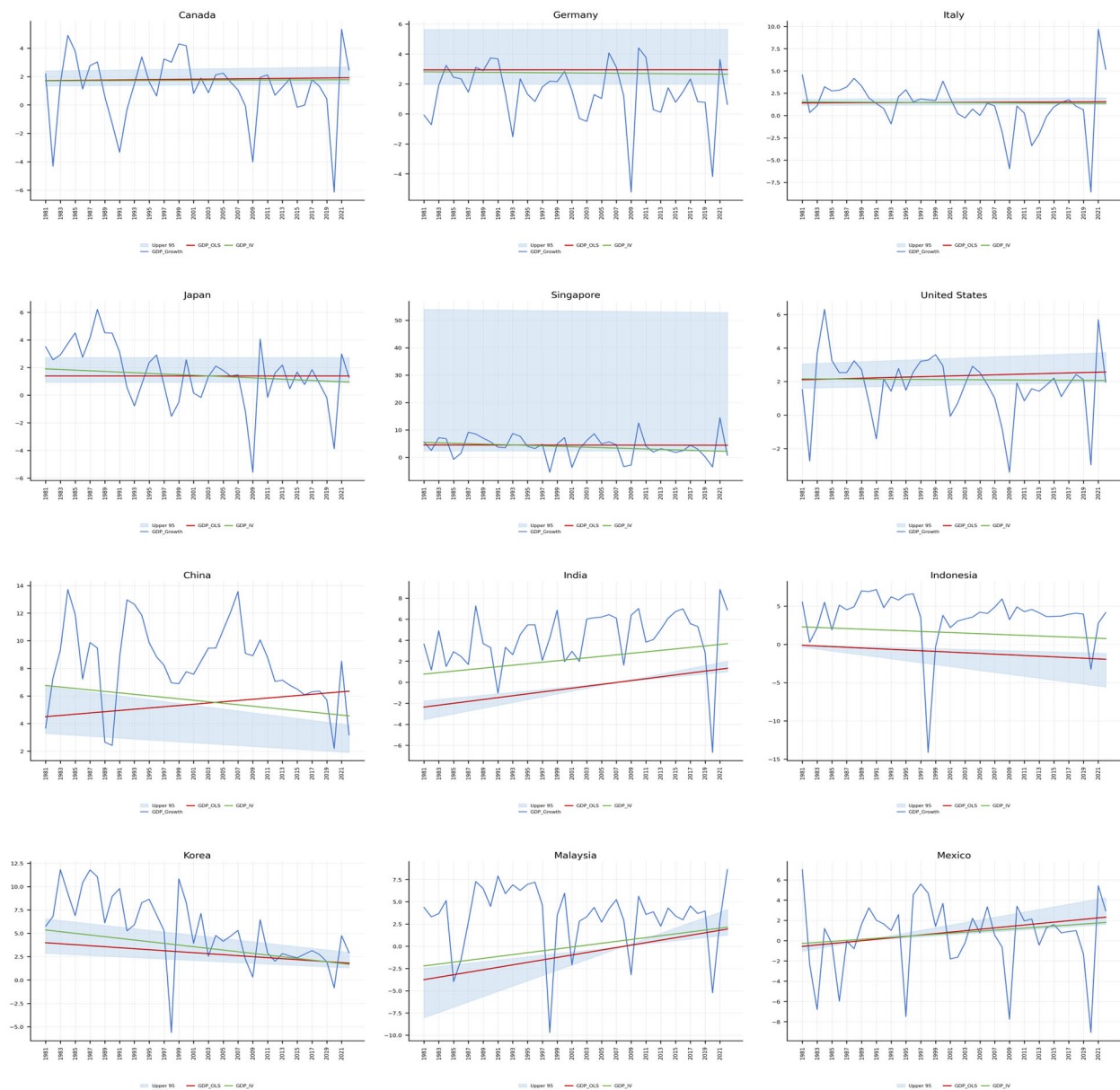


Figure 3. Per-capita GDP growth, GDP OLS, and GDP IV sustainable growth results with 95% confidence interval for developed vs. emerging economies. (Top 3 rows: developed economies; bottom 3 rows: emerging economies).

A further source of estimation uncertainty, particularly evident in the wide confidence intervals for Indonesia, Malaysia, and Singapore, is the presence of structural breaks within the sample period. The Asian Financial Crisis of 1997–1998 generated an abrupt and severe contraction in output across Southeast Asian economies, producing outlier observations that inflate residual variance and widen standard errors around both the coefficient estimates and the derived sustainable growth rates. For Indonesia, for example, per-capita GDP fell by approximately 14% in 1998; this is a shock of such magnitude that a linear model with a constant emissions elasticity cannot plausibly accommodate it within a stable parameter framework.

Table 8 reports the mean sustainable growth gap, its standard deviation, and the t-statistic for the null hypothesis that the mean gap equals zero for both OLS and IV estimates. The results reveal three groups of countries.

Table 8. Sustainable Growth Gap statistics.

Country	OLS		IV		Null Hypothesis Mean = 0 OLS	Null Hypothesis Mean = 0 IV
	Mean	STD	Mean	STD		
Canada	−0.63	0.36	−0.55	0.36	−1.73	−1.52
China	2.76	0.47	1.75	0.42	5.92	4.14
Germany	−1.32	0.35	−1.00	0.35	−3.78	−2.86
India	4.63	0.40	1.55	0.40	11.52	3.90
Indonesia	4.55	0.51	1.57	0.51	8.85	3.05
Italy	−0.10	0.48	−0.08	0.47	−0.21	−0.17
Japan	0.16	0.34	0.14	0.32	0.48	0.44
Malaysia	4.01	0.66	2.95	0.62	6.12	4.74
Mexico	0.20	0.71	0.36	0.72	0.28	0.50
Singapore	2.76	0.66	1.75	0.64	4.17	2.75
South Korea	2.76	0.50	1.75	0.54	5.56	3.22
United States	2.76	0.29	1.75	0.29	9.36	6.02

Group 1—Significantly negative or near-zero gaps (operating within sustainable limits): Germany (OLS gap: −1.32, t-stat: −3.78; IV: −1.00, t-stat: −2.86) has a significantly negative gap under both methods, meaning actual growth has consistently fallen short of the emissions-compatible threshold, which is a reflection of Germany’s combination of slow growth and substantial decarbonization. Canada (−0.63, t-stat: −1.73) and Italy (−0.10, t-stat: −0.21) also show negative gaps, though these are not statistically significant. Japan (0.16, t-stat: 0.48) and Mexico (0.20, t-stat: 0.28) show gaps indistinguishable from zero under both methods. These five economies have, on average, been growing at rates compatible with stable or declining per-capita emissions.

Group 2—Significantly positive gaps and advanced economies: The United States (OLS gap: 2.76, t-stat: 9.36; IV: 1.75, t-stat: 6.02) and Singapore (OLS: 2.76, t-stat: 4.17; IV: 1.75, t-stat: 2.75) both exhibit significantly positive sustainable growth gaps under both estimation methods. For the United States, the gap reflects high sustainable growth during the 1980s when actual per-capita growth exceeded the approximately 2.5% OLS sustainable threshold, while the average actual growth rate fell below it. For Singapore, the gap reflects the exceptionally volatile and high average growth (3.93% per year) relative to a sustainable path that, while rising, has not kept pace.

Group 3—Significantly positive gaps and emerging economies: China (OLS gap: 2.76, t-stat: 5.92; IV: 1.75, t-stat: 4.14), India (4.63, t-stat: 11.52; IV: 1.55, t-stat: 3.90), Indonesia (4.55, t-stat: 8.85; IV: 1.57, t-stat: 3.05), Malaysia (4.01, t-stat: 6.12; IV: 2.95, t-stat: 4.74), and South Korea (2.76, t-stat: 5.56; IV: 1.75, t-stat: 3.22) all show highly significant positive gaps. The OLS gaps for India, Indonesia, and Malaysia are among the largest in the sample, reflecting average actual growth rates of 4.1%, 3.6%, and 3.4%, respectively, set against sustainable thresholds that have risen only gradually. For these countries, the IV estimates are not identified as causal, given the weak instrument; OLS estimates are therefore the primary specification, and any comparison between OLS and IV gaps for these countries is illustrative of the additional work needed in this area. Figure 4 plots the full empirical distributions of OLS- and IV-derived sustainable growth gaps for all economies, and Table 9

provides corresponding aggregate evidence via pooled panel fixed-effects estimates of the cross-sample growth-emission relationship.

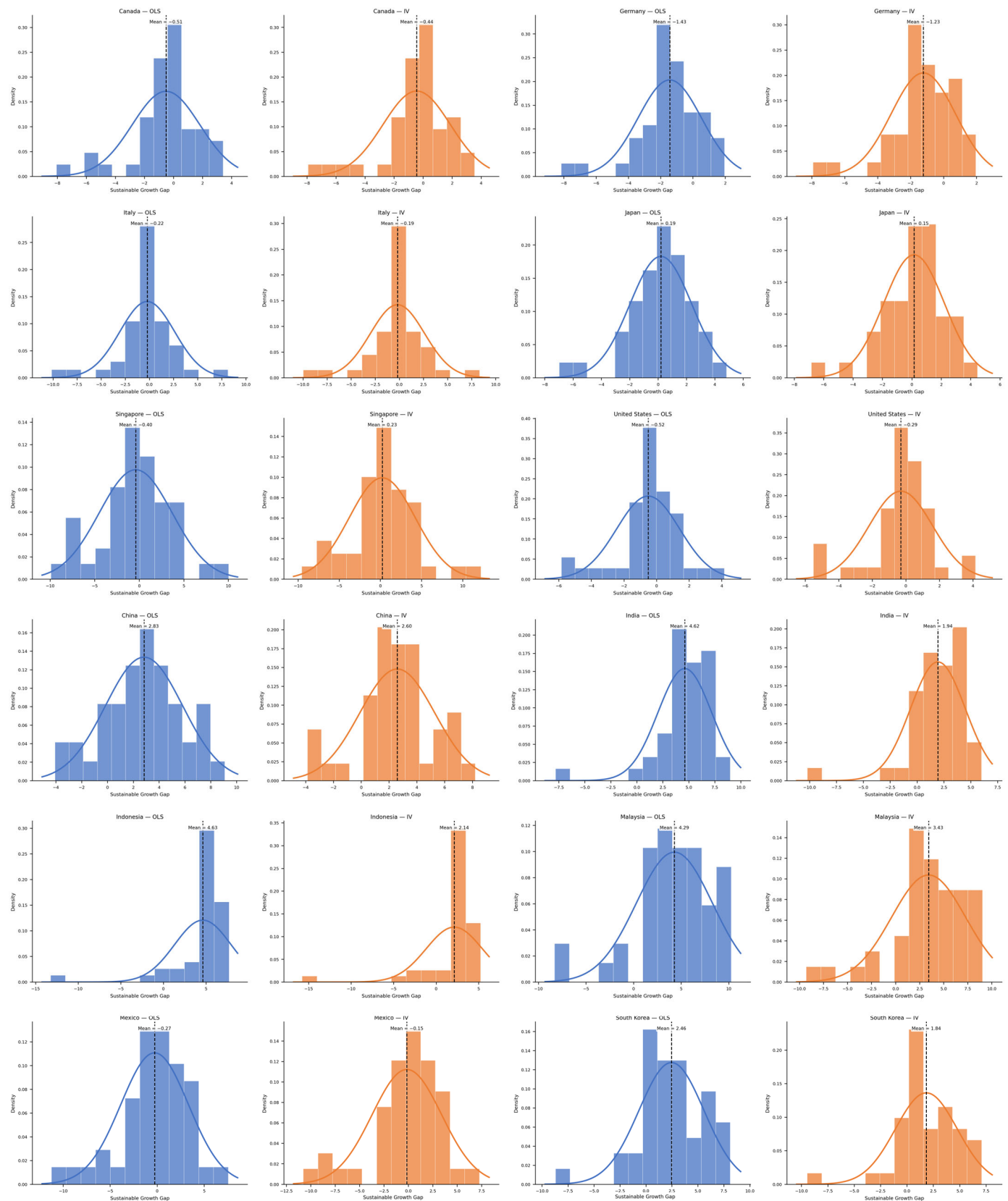


Figure 4. Distributions of the sustainable growth gap for developed economies: OLS vs. IV estimates. Black dashed line is the mean of the distribution. Solid color lines represent the fitted normal distribution curves. (Top 3 rows: developed economies; bottom 3 rows: emerging economies).

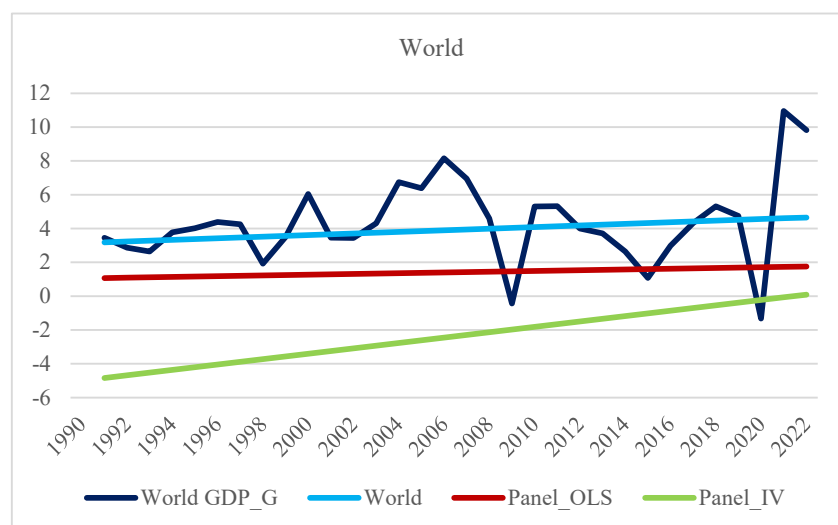
Table 9. Panel Data Results (Fixed Effects).

	OLS Fixed Effects				IV Fixed Effects			
	Coef.	Robust S.E.	t	$p > t $	Coef.	Robust S.E.	z	$p > z $
GDP_G	0.8289	0.0633	13.1000	0.0000	0.2705	1.8957	0.1400	0.8870
trend	−0.0184	0.0130	−1.4200	0.1840	−0.0430	0.0807	−0.5300	0.5940
_cons	−0.8679	0.3802	−2.2800	0.0430	1.3512	7.4565	0.1800	0.8560
Observations	504				504			
Within R ²	0.2309				0.1333			
Overall R ²	0.2802				0.2435			
F/Wald stat	100.1600				86.7600			
rho	0.0778				0.1078			

Notes: Robust standard errors clustered at country level (12 clusters). IV instrumented GDP_G using Trade_G and trend.

The panel fixed-effects OLS estimate of the common GDP_G coefficient is 0.829 (robust SE: 0.063, t-stat: 13.10, $p < 0.001$), which is consistent with the cross-country average of the country-specific estimates, confirming a strong positive emission–growth relationship when slope homogeneity is imposed. The within R² of 0.231 and the F-statistic of 100.16 ($p < 0.001$) confirm the joint significance of the model.

Figure 5 presents the world per-capita GDP growth rate alongside the sustainable growth paths derived from the panel OLS and panel IV estimates, benchmarked against the world-level sustainable growth path. The panel OLS sustainable growth rate (approximately annual 1.5–2% growth) lies persistently below actual world GDP growth for most of the sample period, consistent with the significantly positive aggregate sustainable growth gap. For illustrative purposes only, given the statistically insignificant panel IV coefficient ($p = 0.89$), the panel IV sustainable growth path begins at approximately −5% in the early 1990s and rises gradually toward zero by 2022. This path should not be interpreted as implying a unique and reliable causal estimate; it could suggest a substantially more constrained sustainable path than the one based on OLS estimates. This divergence between OLS and IV panel paths is a direct consequence of the substantially higher emissions elasticity estimated under IV. The world sustainable path, which rises from approximately 3% to 4.5% over the period, captures the improving global emissions intensity as a whole, but notably, this world benchmark exceeds the panel OLS sustainable path throughout, reflecting that the twelve countries in our sample are collectively more carbon-intensive than the global average.

**Figure 5.** OLS and IV panels for selected world countries for sustainable growth comparison.

6. Conclusions and Caveats

The central empirical finding of this paper is that the sustainable growth gap is not a simple function of development status. Among the twelve economies studied, the divide between countries that have exceeded their emissions-compatible growth threshold and those that have not does not align cleanly with the advanced-versus-emerging classification. Germany, Canada, Italy, Japan, and Mexico, a mix of advanced and emerging economies, show gaps indistinguishable from zero or negative growth, while the United States and Singapore join China, India, Indonesia, Malaysia, and South Korea in exceeding their thresholds significantly.

The common thread across the high-gap group is not industrialization per se but a high average pace of GDP growth relative to the country-specific rate of technological decarbonization captured by the time trend. China, India, Indonesia, Malaysia, and South Korea have grown rapidly and so have Singapore and, in a historical perspective, the United States. Germany, Canada, Italy, and Japan have grown slowly, and Germany in particular has decarbonized rapidly enough that its sustainable threshold has exceeded its actual growth for most of the sample. This pattern is consistent with what we term the growth–pace hypothesis: it is the gap between actual growth and the pace of autonomous decarbonization, rather than a country’s income level or industrial structure, which determines whether a country exceeds its emissions-compatible growth threshold.

This finding has important implications for how the international community thinks about the emissions–growth trade-off. Policies that constrain growth uniformly by development tier, for example, imposing carbon-adjustment mechanisms that penalize all emerging economies, may be misdirected if the operative mechanism is the pace of growth rather than development status. Similarly, advanced economies that combine high growth with slow technological decarbonization cannot claim sustainable trajectories simply by virtue of their income level.

The comparison between OLS and IV estimates provides partial evidence on whether the channel of growth matters for its emissions content. For countries with credible instruments, such as Canada, Germany, Italy, Japan, the United States, and to a lesser extent, China and Singapore, IV coefficients systematically exceed OLS coefficients. This upward revision is consistent with the theoretical prediction of Antweiler et al. (2001) who stated that trade-driven growth carries a scale effect that is larger than the average effect of domestic demand-led growth, as trade expansion tends to shift production toward sectors with comparative advantage, which in these economies are often capital- and energy-intensive export sectors.

Correspondingly, IV estimates of the sustainable growth gap are generally smaller than OLS estimates for the same countries, because a higher IV emissions elasticity implies a lower sustainable growth rate, compressing the gap between the threshold and actual growth. For countries where the instrument is weak, this comparison cannot be made reliably, and the sign reversal for South Korea underscores the danger of drawing conclusions from imprecisely estimated IV coefficients when instrument relevance fails.

Limitation and Caveats

Several limitations of this analysis deserve explicit acknowledgment. First, the assumption of a linear time trend for technological progress is a strong simplification. Technological change is unlikely to be linear or uniform across countries: it may be punctuated by policy changes, energy price shocks, and technology adoption waves. The consistency of our stationarity results suggests that the growth-rate specification mitigates the worst consequences of this assumption; therefore, subsample robustness tests and specifications using

fixed effects by year in the panel model would strengthen confidence in the results. We flag these as priorities for revision.

Second, the trade-based instrument performed poorly for half the countries in the sample. This limits the scope for causal inference about the impact of emissions on trade-driven versus domestically driven growth for the most relevant emerging economies, precisely those for which the endogeneity concern is greatest. Alternative instruments, including weather shocks (as used in the agricultural productivity literature), external demand instruments, used by Autor et al. (2013), or global commodity price indices, may offer stronger relevance in these settings and represent a natural extension of this work.

Third, ideally, one would address this by allowing for structural breaks in the regression coefficients, for instance, using the Bai and Perron (1998) multiple breakpoint test to identify endogenous break dates for each country, or estimating separate pre- and post-crisis regimes. However, a fundamental challenge facing this research design is that break dates differ meaningfully across countries: the Asian Financial Crisis is the dominant structural event for Indonesia, Malaysia, South Korea, and Singapore, but not for Canada, Germany, or the United States, where the 2008 Global Financial Crisis or the early 1990s recession represent more salient discontinuities, and for China and India, where rapid structural transformation generates more gradual but persistent parameter instability. Building a single unified model that credibly accounts for the heterogeneity in break timing and magnitude across twelve countries, while preserving the comparability of the sustainable growth rate estimates, is a non-trivial econometric challenge. This remains an important avenue for future research, potentially using time-varying parameter models or rolling-window estimation, and though it lies beyond the scope of the current paper, our results are derived from a potentially useful approach that we pursue here.

Author Contributions: Conceptualization, J.M.; methodology, J.M. and J.D.; software, J.M. and J.D.; validation, J.M., J.D. and S.L.; formal analysis, J.M., J.D. and S.L.; investigation, J.M., J.D. and S.L.; resources; data curation, J.D. and S.L.; writing—original draft preparation, J.D. and S.L.; writing—review and editing, J.D.; visualization, J.M. and J.D.; supervision, J.M.; project administration, J.M. and J.D.; funding acquisition, All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study were derived from public domain resources detailed in the reference list. The raw supporting data can be obtained from the corresponding author upon reasonable request.

Acknowledgments: The authors would also like to acknowledge the very valuable contributions from three anonymous referees in various re-submissions of this work.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

- ¹ A first-order Taylor approximation technique is used to derive the asymptotic distribution of a nonlinear transformation of a random vector. $\text{StandardError}(Y_{it}^s) = \sqrt{[(\partial g / \partial \beta^s)^T \cdot V(\beta^s) \cdot (\partial g / \partial \beta^s)]}$. The standard error is then used to construct 95% confidence intervals computed as $CI = Y_{it}^s \pm 1.96 \cdot SE(Y_{it}^s)$.
- ² Note that a linear trend in the growth rate induces a nonlinear trend in the level.

References

- Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, 102(1), 131–166. [CrossRef] [PubMed]
- Acheampong, A. O. (2018). Economic growth, CO₂ emissions and energy consumption: What causes what and where? *Energy Economics*, 74, 677–692. [CrossRef]

- Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1), 1–51. [CrossRef]
- Ang, B. W. (2004). Decomposition analysis for policymaking in energy: Which is the preferred method? *Energy Policy*, 32(9), 1131–1139. [CrossRef]
- Antweiler, W., Copeland, B. R., & Taylor, M. S. (2001). Is free trade good for the environment? *American Economic Review*, 91(4), 877–908. [CrossRef]
- Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103(6), 2121–2168. [CrossRef]
- Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1), 47–99. [CrossRef]
- Basu, P., & McLeod, D. (1991). Terms of trade fluctuations and economic growth in developing economies. *Journal of Development Economics*, 37(1–2), 89–110. [CrossRef]
- Frankel, J. A., & Romer, D. (1999). Does trade cause growth? *American Economic Review*, 89(3), 379–399. [CrossRef]
- Grossman, G. M., & Krueger, A. B. (1991). *Environmental impacts of a North American Free Trade Agreement*. NBER Working Paper No. 3914. National Bureau of Economic Research. [CrossRef]
- International Energy Agency. (2024). *The relationship between growth in GDP and CO₂ has loosened—It needs to be cut completely*. Available online: <https://www.iea.org/commentaries/the-relationship-between-growth-in-gdp-and-co2-has-loosened-it-needs-to-be-cut-completely> (accessed on 30 September 2025).
- International Monetary Fund. (2025a). *GDP (current prices) from World Economic Outlook Database by country*. Available online: <https://www.imf.org/external/datamapper/NGDPD@WEO/OEMDC/ADVEC/WEOWORLD> (accessed on 30 September 2025).
- International Monetary Fund. (2025b). *GDP per capita, PPP (constant prices) from World Economic Outlook database by country*. Available online: <https://www.imf.org/en/Publications/WEO/weo-database/2025/april/download-entire-database> (accessed on 30 September 2025).
- Kahn, M. E., Mohaddes, K., Ng, R. N. C., Pesaran, M. H., Raissi, M., & Yang, J. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, 104, 105624. [CrossRef]
- Kaya, Y. (1990). *Impact of carbon dioxide emission control on GNP growth: Interpretation of proposed scenarios*. Paper presented to the Energy and Industry Subgroup, Response Strategies Working Group, IPCC, Paris. Available online: <https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1021752> (accessed on 6 May 2026).
- Our World in Data. (n.d.-a). *CO₂ emissions per capita*. Available online: <https://ourworldindata.org/grapher/co-emissions-per-capita> (accessed on 30 September 2025).
- Our World in Data. (n.d.-b). *Trade as a share of GDP*. Available online: <https://ourworldindata.org/grapher/trade-as-share-of-gdp> (accessed on 30 September 2025).
- Panayotou, T. (1993). *Empirical tests and policy analysis of environmental degradation at different stages of economic development*. ILO Working Paper WP238. International Labour Organization.
- Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94(446), 621–634. [CrossRef]
- Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), 79–113. [CrossRef]
- Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3), 557–586. [CrossRef]
- Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World Development*, 32(8), 1419–1439. [CrossRef]
- Su, B., & Ang, B. W. (2012). Structural decomposition analysis applied to energy and emissions: Some methodological developments. *Energy Economics*, 34(1), 177–188. [CrossRef]
- Wang, K., Zhao, B., Fan, T., & Zhang, J. (2022). Economic growth targets and carbon emissions: Evidence from China. *International Journal of Environmental Research and Public Health*, 19(13), 8053. [CrossRef] [PubMed]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.