Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

What Does the Environmental Phillips Curve Measure? Okun's Law, Trends and Cyclical Emissions in the G7, 1975–2024

reda hamza boudjana

boudjana_reda@hotmail.fr

CREAD: Centre de Recherches en Economie Appliquee pour le Developpement https://orcid.org/0009-0006-3733-9034

Research Article

Keywords: Environmental Phillips Curve, Okun's law, CO_2 emissions, business cycle, G7

Posted Date: November 17th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11732292/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

What Does the Environmental Phillips Curve Measure? Okun's Law, Trends and Cyclical Emissions in the G7, 1975–2024

Abstract

The Environmental Phillips Curve (EPC) posits a trade-off between unemployment and environmental pressure. This paper asks what the EPC measures once trends are removed and Okun's law is taken into account. Using G7 data for 1975–2024, we recast the EPC as a chain linking Okun's law and the cyclical emissions–output relationship, estimate every link in levels and in deviations from trend with fixed-effects, mean-group, common-correlated-effects, panel ARDL (pooled mean group) and CS-ARDL estimators, and test the restriction implied by Okun's law with a joint moving-block bootstrap. In deviations from trend, unemployment 10% above trend is associated with CO_2 emissions per capita 1.1% below trend. Okun's law and the emissions–output elasticity account for 83% of this relationship with fixed effects, with a 95% bootstrap interval of 0.62–0.98, and for all of it with the mean-group estimator. The relationship is essentially contemporaneous and robust to the HP, Hamilton and boosted HP filters and to the sample period: across four filters and three periods, the fixed-effects EPC ranges from −0.115 to −0.072 and Okun's law accounts for 83–108% of it. In levels, the EPC is fragile, sensitive to the sample window and absent from both PMG and CS-ARDL estimates in every period. The EPC is therefore best understood as the environmental image of Okun's law, and cyclical emission reductions should not be counted as progress towards decarbonisation targets.

Keywords: Environmental Phillips Curve; Okun's law; CO_2 emissions; business cycle; G7

JEL classification: Q43; Q54; Q56; E24; E32; C22; C23

1. Introduction

Few macroeconomic regularities are as visible in environmental data as the co-movement of emissions with the business cycle. Global fossil CO_2 emissions fell in 2009 and, more sharply, in 2020, when lockdowns cut daily emissions by about 17% at their trough (Le Quéré et al., 2020), and both times they rebounded with the recovery (Peters et al., 2012). The Environmental Phillips Curve (EPC) gives this observation a structural form. By analogy with Phillips (1958), it posits a trade-off between labor-market slack and environmental pressure: when unemployment rises, production, energy use and emissions fall (Kashem and Rahman, 2020). Such a trade-off has been reported for the G7 (Azimi and Rahman, 2024; Ayad and Djedaiet, 2026), BRICST economies (Durani et al., 2023), G20 economies (Deepika et al., 2026) and individual countries (Yavuz et al., 2024; Addison et al., 2024).

For environmental management, the question is what drives this trade-off. If unemployment affects emissions through channels of its own, because job losses fall disproportionately on energy-intensive activities or because commuting and workplace energy use decline with employment, then labor-market conditions determine environmental pressure in their own right, and labor-market policy has environmental consequences. If instead the EPC combines two established regularities, that output falls when unemployment rises (Okun, 1962) and that emissions are procyclical (Doda, 2014; Burke et al., 2015; Sheldon, 2017), then it is the environmental image of the business cycle. Its emission savings are then the counterpart of lost output, reverse in recoveries and say nothing about progress towards decarbonisation.

Existing evidence cannot discriminate between these interpretations, for two reasons. First, most studies relate the levels of emissions, unemployment and income. These series are trending and highly persistent, so levels regressions conflate the short-run co-movement that defines the EPC with the structural transformation of advanced economies (deindustrialisation, the shift to services and the energy transition) that decoupled emissions from income (Stern, 2004). Ferrentino and Vota (2026) show that a gap specification, relating deviations of unemployment from its equilibrium path to deviations of emissions from trend, isolates the cyclical component more cleanly. Trends also affect the more elaborate designs. Nonlinear ARDL models (Djedaiet, 2023; Har et al., 2025) and panel quantile regressions (Durani et al., 2023; Har et al., 2025) are estimated on trending levels, and comparisons of high- and low-unemployment countries (Djedaiet et al., 2026) confound structural differences with the cycle. Second, the EPC has not been confronted with Okun's law. Because output and unemployment are linked by a stable Okun relationship in advanced economies (Ball et al., 2017), the EPC implied by Okun's law and the emissions–output

elasticity can be computed and compared with the estimated EPC. Whether unemployment matters beyond output (Bhandari et al., 2025) thus becomes a testable cross-equation restriction.

This paper addresses both limitations for the G7 over 1975–2024, a sample about twice as long as in most previous G7 studies. We formulate the EPC as one link in a chain that also contains Okun's law and the cyclical emissions–output relationship, estimate all three links in deviations from trend and test whether the EPC equals the product of the other two. For comparability with previous G7 evidence (Azimi and Rahman, 2024; Ayad and Djedaiet, 2026), the levels specification and the gap links are estimated on the same data with the same estimators: one-way and two-way fixed effects, mean-group and common-correlated-effects estimators (complemented in levels by first differences and the augmented mean-group estimator), and two panel ARDL estimators, the pooled mean group (PMG) estimator of Pesaran et al. (1999) and the cross-sectionally augmented ARDL (CS-ARDL) estimator of Chudik and Pesaran (2015). Cointegration is assessed with the bootstrap error-correction tests of Westerlund (2007). The Okun restriction is tested for each estimator and each country with a moving-block bootstrap (Künsch, 1989) that preserves serial and cross-sectional dependence. Cyclical components are extracted with the Hodrick–Prescott (HP) filter, the Hamilton (2018) regression filter and the boosted HP filter of Phillips and Shi (2021). A sensitivity analysis repeats every estimator for each filter and for three sample periods (1975–2024, 1990–2022 and 2000–2024) matching the windows of earlier G7 studies, with both CO_2 emissions and the load capacity factor as measures of environmental pressure.

The results support the second, more parsimonious interpretation. In deviations from trend, unemployment 10% above its trend path is associated with CO_2 emissions per capita about 1.1% below trend, a relationship that is precisely estimated and stable across filters and sample periods. Okun's law and the emissions–output elasticity jointly account for about 83% of it with fixed effects and for all of it with the mean-group estimator, and the restriction is not rejected in any G7 economy. When the common G7 cycle is removed, by cross-sectional averages or year effects, the links weaken and the decomposition becomes imprecise: the EPC is identified from the common business cycle through which Okun's law operates. In levels, the EPC is absent or fragile: its sign and significance depend on the estimator and the sample window, and error-correction tests find little evidence of cointegration, patterns typical of regressions on trending series.

The paper makes three contributions. First, it tests the economic content of the EPC by embedding it in the Okun relationship and quantifies, for each estimator used in the literature and each G7 economy, the share of the EPC that operates through output. Second, by estimating the same models in levels and in gaps on the same data, it shows that the instability, window sensitivity and

estimator dependence of levels-based EPC estimates stem from trends, which helps explain the dispersion of published elasticities. Third, it shows that the cyclical EPC is robust to the measure of environmental pressure, the sample period and the filter, including the boosted HP filter, which addresses the main criticism of the HP filter without losing observations. For environmental management, recession-induced emission reductions should be excluded from assessments of decarbonisation progress, and recoveries are the periods in which structural emission-reduction measures pay off most.

Section 2 develops the conceptual framework and hypotheses, Section 3 describes the data and empirical strategy, Section 4 presents the results, Section 5 discusses them, and Section 6 concludes with implications for environmental policy.

2. Conceptual framework and hypotheses

This section situates the EPC within the macroeconomics of emissions, derives the restriction linking it to Okun's law, explains why trends can distort levels-based estimates and states the hypotheses tested in Section 4.

2.1. The Environmental Phillips Curve and the cyclicality of emissions

Kashem and Rahman (2020) introduced the EPC and reported a significant inverse relationship between unemployment and CO_2 emissions in OECD and Asian newly industrialized economies. Subsequent studies confirm a negative average relationship for the G7 using CS-ARDL and wavelet methods (Azimi and Rahman, 2024) and the load capacity factor (Ayad and Djedaiet, 2026), for BRICST (Durani et al., 2023) and G20 economies (Deepika et al., 2026), for highly globalized European economies, where institutional quality amplifies the relationship (Rahman et al., 2025), and for Türkiye and Ghana (Yavuz et al., 2024; Addison et al., 2024). As Table 1 shows, this literature relies mainly on levels specifications estimated with panel ARDL, CS-ARDL or fixed-effects models, which yield one long-run elasticity per sample, and rarely asks what that elasticity measures in economic terms.

A related literature studies emissions over the business cycle without reference to unemployment. Emissions are procyclical and more volatile than output (Doda, 2014), respond more strongly to expansions than to contractions (York, 2012; Sheldon, 2017), depend in the short run on the sectoral sources of growth (Burke et al., 2015), and recovered quickly after the 2008–2009 crisis (Peters et al., 2012) and the 2020 pandemic (Le Quéré et al., 2020). On the policy side, optimal policy allows emissions to be procyclical (Heutel, 2012), and intensity targets and caps behave very differently under productivity shocks (Fischer and Springborn, 2011). Within the EPC literature, nonlinearity has been examined in three ways, all in levels. Djedaiet (2023) uses panel

nonlinear ARDL for African OPEC members and finds asymmetric effects of increases and decreases in unemployment. Har et al. (2025) combine panel quantile regression with a PMG-NARDL model and find no short-run EPC but long-run effects that differ between high-unemployment and low-emission economies, and Durani et al. (2023) estimate panel quantile regressions for the BRICST economies. Quantile and quantile-on-quantile designs are now common in energy and environmental economics (Sim and Zhou, 2015; Adebayo et al., 2024; Bergougui et al., 2024, 2025), but EPC studies have applied them only to trending levels. Djedaiet et al. (2026) split ten European countries into high- and low-unemployment groups and find a larger long-run effect in the former, which they interpret as a recession–expansion difference. Neither strand connects the EPC to Okun's law or separates the cyclical component of the relationship from its trend.

Table 1. Empirical studies of the Environmental Phillips Curve.

Study	Sample	Method	Indicator	Main finding	Okun / asymmetry tested?
Kashem and Rahman (2020)	OECD and Asian NICs	Panel estimators, levels	CO_2	Inverse unemployment–emissions relation	No
Durani et al. (2023)	BRICST, 1990–2020	Panel quantile regression, levels	CO_2	Effects of controls differ across emission quantiles	Quantiles of emissions only
Djedaiet (2023)	African OPEC, 1990–2019	Panel NARDL	CO_2	EPC holds in long run; positive and negative shocks differ	Sign asymmetry only
Azimi and Rahman (2024)	G7, 1990–2022	CS-ARDL, wavelets	CO_2e	1% more unemployment, about 1% less CO_2	No
Yavuz et al. (2024)	Türkiye	Time series	LCF	EPC supported for LCF	No
Addison et al. (2024)	Ghana	Time series	CO_2	Partial support	No
Rahman et al. (2025)	Globalised European economies	Panel, institutional interaction	LCF	Institutions amplify the EPC	No
Ayad and Djedaiet (2026)	G7, 1980–2021	PMG-ARDL, CS-ARDL	LCF	EPC supported	No
Har et al. (2025)	Panel, 1991–2021	Panel quantile regression, PMG-NARDL	CO_2	No short-run EPC; long-run effects differ by unemployment and emission level	Sign; quantiles
Djedaiet et al. (2026)	10 European countries, 1993–2021	CS-ARDL, PMG-ARDL by unemployment group	LCF	EPC in long run only; larger in high-unemployment countries	Country groups, not cyclical states
Deepika et al. (2026)	G20	Panel ARDL	CO_2	Effects differ by gender of unemployment	No
Ferrentino and Vota (2026)	United States	Gap vs difference EPC	CO_2	Gap specification fits better	Gap; no formal Okun test
This study	G7, 1975–2024	Levels vs gaps; $\beta = \varepsilon\theta$ test by estimator (FE, two-way FE, MG, CCEMG, PMG, CS-ARDL) and by country; HP, Hamilton and boosted HP filters; three sample periods	CO_2, LCF	See Section 4	Yes: Okun, by estimator

Note: NARDL = nonlinear ARDL; CS-ARDL = cross-sectionally augmented ARDL; LCF = load capacity factor.

2.2. Okun's law and the decomposition of the EPC

Okun's law relates the output gap to the unemployment gap. Fifty years of evidence show that it holds well in advanced economies, with coefficients that differ across countries but are stable within them (Ball et al., 2017). Let c, u and y denote log CO_2 emissions per capita, the log unemployment rate and log GDP per capita, and let a tilde denote deviation from trend. The three relationships are

$$\tilde{y}_{it} = \theta \tilde{u}_{it} + e^1_{it} \quad \text{(Okun's law, } \theta < 0) \tag{1}$$

$$\tilde{c}_{it} = \varepsilon \tilde{y}_{it} + \gamma' \tilde{x}_{it} + e^2_{it} \quad \text{(emissions–output link, } \varepsilon > 0) \tag{2}$$

$$\tilde{c}_{it} = \beta \tilde{u}_{it} + \gamma' \tilde{x}_{it} + e^3_{it} \quad \text{(EPC, } \beta < 0) \tag{3}$$

where x contains the cyclical components of technology variables. If unemployment is associated with emissions only through output, substituting the first equation into the second yields the cross-equation restriction $\beta = \varepsilon\theta$. The product $\varepsilon\theta$ is the *Okun-implied* EPC, and the ratio $\varepsilon\theta/\beta$ measures the share of the EPC that Okun's law explains. The coefficient b_1 in

$$\tilde{c}_{it} = b_1 \tilde{u}_{it} + b_2 \tilde{y}_{it} + \gamma' \tilde{x}_{it} + e^4_{it} \tag{4}$$

captures any association between unemployment and emissions at given output. A non-zero b_1 could reflect a composition channel, if the activities that shed labor in a downturn differ in carbon intensity from those that shed capital utilisation, or behavioural channels such as reduced commuting and workplace energy use. It could also reflect measurement error in annual output gaps, which shifts explanatory power towards unemployment. The gap specification of Ferrentino and Vota (2026) motivates the use of deviations from trend; our contribution is to estimate the three links jointly on a common sample and test the restriction that connects them.

2.3. Trends, cycles and the measurement of the EPC

Unemployment, output and emissions are trending, persistent series in advanced economies. Over 1975–2024, the G7 economies deindustrialized, shifted towards services and began the energy transition, and emissions per capita fell while income rose. A regression of emission levels on unemployment levels therefore mixes the short-run co-movement over the business cycle, which the EPC describes, with the long-run association between trends, which reflects structural change and may have any sign. Because the trends break at different dates in different countries, the levels relationship is also likely to be unstable and to depend on the sample window, the control set and the estimator's treatment of common factors.

Appendix A formalises the compositional channel in a two-sector model in which one sector uses a polluting intermediate input more intensively. Employment and emissions co-move when the polluting sector responds to aggregate demand, but the strength of the co-movement depends on

the sectoral composition of output, which varies across states of the economy and countries. The model also implies that technical and compositional change shifts the levels relationship between unemployment and emissions over time, while the relationship between their cyclical components can remain stable.

2.4. Hypotheses

The framework yields two testable hypotheses, both stated for the cyclical components of the variables and confronted with their levels counterparts:

H1 (cyclical EPC). Unemployment above its trend is associated with CO_2 emissions per capita below their trend ($\beta < 0$), conditional on the renewable share and clean-energy RD&D share.

H2 (Okun transmission). The EPC equals the product of the Okun and emissions–output coefficients ($\beta = \varepsilon\theta$), so that unemployment is unrelated to emissions once output is held constant ($b_1 = 0$).

3. Data and empirical strategy

3.1. Data

The panel covers the seven G7 economies (Canada, France, Germany, Italy, Japan, the United Kingdom and the United States) annually from 1975 to 2024 (N = 7, T = 50, 350 observations). Table 2 reports definitions, transformations and sources. CO_2 emissions per capita from fossil fuels and industry come from the Global Carbon Budget (Friedlingstein et al., 2025) and the renewable share of primary energy from the Energy Institute Statistical Review, both distributed by Our World in Data. The unemployment rate is the OECD Economic Outlook series compiled in the Global Macro Database (Müller et al., 2025); for Germany, the pre-1992 series is ratio-spliced to the unified series (ratio 0.998). Real GDP per capita is from the Maddison Project Database 2023 (Bolt and van Zanden, 2025), extended to 2023–2024 with IMF World Economic Outlook growth rates. Public energy RD&D is from the IEA RD&D database (2025 edition), from which we construct the clean-energy share (renewables, end-use efficiency and storage) relative to these categories plus fossil fuels. The load capacity factor, biocapacity divided by the ecological footprint of consumption, is from the National Footprint and Biocapacity Accounts of the Global Footprint Network (2025 edition) and serves as an alternative measure of environmental pressure in the sensitivity analysis.

The IEA does not report clean-energy RD&D for France before 1985 or Italy before 1977; these 12 observations are held at the first reported value and fall outside the 1990–2022 and 2000–2024 samples. Construction steps, including splices of RD&D vintages, are documented in

Supplementary Table S1; Supplementary Table S3 reports collinearity checks, with variance inflation factors below 2.6.

Table 2. Variables, transformations and sources.

Variable	Symbol	Definition and unit	Transformation	Source
CO_2 emissions per capita	CO_2	Tonnes per Person	ln; HP, boosted HP and Hamilton gaps	Global Carbon Budget (via OWID)
Unemployment rate	UNE	% of labor force; Germany before 1992 spliced to unified series	ln; HP, boosted HP and Hamilton gaps	OECD Economic Outlook (via Global Macro Database)
GDP per capita	GDPC	Real, 2011 international $; 2023–2024 extended with IMF WEO growth	ln; HP, boosted HP and Hamilton gaps	Maddison Project 2023; IMF WEO
Renewable energy share	REN	% of primary energy (substitution method)	ln; HP and boosted HP gaps	Energy Institute (via OWID)
Clean energy RD&D share	CLEAN	(renewables + efficiency + storage) / (those + fossil incl. CCS), public RD&D	level (0–1); HP and boosted HP gaps	IEA RD&D database, 2025
Load capacity factor	LCF	Biocapacity per capita / ecological footprint of consumption per capita	ln; HP, boosted HP and Hamilton gaps	Global Footprint Network, 2025

Note: OWID = Our World in Data; HP = Hodrick–Prescott ($\lambda = 6.25$); Hamilton = regression filter (h = 2, two lags). Construction steps and descriptive statistics: Supplementary Tables S1–S2.

3.2. Cyclical components and the levels benchmark

Cyclical components are extracted country by country. The baseline is the Hodrick–Prescott filter with a smoothing parameter of 6.25, appropriate for annual data (Hodrick and Prescott, 1997; Ravn and Uhlig, 2002). Because the HP filter can induce spurious cyclicality and is unreliable near the sample end (Hamilton, 2018), we use two alternatives. The Hamilton (2018) regression filter defines the cycle as the residual from a regression of the variable at t + 2 on its values at t and t − 1; it uses two-year-ahead forecast errors and costs the first three observations of each country. The boosted HP filter of Phillips and Shi (2021) reapplies the HP filter to its own cyclical component until a stopping rule (a Bayesian information criterion or an augmented Dickey–Fuller test on the remaining cycle) is met, and consistently removes stochastic trends without losing observations; following Phillips and Shi (2021), we use $\lambda = 100$ and report both stopping rules. With $\lambda = 6.25$ the information criterion stops after the first iteration for every series, so the boosted and standard HP cycles coincide (Supplementary Table S10). Figure 1 displays the HP cyclical components: the CO_2 and output gaps move closely together and the unemployment gap moves against both, most visibly in 1980–1982, 1991–1993, 2009 and 2020.

For comparison with the existing literature, we also estimate the conventional levels specification derived from the STIRPAT framework (Dietz and Rosa, 1997):

$$\ln \mathrm{CO}_{2it} = f(\ln \mathrm{UNE}_{it}, \ln \mathrm{GDPC}_{it}, \ln \mathrm{REN}_{it}, \mathrm{CLEAN}_{it}) + \mu_i + \delta_t + \varepsilon_{it} \quad (5)$$

where μ_i and δ_t denote country and year effects. The same core controls are used in the PMG and CS-ARDL estimates over the sample windows of the G7 literature. With at most four regressors,

the specification is deliberately parsimonious given the number of annual observations per country.

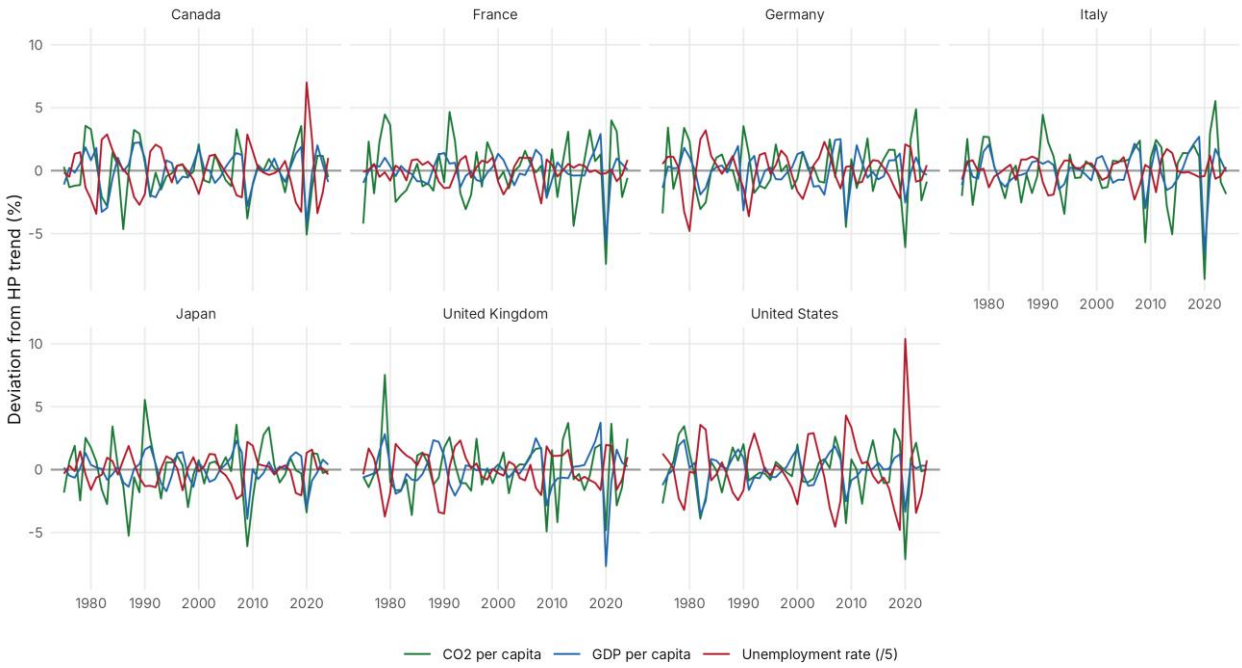


Figure 1. Cyclical components (HP filter, $\lambda = 6.25$) of CO_2 emissions per capita, the unemployment rate and GDP per capita, G7, 1975–2024. The unemployment gap is divided by 5 for readability.

3.3. Estimation strategy

The empirical strategy is applied in parallel to levels and gaps, so that the two can be compared on the same data with the same estimators. It has four components: diagnostics of the time-series properties of levels and gaps; estimation of the EPC in levels and gaps with one-way and two-way fixed effects (Driscoll–Kraay standard errors), mean-group, CCEMG, PMG and CS-ARDL estimators, complemented in gaps by the three links and the test of the Okun restriction, in the panel and by country; a sensitivity analysis across filters and sample periods; and predictive-ordering tests on the gaps. Figure 2 summarises this strategy.

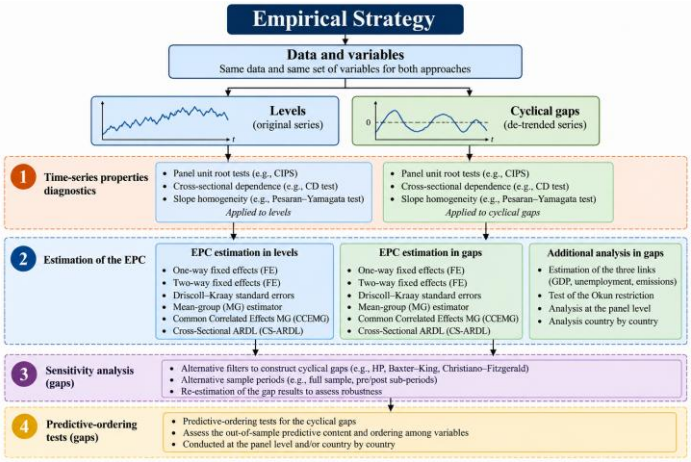


Figure 2. Empirical estimation strategy: parallel analysis of levels and cyclical gaps.

3.3.1. Diagnostics, linear links and the Okun restriction

a) Diagnostics

Cross-sectional dependence is assessed with the CD statistic of Pesaran (2015), unit roots with the CIPS test of Pesaran (2007) and CADF of Karavias and Tzavalis (2014), and slope homogeneity with the test of Pesaran and Yamagata (2008).

Because tabulated CIPS critical values require $N \geq 10$, p-values for $N = 7$ and $T = 50$ are simulated (2,000 replications). We complement CIPS with the underlying country CADF statistics, with p-values simulated in the same way, and with the panel unit-root test of Karavias and Tzavalis (2014), which allows one or two breaks at unknown dates in the intercept (model M1, applied to the gaps) or in the intercept and trend (model M2, applied to the levels) under the null of a unit root without breaks. We use the normal-errors form with cross-sectional demeaning, as implemented by Chen et al. (2022), and take the minimum of the statistic over admissible break dates. Because the test is derived for many cross-sections, p-values for $N = 7$ and $T = 50$ are obtained by Monte Carlo simulation under the null with country-specific innovation variances (999 replications).

b) Linear links and the Okun restriction

The levels specification and each gap link are estimated with the same estimators, so that levels and gaps are compared on the same footing. Estimators with common slopes are first differences, country fixed effects and two-way fixed effects, all with Driscoll and Kraay (1998) standard errors, robust to heteroskedasticity, serial correlation and cross-sectional dependence (Hoechle, 2007). Estimators with country-specific slopes are the mean-group estimator (MG; Pesaran and Smith, 1995), the augmented mean-group estimator (AMG; Eberhardt and Teal, 2010; Bond and Eberhardt, 2013) and the common correlated effects mean-group estimator (CCEMG; Pesaran, 2006). AMG and CCEMG allow for unobserved common factors, AMG through a common dynamic process estimated from the year dummies of a pooled first-difference regression, CCEMG through cross-sectional averages. All six estimators are applied to the levels; for the gaps, first differences and AMG are omitted because they add nothing to one-way fixed effects and MG.

To allow for dynamics, as in Azimi and Rahman (2024) and Ayad and Djedaiet (2026), the levels specification and each gap link are also estimated with the CS-ARDL estimator of Chudik and Pesaran (2015), a country ARDL(1,1) model augmented with the current and lagged cross-sectional averages of all variables. The long-run coefficient is $\lambda_i = (\beta_{0i} + \beta_{1i})/(1 - \varphi_i)$, the short-run coefficient is β_{0i}, and $\varphi_i - 1$ is the error-correction speed; all are averaged across countries. Because the cross-sectional averages absorb common factors (common trends in levels, the common G7

cycle in gaps), CS-ARDL estimates for the gaps should be smaller than those retaining the common cycle. In levels, the model is estimated over 1975–2024, 1990–2022 and 2000–2024.

Because the G7 literature also uses the pooled mean group (PMG) panel ARDL (Ayad and Djedaiet, 2026; Djedaiet et al., 2026), the levels specification and each gap link are also estimated with the PMG estimator of Pesaran et al. (1999). PMG fits the same ARDL(1,1) model in error-correction form by maximum likelihood, constraining the long-run coefficients to be equal across countries while leaving the short-run coefficients, error-correction speeds and error variances country-specific. It thus lies between the mean-group ARDL (Pesaran and Smith, 1995), in which all coefficients differ across countries, and fixed effects, which pool all slopes. Common long-run coefficients are tested against the mean-group ARDL with a Hausman test. Unlike CS-ARDL, PMG does not remove common factors and therefore retains, for the gaps, the common G7 cycle through which Okun's law operates; the two panel ARDL estimators thus bracket the role of the common cycle in a dynamic specification, and the Okun restriction is tested for both. Because the ARDL framework is valid for stationary and non-stationary regressors, PMG can be applied to the gaps, whose long-run coefficients are then cumulative dynamic multipliers (the total effect of a persistent gap) rather than cointegrating relationships. Since PMG assumes cross-sectionally independent errors, which the CD tests reject, inference on the gap links relies on the joint moving-block bootstrap, and the Hausman tests are only indicative.

Cointegration, which the levels long-run coefficients require, is tested with the Westerlund (2007) error-correction tests, against the alternative that at least one country (Gt, Ga) or the panel as a whole (Pt, Pa) is cointegrated. For the stationary gaps, a rejection indicates a stable error-correcting link rather than a common stochastic trend. Given cross-sectional dependence, p-values are bootstrapped by resampling the null-model residuals and regressor changes of all countries by year (Persyn and Westerlund, 2008).

3.3.2. Sensitivity analysis: filters, sample periods and alternative measurement

The results could depend on how the cycle is measured and on the period studied. We therefore repeat the three links, the test of $\beta = \varepsilon\theta$ and the beyond-Okun regression with every estimator for each combination of four filters and three sample periods. The filters are the HP filter, the Hamilton filter and the boosted HP filter with the BIC and ADF stopping rules (Section 3.2), each applied to the full 1975–2024 series of every variable, including the controls, so that the cycles do not depend on the estimation window. The periods are the full sample; 1990–2022, the window closest to Azimi and Rahman (2024); and 2000–2024, after the main wave of deindustrialization. These are also the windows of the levels CS-ARDL benchmark (Table 5), so levels and gaps are compared on the same samples. Each specification is bootstrapped as in the main analysis, with

all estimators re-estimated on the same resampled years, and two-way fixed effects, which remove the common G7 cycle, are reported alongside one-way fixed effects. The exercise is carried out twice: with CO_2 emissions per capita and with the load capacity factor (Yavuz et al., 2024; Ayad and Djedaiet, 2026), whose cyclical component is multiplied by −1 so that, as for CO_2, a negative EPC means lower environmental pressure when unemployment is above trend. The LCF captures consumption-based pressure on all land and marine uses rather than territorial CO_2 alone.

3.3.3. Predictive ordering

Okun's law implies that output and unemployment gaps are jointly determined, while emissions respond to output within the year. We examine the predictive ordering of the three gaps, and of the first differences of the levels, with the Dumitrescu and Hurlin (2012) panel Granger non-causality test, which allows heterogeneous coefficients, using one and two lags and the small-sample $\tilde{Z}$ statistic. The results are read as evidence on predictive precedence, not structural causation.

4. Results

4.1. Preliminary diagnostics

Table 3 reports the panel diagnostics. Cross-sectional dependence is pervasive. The CD statistic is 19.1 for ln CO_2, 9.2 for ln UNE and between 6.5 and 31.6 for the other levels, all significant at the 1% level, and remains 8.3, also significant at the 1% level, for the residuals of the fixed-effects levels model. The cyclical components of CO_2, unemployment and output are also strongly correlated across countries, with CD statistics between 13.8 and 21.2, reflecting a common G7 business cycle, whereas those of the technology controls are not: 0.22 for the renewable share and −1.56 for the clean RD&D share, neither significant. Inference must therefore preserve cross-sectional dependence, which motivates Driscoll–Kraay standard errors and a bootstrap that resamples the same years for all countries.

The CIPS test does not reject a unit root in the levels of ln CO_2, ln UNE, ln GDPC, ln REN or CLEAN, even at the 10% level, but rejects it at the 1% level for every first difference and cyclical component. The levels are thus persistent and plausibly non-stationary, exposing levels regressions to spurious correlation, while the cyclical components are stationary by construction and by test. Slope homogeneity is strongly rejected in the levels model, where the adjusted Δ of 25.6 is significant at the 1% level, and more mildly in the gap links: the adjusted Δ is 6.19 for Okun's law, significant at the 1% level, and 2.14 for the emissions–output link and 1.97 for the

EPC, both significant at the 5% level. Country-specific and mean-group estimates are therefore reported alongside pooled ones.

Table 3. Cross-sectional dependence, panel unit roots and slope homogeneity, 1975–2024.

Variable	CD statistic	p	CIPS, levels or gaps	p	CIPS, first differences	p
ln CO_2	19.12	<0.001	−1.73	0.941	−4.87	<0.001
ln LCF	11.60	<0.001	−1.99	0.799	−5.50	<0.001
ln UNE	9.18	<0.001	−2.53	0.279	−3.81	<0.001
ln GDPC	31.56	<0.001	−1.99	0.801	−4.19	<0.001
ln REN	19.61	<0.001	−2.50	0.309	−5.48	<0.001
CLEAN	6.53	<0.001	−2.18	0.631	−4.63	<0.001
CO_2 gap	15.95	<0.001	−5.99	<0.001	–	–
UNE gap	13.84	<0.001	−5.26	<0.001	–	–
GDPC gap	21.23	<0.001	−5.73	<0.001	–	–
REN gap	0.22	0.827	−6.12	<0.001	–	–
CLEAN gap	−1.56	0.118	−5.81	<0.001	–	–

Note: CD: Pesaran (2015). CIPS: Pesaran (2007), one lag (trend for levels, intercept for differences and gaps); p-values simulated for N = 7, T = 50 (2,000 replications). CD on FE levels residuals: 8.30 ($p < 0.001$). Pesaran–Yamagata adjusted Δ: levels 25.63 ($p < 0.001$); Okun 6.19 ($p < 0.001$), emissions–output 2.14 ($p = 0.016$), EPC 1.97 ($p = 0.024$).

Panel B of Table 3 reports the country CADF statistics and the Karavias–Tzavalis tests with structural breaks (details in Supplementary Tables S8 and S9). The CADF tests confirm the panel results: a unit root is not rejected at the 5% level in any country for ln CO_2, ln UNE, ln REN or CLEAN, and in only one country for ln LCF and ln GDPC, whereas it is rejected for the first differences in most countries and for every cyclical component in every country. Allowing for breaks does not overturn this conclusion for the core variables. The Karavias–Tzavalis test does not reject a unit root in ln CO_2 with one or two breaks, even at the 10% level, with minimum statistics of −0.97 and −2.71, nor in ln UNE, ln GDPC or CLEAN. It rejects at the 1% level for ln LCF and ln REN once two breaks are allowed, with breaks in 1978 and 1998 for ln LCF and in 1993 and 2012 for ln REN, so these series are better described as stationary around broken trends. Every cyclical component rejects the unit-root null at the 1% level by a wide margin, with minimum statistics between −25.75 and −43.28; the estimated break dates for the gaps fall at the beginning or end of the sample, where the minimising date is not informative.

Table 3 (continued). Panel B: country CADF tests and Karavias–Tzavalis (2014) panel unit-root tests with structural breaks.

Variable	CADF: countries rejecting, level or gap	CADF: countries rejecting, first difference	KT, one break: minZ (p)	Break	KT, two breaks: minZ (p)	Breaks
ln CO_2	0 of 7	6 of 7	−0.97 (0.651)	1989	−2.71 (0.253)	1989, 2011
ln LCF	1 of 7	7 of 7	−5.95*** (<0.001)	1998	−6.25*** (<0.001)	1978, 1998
ln UNE	0 of 7	5 of 7	0.77 (0.996)	2022	0.18 (0.996)	2007, 2019
ln GDPC	1 of 7	6 of 7	1.18 (0.999)	1981	−0.12 (0.988)	1997, 2019
ln REN	0 of 7	7 of 7	−3.31* (0.072)	1999	−4.98*** (0.005)	1993, 2012

Variable	CADF: countries rejecting, level or gap	CADF: countries rejecting, first difference	KT, one break: minZ (p)	Break	KT, two breaks: minZ (p)	Breaks
CLEAN	0 of 7	7 of 7	−1.62 (0.467)	1992	−2.50 (0.401)	1978, 1992
CO_2 gap	7 of 7	–	−41.31*** (<0.001)	2023	−39.97*** (<0.001)	2021, 2023
UNE gap	7 of 7	–	−26.05*** (<0.001)	2023	−25.75*** (<0.001)	2019, 2021
GDPC gap	7 of 7	–	−31.55*** (<0.001)	2023	−29.96*** (<0.001)	2021, 2023
REN gap	7 of 7	–	−43.28*** (<0.001)	2023	−41.06*** (<0.001)	2021, 2023
CLEAN gap	7 of 7	–	−39.73*** (<0.001)	2023	−37.57*** (<0.001)	1977, 1979

Note: CADF (Pesaran, 2007), one lag; trend for levels, intercept for differences and gaps; number of countries rejecting at 5% with simulated critical values (−3.81 with trend, −3.28 for gaps). KT: Karavias and Tzavalis (2014) minimum statistic with cross-sectional demeaning (Chen et al., 2022); model M2 for levels, M1 for gaps; H0: unit root without breaks; Monte Carlo p-values (999 replications). Breaks: last year of each regime. Country details: Supplementary Tables S8–S9. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. The levels specification: instability over half a century

Table 4 estimates the conventional levels specification on the full sample with estimators that impose common slopes (Panel A) and estimators that allow country-specific slopes (Panel B), the same estimators later applied to the gaps. The unemployment coefficient proves fragile. With country fixed effects and Driscoll–Kraay standard errors it is −0.043 and significant only at the 10% level; it falls to an insignificant −0.021 in first differences and turns positive and insignificant, at 0.022, with two-way fixed effects. With country-specific slopes, the mean-group and AMG estimates, −0.061 and −0.037, are significant only at the 10% level, and the CCEMG estimate, −0.006, is close to zero and insignificant. Only the renewable share has a robust sign: its elasticity is negative in every estimator (−0.04 to −0.36) and significant at the 5% level in all but the AMG and the CS-ARDL long run.

The CS-ARDL estimator favored in the G7 literature does not recover a levels EPC either (Table 5, Panel B). The long-run unemployment coefficient is 0.003 over 1975–2024, −0.006 over 1990–2022, the window closest to Azimi and Rahman (2024), and 0.005 over 2000–2024, none significant, and the short-run coefficients are equally small and insignificant. None approaches the elasticity of about −1 reported in that study. The other coefficients are highly sensitive to the window: the long-run income elasticity changes sign (0.454, 0.006 and −1.716) and is never significant, and the renewable share lowers emissions in the short run in every window but has no significant long-run effect. The error-correction coefficient rises in absolute value from −0.70 to −0.86 as the window shortens, so that the shorter-window models behave like regressions of annual changes driven by the cyclical co-movement of emissions and income. The Westerlund (2007) tests point the same way: none of the four statistics rejects no cointegration at the 5% level over 1975–2024 or 1990–2022, and over 2000–2024 only Pt rejects, at the 5% level, unsupported by the group-mean Ga statistic. The long-run CS-ARDL coefficients therefore do not rest on a level relationship that the data support, and levels specifications do not provide a reliable basis for inference about the EPC.

The pooled mean group estimator, which constrains the long-run coefficients to be common across countries (Table 5, Panel A), confirms this conclusion. The long-run unemployment coefficient is 0.030 over 1975–2024, −0.035 over 1990–2022 and 0.028 over 2000–2024, never significant, and the short-run coefficients are equally close to zero. The Hausman test does not reject common long-run coefficients at the 5% level in any window, although, given cross-sectional dependence, this is only indicative. The pooled estimates display the same window sensitivity as CS-ARDL: the long-run income elasticity is 0.325 over 1975–2024 but −0.390 and −0.660 over the two shorter windows, all significant. Over the full sample, the error-correction coefficient is only −0.067, implying a half-life of about ten years for deviations from the estimated long-run relationship. Neither panel ARDL estimator recovers a levels EPC.

Table 4. Levels specification, 1975–2024: estimators with common and with country-specific slopes. Dependent variable: ln CO_2 per capita.

Panel A: common slopes	**First differences (Driscoll–Kraay)**	**FE (Driscoll–Kraay)**	**Two-way FE (Driscoll–Kraay)**
ln UNE	−0.021	−0.043*	0.022
	(0.016)	(0.022)	(0.023)
ln GDPC	0.832***	0.039	0.934***
	(0.091)	(0.040)	(0.217)
ln REN	−0.126***	−0.193***	−0.154***
	(0.014)	(0.015)	(0.007)
CLEAN	−0.008	−0.149***	−0.129***
	(0.020)	(0.050)	(0.036)
Panel B: country-specific slopes	**MG**	**AMG**	**CCEMG**
ln UNE	−0.061*	−0.037*	−0.006
	(0.032)	(0.022)	(0.020)
ln GDPC	0.082	0.601***	0.628***
	(0.151)	(0.059)	(0.128)
ln REN	−0.363***	−0.064*	−0.080***
	(0.068)	(0.035)	(0.023)
CLEAN	−0.065	−0.012	0.018
	(0.058)	(0.064)	(0.042)

Note: Core controls ln GDPC, ln REN and CLEAN; N = 7, T = 50. Panel A: Driscoll–Kraay standard errors (Bartlett kernel, lag 2). Panel B: MG (Pesaran and Smith, 1995), AMG (Eberhardt and Teal, 2010) and CCEMG (Pesaran, 2006), mean-group standard errors. CS-ARDL in Table 5. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5. Panel ARDL (PMG) and CS-ARDL estimates of the levels specification, by sample period. Dependent variable: ln CO_2 per capita.

Panel A: panel ARDL, pooled mean group (PMG)	**1975–2024**	**1990–2022**	**2000–2024**
ln UNE, long run	0.030	−0.035	0.028
	(0.054)	(0.060)	(0.048)
ln UNE, short run	−0.024	0.004	0.024
	(0.023)	(0.017)	(0.034)
ln GDPC, long run	0.325***	−0.390***	−0.660**

Panel A: panel ARDL, pooled mean group (PMG)	**1975–2024**	**1990–2022**	**2000–2024**
	(0.090)	(0.147)	(0.305)
ln GDPC, short run	0.752***	0.801***	0.825***
	(0.102)	(0.045)	(0.094)
ln REN, long run	−0.486***	−0.376***	−0.430***
	(0.052)	(0.038)	(0.020)
ln REN, short run	−0.142***	−0.122***	−0.163***
	(0.025)	(0.018)	(0.036)
CLEAN, long run	−0.312**	−0.115	−0.046
	(0.122)	(0.075)	(0.057)
CLEAN, short run	−0.035*	−0.038**	−0.030
	(0.019)	(0.018)	(0.052)
Error-correction coefficient (φ − 1)	−0.067***	−0.153*	−0.218**
	(0.023)	(0.085)	(0.104)
Hausman test, PMG vs MG: χ^2 [p]	4.50 [0.343]	5.05 [0.282]	9.14 [0.058]
Panel B: CS-ARDL	**1975–2024**	**1990–2022**	**2000–2024**
ln UNE, long run	0.003	−0.006	0.005
	(0.033)	(0.069)	(0.070)
ln UNE, short run	−0.026	−0.005	0.026
	(0.027)	(0.035)	(0.056)
ln GDPC, long run	0.454	0.006	−1.716
	(0.289)	(0.367)	(1.586)
ln GDPC, short run	0.558***	0.669**	0.221
	(0.102)	(0.283)	(0.295)
ln REN, long run	−0.036	−0.082	−0.150
	(0.060)	(0.059)	(0.121)
ln REN, short run	−0.108***	−0.113***	−0.199***
	(0.023)	(0.040)	(0.074)
CLEAN, long run	0.010	−0.011	−0.222
	(0.056)	(0.110)	(0.167)
CLEAN, short run	0.007	0.034*	−0.027
	(0.019)	(0.018)	(0.070)
Error-correction coefficient (φ − 1)	−0.701***	−0.794***	−0.857***
	(0.040)	(0.123)	(0.188)
Panel C: Westerlund (2007) cointegration tests, H0: no cointegration	**1975–2024**	**1990–2022**	**2000–2024**
Gt (group mean, t)	−1.85 [0.766]	−2.55 [0.106]	−2.46 [0.068]
Ga (group mean, α)	−19.57 [0.731]	−29.21 [0.277]	−52.06 [0.483]
Pt (panel, t)	−4.40 [0.721]	−6.56 [0.090]	−6.59 [0.040]
Pa (panel, α)	−13.67 [0.671]	−26.95 [0.104]	−50.87 [0.128]

Note: Core controls as in Table 4. ARDL(1,1) by country; long run = $(\beta_0 + \beta_1)/(1 - \varphi)$, short run = β_0. Panel A: PMG (Pesaran et al., 1999), common long run by maximum likelihood, country-specific short run averaged with mean-group standard errors; Hausman test against the mean-group ARDL († computed with the mean-group variance). Panel B: CS-ARDL (Chudik and Pesaran, 2015) with current and one lagged cross-sectional average of all variables. Panel C: Westerlund (2007) tests, lag length by AIC; bootstrap p-values in brackets (B = 499), resampling years for all countries (Persyn and Westerlund, 2008). Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

4.3. The cyclical EPC and Okun's law

Figure 3 displays the three relationships in the pooled cyclical data, and Tables 6 and 7 report the estimates. With country fixed effects, all three links are precisely estimated and correctly signed. By Okun's law, a 10% unemployment gap (for instance, an unemployment rate of 7.7% against a trend rate of 7%) is associated with an output gap of −1.1%, with $\theta = -0.112$ significant at the 1% level. A 1% output gap is associated with a CO_2 gap of 0.83%, with $\varepsilon = 0.835$ also significant at the 1% level. The EPC associates a 10% unemployment gap with a CO_2 gap of −1.1%, with $\beta = -0.113$ significant at the 1% level, which supports H1. Year effects, which absorb the common G7 cycle, weaken all three links ($\theta = -0.045$, $\varepsilon = 0.446$, $\beta = -0.051$); the EPC remains significant at the 1% level but is less than half as large. The mean-group estimates are almost identical to the fixed-effects ones ($\theta = -0.126$, $\varepsilon = 0.880$, $\beta = -0.107$). The CCEMG estimates are smaller ($\theta = -0.085$, $\varepsilon = 0.466$, $\beta = -0.062$) because the cross-sectional averages remove the common cycle, but all remain significant at the 1% level. The panel ARDL estimators in Table 7 point the same way. With PMG, which pools the long-run coefficients but retains the common cycle, the impact coefficients are close to the fixed-effects estimates ($\theta = -0.145$, $\varepsilon = 0.910$, $\beta = -0.140$) and the long-run coefficients somewhat smaller ($\theta = -0.083$, $\varepsilon = 0.680$, $\beta = -0.081$), and the indicative Hausman test does not reject common long-run coefficients for any link, even at the 10% level. With CS-ARDL, which removes the common cycle, the EPC is −0.048 in the long run, at the margin of significance at the 10% level, and −0.065 on impact, significant at the 5% level. For both estimators, error-correction coefficients close to −1 (−0.98 to −1.07 with PMG, −0.89 to −1.17 with CS-ARDL) show that the cyclical relationships are essentially contemporaneous. The Westerlund (2007) tests reject no error correction at the 1% level for every link, with Gt statistics between −7.11 and −6.79; since the gaps are stationary by construction, this indicates stable error-correcting relationships rather than shared stochastic trends, unlike in levels.

Tables 6 and 7 also test H2 for each estimator. With fixed effects, the Okun-implied EPC is $\varepsilon\theta = -0.094$, against an estimated $\beta = -0.113$, so Okun's law accounts for 83% of the EPC, with a bootstrap 95% interval of 0.62–0.98. The difference $\beta - \varepsilon\theta = -0.019$ is insignificant with the delta method and significant only at the 10% level with the joint bootstrap. At given output, the unemployment gap retains only a small coefficient, $b_1 = -0.036$, significant only at the 10% level with the bootstrap, against $b_2 = 0.699$ for the output gap.

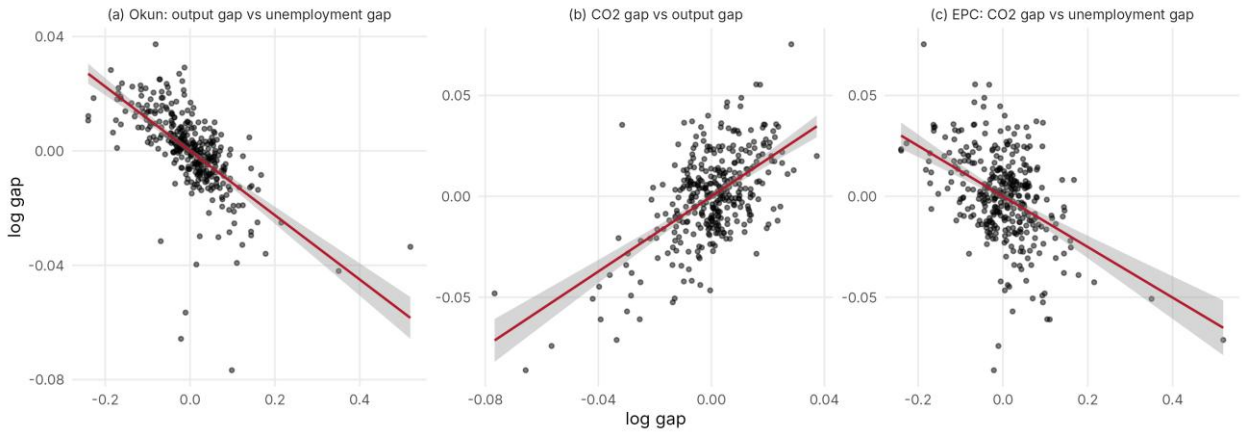


Figure 3. The three links in HP gaps, pooled G7 data, 1975–2024, with OLS fit and 95% band: (a) Okun's law; (b) the emissions–output link; (c) the EPC.

Table 6. The three links in gaps (HP filter) and the test of $\beta = \varepsilon\theta$: fixed-effects and mean-group estimators, G7, 1975–2024.

Panel A: common slopes	**FE (Driscoll–Kraay)**	**Two-way FE (Driscoll–Kraay)**
The three links and the beyond-Okun equation		
θ: output gap on unemployment gap	−0.112***	−0.045*
	(0.008)	(0.026)
ε: CO_2 gap on output gap	0.835***	0.446***
	(0.094)	(0.088)
β: CO_2 gap on unemployment gap (EPC)	−0.113***	−0.051***
	(0.015)	(0.014)
b_1: unemployment gap, output gap held constant	−0.036**	−0.036***
	(0.016)	(0.009)
b_2: output gap, unemployment gap held constant	0.699***	0.354***
	(0.119)	(0.071)
Test of $\beta = \varepsilon\theta$ (is the EPC Okun's law?)		
Okun-implied EPC εθ	−0.094***	−0.020
	(0.015)	(0.014)
$\beta - \varepsilon\theta$ (delta method)	−0.019	−0.031*
	(0.019; p 0.311)	(0.018; p 0.088)
$\beta - \varepsilon\theta$ (joint bootstrap)	−0.019*	−0.031***
	(0.010; p 0.061)	(0.009; p <0.001)
Share explained εθ/β	0.83	0.39
	[0.62, 0.98]	[0.03, 0.76]
b_1, joint bootstrap	−0.036*	−0.036***
	(0.019; p 0.060)	(0.010; p <0.001)
Panel B: country-specific slopes	**MG**	**CCEMG**
The three links and the beyond-Okun equation		
θ: output gap on unemployment gap	−0.126***	−0.085***
	(0.012)	(0.010)
ε: CO_2 gap on output gap	0.880***	0.466***
	(0.089)	(0.107)
β: CO_2 gap on unemployment gap (EPC)	−0.107***	−0.062***
	(0.017)	(0.017)

Panel A: common slopes	FE (Driscoll–Kraay)	Two-way FE (Driscoll–Kraay)
b_1: unemployment gap, output gap held constant	−0.024	−0.027
	(0.017)	(0.019)
b_2: output gap, unemployment gap held constant	0.703***	0.368***
	(0.100)	(0.135)
Test of β = εθ (is the EPC Okun's law?)		
Okun-implied EPC εθ	−0.111***	−0.039***
	(0.019)	(0.009)
β − εθ (delta method)	0.004	−0.023
	(0.023; p 0.876)	(0.020; p 0.257)
β − εθ (joint bootstrap)	0.004	−0.023
	(0.027; p 0.893)	(0.020; p 0.263)
Share explained εθ/β	1.03	0.64
	[0.64, 1.81]	[0.37, 1.52]
b_1, joint bootstrap	−0.024	−0.027
	(0.030; p 0.411)	(0.028; p 0.339)

Note: HP gaps; N = 7, T = 50; emissions equations control for the REN and CLEAN gaps. Panel A: Driscoll–Kraay standard errors (Bartlett kernel, lag 2). Panel B: MG and CCEMG, mean-group standard errors. CS-ARDL in Table 7. Test of β = εθ: standard errors in parentheses and 95% percentile intervals in brackets from a joint moving-block bootstrap over years (block length 4, B = 499; same resampled years for all countries, links and estimators in Tables 6 and 7); the delta-method row treats the equations as independent. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7. The three links in gaps (HP filter) and the test of β = εθ: panel ARDL (PMG) and CS-ARDL estimates, G7, 1975–2024.

Dynamic estimators	PMG long run	PMG short run	CS-ARDL long run	CS-ARDL short run
The three links and the beyond-Okun equation				
θ: output gap on unemployment gap	−0.083***	−0.145***	−0.076***	−0.085***
	(0.011)	(0.011)	(0.005)	(0.017)
ε: CO_2 gap on output gap	0.680***	0.910***	0.273*	0.530***
	(0.152)	(0.113)	(0.143)	(0.111)
β: CO_2 gap on unemployment gap (EPC)	−0.081***	−0.140***	−0.048	−0.065***
	(0.017)	(0.021)	(0.030)	(0.025)
b_1: unemployment gap, output gap held constant	−0.063***	−0.067***	−0.041*	−0.036
	(0.022)	(0.024)	(0.023)	(0.043)
b_2: output gap, unemployment gap held constant	0.303*	0.574***	0.182	0.496***
	(0.181)	(0.124)	(0.177)	(0.128)
Test of β = εθ (is the EPC Okun's law?)				
Okun-implied EPC εθ	−0.056***	−0.132***	−0.021	−0.045***
	(0.017)	(0.021)	(0.013)	(0.013)
β − εθ (delta method)	−0.025*	−0.008	−0.027	−0.020
	(0.015; p 0.089)	(0.028; p 0.762)	(0.031; p 0.384)	(0.028; p 0.485)
β − εθ (joint bootstrap)	−0.025*	−0.008	−0.027	−0.020
	(0.014; p 0.070)	(0.017; p 0.617)	(0.025; p 0.271)	(0.025; p 0.422)
Share explained εθ/β	0.69	0.94	0.43	0.69
	[0.40, 1.01]	[0.64, 1.22]	[−2.09, 2.95]	[0.32, 3.12]
b_1, joint bootstrap	−0.063***	−0.067***	−0.041	−0.036
	(0.022; p 0.005)	(0.024; p 0.006)	(0.083; p 0.622)	(0.039; p 0.365)

Dynamic estimators	PMG long run	PMG short run	CS-ARDL long run	CS-ARDL short run
Error-correction coefficient (φ − 1), by equation				
Okun's law equation	−0.982***		−0.890***	
	(0.059)		(0.084)	
Emissions–output equation	−0.988***		−1.172***	
	(0.037)		(0.037)	
EPC equation	−1.066***		−1.107***	
	(0.039)		(0.041)	
Beyond-Okun equation	−1.015***		−1.103***	
	(0.045)		(0.044)	
Hausman test, PMG vs MG: χ^2 [p], by equation				
Okun's law equation	2.58 [0.108]			
Emissions–output equation	2.49 [0.478]			
EPC equation	1.17† [0.760]			
Beyond-Okun equation	5.91† [0.206]			

Westerlund (2007) tests, H0: no cointegration	Okun's law	Emissions–output	EPC	Beyond Okun
Gt (group mean, t)	−7.11 [<0.002]	−6.79 [<0.002]	−7.10 [<0.002]	−6.90 [<0.002]
Ga (group mean, α)	−92.50 [<0.002]	−93.38 [<0.002]	−91.80 [<0.002]	−101.02 [<0.002]
Pt (panel, t)	−19.04 [<0.002]	−17.09 [<0.002]	−18.41 [<0.002]	−17.57 [<0.002]
Pa (panel, α)	−84.33 [<0.002]	−80.93 [<0.002]	−76.69 [<0.002]	−80.28 [<0.002]

Note: HP gaps; N = 7, T = 50; controls as in Table 6. ARDL(1,1) by country; long run = $(\beta_0 + \beta_1)/(1 - \varphi)$, interpreted for stationary gaps as the cumulative effect of a persistent gap; short run = impact coefficient. PMG (Pesaran et al., 1999): common long run; Hausman test χ^2 [p], indicative only († computed with the mean-group variance). CS-ARDL (Chudik and Pesaran, 2015): one lag of the cross-sectional averages. Standard errors in parentheses: bootstrap for PMG, mean-group for CS-ARDL. Test of $\beta = \varepsilon\theta$ and bootstrap as in Table 6. Westerlund (2007) tests: bootstrap p-values in brackets (B = 499). *** p < 0.01, ** p < 0.05, * p < 0.1.

With two-way fixed effects, Okun's law accounts for only 39% of the EPC, with a 95% interval of 3–76%; the restriction is rejected at the 1% level with the bootstrap, and $b_1 = -0.036$ is significant at the 1% level. The weak two-way Okun coefficient ($\theta = -0.045$) explains why: once year effects remove the common G7 cycle, little of the joint variation in unemployment and output on which Okun's law rests remains, and the remaining EPC is mostly not mediated by output. The mean-group estimator gives the opposite picture: the Okun-implied EPC (−0.111) is almost identical to the estimated EPC (−0.107), the share is 1.03, with a 95% interval of 0.64–1.81, and neither $\beta - \varepsilon\theta = 0.004$ nor $b_1 = -0.024$ is significant. PMG leads to the same conclusion: Okun's law accounts for 69% of the long-run EPC and 94% of the impact EPC, with 95% intervals of 0.40–1.01 and 0.64–1.22, and the restriction is not rejected at the 5% level in either case. PMG is, however, the only estimator retaining the common cycle in which b_1 is significant: it is −0.063 in the long run and −0.067 on impact, both significant at the 1% level with the bootstrap, suggesting that a small direct association at given output may operate through the short-run dynamics. When cross-sectional averages remove the common cycle, the decomposition becomes imprecise, with

shares of 0.64 for CCEMG, 0.43 for the CS-ARDL long run and 0.69 for the CS-ARDL impact coefficients, all with wide intervals. Apart from two-way FE, no estimator rejects the restriction at the 5% level, and b_1 is significant at that level only with PMG. The decomposition is thus sharply identified only from the common G7 cycle, and every estimator that retains this cycle attributes most or all of the EPC to Okun's law. H2 is therefore accepted as a first approximation: most of the EPC is Okun's law, and a small residual association at given output, detected by PMG, is not robust across estimators.

Table 8. Is the EPC Okun's law in every G7 country? Test of $\beta = \varepsilon\theta$ by country and estimator (HP gaps).

	Canada	France	Germany	Italy	Japan	United Kingdom	United States
θ (Okun)							
OLS	−0.132***	−0.119***	−0.091***	−0.130***	−0.164***	−0.167***	−0.081***
ARDL long run	−0.086***	−0.082*	−0.059***	−0.103**	−0.136***	−0.132***	−0.071***
ARDL short run	−0.130***	−0.154***	−0.120***	−0.166***	−0.216***	−0.209***	−0.081***
CCE	−0.106***	−0.046	−0.071***	−0.088***	−0.124***	−0.091***	−0.066***
CS-ARDL long run	−0.072*	−0.060*	−0.074***	−0.082*	−0.099***	−0.065**	−0.079***
CS-ARDL short run	−0.113***	−0.026	−0.078***	−0.055	−0.166***	−0.095***	−0.066***
ε (emissions–output)							
OLS	0.862***	0.898***	0.643*	0.907***	1.083***	0.541**	1.227***
ARDL long run	0.842***	0.383	0.737**	0.274	0.716*	0.391	1.067***
ARDL short run	0.833***	0.833***	0.681**	0.910***	1.088***	0.559**	1.294***
CCE	0.323	0.494	0.155	0.998***	0.569*	0.204	0.520**
CS-ARDL long run	0.203	0.235	0.214	0.966***	0.305	−0.330	0.321
CS-ARDL short run	0.739**	0.553	0.168	0.887***	0.732	0.109	0.520**
β (EPC)							
OLS	−0.134***	−0.046	−0.094***	−0.086	−0.188***	−0.093	−0.111***
ARDL long run	−0.110***	−0.059	−0.059	−0.078	−0.029	−0.093*	−0.081***
ARDL short run	−0.132***	−0.066	−0.164***	−0.098	−0.234***	−0.106	−0.120***
CCE	−0.069	−0.020	−0.011	−0.074	−0.147**	−0.037	−0.076***
CS-ARDL long run	−0.076	0.007	−0.027	−0.211***	−0.026	0.022	−0.027
CS-ARDL short run	−0.066	0.010	−0.013	−0.098	−0.191**	−0.071	−0.027
Share explained εθ/β							
OLS	0.85	n.i.	0.62	n.i.	0.94	n.i.	0.90
ARDL long run	0.65	n.i.	n.i.	n.i.	n.i.	0.55	0.94
ARDL short run	0.82	n.i.	0.50	n.i.	1.01	n.i.	0.87
CCE	n.i.	n.i.	n.i.	n.i.	0.48	n.i.	0.46
CS-ARDL long run	n.i.	n.i.	n.i.	0.37	n.i.	n.i.	n.i.
CS-ARDL short run	n.i.	n.i.	n.i.	n.i.	0.64	n.i.	n.i.
p-value, β = εθ (joint bootstrap)							
OLS	0.060	0.263	0.287	0.706	0.762	0.918	0.155
ARDL long run	0.014	0.720	0.678	0.571	0.283	0.252	0.630
ARDL short run	0.083	0.384	0.039	0.574	0.962	0.770	0.111
CCE	0.245	0.964	0.988	0.700	0.261	0.664	0.032
CS-ARDL long run	0.172	0.807	0.773	0.033	0.989	0.994	0.959
CS-ARDL short run	0.674	0.733	0.989	0.316	0.403	0.353	0.782
b_1, beyond Okun							
OLS	−0.089***	0.049	−0.052	0.002	−0.019	−0.005	−0.056*
ARDL long run	−0.098**	−0.100	−0.027	−0.123	−0.091	−0.124	−0.040
ARDL short run	−0.107**	0.002	−0.116**	−0.055	−0.206*	−0.025	−0.075**
CCE	−0.045	0.015	0.018	0.018	−0.124	−0.040	−0.031
CS-ARDL long run	−0.059	0.072	−0.002	−0.059	−0.113	−0.088	−0.037
CS-ARDL short run	0.023	0.030	0.039	0.033	−0.253*	−0.130	0.010

Note: HP gaps, 1975–2024; controls as in Table 6. OLS and CCE: country regressions without and with cross-sectional averages; ARDL and CS-ARDL: ARDL(1,1) without and with cross-sectional averages. Last column: corresponding panel estimator (Tables 6 and 7). Stars and p-values from the joint moving-block bootstrap (block length 4, B = 499); standard errors and share intervals in Supplementary Table S5. n.i.: β not significant at 10%. Slope homogeneity (Swamy, 1970, with Newey and West (1987) variances, χ^2 [p]; Pesaran and Yamagata, 2008, Δadj [p]): Okun 19.16 [0.004], 6.19 [<0.001]; emissions–output 65.97 [<0.001], 2.14 [0.016]; EPC 57.45 [<0.001], 1.97 [0.024]. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 8 examines whether the decomposition holds within each G7 economy. The country OLS regressions, like the fixed-effects and mean-group estimators, retain the common G7 cycle, and both links of the chain are present in every country. Okun's law is significant at the 5% level everywhere, with θ ranging from −0.081 in the United States to −0.167 in the United Kingdom, and the emissions–output elasticity is positive in all seven economies (0.54 to 1.23) and significant at least at the 10% level in each. The country EPC is negative everywhere and significant at the 5% level in Canada, Germany, Japan and the United States; in France, Italy and the United Kingdom it is too imprecise to be distinguished from zero. The Okun restriction $\beta = \varepsilon\theta$ is not rejected at the 5% level in any country, and where the EPC is precisely estimated, Okun's law accounts for between 62% (Germany) and 94% (Japan) of it. France is the main exception in magnitude: its EPC is less than half what Okun's law predicts ($\beta = -0.046$ against $\varepsilon\theta = -0.107$), consistent with a largely nuclear power system in which demand shocks leave fossil-fuel generation broadly unchanged, although the difference is not statistically significant. The direct association between unemployment and emissions at given output, b_1, is significant at the 5% level only in Canada (−0.089).

These results hold despite substantial cross-country heterogeneity. Slope-homogeneity tests reject equal Okun coefficients at the 1% level with both the Swamy and the Pesaran–Yamagata statistics and, less clearly, equal EPCs, at the 1% level with the Swamy test but only at the 5% level with the Pesaran–Yamagata test. The G7 economies thus differ in how strongly output responds to unemployment and emissions respond to output, yet in each of them the EPC is close to what these two links imply. The other country estimators in Table 8 confirm this. Across the 35 additional country–estimator combinations (seven countries × five estimators: the ARDL and CS-ARDL long- and short-run coefficients and CCE), the restriction is rejected at the 5% level in only four cases: Canada with the ARDL long run, Germany with the ARDL short run, the United States with CCE and Italy with the CS-ARDL long run. Since no country is rejected by more than one estimator, no economy departs systematically from the restriction. The ARDL impact coefficients suggest a direct association at given output in Canada, Germany and the United States, where b_1 is significant at the 5% level, but it fades in the long run, remaining significant only in Canada, and disappears everywhere once common factors are removed with CCE or CS-ARDL, in line with the panel evidence. The country evidence therefore corroborates the panel results: the EPC

is Okun's law in emissions in each G7 economy, not an artefact of pooling heterogeneous countries.

4.4. Predictive ordering of the gaps

The timing of the three gaps provides a further check on the transmission chain. Supplementary Table S6 reports Dumitrescu–Hurlin panel Granger non-causality tests, which establish predictive precedence, not causation. The unemployment and output gaps predict each other: non-causality is rejected at the 1% level in both directions at one lag, with $\tilde{Z}$ statistics of 2.76 and 11.01, as expected for two jointly determined measures of the business cycle. Neither gap predicts the following year's CO_2 gap, because emissions respond to output within the same year, so lagged gaps carry no additional information. Conversely, the CO_2 gap predicts the following year's unemployment gap, with a $\tilde{Z}$ statistic of 3.91 that is significant at the 1% level. The chain implies this pattern if emissions move contemporaneously with output while unemployment adjusts with a lag of about one year, consistent with both the contemporaneous EPC and the familiar lag of unemployment behind output.

4.5. Sensitivity analysis: filters, sample periods and alternative measurement

Table 9 and Figure 4 repeat the analysis for the four filters and the three sample periods. The fixed-effects estimates change little. The EPC is negative and significant at the 5% level in all 12 filter–period combinations, ranging from −0.115 to −0.072; with HP gaps, for example, it is −0.113 over 1975–2024, −0.106 over 1990–2022 and −0.100 over 2000–2024. The levels CS-ARDL estimates in Table 5, by contrast, find no EPC in any window, and their income elasticity changes sign across windows. The decomposition is just as stable: Okun's law accounts for 83–108% of the fixed-effects EPC across the 12 combinations, the restriction $\beta = \varepsilon\theta$ is never rejected at the 5% level, and b_1 is never significant at that level (Supplementary Table S11). The small b_1 found in the baseline with HP gaps over the full sample is not robust to the filter or period; with the Hamilton filter, and in every specification over 2000–2024, the share explained by Okun's law is close to one and b_1 is close to zero (between −0.013 and 0.012). The output channel therefore explains the cyclical EPC whatever the filter or sample period.

Table 9. Sensitivity of the cyclical EPC and of its Okun decomposition to the filter, the sample period and the measure of environmental pressure.

Panel A: CO_2 gap. Filter, period	FE (Driscoll–Kraay)	Two-way FE (Driscoll–Kraay)	MG	CCEMG	PMG long run	PMG short run	CS-ARDL long run	CS-ARDL short run
HP, 1975–2024: β	−0.113***	−0.051***	−0.107***	−0.062***	−0.081***	−0.140***	−0.048*	−0.065**
εθ/β (p for β = εθ)	0.83 (0.061)	0.39 (<0.001)	1.03 (0.893)	0.64 (0.263)	0.69 (0.070)	0.94 (0.617)	0.43 (0.271)	0.69 (0.422)
HP, 1990–2022: β	−0.106***	−0.032**	−0.092***	−0.032	−0.066**	−0.130***	−0.005	−0.034
εθ/β (p for β = εθ)	0.85 (0.148)	0.26 (0.022)	1.32 (0.358)	1.53 (0.487)	0.66 (0.404)	1.12 (0.492)	5.21 (0.980)	1.64 (0.636)
HP, 2000–2024: β	−0.100***	−0.031**	−0.068	−0.027	−0.057	−0.146***	0.046	−0.018
εθ/β (p for β = εθ)	0.95 (0.521)	0.05 (0.004)	2.23 (0.009)	2.10 (0.571)	0.60 (0.687)	1.03 (0.890)	0.10 (0.988)	2.55 (0.977)

Panel A: CO_2 gap. Filter, period	FE (Driscoll–Kraay)	Two-way FE (Driscoll–Kraay)	MG	CCEMG	PMG long run	PMG short run	CS-ARDL long run	CS-ARDL short run
Hamilton, 1975–2024: β	−0.105***	−0.066***	−0.099***	−0.066**	−0.007	−0.105***	−0.071	−0.076***
εθ/β (p for β = εθ)	1.01 (0.931)	0.62 (0.109)	1.25 (0.227)	0.78 (0.483)	6.49 (0.277)	1.14 (0.463)	0.29 (0.685)	0.56 (0.231)
Hamilton, 1990–2022: β	−0.095**	−0.072***	−0.079*	−0.062*	0.006	−0.093**	−0.036	−0.031
εθ/β (p for β = εθ)	1.08 (0.632)	0.63 (0.182)	1.56 (0.073)	0.99 (0.989)	−5.86 (0.416)	1.35 (0.184)	0.87 (0.994)	1.82 (0.659)
Hamilton, 2000–2024: β	−0.103***	−0.068**	−0.085*	−0.075	−0.034	−0.111**	n.i.	−0.050
εθ/β (p for β = εθ)	1.01 (0.970)	0.32 (0.032)	1.55 (0.061)	0.65 (0.554)	1.64 (0.783)	1.27 (0.336)		1.93 (0.970)
Boosted HP (BIC), 1975–2024: β	−0.115***	−0.052***	−0.126***	−0.051**	−0.075***	−0.137***	−0.016	−0.056**
εθ/β (p for β = εθ)	0.88 (0.070)	0.60 (0.012)	0.99 (0.969)	0.79 (0.561)	0.77 (0.303)	1.00 (0.975)	0.73 (0.875)	0.78 (0.609)
Boosted HP (BIC), 1990–2022: β	−0.097***	−0.042***	−0.089***	−0.018	−0.051**	−0.118***	0.036	−0.029
εθ/β (p for β = εθ)	0.87 (0.186)	0.40 (0.023)	1.28 (0.427)	2.03 (0.465)	0.70 (0.662)	1.22 (0.309)	0.71 (0.969)	2.06 (0.563)
Boosted HP (BIC), 2000–2024: β	−0.085***	−0.033**	−0.053	0.021	−0.035	−0.136***	0.127	0.037
εθ/β (p for β = εθ)	0.99 (0.931)	0.33 (0.069)	2.54 (<0.001)	−1.99 (0.140)	0.59 (0.822)	1.08 (0.753)	1.04 (0.999)	−1.01 (0.964)
Boosted HP (ADF), 1975–2024: β	−0.099***	−0.040***	−0.101***	−0.048***	−0.069***	−0.125***	−0.037*	−0.067***
εθ/β (p for β = εθ)	0.90 (0.238)	0.85 (0.505)	1.03 (0.880)	0.65 (0.170)	0.75 (0.294)	1.01 (0.967)	0.36 (0.217)	0.66 (0.223)
Boosted HP (ADF), 1990–2022: β	−0.083***	−0.034***	−0.070***	−0.036	−0.045**	−0.115***	−0.031	−0.047
εθ/β (p for β = εθ)	0.94 (0.570)	0.67 (0.230)	1.28 (0.411)	0.76 (0.620)	1.00 (0.998)	1.25 (0.151)	−0.07 (0.978)	1.31 (0.693)
Boosted HP (ADF), 2000–2024: β	−0.072***	−0.026**	−0.042	−0.012	−0.030	−0.132***	0.065	0.010
εθ/β (p for β = εθ)	1.08 (0.503)	0.70 (0.504)	2.48 (0.006)	2.31 (0.993)	0.88 (0.943)	1.09 (0.643)	0.75 (0.999)	−2.76 (0.981)
Panel B: LCF gap (sign reversed). Filter, period: β [εθ/β]	**FE (Driscoll–Kraay)**	**Two-way FE (Driscoll–Kraay)**	**MG**	**CCEMG**	**PMG long run**	**PMG short run**	**CS-ARDL long run**	**CS-ARDL short run**
HP, 1975–2024	−0.175*** [0.84]	−0.070*** [0.35]	−0.164*** [1.01]	−0.089*** [0.59]	−0.102*** [1.02]	−0.281*** [0.72]	−0.109*** [0.27]	−0.174*** [0.42]
HP, 1990–2022	−0.168*** [0.74]	−0.062** [0.13]	−0.159*** [1.01]	−0.080* [0.32]	−0.081** [0.86]	−0.281*** [0.73]	−0.118 [0.25]	−0.163** [0.44]
HP, 2000–2024	−0.172*** [0.74]	−0.068** [0.02]	−0.175*** [1.11]	−0.110 [0.10]	−0.071 [0.81]	−0.266*** [0.73]	−0.130 [−0.10]	−0.254 [0.11]
Hamilton, 1975–2024	−0.181*** [0.86]	−0.133*** [0.39]	−0.183*** [0.91]	−0.162*** [0.47]	0.010 [−7.31]	−0.196*** [0.83]	−0.181*** [0.48]	−0.175*** [0.39]
Hamilton, 1990–2022	−0.171*** [0.84]	−0.147*** [0.38]	−0.162*** [0.97]	−0.177*** [0.51]	0.004 [−16.38]	−0.185*** [0.92]	−0.215 [0.51]	−0.174*** [0.43]
Hamilton, 2000–2024	−0.149*** [0.92]	−0.122*** [0.20]	−0.139*** [1.15]	−0.159** [0.21]	0.029 [−0.81]	−0.177*** [0.84]	−0.273 [0.24]	−0.200 [0.34]
Boosted HP (BIC), 1975–2024	−0.184*** [0.90]	−0.085*** [0.51]	−0.189*** [1.03]	−0.097*** [0.77]	−0.076*** [1.23]	−0.270*** [0.79]	−0.093** [0.47]	−0.165*** [0.52]
Boosted HP (BIC), 1990–2022	−0.157*** [0.75]	−0.089*** [0.27]	−0.156*** [1.02]	−0.076 [0.60]	−0.064* [0.81]	−0.260*** [0.76]	−0.101 [0.45]	−0.183** [0.53]
Boosted HP (BIC), 2000–2024	−0.145*** [0.75]	−0.080*** [0.18]	−0.165*** [1.06]	−0.081 [0.29]	−0.037 [0.81]	−0.237*** [0.74]	−0.100 [−0.07]	−0.231 [0.23]
Boosted HP (ADF), 1975–2024	−0.169*** [0.91]	−0.084*** [0.66]	−0.166*** [1.00]	−0.104*** [0.68]	−0.080*** [1.19]	−0.259*** [0.79]	−0.123*** [0.38]	−0.168*** [0.53]
Boosted HP (ADF), 1990–2022	−0.135*** [0.84]	−0.085*** [0.48]	−0.128*** [1.02]	−0.097** [0.47]	−0.054* [1.61]	−0.239*** [0.90]	−0.117 [0.24]	−0.184*** [0.47]
Boosted HP (ADF), 2000–2024	−0.129*** [0.82]	−0.079*** [0.38]	−0.127*** [1.10]	−0.081 [0.23]	−0.022 [2.32]	−0.219*** [0.83]	−0.140 [−0.13]	−0.272 [0.12]

Note: Filters applied to the full 1975–2024 series, links estimated over the stated period (Hamilton gaps start in 1978). Boosted HP: λ = 100, BIC or ADF stopping rule. Entries: β with bootstrap stars; εθ/β with the bootstrap p-value of β = εθ in parentheses (joint moving-block bootstrap, block length 4, B = 499). n.i.: not identified. Panel B: LCF gap multiplied by −1; β with the share εθ/β in brackets. Full results: Supplementary Tables S11–S12. Westerlund tests for the LCF gap EPC (HP, 1975–2024): Gt −7.44, Ga −84.61, Pt −19.76, Pa −75.52, all bootstrap p < 0.002. *** p < 0.01, ** p < 0.05, * p < 0.1.

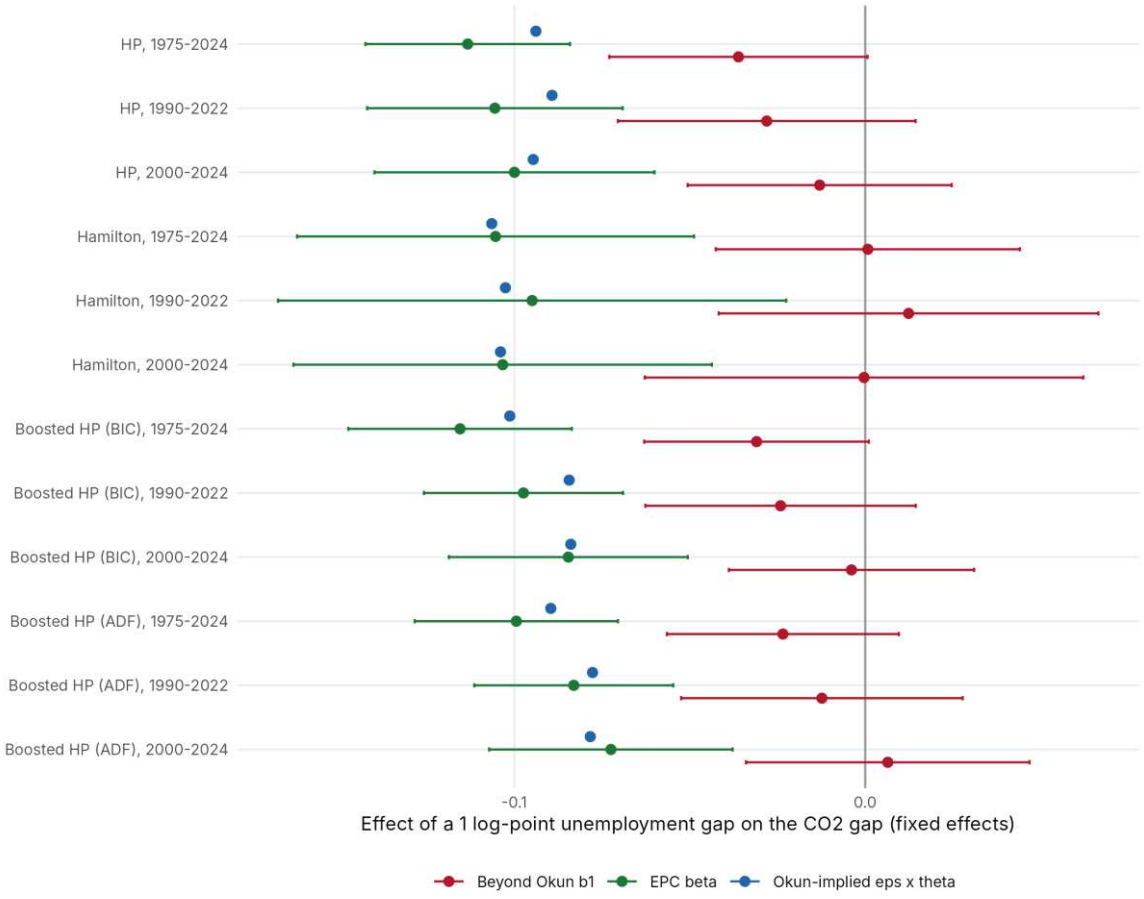


Figure 4. Fixed-effects estimates of the EPC (β, with 95% bootstrap interval), the Okun-implied EPC (εθ) and the beyond-Okun coefficient b_1 (with 95% bootstrap interval), by filter and sample period.

The other estimators qualify these results without overturning them. With two-way fixed effects, the EPC remains significant at the 5% level in all 12 combinations but is smaller (−0.072 to −0.026); Okun's law accounts for only 5–85% of it, and the restriction is rejected in 6 of the 12 cases, because year effects remove most of the common variation through which Okun's law operates. The mean-group estimates confirm the fixed-effects results over 1975–2024 and 1990–2022: the EPC lies between −0.126 and −0.070, is significant at the 5% level in 7 of 8 cases, and the restriction is never rejected. Over 2000–2024 they are weaker: the EPC ranges from −0.085 to −0.042 and is insignificant, and the restriction is rejected for 3 of the 4 filters, reflecting the imprecision of country regressions with only 25 observations rather than a change in the relationship. The PMG estimates, with a common long run and heterogeneous short-run dynamics, confirm the decomposition on impact: the short-run EPC is significant at the 5% level in all 12 combinations (−0.146 to −0.093), Okun's law accounts for 94–135% of it, and the restriction is never rejected, even at the 10% level. The PMG long-run EPC is significant in the 6 cases using HP or boosted HP gaps over 1975–2024 and 1990–2022, again without rejection of the restriction; with Hamilton gaps and over 2000–2024 it is imprecise, because gaps that close within one to two years leave little long-run variation. The estimators that remove the common cycle (CCEMG and

CS-ARDL) are, as in the full sample, much less informative: β is significant in only 8 of the 35 identified cases, the 95% interval of the share always includes one, and in one case (CS-ARDL long run, Hamilton, 2000–2024) the long-run coefficient is not identified.

Panel B of Table 9 repeats the analysis with the load capacity factor (Supplementary Table S12). The cyclical LCF also rises when unemployment is above trend: with the sign reversed, the fixed-effects EPC is −0.175 with HP gaps over 1975–2024, larger than for CO_2 (−0.113), so the relationship extends to the broader ecological footprint. The LCF EPC is significant at the 5% level for every filter and period, ranging from −0.184 to −0.129 with fixed effects and from −0.189 to −0.127 with mean groups, and the Westerlund tests confirm a stable error-correcting relationship: the Gt statistic of −7.44 is significant at the 1% level (Table 9, note). Okun's law accounts for 91–115% of the mean-group LCF EPC, with the restriction never rejected, and for 74–92% of the fixed-effects LCF EPC. The fixed-effects residual is somewhat larger than for CO_2: the restriction is rejected in 4 of the 12 cases, all with HP or boosted HP (BIC) gaps over the shorter windows. With two-way fixed effects, the LCF EPC remains significant (−0.147 to −0.062), but Okun's law accounts for only 2–66% of it. The PMG short-run LCF EPC is significant in all 12 combinations (−0.281 to −0.177), with Okun's law accounting for 72–92% of it; the restriction is rejected in 4 cases (HP over 1975–2024 and 1990–2022, boosted HP over 1975–2024), so the residual not mediated by output is, as with fixed effects, somewhat larger for the LCF. The decomposition therefore holds, to a first approximation, for the ecological footprint as well as for CO_2.

The sensitivity analysis thus confirms the main results for the estimators that retain the common G7 cycle and use the full time dimension, including the PMG short-run estimates: the cyclical EPC and its Okun decomposition depend neither on the filter nor on the sample period. Estimators that remove the common cycle or rely on short country series lose precision in some specifications, but none overturns the conclusion that the EPC operates predominantly through output.

5. Discussion

The estimates confirm the sign of the EPC reported by Kashem and Rahman (2020), Azimi and Rahman (2024) and Ayad and Djedaiet (2026) but change its interpretation. In deviations from trend, the EPC is precisely estimated, stable across filters and sample periods, and mostly accounted for by two independently established regularities: Okun's law and the procyclicality of emissions. The Okun coefficient of −0.112 corresponds, at the G7 average unemployment rate of 6.8%, to about 0.6 percentage points of unemployment per 1% output gap, within the range Ball et al. (2017) report for advanced economies, and the cyclical emissions–output elasticity of 0.83

is consistent with the strong procyclicality documented by Doda (2014), Sheldon (2017) and Burke et al. (2015). Unemployment is informative about emissions chiefly because it is informative about output.

The residual association at given output is small and fragile. In the fixed-effects HP specification it is −0.036, significant with Driscoll–Kraay standard errors but not with the joint bootstrap; it is −0.024 with the mean-group estimator; and with Hamilton and boosted HP gaps it is close to zero or insignificant (0.001 with Hamilton gaps, −0.031 and −0.023 with boosted HP gaps). A residual channel, if it exists, could reflect job losses concentrated in energy-intensive activities or reduced commuting and workplace energy use, but it is equally compatible with measurement error in annual output gaps, which shifts explanatory power towards the better-measured unemployment rate. At annual frequency, unemployment carries little robust information about emissions beyond output.

The contrast between levels and gaps helps reconcile a heterogeneous literature. Levels estimates combine the cycle with decoupling, deindustrialization and the energy transition, which shift the levels relationship over time. With CS-ARDL, we find no levels EPC in any of the three windows, including the one closest to Azimi and Rahman (2024), who find a negative unemployment–emissions relationship for the G7 over 1990–2022 with an effect much larger in magnitude than the cyclical elasticity estimated here; even the long-run income elasticity changes sign across windows. The gap EPC, by contrast, ranges only from −0.115 to −0.072 across the same windows and four filters. Differences in sample windows, control sets and the treatment of trends may therefore account for much of the dispersion of published EPC elasticities.

5.1. Limitations

The analysis has three limitations. First, annual data provide 50 observations per country, which limits the precision of country estimates and of the decomposition once the common cycle is removed; quarterly emissions would allow sharper tests of the residual labor-market channel and of EPC dynamics. Second, filters and sample periods yield slightly different conclusions about the small residual channel, and the shorter windows leave few observations per country for estimators that remove the common cycle; official NAIRU-based unemployment gaps and potential-output estimates would provide a further check. Third, we do not test whether the cyclical EPC differs between rises and falls in unemployment; doing so for cyclical components requires methods designed for stationary series, such as asymmetric local projections, and is left for future research.

6. Conclusion and policy implications

This paper has asked what the Environmental Phillips Curve measures once trends are removed and Okun's law is taken into account, using fifty years of G7 data. It has three findings. First, the EPC is a stable business-cycle regularity: unemployment 10% above its trend path is associated with CO_2 emissions about 1.1% below trend, across the HP, Hamilton and boosted HP filters, the 1975–2024, 1990–2022 and 2000–2024 periods, the estimators, and for the load capacity factor as well as CO_2. Second, it is predominantly Okun's law: the Okun coefficient and the cyclical emissions–output elasticity account for about 83% of the relationship with fixed effects, all of it with the mean-group estimator and 83–108% across filters and periods. Third, levels specifications are fragile, depend on the estimator and the sample window, and do not provide a reliable basis for inference about the EPC.

Emission reductions that accompany rising unemployment are the environmental counterpart of foregone output; they reverse as output recovers and should be excluded from assessments of progress towards national and international decarbonization targets, for example through a cyclical adjustment of emission inventories analogous to the cyclically adjusted budget balance. Nor should they justify relaxing climate policy during downturns: the cyclical component of emissions is transitory, whereas climate targets concern the trend. Because the cyclical EPC is stable and operates largely through output, every percentage point of output recovery restores a predictable quantity of emissions. Recovery and employment programmes are therefore the moment when structural measures such as clean-energy deployment and energy-efficiency investment, which create jobs while reducing emissions per unit of output, yield the greatest joint return. The renewable share is the only structural variable associated with lower emissions in every levels specification, which supports evaluating structural instruments by their effect on the emission trend rather than on the cyclical co-movement of emissions and unemployment.

Future research could use quarterly or sectoral data to establish whether the residual labor-market channel is genuine, test for asymmetric responses to rising and falling unemployment with methods for stationary series, measure the gaps with official NAIRU and potential-output series, and extend the decomposition to emerging economies, where informality may weaken Okun's law and, with it, the Environmental Phillips Curve.

Appendix A. A two-sector model of the Environmental Phillips Curve

Phillips (1958) postulated a negative relationship between money-wage inflation and unemployment. In advanced economies employment generally rises with activity and wage costs are central to inflation; such a relationship presupposes excess capacity or demand-deficient unemployment, at least in the short run. The EPC posits an analogous environment–

unemployment trade-off, premised on greater activity, and hence employment, being associated with greater emissions.

Consider an economy producing a traded good (X) and a non-traded good (N). Let D denote demand, S supply, and P = P_x/P_N the domestic terms of trade. Output is demand-determined:

$$S_x = X(E) + D_x(P, Y) \tag{A1}$$

$$S_N = D_N(P, Y) \tag{A2}$$

Export demand X rises with depreciation (an increase in E). Domestic demand for tradables D_x rises with income Y and falls with P; demand for non-tradables D_N rises with income and with P. Production uses labor and an intermediate input M with price P_M, which may be polluting. Pricing relations are

$$P_x = a_x W + b_x P_M \tag{A3}$$

$$P_N = a_N W + b_N P_M \tag{A4}$$

where W is the wage, a_x and a_N are labor input–output coefficients and b_x and b_N are intermediate-input coefficients, fixed in the short run. We assume a_x > a_N and b_N > b_x, so that the traded good is labor-intensive and the intermediate input is used more intensively in the non-traded sector; reversing these assumptions does not alter the main result. Total employment and income are

$$L = a_x X(E) + a_x D_x(P, Y) + a_N D_N(P, Y) \tag{A5}$$

$$Y = WL \tag{A6}$$

A rise in short-run activity takes the form of a rise in wages. Differentiating (A5) with respect to W gives

$$\frac{dL}{dW} = a_x \left[\frac{\partial D_x}{\partial P}\frac{dP}{dW} + \frac{\partial D_x}{\partial Y}\frac{dY}{dW}\right] + a_N \left[\frac{\partial D_N}{\partial P}\frac{dP}{dW} + \frac{\partial D_N}{\partial Y}\frac{dY}{dW}\right] \tag{A7}$$

With dE = 0 and dP > 0 because a_x > a_N, the first term is negative (a price effect) and the other three are positive. Higher activity raises income and employment provided the price elasticity of demand for traded goods is not too large, and the composition of output may shift. Either way, rising employment raises the use of the polluting input, and an environmental Phillips relationship emerges. Its strength depends on how output and employment respond to the same demand impulse (the Okun relationship of the main text) and on how intensively the expanding sector uses the polluting input (the emissions–output link).

Exogenous technical progress that reduces intermediate-input requirements lowers both supply prices, but the non-traded price falls by more because b_N > b_x, so that P rises. From (A5),

$$\frac{dL}{dP} = a_x \left[\frac{\partial D_x}{\partial P} + \frac{\partial D_x}{\partial Y}\frac{dY}{dP}\right] + a_N \left[\frac{\partial D_N}{\partial P} + \frac{\partial D_N}{\partial Y}\frac{dY}{dP}\right] \tag{A8}$$

Demand for tradables rises and demand for non-tradables falls, while income effects are ambiguous. If the expansion of one sector outweighs the contraction of the other, output and employment rise while emissions fall, and the environmental Phillips relationship weakens or disappears. Over long horizons, such technical and compositional change shifts the levels relationship between unemployment and emissions, which is why the model predicts a stable relationship between their cyclical components but not necessarily between their levels.

References

Addison, R., Akutcha, E., Debrah, G., 2024. Does the environmental Phillips curve hypothesis hold within the Ghanaian context? Scientific African 26, e02400. https://doi.org/10.1016/j.sciaf.2024.e02400

Adebayo, T.S., Özkan, O., Eweade, B.S., 2024. Do energy efficiency R&D investments and information and communication technologies promote environmental sustainability in Sweden? A quantile-on-quantile KRLS investigation. Journal of Cleaner Production 440, 140832. https://doi.org/10.1016/j.jclepro.2024.140832

Ayad, H., Djedaiet, A., 2026. Does the unemployment rate matter for environmental issues in the G7 nations? New testing for the environmental Phillips curve using the load capacity factor. Environment, Development and Sustainability 28(1), 187–217. https://doi.org/10.1007/s10668-024-04956-0

Azimi, M.N., Rahman, M.M., 2024. Examining the environmental Phillips curve hypothesis in G7 nations: critical insights from wavelet coherence and wavelet causality analysis. Quality & Quantity 58(6), 5683–5713. https://doi.org/10.1007/s11135-024-01909-7

Ball, L., Leigh, D., Loungani, P., 2017. Okun's law: fit at 50? Journal of Money, Credit and Banking 49(7), 1413–1441.

Bergougui, B., Boudjana, R.H., Mehibel, S., Ben-Salha, O., Zambrano-Monserrate, M.A., 2025. Assessing the asymmetric effects of clean and dirty energy budgets on load capacity factor: evidence from top investing countries. Journal of Environmental Management 395, 127823. https://doi.org/10.1016/j.jenvman.2025.127823

Bergougui, B., Boudjana, R.H., Mehibel, S., Zambrano-Monserrate, M.A., 2024. How do institutional quality and income asymmetrically affect carbon emissions inequality? A quantile-on-quantile assessment for six major global emitters. Journal of Cleaner Production 483, 144215. https://doi.org/10.1016/j.jclepro.2024.144215

Bhandari, A., Padakandla, S.R., Jena, N.R., 2025. Environmental Phillips curve revisited: network instrumentation and model-free causality. SSRN Working Paper 5622965. https://doi.org/10.2139/ssrn.5622965

Bolt, J., van Zanden, J.L., 2025. Maddison-style estimates of the evolution of the world economy: a new 2023 update. Journal of Economic Surveys 39(2), 631–671.

Bond, S., Eberhardt, M., 2013. Accounting for unobserved heterogeneity in panel time series models. Mimeo, Nuffield College, University of Oxford.

Burke, P.J., Shahiduzzaman, M., Stern, D.I., 2015. Carbon dioxide emissions in the short run: the rate and sources of economic growth matter. Global Environmental Change 33, 109–121.

Chen, P., Karavias, Y., Tzavalis, E., 2022. Panel unit-root tests with structural breaks. Stata Journal 22(3), 664–678. https://doi.org/10.1177/1536867X221124541

Chudik, A., Pesaran, M.H., 2015. Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. Journal of Econometrics 188(2), 393–420.

Deepika, Sharma, R.L., Choudhary, T.F., 2026. Nexus between gender-specific unemployment and environmental degradation in selected G20 countries: insights from novel Environmental Phillips Curve. International Journal of Social Economics 53(4), 569–582. https://doi.org/10.1108/IJSE-08-2023-0649

Dietz, T., Rosa, E.A., 1997. Effects of population and affluence on CO_2 emissions. Proceedings of the National Academy of Sciences 94(1), 175–179. https://doi.org/10.1073/pnas.94.1.175

Djedaiet, A., 2023. Does environmental quality react asymmetrically to unemployment and inflation rates? African OPEC countries' perspective. Environmental Science and Pollution Research 30, 102418–102427. https://doi.org/10.1007/s11356-023-29621-3

Djedaiet, A., Zarrad, O., Ayad, H., Ben-Salha, O., 2026. Testing the Environmental Phillips Curve and Load Capacity Curve hypotheses across different unemployment levels. Discover Sustainability 7, 709. https://doi.org/10.1007/s43621-026-02594-2

Doda, B., 2014. Evidence on business cycles and CO_2 emissions. Journal of Macroeconomics 40, 214–227.

Driscoll, J.C., Kraay, A.C., 1998. Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics 80(4), 549–560.

Dumitrescu, E.-I., Hurlin, C., 2012. Testing for Granger non-causality in heterogeneous panels. Economic Modelling 29(4), 1450–1460.

Durani, F., Bhowmik, R., Sharif, A., Anwar, A., Syed, Q.R., 2023. Role of economic uncertainty, financial development, natural resources, technology, and renewable energy in the environmental Phillips curve framework. Journal of Cleaner Production 420, 138334. https://doi.org/10.1016/j.jclepro.2023.138334
Eberhardt, M., Teal, F., 2010. Productivity analysis in global manufacturing production. Economics Series Working Papers 515, University of Oxford.
Ferrentino, R., Vota, L., 2026. Unemployment, GDP and CO_2 emissions: new theoretical foundations and mathematical tools for the analysis of the environmental Phillips curve. International Journal of Sustainable Economy 18, 120–155. https://doi.org/10.1504/IJSE.2026.152810
Fischer, C., Springborn, M., 2011. Emissions targets and the real business cycle: intensity targets versus caps or taxes. Journal of Environmental Economics and Management 62(3), 352–366.
Friedlingstein, P., et al., 2025. Global Carbon Budget 2024. Earth System Science Data 17(3), 965–1039. https://doi.org/10.5194/essd-17-965-2025
Hamilton, J.D., 2018. Why you should never use the Hodrick–Prescott filter. Review of Economics and Statistics 100(5), 831–843.
Har, W.M., Sek, S.K., Huang, C., 2025. Revisiting the environmental Phillips curve (EPC) hypothesis: a nonlinear panel data approach. International Journal of Global Warming 36(3). https://doi.org/10.1504/IJGW.2025.10070714
Heutel, G., 2012. How should environmental policy respond to business cycles? Optimal policy under persistent productivity shocks. Review of Economic Dynamics 15(2), 244–264.
Hodrick, R.J., Prescott, E.C., 1997. Postwar U.S. business cycles: an empirical investigation. Journal of Money, Credit and Banking 29(1), 1–16.
Hoechle, D., 2007. Robust standard errors for panel regressions with cross-sectional dependence. Stata Journal 7(3), 281–312. https://doi.org/10.1177/1536867X0700700301
Karavias, Y., Tzavalis, E., 2014. Testing for unit roots in short panels allowing for a structural break. Computational Statistics & Data Analysis 76, 391–407. https://doi.org/10.1016/j.csda.2012.10.014
Kashem, M.A., Rahman, M.M., 2020. Environmental Phillips curve: OECD and Asian NICs perspective. Environmental Science and Pollution Research 27(25), 31153–31170. https://doi.org/10.1007/s11356-020-08620-8
Künsch, H.R., 1989. The jackknife and the bootstrap for general stationary observations. Annals of Statistics 17(3), 1217–1241.
Le Quéré, C., Jackson, R.B., Jones, M.W., et al., 2020. Temporary reduction in daily global CO_2 emissions during the COVID-19 forced confinement. Nature Climate Change 10, 647–653.
Müller, K., Xu, C., Lehbib, M., Chen, Z., 2025. The Global Macro Database: a new international macroeconomic dataset. NBER Working Paper 33714.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55(3), 703–708.
Okun, A.M., 1962. Potential GNP: its measurement and significance. Proceedings of the Business and Economic Statistics Section, American Statistical Association, 98–104.
Persyn, D., Westerlund, J., 2008. Error-correction-based cointegration tests for panel data. Stata Journal 8(2), 232–241. https://doi.org/10.1177/1536867X0800800205
Pesaran, M.H., 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica 74(4), 967–1012.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics 22(2), 265–312.
Pesaran, M.H., 2015. Testing weak cross-sectional dependence in large panels. Econometric Reviews 34(6–10), 1089–1117.
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. https://doi.org/10.1080/01621459.1999.10474156
Pesaran, M.H., Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics 68(1), 79–113. https://doi.org/10.1016/0304-4076(94)01644-F
Pesaran, M.H., Yamagata, T., 2008. Testing slope homogeneity in large panels. Journal of Econometrics 142(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010
Peters, G.P., Marland, G., Le Quéré, C., Boden, T., Canadell, J.G., Raupach, M.R., 2012. Rapid growth in CO_2 emissions after the 2008–2009 global financial crisis. Nature Climate Change 2, 2–4.
Phillips, A.W., 1958. The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861–1957. Economica 25(100), 283–299. https://doi.org/10.1111/j.1468-0335.1958.tb00003.x
Phillips, P.C.B., Shi, Z., 2021. Boosting: why you can use the HP filter. International Economic Review 62(2), 521–570. https://doi.org/10.1111/iere.12495
Rahman, M.M., Miçooğulları, S.A., Değirmen, S., Alancıoğlu, E., Moalla, M., 2025. Exploring the environmental Phillips curve: how do globalization, economic growth, and institutional quality shape load capacity factors in

highly globalized European countries? Journal of Environmental Management 390, 126322. https://doi.org/10.1016/j.jenvman.2025.126322
Ravn, M.O., Uhlig, H., 2002. On adjusting the Hodrick–Prescott filter for the frequency of observations. Review of Economics and Statistics 84(2), 371–376.
Sheldon, T.L., 2017. Asymmetric effects of the business cycle on carbon dioxide emissions. Energy Economics 61, 289–297. https://doi.org/10.1016/j.eneco.2016.11.025
Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. Journal of Banking & Finance 55, 1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013
Stern, D.I., 2004. The rise and fall of the environmental Kuznets curve. World Development 32(8), 1419–1439.
Swamy, P.A.V.B., 1970. Efficient inference in a random coefficient regression model. Econometrica 38(2), 311–323. https://doi.org/10.2307/1913012
Westerlund, J., 2007. Testing for error correction in panel data. Oxford Bulletin of Economics and Statistics 69(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x
Yavuz, E., Kilic, E., Caglar, A.E., 2024. A new hypothesis for the unemployment–environment dilemma: is the environmental Phillips curve valid in the framework of load capacity factor in Türkiye? Environment, Development and Sustainability 26(11), 29475–29492. https://doi.org/10.1007/s10668-023-04258-x
York, R., 2012. Asymmetric effects of economic growth and decline on CO_2 emissions. Nature Climate Change 2, 762–764. https://doi.org/10.1038/nclimate1699