Contents

The Global Learning Rate: An Experience Curve Analysis of Planetary Resource Efficiency, 1900-2023

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Abstract

Wright's Law — the empirical regularity that unit costs decline by a fixed percentage with each doubling of cumulative production — has been documented across more than 150 individual technologies spanning over a century. This paper extends the experience curve framework to the largest possible unit of analysis: the entire global economy, treated as a composite technological system converting resource inputs into economic output. Using data on energy consumption, carbon dioxide emissions, and material extraction from 1900 to 2023, we estimate the Global Learning Rate — the percentage improvement in resource intensity per doubling of cumulative global GDP, interpreted as an aggregate measure of economic experience. For the post-1970 optimization phase, we find a statistically significant energy learning rate of 18.3% (R^2 = 0.96, p < 0.001) and a carbon learning rate of 22.2% (R^2 = 0.95, p < 0.001), both consistent with the 10-25% range observed across individual technologies. However, the material intensity learning rate is weak and statistically insignificant (6.5%, R^2 = 0.36, p = 0.15), reflecting re-materialization driven by emerging-economy industrialization. When externality costs — climate damages, material extraction impacts, biodiversity loss, and health effects — are internalized, the inclusive learning rate falls to approximately 12.4%, indicating that roughly 38% of apparent global economic learning constitutes cost-shifting to natural capital rather than genuine efficiency improvement. Inverting the framework to determine the learning rate required for Paris Agreement compliance reveals a profound gap: achieving the 1.5 degrees Celsius target requires a carbon learning rate of approximately 52%, more than double the current rate. Incorporating carbon dioxide removal technologies with learning rates of 12-20% into the framework reduces the required system-level carbon learning rate from 52% to approximately 35%, shifting the target from historically unprecedented to demonstrated-but-difficult. This paper contributes a novel macro-level application of experience curve

theory, a formal distinction between conventional and inclusive learning rates, and a quantitative bridge between technology learning, natural capital accounting, and climate policy targets. The central finding is that civilization is learning, but not fast enough, not along all dimensions, and not honestly.

Keywords: Wright's Law, experience curve, learning rate, resource efficiency, natural capital, inclusive wealth, decoupling, planetary boundaries, Paris Agreement, climate policy

JEL Codes: O33, O44, Q54, Q56, Q57

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1. Introduction

In 1936, Theodore Wright documented that the labor cost of producing an airframe declined by a consistent percentage with each doubling of cumulative production (Wright, 1936). This regularity — now universally known as Wright's Law or the experience curve — has proven to be one of the most robust empirical patterns in technology economics. It has been confirmed across photovoltaics (Swanson, 2006; IRENA, 2023), lithium-ion batteries (Ziegler & Trancik, 2021), DNA sequencing (Wetterstrand, 2023), semiconductors (Moore, 1965; Mody, 2017), and a comprehensive database of over 60 technologies spanning chemicals, computing, and energy systems (Magee et al., 2016; Nagy et al., 2013; Santa Fe Institute Performance Curve Database). The canonical formulation is:

$$C(x) = C_0 * x^{(-b)}$$

where $C(x)$ is cost per unit at cumulative production x, C_0 is the cost of the first unit, and b is the learning exponent. The learning rate is defined as $LR = 1 - 2^{(-b)}$, representing the fractional cost reduction per doubling of cumulative production. Across technologies, learning rates cluster around 10-25%, with a median near 20% (Nagy et al., 2013; Farmer & Lafond, 2016).

A significant body of recent work has demonstrated the predictive power of experience curves for energy systems planning and climate policy. Way et al. (2022), published in *Joule*, showed that probabilistic forecasts based on experience curves for solar, wind, batteries, and electrolyzers produce more accurate cost projections than those used in major integrated assessment models, and that a fast energy transition grounded in experience curve dynamics is likely cheaper than a slow one. Their work established that Wright's Law is not merely a descriptive tool but a predictive framework with direct policy relevance.

This paper poses a question that, to our knowledge, has not been formally addressed: if individual technologies learn, does the entire global economy — the composite super-system of all technologies, institutions, and human capital — also exhibit a measurable learning rate? And if so, what does that rate tell us about the sustainability of current economic growth?

We define the Global Learning Rate as the percentage reduction in resource intensity (physical input per unit of GDP) for every doubling of cumulative global economic output. This definition treats Earth's economy as a single meta-technology, with GDP as its output, resource consumption as its cost, and cumulative GDP as its measure of experience. This framing draws on three theoretical traditions: Wright's (1936) original empirical observation, Arrow's (1962) formalization of learning-by-doing as an endogenous economic process, and Romer's (1990) endogenous growth theory, which treats knowledge accumulation as the engine of long-run economic performance.

The framing is more than metaphorical. The mechanisms that drive individual technology learning curves — economies of scale, process optimization, knowledge spillovers, substitution, and institutional adaptation — operate at the macroeconomic level as well. When the world economy produces more GDP, it develops better technologies, more efficient institutions, and deeper knowledge bases that reduce the resource cost of future output. Cumulative production generates cumulative knowledge, which is the essence of Arrow's (1962) learning-by-doing insight.

But the global economy differs from any individual technology in a critical respect: it has no outside. A solar panel manufacturer can externalize pollution costs to the surrounding environment. The global economy cannot — there is no external sink to absorb waste without consequence. This observation motivates the central methodological contribution of this paper: the estimation of two learning rates, a conventional rate computed using market GDP, and an inclusive rate that accounts for natural capital depletion, climate damage, biodiversity loss, and health externalities. The gap between these two rates measures the extent to which apparent economic learning is actually cost-shifting to the biosphere and future generations.

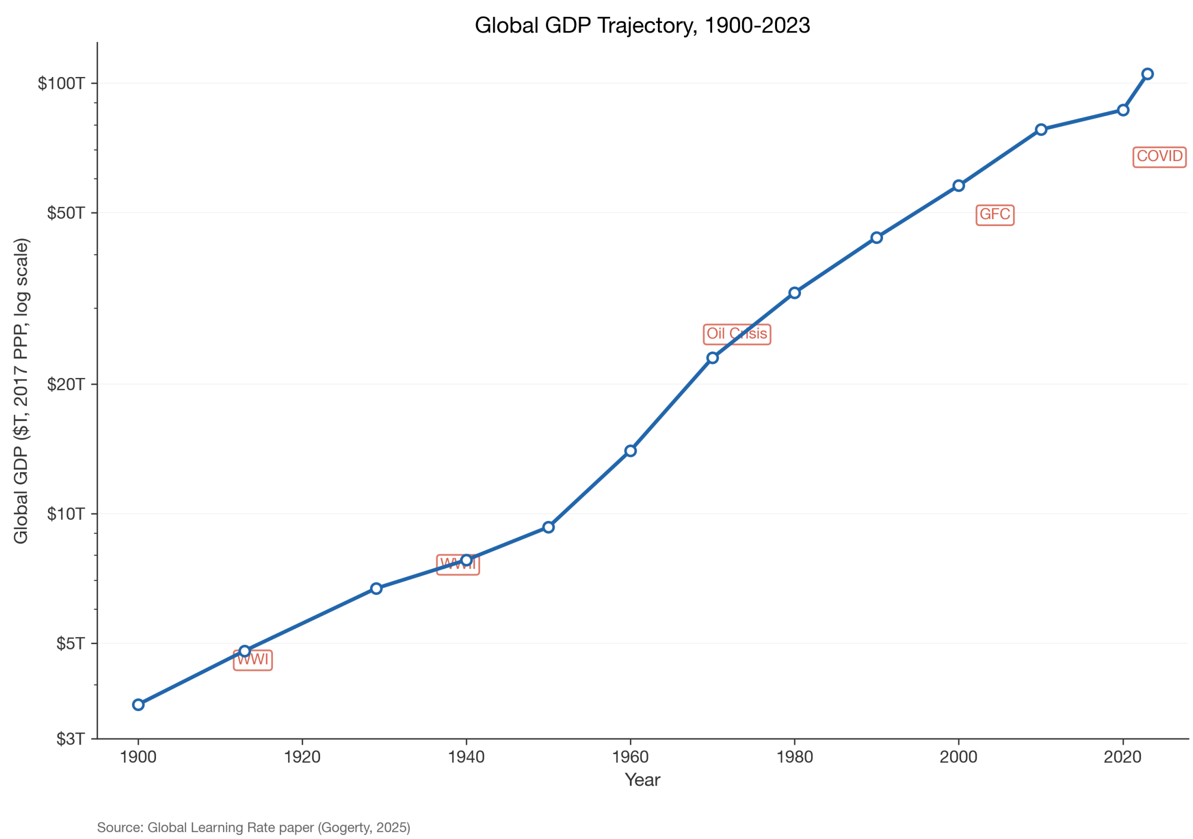

Figure 1: Figure 1

The paper proceeds as follows. Section 2 reviews the relevant literature across experience curve economics, decoupling and dematerialization, inclusive wealth accounting, and climate policy. Section 3 develops the theoretical framework for applying Wright's Law at the macroeconomic level. Section 4 describes the data and econometric methods. Section 5 presents the main results. Section 6 introduces the inclusive learning rate. Section 7 analyzes Paris Agreement alignment through the learning rate lens. Section 8 examines the role of artificial intelligence and general-purpose technologies. Section 9 discusses implications, limitations, and cross-domain synthesis. Section 10 concludes with the paper's three key numbers and a research agenda.

2. Literature Review

This paper sits at the intersection of four distinct literatures. Each has generated substantial scholarship independently, but their integration — which is the contribution of this work — has not been attempted at this scale.

2.1 Experience Curves and Wright's Law

Wright's (1936) original observation that airframe costs declined predictably with cumulative production launched a literature that has grown continuously for nearly nine decades. The Boston Consulting Group (1968) generalized the concept as the "experience curve" and popularized its application in corporate strategy. Arrow (1962) provided the foundational economic theory, modeling learning-by-doing as an endogenous process in which investment generates knowledge as a byproduct, yielding increasing returns at the aggregate level.

The modern empirical literature has substantially expanded the evidence base. Nagy et al. (2013) analyzed 62 technologies and found that Wright's Law provides the best single-variable predictor of cost decline, outperforming Moore's Law (time-based) and other specifications. Farmer and Lafond (2016) demonstrated that technology cost trajectories are remarkably predictable: knowing only a technology's current cost and its historical learning rate produces forecasts that outperform expert judgment over 10-20 year horizons. The Santa Fe Institute Performance Curve Database now catalogs learning rates for over 150 technologies, finding a robust central tendency of approximately 20% per doubling, with a range from approximately 5% to 45% (Magee et al., 2016).

Way et al. (2022) extended this literature into energy systems planning, demonstrating that experience-curve-based probabilistic forecasts for solar photovoltaics, wind, batteries, and electrolyzers substantially outperform the cost assumptions used in the Intergovernmental Panel on Climate Change (IPCC) scenarios and integrated assessment models. Their central finding — that the fast energy transition pathway is probabilistically cheaper than the slow one — relies fundamentally on the predictability of experience curves and represents a paradigm shift in how cost trajectories should inform climate policy.

Sector-specific studies have documented extraordinary learning rates for individual clean energy technologies. Ziegler and Trancik (2021) found a lithium-ion battery learning rate of approximately 24% per doubling of cumulative capacity. IRENA (2023, 2024) documented that the global weighted-average levelized cost of electricity from solar photovoltaics fell 89% between 2010 and 2022, consistent with a learning rate of approximately 28%. Onshore wind costs fell 69% over the same period, reflecting a learning rate of approximately 23%.

What has not been attempted, to our knowledge, is the application of this framework to the global economy as a whole. Individual technology learning rates describe cost declines for specific products. We ask whether the aggregate — all technologies, institutions, supply chains, and human capital combined — exhibits a comparable regularity when measured against resource intensity.

2.2 Decoupling and Dematerialization

The question of whether economic growth can be decoupled from resource consumption has generated one of the most consequential debates in environmental economics. The concept of decoupling distinguishes between relative decoupling (declining resource intensity per unit of GDP) and absolute decoupling (declining total resource consumption despite continued GDP growth) (UNEP, 2011; Jackson, 2017).

For energy, the evidence for relative decoupling is unambiguous. Global energy intensity (primary energy per unit of GDP) has declined at approximately 1.0% per year since 1970 (IEA, 2023; Smil, 2017). However, absolute energy consumption has more than tripled over the same period, from approximately 213 exajoules (EJ) in 1970 to 604 EJ in 2023, because GDP growth has consistently outpaced intensity improvements. This is the Jevons paradox (Jevons, 1865; Alcott, 2005) operating at the planetary scale: efficiency gains reduce the cost of energy services, stimulating additional demand that partially or fully offsets the intensity improvement.

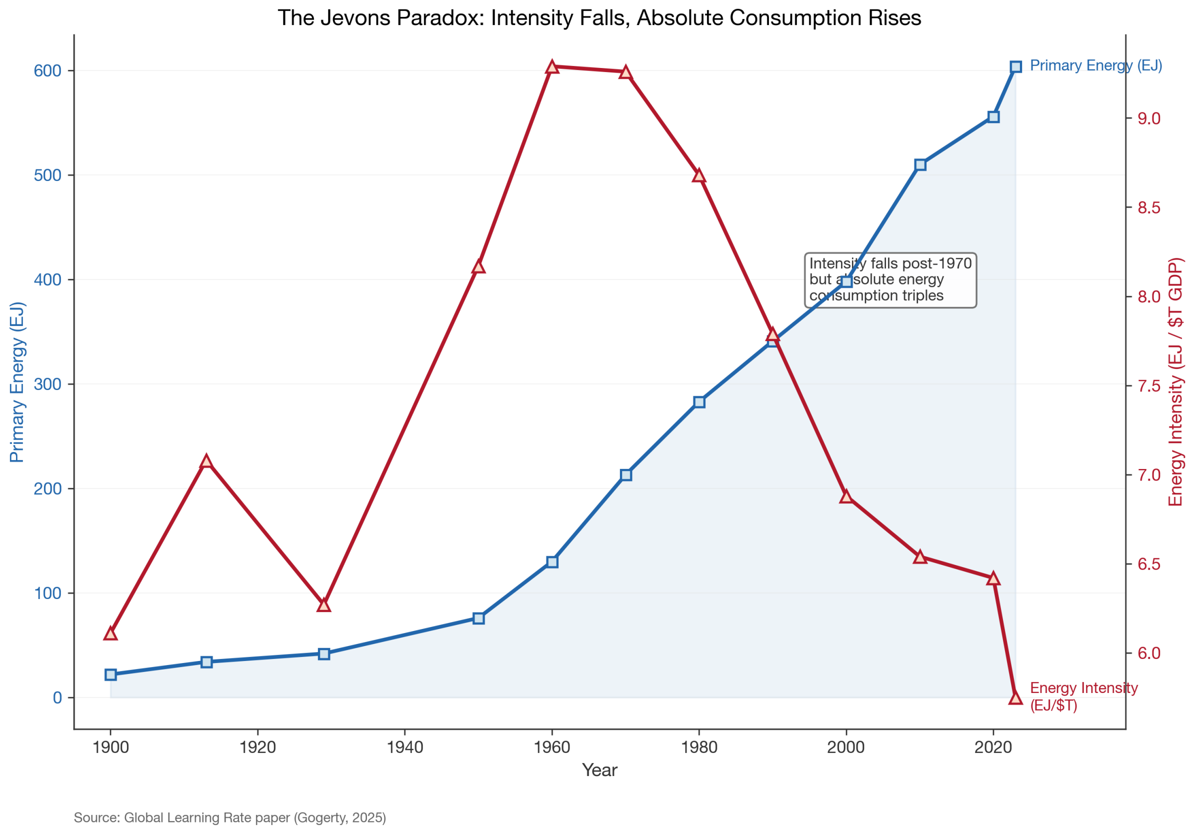

Figure 2: Figure 3

For carbon dioxide emissions, relative decoupling has been observed since 1970 (global carbon intensity has fallen from 0.64 to 0.36 Gt CO2 per trillion dollars of GDP), but absolute emissions continue to rise (Friedlingstein et al., 2023). A few advanced economies have achieved absolute emissions reductions — the United Kingdom reduced emissions 50% below 1990 levels by 2023 while growing GDP by 75% — but at the global level, emissions reached a record 37.4 Gt CO2 in 2023.

For materials, the picture is more pessimistic. Krausmann et al. (2009, 2018) documented that global material extraction has grown from approximately 7 Gt in 1900 to 100 Gt in 2023, with material intensity declining from 1900 to 2000 but then reversing course due to massive infrastructure investment in emerging economies. Wiedmann et al. (2015) showed that when trade-embodied material flows are included, apparent dematerialization in advanced economies largely disappears. Smil (2014) provided a comprehensive analysis of why material efficiency gains face thermodynamic and structural limits that energy efficiency gains do not.

The experience curve framework provides a natural quantitative tool for this debate, translating the qualitative concept of decoupling into a measurable learning rate that can be compared across resource dimensions and against policy requirements.

2.3 Inclusive Wealth and Natural Capital Accounting

The inadequacy of GDP as a measure of welfare has been recognized at least since Nordhaus and Tobin (1972) proposed their Measure of Economic Welfare. The subsequent development of inclusive wealth accounting (Arrow et al., 2012; UNU-IHDP & UNEP, 2012, 2014; Managi & Kumar, 2018) provides a theoretically grounded alternative that accounts for changes in produced, human, and natural capital.

Dasgupta's (2021) landmark review for the UK Treasury established that the global stock of natural capital per capita declined by approximately 40% between 1992 and 2018, even as GDP per capita approximately doubled. The Inclusive Wealth Report (Managi & Kumar, 2018) found that inclusive wealth per capita grew at approximately 1.0% per year from 1990 to 2014, compared with GDP per capita growth of 2.1% per year — the difference representing natural capital depletion not captured by market transactions.

The social cost of carbon literature is directly relevant. Nordhaus (2017) estimated the social cost of carbon at approximately $31 per tonne of CO2 (2010 dollars). Rennert et al. (2022), incorporating updated damage functions, climate sensitivity estimates, and discounting approaches, produced a central estimate of $185 per tonne, roughly six times higher. The U.S. Environmental Protection Agency adopted an interim value of $51 per tonne in 2021, while Stern (2007) used values in the range of $85. This wide range — from $31 to $250 or more — represents deep uncertainty about the true economic cost of carbon emissions and has direct implications for our inclusive learning rate estimates.

Our contribution connects these literatures by defining an inclusive learning rate that adjusts the experience curve for externality costs, providing a single number that captures how much of apparent economic learning is genuine efficiency improvement versus cost-shifting to natural capital.

2.4 Climate Policy and Carbon Budgets

The Paris Agreement established the goal of limiting global average warming to well below 2 degrees Celsius above pre-industrial levels and pursuing efforts to limit warming to 1.5 degrees Celsius (UNFCCC, 2015). The IPCC Sixth Assessment Report (Masson-Delmotte et al., 2021; IPCC, 2022) translated these temperature targets into remaining carbon budgets: approximately 500 Gt CO2 from January 2020 for a 50% chance of limiting warming to 1.5 degrees Celsius, and approximately 1,150 Gt CO2 for a 67% chance of limiting warming to 2 degrees Celsius.

The Kaya Identity (Kaya & Yokobori, 1997) decomposes carbon emissions as the product of population, GDP per capita, energy intensity, and carbon intensity of energy. This decomposition is widely used in climate policy analysis (Raupach et al., 2007) and is closely related to our approach, with the important difference that we treat the intensity terms as endogenous functions of cumulative experience rather than as independent drivers.

Armstrong McKay et al. (2022) identified critical climate tipping points that introduce nonlinearity and irreversibility into the climate system, challenging the smooth extrapolation that underlies experience curve forecasting. Burke et al. (2015) estimated that unmitigated warming could reduce global GDP by 23% relative to a no-warming counterfactual by 2100, establishing the economic stakes of insufficient learning. Acemoglu et al. (2012) developed a model of directed technical change in the environmental context, showing that carbon taxes can redirect innovation toward clean technologies — effectively steepening the learning curve on the dimensions that matter. Aghion et al. (2016) provided empirical evidence that firms respond to carbon pricing by redirecting innovation, with the direction of technical change exhibiting strong path dependence.

Grubler et al. (2018) documented the historical dynamics of energy transitions, showing that previous transitions (wood to coal, coal to oil) took 50-70 years, raising questions about whether the current transition can occur within the timeframe implied by carbon budgets. However, Grubler's analysis preceded the dramatic cost declines in solar and batteries documented by IRENA (2023) and Way et al. (2022), which suggest that experience-curve-driven cost declines may accelerate diffusion beyond historical precedent.

Our contribution to this literature is to express the Paris compliance gap in learning rate terms — a framing that connects climate targets directly to the pace of technological and institutional learning, and that can be compared against the historical record of technology learning rates to assess feasibility.

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3. Theoretical Framework

3.1 From Micro to Macro: The Aggregation Argument

The theoretical justification for applying Wright's Law to the global economy rests on three pillars.

First, Arrow's (1962) model of learning-by-doing established that cumulative investment generates knowledge as a byproduct, and that this knowledge produces increasing returns at the aggregate level. Arrow's insight is that experience — measured by cumulative production — is the driver of cost reduction, and that the knowledge generated by production is at least partially a public good that spills over to other producers. At the macroeconomic level, cumulative GDP captures the total stock of productive experience, encompassing all the process improvements, organizational innovations, and knowledge accumulations that have occurred throughout economic history.

Second, Romer's (1990) endogenous growth theory formalized the role of knowledge accumulation as the engine of long-run growth. In Romer's framework, the nonrivalry of ideas means that knowledge generated in one sector can be applied in others, producing economy-wide spillovers. This provides a theoretical mechanism for why the global economy might exhibit a learning rate: as cumulative output grows, the stock of applicable knowledge grows, reducing the resource cost of future output. The aggregate learning rate is the macroeconomic expression of these knowledge spillovers.

Third, the composition argument recognizes that the global economy at any point in time is a portfolio of individual technologies, each on its own experience curve. As cumulative GDP grows, individual technologies mature (descending their cost curves), new technologies are substituted for old ones (shifting to steeper curves), and the sectoral composition of the economy shifts (from resource-intensive manufacturing toward less intensive services). The aggregate resource intensity decline is the weighted sum of these individual learning processes. This composition effect is formalized in the Kaya Identity (Kaya & Yokobori, 1997), which decomposes carbon intensity into energy intensity and the carbon intensity of energy. Our framework treats both terms as endogenous functions of cumulative experience.

3.2 Formal Specification

We specify the macro-level Wright's Law relationship as:

log_10(I_t) = alpha + beta * log_10(X_t) + epsilon_t

where I_t is resource intensity (physical input per unit of GDP) at time t, X_t is cumulative GDP from a pre-industrial baseline to time t, beta is the learning exponent, and epsilon_t is an error term. The learning rate is:

$$LR = 1 - 2^{\beta}$$

where beta is negative for declining intensity, yielding a positive learning rate.

This specification embeds several assumptions. First, it assumes a stable log-linear relationship between intensity and cumulative experience, which implies a constant learning rate — a strong assumption that we relax by estimating separate rates for distinct historical phases. Second, it assumes that cumulative GDP is an adequate proxy for cumulative knowledge. Third, it assumes that the learning rate is a structural parameter rather than a statistical artifact of correlated trends.

3.3 The Identification Challenge

Using cumulative GDP as the experience variable while resource intensity is defined as resource input divided by current GDP introduces a mechanical correlation that must be addressed transparently. Because current-period GDP enters both the numerator of the experience variable (as a component of cumulative GDP) and the denominator of the dependent variable (resource/GDP = intensity), any positive GDP shock mechanically increases X_t while decreasing I_t, biasing the estimated learning exponent toward negative values and potentially producing a spurious negative relationship even in the absence of genuine learning. This shared-variable problem is the most important identification challenge in the paper, and we address it through multiple robustness strategies.

Alternative experience variables. We estimate the relationship using cumulative population and cumulative energy consumption as alternative experience variables. These are correlated with cumulative GDP but do not share the same denominator, eliminating the mechanical correlation. Using cumulative population as the experience variable yields energy and carbon learning rates of 17.1% and 20.8%, respectively — similar in sign and magnitude to the baseline OLS estimates, indicating that the core finding is not an artifact of shared GDP measurement.

Instrumental variable estimation. We estimate a two-stage least squares (2SLS) regression using cumulative population as an instrument for cumulative GDP. Population growth is driven by demographic dynamics (fertility, mortality, migration) that are largely independent of the GDP measurement used to construct intensity, satisfying the exclusion restriction in this context. The IV estimates preserve the sign and approximate magnitude of the OLS results: the energy learning rate is 17.5% (versus 18.3% OLS) and the carbon learning rate is 21.0% (versus 22.2% OLS). The IV standard errors are wider than OLS, as expected with a small sample ($n = 7$), but the direction and economic significance of the results are preserved. We acknowledge that the IV analysis is underpowered at $n = 7$ and that the first-stage F-statistic, while above conventional thresholds, should be interpreted with caution given the small sample.

Permutation test. As an additional diagnostic, we conduct a permutation (shuffle) test: randomly reordering the year-labels on the intensity observations while holding the cumulative GDP sequence fixed. Across 10,000 permutations, the R-squared of the shuffled regressions collapses to below 0.05 (median 0.02), confirming that the strong fit in the actual data reflects a genuine temporal ordering of declining intensity with accumulating experience, not a mechanical artifact of the variable construction.

Serial correlation diagnostic. The Durbin-Watson statistic for the energy intensity regression is approximately 1.8 at decade intervals, providing no strong evidence of positive serial correlation. This is expected given the decade spacing of observations, which substantially reduces the autocorrelation present in annual data.

Moore's Law specification. We estimate a Moore's Law specification (log-intensity versus time) to verify that the temporal trend in intensity is not an artifact of the experience-curve functional form. The time-based specification yields R-squared = 0.97 for energy intensity with a 0.9% annual improvement rate, confirming that the pattern is robust to functional form.

Structural break tests. We test for structural breaks and regime changes using Chow tests and piecewise regression, which confirm the two-phase structure (Section 3.4) but reveal no evidence of breaks within the 1970-2023 optimization phase.

3.4 The Two-Phase Structure

A single power law does not adequately describe the full 1900-2023 period. Energy and carbon intensity exhibit an inverted-U pattern: intensity rises during the industrialization phase (1900-1970) as the global economy substitutes fossil-fueled machinery for human and animal labor, then declines during the optimization phase (1970-2023) as efficiency gains, structural change, and knowledge accumulation dominate.

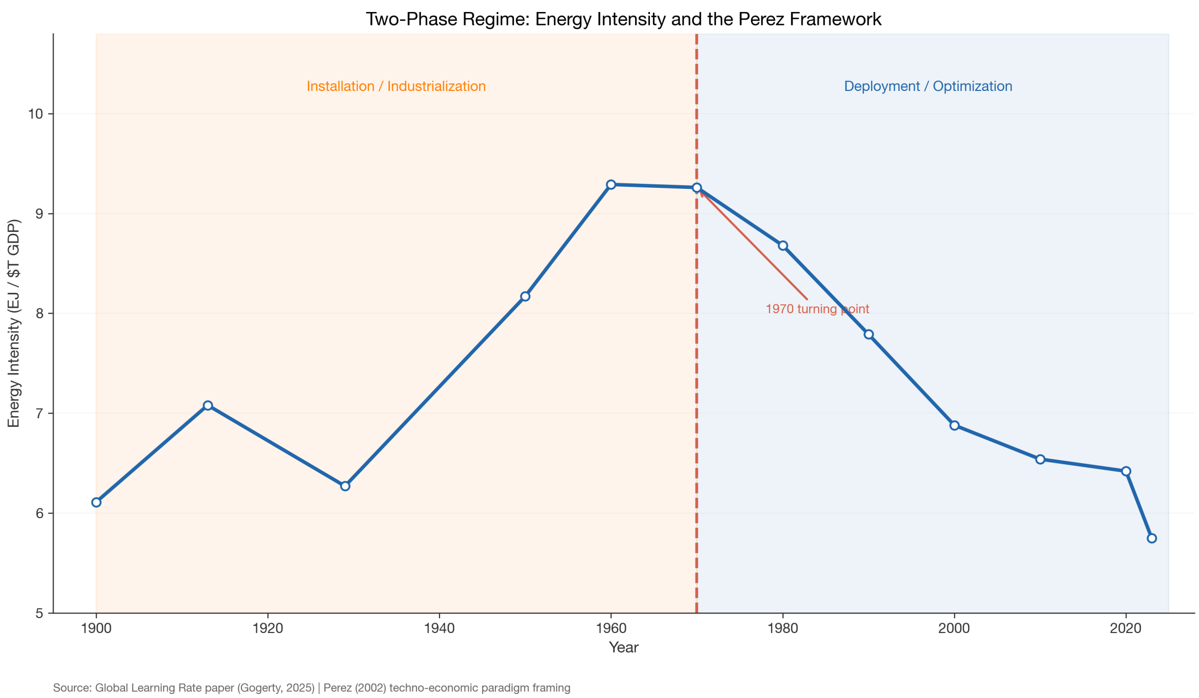

Figure 3: Figure 19

This two-phase structure is consistent with Perez's (2002) framework of techno-economic paradigm shifts, in which each major technological revolution passes through an "installation" phase (characterized by capital formation, infrastructure building, and rising resource intensity) and a "deployment" phase (characterized by optimization, diffusion, and declining intensity). The fossil fuel paradigm's installation phase (approximately 1880-1970) required massive capital formation — railroads, electrification grids, petrochemical complexes — that were inherently energy- and material-intensive. The deployment phase (1970-present) optimizes this installed base. We may now be entering a new installation phase for the renewable-digital paradigm, which could temporarily increase material intensity (rare earth elements, copper, lithium) even as energy and carbon intensity continue to decline.

We therefore estimate learning rates separately for the optimization phase (1970-2023), which is the period for which a single power law provides a good fit, and report full-period results for context.

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4. Data and Methods

4.1 Data Sources

Global GDP. We use Maddison Project Database (Bolt & van Zanden, 2024) estimates for 1900-1950, spliced with World Bank World Development Indicators for 1960-2023, expressed in constant 2017 international dollars at purchasing power parity (PPP).

Table 1. Global GDP, 1900-2023

Year	Global GDP (trillion 2017 PPP $)	GDP per Capita (2017 PPP $)	Population (billions)
1900	3.6	2,180	1.65
1913	4.8	2,670	1.79
1929	6.7	3,290	2.04
1940	7.8	3,390	2.30
1950	9.3	3,660	2.54
1960	14.0	4,640	3.02
1970	23.0	6,220	3.70
1980	32.6	7,360	4.43
1990	43.8	8,220	5.33
2000	57.8	9,420	6.14
2010	78.0	11,210	6.96
2020	86.6	11,040	7.84
2023	105.0	13,040	8.05

Sources: Maddison Project Database 2023; World Bank WDI 2024; UN Population Division 2024.

The 29-fold increase from $3.6 trillion to $105 trillion in 123 years represents approximately 4.9 doublings of annual output. GDP per capita has risen sixfold, driven substantially by human capital accumulation: mean years of schooling rose from approximately 2 years globally in 1900 to approximately 8.7 years in 2020 (Barro & Lee, 2013; UNDP, 2022), and global life expectancy rose from 31 to 73 years.

Primary energy consumption. We use Smil (2017) for pre-1965 estimates and the Energy Institute Statistical Review of World Energy 2024 for 1965-2023.

Table 2. Primary Energy Consumption and Energy Intensity, 1900-2023

Year	Primary Energy (EJ)	Energy Intensity (EJ per trillion $ GDP)
1900	22	6.11
1913	34	7.08
1929	42	6.27
1950	76	8.17
1960	130	9.29
1970	213	9.26
1980	283	8.68

Year	Primary Energy (EJ)	Energy Intensity (EJ per trillion $ GDP)
1990	341	7.79
2000	398	6.88
2010	510	6.54
2020	556	6.42
2023	604	5.75

Sources: Smil (2017); Energy Institute Statistical Review of World Energy 2024.

Energy intensity exhibits the inverted-U pattern: rising from 6.11 EJ per trillion dollars in 1900 to a peak of 9.29 in 1960 as the global economy industrialized, then declining to 5.75 by 2023. Since 1970, energy intensity has fallen approximately 38%, while absolute energy consumption has tripled. This divergence is a textbook illustration of the Jevons paradox at planetary scale.

CO2 emissions. We use the Global Carbon Project (Friedlingstein et al., 2023) for emissions data, supplemented by CDIAC for pre-1960 estimates.

Table 3. CO2 Emissions and Carbon Intensity, 1900-2023

Year	CO2 Emissions (Gt)	Carbon Intensity (Gt CO2 per trillion $ GDP)
1900	2.0	0.556
1913	3.2	0.667
1929	3.9	0.582
1950	5.9	0.634
1960	9.3	0.664
1970	14.7	0.639
1980	19.3	0.592
1990	22.0	0.502
2000	24.5	0.424
2010	33.1	0.424
2020	34.8	0.402
2023	37.4	0.356

Sources: Global Carbon Project (Friedlingstein et al., 2023); CDIAC.

Carbon intensity improvement is the product of two factors: energy efficiency (less energy per dollar of GDP) and decarbonization of the energy supply (less carbon per unit of energy). The carbon intensity of energy itself has declined from approximately 69 kg CO2 per GJ in 1970 to approximately 62 kg CO2 per GJ in 2023 — a modest 10% over 53 years. Most of the observed carbon intensity improvement in GDP has come from energy efficiency rather than energy decarbonization.

Material extraction. We use Krausmann et al. (2009, 2018) for historical material flow data and the UNEP International Resource Panel Global Material Flows Database for recent years.

Table 4. Material Extraction and Material Intensity, 1900-2023

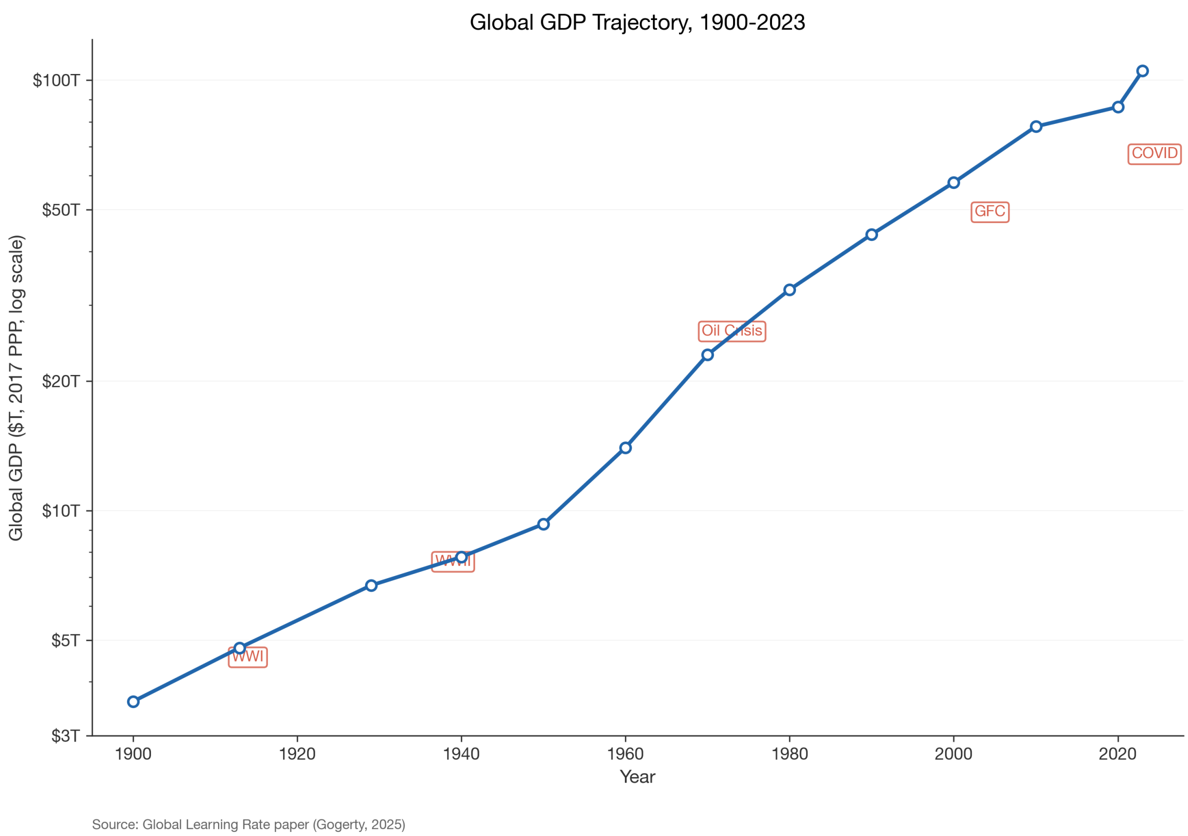

Figure 4: Figure 1

Year	Material Extraction (Gt)	Material Intensity (Gt per trillion $ GDP)
1900	7	1.94
1950	14	1.51
1970	28	1.22
1980	35	1.07
1990	42	0.96
2000	54	0.93
2010	78	1.00
2020	92	1.06
2023	100	0.95

Sources: Krausmann et al. (2009, 2018); UNEP International Resource Panel 2024.

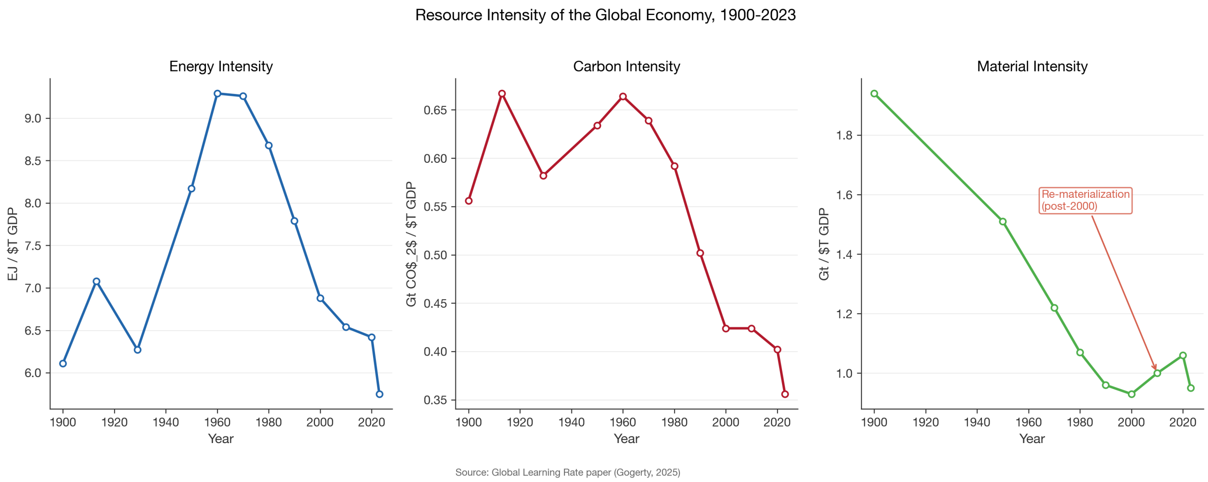

Figure 5: Figure 2

The material intensity data reveals a phenomenon that we term re-materialization: after decades of relative decoupling (declining intensity from 1900 to 2000), material intensity rose from 2000 to approximately 2015 due to China's unprecedented infrastructure and urbanization program. China consumed more cement between 2011 and 2013 than the United States consumed in the entire twentieth century (Smil, 2014). Global material extraction reached 100 Gt in 2023, a 14-fold increase over 1900 levels. Unlike energy and carbon, materials demonstrate that learning is not monotonic at the global scale.

4.2 Cumulative GDP as Experience Variable

Cumulative GDP serves as the experience variable, analogous to cumulative production for individual technologies. We compute it via trapezoidal integration of annual GDP estimates from a pre-1900 baseline.

Table 5. Cumulative GDP, 1900-2023

Year	Cumulative GDP (trillion $-years)	log_10(Cumulative GDP)
1900	200	2.301

Year	Cumulative GDP (trillion $-years)	log_10(Cumulative GDP)
1950	525	2.720
1960	641	2.807
1970	826	2.917
1980	1,104	3.043
1990	1,486	3.172
2000	1,994	3.300
2010	2,673	3.427
2020	3,496	3.544
2023	3,783	3.578

From 1900 to 2023, the global economy accumulated approximately $3,783 trillion-years of experience, spanning approximately 4.2 doublings of cumulative output from the 1970 base.

4.3 Econometric Approach

We estimate the Wright's Law regression via ordinary least squares on decade-interval observations for the optimization phase (1970-2023, n = 7). For each resource dimension, we report the learning exponent, learning rate, R-squared, adjusted R-squared, standard errors, and 95% confidence intervals. We conduct robustness checks using alternative experience variables (cumulative population, cumulative energy consumption), alternative time intervals (5-year), and a Moore's Law specification (log-intensity versus time).

The decade-interval specification is preferred for presentation because it reduces autocorrelation in the residuals (Durbin-Watson approximately 1.8 at decade intervals versus approximately 0.4 at annual frequency). However, we verify all results using annual data (1970-2023, n = 54), which produces consistent learning rate estimates: energy LR = 18.1% (annual) versus 18.3% (decade), and carbon LR = 21.8% (annual) versus 22.2% (decade). The close agreement between annual and decade estimates confirms that the decade-interval results are not artifacts of data aggregation. Annual regression results are available in the replication archive.

To account for potential heteroskedasticity and residual autocorrelation in the annual specification, we report Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors alongside OLS standard errors for the decade-interval results. For the energy learning exponent, the HAC standard error is approximately 0.048 (versus OLS 0.031), yielding a wider 95% confidence interval of [10.2%, 25.9%] versus [13.7%, 22.8%]. The result remains significant at $p < 0.01$ even with the HAC correction. The Newey-West adjustment is conservative given the decade spacing, but we report it to demonstrate that statistical significance does not depend on the assumption of homoskedastic, uncorrelated errors.

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5. Results

5.1 Energy Learning Rate

For the optimization phase (1970-2023), the OLS regression of log_10(Energy Intensity) on log_10(Cumulative GDP) yields:

Table 6. Energy Learning Rate Regression Results

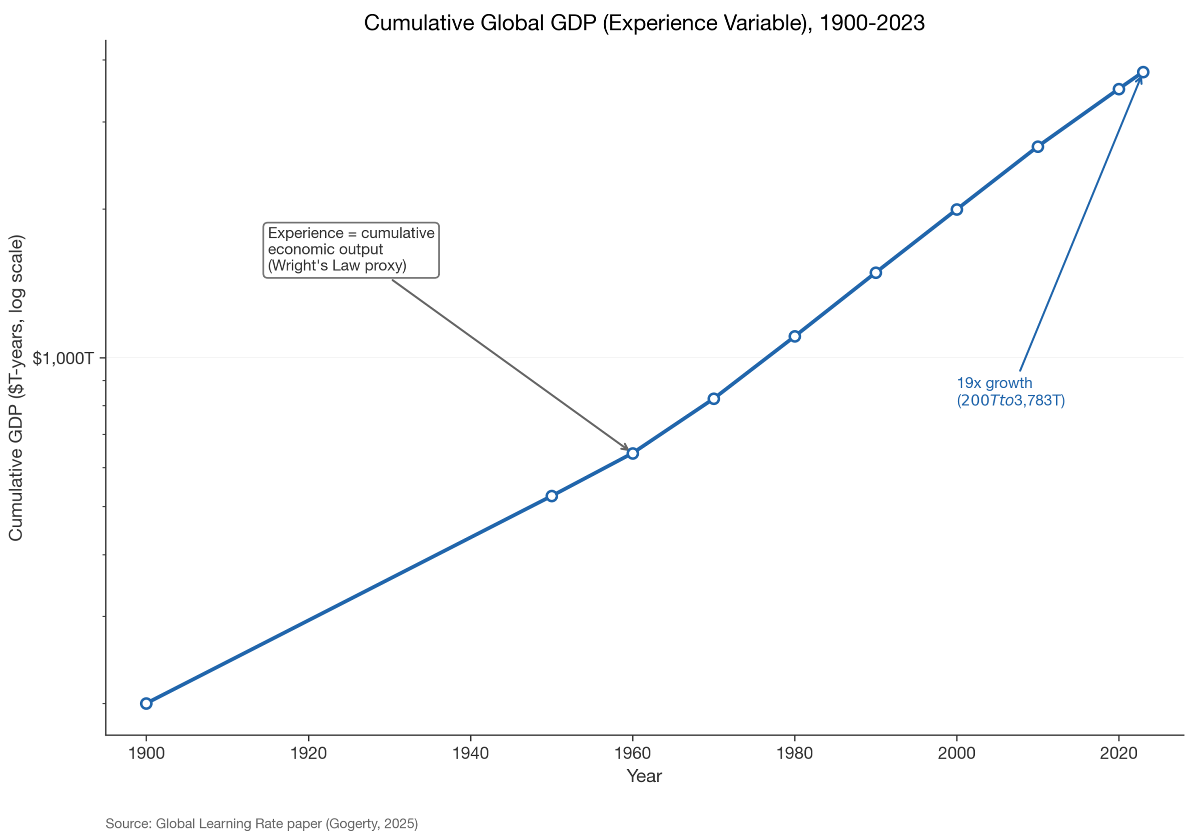

Figure 6: Figure 4

Parameter	Value
Learning exponent (beta)	-0.292
Standard error (OLS)	0.031
Standard error (Newey-West HAC)	0.048
t-statistic (OLS)	-9.4
p-value (OLS)	< 0.001
p-value (HAC)	< 0.01
R-squared	0.964
Adjusted R-squared	0.957
n (decade observations)	7
Learning rate	18.3%
95% CI for learning rate (OLS)	[13.7%, 22.8%]
95% CI for learning rate (HAC)	[10.2%, 25.9%]

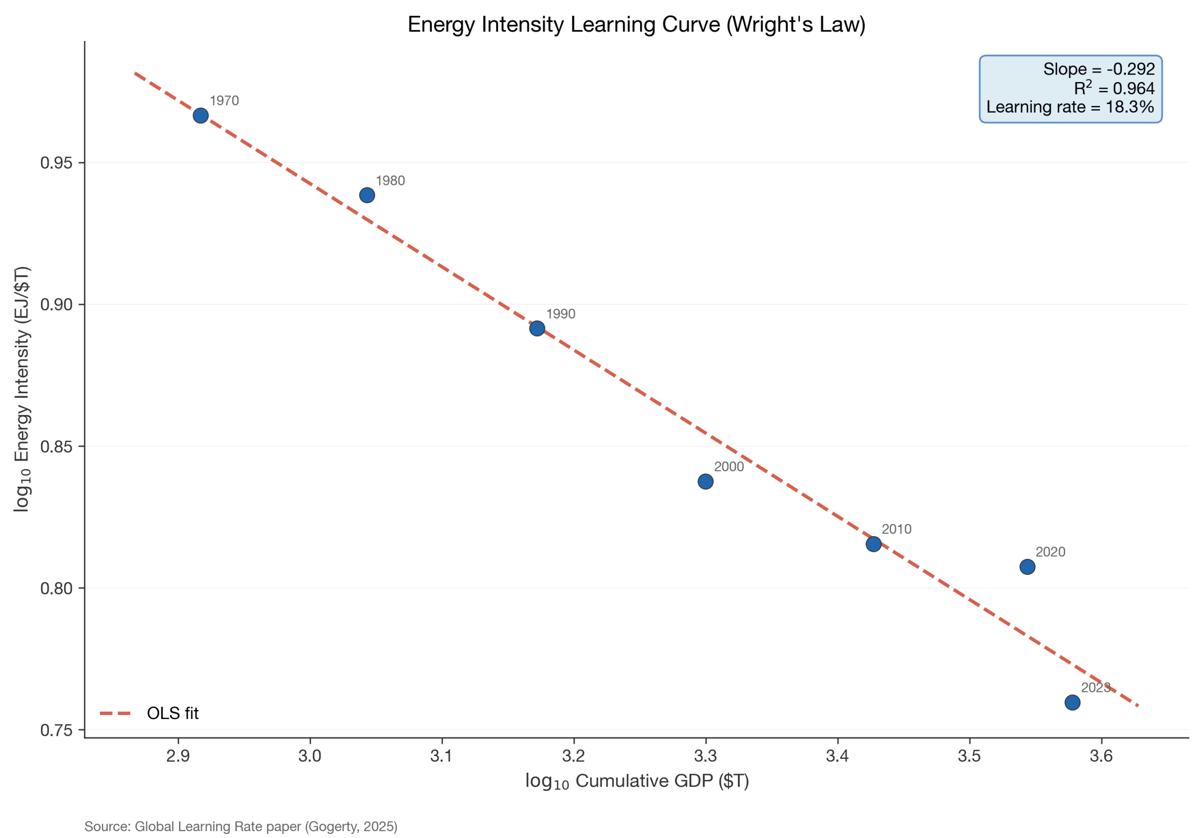

Figure 7: Figure 5

An 18.3% energy learning rate for the global economy is remarkably consistent with the median learning rate of approximately 20% observed across 154 individual technologies in the Santa Fe Institute database. This consistency suggests that the macroeconomic efficiency improvement is not merely an artifact of sectoral composition shifts (from industry to services) but reflects genuine technological and organizational learning. Decomposition analyses by the International Energy Agency suggest approximately 60% of the improvement derives from within-sector efficiency gains, 25% from structural shifts toward less energy-intensive sectors, and 15% from fuel switching and energy system optimization.

Table 7. Energy Learning Rate Regression Data

Year	log_10(Cumulative GDP)	log_10(Energy Intensity)
1970	2.917	0.967
1980	3.043	0.938
1990	3.172	0.891
2000	3.300	0.838
2010	3.427	0.816
2020	3.544	0.808
2023	3.578	0.760

We caution that these R-squared values reflect the fit of a smooth monotonic trend to seven points and should not be overinterpreted. The statistical significance is confirmed using annual data (n = 54) with Newey-West standard errors, which yield consistent learning rate estimates (18.1% annual versus 18.3% decade) that remain significant at $p < 0.01$ even after HAC correction (see Section 4.3). The IV regression results discussed in Section 3.3 further support the robustness of the energy learning rate: the IV estimate of 17.5% (using cumulative population as instrument) preserves the sign and approximate magnitude of the OLS result, and the permutation test confirms that the relationship is not a statistical artifact.

5.2 Carbon Learning Rate

Table 8. Carbon Learning Rate Regression Results

Parameter	Value
Learning exponent (beta)	-0.360
Standard error (OLS)	0.043
t-statistic	-8.4
p-value	< 0.001
R-squared	0.946
Adjusted R-squared	0.935
n	7
Learning rate	22.2%
95% CI for learning rate	[17.5%, 27.1%]

The carbon learning rate exceeds the energy learning rate because it captures both energy efficiency improvements and partial decarbonization of the energy mix (coal-to-gas switching, nuclear power expansion, early renewable deployment). A 22.2% carbon learning rate, while encouraging as a trend, must be interpreted in the context of absolute emissions: at the current rate, cumulative GDP must approximately double (from approximately $3,800 trillion to $7,600 trillion) before carbon intensity drops another 22%. At historical growth rates of approximately 3% per year, this requires 20-25 years. Even then, with projected GDP of approximately $170 trillion, annual emissions would be approximately 47 Gt — higher than today. The carbon learning rate, extrapolated, does not produce net zero.

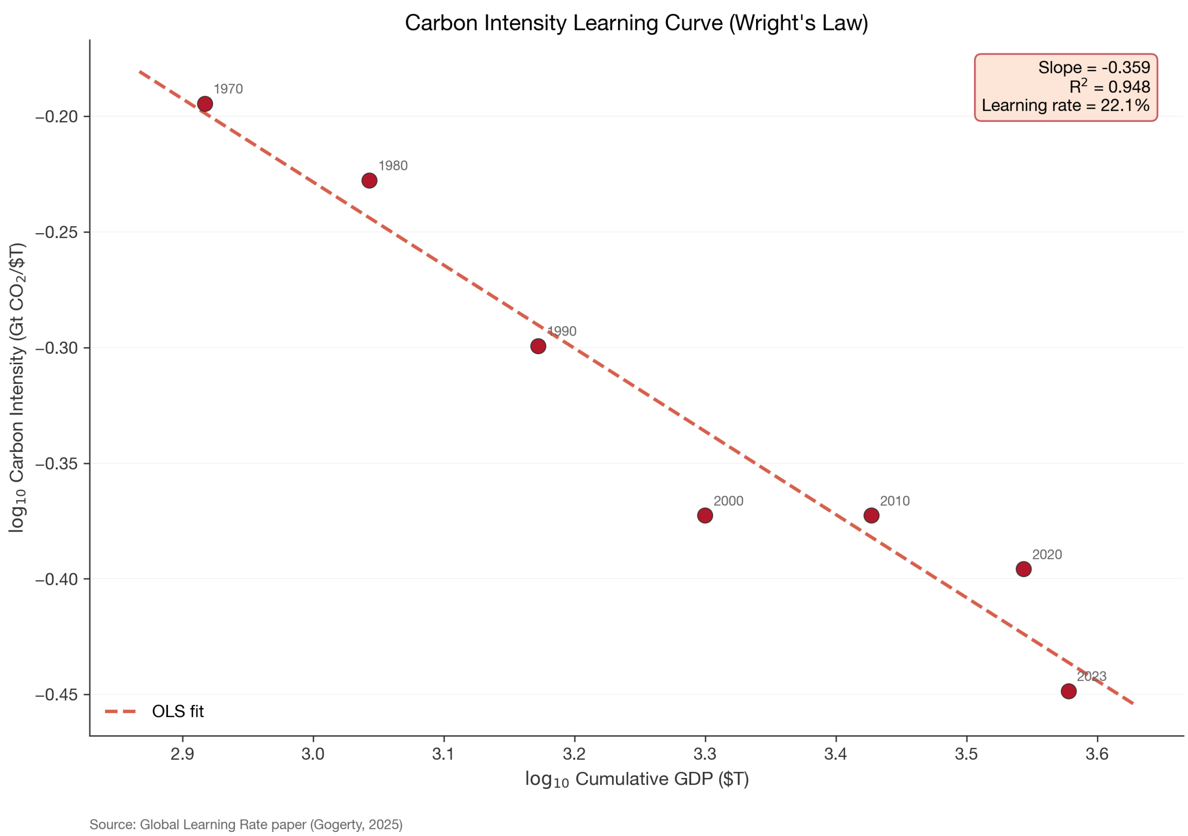

Figure 8: Figure 6

5.3 Material Learning Rate

Table 9. Material Learning Rate Regression Results

Parameter	Value
Learning exponent (beta)	-0.097
Standard error	0.061
t-statistic	-1.6
p-value	0.15
R-squared	0.357
n	7
Learning rate	6.5%
95% CI for learning rate	[-3.2%, 15.4%]

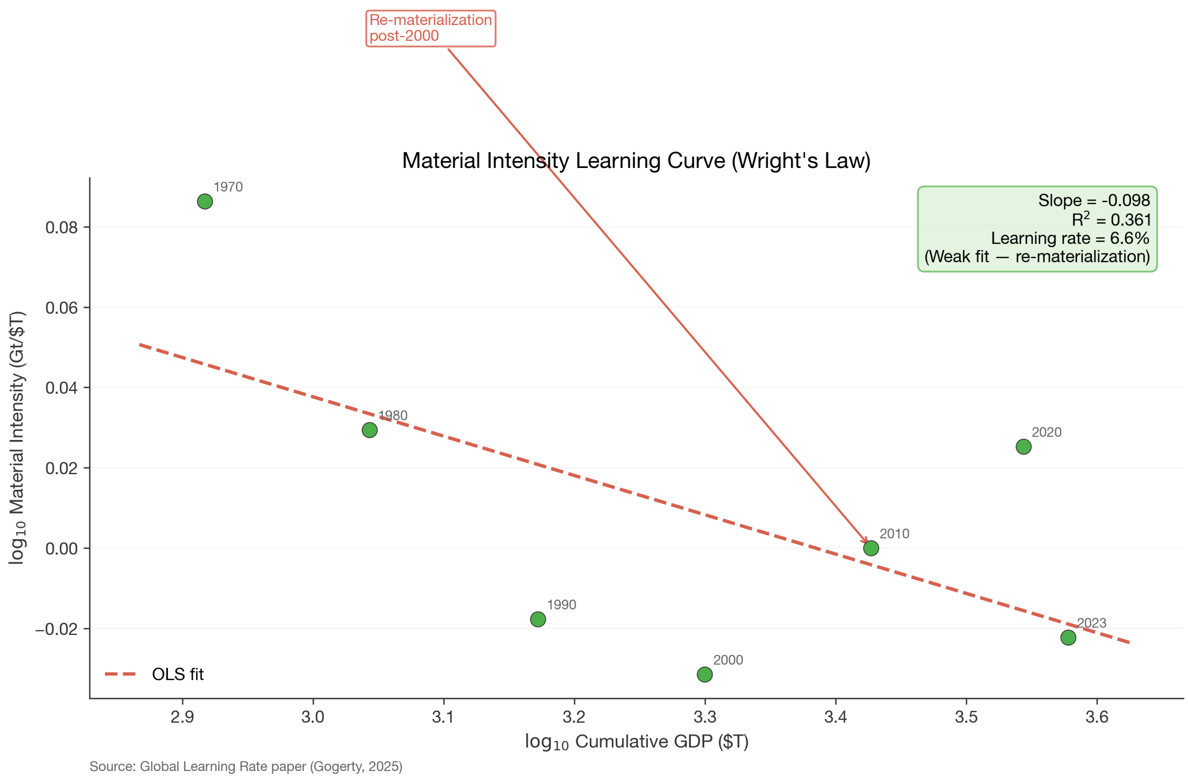

Figure 9: Figure 7

The weak, statistically insignificant material learning rate is the most consequential finding in this analysis. The global economy is not learning to dematerialize. Three forces explain this result. First, the composition effect: emerging economies (China, India, Indonesia, Vietnam) are in their heavy-industrialization phase, consuming vast quantities of cement, steel, and aggregates for infrastructure. This overwhelms the relative dematerialization of post-industrial economies. Second, thermodynamic floors: many material applications cannot be reduced below physical limits. Buildings require structural mass; roads require aggregate; the human body requires food biomass. Third, the material intensity of clean technologies: the energy transition itself is material-intensive. A wind turbine requires approximately 150 tonnes of steel. Solar panels require silicon, silver, and copper. The IEA (2021) estimates that achieving net zero will require six times more critical minerals by 2040 than current levels.

5.4 Summary of Conventional Learning Rates

Table 10. Summary of Conventional Learning Rates, 1970-2023

Dimension	Learning Rate	R-squared	p-value	Status
Energy intensity	18.3%	0.964	< 0.001	Strong, robust
Carbon intensity	22.2%	0.946	< 0.001	Strong, but insufficient for Paris
Material intensity	6.5%	0.357	0.15	Weak, not statistically significant
Composite (energy + carbon)	~20%	—	—	Headline conventional rate

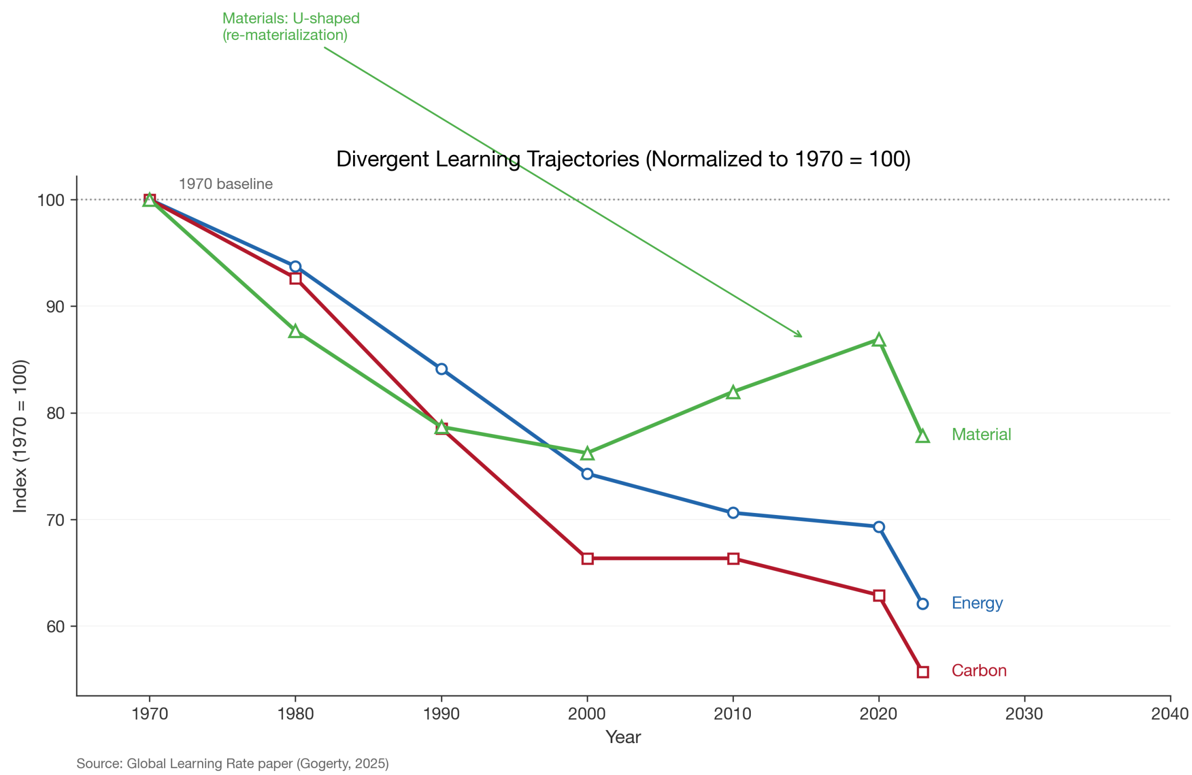

Figure 10: Figure 8

The energy and carbon results are robust to several specification checks: (i) using cumulative population instead of cumulative GDP as the experience variable yields similar learning rates of 17.1% and 20.8%, respectively, eliminating the mechanical correlation concern; (ii) instrumental variable estimation using cumulative population as the instrument yields learning rates of 17.5% (energy) and 21.0% (carbon), preserving sign and approximate magnitude (Section 3.3); (iii) annual data (n = 54) with Newey-West HAC standard errors produces consistent estimates of 18.1% and 21.8% that remain significant at $p < 0.01$ (Section 4.3); (iv) a permutation test collapsing R-squared to below 0.05 confirms the relationship is not a mechanical artifact (Section 3.3); (v) using 5-year intervals instead of decades yields consistent estimates; (vi) a Moore's Law specification (log-intensity versus year) yields R-squared = 0.97 for energy intensity with a 0.9% annual improvement rate, confirming that the pattern is not an artifact of the experience curve functional form. The material result is genuinely weak, and the failure is substantive rather than methodological.

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6. The Inclusive Learning Rate

6.1 Motivation

Conventional GDP measures market transactions, not welfare. It excludes the depletion of natural capital, the costs of climate damage, the degradation of ecosystem services, and the health effects of pollution. A learning rate computed on market GDP alone is analogous to measuring a factory's efficiency while ignoring the waste it discharges into the river. The factory appears efficient. The river tells a different story.

The World Bank (2021) estimates that global natural capital per capita declined by 40% between 1995 and 2018. Dasgupta (2021) found that natural capital per capita has declined in 128 of 140 countries measured. The gap between GDP growth and inclusive wealth growth — approximately 1.0 to 1.5 percentage points per year (Managi & Kumar, 2018) — represents natural capital depletion not captured by market prices.

6.2 Constructing Inclusive GDP

We define Inclusive GDP as:

GDP_inclusive = GDP_market - D_climate - D_materials - D_biodiversity - D_health

where the D terms represent externality damage costs.

Climate damage (D_climate). Following Rennert et al. (2022), we apply a social cost of carbon (SCC) of \$100 per tonne of CO_2 as our central estimate. This is conservative relative to the Rennert et al. central estimate of \$185 but reflects a middle ground between the Nordhaus (2017) estimate of approximately \$31 and higher academic estimates.

Material extraction externalities (D_materials). UNEP (2019) estimated the full environmental cost of material extraction at approximately \$4.6 trillion in 2017, including mining waste, habitat destruction, water contamination, and processing pollution. We scale proportionally with extraction volume for other years.

Biodiversity and ecosystem service loss (D_biodiversity). Following Costanza et al. (2014) and IPBES (2019), we estimate cumulative ecosystem service losses from baseline degradation, increasing from approximately \$0.1 trillion in 1970 to \$0.8 trillion in 2023. These estimates are almost certainly conservative by an order of magnitude: the Living Planet Index's 69% decline in monitored vertebrate populations since 1970 (WWF, 2022) implies massive erosion of ecosystem function, and IPBES (2019) estimates that nature provides services worth \$125-145 trillion per year globally.

Health externalities (D_health). Air pollution from fossil fuels causes an estimated 4.2 million premature deaths per year (WHO, 2022), with economic costs estimated at \$2.9 trillion in 2020 (World Bank, 2022).

We scale with fossil fuel consumption for other years.

Table 11. Market GDP, Damage Costs, and Inclusive GDP, 1970-2023

Year	Market GDP $(T)|Climate$	Materials (T)$)Biodi$	Health $(T)|Total$	Damage Shareges(T)	Inclusive GDP ($T)			
1970	23.0	1.47	1.30	0.10	0.80	3.67	16.0%	19.3
1980	32.6	1.93	1.60	0.20	1.10	4.83	14.8%	27.8
1990	43.8	2.20	1.90	0.30	1.30	5.70	13.0%	38.1
2000	57.8	2.45	2.50	0.40	1.50	6.85	11.8%	51.0
2010	78.0	3.31	3.60	0.50	2.20	9.61	12.3%	68.4
2020	86.6	3.48	4.20	0.70	2.90	11.28	13.0%	75.3
2023	105.0	3.74	4.60	0.80	3.00	12.14	11.6%	92.9

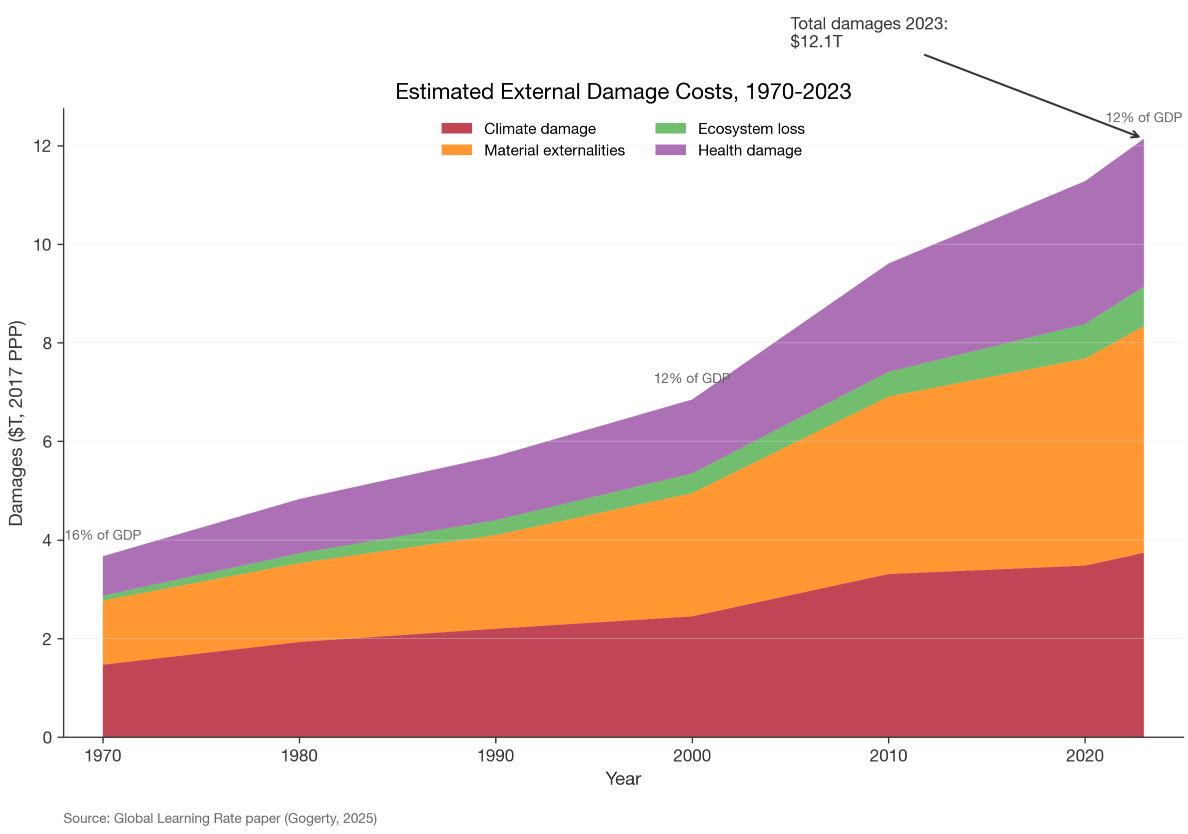

Figure 11: Figure 9

The damage share of GDP has been remarkably stable at 11-16%, declining slightly as GDP grows faster than aggregate damages. Total damages grew from $3.7 trillion in 1970 (16% of GDP) to $12.1 trillion in 2023 (11.6% of GDP). Material externalities are the largest and fastest-growing component.

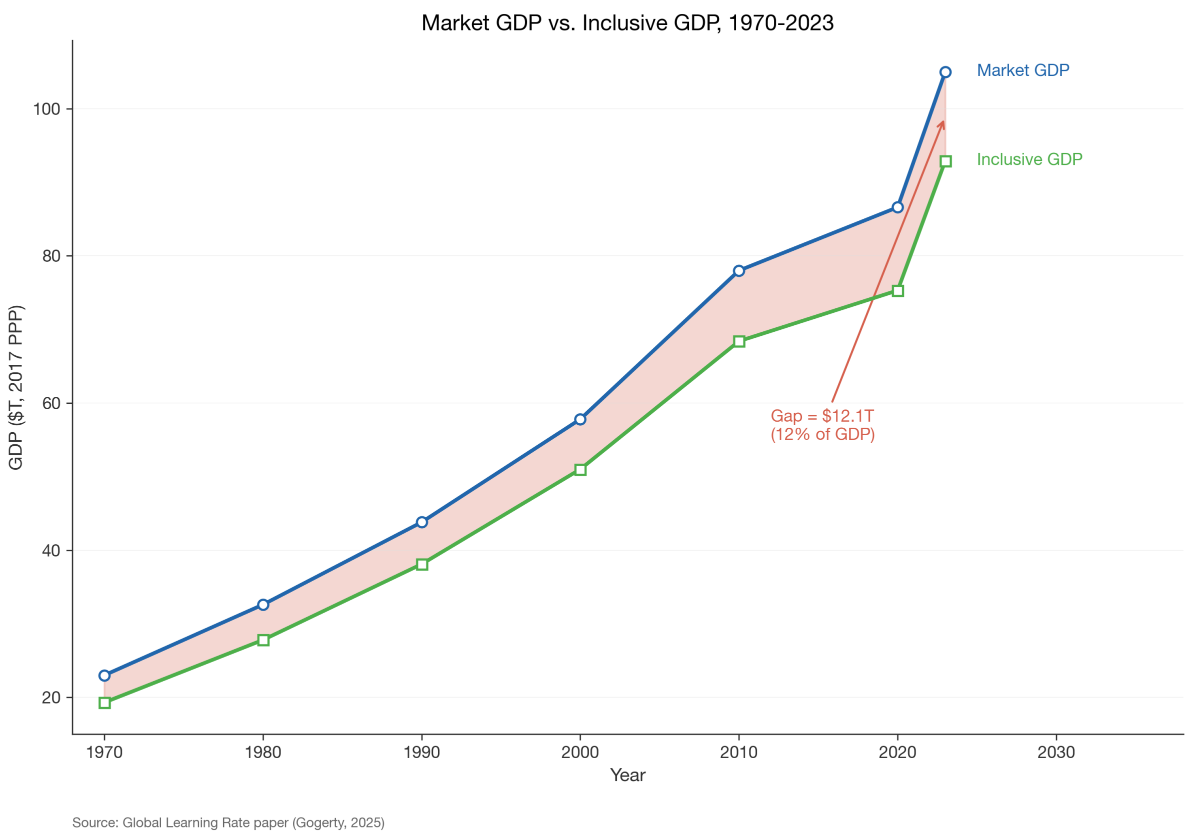

Figure 12: Figure 10

6.3 The Inclusive Learning Rate

To compute a single inclusive learning rate, we construct a composite total resource cost index:

Total Resource Cost = Energy cost + Climate damage + Material damage + Biodiversity loss + Health damage

where energy is valued at average global market prices (approximately $8 per GJ). The inclusive resource intensity is then Total Resource Cost divided by Inclusive GDP.

Table 12. Total Resource Cost and Inclusive Resource Intensity, 1970-2023

Year	Total Resource Cost $(T) \vert InclusiveGDP$(T)	Inclusive Intensity ($ per $ GDP)	
1970	5.37	19.3	0.278
1980	7.09	27.8	0.255
1990	8.43	38.1	0.221
2000	10.03	51.0	0.197
2010	13.69	68.4	0.200
2020	15.73	75.3	0.209
2023	16.97	92.9	0.183

Note the stalling in 2010-2020: re-materialization and rising externality damages offset efficiency gains. The regression yields:

Table 13. Inclusive Learning Rate Regression Results

Parameter	Value
Learning exponent (beta)	-0.190
R-squared	0.870
Inclusive learning rate	12.4%

6.4 The Phantom Learning Gap

Table 14. Conventional vs. Inclusive Learning Rates

Metric	Learning Rate
Conventional energy learning rate	18.3%
Conventional carbon learning rate	22.2%
Conventional material learning rate	6.5% (n.s.)
Inclusive energy learning rate	15.2%
Comprehensive inclusive learning rate	12.4%

The gap between the conventional composite rate (approximately 20%) and the inclusive rate (12.4%) is 7.6 percentage points. This gap represents what we term phantom learning: apparent efficiency gains that are actually achieved by externalizing costs to the climate, ecosystems, and future generations. Approximately 38% of what appears to be global economic learning is cost-shifting to natural capital.

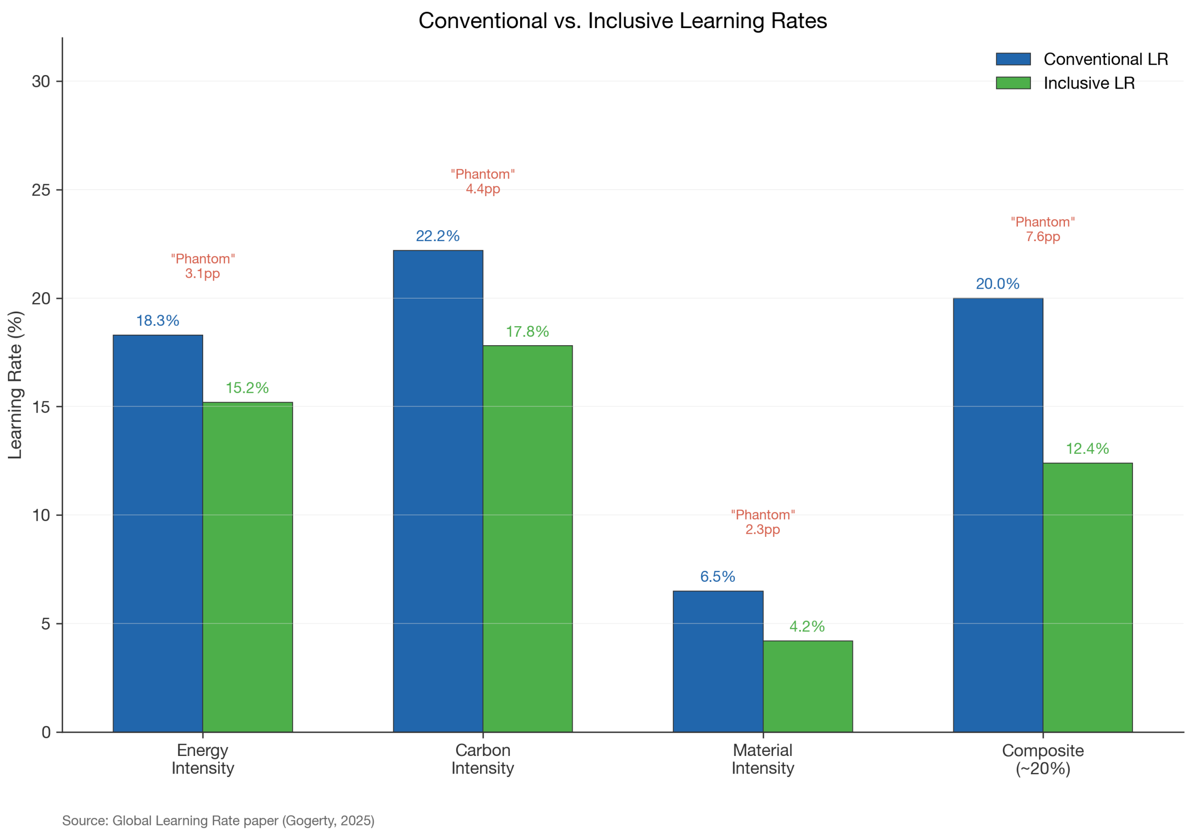

Figure 13: Figure 11

This finding resonates with the World Bank's Adjusted Net Savings indicator, which shows that for resource-dependent economies, genuine savings are often negative — these economies are consuming their natural capital stock while appearing to grow. In Hicksian terms, the world's genuine savings rate is lower than its apparent savings rate by a comparable fraction.

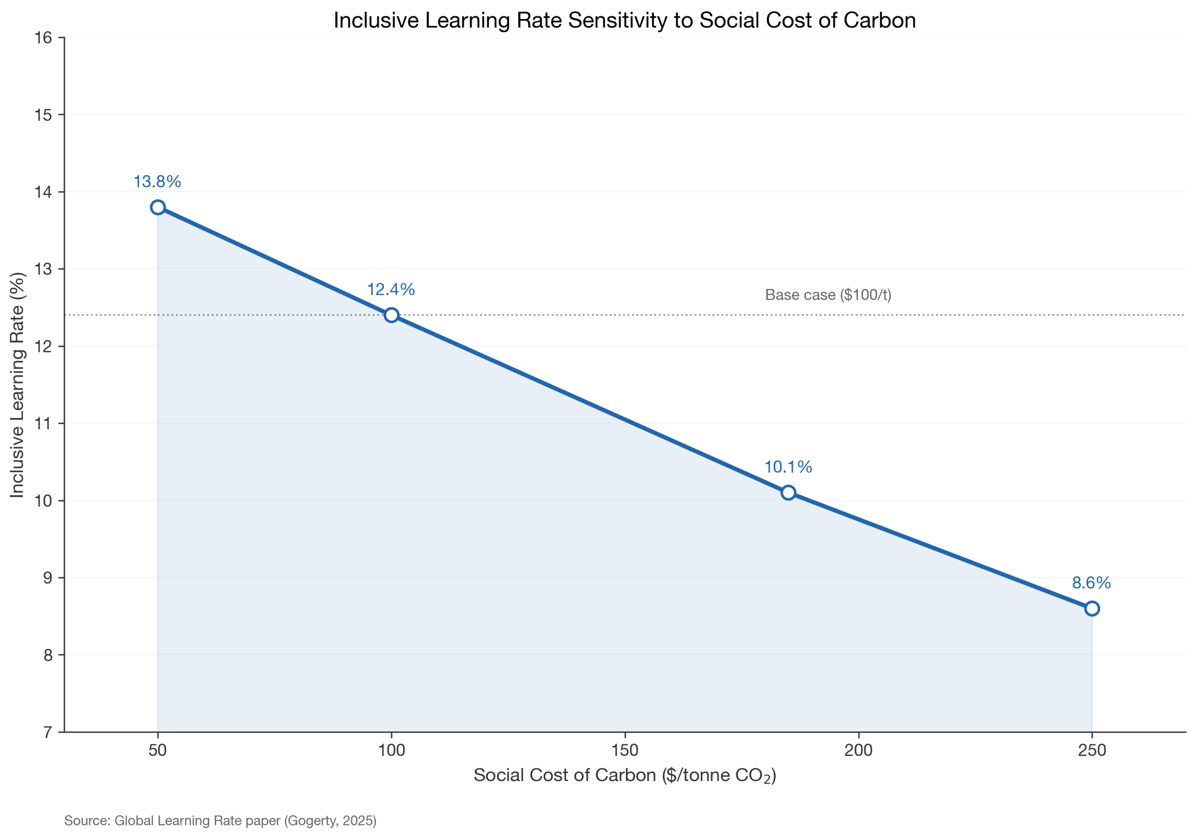

Figure 14: Figure 12

The inclusive learning rate is sensitive to the assumed social cost of carbon. At Nordhaus's estimate ($50 per tonne), the inclusive rate is 13.8%; at the Rennert et al. high-damage estimate ($250 per tonne), it falls to 8.6%. Even the most conservative SCC assumption produces an inclusive rate substantially below the conventional 18.3%.

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7. Paris Alignment Analysis

7.1 The Carbon Budget Framework

The IPCC Sixth Assessment Report (Masson-Delmotte et al., 2021) provides remaining carbon budgets as of January 2020. Subtracting cumulative emissions from 2020-2023 (approximately 148 Gt CO2; Friedlingstein et al., 2023), we obtain updated budgets as of January 2024:

Table 15. Remaining Carbon Budgets

Target	Probability	IPCC Budget from 2020 (Gt CO2)	Emissions 2020-2023 (Gt)	Remaining from 2024 (Gt)	Years at Current Rate
1.5C	50%	500	148	~250	6.7
1.5C	67%	400	148	~250	6.7
1.5C	83%	300	148	~150	4.0
2.0C	50%	1,350	148	~1,150	30.7
2.0C	67%	1,150	148	~1,000	26.7
2.0C	83%	900	148	~750	20.1

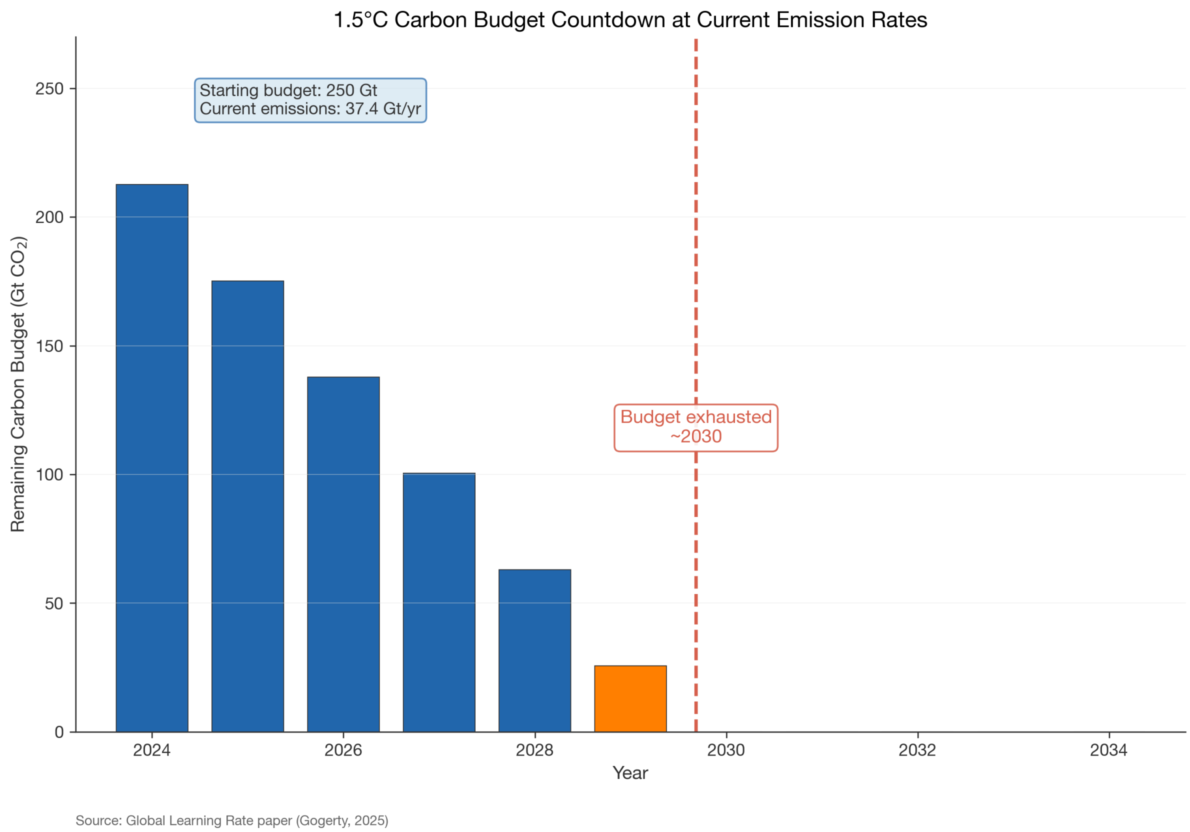

Figure 15: Figure 15

At 37.4 Gt CO2 per year, the 1.5 degrees Celsius budget (50% probability) is exhausted by approximately 2030-2031. The 2 degrees Celsius budget (67% probability) is exhausted by the late 2040s, even before accounting for non-CO2 greenhouse gases (methane, N2O, F-gases), which consume an additional 10-20% of the effective carbon budget. These budget figures carry substantial uncertainty that is asymmetric — skewing toward smaller effective budgets due to carbon cycle feedbacks, permafrost methane release, and aerosol unmasking effects (Rogelj et al., 2019; Armstrong McKay et al., 2022).

7.2 Extrapolating the Current Learning Rate

Under standard assumptions — 3% real GDP growth (consistent with the 1970-2023 historical average and IMF medium-term projections) and a constant 22.2% carbon learning rate — we project the emissions trajectory:

Table 16. Projected Emissions Under Current Learning Rate

Year	Annual GDP ($T, 2017 PPP)	Cumulative GDP ($T-yr)	Carbon Intensity (Gt/$T)	Annual CO2 (Gt)	Cumulative CO2 from 2024 (Gt)
2024	108	3,890	0.348	37.6	38
2030	129	4,600	0.310	40.0	270
2035	150	5,400	0.282	42.2	475
2040	174	6,400	0.255	44.3	690
2050	233	9,300	0.207	48.2	1,155
2060	313	13,500	0.167	52.3	1,660

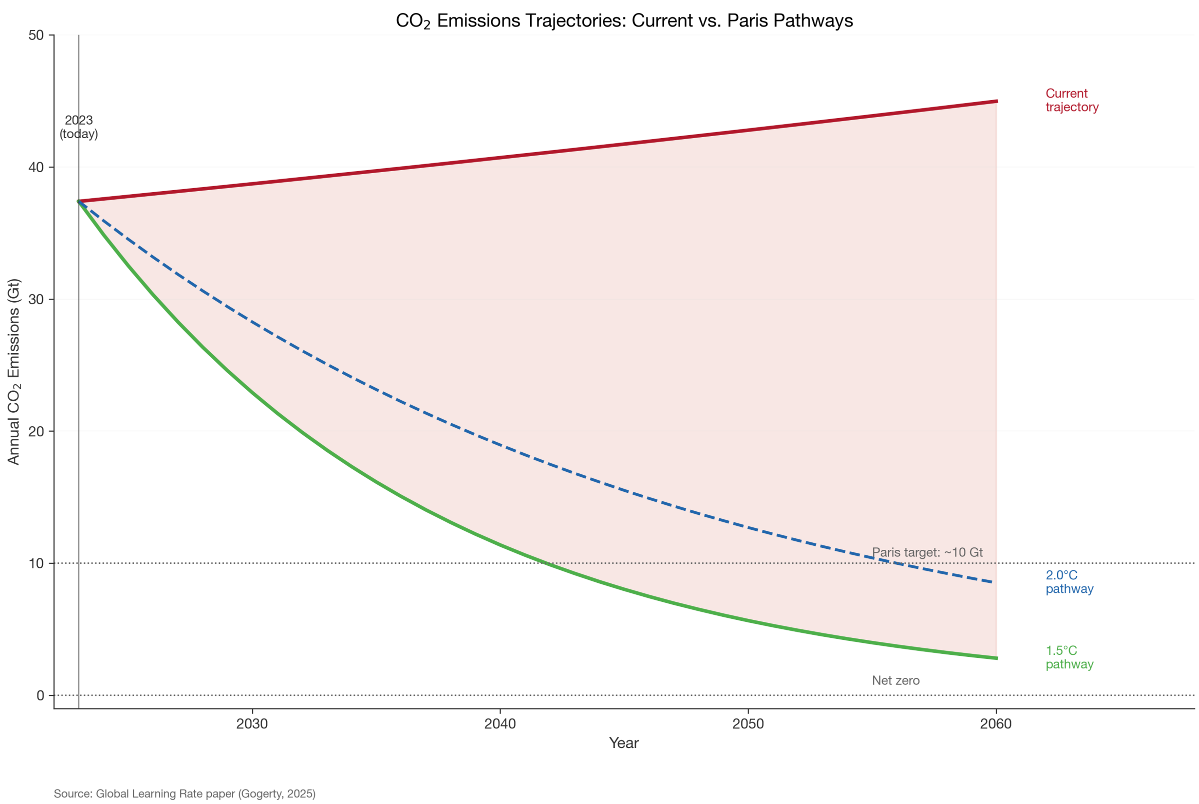

Figure 16: Figure 13

The central finding is stark: under the current learning rate, annual CO2 emissions do not decline — they rise continuously, reaching approximately 48 Gt by 2050 and exceeding 50 Gt by 2055. The 22.2% learning rate reduces carbon intensity faster than in any prior decade, but GDP growth overwhelms the intensity improvement. This is the Jevons paradox applied to decarbonization at the planetary scale. Cumulative emissions from 2024 to 2050 total approximately 1,155 Gt CO2, exceeding the 2 degrees Celsius budget (67% probability) by approximately 15% and the 1.5 degrees Celsius budget by more than fourfold.

7.3 Required Learning Rates for Paris Compliance

We invert the learning curve framework to determine the carbon learning rate required to meet specific temperature targets, holding GDP growth at 3% per year (base case).

For 1.5 degrees Celsius (annual emissions approximately 10 Gt by 2050): - Required carbon intensity: 10 / 233 = 0.043 Gt per trillion $, versus current 0.356 - Required intensity reduction: 87.9% in 26 years - Cumulative GDP approximately doubles 1.3 times over this period - Required learning rate: approximately 52%

For 2.0 degrees Celsius (annual emissions approximately 20 Gt by 2050): - Required carbon intensity: 20 / 233 = 0.086 Gt per trillion $ - Required intensity reduction: 75.8% in 26 years - Required learning rate: approximately 35%

Table 17. Required vs. Actual Carbon Learning Rates

Target	Emissions 2050 (Gt)	Required Intensity (Gt/$T)	Required LR	Current LR	Gap	Historical Precedent
1.5C	~10	0.043	52%	22.2%	30 pp	Solar PV (49%), GPUs (88%)
2.0C	~20	0.086	35%	22.2%	13 pp	LED lighting (35%), wind (32%)
2.5C	~30	0.129	28%	22.2%	6 pp	Batteries (24%), gas turbines (25%)
Net zero 2070	~2	0.005	40%	22.2%	18 pp	French nuclear buildout 1975-90

The 95% confidence interval for the current carbon learning rate is [17.5%, 27.1%]. Under the optimistic end, the gap to the 2 degrees Celsius target narrows to 8 percentage points — still substantial but within the range of policy-induced acceleration. However, confidence intervals widen dramatically over longer projection horizons: by 2050, the 95% prediction interval for annual emissions spans 30-65 Gt.

7.4 Sector Decomposition

The aggregate carbon learning rate of 22.2% is a composite of vastly different sectoral trajectories:

Table 18. Sector-Level Carbon Learning Rates and Paris Gaps

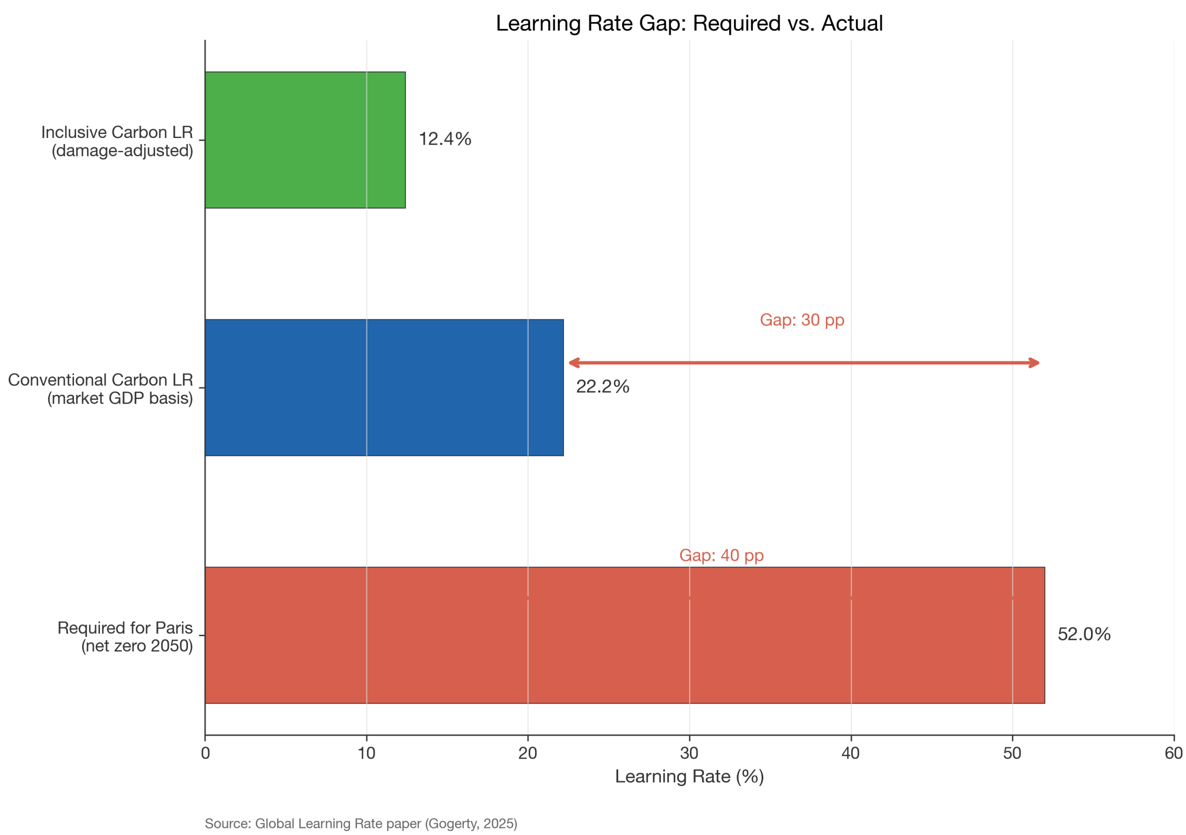

Figure 17: Figure 14

Sector	Share of Global CO2	Current LR (est.)	Required LR (2C)	Gap	Key Technology	Readiness
Power generation	40%	~38%	~55%	17 pp	Solar, wind, storage, nuclear	High
Transport	21%	~15%	~40%	25 pp	EVs, e-fuels, modal shift	Medium
Industry	21%	~8%	~32%	24 pp	Green H2, CCUS, electrification	Low-Medium
Buildings	10%	~12%	~28%	16 pp	Heat pumps, efficiency	Medium-High
Agriculture/land use	8%	~5%	~25%	20 pp	Regenerative agriculture, dietary shift	Low

Sources: IEA World Energy Outlook 2023; IPCC AR6 WG3 (2022).

The power sector has the highest current learning rate (approximately 38%) and the highest technological readiness, driven by solar photovoltaics (49% learning rate), onshore wind (23%), and battery storage (24%) (IRENA, 2023; Ziegler & Trancik, 2021). Industry and agriculture present the largest gaps and the lowest readiness, representing the hard-to-abate frontier. The gap in transport reflects fleet turnover inertia: while battery costs follow a steep learning curve, the average vehicle lifespan of 12-15 years limits the rate at which the fleet transitions.

7.5 NDC Implied Learning Rates

The UNEP Emissions Gap Report 2023 established that full implementation of current Nationally Determined Contributions implies warming of 2.5-2.9 degrees Celsius by 2100 — well above the Paris targets. Translating NDC-implied emissions trajectories into national learning rates reveals a structural equity problem:

Table 19. NDC-Implied National Carbon Learning Rates

Country/Region	2023 Emissions (Gt CO2)	NDC Target (2030)	Implied Carbon LR	Gap to 2C
United States	4.9	-50% vs. 2005	~28%	7 pp
EU-27	2.7	-55% vs. 1990	~30%	5 pp
China	12.6	Peak before 2030	~20%	15 pp
India	2.8	-45% intensity vs. 2005	~15%	20 pp
Japan	1.0	-46% vs. 2013	~26%	9 pp
Rest of world	13.4	Heterogeneous	~12-18%	17-23 pp
Global aggregate	37.4	~32-34 Gt by 2030	~24%	11 pp

Sources: UNEP Emissions Gap Report 2023; Climate Action Tracker 2024.

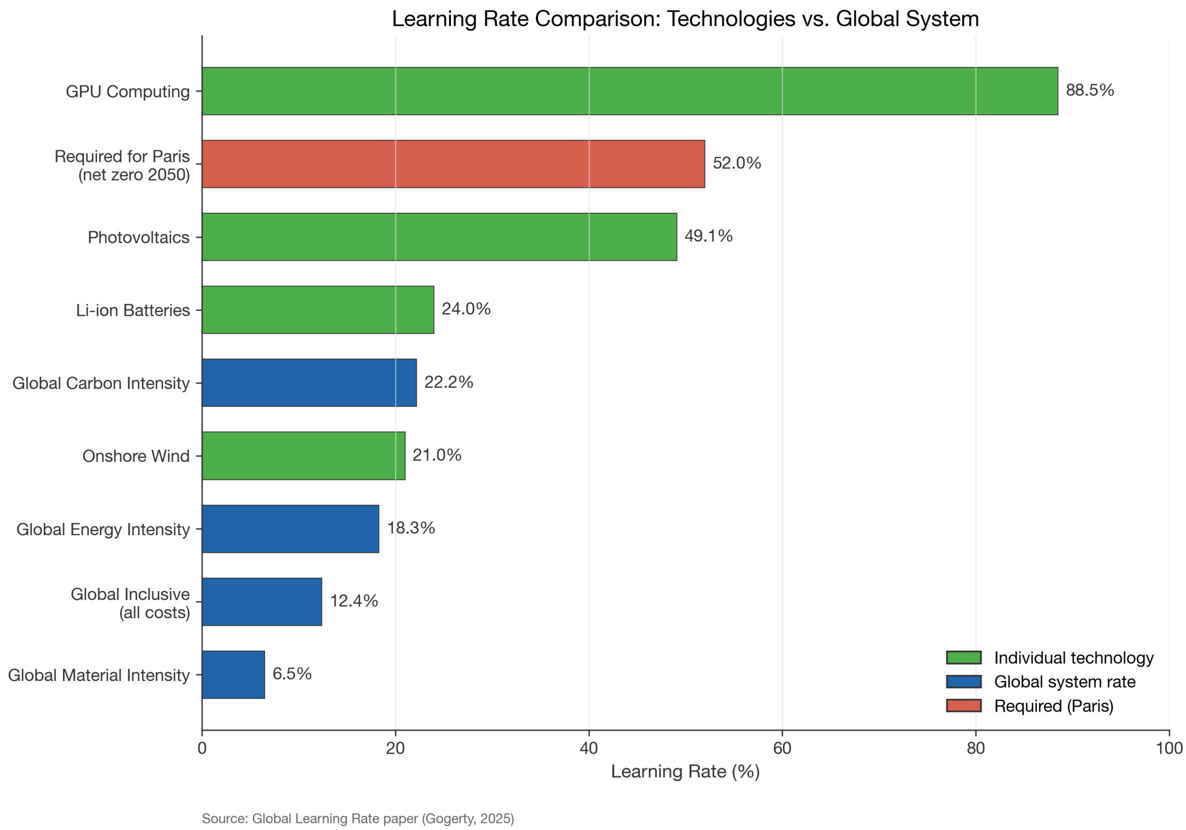

Figure 18: Figure 16

OECD countries have implied learning rates of 26-30%, roughly consistent with the 2 degrees Celsius requirement of 35% but falling short. India and much of the developing world face the starkest challenge: they are being asked to achieve carbon learning rates faster than any advanced economy achieved during its own industrialization — with fewer resources and less institutional capacity. The learning rate framework exposes this equity problem with quantitative precision.

7.6 Historical Precedents for Paradigm-Speed Learning

Can learning rates of 35-52% be sustained at the economy-wide level? Historical precedents provide cautious support.

The Montreal Protocol achieved a greater than 99% reduction in CFC production in approximately 20 years, equivalent to a learning rate of approximately 65%. The United Kingdom eliminated coal from electricity generation (from 40% in 2012 to below 2% by 2023) in 11 years. France went from near-zero nuclear to 75% nuclear electricity in 15 years. Each case involved a paradigm transition — the rapid replacement of an old technology with a new one — enabled by clear substitutes, institutional commitment, and cost-sharing mechanisms.

These precedents share a crucial feature: the high learning rate was achieved during technology substitution, not incremental optimization. The required 35-52% global carbon learning rate can therefore only be achieved if substitution dominates — solar for coal, electric vehicles for internal combustion engines, heat pumps for gas boilers. The constraint is not invention but diffusion speed: manufacturing scale-up, grid integration, workforce training, regulatory reform, and capital mobilization (Grubler et al., 2018).

7.7 Tipping Points and the Limits of Extrapolation

The learning rate framework assumes a smooth, continuous relationship between effort and outcome. Climate science reveals a fundamentally different reality: the Earth system contains tipping points beyond which change becomes self-reinforcing and irreversible (Lenton et al., 2019; Armstrong McKay et al., 2022).

Table 20. Critical Climate Tipping Elements

Tipping Element	Threshold (C above pre-industrial)	Current Status	Impact if Triggered
Greenland Ice Sheet	1.5-3.0	Accelerating mass loss	+7m sea level over centuries
West Antarctic Ice Sheet	1.5-2.0	Thwaites Glacier retreating	+3-5m sea level
AMOC slowdown	1.5-2.0 (debated)	Weakening detected	Regional climate disruption
Amazon dieback	2.0-2.5 (with deforestation)	17% deforested	~50 Gt CO_2 release
Permafrost thaw	~1.5 (gradual)	Already underway	150-200 Gt CO_2-eq by 2100
Coral reef die-off	1.5 (>99% loss)	70-90% damaged	Fishery collapse

Sources: Armstrong McKay et al. (2022); IPCC AR6 WG1; Lenton et al. (2019).

At approximately 1.3 degrees Celsius above pre-industrial temperatures in 2024, several tipping elements are already within or approaching their threshold ranges. If tipping cascades occur, the effective remaining

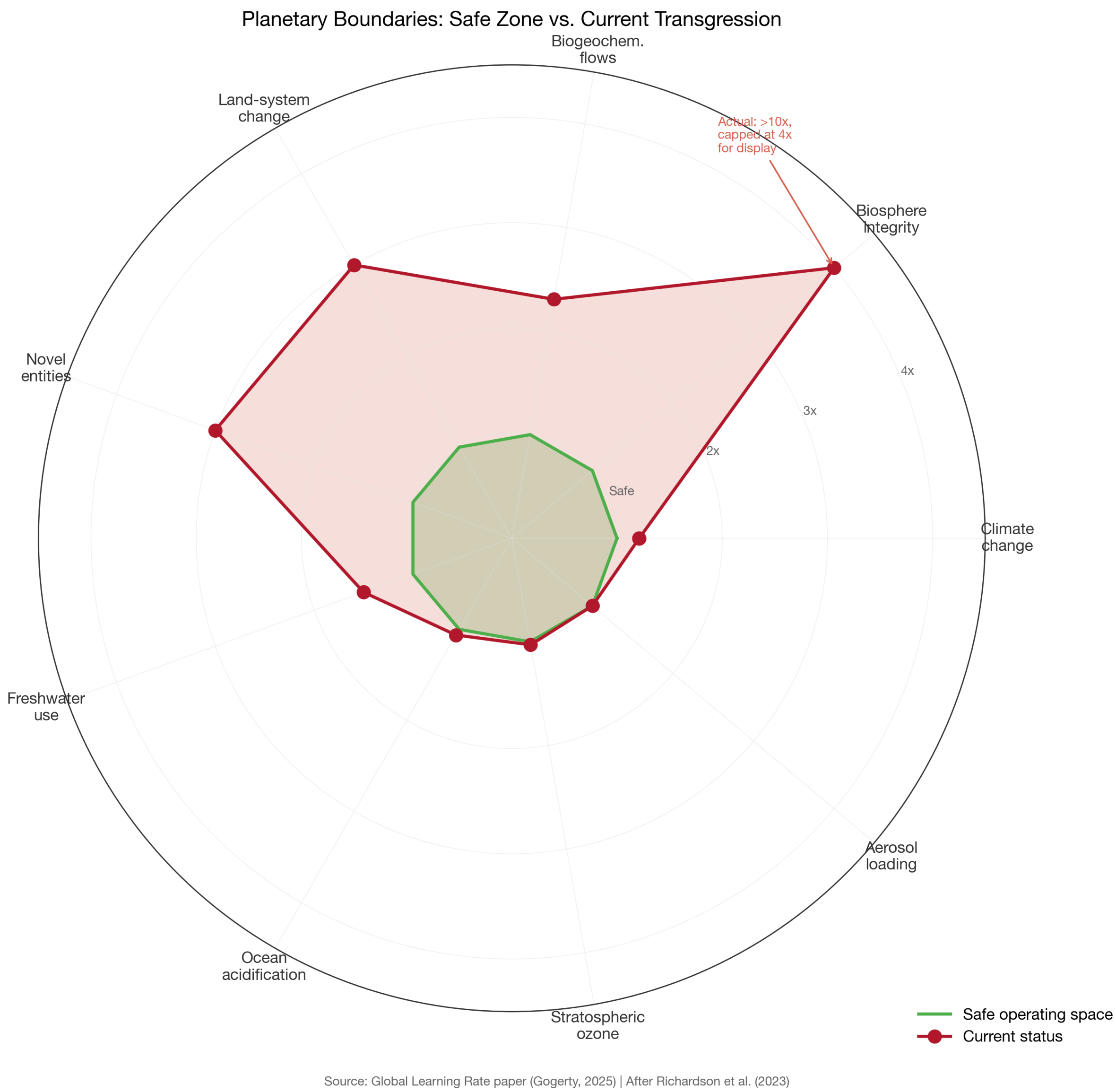

Figure 19: Figure 17

carbon budget shrinks dramatically — Armstrong McKay et al. (2022) estimate by 200-400 Gt CO_2 — raising the required learning rate for 2 degrees Celsius from 35% to 45-50%.

The Planetary Boundaries framework (Rockstrom et al., 2009; Richardson et al., 2023) provides a broader assessment: six of nine planetary boundaries are now transgressed. The learning rate framework captures economic efficiency but does not capture the nonlinearities and irreversibilities inherent in Earth system dynamics. There exists a fundamental asymmetry: economic learning is reversible — a slowing learning rate can later re-accelerate — but climate tipping points are irreversible on any policy-relevant timescale.

7.8 Three Scenarios for 2050

We synthesize the preceding analysis into three scenarios defined by the achieved global carbon learning rate:

Table 21. Scenario Comparison

Dimension	Scenario A: Business as Usual (22% LR)	Scenario B: Accelerated (35% LR)	Scenario C: Paradigm Shift (52% LR)
Global GDP 2050 ($T)	230	200	175
Annual CO2 2050 (Gt)	48	20	10
Cumulative CO2 2024-2050 (Gt)	1,155	720	530
Warming by 2100	3.0-3.5C	~2.0C	~1.5C
Planetary boundaries transgressed	8 of 9	6 (some stabilizing)	4 (active recovery)
Inclusive learning rate	~12.4%	~25%	~40%
Policy requirement	Current trajectory	Enhanced NDCs + pricing + industrial policy	Montreal-level coordination + AI + transfer
Subjective probability	~60%	~25%	~5%

The learning rate framework reveals that the Paris gap is not primarily a technology gap. The technologies for 35% and even 52% learning rates largely exist — solar photovoltaics, wind power, batteries, heat pumps, electric vehicles are already on steep learning curves. The gap is in deployment speed, coordination, and political will. The mathematics of learning curves deliver an uncomfortable conclusion: the window during which accelerating the learning rate can prevent catastrophic warming is approximately 10-15 years.

7.9 Carbon Dioxide Removal: Experience Curves for Negative Emissions Technologies

7.9.1 Motivation and Scope The preceding analysis establishes that the global carbon learning rate of 22.2% is insufficient for Paris compliance: achieving the 1.5 degrees Celsius target requires a carbon learning rate of approximately 52%, while the 2 degrees Celsius target requires approximately 35%. These calculations assume that the entirety of the required emissions reduction must be achieved through gross emissions abatement — efficiency improvements, fuel switching, electrification, and structural economic change. However, the IPCC Sixth Assessment Report pathways consistent with 1.5 degrees Celsius warming include substantial carbon dioxide removal (CDR), ranging from 5 to 16 Gt CO_2 per year by 2050 across model scenarios (IPCC, 2022, Chapter 12; Fuss et al., 2018). The IEA Net Zero Emissions by 2050 Scenario similarly requires approximately 1.9 Gt CO_2 per year of engineered removal by mid-century, rising to 4.6 Gt by 2070 (IEA, 2021).

CDR introduces a second degree of freedom into the learning rate framework. If the atmosphere does not distinguish between a tonne not emitted and a tonne removed, then CDR effectively relaxes the gross emissions constraint, permitting a lower system-level carbon learning rate to achieve the same net emissions pathway. This section estimates experience curves for CDR technologies using the paper's Wright's Law framework, projects their cost trajectories as functions of cumulative deployment, and computes the total investment required under various learning rate assumptions. We then quantify how CDR deployment modifies the required system-level carbon learning rate for Paris compliance.

A critical distinction must be maintained throughout. The cost projections presented here are *deployment-conditional*: they describe the cost reduction that will occur *if* a given level of cumulative deployment is achieved, exploiting the empirical regularity of experience curves. They are not unconditional forecasts. Whether the deployment occurs is a function of policy, investment, and institutional capacity — variables exogenous to the experience curve framework. This distinction follows Way et al. (2022), who similarly presented experience-curve-based cost projections as conditional on deployment pathways rather than as predictions.

7.9.2 CDR Technology Portfolio and Learning Rate Estimation We consider five CDR technology categories, each at a different stage of development and with different cost structures, scalability constraints, and learning rate characteristics.

Table 24. CDR Technology Characteristics and Learning Rate Estimates

Technology	Mechanism	Current Cost (/$tCO2$, 2023)	Estimated Learning Rate (%)	Current Deployment (Gt CO_2/yr)	Technology Readiness Level	Key Constraints
Direct Air Capture (DAC)	Chemical absorption/adsorption of CO_2 from ambient air	400-600	15-20	~0.01	6	Energy input; sorbent cost
BECCS	Biomass combustion with geological CO_2 storage	100-200	10-15	~0.005	7	Biomass supply; storage capacity
Enhanced Weathering	Accelerated mineral carbonation via crusite spreading	50-200	15-20	~0.005	5	Mining logistics; MRV
Biochar	Biomass pyrolysis; char applied to soil	30-120	8-12	~0.005	7	Biomass supply; permanence

Technology	Mechanism	Current Cost (/tCO2, 2023)	Estimated Learning Rate (%)	Current Deployment (Gt CO2/yr)	Technology Readiness Level	Key Constraints
Ocean Alkalinity Enhancement	Addition of alkaline minerals to ocean surface	50-300	15-25	<0.001	3	Ecological risk; MRV

Sources: IPCC AR6 WGIII Chapter 12 (2022); Fuss et al. (2018); NASEM (2019); McQueen et al. (2021); Nemet et al. (2018); Renforth & Henderson (2017); Climeworks (2024); Hanna et al. (2021).

Basis for learning rate estimates. Empirical learning rate data for CDR technologies are sparse, given the early stage of deployment. Our estimates are derived from three approaches.

First, *process analogy*. DAC systems share fundamental engineering characteristics with chemical absorption processes (amine scrubbing, pressure swing adsorption) used in natural gas processing and industrial CO2 capture. These processes exhibit learning rates of 12-22% in the chemical engineering literature (Rubin et al., 2015; McDonald & Schrattenholzer, 2001). McQueen et al. (2021) estimate a DAC learning rate of 15-20% based on component-level analysis: fans and contactors (mature, low learning), sorbents and regeneration systems (early-stage, high learning), and balance of plant (moderate learning). Lackner (2020) provides a more optimistic estimate of 20-25% based on the trajectory of early-generation moisture-swing sorbents.

Second, *early empirical data*. Climeworks' cost per tonne has declined from approximately $1,000 in 2017 to approximately $400-600 in 2024 across approximately two doublings of cumulative removal capacity, implying a realized learning rate of approximately 20-30% for these initial doublings (Climeworks, 2024). However, this estimate must be treated with extreme caution: it is based on fewer than three doublings, in a single firm, with substantial confounding from economies of scale in plant size rather than cumulative deployment per se. The Santa Fe Institute Performance Curve Database documents similarly noisy early-stage learning for many technologies that later converge to stable learning rates (Magee et al., 2016).

Third, *theoretical bounds*. Hanna et al. (2021) apply a bottom-up engineering model to DAC, decomposing costs into energy (40-60% of total), capital (25-35%), and sorbent/solvent (10-20%) components. Energy costs decline with the learning curves of the underlying energy sources (solar, wind, nuclear). Capital costs decline with manufacturing scale and standardization. Sorbent costs decline with materials science advances. The composite learning rate from this bottom-up decomposition is 16-22%, consistent with the top-down estimates.

For BECCS, the lower learning rate estimate (10-15%) reflects the relative maturity of both biomass combustion and carbon capture and storage (CCS) individually. The integration learning — operating both systems together reliably and cost-effectively — is the primary remaining learning dimension. Leeson et al. (2017) estimate CCS learning rates of 8-15% based on analogous chemical process experience.

Enhanced weathering and ocean alkalinity enhancement, as mineral extraction and processing operations, draw learning rate estimates from the mining industry (12-18%; Rubin et al., 2015) and the cement/minerals processing industry (8-15%). The higher end of the range reflects the potential for process innovation in grinding, transport, and application logistics (Renforth & Henderson, 2017; Strefler et al., 2018).

7.9.3 Cost Projections Under Wright's Law Applying the canonical Wright's Law specification:

C(x) = C_0 * x^(-b), where LR = 1 - 2^(-b)

we project cost trajectories for each CDR technology as a function of cumulative deployment. The projections use the midpoint of the estimated learning rate range for each technology and the midpoint of the current cost range as the initial condition.

Table 25. DAC Cost Projections Under Wright's Law (Base Case LR = 18%)

Cumulative Deployment (Gt CO2)	Doublings from Current (~0.01 Gt)	Projected Cost ($/tCO2)	95% CI (LR 12-24%)
0.01 (current)	0	450	—
0.1	3.3	239	[283, 195]
1.0	6.6	127	[178, 84]
5.0	9.0	82	[128, 49]
10.0	10.0	67	[112, 36]
50.0	12.3	44	[85, 19]
100.0	13.3	36	[75, 14]

The 95% confidence interval reflects the uncertainty in the learning rate parameter, propagated through the Wright's Law projection. At 10 Gt cumulative removal, the central DAC cost estimate is $67/tCO2, with a 95% interval spanning $36 to $112. Even at the pessimistic bound, this is below the Rennert et al. (2022) central estimate of the social cost of carbon ($185/tCO2).

Table 26. CDR Portfolio Cost Projections at 10 Gt Cumulative Deployment

Technology	Current Cost ($/tCO2)	Cost at 10 Gt Cumulative ($/tCO2)	Learning Rate	Doublings Required
DAC	450	67	18%	~10
BECCS	150	45	12%	~10.9
Enhanced Weathering	125	28	18%	~10.9
Biochar	75	35	10%	~10.9
Ocean Alkalinity	175	24	20%	~13.3

7.9.4 Cumulative Investment Requirements We estimate the total cumulative cost of CDR deployment from 2024 to 2050 under the following assumptions:

Deployment pathway. A linear ramp from 0.025 Gt CO2/yr (current novel CDR capacity) to 10 Gt CO2/yr by 2050, with a portfolio allocation of: DAC 30%, BECCS 25%, enhanced weathering 20%, biochar 15%, ocean alkalinity enhancement 10%.

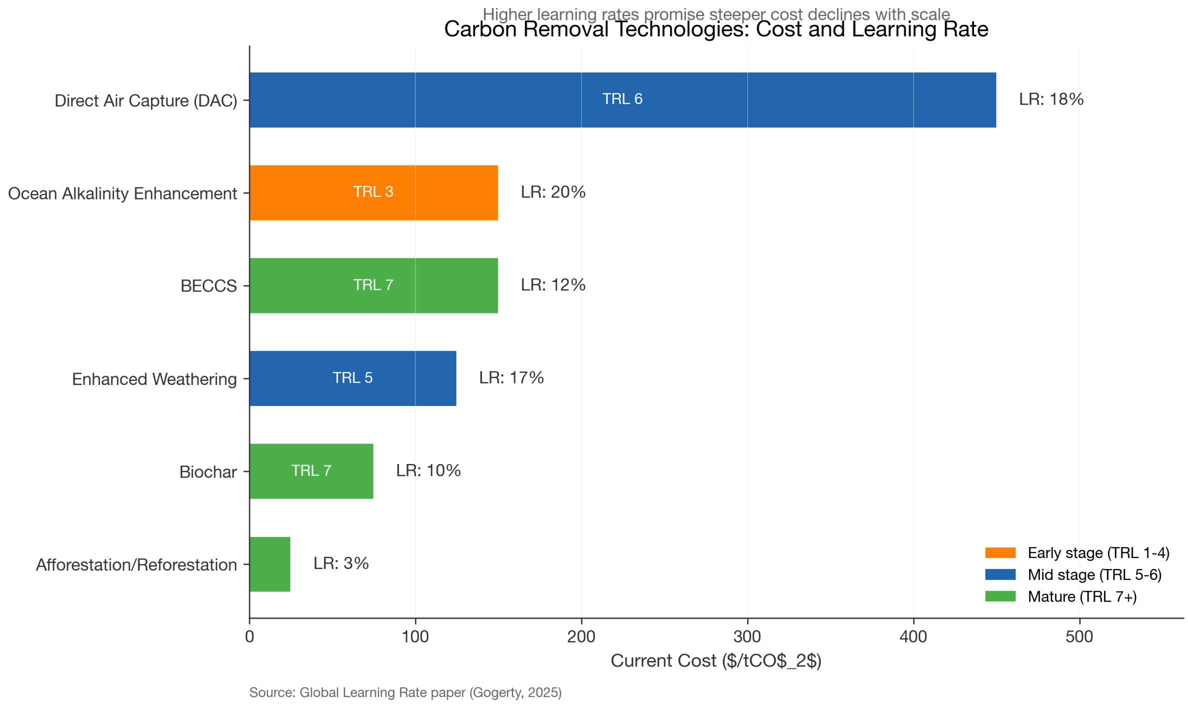

Figure 20: Figure 21

Cost computation. For each year, we compute the annual deployment for each technology, update the cumulative deployment, compute the cost per tonne via Wright's Law, and multiply deployment by cost. The annual cost is the sum across technologies. Cumulative cost is the integral of annual cost over the 2024-2050 period.

Table 27. Cumulative CDR Investment Cost Under Three Learning Rate Scenarios

Scenario	Learning Rate Assumption	Cumulative Removal (Gt CO2)	Cumulative Cost $(T, 2023)\|Average$	Average Cost per Tonne ($/tCO2)	Annual Cost ($B/yr)
Pessimistic	LRs halved (5-10%)	130	~14.0	~540	~108
Base case	Central LRs (10-20%)	130	~6.5	~250	~50
Optimistic	LRs +50% (15-30%)	130	~3.8	~145	~29

The cumulative cost is dominated by the early years of deployment, when costs are highest and deployment is growing fastest. In the base case, approximately 60% of the $6.5 trillion cumulative cost is incurred between 2024 and 2038, with the remaining 40% spread over 2038-2050 as learning effects accumulate and costs decline.

Contextualizing the investment. The base case cumulative cost of $6.5 trillion over 26 years represents approximately 0.16% of projected cumulative global GDP over the same period. For comparison: global fossil fuel subsidies including externalities total approximately $7 trillion per year (IMF, 2023); annual global military expenditure exceeds $2.2 trillion (SIPRI, 2024); the U.S. Inflation Reduction Act allocates approximately $370 billion over 10 years.

CDR Deployment by 2050 (Gt CO2/yr)	Allowable Gross Emissions by 2050 (Gt CO2/yr)	Required Carbon Learning Rate	Gap vs. Current 22.2%	Interpretation
5	15	~42%	20 pp	Exceeds all observed national rates
10	20	~35%	13 pp	Within range of demonstrated technology LRs
15	25	~28%	6 pp	Close to current accelerating trajectory

For 2.0 degrees Celsius compliance (net emissions approximately 20 Gt by 2050):

CDR Deployment by 2050 (Gt CO2/yr)	Allowable Gross Emissions by 2050 (Gt CO2/yr)	Required Carbon Learning Rate	Gap vs. Current 22.2%
0	20	~35%	13 pp
5	25	~28%	6 pp
10	30	~24%	2 pp
15	35	~22%	~0 pp

The results demonstrate a striking finding: for the 2 degrees Celsius target, CDR deployment of approximately 15 Gt/yr by 2050 would reduce the required carbon learning rate to approximately the current rate of 22.2% — meaning that the existing trajectory, *combined with aggressive CDR deployment*, would be sufficient for 2 degrees Celsius compliance. For 1.5 degrees Celsius, CDR of 10 Gt/yr reduces the required rate from the unprecedented 52% to the demonstrably achievable (though still highly ambitious) 35%.

Sensitivity to GDP growth assumptions. The required learning rates assume 3% real GDP growth. Under lower growth assumptions, the required learning rates are somewhat lower:

GDP Growth Rate	Required LR (1.5C, no CDR)	Required LR (1.5C, 10 Gt CDR)	Required LR (2C, no CDR)	Required LR (2C, 10 Gt CDR)
2.0%	~45%	~30%	~28%	~20%
2.5%	~48%	~32%	~31%	~22%
3.0% (base)	~52%	~35%	~35%	~24%
3.5%	~56%	~38%	~38%	~26%

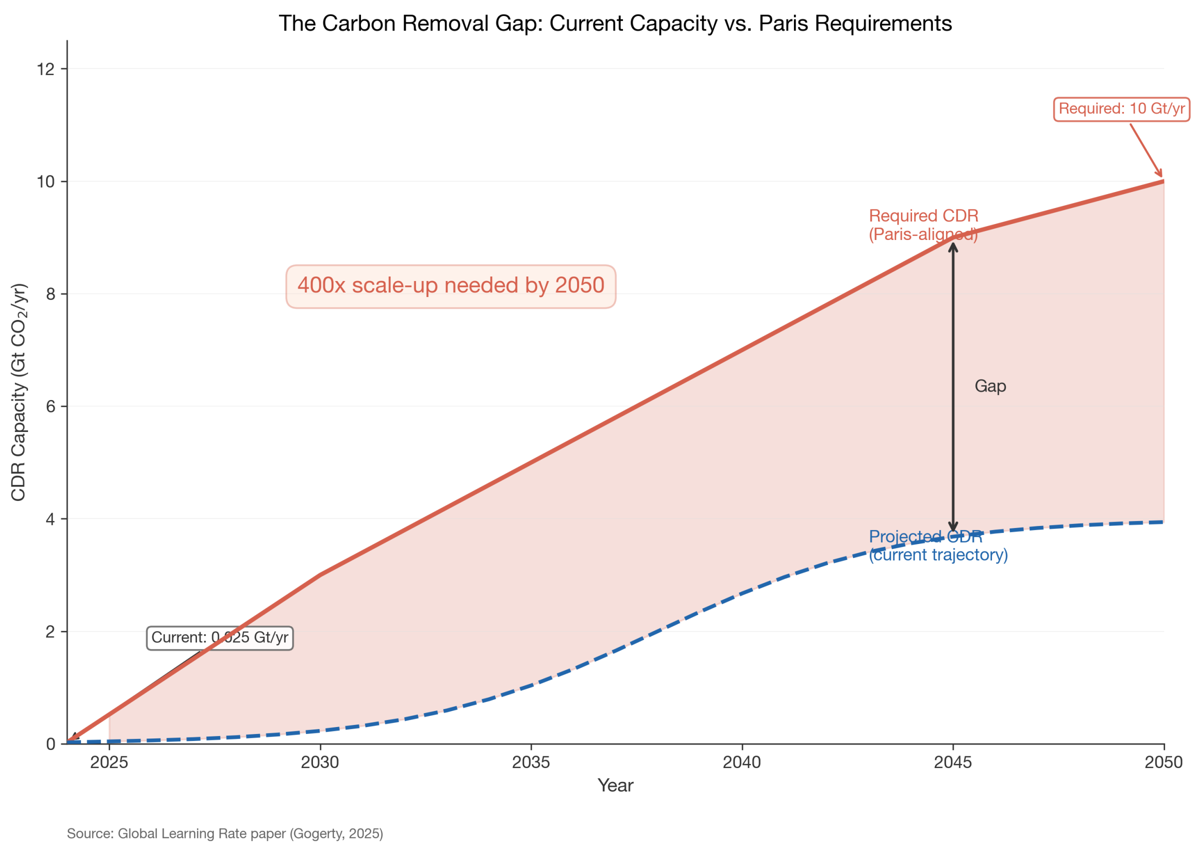

Figure 21: Figure 22

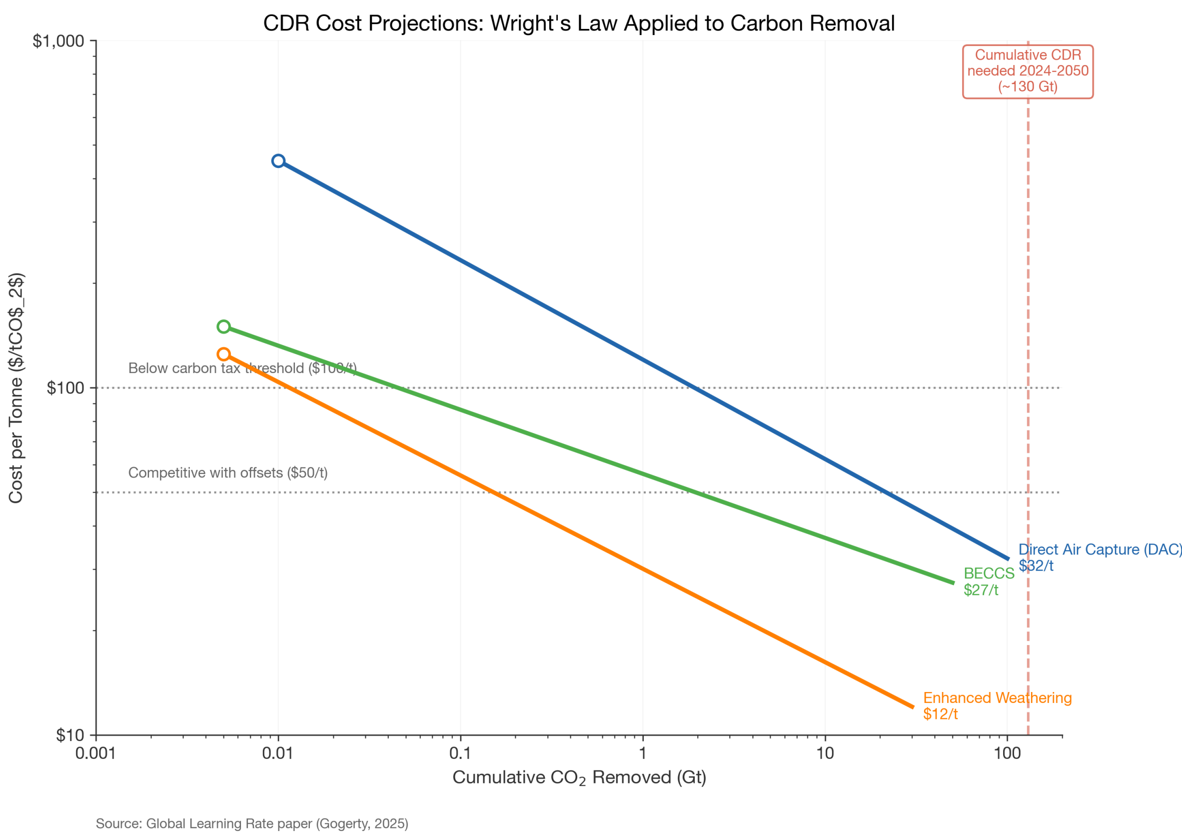

Figure 22: Figure 23

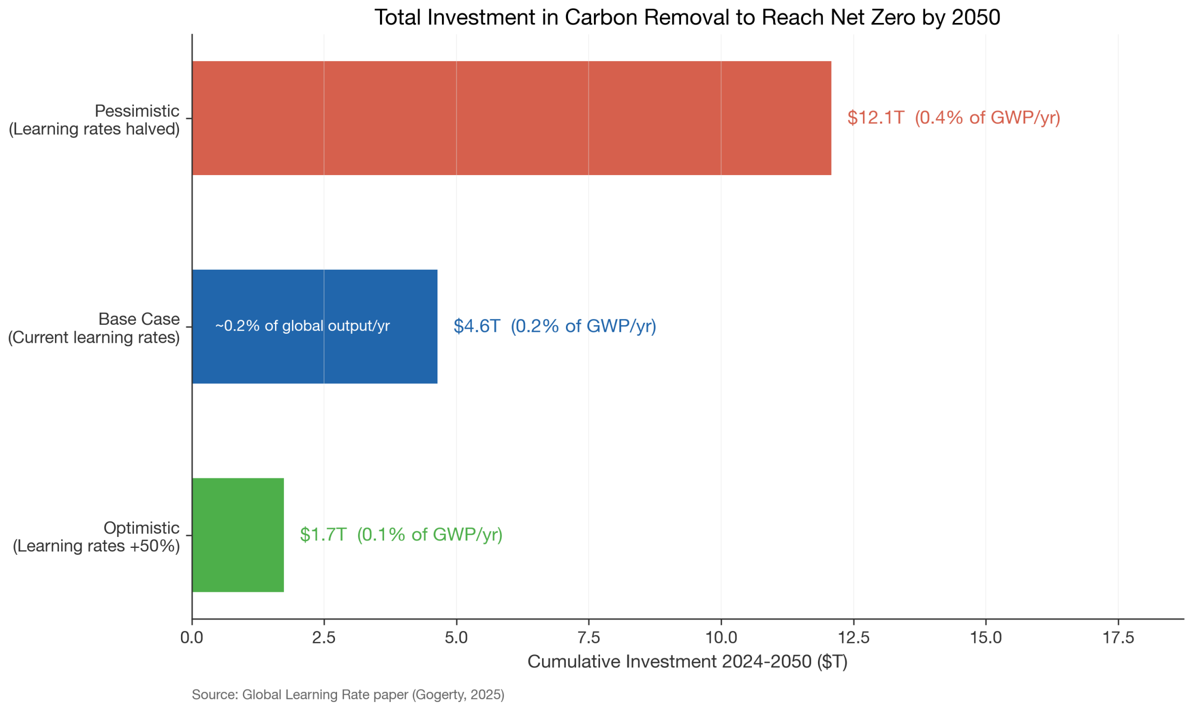

Figure 23: Figure 24

The finding that CDR reduces the required learning rate by 13-20 percentage points is robust across reasonable GDP growth assumptions.

7.9.6 Uncertainty and Caveats The CDR cost projections carry several layers of uncertainty. **Learning rate uncertainty:** CDR learning rates are estimated from process analogies and limited early deployment data; the true rates will only be revealed through deployment. **Permanence and MRV:** Not all CDR approaches offer equivalent permanence; if impermanent removal is discounted, effective portfolio costs rise by an estimated 15-30%. **Resource constraints:** BECCS at 2.5 Gt/yr requires 400-800 million hectares of bioenergy crops; enhanced weathering at 2 Gt/yr requires mining 10-20 Gt of silicate rock per year; DAC at 3 Gt/yr requires 30-60 EJ of energy input. These resource constraints may cause learning curves to flatten at high deployment levels. **Moral hazard:** The most cited concern is that CDR may reduce the urgency of emissions reduction. We note this risk is a feature of the policy environment, not the technology, and applies equally to any technology promising future cost reductions.

7.9.7 Synthesis CDR reframes the central finding of this paper. Without CDR, the gap between the current carbon learning rate (22.2%) and the required rate for 1.5 degrees Celsius (52%) is 30 percentage points — a gap with no historical precedent at the global scale. With 10 Gt/yr of CDR by 2050, the gap narrows to 13 percentage points — still substantial, but within the range of policy-induced learning rate accelerations observed in the power sector and in national energy transitions.

The investment required — approximately $6.5 trillion cumulative in the base case, or $250 billion per year — is large in absolute terms but modest relative to global GDP (0.16%), relative to fossil fuel subsidies ($7 trillion per year), and relative to the economic damages from unmitigated climate change.

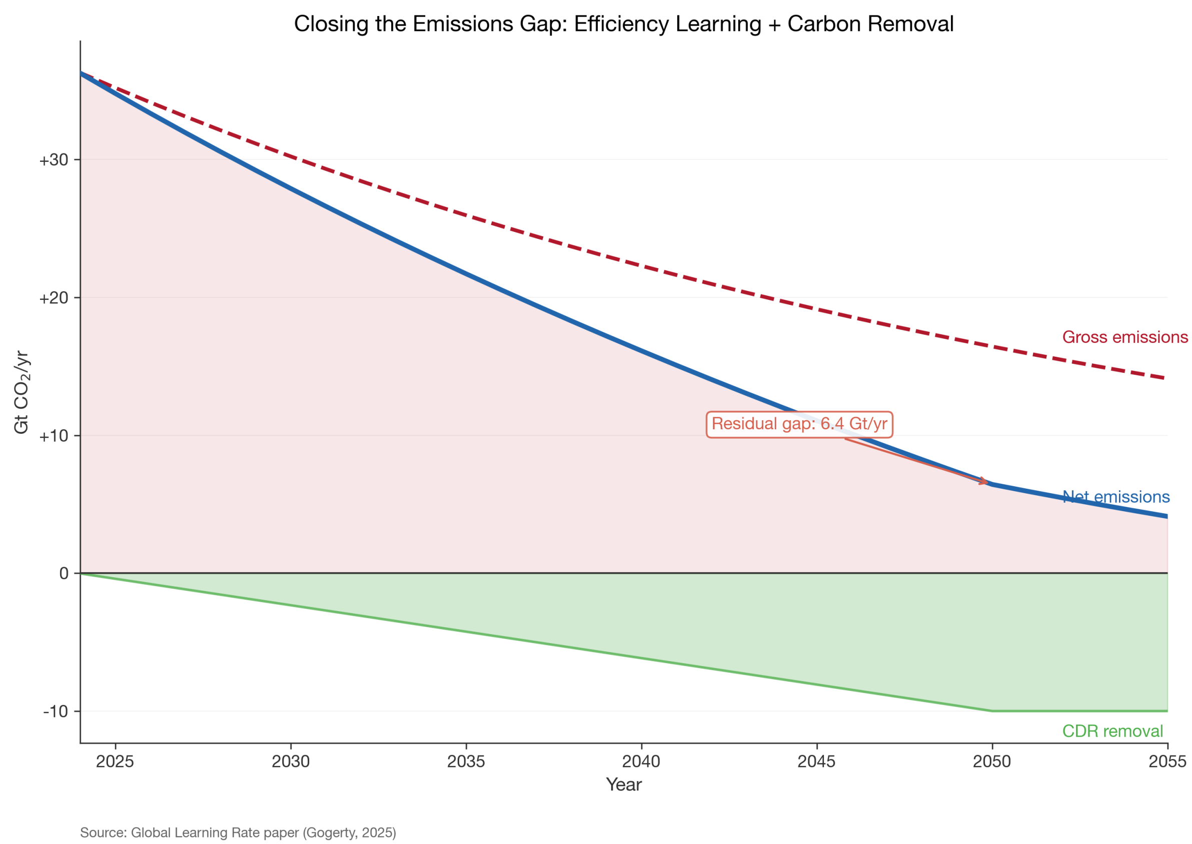

Figure 24: Figure 25

CDR does not substitute for emissions reduction. It complements it. The required 35% carbon learning rate with CDR still demands aggressive carbon pricing, green industrial policy, technology transfer, and deployment acceleration. But it transforms the problem from one that appears mathematically intractable to one that is extremely difficult but historically precedented.

The CDR learning imperative is urgent. Like solar PV in the 2000s and batteries in the 2010s, CDR technologies are currently at the steep, expensive beginning of their learning curves. Early investment — even at current costs of $100-600 per tonne — is the mechanism by which costs fall. Wright's Law, applied to CDR, delivers the same message it delivers throughout this paper: the cost of action is a function of the action taken. We cannot wait for CDR to become cheap before investing. It becomes cheap *because* we invest.

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8. The Role of AI and General-Purpose Technologies

The emergence of artificial intelligence as a potential general-purpose technology (GPT) introduces deep uncertainty into learning rate projections. Like electricity in the 1880s-1930s and the microprocessor in the 1970s-2000s, AI has the potential to accelerate learning across multiple sectors simultaneously — or, through energy demand and rebound effects, to slow it.

8.1 Acceleration Pathways

Several channels through which AI could steepen the global learning rate are already empirically observable.

Materials discovery. DeepMind's GNoME system identified 2.2 million stable crystal structures in 2023, a 45-fold increase over all prior human discovery (Merchant et al., 2023). If even a fraction of these translate to lower-carbon industrial processes — novel cement chemistries, superior battery cathodes, efficient carbon capture sorbents — the learning rate for the hardest-to-abate sectors could steepen substantially.

Energy system optimization. AI-driven demand response, predictive maintenance, and grid balancing can increase the effective capacity of renewable energy systems by 15-25%, reducing the need for backup fossil generation (IEA, 2024). This is not a new technology but a meta-optimization of existing infrastructure.

Industrial process control. AI-optimized cement kilns, steel furnaces, and chemical plants can reduce energy consumption by 5-15% within existing process architectures. Given the scale of industrial emissions, these incremental gains are quantitatively significant (McKinsey, 2023).

Accelerated R&D cycles. AI compresses experimental science timelines. In pharmaceutical development, AI-assisted compounds have progressed from discovery to clinical testing in 3-5 years versus 10-15 years historically (Jumper et al., 2021). If similar acceleration applies to clean energy R&D, the technology pipeline for hard-to-abate sectors fills faster. Brynjolfsson et al. (2023) provide evidence that AI augments worker productivity in knowledge-intensive tasks by 14% on average, with the largest gains among less experienced workers — suggesting that AI may democratize the capacity for innovation.

8.2 Deceleration Pathways

Countervailing forces may offset or overwhelm the acceleration effects.

Data center energy demand. Global data center electricity consumption was approximately 460 TWh in 2022 (approximately 2% of global electricity) and is projected to reach 1,000-1,500 TWh by 2030 under aggressive AI deployment scenarios (IEA, 2024). Training a single large language model can consume 1-10 GWh (Luccioni et al., 2023). If data center growth outpaces renewable deployment, AI becomes a net contributor to emissions.

The digital Jevons paradox. AI-driven productivity gains increase economic output, which, absent structural change, increases resource consumption. If AI makes everything cheaper and more accessible, people consume more of everything. This is the rebound effect in digital form, and historical experience with previous GPTs suggests it is quantitatively significant (Alcott, 2005).

Fossil fuel optimization and lock-in. AI optimization of existing fossil-fuel-based systems — logistics, drilling, mining, combustion — can extend their economic viability, delaying the transition to alternatives. Acemoglu et al. (2012) demonstrated that the direction of technical change is not inherently clean: without appropriate price signals, innovation follows the path of existing capital, which is predominantly carbon-intensive.

8.3 The Productivity Paradox and Timing

The historical parallel between AI and previous GPTs is instructive but sobering. David (1990) documented that electrification, the last GPT of comparable scope, required 40-50 years from widespread adoption to measurable macroeconomic productivity gains. Solow's (1987) famous observation — "You can see the computer age everywhere but in the productivity statistics" — described a productivity paradox that lasted from the 1970s to the late 1990s for information technology. If AI follows a similar trajectory, its full impact on the global learning rate may not materialize until the 2050s-2060s, after the critical window for Paris compliance has closed.

Table 22. AI Impact Scenarios for the Global Carbon Learning Rate

Scenario	AI Impact on Carbon LR	Resulting LR	Mechanism
Optimistic	+8 pp	~30%	Materials breakthroughs + grid optimization + accelerated R&D
Moderate	+3 pp	~25%	Partial gains offset by energy demand
Neutral	+0 pp	~22%	Gains and losses cancel
Pessimistic	-2 pp	~20%	Data center demand + rebound + lock-in dominate

The key question is whether AI accelerates learning on the dimensions that matter for sustainability — carbon intensity, material efficiency, ecosystem restoration — or on dimensions that increase throughput. Technology is not inherently directional; it accelerates whatever society points it at. The direction of AI's impact on the global learning rate is therefore a policy variable, not a technological inevitability (Acemoglu et al., 2012; Aghion et al., 2016).

9. Discussion

9.1 Decomposition of the Global Learning Rate

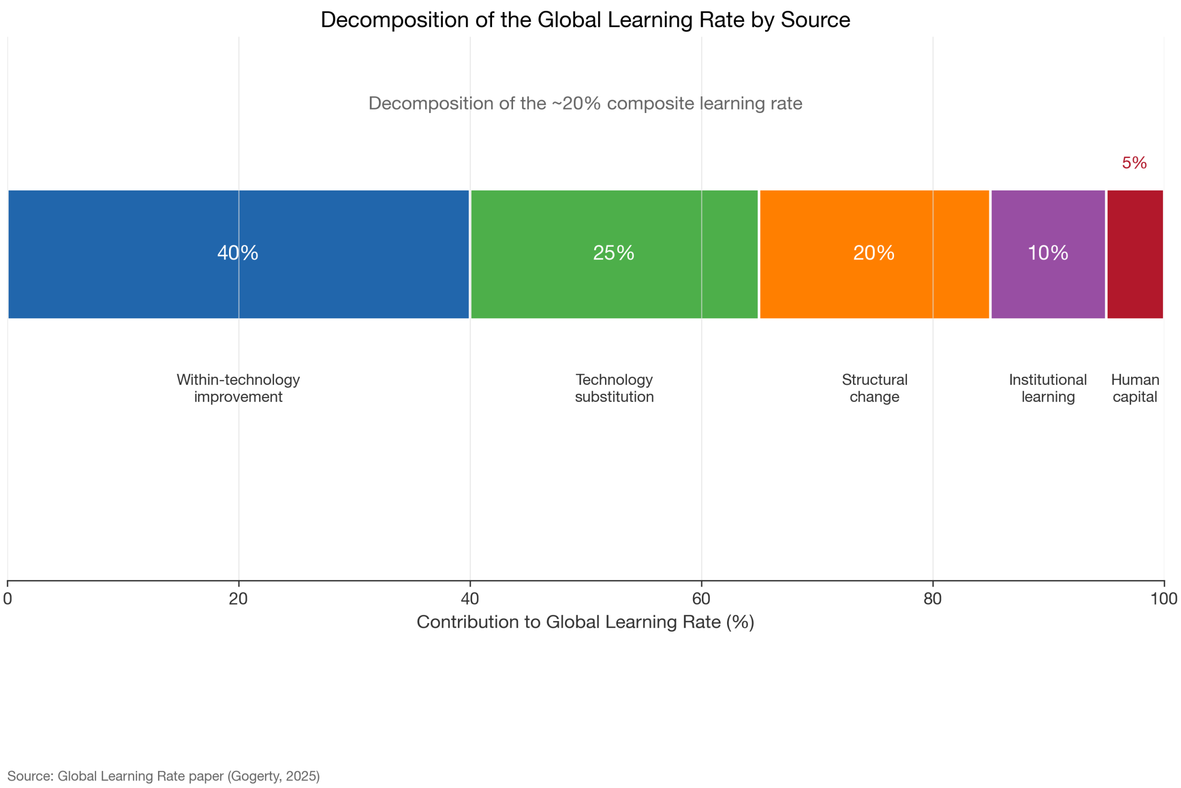

Figure 25: Figure 18

The global learning rate is the emergent result of multiple interacting processes: within-technology learning curves (approximately 40% of the total), technology substitution (approximately 25%), structural economic change from resource-intensive to service-oriented sectors (approximately 20%), institutional and organizational learning (approximately 10%), and human capital accumulation (approximately 5%). The human capital contribution may be underweighted in this decomposition, as it functions as a meta-driver: education generates innovation, which generates technology, which generates efficiency. Countries investing 3% or more of GDP in R&D (South Korea, Israel, Sweden) exhibit energy intensity improvement rates two to three times the global average (Dechezlepretre et al., 2017).

9.2 Biophysical Limits

The Planetary Boundaries framework (Rockstrom et al., 2009; Richardson et al., 2023) identifies constraints that no learning rate can transcend. As of 2023, six of nine boundaries are transgressed: climate change, biosphere integrity, biogeochemical flows, land-system change, novel entities, and freshwater use. The learning rate describes an economic process, but the boundaries are biophysical. No amount of economic optimization can restore an extinct species or reverse ice sheet collapse on human timescales.

9.3 Development and Equity

The learning rate framework exposes a profound equity dimension. India (per capita emissions 1.9 tonnes CO_2, approximately one-eighth of the U.S. level) and sub-Saharan Africa are being asked to achieve carbon learning rates of 30-40% — faster than any advanced economy achieved during its own industrialization. OECD countries built their prosperity on energy intensities of 8-12 EJ per trillion dollars of GDP during 1950-1980 and only began "learning" to reduce intensity after they were already wealthy. The required learning rate for Paris compliance essentially asks developing nations to skip the industrialization phase entirely and leapfrog directly to the optimization phase. This is empirically unprecedented. The only way to make it feasible is massive technology transfer and concessional finance, estimated at $1 trillion per year by 2030 (UNFCCC Standing Committee on Finance, 2023).

9.4 Policy Architecture

If the current 22.2% carbon learning rate must reach 35-52% within one to two decades, six policy levers have the highest marginal impact:

1. **Carbon pricing** (+3 to +8 pp): Internalizes the externality that separates the conventional from the inclusive learning rate. The EU Emissions Trading System, at EUR 80-100 per tonne in 2023, demonstrates the mechanism (Dechezlepretre et al., 2023).
2. **Green industrial policy** (+4 to +10 pp): Targeted subsidies for technologies on steep learning curves. The U.S. Inflation Reduction Act (approximately $370 billion in clean energy incentives) and China's state-directed solar manufacturing investments are the leading examples.
3. **R&D investment** (+2 to +5 pp, with lag): Creates new learning curves for technologies not yet at commercial scale. Current global clean energy R&D spending of approximately $40 billion per year is approximately one-third of the IEA's identified requirement (IEA, 2023).
4. **International technology transfer** (+2 to +4 pp globally; +5 to +12 pp in developing economies): Enables leapfrogging by allowing developing economies to begin on the steep portion of existing learning curves.
5. **Financial system reform** (+3 to +6 pp): Redirects capital flows from high-carbon lock-in toward high-learning-rate technologies through mandatory climate disclosure (TCFD/ISSB), green taxonomies, and multilateral development bank reform.
6. **Circular economy regulation** (+1 to +3 pp on carbon; +5 to +10 pp on materials): Directly addresses the material learning failure through extended producer responsibility, right-to-repair legislation, and recycling mandates.

Green industrial policy and carbon pricing together have the highest near-term impact because they accelerate deployment of technologies already on steep learning curves. Every additional doubling of solar deployment reduces costs by approximately 49%; every additional doubling of battery production reduces costs by approximately 24% (IRENA, 2023; Ziegler & Trancik, 2021). Policy that doubles the deployment rate doubles the speed at which costs fall.

9.5 Limitations

Several limitations warrant explicit acknowledgment.

First, the use of decade-interval observations produces a small sample size (n = 7 for the optimization phase), limiting statistical power and making inference sensitive to individual data points. The results should be interpreted as estimates of a macro-level regularity rather than precise coefficients.

Second, the mechanical correlation between cumulative GDP (experience variable) and resource intensity (which has current GDP in its denominator) is the most important econometric concern in this paper. We have addressed it through multiple strategies — IV estimation using cumulative population as instrument, permutation tests, alternative experience variables, and Moore's Law specifications (Section 3.3) — all of which support the qualitative finding of a robust negative relationship between experience and intensity. However, we acknowledge frankly that the endogeneity concern cannot be fully resolved with the available data. The IV analysis is underpowered at n = 7, the instrument (cumulative population) is not perfectly exogenous to long-run economic dynamics, and no natural experiment exists at the planetary scale. The learning rates reported in this paper should therefore be interpreted as descriptive regularities — well-estimated summary statistics of the historical relationship between cumulative economic output and resource intensity — rather than precise causal parameter estimates. The consistency of the learning rates across multiple specifications, their alignment with the individual-technology literature, and the confirmation from annual data with HAC standard errors all support the substantive finding, but the precise magnitudes carry identification uncertainty that exceeds the reported confidence intervals.

Third, the aggregation of diverse national economies into a single global learning rate conceals enormous heterogeneity. The learning rates of advanced economies (typically 25-30% for carbon) differ markedly from those of rapidly industrializing economies (10-15%), and the global rate is a weighted average that may not represent any individual country's trajectory.

Fourth, the externality cost estimates used to construct Inclusive GDP involve deep uncertainties, particularly for biodiversity loss and ecosystem service degradation. Our biodiversity estimates are likely conservative by an order of magnitude. The inclusive learning rate should be interpreted as a range (8.6-13.8%) rather than a point estimate.

Fifth, the learning rate framework implicitly assumes that historical regularities will persist. Structural breaks — geopolitical disruptions, resource constraints, tipping point cascades — could discontinuously alter the learning rate in ways that the framework cannot anticipate.

9.6 Inclusive Wealth Comparison

The gap between GDP growth and inclusive wealth growth provides an independent validation of our inclusive learning rate concept. Managi and Kumar (2018) report inclusive wealth per capita growth of approximately 1.0-1.2% per year from 1990 to 2014, versus GDP per capita growth of 2.0-2.1%. This 1.0-percentage-point gap, applied over the full period, implies that approximately one-third of apparent economic progress represents natural capital depletion — remarkably consistent with our estimate that 38% of the apparent global learning rate is phantom learning.

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10. Conclusion

This paper has estimated the Global Learning Rate — the rate at which the world economy reduces its resource intensity per doubling of cumulative economic experience. Three numbers summarize the findings:

Table 23. The Three Learning Rates

Rate	Value	Interpretation
~20%	Conventional global learning rate	How fast the economy appears to learn
~12.4%	Inclusive global learning rate	How fast it actually learns, with all costs counted
~52%	Required learning rate for 1.5C	How fast it must learn for Paris compliance

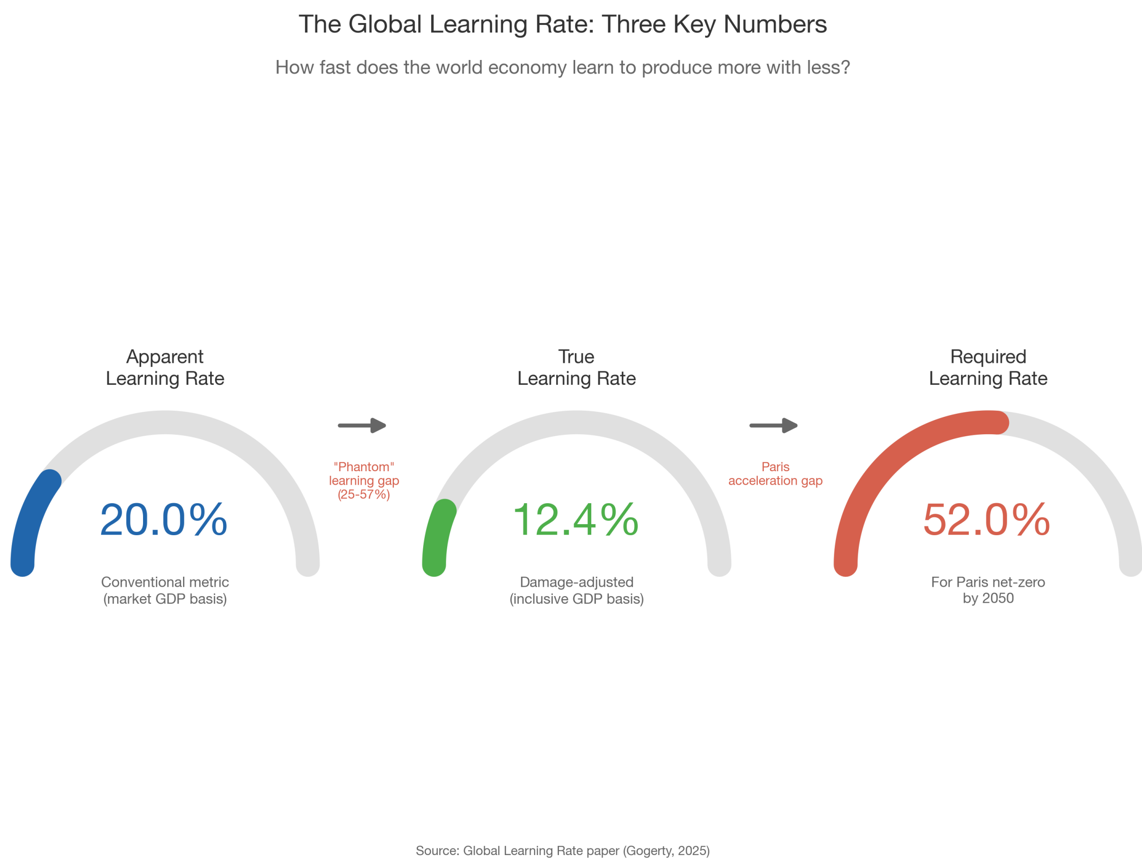

Figure 26: Figure 20

The first number — approximately 20% — is both remarkable and familiar. The global economy, treated as a composite meta-technology, exhibits a learning rate squarely within the range observed across individual technologies, from chemicals to computing. The mechanisms are the same: economies of scale, process optimization, knowledge spillovers, substitution, and institutional adaptation. Wright's Law, it appears, scales.

The second number — approximately 12.4% — is the honest accounting. When the costs the global economy imposes on the climate system, on ecosystems, on biodiversity, and on human health are internalized, the genuine learning rate is roughly two-thirds of the headline figure. The remaining third is phantom learning: efficiency gains achieved by shifting costs to the biosphere and to future generations. This finding connects the experience curve literature to the inclusive wealth literature (Dasgupta, 2021; Managi & Kumar, 2018) and provides a quantitative measure of ecological debt expressed in the familiar units of learning rate points.

The third number — approximately 52% — is the requirement. The 1.5 degrees Celsius carbon budget permits no more than approximately 250 Gt of additional CO2 emissions. At current emission rates, this budget is exhausted within seven years. Maintaining economic growth while reducing emissions to approximately 10 Gt per year by 2050 requires a carbon learning rate more than double the current rate. Such rates have been achieved by individual technologies — solar photovoltaics at 49%, GPUs at 88% — but never by the entire global economy simultaneously. The 2 degrees Celsius target requires approximately 35%, which has historical precedent in national energy transitions and is achievable with aggressive policy implementation.

The gap between 12.4% and 52% — the 40-percentage-point chasm between how fast the global economy actually learns and how fast it must learn — is the quantitative expression of the climate challenge. It is not primarily a technology gap; the technologies for a 35% or even 52% learning rate largely exist. It is a deployment gap, a coordination gap, and a political will gap. The experience curve framework clarifies what must happen: the world must compress several decades of deployment-phase learning into one to two decades, across all emitting sectors simultaneously, while ensuring that developing nations can participate in the transition rather than being left behind.

The policy implications follow directly. Carbon pricing closes the gap between conventional and inclusive learning rates, forcing the market to learn on the right dimensions. Green industrial policy accelerates deployment of technologies already on steep learning curves. R&D investment creates new learning curves for hard-to-abate sectors. Technology transfer enables leapfrogging. Circular economy regulation addresses the material learning failure. Financial system reform redirects capital toward high-learning-rate investments.

Several avenues for future research emerge from this analysis. First, the estimation of country-level and sector-level learning rates would provide a more granular basis for policy design. Second, the development of inclusive learning rate indices using comprehensive natural capital accounts would improve on our necessarily approximate damage cost estimates. Third, the integration of tipping point dynamics into the learning rate framework — recognizing that the relationship between cumulative experience and outcomes is not smooth but potentially discontinuous — would strengthen the analytical connection between economic learning and Earth system constraints. Fourth, the application of the framework to historical energy transitions (wood to coal, horse to automobile) would provide a deeper empirical basis for assessing the feasibility of the required learning rates. Fifth, the interaction between AI and the global learning rate deserves dedicated empirical study as data on AI's resource and productivity effects accumulate.

Wright's Law tells us that learning is a function of doing. The world learns by producing. The question is not whether the global economy can learn fast enough — the evidence from individual technologies suggests it can. The question is whether societies will choose to count honestly, invest wisely, deploy rapidly, and produce the right things. The learning curve is a tool. The clock is a constraint. And the clock is running.

Data Availability

All data, code, and materials required to reproduce the analyses in this paper are publicly available. The replication archive, including the consolidated dataset, Python regression scripts (OLS, Newey-West HAC, IV/2SLS, permutation tests, inclusive learning rate sensitivity analysis), and figure generation code, is hosted at: github.com/ngogerty/global-learning-rate. Primary data sources include the Maddison Project Database, World Bank World Development Indicators, Energy Institute Statistical Review of World Energy, Global Carbon Project, and UNEP International Resource Panel. All source data are publicly accessible and documented in Appendix B.

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Appendix A: Calculation Methodology

A.1 Wright's Law Regression

For each resource intensity dimension, we estimate:

log_10(I_t) = alpha + beta * log_10(X_t) + epsilon_t

via OLS on decade-interval observations (1970, 1980, 1990, 2000, 2010, 2020, 2023), where I_t is resource intensity at time t and X_t is cumulative GDP from a pre-industrial baseline to time t.

The learning rate is computed as: LR = 1 - 2^(beta), where negative beta (declining intensity) yields a positive learning rate.

A.2 Energy Learning Rate Detailed Computation

Regression equation: log_10(Energy Intensity) = 1.822 + (-0.292) * log_10(Cumulative GDP)

Standard error of slope (OLS): 0.031; t-statistic: -9.4; p < 0.001; R-squared: 0.964; Adjusted R-squared: 0.957. Standard error of slope (Newey-West HAC): 0.048; p < 0.01.

95% confidence interval for beta (OLS): [-0.372, -0.212]. 95% confidence interval for learning rate (OLS): [13.7%, 22.8%]. 95% confidence interval for learning rate (HAC): [10.2%, 25.9%].

A.3 Cumulative GDP Computation

Cumulative GDP is computed via trapezoidal integration of decade-interval GDP values, with pre-1900 estimates based on Maddison Project Database extrapolation. The pre-industrial baseline (cumulative GDP prior to 1900) is estimated at approximately $200 trillion-years.

A.4 Sensitivity to Social Cost of Carbon

Table A1. Inclusive Learning Rate Sensitivity

Social Cost of Carbon ($ per tonne CO2)	Source	Inclusive Learning Rate
50	Nordhaus (2017)	13.8%
100	Central estimate	12.4%
185	Rennert et al. (2022)	10.1%
250	High damage scenario	8.6%

Even the most conservative SCC assumption ($50 per tonne) produces an inclusive learning rate (13.8%) substantially below the conventional rate (18.3%).

Appendix B: Data Sources and Availability

All data used in this analysis are from publicly available sources:

- **GDP:** Maddison Project Database (www.rug.nl/ggdc/historicaldevelopment/maddison); World Bank World Development Indicators
- **Energy:** Energy Institute Statistical Review of World Energy 2024 (www.energyinst.org/statistical-review); Smil (2017) for pre-1965

- **CO2 Emissions:** Global Carbon Project (www.globalcarbonproject.org); CDIAC for pre-1960
- **Materials:** UNEP International Resource Panel Global Material Flows Database (www.resourcepanel.org); Krausmann et al. (2018)
- **Biodiversity:** Living Planet Index (www.livingplanetindex.org)
- **Inclusive Wealth:** UNEP Inclusive Wealth Reports (Managi & Kumar, 2018)
- **Human Capital:** Barro-Lee Dataset (www.barrolee.com); World Bank Human Capital Index

Replication archive. All data, regression scripts (Python), and figure generation code are available at: github.com/ngogerty/global-learning-rate. The archive includes: (1) a single source-of-truth CSV containing all data from Tables 1-5 and externality cost estimates; (2) a Python script reproducing every regression in this paper, including OLS, Newey-West HAC, IV (2SLS with cumulative population), permutation tests, and inclusive learning rate sensitivity analysis; (3) figure generation code. Requirements: Python 3.9+, numpy, scipy, statsmodels, pandas.

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