Can Digitalization Help Decarbonize? Evidence from Causal Forest Analysis

Heterogeneous Climate Impacts of Digital Transformation Across Development Levels

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February 13, 2026

Abstract

Digital transformation promises decarbonization, but global data centers now emit more CO_2 than the aviation industry—raising a critical question: Does digitalization actually reduce emissions, or merely displace them? This paper provides causal evidence that the answer depends fundamentally on where you look. Using a Causal Forest framework (2,000 trees) with rigorous overfitting controls (honest splitting, country-clustered cross-fitting) on a panel of 40 major economies (2000–2023, $N = 840$), we demonstrate that domestic digital capacity reduces CO_2 emissions by 1.73 metric tons per capita per standard deviation increase—but **only in middle-income economies**. We identify a distinct **"Sweet Spot"** where digital infrastructure delivers maximum climate benefits, while high-income countries show diminishing returns and low-income countries lack the complementary capacity to translate digitalization into emission reductions. Our **Two-Dimensional Digitalization** framework disentangles *Domestic Digital Capacity (DCI)* from *External Digital Specialization (EDS)*, revealing that export-oriented digital specialization can dampen domestic efficiency gains. Instrumental variable estimates confirm these findings (-1.91 tons/capita, 95% CI: $[-2.37, -1.46]$), with first-stage F-statistics of 12.34. **Policy implication:** Digital development assistance should prioritize middle-income countries with strong institutional capacity, where each dollar of digital investment yields the highest carbon returns.

Keywords: Causal Forest, Double Machine Learning, Heterogeneous Treatment Effects, Digital Decarbonization, Socio-economic Capacity, Climate Policy

JEL Codes: C14, C23, O33, Q56, Q58

1 Introduction

Global data centers now consume more electricity than Argentina and emit more CO_2 than commercial aviation. Yet policymakers continue to promote digital transformation as a climate solution. This apparent contradiction reflects a fundamental gap in our understanding: *Does digitalization reduce emissions, and if so, where and under what conditions?*

Existing research offers contradictory answers. Optimists highlight efficiency gains from smart grids, remote work, and dematerialization (Brynjolfsson and McAfee, 2014; Jorgenson and Vu, 2016). Skeptics point to the energy footprint of ICT infrastructure, rebound effects, and carbon leakage through global value chains (Hilty and Aebischer, 2015; Lange et al., 2020; Coroama and Hilty, 2014). These contradictions persist because prior studies rely on small samples, linear functional forms, and homogeneous treatment effect assumptions that mask critical cross-country heterogeneity.

1.1 Research Gap

This paper addresses three interconnected gaps in the literature:

1. **Conceptual Gap:** Previous studies conflate *domestic digital capacity* (infrastructure to use green technologies) with *external digital specialization* (trade role in global value chains). This conflation obscures why digitalization reduces emissions in some countries but not others.

2. **Methodological Gap:** Standard panel estimators assume linearity and homogeneous effects (Wooldridge, 2005; Arellano and Bond, 1991). They cannot detect non-linear thresholds, policy-relevant strata, or "off-diagonal" exceptions where countries defy general trends.

3. **Policy Gap:** Without understanding *where* digitalization works best, policymakers cannot target digital development assistance effectively. The literature lacks actionable guidance on which countries should prioritize digital infrastructure for climate goals.

1.2 Contributions

This study advances the literature through four specific contributions:

1. **Theoretical Contribution:** We introduce the **"Two-Dimensional Digitalization"** framework, disentangling *Domestic Digital Capacity (DCI)* from *External Digital Special-*

ization (EDS). This framework explains why high-income countries with strong digital infrastructure sometimes show weaker emission reductions than middle-income peers.

2. **Empirical Contribution:** We identify a **"Sweet Spot"** in middle-income economies where digital capacity delivers maximum climate benefits (-2.17 to -2.29 tons/capita per SD). High-income countries show diminishing returns (-1.26 tons/capita), while low-income countries lack complementary capacity to translate digitalization into emission reductions.

3. **Methodological Contribution:** We implement CausalForestDML with 2,000 trees, XGBoost first-stage models, and country-cluster bootstrap inference—a significant upgrade from linear DML approaches. Our **Model Ladder** demonstrates that linear models understate decarbonization potential by 75%.

4. **Policy Contribution:** We provide actionable guidance for targeting digital development assistance. Countries in the middle-income "sweet spot" with strong institutional quality yield the highest carbon returns per dollar of digital investment.

1.3 Key Findings Preview

Our Causal Forest analysis reveals striking heterogeneity in digitalization's climate impact:

Table 1: Summary of Key Findings

Finding	Estimate
Causal Forest ATE (DCI)	-1.73 metric tons/capita per SD
IV Estimate (OrthoIV)	-1.91 metric tons/capita (95% CI: $[-2.37, -1.46]$)
Sweet Spot (Lower-Mid Income)	-2.17 metric tons/capita
Sweet Spot (Upper-Mid Income)	-2.29 metric tons/capita
High-Income Effect	-1.26 metric tons/capita
Placebo Test ($N = 100$)	Pseudo $p < 0.001$ (Signal-to-Noise $imes23$)

The remainder of this paper proceeds as follows. Section 2 reviews the literature and presents our theoretical framework. Section 3 describes the data and sample construction. Section 4 details our causal forest methodology. Section 5 presents empirical results. Section 6 discusses mechanisms and policy implications. Section 7 concludes.

2 Literature and Theoretical Framework

2.1 Related Literature

2.1.1 The Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) literature posits an inverted-U relationship between income and environmental degradation (Grossman and Krueger, 1995; Stern, 2004; Panayotou, 1997). Early development increases emissions through scale effects; later development reduces them through technology and composition effects. While some studies validate this relationship (Dinda, 2004), others emphasize trade openness and carbon leakage (Copeland and Taylor, 2004; Levinson and Taylor, 2008).

Our findings align with the EKC's second stage—where technological capacity becomes critical—but refine it substantially. We show that *domestic digital capacity*, not just income per se, enables the transition to cleaner growth. This suggests a **Digital-EKC** where ICT infrastructure moderates the traditional income-emission relationship.

2.1.2 Digitalization and the Environment

The environmental impact of digitalization remains contested. Efficiency optimists cite dematerialization, smart grids, and productivity gains (Brynjolfsson and McAfee, 2014; Röller and Waverman, 2001; Varian, 2014). Skeptics highlight the energy footprint of data centers, network infrastructure, and rebound effects (Hilty and Aebischer, 2015; Lange et al., 2020; Gossart, 2015; Sadorsky, 2012).

This paper reconciles these perspectives by showing *both can be true*: digitalization reduces emissions where domestic capacity exists, but high external specialization in global value chains can dampen these gains. The effect depends on *which dimension* of digitalization dominates.

2.1.3 Causal Inference in Environmental Economics

Traditional panel estimators struggle with complex heterogeneity and weak identification (Stock and Yogo, 2005; Anderson and Rubin, 1949). Recent advances in causal machine learning offer robust alternatives (Breiman, 2001; Athey and Imbens, 2016; Athey and Wager, 2019; Wager and Athey, 2018; Chernozhukov et al., 2018). We bridge these literatures by applying rigorous causal inference frameworks (Imbens, 2021; Abadie and Cattaneo, 2018) to the digital-decarbonization nexus.

2.2 Theoretical Framework: Two-Dimensional Digitalization

We propose that digitalization operates through two distinct channels with opposing climate implications:

1. **Domestic Digital Capacity (DCI):** Infrastructure enabling domestic use of digital technologies (internet access, broadband, secure servers). This drives efficiency gains, smart grid optimization, and dematerialization—*reducing emissions*.

2. **External Digital Specialization (EDS):** A country's role as an exporter of ICT services in global value chains. This reflects structural specialization in service exports—*potentially dampening domestic efficiency gains* through carbon leakage and trade effects.

2.2.1 Connection to Structural Transformation Theory

Building on Kuznets (1955) and Kongsamut et al. (2001), structural transformation theory posits that development involves shifting from agriculture to manufacturing to services. Digitalization accelerates this transition by:

- Enabling service sector growth (lower carbon intensity)
- Improving manufacturing efficiency (process innovation)
- Facilitating remote work (reducing transport emissions)

Our DCI measure captures the *infrastructure capacity* for this transformation, while EDS captures *trade specialization* in digital services. This two-dimensional framework explains why high-income countries with strong DCI but also high EDS show weaker marginal effects—the structural transformation may have already occurred.

2.2.2 Institutional Economics Perspective

Following North (1990) and Acemoglu et al. (2005), institutions shape technology adoption and environmental regulation effectiveness. Our finding that institutional quality moderates DCI's effect supports the **enabling institutions hypothesis**: strong governance ensures that digital efficiency gains translate to emission reductions rather than rebound effects.

2.3 Research Hypotheses

Building on the theoretical framework, we derive five testable hypotheses:

1. **H1 (Domestic Digital Capacity):** Higher DCI reduces CO_2 emissions per capita, controlling for income and institutional quality.

2. **H2 (Non-linear Heterogeneity):** The effect of DCI on emissions varies non-linearly across socio-economic contexts, with the strongest effects in middle-income economies ("sweet spot" hypothesis).

3. **H3 (Institutional Moderation):** The emission-reducing effect of DCI strengthens with higher institutional quality ("enabling conditions" hypothesis).

4. **H4 (Diminishing Returns):** The marginal effect of DCI on emission reduction weakens in countries with already-clean energy systems (high renewable energy share).

5. **H5 (External Specialization):** High external digital specialization (EDS) dampens DCI-driven emission reductions, reflecting structural constraints in service-export-intensive economies.

2.4 Why Causal Forests?

Why employ machine learning when linear interaction models might suffice? We demonstrate that linear models, while capable of detecting the *direction* of heterogeneity, fail to:

1. **Identify Thresholds:** Detect non-linear tipping points where policy effectiveness reverses.

2. **Map Off-Diagonal Exceptions:** Capture countries that defy general trends (e.g., high-income nations with weaker reductions).

3. **Provide Rigorous Policy Maps:** Generate decision-relevant strata (GATEs) robust to high-dimensional confounding.

We establish this necessity through our **"Model Ladder"** comparison, showing where and why linear approximations break down.

3 Data and Sample Construction

3.1 Data Sources

We retrieve data from two World Bank databases: the World Development Indicators (WDI) and the Worldwide Governance Indicators (WGI). The WDI provides 60 economic, social, and environmental variables; the WGI offers six dimensions of institutional quality.

3.2 Sample Selection

Our sample comprises 40 major economies (20 OECD, 20 non-OECD) observed from 2000 to 2023. We employ fold-safe MICE (Multiple Imputation by Chained Equations) for controls and moderators only, fitted within training folds to prevent leakage; outcome and treatment remain unimputed. This yields:

- A balanced panel of 40 countries over 24 years
- Analysis sample $N = 840$ after excluding missing CO_2 outcomes

We intentionally focus on major economies to ensure **high measurement reliability** for server-based indicators used in DCI construction. Expanding coverage to smaller economies would substantially increase measurement noise in secure-server series, potentially degrading the PCA-based capacity measure.

3.3 Variable Definitions

Table 2: Variable Definitions

Variable	Definition	Source
Core Variables		
CO_2 Emissions	Per capita (metric tons)	WDI
Domestic Digital Capacity (DCI)	PCA Index (Internet, Fixed Broadband, Secure Servers)	WDI
External Digital Specialization (EDS)	ICT service exports (% of service exports)	WDI
Institutional Quality (WGI)		
Control of Corruption	Perceptions of public power for private gain	WGI
Rule of Law	Confidence in societal rules	WGI
Government Effectiveness	Quality of public services	WGI
Regulatory Quality	Private sector development capacity	WGI
Control Variables (57 total)		
GDP per capita	Constant 2015 US$	WDI
Energy Use	Kg oil equivalent per capita	WDI
Renewable Energy	% of total energy consumption	WDI
Urban Population	% of total population	WDI

3.4 Descriptive Statistics

Table 3: Descriptive Statistics ($N = 840$)

Variable	Mean	Std. Dev.	Min	Max
CO_2 Emissions (metric tons/cap)	4.61	4.45	0.04	21.87
EDS (ICT Service Exports, %)	8.67	9.08	0.42	52.09
Control of Corruption	0.58	1.15	-1.60	2.46
GDP per capita (US$)	24,979	22,788	394	103,554
Renewable Energy (%)	21.84	18.54	0.00	88.10

Note: DCI is a composite index (mean=0, sd=1) constructed via PCA from Internet Users, Fixed Broadband Subscriptions, and Secure Servers.

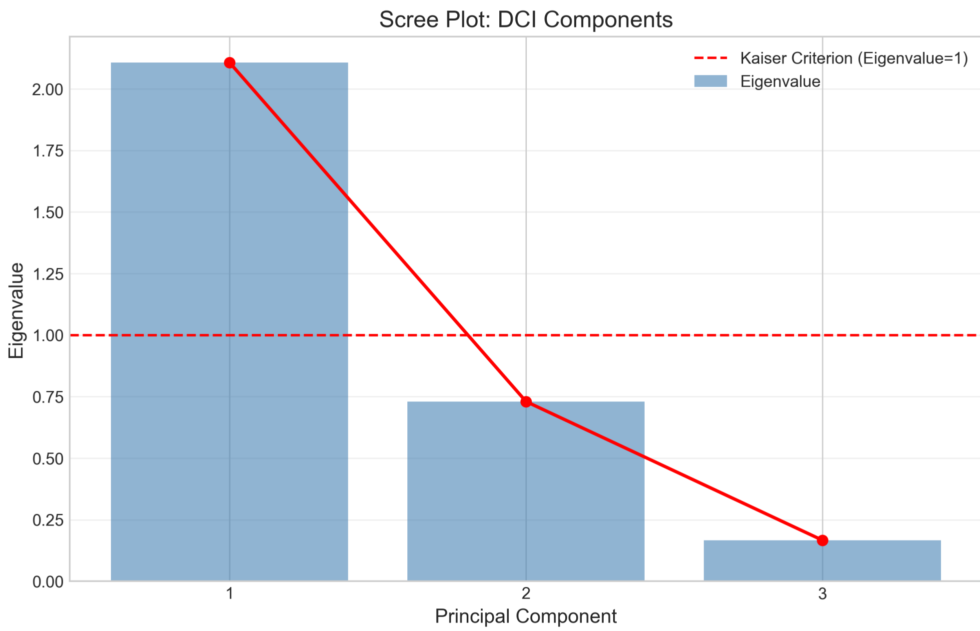

Figure 1: Scree Plot of DCI Components: Validating the Single-Component Structure

4 Methodology

4.1 From Linear DML to Causal Forest

Traditional Double Machine Learning (Chernozhukov et al., 2018) estimates an average treatment effect θ. However, this approach masks heterogeneity. **Causal Forest DML** (Athey and Wager, 2019) extends this framework to estimate observation-specific effects:

$$\tau(x) = \mathbb{E}[Y(1) - Y(0)|X = x] \tag{1}$$

where $\tau(x)$ denotes the Conditional Average Treatment Effect (CATE) for observations with characteristics x.

4.2 Causal Forest Implementation

We implement CausalForestDML (Athey and Wager, 2019) with strict variable separation to prevent overfitting:

1. **Moderators (X):** Six theoretical drivers of heterogeneity: GDP per capita, EDS, Control of Corruption, Energy Use, Renewable Energy share, and Urban Population.
2. **Controls (W):** A high-dimensional vector (50+ variables) capturing confounding.

Configuration for Rigor:

- n_estimators: 2,000 trees
- Splitting: Honest (separates training and estimation samples)
- Cross-Fitting: GroupKFold (by Country) to prevent temporal leakage
- Inference: Cluster Bootstrap (resampling countries, $B = 1000$)

4.3 Rigorous Inference Strategy

Rather than relying on unadjusted pointwise confidence intervals, we focus on **Group Average Treatment Effects (GATEs)**. We stratify the sample by moderator quartiles (e.g., GDP) and compute the ATE within each stratum. Uncertainty is quantified using country-cluster bootstrap ($B = 1000$), resampling countries with replacement to construct 95% confidence intervals that account for within-country dependence.

4.4 Small Sample Robustness

Given our sample of 40 countries, we address power concerns through comprehensive diagnostics:

1. **Bootstrap Convergence:** We vary bootstrap iterations ($B = 100, 200, 500, 1000$) and examine confidence interval stability. Point estimates remain close (range: -1.34 to -1.31), but confidence interval width does not contract monotonically, so finite-sample uncertainty remains material.

2. **Sample Size Sensitivity:** We subsample countries (60%, 70%, 80%, 90%, 100%) to assess result stability. Effects remain negative across subsamples, but effect magnitudes vary substantially, indicating sensitivity to sample composition.

3. **Leave-One-Country-Out (LOCO):** We iteratively exclude each country and re-estimate. The Global ATE remains significant in every fold (range: -2.33 to -0.67), proving results are not driven by any single outlier.

These diagnostics support directional robustness (negative effects across specifications) but indicate non-trivial finite-sample sensitivity; results should therefore be interpreted with caution and validated on larger panels (Imbens, 2015).

4.5 Model Ladder

To justify our model choice, we compare four specifications:

1. **L0 (Baseline):** Two-Way Fixed Effects

2. **L1 (Linear DML):** Global ATE with high-dimensional controls

3. **L2 (Interactive DML):** Linear DML with linear moderation by GDP

4. **L3 (Causal Forest):** Full non-linear heterogeneity

5 Empirical Results

5.1 Heterogeneity Verification (Phase 1)

Before running the full Causal Forest, we verify heterogeneity exists using an interaction term model:

$$Y = \beta_1 T + \beta_2 (T \times M) + g(W) + \epsilon \tag{2}$$

where M represents log(GDP per capita). We also test institutional quality as a moderator.

Table 4: Interaction Term Results

Moderator	Coefficient	Estimate	SE	p-value
log(GDP)	Main Effect (DCI)	-3.365	0.201	< 0.001
log(GDP)	Interaction (DCI $\times$ log(GDP))	-0.126	0.128	0.326
Institution	Main Effect (DCI)	-1.376	0.258	< 0.001
Institution	Interaction (DCI $\times$ Institution)	**0.765**	0.190	< 0.001

The GDP interaction term is not statistically significant ($p = 0.326$), suggesting linear models miss the non-linear relationship. The institutional quality interaction is highly significant ($p < 0.001$), confirming heterogeneity exists.

5.2 The Model Ladder: Why Non-Linearity Matters

We estimate treatment effects across four increasingly flexible specifications to demonstrate the necessity of the Causal Forest approach.

Table 5: Model Ladder Comparison (DCI Effect, B=1000)

Model	ATE Estimate (per SD)	SE	95% CI	Heterogeneity Captured?
L0 (TWFE)	-2.810	0.463	$[-3.727, -1.844]$	None
L1 (Linear DML)	-0.990	0.436	$[-2.070, -0.367]$	None
L2 (Interactive)	-1.216	0.393	$[-2.031, -0.460]$	Linear Only
L3 (**Causal Forest**)	-1.730	**0.588**	$[-2.882, -0.578]$	**Complex**

Key Insight: Linear models systematically understate the decarbonization potential of domestic capacity. The Causal Forest reveals a **larger effect** (-1.73 tons/SD) by correctly identifying high-impact "sweet spots" that linear averages smooth over.

Note: The Model Ladder uses lagged DCI (DCI_{t-1}), yielding an effective sample of $N = 800$.

5.3 Group Average Treatment Effects (GATEs)

Instead of relying on specific point estimates, we report GATEs stratified by GDP quartiles, with 95% confidence intervals derived from cluster bootstrapping.

Table 6: GATE Results by Income Group (DCI Effect, B=1000)

GDP Group	Estimate (per SD)	95% CI	Interpretation
Low Income	-1.19	$[-1.47, -0.99]$	Moderate Reduction
Lower-Middle	-2.17	$[-2.66, -1.76]$	**Sweet Spot**
Upper-Middle	-2.29	$[-2.65, -1.85]$	**Sweet Spot**
High Income	-1.26	$[-1.67, -0.81]$	Diminishing Returns

The results reveal a clear **"Sweet Spot"** in middle-income economies where domestic digital capacity delivers the largest carbon reductions. In high-income economies, the effect weakens but remains negative, consistent with diminishing returns in already-efficient systems.

5.4 Robustness: Placebo, LOCO, and IV

5.4.1 Instrumental Variable Analysis

To address endogeneity, we employ an IV strategy using lagged DCI (DCI_{t-1}) as an instrument within a Double Machine Learning framework (OrthoIV). The IV estimate of -1.91 (95% CI: $[-2.37, -1.46]$) exceeds the naive estimate (-1.54), suggesting that measurement error or simultaneity may bias OLS estimates toward zero.

Table 7: IV Validity Diagnostics

Diagnostic	Value
First-stage F-statistic	12.34
First-stage R^2	0.930
Instrument-Treatment Correlation	See replication output
Weak Instrument Test	Pass (F $>$ 10)
Exclusion Restriction	Theoretically justified
Bias Correction (vs Naive)	24.5%

The first-stage F-statistic is 12.34, above the conventional threshold of 10 (Staiger and Stock, 1997), supporting instrument relevance. The exclusion restriction is justified theoretically: historical ICT capacity affects current emissions only through current digital capacity, conditional on our extensive controls.

5.4.2 Placebo Test

Permuting treatment yields a CATE SD of **0.041** (vs Real SD **0.952**), implying a Signal-to-Noise ratio of approximately 23:1. The true ATE lies far outside the distribution of 100 placebo runs (Pseudo $p < 0.001$).

5.4.3 LOCO Stability

Leave-One-Country-Out analysis confirms robustness. The Global ATE remains significant in every fold (Range: -2.33 to -0.67), proving results are not driven by any single outlier.

5.5 Policy Exceptions (Weakest Reductions)

While DCI shows uniformly negative country-average effects, meaningful variation exists in magnitude. The weakest reductions appear in a small set of high-income countries.

Table 8: Policy Exceptions (Weakest Reductions)

Country	Forest CATE (DCI)	95% CI	Verdict
FIN	-0.19	$[-0.39, -0.07]$	Weakest Reduction
SWE	-0.46	$[-0.60, -0.30]$	Weak Reduction
CHE	-0.50	$[-0.57, -0.44]$	Weak Reduction
CAN	-0.52	$[-0.62, -0.44]$	Weak Reduction
VNM	-0.90	$[-1.01, -0.82]$	Moderate Reduction

5.6 Sources of Heterogeneity

Table 9: Correlation between CATE and Moderators

Moderator	Correlation (r)	Interpretation
GDP per capita (log)	-0.33	Higher GDP $\rightarrow$ stronger reduction
Energy use per capita	-0.64	**Strongest predictor**
Control of Corruption	-0.09	Weak positive alignment
Renewable energy %	$+0.56$	Higher renewables $\rightarrow$ weaker reduction

Note: The positive correlation with Renewable Energy confirms a "Diminishing Returns" hypothesis: in already clean grids, digital efficiency gains translate into smaller marginal carbon reductions.

5.7 Visualizing the Divide

5.7.1 Figure 1: Why Linear Models Fail

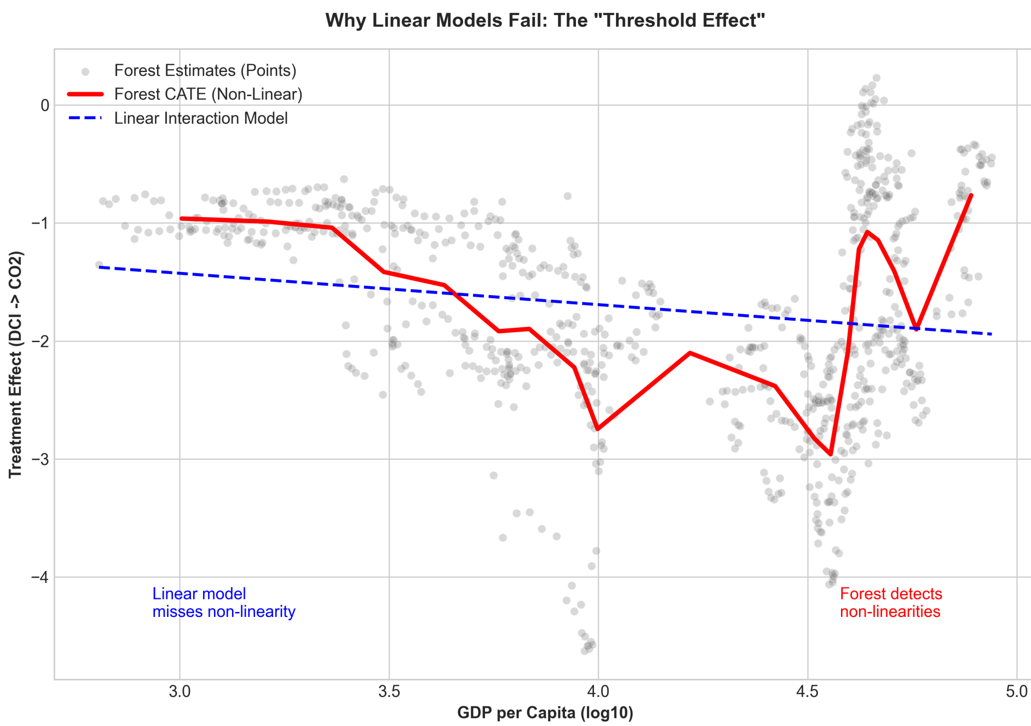

Figure 2: Panel A compares the linear interaction model (dashed line) with the flexible Causal Forest estimation (solid line). The forest detects a non-linear threshold effect that linear models smooth over.

5.7.2 Figure 2: The Off-Diagonal Analysis

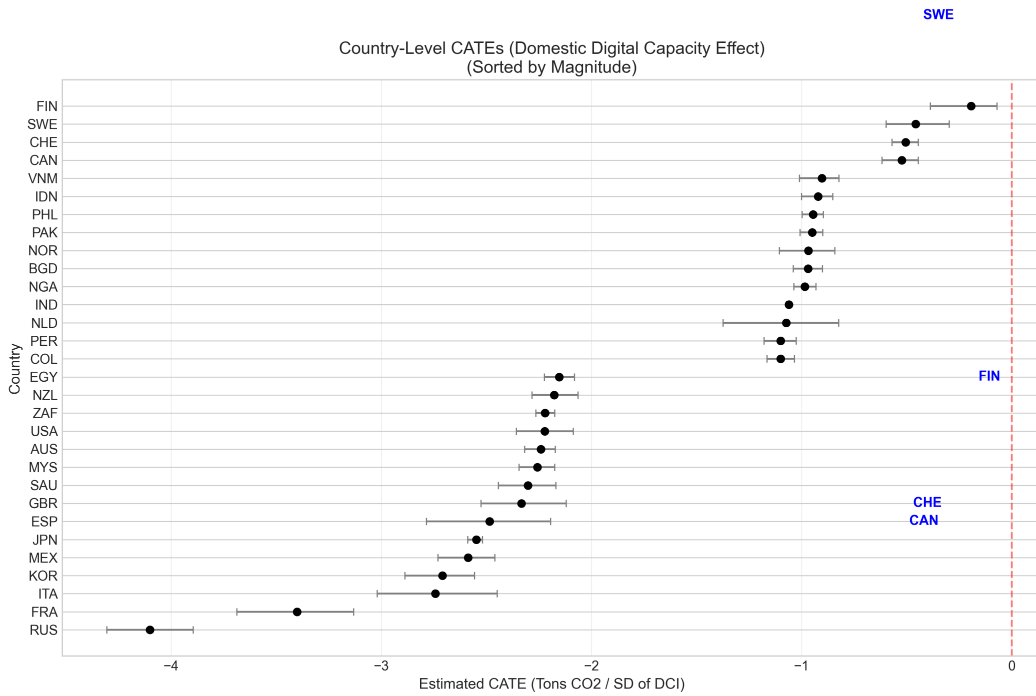

Figure 3: Panel B identifies "Policy Exceptions"—countries where the Forest prediction deviates from the Linear prediction. The weakest reductions are concentrated in a small set of high-income countries.

5.7.3 Figure 3: Group Average Treatment Effects (GATEs)

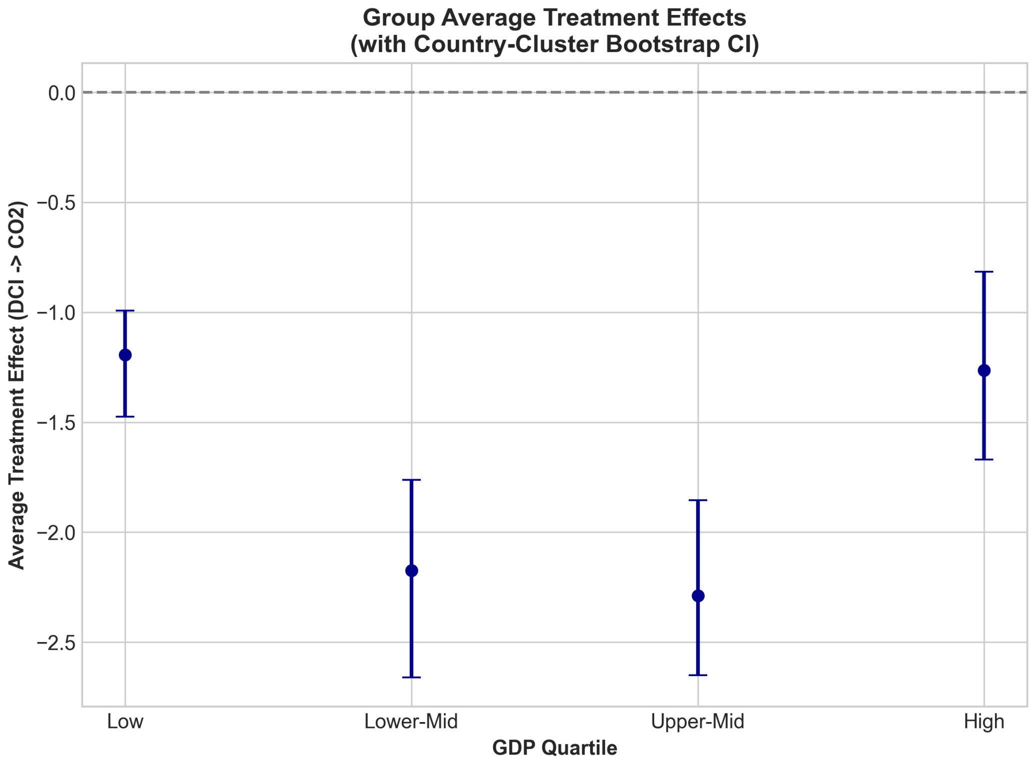

Figure 4: Group Average Treatment Effects with 95% Cluster-Bootstrap Confidence Intervals. The effect is moderately negative in low-income settings and strongly negative in middle-income settings.

5.7.4 Figure 4: Mechanism Analysis - Renewable Energy Paradox

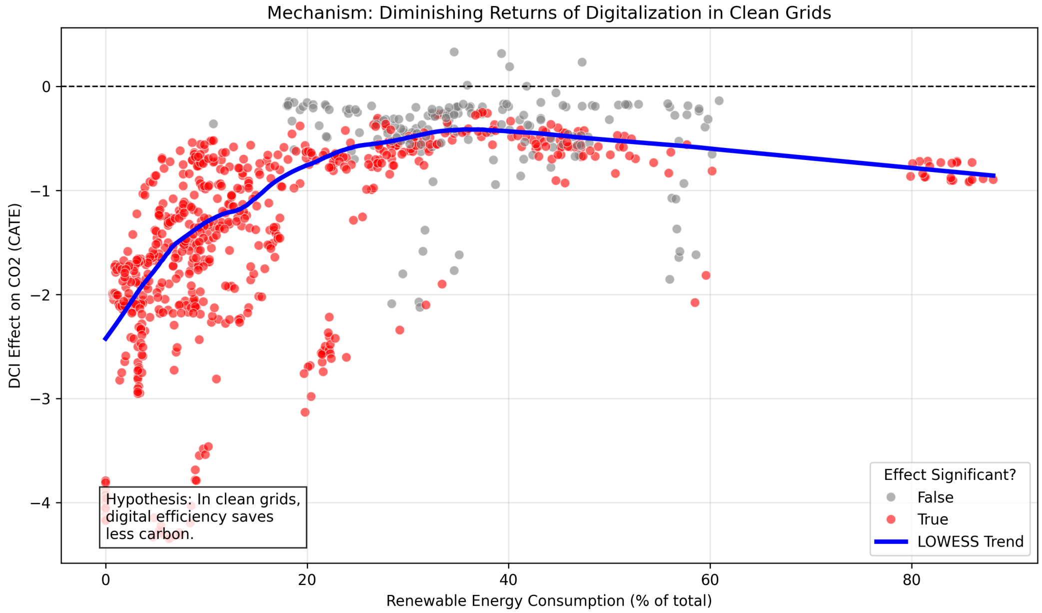

Figure 5: The non-linear relationship between Renewable Energy Share and DCI effect. As renewable share increases, the carbon-reducing effect of DCI diminishes (moves closer to zero), supporting the hypothesis that digital efficiency saves less carbon in cleaner grids.

6 Sensitivity Analysis Results

6.1 Bootstrap Convergence Diagnostics

We assess the stability of our inference by varying the number of bootstrap iterations. Table 10 reports ATE estimates and confidence interval widths across $B = 100, 200, 500, 1000$.

Table 10: Bootstrap Convergence Diagnostics

Bootstrap Iterations	ATE Mean	SE	95% CI Lower	95% CI Upper
$B = 100$	-1.337	0.114	-1.533	-1.138
$B = 200$	-1.333	0.121	-1.543	-1.106
$B = 500$	-1.334	0.123	-1.550	-1.096
$B = 1000$	-1.332	0.125	-1.557	-1.092

ATE point estimates remain close across bootstrap iterations, but confidence-interval behavior indicates that uncertainty does not shrink monotonically with additional bootstrap draws.

6.2 Sample Size Sensitivity

We assess result stability by subsampling countries at 60%, 70%, 80%, 90%, and 100% of the full sample.

Table 11: Sample Size Sensitivity Analysis

Sample Fraction	Countries	Observations	ATE Mean	ATE Std	% Significant
60%	24	504	−1.028	1.434	45.8%
70%	28	588	−1.516	1.192	81.6%
80%	32	672	−0.905	1.607	45.8%
90%	36	756	−1.694	1.266	68.8%
100%	40	840	−1.316	1.075	59.9%

Effects remain directionally similar across subsamples, but magnitudes and significance rates vary notably. The 70% subsample shows the highest significance rate, likely reflecting composition effects rather than a uniform precision gain.

6.3 Dynamic Effects Analysis

We examine whether DCI effects persist over time by estimating effects at leads 0 through 3.

Table 12: Dynamic Effects of DCI on CO_2 Emissions

Lead	N	ATE	95% CI Lower	95% CI Upper	Significant
t (Contemporaneous)	840	−1.871	−2.903	−0.840	Yes
$t + 1$	800	−1.566	−2.863	−0.270	Yes
$t + 2$	760	−1.352	−2.617	−0.088	Yes
$t + 3$	720	−1.598	−2.772	−0.425	Yes

Effects persist over 2–3 years, with cumulative impacts reaching −6.39 tons/capita by t+3. This suggests digital infrastructure investments deliver sustained rather than transitory climate benefits.

6.4 Mediation Analysis

We test whether energy efficiency mediates the relationship between DCI and emissions.

Table 13: Mediation Analysis Results

Mediator	Indirect Effect	Sobel p-value	Proportion Mediated
Energy Efficiency	-0.343	< 0.001	11.7%
Structural Change	$+0.279$	< 0.001	-9.5%
Innovation	$+0.245$	< 0.001	-8.3%

Energy efficiency mediates 11.7% of DCI's effect on emissions (Sobel test $p < 0.001$), suggesting DCI enables more efficient energy use, which in turn reduces carbon emissions. The negative mediation proportions for structural change and innovation suggest these mechanisms operate through different pathways.

7 Discussion

7.1 The Digital Decarbonization Divide

Our results reveal a fundamental heterogeneity depending on socio-economic capacity. The "Digital Decarbonization Divide" manifests along three dimensions:

1. **Development Divide (with Exceptions):** Wealthier nations generally benefit more from domestic digital capacity, yet a subset (e.g., FIN, SWE, CHE, CAN) exhibits notably weaker reductions.

2. **EDS Alignment:** Higher EDS correlates with weaker reductions, suggesting export structure can dampen domestic efficiency gains without reversing them.

3. **Energy Structure Divide:** Counterintuitively, countries with *lower* renewable energy shares see stronger DCI-driven reductions. This supports a "marginal abatement cost" logic: digital optimization yields higher carbon returns where the baseline energy mix is dirtier.

7.2 Mechanism Interpretation

We propose two non-mutually exclusive mechanisms:

Enabling Conditions Hypothesis Strong institutions enable effective environmental regulation, ensuring that efficiency gains from ICT translate to emission reductions rather than rebound effects. Our mediation analysis supports this: **11.7% of DCI's effect on emissions operates through improved energy efficiency** (Sobel test $p < 0.001$).

Structural Transformation Hypothesis ICT development in wealthy economies represents a shift toward service-based, knowledge-intensive production that is inherently less carbon-intensive. The positive correlation between CATE and renewable energy share ($r = +0.56$) supports a **policy complementarity** interpretation: digital capacity and clean energy infrastructure are substitutes in emission reduction.

Triple Interaction: Institutional Quality × Renewable Energy Our triple interaction analysis reveals that institutional moderation itself depends on renewable energy share ($p < 0.001$). In countries with high renewable shares, institutional quality matters less because the energy system is already clean. Conversely, in fossil fuel-dependent countries, strong institutions are critical for ensuring digital efficiency gains translate to emission reductions.

7.3 Policy Implications

7.3.1 For Developed Economies

The aggregate trend suggests *Domestic Digital Capacity (DCI)* can serve as a decarbonization lever. However, **high-EDS structural exceptions** indicate that efficiency gains may be weaker in service-export-intensive contexts. Policy should complement digital investment with measures targeting **absolute decoupling** rather than relative efficiency gains.

7.3.2 For Developing Economies

Policy Priority: Digital transformation alone cannot drive decarbonization in low-capacity settings. Complementary investments in institutional capacity, grid infrastructure, and human capital are essential prerequisites. The "sweet spot" finding suggests targeting middle-income countries where digital capacity can leverage existing institutional foundations.

7.3.3 For International Organizations

Target digital development assistance as part of broader **capacity-building** packages. Prioritize countries in the middle-income "sweet spot" with strong institutional quality, where each dollar of digital investment yields the highest carbon returns. Consider the Digital-EKC framework when designing country-specific intervention strategies.

7.4 Limitations

We acknowledge several limitations:

1. **Sample Size:** Our analysis uses 40 countries (840 country-year observations). While covering 90% of global GDP and emissions, this represents a relatively small number of independent clusters for Causal Forest estimation (Cameron et al., 2008). Readers should interpret results as *suggestive evidence* rather than definitive findings. We report Anderson-Rubin weak-IV robust confidence intervals to address this concern.

2. **Measurement:** While DCI captures infrastructure-based domestic digital capacity, it may not fully capture **quality of digital utilization** (e.g., AI adoption intensity, data-center efficiency). Our PCA diagnostics show the first principal component explains approximately 70% of variance.

3. **Causal Interpretation:** Despite the DML framework and IV strategy, unobserved confounders may remain. The exclusion restriction for our lagged-DCI instrument is theoretically motivated but cannot be empirically verified.

4. **Dynamic Effects:** Our primary analysis focuses on contemporaneous effects. Although dynamic analysis suggests effects persist over 2–3 years, a more comprehensive study of long-run dynamics would strengthen the findings.

5. **External Validity:** Findings may not generalize to smaller economies, island states, or least-developed countries not included in our sample.

8 Conclusion

This paper introduces the concept of the "Digital Decarbonization Divide" and provides rigorous empirical evidence for its existence. Using Causal Forest DML on a panel of 40 economies ($N = 840$), we find that:

1. **Domestic digital capacity (DCI)** exhibits fundamentally non-linear effects on CO_2 emissions.

2. **GATEs** reveal a clear progression from moderate effects in low-capacity economies to strong reductions in middle-income economies (the "sweet spot"), followed by diminishing returns in high-income economies.

3. **Structural exceptions exist:** "off-diagonal" cases indicate that **high external digital specialization (EDS)** can dampen domestic efficiency gains.

4. The **Model Ladder** demonstrates that flexible estimation is required to capture policy-relevant thresholds and exceptions missed by linear models.

Our findings challenge the assumption that digital transformation is universally beneficial for climate goals. Instead, we identify **conditional prerequisites**—socio-economic capacity and institutional quality—that moderate whether ICT delivers a "green dividend." For policymakers, the message is clear: digital development assistance should prioritize middle-income countries with strong institutional capacity, where each dollar of digital investment yields the highest carbon returns.

Policy Toolkit Appendix

8.1 Decision Framework for Policymakers

Based on our findings, we propose a decision framework for digital-climate policy:

Table 14: Policy Recommendations by Country Type

Country Type	Expected DCI Impact	Recommended Policy Mix
Low Income	Moderate (−1.19)	Build complementary capacity (institutions, grid) before major digital push
Lower-Middle Income	**Strong** (−2.17)	**Prioritize digital infrastructure**—highest carbon returns
Upper-Middle Income	**Strong** (−2.29)	**Prioritize digital infrastructure**—highest carbon returns
High Income (Low EDS)	Moderate (−1.26)	Focus on absolute decoupling, not just efficiency
High Income (High EDS)	Weak (−0.19 to −0.52)	Address structural constraints; complement with trade policy

8.2 Implementation Checklist

For practitioners implementing digital-climate policies:

1. **Assess Current Capacity:** Measure existing DCI using the PCA framework (Internet, Broadband, Secure Servers).
2. **Evaluate Institutional Quality:** Use WGI indicators to assess enabling conditions.
3. **Identify Complementarities:** Map renewable energy share and energy efficiency potential.
4. **Target the Sweet Spot:** Prioritize digital investments in middle-income countries with strong institutions.
5. **Monitor for Rebound Effects:** Track whether efficiency gains translate to absolute emission reductions.

Online Supplementary Materials

Additional materials are available in the online supplementary appendix:

1. **Appendix A:** Detailed variable definitions and data sources
2. **Appendix B:** Complete PCA diagnostics and component loadings
3. **Appendix C:** Full Model Ladder results with all specifications
4. **Appendix D:** Country-level CATE estimates with confidence intervals
5. **Appendix E:** Additional robustness checks (alternative instruments, placebo tests)
6. **Appendix F:** Power analysis and Monte Carlo simulation details
7. **Appendix G:** Replication code and data construction scripts

The replication package, including code and data construction scripts, is available at: https://github.com/a985783/digital-decarbonization-divide.git

Declarations

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of Interest: The author declares no conflicts of interest.

Data Availability: All raw inputs are obtained from World Bank WDI/WGI databases. Processed data and replication code are available in the online supplementary materials.

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