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The carbon shadow of the AI ready state: Digital state capacity, participatory impact assessment and climate outcomes in 161 countries

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Abstract

Governments are building digital and AI ready capacity fast, while impact assessment still relies on participation and impartial administration to curb environmental harm. We ask whether these two forces shape national carbon intensity, and whether they work together. Using a balanced panel of 161 countries from 2000 to 2022, we build an Impact Assessment Governance Index and a Digital State Capacity index from Varieties of Democracy data and link them to Global Carbon Budget emissions. We estimate two way fixed effects, panel threshold, fixed effects quantile, system GMM and instrumental variable models, and we split carbon intensity into energy intensity and carbon content with the Kaya identity. Digital state capacity carries a robust carbon shadow: a one standard deviation rise within a country goes with about 4% higher carbon intensity, through both more energy per unit of output and dirtier energy. The result holds under country clustered errors and a wild cluster bootstrap. Assessment governance has no average effect, because efficiency gains are offset by a slower cleaning of the energy mix. Its effect turns negative where digital capacity is high, with a significant threshold, but this complementarity loses significance under country clustering. Stronger assessment governance also coincides with more carbon embodied in imports. Digital government and national AI strategies should be screened through strategic environmental assessment, and assessment systems should widen their scope to emissions that cross borders.

Keywords: Impact assessment governance; Digital state capacity; Artificial intelligence; Carbon intensity; Public participation; Panel threshold

1. Introduction

Governments now build digital capacity at a speed that few environmental agencies can match. Most of this is sold as modernization, and part of the promise is environmental. Satellite monitoring can spot illegal clearing, smart meters can trim waste, and algorithmic screening could make environmental impact assessment (EIA) faster and sharper (Kaack et al., 2022; Rolnick et al., 2022; Vinuesa et al., 2020). Yet the hardware and the energy behind digital states are physical. Data centres draw power, networks run all day, and digital build out tends to arrive together with new consumption and new infrastructure (Freitag et al., 2021; Lange et al.,

2020; Masanet et al., 2020). Whether a more digital, more AI ready state leaves a lighter or a heavier carbon footprint is therefore an open empirical question.

Impact assessment sits right at this junction. EIA and strategic environmental assessment (SEA) have become the main procedural tools that ask whether a project, plan or policy will harm the environment before it goes ahead (Morgan, 2012). Their strength rests on two things. The first is participation: people who will live with an impact get a chance to see it, question it and shape it (Glucker et al., 2013; O'Faircheallaigh, 2010). The second is predictable, impartial administration that turns assessment findings into binding conditions (Cashmore, 2004; Loomis & Dziedzic, 2018). We call the bundle of these features impact assessment governance. The field has long asked whether such governance actually changes outcomes, the so called effectiveness question (Cashmore et al., 2004; Pope et al., 2013). Most answers come from case studies or single jurisdictions. Very few studies test, across many countries and many years, whether societies with more participatory and better enforced assessment regimes become less carbon intensive.

This paper brings the two threads together. We ask three questions. First, does participatory impact assessment governance lower the carbon intensity of national output? Second, does the digital capacity of the state, which we treat as the institutional base of AI readiness, push carbon intensity up or down? Third, do the two work together, so that participation bites only when the state has the technical capacity to monitor, process and act on what participation reveals? We also ask through which physical channels these effects run, and whether domestic gains are partly paid for by carbon embodied in imports.

To answer, we build a balanced panel of 161 countries observed every year from 2000 to 2022, a total of 3,703 country years. Carbon and energy data come from the Global Carbon Budget and the Our World in Data energy series (Friedlingstein et al., 2025; Jones et al., 2023). Governance and digital capacity come from the Varieties of Democracy project, version 16, including its Digital Society module (Coppedge et al., 2026). From expert coded V-Dem items we derive an Impact Assessment Governance Index (IAGI) and a Digital State Capacity index (DSC). We then estimate two way fixed effects models with Driscoll and Kraay (1998) errors, Hansen (1999) panel threshold regressions, fixed effects quantile regressions (Canay, 2011), system GMM (Blundell & Bond, 1998) and an instrumental variable design, and we decompose carbon intensity with the Kaya identity into energy intensity and the carbon content of energy (Ang, 2004).

The clearest finding is what we call the carbon shadow of the AI ready state. Within the same country, years with higher digital state capacity go with higher carbon intensity of GDP. The link holds with every error structure we try, including country clustered errors and a wild cluster bootstrap, and it survives dynamic and quantile models. It runs through both Kaya channels: more energy per unit of output and more carbon per unit of energy. Participatory impact assessment governance, by contrast, shows no average effect on territorial carbon intensity. Where digital capacity is high, the estimated effect of participation turns negative, in line with a complementarity story. That pattern appears in the threshold and quantile models, but it loses significance once errors are clustered by country. Finally, stronger assessment governance goes together with higher consumption based carbon intensity, a sign that part of the territorial picture may be displaced abroad.

The study makes four contributions. First, it moves the EIA effectiveness debate from procedure to measured climate outcomes across 161 jurisdictions, which answers calls for comparative, outcome based evidence (Loomis & Dziedzic, 2018; Pope et al., 2013). Second, it identifies digital state capacity as an impact in its own right. We show that the capacity of the state itself carries a carbon signature, which means that digital government and public AI programmes should fall inside the scope of SEA. Third, we test a complementarity hypothesis between participation and processing power, using threshold, interaction and quantile designs together, and we report plainly where the evidence is strong and where it is fragile. Fourth, by adding consumption based accounts we show that assessment regimes focused on territory can miss impacts that move across borders, which matters for cumulative and transboundary assessment (Peters et al., 2011).

2. Literature review and hypotheses

2.1. Theoretical framing

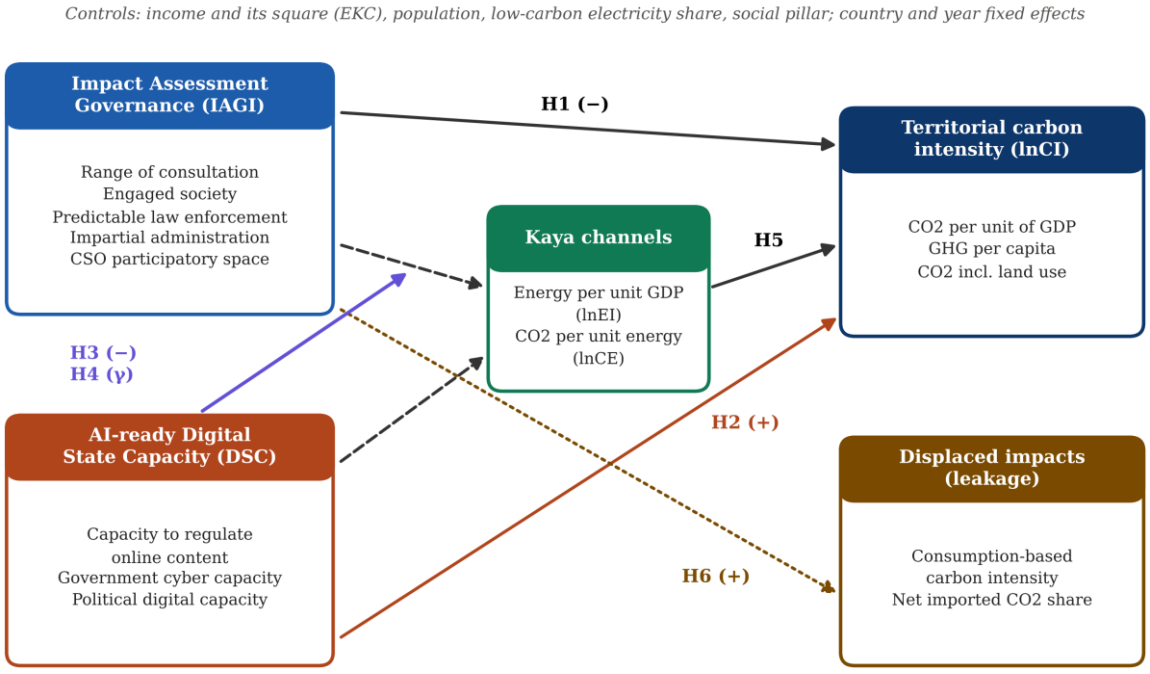
Three bodies of theory frame the study. Ecological modernization theory argues that capable states and modern technology can decouple growth from environmental harm, because better information and stronger institutions let societies steer production toward cleaner paths (Mol & Spaargaren, 2000). Its critics answer that efficiency gains feed new demand and that the material base of modern technology is often overlooked (York & Rosa, 2003). The rebound and Jevons literature gives that critique a mechanism: when a service becomes cheaper to deliver, more of it is used (Sorrell, 2009). Digital capacity is an obvious case. Cheaper

computation and data handling expand what states and economies do, and the total energy bill can rise even as each task becomes more efficient (de Vries, 2023; Freitag et al., 2021).

The second frame is participatory and deliberative governance. Fung (2006) showed that the design of participation, meaning who takes part, how they communicate and how much authority they hold, decides whether it changes decisions. In the impact assessment field, participation is valued for better information, for legitimacy and for the chance it gives affected groups to defend their interests (Glucker et al., 2013; O'Faircheallaigh, 2010). But participation can also be captured or turned into a box ticking exercise (Enríquez-de-Salamanca, 2018), and streamlining reforms can hollow it out (Bond et al., 2014).

The third frame is the capacity of the state to process what it learns. Digital era governance theory argues that information technology reshapes how public bodies gather data and act on it (Dunleavy et al., 2006). Work on AI in the public sector stresses that algorithmic tools change both what governments can see and what they choose to do (Wirtz et al., 2019; Zuiderwijk et al., 2021). Put together, these frames suggest that participation supplies the signal, digital capacity supplies the processing, and enforcement converts both into outcomes. Fig. 1 summarizes the framework.

Fig. 1. Theoretical framework and hypotheses.



Note: IAGI is built from five V-Dem items and DSC from three Digital Society Project items (Section 3.2). Dashed arrows are the Kaya channels tested in H5. The dotted arrow is the displacement channel in H6. H3 and H4 describe moderation of the IAGI path by DSC.

2.2. Impact assessment governance and carbon intensity

The case for a direct effect is simple. Where consultation is broad and society is engaged, proposals with high emissions face more scrutiny and more demands for mitigation. Where laws are enforced in a predictable way and administration is impartial, assessment conditions are more likely to be applied rather than ignored (Cashmore et al., 2004; Morgan, 2012). Cross country studies on political institutions support part of this view. More democratic systems tend to adopt more climate policy (Fredriksson & Neumayer, 2013), and institutions can weaken the link between income and emissions (Lægreid & Povitkina, 2018). Other work finds that democracy alone does little for emissions unless the quality of government is high (Povitkina, 2018). Climate considerations have also been slow to enter EIA and SEA practice (Wende et al., 2012). On balance, the theory points to a negative effect, while the evidence suggests it may be weak.

H1. Higher impact assessment governance quality is associated with lower carbon intensity of GDP.

2.3. The digital carbon shadow

A state with more digital capacity runs more servers, buys more devices and supports more digital services across the economy. The direct footprint of computing is not trivial and is growing with AI (de Vries, 2023; Masanet et al., 2020; Strubell et al., 2019). The indirect effects can be larger still. Digital infrastructure lowers transaction costs, which can raise activity in energy intensive sectors, and digital governance projects often come together with physical infrastructure and new energy demand (Lange et al., 2020). Studies on ICT and emissions report mixed results, with effects that depend on income and on the stage of digital development (Higón et al., 2017). There is also a governance reading. Digital capacity can be used for control as well as for public service, and a state that invests in surveillance and content regulation does not necessarily invest in environmental oversight. We therefore expect a positive association between digital state capacity and carbon intensity, which we call the digital carbon shadow.

H2. Higher digital state capacity is associated with higher carbon intensity of GDP.

2.4. Participation and processing power

Participation produces information: objections, local knowledge, and evidence of harm. Turning that information into better decisions requires capacity to collect it, sort it, check it and

follow up on compliance. AI and digital tools can extend that capacity by screening documents, tracking land use from satellites or linking permits with emissions data (Kaack et al., 2022; Rolnick et al., 2022). Without such capacity, participation can stay symbolic; with it, participation can shape outcomes. This reasoning suggests complementarity: the effect of assessment governance should become more negative as digital capacity rises. It also suggests the relation may not be smooth. Below some level of capacity, participation may have no effect or even a perverse one, for example when consultation delays cleaner projects without improving dirty ones. Above it, the relationship may change sign. A threshold model lets the data decide where that switch happens (Hansen, 1999).

H3. The negative association between impact assessment governance and carbon intensity strengthens as digital state capacity rises.

H4. The association between impact assessment governance and carbon intensity changes regime when digital state capacity crosses a threshold.

2.5. Physical channels

Carbon intensity of GDP is the product of energy used per unit of output and carbon emitted per unit of energy. This Kaya identity is standard in decomposition work (Ang, 2004). Governance can act on both parts. Assessment of projects and plans can push for efficiency, which lowers energy intensity, and can steer the energy mix toward low carbon sources, which lowers the carbon content of energy. Digital capacity can do the same in principle, yet the rebound argument suggests it may raise energy intensity in practice (Sorrell, 2009).

H5. Impact assessment governance and digital state capacity affect carbon intensity through energy intensity and through the carbon content of energy.

2.6. Displacement of impacts

Territorial accounts record emissions where they occur. Consumption based accounts record emissions where final goods are used (Davis & Caldeira, 2010). The gap between the two has grown as rich countries import goods made with carbon intensive energy elsewhere (Peters et al., 2011). Pollution haven theory predicts that stricter regulation can push dirty production abroad, although the size of the effect is debated (Copeland & Taylor, 2004; Levinson & Taylor, 2008). Impact assessment focuses on projects inside a jurisdiction, so strong assessment governance could shift polluting activity across borders rather than remove it. This is a cumulative and transboundary impact that territorial assessment does not see.

H6. Higher impact assessment governance quality is associated with higher consumption based carbon intensity and a larger share of carbon embodied in net imports.

3. Data and methodology

3.1. Sample and sources

We merge three public sources. Territorial CO_2, consumption based CO_2, emissions including land use change, greenhouse gases per capita, GDP and population come from the Our World in Data CO_2 dataset, which compiles the Global Carbon Budget and national greenhouse gas inventories (Friedlingstein et al., 2025; Jones et al., 2023). Energy use and the low carbon share of electricity come from the Our World in Data energy dataset, which draws on the Energy Institute and Ember. Governance and digital capacity come from the V-Dem country year dataset, version 16 (Coppedge et al., 2026). We keep sovereign states with ISO codes, restrict the window to 2000 to 2022 because the Digital Society items start in 2000 and GDP in the carbon dataset ends in 2022, and keep countries with complete data in every year. The result is a balanced panel of 161 countries and 3,703 observations. Fifty of these countries are members of the Organization of Islamic Cooperation (OIC), which lets us test whether results differ in that group. Supplementary Table S1 lists all countries.

3.2. Measuring impact assessment governance and digital state capacity

No cross country dataset scores EIA systems every year. We therefore measure the governance conditions that the impact assessment literature identifies as necessary for effective assessment. Five V-Dem items capture them: the range of consultation at elite and societal levels on policy changes (v2dlconslt), the degree to which society is engaged in public deliberation (v2dlengage), transparent laws with predictable enforcement (v2cltrnslw), rigorous and impartial public administration (v2clrspct), and the participatory environment for civil society organizations (v2csprtcpt). The first two describe participation, the middle two describe the administration that turns assessment into conditions, and the last describes the space for the non-governmental actors who most often take part in EIA hearings. Each item is standardized and the index is the first principal component:

$$IAGI_{i,t} = \sum_{k=1}^{5} w_k z_{k,i,t}, \; z_{k,i,t} = \frac{x_{k,i,t} - \bar{x}_k}{s_k} \quad (1)$$

Where $x_{k,it}$ is item k for country i in year t and w_k are the first eigenvector loadings. The first component explains 78.8% of the pooled variance, and loadings are nearly equal (0.41 to 0.46), so the index is close to a simple average. We rescale it to mean zero and unit standard deviation.

Digital state capacity is measured from the Digital Society Project items in V-Dem: government capacity to regulate online content (v2smregcap), government cyber security capacity (v2smgovcapsec) and the digital capacity of political parties and actors (v2smpolcap). These describe the technical and human capacity that a state can deploy on digital systems. That is the institutional base on which public sector AI rests: data infrastructure, skilled staff and the legal and technical tools to act on data streams (Mergel et al., 2019; Wirtz et al., 2019). We do not claim it measures AI use directly. The index is again the first principal component:

$$DSC_{i,t} = \sum_{m=1}^{3} v_m z_{m,i,t}\,,\ \sum_{m=1}^{3} {v_m}^2 = 1 \qquad (2)$$

The first component explains 78.3% of the variance with loadings of 0.56 to 0.61. Supplementary Table S2 gives item wording and loadings, and Supplementary Table S3 defines all variables and sources.

3.3. Kaya decomposition of carbon intensity

To test H5 we split carbon intensity into its two multiplicative parts:

$$CI_{i,t} = \frac{CO_{2i,t}}{GDP_{i,t}} = \frac{E_{i,t}}{GDP_{i,t}} \times \frac{CO_{2i,t}}{E_{i,t}} \Rightarrow lnCI_{i,t} = lnEI_{i,t} + lnCE_{i,t} \qquad (3)$$

Where E is primary energy. Because the identity is additive in logs, a coefficient on lnCI equals, up to small differences from sample coverage, the sum of the coefficients on lnEI and lnCE. That gives a clean way to see which channel carries each effect.

3.4. Baseline model

The baseline is a two way fixed effects model with an interaction:

$$lnCI_{i,t} = \alpha_i + \lambda_t + \beta_1 IAGI_{i,t} + \beta_2 DSC_{i,t} + \beta_3\left(IAGI_{i,t} \times DSC_{i,t}\right) + \sum_{j=1}^{J} \theta_j X_{j,i,t} + \varepsilon_{i,t} \qquad (4)$$

Where α_i removes all stable country traits such as geography, legal origin and resource endowments, λ_t removes shocks common to all countries such as oil prices or the 2008 and 2020 recessions, and $X_{j,it}$ holds the controls. Following the STIRPAT tradition (Dietz & Rosa, 1997; York et al., 2003), we control for affluence (ln GDP per capita and its square, which allows an environmental Kuznets shape as in Grossman & Krueger, 1995, and Stern, 2004),

population and the low carbon share of electricity. We also control for the social pillar, SOC, so that IAGI is not simply picking up broader social development. Coefficients therefore come from changes within countries over time, relative to the global trend.

With the interaction in place, the effect of IAGI depends on DSC:

$$\frac{\partial lnCI_{i,t}}{\partial IAGI_{i,t}} = \beta_1 + \beta_3 DSC_{i,t},\ Var = Var(\beta_1) + DSC_{i,t}{}^2 Var(\beta_3) + 2DSC_{i,t} Cov(\beta_1, \beta_3) \quad (5)$$

We plot this marginal effect across the full range of DSC and find the Johnson and Neyman bound where it becomes significant (Bauer & Curran, 2005; Brambor et al., 2006). Because a linear interaction can hide nonlinear patterns (Hainmueller et al., 2019), we also use the threshold and quantile models below.

Country panels of this kind share common shocks, so errors are likely to be correlated across countries. We therefore use Driscoll and Kraay (1998) standard errors as the baseline. They are robust to heteroscedasticity, serial correlation and cross sectional dependence of general form (Supplementary Methods S1). Because this estimator relies on the time dimension, which is only 23 years here, we report every key result also with errors clustered by country, with two way clustering by country and year, and with a wild cluster bootstrap that imposes the null hypothesis (Cameron et al., 2008). Where these disagree, we say so.

3.5. Panel threshold model

To test H4 we use the fixed effects threshold model of Hansen (1999), with DSC as the threshold variable and the IAGI slope allowed to differ by regime:

$$lnCI_{i,t} = \alpha_i + \lambda_t + \beta_L IAGI_{i,t} \cdot I(DSC_{i,t} \le \gamma) + \beta_H IAGI_{i,t} \cdot I(DSC_{i,t} > \gamma) + \delta DSC_{i,t} + \theta' X_{i,t} + \varepsilon_{i,t} \quad (6)$$

$I(\cdot)$ is an indicator and $X_{i,t}$ is the vector of controls with coefficients θ. The model is estimated after removing country and year means, which is exact in a balanced panel. The threshold γ is chosen by grid search over 161 quantiles of DSC between the 10th and 90th percentiles to minimize the residual sum of squares $S_1(\gamma)$. The p value of the threshold test comes from 300 bootstrap draws that resample whole country blocks of residuals, and the confidence set for γ follows the likelihood ratio method of Hansen (1999); Supplementary Methods S2 gives the formulas.

3.6. Dynamic panel and instrumental variables

Carbon intensity moves slowly, and governance may respond to emissions as well as shape them. We therefore add the lagged dependent variable to Eq. (4) and estimate it by two step system GMM (Arellano & Bond, 1991; Blundell & Bond, 1998), with collapsed instruments (Roodman, 2009b) and Windmeijer (2005) corrected errors. As a second check we use fixed effects two stage least squares, where a country's IAGI is instrumented by the average IAGI of the other countries in its V-Dem region in the same year, and the interaction by that average times DSC. Governance norms diffuse within regions, while a neighbour's governance score should not change a country's carbon intensity except through its own governance. This exclusion restriction is strong, so we treat the IV results as a check rather than as the main evidence. Supplementary Methods S3 gives the equations and moment conditions.

3.7. Fixed effects quantile regression

Mean effects can hide differences between clean and dirty economies. We use the two step estimator of Canay (2011), which removes fixed effects first and then runs quantile regressions, at τ = 0.10, 0.25, 0.50, 0.75 and 0.90. Standard errors come from 200 bootstrap draws that resample countries and re estimate both steps (Supplementary Methods S4).

3.8. Pre estimation tests and displacement measure

We test cross sectional dependence with the Pesaran (2015) CD statistic and unit roots with the cross sectionally augmented CIPS test of Pesaran (2007), using critical values simulated for N = 161 and T = 23 (Supplementary Methods S5). For H6 we use consumption based carbon intensity and the net share of CO_2 embodied in trade:

$$LEAK_{i,t} = 100 \times \frac{CO_{2i,t}^{cons} - CO_{2i,t}^{terr}}{CO_{2i,t}^{terr}} \quad (7)$$

A positive LEAK means a country consumes more carbon than it emits at home. Consumption accounts cover fewer countries, so these models use 2,731 observations. Supplementary Table S17 lists the replication files.

4. Results

4.1. Descriptive statistics

Supplementary Table S4 reports descriptive statistics. Carbon intensity varies widely: ln CI ranges from 3.33 to 7.67, which means the most carbon intensive economy in the sample emits

about 77 times more CO_2 per dollar of output than the cleanest. Low carbon sources supply on average 40% of electricity. Supplementary Fig. S1 shows how the two governance indices moved. Average digital state capacity rose by about half a standard deviation between 2000 and 2022, while average assessment governance drifted slightly down after 2012. Carbon intensity fell by about a quarter over the same period.

4.2. Correlations and diagnostics

Supplementary Table S5 shows that IAGI is only weakly correlated with carbon intensity in the pooled data ($r = -0.11$), while DSC is positively correlated with it ($r = 0.37$). IAGI is highly correlated with the electoral democracy index ($r = 0.87$), so we keep democracy out of the baseline and add it only as a robustness check. Variance inflation factors in the baseline set are all below 3.6. Adding democracy and corruption raises the VIF of IAGI to 5.05, still below the usual cut off of 10.

Supplementary Table S6 confirms strong cross sectional dependence in every variable, with average absolute pairwise correlations between 0.42 and 0.91. The CD statistic on the residuals of the baseline model is 4.64, so dependence remains after year effects, which supports the use of Driscoll and Kraay errors. CIPS tests show that most series are integrated of order one in levels and stationary in first differences. Because fixed effects and time effects absorb common trends and the dependent variable and key regressors share the same order of integration, the levels regressions are interpretable as long run within country associations. We confirm results with first differences inside the GMM.

4.3. Baseline estimates

Table 1 reports the main results. In column 1, IAGI has a small negative coefficient (−0.013) that is far from significant. Countries that improve their assessment governance do not, on average, become less carbon intensive relative to the global trend. H1 is not supported. Column 2 adds DSC. Its coefficient is 0.159 and highly significant, while IAGI stays close to zero. Column 3 adds the interaction. DSC remains positive (0.155) and the interaction is negative (−0.035), significant at the 1% level with Driscoll and Kraay errors.

The size of the DSC effect is easier to read in within country units (Supplementary Table S7). The typical within country standard deviation of DSC is 0.25. A one standard deviation rise in DSC within a country goes with about 3.9% higher carbon intensity, other things equal. Average DSC rose by 0.50 between 2000 and 2022. Taken at face value, that rise is linked to

carbon intensity about 8% higher than it would otherwise have been, against an observed fall of about 25%. In other words, the digital carbon shadow is large enough to have slowed the decline in carbon intensity by roughly a quarter to a third. H2 is supported.

The controls behave as expected. A 10 percentage point rise in the low carbon share of electricity goes with about 5% lower carbon intensity. Column 4 adds democracy and corruption. The interaction grows slightly to −0.041 and the IAGI main effect becomes marginally negative (−0.049, p = 0.055), which suggests that part of what assessment governance does is masked when broader regime traits are left out. Democracy itself has no significant effect, in line with Povitkina (2018).

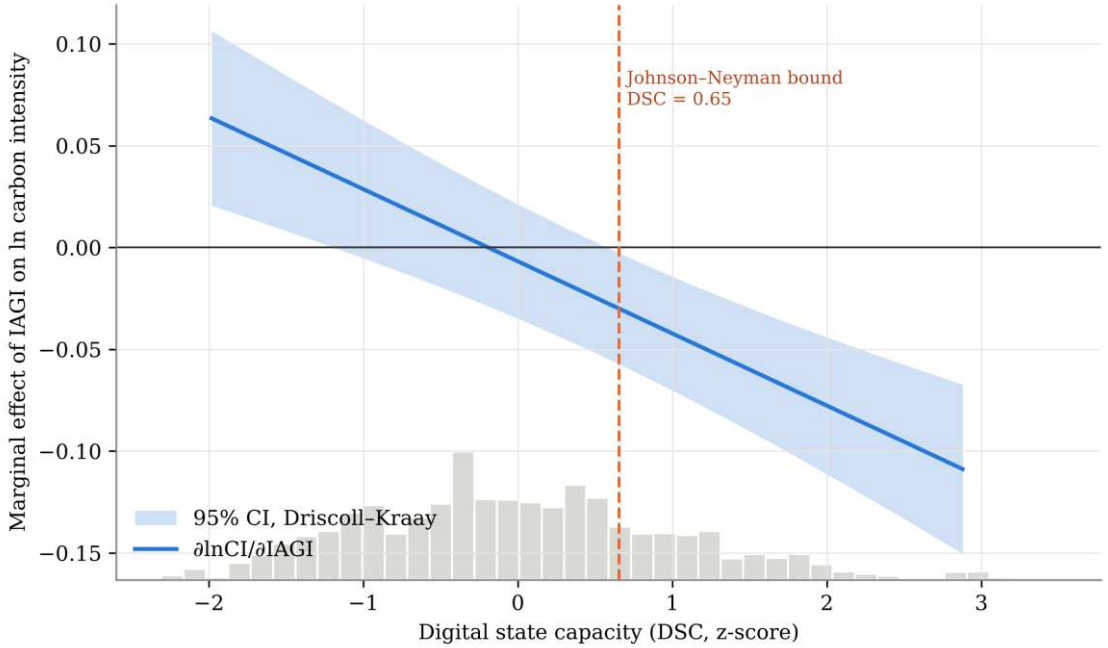
Table 1. Baseline two way fixed effects estimates. Dependent variable: ln carbon intensity of GDP.

Variable	(1) Base	(2) + DSC	(3) Interaction	(4) + DEM, CORR	(5) Clustered SE
IAGI	−0.013	−0.003	−0.007	−0.049*	−0.007
	(0.015)	(0.014)	(0.014)	(0.025)	(0.031)
DSC		0.159***	0.155***	0.154***	0.155***
		(0.026)	(0.024)	(0.022)	(0.048)
IAGI × DSC			−0.035***	−0.041***	−0.035
			(0.007)	(0.007)	(0.034)
Electoral democracy (DEM)				0.108	
				(0.091)	
Political corruption (CORR)				−0.211***	
				(0.062)	
ln GDP per capita	2.858***	2.737***	2.689***	2.647***	2.689***
	(0.377)	(0.361)	(0.363)	(0.356)	(0.545)
(ln GDP per capita)²	−0.185***	−0.180***	−0.178***	−0.175***	−0.178***
	(0.017)	(0.016)	(0.016)	(0.016)	(0.028)
ln Population	0.141*	0.171***	0.158**	0.184***	0.158
	(0.072)	(0.066)	(0.068)	(0.063)	(0.127)
Low carbon electricity share	−0.517***	−0.514***	−0.517***	−0.514***	−0.517***
	(0.047)	(0.049)	(0.048)	(0.050)	(0.163)
Social pillar (SOC)	0.014	0.004	0.009	0.007	0.009
	(0.033)	(0.032)	(0.031)	(0.030)	(0.046)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,703	3,703	3,703	3,698	3,703
Countries	161	161	161	161	161
Within R^2	0.364	0.353	0.359	0.349	0.359
F statistic	210.61	197.27	174.86	139.86	174.86

Note: Columns 1 to 4 report Driscoll and Kraay standard errors in parentheses. Column 5 repeats column 3 with standard errors clustered by country. Significance: * **p < 0.01,** p < 0.05, * p < 0.10.

Fig. 2 plots the marginal effect of IAGI implied by column 3. At low digital capacity, the effect is positive: at the 10th percentile of DSC it is 0.037 (t = 2.03). It crosses zero near the median and becomes significantly negative above DSC = 0.65, the Johnson and Neyman bound. About 24% of observations lie above that bound. At the 90th percentile of DSC, a one standard deviation rise in IAGI goes with 5.3% lower carbon intensity (t = −3.58). Supplementary Table S8 gives values at each percentile. The picture fits H3: participation appears to cut carbon only where the state can process what participation brings, and it may even raise intensity where capacity is low.

Fig. 2. Marginal effect of IAGI on ln carbon intensity across digital state capacity.



Note: Based on Table 1, column 3. The shaded band is the 95% confidence interval with Driscoll and Kraay errors. The grey histogram shows the distribution of DSC. The dashed line marks the Johnson and Neyman bound beyond which the effect is significant at 5%.

4.4. How sensitive is inference?

Column 5 of Table 1 shows why we do not stop there. With errors clustered by country, the DSC coefficient stays significant (p = 0.001) but the interaction does not (p = 0.297). Supplementary Table S9 explores this across outcomes and error structures. For the main outcome, Driscoll and Kraay errors give the same answer at bandwidths of 3, 6 and 10 years. Clustering by country, or by country and year, inflates the standard error of the interaction about sixfold. A wild cluster bootstrap with 999 draws that imposes the null gives p = 0.335 for the interaction and p < 0.001 for DSC.

The two approaches answer different questions. Driscoll and Kraay errors protect against common shocks that hit many countries at once but assume that serial correlation within a country dies out within the bandwidth. Country clustering allows any pattern of serial correlation inside a country but ignores correlation across countries. With 161 countries and 23 years, country clustering is the more reliable guide for slow moving governance variables, so we read the interaction as suggestive rather than established. DSC passes every test. This is the main reason we treat the digital carbon shadow as the headline result.

4.5. Channels: energy intensity and carbon content

Table 2 decomposes the effects using Eq. (3). The digital carbon shadow works through both channels. DSC raises energy use per unit of GDP (0.081) and carbon per unit of energy (0.075), and the two add up almost exactly to the total effect on lnCI (0.155). Both channel coefficients remain significant with country clustered errors ($p = 0.047$ and $p = 0.018$). So the shadow is not only about more energy use; digital capacity also goes with a dirtier energy mix, perhaps because digital loads raise baseload demand that is met by fossil plants in many countries.

The IAGI decomposition is more revealing. Assessment governance lowers energy intensity (−0.041) but raises the carbon content of energy (0.033). The two effects cancel, which explains the null total effect. One reading is that participatory scrutiny helps efficiency while slowing new energy projects, including low carbon ones such as hydropower, wind farms and transmission lines that often face local opposition in EIA hearings. This offsetting pattern is significant under Driscoll and Kraay errors but not under country clustering, so it should be taken as a lead for future work. The IAGI × DSC term is negative in both channels. Results for greenhouse gases per capita and for CO_2 including land use change have the same signs (Supplementary Table S10). Supplementary Fig. S2 shows the DSC and interaction coefficients with country clustered confidence intervals. H5 is supported for DSC and partly supported for IAGI.

Table 2. Kaya channels and displacement outcomes.

Variable	(1) lnCI	(2) lnEI	(3) lnCE	(4) lnCCI	(5) LEAK
IAGI	−0.007	−0.040**	0.033***	0.055***	1.163
	(0.014)	(0.017)	(0.005)	(0.020)	(1.941)
DSC	0.155***	0.081***	0.075***	0.039	−14.179***
	(0.024)	(0.016)	(0.012)	(0.028)	(5.227)
IAGI × DSC	−0.035***	−0.024***	−0.010**	−0.013	6.024***
	(0.007)	(0.009)	(0.004)	(0.017)	(1.442)
ln GDP per capita	2.689***	1.662***	1.028***	2.548***	−96.491***

Variable	(1) lnCI	(2) lnEI	(3) lnCE	(4) lnCCI	(5) LEAK
	(0.363)	(0.261)	(0.194)	(0.549)	(19.208)
(ln GDP per capita)²	−0.178***	−0.120***	−0.057***	−0.154***	5.403***
	(0.016)	(0.013)	(0.010)	(0.026)	(1.093)
ln Population	0.158**	0.269***	−0.116**	0.216***	−0.875
	(0.068)	(0.036)	(0.051)	(0.030)	(5.074)
Low carbon electricity share	−0.517***	−0.310***	−0.209***	−0.442***	4.970
	(0.048)	(0.045)	(0.052)	(0.060)	(6.199)
Social pillar (SOC)	0.009	0.034	−0.024	0.067*	4.848**
	(0.031)	(0.032)	(0.017)	(0.035)	(1.972)
Country and year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,703	3,697	3,697	2,731	2,731
Within R^2	0.359	0.317	0.064	0.177	−0.007

Note: Two way fixed effects with Driscoll and Kraay standard errors in parentheses. Column 1 repeats Table 1, column 3. lnEI and lnCE are the Kaya components of lnCI. Columns 4 and 5 use consumption based CO_2 per unit of GDP (lnCCI) and the net share of CO_2 embodied in trade (LEAK, Eq. 7), which cover 119 countries. Results for greenhouse gases and for CO_2 including land use change are in Supplementary Table S10. Significance: * **p < 0.01,** p < 0.05, * p < 0.10.

4.6. Threshold results

Supplementary Table S11 reports the Hansen threshold model. The test for one threshold rejects linearity (F = 111.52, bootstrap p = 0.010). The test for a second threshold does not reject a single threshold (p = 0.243). The estimated threshold is DSC = −1.151, sharply identified, as the likelihood ratio profile in Supplementary Fig. S3 shows. Only 12% of observations fall below it, mostly countries with very limited digital capacity in the early 2000s. The number of countries above the threshold rose from 134 in 2000 to 153 in 2022.

Below the threshold, the IAGI slope is positive (0.204); above it, it is slightly negative (−0.025). Neither regime slope is precise on its own, but the switch of sign is consistent with Fig. 2. Where the state lacks basic digital capacity, stronger participation and administration go with higher carbon intensity, perhaps because process without processing delays projects of all kinds. Once basic capacity is in place, that perverse effect disappears. The threshold test supports H4 for the existence of a regime change; the regime slopes do not by themselves show that participation lowers carbon above the threshold. DSC remains positive and significant inside the threshold model (0.130).

4.7. Quantile results

Supplementary Table S12 and Supplementary Fig. S4 report fixed effects quantile estimates. DSC is positive and significant at every quantile, rising gently from 0.136 at the 10th percentile to 0.161 at the 90th. The digital carbon shadow is therefore not driven by a few dirty economies; if anything it is a bit larger in the most carbon intensive ones. The IAGI × DSC term is negative

at all quantiles and largest in absolute size in the cleanest economies (−0.059 at the 10th percentile), but with fully re estimated bootstrap errors none of these is significant at 5%. This matches the pattern so far: a robust digital shadow and a consistent but imprecise complementarity.

4.8. Dynamics and endogeneity

Supplementary Table S13 reports the system GMM and IV estimates. Carbon intensity is highly persistent, with a lag coefficient of 0.92 to 0.97. AR(2) tests do not reject, so the lag structure is adequate. In column 1, DSC remains positive and significant (0.116, p = 0.025) and the interaction is negative (−0.036, p = 0.072). The Hansen test, however, rejects at 5% (p = 0.031), which casts doubt on instrument validity in that specification. Column 2 widens the lag window and treats the energy mix as endogenous. The Hansen test now passes (p = 0.087), DSC is still significant (0.104, p = 0.024), but the interaction shrinks to −0.019 and loses significance.

Column 3 reports the IV estimates. The regional diffusion instrument is strong for the interaction term (first stage F = 43.7) but weak for IAGI itself (F = 2.4). With such a weak first stage the IAGI coefficient carries little information. The interaction is negative and about three times larger than in the baseline (−0.121), but imprecise (p = 0.176), and DSC remains positive (0.181, p = 0.064). The Wu and Hausman test gives weak evidence of endogeneity (p = 0.077). Overall, the dynamic and IV checks keep the sign pattern intact, confirm the DSC result, and add to the doubts about the precision of the interaction.

4.9. Displacement of impacts

Columns 4 and 5 of Table 2 turn to consumption based measures, and Supplementary Table S14 gives the full set of models. A one standard deviation rise in IAGI goes with about 5.5% higher consumption based carbon intensity (p = 0.005 with Driscoll and Kraay errors; p = 0.106 with country clustering). Since IAGI has no effect on territorial intensity, this gap points to carbon that is embodied in what a country imports. The LEAK models tell a related story. DSC lowers the net import share of carbon (−14.2 percentage points per standard deviation), consistent with digital economies doing more carbon intensive work at home. The interaction is positive (6.0), so where both assessment governance and digital capacity are high, a larger share of the carbon a country consumes is emitted elsewhere. These estimates are significant with Driscoll and Kraay errors and lose significance with country clustering (Supplementary Table S9). H6 is partly supported. The finding is uncomfortable for assessment practice: the

same governance features that may help territorial outcomes in capable states may also coincide with moving impacts beyond the reach of national assessment.

4.10. Robustness

Supplementary Table S15 reports six checks on the baseline. Lagging all regressors by one year (column 1) reduces concern about reverse causality from the same year; the DSC coefficient rises to 0.178 and the interaction to −0.040. An equal weight IAGI instead of principal component weights (column 2) gives nearly identical results. Using only the regulatory capacity item for DSC (column 3) keeps a positive and significant DSC (0.108) but removes the interaction, which shows that the complementarity depends on the broader notion of capacity that includes cyber security and political digital capacity. Dropping the pandemic years 2020 to 2022 (column 4) and dropping the four largest emitters (column 5) change little. Region by year fixed effects with clustered errors (column 6), which absorb any shock common to a region in a given year, keep DSC positive and significant (0.128, $p = 0.006$) but cut the interaction to −0.018 with no significance. Across all six, DSC is positive and significant; the interaction is negative in every column but its significance depends on the specification.

4.11. Heterogeneity

Supplementary Table S16 splits the sample. The digital carbon shadow appears in every group. It is about two and a half times larger in non OIC countries (0.197) than in OIC countries (0.082), and five times larger below median income (0.214) than above it (0.041). The complementarity looks very different across groups. In non OIC countries the interaction is large and negative (−0.067), while in the 50 OIC countries it is positive and insignificant (0.026). Within the OIC group, IAGI on its own has a negative coefficient (−0.061, $p = 0.106$). One interpretation is that in many OIC economies, which include major fossil fuel producers, digital capacity has grown mainly in security and information control rather than in environmental administration, so that it does not yet amplify participation. The interaction is negative in both income groups. Supplementary Table S18 summarises the tests of all six hypotheses.

5. Discussion

5.1. What the findings add to impact assessment theory

The effectiveness debate in impact assessment has long distinguished procedural success from substantive outcomes (Cashmore et al., 2004; Loomis & Dziedzic, 2018). Our results suggest that, at the national scale and over two decades, better procedural conditions for assessment do not by themselves deliver lower carbon intensity. This is not proof that EIA does nothing for climate. Project level assessment may prevent harms that never appear in national aggregates. But it does challenge the assumption that more participation and better administration will on their own move national climate outcomes. The Kaya results give a reason: assessment governance seems to improve efficiency while making the energy mix no cleaner, possibly because new low carbon infrastructure also has to pass through participatory processes.

The complementarity results speak to a deeper theoretical point. Participation is a source of information, and information only matters if someone can act on it. Where digital capacity is high, the estimated effect of participation is negative; where it is very low, the effect is positive and a threshold separates the two regimes. This pattern fits a view of assessment as a joint product of voice and processing power, closer to digital era governance (Dunleavy et al., 2006) than to a purely procedural model. We stress, however, that this pattern does not survive the most conservative inference. It is a hypothesis with consistent but fragile support, and it deserves tests with direct measures of EIA practice.

5.2. The digital state as an impact to be assessed

The most robust result is that digital state capacity is linked to higher carbon intensity, through both more energy per unit of output and more carbon per unit of energy. This has a direct implication for practice. Digital government strategies, national AI plans, data centre programmes and electronic government platforms are rarely screened by SEA. They are treated as administrative modernization rather than as plans with physical impacts. Our evidence suggests they should be screened. A national AI strategy is a plan in the SEA sense: it sets a framework for future projects such as data centres, grid connections and procurement of computing. Its cumulative energy and carbon effects can be predicted and mitigated, for example by linking new data centre capacity to additional low carbon supply, by setting energy disclosure rules for public AI systems, and by including digital loads in national energy and climate plans (de Vries, 2023; Kaack et al., 2022).

This finding also qualifies the optimism around AI for climate. AI can help monitor deforestation, screen EIA documents and optimize grids (Rolnick et al., 2022; Vinuesa et al., 2020). Our results do not deny those uses. They show that, so far, the capacity on which such tools rest has come with a carbon cost at the national scale. The net effect of AI on climate will depend on whether that capacity is aimed at environmental administration or at other goals, which is a governance choice rather than a technical given.

5.3. Borders, consumption and cumulative assessment

The displacement results point to a blind spot. Impact assessment evaluates projects and plans inside a jurisdiction, and national climate targets count territorial emissions. Our results suggest that stronger assessment governance coincides with higher consumption based carbon intensity, and that in states with high digital capacity a larger share of consumed carbon is emitted abroad. That is consistent with modest pollution haven effects (Levinson & Taylor, 2008) and with the long rise in emission transfers through trade (Peters et al., 2011). For assessment practice, it argues for including embodied and imported emissions in SEA of trade, industrial and procurement policies, and for transboundary cumulative assessment. For sovereign ESG analysis, it warns that country scores built on territorial data can reward governance that exports impacts (Berg et al., 2022; Capelle-Blancard et al., 2019).

5.4. Relevance for OIC and lower income economies

The digital carbon shadow is largest in lower income countries, where digital build out often relies on fossil power. In OIC countries, the shadow is smaller and assessment governance does not interact with digital capacity in the same way as elsewhere. For these economies, a practical priority is to direct digital capacity toward environmental administration, for instance satellite based compliance monitoring and open EIA registries, and to pair digital expansion with low carbon electricity. Since the low carbon share of electricity is one of the strongest predictors of lower carbon intensity in every model, energy policy and digital policy should be planned together.

6. Conclusions, limitations and future research

This study asked whether participatory impact assessment governance and the digital, AI ready capacity of the state shape national carbon intensity. We find four things. First, digital state capacity carries a robust carbon shadow: within countries, more capacity goes with higher carbon intensity, through both energy intensity and the carbon content of energy. Second,

assessment governance has no average effect on territorial carbon intensity, because its efficiency gains are offset by a slower cleaning of the energy mix. Third, there is consistent but fragile evidence that participation lowers carbon intensity only where digital capacity is high, with a clear threshold below which the relationship is reversed. Fourth, stronger assessment governance coincides with more carbon embodied in imports.

For practitioners and regulators the message is twofold. Digital government and public AI programmes should be treated as plans with environmental impacts and screened through SEA. And impact assessment systems that rely on participation should invest in the capacity to process and act on what participation produces, while widening their scope to emissions that cross borders.

The study has limits. Our governance indices measure the conditions for effective assessment, not the content of national EIA laws or the quality of individual assessments. DSC measures the institutional base of AI readiness rather than AI use, and it may partly capture state capacity for control. The V-Dem items are expert assessments with measurement error, which would bias coefficients toward zero. Identification rests on within country variation and on instruments whose exclusion restriction may not hold, so our estimates are associations conditioned on rich fixed effects rather than clean causal effects. Inference for the interaction depends on how errors are clustered, as we document. The data do not allow us to examine sex and gender dimensions, which we note as a limit to generalization. Future work should code national EIA and SEA laws over time, use direct measures of public sector AI adoption and data centre capacity as they become available, and test the complementarity hypothesis at the project level, where participation and digital tools meet in practice.

Ethics Approval

Not applicable. This study analyses only publicly available, country-level secondary data (Our World in Data and the Varieties of Democracy dataset). It involves no human participants, no personal or identifiable data and no animals. No approval from an Ethics Committee or Institutional Review Board was required, and no approval number exists.

Consent to Participate

Not applicable. This study involves no human participants. Informed consent to participate was not required.

Consent for Publication

Not applicable. The manuscript contains no identifiable information, images or data relating to any individual person. Written informed consent for publication was therefore not required.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Muhammad Saeed Iqbal: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft. Sofi Mohd Fikri: Supervision, Validation, Writing – review and editing. Irum Saba: Conceptualization, Writing – review and editing. Jawad Iqbal: Investigation, Visualization, Writing – review and editing. Sobia Iqbal: Data curation, Validation, Writing – review and editing. All authors read and approved the final manuscript.

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Availability of Data and Materials

The datasets analysed during the current study are publicly available. Our World in Data CO_2 dataset: https://github.com/owid/co2-data. Our World in Data energy dataset: https://github.com/owid/energy-data. Varieties of Democracy country-year dataset, version 16: https://doi.org/10.23696/vdemds26. The merged country-year panel (161 countries, 2000–2022), the code that builds the indices and reproduces every table and figure, and the codebook listed in Supplementary Table S17 are available from the corresponding author on reasonable request.

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Declaration of generative AI in the manuscript preparation process

During the preparation of this work the authors used a generative AI assistant to improve the language and readability of selected passages and to format tables. After using this tool the authors reviewed and edited the content as needed and take full responsibility for the content of the publication. No part of the research design, data collection, estimation or interpretation was delegated to an AI tool.

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