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What Drives Country-Level Exposure to the Social Cost of Carbon? Discounting, Economic Scale, and Equity in Developing Economies

Shipra Aggarwal[1,2]*, Manish Aggarwal[3]

[1]Babson College, Wellesley, Massachusetts, USA, [2]Pelham Community Pharmacy, Waltham, Massachusetts, USA, [3]R&D, Aspen Technology (Emerson)., Bedford, Massachusetts, USA. *Email: saggarwal@pelmeds.com, manish.aggarwal@emerson.com

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ABSTRACT

The social cost of carbon (SCC) is the central price signal in climate policy, and a recent literature decomposes it into country-level shares of global damage. This paper asks what explains cross-country variation in this country-level SCC (CSCC), and whether developing economies bear a disproportionate share once economic size is taken into account. Using the Ricke et al. (2018) CSCC database merged with macroeconomic and emissions data for 169 countries, an OLS model explains 93% of cross-country variation in log CSCC, driven almost entirely by GDP per capita and population. A machine learning ensemble, interpreted with SHAP attribution, confirms this finding. A population-neutral equity measure -- CSCC as a share of GDP -- shows no significant excess burden on developing economies under the baseline specification. Across 24 alternative specifications, the equity conclusion is highly sensitive to the discounting assumption: constant-rate discounting produces a large, significant gap favoring the conventional equity narrative, while Ramsey discounting narrows or eliminates it. The results imply that discounting, not the damage function or emissions scenario, is the decisive choice when integrating country-level SCC estimates into carbon pricing and climate finance policy in developing economies. Both the scale finding and the equity result replicate closely on an independent, newly published national SCC dataset built on an entirely different damage-function methodology.

Keywords: Social Cost of Carbon, Climate Policy, Developing Economies, Discounting, Machine Learning, Equity
JEL Classifications: Q54, Q56, O44, C53

1. INTRODUCTION

The social cost of carbon (SCC) measures the economic damage caused by one additional tonne of carbon dioxide. It is arguably the single most consequential number in climate policy. Governments use it to set carbon prices, justify regulations, and design climate finance commitments. Yet the global SCC obscures a basic fact: Climate damage is not evenly spread. Some countries lose far more than others, for the same tonne of emissions.

Ricke et al. (2018) addressed this gap directly. They decomposed the global SCC into country-level shares, combining climate and economic projections with an empirical growth-damage function. Their headline finding was striking: A small number of large economies, including India, China, Saudi Arabia, and the United States, account for most of the global cost. This finding has since been cited widely in debates over climate finance and loss-and-damage funding, often as evidence that developing economies bear a disproportionate burden from climate change.

This paper asks whether that reading holds up to closer scrutiny. We treat the Ricke et al. (2018) country-level SCC (CSCC) database as the dependent variable in a structured empirical exercise, organized around three questions. First, what observable country characteristics predict CSCC, using both linear regression and a machine learning ensemble? Second, does a population-neutral measure of relative exposure -- CSCC as a share of national GDP -- show a systematic equity gradient by income group? Third, how sensitive is any such gradient to the damage-function, climate-scenario, and discounting choices embedded in the underlying database?

The findings complicate the conventional reading. Country-level SCC is overwhelmingly a function of economic scale -- a country's GDP per capita times its population -- which is close to mechanical. A growth-damage function assigns more dollars of damage to bigger economies almost by construction, since it multiplies a percentage growth loss against the level of GDP. Once CSCC is normalized by GDP, developing economies do not show a robust, unconditional excess burden. The result depends entirely on the discounting assumption built into the calculation. Constant-rate discounting produces a clear equity gradient favoring the conventional narrative. Ramsey discounting, which adjusts the discount rate for each country's expected consumption growth, narrows or reverses it.

This matters for policy. The special issue motivating this paper calls for integrating the SCC into national and regional policymaking in developing economies. Doing so responsibly requires being explicit about discounting, not just the damage function or warming scenario. A government or development bank citing a country-level SCC estimate to justify a carbon price, or a climate finance allocation, is also taking an implicit position on intergenerational equity and growth expectations. We argue that this choice should be stated openly, not buried in a model appendix.

The remainder of the paper proceeds as follows. Section 2 reviews the SCC literature and the country-level decomposition approach. Section 3 describes the data. Section 4 sets out the empirical strategy. Section 5 presents results. Section 6 discusses policy implications for developing economies. Section 7 notes limitations and directions for future research. Section 8 concludes.

2. BACKGROUND AND LITERATURE

The theoretical foundation for the SCC is straightforward. It is the present value of all future damage caused by emitting one additional tonne of CO_2 today (Pizer et al., 2014; National Academies of Sciences, 2017). In a first-best world, it also equals the optimal Pigouvian carbon tax. Estimating it in practice requires a long chain of assumptions: A climate model, a damage function linking warming to economic loss, a socioeconomic projection, and a discount rate to bring future damage back to present value.

Two broad families of damage function dominate the literature. Integrated assessment models such as DICE and FUND treat damage as a smooth function of the level of warming, calibrated mostly to sector-level studies (Nordhaus, 2017; Tol, 2018). A newer empirical literature instead estimates damage as an effect on the growth rate of the economy, not just its level. Burke et al. (2015) found that temperature deviations reduce GDP growth, with effects that persist for years after the initial shock. Dell et al. (2012) found a related but more limited level effect. Because growth effects compound, growth-damage models tend to produce larger and more uncertain SCC estimates than level-damage models (Moore and Diaz, 2015). The growth-damage specification is not without critics: Newell et al. (2021) argue that the underlying GDP-temperature relationship overstates total, and hence marginal, impacts in already-hot countries while understating them in cold ones, a concern we return to in Section 7.

Ricke et al. (2018) combined a growth-damage framework with country-level socioeconomic and climate projections to decompose the global SCC into national shares. This let researchers ask, for the 1st time at scale, which countries bear the cost of a given tonne of global emissions, rather than only how large the global total is. The finding entered the policy conversation quickly. Loss-and-damage advocates and some development economists have cited the country-level concentration of CSCC as evidence that the largest economic costs of climate change fall on developing countries (Diffenbaugh and Burke, 2019; Callahan and Mankin, 2022).

That reading conflates two different things: The absolute dollar magnitude of damage, which scales with the size of an economy, and the relative burden, which depends on damage scaled by the capacity to bear it. The distinction matters for how the SCC gets used in policy. A national carbon price benchmarked to a country's absolute CSCC looks very different from one benchmarked to a CSCC-to-GDP ratio.

The choice of discount rate compounds this ambiguity. The long-running disagreement between Stern (2007) and Nordhaus (2007) was, at its core, about discounting ethics -- how much weight to place on damage borne by future, likely wealthier, generations. Ramsey discounting ties the discount rate to expected consumption growth, so faster-growing economies discount their own future damage more heavily (Arrow et al., 2013; Drupp et al., 2018). A constant discount rate makes no such adjustment. Recent upward revisions to the United States government's official SCC estimate, from about \$51 per tonne to a central value near \$190 (Rennert et al., 2022; U.S. EPA, 2023), reflect updated discounting and damage-function choices as much as new climate science, a pattern documented more broadly across the published social-cost-of-carbon literature (Tol, 2023). Section 5 shows that the same sensitivity, applied at the country level, can flip the conclusion about which economies bear the largest relative burden.

3. DATA

We combine three public sources.

3.1. Country-Level Social Cost of Carbon

We use the version-2 database from Ricke et al. (2018), covering 170 countries and a "WLD" global aggregate. The database reports the median and the 16.7th and 83.3rd percentile CSCC for each country, across combinations of damage function, shared socioeconomic pathway (SSP), representative concentration pathway (RCP), and discounting approach. Our baseline specification uses the BHM long-run (5-lag) pooled damage function, which allows for gradual economic adaptation to warming, paired with SSP2 ("Middle of the Road"), RCP6.0, and Ramsey discounting with a 2% pure rate of time preference and an elasticity of marginal utility of 1.5. We treat the remaining 23 combinations in the database -- spanning the BHM short-run damage function, RCP4.5 and RCP8.5, an alternative Ramsey calibration, and two constant discount rates -- as a robustness grid, described in Section 4.3.

3.2. Macroeconomic and Emissions Covariates

We draw GDP, population, CO_2 emissions, energy consumption, and fuel-mix data from the Our World in Data CO_2 and Greenhouse Gas Emissions dataset (Our World in Data/Global Carbon Project, 2024), which compiles figures from the Global Carbon Project, the Energy Institute Statistical Review of World Energy, and the Maddison Project Database. We average each covariate over 2018-2022 to smooth short-run noise. Since CSCC is a structural parameter rather than a calendar-year outcome, a multi-year average is more defensible than a single reference year.

3.3. Income Classification

We classify countries using the World Bank's fiscal year 2026 income groups (World Bank, 2025), based on 2024 GNI per capita under the Atlas method. We deliberately avoid building our own income threshold from the OWID GDP series, which is purchasing-power-parity adjusted on a Maddison Project basis, since this is not on the same footing as the Atlas-method, current-dollar thresholds the World Bank uses. Mixing the two bases misclassifies several countries; China is the clearest case, since its PPP-adjusted GDP per capita sits above the high-income cutoff while its Atlas GNI per capita places it solidly in the upper-middle-income group. We use the official classification instead.

After merging, we retain 169 countries with a non-missing baseline CSCC and matched OWID covariates. Venezuela and Ethiopia are excluded from income-group comparisons, since the World Bank currently lists both as unclassified pending updated national accounts data. Table 1 summarizes coverage.

4. METHODOLOGY

4.1. Linear Model

We estimate a cross-sectional OLS regression of log country-level SCC on a small set of economic and emissions covariates, plus continent fixed effects:

$$\log(CSCC_i) = \beta_0 + \beta_1 \log(GDPpc_i) + \beta_2 \log(Pop_i) + \beta_3\, CO2pc_i + \beta_4\, EnergyIntensity_i + \beta_5\, \Delta Temp_i + ContinentFE_i + \varepsilon_i$$

Table 1: Sample coverage and baseline CSCC by income group

Income group	Countries (n)	Mean CSCC ($/t$CO_2$)	Median CSCC ($/t$CO_2$)
Low income	23	0.32	0.21
Lower-middle income	46	1.91	0.28
Upper-middle income	46	4.19	0.61
High income	51	9.46	1.80

CSCC values are baseline specification (BHM long-run, SSP2-RCP6.0, Ramsey discounting, prtp=2%, eta=1.5). Venezuela and Ethiopia excluded (World Bank: Unclassified, FY2026)

All variables are measured at the country level. We use HC3 heteroskedasticity-robust standard errors throughout, appropriate for a small, heterogeneous cross-sectional sample. CSCC, GDP per capita, and population are log-transformed given their heavy right skew.

4.2. Machine Learning Ensemble

We complement the linear model with three tree-based ensembles -- Random Forest, XGBoost, and LightGBM -- estimated on an expanded set of 13 covariates, including fuel-specific emissions intensities (coal, oil, gas, methane, nitrous oxide). Given the modest sample (n = 153 after dropping rows with incomplete covariates), we evaluate out-of-sample performance using leave-one-out cross-validation, the most defensible approach at this sample size. We use SHAP (Shapley Additive Explanations) values to attribute predictions to individual features, cross-checked against Random Forest impurity-based importance.

Two data-cleaning choices are worth flagging. Trade-embodied and consumption-based CO_2 figures are missing for 54 of 169 countries, concentrated in smaller and lower-income economies; since a missing value here reflects unavailable accounting rather than zero trade, we drop these variables rather than impute or drop the affected rows, which would have biased the sample toward wealthier, data-rich countries. Fuel-specific per-capita emissions (coal, oil, gas, methane, nitrous oxide) are missing for a smaller set of countries with negligible use of that fuel; here we impute zero, since the missingness pattern is concentrated in exactly the low- and lower-middle-income economies with minimal use of that fuel type.

4.3. Equity Measure and Robustness

We construct a population-neutral equity measure: CSCC as a share of total GDP, expressed as dollars of CSCC per billion dollars of GDP. We initially considered a simpler CSCC-to-GDP-per-capita ratio, but rejected it after finding it confounded by population size, since CSCC scales roughly linearly with population (Section 5.1); dividing by GDP per capita alone leaves population in the numerator, undermining the cross-country comparison. Dividing by total GDP removes this confound.

We compare this measure across World Bank income groups using Welch's t-test (developing versus high-income economies), then repeat the comparison across all 24 specification combinations in the Ricke et al. (2018) database, varying the damage function (BHM long-run/short-run), RCP scenario (4.5/6.0/8.5), and discounting approach (Ramsey, prtp = 1% or 2%, eta = 1.5; constant 3% or 5%). We also compute the Spearman rank correlation between each alternative specification's country ranking and the baseline ranking, to assess how much the choice of damage function and discounting reshuffles which countries appear most exposed.

5. RESULTS

5.1. What Predicts Country-Level SCC?

Figure 1 shows the top 20 countries by baseline country-level SCC, colored by income group. Table 2 reports the OLS results.

The model explains 93% of cross-country variation in log CSCC (n = 153, Adj. $R^2 = 0.930$). GDP per capita and population both enter with an elasticity close to one: A 1% increase in either is associated with roughly a 1% increase in CSCC. Per-capita CO_2 emissions enter positively and significantly, but with a smaller coefficient (0.049). Energy intensity and the temperature change attributable to a country's own greenhouse gas emissions are not significant once GDP and population are included.

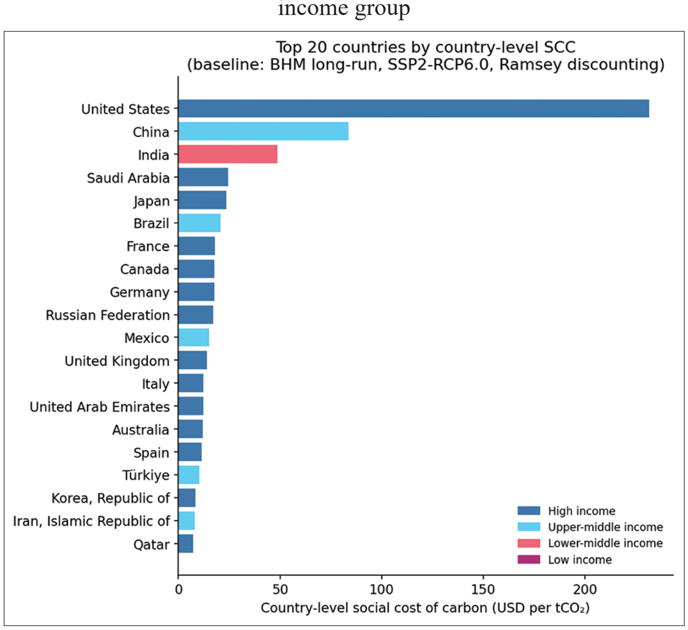
This pattern has a simple interpretation. A growth-damage function translates a percentage loss in GDP growth into a dollar figure by multiplying against the level of GDP. Bigger economies, in dollar terms, lose more for the same percentage damage. CSCC, as constructed in this literature, is mechanically close to a population-and-income-weighted damage share, not a free-standing measure of physical vulnerability.

The machine learning results confirm this. All three ensemble methods achieve leave-one-out R^2 between 0.89 and 0.91, in line with the linear model (Table 3). SHAP attribution (Figure 2) ranks primary energy consumption as by far the most important feature, followed by a country's share of global CO_2 emissions and its population. Primary energy consumption is itself highly correlated with the size of an economy, so this is consistent with the OLS finding rather than contradicting it. Fuel-specific intensities and energy intensity per unit of GDP carry meaningfully smaller, second-order influence.

5.2. Is the Burden Disproportionate for Developing Economies?

Table 4 reports CSCC as a share of GDP, by income group, under the baseline specification. Low-income economies show the highest median ratio, but the difference between developing economies as a whole and high-income economies is not statistically significant (Welch's $t = -1.69$, $P = 0.096$). If anything, the point estimate runs opposite to the conventional equity narrative: high-income economies show a marginally higher mean CSCC-to-GDP share than developing economies ($0.0073 vs. $0.0060 of CSCC per billion dollars of GDP).

Figure 1: Top 20 countries by baseline country-level SCC, colored by income group



A continuous-form regression of log(CSCC/GDP share) on log(GDP per capita) confirms the same conclusion with more statistical power: The income elasticity of the burden ratio is small (0.062) and not significant ($P = 0.139$, $R^2 = 0.017$). Under the baseline discounting assumption, a country's relative economic exposure to global carbon damage is essentially flat across the income distribution. This is the opposite of what a naive reading of the Ricke et al. (2018) country rankings -- dominated by India, China, and other large emerging economies -- might suggest, once the comparison is normalized for economic size.

5.3. Robustness: The Equity Result Depends on Discounting

Table 5 repeats the developing-versus-high-income comparison across the full robustness grid, averaged within each discounting category across both damage functions and all three RCP scenarios. The pattern is stark. Under constant-rate discounting, developing economies show a CSCC/GDP share roughly an order of magnitude higher than high-income economies, and the gap is highly significant ($P < 0.001$ at both 3 and 5% constant

Table 2: OLS regression: Drivers of log (country-level SCC)

Variable	Coefficient	Robust SE	P-value
log (GDP per capita)	1.025	0.087	<0.001
log (Population)	1.019	0.038	<0.001
CO_2 per capita	0.049	0.016	0.003
Energy intensity (per GDP)	0.017	0.130	0.895
Temperature change (own GHG)	−0.751	3.135	0.811
Continent: Asia (vs. Africa)	−0.431	0.188	0.022
Continent: Europe (vs. Africa)	−0.468	0.196	0.017
Continent: N. America (vs. Africa)	−0.312	0.185	0.092
Continent: Oceania (vs. Africa)	−0.501	0.367	0.172
Continent: S. America (vs. Africa)	−0.062	0.227	0.785
Intercept	−26.458	0.881	<0.001

HC3 robust standard errors. n=153. R^2=0.934, Adj. R^2=0.930

Table 3: Machine learning ensemble: Out-of-sample performance (LOOCV)

Model	LOOCV R^2	MAE (log scale)	MAE ($/t$CO_2$)
Random Forest	0.892	0.507	2.98
XGBoost	0.907	0.473	2.72
LightGBM	0.902	0.492	2.93

Leave-one-out cross-validation, n=153, 13 covariates

Table 4: CSCC as a share of GDP, by income group (baseline specification)

Income group	n	Mean ($/bn GDP)	Median ($/bn GDP)
Low income	20	0.0081	0.0075
High income	48	0.0073	0.0056
Upper-middle income	41	0.0057	0.0049
Lower-middle income	42	0.0048	0.0042

CSCC per $1 billion of national GDP, a population-neutral exposure measure. Developing (n=103) versus high-income (n=48): Welch t=−1.69, P=0.096

rates). Under Ramsey discounting, the gap narrows to statistical insignificance (P = 0.23 at prtp = 1%, P = 0.14 at prtp = 2%, our baseline). Figure 3 illustrates this reversal across both damage-function specifications.

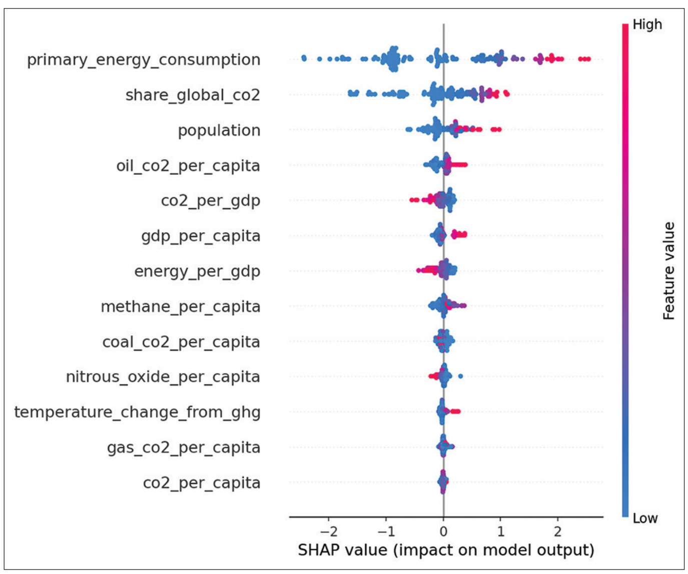
Whether the standard equity narrative holds, then, is not a question the physical climate science or the damage function can answer on its own. It is decided by the discount rate. Constant discounting treats a dollar of damage borne by a fast-growing, currently poorer country the same as a dollar borne by a slow-growing, currently richer one. Ramsey discounting does not: It discounts the future

Table 5: Equity result by discounting approach (averaged across damage functions and RCPs)

Discounting	Developing mean	High-income mean	Avg. P-value
Constant, 3%	0.0204	0.0004	<0.001
Constant, 5%	0.0067	0.0005	<0.001
Ramsey, prtp=1%	0.0163	0.0164	0.233
Ramsey, prtp=2% (baseline)	0.0080	0.0068	0.144

CSCC per $1 billion of GDP, averaged across BHM long-run/short-run and RCP4.5/6.0/8.5

Figure 2: SHAP feature attributions for log (country-level SCC), XGBoost model



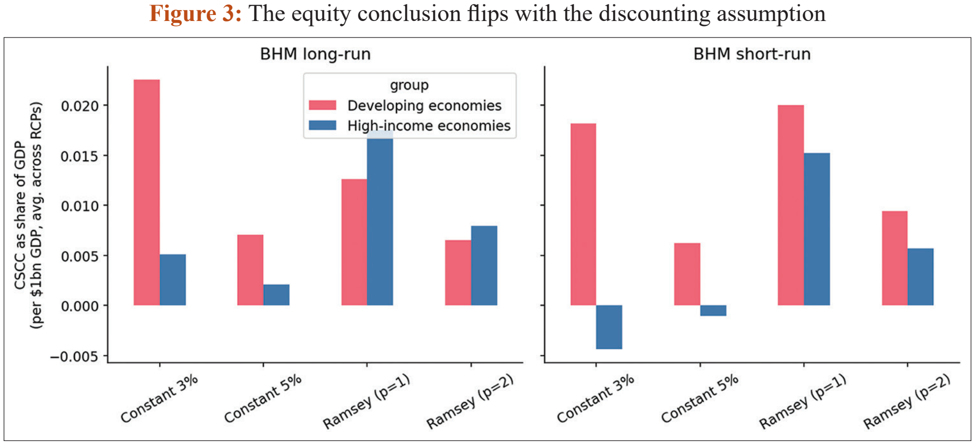
damage of fast-growing economies more heavily, on the logic that their future selves will be better placed to absorb it. That logic, whatever its merits, mechanically shrinks the apparent burden on today's developing economies, many of which are assumed to grow faster than today's high-income economies over the projection horizon.

Country rankings are also sensitive to the choice of damage function, more so than to the choice of discounting or RCP scenario. The Spearman rank correlation between each alternative specification and the baseline ranking averages 0.95 across all RCP and discounting combinations that retain the BHM long-run damage function, but only 0.38 across combinations that switch to the BHM short-run, no-lag specification (Figure 4). Assuming countries can or cannot adapt gradually to warming reshuffles which countries appear most exposed far more than any other modeling choice we test.

5.4. External Validation against an Independent Secondary Dataset

A natural concern with any single-database analysis is that both headline findings -- the dominance of economic scale, and the discounting-sensitive equity result -- could be artifacts of the particular damage-function family underlying the CSCC database, the BHM empirical growth-damage approach. We address this by re-estimating both results on an entirely independent, recently published secondary dataset: Agarwala and Tol (2026), part of a new Climate Change Economics special issue on the national social cost of carbon published alongside this submission window. Agarwala and Tol estimate a national social cost of carbon (NSC) using a DICE-type integrated assessment model with a Bayesian model-averaged impact function calibrated to a 2024 meta-analysis of climate damage estimates (Tol, 2024) and an income elasticity of vulnerability of −0.36, following Schelling (1984; 1992) in assuming richer countries are less vulnerable to a given degree of warming and Diaz and Moore (2017) in letting relative impacts fall as economies grow. The national-level impact functions are imputed from the global calibration using the method of Tol (2019), a methodology with no mechanical relationship to the BHM growth-damage approach underlying our primary database. The same special issue contains several other independent re-estimates of the country-level SCC, including a revised PAGE model (Rising, 2026), a FUND-based

Figure 3: The equity conclusion flips with the discounting assumption

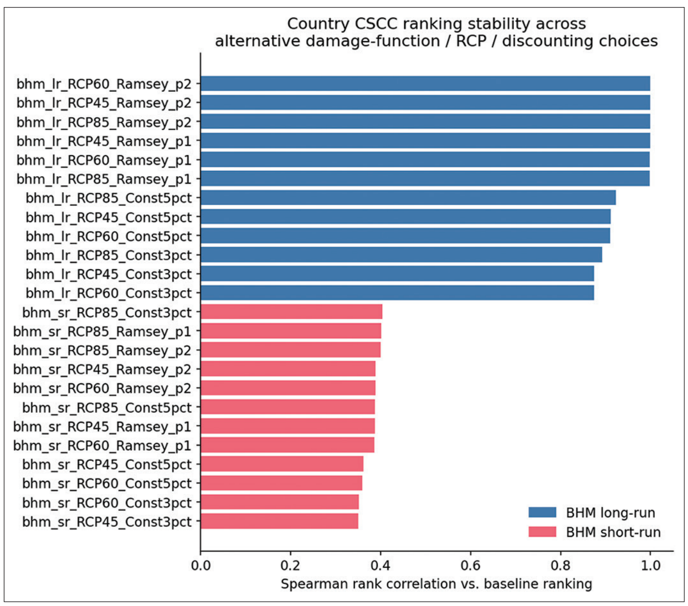


national application (Hwang and Tol, 2026), and a probabilistic geographic decomposition (Chiani et al., 2026); see Yoo (2026) and Yoo et al. (2026) for a synthesis across these approaches. We focus our validation on Agarwala and Tol because their paper is the one publishing a complete country-by-scenario results table alongside the manuscript.

We matched their published country-level NSC table to our analysis panel by country name, recovering 165 of their 198 countries (the 33 unmatched countries are micro-states and territories, such as Andorra, Monaco, and Tuvalu, that are also absent from the Ricke et al., database). We then re-ran our baseline OLS specification -- log(NSC) on log GDP per capita, log population, and the same controls -- on this independent outcome variable, and repeated the developing-versus-high-income comparison from Section 5.2.

Both findings replicate closely. The scale elasticities are statistically indistinguishable from the primary estimates: A GDP-per-capita elasticity of 0.81 (vs. 1.03 in the primary analysis) and a population elasticity of 0.98 (vs. 1.02), both significant at $P < 0.001$, with an even higher R^2 of 0.97 (Table 6 and Figure 5, panel A). The equity result also replicates: The developing-versus-high-income gap in NSC per dollar of GDP is statistically insignificant at Agarwala and Tol's baseline discount rate ($P = 0.45$), and remains insignificant whether the pure rate of time preference is pushed down to 1.0% ($P = 0.52$) or up to 3.0% ($P = 0.30$).

Figure 4: Country CSCC ranking stability across 24 alternative specifications



One scope limitation is worth stating plainly. Agarwala and Tol vary the pure rate of time preference within a Ramsey-type discounting framework throughout (1.0%, 1.5%, and 3.0%); they do not implement a constant-rate discounting alternative comparable to our primary robustness grid's contrast between Ramsey and constant discounting. Their data therefore cannot directly test whether the discounting regime itself, rather than the prtp parameter within Ramsey discounting, is what drives the equity flip. What their data do show is that prtp variation alone, holding the Ramsey structure fixed, does not flip the equity conclusion -- consistent with our own finding that the gap remains insignificant across prtp = 1% and prtp = 2% within the Ramsey family (Table 5). This sharpens rather than undercuts our central claim: it is specifically the choice between a constant discount rate and Ramsey discounting, not the particular prtp value chosen within a Ramsey framework, that decides whether the equity narrative holds.

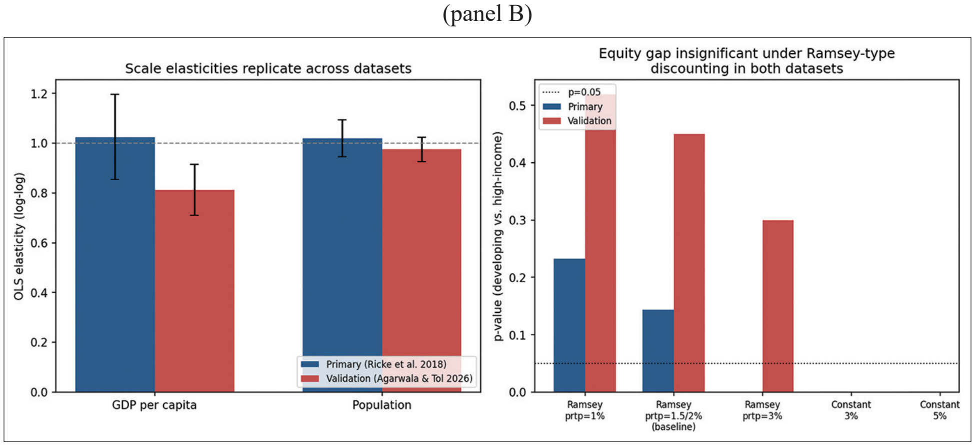
6. DISCUSSION: IMPLICATIONS FOR POLICY IN DEVELOPING ECONOMIES

These results have three direct implications for the special issue's call to integrate the SCC into policy and practice in developing economies.

Table 6: External validation: Scale elasticities, primary versus independent dataset

Variable	Primary (Ricke et al.,)	Validation (Agarwala and Tol)
log (GDP per capita)	1.025 (P<0.001)	0.813 (P<0.001)
log (population)	1.019 (P<0.001)	0.975 (P<0.001)
R^2	0.934	0.966
n (countries)	153	151

Figure 5: External validation against Agarwala & Tol (2026): Scale elasticities (panel A) and equity P-values across discounting specifications (panel B)



First, a country-level SCC figure quoted in isolation – "India's share of the global SCC is the second largest in the world" -- is not, by itself, evidence of disproportionate vulnerability. It is heavily a statement about the size of India's economy and population. Policymakers and development institutions citing country-level SCC rankings to support climate finance claims should report the GDP-normalized figure alongside the absolute one, or risk conflating economic scale with relative exposure.

Second, any carbon price, loss-and-damage allocation, or NDC target benchmarked to a country-level SCC estimate is implicitly also a statement about discounting ethics (Kelleher, 2025). A government adopting a constant-discount-rate CSCC figure to justify higher climate finance transfers to developing economies is making a defensible but contestable ethical choice, not reporting a neutral fact. Transparency about which discounting convention underlies a quoted SCC figure should be a basic requirement for using it in negotiation or legislation, in the same way that a discount rate is now a standard disclosure in any cost-benefit analysis submitted to a regulator.

Third, the choice of damage function deserves at least as much policy attention as the discount rate, since it does more to reshuffle which countries appear most exposed. A long-run, adaptation-consistent damage function is also a claim about a country's institutional and economic capacity to adjust to a changing climate over time -- a claim with direct relevance to adaptation finance design, not just mitigation policy. Linking SCC-based mitigation policy to SCC-based adaptation finance, using a single, internally consistent damage- function choice, would tie the two halves of the special issue's mandate together more coherently than treating them as separate exercises.

7. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

Country-level decompositions of the social cost of carbon have become an influential input into climate finance and equity arguments. This paper shows that the headline finding behind much of that influence -- that a handful of large, often middle-income economies bear most of the global cost -- is largely a function of economic scale, not a free-standing measure of relative vulnerability. Once normalized by GDP, the equity conclusion is not robust: It depends on the discounting assumption chosen, more than on the emissions scenario or, to a lesser extent, the damage function. For developing economies and the institutions advocating on their behalf, this means the technical choice of discount rate is not a footnote. It is the variable that decides whether the social cost of carbon supports, or undercuts, the case for a disproportionate economic burden.

Several limitations bound these conclusions. The underlying CSCC database relies on a single empirical damage-function family (BHM and its income-split variant, plus DJO as an alternative); a fuller robustness exercise would incorporate the broader integrated-assessment-model literature, including DICE- and FUND-based country disaggregations, where available. This matters in part because the BHM specification itself has been questioned: Newell et al. (2021) argue it overstates marginal climate impacts in already-hot countries and understates them in cold ones, a directional bias that, if correct, would tend to inflate our primary database's CSCC estimates for many of the same lower-latitude developing economies whose equity burden is the focus of this paper. Our external validation in Section 5.4 partially addresses this concern, since the Agarwala and Tol national SCC estimates do not share this specific critique, but a full re-analysis using a damage function immune to it remains for future work. Our covariates are limited to publicly available macroeconomic and emissions data; a natural extension would add climate-vulnerability indices such as ND-GAIN, carbon pricing adoption from the World Bank Carbon Pricing Dashboard, and institutional quality measures, none of which we were able to incorporate within the compressed timeline of this submission. The cross-sectional design also cannot speak to how these relationships evolve as countries develop; a panel extension, tracking how a country's CSCC/GDP exposure changes as it crosses income-group thresholds, is a promising direction for follow-up work.

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