Extreme weather and climate policy

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Abstract

What effect does extreme weather have on climate policy? Existing studies show that weather shocks have negative economic impacts and increase public awareness of climate change. These findings help identify the impacts of climate change on economic and social systems, and provide reasons for governments to adopt climate policy reforms. However, questions remain about the overall link between local extreme weather shocks and government climate policy. I investigate the effect of temperature shocks and natural disasters on a range of national, international, and subnational climate policies in samples spanning 1990–2018. I find that neither temperature shocks nor natural disasters generate climate mitigation reforms. Given that climate policy is currently insufficient to manage climate change and climate impacts are expected to increase this century, these findings suggest that future climate shocks are unlikely to catalyze meaningful climate action.

Keywords

climate change; climate mitigation; environmental politics; external shocks; natural disasters; policy responsiveness

Supporting information for: "Extreme weather and climate policy"

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APP-I Estimating equations

Specification	Estimating equation	Visual
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Baseline, 1-, 2-, 3-year lags	APP-1	Figure 2
Temperature bins	APP-2	Figure 3, APP-2
Cumulative shocks	APP-3	Figure APP-3, APP-4
Natural disasters	APP-1	Figure 4
Heterogeneous effects	APP-4	Figure 5, APP-5
US subnational, 1-, 2-, 3-year lags	APP-1	Figure APP-8

Baseline two-way fixed effects estimator: (APP-1)

$$\text{Policy}_{i,t}^{k} = \beta\, \text{Temperature}_{i,t-l} + \gamma_i + \delta_t + \theta_i\, t + \epsilon_{i,t}$$

for l in $\{1, 2, 3\}$ years, and where Temperature is the average annual or seasonal temperature in a country's hottest season.

Non-parametric temperature bins estimator: (APP-2)

$$\begin{aligned}\text{Policy}_{i,t}^{k} = {} & \beta_1 \text{Temperature}_{i,t-1}^{(-\infty,10]} + \beta_2 \text{Temperature}_{i,t-1}^{(10:15]} + \beta_3 \text{Temperature}_{i,t-1}^{(20:25]} \\ & + \beta_4 \text{Temperature}_{i,t-1}^{(25:30]} + \beta_5 \text{Temperature}_{i,t-1}^{(30:35]} + \beta_6 \text{Temperature}_{i,t-1}^{(35:\infty)} + \gamma_i \\ & + \delta_t + \theta_i t + \epsilon_{i,t}\end{aligned}$$

where Temperature is the count of days in a country's hottest season where the local measured temperature is within that bin.

Cumulative temperature shocks (intensification) estimator: (APP-3)

$$\begin{aligned}\text{Policy}_{i,t}^{k} = {} & \beta_1 \text{Temperature}_{i,t-1} + \beta_2 \text{Cumulative Temperature Shocks}_{i,t-2} \\ & + \beta_3 \text{Temperature}_{i,t-1} \times \text{Cumulative Temperature Shocks}_{i,t-2} + \gamma_i + \delta_t + \epsilon_{i,t}\end{aligned}$$

where Temperature is the average annual temperature or average seasonal temperature in a country's hottest season, and Cumulative Temperature Shocks standardizes temperature within countries, then cumulatively sums positive z-scores within countries over time, replacing negative z-scores with 0 to create a continuous measure of the intensity of past temperature shocks. The results presented in figure APP-4 are for Cumulative Temperature Shocks re-coded into low, medium, and high following Hainmueller et al. (2019)'s example of a binning estimator to investigate the linearity assumption in multiplicative interaction models.

Heterogeneous treatment effects estimator: (APP-4)

$$Policy_{i,t}^{k} = \begin{cases} \beta \text{Temperature}_{i,t-l} + \gamma_i + \delta_t + \theta_i\, t + \epsilon_{i,t}, & Democracy_i = 1 \\ \beta \text{Temperature}_{i,t-l} + \gamma_i + \delta_t + \theta_i\, t + \epsilon_{i,t}, & Democracy_i = 0 \end{cases}$$

for l in $\{1, 2, 3\}$ years, and where Temperature is the average annual or seasonal temperature in a country's hottest season, estimated separately for democracies and non-democracies.

APP-II Supplementary analysis figures

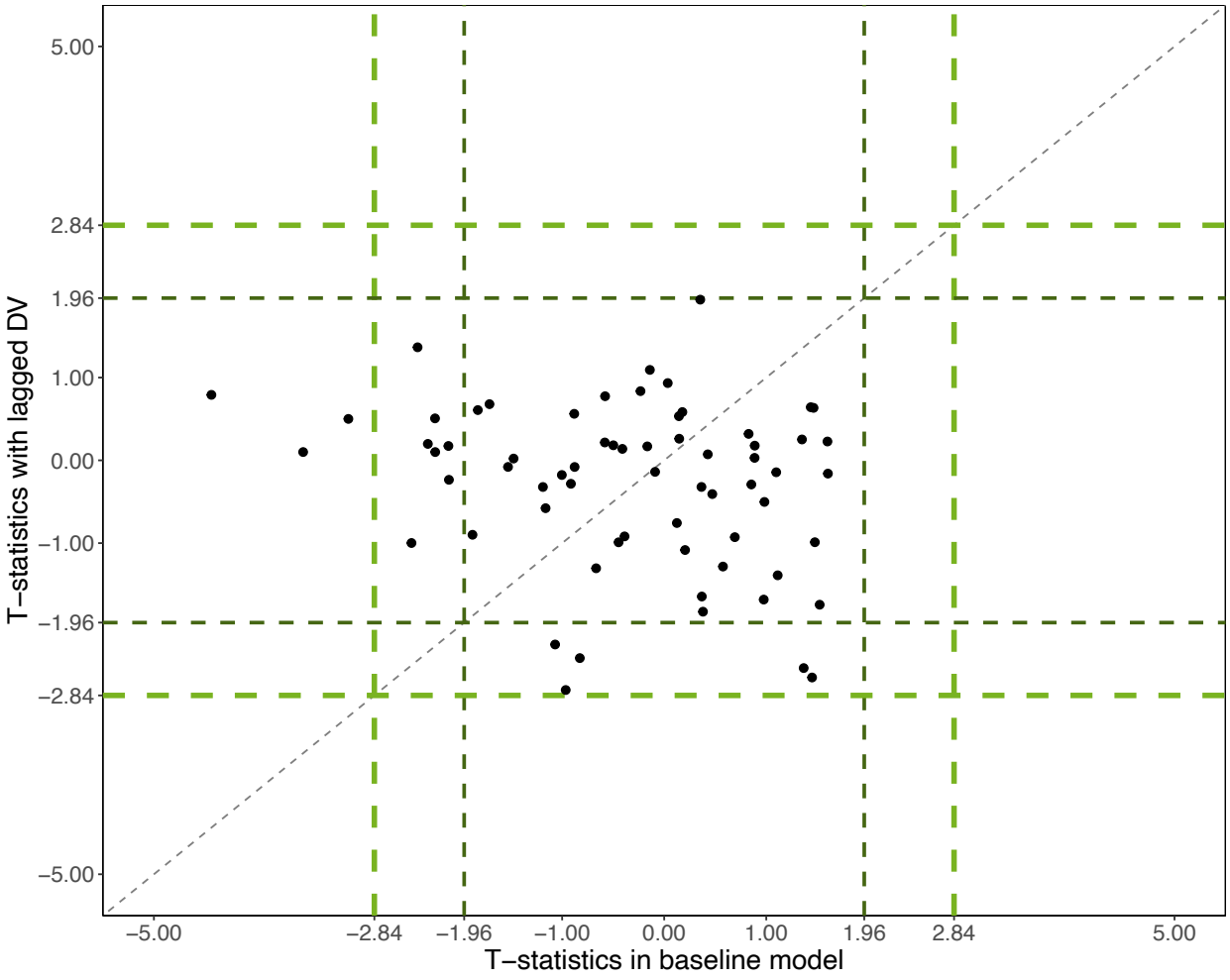

Figure APP-1: *Lagged dependent variable*. Main results from figure 2 are robust to the inclusion of a lagged dependent variable. Vertical/horizontal lines are uncorrected 95% confidence intervals (dark green, $t = |1.96|$) and Bonferroni-corrected confidence intervals (light green, $t = |2.84|$); diagonal line is $y = x$.

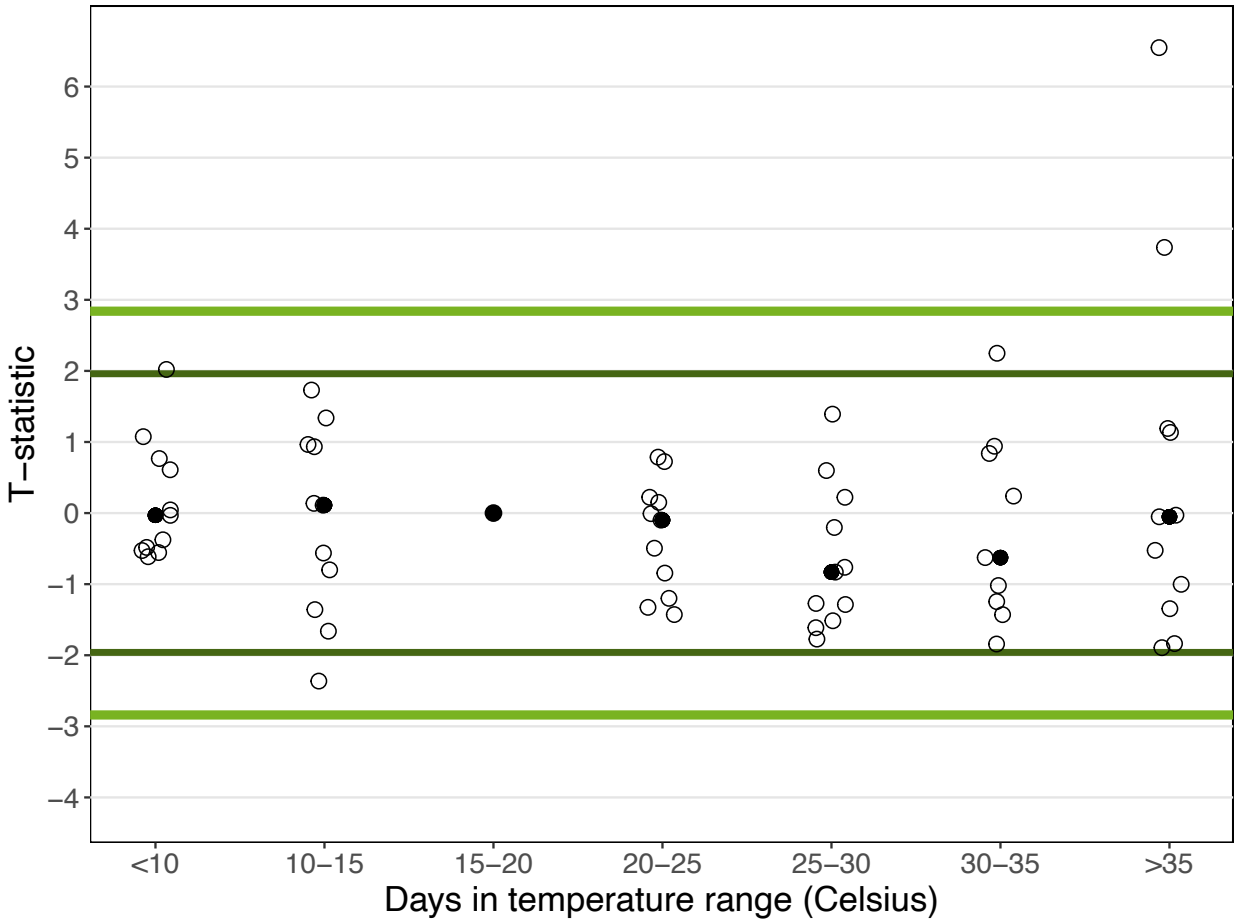

Figure APP-2: *Temperature bins*. Distribution of t-statistics from temperature bin models, equation APP-2 and figure 3. Solid marker point is the mean t-statistic within that temperature bin. Horizontal lines indicate statistical significance thresholds for $\alpha = 0.05$ and multiple comparisons $\alpha = 0.05/11 \rightarrow 0.0045$

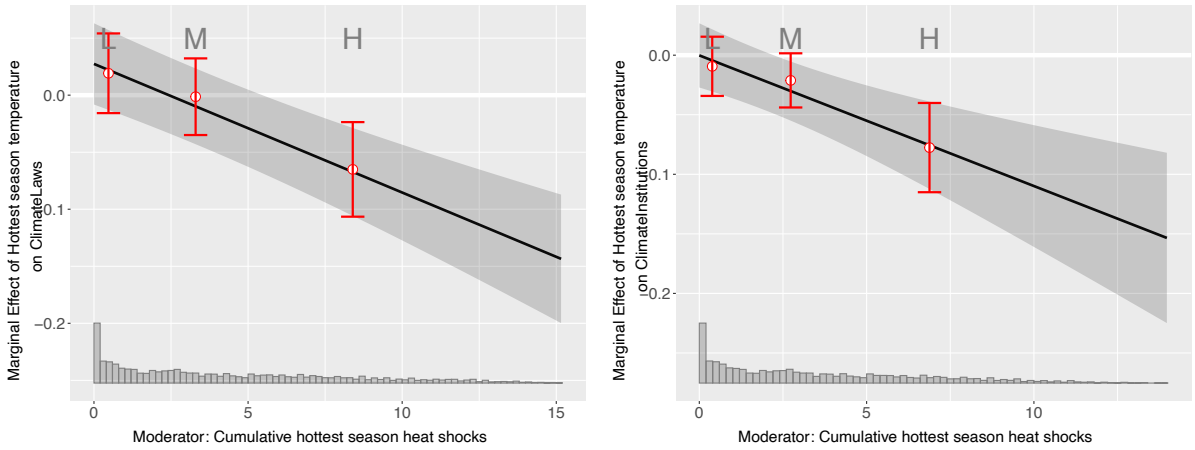

Figure APP-3: *Cumulative shocks*. Intensification of temperature shocks over time. Estimates are from OLS models that allow the marginal effect of temperature shocks to vary based on cumulative recent temperature shocks. Outcomes are climate laws (left panel), and climate institutions (right panel). 95% confidence intervals are not corrected for multiple comparisons. See figure APP-4 for corrected significance levels and all outcomes variables.

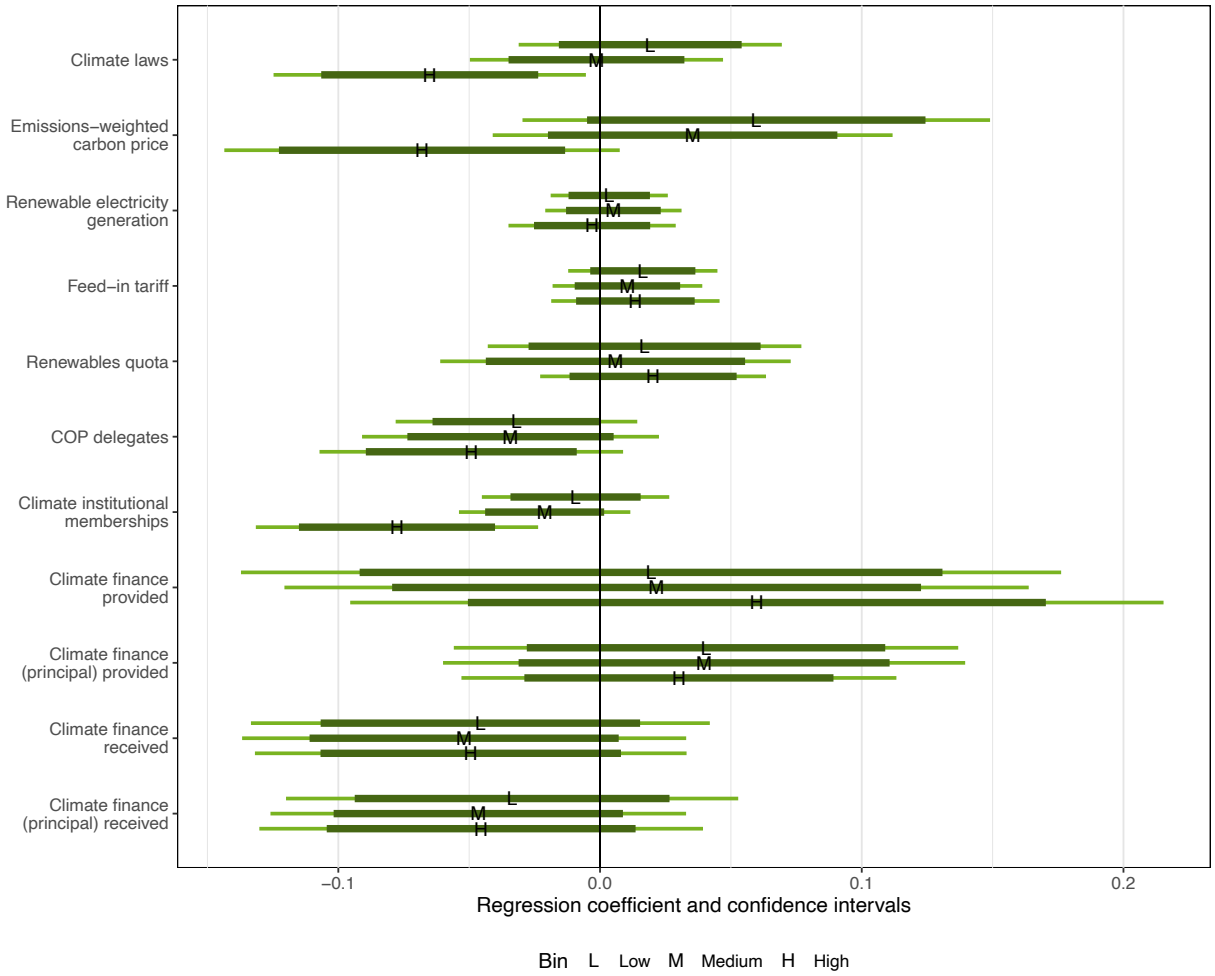

Figure APP-4: *Cumulative shocks*. Effect of lagged hottest season temperature shock, conditional on stock of accumulated temperature hazards, equation APP-3 and figure APP-3. Linear interaction term trichotomized into low, medium, and high values of the moderator (cumulative temperature shocks), using interflex from Hainmueller et al. (2019). Outcome variables are standardized prior to estimation to facilitate comparison. Horizontal bars are uncorrected 95% confidence intervals (thicker, dark green) and Bonferroni-corrected confidence intervals for 11 comparisons (thinner, light green).

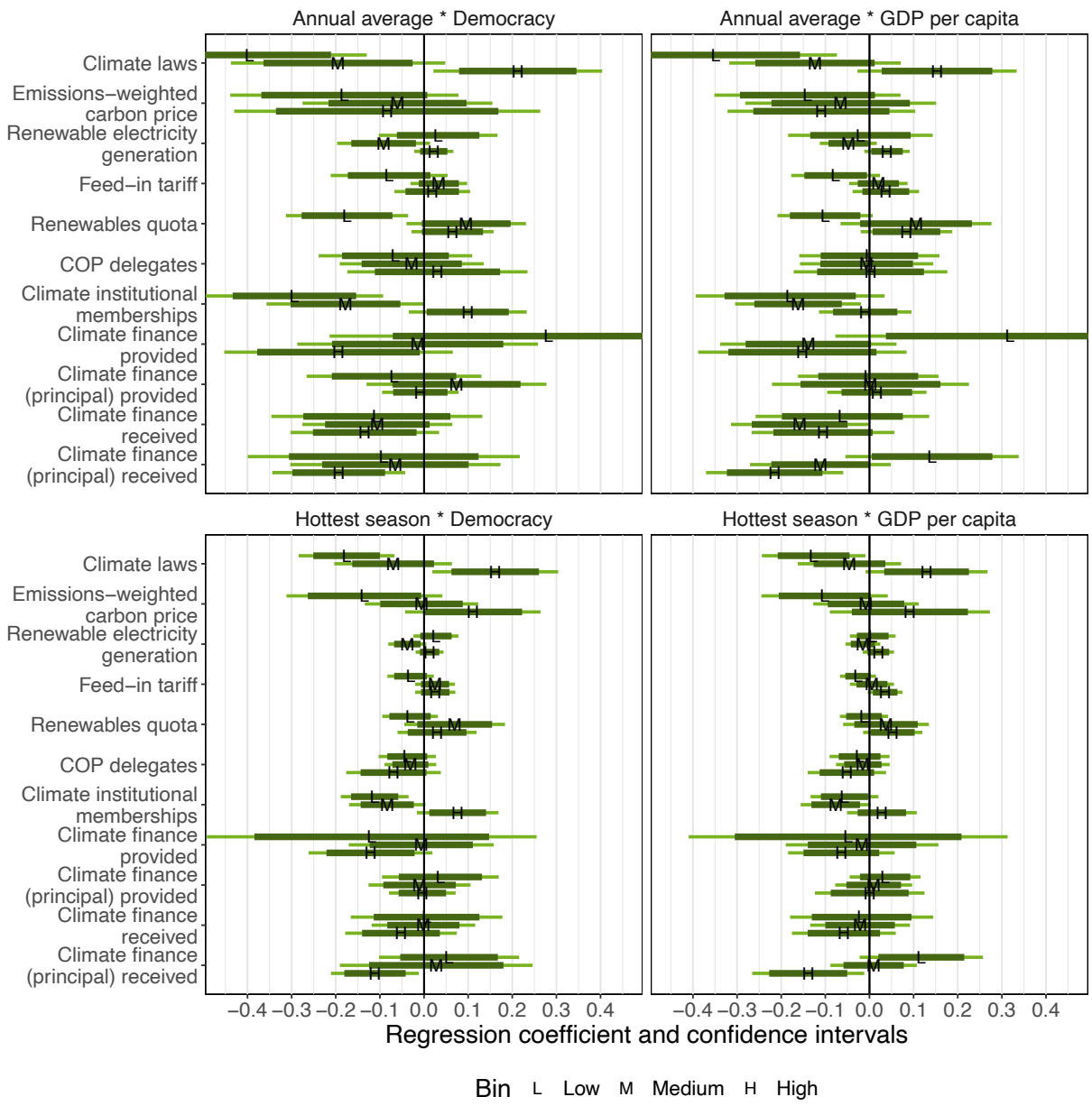

Figure APP-5: *Continuous interaction effects*. Heterogeneous effects across political contexts using continuous moderators. Linear interaction term trichotomized into low, medium, and high values of the moderator (V-Dem's democracy index or logged GDP per capita), using interflex from Hainmueller et al. (2019). Outcome variables are standardized prior to estimation to facilitate comparison. Horizontal bars are uncorrected 95% confidence intervals (thicker, dark green) and Bonferroni-corrected confidence intervals for 11 comparisons (thinner, light green).

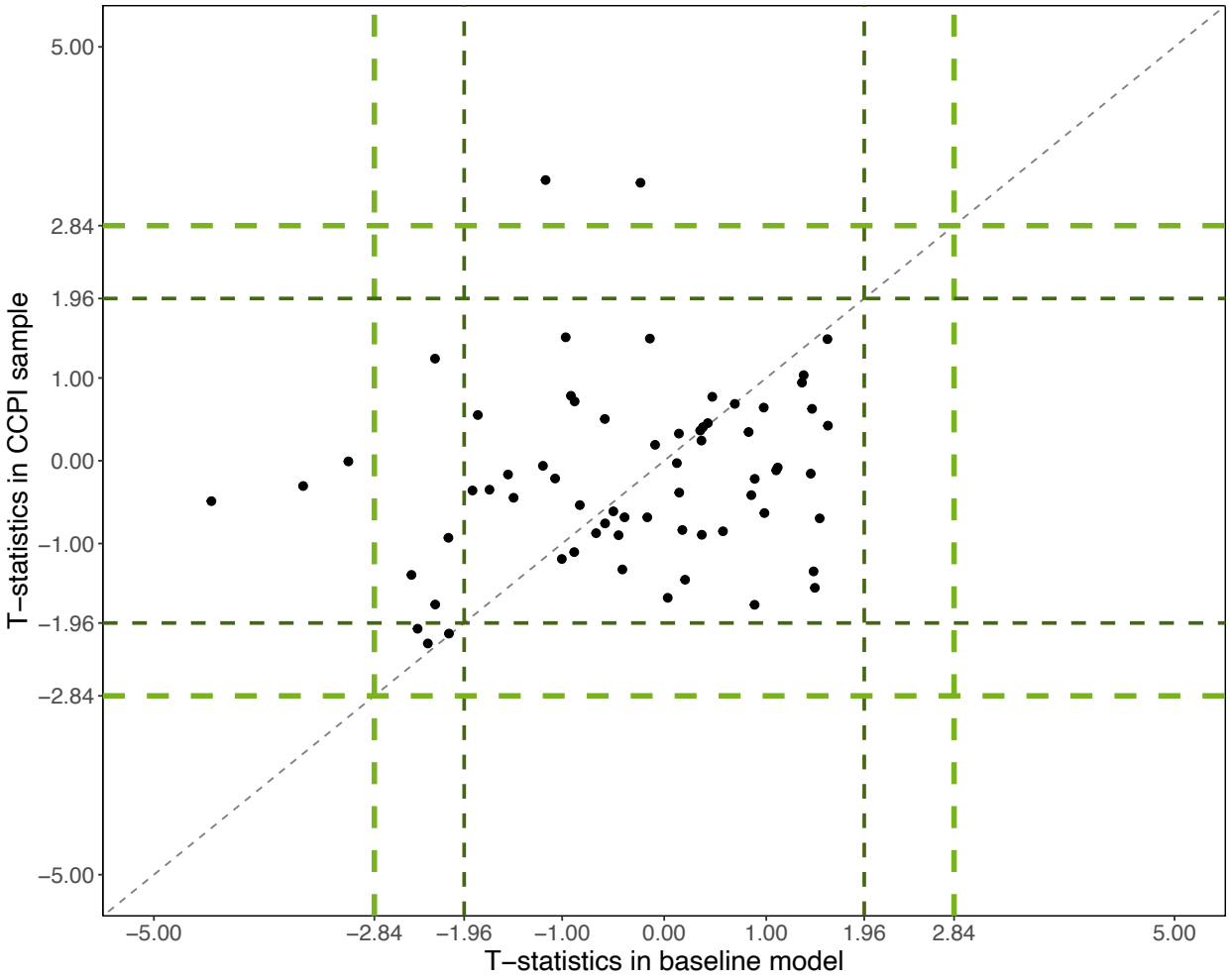

Figure APP-6: *Matched sample to Peterson (2021)*. Main results from figure 2 are robust to restricting the sample of countries and years to those covered by the Germanwatch Climate Change Policy Index, as used in Peterson (2021). Vertical/horizontal lines are uncorrected 95% confidence intervals (dark green, $t = |1.96|$) and Bonferroni-corrected confidence intervals (light green, $t = |2.84|$); diagonal line is $y = x$. Two positive coefficients (2 of 66 = 3.0%) are statistically significant: the effect of temperature shocks on the share of electricity generated from renewable sources measured using one-year lags for annual and hottest season temperature.

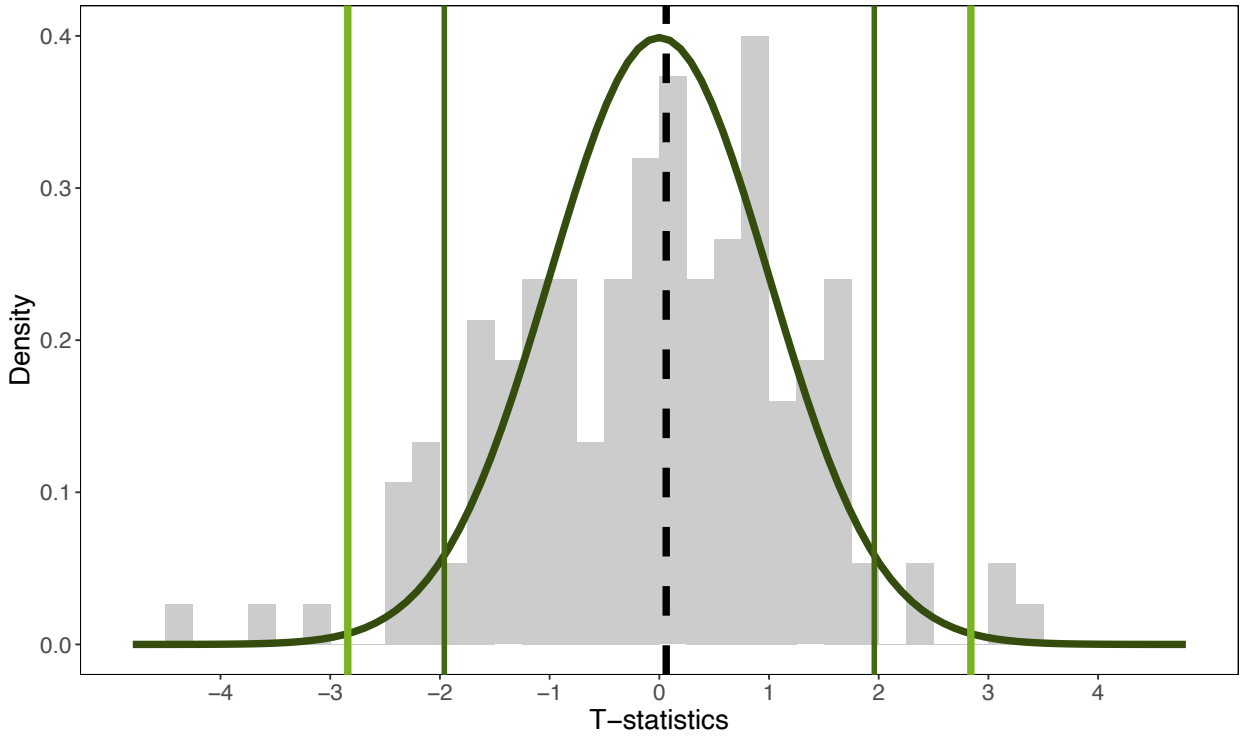

Figure APP-7: *Null distribution*. Distribution of t-statistics from models in figures 2 and APP-1. 6 of 150 (4%) t-statistics are larger than |2.84|, roughly what we would expect under a sharp null hypothesis. Vertical lines are uncorrected 95% confidence intervals (dark green, t = |1.96|) and Bonferroni-corrected confidence intervals (light green, t = |2.84|). Dashed line is the median t-statistic. Smooth curve shows the normal distribution.

APP-III Subnational analysis in American states

Climate research increasingly emphasizes that decarbonization faces similar structural challenges at the international, national, and subnational levels. I now extend the cross-country analysis to examine the relationship subnationally in US states. The United States has developed lacklustre climate policies nationally, but US states have been highly innovative. A growing body of research examines the political factors that determine US subnational outcomes, especially in terms of renewable energy promotion (Carley et al. 2017; Stokes 2020; Trachtman 2020). The US is a wealthy, democratic country with substantial devolved powers over climate-related domains. Much of the existing research on the negative economic consequences and changes in public attitudes following temperature shocks is evaluated in US samples. This suggests the US should be a likely case for a relationship between adverse climate impacts and climate policy. But as with the global sample, the effect of climate impacts on policy is poorly understood.

I estimate equation 1, now with US state and year fixed effects to identify the effect of temperature shocks from state-level averages and national-level trends. Many underlying differences across countries are eliminated in this subnational design that only allows within-case variation—or "within–within-case" variation, given the country fixed effects. I investigate average annual temperature and average summer temperature. Figure APP-8 reports results for three continuous state-level outcome variables, which reflect the stringency of state-level renewable energy portfolio standards, the development of distributed electricity generation capacities, and energy efficiency policies, all of which vary at the state-year level. State-level climate policy outcomes are taken from Trachtman (2020)'s research on the partisan drivers of state-level policy adoption. I find no consistent effect for temperature shocks on any subnational outcome.

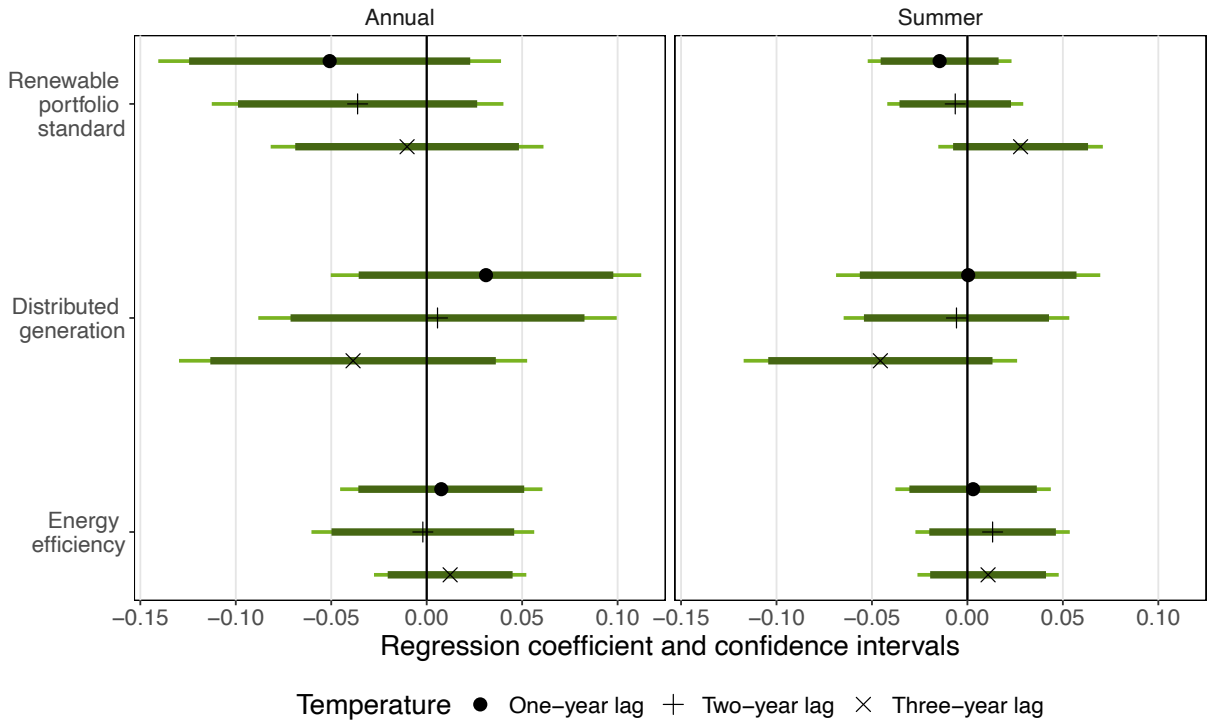

Figure APP-8: Effect of temperature shocks on US subnational climate policy. Dependent variables are standardized prior to estimation, and effect sizes are for a +1°C temperature shock. Point estimates are coefficients from OLS models with state and year fixed effects, lagging temperature by 1, 2, and 3 years. Horizontal bars are uncorrected 95% confidence intervals (thicker, dark green) and Bonferroni-corrected confidence intervals for 3 comparisons (thinner, light green).

APP-IV Description of variables

Measure	Countries	Years
National policies		
Count of climate laws	190	1990–2018
Emissions-weighted carbon price	29	1990–2018
Share of renewables in electricity generation	191	1990–2015
Probability that feed-in tariff exists	62	1991–2013
Probability a renewable energy quota exists	19	1991–2013
International policies		
Number of COP delegates	186	1995–2015
Number of climate institutional memberships	191	1990–2015
Sum of climate finance provided: total definition	45	2012–2017
Sum of climate finance provided: principal definition	45	2012–2017
Sum of climate finance received: total definition	143	2000–2017
Sum of climate finance received: principal definition	143	2000–2017

Global climate policy outcome variables

Climate change laws *Climate Change Laws of the World* database compiles national-level climate change legislation. The database covers climate and climate-related laws, as well as laws and policies promoting low carbon transitions, which reflects the relevance of climate policy in areas including energy, transport, land use, and climate resilience. Final variable is a count of the number of existing climate change laws in a country, including amendments. Source: Grantham Research Institute on Climate Change (2020)

Emissions-weighted carbon price Continuous measure of national carbon price in a given year. When sectors of the economy have different carbon prices, these different prices are weighted by their share of national emissions. Source: World Bank (2020)

Renewable electricity generation Electricity generated from renewable energy sources (rather than fossil fuels) as a share of total electricity generation. Data collected by the International Energy Agency (IEA), and compiled by the World Bank. Source: World Bank (2018)

Feed-in tariff Binary indicator for whether a country has a feed-in tariff for renewable energy in a given year. Source: Baldwin et al. (2019)

Renewable energy quota Binary indicator for whether a country has a renewable energy quota in a given year. Source: Baldwin et al. (2019)

United Nations climate conference delegates Count of the number of delegates a country sends to the annual United Nations Framework Convention on Climate Change Conference of the Parties (COP). Source: Kaya and Schofield (2020)

Membership in climate institutions Count of the number of international institutions established to address climate change that a country is a member of in a given year. Source: Rowan (2021)

Climate finance The OECD DAC measures bilateral development finance targeting climate change objectives using the Rio markers. Bilateral funds are subset to consider only development finance flows "principally" intended to address climate change, as compared to flows that are "significantly" intended to address climate change. Countries are either providers or recipients of climate finance, which are measured separately. All measures are log transformed. Source: Organization for Economic Cooperation and Development (2020)

US climate policy outcome variables

Renewable portfolio standard The stringency of a renewable portfolio standard, defined by Carley et al. (2017) as the amount of increased renewable electricity generation mandated, divided by the number of years given to meet the standard, weighted by the percentage of that state's electricity generation that is included in the standard. Source: Trachtman (2020)

Distributed generation Distributed electricity generation refers to electricity generated at smaller scales (e.g., rooftop) than the large utilities that RPS's are designed to cover. States can promote distributed generation, and these efforts are scored by Freeing the Grid, a website hosted by solar energy interest groups. Source: Trachtman (2020)

Energy efficiency Scorecard data for state-level mechanisms intended to reduce energy consumption, graded by the American Council for an Energy Efficient Economy. Source: Trachtman (2020)

Explanatory variables

Country-level temperature Country-level time-series data on daily average national temperature. Gridded climate observations are weighted by gridded population data at the same resolution: $0.25^{\circ} \times 0.25^{\circ}$. Reanalysis data uses station and satellite data and fits a climate model to the observed data to fill gaps in data coverage. The ERA5 global reanalysis data is produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) Copernicus Climate Change Service (C3S). Data are aggregated to the country level using spatial population data from Natural Earth. Source: Hersbach et al. (2020)

Country-level natural disasters Country-level time-series data on annual national disasters. Natural disasters data are subset to include only events in the "meteorological" (e.g., extreme temperature, storm), "climatological" (e.g., drought, wildfire), and "hydrological" (e.g., flood, landslide) categories. "Count" takes the raw number of annual natural disasters within a country; "persons affected" is the count of persons affected by disasters, summed annually within a country and log transformed. Source: This is the Emergency Events Database (EM-DAT) compiled by the Centre for Research on the Epidemiology of Disasters (CRED) (2020).

US state-level temperature State-level time-series data on average annual temperature. Data are aggregated from 344 NOAA historical regional divisions that reflect combinations of area and population weights. Final annual-, state-level data average monthly measurements at the state-level. Source: National Centers for Environmental Information (2020)

Stratifying variables

Democratic political institutions Binary measure of whether a country is a democracy (n = 106) or an autocracy (n = 84). Source: Boix et al. (2013)

Rich Binary measure of rich (n = 64) and poor rich (n = 119) countries, based whether a country has high GDP per capita (NY.GDP.PCAP.PP.KD) in 1990. Cutoff is roughly the 70th empirical percentile, ~ 11,500 in 1990 USD. Source: World Bank (2018)

APP-V Descriptive trends in variables

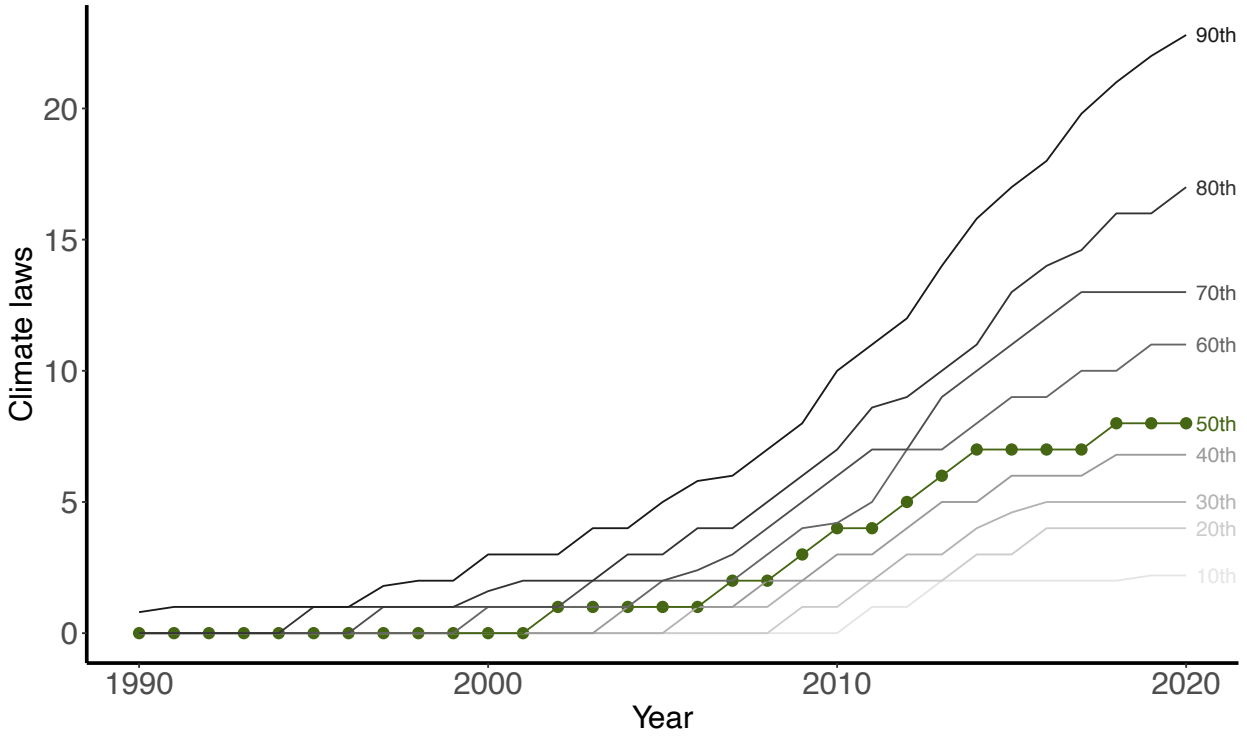

Figure APP-9: Distribution of climate laws (lines are percentiles)

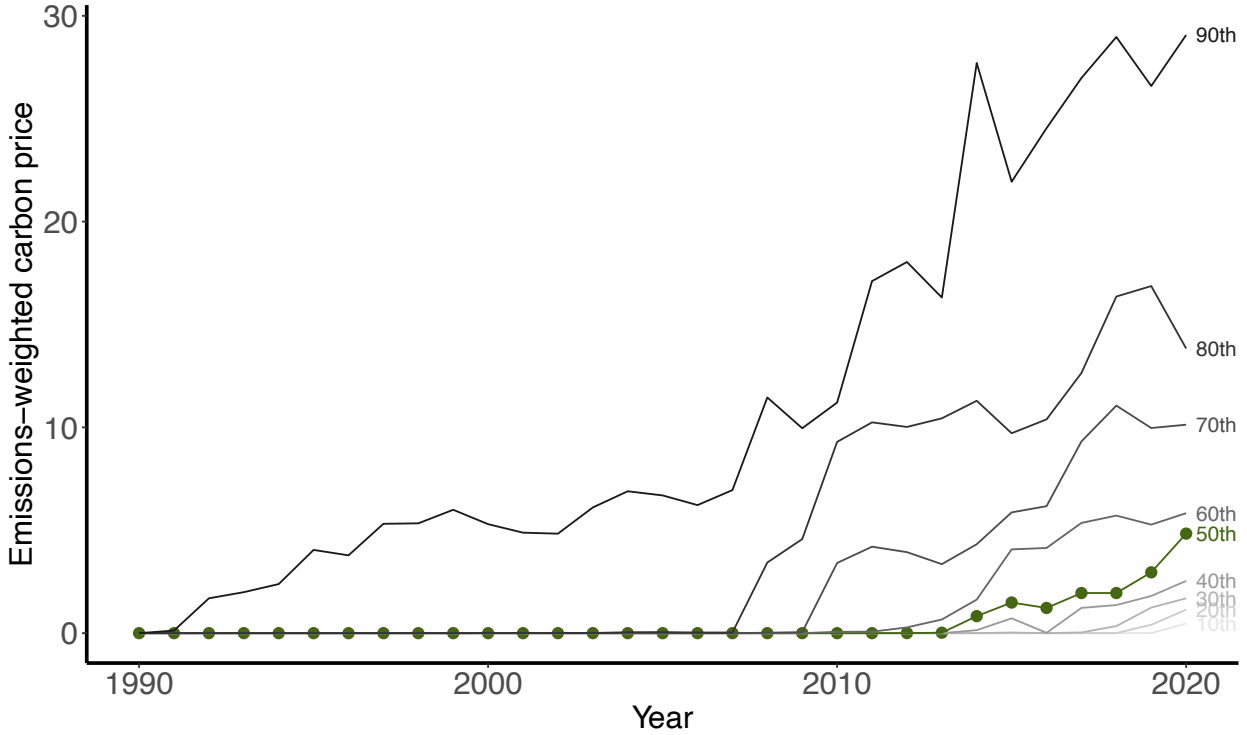

Figure APP-10: Distribution of emissions-weighted carbon price

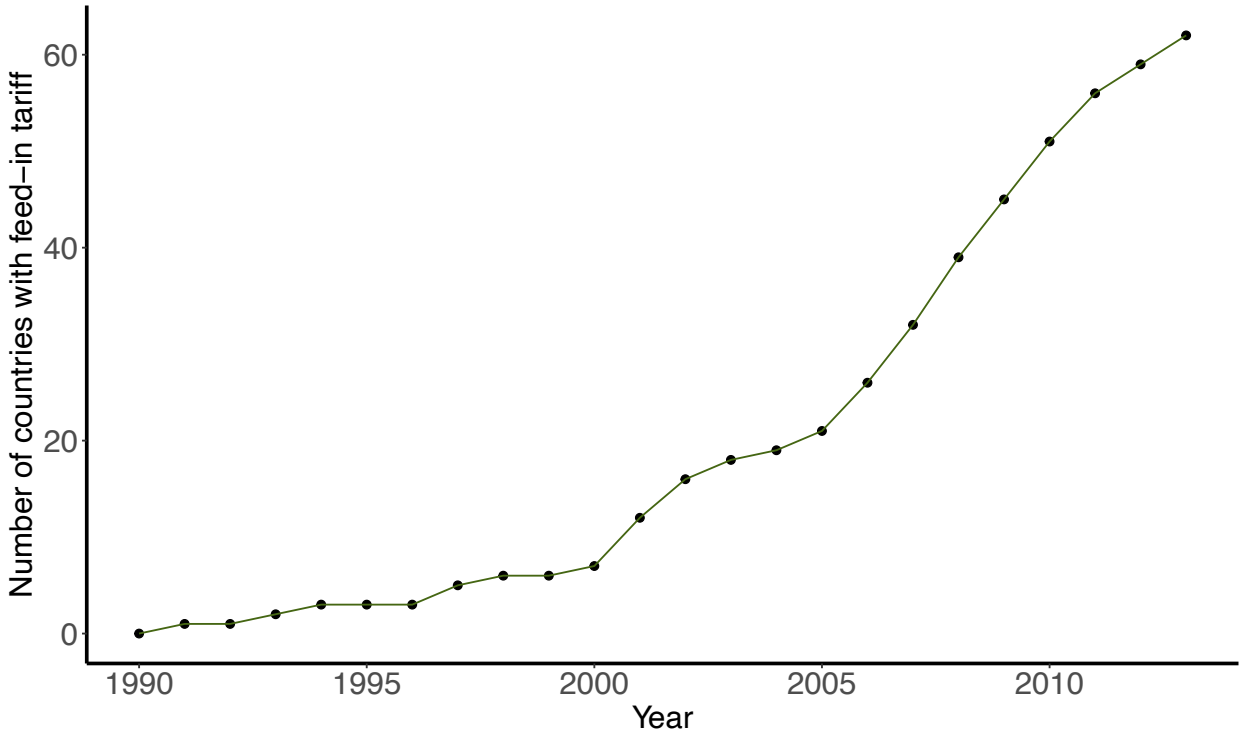

Figure APP-11: Distribution of feed-in tariff

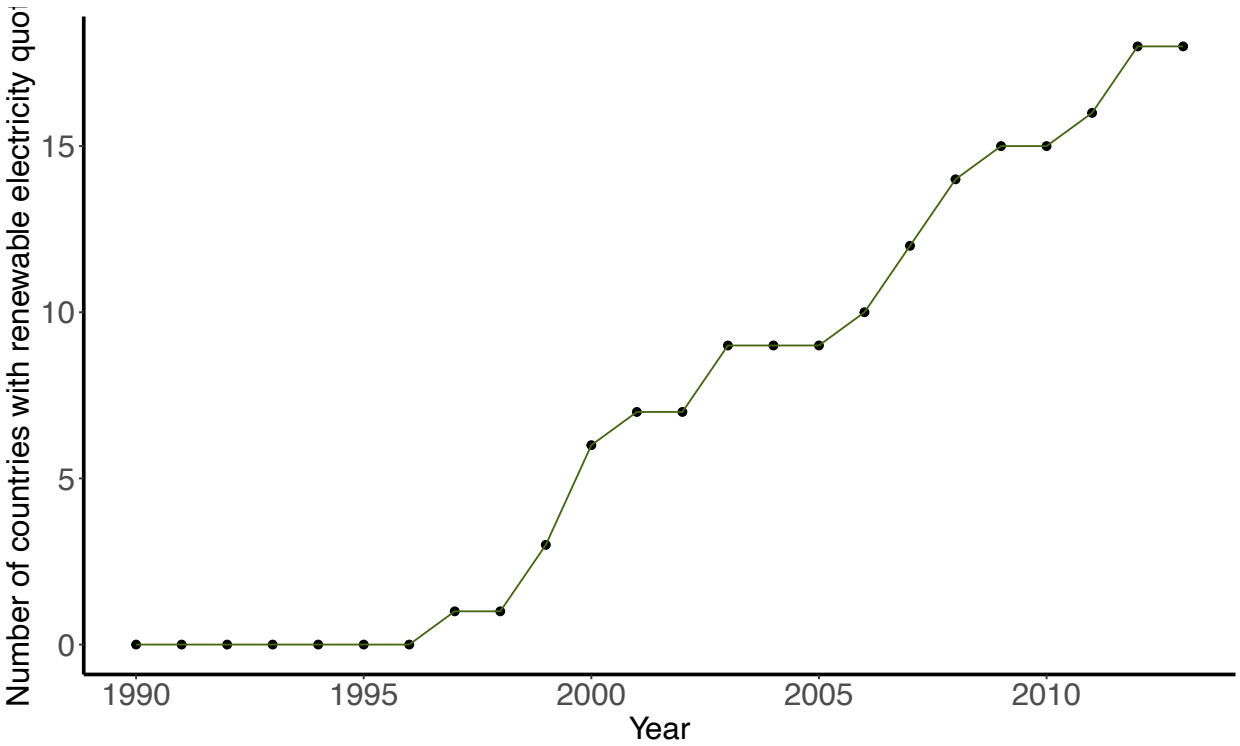

Figure APP-12: Distribution of renewable electricity quota

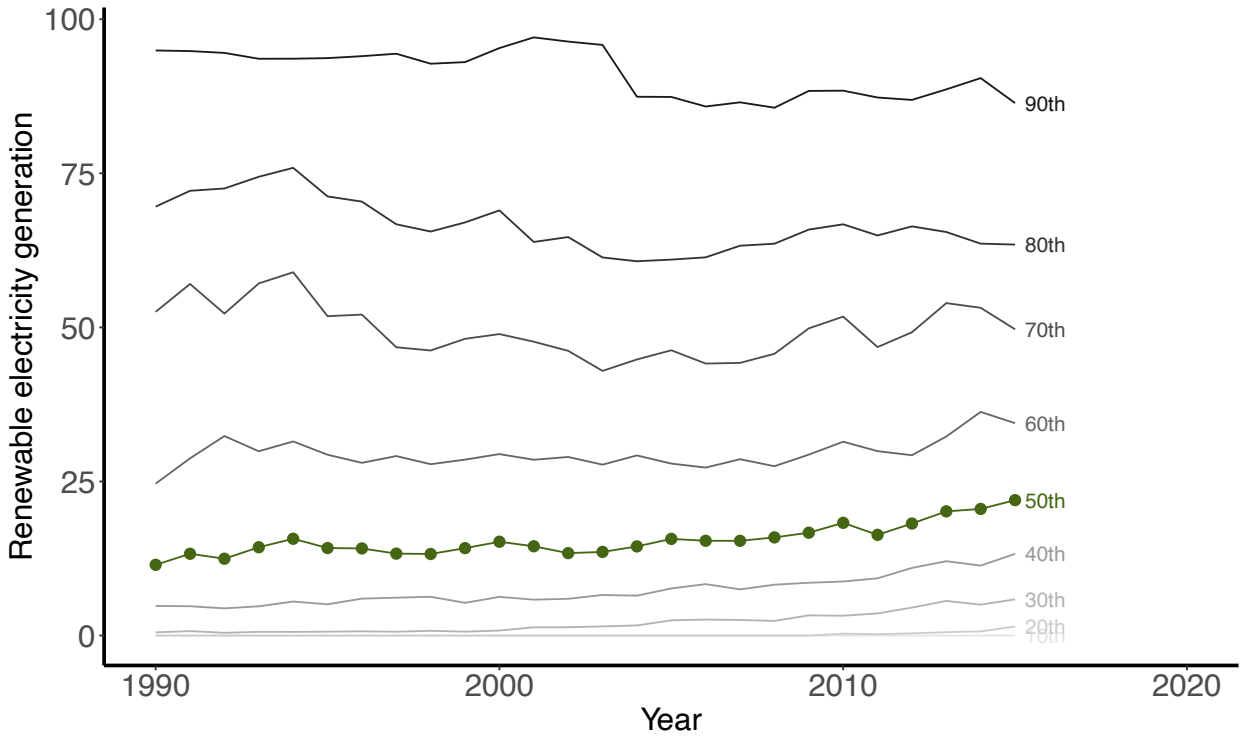

Figure APP-13: Distribution of renewable electricity generation

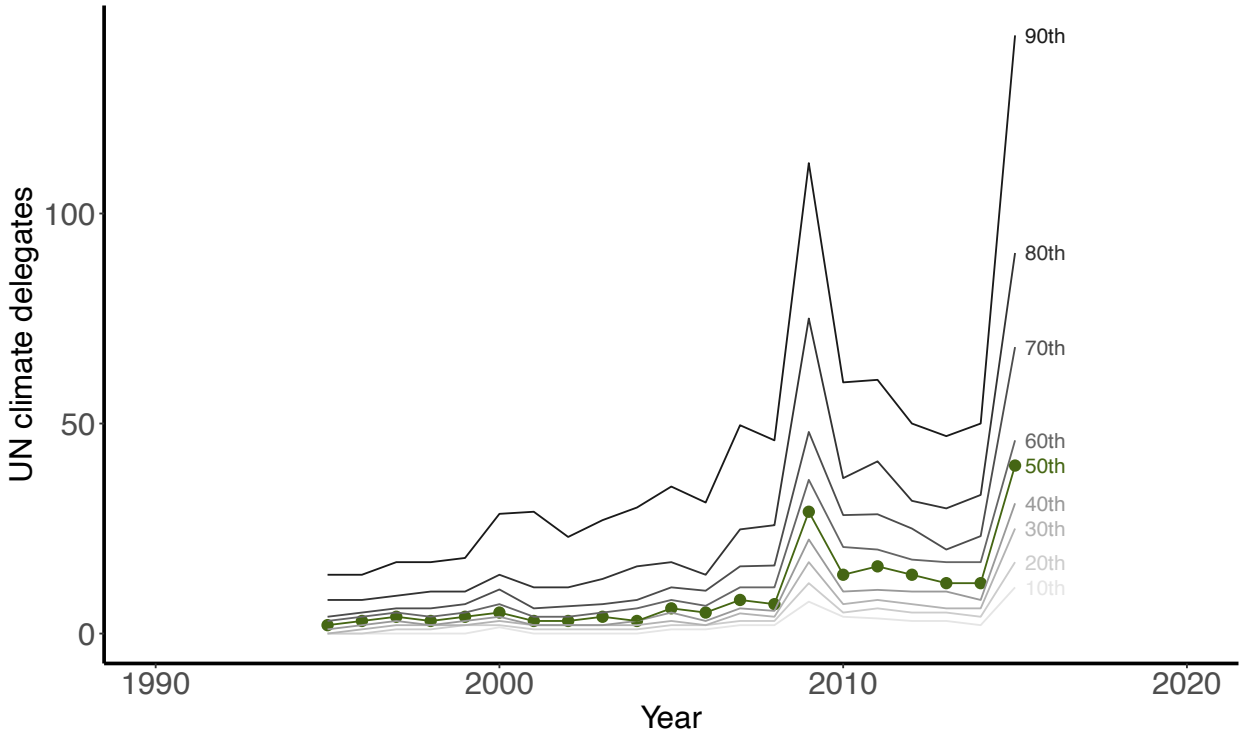

Figure APP-14: Distribution of UN climate delegates

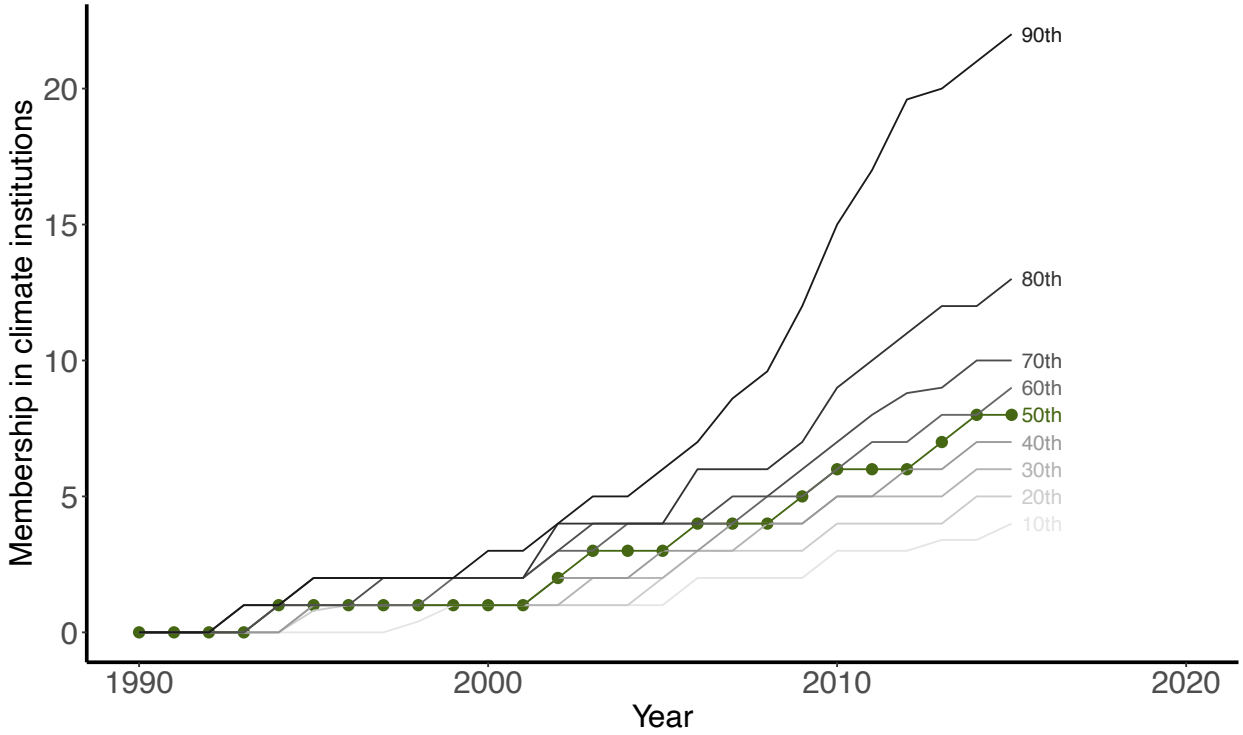

Figure APP-15: Distribution of membership in climate institutions

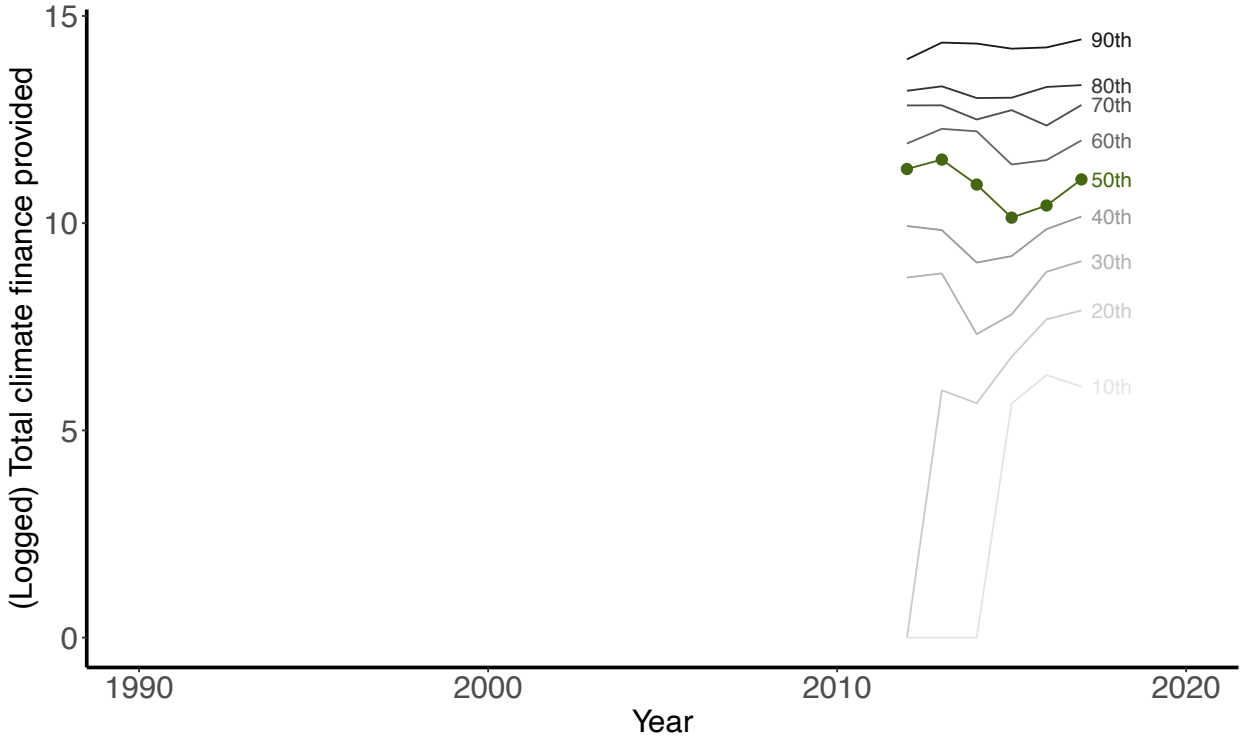

Figure APP-16: Distribution of total climate finance provided

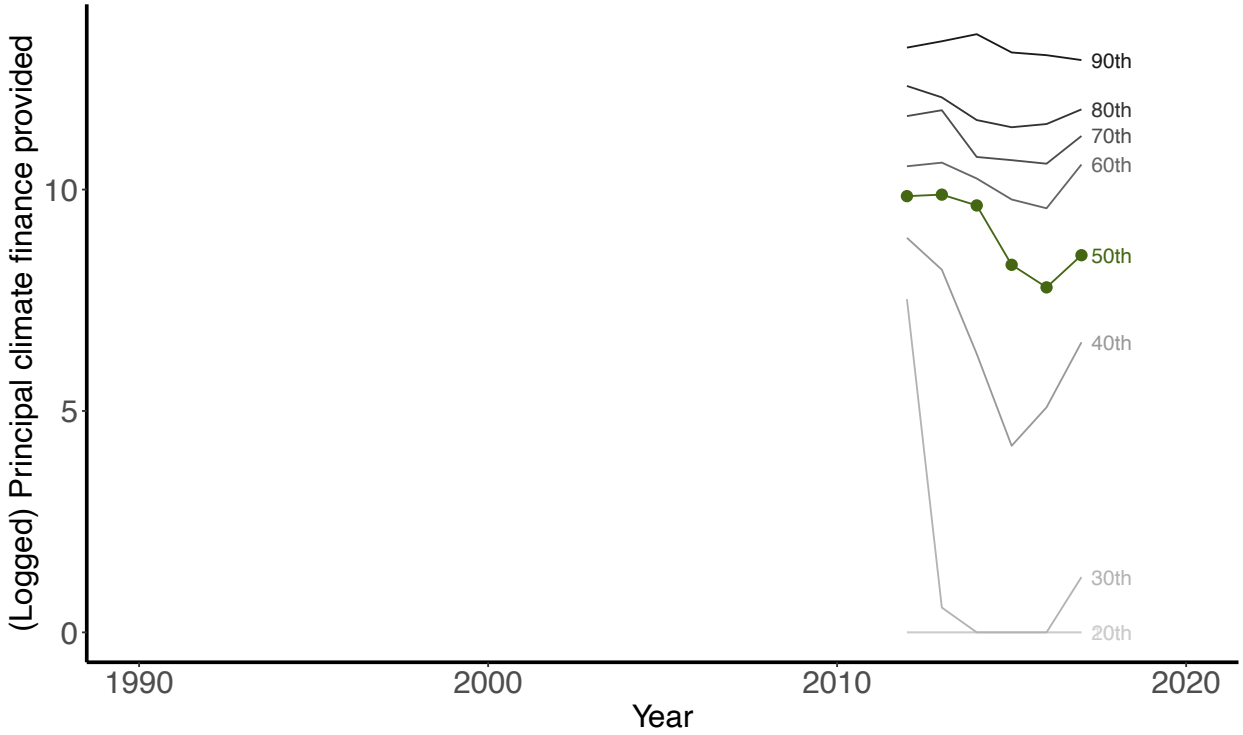

Figure APP-17: Distribution of principal climate finance provided

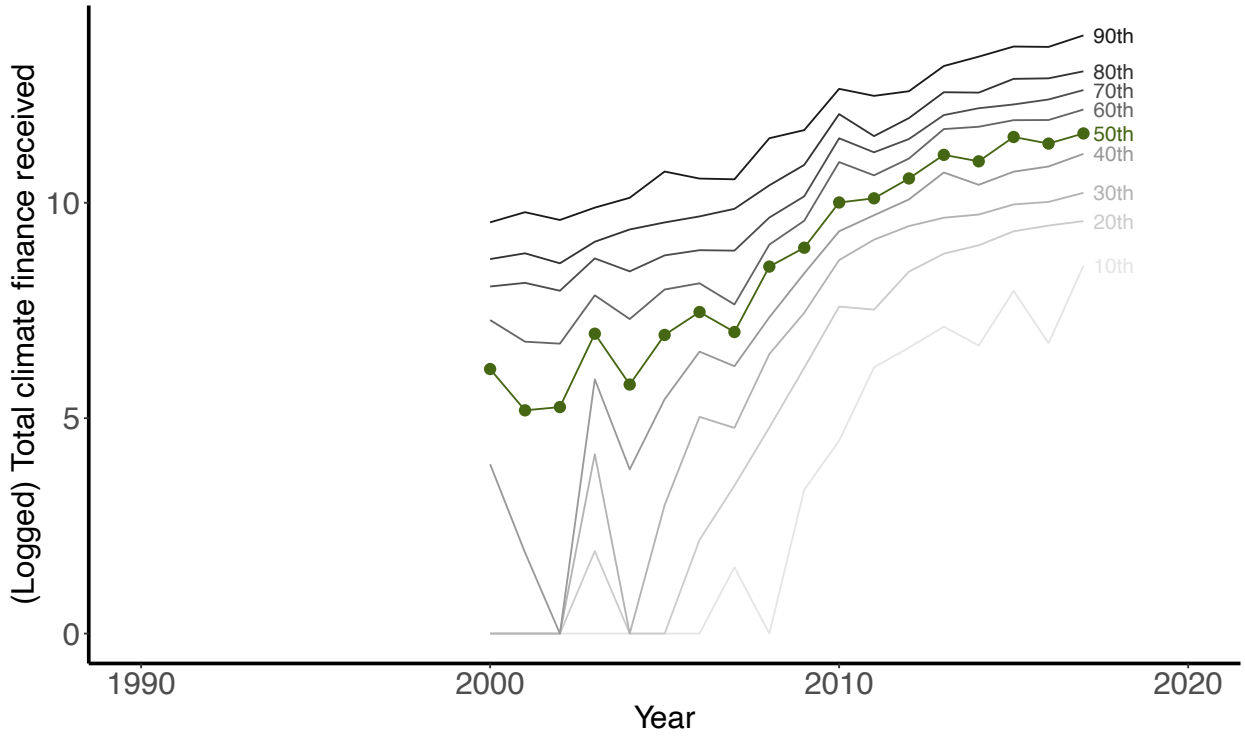

Figure APP-18: Distribution of total climate finance received

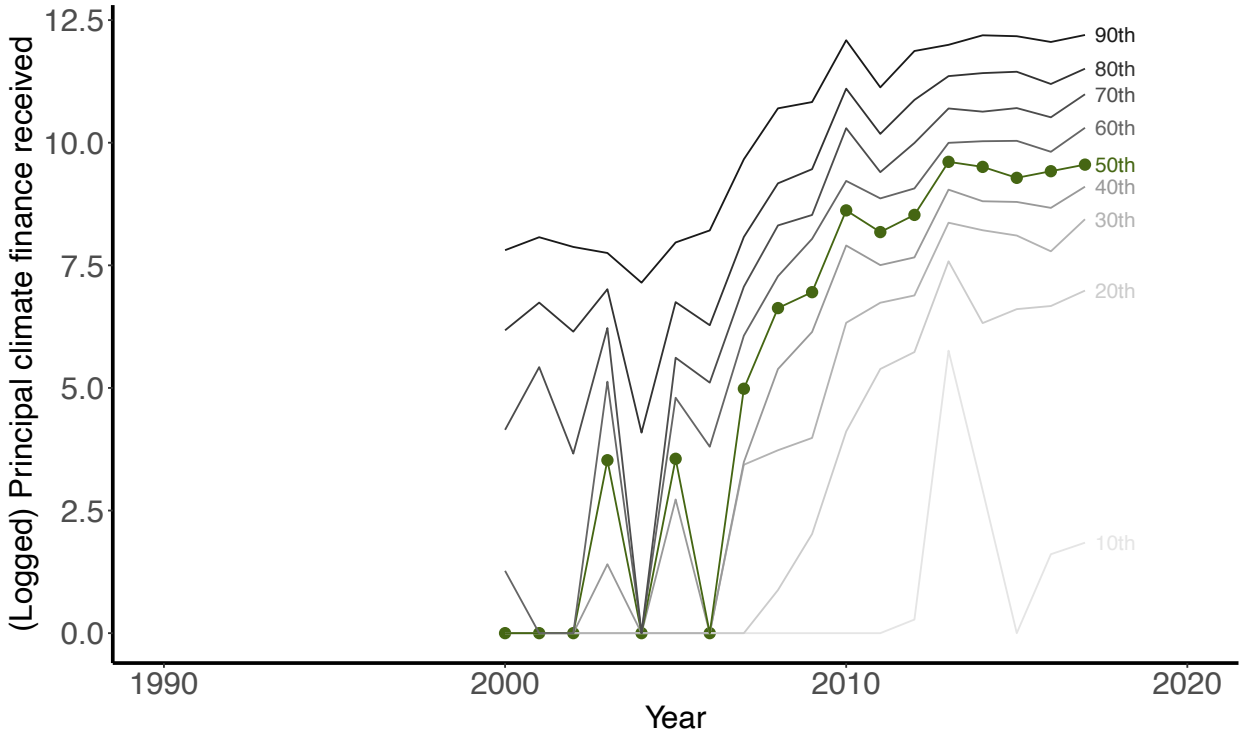

Figure APP-19: Distribution of principal climate finance received

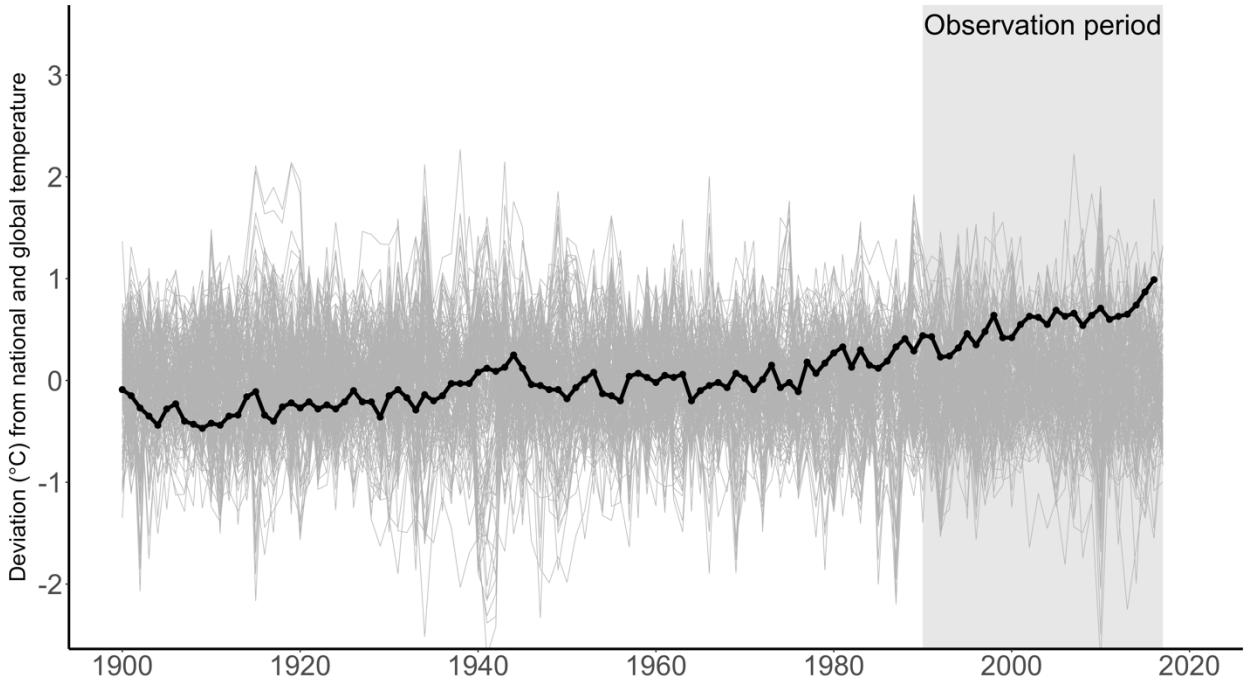

Figure APP-20: National temperatures demeaned from country and annual means. Global average temperature is plotted in black.

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