Learning and Free-Riding in International Climate Policymaking*

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Job market paper. Please read the latest version of the paper and the appendix.

Abstract

International climate cooperation is often presented as a case of the tragedy of the commons, where individual countries have incentives to free-ride on other nations' emissions reduction efforts. I present empirical evidence to the contrary: countries' climate actions are positively correlated over time, exhibiting a pattern of complementary efforts across nations. I explain this discrepancy with a formal model in which—in addition to providing the global public good of reducing emissions—other countries' mitigation efforts signal information about the economic value and policy success of a green transition. These learning effects are strongest when a country's belief in the economic success of green policy dominates its aversion to risk incurred investing in climate policies with uncertain returns. I test this learning mechanism using survey data on both mass and elite beliefs, showing that optimism about climate policy diffuses across borders and predicts more stringent mitigation efforts.

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How does the behavior of other nations influence interstate climate policy adoption? Long-standing scholarship emphasizes the temptations to free-ride inherent to collective action concerns (e.g., Olson 1965; Ostrom 1990; Barrett 2003; Stern 2007; Bernauer 2013; Keohane and Victor 2016). Per this view, the local costs of mitigation outweigh the global benefits of environmental protection, and there are diminishing marginal returns to global abatement efforts, so countries' emissions reduction efforts should be negatively correlated.

This paper engages in three tasks that demonstrate that a free-rider explanation of international climate cooperation is incomplete. First, I document a positive relationship between other nations' behavior and climate mitigation efforts. This reflects potential complementarities in countries' environmental policies on average rather than effort substitution, and suggests that free-riding may not be the only mechanism affecting international climate policymaking. Second, to unpack this empirical finding, I develop a formal model that introduces an additional causal mechanism—learning about the success of green policies—into the global public goods problem of climate mitigation. The theory demonstrates that cross-country climate actions are positively correlated when a country's belief in the economic benefits of green policy, though uncertain, outweighs the risk generated by implementing costly climate policies with unknown success. Finally, I examine empirical implications of the learning mechanism by testing how mass publics' and climate elites' perceptions of the importance of climate efforts map onto downstream mitigation stringency, providing reduced-form evidence of the learning effect.

The theory blends classical collective action frameworks of global public goods provision with arguments about observational learning to demonstrate the dual mechanisms of free-riding and learning in international climate cooperation. In the model, countries engage in climate policymaking over time and observe the mitigation measures implemented by other nations. As in collective action theories, everyone is better off when nations exert more effort to abate the effects of climate change, but there are diminishing marginal returns to subsequent efforts, and taking action is locally costly. However, in contrast to conventional models, there is a fundamental uncertainty about the economic gains from the green transition: countries want to make costly climate policy investments that are commensurate with their beliefs that the green transition will be successful. Optimal emissions reduction policies balance countries' willingness to institute green policies that carry uncertain economic benefits, their marginal impact on global mitigation efforts, and the political costs of implementation (e.g., Bechtel and Scheve 2013; Stokes 2016; Gazmararian and Tingley 2023; Voeten 2025).

I demonstrate that other nations' climate remediation policies influence the decision to implement environmental reforms via two channels. On one hand, previous mitigation efforts diminish the marginal contributions of subsequent policies, which incentivizes free-riding. This causal pathway, well-formalized in the literature (e.g., Harrison and Lagunoff 2017; McAllister and Schnakenberg 2022; Kennard and Schnakenberg 2023), induces strategic substitution in countries' climate investments. Concomitantly, the adoption of climate policies by other countries is a signal of public optimism in a green economy, which can spur subsequent climate action as other nations learn about the economic success of climate investments and thereby engender complementarities in actions. The exploration of this mechanism is novel and underexplored. These dual effects imply that some countries, looking at their expected costs and benefits, do as the conventional literature says: free-ride. But other nations in equilibrium conclude that they can reinforce the effects of global cooperation via diffused learning (Elkins and Simmons 2005; Simmons, Dobbin and Garrett 2006), simply "following the leader" upon observing ambitious climate reforms (Torney 2019; Busby and Urpelainen 2020).[1]

[1]This mechanism is distinct from other "tipping point" explanations in which policy diffuses because new technologies decrease costs of effort. I argue that complementarity arises not from decreased costs of inputs but rather from learning about common economic benefits. See Barrett (2003) for the example of the Montréal Protocol.

Additionally, the theory characterizes when learning effects dominate free-riding effects, implying a positive correlation in countries' climate actions. Learning effects are strongest when a country's belief in the economic success of green policy dominates the risk from implementing costly climate policies with uncertain returns. The implications of the collective action problem on international climate cooperation are thus conditional: the central dilemma of global environmental politics need not be the inevitability of free-riding. Instead, nations' mitigation investments hinge crucially on the diffusion of their expectations of positive economic benefits from remediation.

The learning mechanism produces several empirical implications about the relationship between countries' beliefs and their climate efforts that the free-riding mechanism would not predict. To test, I analyze both public and elite beliefs about climate change. Using Eurobarometer surveys across 27 European countries, I show that public concern about climate change diffuses across borders, shapes domestic policy stringency, and responds to the actions of other states. Complementing this, a survey of nearly 900 climate negotiators and scientists (Victor, Lumkowsky and Dannenberg 2022) demonstrates that experts' expectations about the ambition and credibility of nationally determined contributions are correlated across respondents, shaped by past policy effort, and predictive of subsequent climate action. Together, these analyses reveal that beliefs and policies are mutually reinforcing at both the mass and elite levels, consistent with the theory's central claim that international climate cooperation is structured not only by free-riding temptations but also by cross-national learning about the viability of the green transition.

Understanding the effects of learning and policy diffusion also has important consequences for international institutional design. Scholars and policymakers have viewed the free-rider problem as the dominant impediment to progress on international climate policymaking (see Carattini, Levin and Tavoni 2019; Weitzman 2017). Much of the extant literature around international climate cooperation has emphasized deterring free-riding through institutional punishments (Barrett 2003; Victor 2011). This paper argues that a more effective approach may lie in fostering policy complementarities through information-sharing and expectation management. Institutions, as disseminators of information (e.g., Keohane 1982; Johns 2007; Fang and Stone 2012), can play a central role in shaping optimistic and informed expectations about the value of green investments, thus inspiring bolder action (Hale 2020).

The primary contribution of this paper is to provide an overarching, system-level theory of international climate politics that serves as an alternative to canonical free-riding explanations. I argue that countries' incentives to exert costly effort into climate remediation are shaped by more than just free-riding concerns, and are also a function of cross-national learning about the economic success of a green transition. As will be shown, the core implication of free-rider theories, that countries' actions are negatively correlated, does not, on average, find empirical support. I develop a theory that is consistent with the empirical evidence: learning can engender a positive correlation in countries' climate actions.

The learning effect appeals to the literature on path dependence and policy diffusion (Pierson 2000; Elkins and Simmons 2005; Simmons, Dobbin and Garrett 2006; Carattini, Gosnell and Tavoni 2020). Scholars have demonstrated evidence of policy diffusion in carbon pricing (Harrison 2010; Ward and Cao 2012; Thisted and Thisted 2020; Linsenmeier, Mohommad and Schwerhoff 2023), feed-in tariffs (Baldwin, Carley and Nicholson-Crotty 2019), and domestic and international climate legislation (Bernauer et al. 2010; Sauquet 2014; Fankhauser, Gennaioli and Collins 2016). Rowan (2025) finds evidence of "conditional cooperation" by demonstrating a positive relationship between countries' Paris targets and subsequent pledges, similar to the diffusion effect described here.

Studies of the value of "increasing returns" to policymaking have identified how action by early movers generates greater effort by subsequent actors (Urpelainen 2011; Levin et al. 2012; van der Ven, Bernstein and Hoffmann 2017). Other scholars have encouraged policy experimentation in order to identify successful policies and ultimately lower costs and increase benefits (Hoffmann 2011; Sabel and Victor 2017). In a closely related paper, Hale (2020) considers how the incentive to act, or lack thereof, affects policymaking and subsequent institutional design. Sabel and Victor (2022) discuss how decarbonization policy, analogous to other developmental policies, may have local co-benefits which can incentivize policy adoption. I build on these studies by formalizing the diffusion-by-learning effect and integrating this mechanism into an environment with free-riding, thereby demonstrating when the value of learning can outweigh free-riding temptations.

This paper is not the first to question the dominance of free-rider temptations in international climate policymaking. Indeed, a burgeoning strand of literature argues for a focus on domestic distributive cleavages in explaining variation in climate policymaking (e.g., Aklin and Mildenberger 2020; Colgan, Green and Hale 2021; Ross 2025). In these accounts, expectations about the benefits and costs of decarbonization on domestic interest groups underpin the adoption of climate reforms, with some claiming that international collective action is irrelevant for explaining mitigation (Urpelainen and Van de Graaf 2018). However, in eschewing free-riding, scholars of redistributive politics sidestep the question of how international factors affect climate policy decisionmaking—heterogeneity of preferences domestically could still be compatible with a free-riding story at the international level (Kennard and Schnakenberg 2023). I complement domestic-focused explanations by providing an alternative mechanism that characterizes nations' climate policymaking behavior at an international level. Moreover, I provide an international rationale for the domestic distributional dynamics highlighted within this literature: policy diffusion can be a source of learning about the benefits of decarbonization, which then animate domestic political conversations about winners and losers.

How Do Countries' Climate Actions Correlate?

In a typical story of global climate policymaking, the marginal value of taking climate action is decreasing in the actions of other countries. This is because the benefits of abatement are global while the marginal costs are local. This theoretical account emphasizes the temptations to free ride off of other nations, often formally assuming that countries' actions are *strategic substitutes* (see Harrison and Lagunoff 2017; McAllister and Schnakenberg 2022; Kennard and Schnakenberg 2023).[2] This assumption, the core of extant theoretical approaches to global climate cooperation, implies that when other nations do more, it is a best response to do less, and when other nations do less, it is a best response to do more.

This section establishes a series of empirical facts about the relationship between a country's climate policy decisionmaking and the behavior of other nations. To operationalize countries' behavior, I study the climate laws that they pass as well as the stringency of their environmental policies. The first exercise studies the enactment and stringency of climate actions as a function of previously adopted climate policies by others. The second exercise leverages United States presidential elections as discontinuities in time to tease out how countries respond to exogenous shocks to expected international climate efforts.

In the theoretical literature on strategic complementarities, it is standard to make comparisons between the average or aggregate action of agents and an agent's own action (e.g., Morris and Shin 2003). The empirical assessments that I conduct operationalize this objective to "test" for the substitutability or complementarity between countries' climate actions in reduced form. To be clear, these strategic adjustments are often assumptions of theoretical models, not equilibrium implications. Hence the results in this section should be treated

[2] Strategic substitutability is conceptually distinct from decisionmakers' failure to internalize their negative externalities, or to "under-provide" effort, both of which are often invoked when discussing temptations to free-ride. However, these arguments require a normative optimum so that one can compare equilibrium effort levels to what is socially optimal, and thus demand significantly more theoretical and empirical structure than the exercises here.

as empirical probes into the validity of these modeling features, capturing simple conditional correlations between nations' actions, rather than as causal statements.

Climate Law Adoption and Environmental Policy Stringency

I study the relationship between a nation's likelihood of taking climate action and the actions previously taken by other countries using data about climate law adoption and the stringency of a country's environmental policies. Contrary to free-rider based expectations, I find positive correlations across countries' propensities to enact laws and pursue more stringent environmental policies. These results point toward a strategic complementarity in countries' climate actions rather than effort substitution.

To examine law adoption, I use data from the Climate Change Laws of the World project (Nachmany et al. 2017), which provides information on adopted climate laws from 1990 to 2024. The data covers laws adopted by the national governments of 199 countries plus the European Union. Laws passed by the E.U. are coded at the E.U. level. To be included in this dataset, a document must have full legal force or delineate a current set of government policy objectives, which pertain specifically to challenges of climate change (mitigation, adaptation, loss and damages, climate change research, etc.).

For each country i, I observe the number of climate laws adopted in year t as well as the total count of laws adopted by all other nations besides i (notated as $-i$). To capture the correlation between country i's climate law adoption and that of other nations, I run the following regression model via ordinary least squares with country-clustered standard errors:

$$\text{Laws}_{i,t} = \beta \ \log(\text{Other Laws}_{-i,t-1}) + \alpha_i + \lambda_{i,t} + \varepsilon_{i,t}.$$

The dependent variable $\text{Laws}_{i,t}$ is either the logged count of laws that country i passed in year t, or a binary indicator for whether or not country i passed any laws in year t.

The independent variable Other $\text{Laws}_{-i,t-1}$ is the count of laws adopted by all other nations around in the globe besides i, which I lag by one year to avoid simultaneity concerns. Country fixed effects α_i capture any time-invariant factors that affect country i's likelihood of climate policy adoption. Finally, I include country-specific time trends $\lambda_{i,t}$ which should parse out any secular increases over time in countries' climate policymaking behavior or increases in demand for climate policy over time within countries. Additionally, these terms intend to separate general equilibrium effects, or any global benefits to increased mitigation that could correlate with a contemporaneous rise in climate law adoption across countries.

In addition to lawmaking, I also examine policy stringency, a continuous and cumulative measure of efforts into climate remediation that probes the intensive margin of countries' policies. I use two measures of policy stringency, the OECD's Environmental Policy Stringency (EPS) index (Botta and Koźluk 2014; Kruse et al. 2022) and the Climate Action Policies and Measurement Framework (CAPMF) developed by Nachtigall et al. (2024). The EPS covers 40 countries between 1990 and 2020 and ranges from 0 to 6, where greater values imply greater stringency. Stringency is defined as the ability to explicitly or implicitly place a price on pollution through market-based (taxes, trading schemes, feed-in tariffs, and deposit and refund schemes) and non-market policies (command-and-control standards and subsidies). The CAPMF runs between 1990 and 2023 and measures the breadth of mitigation policy actions for 49 countries and the European Union on a scale from 0 to 10.[3]

For country i in year t, I run the following regression via ordinary least squares with country-clustered standard errors:

$$\text{Stringency}_{i,t} = \beta \text{ Average Other Stringency}_{-i,t-1} + \alpha_i + \lambda_{i,t} + \varepsilon_{i,t},$$

which fits country i's policy stringency in year t as a function of the average policy stringency

[3] I focus on the CAPMF's measurement of the stringency of "sectoral policies" rather than "cross-sectoral policies" or "international frameworks" although results are robust to the inclusion of these policy variables as well.

of all other nations besides i in year $t-1$. I also include country fixed effects α_i and country-specific time trends $\lambda_{i,t}$.

In all specifications, I divide independent and dependent variables by their within-country standard deviations so the coefficient β targets the within-country correlation between countries i's behavior and the behavior of other nations. The estimand of interest is its sign, which in reduced form captures the marginal value of country i's climate policymaking behavior—either the laws it passes or the stringency of its environmental policies—given what others have done. Extant theoretical approaches, in which mitigation efforts are substitutable, would expect $\beta < 0$: the passing of laws or more stringent policies by others reduces country i's tendencies to pass its own laws or adopt its own stringent policies.

	Laws (Count) (1)	Laws (Binary) (2)	EPS (3)	CAPMF (4)
log(Other Laws)	0.819***	0.867***		
	(0.049)	(0.053)		
Avg. Other Stringency			0.706***	0.818***
			(0.143)	(0.051)
Observations	7,000	7,000	1,200	1,650
R^2	0.331	0.344	0.904	0.962
Within R^2	0.307	0.305	0.852	0.960
DV Mean	0.643	0.713	2.04	1.25
Number of Countries	200	200	40	50
Country fixed effects	✓	✓	✓	✓
Country × Year trends	✓	✓	✓	✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table 1: Effects of Previous Law Adoption and Policy Stringency on Climate Policymaking

Contra prior theoretical expectations, there is a *positive* and statistically significant correlation across climate actions, as shown in Table 1. Across the board, increased effort by other nations, measured either as the adoption of laws or more stringent environmental policy, is associated with greater mitigation measures. A one standard deviation increase in the laws or stringency of environmental policies by other nations is associated with between 0.7 and 0.9 standard deviations of one's own adoption of climate actions, a substantively meaningful effect. This relationship holds even guarding against the possibility that nations are secularly increasing their passage of climate laws over time without regard for the behavior of other nations, as captured by the time trends. Since this correlation is positive, it suggests a complementarity rather than a substitutability in the adoption of climate laws across countries. Additionally, the stringency results in models 3 and 4 are particularly striking, as the sample of nations for which stringency data is available is more limited, and mostly includes larger countries. These nations, which generally have a larger impact on the climate, are likely the places where we may have expected to observe greater effort substitution, but the findings in Table 1 indicate the opposite result. Results are robust to alternative time trend specifications, the inclusion of time-varying controls, as well as weighting by GDP per capita or emission per capita. Additionally, results hold excluding country fixed effects, thereby targeting a cross-country correlation, as well as with the inclusion of year random effects; see Appendix B.1.

These results are suggestive of a complementary relationship between efforts across countries, but we may still be worried about an omitted variable or some other general equilibrium effect that produces a positive correlation on average, even if the partial equilibrium relationship across countries is negative. In the specifications above, the country-year time trends attempt to correct for this concern, but it should again be noted that this exercise serves as a probe into a theoretical and conceptual assumption rather than a causal test. The next empirical exercise attempts to localize the partial effect in a more disciplined way.

U.S. Presidential Elections

As an additional test, I examine the effects of United States presidential elections on the adoption of climate laws. As one of the globe's largest emitters, the identity of the American president heavily skews the incentives to enact climate laws around the globe: in 2016, Donald Trump campaigned on withdrawing the United States from the Paris Agreement and retrenching the U.S. from the global climate regime, while Joe Biden's 2020 campaign promoted American engagement in climate policymaking. The outcome of the 2016 (2020) election thus represents a negative (positive) perturbation to other countries' best responses and subsequently informs their optimal decisionmaking in light of expected American behavior following the election. The classical logic then predicts that other nations should increase (decrease) their adoption of climate laws following Trump's (Biden's) victory.

To capture the effects of the elections, I run a regression discontinuity in time at the country-month level using the following local linear regression specification:

$$\text{Laws}_{i,m} = \beta \mathbb{1}(m > t_k) + \varphi f(m - t_k) + \alpha_i + \varepsilon_{i,m}.$$

The dependent variable is either, as in the first empirical test, a binary indicator for whether country i adopted a climate law in month m or the logged count of climate laws adopted by country i in month m. As the running variable is time, the independent variable of interest is an indicator of whether time at month m has exceeded t_k, the calendar date of the election (either November 8 2016 or November 3 2020), and $f(\cdot)$ is a smooth function of time, which is measured in days until the election. Fixed effects at the country level α_i are also included to capture country-specific idiosyncrasies in law adoption. I report bias-corrected estimates with optimal bandwidth selection, weight observations using a triangular kernel (Calonico, Cattaneo and Titiunik 2014), and cluster standard errors by country.

The sign of β identifies the sign of the local average treatment effect of the U.S. election on other nations' adoption of climate laws right at the date of the election.[4] Hence this estimate should be thought of as countries' expectations of the value of future effort given the winner of the election. A free-riding argument would expect the sign of β to be positive (negative) in 2016 (2020). In this account, Trump's apathy toward climate policies increases the marginal value of policymaking for other nations to compensate, while Biden's willingness to enact climate policy decreases the incentives for others to exert costly effort.

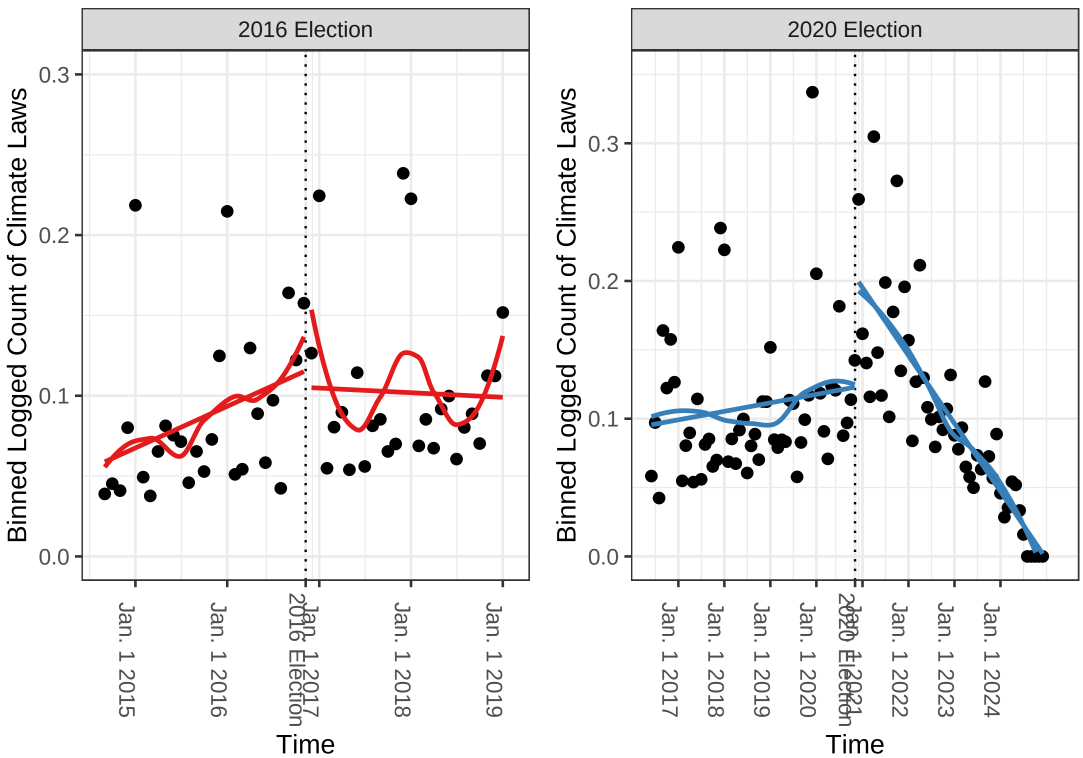

Figure 1: RD Plots of U.S. Presidential Elections on Climate Law Adoption

Figure 1 presents graphical evidence of a change in countries' propensities to adopt climate laws around the 2016 and 2020 United States elections.[5] I fit a linear polynomial as

[4]Given the design, bias in the LATE would emerge if countries strategically adopt climate laws before or after the election. For example, in 2016, the relevant bias in favor of the free-riding argument is if countries were to delay adoption of climate laws until after the election, attenuating the LATE. However, such a case seems unlikely as adoption would only become more difficult with a U.S. president who is less favorable to climate action in power.

[5]RD plots use the logged count outcome; plots for the binary dependent variable display similar results.

well as a loess smoother on each side of the election cutoff. The left panel of the figure suggests that there is a small reduction in the adoption of climate laws when Donald Trump wins the election in 2016. By contrast, the right panel documents a large positive surge in the number of laws adopted when Joe Biden wins the election in 2020.

Table 2 formalizes these estimates, documenting a negative, but statistically indistinguishable from zero, effect in 2016, and a positive and statistically significant effect in 2020. In both cases, the sign of the RD estimate refutes a story of strategic substitutes. That is, the data do not show that countries found it in their interest to do more when the U.S. signaled it would do less by electing Trump, nor would other countries do less when the U.S. elected Biden. When an anti-climate leader was elected in 2016, other countries followed suit and enacted fewer climate laws. In 2020, with the emergence of a pro-climate U.S. presidential winner, the international community responded with more climate action. Results are robust to the inclusion of month fixed effects and country-month trends—which account for the influence of factors like the signing of new international environmental treaties, the onset of a global pandemic, or secular increases in worsening climate that may demand more action—see Appendix B.2. Also see Appendix B.2 for robustness tests on sorting, alternative bandwidths, placebo cutoffs, and an alternative definition of the running variable in months rather than days. I also estimate the effects of U.S. presidential elections as an interrupted time series and find similar results.

Taken together, these empirical findings call into question conventional theoretical accounts of global climate policymaking in which an increase in the effort of other nations decreases the likelihood of effort by other countries. In fact, the evidence suggests the opposite: effort by other nations correlates *positively* with the likelihood that nations take climate action. In what follows, I argue that these empirical findings can be reconciled by augmenting collective action theories of global public goods provision to introduce diffused learning as an additional mechanism affecting mitigation investments. Learning effects can

	Trump (2016)		Biden (2020)	
	(1)	(2)	(3)	(4)
RD Election Effect	-0.009	-0.020	0.067***	0.070***
	(0.017)	(0.019)	(0.022)	(0.020)
DV	Count	Binary	Count	Binary
DV Mean	0.094	0.109	0.105	0.116
Bandwidth	809.875	781.846	1616.020	1504.237
Effective Observations	10547	10149	20497	19701

Table 2: RD Estimates of U.S. Presidential Elections on Climate Law Adoption

engender complementarities, and, if they dominate free-riding temptations, imply positive correlations across climate actions. The formal model now considers how countries' climate policymaking incentives are affected by both free-riding and learning mechanisms.

Model

Consider climate policymaking by $n = 2$ countries indexed by i. Each country determines a level of climate mitigation efforts $a_i \in \mathbb{R}$. Positive levels of effort $a_i > 0$ signify climate reforms that contribute to global abatement and remediation, while negative effort $a_i < 0$ can be thought of as anti-climate measures like deforestation or other means of increasing carbon emissions. The game features sequential moves, meaning that country 1 ("he") moves before country 2 ("she"), and country 2 observes country 1's choice prior to taking an action. While I refer to countries as unitary actors, we can think of each nation as being ruled by a policymaker who is determining remediation policy, or we can think of a median voter in each nation deciding how much to comply with environmental regulations.

Countries' payoffs from efforts toward climate reform depend on a fundamental uncertainty, the global economic returns from a green transition. This is modeled as a state of the world, θ. Neither country knows the true realization of θ—whether or not the green transition will ultimately pay off is unknown—but share the common prior $\theta \sim N(\mu, \frac{1}{\gamma})$. In addition, each country observes a noisy signal of the state of the world, $x_i = \theta + \varepsilon_i$ where $\varepsilon_i \sim N(0, \frac{1}{\beta})$. Countries' signals are their private information and are thus their private beliefs about the economic returns to green policy; higher signals are on average more likely to indicate larger θ, so a country with a higher signal is more optimistic about the success of a green transition. Countries' returns from effort depend on the value of θ and thus capture the idea that countries only want to exert effort in mitigating the effects of climate change if they are sufficiently optimistic that a green transition would reap economic benefits.

As in conventional theoretical accounts of international climate policymaking, countries' abatement efforts generate global benefits but impose local costs. Let $A = a_1 + \lambda a_2$ be the weighted average of global efforts where $\lambda \geq 0$ parameterizes the relative weight of country 2's subsequent efforts vis-à-vis country 1's effort. This parameter can be interpreted either as the relative size and scale between the two countries or as a measure of temporal discounting in mitigation efforts. Countries receive a global benefit of $g(A)$ given total global policy implementation where $g(\cdot)$ is an increasing and concave function. Additionally, adopting climate-friendly policies is costly—there are technological, financial, and political consequences from imposing costs on citizens or large domestic polluters to implement reforms—and exerting effort comes at a cost $c(a_i)$ where $c(\cdot)$ is an increasing and convex function. To keep the problem tractable, let

$$g(A) = \begin{cases} \sqrt{A} & A \geq 0 \\ -\sqrt{|A|} & A < 0, \end{cases}$$

and $c(a_i) = c_i|a_i|$.[6]

[6] These functional forms allow substantively for the inclusion of negative effort, rather than truncating effort at zero, but are also useful technically in allowing for feasible integration over negative-valued signals, obtaining a one-to-one mapping between signals and effort.

Putting things together, country i's utility is written as

$$u_i(a_i, A; \theta) = \theta g(A) - c(a_i).$$

Countries' utility functions capture the logic of strategic substitutes encoded in canonical models—countries derive global benefits from mitigation actions but these gains exhibit diminishing marginal returns—while also allowing for the generation of strategic complementarities in countries' behavior because of the incentives to learn about the economic returns to green policy from the actions of others. Both mechanisms are present in countries' effort decisions and the goal of the theoretical analysis will be to characterize the conditions under which one effect dominates the other. Formally, the theory targets the sign of $\frac{da_2}{da_1}$.

I examine weak Perfect Bayesian equilibria. Country 1's strategy is a function $\alpha_1 : \mathbb{R} \to \mathbb{R}$ that maps his signal x_1 into an effort level a_1. Country 2's strategy is a function $\alpha_2 : \mathbb{R}^2 \to \mathbb{R}$ that maps her signal x_2 and country 1's effort a_1 into an effort level a_2. Beliefs about θ are formed via Bayes's rule.

Comments on the Model

The model's assumptions are motivated by canonical theories of observational learning (for a review, see Bikhchandani et al. 2024). In particular, two assumptions require further comment: the restriction to $n = 2$ countries, the sequentiality of moves among them. In contrast to extant observational learning models which allow the number of agents n to grow arbitrarily large, I fix the number of countries at $n = 2$. By way of interpretation, we can think of the first mover as a bloc of countries in reduced form, while the second mover is an additional country considering how its effort affects global climate remediation on the margin. I make this simplification because agents in these models are typically backward-looking as their behavior is only linked through the information conveyed by prior movers, essentially boiling down to a decision-theoretic problem. However, since countries' actions exhibit forward-looking strategic interdependence in this model, increasing the number of countries adds mathematical complexity without developing further theoretical nuance. In Appendix C, I present a simplified model with more than two countries that is closer to the traditional observational learning setup.

In a departure from extant collective action models of international climate policymaking (e.g., Kennard and Schnakenberg 2023), I introduce uncertainty about the benefits accrued from climate abatement efforts and sequential moves. Both of these elements are necessary to model the learning mechanism. In introducing sequential moves, I treat the timing of countries' climate actions as exogenously determined. This is a simplifying assumption, and there are plausible foundations for endogenizing the order of moves. For instance, differences in the precision of countries' information, such as more reliable assessments of the economic or technological feasibility of a green transition, could lead better-informed countries to act earlier (e.g., Zhang 1997). Similarly, variation in climate vulnerability may create incentives for more exposed countries to lead. In both cases, strategic first-mover behavior is consistent with a strong learning mechanism.

Analysis

I begin by establishing the equilibrium of the game (Proposition 1). Then I demonstrate that learning effects dominate free-riding concerns when optimism about the green transition's success outweighs the risk of investment in policy with uncertain returns (Proposition 2).

Equilibrium Climate Efforts

To solve for the equilibrium of the model, I conjecture the existence of country 1's strategy $a_1 = \alpha_1(x_1)$ where $\alpha_1(\cdot)$ is one-to-one. Then, for any a_1 that country 2 observes, she can infer country 1's signal, $x_1 = \alpha_1^{-1}(a_1)$. This means that, conditional on her signal x_2 and country 1's effort level a_1, country 2 believes that $\theta | x_2, a_1 \sim N(\frac{\gamma\mu + \beta\alpha_1^{-1}(a_1) + \beta x_2}{\gamma + 2\beta}, \frac{1}{\gamma+2\beta})$. Given her private signal x_2 and country 1's effort a_1, country 2's expected utility is

$$u_2(a_2; x_2, a_1) = E[\theta|x_2, a_1] g(a_1 + \lambda a_2) - c(a_2),$$

where her optimal mitigation effort $\alpha_2(x_2, a_1)$ solves the following first-order condition:

$$\underbrace{E[\theta|x_2, a_1]}_{\text{expected green benefits}} \cdot \underbrace{g'(a_1 + \lambda\alpha_2(x_2, a_1))\lambda}_{\text{marginal global contribution}} - \underbrace{c'(\alpha_2(x_2, a_1))}_{\text{marginal costs}} = 0.$$

This can be solved explicitly given functional form specifications:

$$\alpha_2(x_2, a_1) = \begin{cases} -\frac{1}{\lambda}a_1 + \frac{\lambda(\gamma\mu + \beta\alpha_1^{-1}(a_1) + \beta x_2)^2}{4c_2^2(2\beta+\gamma)^2} & x_2 \geq -\frac{\gamma\mu}{\beta} - \alpha_1^{-1}(a_1) \\ -\frac{1}{\lambda}a_1 - \frac{\lambda(\gamma\mu + \beta\alpha_1^{-1}(a_1) + \beta x_2)^2}{4c_2^2(2\beta+\gamma)^2} & x_2 < -\frac{\gamma\mu}{\beta} - \alpha_1^{-1}(a_1). \end{cases} \tag{1}$$

Note that if $x_2 < -\frac{\gamma\mu}{\beta} - \alpha_1^{-1}(a_1)$ then country 2 has particularly pessimistic signal about the value from exerting effort toward mitigating the effects of climate change, and would exert negative effort because $E[\theta|x_2, a_1] < 0$.

Quite naturally, country 2's optimal efforts increase when she is more optimistic about the economic returns to green policy. Formally, $\alpha_2(x_2, a_1)$ is increasing in x_2, country 2's private signal of the economic returns from climate policies.

Country 1's effort a_1 affects country's optimal mitigation investment $\alpha_2(x_2, a_1)$ through two channels. First, as seen in the first term of $\alpha_2(x_2, a_1)$ in Equation 1 above, country 1's effort has a direct effect of changing country 2's marginal contribution to global mitigation cooperation. That is, if country 1 has already committed to large emissions reductions, then country 2's policies have a smaller marginal impact on global abatement, thereby creating a temptation to free-ride. In this way, country 1's behavior engenders a substitutability across nations' mitigation actions, which is reminiscent of classical collective action pathologies.

Moreover, country 1's effort also affects country 2 through a second, informational channel—her expectations about the benefits from green policies—given by $\alpha_1^{-1}(a_1)$ in the second term of $\alpha_2(x_2, a_1)$. When country 1 exerts more effort, it leads country 2 to believe that country 1's signal x_1 was higher, and thus more optimistic about the economic returns from a green transition. Country 2 updates positively about the value of green policy, quantified by an increase in her posterior mean $E[\theta|x_2, a_1]$, which then motivates her to also exert greater effort. Having learned from country 1 by observing his remediation efforts, country 2 then also adopts more ambitious climate reforms.

Now consider the problem of country 1, who faces a similar decision but knows that his actions will influence the trajectory of global climate efforts. Given his signal x_1, country 1 has a posterior belief about the state $\theta|x_1 \sim N(\frac{\gamma\mu+\beta x_1}{\gamma+\beta}, \frac{1}{\gamma+\beta})$ as well as country 2's signal $x_2|x_1 \sim N(\frac{\gamma\mu+\beta x_1}{\gamma+\beta}, \frac{2\beta+\gamma}{\beta(\beta+\gamma)})$. Since he does not know x_2, country 1 does not know how much effort country 2 will commit to downstream, and thus has expected utility

$$u_1(a_1; x_1) = E_{x_2}\Big[E[\theta|x_1]g(a_1 + \lambda\alpha_2(x_2, a_1))\Big] - c(a_1),$$

and his optimal mitigation effort $\alpha_1(x_1)$ satisfies the following first-order condition:

$$E_{x_2}\Big[\underbrace{E[\theta|x_1]}_{\text{expected green benefits}} \cdot \underbrace{g'(a_1 + \lambda\alpha_2(x_2, a_1))}_{\text{marginal global contribution}} \underbrace{\left(1 + \lambda\frac{d\alpha_2(x_2, a_1)}{da_1}\right)}_{\text{expected impact on country 2}}\Big] - \underbrace{c'(a_1)}_{\text{marginal costs}} = 0.$$

Analogous to country 2, notice that if $x_1 < -\frac{\gamma\mu}{\beta}$ then $E[\theta|x_1] < 0$ and country 1's inference about the returns from climate investments are particularly dour. Given the functional form assumptions, a closed-form solution for country 1's effort can be found,

$$\alpha_1(x_1) = \begin{cases} \frac{\beta\lambda x_1(2\gamma\mu+\beta x_1)+\lambda\gamma^2\mu^2}{4c_1c_2(2\beta^2+3\beta\gamma+\gamma^2)} & x_1 \geq -\frac{\gamma\mu}{\beta} \\ \frac{-\beta\lambda x_1(2\gamma\mu+\beta x_1)-\lambda\gamma^2\mu^2}{4c_1c_2(2\beta^2+3\beta\gamma+\gamma^2)} & x_1 < -\frac{\gamma\mu}{\beta}. \end{cases} \tag{2}$$

The following proposition summarizes the equilibrium (with formal proofs in Appendix A).

Proposition 1. *There exists a unique equilibrium characterized by the functions* $\alpha_1(x_1)$, $\alpha_2(x_2, a_1)$ *such that* $a_1^* = \alpha_1(x_1)$, *as defined in Equation 2, and* $a_2^* = \alpha_2(x_2, a_1^*)$, *as defined in Equation 1. Country 1 has beliefs* $\theta|x_1 \sim N(\frac{\gamma\mu+\beta x_1}{\gamma+\beta}, \frac{1}{\gamma+\beta})$ *and country 2 has beliefs* $\theta|x_2, a_1^* \sim N(\frac{\gamma\mu+\beta\alpha_1^{-1}(a_1^*)+\beta x_2}{\gamma+2\beta}, \frac{1}{\gamma+2\beta})$.

In equilibrium, country 1 balances the temptation to free-ride off of the possible climate implementation efforts of country 2 with the possibility that his own inaction could discourage subsequent reforms by sending a bad signal about the viability of a green transition. His actions are influential in determining the course of global climate investments because, on one hand, country 1 could jumpstart a sizable contribution to international climate cooperation; but on the other hand, he might wish to avoid the domestic costs of mitigation measures with the anticipation that country 2 will provide global benefits.[7] I now study how both nations optimally navigate this tradeoff.

The following corollary establishes the learning mechanism: country 1's effort is informative to country 2 about the value of green policy. When country 1 is more optimistic, he exerts greater effort. Having observed greater effort, country 2's expectations about the economic returns to climate policy increase, which further motivates downstream effort. Since countries only want to engage in costly climate investments if they are sufficiently optimistic that they will pay off, this information transmission is critical to calibrating country 2's

[7]While country 2 is clearly advantaged from an informational perspective, country 1's first-mover advantage is his marginal contribution, which is always weakly greater than country 2's. For a strong enough signal x_1, he can guarantee some international effort in the event that country 2 takes minimal action.

equilibrium efforts.

Corollary 1. *Country 1's climate policy is informative about* θ*:*

- *Country 1's equilibrium climate effort is increasing in its signal* x_1*,* $\frac{da_1^*}{dx_1} > 0$*;*
- *Country 2's posterior expectation of* θ *is increasing in country 1's effort,* $\frac{dE[\theta|x_2,a_1^*]}{da_1} > 0$.

Complements and Substitutes, Learning and Free-Riding

I now characterize how two mechanisms, free-riding and learning, affect incentives for countries to enact climate policy. The presence of these two mechanisms, countervailing in sign, generate the fundamental tradeoff that countries face when determining mitigation investments: under what conditions are nations' climate actions strategic complements or substitutes? Formally, when is $\frac{d\alpha_2(x_2,a_1)}{da_1}$ positive, and when is it negative? The sign of this relationship underpins whether and how mitigation actions are correlated.

Fix two possible effort levels by country 1, $a_1' > a_1$, and recall that country 2's optimal effort level solves

$$\underbrace{E[\theta|x_2, a_1]}_{\text{expected green benefits}} \cdot \underbrace{g'(a_1 + \lambda\alpha_2(x_2, a_1))\lambda}_{\text{marginal global contribution}} = \underbrace{c'(\alpha_2(x_2, a_1))}_{\text{marginal costs}},$$

such that country 2 trades off the marginal domestic costs of implementation with her beliefs in a successful green transition and her marginal contribution to global abatement efforts.

The left-hand side of this equation has two components that are in tension with one another. Given country 1's efforts, country 2's marginal contribution to global abatement is smaller when country 1 has already invested large amounts of effort into providing the global benefit of mitigation, $g'(a_1' + \lambda a_2) < g'(a_1 + \lambda a_2)$. There are smaller marginal gains from additional costly remediation, which tempts country 2 to free-ride off of country 1's efforts.

This force engenders substitution across countries' climate policies because the effort exerted by country 1 discourages reforms from country 2. However, country 1, having adopted costly climate reforms, signals belief in a successful green transition to country 2, $E[\theta|x_2, a_1'] > E[\theta|x_2, a_1]$. Emboldening country 2 to take more ambitious climate action, country 1's efforts generate complementarities in countries' behavior. This also implies that by contrast, a smaller level of effort from country 1 makes country 2's marginal contribution more impactful and, from country 1's perspective, could provide greater global benefits; however, this also diminishes country 2's expectations about the economic returns to green policy because country 1's lack of climate action is a signal of his pessimism.

Countries' actions therefore influence each other through two channels. The temptation to free-ride, stemming from diminished marginal contributions, creates a strategic substitutability in countries' climate policies; however, the incentive to learn about a successful green transition by signaling information induces strategic complementarities. These two forces push in opposite directions when attempting to ascertain the marginal effect of country 1's effort on country 2's behavior. Corollary 2 formalizes this discussion by decomposing $\frac{d\alpha_2(x_2,a_1)}{da_1}$ into these two constituent effects, where a_1 represents the direct returns from country 1's effort and $\alpha_1^{-1}(a_1)$ represents the informational value.

Corollary 2. *Country 2's optimal mitigation effort is:*

- *Decreasing in the direct effect of country 1's effort,* $\frac{\partial\alpha_2(x_2,a_1)}{\partial a_1} \leq 0$*;*
- *Increasing in the informational effect of country 1's effort,* $\frac{\partial\alpha_2(x_2,a_1)}{\partial\alpha_1^{-1}(a_1)} \geq 0$.

Figure 2 illustrates the effects of the free-riding and learning mechanisms, plotting country 2's effort $\alpha_2(a_1, x_2)$ as a function of the behavior for country 1 a_1 given different possible signals x_2. The first panel depicts the direct effects increasing country 1's mitigation policies, holding constant the informational value of such effort. This begets less ambitious climate action from country 2 because her marginal contributions are diminished, generating free-riding temptations, indicated by the negative slope of the lines in the panel. The second panel shows that, holding constant the direct effect from country 1's effort, country 2 is incentivized to exert greater effort when she receives a stronger signal from country 1 about the success of the green transition. The positive slope of the lines in this panel reflect this value of learning. Finally, the third panel demonstrates the total effect: countries' actions, depending on which mechanism dominates, can either be substitutes or complements. Whether nations' actions are complements or substitutes in equilibrium determines the sign of the correlation between their efforts. Here, when the slope of the line is positive, then the learning channel dominates the free-riding channel; when it is negative, the free-riding channel dominates the learning channel. Then in the former case countries' climate actions are positively correlated, while in the latter case they are negatively correlated.

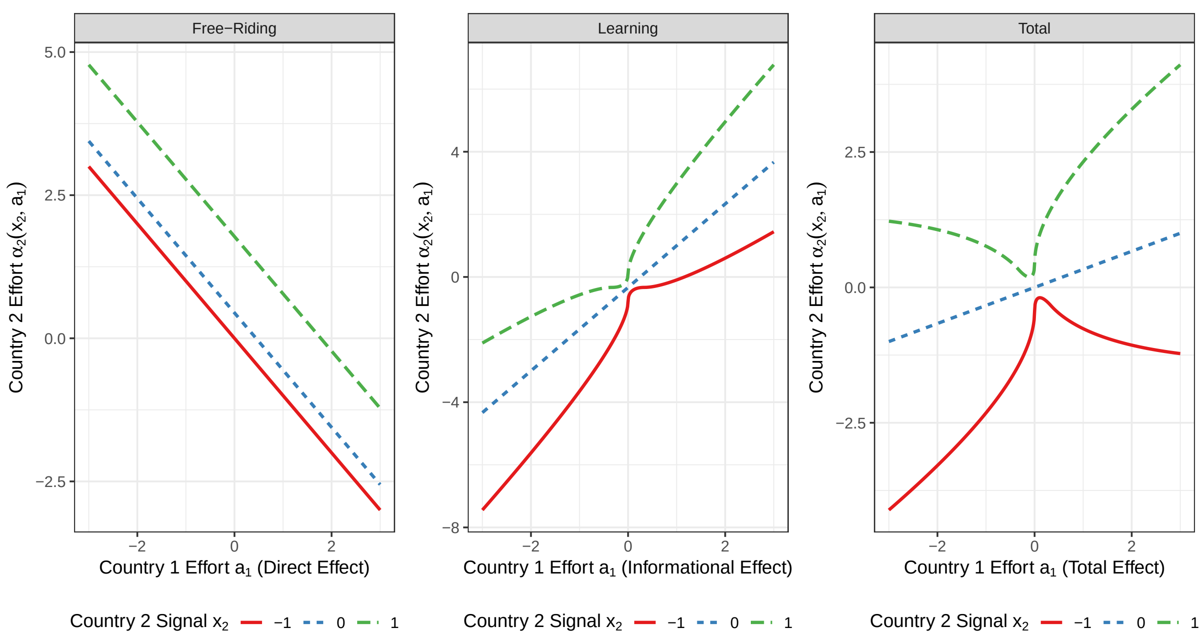

Figure 2: Substitutes and Complements Mechanisms on Climate Mitigation Efforts
$\mu = 0.5,\ \gamma = 1,\ \beta = 1,\ \lambda = 1,\ c_1 = 0.5,\ c_2 = 0.25$

Which effect dominates? I now consider the conditions under which the effects of changing country 1's information outweigh the direct effects of his effort on country 2's decision-making. The result is simple: when country 2's posterior update about the success of a green transition, the public optimism from country 1 along with her private signal x_2, dominates her aversion toward exerting costly effort into policies with unknown return, then the learning channel that engenders strategic complementarities is stronger than the free-riding channel that generates strategic substitutes. Alternatively, when the risk involved in implementing green policies is large—the returns to such investments are unknown and their implementation is domestically politically costly—then substitution effects dominate learning incentives.

Proposition 2. *Learning effects dominate free-riding effects when public optimism is large relative to the risks of green policy investment,*

$$\underbrace{\left(-\frac{g''(A)}{g'(A)}\right)^{-1}}_{\substack{\textit{risk aversion from} \\ \textit{costly climate investment}}} < \underbrace{\frac{|\gamma\mu + \beta\alpha_1^{-1}(a_1) + \beta x_2|}{\beta}}_{\textit{posterior optimism}}. \tag{3}$$

Proposition 2 determines the dominant mechanism, either the free-riding effect or the learning effect, on country 2's climate policy decisionmaking. These two mechanisms are both always operant, but the proposition determines which outweighs the other. That is, it tells us the sign of the correlation between countries' climate efforts. Moreover, the proposition states that we can assess the dual effects of complementarity and substitutability based on the interplay between public assessments of optimism toward green policy and the induced risk that comes with implementing costly mitigation policies with unknown economic returns.

The right-hand side of the inequality approximates country 2's expectations about θ, the informational returns from country 1's costly climate investments, while the left-hand side is a measure of country 2's Arrow-Pratt "risk aversion." Since the economic value of the green transition is unknown, the value of country 1's effort on country 2's posterior update must outweigh her tolerance for implementing policies with uncertain returns in order for the total effect of country 1's effort on her own effort to be positive. The result also underscores that uncertainty exacerbates the temptation to free-ride (McAllister and Schnakenberg 2022): if country 2 becomes less willing to tolerate the uncertainties of the green transition's benefits, thereby increasing the left-hand side of the inequality, country 2's incentive to free-ride becomes stronger relative to her incentive to learn.

The proposition demonstrates that the implications of the collective action structure for international climate politics are conditional. While free-riding temptations are always baked into countries' investment considerations, the system-level incentives to invest in mitigation are not, on net, plagued by a tragedy of the commons if Equation 3 holds. Instead, when optimism about the economic returns to green policy outweighs risk aversion, other countries' actions no longer crowd out but instead reinforce one's own. The central dilemma of international climate cooperation need not be the inevitability of free-riding but the calibration of positive expectations about the economic returns to mitigation.

Implications of the Learning Mechanism

The model yields four empirical implications that allow us to evaluate whether countries learn from one another when adopting climate policies. At its core, the theory predicts that beliefs about the economic value of the green transition shape policy choices, and that these beliefs are mutually reinforcing across borders. Testing these implications thus provides a bridge between the formal model and observed patterns of international climate cooperation.

First, by construction, national beliefs about the prospects of a successful green transition should be positively correlated across countries, $cor(x_i, x_j) > 0$. Because all nations face the same global uncertainty regarding the economic benefits of green investment, optimistic signals in one country increase the likelihood that others observe similar signals. This relationship is not, in itself, evidence of learning; rather, it serves as a baseline consistency check that observed beliefs reflect a common uncertainty.

Second, Corollary 1 establishes that a country's own climate efforts are informative of its beliefs. Accordingly, we should observe a positive correlation between a country's optimism and the stringency of its domestic mitigation policies, $cor(x_i, a_i) > 0$. More favorable assessments of the returns to green policy should translate into greater effort. Third, the same corollary implies a cross-national updating effect: when countries observe ambitious efforts abroad, they should revise their own beliefs upward about the economic returns to mitigation, $cor(x_j, a_i) > 0$. This reflects a direct learning channel, as one nation's actions provide information that reshapes the expectations of another.

Finally, the most demanding test of learning is whether one country's optimism directly induces greater climate action elsewhere $cor(x_i, a_j) > 0$. This reduced-form relationship implies that optimistic signals foster greater effort at home, which in turn leads others to update their beliefs favorably and respond with stronger policies. Demonstrating this effect would provide the strongest evidence of learning, though it is also the most difficult to isolate empirically, since strategic considerations such as free-riding may counteract downstream effort provision.

To probe these implications, I examine the relationship between beliefs and subsequent policy stringency using both mass-level and elite-level data. These empirical strategies extend the sparse information structure of the model by incorporating survey-based measures of beliefs that plausibly proxy the private signals in the theory for two substantively meaningful sets of domestic actors. At the mass level, I use repeated cross-sectional Eurobarometer data to capture public opinion on the seriousness of climate change across 27 European countries (2011–2021). At the elite level, I leverage a dataset of nearly 900 climate negotiators and scientists surveyed in 2020–21 (Victor, Lumkowsky and Dannenberg 2022). While neither dataset perfectly maps onto the model's core uncertainty, whether green policies will be economically beneficial, they provide substantively meaningful indicators of how publics and elites form expectations about climate policy demand and success. Additionally, both datasets have notable advantages. The Eurobarometer data is dynamic, allowing for the study of changes in country's beliefs and subsequent policies over time, and the elite data studies the beliefs of a substantively relevant population of interest (Yarhi-Milo, Kertzer and Renshon 2018; Saunders 2022).

The empirical tests proceed in parallel across the two data sources. With the Eurobarometer surveys, I assess all four implications by linking shifts in mass concern over time about climate change to downstream policy stringency and to cross-border updating. With the elite survey, I exploit within-respondent variation in evaluations of multiple countries' nationally determined contributions (NDCs) to examine whether optimism about the ambition or credibility of other nations' pledges predicts subsequent policy outcomes.

Mass Beliefs

Between 2011 and 2021, Eurobarometer asks citizens to assess whether they believe that climate change is a serious problem on a scale from 1 to 10, where 1 is "not at all a serious problem" and 10 is "an extremely serious problem" (recoded to a 1-4 scale). The dynamic nature of the Eurobarometer data allows for an assessment of all four empirical implications of the learning mechanism. Since policy stringency is measured at the country-year level, I aggregate all respondents' beliefs about the importance of climate change by taking the average within countries for each year.

First, to examine correlation across countries' signals, I estimate the following regression,

$$\text{CC Serious}_{i,t} = \beta \text{ Average Other CC Serious}_{-i,t-1} + \alpha_i + \lambda_{i,t} + \varepsilon_{i,t}.$$

This model regresses the (average country-year) level of concern for climate change within country i in year t on the average level of seriousness across all other countries besides i in the preceding year $t-1$, where higher values indicate greater seriousness. I also include country fixed effects α_i to account for baseline differences in assessments of climate change importance across countries. I also report results including country-year time trends $\lambda_{i,t}$ to account for secular changes in beliefs over time. The theory anticipates that $\beta > 0$, meaning that countries are more likely to have optimistic signals if other nations do as well.

The second implication concerns the within-country relationship between beliefs and climate efforts, which I test by estimating

$$\text{Stringency}_{i,t} = \beta \text{ CC Serious}_{i,t-1} + \alpha_i + \lambda_t + \varepsilon_{i,t},$$

where climate policy stringency is measured using the CAPMF. Since comparisons are entirely within countries, there is enough variation in the independent variable to estimate a set of year fixed effects rather than a country-year time trend. We should expect $\beta > 0$: more optimistic signals lead countries to invest in more stringent environmental policies.

Third, I test if climate policies convey information across countries, with the specification

$$\text{CC Serious}_{i,t} = \beta \text{ Average Other Stringency}_{-i,t-1} + \alpha_i + \lambda_{i,t} + \varepsilon_{i,t}.$$

Here, we should again expect $\beta > 0$ if the (average) climate policy stringency of other nations from year $t-1$ encourages country i to update its beliefs positively in year t. I again include country fixed effects and country-year time trends to target the within-country effect of others' actions on beliefs about the seriousness of climate change.

The fourth implication, in which downstream policy correlates with beliefs, is tested via

$$\text{Stringency}_{i,t} = \beta \text{ Average Other CC Serious}_{-i,t-1} + \alpha_i + \lambda_{i,t} + \varepsilon_{i,t}.$$

Here, the coefficient β captures the relationship between average seriousness of climate change in other countries and its downstream effect on climate policy stringency in country i. I also include country fixed effects and country-year trends. The theory again predicts that $\beta > 0$, which would give the strongest evidence of learning in reduced form.

In all specifications, the dependent and independent variables are divided by their within-country standard deviation to more cleanly estimate correlations between climate actions and beliefs. Then, β targets the average within-country correlation in specifications with just country fixed effects. Adding the country-year trends targets the detrended average within-country correlation.

The results of these four tests are found in Table 3. Each panel of the table corresponds to the findings for a separate empirical implication of the learning mechanism. While the theory's implications become more stringent in ascending order, and evidentiary weight thus should be placed accordingly, we find suggestive evidence consistent with the learning mechanism across the board. First, Panel A confirms that public concern about climate change is positively correlated across countries. This finding is consistent with the model's baseline assumption: as all publics confront a shared global uncertainty about the economic returns to green policy, optimism in one context increases the likelihood of optimism elsewhere. These beliefs are tightly correlated, as a one standard deviation increase in the average beliefs of others is associated with a 0.37 standard deviation increase in the average beliefs within countries.

Turning to Panel B, a slightly more stringent test shows that within countries, higher levels of concern are generally associated with more stringent climate policies. The relationship is positive and significant under standard specifications—a one standard deviation increase in beliefs is associated with a 0.33 standard deviation increase in downstream stringency—though it flips sign and loses significance once year fixed effects are included. This attenuation reflects the difficulty of separating gradual, long-run shifts in climate seriousness from

Panel A: $cor(x_i, x_j)$	CC Serious	
	(1)	(2)
Avg. Other CC Serious	0.585***	0.371***
	(0.058)	(0.090)
Observations	323	323
Within R^2	0.347	0.520
Country fixed effects	✓	✓
Country × Year trends		✓

Panel B: $cor(x_i, a_i)$	Stringency	
	(1)	(2)
CC Serious	0.326***	-0.007
	(0.068)	(0.019)
Observations	322	322
Within R^2	0.182	0.0005
Country fixed effects	✓	✓
Year fixed effects		✓

Panel C: $cor(a_i, x_j)$	CC Serious	
	(1)	(2)
Avg. Other Stringency	0.461***	-0.490**
	(0.089)	(0.178)
Observations	349	349
Within R^2	0.210	0.481
Country fixed effects	✓	✓
Country × Year trends		✓

Panel D: $cor(x_i, a_j)$	Stringency	
	(1)	(2)
Avg. Other CC Serious	0.532***	-0.148***
	(0.023)	(0.034)
Observations	324	324
Within R^2	0.474	0.875
Country fixed effects	✓	✓
Country × Year trends		✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table 3: Empirical Implications of the Learning Mechanism, Mass Beliefs

immediate policy responsiveness. Nevertheless, the results broadly align with the model's expectation that more optimistic beliefs encourage stronger domestic action.

Panels C and D constitute both more difficult and novel assessments of cross-border updating and learning. Consistent with the learning mechanism, Panel C shows that publics exhibit greater concern about climate change when other countries adopt more stringent policies. The final results in Panel D also highlight a positive correlation between the beliefs of other nations and policy stringency, showing how other nations' optimism can diffuse across borders. These are large effects: increasing the stringency of other nations is associated with almost a 0.5 standard deviation in average seriousness, meaning that other nations' actions have nontrivial impacts on belief updating. The effects in Panel D are of similar magnitude: nations' downstream stringency responds strongly to how individuals in other countries problematize climate change.

Interestingly, including country-year time trends flips the sign of the relationship between climate policy stringency and mass beliefs about the importance of climate change (second column in Panels C and D). The estimated coefficient is, albeit with a smaller magnitude, negative and statistically significant. In these specifications, variation contributing to β, the coefficient of interest, comes from within-country deviations from a long-run trend. The theory provides useful insight in interpreting this relationship, as countries are simultaneously learning from one another and navigating free-riding temptations. In the short run, it may be the case that, as shown from the second column of Panel D, optimistic beliefs in one country may depress policy responses in another country in the short run—because that country may be free-riding—but ultimately the learning effect dominates the free-rider effect in the long run, as evidenced by the other positive and significantly estimated correlations.

The results are broadly consistent with the theoretical expectations. Mass beliefs about the seriousness of climate change are positively correlated across countries, consistent with the idea that publics face a common uncertainty. Within countries, greater public concern predicts more stringent downstream climate policies. Moreover, citizens in one country appear to update their assessments when others pursue ambitious policies, and, in turn, these shifting beliefs spill over into more stringent domestic efforts.

Elite Beliefs

Turning to elite beliefs, I consider how climate policymakers assess the nationally determined contributions of other nations and correlate these beliefs with the subsequent behavior of those nations. Respondents were asked to assess pledges made by Australia, Brazil, China, the European Union, India, Russia, Saudi Arabia, South Africa, the United States, and their own country. Specifically, they were asked whether they believe these countries' NDCs are ambitious relative to their economic strength, and whether these countries are likely to fulfill their commitments, each on a scale from 1 to 5. Since experts were asked to provide assessments of multiple countries' climate commitments, I exploit the within-expert variation to test the first three implications of the learning mechanism.

Suppose that elite respondent r was asked to assess the NDC of country i. The first empirical implication tests that the beliefs held by all other experts besides r about i's commitment should positively correlate, which can be captured by the following specification,

$$\text{Beliefs}_{r,i} = \beta \text{ Average Other Beliefs}_{-r,i} + \eta_r + \varepsilon_{r,i}.$$

The left-hand side is either respondent r's belief that country i's NDC is ambitious or will be fulfilled. The independent variable of interest is the average belief about country i's NDC by all other elites besides respondent r. I also include respondent fixed effects. Similar to above, this first empirical implication is simply meant as a check of consistency that elites are cuing off of the same uncertainties, as we should expect positively correlated beliefs across individuals about the same country's NDC.

Second, I look at the within-country assessment of beliefs and downstream policy stringency. Since beliefs are measured about multiple countries from the same expert, I estimate

$$\text{Stringency}_{i,t} = \beta \text{ Beliefs}_{r,i} + \alpha_i + \eta_r + \varepsilon_{r,i}.$$

Unfortunately, beliefs are only measured once for each expert, so these correlations are a snapshot of how elites assessed countries' NDCs at the end of 2020. I therefore examine the relationship between beliefs and countries' climate policy stringency, again measured using the CAPMF, in the years following the elicitation of beliefs. The dependent variable is thus specified as country i's CAPMF score in 2021, 2022, and 2023. I estimate respondent fixed effects η_r to control for any expert-specific biases in assessments across countries as well as country fixed effects α_i to capture baseline levels of variation in the ambition in countries' climate commitments.

To study how past efforts lead experts to update their beliefs, I estimate how other countries' CAPMF scores in 2019 affect elite assessments measured in 2020. The third empirical implication is thus tested by estimating

$$\text{Beliefs}_{r,i} = \beta \text{ Average Other Stringency}_{-i,t-1} + \eta_r + \varepsilon_{i,r}.$$

In this test, the theory expects $\beta > 0$ because past efforts by other nations should lead experts to positively update their beliefs about the ambition and likelihood that country i will follow through on its climate commitment, given the joint economic returns from decarbonization. I also include expert fixed effects to account for baseline differences in expert assessments.

Analogous to the standardization undertaken in the mass beliefs analysis, I divide all dependent and independent variables by the within-respondent standard deviation. This allows for the estimation of β to target the average within-respondent correlation between beliefs and actions.

The elite survey evidence provides a complementary test of the learning mechanism, with results summarized in Table 4. In Panel A, we see that other experts' beliefs correlate positively with an elite's assessments of the NDCs of a particular nation. As before, this statistical pattern establishes the benchmark that experts have correlated assessments of a common underlying uncertainty, which in this case is defined as whether nations will fulfill their climate commitments.

Second, Panel B examines whether past policy efforts by others shape experts' beliefs, the third empirical implication of the learning mechanism. Here we find a positive and significant relationship between other countries' policy stringency in 2019 and expert assessments

Panel A: $cor(x_i, x_j)$	Belief Ambitious (1)	Belief Fulfilled (2)
Avg. Other Belief NDC Ambitious	0.552*** (0.013)	
Avg. Other Belief NDC Fulfilled		0.513*** (0.013)
Observations	5,097	5,313
Within R^2	0.316	0.272
Respondent FE	✓	✓

Panel B: $cor(a_i, x_j)$	Belief Ambitious (1)	Belief Fulfilled (2)
Avg. Other Stringency	0.452*** (0.013)	0.366*** (0.014)
Observations	4,052	4,220
Within R^2	0.198	0.137
Respondent FE	✓	✓

Panel C: $cor(x_i, a_i)$	Stringency$_{2021}$		Stringency$_{2022}$		Stringency$_{2023}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Belief NDC Ambitious	0.019*** (0.007)		0.017** (0.007)		0.017** (0.007)	
Belief NDC Fulfilled		0.013** (0.006)		0.012** (0.006)		0.015** (0.006)
Observations	3,824	3,983	3,824	3,983	3,824	3,983
Within R^2	0.004	0.002	0.003	0.002	0.003	0.003
Respondent fixed effects	✓	✓	✓	✓	✓	✓
Surveyed Country fixed effects	✓	✓	✓	✓	✓	✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the respondent level

Table 4: Empirical Implications of the Learning Mechanism, Elite Beliefs

collected in 2020. The effect sizes are similar to the mass beliefs analysis: a one standard deviation in others' policy stringency is associated with a 0.4-0.45 standard deviation increase in experts' beliefs about the ambition and credibility of NDCs. But as the theory anticipates, observed actions serve as signals of economic viability, leading elites to update their expectations favorably. This dynamic provides clear evidence of the learning channel.

Panel C asks whether elite beliefs predict subsequent policy outcomes. The results are positive and significant: countries deemed by experts to have ambitious or credible NDCs in

2020 went on to implement more stringent climate policies in 2021–23. While the effect sizes are much smaller—as a one unit increase in expert optimism is associated with an increase of about 0.01-0.02 standard deviations in stringency— this finding is particularly important because it suggests that elites' expectations not only reflect prior effort but also foreshadow future policy trajectories. Optimism among experts thus appears to be a meaningful driver of climate action, providing reduced form evidence of learning.

The elite survey evidence reinforces these findings. Experts' assessments of NDC ambition and credibility are correlated across respondents, suggesting they cue on a common uncertainty. More importantly, optimism about a country's pledges predicts more stringent climate action in subsequent years. Experts also appear to condition their expectations on observed past effort, as the theory predicts. Taken together, these results show that beliefs are systematically related to policy outcomes, bolstering the claim that learning shapes global climate cooperation.

The quantitative evidence demonstrates that beliefs and actions are intertwined from the perspective of both publics and elites. These findings are not only consistent with the model's predictions but also crucial for distinguishing learning from free-riding. Free-rider explanations predict no systematic relationship between beliefs and effort. By contrast, the observed correlations between optimism and action, within and across countries, provide empirical support for the learning channel as a driver of international climate policy.

Qualitative Accounts of Learning

In addition to the quantitative evidence presented in the previous section, qualitative evidence also corroborates the notion that countries are learning from other nations when implementing climate policies. Numerous studies document diffusion effects in climate policy implementation, like carbon pricing (e.g., Harrison 2010; Thisted and Thisted 2020;

Linsenmeier, Mohommad and Schwerhoff 2023). This section documents several cases that are illustrative of the learning mechanism.

Following then-President Joe Biden's U.S. presidential victory in 2020, the United States had proposed the Build Back Better Act—an act that Biden personally championed and expended large amounts of political capital to realize, ultimately becoming the Inflation Reduction Act, the largest investment in clean energy in the world—as its cornerstone legislative program. Meetings with international leaders further inspired action around the globe based on Biden's beliefs in the economic value of the green transition. Indeed, in talks with then-Canadian Prime Minister Justin Trudeau in February 2021, the two leaders "expressed their shared commitment to taking real action to fighting climate change while growing the economy and creating good jobs," and announced a formal diplomatic project to "align [their] policies and [their] goals to increase ambition to tackle the climate crisis."[8] Two months later, the Canadian government announced several new, expanded climate policies to enhance their NDC in early 2021. Trudeau initiated programs to incentivize Canadian businesses to achieve net-zero emissions and develop cleaner industry.[9] Importantly, Trudeau emphasized cooperation on climate issues with the United States, as both countries recognized the economic value in ambitious climate investments,[10] and affirmed a common belief that greater ambition would realize greater policy success.

Another example of learning across borders comes from South Korea's 2020 legislative elections. The incumbent Democratic Party won in a landslide victory, in part due to the party's emphasis on ambitious climate spending. Then-President Moon Jae-in campaigned on a European Union-style Green Deal, explicitly referring to the E.U.'s climate plan as a

[8] https://www.pm.gc.ca/en/news/news-releases/2021/02/23/prime-minister-canada-welcomes-plan-revitalize-and-expand-ties-united

[9] https://www.pm.gc.ca/en/news/news-releases/2021/04/22/prime-minister-trudeau-announces-increased-climate-ambition

[10] https://www.canada.ca/en/environment-climate-change/news/2021/02/canada-us-high-level-climate-ministerial.html

template for Korean policy.[11] In its own Green New Deal, South Korea committed to carbon neutrality by 2050, and the plan includes large-scale investments in renewable energy, the introduction of a carbon tax, the phaseout of coal financing by public institutions, and the creation of a jobs transition programs to support workers who relocate into green jobs.[12] This was facilitated by the formation of a working group between the Koreans and the Europeans, initiated to share ideas and harmonize policy solutions[13]—allowing the Koreans to learn from the Europeans' optimism—and, in 2021, the two countries compared policy proposals. The two countries highlighted their commonalities and complementarities in their approaches to tackling climate change, confirming that "climate, energy and environment policies have to be addressed holistically, in the light of the interdependence of challenges."[14]

Finally, consider the climate commitment pledged by then-South African President Jacob Zuma at the Copenhagen climate summit in 2009. The summit's final document, the Copenhagen Accord, was largely panned as incomplete. However, Zuma, who initially considered ditching the summit,[15] was considered "one of the stars" of the negotiations by committing to reduce emissions by 34% below current expected levels by 2020 and by about 42% by 2025.[16] The target was particularly unexpected because it was the first time the country had ever made such a pledge, and because of the resistance from influential, pro-status quo actors like Eskom, the country's public utility company. Observers note that, while Zuma never justified his sudden commitment—which transformed national dialogue inside of South Africa toward building a green economy—it may have been due to similarly ambitious pledges from peer countries like China, India, and Brazil (Hochstetler 2020, 40),

[11] https://www.forbes.com/sites/davidrvetter/2020/04/16/south-korea-embraces-eu-style-green-deal-for-covid-19-recovery/

[12] https://www.climatechangenews.com/2020/04/16/south-korea-implement-green-new-deal-ruling-party-election-win/

[13] https://www.mofa.go.kr/eng/brd/m_5658/view.do?seq=318785

[14] https://www.eeas.europa.eu/eeas/eu-republic-korea-joint-press-release-following-working-group-energy-environment-and-climate-change_en

[15] https://unfccc.int/sites/default/files/cop15_mw_091211_sa.pdf

[16] http://news.bbc.co.uk/2/hi/africa/8398775.stm

suggestive of complementarities in climate commitments across developing nations.

Consequences for International Institutions

Scholars and policymakers, underscoring free-riding concerns, have proposed a set of institutional solutions in an attempt to facilitate international climate cooperation. For example, the fines included in the Kyoto Protocol aimed to deter potential free-riding by raising the costs of noncompliance with reduction targets (Barrett 2003; Victor 2011; Hovi, Ward and Grundig 2015). Other proposals like "climate clubs" seek to minimize free-riding by restricting abatement efforts to a smaller number of participating nations while levying tariffs on those not in the club (Nordhaus 2015). However, temptations to free-ride, while certainly present, may not be the dominant concern when states enact climate policy and consider possible investments by others. Institutions with intentions to maximize global mitigation investments should therefore be designed to exploit the complementarity effects of nations' climate policymaking behavior rather than solely to punish potential free-riders. This means managing the dual effects—the direct effect associated with free-riding as well as the informational effect from learning—of the impacts of countries' mitigation actions on subsequent effort.

Per this paper's theoretical takeaways, institutional designers may wish to adopt an alternative set of principles that foreground the roles of information and expectations in shaping international climate cooperation. The importance of international institutions in reducing uncertainty is well-established (Keohane 1982; 1984), as institutions can generate and disseminate information via review processes (Abbott 2017; Aldy 2018), which allow for the transmission of knowledge about how best to structure policies and approach the problem of climate change mitigation (Chayes and Chayes 1995). As the theoretical analysis illustrates, when expectations about the success of a green transition outweigh risk aversion from uncertain climate investments, efforts to address climate change are complementary.

Institutions, therefore, have a natural role in shaping prior beliefs about the returns to climate investments by transmitting information about policy effectiveness (captured by μ and γ in the model). This is reminiscent of arguments that international organizations can be used to disseminate information bolstered by policy domain expertise (Johns 2007; Fang 2008; Johnson and Urpelainen 2014). In terms of engendering complementarities, it is always better for countries to have more optimistic prior expectations, and more precise information is beneficial to accompany this optimism.

Institutions can also influence countries' risk perceptions, counteracting aversions that discourage remediation and enable free-riding. The tradeoff between free-riding effects and learning effects is dampened if marginal contributions to global output are high (the shape of $g(\cdot)$) or marginal costs are lower (the shape of $c(\dot{})$), so institutions could facilitate the dissemination of technology that raises the benefits from potential mitigation investments. By modifying how the benefits and costs of mitigation are perceived, institutions can generate "increasing returns" (Pierson 2000; Hale 2020).

The information dissemination provisions in the Paris Agreement demonstrate the possibility of institutional infrastructure to facilitate learning dynamics that the model highlights. Articles 13, 14, and 15 of the Paris Agreement outline the review process of individual country progress toward climate commitments, a worldwide discussion of aggregate performance, as well as nonpunitive troubleshooting of obstacles to policy implementation (UNFCCC 2015). While this "global stocktake" process is not intended to single out any individual country for its failure to comply with targets—as any "naming and shaming" is supposed to flow from the global stocktake by other public actors (Milkoreit and Haapala 2017)—this institutional framework could be used to disseminate information about countries' policy successes, which could bolster common, public expectations about the value of green investments.

Beyond Paris's pledge-and-review structure, institutions may also assist in expectations management by providing a platform for nations to pool common information. For example, the World Bank launched the Partnership for Market Readiness (PMR) in 2011, which "supports countries to assess, prepare, and implement carbon pricing instruments [and] serves as a platform for countries to share knowledge and work together to shape the future of cost-effective climate change mitigation" (World Bank Partnership for Market Readiness 2017). This institution has been accredited with transforming global familiarity with, understanding of, and comfort with carbon pricing instruments, leading to a larger uptake of carbon pricing (Dickman and Larkin 2017). By dispersing knowledge on carbon pricing and supporting its implementation, institutions like the PMR have promoted carbon pricing and have succeeded in making it a more accessible policy tool, thereby facilitating learning among nations about policies that can assist in the green transition (Thisted and Thisted 2020, 816).

Conclusion

This article reassesses the notion that countries' efforts to mitigate the effects of climate change are solely substitutable and proposes an alternative theoretical framework in which they may also be complementary. While free-riding concerns may entice nations to shirk in their mitigation investments, I argue that the implementation of environmental policies is also a signal about the expected policy success of costly climate investments. Hence, the strength of positive or negative incentives to take climate action upon observing action by other countries is not *ex ante* clear. With theoretical analysis, I show that when nations' optimism about the expected economic returns from climate investment outweigh their aversion toward investing in a risky policy such as climate mitigation, then the positive effects from learning dominate free-rider temptations.

The theory provides several implications for international climate cooperation and the design of international climate institutions. As discussed above, the model suggests a departure from institutional mechanisms that punish free-riders and toward a design that centers around shaping expectations about successful policy implementation. Future research could consider the optimal design of institutions that are explicitly geared toward maximizing countries' expectations about the success of climate policy implementation. Additionally, other work expanding on this article might also consider how best to maximize cross-country learning in terms of factors such as policy instrument choice or geographic concentration.

Beyond climate cooperation, the theoretical framework advanced in this paper might assist in studying global public goods problems in other realms of international politics. The core tension of the model boils down to when countries should invest in global public goods as a function of their collective beliefs about the success of these investments and the temptations to free-ride off of others; when the former dominates the latter, then global public goods contributions are complementary. For example, in the realm of collective security, countries often face the dilemma of whether to arm in the face of a potential adversary, whose strength may be unknown, or whether to free-ride on the security provided by other nations. Contributing to collective defense is costly, but observing greater investments may be a signal that a contributing state believes the adversary is particularly strong, and therefore greater investment is worthwhile. The model helps us understand, in broadest terms, the incentives nations face to cooperate in an environment of common values uncertainty.

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Appendix: Learning and Free-Riding in International Climate Policymaking

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Contents

A Formal Proofs

Proof of Proposition 1. To solve for the equilibrium, I conjecture the existence of a strategy for country 1 $a_1 = \alpha_1(x_1)$ and assume that $\alpha_1(x_1)$ is one-to-one. Proceeding by backward induction first consider country 2's effort investment given her signal x_2 and country 1's effort a_1. Given that $\alpha_1(x_1)$ is one-to-one, we have $x_1 = \alpha_1^{-1}(a_1)$ and so country 2's posterior update about θ is $\theta|x_2, a_1 \sim N(\frac{\gamma\mu+\beta\alpha_1^{-1}(a_1)+\beta x_2}{\gamma+2\beta}, \frac{1}{\gamma+2\beta})$. Country 2 therefore solves

$$\max_{a_2} \; E[\theta|x_2, a_1]g(a_1 + \lambda a_2) - c(a_2).$$

Differentiating with respect to a_2, country 2's first-order condition is

$$E[\theta|x_2, a_1]g'(a_1 + \lambda a_2)\lambda - c'(a_2) = 0.$$

Note that if $E[\theta|x_2, a_1] < 0$, which occurs when $x_2 < -\frac{\gamma\mu}{\beta} - \alpha_1^{-1}(a_1)$ then $E[\theta|x_2, a_1] < 0$ and country 2 exerts effort in the opposite direction. Given the functional form specifications and solving the above first-order condition, we have the following piecewise function:

$$\alpha_2(x_2, a_1) = \begin{cases} -\frac{1}{\lambda}a_1 + \frac{\lambda(\gamma\mu+\beta\alpha_1^{-1}(a_1)+\beta x_2)^2}{4c_2^2(2\beta+\gamma)^2} & x_2 \geq -\frac{\gamma\mu}{\beta} - \alpha_1^{-1}(a_1) \\ -\frac{1}{\lambda}a_1 - \frac{\lambda(\gamma\mu+\beta\alpha_1^{-1}(a_1)+\beta x_2)^2}{4c_2^2(2\beta+\gamma)^2} & x_2 < -\frac{\gamma\mu}{\beta} - \alpha_1^{-1}(a_1) \end{cases}$$

It is clear from the second-order condition that for any x_2 and any a_1, $\alpha_2(x_2, a_1)$ is unique as the second-order condition as always negative:

$$E[\theta|x_2, a_1]g''(a_1 + \lambda a_2)\lambda^2 - c''(a_2) < 0.$$

Now consider country 1's effort choice. Given his own signal x_1, he believes that $\theta|x_1 \sim N(\frac{\gamma\mu+\beta x_1}{\gamma+\beta}, \frac{1}{\gamma+\beta})$ and that country 2's signal $x_2|x_1 \sim N(\frac{\gamma\mu+\beta x_1}{\gamma+\beta}, \frac{2\beta+\gamma}{\beta(\beta+\gamma)})$. Let $m = \frac{\gamma\mu+\beta x_1}{\gamma+\beta}$ and $z = \sqrt{\frac{\beta(\beta+\gamma)}{2\beta+\gamma}}$. Further, denote $q = \frac{\lambda(\gamma\mu+\beta\alpha_1^{-1}(a_1)+\beta x_2)^2}{4c_2^2(2\beta+\gamma)^2}$ and $t = -\frac{\gamma\mu}{\beta} - \alpha_1^{-1}(a_1)$. By backward induction, country 1's problem is to maximize

$$\max_{a_1} \int_{-\infty}^{t} \Big[mg(-q)z\phi(z(x_2 - m))\Big] \, dx_2 + \int_{t}^{\infty} \Big[mg(q)z\phi(z(x_2 - m))\Big] \, dx_2 - c(a_1).$$

Differentiating with respect to a_1, country 1's first-order condition is

$$\begin{aligned} FOC &= mg(0)z\phi(z(t-m))\frac{dt}{da_1} + \int_{-\infty}^{t} -mg'(-q)\frac{dq}{da_1}z\phi(z(x_2 - m)) \, dx_2 \\ &\quad - mg(0)z\phi(z(t-m))\frac{dt}{da_1} + \int_{t}^{\infty} mg'(q)\frac{dq}{da_1}z\phi(z(x_2 - m)) \, dx_2 - c_1 = 0 \\ &= \int_{-\infty}^{t} \frac{m\beta\lambda}{2c_2(2\beta+\gamma)} \frac{1}{\alpha_1'(\alpha_1^{-1}(a_1))} z\phi(z(x_2 - m)) \, dx_2 \end{aligned}$$

$$+ \int_t^\infty \frac{m\beta\lambda}{2c_2(2\beta+\gamma)} \frac{1}{\alpha_1'(\alpha_1^{-1}(a_1))} z\phi(z(x_2-m))\; dx_2 - c_1 = 0$$

$$\Leftrightarrow\ \alpha_1'(\alpha_1^{-1}(a_1)) = \frac{(\gamma\mu+\beta x_1)\beta\lambda}{2c_2c_1(2\beta+\gamma)(\gamma+\beta)}.$$

It is clear that since q is increasing in $\alpha_1^{-1}(a_1)$, country 1's optimal strategy does not contain any "flat spots" as it is always optimal for him to induce greater effort from country 2. Observe that for $x_1 < -\frac{\mu\gamma}{\beta}$, $m < 0$ and so country 1 would then exert effort in the negative direction. By equilibrium conjecture, $a_1 = \alpha_1(x_1)$ so $\alpha_1^{-1}(a_1) = x_1$ and integrating with respect to x_1 yields

$$\alpha_1(x_1) = \frac{\beta\lambda x_1(2\gamma\mu+\beta x_1)}{4c_1c_2(2\beta^2+3\beta\gamma+\gamma^2)} + C.$$

The constant of integration is pinned down by the boundary condition that, at $x_1 = -\frac{\gamma\mu}{\beta}$, we have $E[\theta|x_1] = 0$. The equilibrium effort is thus

$$\alpha_1(x_1) = \begin{cases} \frac{\beta\lambda x_1(2\gamma\mu+\beta x_1)+\lambda\gamma^2\mu^2}{4c_1c_2(2\beta^2+3\beta\gamma+\gamma^2)} & x_1 \geq -\frac{\gamma\mu}{\beta} \\ \frac{-\beta\lambda x_1(2\gamma\mu+\beta x_1)-\lambda\gamma^2\mu^2}{4c_1c_2(2\beta^2+3\beta\gamma+\gamma^2)} & x_1 < -\frac{\gamma\mu}{\beta}. \end{cases}$$

Note that this is one-to-one in x_1, confirming that $\alpha_1(x_1)$ is one-to-one in equilibrium. This means that $\alpha_1^{*^{-1}}(\cdot)$ is well-defined so country 2 knows $x_1 = \alpha_1^{*^{-1}}(a_1)$ in equilibrium.

Finally, observe that the second order condition is

$$-\frac{m\beta\lambda}{2c_2(2\beta+\gamma)} \frac{\alpha_1''(\alpha_1^{-1}(a_1))}{(\alpha_1'(\alpha_1^{-1}(a_1)))^3} < 0,$$

so the solution $\alpha_1(x_1)$ is the unique maximizer of country 1's utility. □

Proof of Corollary 1. Immediate given the equilibrium strategy of country 1:

$$\frac{d\alpha_1(x_1)}{dx_1} = \frac{2\beta\lambda(\gamma\mu+\beta x_1)}{4c_1c_2(2\beta^2+3\beta\gamma+\gamma^2)} \geq 0.$$

$$\frac{dE[\theta|x_2,a_1]}{da_1} = \frac{\beta}{\beta+\gamma}\frac{1}{\frac{d\alpha_1(x_1)}{dx_1}} \geq 0.$$

□

Proof of Corollary 2. Given country 2's first-order condition,

$$\frac{\partial^2 u_2}{\partial a_2 \partial \alpha_1^{-1}(a_1)} = \frac{\beta}{\gamma+2\beta} g'(a_1+\lambda a_2)\lambda > 0 \ \Leftrightarrow\ \frac{\partial \alpha_2(x_2,a_1)}{\partial \alpha_1^{-1}(a_1)} \geq 0.$$

$$\frac{\partial^2 u_2}{\partial a_2 \partial a_1} = E[\theta|x_2,a_1]g''(a_1+\lambda a_2)\lambda < 0 \ \Leftrightarrow\ \frac{\partial \alpha_2(x_2,a_1)}{\partial a_1} \leq 0.$$

□

Proof of Proposition 2. From Corollary 2,

$$
\begin{aligned}
\Big|\frac{\partial \alpha_2(x_2,a_1)}{\partial \alpha_1^{-1}(a_1)}\Big| &> \Big|\frac{\partial \alpha_2(x_2,a_1)}{\partial a_1}\Big| \\
\Leftrightarrow \ \frac{\beta}{\gamma+2\beta} g'(a_1+\lambda a_2)\lambda &< -|E[\theta|x_2,a_1]| g''(a_1+\lambda a_2)\lambda \\
\Leftrightarrow \ \frac{\beta}{|\gamma\mu+\beta\alpha_1^{-1}(a_1)+\beta x_2|} &< -\frac{g''(A)}{g'(A)} \\
\Leftrightarrow \ \left(-\frac{g''(A)}{g'(A)}\right)^{-1} &< \frac{|\gamma\mu+\beta\alpha_1^{-1}(a_1)+\beta x_2|}{\beta}.
\end{aligned}
$$

□

B Additional Tables and Figures

B.1 Climate Law Adoption and Environmental Policy Stringency

The main results employ country × year time trends. Table A.1 shows robustness of the findings without any temporal controls.

	Laws (Count)		Laws (Binary)		EPS		CAPMF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Other Laws)	0.530***	0.819***	0.526***	0.867***				
	(0.012)	(0.049)	(0.011)	(0.053)				
Avg. Other Stringency					0.918***	0.706***	0.972***	0.818***
					(0.013)	(0.143)	(0.003)	(0.051)
Observations	7,000	7,000	7,000	7,000	1,200	1,200	1,650	1,650
R^2	0.302	0.331	0.314	0.344	0.900	0.904	0.960	0.962
Within R^2	0.277	0.307	0.273	0.305	0.845	0.852	0.958	0.960
DV Mean	0.643	0.643	0.713	0.713	2.04	2.04	1.25	1.25
Number of Countries	200	200	200	200	40	40	50	50
Country fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Country × Year trends		✓		✓		✓		✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.1: Effects of Previous Law Adoption and Policy Stringency on Climate Policymaking (with and without Time Trends)

The main results include a country fixed effect to parse out any time-invariant factors that lead countries to adopt laws or pursue environmental policies in a heterogeneous fashion. However, in so doing, the regression coefficient β thus targets the within-country correlation of the effect of other nations' climate actions on the adoption of climate laws. Table A.2 removes country fixed effects and shows that the results still hold.

	Laws (Count)		Laws (Binary)		EPS		CAPMF	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Other Laws)	0.530***	0.803***	0.525***	0.849***				
	(0.012)	(0.048)	(0.012)	(0.052)				
Avg. Other Stringency					0.904***	0.409**	0.971***	0.801***
					(0.013)	(0.152)	(0.003)	(0.051)
Observations	7,000	7,000	7,000	7,000	1,200	1,200	1,650	1,650
R^2	0.267	0.270	0.257	0.262	0.529	0.536	0.909	0.911
Adjusted R^2	0.267	0.270	0.257	0.262	0.528	0.536	0.909	0.910
DV Mean	0.643	0.643	0.713	0.713	2.04	2.04	1.25	1.25
Year trends		✓		✓		✓		✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.2: Effects of Previous Law and Policy Stringency on Climate Policymaking (without Country Fixed Effects)

Climate Laws

In the main text, I employ country × year time trends to capture the effects of potential secular increases in the demand for climate policy. Table A.3 shows that results are robust to different types of time trends. Specifically, I estimate linear, quadratic, and cubic yearly time trends. I also estimate year random effects.

	Laws (Count)			Laws (Binary)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(Other Laws)	0.819***	0.968***	0.388***	0.867***	0.911***	0.315***
	(0.048)	(0.047)	(0.064)	(0.052)	(0.052)	(0.064)
Observations	7,000	7,000	7,000	7,000	7,000	7,000
R^2	0.305	0.310	0.330	0.319	0.319	0.340
Within R^2	0.280	0.285	0.306	0.278	0.279	0.301
Country fixed effects	✓	✓	✓	✓	✓	✓
Time trends	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.3: Effects of Climate Laws with Alternate Time Trends

	Laws (Count)	Laws (Binary)
	(1)	(2)
(Intercept)	−1.019***	−0.963***
	(0.213)	(0.192)
log(Other Laws)	0.530***	0.526***
	(0.050)	(0.040)
Country fixed effects	✓	✓
AIC	17652.524	17938.139
BIC	19043.818	19329.433
Log Likelihood	−8623.262	−8766.069
Num. obs.	7000	7000
Num. groups: year	35	35
Var: year (Intercept)	0.082	0.052
Var: Residual	0.655	0.685

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table A.4: Effects of Climate Laws with Year Random Effects

While the results between other nations' laws and the tendency to adopt laws should be treated as descriptive or correlational, I also estimate these models with the inclusion of some time-varying controls. These control variables are meant to parse time-varying variation away from nations' climate policymaking behavior. Specifically, I estimate the revised model

$$\text{Laws}_{i,t} = \beta \ \log(\text{Other Laws}_{-i,t-1}) + X'_{i,t-1}\gamma + \alpha_i + \lambda_{i,t} + \varepsilon_{i,t},$$

where the term $X'_{it-1}\gamma$ captures these controls. I include a lagged dependent variable, GDP per capita, population, and a country's growth rate (all from the World Bank), and the size of a country's winning coalition to proxy for regime type (Bueno de Mesquita and Smith 2022). Results are shown in Table A.5.

	Laws (Count)		Laws (Binary)	
	(1)	(2)	(3)	(4)
log(Other Laws)	0.557***	0.005	0.544***	0.224***
	(0.033)	(0.076)	(0.035)	(0.079)
Lagged DV	0.071***	0.023	0.041**	0.003
	(0.019)	(0.019)	(0.016)	(0.017)
log(GDP per capita)	0.148	-0.097	0.168	0.027
	(0.101)	(0.196)	(0.104)	(0.227)
log(Population)	0.089	-0.246	0.141	0.154
	(0.092)	(0.655)	(0.105)	(0.552)
Growth	0.004	0.002	0.005*	0.003
	(0.003)	(0.003)	(0.003)	(0.004)
Winning Coalition Size	-0.419**	-0.766***	-0.242	-0.447*
	(0.174)	(0.249)	(0.183)	(0.244)
Observations	5,075	5,075	5,075	5,075
R^2	0.366	0.396	0.366	0.389
Within R^2	0.345	0.376	0.331	0.355
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓
Controls	✓	✓	✓	✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.5: Effects of Climate Laws with Controls

We may be worried that only richer countries or only countries that are emissions-intensive need to pass laws. Tables A.6 and A.7 weight results by countries' GDP per capita and emissions per capita.

	Laws (Count)		Laws (Binary)	
	(1)	(2)	(3)	(4)
log(Other Laws)	0.613***	0.004	0.597***	0.248***
	(0.011)	(0.076)	(0.011)	(0.077)
Observations	5,863	5,863	5,863	5,863
R^2	0.350	0.381	0.355	0.379
Within R^2	0.327	0.360	0.318	0.343
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓
Weights	GDP per capita	GDP per capita	GDP per capita	GDP per capita

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.6: Effects of Climate Laws (Weighted by GDP per capita)

	Laws (Count)		Laws (Binary)	
	(1)	(2)	(3)	(4)
log(Other Laws)	0.506***	0.677***	0.498***	0.752***
	(0.031)	(0.100)	(0.031)	(0.097)
Observations	6,545	6,545	6,545	6,545
R^2	0.293	0.329	0.301	0.335
Within R^2	0.257	0.295	0.245	0.282
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓
Weights	GHG per capita	GHG per capita	GHG per capita	GHG per capita

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.7: Effects of Climate Laws (Weighted by Emissions per capita)

Policy Stringency

Figures A.1 and A.2 plot the raw data of each country's EPS and CAPMF score (solid line) as well as the average stringency of all other countries (dashed line) over time. It is evident that for almost all countries, stringency is increasing over time and is positively correlated with the actions of others.

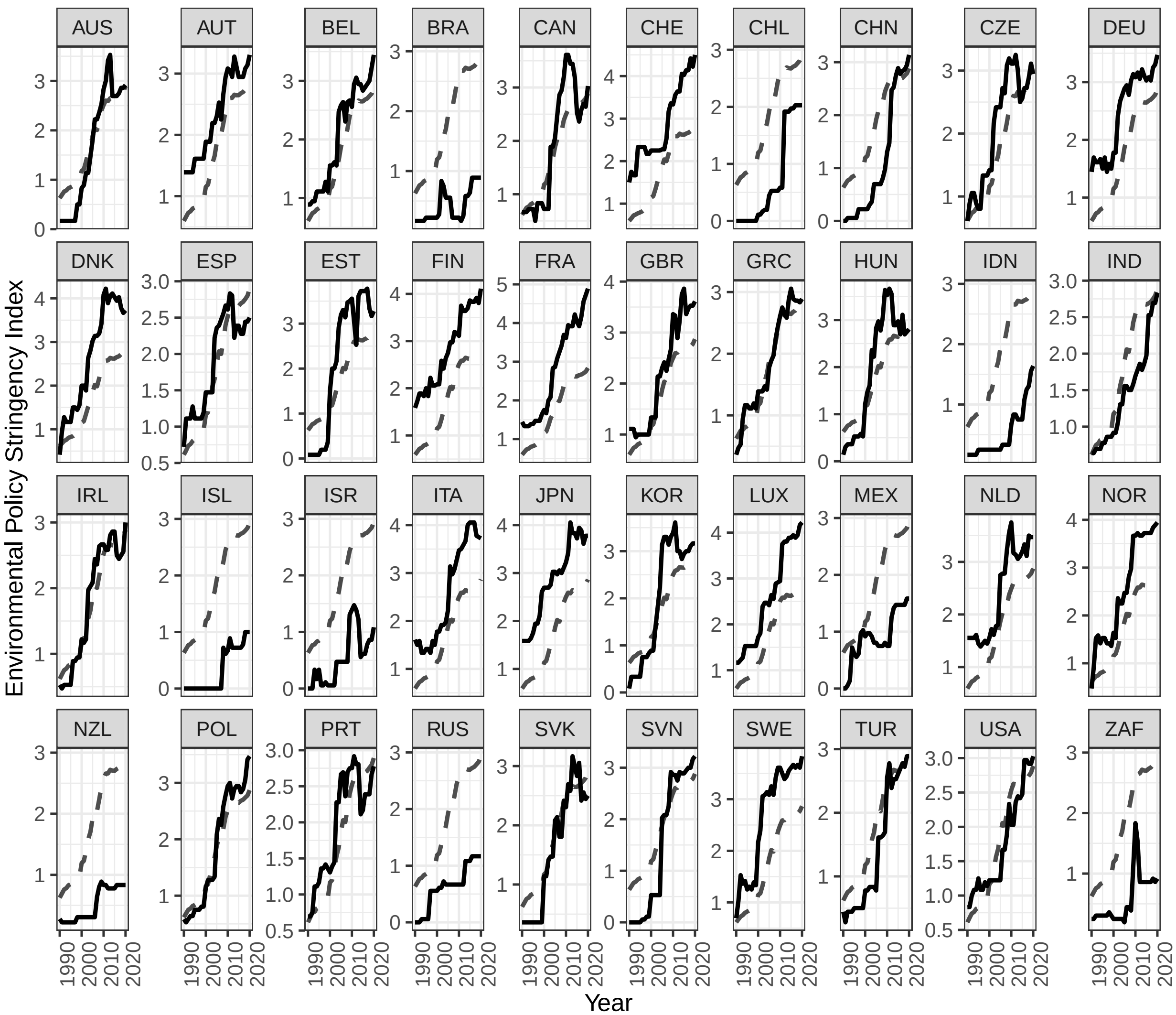

Figure A.1: Environmental Policy Stringency 1990-2020

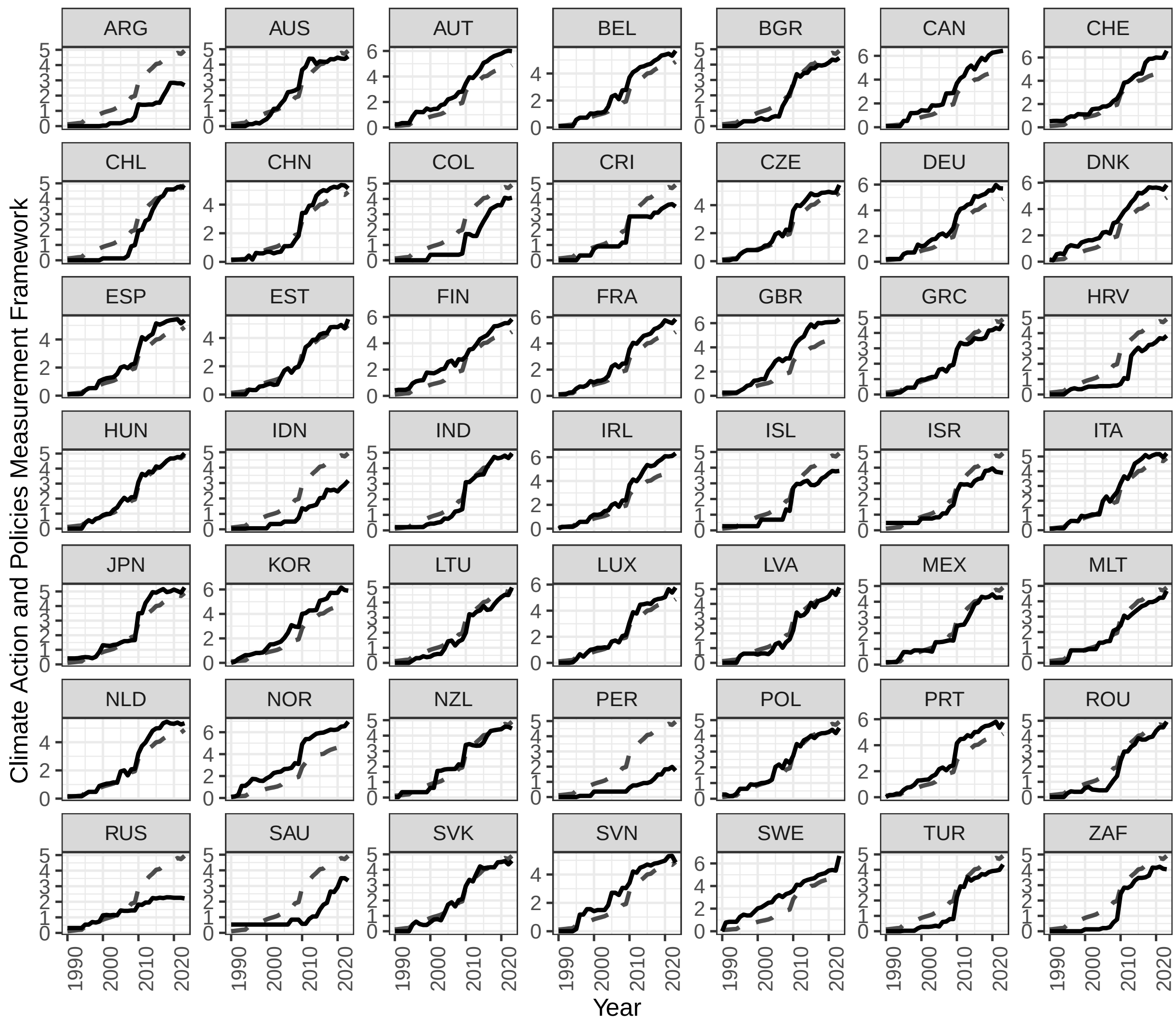

Figure A.2: Climate Action Policy Mitigation Framework 1990-2023

In the main text, I employ country × year time trends to capture the effects of potential secular increases in the demand for climate policy. Table A.8 shows that results are robust to different types of time trends. Specifically, I estimate linear, quadratic, and cubic yearly time trends. I also estimate year random effects.

	EPS			CAPMF		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Other Stringency	0.705***	0.698***	0.339	0.818***	0.823***	0.646***
	(0.141)	(0.137)	(0.224)	(0.051)	(0.055)	(0.047)
Observations	1,200	1,200	1,200	1,650	1,650	1,650
R^2	0.901	0.901	0.902	0.962	0.962	0.963
Within R^2	0.847	0.847	0.848	0.960	0.960	0.961
Country fixed effects	✓	✓	✓	✓	✓	✓
Time trends	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.8: Effects of Policy Stringency with Alternate Time Trends

	EPS	CAPMF
	(1)	(2)
(Intercept)	−0.546***	−0.327***
	(0.078)	(0.041)
Average Other Stringency	0.916***	0.966***
	(0.015)	(0.017)
Country fixed effects	✓	✓
AIC	1320.345	−540.609
BIC	1539.218	−253.957
Log Likelihood	−617.172	323.305
Num. obs.	1200	1650
Num. groups: year	30	33
Var: year (Intercept)	0.003	0.008
Var: Residual	0.148	0.033

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table A.9: Effects of Policy Stringency with Year Random Effects

While the results between other nations' stringency and the country i's policy stringency should be treated as descriptive or correlational, I also estimate these models with the inclusion of some time-varying controls. These control variables are meant to parse time-varying variation away from nations' climate policymaking behavior. Specifically, I estimate the revised model

$$\text{Stringency}_{i,t} = \beta \text{ Average Stringency}_{-i,t-1} + X'_{i,t-1}\gamma + \alpha_i + \lambda_{i,t} + \varepsilon_{i,t},$$

where the term $X'_{it-1}\gamma$ captures these controls. I include a lagged dependent variable, GDP per capita, population, and a country's growth rate (all from the World Bank), and the size of a country's winning coalition to proxy for regime type (Bueno de Mesquita and Smith 2022). Results are shown in Table A.10.

	EPS		CAPMF	
	(1)	(2)	(3)	(4)
Average Other Stringency	0.184***	0.134**	0.213***	0.080***
	(0.031)	(0.056)	(0.034)	(0.028)
Lagged DV	0.745***	0.738***	0.767***	0.753***
	(0.024)	(0.024)	(0.034)	(0.036)
log(GDP per capita)	0.158***	0.529*	0.107***	-0.097
	(0.053)	(0.262)	(0.025)	(0.090)
log(Population)	0.238*	-0.389	0.143***	-0.873*
	(0.125)	(0.924)	(0.037)	(0.438)
Growth	-0.006*	-0.005	0.002	-0.0002
	(0.003)	(0.003)	(0.001)	(0.001)
Winning Coalition Size	0.057	0.116	0.045	-0.234
	(0.242)	(0.510)	(0.091)	(0.145)
Observations	1,165	1,165	1,469	1,469
R^2	0.952	0.954	0.977	0.978
Within R^2	0.927	0.930	0.975	0.977
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓
Controls	✓	✓	✓	✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.10: Effects of Policy Stringency with Controls

We may be worried that only richer countries or only countries that are emissions-intensive have greater policy stringency. Tables A.11 and A.12 weight results by countries' GDP per capita and emissions per capita.

	EPS		CAPMF	
	(1)	(2)	(3)	(4)
Average Other Stringency	0.923***	0.732***	0.968***	0.796***
	(0.013)	(0.137)	(0.005)	(0.052)
Observations	1,170	1,170	1,523	1,523
R^2	0.898	0.902	0.958	0.961
Within R^2	0.845	0.852	0.956	0.959
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓
Weights	GDP per capita	GDP per capita	GDP per capita	GDP per capita

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.11: Effects of Policy Stringency (Weighted by GDP per capita)

	EPS		CAPMF	
	(1)	(2)	(3)	(4)
Average Other Stringency	0.927***	0.785***	0.972***	0.782***
	(0.011)	(0.131)	(0.004)	(0.052)
Observations	1,200	1,200	1,617	1,617
R^2	0.903	0.907	0.958	0.960
Within R^2	0.854	0.859	0.956	0.959
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓
Weights	GHG per capita	GHG per capita	GHG per capita	GHG per capita

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.12: Effects of Policy Stringency (Weighted by Emissions per capita)

Table A.13 shows robustness to measuring the behavior of other nations at the median rather than the average policy stringency, which eases concerns about extreme values.

	EPS		CAPMF	
	(1)	(2)	(3)	(4)
Median Stringency	0.919***	0.746***	0.972***	0.877***
	(0.013)	(0.168)	(0.003)	(0.051)
Observations	1,200	1,200	1,650	1,650
R^2	0.900	0.904	0.962	0.963
Within R^2	0.844	0.850	0.960	0.961
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.13: Effects of Median Policy Stringency

Table A.14 re-estimates the results in the main text but excludes the influences of China.

	EPS		CAPMF	
	(1)	(2)	(3)	(4)
Average Other Stringency	0.920***	0.749***	0.971***	0.801***
	(0.013)	(0.165)	(0.003)	(0.053)
Observations	1,170	1,170	1,617	1,617
R^2	0.898	0.902	0.959	0.961
Within R^2	0.843	0.849	0.957	0.959
Country fixed effects	✓	✓	✓	✓
Country × Year trends		✓		✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.14: Effects of Policy Stringency Excluding China

B.2 U.S. Presidential Elections

Table A.15 estimates the RD effect of U.S. elections without country fixed effects.

	Trump (2016)		Biden (2020)	
	(1)	(2)	(3)	(4)
RD Election Effect	-0.009	-0.020	0.067***	0.070***
	(0.017)	(0.019)	(0.022)	(0.020)
DV	Count	Binary	Count	Binary
Bandwidth (days)	810.142	782.037	1616.285	1504.298
Effective Observations	10547	10149	20497	19701

Table A.15: RD Estimates without Country Fixed Effects

The RD specification in the main text does not adjust for any other temporal shocks. Tables A.16 and A.17 control for country-month time trends and month fixed effects, respectively. These terms capture factors like signing of international agreements, the onset of global pandemic, or other time shocks that correlated with the adoption of climate laws around the election.

	Trump (2016)		Biden (2020)	
	(1)	(2)	(3)	(4)
RD Election Effect	-0.014	-0.025	0.065***	0.066***
	(0.017)	(0.019)	(0.022)	(0.020)
DV	Count	Binary	Count	Binary
Country fixed effects	✓	✓	✓	✓
Country $\times$ Month time trends	✓	✓	✓	✓
Bandwidth (days)	829.619	824.242	1610.132	1510.144
Effective Observations	10746	10746	20298	19701

Table A.16: RD Estimates with Country-Month Time Trends

	Trump (2016)		Biden (2020)	
	(1)	(2)	(3)	(4)
RD Election Effect	-0.014	-0.025	0.065***	0.066***
	(0.017)	(0.019)	(0.022)	(0.020)
DV	Count	Binary	Count	Binary
Country fixed effects	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓
Bandwidth (days)	829.619	824.242	1610.132	1510.144
Effective Observations	10746	10746	20298	19701

Table A.17: RD Estimates with Month Fixed Effects

Figures A.3 and A.4 serve as placebo tests for the RD effects that vary the cutoff in the running variable. I look at the 90 day period around each election. The estimate highlighted in red is the actual estimate.

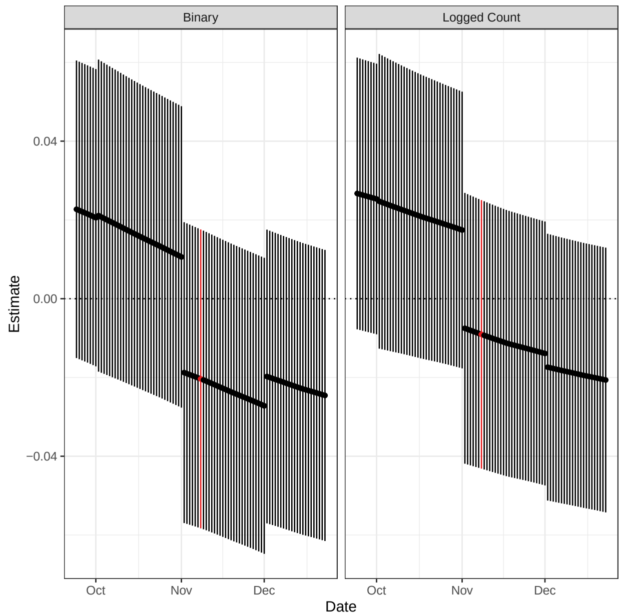

Figure A.3: RD Placebo Test (Trump)

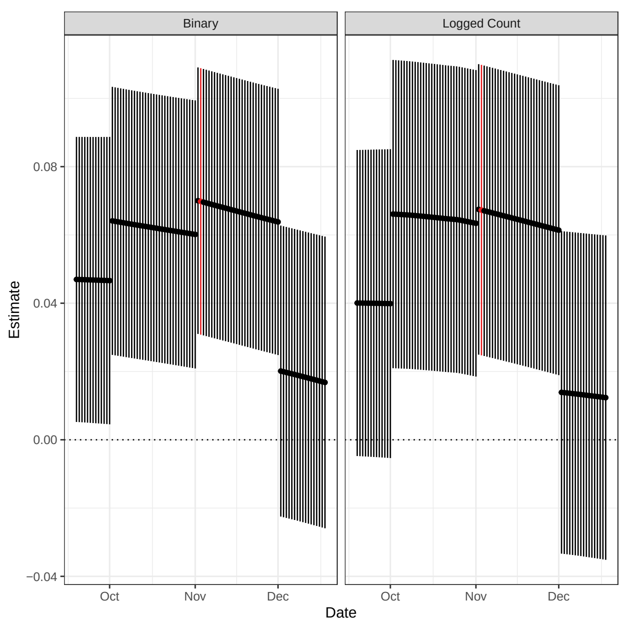

Figure A.4: RD Placebo Test (Biden)

Table A.18 shows the results of two tests of the no-sorting assumption, one based on McCrary (2008) and another based on Cattaneo et al. (2018). In both tests, the null hypothesis is that of no sorting. While the McCrary test is marginally significant for the Trump discontinuity, these results are suggestive of a lack of sorting in climate laws before/after the two U.S. elections.

Test	Election	p-value
McCrary (2008)	2016	0.091
McCrary (2008)	2020	0.149
Cattaneo et al. (2018)	2016	0.985
Cattaneo et al. (2018)	2020	0.931

Table A.18: RD Sorting Checks

Figure A.5 also shows how RD estimates are robust to different bandwidths. The estimate highlighted in red is the actual estimate. The Biden estimates are clearly robust; some of the Trump estimates change sign with very small bandwidths but they are not statistically significant.

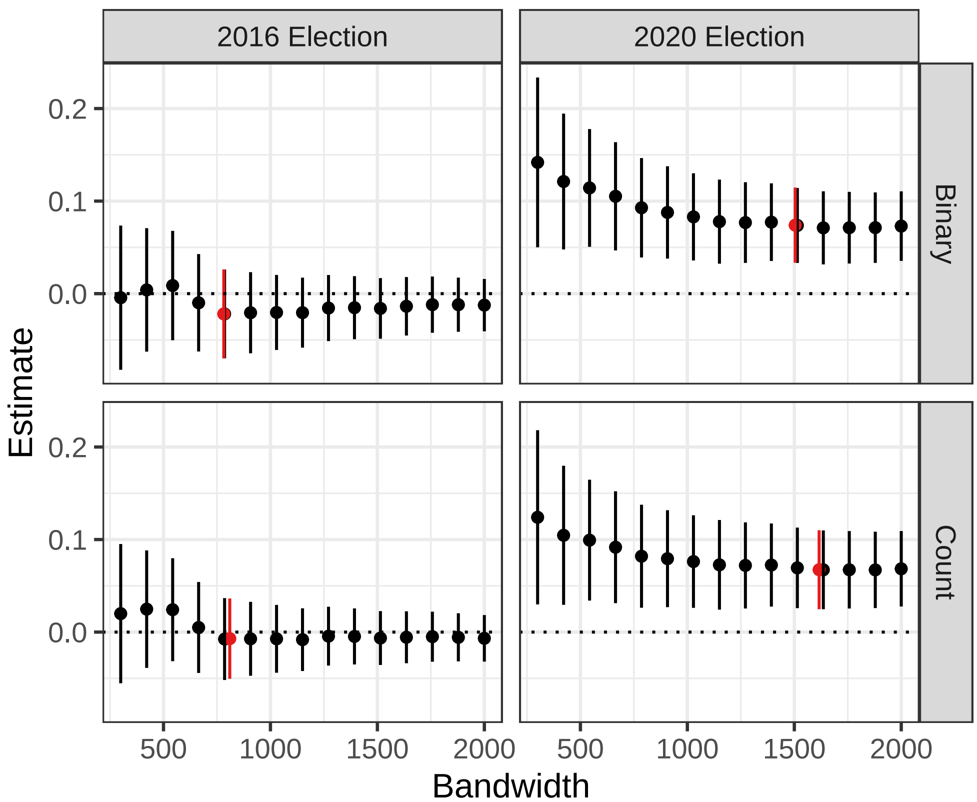

Figure A.5: RD Estimates with Alternative Bandwidths

Table A.19 shows that the main results hold if we define the running variable as months until the election instead of days.

	Trump (2016)		Biden (2020)	
	(1)	(2)	(3)	(4)
RD Election Effect	-0.005	-0.015	0.073***	0.078***
	(0.016)	(0.018)	(0.024)	(0.022)
DV	Count	Binary	Count	Binary
DV Mean	0.091	0.105	0.117	0.129
Bandwidth	30.714	31.677	51.471	47.863
Effective Observations	12139	12537	17711	16915

Table A.19: RD Estimates with Monthly Running Variable

Interrupted Time Series

The main text estimates the effects of U.S. presidential elections using a regression discontinuity in time design, which identifies the immediate effect of the election on climate law adoption. I also estimate an interrupted time series to examine the longer-term effects of elections on policy adoption. Let t_k be the time until election k and $\mathbb{1}(m > t_k)$ be an indicator that a month is after the election. For each country-month, I then estimate

$$\text{Laws}_{i,m} = \beta_1 t_k + \beta_2 \mathbb{1}(m > t_k) + \beta_3 t_k \times \mathbb{1}(m > t_k) + \alpha_i + \varepsilon_{i,m}.$$

The coefficient β_1 estimates the pre-election slope, β_2 estimates the immediate effect of the election (similar to the estimand of the RD), and β_3 estimates the post-election slope. As in the main text, I also fit country fixed effects α_i and cluster standard errors by country. I use the optimal bandwidths as estimated by the RD procedure to define the ITS window.

	Trump (2016)		Biden (2020)	
	(1)	(2)	(3)	(4)
Time to Election	$7.09 \times 10^{-5***}$	$8.34 \times 10^{-5***}$	$1.69 \times 10^{-5**}$	5.55×10^{-6}
	(1.31×10^{-5})	(1.71×10^{-5})	(6.8×10^{-6})	(6.94×10^{-6})
Post-Election	-0.010	-0.010	0.080***	0.089***
	(0.010)	(0.013)	(0.010)	(0.009)
Time to Election × Post-Election	$-7.88 \times 10^{-5***}$	-0.0001***	-0.0002***	-0.0001***
	(2.04×10^{-5})	(2.51×10^{-5})	(1.51×10^{-5})	(1.32×10^{-5})
Total Post-Election Effect	-8×10^{-6}	$-3.2 \times 10^{-5}*$	-0.000135^{***}	-0.000141^{***}
	1.6×10^{-5}	1.9×10^{-5}	1×10^{-5}	9×10^{-6}
DV	Count	Binary	Count	Binary
Bandwidth	809.9	781.8	1,616.0	1,504.2
Observations	10,547	10,149	20,497	19,701
R^2	0.066	0.057	0.127	0.114
Within R^2	0.003	0.003	0.019	0.020
Country fixed effects	✓	✓	✓	✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.20: Interrupted Time Series of U.S. Presidential Elections

Table A.20 shows the results, which are broadly consistent with the findings from the RD. For example, the post-election dummy is negative and not statistically significant for the 2016 election (columns 1 and 2), but it is positive and significant for the 2020 election (columns 3 and 4). Following all elections, there is a negative trend in climate law adoption, although the effect sizes are almost zero.

The elections of 2008 and 2012 in which Barack Obama was elected and reelected to the U.S. presidency also provide evidence of complementarities in climate policy adoption. Figure A.6 shows the RD plots and Table A.21 confirms the positive local treatment effect of climate policy adoption around Obama's elections.

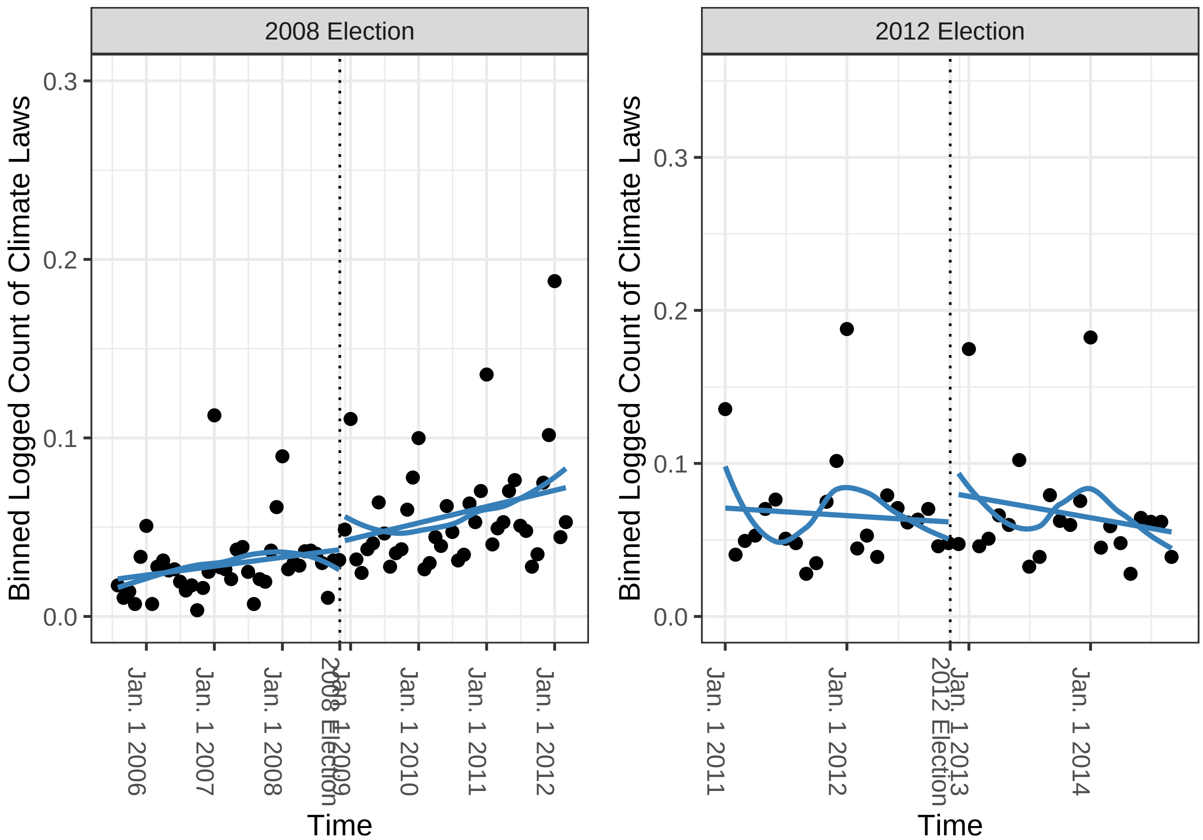

Figure A.6: RD Plots for 2008 and 2012 Elections

	Obama (2008)		Obama (2012)	
	(1)	(2)	(3)	(4)
RD Election Effect	0.015	0.015	0.025*	0.034**
	(0.009)	(0.010)	(0.013)	(0.015)
DV	Count	Binary	Count	Binary
DV Mean	0.043	0.053	0.067	0.081
Bandwidth	1214.288	1297.451	678.854	699.373
Effective Observations	15920	16915	8955	9154

Table A.21: RD Estimates for 2008 and 2012 Elections

B.3 Implications of the Learning Mechanism

Using the mass beliefs, I examine the mean and variance over time on how respondents assess the seriousness of climate change. This exercise allows us to examine belief dynamics: if countries are learning, then the variance in respondents' beliefs should decrease, and the average seriousness of climate change should converge to the truth.[1] In Figure A.7, pooled means and variances over time are in red while country-specific trends are in grey. The left panel of the figure show that over time, there is a slight increase in the average seriousness rating that respondents assign to the problem of climate change. In the right panel of the figure, the variances across respondents are fairly constant in Europe.

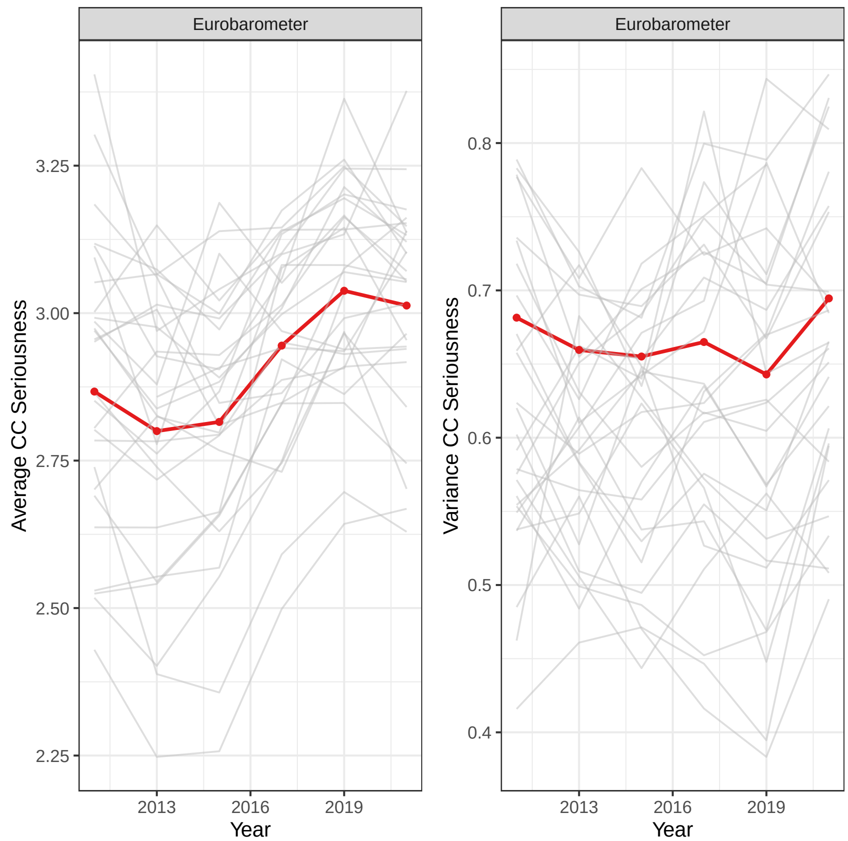

Figure A.7: Mass Belief Means and Variances of Climate Change Seriousness

[1]This extrapolates slightly from the model since the theory does not generate results about convergence—although the model does imply full information transition from country 1 to country 2, so if this game were repeated across more countries then beliefs should converge on the true value of θ—but over time we should observe a convergence of average seriousness to the truth as well as a decline in variance of beliefs. The dynamic model developed in Appendix C does however produce results about belief convergence that are consistent with the results in Figure A.7.

The results in Table 3 are robust (although some results lose statistical significance) to the inclusion of lagged dependent variables, shown below in Table A.22.

Panel A: $cor(x_i, x_j)$	CC Serious (1)	CC Serious (2)
Avg. Other CC Serious	0.233***	0.098
	(0.038)	(0.078)
Observations	322	322
R^2	0.997	0.997
Within R^2	0.518	0.579
Country fixed effects	✓	✓
Lagged DV	✓	✓
Country × Year trends		✓

Panel B: $cor(x_i, a_i)$	Stringency (1)	Stringency (2)
CC Serious	0.001	-0.016
	(0.018)	(0.017)
Observations	322	322
R^2	0.967	0.984
Within R^2	0.835	0.182
Country fixed effects	✓	✓
Year fixed effects		✓
Lagged DV	✓	✓

Panel c: $cor(a_i, x_j)$	CC Serious (1)	CC Serious (2)
Avg. Other Stringency	0.351***	0.317
	(0.047)	(0.227)
Observations	322	322
R^2	0.997	0.997
Within R^2	0.551	0.580
Country fixed effects	✓	✓
Lagged DV	✓	✓
Country × Year trends		✓

Panel D: $cor(x_i, a_j)$	Stringency (1)	Stringency (2)
Avg. Other CC Serious	0.047**	-0.119***
	(0.019)	(0.024)
Observations	324	324
R^2	0.968	0.978
Within R^2	0.834	0.886
Country fixed effects	✓	✓
Lagged DV	✓	✓
Country × Year trends		✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the country level

Table A.22: Mass Beliefs with Lagged DV

The panels in Table A.23 disaggregate the elite belief results by climate negotiators and climate scientists. Both groups are optimistic about the ambition of countries' climate commitments although scientists' beliefs are more strongly correlated with nations' future mitigation measures. Turning to confidence in NDC fulfillment, this relationship appears to be driven by climate negotiators rather than scientists; scientist confidence in commitment fulfillment is still positively correlated with policy stringency although weakly so, and this correlation fails to reach conventional levels of statistical significance.

Panel A: Negotiators

	Stringency_{2021}		Stringency_{2022}		Stringency_{2023}	
	(1)	(2)	(3)	(4)	(5)	(6)
Belief NDC Ambitious	0.020**		0.018*		0.020**	
	(0.010)		(0.009)		(0.010)	
Belief NDC Fulfilled		0.016**		0.015**		0.021***
		(0.007)		(0.007)		(0.007)
Observations	3,008	3,069	3,008	3,069	3,008	3,069
R^2	0.922	0.932	0.925	0.934	0.924	0.933
Within R^2	0.003	0.002	0.003	0.002	0.003	0.004
Respondent fixed effects	✓	✓	✓	✓	✓	✓
Belief Country fixed effects	✓	✓	✓	✓	✓	✓

Panel B: Scientists

	Stringency_{2021}		Stringency_{2022}		Stringency_{2023}	
	(1)	(2)	(3)	(4)	(5)	(6)
Belief NDC Ambitious	0.042***		0.037**		0.045***	
	(0.015)		(0.014)		(0.016)	
Belief NDC Fulfilled		0.009		0.007		0.011
		(0.010)		(0.009)		(0.010)
Observations	1,060	1,224	1,060	1,224	1,060	1,224
R^2	0.950	0.950	0.947	0.947	0.941	0.941
Within R^2	0.019	0.0009	0.015	0.0006	0.018	0.001
Respondent fixed effects	✓	✓	✓	✓	✓	✓
Belief Country fixed effects	✓	✓	✓	✓	✓	✓

p-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors clustered at the respondent level

Table A.23: Elite Beliefs and Climate Policy Stringency: Negotiators and Scientists

C Alternative Model with $n > 2$ Countries

The model in the main text assumes a two-country interaction. The theoretical purchase of this approach was that it allowed for a parsimonious study of forward-looking incentives to exert effort or not. In this section, I describe a model that features $n > 2$ countries but remove this strategic interdependence. Similar to observational learning models (Banerjee 1992; Bikhchandani, Hirshleifer and Welch 1992; Smith and Sørensen 2000), countries are only backward-looking in their valuation of contributions to global effort.

C.1 Model Setup

Consider sequential climate policymaking between n countries indexed by $i = 1, \ldots, n$ who decide whether to pursue climate reforms $a_i = 1$ or not $a_i = 0$. The action $a_i = 1$ represents climate reforms or policies instituted to facilitate a green transition in country i, while $a_i = 0$ represents maintaining the status quo. These countries take actions in a fixed order and can observe the choices of all countries before them.

Countries' payoffs to climate reform depend on two uncertain elements: the global benefit to a green transition and the private domestic cost of implementing reforms. The global benefit to a green transition is a binary state variable $\theta \in \{0, 1\}$. No country knows the true realization of θ—whether or not the green transition pays off or will be "successful" is unknown—but share the common prior $P(\theta = 1) = \pi \in (0, 1)$. If a country does not take climate action, it receives a payoff of zero. By taking climate action, country i receives a benefit normalized to 1 only if $\theta = 1$: this captures the idea that countries only want to pursue climate reforms if it is appropriate to do so or if the green transition is sufficiently likely to be successful.

While the benefits of a green transition are state dependent, their costs are not: choosing $a_i = 1$ comes at a cost $c_i \sim U[0, 1]$. These costs represent the domestic political feasibility of the green transition. Country i's costs of implementation are privately known, drawn independently for each country, and are independent of θ.

There are two information sources that countries have at their disposal when determining whether to implement climate policy. The first is the history of observed actions, $h_i = (a_1, \ldots a_{i-1})$. Countries learn about the suitability of green policy θ through the behavior of others. They also receive conditionally independent private signals, which, along with the prior, generate private beliefs $p_i \in [0, 1]$. I work with these beliefs rather than signals and the prior π directly (p_i is a sufficient statistic). These beliefs are not publicly known, but insofar as they translate into actions they may partially inferred. Let the cumulative distribution function of a private belief p in state θ be $F(p|\theta)$ with density $f(p|\theta)$ such that $F(p|1) < F(p|0)$.[2]

[2]By Bayes's Rule, the state-conditional densities $f(p|\theta)$ satisfy $p = \frac{\pi f(p|1)}{f(p)}$ and $1 - p = \frac{(1-\pi) f(p|0)}{f(p)}$ with $f(p) = \pi f(p|1) + (1 - \pi) f(p|0)$. Then $\frac{f(p|1)}{f(p|0)} = \frac{p}{1-p} \frac{1-\pi}{\pi}$; this stochastic ordering implies that the conditional distributions are mutually absolutely continuous, share the same support, and that $F(p|1) < F(p|0)$ for all private beliefs strictly inside the support.

Given some history of countries' climate policies h_i, define the public belief $P(\theta = 1|h_i)$ as the informational content about the suitability of the green transition. There is an associated public likelihood ratio $\ell_i = \frac{1-P(\theta=1|h_i)}{P(\theta=1|h_i)}$ such that lower values of ℓ_i imply a greater likelihood that $\theta = 1$, or that a green transition would be successful.

The climate problem is often described as one of strategic substitutes because it is nationally costly to exert effort to address climate change despite that this effort provides a global benefit. To capture this tension, I introduce *collective action penalties*, which are action-specific, history-dependent costs (Eyster et al. 2014). It becomes more costly to pursue climate reform if many other countries have done so already. In reduced form, these penalties capture the strategic substitutability of climate actions across countries present in other models. Denote collective actions penalties as $z(h_i)$ (and suppress dependence on h_i where it is not confusing). This function is increasing in the number of countries who have already taken climate action, or $\sum h_i$. For simplicity, assume the penalty is bounded, $z_i \in [0, 1]$; since the domestic costs c_i are on the same scale, there is no explicit assumption as to whether implementation costs are greater than collective action penalties. As an example, consider a linearly proportional cost function for any country $i \geq 2$ (with $z_1 = 0$),

$$z_i = \frac{\sum h_i}{i-1}.$$

In countries' payoffs I scale these externalities by $k > 0$ in order to parameterize the extent to which countries weigh potential complementarities (generated by information about θ) and potential substitutes (generated by collective action penalties). This parameter can be thought of as scaling the extent to which countries internalize free-riding concerns; larger k implies stronger free-riding incentives as collective action penalties are weighted more heavily.

Given this setup, country i's payoff can be written as

$$u_i(a_i, h_i, \theta; c_i) = a_i(\theta - c_i - kz(h_i)).$$

A strategy for country i is a choice to implement climate reforms or not, $a_i \in \{0, 1\}$, given the choices of other prior-moving countries contained in history h_i, and its type (p_i, c_i), comprised of its private belief about θ and its domestic costs of implementing green policy. I examine weak perfect Bayesian equilibria and derive all posterior beliefs via Bayes's Rule.

C.2 Results and Proofs

Fix a history $h_i = (a_1, \ldots, a_{i-1})$ of past climate policy adoption decisions that induce a public likelihood ratio ℓ_i and potential collective action penalties z_i. Given ℓ_i and the private belief p_i, country i can make an assessment about the appropriateness of climate policy, i's posterior belief that $\theta = 1$ is defined as

$$\mu_i = P(\theta = 1|p_i, \ell_i) = \frac{p_i}{p_i + (1-p_i)\ell_i}.$$

Then, country i prefers to implement climate reforms if and only if

$$\begin{aligned}
\mu_i - c_i - kz_i &\geq 0 \\
\Leftrightarrow \ \mu_i &\geq c_i + kz_i \\
\Leftrightarrow \ p_i &\geq \frac{\ell_i(c_i + kz_i)}{1 - (c_i + kz_i) + \ell_i(c_i + kz_i)} \ \equiv \ \tilde{p}(c_i, \ell_i).
\end{aligned}$$

Country i pursues climate action if and only if their private belief about a successful green transition is sufficiently high, given the domestic political costs of implementing climate reforms and the potential collective action penalties. If $\tilde{p}(c_i, \ell_i) > 1$, then i never takes climate action regardless of the value of p_i, which occurs whenever $c_i > 1 - kz_i \ \equiv \ \bar{c}_i$. Intuitively, if the domestic costs of implementing climate policy are prohibitively high, it does not matter how optimistic i is about the green transition, implementing green policy is not domestically feasible. Then, for any $c_i \in [0, \ \bar{c}_i]$, i pursues climate action if and only if $p_i > \tilde{p}(c_i, \ell_i)$, which occurs with probability $1 - F(\tilde{p}(c_i, \ell_i)|\theta)$.

Lemma A.1. *The threshold $\tilde{p}(c_i, \ell_i)$ is:*

- *increasing in the public likelihood ratio ℓ_i;*
- *increasing in domestic implementation costs c_i;*
- *increasing in collective action penalties z_i;*
- *increasing in the strength of free-riding incentives k.*

Proof of Lemma A.1.

$$\begin{aligned}
\frac{\partial \tilde{p}(c_i, \ell_i)}{\partial \ell_i} &= \frac{(1 - c_i - kz_i)(c_i + kz_i)}{(1 - (c_i + kz_i) + \ell_i(c_i + kz_i))^2} \ \geq \ 0. \\
\frac{\partial \tilde{p}(c_i, \ell_i)}{\partial c_i} &= \frac{\ell_i}{(1 - (c_i + kz_i) + \ell_i(c_i + kz_i))^2} \ \geq \ 0. \\
\frac{\partial \tilde{p}(c_i, \ell_i)}{\partial z_i} &= \frac{k\ell_i}{(1 - (c_i + kz_i) + \ell_i(c_i + kz_i))^2} \ \geq \ 0. \\
\frac{\partial \tilde{p}(c_i, \ell_i)}{\partial k} &= \frac{\ell_i z_i}{(1 - (c_i + kz_i) + \ell_i(c_i + kz_i))^2} \ \geq \ 0.
\end{aligned}$$

□

Proposition A.1. *Let $\alpha^*(a_i|\ell_i, \theta)$ be the probability that country i takes climate action a_i in state θ. Then*

$$\alpha^*(1|\ell_i, \theta) = \int_0^{\bar{c}_i} 1 - F(\tilde{p}(c_i, \ell_i)|\theta) \ dc_i \ = \ 1 - \alpha^*(0|\ell_i, \theta).$$

Proof of Proposition A.1. Immediate from text. $\square$

Corollary A.1. *Climate policy is informative about θ. The probability of climate action is greater when $\theta = 1$ versus $\theta = 0$: $\alpha^*(1, \ell_i, 1) > \alpha^*(1, \ell_i, 0)$. The probability of climate inaction is greater when $\theta = 0$ versus $\theta = 1$: $\alpha^*(0, \ell_i, 1) < \alpha^*(0, \ell_i, 0)$.*

Proof of Corollary A.1.

$$\begin{aligned}\alpha^*(1|\ell_i, 1) - \alpha^*(1|\ell_i, 0) &= \Big(\int_0^{\overline{c}_i} 1 - F(\tilde{p}(c_i, \ell_i)|1)\ dc_i\Big) - \Big(\int_0^{\overline{c}_i} 1 - F(\tilde{p}(c_i, \ell_i)|0)\ dc_i\Big) \\ &= \int_0^{\overline{c}_i} F(\tilde{p}(c_i, \ell_i)|0) - F(\tilde{p}(c_i, \ell_i)|1)\ dc_i > 0,\end{aligned}$$

where the result follows from the stochastic ordering of private beliefs. $\square$

Corollary A.2. *The probability of climate action is increasing in the public optimism about a successful green transition, $\frac{d\alpha^*(1|\ell_i,\theta)}{d\ell_i} \leq 0$.*

Proof of Corollary A.2. Differentiating with respect to ℓ_i yields

$$\frac{d\alpha^*(1|\ell_i, \theta)}{d\ell_i} = -\int_0^{\overline{c}_i} f(\tilde{p}(c_i, \ell_i)|\theta)\frac{\partial \tilde{p}_i}{\partial \ell_i}\ dc_i \leq 0.$$

$\square$

Corollary A.3. *The probability of climate action is decreasing in collective action penalties, $\frac{d\alpha^*(1|\ell_i,\theta)}{dz_i} \leq 0$.*

Proof of Corollary A.3. By the Leibniz integral rule, differentiating with respect to z_i yields

$$\begin{aligned}\frac{d\alpha^*(1|\ell_i, \theta)}{dz_i} &= \frac{\partial \overline{c}_i}{\partial z_i} - F(\tilde{p}(\overline{c}_i, \ell_i)|\theta)\frac{\partial \overline{c}_i}{\partial z_i} - \int_0^{\overline{c}_i} f(\tilde{p}(c_i, \ell_i)|\theta)\frac{\partial \tilde{p}(c_i, \ell_i)}{\partial z_i}\ dc_i \\ &= -\int_0^{\overline{c}_i} f(\tilde{p}(c_i, \ell_i)|\theta)\frac{\partial \tilde{p}(c_i, \ell_i)}{\partial z_i}\ dc_i \leq 0.\end{aligned}$$

where the first two terms simplify because $\tilde{p}(\overline{c}_i, \ell_i) = 1$. $\square$

Corollary A.2 states that more optimistic public beliefs about a successful green transition begets more climate action. That is, these beliefs endogenously generate *complementarities* in countries' climate actions. Conversely, increased collective action penalties—which arise because more countries have already pursued climate policies—depress subsequent climate action, as stated in Corollary A.3. The actions of prior movers induce *substitution* in the behavior of later policymakers.

Which factor dominates? Under what conditions are countries' actions strategic complements or strategic substitutes in equilibrium? To conceptualize this, I consider the ratio of the marginal effects of public beliefs and collective action penalties. Define $\rho(\ell_i, z_i|\theta)$ as

$$\rho(\ell_i, z_i|\theta) = \frac{d\alpha^*(1|\ell_i, \theta)}{d\ell_i} \Big/ \frac{d\alpha^*(1|\ell_i, \theta)}{dz_i}.$$

The magnitude of $\rho(\ell_i, z_i|\theta)$ is always positive, but we can think about which factor dominates—strategic complementarities that stem from increased public beliefs or strategic substitutes from collective action penalties—based on where it is greater than or less than 1. If $\rho(\ell_i, z_i|\theta) > 1$, then, all else equal, varying public beliefs has a larger effect on the equilibrium probability of climate action than does varying collective action penalties. In this case, we can say that the net effect of other countries' behavior generates complementarities for country i. By contrast, when $\rho(\ell_i, z_i|\theta) < 1$, then the incentives to free ride swamp the potential benefits from climate policy investment.

Proposition A.2. *Complementarity effects dominate when free-riding incentives are small, and substitution effects dominate when free-riding incentives are large: there exists a threshold* $\overline{k}_i$ *such that if* $k < \overline{k}_i$ *then* $\rho(\ell_i, z_i|\theta) > 1$.

Proof of Proposition A.2. It follows that

$$\rho(\ell_i, z_i|\theta) > 1 \;\Leftrightarrow\; \int_0^{\overline{c}_i} f(\tilde{p}(c_i, \ell_i)|\theta) \frac{\partial \tilde{p}_i}{\partial \ell_i}\; dc_i > \int_0^{\overline{c}_i} f(\tilde{p}(c_i, \ell_i)|\theta) \frac{\partial \tilde{p}(c_i, \ell_i)}{\partial z_i}\; dc_i.$$

Define $Q(k) = (1 - (c_i + kz_i) + \ell_i(c_i + kz_i))^2 \geq 0$, which is the denominator of the comparative statics on $\tilde{p}(c_i, \ell_i)$. Simplifying yields

$$\int_0^{\overline{c}_i} \frac{f(\tilde{p}(c_i, \ell_i)|\theta)}{Q(k)} \Big((1 - c_i - k_i)(c_i + kz_i) - k\ell_i\Big)\; dc_i > 0.$$

Now note that for any $k < \frac{1}{z_i}$, the integral is well-defined (otherwise $\overline{c}_i = 0$). Furthermore, for any $k < \frac{1}{z_i}$, $\frac{f(\tilde{p}(c_i,\ell_i)|\theta)}{Q(k)} \geq 0$ and we are integrating over a positive interval of the c_i space. So the integrand is negative if and only if

$$(1 - c_i - k_i)(c_i + kz_i) - k\ell_i < 0,$$

which simplifies to $k > \frac{z_i - 2c_iz_i - \ell_i + \sqrt{\ell_i^2 - 2\ell_iz_i + 4c_i\ell_iz_i + z_i^2}}{2z_i^2} \equiv \overline{k}_i$. Hence a sufficient condition for the integrand to be negative is if $k > \overline{k}_i$ which implies that $\rho(\ell_i, z_i|\theta) < 1$. □

We can now use the model to think about the long-run dynamics of climate policy across countries based on the analysis in the previous subsection. We have shown that the decision problem facing each country at the time of climate adoption is static, meaning history-relevant parameters such as ℓ_i and z_i can be treated in reduced form, but now wish to trace the evolution of actions and beliefs across countries.

Since private signals are conditionally independent, the likelihood ratio updates such that

$$\ell_{i+1} = \varphi(a_i, \ell_i) = \ell_i \frac{\alpha^*(a_i|\ell_i, 0)}{\alpha^*(a_i|\ell_i, 1)}.$$

Observe that by Corollary A.1, relative to ℓ_i, ℓ_{i+1} shrinks if $a_i = 1$ but ℓ_{i+1} grows if $a_i = 0$. The public belief becomes more or less optimistic depending on the previous action a_i, which in turn informs the decision to enact climate policy in the subsequent period. Then, given the updated public belief and any additional collective action penalties, country $i+1$ considers the tradeoff between implementing climate reforms and incurring domestic implementation costs and collective action penalties or free-riding, where climate policy occurs with probability $\alpha^*(1|\ell_{i+1}, \theta)$.

As is standard in the informational cascades and herding literature (e.g., Smith and Sørensen 2000), convergence results are stated conditioning on $\theta = 1$. This is also the more interesting case from a substantive perspective anyway, as this is where the tradeoff between the two mechanisms is present.

Lemma A.2. *Conditional on $\theta = 1$, the public likelihood ratio $< \ell_i >$ is a martingale.*

Proof of Lemma A.2. Recall that the public likelihood ratio updates according to

$$\ell_{i+1} = \ell_i \frac{\alpha^*(a_i|\ell_i, 0)}{\alpha^*(a_i|\ell_i, 1)},$$

by the conditional independence of signals. Taking expectations yields

$$\begin{aligned} E[\ell_{i+1}|\ell_1, \ldots, \ell_i, \theta = 1] &= \sum_{a \in \{0,1\}} \alpha^*(a|\ell_i, 1)\ell_i \frac{\alpha^*(a|\ell_i, 0)}{\alpha^*(a|\ell_i, 1)} \\ &= \ell_i \sum_{a \in \{0,1\}} \alpha^*(a|\ell_i, 0) \\ &= \ell_i. \end{aligned}$$

□

Proposition A.3. *In the limit, countries learn whether the green transition will be successful: public beliefs converge to the true state of the world almost surely.*

Proof of Proposition A.3. Without loss of generality condition on state $\theta = 1$. Since $< \ell_i >$ is a martingale and all values are nonnegative, it converges almost surely to a random variable $\ell_\infty = \lim_{i \to \infty} \ell_i$ with support $[0, \infty)$ by the Martingale Convergence Theorem (Doob 1953).

This rules out nonstationary limit beliefs. Since private beliefs p_i are unbounded within $[0,1]$, then the only stationary finite likelihood ratio in state $\theta = 1$ is 0, so $\ell_\infty \to 0$ almost surely (Smith and Sørensen 2000, Theorem 1). $\square$

Proposition A.4. *In the limit, countries take the correct action $a_i = \theta$ if and only if $c_i \leq \bar{c}_i$.*

Proof of Proposition A.4. Recall that i chooses $a_i = 0$ if $c_i > \bar{c}_i$ for any private belief p_i, which occurs with probability $P(c_i > \bar{c}_i) = kz_i$. This probability is increasing in z_i, which increases in the number of countries that choose $a_i = 1$. Now suppose that $\theta = 1$ and $c_i \leq \bar{c}_i$ so i chooses $a_i = 1$ iff $p_i \geq \tilde{p}(c_i, \ell_i)$. By Proposition A.3, the likelihood ratio converges almost surely to $\ell_i \to 0$. Then we have $\lim_{\ell_i \to 0} \tilde{p}(c_i, \ell_i) = 0$. Hence conditional on $c_i < \bar{c}_i$, i chooses $a_i = 1 = \theta$ for any private belief.

If countries are taking action on a measure zero subset, $\bar{c}_j \to 0$ or $k > \frac{1}{z_j}$ for some $j \leq n$, then countries pool on $a_j = 0 \ \forall j, \ldots, n$. $\square$

Corollary A.4. *Let $z_i(h_i) = \frac{\sum h_i}{i-1}$. The probability of climate action converges to $\frac{1}{1+k}$.*

Proof of Corollary A.4. Conditional on state $\theta = 1$, climate action occurs with probability $\bar{c}_i$, as $\tilde{p}(c_i, \ell_i) \to 0$ as $\ell_i \to 0$. Moreover, given that $z_i = \frac{\sum h_i}{i-1}$, it is a linear proportional function of previous actions, so in the limit, $z_i \to \alpha^*(1|\ell_i, \theta)$. Then we have

$$\begin{aligned} \alpha^*(1|\ell_i, \theta) &= \bar{c}_i = 1 - kz_i \\ &= 1 - k\alpha^*(1|\ell_i, \theta) \\ \Leftrightarrow \quad \alpha^*(1|\ell_i, \theta) &= \frac{1}{1+k}. \end{aligned}$$

$\square$

Corollary A.5. *In the limit, $\rho(\ell_i, z_i|\theta) > 1$ if $k < 1 - c_i$.*

Proof of Corollary A.5. Per Proposition A.2, a sufficient condition for $\rho(\ell_i, z_i|\theta) > 1$ is $k < \bar{k}_i$ where $\bar{k}_i = \frac{z_i - 2c_i z_i - \ell_i + \sqrt{\ell_i^2 - 2\ell_i z_i + 4c_i \ell_i z_i + z_i^2}}{2z_i^2}$. Then in the long run, $\lim_{\ell_i \to 0} \bar{k}_i = 1 - c_i$. $\square$