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Public policies and global forest conservation: Empirical evidence from national borders

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ABSTRACT

Protecting the world's remaining forests is a global policy priority. Even though the value of the world's remaining forests is global in nature, much of the protection has to come from national policies. Here, we combine global, high resolution remote sensing data on forest outcomes (tree-cover loss, forest degradation, net primary production) and two complementary econometric research designs for causal inference to first quantify how much it matters in which country a forest is located, secondly, the role of public policies, and third, under which conditions such pubic policies tend to be most successful. We find considerable border discontinuities in remotely sensed forest outcomes around the world (in a regression discontinuity design) and these are largely explained by countries' policies (using a differences-in-discontinuities design). We estimate that public policies reduce the risk of tree cover loss by almost 4 percentage points globally, but there is large variation around this. The best explanations we find for these heterogenous treatment effects are a country's policy enforcement, its policy stringency, its property rights, and its rule of law (in that order). Our results motivate international cooperation to finance and improve (a) countries' public policies for forest protection and (b) countries' capacity to implement and enforce them well.

1. Introduction

Forest landscapes are complex socio-ecological systems and an integral part of terrestrial ecosystems, rural livelihoods, and the global economy (Foley et al., 2005, Leemans and De Groot, 2003, Food and Agriculture Organization of the United Nations, 2010). Yet, globally, forests are under threat, especially from the expansion of agricultural areas (Pendrill et al., 2022, Wuepper et al., 2023a, Busch and Ferretti-Gallon, 2023). A major issue underpinning ongoing deforestation and forest degradation at the global level is that individual land users gain immediate private returns from forest exploitation, even though these are often outweighed by the lost societal benefits that would otherwise result from forest conservation (e.g., habitat for biodiversity, carbon sequestration, clean water, disease prevention[1]) (Angelsen, 2010, Börner et al., 2020, Garrett et al., 2021a, Tollefson, 2020, Gibb et al., 2020). Addressing this mismatch, and the associated welfare loss to society, represents an important and interesting global policy challenge (Mirzabaev and Wuepper, 2023, Balboni et al., 2023, Harstad, 2023, Harstad, 2022, Harstad and Storesletten, 2023, Busch and Ferretti-Gallon, 2023).

Below, we first quantify how much countries generally impact forests dynamics, relying on a spatial regression discontinuity design (Wuepper

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[1] The link between forest disturbance / degradation and the risk of diseases is that animal hosts of dangerous pathogens come into contact with human populations when humans expand their land use into their habitats.

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and Finger, 2023). We then quantify the particular role of public policies, including direct forest conservation and restoration policies, as well as indirectly relevant policies, such as agricultural land use regulations that constrain agricultural area expansion, relying on a difference-in-discontinuities design (Wuepper and Finger, 2023). Finally, we analyze under which conditions such policies tend to be effective and under which do not.

In the last decades, all around the world countries have designed and implemented policies to conserve and/or restore their forests, following very different strategies, such as command and control, payment-based, and many mixes and combinations (Börner et al., 2020, Wunder et al., 2020, Mirzabaev and Wuepper, 2023). Moreover, countries differ in their implementation of environmental policies because of differences in institutions and political priorities (Garrett et al., 2021a, Food and Agriculture Organization of the United Nations, 2010, Sanford, 2021). As a result, we observe quite different forest dynamics around the world, notably including abrupt border discontinuities between countries.

The particular role of national policies remains a matter of increased scientific interest (Börner et al., 2020, Wunder et al., 2020, Börner et al., 2016, Busch and Ferretti-Gallon, 2017, Balboni et al., 2023, Assunção et al., 2022, Cisneros et al., 2021, Sanford, 2021). Especially understanding how well such policies protect the world's forests in different countries, and what this depends on, is critically important to design effective policies.

To answer our research questions, we have compiled a uniquely comprehensive dataset at a resolution of 1 km^2, globally, from 2001 to 2017/2018, which provides us with 95 million datapoints, quantifying the probability of tree-cover loss, changes in forests' enhanced vegetation index, net primary productivity, and forest degradation and improvement (based on changes in a vegetation index without detected tree-cover change). We also collated countries' forest policies as well as various country characteristics that plausibly affect their effectiveness. These policies are included in a larger database on policies at the intersection of agriculture and the environment (Wuepper et al., 2023b).

The tested mediating factors for policy effectiveness include countries economic institutions (Ouattara and Standaert, 2020), stringency and enforcement of environmental policies (Browne et al., 2014), political institutions (Freedom House, 2019), economic institutions (Heritage Foundation, 2020) and the Human Development Index (UNDP, 2020). Most importantly, we are able to establish causality where prior studies could only identify correlations, explained below.

The main empirical challenge to identify the causal effect of national policies is that their implementation is not random, so there exists a long list of potential confounding factors that could explain both forest dynamics and chosen policies. There is even plausibly reverse causality, because high rates of deforestation and forest degradation might lead to new conservation policies, in addition or instead of these policies reducing these dynamics, or alternatively, high rates of deforestation and forest degradation could lead to fewer conservation policies if there is a growing lobby of those benefitting from forest exploitation.

We address these issues by using two state-of-the-art econometric approaches: A spatial regression discontinuity design, to first of all identify the overall importance of countries for global forest outcomes, and then a differences-in-discontinuities design to identify the specific causal effect of countries' forest policies (Wuepper and Finger, 2023). These two empirical approaches are based on two fundamental ideas. The first is that international borders provide a type of "natural experiment" (Dunning, 2012, de Janvry et al., 2010). Often, the two sides of countries' borders are naturally approximately comparable to each other as long as one restricts the sample relatively close to the border area (Wuepper et al., 2020b, Wuepper et al., 2020a). Below, we quantify exactly how often this is the case. Then, border discontinuities in forest dynamics that cannot be explained by natural environmental variables reveal socio-political country-effects. Secondly, because countries' policies are implemented at specific points in time, one can quantify how border discontinuities in forest dynamics change from before to after policy implementation. Under empirically falsifiable assumptions, this reveals their causal effect (Butts, 2021, Wuepper and Finger, 2023). The important strength of this approach is that slow- or non-changing country differences are absorbed by fixed effects, so potential cofounding factors such as general cultural, political, or economic differences are controlled for. In addition, we also conduct a battery of robustness checks such as explicitly controlling for a long list of country characteristics and show that our results remain robust. Many borders around the world provide visible examples of forest discontinuities right where the influence of countries changes (Fig. 1).

2. Materials and methods

For our analyses, we rely on a large new dataset of forest dynamics in high spatial and temporal resolution, as well as forest policies and other relevant country characteristics (Table 1), and two complementary econometric research designs for causal inference (Sub-Sections 2.1 and 2.2).

We first covered the world with a grid of 1 km^2 cells, within a distance of maximum 100 km away from the next international border. We then created a composite of covariate layers, including the location of all the world's forests (Hansen et al., 2013) in each year, vegetation indices (such as the Enhanced Vegetation Index (Didan et al., 2020)), measures of forest productivity (such as Net Primary Production (Running et al., 2015)), tree cover and loss (Hansen et al., 2013), natural forest potential (Bastin et al., 2019), and the distance to international borders from the center of each grid cell for each year from 2000 to 2017/2018.

All covariate layers were resampled and reprojected to an equal area pixel grid in EPSG:6933 (WGS84) at the same resolution of 1 km2. In order to account for missing data due to cloud coverage, the remotely sensed vegetation indices and forest productivity estimates were calculated as means and medians of a three-year window around the year of observation, i.e. Enhanced Vegetation Index values of the year 2001 are calculated using values from the years 2000, 2001 and 2002. For the country borders, we used the United States Office of the Geographer's Large Scale International Boundary (LSIB) dataset. We excluded all grid cells that are further away from any international border than 100 km and those not containing a minimum of 30 % tree cover.[2]

We matched a wide range of relevant socio-economic variables at the country level to each cell.[3] The single-most important socio-economic variable for our study comes from the database of Wuepper et al., (2023b), who provide a systematic collection of countries' public environmental policies targeting various issues, including forests, biodiversity, and land-use, and both command and control policies (e.g. legislative changes) as well as incentives-based policies (i.e. payments for ecosystem services). We selected only policies that are most relevant at national level, i.e. predominantly public in nature and focusing on issues with a clear connection to forest conservation, and not too regional in scope.[4] As control variables and to examine what makes such

[2] There are various competing definitions of what is a forest. Often 10% is used (https://www.nature.com/articles/news.2009.842). For many of our analyses of the various forest dynamics, grid cells with less tree cover are less reliable than those with more, and we have a very large sample, so we can afford to exclude grid cells that already started with low tree cover to begin with. Also, for both climate and biodiversity protection, especially forests with a high percentage of tree cover are the most valuable.

[3] Alternatively, one could use pixel or border region values of these variables (whenever available) but this would answer a different research: Here, we are interested in the role of country-level differences and not only border-region or even pixel-level differences.

[4] The criterion that a policy must be nationally relevant means that policies exclusively implemented in a single region (e.g. a federal state, a province) are not included. For the opposite case of super-national policies, such as those of the EU, we include the national implementation of those policies.

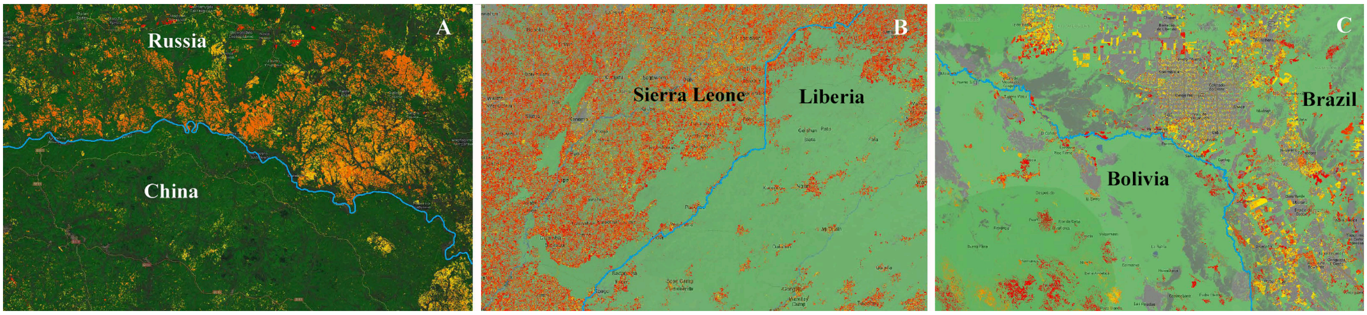

Fig. 1. Illustrating Examples of Border Discontinuities in Forest Dynamics. Green is tree cover, blue are political borders, yellow, orange, and red tones indicate tree cover loss in different periods (yellow = early 2000 s, orange = early 2010 s, red = late 2010 s). It can be seen that right at the border, there is an abrupt, unnatural change in forest dynamics. This suggest a country impact. . (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Source: https://earthenginepartners.appspot.com/science-2013-global-forest

Table 1
Variables and Sources.

Variable	Description	Original Resolution	Units/ range	Source
annual tree cover	Trees are defined as vegetation taller than 5 m in height and tree cover is then expressed in % per pixel that is tree covered	1 arcsec (≈30 m at equator)	%	Google Earth Engine Hansen Dataset v1.6 (2018)
annual tree cover loss	Indicator for whether there was any stand-replacement disturbance, or a change from a forest to non-forest state, within a grid-cell.	1 arcsec	1/0	Google Earth Engine Hansen Dataset v1.6 (2018)
enhanced vegetation index change	quantifies year-to-year changes in vegetation greenness proxying overall forest dynamics	1000 *m*	−1:1	Google Earth Engine MODIS (2018b)
net primary production	Mean and median of the net amount of carbon produced by plants (gross primary production minus maintenance and respiration)	1000 *m*	kg*C/ m^2	Google Earth Engine MODIS (2018a)
potential forest cover	The potential natural forest cover per pixel without human impact	1000 *m*	%	Bastin et al. (2019)
public policies	Sum of each country's forest-related public policies in each year, including legislative changes, new regulations, payments for ecosystem services, policy reforms, monitoring.	country level	Count	Wuepper et al., (2023b)
property rights index (0–100)	Measure of economic institutions, reflecting the degree to which a country's laws protect private property rights and the degree to which those laws are enforced.	country level	0–100	Heritage Foundation (2020)
rule of law index	Measure of political institutions, reflecting judiciary independence; extent to which rule of law prevails in civil and criminal matters; the existence of direct civil control over the police; and many other indicators.	country level	0 100	Freedom House (2019)
human development index	The Human Development Index (HDI) is a summary measure of average achievement in 3 key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living.	country level	0–100	UNDP (2020)
env. policy stringency	Rating from a business leader survey. The question was: How would you assess the stringency of your countries' environmental policy? (scale: 1 = very lax – 7 = among the world's most stringent).	country level	1–7	Browne et al. (2014)
env. policy enforcement	Rating from a business leader survey. The question was: How would you assess the enforcement of environmental regulations in your country? (scale: 1 = very lax; 7 = among the world's most rigorous).	country level	1–7	Browne et al. (2014)
gdp per capita	Annual gross domestic product per capita (current and constant in 2010 USD)	country level	USD	World Bank (2020)
gdp share agriculture	The contribution of the agricultural sector to GDP	country level	%	World Bank (2020)
population density	Average population density of each country	country level	Per km^2	World Bank (2020)
rural population share	The share of the population that lives in rural areas	country level	%	World Bank (2020)
population growth	Average annual population growth per country	country level	%	World Bank (2020)

policies more effective, we matched data on countries' protection of private property[5] (Heritage Foundation, 2020) (an indicator for their economic institutions (Acemoglu and Johnson, 2005)), their rule of law (Freedom House, 2019) (an indicator for their political institutions (Acemoglu and Johnson, 2005)), their Human Development Index (UNDP, 2020), and the stringency and enforcement of their environmental policies (Browne et al., 2014) (based on perceptions of surveyed business leaders in each country). Finally, important additional socio-economic control variables are countries' GDP (current and constant), and population density, GDP share of agriculture, percentage of the population in rural areas, and population growth, all from the World Bank (2020).

[5] This protection of private property considers both the risk from private and from state actors themselves.

Table 2 shows the mean, min, and max of our key variables, divided into grid cell data (panel A) and country data (panel B). Two groups of variables are important to explain. First, one of our key outcome variable we consider is the probability of tree cover loss, which is on average 10 % in our data. This is an indicator variable that takes the value of one whenever there is any tree cover loss within a grid cell according the Google Earth Engine Hansen Dataset v1.6 (2018), and zero otherwise. The overall rate of deforestation is much lower, at 0.3 % (per year). This difference in magnitudes is important to keep in mind when interpreting our results and e.g. comparing them to other studies. The other variables that deserve particular attention are the relevant public policies. The average country in our data has nationally implemented 2 forest policies, 2.7 relevant biodiversity policies, 1.5 land use policies, 0.5 agricultural policies, 0.6 ecosystem payment schemes (e.g. paying land owners to conserve the trees on their land), and together with other policies, such as larger regional policies e.g., the average country in our

Table 2
Descriptive Statistics.

Panel A: Grid Cell Data	Mean	Min	Max	Unit and explanation
probability of tree cover loss	10.60	0	100	Probability that a gridcell lost any forest (%)
deforestation	0.30	0	100	Amount of detected deforestation per gridcell (%)
enhanced vegetation index change	6.83	−3962.25	1815.75	Index points change
enhanced vegetation index	4086.76	−1356.50	7958.66	Index points
net primary production	9317.76	0.33	24374.67	kg*C/m^2
normalized difference in vegetation index	7227.08	−1173.00	9200.55	Index points
evergreen deciduous trees	6.647	0	100	Percentage of this tree type per gridcell
evergreen broadleaf trees	60.40	0	100	Percentage of this tree type per gridcell
deciduous broadleaf trees	10.08	0	100	Percentage of this tree type per gridcell
mixed and other trees	22.88	0	100	Percentage of this tree type per gridcell
potential forest cover	76.81	0	100	natural tree cover of each gridcell absent humans (%)
Natural border	22.20	0	100	share of borders with natural discontinuities
Panel B: Country Data[1]				
national forest legislation	2.14	0	19	count of policies per country
national biodiversity legislation	2.73	0	15	count of policies per country
national land use legislation	1.44	0	10	count of policies per country
national agriculture legislation	0.53	0	11	count of policies per country
payments for ecosystem services	0.57	0	6	count of policies per country
all public policies	8.10	0	40	count of policies per country
policy stringency	40.48	15	64	Rating in percentage
policy enforcement	55.14	27.43	87.42	Rating in percentage
Rule of law index	6.66	0	16	Index from 0 to 16
Property rights index	39.26	0	95	Index from 0 to 100
human development index	65.00	29	95	Index from 0 to 100
GDP per capita (constant value)	9597.87	194.87	141200.40	In US Dollars
population density	44.98	1.55	1226.63	population per km^2
population growth	1.40	−9.08	7.78	change in population

[1]All explanatory variables such as countires‘ public policies are measured at the national level because the policies and other socio-economic characteristics of *countries* are the treament and not of *regions*. In general, using data only from the immediate border region would potentially lead to higher estimated treatment effects but with lower external validity. In addition, many socio-economic variables are not currently available at a sub-national scale with global coverage. For example, many local policies are likely difficult to find remotely and collecting contextual factor data such as property rights or policy enforcement subnationally would imply a major research project on ist own.

data overall implemented 8 forest conservation relevant public policies from 2000 to 2017.

The hypotheses that better institutions (both political and economic), further economic development, and more stringency and enforcement (i.e. implementation) make conservation policies more likely to be successful are derived from a large literature on the topic, such as Burgess et al. (2023) who show that the protection of the Brazilian Amazon changed considerably, not only in response to policy changes, but especially the stringency and enforcement of already existing policies. This was also found by Ceddia et al. (2014) for six countries in Latin America. The empirical evidence is especially strong for the negative effect of corruption (Sommer, 2017, Wolfersberger et al., 2015, Barbier et al., 2005). There is also empirical evidence that protected areas are more effective in countries with better corruption control and protection of property rights (Abman, 2018) and the association between state spending and forest protection positively depends on corruption control, government effectiveness, and regulatory quality (Sommer, 2018). Finally, Bonilla-Mejía and Higuera-Mendieta (2019) also similarly on protected areas and find various relevant interactions between environmental policy and institutions. Moreover, recent literature review make clear that how policies are actually being implemented is a major factor for their effectiveness (Mirzabaev and Wuepper, 2023, Balboni et al., 2023, Börner et al., 2020).

2.1. Quantifying the importance of countries overall

We use a spatial regression discontinuity design (Wuepper and Finger, 2023) to estimate the net-effect of all country differences at each border (e.g. different economic and political institutions, public and non-public policies, economic and demographic factors). This quantifies how important it is generally to which country a forest belongs (see e.g. Fig. 1 that forest dynamics can differ greatly depending on the country). We quantify for each year in our sample, the global average border discontinuity in various forest outcomes, with a special focus on tree cover loss.

The fundamental idea of the regression discontinuity design is that many international borders cross natural forests that are thus divided into two parts,[6] akin to an experiment in which groups are created for different treatments.[7] Close to the border, both sides are environmentally comparable and thus feasible counterfactuals to each other. This can be thought of as a “natural experiment” (Keele and Titiunik, 2016). We estimate regressions of the following form, for each year (2001–2017):

$$Y_i = \alpha + \beta_1 D_i + \beta_2 d_i^A + \beta_3 d_i^B + \beta_4 Nat_i + \theta_j + \vartheta_i + \epsilon_i \qquad if \;\; d_i \leq \varphi^* \tag{1}$$

where Y_i is the outcome of interest (annual tree cover loss, annual forest degradation or improvement, change in the enhanced vegetation index, change in a net primary production) for 1 km^2 pixel i and D_i is one if a pixel is in country A and zero if it is in country B.[8] To estimate global

[6] Sometimes a grid cell falls right on the border and thus measured forest outcomes come from both sides of the border. We assign such grid cells to the side with the majority of the grid cell.

[7] Also akin to an experiment, an important prerequisite here is that absent treatment, the groups would be the same statistically. For the world’s forests, this means that under the hypothetical absence of countries, the two sides of a forest would look the same. We explain below how we test this and Fig. 6 and the results presented in the Supplementary Materials provide ample empirical evidence consistent with this assumption.

[8] In all our global specifications, the estimated treatment effect is weighted by the number of observations per border, so datapoints from the longest borders and with the most tree cover affect our results the most.

average border discontinuities between countries, they are sorted according to the outcome of interest[9] at the country level.[10] To control for all continuously distributed confounding factors, we control for the distance from each grid cell to the border, separately in country A and B, given by d_i^A and d_i^B.[11] We also control for the natural tree cover potential, which summarizes a long list of forest-relevant environmental variables. This is given by Nat_i, measured in percentage.[12] Finally, θ_j are border fixed effects,[13] ϑ_i are longitude and latitude,[14] $\in_i$ is the error term, and φ^* is the optimal maximum border distance (the bandwidth) beyond which we exclude observations (because they are not sufficiently comparable anymore). In our context, this is approximately 30 km.[15] The basic logic is that the closer we restrict the bandwidth to the border, the less bias we have from unobserved confounders. However, the more we restrict our data, the more we shrink our dataset, which makes our estimate increasingly imprecise. The optimal bandwidth balances this trade-off by giving us the largest possible, least biased dataset[16] (Cattaneo and Vazquez-Bare, 2016, Imbens and Kalyanaraman, 2012, Calonico et al., 2019). Depending on the specification, standard errors are clustered by border, country, or location (based on longitude and latitude). We show plots of our data in Fig. 2 and formal regression discontinuity estimates based on equation (1) in Fig. 3.

2.1.1. Assumptions

A number of identifying assumptions is required to be valid for the interpretation that estimated border discontinuities in forests reflect the causal effect of all the neighboring countries. We show a battery of falsification tests of all these assumptions in the Appendix A.

2.1.1.1. Natural discontinuities as confounding factors. Some international borders follow natural features (see Table 2). For example, environmental obstacles such as a mountain range might have been used to decide the location of a border, and an estimated forest loss discontinuity e.g. could be equally explained by the institutions and policies of the countries, or simply by the abrupt change in elevation that makes forest exploitation easier and more profitable on one side of such a border compared to the other (Busch and Ferretti-Gallon, 2017). We follow complementary strategies to ensure that our estimated discontinuities have no natural explanation. First of all, we use the variable *natural tree cover potential* of Bastin et al. (2019) to examine whether this shows a similar border discontinuity as do tree cover loss, forest degradation, vegetation index changes, or productivity changes. Figure A1 is a simple plot of this data, showing no sharp discontinuity at the aggregate level. Figure A2 shows the result from formally testing for border discontinuities in the natural tree cover potential for each border separately, using a spatial regression discontinuity design in which the outcome variable is the natural tree cover potential instead of an actual forest outcome. We subsequently use this to exclude all "natural borders" for certain robustness checks. Additionally, we also quantified the shape of border segments. We differentiate between border segments with an "artificial" shape (perfectly straight lines and angles) and "natural" shapes (wiggly curves). This is an independent, and alternative approach to separate natural and non-natural borders. Figure A3 then shows our main estimate (the global discontinuity in tree cover loss) and compares this to the estimates from seven robustness checks. These robustness checks include the just mentioned exclusion of natural borders, and for comparison, we also once focus only on these natural borders. The estimated discontinuity in tree cover loss is the same across all three specifications. We find the same for border segments that have a natural and a non-natural shape. Across all these robustness checks, the global discontinuity in forest loss is highly robust and cannot be explained by natural environmental conditions.

2.1.1.2. Sensitivity to bandwidth choice. Regression discontinuity estimates can be sensitive to bandwidth choice, but not in this case. As shown in Figure A3, we can change the bandwidth once to 10 km smaller and once to 10 km wider than estimated to be optimal and obtain the same estimate.

2.1.1.3. External validity. A potentially important concern with the regression discontinuity design is external validity. We achieve high internal validity right at the international borders, but some of these borders are not representative for the rest of the countries. One simple assessment is shown in Figure A4. Separately in the three major forest biomes (boreal, temperate, tropical), we plot three vegetation indices (NDVI, EVI, NPP) as a function of border distance for the first 100 km. Overall, no clear trends are discernable and thus we might carefully extrapolate our estimates to the rest of the countries, in the aggregate (at individual borders this might fail). It should, however, be noted, that in some, particularly large countries like Brazil e.g., we are not only picking up the effect of national forest impacts, but also regional ones, such as policies implemented only within one or two states that happen to be at the border.

2.1.1.4. Additional robustness checks by biome. Tables A1 – A3 show additional robustness checks, separately by biome, as both natural and socio-economic conditions tend to be different between boreal, temperate, and tropical forests. The outcome variable is the enhanced vegetation index, which is our most comprehensive measure of all forest dynamics. In each table, the first specification is our main estimate, the following seven are robustness checks. The first robustness check is to exclude all covariates. The next two are again changes in the bandwidth, but here we once double and once halve it. The next two specifications are estimated again once for natural and once for non-natural borders. We also test including higher order polynomials of latitude and longitude, which has the potential to better control for spatially continuously distributed confounders, but could also bias the estimates by overcontrolling (Gelman and Imbens, 2019), which is why we do not use them in the main specifications. The final robustness check is to exclude

[9] This sorting is necessary so that in the aggregate, positive and negative discontinuities do not cancel each other out.

[10] This sorting implies that depending on the border, datapoints from the same country are sometimes on the left side and sometimes on the right, depending on which country it is compared to.

[11] In practice, this is achieved with an interaction term, i.e. using distance d_i and distance interacted with the treatment. D_i

[12] The predicted natural tree cover of each pixel can be seen as a summary measure of all relevant features of the natural environment that affect forests. It is based on a machine learning algorithm that has been trained with data from protected areas all around the world.

[13] Border fixed effects control for all general differences between the borders (j indexes borders) and ensure that we only estimate discontinuities between each set of two contiguous countries[14].

[14] Longitude and latitude control for spatially smoothly distributed confounding factors, similar to the border distances of each pixel. For identification of the discontinuities, only one is required (border distances or longitude and latitude) but including both either has no effect or improves the model[63]. This is because either of these sets of variables controls for spatial trends across the border, e.g. because of a temperature or rainfall gradient. In addition, adding covariates to a regression discontinuity design can make the estimates more precise (potentially reducing standard errors).

[15] This is the approximately optimal value globally. For each individual border the optimal bandwidth is different. Also, at some borders, or border segments, there is only data within 20 km, and beyond that, there might be no more tree-cover (e.g. a lake) or a different country.

[16] In practice, the two most common approaches are to either minimize the mean square error (MSE) or the coverage error (CE). Furthermore, there is a list of choices, such as whether to consider both side of the border separately or not, the order of the local polynomial, the kernel function used, etc. Because these choices can affect the estimated optimal bandwidth, it is advisable to estimate specifications with different bandwidths. We report such results in the Supplementary Materials.

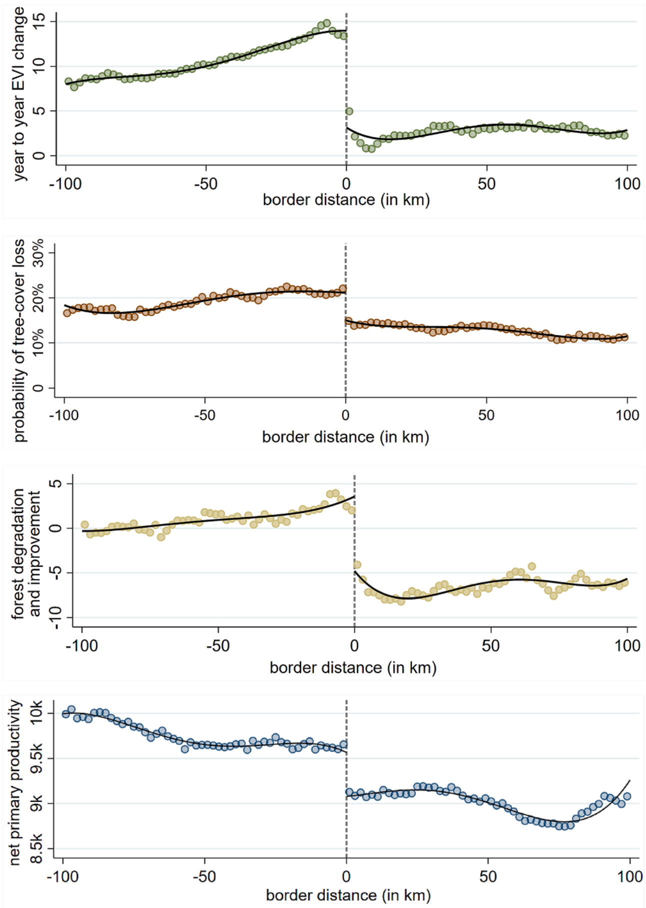

Fig. 2. Forest Dynamics near International Borders. We aggregate all 95 million forest data points into a small number of regionally averaged (2 km) bins and plot them as a function of border distance for easy visual interpretation. Bins from countries with a higher average outcome value are plotted on the left and all others on the right. The result can be interpreted as the global average border discontinuity for a each outcome. The fitted non-parametric regression lines show the general spatial trend separately on each side of the border. Their general shape is uninformative, as it is driven by all kinds of conditions and processes but what is of interest here is whether there are border discontinuities or not, because these are the basis for our empirical identification of global policy impacts. In all four plots, stark border discontinuities are clearly visible, and these foreshadow our rigorous econometric estimates, suggesting sizeable impacts of countries on their forests, and that an important explanation for this is their policies. Take for example the first plot, showing the discontinuity in the year-to-year change of the enhanced vegetation index. Without the "country effect", the enhanced vegetation index would likely show a slightly concave shape, smoothly and uninterrupted from the left to the right. Actually, however, right at the average global border, there is a steep drop of the right part of the function, which is because it belongs to those countries that cause less change in the index, compared to their neighbors on the left.

the 25 % borders with the least data (not all borders have the same amount of tree cover). These borders could be less reliable, especially if tree cover is missing near the border and we end up comparing forests that are further apart than expected. However, also here, the estimated discontinuity remains the same as before.

2.2. Quantifying the effect of countries' public policies

The estimated border discontinuities quantify the overall effect of a forest grid cell being in one country and not in its neighboring country. It is the net-effect of all relevant differences in political and economic institutions, policies, markets, infrastructure, demographics, and so on. To separate the effect of countries' public policies, we use a difference-in-discontinuities design (Butts, 2021, Wuepper and Finger, 2023). This is a combination of difference-in-differences and spatial regression discontinuity design and combines both approaches' strengths while compensating their respective weaknesses. It is based on estimating how border discontinuities change in response to countries implementing forest conservation policies. The main assumption is that without changing policy differences, both sides of the borders would have parallel trends in tree cover loss on average, and thus actual changes in discontinuities identify the causal impact of the changes in policy differences. Whether this is a sensible assumption in our context is an empirical question that we analyze in complementary ways. Just as one would do in a difference-in-differences setting, we estimate "leads" to confirm that future policies do not explain past tree cover loss. If they would, this would suggest that the parallel trends assumption does not hold in our context.[17] We try out different leads (+2 to + 5 years) and as we show in Fig. 5 above, their coefficients are precisely zero. We also test whether there is a discontinuity in the natural tree cover potential between countries that implement more forest conservation policies than their neighbors. Again, we find a precisely estimated zero correlation. Moreover, we estimate the difference-in-discontinuities for actual tree cover loss and countries' forest conservation policies, subsequently including control variables. Most importantly, we control for countries' rule of law, their property rights, their human development index, their GDP in constant 2010 USD and in current values, countries' population density, their share of population in rural areas, and their population growth rate. All these controls vary year by year, so we can rule out that such socio-economic changes confound our estimated policy effects. In all these specifications, we also include country and year fixed effects. The country fixed effects control for all time-invariant, general country differences (e.g. differences in tree cover, income-level, location, culture). The year fixed effects control for all year-specific changes that affected all countries (e.g. global agricultural and timber prices, growth of the world economy, global technological change).

Formally, we estimate:

$$Y_{i,t} = \omega + \sigma_1 D_{i,t} + \sigma_2 \left(d_i{}^* D_{i,t}\right) + \sigma_3 d_i + Country_i + Year_t + \sigma_4 Nat_i + \vartheta_i + \epsilon_{i,t} \; if \; d_i \leq \varphi^* \tag{2}$$

where Y_i is annual forest loss per 1 km^2 grid cell i at time t. $D_{i,t}$ is an indicator function for whether grid cell i is in a country in which over the past years more public forest conservation policies have been implemented (cumulatively). d_i is the distance to the border, $Country_i$ and $Year_t$ are fixed effects that control for time-invariant country characteristics and general time trends that affect all countries the same, Nat_i is the predicted natural tree cover of each grid cell that we would see without any human impact (in percentage) (Bastin et al., 2019), ϑ_i are longitude and latitude, ϵ_i is the error term, and φ^* is the approximately optimal maximum border distance beyond which the observations become too different in observed and unobserved dimensions to allow an unbiased estimation of effect of countries' policies on their forests (Wuepper and Finger, 2023).

2.3. Identifying explanations for heterogeneous policy effects

To identify what makes public policies more or less effective, we begin by estimating a difference-in-discontinuities model for each border separately. This gives us a world map that shows at which

[17] The parallel trends assumption holds if without a change in policy differences, the discontinuities in forest outcomes would have remained constant. Finding that countries that implemented policy changes had an increase or a slowdown of forest loss compared to their neighboring country right before their policy change would suggest that the two countries were not in fact on a parallel trajectory.

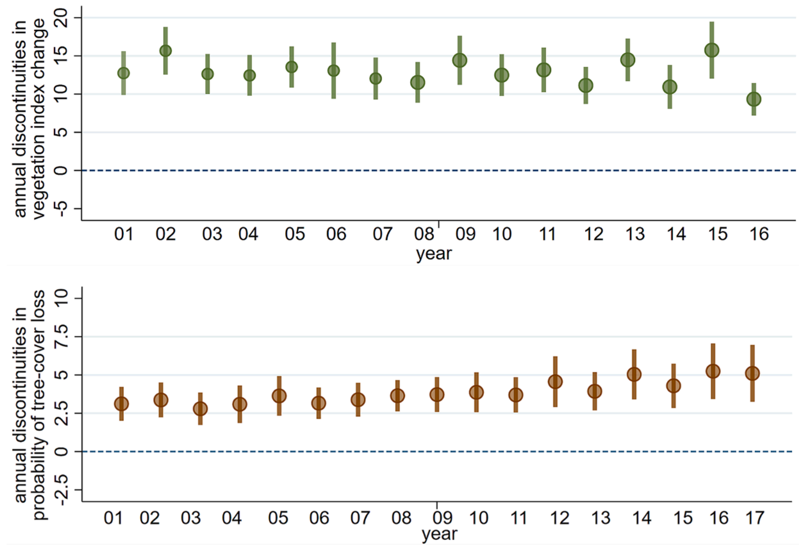

Fig. 3. Regression Discontinuity Estimates. Rigorous regression discontinuity design estimates for each year show that especially for the probability of tree-cover loss, country differences have become more important over time. Circles show point estimates and bars show 95% confidence intervals of these point estimates. All border discontinuities are statistically significant in every single year.

borders in the world, policies achieved the largest reduction in tree cover loss. In a second step, we regress whether a policy was effective at all, or not on, five potential explanations suggested by theory. These are countries' political and economic institutions (rule of law (Freedom House, 2019) and safety of property rights (Heritage Foundation, 2020)), their human development index (UNDP, 2020), and the general stringency and enforcement of environmental policies (Browne et al., 2014).

3. Results and discussion

We proceed in three steps. First, we analyze the effect of countries overall on their forests, by quantifying forest discontinuities at their borders. If countries had no causal effect on their forests, there would not be forest discontinuities at their borders. However, we find sharp discontinuities, reflecting the importance of countries' institutions, markets, and policies (sub-section 3.1). Next, we analyze the role of countries' public policies, by quantifying how border discontinuities changed in response to policy changes (sub-section 3.2). Finally, we analyze what country and policy characteristics best predict whether a policy is effective. For this, we first estimate policy effects border by border and then regress the result on policy stringency and enforcement, countries' rule of law index, property rights index, and human development index (sub-section 3.3).

3.1. *The effect of countries on their forests*

Unifying patterns can be found around the world, as we can observe discontinuities at national borders for the four complementary measures of forest status and change. This is the baseline to which we subsequently compare policy effects, allowing us e.g. to quantify (a) how much the world's forests are currently shaped by national-level socio-economic factors and (b) how much of this is via national public policies. Our data, which we plot as a function of border distance, visually show that forest dynamics and status are overall distributed discontinuously across the world's international borders (Fig. 2).

A continuous distribution would imply that political borders are irrelevant and national socio-economic factors are not that important. However, consistent with prior research (Crespo Cuaresma et al., (2017), Cuaresma and Heger (2019), Grau et al. (2022), Piquer-Rodríguez et al. (2021), Burgess et al. (2023)), we find marked discontinuities at political borders, reflecting how important country-contexts are for forests. The corresponding plots show the global average border discontinuity for various indicators, namely: Year to year changes in the Enhanced Vegetation Index (EVI) (Didan et al., 2020), probability of tree cover loss (the probability of any detectable tree cover loss within a given grid cell) (Hansen et al., 2013), forest degradation and improvement (combining EVI and tree cover loss information) (Hansen et al., 2013, Didan et al., 2020), and forests' net primary productivity (i.e. how much carbon is accumulated per year) (NASA LP DAAC, 2021). This result suggests that if one travels across the border of a country with more change in the Enhanced Vegetation Index to its neighboring country with less change, there is an abrupt shift right at the border of approximately ten index points (on average). For tree-cover loss, this shift corresponds to approximately four percentage points and for forest improvement it amounts to approximately nine EVI points (on average). Finally, the border discontinuity in forests' net primary productivity is about 500 Kg C/m2.

Our first econometric results are annually estimated discontinuies in the change of the Enhanced Vegetation Index (EVI) from year to year and the probability of forest loss (Fig. 3). Every single year in our sample exhibits a sharp border discontinuity in both indicators. Interestingly, and for the probability of forest loss in particular, we can see that country-level socio-ecnomic variables have become more important over time. During 2001—2007, the discontinuity between countries was about 2.6 percentage points, which over time doubled to 5 percentage points in 2014—2017. Additional analyses and results, by biome, are shown in the Appendix B in Figures B1 – B8.

3.2. *The effect of countries' public policies*

The analyses above beg the question of what countries are doind so differently. In this section, we examine the effect of public policies that aim to protect forests or to meet a forest-relevant sustainability goal, such as conserving carbon stocks or biodiversity. As shown in Fig. 4, countries differ substantially in terms of how many forest-relevant conservation policies they have implemented over time. An obvious caveat of this is that the number of implemented policies might or might not reflect overall policy investments, as policies differ in stringency, enforcement, institutional support, and last but not least budgets. In our

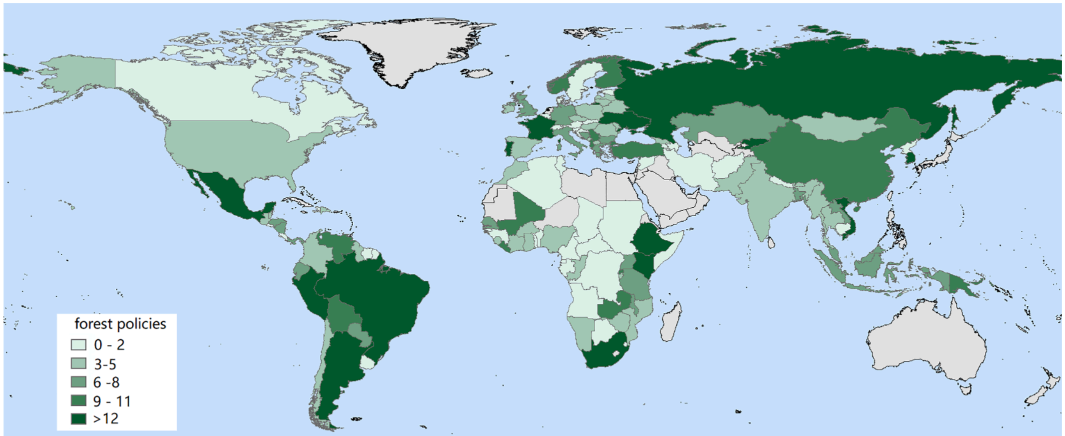

Fig. 4. World Map of National Forest-Scale Policies. There is large variation globally in the number of forest conservation policies. Further below, we also take into account contextual and policy characteristics.

Fig. 5. Placebo Test: The "Effect" of Future Policies. Significant associations between past forest dynamics and future policy changes would be indicative of deviation from parallel trends. However, here the estimated pattern suggests that parallel trends is a valid assumpition.

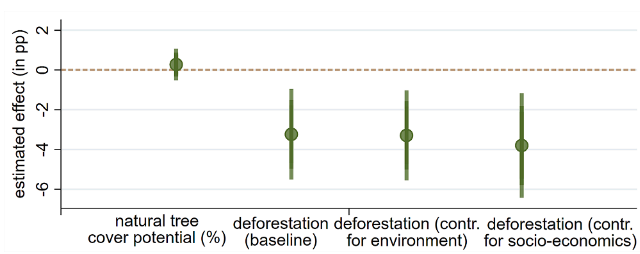

Fig. 6. Policy Effect Estimates. The first specification is another placebo test, quantifying the association between implemented policies and the natural tree cover potential. The other three specifications are the actual policy treatment effects, first without additional controls, then with the natural tree cover potential included, and then with a large vector of time-varying socio-economic variables. Circles show point estimates and bars the corresponding 95% confidence interval.

analyses below, we thus begin by treating all policies the same, i.e. we estimate how the above identified border discontinuities in the probability of tree cover loss change in response to a change in the sum of forest policies on either side. But then, we continue with an examination of the context in which such policies are most likely to have an impact.

The analytical framework is a difference-in-discontinuities design and its main assumption is "parallel trends", i.e. that forest discontinuities would have remained stable without the policy change. We carefully assess the plausibility of this important assumption below, as shown in Figs. 5 and 6. The difference-in-discontinuities specifications include country and year fixed effects, which absorb country-specific time-invariant differences as well as year-specific country-invariant differences (Wuepper and Finger, 2023, Butts, 2021). We begin by examining the validity of the "parallel trends" assumption using placebo specifications that estimate "treatment effects" of future policy changes (Fig. 5). Under parallel trends, there should be no correlation between past forest dynamics and future policy changes. Independent of whether we consider a change in forest policy over the next 2, 3, 4, or 5 years, we estimate precise zero effects in these specifications. This is important, because if e.g., the countries with initially more threatened forests were globally either more or less likely to respond with policies, this would make it more difficult to identify the impact of those policies (Wuepper and Finger, 2023).

Another test is shown in Fig. 6. Instead of estimating the effect of forest policies on current tree-cover loss, we estimate their "effect" on the natural tree cover potential that we otherwise use as a covariate. It is not possible that countries' policies affect the *natural* tree cover potential, so if we would estimate an association here, this would imply that

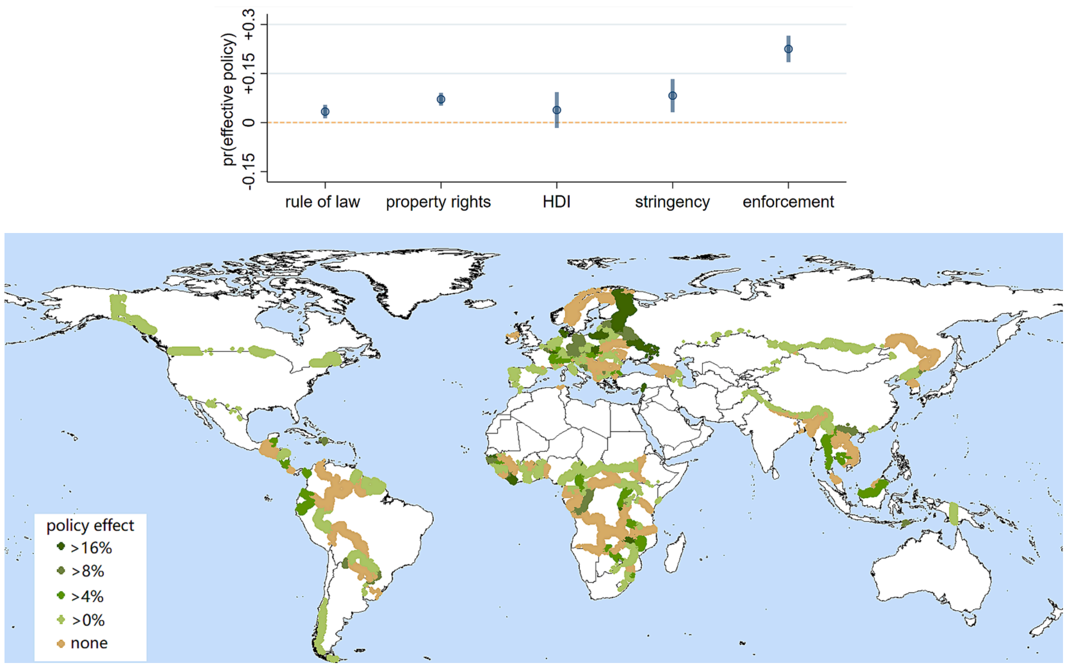

Fig. 7. Conditions under which Public Policies are Effective. By estimating the effect of public policies per border (probability of reduced tree cover loss in percentage), we can globally map the heterogeneity in impacts (upper panel) and regress whether public policies effectively reduced the degree of tree cover loss on explanatory factors such as countries' rule of law, the security of private property, human development index, and the stringency and enforcement of environmental policies (lower panel). Globally, we find more effective policies in countries with better political institutions (higher "rule of law" index) and economic institutions (higher "property rights" index), higher development ("human development index"), and generally more stringent and better enforced environmental policies. The coefficient plot shows for each explanatory variable the effect of a one standard deviation increase in that variable on the probability that a policy is effective (in percentage).

the countries that have implemented more forest policies are located in locations with a discontinuously different environment.[18] However, we estimate a precise zero correlation between policy changes and natural tree cover potential. Finally, Fig. 6 shows the actually estimated policy treatment effects, including three different sets of control variables. Showing the robustness to the inclusion and exclusion of these control variables is another important test here, as the observed coefficient stability suggests the likely overall selection, e.g. based on income, population, institutional, or other changes. For example, sometimes forest policies might be implemented after a new government comes into power, and then more than only forest policy changes. The baseline specification includes no additional covariates. However, in the next specification, we include the natural tree cover potential as a proxy for all relevant natural environmental characteristics (Bastin et al., 2019). In the final specification, we include a long vector of time-varying socio-economic country characteristics. These include their rule of law index (Freedom House, 2019), property rights index(Heritage Foundation, 2020), human development index (UNDP, 2020), share of agriculture in gross domestic product (FAOSTAT, 2021), gross domestic product absolute and per capita (World Bank, 2020), population density and growth, as well as the share of the rural population (World Bank, 2020).

Across all specifications, we estimate that public policies reduced the probability of forest loss by about four percentage points per year. This suggests that most of the observed global discontinuities in forest dynamics are the result of differences in public policies between countries.

[18] The tree cover potential is extrapolated from the tree cover observed in protected areas, which are plausibly affected by country level influences (e.g. management budgets, monitoring capacity, political stability, etc.). However, the extrapolation itself is then based on high-resolution natural environmental data (e.g. grid cell rainfall), so we would not expect artifactual border discontinuities in the final layer.

Beyond this global average, however, we are interested in the country-specific variation of this policy treatment effect and whether it can be explained, for example, by variation in institutional quality, economic development, and policy implementation styles. We turn to this question next.

3.3. Under which conditions are public policies effective?

To understand when and where public policies are most effective in protecting forests, we start with treatment effect estimates per border, as shown in the **upper panel of** Fig. 7. These are for the years 2001 – 2017 and come from a differences-in-discontinuities design that compares the risk of tree cover loss before new public policies for forest conservation were implemented, between the countries that implemented more of such policies to those that implemented less. We then test five factors that might explain where public policies were effective and were not. These are the rule of law, property rights, human development index, and general stringency and enforcement of environmental policies (**lower panel of** Fig. 7). Our difference-in-discontinuities analysis suggests that countries' economic and political institutions, their level of human development, and the stringency and enforcement of their environmental policies are all positively associated with effective forest conservation policies. From these, policy enforcement stands out as the strongest predictor. A one standard deviation increase in better enforcement is associated with a 20 % higher probability that a policy is effective. This is followed by policy stringency, which increases the probability that a policy is effective by 10 % for each standard deviation increase. The other three factors have a similar or smaller magnitude, but all positive too. The association with the human development index is not statistically significant at 95 % confidence level. This reflects that economic development is generally associated with more and better environmental policies but this is not deterministic and there are multiple counterexamples to this trend, creating heterogeneity. An interesting in-depth analysis for the case of protecting the Brazilian Amazon is provided by Burgess et al. (2023).

4. Conclusions

The loss and degradation of forests is a global sustainability challenge. In our analysis, we address three questions to support and guide policy responses. First, we quantify the overall importance of countries for forest outcomes. Using a spatial regression discontinuity design, we estimate e.g. that a third of the risk of tree cover loss is determined at the national level (e.g. national institutions, polices, markets). This corroborates the critical importance of country-level governance as a critical mechanism to promote conservation the world's remaining forests. Secondly, we quantify the role of national public policies, using a difference-in-discontinuities design. Across the globe, these policies reduced the probability of tree cover loss by almost four percentage points on average, which is close to two thirds of the overall impact that countries have. Third, we analyze which country characteristics best predict whether a forest policy is effective or not. The two most important predictors are countries' general enforcement (most important) and strictness (second important) of environmental policies. These are followed by countries' property rights and their rule of law. Countries' human development index, in contrast, is positively associated, but not statistically significant,

An interesting additional finding we make is that past forest dynamics do not predict future policy responses. Instead, the countries implementing new forest conservation, either by creating a new policy or by strengthening an existing one, equally include those with low and high initial deforestation and forest degradation threats.

Before we conclude with our policy recommendations, we like to point to a five caveats and characteristics of our analyses that matter for the interpretation of our results. First, we have here treated countries as homogenous entities and ignored all heterogeneity within countries. Secondly, even highly specific processes such as tree cover loss can be measured in quite different ways and this limit the comparability of findings. One of our main outcomes is tree cover loss, which is a binary variable that takes the value one if there was any deforestation within a 1 km^2 grid-cell, and zero otherwise. This measure is more sensitive than a definition based on the share of a grid-cell that was deforested, which matters when comparing estimates across different studies. Third, and related to the previous point, the definition and measurement of deforestation by Hansen et al. (2013) is not the only one available, and includes and excludes specific types of deforestation (Pendrill et al., 2022). Fourth, because forests tend to produce clouds, tree cover loss is not homogenously measured everywhere (Alix-García and Millimet, 2023). Fifth, the estimates from our regression discontinuity design and our difference-in-discontinuities design are highly local in nature, whereas we try to learn something about entire countries and their policies.

The policy implications of our analysis are clear and straightforward. First, national governments are playing a key role when it comes to protecting the word's remaining forests. The effectiveness of many complementary conservation efforts, such as private supply chain governance, local community collective action and certifications or standards, depends on national environmental legislations and their rigorous implementation (Hänggli et al., 2023). Local and bottom-up conservation initiatives cannot substitute for effective public policy, but often fill important governance gaps and can contribute to the design of better and more equitable forest policy (McDermott et al., 2015). Second, solid governance generally improves the performance of public policies, with at least two causal channels at work: First, improving institutional quality potentially increases deforestation pressures (Liscow, 2013, Abman and Carney, 2020, Probst et al., 2020, Wuepper et al., 2023a) creating additional need for forest protection, but eventually also promotes the development of economic sectors that do not rely on land-based resources. Secondly, good institutions enable countries to design, target, and effectively enforce policies. More ambitious environmental policies and improved collective action in the form of international cooperation to protect forests is urgently needed. Scaling up environmental legislation, monitoring and policy enforcement (Moffette et al., 2021a), international compensation schemes, such as REDD+ (Börner et al., 2020), and binding rules toward eliminating deforestation embedded in supply chains of globally traded agricultural and forest commodities (Garrett et al., 2021b, Grabs et al., 2021) may help to shift towards a more sustainable global forest governance. Importantly, improved forest protection and agricultural productivity need not be at odds. In fact, conservation policies in different countries (e.g. in Brazil) were shown to encourage land use intensification and thereby improved productivity (Moffette et al., 2021b). But forest protection must be an explicit policy goal and it is risky to assume that e.g. improved tenure security (Abman and Carney, 2020, Probst et al., 2020) or democracy (Sanford, 2021) will automatically lead to better forest protection. In fact, in our global analysis, we find a positive association between countries human development index and effective forest policies, but it is not statistically significant, because there is too much variation. What is needed is strong political will and international collaboration.

5. Data and Code

ZENODO: Data and Code 1/3 "Public Policies and Global Forest Conservation: Empirical Evidence from National Borders" https://doi.org/10.5281/zenodo.10044838.

ZENODO: Data and Code 2/3 "Public Policies and Global Forest Conservation: Empirical Evidence from National Borders" https://doi.org/10.5281/zenodo.10045135.

ZENODO: Data and Code 3/3 "Public Policies and Global Forest Conservation: Empirical Evidence from National Borders" https://doi.org/10.5281/zenodo.10046753.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2023.102770.

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