HWWI Working Paper Series

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HWWI
Hamburgisches WeltWirtschaftsInstitut

HWWI Working Paper No. 1/2024

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Imprint

Publication Series: HWWI Working Paper Series, ISSN 2750-6355
Responsible editor: Michael Berlemann

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Do climate-related disasters cause dissatisfaction with environmental policies?

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Abstract

Climate policies need public support to be successfully implemented as they typically come with short-term costs, whereas their revenues accrue far in the future. We study whether the occurrence of climate-related natural disasters have a systematic impact on dissatisfaction with actual environmental policies. Based on geo-referenced worldwide survey data we find robust empirical evidence in favor of the hypothesis that the experience of heatwaves, tropical storms and flood events trigger environmental policy dissatisfaction, at least when controlling for disaster severity. Thus, climate-related natural disasters, which will occur either more often or gain in severity in the course of global warming might significantly contribute to a rising public demand for more effective environmental and climate policies. However, the effect turns out to diminish over time.

Keywords: policy preferences, natural disasters, climate policy, environment, Gallup World Poll

1 Introduction

Environmental policies in democracies urgently need public support to have a chance of being successfully implemented (Bernauer and McGrath 2016). This is mainly due to the fact that democratic governments want to be re-elected and will therefore rarely opt for policies that are unpopular among large parts of the electorate (Bernauer 2013; Stehr 2015). The effects of environmental policies are often invisible because the counterfactual cannot be observed. Moreover, they typically come with considerable costs in the short term, while their revenues are typically only realised in the long run. This logic applies in particular to climate policy. As an example, to reduce CO_2 emissions, fossil fuels have to be replaced by more expensive renewable energies. While households and industry will have to bear the increased energy costs directly, the effect of lower emissions will only materialise decades later (Tebaldi and Friedlingstein 2013; Marotzke 2018; Samset, Fuglestvedt, and Lund 2020). Moreover, as climate change mitigation is a global public good, free-riding is a superior strategy for national governments (Bernauer 2013). Against this background, it is not surprising that the appetite of most governments for effective climate change policies has been rather limited.

Various strategies have been discussed to increase public support for climate policy. One of the most widely discussed strategies is to reframe the debate on the merits of mitigation by emphasising the benefits, which may be more appealing to voters. Benefits include increased energy security (Lockwood 2011), technological progress (Bernauer and McGrath 2016; Bain *et al.* 2016), community building (Bain *et al.* 2016; Bernauer and McGrath 2016) or health benefits (Myers *et al.* 2012; Petrovic, Madrigano, and Zaval 2014). However, the evidence on the success of this strategy is mixed at best (Bernauer and McGrath 2016).

An interesting question is whether the ongoing process of global warming itself might have an impact on public support for climate or, in more general, environmental policy. While gradual changes

HWWI Working Paper

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Edited by
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in climate variables such as temperature and precipitation seem to have little effect on awareness and support for climate policies (Brooks *et al.* 2014), sudden-onset events such as climate-related natural disasters may be more relevant. The process of global warming has increased the frequency and severity of several climate-related disasters such as heat waves (Perkins-Kirkpatrick and Lewis 2020), tropical storms (Peduzzi *et al.* 2012), floods (Tellman *et al.* 2021), droughts (Trenberth *et al.* 2014) and wildfires (Liu, Stanturf, and Goodrick 2010). Thus, if there would be a causal link between the occurrence (and experience) of climate-related disasters and support for climate policies, the process of global warming would generate a somewhat self-reinforcing support for environmental policies.

Public support for stricter environmental or climate policies, caused by the experience of natural disasters, has been investigated in various ways. One strand of literature looks at the effect of natural disasters on election outcomes and voting behaviour. A recent paper by Hoffmann *et al.* (2022) found that the experiences of temperature anomalies, heat episodes and drought events that occurred over the past 12 months significantly increased environmental concerns and the tendency to vote for Green parties in Europe. The authors also show that the effects diminish over time. This effect is likely driven by the greater salience of more recent experiences (Hoffmann *et al.* 2022). A number of studies used a recent flood event in Germany in 2021 and report a systematic effect on voting behaviour towards the Green party (Garside and Zhai 2022; Hilbig and Riaz 2022; Holub and Schündeln 2023; Devereux *et al.* 2023). Baccini and Leemann (2021) use referendum votes on pro-climate measures in Switzerland together with geo-spatial data on natural disasters (e.g., floods, rockfall, landslides) to perform a difference-in-difference estimation. They find that the experience of local disaster events causally increases voting in favor of climate protection measures. However, the effect again fades out in the course of time. Ten months after a natural disaster, no difference exists between affected and non-affected areas. Similarly, Hazlett and Mildenberger (2020) find that the experience of wildfires increased the voting share for pro-environmental measures in California, but primarily in Democratic-dominated voting areas.

Other studies rather analyse changes in public attitudes towards specific policy interventions after disaster or extreme weather events. Using survey responses from the UK Demski *et al.* (2017) show that people exposed to flood events were more in favour of climate change mitigation and that people which experienced wildfires were more likely to support adaptation policy measures (e.g. land use policies) in the western United States (Craig *et al.* 2020). Kim, Seo, and Sinclair (2021) found that both long- and short-term temperature deviations from the trend increase individual support for climate change policies. However, not all studies on the impact of climate-related natural disasters on support for environmental or climate policies find systematic effects. Lee, Loveridge, and Winkler (2018), for instance, report only a weak relationship between extreme heat episodes and public support for government actions against climate change. Likewise, Ray *et al.* (2017) find no robust effect for weather extremes on support for climate policies based on the US 2014 Cooperative Congressional Election Study. No effect of weather extremes on policy preferences at all were identified by Gärtner and Schoen (2021) for German data.

A major problem with the existing literature is that the vast majority of studies are single-country studies and it remains unclear whether the results can be generalised in a meaningful way. Moreover, most of these studies focus on the US, where voters might be specific in many ways. The few existing multi-country studies are based on cross-sectional data, which makes it difficult to draw causal conclusions and to correct for unobserved heterogeneity. Moreover, the literature varies widely in terms of sample periods, data used and estimation strategies (Bumann 2021).

Our study adds to the literature by providing the first global study of the impact of different climate-related natural disasters on environmental policy satisfaction. We use repeated cross-sectional data from nine waves of the Gallup World Poll covering 2431 world regions between 2010 and 2018. We combine the data with disaster data from various different sources. When using advanced and systematic data sources such as climate data from the European Space Agency's Copernicus programme, storm data from the International Best Track Archive for Climate Stewardship (IBTrACS), and global raster images of flood events published by Tellman *et al.* (2021), we find robust evidence that heatwaves, tropical storms and floods cause environmental policy dissatisfaction as long as we control for disaster severity. However, the effects turn out to be relatively short-lived and diminish over time.

2 Empirical Approach

For our empirical analysis we use nine waves of survey data from the Gallup World Poll and combine them with data on extreme events, derived from various different sources via geo-referencing. We then regress a measure of environmental policy dissatisfaction on a number of individual-level controls and various indicators describing the frequency or severity of three types of climate-related extreme events: floods, tropical storms and heatwaves. Thus, the baseline model to be estimated is

$$d_{i,t,r} = \mu_r + \gamma_t + \beta_1 \cdot X_{i,t,r} + \beta_2 \cdot c_{r,t} + \beta_3 \cdot \Omega_{r,t} + \epsilon_{i,t,r} \qquad (1)$$

The left hand variable $d_{i,t,r}$, is a binary variable indicating whether individual i in region r and month t reports to be dissatisfied with current efforts to preserve the environment. Rather than employing generalized linear models to estimate equation 1 we opt for linear probability models as they allow to control for unobserved heterogeneity by including region- (μ_r) and time-fixed effects (γ_t).

As control variables we use various socio-economic variables on the individual level, captured by the vector $X_{i,t,r}$. We also control for the regional level of CO2 emissions at time t, $c_{r,t}$. However, our variables of primary interest are disaster exposure indicators $\Omega_{r,t}$ describing whether respondents, living in region r at time t were exposed to natural disasters over the recent past (in general over the year preceding the survey date). Whereas we start out with studying the three disaster types separately, we also estimate model variants which include indicators for all three disaster types. We use various different disaster indicators and conduct numerous stability tests, which will be explained later in more detail.

3 Data

3.1 Environmental Policy Dissatisfaction

Our left hand variable, environmental policy dissatisfaction, comes from the Gallup World Poll (as well as the later explained individual control variables). We use data from the Gallup World Poll for the period 2010 to 2018, covering altogether as much as 165 countries. The poll is typically conducted once a year among 1,000 randomly selected people aged 15 and over. In larger countries such as Russia and China, at least 2000 people are interviewed. Interviews are conducted either by telephone or face-to-face. The survey includes questions on a broad range of topics including socio-demographics, well-being, employment, food and housing, migration, personal health, financial issues, civic engagement, and environment and energy (see the Appendix A for more details on the survey methodology). The Gallup World Poll is one of the very rare annually repeated, internationally comparable surveys which also covers environmental issues.

The Gallup World Poll data include information on the place of living of the respondent on the country level. However, for most countries in the sample the name of the region, the respondent lives in, is also available (often in local language). As it is our aim to match the place of living as close as possible with natural disaster data we exploit the regional information in the database to the largest extent possible. To obtain the geographical location of the Gallup World Poll regions, we match their names with spatial polygons of administrative units from the Global Administrative Areas (GADM, v.3.6) (GADM 2018). Matching was based on (similarity of) region names. In most

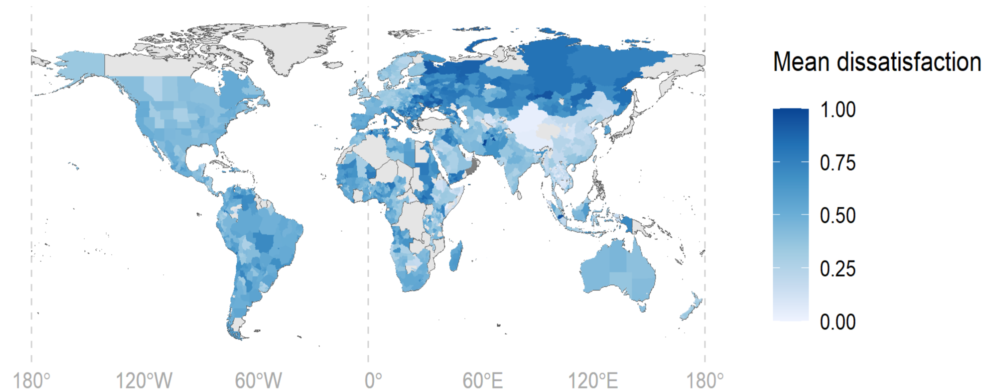

Figure 1. Mean environmental policy dissatisfaction between 2010-2018. The variable is coded as a dummy variable with 1 = 'dissatisfied' and 0 = 'satisfied'. Dark blue regions have the highest share of individuals who are dissatisfied with environmental policies. Grey areas depict countries and country borders with missing data. Coordinate references system = WGS 84 (EPSG-Code 4326).

cases, the region names of the GADM first-order administrative units were suitable. However, for Albania, Belgium, Luxembourg and Taiwan, name matching had to be performed on second-order GADM administrative units. A number of countries had to be excluded from the analysis completely because their Gallup regional classification was inconsistent with the GADM regions (Botswana, Congo Kinshasa, Hong Kong, Iceland, Japan, Sri Lanka, Macedonia, Nagorno-Karabakh, Philippines, Somaliland, Turkey). The final data set includes Gallup World Poll respondents from 2431 regions all over the world. Each region was assigned a unique region ID.

The survey item we use to construct our central left-hand variable is: 'In this country, are you satisfied or dissatisfied with efforts to preserve the environment?' (WP132).[1] Respondents could refuse to answer the question or answer 'dissatisfied', 'satisfied' or 'don't know'. In Figure 1 we show a map displaying the mean values of environmental policy dissatisfaction over the entire sample period. For our empirical analysis we re-coded the responses to this question as a binary variable with the categories 'dissatisfied' = 1 and 'satisfied' = 0 to make the interpretation of the empirical results more intuitive. Refused' or 'don't know' responses were coded as missing values.

Table 1. Environmental policy dissatisfaction and climate change perceptions

	Environmental Policy Dissatisfaction		
	(1)	(2)	(3)
Constant	-0.0019	-0.1452***	-0.3719***
	(0.0486)	(0.0437)	(0.0539)
Climate change knowledge	-0.0191		
	(0.0507)		
Climate change human caused		0.2060***	
		(0.0400)	
Climate change risk			0.4618***
			(0.0511)
Observations	54,279	39,637	39,966
Pseudo R^2	0.00001	0.00187	0.00703
AIC	75,246.1	54,842.8	55,014.0

Logit model without control variables and fixed effects. SEs are clustered on region level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

1. The availability of this question restricts our sample period to 2010 to 2018, as this question was consistently asked in the Gallup World Poll only over this time period.

The primary reason why we use environmental policy dissatisfaction as left hand variable in our main empirical study is that it is the only climate-related question which has been asked consistently over time in the Gallup World Poll. Obviously, the employed question does not exclusively focus on climate issues but asks for satisfaction with environmental policy in a more general sense. However, climate policies are typically understood as an integral part of policies preserving the environment.

In order to illustrate the close connection between environmental and climate policy we make use of data on individual climate change awareness and perception, collected by the Gallup World Poll in 61 countries between February and December of 2010 We basically employ three items from this survey. First, we use the answers to a climate awareness question. This question reads 'How much do you know about global warming or climate change?'. The answering options included 'I have never heard of it,' 'I know something about it,' and 'I know a great deal about it.' We coded this survey question as a dummy variable taking the value of one whenever a respondent answered 'I know something about it' or 'I know a great deal about it.' and zero otherwise. Respondents reporting to know at least something about climate change were asked two additional questions. These respondents were also requested to report on their perceived climate risk by asking 'How serious of a threat is global warming to you and your family?' Respondents could either answer 'very serious', 'somewhat serious', 'not very serious' or 'not at all serious.' We summarize the answers in a dummy variable which takes the value of one whenever people answered that climate change it is a 'somewhat serious' or 'very serious' threat to themselves and their family and zero otherwise. Moreover respondents were requested to reveal their opinion the causes of climate change. Here, the respondents were asked 'Temperature rise is a part of global warming or climate change. Do you think rising temperatures are ...?' Answer options were, 'a result of human activities', 'a result of natural causes' or 'both'. We summarize the results in a dummy variable taking on the value of one whenever individuals chose 'a result of human activities.' as an answer.

When regressing the variables of climate knowledge, climate change causes and the climate risk perception variables on our measure of environmental policy dissatisfaction we find the results reported in 1. We do not find a systematic connection between self-reported climate knowledge and environmental policy dissatisfaction. However, individuals reporting that climate change is caused by human behavior also report systematically higher dissatisfaction with environmental policy. The same holds true for individuals reporting that climate change is perceived as an individual threat. We interpret these results as a strong indication that climate policies are perceived as integral parts of environmental policies in general.

3.2 Individual-level control variables

In our estimation approach we control for various socio-demographic factors which might have an influence on the likelihood to express dissatisfaction with environmental policies (see Appendix B for summary statistics). The choice of these variables follows the related literature (see e.g. Bumann 2021), but is restricted by data availability in the Gallup survey. We control for gender as other studies have often reported men and women to have different perceptions on causes of climate change. In general women have found to be more fatalistic than men about climate change (Sanaul Haque, Kumar, and Bhullar 2023). As as example, more women than men perceive climate change as God's will and results of our sinful acts (see Haq and Ahmed 2017, Mnimbo et al. 2017). We also control for age and allow for a linear-quadratic relationship between age and policy dissatisfaction. Various studies have showed that the demand for climate action significantly correlates with age (Bumann 2021). Moreover, we control for income (by including dummies for income quantiles) and education (by including dummies for secondary or tertiary education). Finally, we control for self-reported health as health problems might foster dissatisfaction with environmental policy.

3.3 Regional greenhouse gas emissions

As the process of global warming is driven by greenhouse gas (GHG) emissions, it seems to be reasonable to control for the level of these emissions in our regression approach. In line with our regional approach, we add a measure of the regional GHG emissions to the regressions. As indicator of regional GHG emissions we estimated the average amount of CO2 emitted over a 12-month period for every GADM region and month between 2010 and 2018. The estimations were weighted by the average population density within each GADM region. Calculations were based on the Open-Source Data Inventory for Anthropogenic CO2 (ODIAC) database, which is accessible via the website of the Center for Global Environmental Research at the Japanese National Institute for Environmental Studies (https://db.cger.nies.go.jp/dataset/ODIAC/). We used the latest version of the ODIAC database (ODIAC 2022) with downscaled fossil CO2 emissions estimated from the Carbon Dioxide Information Analysis Center (CDIAC) on a global 1x1 degree grid (Oda and Maksyutov 2015).[2] Information on global population density was obtained from the Gridded Population of the World data set (GPWv4), provided by the the NASA Socioeconomic Data and Applications Center (SEDAC). Average population density was calculated with 2015 data (Center for International Earth Science Information Network (CIESIN), Columbia University 2018).

3.4 Disaster indicators

For our analysis of the impact of natural disasters on environmental dissatisfaction, we use different disaster exposure indicators, based on calculations from different databases. One possible source of data is the geocoded (G)EM-DAT database. As it has been used extensively in the related literature, likely because the easy data access, we also use this data source in our baseline estimations. However, as the database has it serious shortcomings, we mostly rely on more advanced data from more specialized sources. In the following, we explain all data sources in more detail.

The Emergency Events Database (EM-DAT) is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain. This database contains a global collection of different types of natural or technological disaster events (Guha-Sapir, Below, and Hoyois 2014). It has been widely used in the literature to study issues such as the economic damage caused by disaster events (Coronese *et al.* 2019), the impact of disasters on agricultural crop production (Lesk, Rowhani, and Ramankutty 2016) or the impact of disasters on economic growth (Cavallo *et al.* 2013). Recently, information on spatial geometry and latitude/longitude coordinates has been added to most disaster events in the EM-DAT database (Rosvold and Buhaug 2021). This allows the data to be matched to the administrative units of the GADM database (v.3.6). In total, GEM-DAT contains information on 9,924 disaster events in 39,953 locations worldwide between 1960 and 2018. This corresponds to 89.5% of the disaster events recorded in EM-DAT (Rosvold and Buhaug 2021).

GEM-DAT can be obtained from the web portal of the Socioeconomic Data and Application Center at Columbia University. In addition, we acquired the original EM-DAT data to obtain additional disaster event-specific information (e.g., disaster subtypes, start and end dates). After retrieving the data, we merged the GEM-DAT and EM-DAT data using unique disaster IDs. Then, for the disaster subtypes heatwaves (n = 32), tropical cyclones (n = 276), and flash floods (n = 223), we selected all disaster events that occurred between 2009 and 2018. Each disaster event was assigned to the first day of a month following the event, based on the reported end date of the disaster. We then calculated the respective number of heat waves, tropical storms and floods that occurred within 12 months for each month between 2010 and 2018 and each region, and used the resulting indicators in our regressions.

Hopwever, the natural disasters recorded in EM-DAT, as well as in the GEM-DAT database, have to

2. The details of the ODIAC emission data products are described in Oda and Maksyutov 2011; Oda et al. 2018).

fulfil certain requirements before being included in the directory (see Supplementary Information for the selection criteria). As a result, the data are subject to several biases. Smaller or historical disasters may be under-represented in the database (Acevedo 2016; Coronese *et al.* 2018). In addition, data on economic losses are known to be poorly reported or missing (Coronese *et al.* 2019; Jones, Guha-Sapir, and Tubeuf 2022). These shortcomings of the database need to be considered when using the disaster data for research purposes.

As an alternative to the GEM-DAT heatwave data, we constructed several heatwave exposure indicators from publicly available temperature data. Several definitions of heatwaves have been used in the literature (Xu *et al.* 2016). In this study, we define a heatwave as a period of more than three consecutive days with daily maximum temperatures above the temperature threshold for the historical reference period of 1981-2010 (Russo, Sillmann, and Fischer 2015). The threshold is estimated based on the 99^{th} percentile of historical daily maximum temperatures centred on a 31-day moving window. Hot days are defined as days where the maximum temperatures exceed the same threshold.

To identify heatwave events around the world, we used global climate data from the European Space Agency's Copernicus programme. We downloaded global daily maximum temperature data (at 2 metres above ground) based on the ERA5 hourly reanalysis product and a 6-hour frequency for the years 1981 to 2018 (0.5x0.5 degree grid resolution). Daily averages were then calculated for each GADM region. Using the averaged daily climate data and our heatwave definition, we created three indicators of heatwave exposure: (i) the number of heatwaves, (ii) the sum of heatwave days and (iii) the number of hot days. The number of hot days indicator simply counts the number of days on which the temperature exceeded the threshold, without taking into account the heatwave restriction of consecutive days Shafiei Shiva, Chandler, and Kunkel 2019. Each heatwave indicator was calculated for the period of 12 months preceding each month between 2010 and 2018, respectively, and for each GADM region.

For tropical storms, we used the International Best Track Archive for Climate Stewardship (IBTrACS) as an alternative to the GEM-DAT database (Knapp *et al.* 2018). The IBTrACS database provides the most comprehensive global data set of tropical cyclones (Knapp *et al.* 2010), collected from various meteorological centres. It contains detailed information on the geographical coordinates and climatic characteristics of each tropical cyclone event. For our analysis, we considered only tropical storms that occurred between 2008 and 2018 and had a maximum distance <=200km from land (n = 720). Since the IBTrACS data do not provide storm-specific continuous wind fields, we calculated storm wind fields for each selected storms event using the open-source CLIMADA Python package (v. 3.0.1), a tool developed to study the risk and socio-economic impacts of global hazards (Bresch and Aznar-siguan 2021). This approach provides realistic distributions of surface winds around the centre of tropical cyclones (Geiger, Frieler, and Bresch 2018), as well as good approximations of storm exposure for the regions studied.

Wind fields were successfully estimated for 694 storms on a 0.25x0.25 degree grid (EPSG = 4326) covering the extent of each respective storm track. The produced data was used to identify intersecting areas between GADM regions and storm wind fields, and to calculate the maximum wind speeds of these areas. We then calculated the number of tropical storm events as well as the sum of maximum wind speeds happening in each region over a 12-month period before each month in a year between 2010 and 2018. Calculations were done for two categories of storms, for all storms with wind speeds of >0 m/s and for storm events classified as hurricanes where wind speeds are greater than 33 m/s. We also created additional storm exposure variables to account for the severity of storms and wind speeds. To do this, we first weighted each storm event or maximum wind speed within a region by the proportion of the region's area covered by storm wind fields with maximum wind speeds of at least 25m/s. We chose a threshold of 25m/s because this threshold is typically used in insurance studies to estimate the area of damaging storm winds in Europe (Roberts *et al.* 2014). The resulting scores for storms with maximum wind speeds >0m/s and >33m/s were then, as before, summed over 12 month period to obtain severity indicators for each GADM region and month between 2010 and 2018.

In the case of flood events, we used data from the Global Flood Database (Tellman *et al.* 2021) as an alternative to the GEM-DAT data. This database is an extension of the flood data collected by the Dartmouth Flood Observatory (DFO). Unlike the Dartmouth Flood Observatory data, the Global Flood Database includes information on the maximum observed surface water extent during flood events, available as raster images. It should be noted, however, not all flood events within the Dartmouth Flood Observatory are included in the Global Flood Database. This is because either clouds obscured the entire satellite image, no flooded areas were identified, or due to quality control Tellman *et al.* 2021.

We used all available flood raster images between 2008 and 2018 (n = 894) from the Global Flood Database online website (see Supplementary Information). Each flood raster image was assigned to the original flood event data from the Dartmouth Flood Observatory (Brakenridge 2021) by a common flood disaster ID. Through this step, we obtained additional information for each flood event such as start date, end date, or severity score, a variable that classifies floods into three impact categories (large flood events, very large events, extreme events). From the resulting data set, we constructed several indicators of flood exposure. First, we simply count the number of flood events occurring in each GADM region over a 12 months long time period for the months between 2010 and 2018. A region is counted as flooded if it overlaps to some extent with a flooded area. While this indicator covers all flood events in the database, we constructed an additional indicator by counting only flood events of the most severe category (extreme events). To further account for region-specific flood impacts, we constructed two additional indicators using area weights. To do this, we weight each flood event by the maximum proportion of area flooded during the event within a region. We calculate this indicator for all flood events and for the subset of the most extreme floods.

4 Empirical Results

In the following we report our estimation results for the impact of the occurrence of the three types of natural disasters on environmental policy dissatisfaction. Relying on the basic estimation approach outlined in Section 2 we start out with reporting the results for heatwaves. We then turn to tropical storms and flood events.

4.1 Heatwaves

In the first step of our empirical analysis we study whether the experience of heatwaves have a systematic impact on environmental policy dissatisfaction. We begin our analysis with studying whether the number of heatwaves events, an individual experienced over the year preceding the survey date, has a systematic impact on the likelihood to report environmental policy dissatisfaction. We calculate the count indicators for both databases, GEM-DAT (Heatwave Number (GEM-DAT)) and Copernicus (Heatwave Number (Copernicus)). As shown in Table 2, the coefficients of both indicators turn out to be not significantly different from zero. Thus, we do not find a systematic effect of the number of experienced heatwaves on dissatisfaction with environmental policy.

One might argue that our (non-) result is driven by the fact that simple count indicators neglect the duration of heatwaves. This might be problematic as the length of a heatwave is an important factor in measuring the severity of a heatwave event. To account for event severity we calculate two additional indicators based on additional climate data. As first severity indicator we calculate the exact number of heatwave days over the year preceding the survey (Sum of heatwave days). In addition, we calculate the number of hot days (Number of Hot Days), based on the same temperature

Table 2. Environmental policy dissatisfaction and Heatwaves

	Environmental Policy Dissatisfaction			
	(1)	(2)	(3)	(4)
Income 2qt	-0.0022	-0.0023	-0.0022	-0.0022
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Income 3qt	-0.0007	-0.0008	-0.0008	-0.0008
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Income 4qt	0.00002	-0.000007	0.00002	0.00001
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Income 5qt	-0.0018	-0.0018	-0.0018	-0.0018
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Age	0.0035^{***}	0.0035^{***}	0.0035^{***}	0.0035^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age2	-0.00004^{***}	-0.00004^{***}	-0.00004^{***}	-0.00004^{***}
	(0.000002)	(0.000002)	(0.000002)	(0.000002)
Male	0.0058^{***}	0.0058^{***}	0.0058^{***}	0.0058^{***}
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Sec. education	0.0522^{***}	0.0523^{***}	0.0522^{***}	0.0522^{***}
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Ter. education	0.1065^{***}	0.1066^{***}	0.1064^{***}	0.1064^{***}
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Health problems	0.0169^{***}	0.0169^{***}	0.0169^{***}	0.0169^{***}
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Mean CO2 emissions	-0.00002	-0.00003	-0.00003	-0.00003
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Heatwave number (GEM-DAT)	0.0189			
	(0.0203)			
Heatwave number		0.0011		
		(0.0008)		
Sum of heatwave days			0.0002^{***}	
			(0.00007)	
Number of hot days				0.0002^{***}
				(0.00008)
Observations	926,487	926,487	926,487	926,487
Adjusted R^2	0.13572	0.13573	0.13577	0.13578
F-test	3.4545	3.4548	3.4559	3.4563
Region fixed effects	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓

Linear probability regression with clustered SEs on region level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

threshold as for heatwaves. Here, we neglect the requirement that heatwaves in principle require three subsequent hot days before they are counted as heatwave days. For both severity indicators we find a positive and highly significant effect on dissatisfaction with environmental policy Table 2.

To obtain an impression of the size of the effects, we consider the city state of Hamburg in Germany. The average number of hot days in Hamburg over the sample period is 24. The maximum number of hot days over 12 months in Hamburg was 78. Thus, the occurrence of an additional 54 hot days increases the probability of dissatisfaction with environmental policy in Hamburg by about 1 percentage point. The effect is thus small in the case of Hamburg, a city in the northern hemisphere. However, in regions that have become significantly hotter in recent decades, the effect is substantial, as illustrated by the case of Mecca (Saudi Arabia). Here, for large parts of the sample period, almost all days in the previous year of a month must be classified as hot days. As a result, more than 7 percentage points of dissatisfaction with environmental policy (which amounted to 37.4 per cent over the entire sample period) can be attributed to hot days. Thus, almost 20 per cent of environmental dissatisfaction in Mecca can be attributed to hot temperatures. We find similar effects in many other equatorial regions.

4.2 Tropical storms

Turning to the case of tropical storms, we again start out with studying two count indicators. The first indicator again relies on the GEM-DAT database (Storm number (GEM DAT)), the second one is based on the IBTrACS archive (Storm number (IBTrACS)). As Table 3 shows, for both simple count indicators the coefficients turn out to be not significantly different from zero. Even when restricting the analysis to major tropical storms with wind speeds larger than 33 metres per second, the coefficients remain to be insignificant (Storm number (>33 m/s)). Note that this analysis is only possible for the IBTrACS archive as the GEM-DAT database does not contain wind speed data. Likewise, the sum of maximum wind speeds for all storms (Sum max wind speed) and for major storm events (Sum max. wind speed (>33m/s)) does not show any significant effect on policy dissatisfaction.

One might argue that our non-finding of significant effects of the occurrence of tropical storms on environmental policy dissatisfaction is due to the fact that we do not account for the size of the affected areas. While we did not correct for affected areas in our earlier analysis of the effects of heatwaves, do so was unnecessary in this case as temperature is highly correlated in space (Auffhammer *et al.* 2013). Thus, whenever a heatwave occurs it is quite likely that the whole region suffers from very similar temperature patterns. For tropical storms this argument does not hold. We therefore construct additional storm indicators from the IBTrACS database by weighting the storm number and the wind speed indicators with the proportion of the affected area. An affected area is defined as an area where maximum wind speeds exceed the threshold of 25 metres per second (see Appendix B). We calculate these indicators for all tropical storms (Area-weighted storm number, Area-weighted sum max. wind speed) and for all major storms (Area-weighted storm number (>33 m/s), Area-weighted sum max. wind speed (>33m/s)). When using these indicators in our estimations, all their coefficients turn out to be positive and significant at least on the 95-percent confidence level (see Table 3).

We illustrate the size of the effects using a tropical storm event that occurred during our sample period. One of the most devastating tropical storms which occured in the US was Hurricane Irma, which developed in late August 2017 and caused widespread and catastrophic damage, particularly in the northeastern Caribbean and the Florida Keys. Based on the estimated area-weighted storm severity indicator (Area-weighted sum max. wind speed (>33m/s)) the model predicts that Irma alone increased environmental policy dissatisfaction by 3.5 percentage points. Given that the average political dissatisfaction in Florida was 42.9 percent, this is an increase of almost 8 percent. Another example is Typhoon Haiyan, which formed over Micronesia in early November 2013 and then made its way to the Philippines and the southern coast of China, where it made landfall again. One of the hardest hit regions in China was Hainan, where more than 40 percent of the island was affected and the maximum wind speed exceeded 50 m/s. According to our estimates, Typhoon Haiyan caused a 1.5 percentage point drop in environmental policy satisfaction. Given an average policy dissatisfaction rate of 26.9 percent in the Hainan region over the entire sample period, this is an increase of more than 5.5 percent.

4.3 Environmental policy dissatisfaction and Floods

Finally, we turn to the case of flood events. Again we start out with employing simple count indicators of flood events in our regressions. While the first indicator is again based on the GEM-DAT database (Flood number (GEM-DAT)), the second one refers to the Global Flood Database Tellman *et al.* 2021 with geodata of floods documented by the Dartmouth College Flood Observatory

Table 3. Environmental policy dissatisfaction and Tropical Storms

	Environmental Policy Dissatisfaction								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income 2qt	-0.0022	-0.0022	-0.0022	-0.0022	-0.0022	-0.0022	-0.0022	-0.0022	-0.0022
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Income 3qt	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008	-0.0008
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Income 4qt	0.00002	0.00002	0.000007	0.00001	0.000004	0.000007	0.000001	0.000006	0.000003
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Income 5qt	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018	-0.0018
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Age	0.0035***	0.0035***	0.0035***	0.0035***	0.0035***	0.0035***	0.0035***	0.0035***	0.0035***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age2	-0.00004***	-0.00004***	-0.00004***	-0.00004***	-0.00004***	-0.00004***	-0.00004***	-0.00004***	-0.00004***
	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)	(0.000002)
Male	0.0058***	0.0058***	0.0058***	0.0058***	0.0058***	0.0058***	0.0058***	0.0058***	0.0058***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Sec. education	0.0523***	0.0523***	0.0523***	0.0523***	0.0523***	0.0523***	0.0523***	0.0523***	0.0523***
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Ter. education	0.1065***	0.1066***	0.1066***	0.1066***	0.1066***	0.1066***	0.1066***	0.1066***	0.1066***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Health problems	0.0169***	0.0169***	0.0169***	0.0169***	0.0169***	0.0169***	0.0169***	0.0169***	0.0169***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Mean CO2 emissions	-0.00003	-0.00003	-0.00003	-0.00003	-0.00003	-0.00003	-0.00003	-0.00003	-0.00003
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Storm number (GEM DAT)	0.0026								
	(0.0063)								
Storm number		0.0007							
		(0.0069)							
Storm number (>33 m/s)			0.0173						
			(0.0142)						
Sum max. wind speed				0.0003					
				(0.0003)					
Sum max. wind speed (>33 m/s)					0.0004				
					(0.0003)				
Area-weighted storm number						0.0248**			
						(0.0120)			
Area-weighted storm number (>33 m/s)							0.0302***		
							(0.0117)		
Area-weighted sum max. wind speed								0.0006**	
								(0.0003)	
Area-weighted sum max. wind speed (>33 m/s)									0.0007***
									(0.0002)
Observations	926,487	926,487	926,487	926,487	926,487	926,487	926,487	926,487	926,487
Adjusted R^2	0.13571	0.13571	0.13573	0.13572	0.13573	0.13572	0.13572	0.13572	0.13572
F-test	3.4541	3.4541	3.4547	3.4545	3.4547	3.4545	3.4546	3.4546	3.4547
Region fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓

Linear probability regression with clustered SEs on region level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(Flood number (Dartmouth)). The estimation results are shown in Table 4. As for heatwaves and tropical storms the regression analyses using count indicators do not deliver statistically significant coefficients.

However, we again obtain a positive and significant coefficient when we account for flood severity in a meaningful way. When counting only those floods classified by the Dartmouth College Flood Observatory as severe flood events (Severe flood number) with the highest flood severity score the estimated coefficients turns out to be positive and highly significant. As in the case of tropical storms it also seems to be reasonable to control for the area affected by the flood event. When using area-weighted severe flood events (Area-weighted severe floods) we again find a positive and significant effect of the related coefficient.

Various flood events around the world have been assigned the highest flood severity category in the Dartmouth College Flood Database. For example, the spring 2012 flood in Queensland, Australia, received a severity rating of 2 and inundated 78.6 percent of the area of Queensland. Applying the coefficients of the estimation model (Area-weighted severe floods) would imply that this flood event should increase political dissatisfaction in the affected region by up to 13.7 percentage points. Given that the average environmental policy dissatisfaction in Queensland over the entire sample period was 39.5 percent, the 2012 spring flood is expected to increase policy dissatisfaction by about 34.7 percent. Another example is the August 2017 flood in the Dhaka region of Bangladesh. Again, this event is classified as a severe flood and affected 48.6 percent of the region. The expected increase in political dissatisfaction in this case is 8.5 percentage points, an increase in average policy dissatisfaction in the region of 45.2 percent.

Table 4. Environmental policy dissatisfaction and Floods

	Environmental Policy Dissatisfaction			
	(1)	(2)	(3)	(4)
Income 2qt	-0.0022	-0.0022	-0.0022	-0.0023
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Income 3qt	-0.0008	-0.0008	-0.0008	-0.0008
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Income 4qt	0.00002	0.00002	0.00002	0.00002
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Income 5qt	-0.0018	-0.0018	-0.0017	-0.0018
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Age	0.0035^{***}	0.0035^{***}	0.0035^{***}	0.0035^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age2	-0.00004^{***}	-0.00004^{***}	-0.00004^{***}	-0.00004^{***}
	(0.000002)	(0.000002)	(0.000002)	(0.000002)
Male	0.0058^{***}	0.0058^{***}	0.0058^{***}	0.0058^{***}
	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Sec. education	0.0523^{***}	0.0522^{***}	0.0522^{***}	0.0523^{***}
	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Ter. education	0.1065^{***}	0.1065^{***}	0.1064^{***}	0.1065^{***}
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Health problems	0.0169^{***}	0.0169^{***}	0.0170^{***}	0.0170^{***}
	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Mean CO2 emissions	-0.00003	-0.00003	-0.00003	-0.00003
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Flood number (GEM DAT)	0.0039			
	(0.0093)			
Flood Number		0.0035		
		(0.0026)		
Severe flood number			0.0114^{***}	
			(0.0035)	
Area-weighted severe floods				0.1739^{**}
				(0.0727)
Observations	926,487	926,487	926,487	926,487
Adjusted R^2	0.13571	0.13573	0.13578	0.13573
F-test	3.4542	3.4547	3.4562	3.4548
Region fixed effects	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓

Linear probability regression with clustered SEs on region level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

4.4 Models with multiple disaster variables

In the previously presented regressions we restricted the analysis on one type of disaster events. To test the robustness of our empirical results, it seems to be appropriate to include indicators for all three disaster types in the same model. In order to do so we combined all indicators which turned out to be significant in our earlier regressions in permuted models with three disaster indicators. The results are displayed in Table 5 and 6. In all tested model variants all three employed indicators turn out to be positive and significantly different from zero. The size of the coefficients for the flood indicators turn out to be higher in the multi-variables models, while they only slightly change for tropical storm indicators and exhibit almost no change for the heatwaves indicators.

4.5 Effect longevity

One might also be interested in the longevity of the estimated effects. In order to study this aspect we repeated our estimations for various lags of the included disaster indicators. In Figure 2 we show the estimation results for various models with time lags of the disaster indicators of up to 12 months. For the case of heatwaves, the two employed indicators turn out to be positive and significant for up to a lag of six months. For flood events, the indicators deliver positive and significant effects for lags up to 3 months. For tropical storms the effects turn out to be highly short-lived as they become insignificant for all lags of the employed indicators.

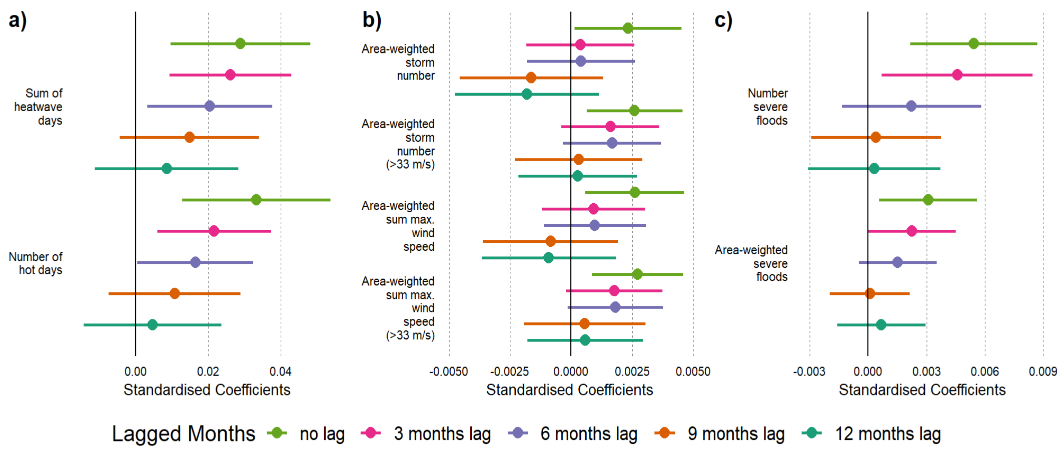

Figure 2. Coefficient plots for models with time lagged disaster exposure variables and policy dissatisfaction as he left-hand variable. Shown are standardized coefficients with 95% confidence intervals for a) selected heatwaves variables, b) tropical storm variables and c) flood exposure variables. Coefficients for the variables with no time lag correspond to the model results reported in Tables 2, 3 and 4.

5 Summary and conclusions

The existing literature on the effects of natural disasters on the support of environmental policy in general and especially climate policy has yet not generated a systematic picture. This is not too surprising, as most existing studies are single-country or even single-event studies. Moreover, the employed data sources, sample periods and the applied estimation techniques vary a lot. This paper tries to overcome these problems. First, all our analyses are based on the same data set, at least as far as the left-hand variable and the set of control variables are concerned. The empirical analyses thus differ only in the employed disaster indicators. We also use exactly the same sample period for all analyses. Second, our worldwide panel analysis avoids relying on country-specific results as is often done in the literature (Howe *et al.* 2019; Gärtner and Schoen 2021; Lee, Loveridge, and Winkler 2018), but rather derives inference from a broad set of countries and regions. While this holds also true for the existing cross-sectional studies(e.g. Broomell et al. 2015), our approach comes at the advantage that we can control for unobserved but time-invariant heterogeneity on the regional level. Third, our empirical approach always uses the same estimation method, which ensures that differences for the three disaster types can not be attributed to the applied estimation technology.

In our empirical analysis we do not find any effect of the occurrence of natural disasters as long as we employ simple count indicators of disasters, as it is often done in the related literature (Ray *et al.* 2017; Hoffmann *et al.* 2022; Baccini and Leemann 2021). This result holds regardless of

Table 5. Models with multiple disaster exposure variables I

	Environmental Policy Dissatisfaction							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of hot days	0.0003***	0.0002***	0.0003***	0.0002***	0.0003***	0.0002***	0.0003***	0.0002***
	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
Area-weighted storm number	0.0253**	0.0253**						
	(0.0121)	(0.0120)						
Area-weighted storm number (>33 m/s)			0.0310***	0.0308***				
			(0.0118)	(0.0117)				
Area-weighted storm severity					0.0006**	0.0006**		
					(0.0003)	(0.0003)		
Area-weighted storm severity (>33 m/s)							0.0007***	0.0007***
							(0.0002)	(0.0002)
Severe flood number	0.0121***		0.0122***		0.0122***		0.0122***	
	(0.0034)		(0.0034)		(0.0034)		(0.0034)	
Area-weighted severe floods		0.1786**		0.1789**		0.1786**		0.1788**
		(0.0727)		(0.0728)		(0.0727)		(0.0728)
Observations	926,487	926,487	926,487	926,487	926,487	926,487	926,487	926,487
Adjusted R^2	0.13587	0.13582	0.13588	0.13582	0.13588	0.13582	0.13588	0.13582
F-test	3.3943	3.3928	3.3945	3.3929	3.3945	3.3929	3.3945	3.3930
Control variables	✓	✓	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Linear probability regression with clustered SEs on region level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 6. Models with multiple disaster exposure variables II

	Environmental Policy Dissatisfaction							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sum of heatwave days	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)
Area-weighted storm number	0.0251**	0.0251**						
	(0.0121)	(0.0120)						
Area-weighted storm number (>33 m/s)			0.0309***	0.0307***				
			(0.0118)	(0.0117)				
Area-weighted storm severity					0.0006**	0.0006**		
					(0.0003)	(0.0003)		
Area-weighted storm severity (>33 m/s)							0.0007***	0.0007***
							(0.0002)	(0.0002)
Severe flood number	0.0120***		0.0121***		0.0120***		0.0121***	
	(0.0034)		(0.0034)		(0.0034)		(0.0034)	
Area-weighted severe floods		0.1791**		0.1794**		0.1791**		0.1793**
		(0.0727)		(0.0728)		(0.0727)		(0.0728)
Observations	926,487	926,487	926,487	926,487	926,487	926,487	926,487	926,487
Adjusted R^2	0.13586	0.13581	0.13587	0.13581	0.13586	0.13581	0.13587	0.13581
F-test	3.3940	3.3925	3.3941	3.3926	3.3941	3.3926	3.3942	3.3927
Control variables	✓	✓	✓	✓	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

Linear probability regression with clustered SEs on region level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

whether we employ the often used (but also often criticized) GEM-DAT database or more sophisticated and complete specialized databases. However, when controlling for disaster severity in an adequate manner, we consistently find that all three sorts of natural disasters we studied, e.g. heatwaves, floods and tropical storms, turn out to increase dissatisfaction with environmental policy significantly. Moreover, the effects have considerable effect sizes. Given that our left-hand variable is not dissatisfaction with climate policy but with environmental policy in general, one might suspect that the effects on dissatisfaction with climate policy are even larger.

It is well known that enormous efforts are necessary to decelerate or even stop the process of global warming. As the necessary measures come with considerable short-term costs there is an urgent need of public support for more ambitious environmental and climate policies. Our results indicate that the by-products of the process of global warming, more frequent or more severe climate-related natural disasters such as storms, floods or heatwaves (Field *et al.* 2012) might help to increase public support for these policies. The effects of sudden-onset climate events are much more visible than those of slow-onset events (Vugt, Griskevicius, and Schultz 2014) and therefore at least in the short-run more effective in fostering the demand for better climate policies. However, our results also show that the effects of natural disasters on policy preferences are decaying over time (Hoffmann *et al.* 2022). Thus, it is somewhat unlikely that more frequent or more severe natural disasters alone are sufficient to organize the necessary public support.

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Appendix

A Gallup World Poll methodology

The Gallup World Poll is typically conducted annually using either telephone or face-to-face interviews. Questions are translated into the main languages of each country. Telephone interviews are used in countries with more than 80% telephone coverage or where this is the traditional survey method. The sampling frame covers all inhabited places in each country, both rural and urban. In countries where face-to-face interviews are carried out, 100 to 135 final clusters (sampling units) consisting of clusters of households are selected. Sampling units are stratified by population size or geography and clustering is achieved through one or more stages of sampling. Where population information is available, sample selection is based on probabilities proportional to population size, otherwise simple random sampling is used. Samples are drawn independently of samples drawn for previous years' surveys. Within sampling units, random routes are used to sample households. Within households, respondents are randomly selected using a Kish grid. In countries where telephone interviews are used, random digit dialling or a nationally representative list of telephone numbers is used. In countries with high mobile phone penetration, a dual mobile/landline sampling frame is used (for a full discussion of the methodological approach, the reader is referred to the World Poll methodology at: https://www.gallup.com/178685/methodology-center.aspx). Each respondent is assigned to a Gallup World Poll region. The names of these regions were matched to GADM administrative units (see Materials and Methods) to obtain the geographic location of each Gallup World Poll participant.

B Figures and Tables

Table B.1. Summary Statistics I

Variable	NotNA	Min	Mean	Median	Max	Sd
Age	926487	13	41.1	38	100	17.6
Dissatisfied with efforts to preserve the environment, refused + dont know = NA	926487	0	0.458	0	1	0.498
Mean population-weighted CO2 emissions	926487	0	131	2.33	13865	742
Heatwave number (GEM-DAT)	926487	0	0.0116	0	2	0.115
Heatwave number	926487	0	6.21	4	36	6.52
Sum of heatwave days	926487	0	170	152	366	139
Number of hot days	926487	0	177	168	366	138
Storm number (GEM DAT)	926487	0	0.0455	0	5	0.251
Storm number	926487	0	0.113	0	7	0.479
Storm number (>33 m/s)	926487	0	0.0244	0	4	0.181
Area-weighted storm number	926487	0	0.0113	0	2.65	0.093
Area-weighted storm number (>33 m/s)	926487	0	0.00816	0	2.65	0.0855
Area-weighted sum max. wind speed	926487	0	0.459	0	109	4.08
Area-weighted sum max. wind speed (>33 m/s)	926487	0	0.366	0	109	3.93
Flood number (GEM DAT)	926487	0	0.0263	0	3	0.166
Flood Number	926487	0	0.434	0	10	0.882
Severe flood number	926487	0	0.173	0	4	0.481
Area-weighted severe floods	926487	0	0.00164	0	0.748	0.0177

Table B.2. Summary Statistics II

Variable	N	Percent
Per Capita income quintiles	926487	
... 1	149925	16%
... 2	163992	18%
... 3	178394	19%
... 4	197206	21%
... 5	236970	26%
Education level: 1 = Elementary, 2 = Secondary, 3 = Tertiary	926487	
... 1	310105	33%
... 2	466328	50%
... 3	150054	16%
Gender, male = 1, female = 2	926487	
... 1	431889	47%
... 2	494598	53%
Health Problems, yes = 1, no = 2	926487	
... 1	229985	25%
... 2	696502	75%

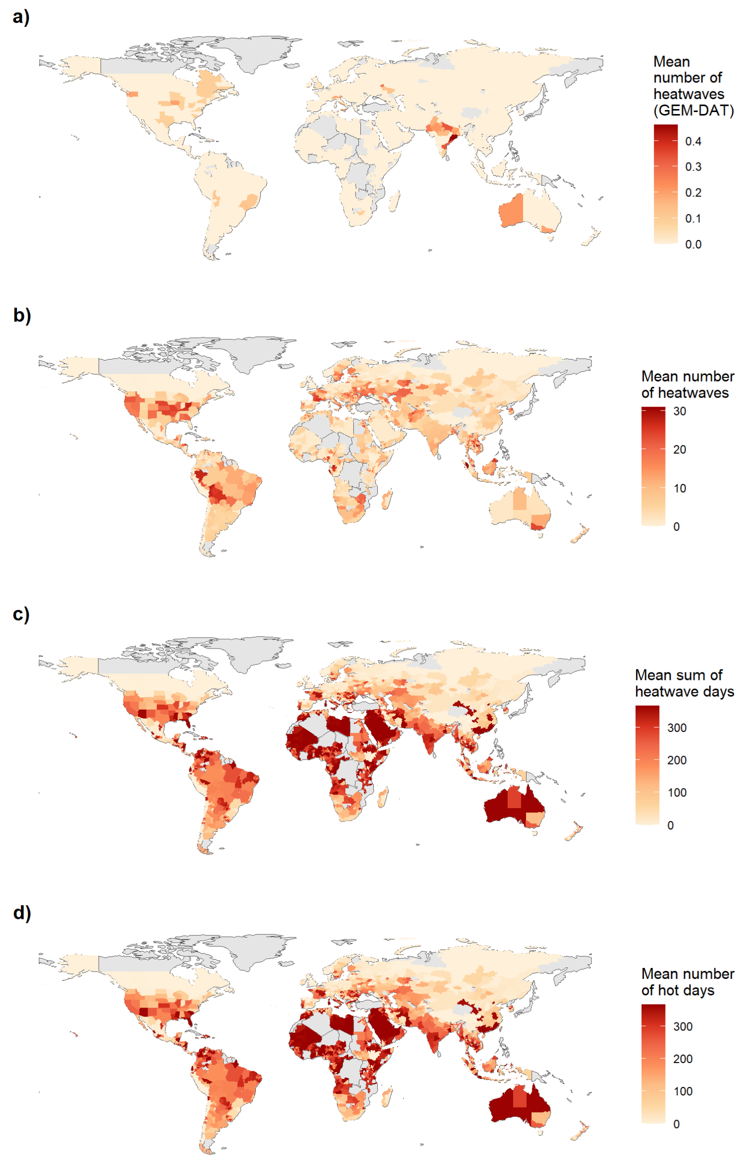

Figure B.1. Global maps of lagged heatwave exposure variables for every region used in this study. a) = Mean 'Heatwave number (GEM-DAT)' 2010-2018. The variable is based on the geo-coded EM-DAT database (GEM-DAT) and describes the number of heatwave events over 12 months. b) = Mean 'Heatwave number' 2010-2018. The variables describes the number of heatwave events over 12 months. Based on calculations with global climate data and our heatwave definition with a 99^{th} percentile threshold. c) = Mean 'Sum of heatwave days' 2010-2018. The variable describes the total number of heatwave-days over 12 months. Based on calculations with global climate data and our heatwave definition with 99^{th} percentile threshold. d) = Mean 'Number of hot days' 2010-2018. The variables describes the number of hot days over 12 months. Based on calculations with global climate data and our heatwave definition with a 99^{th} percentile threshold. Grey areas indicate regions with no available Gallup World Poll data available between 2010-2018.

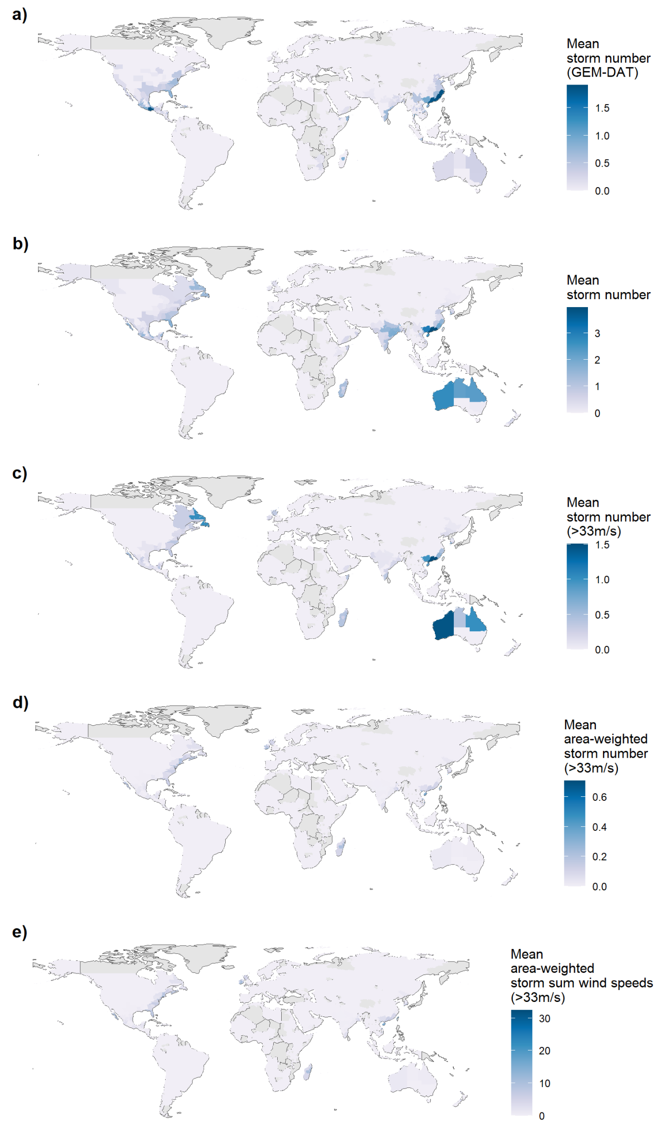

Figure B.2. Global maps of lagged tropical storm exposure variables for every region used in this study. a) = Mean 'Storm number (GEM-DAT)' 2010-2018. The variable describes the number of tropical storm events over 12 months. Based on the geo-coded EM-DAT database (GEM-DAT), b) = Mean 'Storm number ' 2010-2018. The variable describes the number of tropical storm events over 12 months. c) = Mean 'Storm number (>33m/s)' 2010-2018. The variable describes the number of tropical storm events over 12 months. d) = Mean 'Area weighted storm number (>33m/s)' 2010-2018. The variable describes the number of tropical storm events with wind speeds >33 m/s over 12 months. Each storm event is weighted with the proportion of area covered by wind fields with >25m/s in the respective region. e) = Mean 'Area weighted storm severity (>33m/s)' 2010-2018. The variable describes the sum of maximum wind speeds of storms with at least >33 m/s over the past 12 months. Each maximum wind speed is weighted with the proportion of area covered by wind fields with >25m/s in the respective region. Grey areas indicate regions with no available Gallup World Poll data available between 2010-2018.

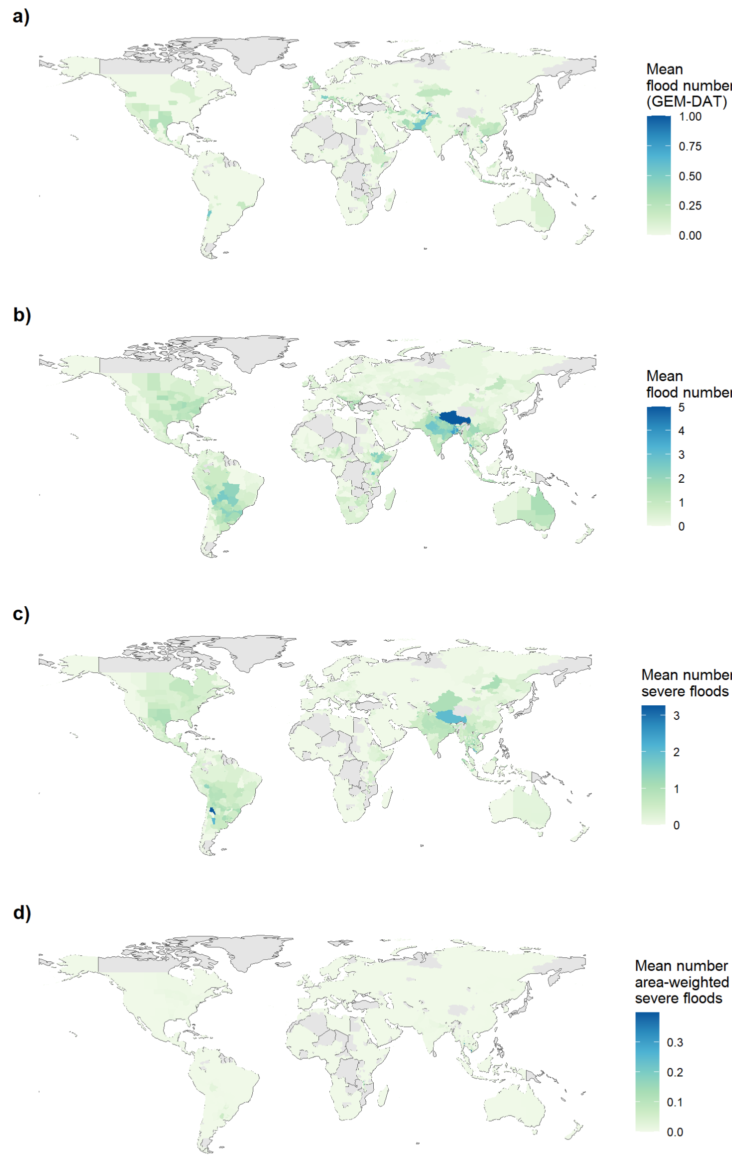

Figure B.3. Global maps of lagged flood exposure variables for every region used in this study. a) = Mean 'Flood number (GEM-DAT)' 2010-2018. The variable describes the number of flash flood events over 12 months. Based on the geo-coded EM-DAT database (GEM-DAT), b) = Mean 'Flood number' 2010-2018. The variable describes the number of all flood events within a 12 months long period. Flood events were collected from the Global Flood Database. c) = Mean 'Number of severe floods' 2010-2018. The variable describes the number of severe flood events over 12 months. Severe floods are categorized by the Dartmouth Flood Observatory's flood severity indicator with "category 2". Flood events were collected from the Global Flood Database. d) = Mean 'Area weighted severe floods' 2010-2018. The variable describes the number of severe floods over 12 months weighted by the proportion of area flooded in the region during the event. Flood events were collected from the Global Flood Database. Grey areas indicate regions with no available Gallup World Poll data available between 2010-2018.