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Uncovering climate change opinion: weather events and economic factors

Zélie GANKON [1,*2,*3*]

Public discourse on climate change has extended beyond scientific realms, permeating various networks and media platforms. This study investigates the drivers of climate change opinion, with a particular focus on extreme weather events. To conduct this study, I use a worldwide data set from a recent Meta survey conducted on Facebook, combined with information on extreme weather events from the EM-DAT database. Specifically, I examine how country-level occurrences of such events influence climate awareness and risk perception. The descriptive statistics reveal distinct patterns in climate awareness and risk perception between Global North and Global South countries, which shape the outcomes of the estimations. The findings underscore the significant effect of exposure to extreme weather events—measured by the recurrence of such events over a decade—on individual risk perception, though no significant link is found with climate awareness. Interestingly, the distance to the trend of event occurrences shows a positive correlation with climate awareness but a negative relationship with risk perception. Further heterogeneity analyses complement the main regressions, exploring variations across different time lags for weather events, country frequency groups, and demographic categories such as age and gender.

JEL CODES: D10, Q28, Q54, Q58.

1* Paris Dauphine-PSL University, LEDa, France.
2* Climate Economics Chair – IEF/ILB, France.
3* Mohammed VI Polytechnique University, Morocco, IEAE Chair.

KEYWORDS

Climate change | Awareness | Risk perception | Extreme weather events

Executive summary

Climate change issues are more and more discussed and by all categories of society, as it affects most economic aggregates. It becomes important to examine the determinants of public opinion, as this later determines political votes. This article proposes an empirical relation between climate change opinion at the world scale and its determinants, with a special focus on extreme weather events.

Key findings

1. **Weather events and climate knowledge.** Experiencing more disasters is associated with more perception of knowledge. This awareness is particularly noticeable for individuals in developed countries, while the global South shows the lowest levels of awareness.
2. **Weather events and risk perception.** In contrast to awareness, countries in the Global South demonstrate stronger perceptions of climate risk. With regards to this risk perception, more weather events are associated with higher perception of risk. But a greater deviation in the number of events from the trend over the decade is negatively associated with the perception of risk.
3. **Demographic and economic influences.** Climate change awareness in high-income countries is affected to a greater extent by recurrence of weather events. In terms of age groups, individuals from 18 to 29 years old appear to have a higher effect of weather events on opinion.

Policy Recommendations

- **Bridge the Awareness-Risk perception gap.** As higher awareness does not naturally lead to increased climate action, governments should design interventions that translate awareness into behavioral change.
- **Strengthen Disaster Preparedness and Response.** Investments in climate adaptation should consider regional disparities in awareness and risk perception to ensure effective engagement and implementation
- **Enhance Climate Education.** Governments should invest in educational programs that go beyond basic climate science to address behavioral implications of climate change.

Conclusion

These findings shed light on the ability of individuals to recall the extreme weather events faced over the years in the country where they live, and to integrate them in their global opinion about climate change. Understanding the heterogeneous map of climate change opinion around the world is essential for designing effective climate policies that resonate with diverse populations worldwide.

1 Introduction

The subject of climate change is no longer debated only among the most dedicated scientists, but also on all social networking occasions. This can be seen in the various movements and organised groups created over the last decade. The investigation of international climate opinion is of crucial importance. Climate change is a global challenge that requires a thorough understanding of global perceptions and attitudes. By understanding and integrating how people in different countries perceive climate issues, decision-makers can scale up actions to limit global warming and achieve successful ecological transition. This also allows the acceptability of mitigation policies and activities that may appear costly. In addition, understanding the views and priorities of different nations can help to build stronger international coalitions and agreements, promoting concerted actions.

To better perceive what people around the world understand about climate change, Meta [1] conducts the annual Climate Change Opinion Survey, in partnership with the Yale Program on Climate Change Communication. The survey was conducted on Facebook, and collected information about knowledge, behaviour, policy preferences, and risk perception on climate change, as well as some socio-demographic characteristics. As of now, the survey has been conducted thrice: February-March 2021; March-April 2022; and late 2023. It is the first time that a resource of this scale exists on a social network. Meta through the *Data For Good* is harnessing the power of the Internet as an increasingly dominant source of information. Figure 1 represents the percentage of respondents stating they use daily or weekly the mentioned sources to be informed on what is going on in their countries. As illustrated, Internet and Mobile phones have progressively replaced other information sources like Daily Newspapers and TV news between 2010 and 2020. In an attempt to explore the mobile phone source, Meta team has been committed over the past years, to gathering data on the Facebook platform, for the benefit of diverse communities.

This paper studies some determinants of global climate change opinion, in particular extreme climate events, and differences in synergies between countries groups. It does so using the 2022 Meta Survey on climate change opinion of a hundred thousand people around the world, with information on awareness, risk perception, policy preferences and socio-demographic characteristics. The survey questions the opinion of individuals on several aspects. It introduces questions about climate awareness and risk perception, such as "How much do you know about climate change?" and "How worried are you about climate

[1] Formerly named Facebook, Meta is the American multinational technology conglomerate that owns and operates Facebook, Instagram, Threads, and WhatsApp

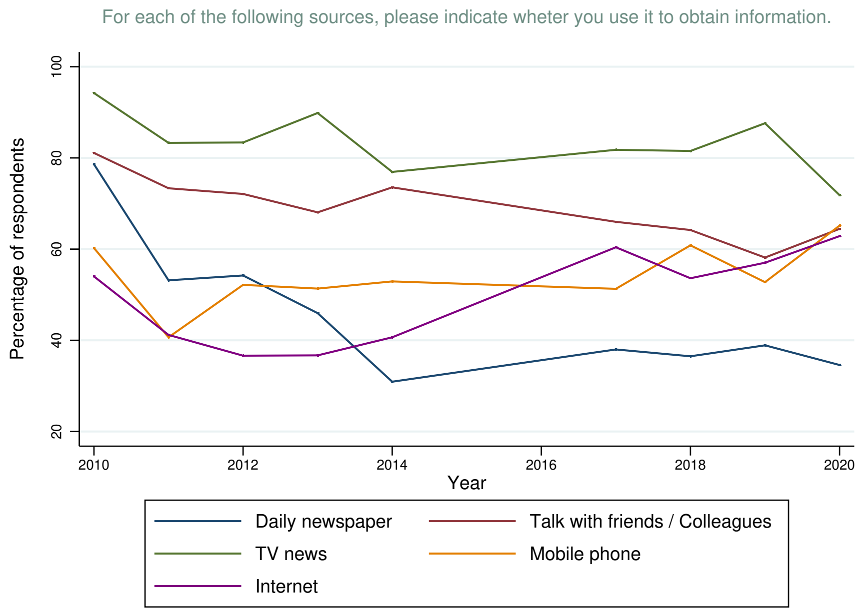


Figure 1: Information source. Data: World Values Survey 2010-2020.

change?". Respondents also answer questions about the responsibility they attribute to economic actors and their countries to fight against climate change. Furthermore, in the context of this survey, expectations regarding the preferred type of energy to be used in the country are also identified.

To assess the impact of climate disasters, I merge this survey to a dataset of recorded occurrences from EM-DAT, covering the decade leading up to the Meta survey. The dataset includes events classified as hydrological, meteorological, and climatological, such as floods, droughts, storms, and landslides. My empirical strategy involves using the number of events recorded over the decade preceding the Facebook survey, and the trend of occurrences over the whole period compared to the realised occurrences of 2022. Specifically, I measure the effect of more or less disasters in 2022, on the likelihood of individuals positioning themselves into different categories of awareness and risk perception. I begin by demonstrating that the various categories of climate change opinions worldwide exhibit significant heterogeneity across regions and levels of development.

Previous empirical analyses reveal the high importance of dissecting global opinion and beliefs about climate change. Dechezleprêtre et al. (2022) made it a focal point to their economic analysis, by computing french climate policies preferences. As in other approaches, it is a national survey that captures only internal behaviour within countries.

However, few papers study awareness and risk perceptions across countries (Lee et al., 2015). The reason why this is important is that risk perception in general (climate change risk perception in this case) tends to cross national boundaries (Siegrist and Árvai, 2020); and we believe in it even more as information flow is more fluid across countries. Despite the importance of the question, little consensus has emerged from the economic literature to date, explaining the disparities between groups of countries.

One factor identified as a driver of climate change opinion is the exposition to extreme climate events. It is for instance conceivable that flood or air pollution victims are more concerned about climate change (Whitmarsh, 2008). Similarly, other experiences of weather events seem to influence perceptions and behaviour: heatwaves (Dai et al., 2015), long-run temperature fluctuations (Deryugina, 2013), repeated drought events (Zappalà, 2022). More related to social media results, Berglez and Al-Saqaf (2021) examine periods of intensified co-occurrence of mentions of extreme weather and climate change on almost one million tweets. Their results suggest an increasing causality discourse between climate change and extreme weather especially during the years 2010, 2011 and 2017. This cited paper participates to the vast and growing literature of sentiment analysis through social media text as data (Cody et al., 2015, Liu and Zhao, 2017, Kirilenko et al., 2015, Veltri and Atanasova, 2015).

In an attempt to elucidate disparities of climate opinion in Europe, Angrist et al. (2024) investigate the factors that cause pro-climate beliefs, policy preferences, and voting for green parties, in 16 European countries. More precisely, the authors focus on human capital and find that an additional year of education is in a favour of the above-mentioned climate values. By this result, they confirm the idea that more educated people are better equipped to understand the issues of climate change and to invest in actions against it.

The novelty of this research lies primarily in its analysis of a dataset collected from a social media platform, approached from an economic perspective. With almost 60% of the world population of social media according to the *Digital 2023 April Global Statshot Report* [2], overlooking this communication channel could result in a significant gap in economic analysis. Although we cannot guarantee the representativeness of the respondents on the population, the strong presence of populations on social networks make them a fertile source of data. This database with such a large set of countries, provides valuable insights into the international variations in climate change opinion within the economic literature, grounded in precise explanatory factors. Additionally, a key contribution of this research is

[2] That is 4.9 billion people. It is however precise that this figure may not represent unique individuals, because the data used for the statistics includes a certain degree of duplication and “false” accounts.

the integration of this social media dataset with information on weather events from EM-DAT, enabling a direct linkage between risk perception and actual occurrences of climate disasters.

This paper has three main sets of findings. First, it appears that experiencing more disasters is associated with more awareness. While people are globally aware of the issues of climate change, the knowledge perception lies at different stages. This awareness is particularly noticeable for individuals in developed countries, while the global South shows the lowest levels of awareness. I run three different specifications for the definition of climate events occurrence: the gross number of events over 10 years per country, the deviation of occurrences between the year of the survey and the trend of events based on data for the previous decade, and a binary variables stating if a country has actually recorded more or less events than the occurring trend. The correlation with awareness remains positive in every case, but not significant in the first specification. Important socio-demographic variables are also worth mentioning for this recent data set. For instance, the effect of extreme events occurrences appears to be more important on awareness for the youngest generation of the survey (18-29 years old). Also male respondents tend to be more aware than females. This observation is not common in the literature. Indeed, most of the previous papers have found the opposite result (Hamilton, 2011; Dai et al., 2015). I explain this by the fact that the Meta survey asks respondents about their knowledge perception, which may be higher for men.

Second, the surveys reveal higher levels of risk perception for the global south, and intuitively, for countries experiencing the most the physical impacts of climate change. When estimating risk perception with climate events occurrence (first specification), I obtain a positive correlation, but negative with the second specification. Regarding gender, I found that female respondents perceive more risk for themselves than male respondents, and this is verified for other indices of risk perception (threat in the next 20 years, threat for future generations). One possible explanation of this gender effect is found in the literature on risk perception. Davidson and Freudenburg (1996) argue that traditional gender roles make women worry more about health and safety. That *Safety Concerns Hypothesis* states that as nurturers and care providers, women tend to have higher concerns levels. To link with the negative coefficient of the previous result, another hypothesis commonly tested in existing literature [3] also adds that people who are more aware will be less concerned about risks (Mitchel, 1984).

[3] Knowledgeable Support Hypothesis (Davidson and Freudenburg, 1996)

Third, heterogeneity analysis conduct to important remarks. Income groups form a disparity in the effect studied. For instance, awareness in high-income countries is affected to a greater extent by the recurrence of weather events. It should also be pointed that the negative association between risk perception and the recurrence of events is significant only for high-income countries. In terms of age groups, people from 18 to 29 years old, i.e. individuals from the survey with the lowest historical memory, appear to have a higher effect of extreme weather events on awareness. Macroeconomic variables also appear to play a key role in determining climate change opinion. To cite one, regressions show that individuals facing high country food insecurity also perceive more risk.

The overall analysis suggests a misconnection between awareness and risk perception when approaching climate change issues. This is primarily visible in differences in opinion between the Global North (more aware but less perceptive of risk) and the Global South (less aware but more perceptive of risk). It is important to discuss the fact that such disparities undoubtedly affect the orientation of climate policies, as well as the pro-environmental votes of populations.

The remainder of the paper is organised as follows. Section 2 presents the data description, followed by the empirical analysis in Section 3. And finally, Section 4 draws some conclusions.

2 Data description

Several databases were used to carry out this study: the climate change opinion survey, disasters data from EM-DAT, and macroeconomic data from the World Bank.

2.1 Climate change opinion survey

The survey sample was drawn from the population of monthly active Facebook users, ages 18 and older. They received an invitation to answer a short survey at the top of their Facebook News Feed and had the option to click the invitation to complete the survey on the Facebook platform [4].

In total, 108946 Facebook users spread over 192 countries and territories completed the survey in 2022.They were subjected to 12 questions on the challenges of climate change, and 4 questions of socio-demographic nature. These variables are presented in Table 1.

[4] Facebook Data for Good and the Yale Program on Climate Change Communication. 2021. Climate Change Opinion Survey, 2022.

For 4 countries, individuals are identified at the regional or state level. These are France, Germany, India, and the United States. The data therefore contains weights for each region. Table 1 in Appendix lists the countries and the number of people surveyed in them. Three geographical groups (Caribbean, Asian & Pacific Islands, and Sub-Saharan Africa) were sampled in proportion to the population of Facebook users due to a lack of publicly available benchmarks.

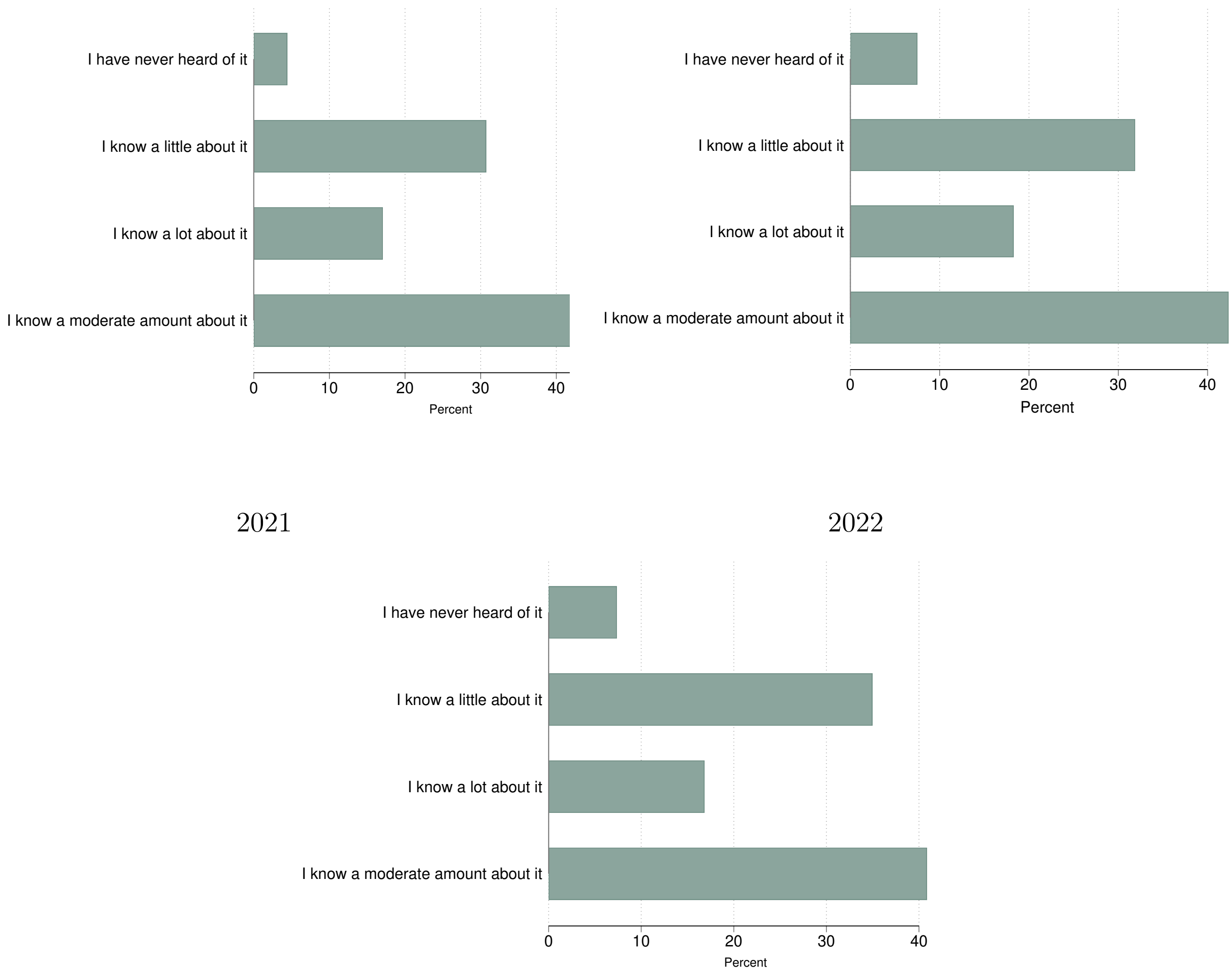
Table 1: Descriptive statistics of survey variables.

Variables	Number of observations	Mean	sd	min	max
Weight	108,946	1	1.103	0.00537	9.316
Climate awareness	108,946	1.753	0.891	0	4
Climate change happening	108,946	1.046	0.358	0	3
Government priority	108,946	2.048	0.985	0	4
Organised group	108,946	3.848	1.521	1	7
Harm future generations	108,946	3.332	1.175	0	5
Climate worry	108,946	2.174	0.926	0	4
Threat 20 years	108,946	2.207	0.948	0	4
Economic impact	108,946	2.13	0.805	1	4
Renewable more or less	108,946	5.026	1.52	1	7
Fossil more or less	108,946	3.487	1.713	1	7
Country responsibility	108,946	3.21	1.173	1	6
Climate importance	108,946	2.686	1.109	0	5
Most respnsible	108,946	3.011	1.141	1	6
Frequence hear	108,946	3.455	1.492	0	6
Urbanicity	108,946	2.17	1.242	1	5
Education	108,946	7.207	1.654	1	10
Age	108,946	2.417	1.085	1	4
Gender	108,946	0.662	0.623	0	3

Data presented on Table 1 has then been filtered at several steps, to simplify the analysis and make them match with macro data. On the first level, observations from the three geographical groups with unspecified countries have been removed. It is not possible to include them as the precise distribution of observations per country is not known. On the second level, I exclude observations whose territories don't appear in the climate disasters database and in macro data from the World Bank. These are territories with contested country status. A third filter places missing values responses that are difficult to analyse. This implies the binarisation of some variables (gender, urbanicity). In the same way, responses labelled as *"Refused to answer"* have been marked as missing values. If these answers can be indicative of a lack of engagement with climate change issues, I believe their low prevalence across all responses justifies their exclusion from the analysis. This is all the more justified given that *"Don't know"* is most of the time accessible.

2.1.1 Climate awareness

As in similar studies, awareness refers to the own knowledge perception of climate change. Several questions measure it in this survey. First, individuals value their knowledge by answering the question *"How much do you know about climate change?"*



2021 2022

2023

Figure 2: Climate awareness around the world, from 2021 to 2023.

Figure 2 shows that more than 90% of individuals surveyed know at least a little bit about climate change, while 7.37% have never heard of it. When breaking down these statistics regarding urbanicity, it is clear that most of those of who know at least a little bit live in cities. The awareness in villages is however not negligible, and even slightly higher than what is perceived in suburbs and towns (Figure 3).

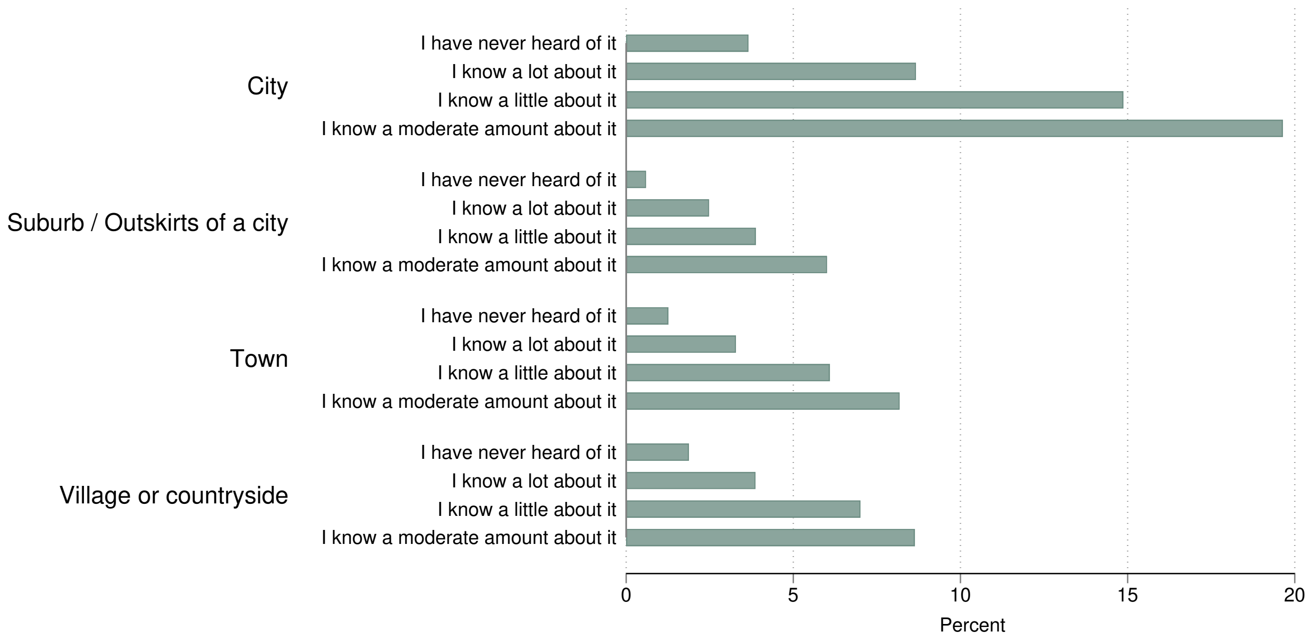


Figure 3: Climate awareness by urbanicity.

It is however important to note that these figures are very heterogeneous when considering the countries of respondents. On Figure 4, answers to that same question have been gathered and binarised to obtain the percentage of people aware per country. The first thing to note is that the global North has the highest levels of climate change awareness, compared to the Global South. A noticeable disparity is also evident within the African continent. Among the countries with available data, individuals in Sub-Saharan countries are globally more aware than in North Africa, precisely Algeria, Libya and Egypt with percentages of people aware between 20 and 30%.

Respondents are then asked if they think that climate change is happening [5]. 87.95 % of the surveyed population think it is. As to what would cause climate change, the majority of people (45.84%) are of the view that it is caused mostly by human activities. 12.39% rather think that it is due to natural changes in the environment, while 34.58% think that it is equally both reasons (Figure 5) .

[5]This question is preceded by a simple definition of climate change: "Climate change refers to the idea that the world's average temperature has been increasing over the past 150 years, will increase more in the future, and that the world's climate will change as a result. What do you think: Do you think that climate

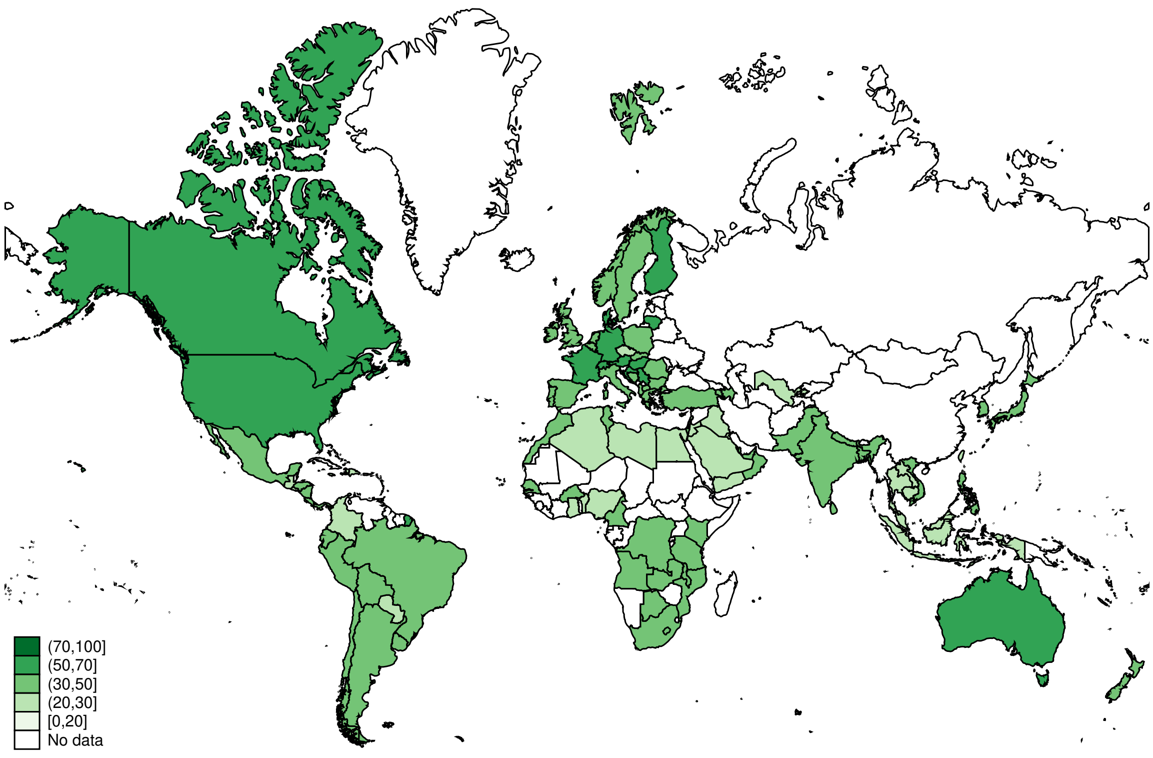


Figure 4: Climate awareness around the world.

Geographical pattern of climate change opinion poll in 2022. The represent the percentages of people in each country, who know a moderate amount (weighted by .5) or a great deal (weighted by 1) about climate change.

To approach the global societal implications of these variables, opinion on climate awareness are summarised in a single index constructed by Htitich, Mohamed et al. (2022). This index is scaled from 0 to 100, from the worst scenario to the best one[6]. Figure 6 relates that index.

Among the 109 countries evaluated, the country with the highest climate perception among the population is Portugal, followed by four Latin American countries: Chile, Mexico, Costa Rica, Brazil. The disaggregation of this index into its three components reveals different profiles of countries, that will be better appreciated in the empirical analysis.

change is happening?"

[6]The methodology of this index is as follows: each of the questions forming the index is scored according to the percentage of respondents who agree with the statement. For example for the question about climate happening, if a country has 57% of respondents agreeing, their score will be 57.

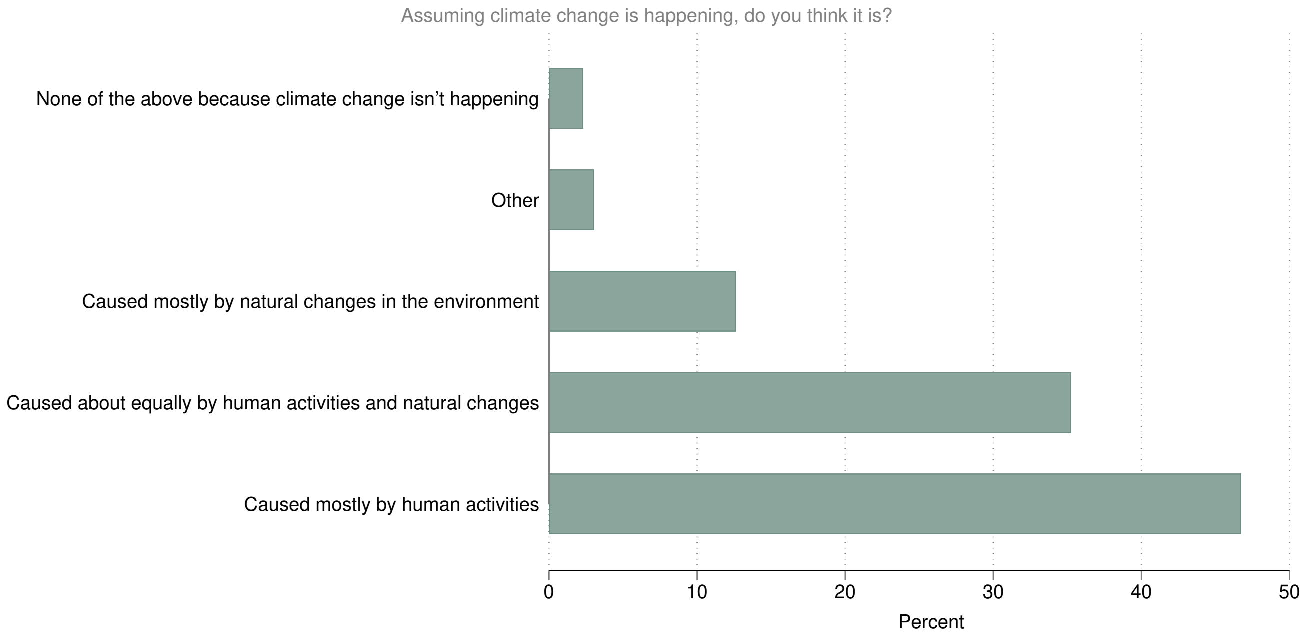


Figure 5: Climate change main cause.

2.1.2 Risk perception

Risk perception in this survey refers to the level at which the respondents think climate change is a real threat for them or for future generations (Lee et al, 2015). To the question to know about how worried are people about climate change, more than 85% of respondents pretend to be somewhat or very worried. When looking at data by country, this survey suggests a high heterogeneity of risk perception with regards to climate change. Figure 7 illustrates how people perceive climate change as a personal harm. It clearly suggests a different distribution of higher responses with respect to climate change awareness displayed in Figure 4. More specifically, countries of the global South perceive more risk than countries in the North.

The differences in the distribution of responses revealed in Figure 4 and Figure 7 is worth noting. Over the whole sample of 106508 individuals, some frequencies appear predictable. For instance, it is normal that those who know a moderate amount or a lot about climate change think it will be a very serious threat over the next 20 years. On the other hand, 5629 of those who know a moderate amount or a lot also respond climate change will not be a threat at all. This unexpected dissonance can be explained by several factors. Among other reasons, it is possible that these individuals highly aware about climate change (possibly

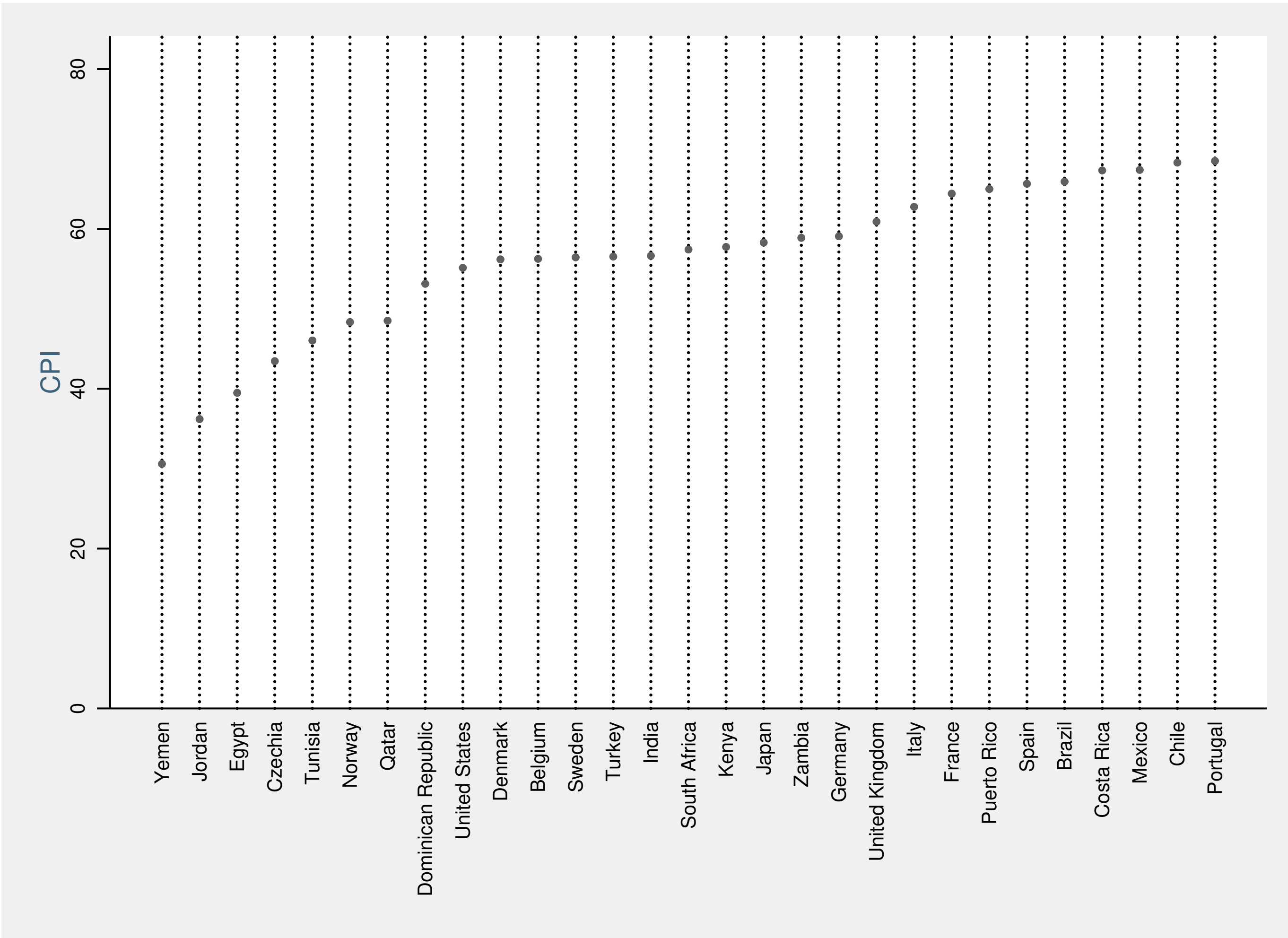


Figure 6: Climate Perception Index by country.

thanks to education), also live in territories with low vulnerability to climate change. This could be the case either in terms of exposition to disasters, or in terms of corresponding economic and political responses. To gain a deeper comprehension of this situation, the analysis will therefore be carried out on these two components: climate awareness and risk perception.

2.1.3 Environmental preferences

Individuals are also questioned about their global sentiment on the position their country should adopt. This group of questions can be considered as an evaluation of the willingness to adopt pro-environmental behaviour. When asked what should be the priority level placed on climate change, around 55% of respondents perceive climate change issues as *very* or

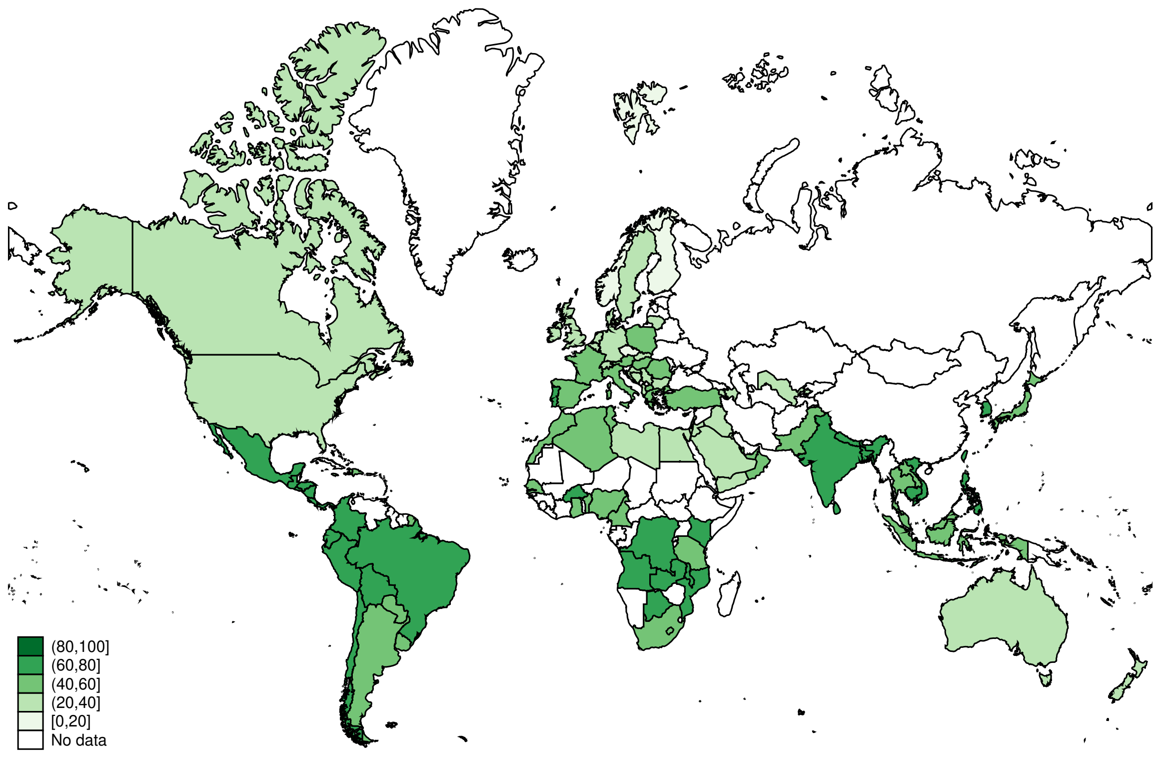


Figure 7: Personal harm of climate change.

extremely important. When zooming these figures by continent, it appears that those results are mostly driven by North and South Americas.

2.2 Climate disasters

The global analysis of the Climate Change Opinion survey reveals fairly high results for some subregions (Latin America and Sub-Saharan Africa, at least in terms of risk perception) as mapped in Figure 7. This section is an approach to finding the reasons of that disparity, emphasising the degree of exposure to climate disasters.

To bring extreme climate events to the analysis, I use the international disaster database EM-DAT [7]. It lists thousands of disasters around the world and their impacts. For the present analysis, three types of disasters have been selected. The first one covers climatological events. These are hazards caused by atmospheric processes and ranging from intra-seasonal to muti-decadal climate variability. Then we have hydrological events that

[7]A disaster is a situation or event which overwhelms local capacity, necessitating a request to the national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction, and human suffering *(EM-DAT)*.

Table 2: Cross-tabulation between *Climate Awareness* and *Risk Perception (Climate change as a threat in 20 years)*.

Climate awareness	Threat in 20 years				
	Not a threat at all	Don't know	Somewhat serious threat	Very serious threat	Total
I have never heard of it	874	2496	1594	2917	7881
I know a little about it	2990	4281	12000	14669	33940
I know a moderate amount about it	3577	2511	18189	20931	45208
I know a lot about it	2052	815	5200	11412	19479
Total	9493	10103	36983	49929	106508

are about movements of surface and subsurface freshwater and saltwater. And finally meteorological events that cover episodes of extreme weather and atmospheric conditions. Table 5 in Appendix represents the subtypes of these categories and their geographical areas of prevalence. Data reveals that almost every country in the world is concerned about extreme weather events, the precise event depending on the type of climate prevailing in the area. South-Eastern Asia appears as the region recording the highest number of disasters, followed by South America. These two areas are continually hit by floods which can be very severe, based on the data on the respective number of people affected (Figure 9).

There are reasons to believe that people surveyed in countries with the most climate events hold high indices of climate change opinion. One reason is that people living in affected areas directly witness the effects of climate change, and can thus better perceive the risk. This channel exists however as long as individuals are able to connect disasters happening, to climate change. It is also worth highlighting that risk perception can also be extended to neighbouring regions as information about extreme climate events are rapidly diffused, particularly through social network.

Three specifications will be tested in the empirical analysis, all implying a different consideration of disasters data. The first one considers the simple number of disasters over a period before the year of the survey. At this level, I consider the number of occurrences of disasters from 2011 to 2022 for each country. However, this specification might overlook the fact that individuals accustomed to climate disasters may not perceive climate change issues to the same extent as those who are unaccustomed to such events. Hence the importance of the other specifications. Next, I create a variable that represents the deviation of occurrences in 2022 from the trend of occurrences observed between 2011 and 2022. This variable signifies a shock in 2022, as the disparity between 2022 and the preceding years may be substantial. For countries encountering fewer disasters in 2022, the variable takes a negative value. This comparison allows for an assessment of individuals based on the extent to which the number of disasters in 2022 deviates from the occurrences of the preceding

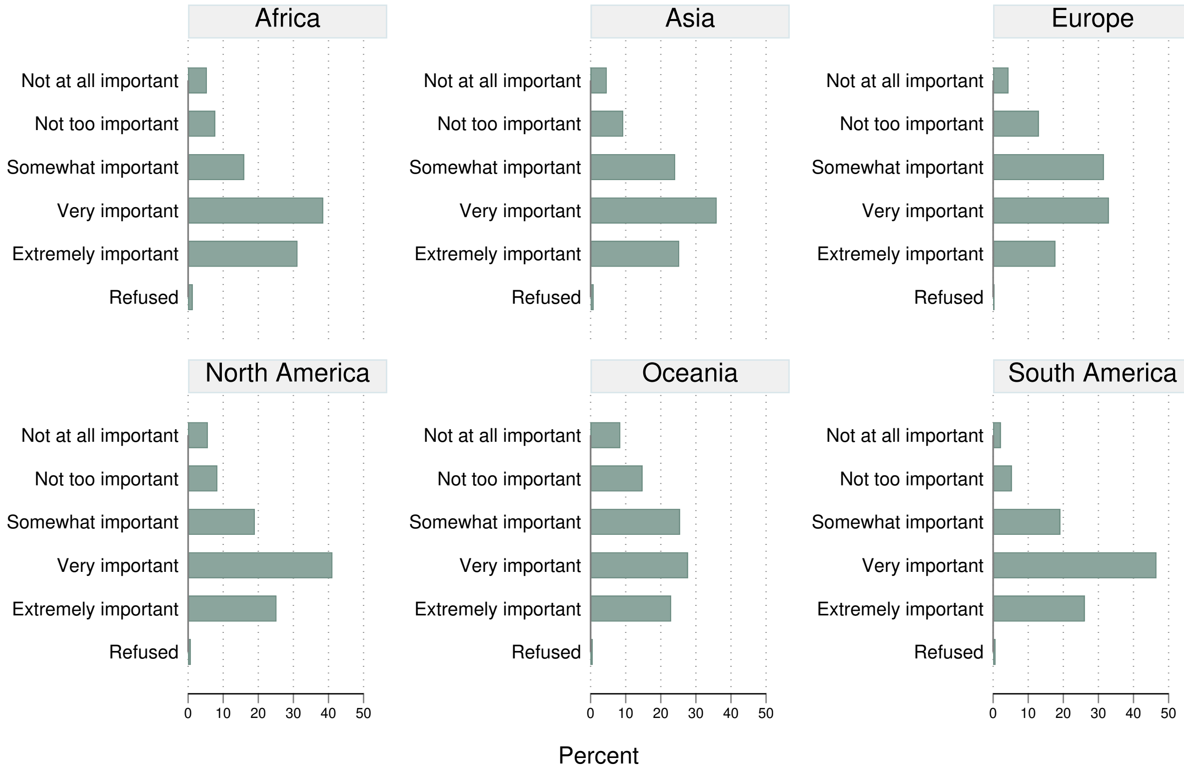


Figure 8: Perceived importance of climate change issue, by continent.

decade. Then, to differentiate countries that are below the trend to those that are above, I create a dummy variable that interacts with the previous deviation to the trend.

3 Empirical analysis

The aim of this section is to estimate to what extent the occurrence of climate disasters has an effect on some dimensions of climate opinion. To do that, I run a Ordered Logit model of climate opinion, over the recurrence of disasters. This method has been chosen to deal with the categorical and ordered nature of the explained variables. The interpretation will thus be on the odds of being in a higher category of opinion. Climate opinion will be represented by multiple questions selected in the survey that value awareness, risk perception, and political preferences.

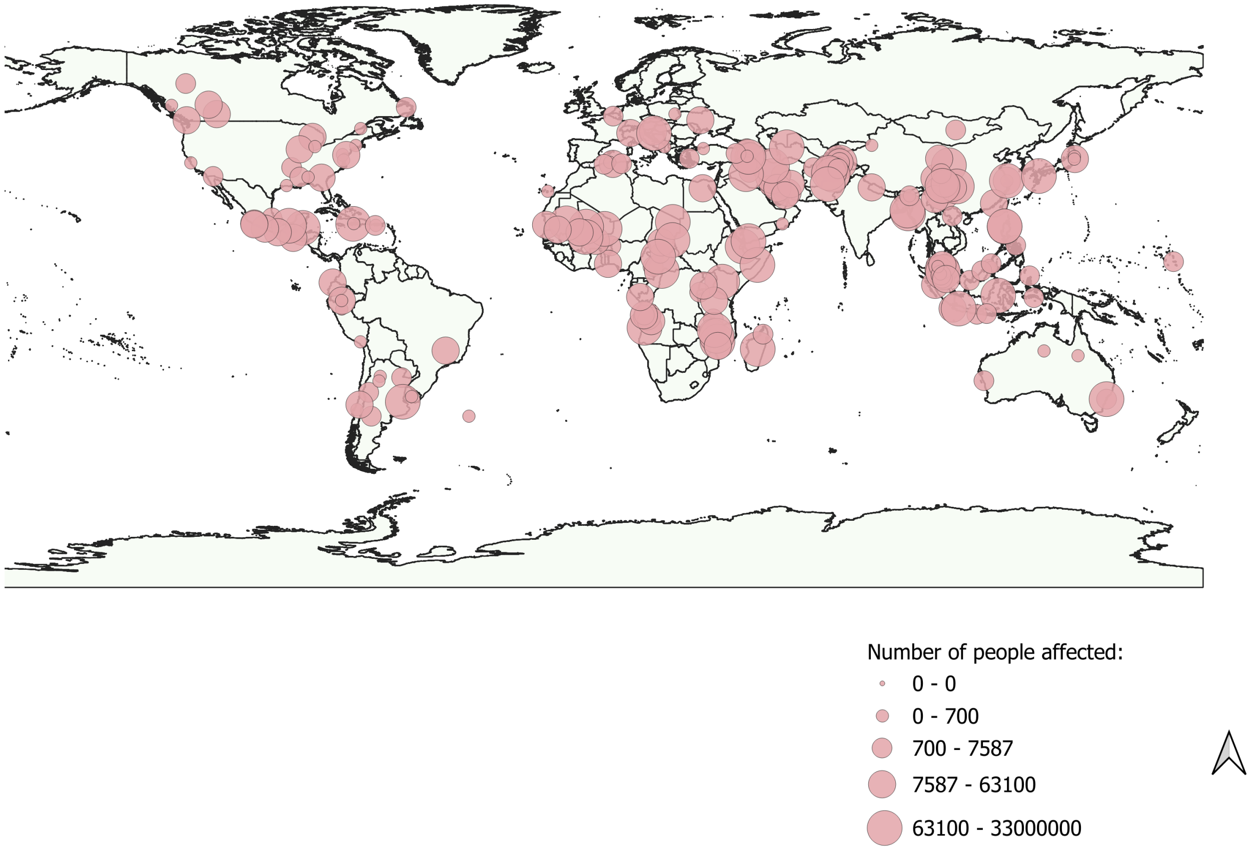


Figure 9: Climate disasters around the world (2020-2022). *Elaborated by the author with EM-DAT data.*

3.1 Results

Table 3 reports the Ordered Logit estimation of climate awareness over the recurrence of climate disasters and some control variables. The first column specifies exposition to climate change events by the total number of disasters recorded from 2011 to 2022. The coefficient estimated is positive but non significant, meaning that the number of weather events in 10 years doesn't affect the awareness. The second specification assesses the deviation of events in 2022 relative to the trend of disasters observed from 2011 to 2022. Specifically, it involves measuring, for each country, the difference between the actual number of disasters recorded in 2022 and the number of disasters predicted based on the trend over the past decade. The implied coefficient (in column 2) is positive and significant at the 1% level. This finding indicates that each additional unit of deviation from the trend is associated with a 4.2% increase in the odds of heightened awareness.

Usual demographic characteristics also appear to play a key role in this estimation. All over the three specifications, higher education is associated with an increase in more than 100% in the odds of awareness. The urbanicity variable also reveals a positive correlation. But the high number of respondents living in urban areas doesn't allow to deepen the interpretation of this estimation. A second variable worth noticing is gender. Table 3 shows that male respondents are 23% more likely to state that they are more aware about climate change than women. This variable is significant for all the specifications and at the same magnitude. The age group estimation doesn't go as expected. While we would have expected young respondents to be more aware about climate change, results show that individuals in higher groups age hold more likelihood to awareness. However when interacting age group with gender, we can see that male over 60 years old tend to show less awareness. Several heterogeneity analysis are carried out in the following to better understand these results.

I begin by running different regressions for various income groups using the preferred model, which defines the recurrence of extreme weather events based on the distance to trend. Results are displayed in Table 6 (Appendix). For high-income countries (HIC) in column 1, where discourse on climate change is most prevalent, the coefficient for the variable of interest is the highest. A one-unit deviation from the trend is associated with a 6.7% increase in the probability of a higher category of awareness. In middle-income countries (MIC) shown in column 2, the coefficient is lower than in HIC but still significant, indicating a 3% increase in awareness. For low-income countries (LIC), the coefficient is very low and not significant. Although developed countries do not experience significantly more disasters than developing countries, this analysis reveals that individuals in high-income countries tend to be more sensitive to weather events in terms of their climate awareness. The second point to note is the correlation with the set of macro variables. Notably, unlike the previous general regression, there is a significant correlation with GDP. In low-income countries , a higher GDP per capita is associated with greater climate awareness. However, the coefficient for middle-income countries is negative, and it is non-significant for high-income countries. Similarly, increased food insecurity is correlated with greater awareness in LIC.

Table 3: Dependent variable: climate awareness, Ordered Logit estimates at individual level.

Variables	(1) Climate awareness	(2) Climate Awareness	(3) Climate Awareness
Nb disasters	0.00458		
	(0.00279)		
Distance to trend		0.0412***	
		(0.00490)	
Distance to trend binary			0.188***
			(0.0157)
Higher Edu	0.791***	0.792***	0.789***
	(0.0150)	(0.0150)	(0.0150)
Urban	0.109***	0.0989***	0.0936***
	(0.0173)	(0.0173)	(0.0173)
30-44	0.0475	0.0462	0.0490
	(0.0299)	(0.0299)	(0.0300)
45-59	0.316***	0.313***	0.306***
	(0.0318)	(0.0318)	(0.0319)
60+	0.549***	0.544***	0.533***
	(0.0319)	(0.0319)	(0.0320)
Male	0.208***	0.208***	0.217***
	(0.0305)	(0.0305)	(0.0308)
Male*30-44	0.110***	0.112***	0.101**
	(0.0406)	(0.0406)	(0.0409)
Male*45-59	0.0891**	0.0912**	0.0859**
	(0.0421)	(0.0421)	(0.0423)
Male*60+	-0.0713*	-0.0712*	-0.0770*
	(0.0418)	(0.0418)	(0.0420)
AFF	-0.0238***	-0.0209***	-0.0260***
	(0.00215)	(0.00217)	(0.00214)
Population growth	-0.00425	0.000188	0.00563
	(0.00702)	(0.00701)	(0.00706)
Food Insecurity	-0.00226***	-0.00248***	-0.00213***
	(0.000738)	(0.000700)	(0.000705)
GDP	-0.0379	-0.0159	-0.0388*
	(0.0236)	(0.0234)	(0.0233)
Political Stability	0.185***	0.180***	0.173***
	(0.0162)	(0.0161)	(0.0162)
Press freedom score	-0.0104***	-0.00949***	-0.00877***
	(0.000765)	(0.000765)	(0.000773)
Observations	68,516	68,516	67,969

Existing literature and observations from public events highlight the importance of considering generational differences in climate change beliefs. Studies conducted across various countries consistently find that younger age groups express greater concern about climate change (Poortinga et al., 2023; Ballew, Matthew et al., 2019). To better analyse the results in Table 3, I investigate whether this common intuition extends to the assessment of extreme weather events. To do so, I run the estimations by the different age groups of the survey (see Figure 10 and Table 7 in Appendix).

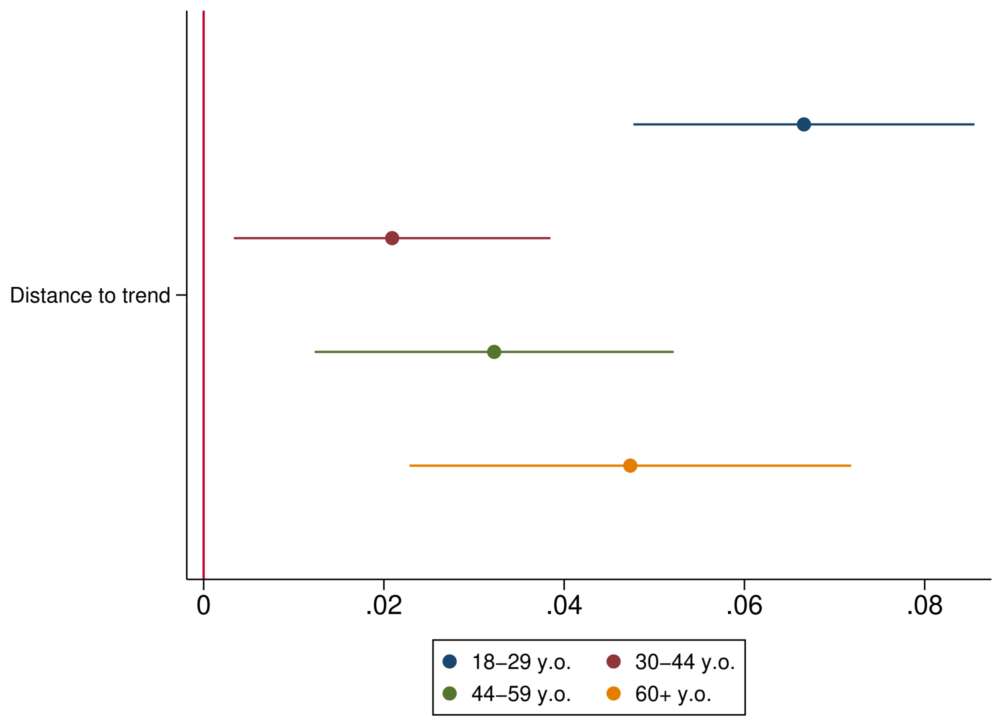


Figure 10: Dependent variable: climate awareness, weather events coefficient plot by age group.

The results reveal a stronger association between weather disasters and climate awareness among the younger cohort (18-29 years old), followed by the oldest group (60+). The heightened effect observed among young individuals aligns with media coverage, educational efforts and their connectivity to rapid news around the world. The coefficient for the oldest group can be attributed to their greater personal experiences with disasters. Additionally, it is noteworthy that urbanicity does not appear to significantly influence climate change awareness among the oldest age group.

The second part of the analysis aims at measuring the correlation between weather events and risk perception about climate change. The specifications on the recurrence of weather events are the same as previously. I first run the estimation for the perception of personal harm (see Table 4). The correlation between the cumulative number of disasters and the perception of personal risk is positive and significant. However when running the estimation with the deviation to the trend, the coefficient is negative and significant. It says that one more unit of distance to trend is associated to a 4.1% decrease in the odds of perceiving more risk for oneself. This difference with the first estimation in Table 3 has already been noticed in the descriptive statistics of the survey. Literature on risk perception elucidates the reasons behind the potential for divergent directional effects of climate awareness and risk perception, by hypothesising that awareness and knowledge moderate risk perception (Mitchel, 1984). In other words, once people know about climate change, they don't perceive risk. Table 4 however reveals a counter intuitive result with a negative correlation between the recurrence of disasters and risk perception (on Column 2, preferred model). A likely explanation is that spacial effects may bias the estimation. In fact, one may think that people's perception about climate change is not only a consequence of disasters occurring in their country, but may also be of the influence of events occurring on neighbour States, or climate perception in those other States.

In this estimation, male respondents appear to perceive risk more than women. This is also part of the literature explaining why empirically women tend to perceive and take less risk.

Several heterogeneity analysis accompany this analysis. The first one disentangle the estimation per income group. The regression analyses conducted within different income groups indicate that the association between the frequency of weather events and risk perception is significant only in high-income countries (see Table 10), characterised by a consistent negative coefficient similar to previous estimations. Conversely, for middle and low-income countries, the estimations show no statistically significant relationship.This finding suggests that individuals in these countries may not strongly link their experiences with weather events to their perceived risk of climate change. However, when evaluating the level of concern regarding climate change [8] (see Table 11), a notable positive and significant effect of weather events is observed only in low-income countries. Meanwhile, no such association is evident for lower-middle-income countries, while the correlation remains negative for both high-income and upper-middle-income countries.

[8] Question in the survey: *"How worried are you about climate change?"* Answers from *"Not at all worried"* to *"Very worried"*.

A second heterogeneity analysis looks at the frequency level of extreme weather events. To do that, I construct a variable that classifies the countries based on the number of disasters encountered over the decade. We obtain high and low frequency groups of countries [9]. Results from this estimation using distance to trend as specification, are displayed in Table 12 in Appendix. It appears that the negative correlation between weather events and risk perception are driven by low frequency countries. For high frequency countries, the odds of reaching an upper category of risk perception are 1.085 times higher when an individual has faced an additional unit in distance to the trend of disasters. This result translates the fact that the individuals who perceive more risk are those who more frequently experiment extreme weather events.

Finally, I test the ability of respondents of the survey to remember the extreme weather events. To do that, I also run the model with a 5 years lag in the EM-DAT database. Results of this estimation can be found in Table 13 in Appendix. The direction of the correlation is the same as in the main estimations; meaning a positive correlation with the number of disasters and a negative one with distance to trend, whatever the lag.

3.2 Discussion

Several features of the present findings carry interesting implications. First of all, Facebook users seem sensitive to climate change issues[10]. Indeed, the results suggest that they respond to climate disasters and to their countries' economic performance. This point undermines the importance of communicating more widely on the climate change subjects on the platform, and more broadly on social networks. In addition to increasing civic awareness, social media have turned out to be a focal point of disaster management with safety checks and support. Secondly, the heterogeneity of characteristics of Facebook users makes it an important source of data collection and deserves higher recognition.

Although it is not possible to attest to the representativeness of the people surveyed, the choice of social network as a data basis is relevant in several ways. More precisely, the Climate Change Opinion survey conducted by Meta is a promising tool for research analysis in climate behaviour. Firstly, the rapid and simple access to several thousands

[9] Countries with a "high frequency" of disasters have been selected on a threshold of at least 7 events in the past decade. This group includes *Brazil, Colombia, India, Indonesia, Philippines, South Africa, Thailand, United States* and *Vietnam*. Countries with a "low frequency" have experienced less than 7 events.

[10] However it should be noted that randomly selected Facebook users were proposed to participate to a climate change survey. Thus, we cannot rule out the possibility of an over-representation: more aware people might be more likely to participate to the survey.

Table 4: Dependent variable: Personal harm of climate change, Ordered Logit estimates at individual level.

Variables	(1) Harm personally	(2) Harm personally	(3) Harm personally
Nb disasters	0.0538***		
	(0.00280)		
Distance to trend		-0.0408***	-0.0243**
		(0.00472)	(0.0108)
Distance to trend binary			-0.338***
			(0.0239)
Distance to trend* Distance to trend binary			0.129***
			(0.0138)
Higher Edu	0.203***	0.185***	0.194***
	(0.0144)	(0.0144)	(0.0144)
Urban	0.0507***	0.0531***	0.0686***
	(0.0168)	(0.0168)	(0.0168)
30-44	0.124***	0.120***	0.118***
	(0.0297)	(0.0297)	(0.0297)
45-59	0.209***	0.205***	0.218***
	(0.0315)	(0.0315)	(0.0315)
60+	0.0556*	0.0366	0.0717**
	(0.0311)	(0.0311)	(0.0312)
Male	-0.134***	-0.141***	-0.134***
	(0.0301)	(0.0301)	(0.0301)
Male*60+	-0.0451	-0.0367	-0.0530
	(0.0408)	(0.0408)	(0.0408)
AFF	-0.0506***	-0.0616***	-0.0493***
	(0.00224)	(0.00227)	(0.00235)
Population growth	0.0301***	0.0420***	0.0297***
	(0.00693)	(0.00691)	(0.00695)
Food Insecurity	0.0141***	0.00987***	0.0106***
	(0.000738)	(0.000704)	(0.000719)
GDP	-0.510***	-0.602***	-0.532***
	(0.0240)	(0.0240)	(0.0242)
Political Stability	0.257***	0.206***	0.258***
	(0.0175)	(0.0173)	(0.0179)
Press freedom score	0.0105***	0.0121***	0.0107***
	(0.000760)	(0.000756)	(0.000762)
Observations	67,818	67,818	67,818

individuals surveyed makes the data collection not very expensive. On top of this, comes the advantage that the database contains no missing values, unlike data base alternatives such as the *World Value surveys*. However, for simplification, missing values have been created on the basis of people who refused to answer some questions.

Secondly, social networks are now one of the main sources of information. The Reuters Institute Digital has tracked 46 countries from 2014 to 2023 with more than 2000 respondents in each country. According to the results reported 33% of individuals surveyed say social media is their main way of getting news online, and only around a fifth of respondents (22%) now say they prefer to start their news journeys with a website or app. Furthermore, Facebook remains one of the most-used social networks for news overall. The survey also questions the most topical subjects. Among the types of content people mostly pay attention on, publications on climate constitute one of the most trending in all social media platforms. However climate change is also among the topics people say they saw false or misleading information (as well as politics, COVID-19 and war in Ukraine). In any case, this report supports the argument that social media are now unavoidable to analyse social behaviours.

The survey is however limited in several ways. The main reason is the geographic unit. Individuals are only identified at the country level, except for France, Germany, India and the United States where information on regions/states are available. This specification doesn't allow a precise estimation of the effect of climate disasters, while that EM-DAT used here provides geolocalised information. Moreover, it doesn't allow to see the contamination effect of climate events to individuals living in neighbouring countries. The extension of the Climate Change Opinion Survey by Meta during the next years, will allow to legitimately express a causality between opinion and the variables suggested above. A case study on India, where individuals are localised at the state level, is provided in the Appendix of this paper. Although this doesn't address the auto-correlation issues, it represents an attempt to compare more granular results with those at the global level.

While this study tries to analyse climate change opinion in the light of climate knowledge and risk perception, it doesn't assess real individual's knowledge but rather a perception of it. This perception bias may explain the disparity of results obtained when examining different sets of countries. Stoutenborough and Vedlitz (2014) insist on distinguishing both values that they call subjective and objective knowledge, and state that different factors are influencing the two measures. Objective knowledge (measured for instance by answering a series of questions about scientific facts of climate change) thus appears more relatable to reduce the knowledge deficit with experts. They further point out that shrinking this gap will then result in a greater support for environmental policies. This is also the concern raised by Ferraro (2010) who compares competence and self-awareness. They confirm the hypothesis that "the less competent a subject, the less accurate and more overconfident is the subject's evaluation of his or her absolute an relative performances". What this discussion highlights is the need to of support policies with training based on the real level of knowledge of populations.

4 Conclusions

Climate change opinion is at the forefront of an important policy debate. Policy makers at the country and regional levels worry about the take-off of adaptation reforms in common behaviour and people around the world perceive their importance differently. This paper highlights some individual and country-level determinants of climate change opinion. While this study cannot track individual changes in opinion over time, it provides evidence of the implications of various determinants across different countries.

This research utilises a unique international poll conducted on the Facebook platform, gathering information on awareness about climate change issues, opinions on the responsibility of countries, perceptions of risk, and willingness to participate in organised groups. From this dataset, I examine the cross-country determinants of climate awareness and risk perception, based on individual socio-demographic characteristics and exposure to climate disasters.

The data set is rich and allows to have a look on the climate opinion of every region of the world, including regions often neglected in climate economics research. Interesting information is thus collected on the results. Starting with extreme weather events, they appear to have ambiguous effects. The first specification reveals that the simple recurrence of disasters are associated to an increase in the odds of being more aware and of perceiving more risk. Given the heterogeneity in the recurrence of those disasters per country, a second specification is compiled using the distance to the trend of disasters per country. While the correlation is positive and significant for awareness, the effect is negative for all the dimensions of risk perception. The results in relation to socio-demographic variables for their part, propose similar results to those found in the literature: people's opinion about climate is very sensitive to education, age, gender and urbanicity. More specifically, higher education tends to double the odds of awareness and risk perception. The analysis also implies that male respondents perceive to be more aware, while female respondents perceive more risk. This opposition in the determinant role of gender is in line with some arguments in the literature that theoretically and empirically states the different perception of risk across genders. The results presented underscore the strong need for conducting heterogeneity analysis. This study proposes various classification schemes based on different variables, including frequency groups of extreme events, age groups, gender, and countries' income levels.

These findings shed light on the ability of individuals to recall the extreme weather events faced over the years in the country where they live, and to integrate them in their global opinion about climate change. This is mostly the case for awareness compared to risk perception; but an intuition says that risk perception needs more time to be integrated in public climate change opinion, as it imposes to be followed by concrete actions of mitigation and adaptation.

One of the limitations of this study paves the way for future research. Data do not account for spatial auto-correlation, which implies a potential bias if the contamination effects of weather events and climate change opinions from neighbouring countries are not considered. The Facebook survey project appears promising in this sense. The most recent survey includes questions about exposure to weather events at the individual level, which would allow a finer analysis of the effect of exposure. Moreover, the current study deserves an in-depth analysis using previous and upcoming waves of the survey to better capture the evolution of opinion around the world.

Understanding the heterogeneous map of climate change opinion around the world and all its drivers is salient to better integrate ecological transition policies among common behaviour. Given the major role of social media in shaping information sources and in transmitting attitude and behaviour, it is crucial to leverage this communication channel in climate change behaviour research.

5 Appendix

5.1 Appendix 1: Case study of India

After the global results using information at the world scale, this part is dedicated to a zoom analysis on one country. The case of India is interesting in more than one way. First, the Meta survey provides information on the residence State of respondents in India, while so far analysis has been made at the country level. Given that this paper is primarily limited by the lack of spatial information in the survey (driving omitted spacial auto-correlation), focusing on one country allows to get results at a finer scale an compare them to the main analysis. The vast expanse of India and the great diversity of its population make the country an interesting subject for analysis at a more granular geographical level. Second, India has experienced an important number of disasters this last decade and in all States. This reality of India has been exposed at the pre-industrial period with various types of extreme weather events: worse droughts, flash floods, landslides and cyclones (Hall, 2023). The Ministry of Earth Sciences has published a climate-change assessment in 2020 based on data from 1901 to 2018. This report reveals a rise of 0.7°C in temperature. Moreover, March

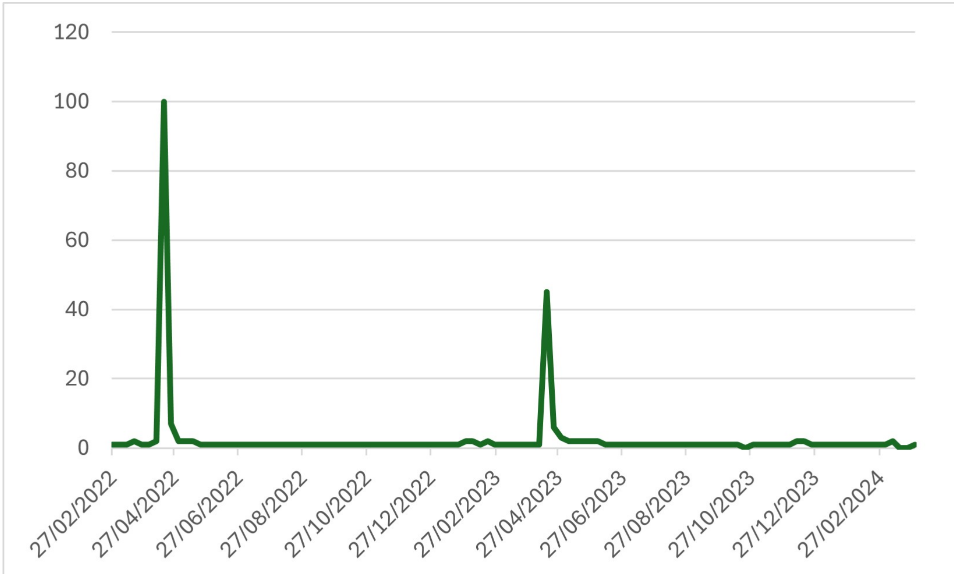


Figure 11: Google trends of the expression "Climate change" in India.

The trend has been plotted based on the Hindi expression for "climate change". The figures are roughly the same when using the expression in English.

2022 (period of the Meta survey) appears to have been the hottest march ever in these lasts 122 years according to the India Meteorological Department. The heatwave lasted 3 months and counts and led to schools closures in the most affected states like Tripura and West Bengal. Figure 11 shows the magnitude of the Google searches for "Climate change", in relative values over the period March 2022 - March 2024. It clearly reveals a peak in the interest in climate change knowledge during the heatwave. The second peak happens one year after, during another heatwave at the same period in the country.

In addition to these high temperatures, thunderstorms and lightning have also been seriously deadly. This has been particularly marked in States such as Bihar, Odisha, Jharkhand and Madhya Pradesh [11].

All this argues in favour of examining the particularity of India. The country already has some background in the scientific literature. A report from a 2022 survey in India [12] believes there is a lack of awareness among citizens who don't relate changes in global weather to global climate change. The scientific literature has focused on the adaptability of Indian farmers based on their awareness of climate change (Shukla et al, 2015; Raghuvanshi et al, 2017).

[11] Source: The Times Of India, January 7, 2023; Extreme weather killed 2,227 in India in 2022.
[12] Climate Change in the Indian Mind, 2022

Figure 12 captures the number of people affected over the whole period of the selected data (2010-2022). It reveals that the Northeast region, especially Assam state, is particularly vulnerable to extreme weather events, with large numbers of people affected. Highlighting the variability in the recurrence of shocks across States will lead to a more precise estimation. This analysis will also serve as robustness for the unexpected results of the previous subsection.

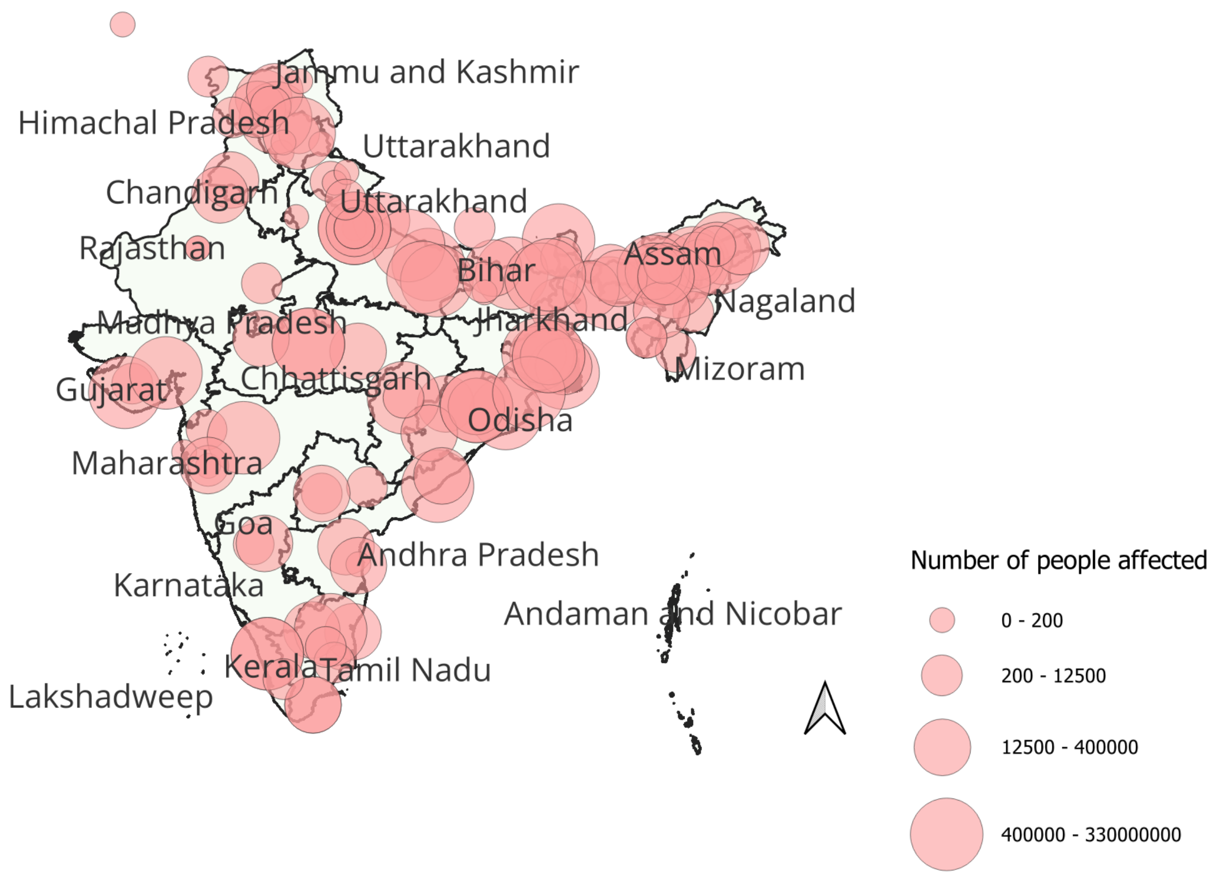


Figure 12: Climate disasters in India (2010-2022). *Elaborated by the author with EM-DAT data.*

A new database structure has been created to perform this analysis.

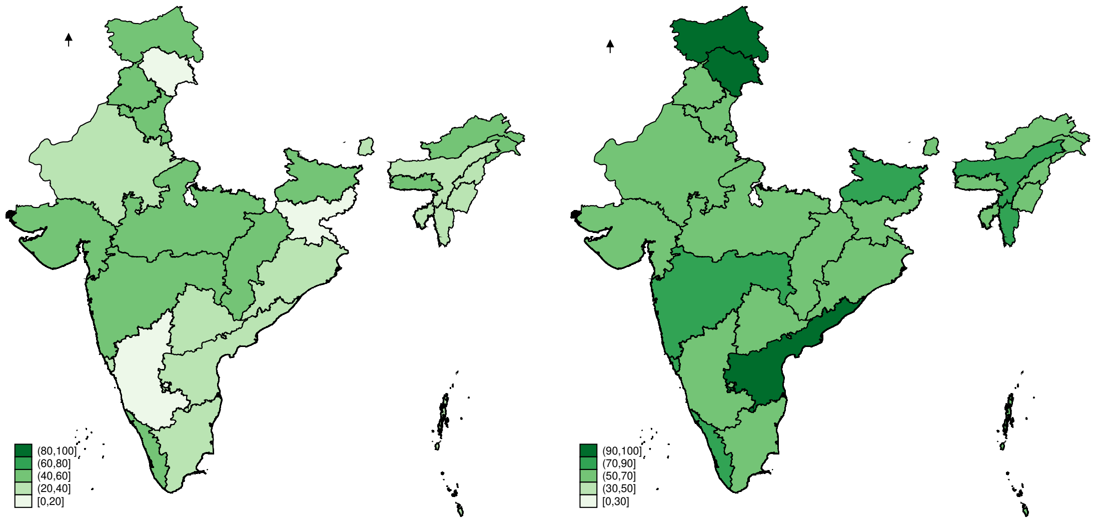
- In the Meta climate change opinion survey, only respondents in India have been kept. This amounts to 2574 individuals before dealing with missing values and the merging with macroeconomic data.

- EM-DAT provides GPS coordinates of the impact zone of disasters that have occurred. When not available, information on state is always available and is used in the analysis to merge with the survey. Some events have affected several States at once. In those cases, I simply count one event for each of the Sate implied in the event. Given that the interest variable for this study is related to the recurrence of events over a given period, this process doesn't bias the results. Table 14 (Appendix) lists the disasters per State obtained after compiling EM-DAT data for India.

- I also collect State wise macroeconomic data to complete the estimations. The *Ministry of statistics and programme implementation* provides data on GDP, population growth, AFF in GDP. I also include State wise data on food security proposed by the *Ministry of Consumer Affairs, Food & Public Distribution* .

Data analysis for the precise case of India leads to several findings. First, descriptive statistics reveal a similar dispersion of climate change opinion to the global dispersion. Almost 40% of respondents just know a little bit about global warming or have never heard of it (compared to 38% in the global analysis). Also, more than 58% of respondents know a moderate amount or a great deal about climate change (around 60% in the global data). The data also reveals a disparity of responses across states (see 13). Madhya Pardesh and Himachal Pradesh appear to be the sates with the highest level of awareness. Concerning risk perception, the percentages are much higher in all states[13].

[13]Some locations are to be ignored because of the very low number of respondents, and thus a falsely apparent high index of opinion. These are some Union Territories as Ladakh and Mizoram.



Climate change awareness *Personal harm of climate change*

Figure 13: State wise climate change opinion in India.

The results however don't go in the same direction as in the cross-countries analysis. We don't observe any correlation between climate awareness and the interest variables representing extreme weather events. However, when estimating the odds of responding that climate change is happening, the coefficient is positive and significant for the second specification at 10% (Table 15). This result is plausible as it is the second question of the survey, and it is preceded by a brief definition of the notion of *climate change* [14].

When estimating the preferences of government's priority on climate change [15], the coefficient on the recurrence of events is positive and significant for the first specification (Table 16), and non-significant for the second one.

Overall, I suspect the spatial effect to be stronger inside of a country than at the world scale. Spatial externalities would mean that an individual can be affected by disasters events occurring in neighbourhood states, or by the climate opinion of individuals living in neighbourhood states. Unfortunately, the data set doesn't allow to fix this potential spacial effect problem.

[14]Explained in Section 3.1.1.

[15]Question in the survey: *Do you think climate change should be a very high, high, medium, or low priority for the government of the country (or territory) where you live?*

5.2 Appendix 2

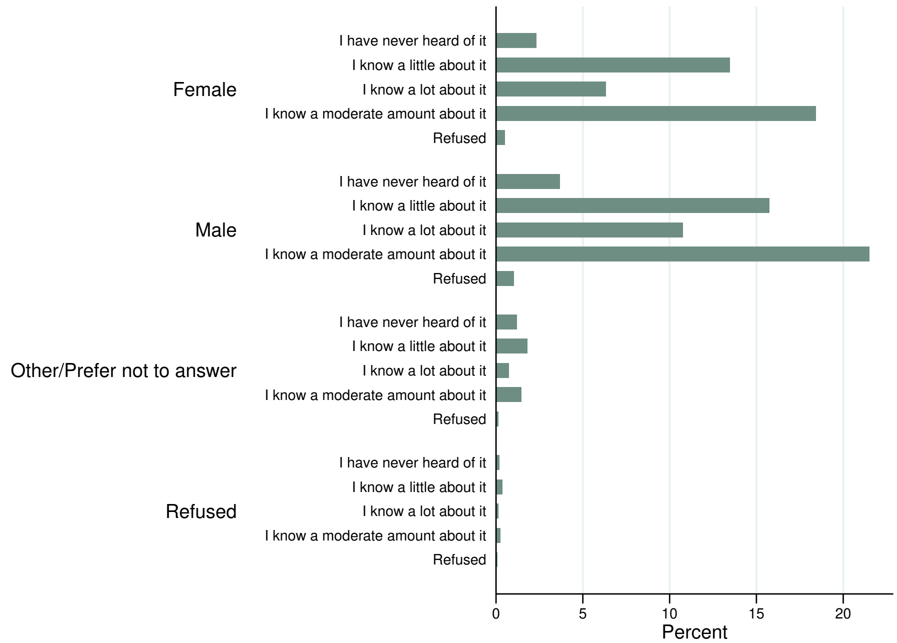


Figure 14: Climate awareness by gender.

Table 5: Disasters occurrence per region: 2020-2022.

Subregion	Disaster Type							
	Drought	Extreme temperature	Flood	Glacial lake outburst flood	Mass movement (wet)	Storm	Wildfire	Total
Australia and New Zealand	2	2	27	0	0	19	14	64
Central Asia	1	5	22	0	6	1	0	35
Eastern Asia	12	26	146	0	24	213	4	425
Eastern Europe	4	38	59	0	1	29	8	139
Latin America and the Caribbean	37	11	376	0	35	190	20	669
Melanesia	3	0	14	0	4	26	0	47
Micronesia	5	0	2	0	0	9	0	16
Northern Africa	3	9	36	0	1	7	4	60
Northern America	10	9	65	0	2	210	44	340
Northern Europe	2	20	14	0	2	24	2	64
Polynesia	4	0	1	0	0	12	0	17
South-eastern Asia	14	2	324	0	37	178	2	557
Southern Asia	11	29	257	2	48	107	4	458
Southern Europe	4	35	84	1	3	29	18	174
Sub-Saharan Africa	88	1	407	0	30	100	6	632
Western Asia	2	5	79	0	5	33	6	130
Western Europe	1	35	35	0	1	71	1	144
Total	203	227	1948	3	199	1258	133	3971

Table 6: Dependent variable: Climate awareness, Ordered Logit estimates per income groups of countries.

Variables	HIC	MIC	LIC
Distance to trend	0.0650***	0.0339***	0.00944
	(0.0124)	(0.00581)	(0.0307)
Higher Edu	0.700***	0.861***	0.903***
	(0.0244)	(0.0214)	(0.0487)
Urban	-0.00101	0.250***	0.197***
	(0.0259)	(0.0267)	(0.0560)
30-44	0.118*	-0.00596	0.0349
	(0.0609)	(0.0380)	(0.0906)
45-59	0.381***	0.229***	0.292**
	(0.0592)	(0.0435)	(0.129)
60+	0.596***	0.450***	0.656***
	(0.0570)	(0.0487)	(0.212)
Male	0.451***	0.107***	0.326***
	(0.0748)	(0.0383)	(0.0703)
Male*30-44	0.0485	0.0980*	0.0974
	(0.0895)	(0.0522)	(0.109)
Male*45-59	-0.0666	0.131**	0.146
	(0.0862)	(0.0578)	(0.151)
Male*60+	-0.287***	0.0612	-0.430*
	(0.0832)	(0.0638)	(0.244)
AFF	-0.0637***	-0.0262***	-0.153***
	(0.0238)	(0.00258)	(0.0119)
Population growth	0.560***	-0.0670***	0.711***
	(0.0363)	(0.00824)	(0.0675)
Food Insecurity	0.000779	-0.00191**	0.00864***
	(0.00728)	(0.000810)	(0.00201)
GDP	-0.115	-0.165***	0.402***
	(0.0867)	(0.0336)	(0.111)
Political Stability	0.00889	0.142***	0.680***
	(0.0881)	(0.0186)	(0.0566)
Press freedom score	0.0321***	-0.00497***	-0.0376***
	(0.00292)	(0.000914)	(0.00366)
Observations	27,820	33,470	6,679

Table 7: Dependent variable: Climate awareness, Ordered Logit estimates by age group.

Variables	18-29	30-44	45-59	60+
Distance to trend	0.0665***	0.0209**	0.0318***	0.0480***
	(0.00965)	(0.00896)	(0.0102)	(0.0125)
Higher Edu	0.768***	0.889***	0.753***	0.711***
	(0.0321)	(0.0289)	(0.0320)	(0.0322)
Urban	0.165***	0.158***	0.102***	-0.00216
	(0.0371)	(0.0340)	(0.0365)	(0.0363)
Male	0.188***	0.304***	0.295***	0.159***
	(0.0306)	(0.0281)	(0.0310)	(0.0308)
AFF	-0.0310***	-0.0108***	-0.0162***	-0.0149**
	(0.00371)	(0.00404)	(0.00517)	(0.00692)
Population growth	0.0183	-0.00893	-0.0173	0.00480
	(0.0202)	(0.0136)	(0.0145)	(0.0129)
Food Insecurity	-0.00617***	-0.00182	0.00339**	0.00764***
	(0.00121)	(0.00127)	(0.00162)	(0.00219)
GDP	-0.163***	0.00671	0.204***	0.521***
	(0.0417)	(0.0439)	(0.0552)	(0.0727)
Political Stability	0.183***	0.223***	0.0544	-0.00124
	(0.0299)	(0.0329)	(0.0428)	(0.0550)
Press freedom score	-0.00414***	-0.0132***	-0.0112***	-0.000309
	(0.00137)	(0.00145)	(0.00185)	(0.00221)
Observations	14,837	18,072	15,224	15,563

Table 8: Dependent variable: climate awareness, Ordered Logit estimates per extreme events frequency group.

Variables	Low frequency	High frequency
Distance to trend	0.0274***	-0.00507
	(0.00691)	(0.0152)
Higher Edu	0.804***	0.737***
	(0.0158)	(0.0500)
Urban	0.0851***	0.0221
	(0.0182)	(0.0592)
30-44	0.0838***	-0.162*
	(0.0320)	(0.0847)
45-59	0.360***	0.0417
	(0.0338)	(0.0956)
60+	0.577***	0.252**
	(0.0336)	(0.122)
Male	0.226***	0.104
	(0.0327)	(0.0860)
Male*30-44	0.107**	0.134
	(0.0433)	(0.118)
Male*45-59	0.0834*	0.166
	(0.0447)	(0.128)
Male*60+	-0.0848*	0.00411
	(0.0439)	(0.158)
AFF	-0.0224***	-0.291***
	(0.00228)	(0.0313)
Population growth	-0.00514	-7.204***
	(0.00714)	(0.802)
Food Insecurity	-0.00837***	0.0373***
	(0.000793)	(0.00368)
GDP	-0.149***	-13.11***
	(0.0252)	(1.503)
Political Stability	0.112***	
	(0.0182)	
Press freedom score	-0.0146***	
	(0.000962)	
Observations	62,113	6,403

Table 9: Dependent variable: climate awareness, Ordered Logit estimates with 10 and 5 years lag of extreme weather events.

Variables	(1) 10 years lag	(2) 10 years lag	(3) 5 years lag	(4) 5 years lag
Nb disasters	0.00458			
	(0.00279)			
Distance to trend		0.0412***		
		(0.00490)		
Nb disasters_5			0.00313	
			(0.00287)	
Distance to trend_5				0.0594***
				(0.00585)
Higher Edu	0.791***	0.792***	0.795***	0.795***
	(0.0150)	(0.0150)	(0.0151)	(0.0150)
Urban	0.109***	0.0989***	0.111***	0.0982***
	(0.0173)	(0.0173)	(0.0173)	(0.0173)
30-44	0.0475	0.0462	0.0512*	0.0492
	(0.0299)	(0.0299)	(0.0300)	(0.0300)
45-59	0.316***	0.313***	0.323***	0.319***
	(0.0318)	(0.0318)	(0.0319)	(0.0319)
60+	0.549***	0.544***	0.560***	0.553***
	(0.0319)	(0.0319)	(0.0320)	(0.0320)
Male	0.208***	0.208***	0.207***	0.207***
	(0.0305)	(0.0305)	(0.0307)	(0.0307)
Male*30-44	0.110***	0.112***	0.113***	0.115***
	(0.0406)	(0.0406)	(0.0408)	(0.0408)
Male*45-59	0.0891**	0.0912**	0.0908**	0.0944**
	(0.0421)	(0.0421)	(0.0423)	(0.0423)
Male*60+	-0.0713*	-0.0712*	-0.0719*	-0.0703*
	(0.0418)	(0.0418)	(0.0420)	(0.0420)
AFF	-0.0238***	-0.0209***	-0.0246***	-0.0218***
	(0.00215)	(0.00217)	(0.00218)	(0.00218)
Population growth	-0.00425	0.000188	-0.00278	0.00209
	(0.00702)	(0.00701)	(0.00704)	(0.00702)
Food Insecurity	-0.00226***	-0.00248***	-0.00255***	-0.00337***
	(0.000738)	(0.000700)	(0.000750)	(0.000706)
GDP	-0.0379	-0.0159	-0.0454*	-0.0297
	(0.0236)	(0.0234)	(0.0237)	(0.0233)
Political Stability	0.185***	0.180***	0.182***	0.170***
	(0.0162)	(0.0161)	(0.0162)	(0.0162)
Press freedom score	-0.0104***	-0.00949***	-0.0100***	-0.00880***
	(0.000765)	(0.000765)	(0.000776)	(0.000775)
Observations	68,516	68,516	68,009	68,009

Table 10: Dependent variable: Personal harm of climate change, Ordered Logit estimates per income groups of countries.

Variables	HIC	MIC	LIC
Distance to trend	-0.135***	0.0125**	0.0559*
	(0.0117)	(0.00555)	(0.0308)
Higher Edu	0.231***	0.170***	0.333***
	(0.0227)	(0.0206)	(0.0500)
Urban	0.209***	-0.00119	-0.201***
	(0.0245)	(0.0262)	(0.0590)
30-44	-0.0205	0.0414	0.426***
	(0.0572)	(0.0376)	(0.0951)
45-59	-0.0213	0.190***	0.524***
	(0.0558)	(0.0432)	(0.140)
60+	-0.175***	0.0358	0.356
	(0.0534)	(0.0480)	(0.227)
Male	-0.346***	-0.117***	0.204***
	(0.0703)	(0.0373)	(0.0699)
Male*30-44	0.0787	0.0926*	-0.0486
	(0.0843)	(0.0511)	(0.114)
Male*45-59	0.00778	-0.0191	0.0318
	(0.0812)	(0.0568)	(0.164)
Male*60+	0.0751	0.0909	-0.0219
	(0.0782)	(0.0624)	(0.261)
AFF	-0.315***	-0.0455***	-0.121***
	(0.0223)	(0.00259)	(0.0124)
Population growth	0.195***	0.0903***	0.544***
	(0.0339)	(0.00795)	(0.0671)
Food Insecurity	0.0583***	0.00586***	0.0110***
	(0.00692)	(0.000785)	(0.00209)
GDP	-0.273***	-0.510***	0.458***
	(0.0818)	(0.0338)	(0.112)
Political Stability	-0.711***	0.366***	0.600***
	(0.0830)	(0.0183)	(0.0603)
Press freedom score	0.0404***	0.00534***	-0.0268***
	(0.00274)	(0.000882)	(0.00372)
Observations	27,855	33,831	6,824

Table 11: Dependent variable: Level of worrying climate change, Ordered Logit estimates per income groups of countries.

Variables	HIC	UMIC	LMIC	LIC
Distance to trend	-0.0877***	-0.0483***	0.0161	0.0912**
	(0.0135)	(0.00898)	(0.0104)	(0.0440)
Higher Edu	0.260***	0.00155	0.155***	0.139**
	(0.0251)	(0.0286)	(0.0344)	(0.0558)
Urban	0.277***	0.0197	-0.0667	-0.358***
	(0.0267)	(0.0360)	(0.0435)	(0.0663)
30-44	0.104*	0.248***	0.0353	0.177*
	(0.0618)	(0.0537)	(0.0587)	(0.103)
45-59	0.291***	0.503***	0.284***	0.245
	(0.0603)	(0.0589)	(0.0746)	(0.151)
60+	0.436***	0.512***	0.350***	0.0942
	(0.0578)	(0.0624)	(0.0980)	(0.236)
Male	-0.550***	-0.132**	-0.139**	0.0258
	(0.0751)	(0.0572)	(0.0541)	(0.0780)
Male*30-44	0.166*	0.0361	0.164**	0.316**
	(0.0903)	(0.0749)	(0.0786)	(0.126)
Male*45-59	0.161*	-0.0324	0.0863	0.197
	(0.0872)	(0.0798)	(0.0958)	(0.177)
Male*60+	0.0776	-0.0550	0.0463	0.294
	(0.0840)	(0.0840)	(0.121)	(0.276)
AFF	-0.0809***	-0.115***	-0.0284***	-0.0651***
	(0.0266)	(0.00720)	(0.00380)	(0.0139)
Population growth	-0.0242	0.131***	-0.436***	0.431***
	(0.0358)	(0.00906)	(0.0357)	(0.0769)
Food Insecurity	-0.00271	0.0137***	-0.00127	0.00236
	(0.00727)	(0.00140)	(0.00153)	(0.00236)
GDP	-0.481***	-0.515***	-1.439***	-0.0773
	(0.0831)	(0.0768)	(0.0799)	(0.122)
Political Stability	-0.579***	0.206***	0.253***	0.196*
	(0.0880)	(0.0540)	(0.0334)	(0.106)
Press freedom score	0.0114***	0.00647***	-0.00263*	-0.00477
	(0.00288)	(0.00215)	(0.00144)	(0.00814)
Observations	25,045	19,224	13,638	6,293

Table 12: Dependent variable: Personal harm of climate change, Ordered Logit estimates per extreme events frequency group.

Variables	Low frequency	High frequency
Distance to trend	-0.103***	0.0824***
	(0.00726)	(0.0146)
Higher Edu	0.192***	0.199***
	(0.0157)	(0.0490)
Urban	0.0557***	0.0101
	(0.0183)	(0.0575)
30-44	0.155***	-0.0767
	(0.0326)	(0.0847)
45-59	0.259***	-0.107
	(0.0345)	(0.0950)
60+	0.0887***	-0.234*
	(0.0337)	(0.121)
Male	-0.136***	-0.0962
	(0.0330)	(0.0861)
Male*60+	0.0554	-0.0264
	(0.0439)	(0.118)
AFF	-0.0630***	-0.320***
	(0.00249)	(0.0309)
Population growth	0.0428***	-9.972***
	(0.00709)	(0.798)
Food Insecurity	0.00845***	0.0171***
	(0.000803)	(0.00384)
GDP	-0.686***	-18.93***
	(0.0264)	(1.482)
Political Stability	0.204***	
	(0.0213)	
Press freedom score	0.00547***	
	(0.00103)	
	(0.294)	
Observations	57,721	6,498

Table 13: Dependent variable: Personal harm of climate change, Ordered Logit estimates with 10 and 5 years lag of extreme weather events.

Variables	(1) 10 years lag	(2) 10 years lag	(3) 5 years lag	(4) 5 years lag
Nb disasters	0.0601***			
	(0.00274)			
Distance to trend		-0.0387***		
		(0.00471)		
Nb disasters_5			0.0553***	
			(0.00281)	
Distance to trend_5				-0.0396***
				(0.00554)
Higher Edu	0.207***	0.187***	0.210***	0.196***
	(0.0143)	(0.0143)	(0.0144)	(0.0143)
Urban	0.0528***	0.0524***	0.0565***	0.0574***
	(0.0167)	(0.0167)	(0.0167)	(0.0168)
30-44	0.118***	0.113***	0.119***	0.114***
	(0.0294)	(0.0294)	(0.0296)	(0.0295)
45-59	0.204***	0.198***	0.208***	0.204***
	(0.0312)	(0.0312)	(0.0314)	(0.0313)
60+	0.0561*	0.0335	0.0594*	0.0423
	(0.0310)	(0.0309)	(0.0311)	(0.0310)
Male	-0.138***	-0.148***	-0.138***	-0.146***
	(0.0297)	(0.0297)	(0.0298)	(0.0298)
Male*30-44	0.0626	0.0646	0.0641	0.0650
	(0.0397)	(0.0396)	(0.0398)	(0.0398)
Male*45-59	-0.0546	-0.0494	-0.0582	-0.0552
	(0.0410)	(0.0409)	(0.0412)	(0.0411)
Male*60+	-0.0385	-0.0269	-0.0400	-0.0311
	(0.0404)	(0.0404)	(0.0406)	(0.0406)
AFF	-0.0430***	-0.0525***	-0.0458***	-0.0552***
	(0.00217)	(0.00221)	(0.00220)	(0.00222)
Population growth	0.0254***	0.0364***	0.0293***	0.0412***
	(0.00688)	(0.00687)	(0.00690)	(0.00688)
Food Insecurity	0.0122***	0.00688***	0.0112***	0.00655***
	(0.000725)	(0.000683)	(0.000736)	(0.000691)
GDP	-0.585***	-0.703***	-0.605***	-0.711***
	(0.0235)	(0.0233)	(0.0236)	(0.0233)
Political Stability	0.356***	0.329***	0.346***	0.321***
	(0.0160)	(0.0160)	(0.0160)	(0.0161)
Press freedom score	0.00833***	0.00988***	0.00934***	0.0112***
	(0.000745)	(0.000745)	(0.000758)	(0.000755)
Observations	69,076	69,076	68,563	68,563

Table 14: Disasters occurrence per State in India: 2010-2022.

Location	Disaster Type							
	Drought	Extreme temperature	Flood	Glacial lake outburst flood	Mass movement (wet)	Storm	Wildfire	Total
Andhra Pradesh	0	3	12	0	0	6	0	21
Arunachal Pradesh	0	0	9	0	0	0	0	9
Assam	0	2	27	0	2	2	0	33
Bihar	0	6	12	0	0	6	0	24
Chhattisgarh	0	0	3	1	1	0	0	5
Goa	0	0	2	0	0	0	0	2
Gujarat	0	2	8	0	0	4	0	14
Haryana	0	0	4	0	0	2	0	6
Himachal Pradesh	0	0	3	0	0	14	0	17
Jammu and Kashmir	0	0	7	0	0	6	0	13
Jharkhand	0	3	5	0	1	1	0	10
Karnataka	0	0	12	0	0	0	0	12
Kerala	0	0	8	0	1	2	0	11
Ladakh	0	0	1	0	0	0	0	1
Madhya Pradesh	2	6	1	0	0	1	0	10
Maharashtra	0	0	7	0	1	20	0	28
Manipur	0	0	3	0	1	1	0	5
Meghalaya	0	2	0	0	1	1	0	4
Mizoram	0	0	0	0	0	4	0	4
NCT of Delhi	0	1	2	0	1	0	0	4
Nagaland	0	1	3	0	0	1	0	5
Odisha	0	1	17	0	0	8	0	26
Puducherry	0	0	1	0	0	3	0	4
Punjab	0	0	5	0	0	1	0	6
Rajasthan	0	0	17	0	0	0	0	17
Sikkim	0	0	2	0	0	0	0	2
Tamil Nadu	0	0	5	0	1	9	0	15
Telangana	0	0	1	0	0	2	1	4
Tripura	5	0	0	0	0	2	0	7
Uttar Pradesh	9	4	15	0	1	14	0	43
Uttarakhand	0	3	4	0	0	14	0	21
West Bengal	0	0	15	1	1	6	1	24
Total	16	34	211	2	12	130	2	407

Note: EM-DAT proceeds to the update of data per event. For events appearing in several States at once, I count them as one event for each state mentioned. For example, the flood registered in 2018 that has affected Sates of *Odisha* and *Pudducherry* counts as one flood event in *Odisha*, and one flood event in *Pudducherry*.

Table 15: Dependent variable: Climate Change happening, Logit estimates, India.

Variables	(1)	(2)	(3)
Nb disasters	-0.00239		
	(0.0112)		
Distance to trend		0.100*	0.0639
		(0.0514)	(0.0690)
Distance to trend binary			-1.014*
			(0.562)
Distance to trend* Distance to trend binary			0.392*
			(0.204)
Higher Edu	0.886***	0.870***	0.895***
	(0.219)	(0.219)	(0.220)
Urban	0.161	0.172	0.138
	(0.244)	(0.244)	(0.245)
30-44	-0.852*	-0.794*	-0.817*
	(0.466)	(0.468)	(0.469)
45-59	-0.0689	0.00102	-0.00763
	(0.573)	(0.574)	(0.575)
60+	-0.339	-0.301	-0.292
	(0.647)	(0.647)	(0.649)
Male	-0.268	-0.243	-0.244
	(0.476)	(0.477)	(0.477)
Male*30-44	0.419	0.366	0.366
	(0.571)	(0.572)	(0.573)
Male*45-59	0.379	0.326	0.317
	(0.715)	(0.716)	(0.717)
Male*60+	-0.0317	-0.0445	-0.0445
	(0.748)	(0.748)	(0.750)
AFF	1.653	1.339	1.896
	(2.180)	(2.153)	(2.205)
Population growth	-41.91	-39.84	-33.13
	(25.53)	(26.37)	(26.23)
Food Security	-1.705	-2.388	-3.635*
	(1.910)	(1.963)	(2.080)
GDP	0.517	0.445	0.454
	(0.323)	(0.288)	(0.282)
Constant	-1.582	-0.192	0.433
	(4.432)	(4.285)	(4.129)
Observations	2,166	2,166	2,121

Table 16: Dependent variable: Government priority, Ologit estimates, India.

Variables	(1) Gov. priority	(2) Gov. priority	(3) Gov. priority
Nb disasters	0.0116**		
	(0.00466)		
Distance to trend		-0.0191	-0.0540**
		(0.0167)	(0.0261)
Distance to trend binary			0.0950
			(0.245)
Distance to trend* Distance to trend binary			0.0593
			(0.0550)
Higher Edu	0.288***	0.289***	0.294***
	(0.0835)	(0.0836)	(0.0847)
Urban	-0.0655	-0.0491	-0.0605
	(0.101)	(0.101)	(0.103)
30-44	0.369**	0.365**	0.317*
	(0.163)	(0.164)	(0.167)
45-59	0.402**	0.404**	0.404**
	(0.177)	(0.177)	(0.180)
60+	0.330	0.332	0.248
	(0.208)	(0.207)	(0.212)
Male	0.233	0.228	0.217
	(0.164)	(0.164)	(0.167)
Male*30-44	-0.155	-0.144	-0.102
	(0.212)	(0.212)	(0.215)
Male*45-59	-0.290	-0.299	-0.296
	(0.230)	(0.231)	(0.234)
Male*60+	-0.140	-0.150	-0.0806
	(0.256)	(0.256)	(0.260)
AFF	1.689**	1.330	1.820**
	(0.840)	(0.828)	(0.863)
Population growth	28.77***	26.43***	23.80**
	(9.402)	(9.410)	(9.566)
Food Security	-2.039***	-1.527**	-1.581**
	(0.710)	(0.708)	(0.769)
GDP	0.230*	0.0745	0.0751
	(0.131)	(0.112)	(0.115)
/cut1	-0.349	-2.046	-1.988
	(1.755)	(1.585)	(1.597)
/cut2	1.234	-0.464	-0.415
	(1.754)	(1.583)	(1.596)
/cut3	2.589	0.888	0.948
	(1.755)	(1.583)	(1.596)
Observations	2,267	2,267	2,217

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