Disasters, politics, and the economy : the interplay between tropical cyclones, political opinions, and economic growth

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ÉCOLE DOCTORALE
DROIT ET SCIENCES POLITIQUES, ÉCONOMIQUES ET DE GESTION

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Désastres, politique et économie :

l'interaction entre les cyclones tropicaux, les opinions politiques et la croissance économique

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Présentée en vue de l'obtention du grade de docteur en Sciences Économiques d'Université Côte d'Azur et de Scuola Universitaria Superiore Sant'Anna

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Soutenue le : 20/12/2024

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Résumé de la thèse en français

Title: Désastres, politique et économie : l'interaction entre les cyclones tropicaux, les opinions politiques et la croissance économique

Cette dissertation vise à combler d'importantes lacunes dans l'étude de l'impact des cyclones tropicaux sur (i) la croissance économique infranationale ; (ii) le lien entre les cyclones tropicaux et la polarisation politique ; et (iii) la relation entre les nouvelles sur le changement climatique et les opinions des individus.

Chapitre 1 : "La vitesse du vent entraîne des dommages économiques infranationaux dus aux cyclones tropicaux" (en collaboration avec Sven Kunze, Christian Otto et Leonie Wenz)

Les cyclones tropicaux causent des dommages et des préjudices considérables, et la proportion des tempêtes les plus intenses devrait augmenter avec le réchauffement futur. Les analyses précédentes étaient limitées à des régions spécifiques, à des niveaux de pays ou à des dangers uniques liés aux cyclones tropicaux, principalement la vitesse du vent. Ce chapitre évalue l'effet combiné des trois principaux dangers des cyclones tropicaux—la vitesse du vent, l'onde de tempête et les pluies—sur la croissance macroéconomique infranationale à l'échelle mondiale. À cette fin, nous combinons des données d'intensité des cyclones tropicaux modélisées spatialement avec des données de croissance économique provenant de 1.642 régions infranationales pour les années 1980-2020. Nous mettons en évidence que, bien que la vitesse du vent entraîne les plus grandes pertes macroéconomiques, il est important de tenir compte des deux autres dangers. L'onde de

tempête cause d'autres pertes, tandis que l'effet des pluies est bénéfique jusqu'à un certain seuil de précipitations.

Chapitre 2 : "Événements extrêmes, changements idéologiques et polarisation : preuves des cyclones tropicaux aux États-Unis" (en collaboration avec Matteo Coronese et Francesco Lamperti)

La littérature a examiné l'impact des extrêmes climatiques sur les préférences politiques, mettant en évidence un déplacement positif vers des positions environnementales et démocrates. Cependant, elle n'a pas abordé les effets potentiellement polarisants sur l'opinion publique. Ce chapitre examine la relation entre les cyclones tropicaux et la polarisation politique aux États-Unis, offrant de nouvelles perspectives sur ce sujet. Pour ce faire, nous utilisons la base de données du Cooperative Election Study pour l'idéologie politique et des données modélisées sur la vitesse maximale du vent pour mesurer les dommages causés par les tempêtes pendant la période 2010-2018. Nous constatons que les cyclones tropicaux particulièrement destructeurs sont associés à une augmentation de la polarisation politique au sein de la population. En particulier, les démocrates présentent une augmentation des opinions libérales, tandis que les républicains s'orientent vers des opinions plus conservatrices.

Chapitre 3 : "Dernières nouvelles : exposition médiatique et déni du changement climatique aux États-Unis"

La littérature existante a montré que les actualités sur le changement climatique influencent positivement l'acceptation de sa réalité. Cependant, il n'a pas été examiné si ces actualités contribuent à une plus grande stabilité des opinions, en tenant compte à la fois de l'acceptation et du déni du changement climatique. Ce chapitre aborde une avenue inexplorée en se concentrant sur la question de savoir si les actualités sur le changement climatique renforcent l'adhésion à l'opinion de l'individu et écartent les perspectives opposées concernant la réalité du changement climatique parmi les résidents américains. J'utilise les données historiques d'enquêtes sur plus de 9.000 individus recueillis durant les années paires de la période 2010-2014. J'ai constaté qu'une plus grande

exposition aux actualités sur le climat augmente la probabilité d'avoir (i) une acceptation stable du changement climatique parmi les démocrates ; (ii) un déni stable du changement climatique parmi les républicains ; (iii) un déni instable du changement climatique parmi les démocrates ; et (iv) une acceptation instable du changement climatique parmi les républicains.

Mots-clés : Cyclones tropicaux ; Opinions des individus ; Polarisation politique ; Nouvelles sur le changement climatique ; Impact économique ; Croissance économique.

Summary in English language

Title: Disasters, politics, and the economy: the interplay between tropical cyclones, political opinions, and economic growth

This dissertation aims at closing important research gaps in the study of (i) the effect of tropical cyclones on subnational economic growth; (ii) the linkage between tropical cyclones and political polarization; and (iii) the relation between climate change news and individuals' opinions.

Chapter 1: "Wind speed drives subnational economic damage from tropical cyclones" (in collaboration with Sven Kunze, Christian Otto, and Leonie Wenz)

Tropical cyclones cause substantial damage and harm, and the proportion of the most intense storms is projected to increase under future warming. Previous analyses are limited to specific regions, country levels, or single tropical cyclone hazards, mainly wind speed. This chapter assesses the compound effect of all three main tropical cyclone hazards—wind speed, storm surge, and rainfall—on subnational macroeconomic growth globally. To this end, we combine spatially modeled tropical cyclone intensity data with economic growth data from 1,642 subnational regions for the years 1980-2020. We find that while wind speed induces the largest macroeconomic losses, accounting for the other two hazards is important. Storm surges cause further losses, whereas the effect of rainfall is beneficial up to a certain rainfall amount.

Chapter 2: "Extreme events, ideological shifts and polarization: evidence from US tropical cyclones" (in collaboration with Matteo Coronese and Francesco Lamperti)

Previous literature has examined the impact of extreme events on political preferences, high-

lighting a positive shift towards environmental and Democratic positions. However, it has not addressed the potential polarizing effect on public opinion. This chapter investigates the relation between tropical cyclones and political polarization in the United States, offering new insights into this topic. To do so, we use the Cooperative Election Study database for political ideology and scientific maximum wind-speed modeled data for measuring storm damage over the 2010-2018 period. We find that extremely damaging tropical cyclones are associated with increased political polarization within the population. Specifically, Democrats exhibit an increase in liberal opinions, while Republicans shift towards more conservative views.

Chapter 3: "Breaking news: media exposure and climate change denial in the United States"

Existing literature has shown that climate change news positively influences the acceptance of climate change. However, there has been no examination of whether climate change news contributes to greater stability in opinions, taking into account both acceptance and denial of climate change. This chapter addresses an unexplored avenue by focusing on whether climate change news reinforces adherence to the individual's opinion and discards opposing perspectives about the existence of climate change among U.S. residents. I use individuals' historical survey data on over 9,000 individuals collected during the even years of the 2010-2014 period and find that greater exposure to climate news increases the probability of having (i) stable climate change acceptance among Democrats; (ii) stable climate change denial among Republicans; (iii) unstable climate change denial among Democrats; and (iv) unstable climate change acceptance among Republicans.

Keywords: Tropical cyclones; Individuals opinions; Political polarization; Climate change news; Economic impact; Economic growth

Acknowledgments

I would like to thank to all people that has been part of my important and enriching PhD journey. To start with, I would like to express my sincere gratitude to my supervisors, Lionel Nesta and Francesco Lamperti, for their invaluable guidance and support throughout my thesis journey. Your expertise and insights have been immensely important in shaping my PhD path, both from a scientific and personal development perspective. I truly appreciate your encouragement and constructive feedback, which have motivated me to continuously improve. Thank you for believing in me, sharing your expertise, and being part of my academic growth. I feel honored to have had the opportunity to learn from you and to have you as my mentors.

I would like to extend my sincere gratitude to Professors Wouter Botzen, Andreas Chai, and Katrin Millock for kindly agreeing to be part of my thesis jury. Your participation in my PhD examination is a great honor and I am truly grateful to be receiving your insights and feedback. I have also greatly appreciated my discussions with Katrin during my Paris School of Economics summer school regarding my early-stage PhD research.

Moreover, I wish to express my special thanks to Mauro Napoletano for being such an important point of reference in the PhD program and for his valuable guidance. I am deeply grateful for the opportunity to have participated in the International PhD in Economics, which has significantly contributed to my intellectual growth and expanded my knowledge and skills in economics research. I also thank Federico Tamagni and Alessio Moneta for serving as mentors throughout the PhD program in Pisa.

I wish to thank Leonie Wenz for the opportunity of having a visiting stay at the Potsdam Institute for Climate Impact Research. This experience has been especially inspiring and profes-

sionally enriching. I am very glad to have had the opportunity to work under your supervision, so as to have collaborated with Sven Kunze and Christian Otto in the framework of the first chapter of my dissertation. I have extremely appreciated our discussions and collaboration. I express my gratitude also to Matteo coronese, for his valuable feedback and input in the framework of the second chapter of the thesis.

Then, my gratitude also goes to the many professors at the laboratory who have supported me over the years and provided valuable professional development and research advice: Jackie Krafft, Michele Pezzoni, Flora Bellone, Marco Baudino, and Simone Vannuccini.

Moreover, I am indebted to the entire administrative team at GREDEG and DESPEG for their precious help, which have contributed to facilitate the administrative related part of my research: Véronique, Nathalie, Catherine, Sami, Thuy, Ludivine, Agnès, Laurence, and Iwona. I also wish to thank Anja for her support at the Potsdam Institute for Climate Impact Research.

Throughout my PhD journey, I have had the privilege of meeting incredible colleagues who have constantly supported me and enriched me with their precious friendships. Martin, Isabel, Anel, Marie, Leonardo, Matteo, Riccardo, Christian, Francesco, Ilona, Manon, Arnaud, Alexandre, Alberto, Xijie, Giannina, Natalie, David, Simon, Camille, Basheer, Pedro and Yassine: I would like to thank you for all the fun and good moments we shared in and outside the laboratory.

Next, I would also like to thank the colleagues and friends at the Potsdam Institute for Climate Impact Research (Anna, Katharina, Maria, Xudong, Anja, Max, Jakob, Timoté, Lennart, Annika, Claus, Tanja, Robert, Noah, Clemens, Diana, Nico, Sijmen, Lisa, Sarah, Giorgia, and Enrique) for having warmly welcomed me at the laboratory, having shared many moments of laughter, and having been important points of reference for me in my Potsdam experience.

Additonally, my PhD journey would not have been the same without the encouragement, listening, humor, and companionship of my friends Nicolò, Maddalena, Elisa, Carolina, Marta, Mary, Alberto, Carlotta, Martina, Rina, Daljia, Yasser, Barbara, Sophie, Ezgi, Mahur, Veronica, Aurélie, Solci, David, Marco, Elita, Ronald and Sofia.

Last but not least, I would like to express my deep gratitude to family for their full support, and belief in me throughout my academic path. This academic path would have not been the

same without your encouragements. You inspired me to push beyond my limits. I wish to thank Alessandro for being the greatest supporter in my PhD journey. Your encouragement and presence through every step and decision of my career have been an exceptional source of strength and motivation for me.

Contents

List of Figures

List of Tables

Introduction

This dissertation analyzes the effects of climate change on society by progressively exploring impacts with decreasing salience. It begins with observable, quantifiable economic consequences and transitions to the subtler opinion-related aspects influenced by extreme events, considering both direct and indirect exposure.

Background and topic relevance

The direct experience of tropical cyclone (TC) hazards, which are among the most destructive extreme events globally,[1] causes tangible devastation and economic impacts. These include damage to infrastructure (Murià-Vila et al., 2018), loss of life (Kishore et al., 2018), rising unemployment (Groen et al., 2020), and long-term economic shocks (Hsiang and Jina, 2014). Moreover, natural disasters also affect migration (Acosta et al., 2020; Millock, 2015) and increase economic inequality (Cappelli et al., 2021).

Tropical cyclones represent a vector of phenomena, composed of three concurrent hazards: wind speed, rainfall, and storm surge,[2] all of which contribute to the damage caused by tropical cyclones (Alipour et al., 2022). The immediate impact of tropical cyclone wind is particularly severe on agriculture and tourism, although the construction sector may experience some temporary growth (Kunze, 2021; Hsiang, 2010). Extreme rainfall from tropical cyclones is also highly damaging. For example, over a 20-year period in the Caribbean, TC events led to direct damage

[1] World Meteorological Organization - Tropical Cyclones.

[2] Storm surge is a tropical cyclone-driven abnormal rise in sea level over and above the predicted astronomical tides contributing to coastal flooding. See https://www.weather.gov/phi/stormSurge.

equivalent to 1.5% of GDP, with rainfall being the primary or secondary cause of damage in 75% of cases (Collalti and Strobl, 2022). Heavy rainfall often exacerbates flooding, further compounding the damage (Davenport et al., 2021). Storm surges, often considered the most destructive component of hurricanes, cause fatalities and significant infrastructure damage, negatively impacting key sectors such as agriculture, transportation, and energy (Strobl, 2011; Needham et al., 2015). While the previous discussion has focused on the impacts of TC hazards considered one at the time, it is important to note that the most devastating outcomes arise when multiple tropical cyclone hazards occur simultaneously. Compound events, episodes where two or more TC hazards occur, are particularly destructive, producing a greater total impact than the sum of their individual effects (Wahl et al., 2015).

Turning to the more subtle psychological and opinion-changing aspects of climate-related extreme hazards, tropical cyclones are events that significantly influence citizens' political opinions (Baccini and Leemann, 2021; Boudet et al., 2020). One potential outcome of this influence is the widening divergence in political opinions across political groups, known as political polarization (Fiorina and Abrams, 2008). The phenomenon of political polarization is a crucial subject of analysis due to its societal and economic consequences, which have become increasingly evident in recent years both in the United States[3] and in Europe (Casal Bértoa and Rama, 2021).

From a societal point of view, polarization can undermine democratic processes (Casal Bértoa and Rama, 2021), hinder the implementation of ambitious policies (Mccarty, 2007), and increase conflicts and social unrest (Piazza, 2023). A greater perception of partisan divide is related with an erosion of societal trust in the United States (Lee, 2022). On the economic side, it has been shown that it increases policy uncertainty (Baker et al., 2020), distorts economic forecasts (Guirola, 2021) and deters investments by firms in highly polarized regions (Zhu, 2021).

Multiple mechanisms can influence the impact of tropical cyclones on polarization. First, extreme events lead to feelings of isolation, abandonment, anger, and fear, especially when displacement occurs (Riad and Norris, 1996). These conditions can, in turn, fuel the growth of

[3] http://www.people-press.org/interactives/political-polarization-1994-2017.

more extreme perspectives (van Prooijen and Krouwel, 2019). Second, an unequal distribution of post-disaster government relief aid has the potential to intensify political polarization within U.S. society. In scenarios where income and public budgets are severely constrained and natural resources and infrastructure are devastated, there could be an enhancement of social conflicts and resource competition, further driving political polarization (Casal Bértoa and Rama, 2021; Levin, 2014; Roche et al., 2020). Third, another contributing factor could be the increased consumption of news by those impacted by extreme events, as they seek information on causes, relief and policy responses (Miller and Goidel, 2009). Given the polarized nature of the media (Levendusky, 2013), this heightened engagement can further boost existing political polarization (Hoewe and Peacock, 2020; Carmichael et al., 2017). Research has also found that personal financial resources limitations can push individuals to behave in a more goal-oriented way (Huijsmans et al., 2019).

Research gaps and dissertation contribution

Despite the extensive literature examining the linkages among disasters, political opinions, and the economy, some knowledge gaps remain. This dissertation aims to address these issues through three key contributions. The first contribution of this dissertation (chapter 1) focuses on the materialistic aspects, specifically the impact of tropical cyclones on economic growth. It highlights the measurable economic consequences of exposure to these hazards, providing relevant insights on how environmental shocks can influence economic performance. The second contribution (chapter 2) continues to explore the effects of direct exposure to tropical cyclones, this time focusing on how such experiences shape collective opinions, revealing less tangible yet significant alterations in political opinions. The third empirical work (chapter 3) examines the effects of climate change news, representing a more remote form of exposure. By analyzing how media coverage shapes beliefs about climate issues, this chapter delves deeper into the social and psychological dimensions at play.

Starting with the economic impact of direct exposure to tropical cyclones, despite numerous contributions, no study has addressed this question globally at the subnational level using official economic statistics. A recent study examines the global economic impacts of tropical cyclones at the subnational level, using nighttime light data as a proxy for economic activity (Felbermayr et al., 2022), though this is an imperfect measure of economic activity. Other research has focused on subnational studies within single countries (Strobl, 2011; Collalti and Strobl, 2022; Parida et al., 2021) or on global and macro-regional analyses at the country level (Hsiang and Jina, 2014; Strobl, 2012; Berlemann and Wenzel, 2018). Secondly, while tropical cyclones involve multiple concurrent hazards, the existing literature on natural hazard risk (Zscheischler et al., 2018) and economic impacts quantification has predominantly focused on the effect of a single TC hazard (Bertinelli and Strobl, 2013; Collalti and Strobl, 2022; Fang et al., 2014), particularly wind speed, therefore underestimating the impact of compound tropical cyclones (Rezapour and Baldock, 2014). Neglecting the impacts of tropical cyclone rainfall and storm surge results in a significant underestimation of cyclone damage, especially given their projected intensification (Bakkensen et al., 2018; Rahmstorf, 2017) and the relatively minor increase in wind speed intensity (Patricola and Wehner, 2018).

My research makes several contributions to the study of tropical cyclones' economic impacts. To begin with, it is the first one analysing the economic growth impacts of tropical cyclones at the subnational level with a global coverage using official statistics economic data. In terms of economic impacts, I analyse several aspects of economic damage: different economic sectors, short- and long-run effects, and heterogeneity impacts based on income and insurance penetration. Second, by examining all three concurrent hazards of tropical cyclones—wind, rainfall, and storm surge—this dissertation offers a novel and more accurate assessment of economic damage by including these factors simultaneously in the econometric model. Complementing wind data with information on rainfall and storm surge is crucial, especially given the climate change-driven increase in the intensity of rainfall and surge. It is indeed important to understand the combined impact of all three hazards on economic growth to quantify the effects of tropical cyclones on growth more precisely.

Regarding the less salient societal consequences of tropical cyclones, while numerous studies have explored changes in political preferences among residents affected by hurricanes (particularly in the U.S.) and proposed various theories, none have investigated political polarization as a consequence of this extreme event. A recent area of research on the consequences of disasters and weather anomalies focuses on changes in environmental opinions following natural hazards (Boudet et al., 2020; Hoffmann et al., 2022), particularly among left-wing citizens (Boudet et al., 2020; Hazlett and Mildenberger, 2020) and analysing Western countries. This shift in environmental views can extend beyond behavioral changes, such as voting (Hazlett and Mildenberger, 2020; Baccini and Leemann, 2021), to include other actions, like donations (Liao and Ruiz Junco, 2022).

The literature on the impact of non-natural shocks on political polarization presents few contributions. A recent study outlines that growing Chinese import competition leads to a rightward shift in the media-viewing habits of adults and greater polarization in the ideological orientation of campaign contributors in the U.S. (Autor et al., 2020). A second contribution finds that wind turbine installations in Germany have contributed to political polarization, increasing both AfD and Green Party vote shares (Otteni and Weisskircher, 2022), while a third one shows that higher exposure to automation increases support for radical-right parties and political polarization (Anelli et al., 2021). However, no study has specifically examined the impact of a natural hazard, such as tropical cyclones, on political polarization in the United States.

By addressing this previously unexplored research question within the context of tropical cyclones, I aim to enhance our understanding of post-disaster societal changes. This insight is crucial for anticipating interventions designed to mitigate declines in societal trust (Lee, 2022) and the rise in conflicts (Piazza, 2023) following disasters. If tropical cyclones are shown to influence political polarization, the issue may become more pronounced in the future, particularly with the anticipated increase in damage from these events (Emanuel, 2005).

Furthermore, this dissertation aims to enhance our understanding of remote exposure to climate change through climate change news and its relationship with a less measurable aspect of society: climate change opinions. The literature on climate change preferences is primarily built around the "Information Deficit Model" (Dickson, 2005), which posits that public skepticism about modern scientific topics stems from a lack of knowledge and, consequently, that providing more science-based information about climate change will increase public acceptance (Suldovsky, 2017). Indeed, there are several contributions that find an increase in climate change acceptance following greater exposure to climate change news (Bain et al., 2012; Bakaki and Bernauer, 2017; Happer and Philo, 2016). An alternative theory called "directional motivated reasoning" (Druckman and McGrath, 2019) suggests that people have specific goals related to reaching a desired conclusion via news. Because of this, they look for information that confirms their existing beliefs and discard information that goes against them. This tendency is influenced by factors as the desire to conform to the values of social groups and the need to maintain coherence with established beliefs and moral values.

I aim to contribute to examine in my dissertation this less-explored hypothesis regarding the relationship between news and public opinion. Specifically, I will test whether and how citizens' exposure to climate change news is related to their persistence in opinions, focusing on both acceptance and denial of climate change. Moreover, I seek to provide new evidence in a less explored field and to alert society to potential unintended side effects of climate change news, which could exacerbate polarization on the topic. This is particularly relevant in an era where both visual and written information are increasingly susceptible to manipulation.

In this dissertation I will utilize several databases to study opinion dynamics through statistical analysis, incorporating various robustness checks, extensions, and placebo tests. Each database possesses unique characteristics, presenting distinct advantages and disadvantages. The careful manipulation of the data will be a key value-added component of this dissertation.

Research questions and hypotheses

The research questions I make in this dissertation are the following:

Chapter 1: To what extent do tropical cyclones affect subnational economic growth globally, and what is the contribution of wind speed, rainfall, and storm surge to the damage caused by tropical cyclones?

Chapter 2: Are tropical cyclones positively related with political polarization?

Chapter 3: Is increased exposure to climate change news associated with greater stability in public opinions?

Chapter 1 evaluates the extent to which global subnational economic growth is affected by tropical cyclones, based on the assumption that they produce short- and long-term severe macroeconomic and sectoral impacts, also depending on the economic development level. Furthermore, this chapter infers that the three concurrent hazards, wind, rainfall, and storm surge, have heterogeneous effects on economic growth, providing insights into which hazard is the most damaging.

Chapter 2 hypothesizes that extreme tropical cyclone damage is associated with heightened political polarization in the U.S. population. Specifically, it expects Democrats to adopt more liberal political views, while Republicans are predicted to shift towards more conservative positions when exposed to severe levels of tropical cyclone damage.

Chapter 3 investigates whether increased consumption of climate change news is: (i) positively associated with opinion stability on climate change in the general population; (ii) positively linked to stronger alignment with an individual's predominant political views (reinforcement of pre-existing beliefs); and (iii) negatively related to stability in opposing viewpoints (increased disagreement with opposing perspectives).

Methods

Chapter 1: This chapter evaluates the impact of tropical cyclones on global subnational economic growth, assuming significant short- and long-term macroeconomic and sectoral effects. The fixed effects approach is employed through Least Squares Dummy Variable (LSDV) regressions, using a panel dataset that covers more than a thousand subnational units from nearly 100 countries over the period from 1980 to 2020. The incorporation of subnational and year fixed effects, along with Conley standard errors, effectively addresses geographical and temporal heterogeneity, as well as spatial correlation. The inclusion of wind speed, rainfall and storm surge data provides a comprehensive economic assessment of tropical cyclone impacts.

Chapter 2: This chapter explores the association between extreme tropical cyclone damage and political polarization in the U.S. population, hypothesizing that severe damage influences political preferences. Methodologically, it employs Ordinary Least Squares (OLS) regressions with year and county dummies and clustered standard errors at the county level. It utilizes a repeated cross-sectional database that includes hundreds of thousands of individuals.

Chapter 3: This chapter examines how increased consumption of climate change news affects opinion stability, alignment with predominant views and stability in opposing stances. Probit regressions are used in the analysis, with data drawn from a panel dataset of thousands of survey respondents. The chapter primarily focuses on the individual level of analysis, offering insights into how individuals' opinions respond to climate change news exposure.

Our methodology has several strengths, particularly through the use of rich and detailed databases. All dissertation contributions are based on a great number of statistical units. The surveys exploited present very well grained information (county or region level) about the residence of the individual. Moreover, the use of survey data has enabled, compared to other sources like web-extracted big data, to have U.S. nation level representativeness, so as to extrapolate many individuals' information on a vast set of characteristics. This data can be used as control variables and to reduce the omitted variable bias. Additionally, the three empirical contributions of this thesis also present an excellent geographical coverage: chapter 1 presents a very good global subnational coverage, while in chapters 2 and 3 all U.S. states and the majority of U.S. counties are covered. In terms of the empirical approach, a natural experiment framework is adopted in the chapters related to tropical cyclones. These storms are exogenous events, as their origin, timing, trajectory, and intensity cannot be predicted in advance (Wang et al., 2018), which naturally delineates a treatment and control groups. Finally, the empirical analyses in the chapters are supported by robustness checks, analyses of heterogeneous impacts, and additional extensions.

Chapter 1

Wind speed drives subnational economic damage from tropical cyclones[*]

1.1 Introduction

Tropical cyclones (TCs) produce destructive effects on the economy in terms of loss of human lives (Kishore et al., 2018), fall in economic growth (Hsiang and Jina, 2014), unemployment (Groen et al., 2020), human capital stock (Opper et al., 2023), and damage to assets and infrastructures (Murià-Vila et al., 2018). They rank among the most destructive natural disasters worldwide[1] and are projected to become more intense under future global warming (Estrada et al., 2015). On top of this, the most damaging tropical cyclones are compound events (Zscheischler et al., 2018), episodes involving the occurrence of at least two tropical cyclone hazards, as they result in a greater overall impact than the sum of the individual events (Wahl et al., 2015).

Studying the economic impacts of tropical cyclones at the subnational level is highly impor-

[*]In collaboration with Sven Kunze, Christian Otto, and Leonie Wenz.

[1]https://wmo.int/topics/tropical-cyclone.

tant, as local vulnerability significantly influences the extent of damage (Nordhaus, 2010). Yet, the global subnational economic impact of tropical cyclones on economic growth in the short- and long-term and across sectors remains unclear. A previous study performed a global subnational analysis on the economic impact of tropical cyclones for the 1992-2013 period, yet relying on nighttime light data, which is an imperfect proxy of economic growth (Felbermayr et al., 2022). This study finds that one additional standard deviation (s.d) in wind speed leads to a decrease in income growth of 0.33% points. The literature on the economic impact of tropical cyclones also includes single-country subnational studies (Strobl, 2011; Collalti and Strobl, 2022; Parida et al., 2021) and global and macro-regions country level studies (Hsiang and Jina, 2014; Strobl, 2012; Berlemann and Wenzel, 2018). However, these studies either miss capturing the local level of analysis or provide only a partial picture of subnational effects on a global scale. Considering the first strand of literature, it has been found, using a panel of U.S. counties, that hurricanes lead to a decrease in annual economic growth of a magnitude of 0.45% points (Strobl, 2011). As for the second strand of literature, it has been shown, conducting a long-run global country level study for the period 1950-2008, that national income not only fall compared to a counterfactual scenario without a tropical cyclone, but also take approximately 20 years to recover (Hsiang and Jina, 2014).

Moreover, the assessment of compound tropical cyclones events and the contemporaneous inclusion of all tropical cyclones hazards (wind speed, rainfall, and storm surge) is missing from most assessments of the cost of climate change. Most studies focus on wind speed or on a single tropical cyclone hazard only (Bertinelli and Strobl, 2013; Collalti and Strobl, 2022; Fang et al., 2014), to measure the effect of TC, thereby neglecting the potentially damaging and even greater than single hazard episodes, impact of compound events (Wahl et al., 2015; Rezapour and Baldock, 2014). A study reveals that that a 20-year period of TC events in the Caribbeans leads to a direct damage of 1.5% of GDP and calculate that in 75% of cases TC rainfall events are the first or secondary cause of TC damage in the Caribbeans (Collalti and Strobl, 2022). Moreover, severe rainfall is often combined with important flood phenomena (Davenport et al., 2021) and both elements contribute to damage. Including all three hazards is also relevant given the projected increase in rainfall and storm surge intensity due to global warming, alongside the minimal rise in wind speed intensity (Bakkensen et al., 2018; Rahmstorf, 2017). However, the combined effect of all three hazards has not been addressed in the literature on the economic impact of tropical cyclones with global subnational coverage.

Next, the literature analyzed the sectoral impacts of tropical cyclones analyzing one single hazard, omitting the simultaneous presence of compound tropical cyclones effects. Hurricane wind speed has an immediate and dramatic damaging effect, mostly on the agriculture and tourism sectors, despite a positive impact on the construction sector (Kunze, 2021; Hsiang, 2010). Storm surges lead to negative economic impacts especially in the agriculture, transportation, and energy sectors (Needham et al., 2015). Non-extreme rainfall levels are beneficial especially to the agricultural (Lesk et al., 2020), manufacturing (Islam and Hyland, 2019), and services (Mytton, 2021) sectors.

Various hypotheses regarding recovery from tropical cyclones have been proposed, with previous studies showing mixed results. For example, some studies find that natural disasters lead to long-run economic growth rates that exceed pre-disaster levels due to the triggering of innovation and the replacement of lost capital with newer and more modern assets, particularly in the construction sector (Cole et al., 2019). Other works suggest that the initial disaster-induced economic shock is absorbed in the long run, with the economy returning to its pre-disaster growth rate. This recovery happens as output levels catch up to pre-disaster levels, driven by an increase in marginal capital (Strobl, 2011; Miranda et al., 2020). Finally, some authors observe that in the long run, economic growth remains permanently below the trajectory that characterized the period before the disaster shock (Hsiang and Jina, 2014).

Here we address these limitations in the literature by constructing a novel dataset that combines subnational data on economic growth for the 1980-2020 period and 1,656 regions around the world with information on all three tropical cyclone-related hazards (wind speed, rainfall, and storm surge). This allows us to assess TC impacts on macroeconomic growth from these three different components globally at a high-level of spatial detail over several years. Complementing our database with sector-level data and socioeconomic characteristics, we can obtain further insights into underlying mechanisms and moderating effects.

We employ spatially modeled tropical cyclone intensity data within a regional fixed-effects panel framework and make use of a natural experiment based on the exogenous variation in TC incidence across time and space (Gagliarducci et al., 2019; Wang et al., 2018), where the treated and control groups are selected by nature. We find that wind speed is the concurrent hazard driving the largest economic growth losses. We examine various aspects of the economic damage caused by tropical cyclones, considering the separate and joint TC hazards impact, sector-specific economic impacts, variations based on economic development and long-term effects.

1.2 Materials and Methods

1.2.1 Data

Our matched database covers the period 1980–2020 and contains 1,656 subnational administrative level 1 units belonging to 97 countries and 14 Caribbeans level 0 (country) units. The database contains information on the dependent variable, Gross Regional Product per capita (GRP PC) growth, the independent variable (tropical cyclones exposure), so as on a set of additional variables. For the national and subnational borders we follow the Global Administrative Areas (GADM) 3.6 database.[2]

We also collected grid level information on yearly mean temperature (°C), total annual precipitation (mm), maximum difference between winter and summer temperature (°C), and day-to-day temperature variability (°C) (Kotz et al., 2021). The source of information is the W5E5D version 2.0 (Cucchi et al., 2020; Lange et al., 2021). This bias-adjusted ERA5 (Hersbach et al., 2020) re-analysis dataset covers the entire globe at 0.5° horizontal and daily temporal resolution. Furthermore, we use data on insurance penetration (life, non-life, and other insurance) from the OECD database[3] and extract societal development information from the Global Data Lab's subnational Human Development and Educational Indexes (Smits and Permanyer, 2019).

[2] https://gadm.org/.

[3] https://www.oecd-ilibrary.org/finance-and-investment/data/oecd-insurance-statistics_ins-data-en.

1.2.2 Gross Regional Product per capita growth

Our dependent variable is the yearly Gross Regional Product per capita (GRP PC) growth rate in 2015 constant USD, computed as the first difference of the logarithm of the Gross Regional Product per capita between the current and previous year. Gross regional product per capita has been obtained from official statistical sources of data (EUROSTAT, OECD regional statistics, national statistical institutes, grey literature, and UN human development reports).

For subnational economic data, we use the DOSE database, a global dataset of reported subnational economic output (Wenz et al., 2023). Due to the lack of subnational economic information in this database for the Caribbean countries, we only consider national Gross Domestic Product (GDP) for the following 14 nations: Antigua and Barbuda, Barbados, Cayman Islands, Dominica, Grenada, Jamaica, Saint Kitts and Nevis, Saint Lucia, Montserrat, Puerto Rico, Turks and Caicos Islands, Trinidad and Tobago, Saint Vincent and the Grenadines, and British Virgin Islands.

1.2.3 Tropical Cyclone Exposure

To generate physical exposure data for the three different types of tropical cyclone damage, we rely on already established models for wind speed (Kunze, 2021), rainfall (Kunze and Strobl, 2024), and storm surge (Kunze and Strobl, 2024). The tropical cyclones raw data originate from the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al., 2010). To calculate a spatial exposure of wind speed for each storm track we use the the well-established Holland (Holland, 1980) analytical wind speed field model as implemented in the CLIMADA model (Aznar-Siguan and Bresch, 2019). The model calculates wind speed maps of maximum sustained wind speed (in (km/h^{-1})) for each tropical cyclone for our sample period. Similarly, for the tropical cyclone rainfall we use the R-CLIPER model (Lonfat et al., 2007) to produce rain field maps containing the total sum of rainfall (in mm) per tropical cyclone. The storm surge model calculates based on wind speed fields, pressure drop fields, bathymetry, and tidal conditions the maximum storm surge-related water level above sea level for each tropical cyclone (in meters). All variables are calculated at a resolution of $0.1°$.

To aggregate the modeled tropical cyclone intensity data to the administrative level 1, we conduct the following routine (see Figure 1.B.8 for an overview): in case of multiple tropical cyclones per grid cell and year we take the maximum value of each of the variables (wind speed, rainfall, and storm surge) described. To aggregate the variables to the spatial level of the sample, we calculate the population weighted mean per administrative level 1 and year. As population weight we use the grid-level population data from the HYDE data set 3.2.1 (Klein Goldewijk et al., 2017). To make them temporal consistent with the other data sources, we interpolate the population to generate yearly observations if only decadal data are available (before 2000). In detail, we calculate the following region-year variables:

$$X_{i,t} = \frac{\sum_{g \in i} w_{g,t-1}}{W_{i,t-1}} * \sum_{g \in i} S(max)_{g,t}, for X = \{Wind\ speed, Rainfall, Storm\ surge\} \quad (1.1)$$

where $w_{g,t-1}$ are the population weights in grid g in period $t-1$. They are divided by the total sum of the population weights $W_{i,t-1}$ in the administrative region i in period $t-1$. This index is then multiplied with the maximum tropical cyclone intensity variables $S(max)_{g,t}$ for $S = \{Wind\ speed, Rainfall, Storm\ surge\}$ in grid g and year t.

The results address potential biases related to population weighting by using population weights at year $t-1$. This well-established approach in the literature (Kunze, 2021) ensures that the exposure measure reflects the population distribution prior to the event. Omitting weights, indeed, could introduce significant measurement issues, potentially attributing exposure to unpopulated areas.

1.2.4 Regression Analyses

We apply a fixed effects panel regressions estimator for the period 1980–2020 with year and region fixed effects and regional specific linear time trends to estimate the impact of tropical cyclone damage on subnational economic growth. The model is the following:

$$\text{GRP PC Growth}_{i,t} = \alpha + \beta_1 \text{Wind speed}_{i,t} + \beta_2 \text{Rainfall}_{i,t} + \beta_3 \text{Rainfall}^2_{i,t} + \beta_4 \text{Storm surge}_{i,t} + \gamma' X_{i,t} + \delta_i + \mu_t + \eta_{i \cdot t} + \epsilon_{i,t} \tag{1.2}$$

Where $GRP\ PC\ Growth_{i,t}$ refers to the Gross Regional Product per capita growth rate in region *i* and year *t*. Wind speed$_{i,t}$, rainfall$_{i,t}$ and storm surge$_{i,t}$ are the regional population-weighted tropical cyclone hazard intensity measures in region *i* and year *t*, aggregated across grid cells by selecting the maximum magnitude. δ, μ and η are, respectively, the year fixed effects, region fixed effects and regional-specific linear time trends. X represents a vector of temperature and precipitation related controls at the regional level. We make use of Conley standard errors with a 200-km cut-off. This methodology allows to account for similarity in characteristics across subnational units within this distance. The 200-km distance was chosen as it represents the 99th percentile of the maximum wind radius, where tropical cyclone damage is expected to be most severe. This methodology ensures similarity in characteristics across subnational units within this distance (Wu et al., 2018). The results stemming from the baseline regression are reported in Table 1.A.1.

The identification strategy relies on the use of fixed effects and on the exogenous nature of tropical cyclone incidence across years, as well as on the randomness of their paths (Wang et al., 2018). Our fixed effects panel approach incorporates both time and geographic fixed effects: year fixed effects control for year-specific shocks common to all regions, while geographic fixed effects account for region-specific, time-invariant characteristics. Tropical cyclones serve as exogenous events that create a natural experiment setup, allowing us to define treated and control groups based on their occurrence.

1.2.5 Heterogeneity Analyses

To further analyze heterogeneous responses to tropical cyclone hazards, we conduct several specifications, including sectoral impacts, long-run growth, and economic development effects.

First, we test for sectoral impacts. We replace the dependent variable by agriculture, manufacturing, and services GRP PC growth: all other variables remain as defined in equation 1.2. In a further specification we investigate how TC proxies affect economic growth depending on different values of Z, which consists of a set of economic (insurance penetration and income) (Fig. 1.3) and societal development (Human Development Index and Educational Index) (1.C.4) variables. All variables in Z are usually regional fixed-over-time period means (for insurance penetration, Human Development Index, and Educational Index) or median (for income) information. The baseline model terms (TC independent variable and controls) in equation 1.2 have been inserted both separately and with the interaction with Z.

Next, we present the cumulative growth distributed-lag model (see Fig. 1.4 and Equation 1.3), which includes both the contemporaneous and lagged impacts up to 10 years. Both the independent and the control variables are lagged. Given the use of variables which are not first-differenced, here we make use of a growth effect model. Despite its less parsimonious nature (Kotz et al., 2021) in considering any change in growth as permanent (Kotz et al., 2023), this is the most common type of growth model used in the natural disasters literature (see Hsiang and Jina, 2014; Berlemann and Wenzel, 2018; Kunze, 2021).

$$\begin{aligned}\text{Cumulative PC GRP Growth}_{i,t} = \alpha + \sum_{k=0}^{10} \beta_1^k \text{Wind}_{i,t-k} + \sum_{k=0}^{10} \beta_2^k \text{Rainfall}_{i,t-k} + \sum_{k=0}^{10} \beta_3^k \text{Rainfall}_{i,t-k}^2 \\ + \sum_{k=0}^{10} \beta_4^k \text{Surge}_{i,t-k} + \sum_{k=0}^{10} \gamma'^k X_{i,t-k} + \delta_i + \mu_t + \eta_{i \cdot t} + \epsilon_{i,t}\end{aligned} \tag{1.3}$$

To conclude, we control cumulative impacts of tropical cyclones, as Deryugina (2017), in order to test if a greater total exposure to TC hazards reduces the marginal impact on economic growth (Figure 1.C.5). Sen et al. (2023) suggest that there is a diminishing marginal impact of cyclones on economic activity, meaning that regions with frequent past exposure to natural disasters, such as cyclones, become more adapted over time and are less likely to be significantly affected by future events. This insight motivated to account for whether regions with a history of frequent cyclone occurrences might exhibit lower sensitivity to new events.

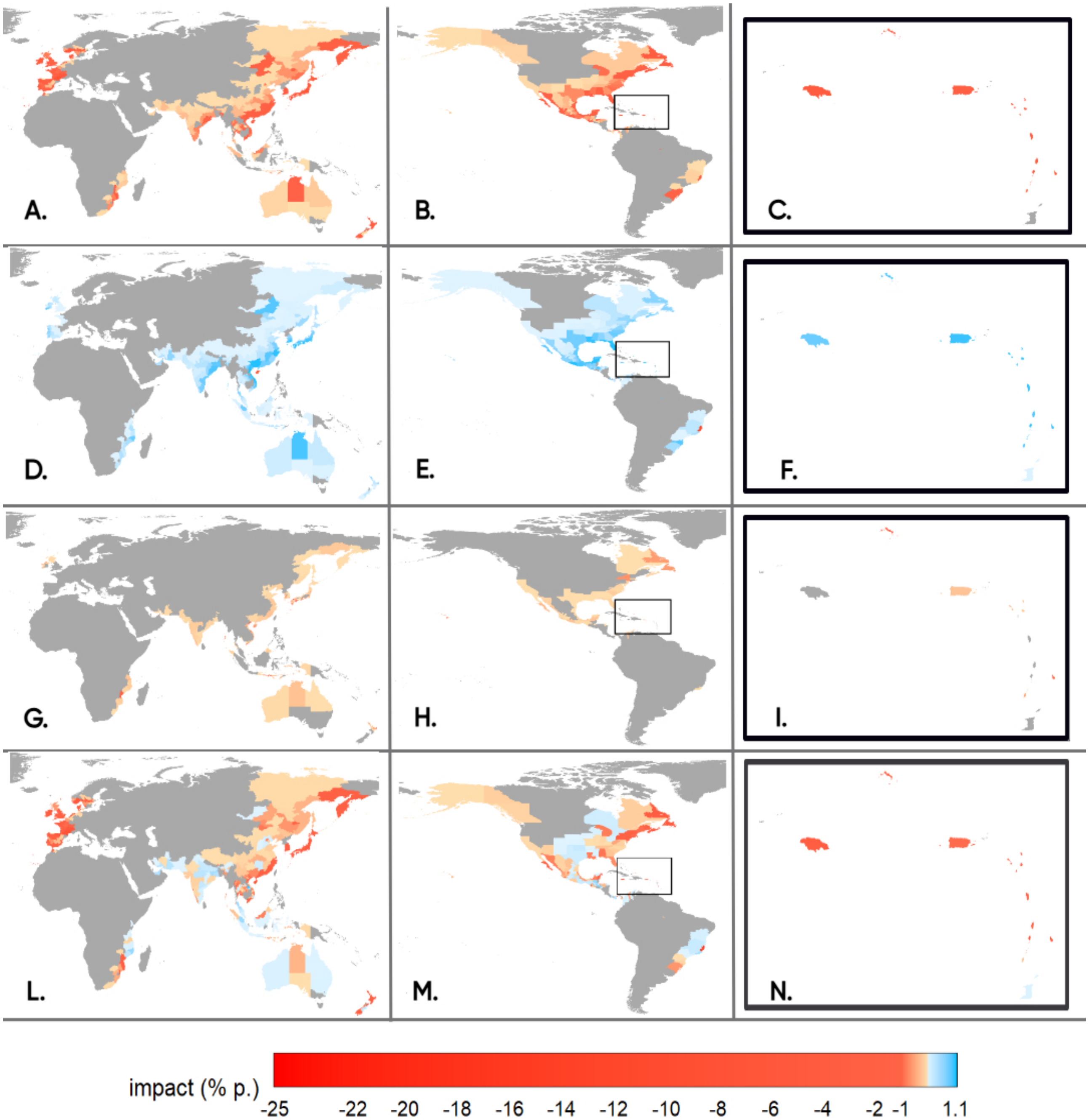
1.3 Results

1.3.1 Wind speed creates the largest economic growth damage

Figure 1.1 presents the median separate concurring hazard (panels A-I) and the median additive impact of the three median hazards on GRP PC growth (panels L-N).

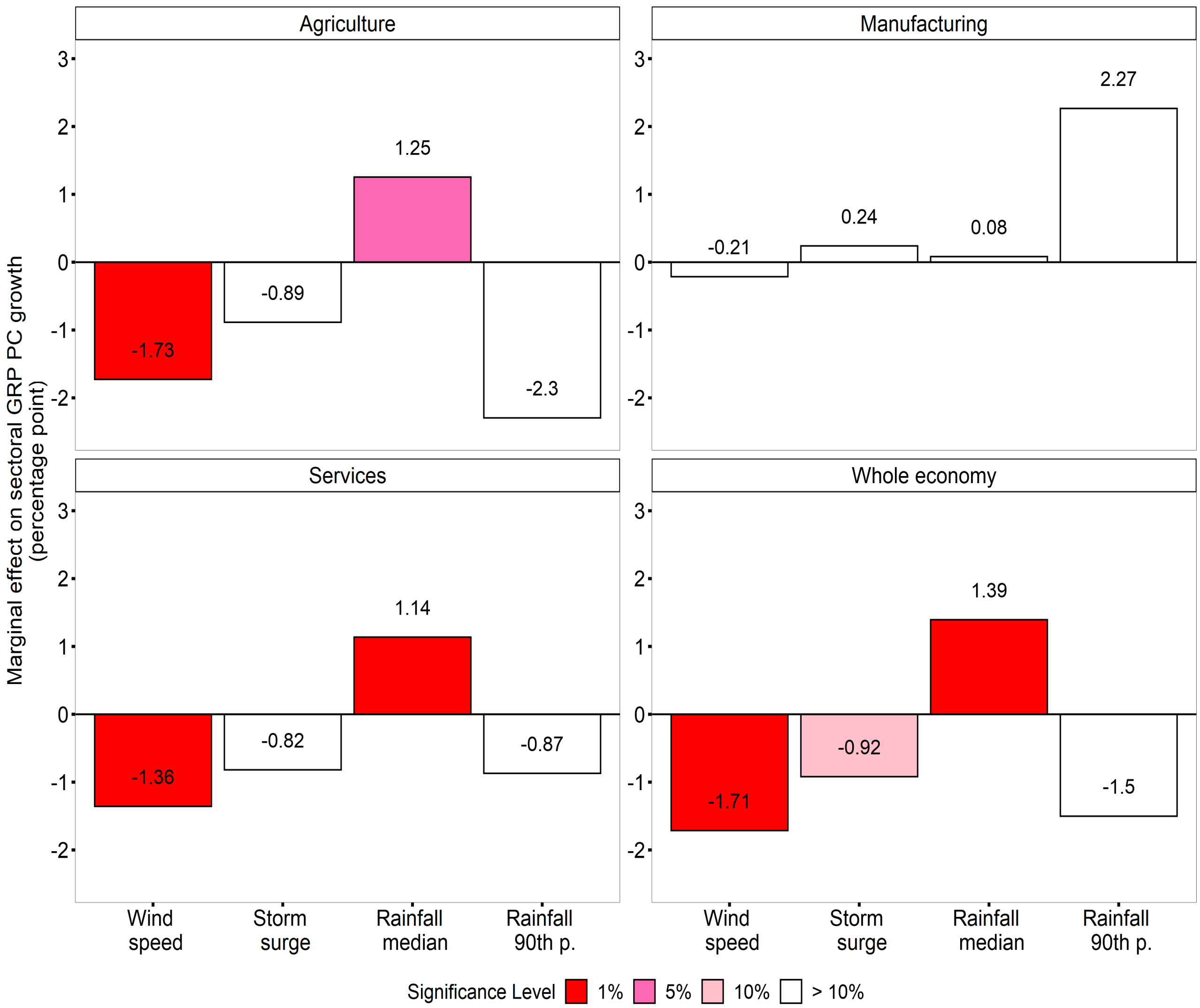
We find that wind speed is the most destructive hazard to economic growth globally. The most heavily impacted by TC hazards areas are North and Central America, the Caribbeans, Southeast Asia, and several Pacific islands. Areas that are less adversely affected by tropical cyclones, or even benefit from them, are typically inland rather than coastal. This is because they gain significant advantages from small TC rainfall levels, while experiencing negligible negative wind speed impacts and no storm surge. The additive tropical cyclones hazards median shocks can generate contractions in economic growth even up to 18% points, while separate median TC hazards losses does not go beyond 11% points for wind speed, 8.7% points for rainfall and 2.4% points for storm surge (Table 1.B.6). In Appendix Figure 1.C.2 shows the 90th percentile TC impact on GRP PC growth separately for wind speed, rainfall, and storm surge and the compound TC 90th percentile additive impact on regional economic growth. In general, an intensification of the 90th percentile separate and additive TC impacts is evident, compared to the median shocks case. For the 90th percentile scenario, the combined shocks from tropical cyclone hazards can lead to economic growth losses of up to 25% points. In contrast, the 90th percentile negative individual TC hazards impacts do not exceed 11% points for wind speed, 19% points for rainfall, and 4.6% points for storm surge (Table 1.B.6). However, there is considerable uncertainty surrounding the 90th percentile shocks related to rainfall (Figure 1.C.1). See Table 1.B.6 for visualizing the range of impacts for the separate and additive impacts on GRP PC growth, for both the median and 90th percentile shocks cases.

Figure 1.1: Impact of tropical cyclone hazards on GRP PC growth (separate and additive median TC hazards impacts)



This figure depicts the percentage points impacts on GRP PC growth of the separate median wind speed (panels A, B and C), rainfall (D, E and F) and storm surge events (G, H and I) and the additive impacts of the three median hazards shocks (L, M and N) per each subnational unit. Focus on the Eastern hemisphere is in figures A, D, G and L. Focus on the Western hemisphere is in figures B, E, H and M. Figures C, F, I and N zoom on the Caribbean islands. A median region-level TC intensity episode is defined as the median intensity shock, for each region, over the 1980-2020 period. Wind speed$_{i,t}$, rainfall$_{i,t}$ and storm surge$_{i,t}$ are the regional population-weighted tropical cyclone hazard intensity measures in region i and year t, aggregated across grid cells by selecting the maximum magnitude. Regions never experiencing a single TC hazard (panels A-I) or, tropical cyclones, in general (panels L-N) are coloured in grey.

Figure 1.2: Impact of TCs hazards on sectoral GRP PC growth



The figure represents the change in sector and whole economy GRP PC growth with respect to 1 s.d change in TC concurring hazards. To obtain sector-specific results (agriculture, manufacturing and services), three different regressions were run, substituting the GRP PC dependent variables with the respective sector-related growth variables: agriculture GRP PC growth, manufacturing GRP PC growth and services GRP PC growth. The analysis has been restricted to regions presenting information for all three sectors. Wind speed$_{i,t}$, rainfall$_{i,t}$ and storm surge$_{i,t}$ are the regional population-weighted tropical cyclone hazard intensity measures in region *i* and year *t*, aggregated across grid cells by selecting the maximum magnitude. The standard deviations of wind speed, rainfall, and storm surge, considering positive values only, are respectively equal to 43.7 km/h, 39.1 mm and 0.4 m.

1.3.2 Wind speed is the most harmful hazard across economic sectors

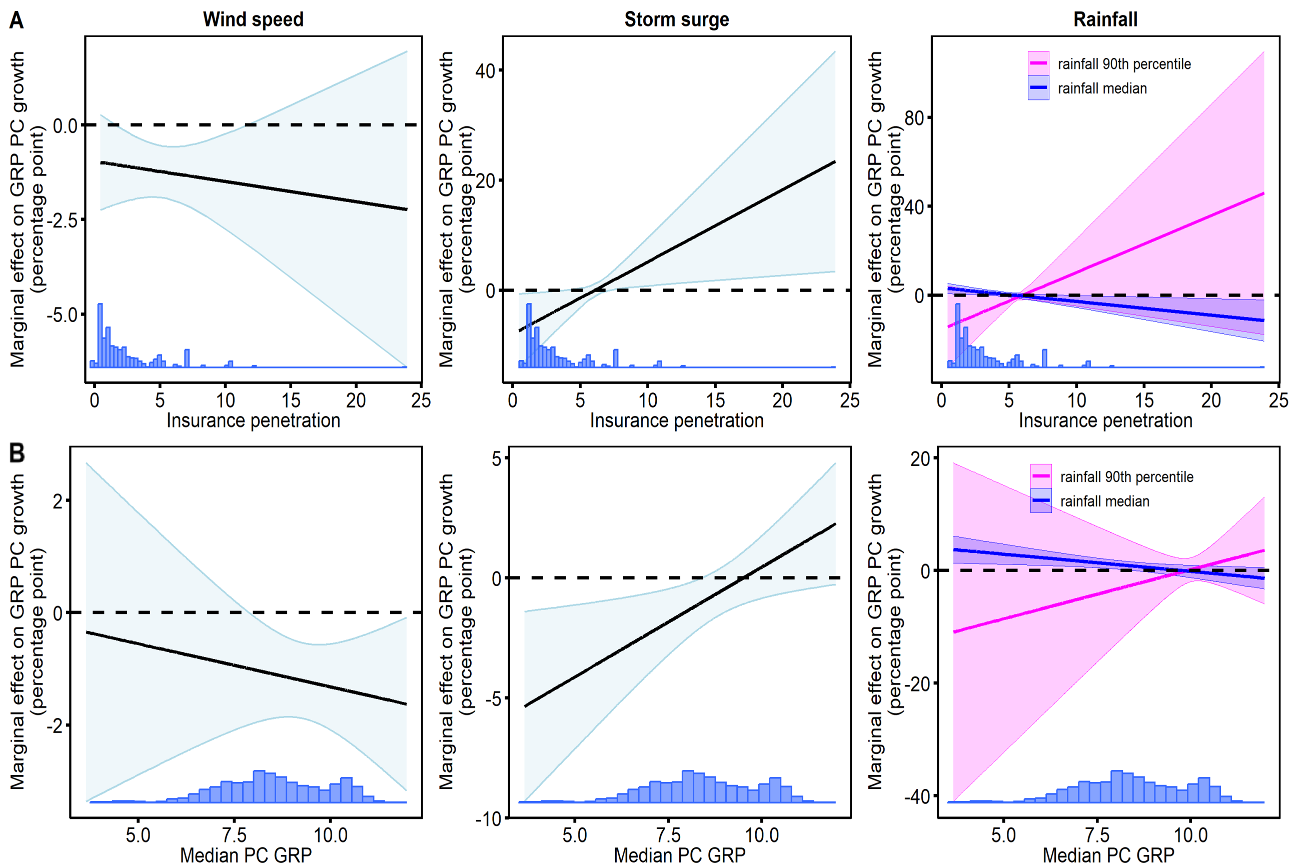
In terms of sectoral heterogeneity (Figure 1.2), wind is the TC hazard leveraging the greatest negative marginal effect to the whole economy (-1.71% points) and to the the agricultural (-1.73% points) and services (-1.36% points) GRP PC growth, given 1 standard deviation (s.d) increase in TC shock magnitude. The agriculture sector is also particularly harmed by extreme rainfall (given 1 s.d increase in rainfall at the 90th percentile of the distribution there is a reduction of 2.3% points in GRP PC growth). Then, considering 1 median s.d TC rainfall shock, this exerts a positive and significant impact on agriculture (1.25% points increase in economic growth rate). As for the manufacturing sector, none of the TC proxies resulted to be statistically significant, and this is line with the TC literature which highlights the positive impact of TCs in the construction sector but does not discover any significant impact for the manufacturing one (Kunze, 2021). Results for coastal regions only are reported in Figure 1.C.3.

1.3.3 Poor regions benefit the most from small levels of TC rainfall

Next, we study how the marginal effects of TC hazards on economic growth is influenced by insurance penetration coverage (A) and logarithm of median GRP PC (B) (Figure 1.3).

We conclude that the marginal impact of small-intensity rainfall (at the median value of tropical cyclone rainfall distribution) for low development level regions is positive and decreases with development level. As for the marginal effect of the 90th percentile of rainfall, this inversely mirrors the effect of the median one: for low-development regions, there is a negative marginal effect on economic growth that attenuates with increased development. However, there is significant uncertainty surrounding this variable, preventing us from drawing a definitive conclusion. Then, Figure 1.C.6 presents the same analysis but uses the initial level of GRP per capita from the first available year in the database for each region. The results appear to be highly similar to those in Figure 1.3. Figure 1.C.4 repeats the marginal effect of TC hazards on economic growth exercise conditional on two societal development indicators: Human Development Indicator (HDI) (A) and Education Indicator (EI) (B). The marginal effects of TC hazards conditional on societal develop-

Figure 1.3: Impact of TC on GRP PC growth mediated by economic variables coverage



The marginal effect of the interaction between each concurring hazard (wind speed, rainfall, and storm surge) and two economic variables, insurance penetration (panel A) and median PC GRP (panel B) is the focus of this figure. 90% confidence bands are used. Insurance penetration and median GRP PC are regional specific variables which are fixed over time. Y axis data information is the percentage points change in the dependent variable GRP PC growth. Concurring hazard variables have been scaled by their standard deviation. Wind speed$_{i,t}$, rainfall$_{i,t}$ and storm surge$_{i,t}$ are the regional population-weighted tropical cyclone hazard intensity measures in region i and year t, aggregated across grid cells by selecting the maximum magnitude. In addition, 1.C.6 replicates the above indicated analysis interacting the TC variables by the initial level of GRP PC from the first available year in the database for each region.

ment are extremely similar to the economic development results, suggesting a possible spurious correlation due to the strong relationship between societal and economic development.

1.3.4 Long recovery time after wind speed events

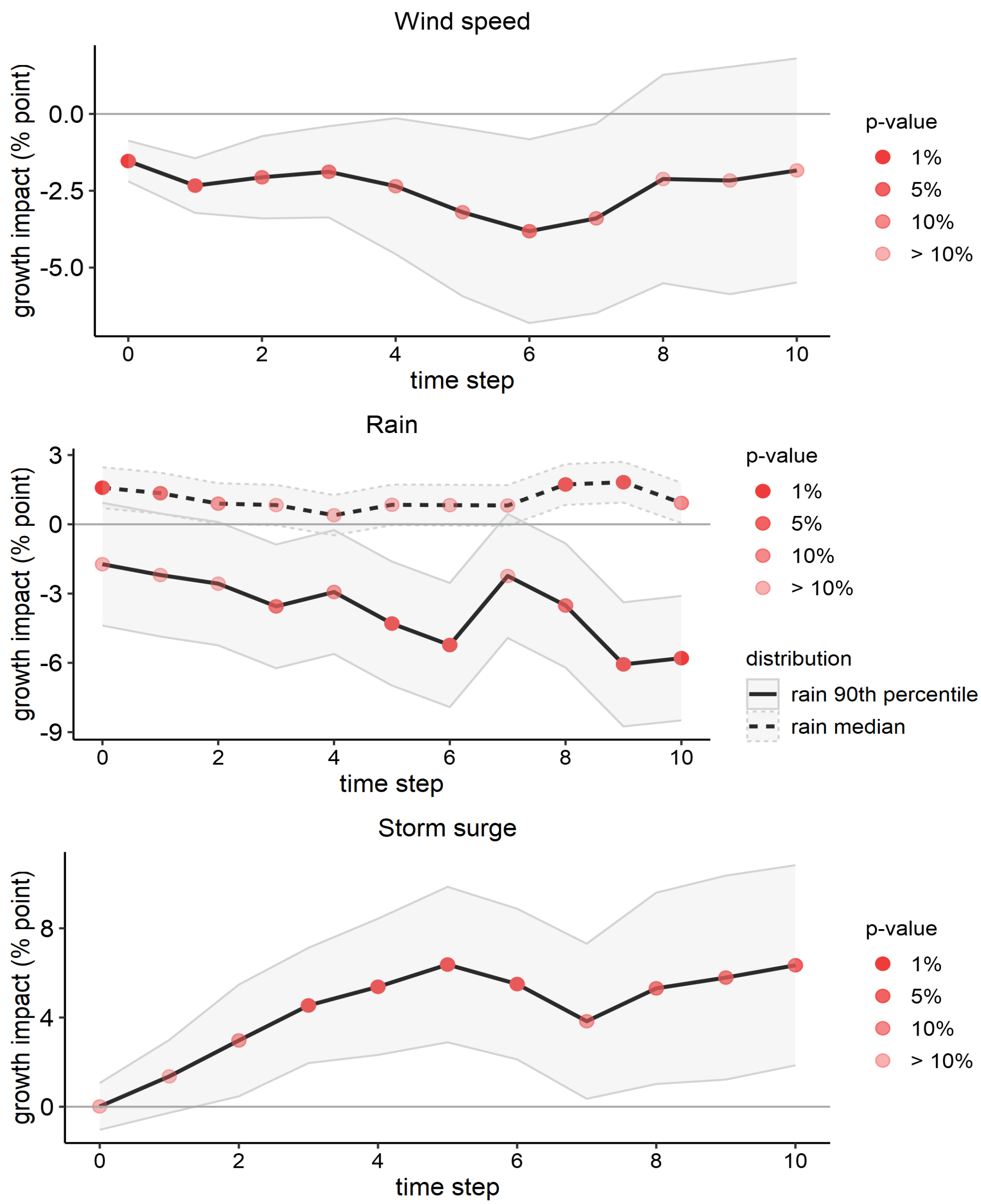
Next, we asses the long-run economic growth impacts (over a 10-year period) of tropical cyclones through the use of a cumulative growth distributed-lag model (Figure 1.4).

After 10 years, the economy has not fully recovered from the impacts of wind speed, though it is close to doing so. A no recovery hypothesis is corroborated for TC wind speed and the 90th percentile of TC rainfall, while a permanent positive cumulative growth is detected for median TC rainfall. For TC surge, the "build back better" hypothesis would be supported, but the very low statistical significance of the coefficients hinders us from making definitive conclusions about this hazard.

1.3.5 Robustness checks

A set of robustness checks for the whole economy impact of TC (see marginal effects results in Figure 1.C.1) are contained in the "robustness checks" subsection of the Appendix (Figures 1.D.1-1.D.4). Figure 1.D.1 contains different TC hazards specifications and TC variables weighting models. Figure 1.D.2 investigates alternative models where there are different controls, an alternative dependent variable specification and a rainfall threshold set to 100mm. Then, Figure 1.D.3 explores alternative standard error models and Figure 1.D.4 different database sub-samples. Wind speed appears to be consistently significant at least at 10% levels in all Figure 1.D.1 specifications, in half of Figure 1.D.2 models, in the "regional standard error" specification in Figure 1.D.3 and in all database sub-samples specifications in Figure 1.D.4. Wind speed exhibits a great statistical robustness to model variations, compared to rainfall and storm surge.

Figure 1.4: Cumulative growth distributed lag model - 10 lags



Distributed lag model with 10-year lags. Marginal effects of TC concurring hazards on economic growth are cumulative over time. All control variables have been lagged with same number of lags as the concurring hazards (10-year lags). Fixed effects model is used. All other baseline regressions features are maintained. Wind speed$_{i,t}$, rainfall$_{i,t}$ and storm surge$_{i,t}$ are the regional population-weighted tropical cyclone hazard intensity measures in region i and year t, aggregated across grid cells by selecting the maximum magnitude.

1.4 Conclusions

Overall, this work has contributed to a better understanding of the global impacts of tropical cyclones (TCs) on economic growth at subnational level with a global coverage, while also simultaneously considering the three main compound aspects of TCs (wind speed, rainfall, and storm surge). First, we find that, despite wind speed being the most destructive hazard to global economic growth in our analysis, failing to account for the combined impacts of rainfall and storm surge can lead to an underestimation or overestimation of the overall effect of tropical cyclones on economic growth. Second, when considering sectoral GRP growth, we find that wind speed is the most damaging hazard to agricultural and services GRP PC growth. Third, regions with a low level of economic development are those benefiting the most from median levels of TC rainfall. Finally, we show that wind speed exhibits long recovery patterns. The findings of this study align with existing literature on the economic impacts of tropical cyclones, particularly reinforcing the evidence that wind speed is a major driver of short and long-term economic damage (Bertinelli and Strobl, 2013; Hsiang and Jina, 2014).

Our research reveal new findings in the literature by demonstrating that wind speed causes more severe damage compared to rainfall and storm surge and that this effect is consistent both in the whole economy and in the different economic sectors. Our study confirms that across all TC hazards the agricultural sector suffers the most damage from tropical cyclones, while the manufacturing sector shows no significant impact, aligning with the wind speed sectoral impacts literature (Kunze, 2021). Considering all concurring hazards to quantify tropical cyclones damage in the analysis proved to be crucial. As a novel contribution compared to the literature including only extreme levels of tropical cyclone precipitation (Collalti and Strobl, 2022), our study reveals that small levels of rainfall can mitigate some of the devastating effects of wind speed and storm surge, particularly by benefiting agriculture.

We find that a one standard deviation increase in wind speed reduces economic growth by 1.71 percentage points. Compared to previous researches analyzing wind speed in isolation at the country and subnational levels, our estimates are slightly larger. At the subnational level, Strobl

(2012) estimates that, on average, a hurricane strike in Central America and the Caribbean leads to a reduction in output growth of at least 0.83 percentage points. Similarly, Bertinelli and Strobl (2013) conduct a local-level analysis and find that an average hurricane decreases income growth by 1.5%. At the country level, Strobl (2011) reports that hurricanes in the U.S. have an immediate negative impact on county-level per capita growth, reducing it by approximately 0.8 percentage points. The partially larger magnitude of our estimates may be attributed to the higher spatial resolution of our dataset, which allows for a more detailed subnational analysis compared to a country level one and to the fact that our sample encompasses both developed and lower-income areas, capturing a broader range of economic vulnerabilities to tropical cyclone hazards.

Nevertheless, this study faces some limitations. The lack of comprehensive DOSE data in key regions, such as Africa, South America and Asia-Pacific, hinders a fully global analysis and limits the precision of economic impact estimates for these areas. Moreover, this analysis focuses solely on direct economic impacts, without accounting for indirect impacts regarding non-market effects, such as income inequality, educational attainment, and healthcare access, as these dimensions are essential for understanding long-term resilience and recovery capacity (Sen et al., 2023).

Future research should focus on crucial areas like the role of early warning systems and preparedness measures in reducing economic damage and speeding up recovery. It would also be valuable to examine the effectiveness of specific adaptation strategies, such as infrastructure development and disaster risk reduction programs, in mitigating TC impacts. Another promising avenue for future research would be to examine the role of trade openness as a potential adaptation mechanism to tropical cyclone hazards. Integrating trade openness as an interaction term in our analysis could help assess whether greater trade integration mitigates the economic impacts of extreme weather events by facilitating access to essential goods, infrastructure, and post-disaster recovery resources. Finally, exploring whether higher trade penetration fosters the transfer of disaster-management and resilience technologies could provide valuable insights into the broader role of trade in enhancing economic resilience to climate shocks.

Appendix

1.A Main regression model

Table 1.A.1: Baseline results: gross regional product per capita (GRP PC) growth

	(1) GRP PC growth
Wind speed	-1.71*** (0.38)
Rainfall	2.15** (0.92)
Rainfall squared	-0.99 (0.66)
Storm surge	-0.92* (0.52)
Temperature mean	1.69*** (0.51)
Temperature mean squared	-0.09*** (0.02)
Precipitation tot	1.1e-03 (1.7e-03)
Precipitation tot squared	9.71e-08 (3.45e-7)
Temperature tstd	11.40 *** (0.94)
Temperature tstd × temperature seasonal difference	0.22*** (0.02)
Structural change	-5.51*** (1.76)
Adjusted R^2	0.19
Observations	39,013
Fixed effects included	ID, year
Slope heterogeneity included	trend × ID

Notes: Fixed effects panel regression baseline results. Conley standard errors (200 km cutoff) are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Gross regional product per capita growth is expressed as percentage point change. Wind speed, rainfall, and storm surge represents region-year maximum tropical cyclone concurring hazards exposure intensity and are expressed as a change in TC proxies standard deviation. The control variables are yearly mean temperature (°C), total annual precipitation (mm), max. difference between winter and summer temperature (°C), and day-to-day temperature variability (°C). Structchange is a dummy variable which takes value 1 when a region-year data point experiences the introduction of a novel raw data source. The standard deviations of wind speed, rainfall, and storm surge, considering positive values only, are respectively equal to 43.7 km/h, 39.1 mm and 0.4 m.

1.B Descriptive statistics and methods

This appendix section presents a series of descriptive statistics and of database-related statistical information plots. In addition, a figure regarding the data collection process and method is present as well.

As for the descriptive statistics tables, Table 1.B.1 is a descriptive statistics table presenting the final database raw data. Similarly, Table 1.B.2 presents the descriptive statistics for the TC concurring hazard variables, both unscaled and scaled by standard deviation. Notably, all results in this study are expressed in terms of a 1 standard deviation increase in these concurring hazards. This table illustrates descriptive statistics information for positive tropical cyclone intensity values only. Table 1.B.3 follows. It indicates the TC wind speed, rainfall, and storm surge distribution values, with special attention to extreme distribution numbers (min, median, 75%, 90%, 99% percentiles and max). Table 1.B.4 (upper part) reports one of the Bloemendaal et al. (2021) comprehensive hurricane category classification, where also hurricane rainfall and storm surge are categorized into the original Saffir-Simpson Hurricane Wind Scale. The lower part of 1.B.4 shows the percentage of positive TC intensity values belonging to our dataset that falls into each Bloemendaal et al. (2021) TC category. Finally, Table 1.B.5 shows the frequency (in absolute and% terms) for each combination of TC hazards.

Considering now the database information figures, first of all, Fig. 1.B.1 represents a Kernel density plot for the TC wind speed, TC rainfall and storm surge. Only positive tropical cyclone intensity values have been considered in the computation. Gaussian Kernel and rule-of-thumb bandwidth are used. Secondly, Fig. 1.B.2 is a Kernel density plot for GRP PC growth. Next, Fig. 1.B.3 is a Pearson correlation heatmap considering the the dependent variable GRP PC growth, the independent variable TC (containing the three concurring hazards and scaled in standard deviation), the climatic control variables and GRP PC information. Figures 1.B.4-1.B.6 are mean tropical cyclones exposure figures which investigate the mean regional exposure over the dataset period for each TC hazard. Tropical cyclones wind speed, rainfall, and storm surge's values equal zero are also considered in the computation of the mean TC magnitude for each hazard. Subsequently,

Fig. 1.B.7 describes the marginal effects of TC rainfall on economic growth at various levels of rainfall shocks. Indeed in our regression analysis we include both linear and quadratic terms for TC rainfall. Additional information on the minimum and maximum marginal effect, median and 90th percentile rainfall and value at which the marginal effect is equal to zero is reported in figure caption.

Then, Fig. 1.B.8 is the figure describing how the entire data collection process has been performed in order to obtain TC wind speed, rainfall, and storm surge information. Relevant methodological choices are highlighted (concerning the model from where data was extracted, yearly TC-grid cell aggregation, region-year aggregation from grid cells information and weighting typology).

Finally, Fig. 1.B.9 illustrates the number of years for which country-level information is available in the DOSE database for the period 1980–2020.

Table 1.B.1: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
GRP PC growth (%)	39,013	2.85	15.79	−267.12	212.81
Wind speed (km/h^{-1})	39,013	5.43	21.13	0.00	276.38
Rainfall (mm)	39,013	3.94	15.93	0.00	657.19
Storm surge (m)	39,013	0.01	0.05	0.00	2.18
Temperature mean (°C)	39,013	15.07	8.02	−13.94	29.51
Precipitation tot (mm)	39,013	1,155.47	744.86	0.19	6,285.06
Temperature tstd (°C)	39,013	2.38	1.20	0.28	6.15
Temperature seasonal difference (°C)	39,013	16.92	10.66	0.41	58.58
Structural change	39,013	0.04	0.19	0.00	1.00
GRP PC (USD)	41,667	13,504.10	17,587.60	7.70	189,345.80
Ever exposed to TC	217,648	0.50	0.50	0.00	1.00
Agriculture GRP PC growth (%)	30,116	0.70	21.00	−453.30	812.40
Manufacturing GRP PC growth (%)	30,205	3.00	18.20	−363.00	322.20
Services GRP PC growth (%)	30,165	3.60	13.30	−267.60	242.10
Insurance penetration (%)	93,590	2.90	2.60	0.40	23.90
Mean GRP PC (USD)	115,920	12,392.80	16,674.60	121.30	156,168.40
Median GRP PC (USD)	115,920	12,501.20	17,136.50	38.40	159,131.90

Table 1.B.2: TC proxies descriptive statistics - nonzero values only

Unscaled variables					
Statistic	N	Mean	St. Dev.	Min	Max
Wind speed (km/h^{-1})	20,333	49.3	43.7	0.0	342.1
Rainfall (mm)	31,765	28.6	39.1	0.0	657.2
Storm surge (m)	6,937	0.2	0.4	0.0	6.5
Variables scaled by their standard deviations					
Statistic	N	Mean	St. Dev.	Min	Max
Wind speed (km/h^{-1})	20,333	1.2	1.0	0.0	8.1
Rainfall (mm)	31,765	0.7	1.0	0.0	16.3
Storm surge (m)	6,937	0.6	1.0	0.0	18.0

Table 1.B.3: Hazards distribution and category thresholds for each hazard

Statistic	Min	50%	75%	90%	99%	Max
Wind speed (km/h^{-1})	0.00	40.44	73.76	108.23	183.31	342.10
Rainfall (mm)	0.00	15.40	38.60	74.25	174.46	657.20
Storm surge (m)	0.00	0.08	0.22	0.52	1.84	6.50

Table 1.B.4: Category thresholds for each hazard

	Category thresholds quantities as in Bloemendaal et al. (2021)		
Category	Wind speed (km/h^{-1})	Rainfall (mm)	Storm surge (m)
5	$\geq$252	$\geq$750	$\geq$4.00
4	209-251	589-749	3.15-3.99
3	178-208	426-588	2.35-3.14
2	154-177	263-425	1.55-2.34
1	119-153	100-262	0.75-1.54
0	$\leq$118	$\leq$100	$\leq$0.75
Event category frequency in our database (%) (nonzero events only)			
Category	Wind speed (km/h)	Rainfall (mm)	Storm surge (m)
5	0.00%	0.00%	0.03%
4	0.39%	0.025%	0%
3	0.65%	0.01%	0.26%
2	1.18%	0.21%	1.64%
1	4.82%	5.08%	4.92%
0	92.62%	94.66%	93.12%

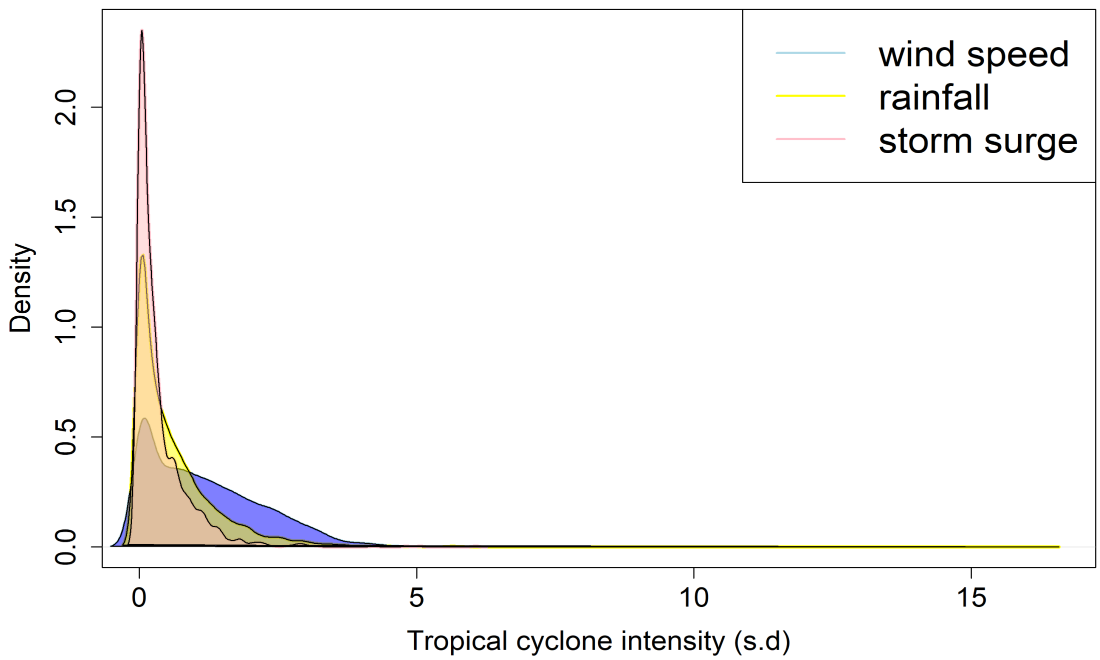
Table 1.B.5: Combinations of hazards events (economic TC-growth matched database) frequency

	N	%
Only wind speed	241	3.89%
Only rainfall	1742	28.09%
Only storm surge	2	0.03%
Only wind speed and rainfall	2599	41.91%
Only wind speed and storm surge	0	0%
Only rainfall and storm surge	179	2.88%
All (wind speed, rainfall, and storm surge)	1438	23.18%
At least 1 hazard	6201	100%

Table 1.B.6: Impact of TC hazards on economic growth (separate and additive impact)

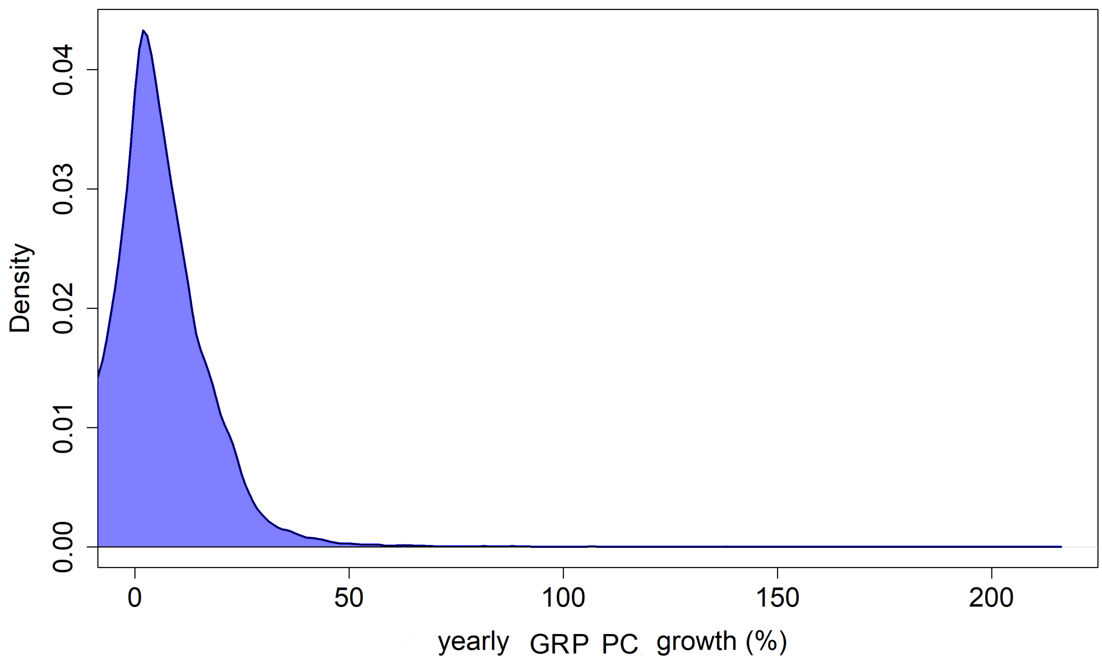
	Median impacts		
Impact type	Hazard	Min	Max
Separate	Wind speed	-11% p.	0% p.
Separate	Rainfall	-8.7% p.	1.2% p.
Separate	Storm surge	-2.4% p.	0% p.
Additive	Wind speed, rainfall, and storm surge	-18% p.	1.1% p.
	90th percentile impacts		
Impact type	Hazard	Min	Max
Separate	Wind speed	-11% p.	0% p.
Separate	Rainfall	-19% p.	1.2% p.
Separate	Storm surge	-4.6% p.	0% p.
Additive	Wind speed, rainfall, and storm surge	-25% p.	1.1% p.

Figure 1.B.1: Kernel density plot



Kernel density plot with Gaussian Kernel and rule-of-thumb bandwidth. Density is computed on TC variables excluding zero values and on the TC - GRP PC growth matched database.

Figure 1.B.2: Kernel density plot - PC Gross Regional Product Growth



Kernel density plot with Gaussian Kernel and rule-of-thumb bandwidth. Density is computed on the TC - GRP PC growth matched database.

Figure 1.B.3: Correlation heatmap for TCs and climatic variables

Figure 1.B.4: Average wind speed regional exposure

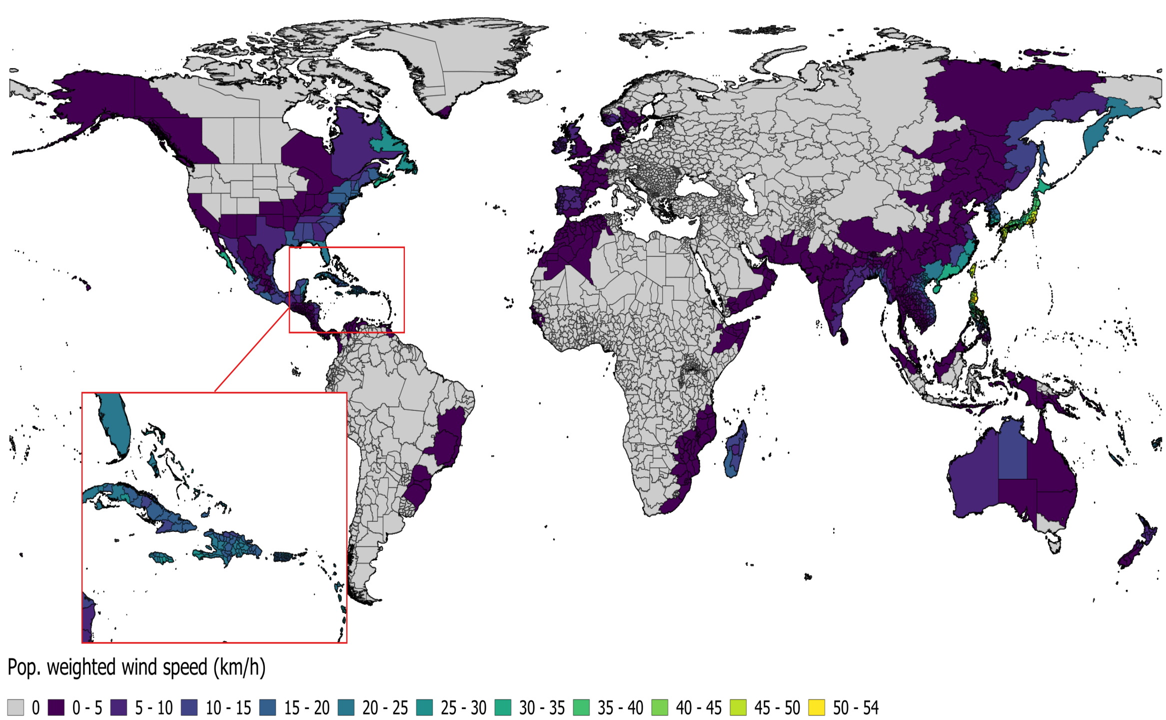


Figure 1.B.5: Average rainfall regional exposure

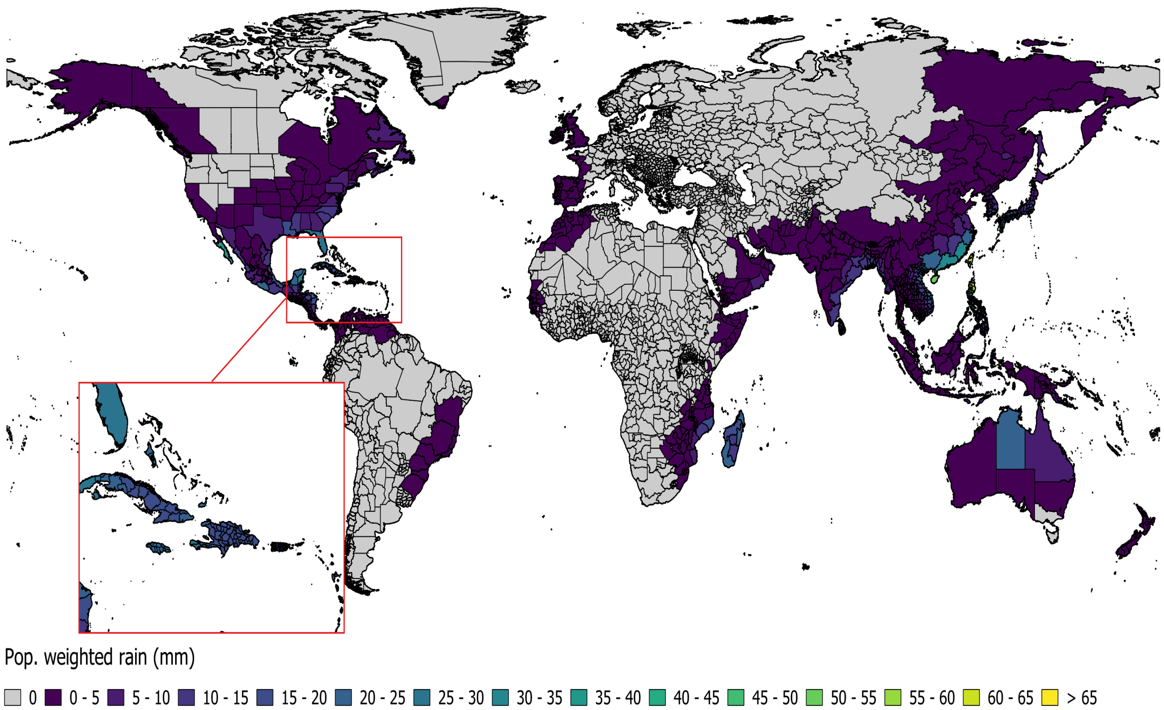


Figure 1.B.6: Average storm surge regional exposure

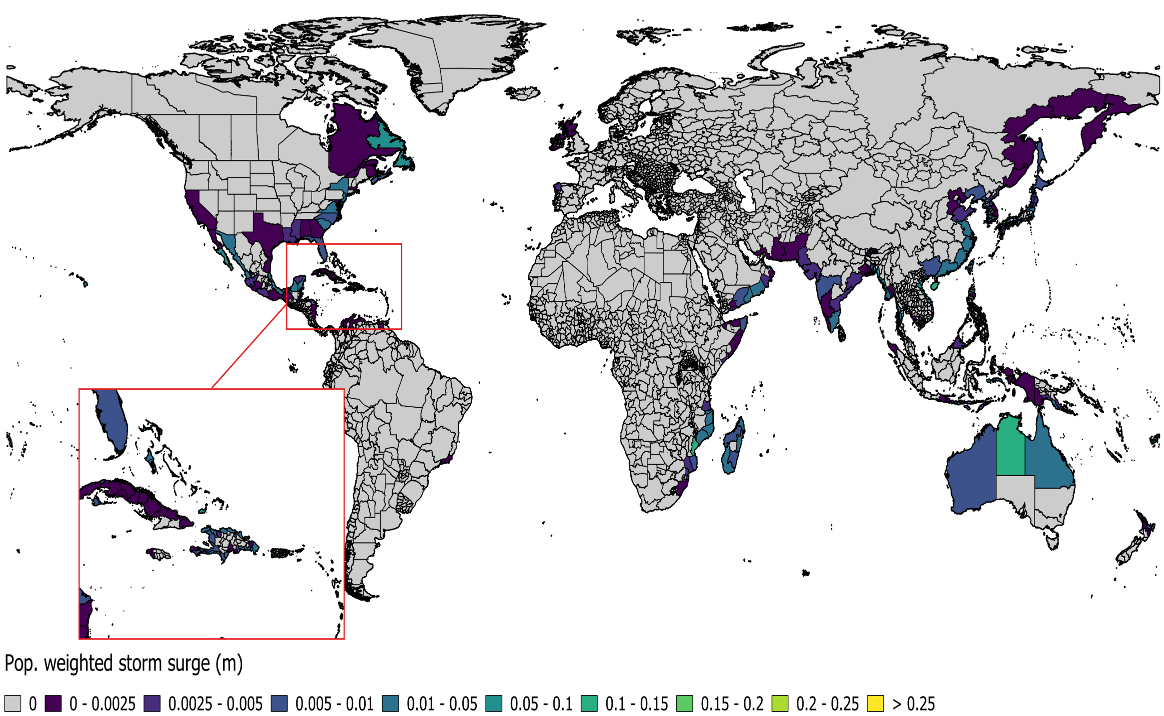
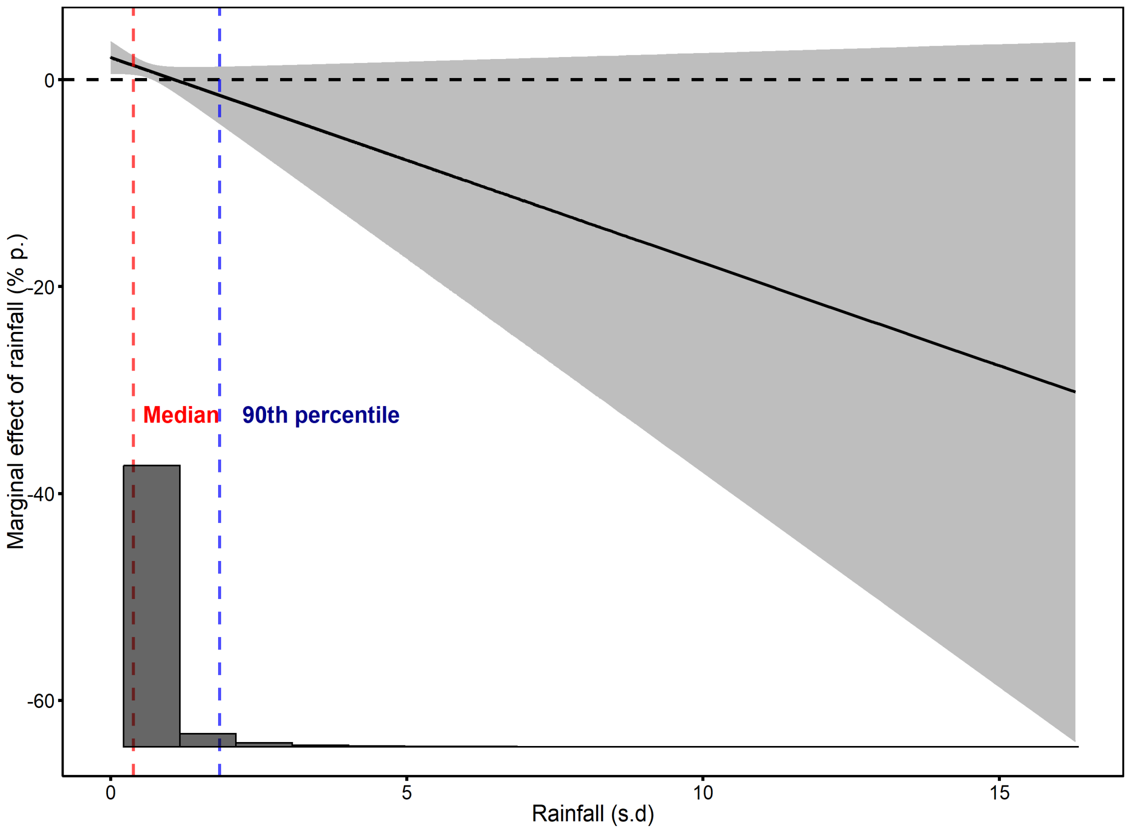


Figure 1.B.7: Impact of rainfall on GRP PC at various rainfall s.d shocks intensities



The marginal effect of TC s.d rainfall variations on economic growth is positive up to 1.08 mm. The median rainfall value (red dotted vertical line) corresponds to 0.38mm, while the 90th percentile (blue dotted line) to 1.84 mm. The marginal effect ranges between 2.15 (% p.) and -30.19 (% p.). 90% confidence bands are represented in gray. Dark gray histogram is a TC rainfall frequency representation (bin width equal 1). 92.69% of TC rainfall observations are below the median. Only 1.46% of rainfall data is above the 90th percentile. Finally, 96.84% of rainfall observations is below 1.08 mm.

Figure 1.B.8: Data collection methodological flow

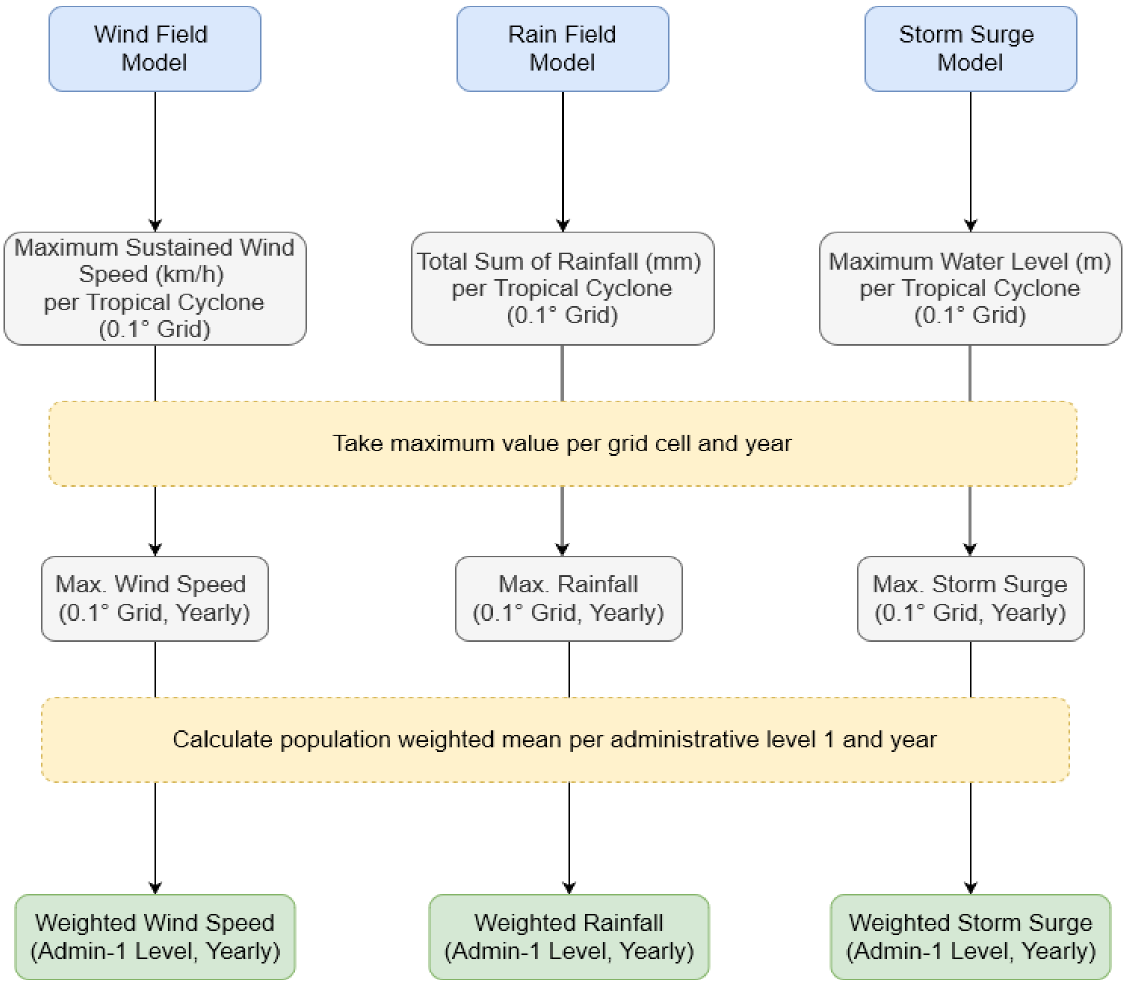
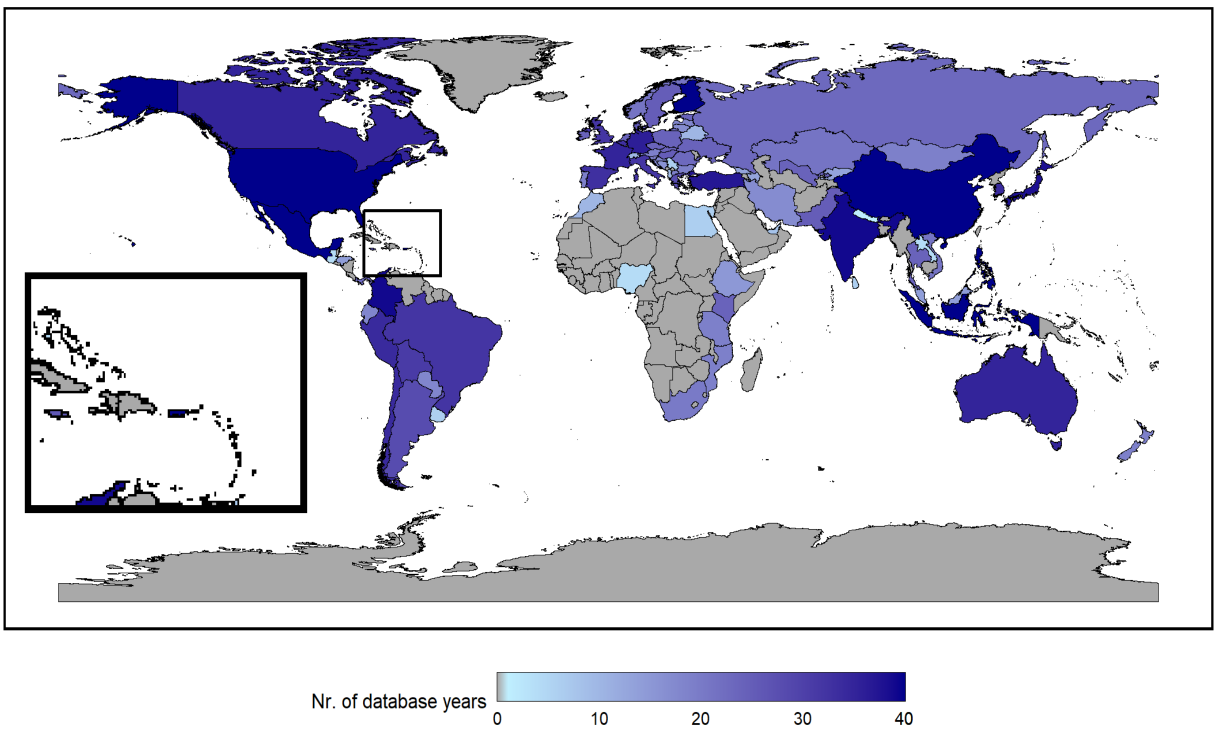
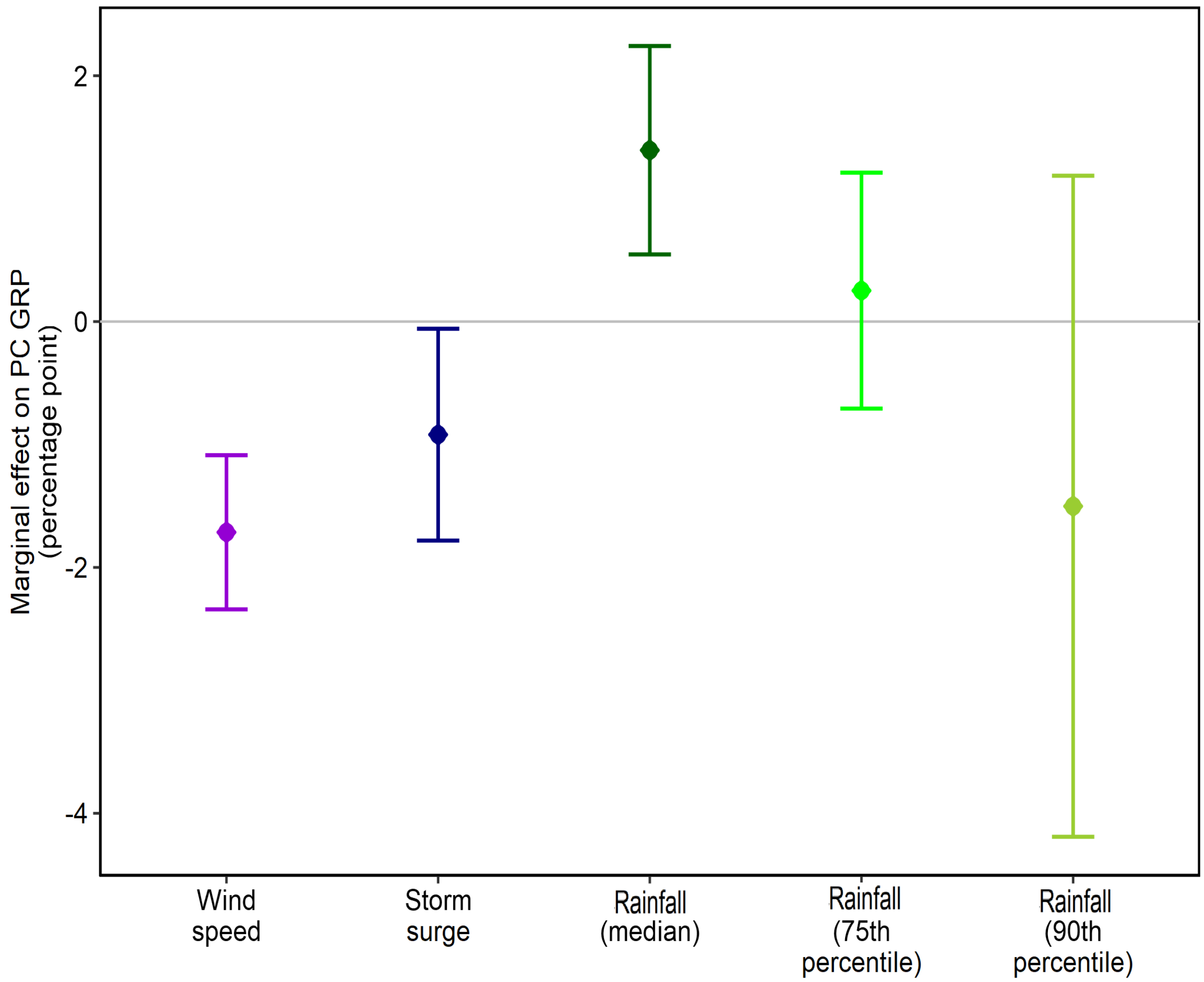


Figure 1.B.9: Number of years covered in the DOSE database by country, 1980-2020



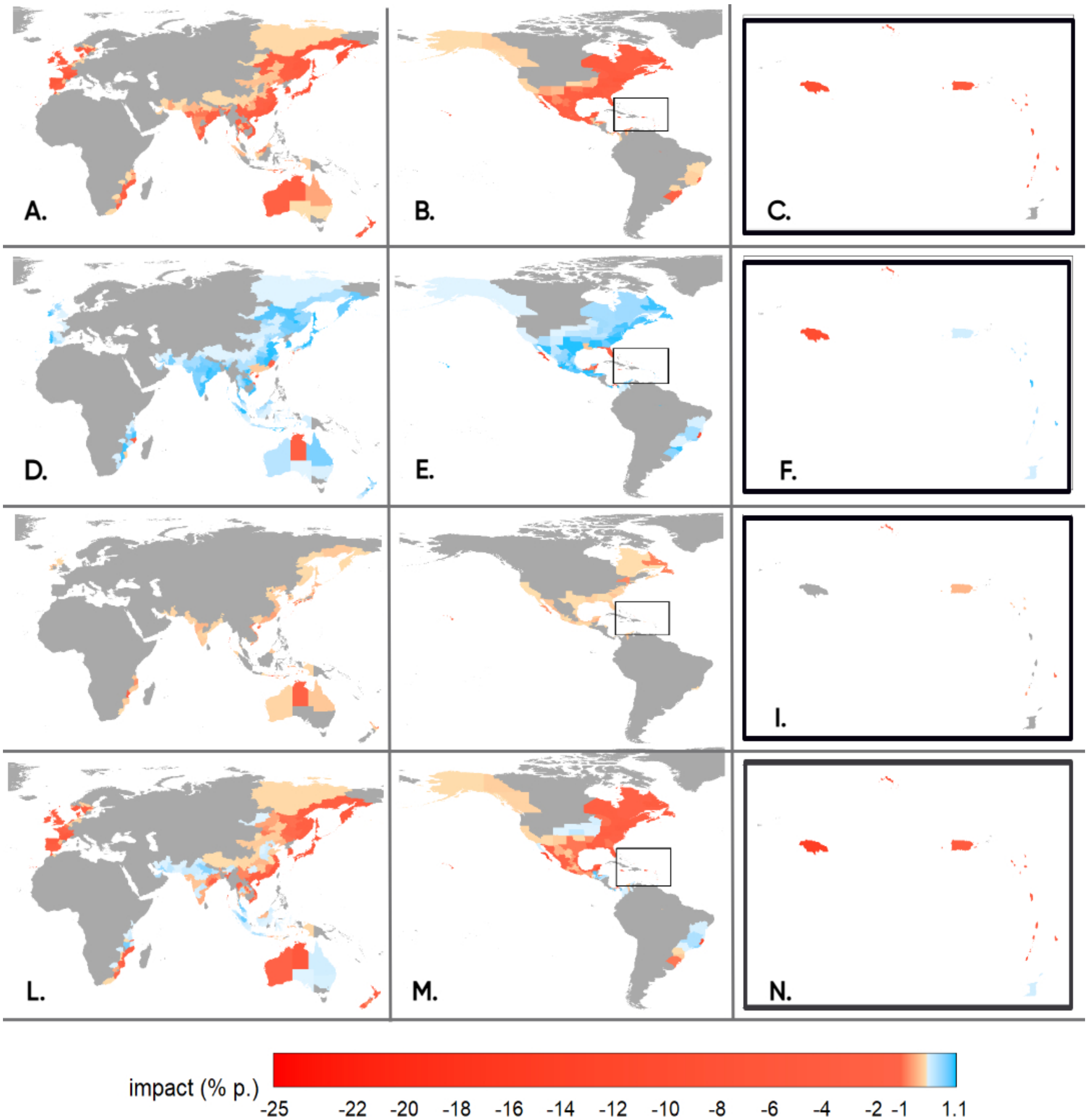
1.C Extensions

Figure 1.C.1: Impact of tropical cyclone hazards on per capita growth rate



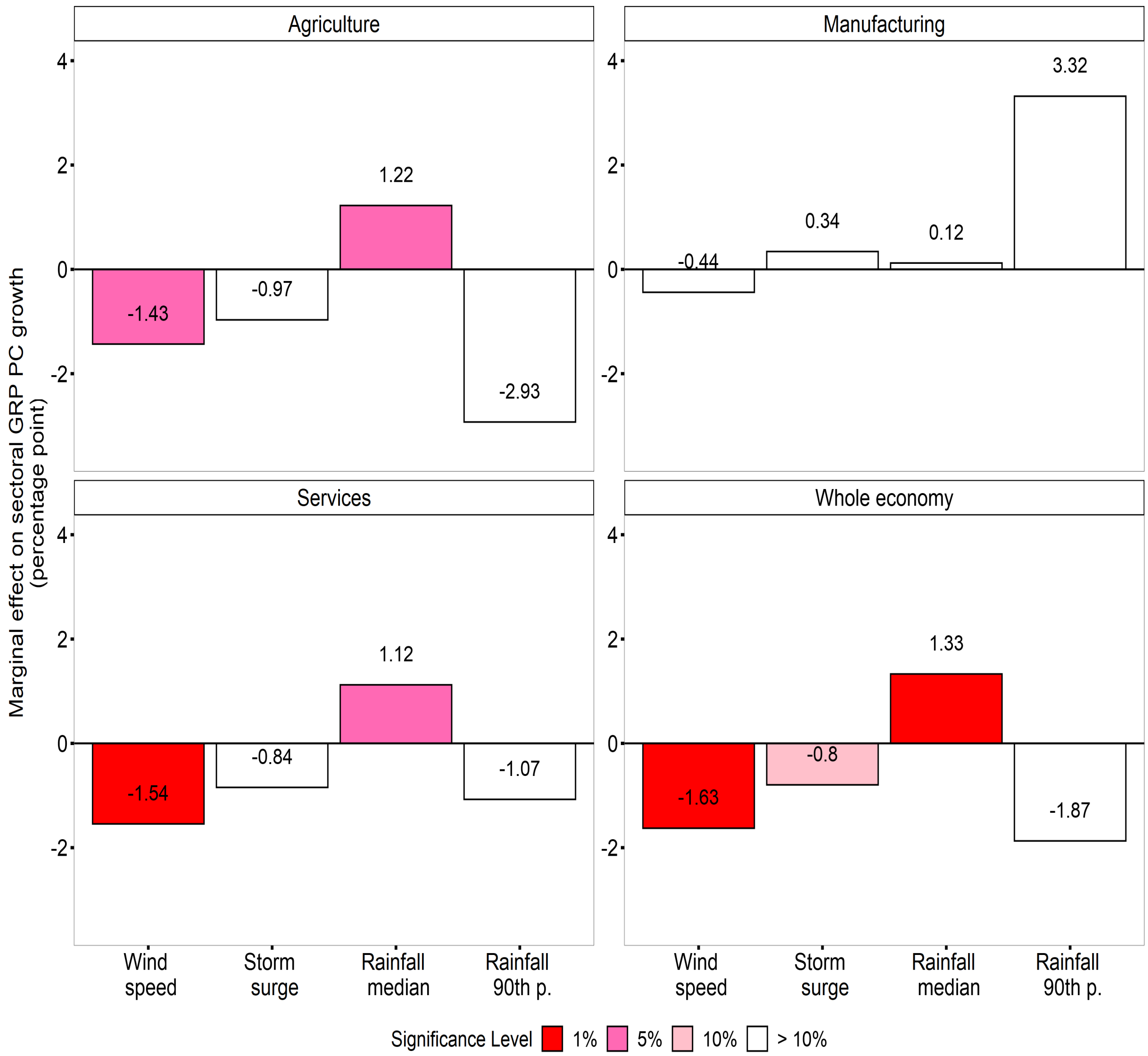
Marginal effects plot. Marginal effects are expressed as a one standard deviation increase, with 90% confidence bands used. For rainfall, median, 75th percentile and 90th percentile representative values were chosen in the marginal effects computation due to the presence of both linear and quadratic terms for rainfall in the baseline regression (Equation 1.2). The standard deviations of wind speed, rainfall, and storm surge, considering positive values only, are respectively equal to 43.7 km/h, 39.1 mm and 0.4 m.

Figure 1.C.2: Impact of tropical cyclone hazards on GRP PC growth (separate and additive 90th percentile impacts)



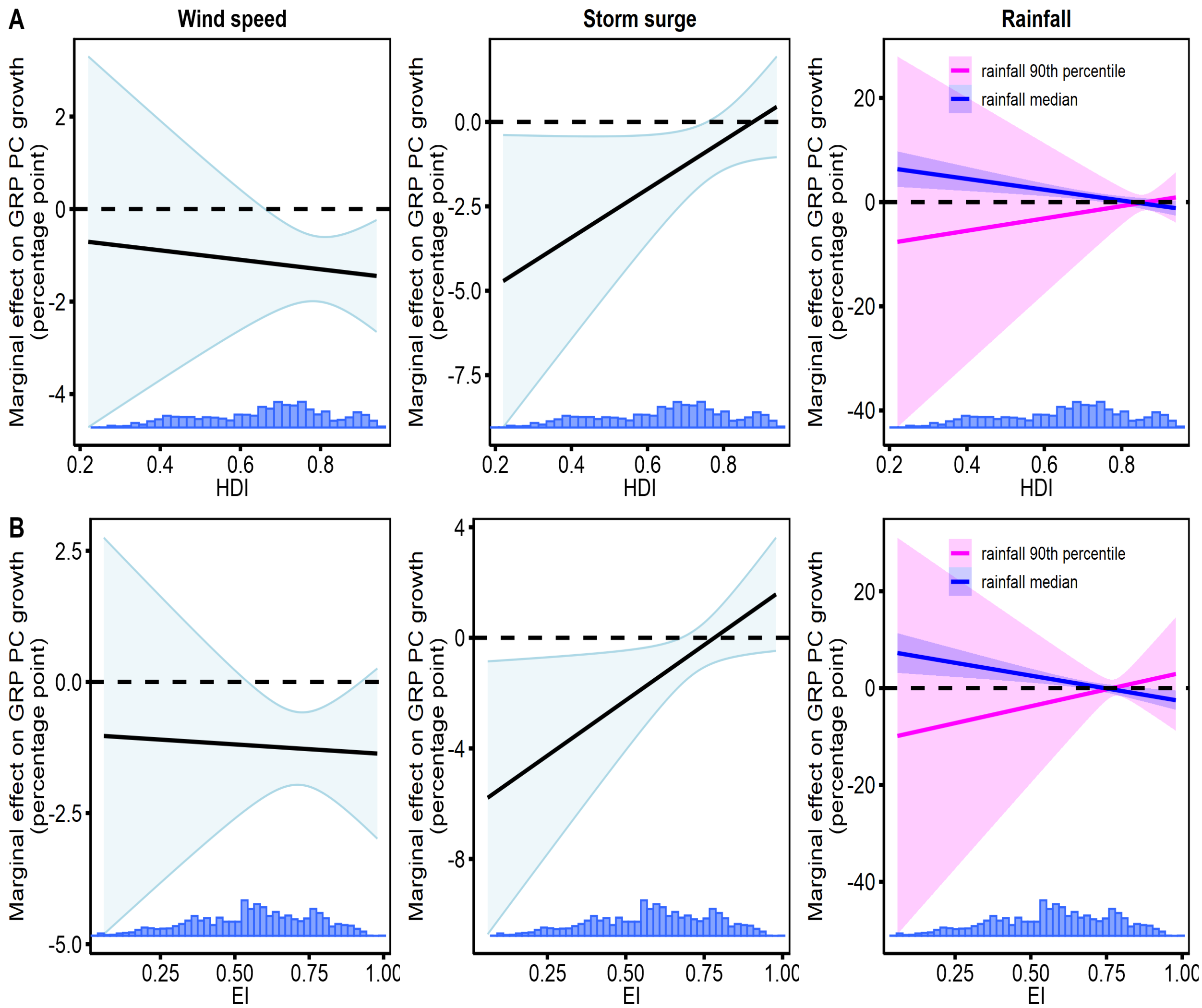
This figure depicts the percentage points impacts on GRP PC growth of the separate 90th percentile wind speed (panels A, B and C), rainfall (D, E and F) and storm surge events (G, H and I) and the additive impacts of the three 90th percentile hazards shocks (L, M and N) per each subnational unit. Focus on the Eastern hemisphere is in figures A, D, G and L. Focus on the Western hemisphere is in figures B, E, H and M. Figures C, F, I and N zoom on the Caribbean islands. A 90th percentile region-level TC intensity episode is defined as the 90th percentile intensity shock, for each region, over the 1980-2020 period. Regions never experiencing a single TC hazard (panels A-I) or, tropical cyclones, in general (panels L-N) are coloured in grey.

Figure 1.C.3: Impact of TCs hazards on sectoral GRP PC growth - coastal regions only



The figure represents the change in sector and whole economy GRP PC growth with respect to of 1 s.d change in TC concurring hazards. To obtain sector (agriculture, manufacturing and services) level results three different regressions have been run substituting the GRP PC dependent variables with the respective sector related growth variables (agriculture GRP PC growth, manufacturing GRP PC growth and services GRP PC growth). The analysis has been restricted to regions presenting information for all three sectors. This figure includes only regions which share the border with sea.

Figure 1.C.4: Impact of TC proxies on GRP PC mediated by societal development indicators



The marginal effect of the interaction between each concurring hazard (wind speed, rainfall, and storm surge) and two societal variables, Human Development Index (HDI) (panel A) and Education Index (EI) (panel B) is the focus of this figure. 90% confidence bands are used. Human Development Index (HDI) and Education Index (EI) are regional specific information which are fixed over time. Y axis data information is the percentage points change in the dependent variable GRP PC growth. Concurring hazard variables have been scaled by standard deviation.

Figure 1.C.5: Cumulative impacts exposure heterogeneity

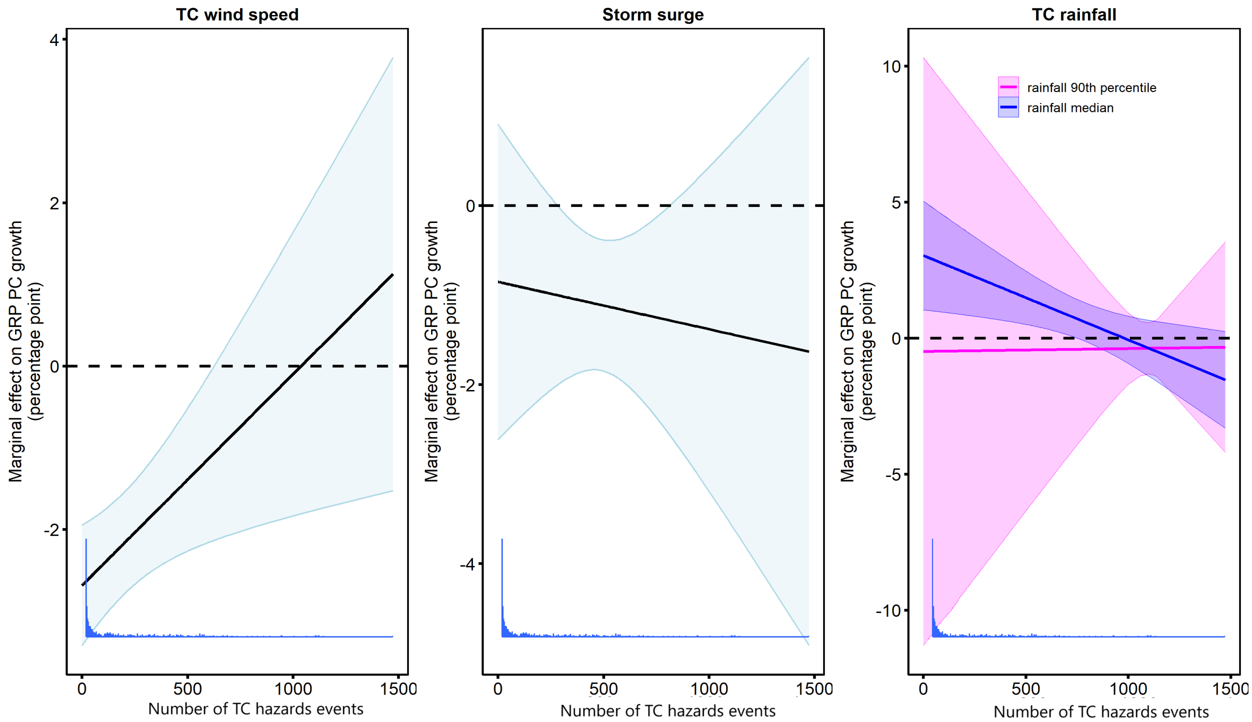
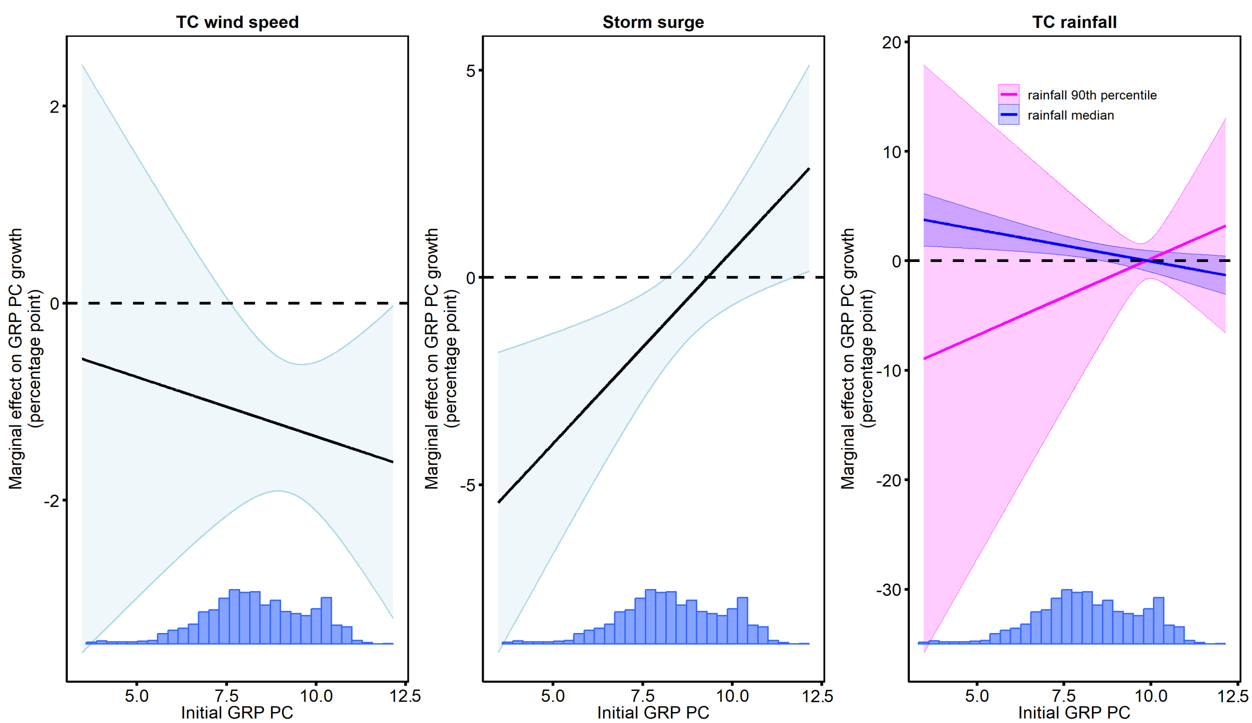
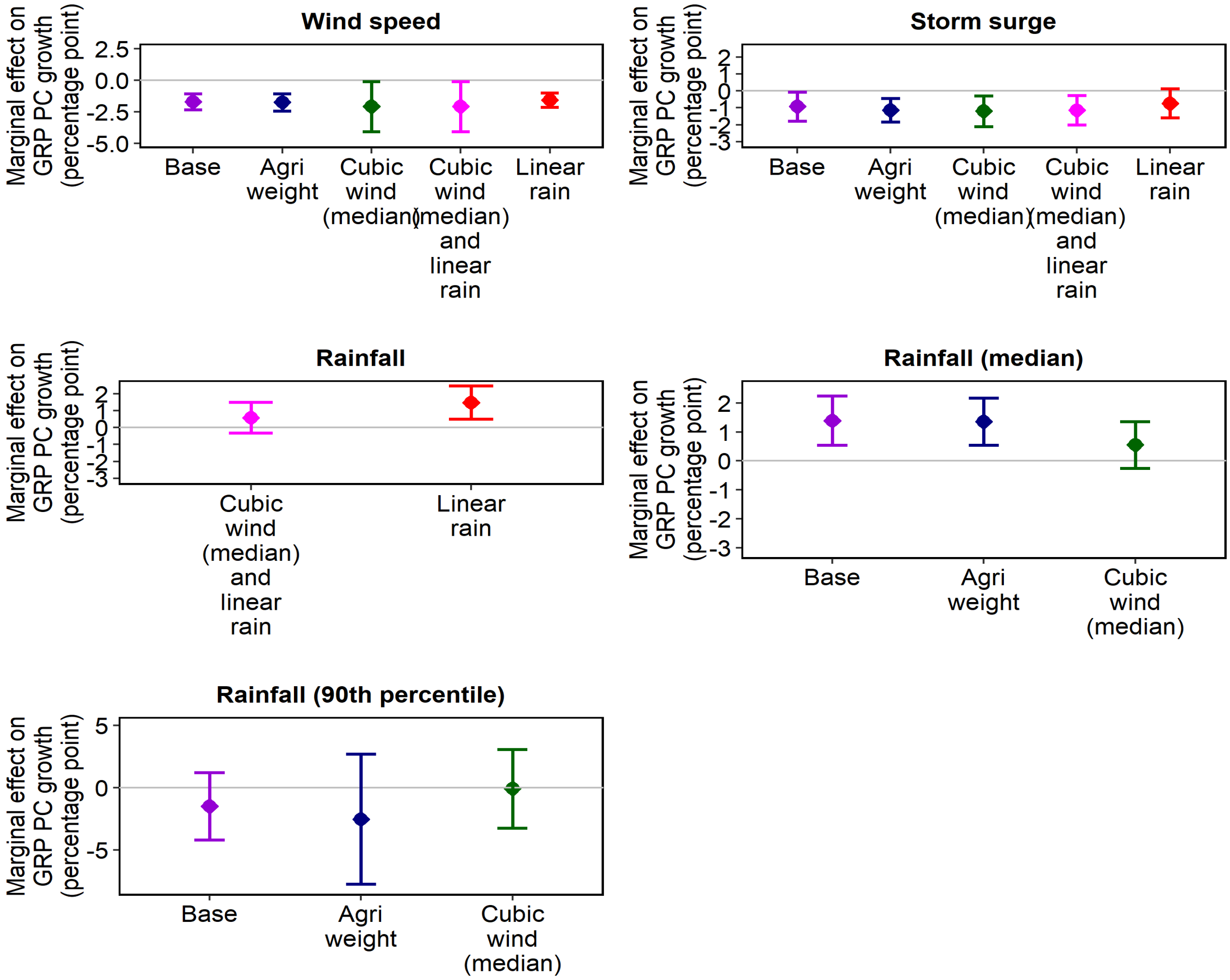


Figure 1.C.6: Impact of TC proxies on GRP PC mediated by the GRP PC on first year of database



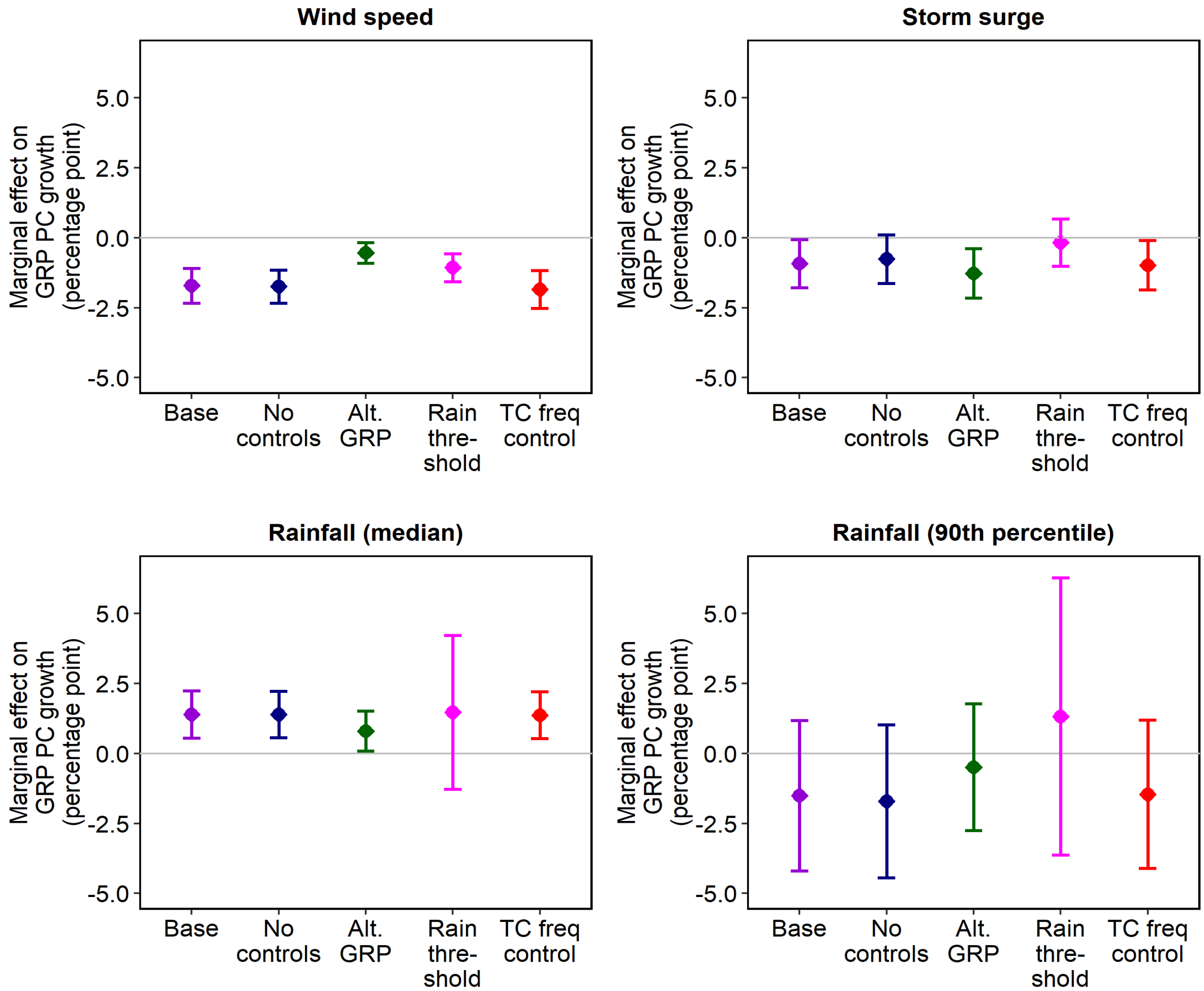
1.D Robustness checks

Figure 1.D.1: Robustness check - different TC proxy models and weighting



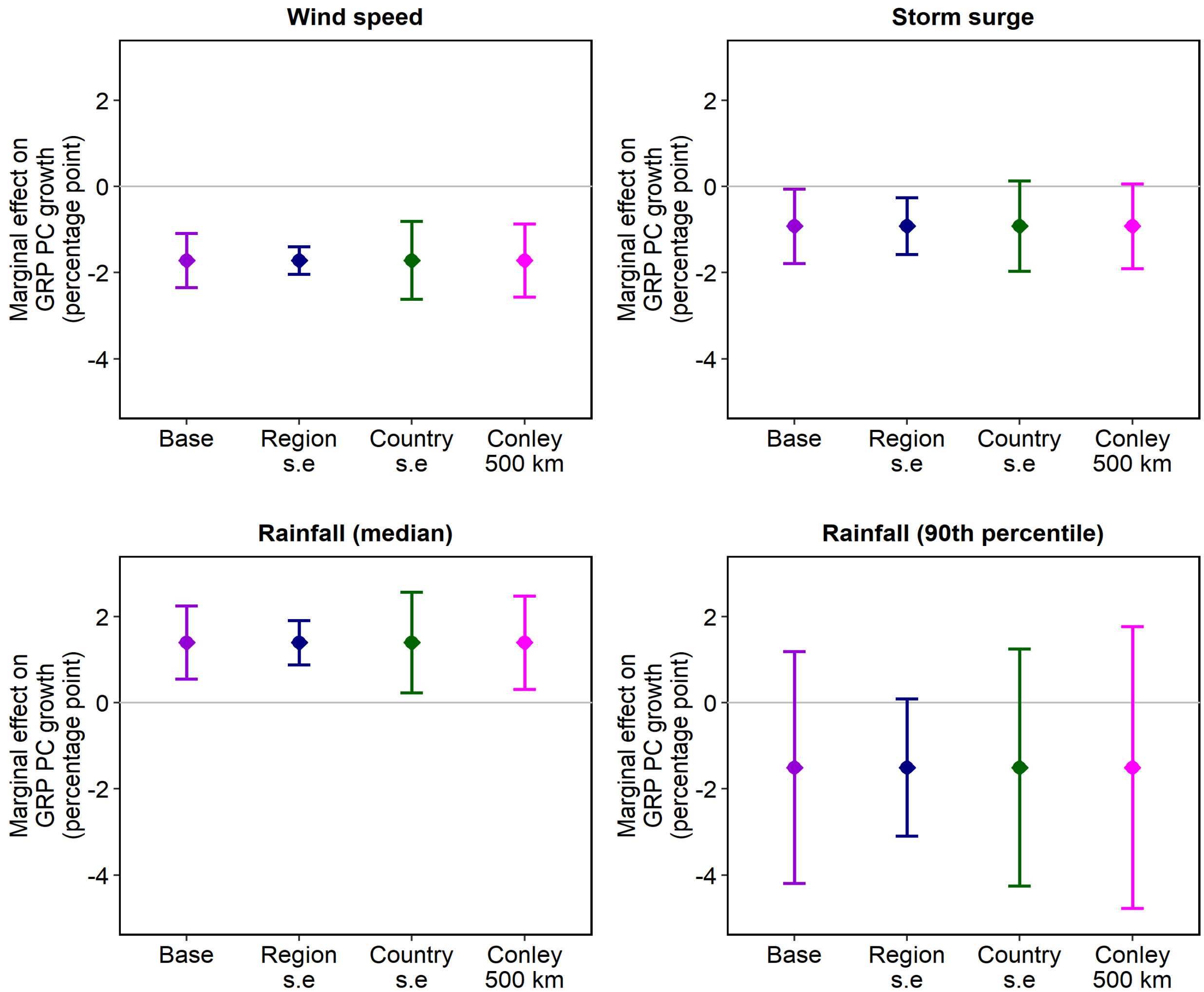
Marginal effects of 1 standard deviation increase in TC concurring hazards magnitude on GRP PC growth. Coefficients are to be interpreted as percentage point variations in the dependent variable. Coefficient bars indicate 90% confidence bands. The different coefficients and confidence bands colors indicate different regression models. The four boxes separate the different regression results according to the different concurring hazards proxies. Given the presence of linear and quadratic terms for rainfall, there are few boxes for different representative values. In this plot we consider different TC proxy variables form in terms of linearity or alternative non-linear specification or combinations of the two. Moreover we control for an alternative weighting of TC variables. The dark violet model is the baseline one. The blue model indicates a model where instead of using population weight we consider agricultural weighting (where the land available for agriculture and grazing is substituted to population count in equation 1.1, while the green model makes use of the wind speed variable in cubic form. Then, the pink model uses the cubic wind speed variable and the linear term for TC rainfall only (instead of linear wind speed and linear and quadratic terms for TC rainfall). The red model refers to a regression where only the linear term for rainfall is present, instead of having both the linear and quadratic ones. Cubic wind speed variables always consider the median value as representative one in the marginal effects computation. Apart from the above indicated modifications, all other baseline model elements apply to the robustness checks, as well.

Figure 1.D.2: Robustness check - different controls, independent variable and rainfall threshold



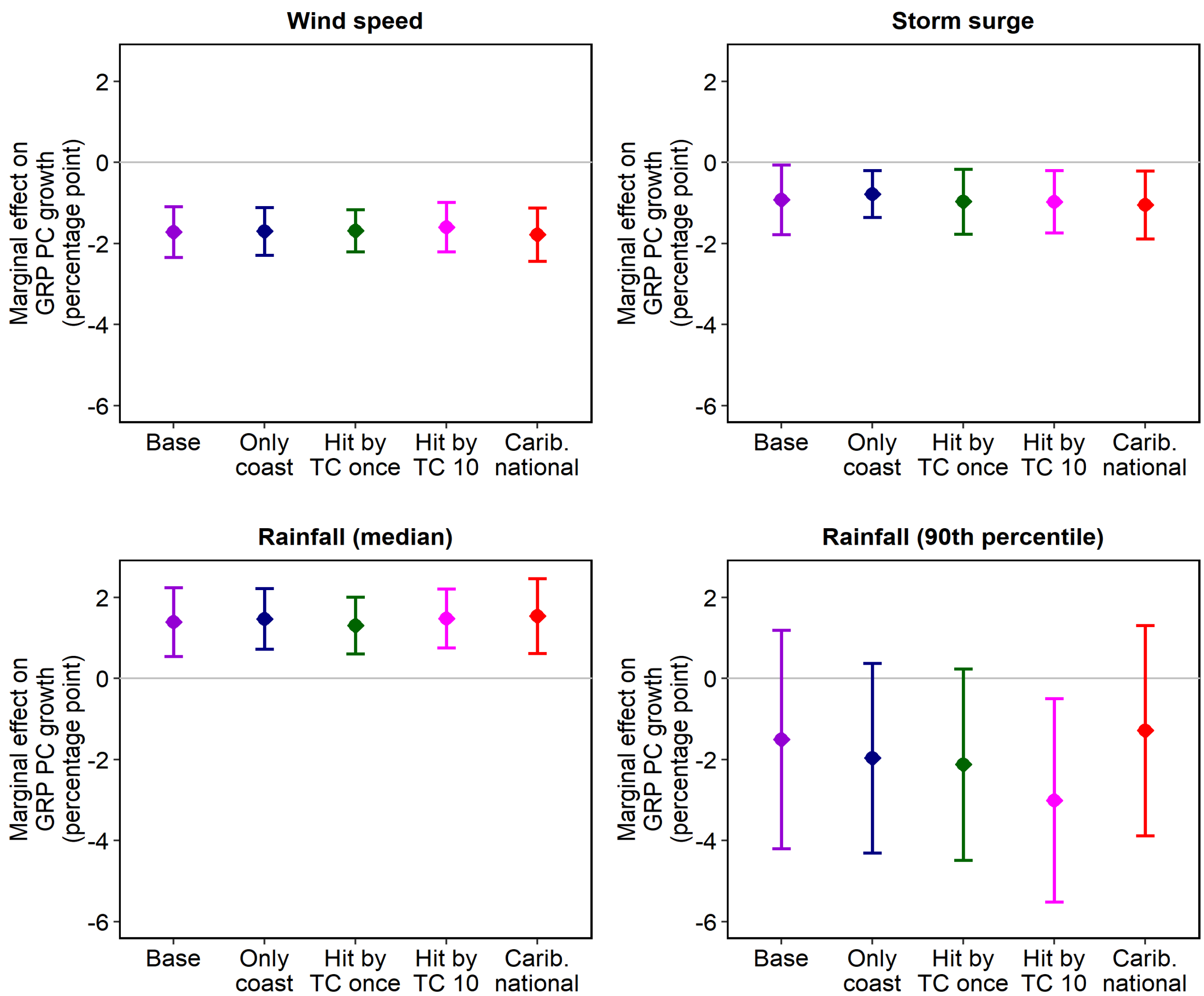
Marginal effects of 1 standard deviation increase in TC concurring hazards magnitude on GRP PC growth. Coefficients are to be interpreted as percentage point variations in the dependent variable. Coefficient bars indicate 90% confidence bands. The different coefficients and confidence bands colors indicate different regression models. The four boxes separate the different regression results according to the different concurring hazards proxies. Given the presence of linear and quadratic terms for rainfall, there are few boxes for different representative values. In this plot we consider different control variables specification, an alternative dependent variable indicator and an alternative TC rainfall variable. The dark violet model is the baseline one. The blue model indicates a model without any control variable (only the tropical cyclone measures are retained), while the green model makes use of an alternative GRP PC variable, where first the US 2015 base year deflator has been used and, subsequently, the conversion from local currency to US dollars (reference year: 2015) has been performed using the exchange rate. Then, the pink model uses a different rainfall variable where a threshold has been taken into account: all rainfall values below 100 mm are set to be equal zero. The red model refers to a regression where an additional control is inserted: a count of grid cells in each region that during each year where hit by the concurring hazard considered. All other baseline model elements apply to the robustness check models, as well.

Figure 1.D.3: Robustness check - different standard errors specifications



Marginal effects of 1 standard deviation increase in TC concurring hazards magnitude on GRP PC growth. Coefficients are to be interpreted as percentage point variations in the dependent variable. Coefficient bars indicate 90% confidence bands. The different coefficients and confidence bands colors indicate different regression models. The four boxes separate the different regression results according to the different concurring hazards proxies. Given the presence of linear and quadratic terms for rainfall, there are few boxes for different representative values. In this plot we consider different standard errors model specifications. The dark violet model is the baseline one. The blue model indicates a model with regionally clustered standard errors, while the green model makes use of country level error clustering. Then, the pink model uses a different spatial cutoff for the Conley standard errors typology (500 km instead of 200 km). Apart from the above indicated modifications, all other baseline model elements apply to the robustness checks, as well.

Figure 1.D.4: Robustness check - different database sample subsets



Marginal effects of 1 standard deviation increase in TC concurring hazards magnitude on GRP PC growth. Coefficients are to be interpreted as percentage point variations in the dependent variable. Coefficient bars indicate 90% confidence bands. The different coefficients and confidence bands colors indicate different regression models. The four boxes separate the different regression results according to the different concurring hazards proxies. Given the presence of linear and quadratic terms for rainfall, there are few boxes for different representative values. In this plot, we consider different database subset specifications. The dark violet model is the baseline one. The blue model indicates a model with only coastal regions, while the green model makes use of a sample where only regions hit at least once by by TC wind speed are included. Then, the pink model uses where only regions hit at least ten times by TC wind speed are included. Red model considers Caribbean regions instead of Caribbean countries. Apart from the above indicated modifications, all other baseline model elements apply to the robustness checks, as well.

1.E Appendix references

[1] Bloemendaal, N. *et al.*. Adequately reflecting the severity of tropical cyclones using the new Tropical Cyclone Severity Scale. *Environmental Research Letters* **16**(1) (2021).

Chapter 2

Extreme events, ideological shifts and polarization: evidence from US tropical cyclones[*]

2.1 Introduction

The U.S. is currently experiencing the highest levels of political polarization in ideological terms. A comparison between 1994 and 2014 revealed that the Republican electorate has moved toward more conservative views, while the Democratic electorate has become more liberal.[1] On the political supply side, both the Democratic and Republican parties have shifted from moderate views toward more extreme political ideologies. Today, there are only a few dozen moderate politicians in Congress, compared to the 160 members in 1971–1972.[2]

Political polarization in ideological terms refers to an increase in the divergence of political opinions (Fiorina and Abrams, 2008). This paper focuses on studying the ideological polarization

[*] In collaboration with Matteo Coronese and Francesco Lamperti.

[1] https://www.pewresearch.org/politics/2014/06/12/political-polarization-in-the-american-public/

[2] https://www.pewresearch.org/fact-tank/2022/03/10/the-polarization-in-todays-congress-has-roots-that-go-back-decades/

of the electorate rather than that of political parties.

Studying polarization is highly relevant given its potential socioeconomic effects: the literature suggests it amplifies policy uncertainty (Baker et al., 2020), distorts economic expectations (Guirola, 2021), reduces firms' investment in polarized areas (Zhu, 2021), hampers democracy (Casal Bértoa and Rama, 2021), and impedes law approvals and ambitious policymaking (Mccarty, 2007). The U.S. public is even divided on significant issues such as COVID-19 (Flores et al., 2022), hurricane risk perception (Long et al., 2020), and climate change (Egan and Mullin, 2017).

Hurricanes cause destructive effects on the economy, including loss of life, declines in economic output, unemployment, and damage to assets and infrastructure (Carleton and Hsiang, 2016). The income decline caused by cyclones can be comparable to economic shocks like a 1% increase in taxes, a currency crisis, or a political crisis (Hsiang and Jina, 2014). Hsiang and Jina (2014), in their analysis of the effects of cyclone strikes on macroeconomic conditions worldwide between 1950 and 2008, found that national income remains below its cyclone-free counterfactual for more than 20 years after the disaster. Temperature and weather anomalies reduce labor productivity and industrial production while increasing health-related issues, conflicts, disputes over resources, societal aggression, and energy consumption (Dell et al., 2014). Furthermore, temperature abnormalities increase media coverage of climate change in the U.S. (Pianta and Sisco, 2020). Lastly, natural disasters also have an inequality-enhancing effect (Cappelli et al., 2021).

Despite this evidence, research on the polarizing effects of climate hazards on political opinions remains limited. To the best of our knowledge, no studies have examined whether tropical cyclones contribute to such polarization. Researchers have generally focused on electorate environmental concerns or green/Democrat political party preferences (Hoffmann et al., 2022; Boudet et al., 2020; Hazlett and Mildenberger, 2020).

An exception is the work of Pianta and Rettl (2022), which finds that Brazilian wildfires increased both Silva's environmental party vote share and Bolsonaro's anti-environmental party vote share, indicating a polarization effect in voters' demand for environmental issues. However, our focus is on tropical cyclones and shifts in general political ideology in the U.S.

Some studies have analyzed political polarization as a consequence of macroeconomic phenomena. Autor et al. (2020) examined the effect of the Chinese import shock on cable TV news consumption, campaign donations, and voting patterns in the U.S., discovering that it increased political polarization. Anelli et al. (2021) concluded that higher vulnerability to robot adoption leads to greater support for radical right parties at the individual level in Western Europe. However, these studies do not focus on natural phenomena but rather economic ones.

Additionally, while literature has identified the severe economic impacts of tropical cyclones (Carleton and Hsiang, 2016) and the ways economic downturns may fuel polarization and extreme political support (Casal Bértoa and Rama, 2021), no study has explored the effects of climate hazards on political polarization.

This paper aims to examine whether exposure to U.S. tropical cyclones (including hurricanes and tropical storms) is associated with increased political polarization. We hypothesize that as the intensity of tropical cyclone damage increases (considering the top 10th and bottom 90th percentiles of the damage distribution), Democrats will become more liberal and Republicans more conservative in their political opinions.

To study polarization, we created a very liberal-to-very conservative ideological scale using 26 questionnaire responses across seven macro-topics (abortion, environment, immigration, guns, health, gay rights, and affirmative action). We collected this information from a large U.S. representative political micro-survey, the Cooperative Election Study (CES) policy preferences database, which includes data from 2006 to 2021.[3] We also complemented our dataset with individuals' socio-economic characteristics from the CES 2006–2021 unbalanced repeated cross-sectional study.[4]

To track tropical cyclone exposure, we used information from a county-based tropical cyclone wind-speed economic damage function (Henry et al., 2020), incorporating scientific maximum wind speed data from modeled wind information (Willoughby et al., 2006). We leveraged exogenous variation in county-specific and year-to-year tropical cyclone origin, path, and intensity exposure (Wang et al., 2018). We chose to focus on tropical cyclones over other phenomena like

[3]CCES Cumulative Policy at https://cces.gov.harvard.edu.

[4]Cooperative Election Study Common Content at https://cces.gov.harvard.edu.

temperature anomalies, wildfires, or floods because they are highly destructive and more likely to leave lasting impacts on citizens' political and environmental attitudes (Egan and Mullin, 2017).

Finally, we considered individual-level analysis due to its limited attention in the political and environmental concern/vote effects literature on climate hazards and weather anomalies.[5] The importance of this approach lies in the fact that aggregating data at higher levels may obscure important underlying trends, such as those between "losers" and "winners" of a macro phenomenon (Anelli et al., 2021). Furthermore, no studies in the literature consider opinions in detail, focusing instead on concrete actions, such as voting, and involving only U.S. citizens rather than residents.

The remainder of this paper is organized as follows: Section 2.2 presents the reviewed literature. Section 2.3 introduces the data. Section 2.4 describes the empirical models and identification strategy. Section 2.5 discusses the main findings, with robustness checks in Section 2.6. Section 2.7 illustrates the relevant channels of influence, and Section 2.8 concludes.

2.2 Literature review

2.2.1 Blind Retrospective and Retrospective Literature

A well-established strand of political science literature examines the effect of natural disasters on politics. This body of work primarily employs empirical and descriptive approaches, often focusing on the United States. Two alternative hypotheses concerning the electoral punishment or reward of the incumbent politician after a disaster are prominent: the "blind retrospective" hypothesis (Achen and Bartels, 2004; Heersink et al., 2017) and the "retrospective" hypothesis (Acuña-Duarte and Salazar, 2021; Gasper and Reeves, 2011; Neugart and Rode, 2021).

The blind retrospective hypothesis suggests an automatic electoral punishment (i.e., non-re-election and a reduction in vote share) of the incumbent for events beyond the government's control. It views disaster-affected populations as irrational in their electoral decisions, lacking cognitive capabilities for responsibility attribution. Achen and Bartels (2004) analyze electoral

[5]None of the works reviewed in this section focused on individual-level data. These studies typically consider municipalities, counties, states, electoral districts, and census blocks.

reactions to floods and droughts during 27 U.S. presidential elections (1896–2000), using pooled regression analyses at the state level. Their findings indicate that the president's party's electoral performance is negatively affected by these disasters. They argue that this effect is not coincidental or linked to citizens' assessments of the president's disaster response but instead reflects citizens' irrational punishment. Heersink et al. (2017), applying a difference-in-differences methodology, find that U.S. counties affected by the Great Mississippi Flood punished the president with a 10% lower vote share, even though the president had distributed unprecedented financial disaster aid. While supporting the Achen and Bartels (2004) hypothesis, the authors (2017) call for further investigation into the mechanisms driving this effect.

In contrast, the retrospective hypothesis rejects the notion of irrationality, suggesting that citizens punish or reward incumbents based on their evaluation of government disaster responses and relief efforts. Acuña-Duarte and Salazar (2021), using a difference-in-differences methodology with a correlated random-effects probit model and county-level data, examine the 2010 Chile earthquake's impact on incumbent mayors' re-election probabilities and vote shares. They find that while natural disasters negatively affect incumbents, this effect is mitigated by human capital and post-disaster evaluations. Gasper and Reeves (2011) analyze U.S. gubernatorial and presidential elections from 1970 to 2006, showing that governors who issued disaster declarations requesting financial aid were rewarded by voters. The electoral benefits of an effective government response outweighed the disaster's negative effects, especially when declarations were approved by the president. Neugart and Rode (2021) study retrospective voting in the context of the 2013 flood in Germany, examining the mediating role of democratic experience. They find that the incumbent party's disaster relief program increased its vote share by 2.2% in flood-affected East German municipalities compared to West Germany.

2.2.2 The Effect on Electoral Green and Left-Wing Preferences

Recent literature has increasingly explored how hurricanes, floods, fires, and temperature anomalies influence citizens' environmental concerns and voting behavior (Baccini and Leemann, 2021; Hoffmann et al., 2022), particularly among left-wing voters (Boudet et al., 2020; Hazlett and

Mildenberger, 2020). Baccini and Leemann (2021) find that Swiss voters' experiences of extreme weather events, such as flooding, increase support for climate protection measures by approximately 20%. Using micro-level geospatial data on natural disasters and municipal referendum votes, their difference-in-differences analysis shows that the effect lasts around 10 months. Hoffmann et al. (2022) examine European subnational responses to temperature anomalies, heat, and drought episodes in terms of environmental concerns and voting. Using a 12-month lag to measure electoral outcomes, they validate the positive impact of climate-related phenomena on these variables through fixed-effects regressions. Boudet et al. (2020) highlight that extreme weather events between 2012 and 2015 in 15 U.S. communities led to increased environmental discussions and collective actions, particularly among Democratic voters compared to Republicans. Their systematic case study analysis underscores the importance of partisanship. Hazlett and Mildenberger (2020) analyze three pro-environment ballot initiatives (2006, 2008, and 2010) and find that communities closer to California wildfires exhibit stronger environmental support than those farther away. Voting behavior is more significantly influenced by wildfires in Democratic census blocks.

Experiencing climate change's adverse effects is also linked to increased Democratic preferences in the U.S. electorate (Liao and Ruiz Junco, 2022), as Democratic politicians often advocate for greater environmental expenditure and legislative action (Herrnstadt and Muehlegger, 2014; Gagliarducci et al., 2019). Liao and Ruiz Junco (2022) demonstrate that temperature anomalies at the county-week level in the U.S. lead to short-term increases in donations to Democratic politicians. While contribution rates rise significantly, the average donation amount does not. This aligns with findings that individuals affected by weather anomalies feel closer to Democratic positions, as shown by the political orientation of donations. On the policy supply side, Gagliarducci et al. (2019) report that congress members from hurricane-affected districts introduce more green legislation, with effects observable after a one-year lag. Additionally, voters become more aware of climate change and support environmental policies after a hurricane, though these effects are temporary.

2.2.3 The effect of natural disasters and macro phenomena on radical ideologies and polarization

Having discussed the literature on environmental concerns and Democratic voting in the aftermath of natural disasters, it is important to highlight that such events may also lead to adverse environmental concerns and other political shifts, including radical preferences and ideologies. Natural disasters can induce psychological distress, such as loneliness, feelings of abandonment, anger, and fear (Warsini et al., 2014; Riad and Norris, 1996), often exacerbated by displacement. This negative psychological impact may, in turn, foster extreme political ideologies (van Prooijen and Krouwel, 2019). Stechemesser et al. (2021) analyzed the effect of temperature anomalies on the prevalence of racist and xenophobic tweets and likes in Europe from 2012 to 2018 using fixed-effects regression. They found a positive nonlinear relationship, with a quasi-quadratic response of these variables to average daily temperature. Paradoxically, climate change denial may increase following climate-related hazards. According to environmental psychology literature, denial or avoidance of climate change issues can serve as a coping strategy to manage post-disaster environmental distress (Reser and Swim, 2011; Haltinner and Sarathchandra, 2018). Moreover, natural disasters have been linked to increased religiosity (Bentzen, 2019).

In the environmental politics literature, polarization related to environmental issues has also been explored. For instance, Pianta and Rettl (2022) demonstrated that Brazilian wildfires led to increased support for both Silva's pro-environmental party and Bolsonaro's anti-environmental party, signaling environmental polarization. Silva's party saw less support in municipalities where sectors benefiting from wildfires, such as cattle ranching and soy farming, were prominent. This, the authors argue, highlights an interaction between environmental concern and self-interest. Similarly, Otteni and Weisskircher (2022) found that the construction of wind turbines increased support for both the radical-right populist party Alternative für Deutschland (AfD) and the Green Party. The Green Party attracted voters with positive attitudes toward wind turbines in their areas, while AfD gained support from those opposed to such developments. Babutsidze et al. (2023), using large-scale survey data from multiple European countries between 2002 and 2010, observed that while traditional media consumption (radio, newspapers, and TV) did not contribute to the polarization of environmental attitudes in Europe, digital media consumption was positively associated with polarization dynamics in this context. For progressive and green voters, increased internet use is linked to stronger environmental attitudes, whereas for conservative voters, it appears to be associated with more negative environmental views.

Finally, a broader literature analyzes the political effects of macroeconomic and natural shocks, such as automation, globalization (Anelli et al., 2021; Autor et al., 2020), and earthquakes (Cerqua et al., 2021). These studies suggest such phenomena often lead to increased populism and radical voting. For instance, Cerqua et al. (2021) compared the effects of earthquakes in the Italian regions of L'Aquila and Emilia-Romagna. They found that the L'Aquila earthquake was associated with a rise in populist voting, while this was not observed in Emilia-Romagna. The authors attribute this difference to varying economic and social contexts, levels of inequality, citizens' trust, unmet promises from Berlusconi's "Forza Italia," and differing reconstruction patterns. Autor et al. (2020) examined the effects of the Chinese import shock on U.S. cable news users, campaign donor activities, and voting patterns, finding that it led to increased political polarization. Similarly, Anelli et al. (2021) concluded that greater vulnerability to robot adoption is associated with increased support for radical-right parties and political polarization in Western Europe.

2.3 Data

2.3.1 Political ideology

The data source used to create our political ideology variable is the 2006–2021 Cooperative Election Study (CES) policy preferences database.[6] This survey represents, to our knowledge, one of the most important open-access sources of information regarding U.S. residents' political opinions before and after elections. It contains data for a very large, representative sample of U.S. adults, with information on their county of residence and political ideology, ranging from very liberal to

[6] CCES Cumulative Policy at https://cces.gov.harvard.edu. A survey guide is also available at the same link for consultation.

very conservative. Knowing the county of residence is essential for linking county-level tropical cyclone data to the individuals.

The survey is administered to U.S. residents in October, ahead of the November U.S. elections. It is conducted online and includes a representative sample of American adults. A broad range of questions is asked regarding respondents' opinions on various past, current, or hypothetical policies and government actions. We collected data for the 2010–2018 period from the available 2006–2021 years to capture the greatest number of survey questions and topics that remained consistent over recent years.

To develop the political ideology indicator (see subsection 2.1.1 in the appendix for a complete overview of the creation procedure), we analyzed 26 survey questions covering a range of macro topics from the database, including abortion, the environment, immigration, LGBTQ+ rights, affirmative action, gun control, and healthcare. The selection of topics is based on the research of Jacobson (2012), who identified questions from the 2010 repeated cross-section CES survey addressing issues such as environmental protection, immigration, abortion, social rights, and firearm regulations to assess ideological positions. These topics are particularly relevant, as they represent some of the most polarizing issues among the U.S. public.[7] To create the continuous political ideology indicator, we first developed a categorical variable ranging from 0 to 1 for each of the five annual topics. We then aggregated the scores across the five topics and divided the total by the number of topics, resulting in a final continuous score between 0 and 1. This final measure of political ideology reflects a spectrum from very liberal (scores closer to 0) to very conservative (scores closer to 1).

Our ideology indicator allowed us to create an unbalanced repeated cross-sectional database from a large, representative U.S. sample, tracking ideology very close to the timing of the midterm and presidential elections. See Figure 2.A.1 for the mean 2010–2018 ideology indicators across U.S. states. Our ideology proxy correlates well with an alternative survey-based proxy, a 5-point ideological scale (very liberal, liberal, moderate, conservative, and very conservative); there is a

[7]https://www.pewresearch.org/politics/2020/02/13/as-economic-concerns-recede-environmental-protection-rises-on-the-publics-policy-agenda/.

Spearman correlation of 69.27%.

We also complement our database with individuals' socio-economic characteristics, extracted from the Cooperative Election Study (CES) 2006–2021 unbalanced cross-sectional study.[8] From the CES common content database, we retained information on partisanship (Democratic, Independent, or Republican). This variable indicates the party of the U.S. presidential candidate that the individual voted for in the most recent pre-survey election. Other political party choices or unclear/unprovided answers on party preference were classified as missing.

We also retained data on individuals' age, gender, race, education, employment status (unemployed, employed, inactive, or other status), religious affiliation, family income, health insurance status (insured or not), citizenship, housing status, union membership status, and degree of interest in political and government affairs. Race is a 3-value categorical variable (Black, White, and other). The education variable is a 6-value categorical variable indicating the highest educational attainment, ranging from "no high school" to "postgraduate." Employment status is represented by dummy variables: employed, unemployed, inactive, and other working status. Religious affiliation is a 14-category variable, including several religions as well as agnostic, atheist, and other categories. Family income is a categorical variable with 12 different income thresholds. Health insurance is a dummy variable indicating whether the individual has health insurance at the time of the interview. Interest in government and political affairs is measured by a 4-value variable indicating the individual's level of interest in political and government news. The housing variable consists of three categories (tenant/owner/other), indicating whether the individual owns, rents, or has another housing arrangement.

Our source of ideological information, as previously indicated, is a survey, a common approach in the literature (Treier and Hillygus, 2009). There are various methods in the literature for collecting data from this source: one can consider self-placement on a left-right scale (Lesschaeve, 2017), count policy responses consistent with conservative or liberal positions (Abramowitz and Saunders, 2008), or use factor analysis (Laméris et al., 2018), among others. This work aligns with the approach of averaging multi-topic ideology (Ansolabehere et al., 2008). Compared to the methods

[8] Cooperative Election Study Common Content at https://cces.gov.harvard.edu.

mentioned earlier, our approach offers several advantages. First, our indicator avoids a simplistic liberal-conservative or left-right classification of responses, which is often used in the literature to count ideological policy responses (we consider more nuanced answer differences). Second, our indicator represents latent ideology, not self-placement, thus avoiding the over-representation of moderate individuals (Treier and Hillygus, 2009). Finally, unlike the left-right scale or counting policy responses consistent with conservative or liberal views (Abramowitz and Saunders, 2008), it is a continuous measure, allowing us to use OLS regression for empirical analysis.

Another source of ideological information in the literature is the observation of behavioral actions, such as voting and related ideological measures[9], partisan donations (Liao and Ruiz Junco, 2022), and TV channel partisan news (Autor et al., 2020). Compared to these behavioral approaches, the indicator we created has the advantage of avoiding several selection biases due to the effects of tropical cyclones (see Debbage et al., 2014; Meer and Priday, 2021). First, individuals affected by tropical cyclones might be unable to vote because of disaster damage, relocation, and difficulties in reaching voting facilities (Debbage et al., 2014). Second, donations from cyclone-affected areas might primarily come from the least economically affected individuals, given the positive relationship between economic resources and donation magnitude (Meer and Priday, 2021). Additionally, the U.S. vote is essentially binary, measuring partisanship rather than ideology, and does not allow for consideration of individual-level data, as official data is collected at higher levels. Furthermore, only U.S. citizens are eligible to vote in federal elections, whereas the CES survey includes both U.S. citizens and non-citizens.

Finally, another source of ideological data is social media or public debate data. For example, there are studies analyzing the content and sentiments of social media platforms like Twitter and Facebook (see e.g., Caravaca et al., 2022). However, social media platforms are unrepresentative of the U.S. population. The Pew Research Center, for example, reports that Twitter users are predominantly Democratic and young individuals.[10] (Argyle et al., 2021) analyzes college students' real-time reactions to U.S. presidential and vice-presidential debates. However, this study is cross-

[9] See Center of Gravity in (Colantone et al., 2021).

[10] https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users.

sectional, focusing only on the 2012 political speeches, which suggests limitations in creating a panel database from this source.

2.3.2 Tropical cyclones

We measure tropical cyclone wind speed damage using modeled county-level continuous "best tracks" of maximum sustained wind speeds, as reported by (Anderson et al., 2020), based on wind speed data (in m/s) from (Willoughby et al., 2006). Wind speed damage refers to an economic damage function based on wind speed (see Henry et al., 2020), where wind speed values for each tropical cyclone event are aggregated at the county level and subsequently assigned to individuals within each county. The wind-speed damage function is as follows:

$$(\text{tropical cyclone}_{i,t})^2 = \mu\left(\eta_{1,i,t} + \eta_{2,i,t} + \cdots + \eta_{n,i,t}\right) = \sum_{j=1}^{n} s_{j,i,t}^2 \tag{2.1}$$

We consider both tropical storms and hurricanes in the creation of the tropical cyclone damage function. According to scientific guidelines on tropical cyclone classification, a tropical depression has a maximum wind speed lower than 17.5 m/s (34 knots), while an event with a maximum wind speed between 17.5 m/s and 32.92 m/s (64 knots) is classified as a tropical storm. A hurricane, on the other hand, has a maximum wind speed equal to or greater than 32.9 m/s (64 knots).[11] The lowest recorded tropical cyclone maximum sustained wind speed in our database, based on this data source, is 17.5 m/s (34 knots), which marks the threshold for tropical storms. The highest recorded wind speed is 53.07 m/s (103 knots – a category 3 hurricane).

Of the counties affected by at least one tropical cyclone in a given year, 3.7% were affected by two different tropical storms, while 0.7% were struck three times. The remaining 95.6% of counties were affected by one tropical storm. For the years 2010–2018, we assign the tropical storm variable based on storm characteristics.

The temporal window of data collected regards the 6 months before the CES survey for each year in the 2010-2018 period. Such tropical cyclone window captures most of the hurricane season

[11] https://www.weather.gov/mob/tropical$_{d}efinitions$.

(which officially runs from the 1st of June to the 30th of November), since the survey is conducted during the month of October.

Subsequently, we obtained from the continuous wind variable two tropical cyclone percentile dummies: (1) below the 90th percentile dummy and (2) in the top 10th percentile of tropical cyclone damage. Wind speed values equal zero or not classifiable as at least a tropical storm in terms of intensity are not included in the bottom 90th percentile.

Figure 2.A.2 illustrates the wind speed damage tropical cyclone exposure Kernel density, while Figure 2.A.3 shows the mean 2010-2018 tropical cyclone wind damage continuous indicator indicators across U.S. counties (only positive wind speed is considered in the computation of mean value). Categorical tropical cyclone exposure measures are widely used in the literature (see, e.g., Lang and Ryder, 2016). The use of continuous wind speed information, as reported by (Anderson et al., 2020), is important for our work to focus the most extreme tropical cyclones damage. The reason for isolating on extreme damage (top 10th percentile vs the bottom 90th) is due to the strong persistence of individual opinions and the importance of studying particularly destructive hazards which can lead to a heightened political and environmental memory effect among U.S. residents (Egan and Mullin, 2017). The use of the wind speed in order to track the occurrence or not of a tropical cyclone, compared to tropical cyclone-related flooding/rain or tropical cyclone surge measures, is due to the large use in literature and from the greater data availability (Bertinelli and Strobl, 2013).

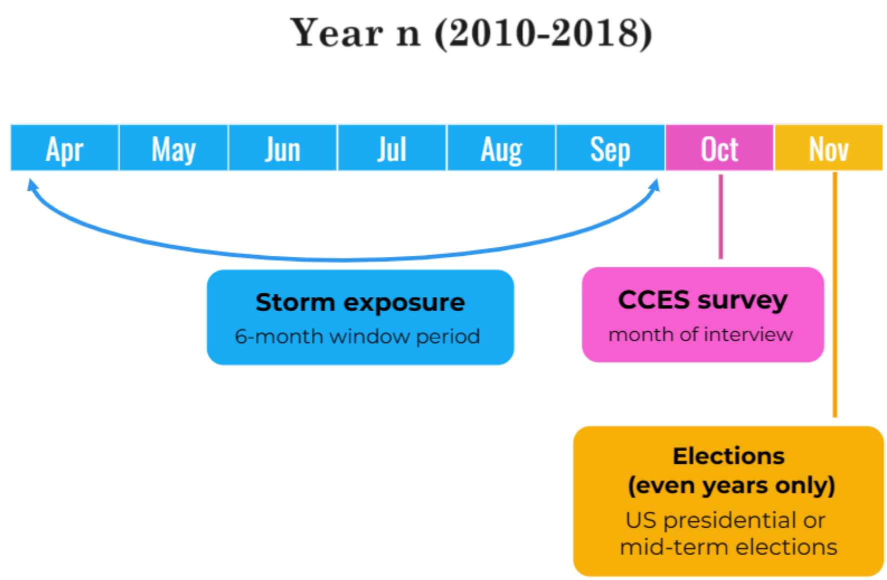
2.3.3 Final database and descriptive statistics information

The final ideology-tropical cyclones database is constituted by 207,229 individuals (see subsection 2.1.1 in the appendix for an overview about data cleaning). Every individual in the Cooperative Election Study database has been indeed merged with the county-tropical cyclone exposure measure information for each 6-month pre-survey period[12].

Figure 2.1 represents a timeline regarding our data collection period of events, applicable to all years of our database (going from 2010 to 2018). The timing of the ideology data collection is ideal,

[12] All Cooperative Election Study individuals present tropical cyclones information

Figure 2.1: Timeline of events



as it occurs between the end of the tropical cyclone season and the start of relevant political events (the Midterm elections of November 2010, 2014 and 2018 and to the U.S. presidential elections of November 2012 and 2016) period.

The final database sample descriptive statistics is observable from Table 2.1. On average the sample presents moderate political ideologies, slightly tending towards liberal. The percentage of individuals for each political group which experienced respectively a tropical storm/cyclone of a bottom 90th or top 10th percentile intensity is also reported. 3.7% of the sample of individuals has been subject to tropical cyclones. The Republican group of individuals is the most affected by tropical cyclones of great intensity (comparing tables 2.A.3, 2.A.4, and 2.A.5), although the difference between groups is minimal. The mean age of the interviewees is quite high (52) and half of the interviewees is male. On average, the respondents had a family income between 50,000-60,000 dollars. The 78% the respondents are white and half of respondents are employed.

Figure 2.2 displays the total number of interviewees in the final sample for each county over the 2020-2018 period. It is evident that the central U.S. is largely uncovered, while the Eastern region is well represented. The final dataset includes all U.S. states and 2,950 counties (94% of U.S. counties and county equivalents). Most counties have fewer than 100 respondents, with only

Table 2.1: Descriptive statistics of sample variables

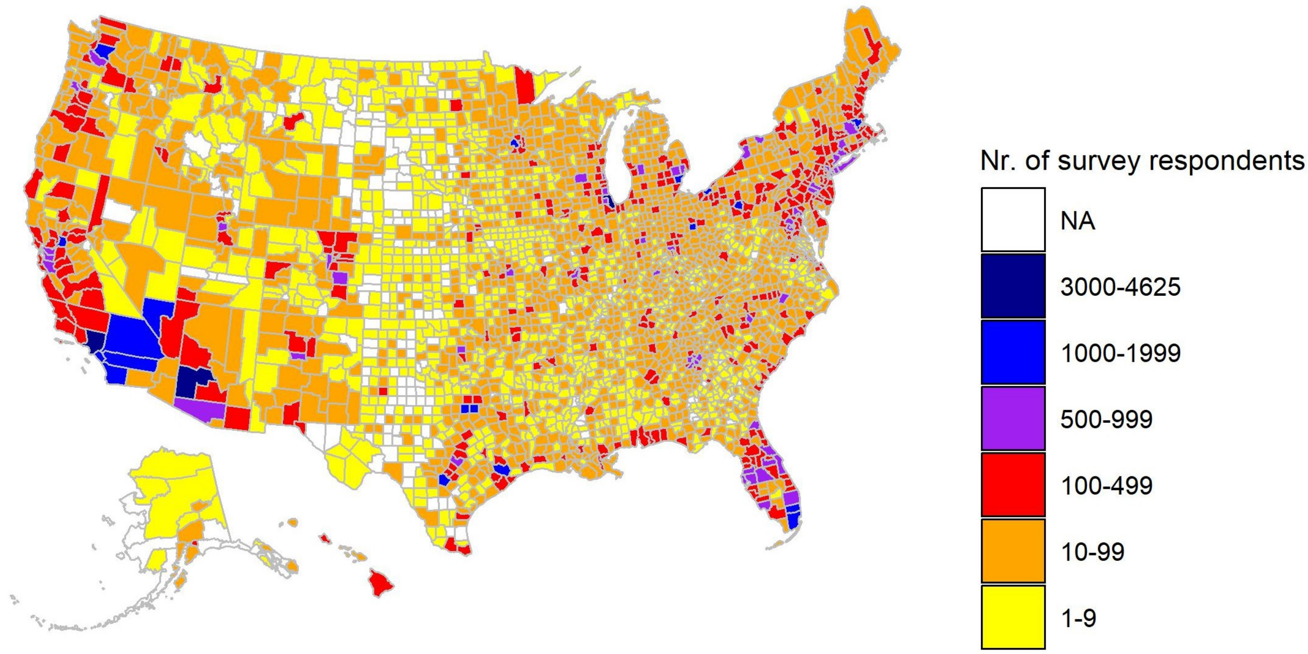
Statistic	N	Mean	St. Dev.	Min	Max
Ideology	207,229	0.431	0.290	0	1
Tropical cyclone bottom 90th percentile and Democrat	207,229	0.017	0.128	0	1
Tropical cyclone bottom 90th percentile and Republican	207,229	0.015	0.122	0	1
Tropical cyclone bottom 90th percentile and Independent	207,229	0.002	0.044	0	1
Tropical cyclone top 10th percentile and Democrat	207,229	0.001	0.038	0	1
Tropical cyclone top 10th percentile and Republican	207,229	0.002	0.041	0	1
Tropical cyclone top 10th percentile and Independent	207,229	0.0002	0.015	0	1
Tropical cyclone wind damage	207,229	19.99	112.42	0	2816.49
Age	207,229	52.434	15.555	18	96
Education	207,229	3.853	1.453	1	6
Gender: male	207,229	0.496	0.500	0	1
Race: black	207,229	0.094	0.292	0	1
Race: white	207,229	0.783	0.412	0	1
Race: other	207,229	0.123	0.329	0	1
Family income	207,229	6.616	3.125	1	12
Job: employed	207,229	0.532	0.499	0	1
Job: unemployed	207,229	0.050	0.217	0	1
Job: inactive	207,229	0.397	0.489	0	1
Job: other job type	207,229	0.021	0.144	0	1

a limited number of counties having a few thousand respondents. Only 6% of counties have 1 interviewee in total.

Figure 2.3 shows the distribution of the very liberal to very conservative ideology variable across even years in our database, for both the full sample and each political party group. Cold colors are used for the Democrats governing years (Barack Obama), and warm colors for the Republican ones (Donald Trump). It is noticeable that political ideology is close to be representing a classic "double-peak" distribution of political preferences. As for the Democrat group, the increase over time of liberal values is evident, so as the fact that conservative values increased for the Republicans. As regards the full sample, an erosion of the moderate center emerges. The moderate group, finally, switched towards more liberal values in recent years.

Table 2.2 presents data on media information preferences from the 2010–2014 CES panel database (limited to the years 2010, 2012, and 2014). Despite relying on a different data source, the table helps assess Americans' media interests. Each media variable takes a value of 0 or 1, where 1 indicates that the individual was exposed to that specific type of media in the 24 hours

Figure 2.2: 2010-2018 average number of county individuals interviewed - final database sample information



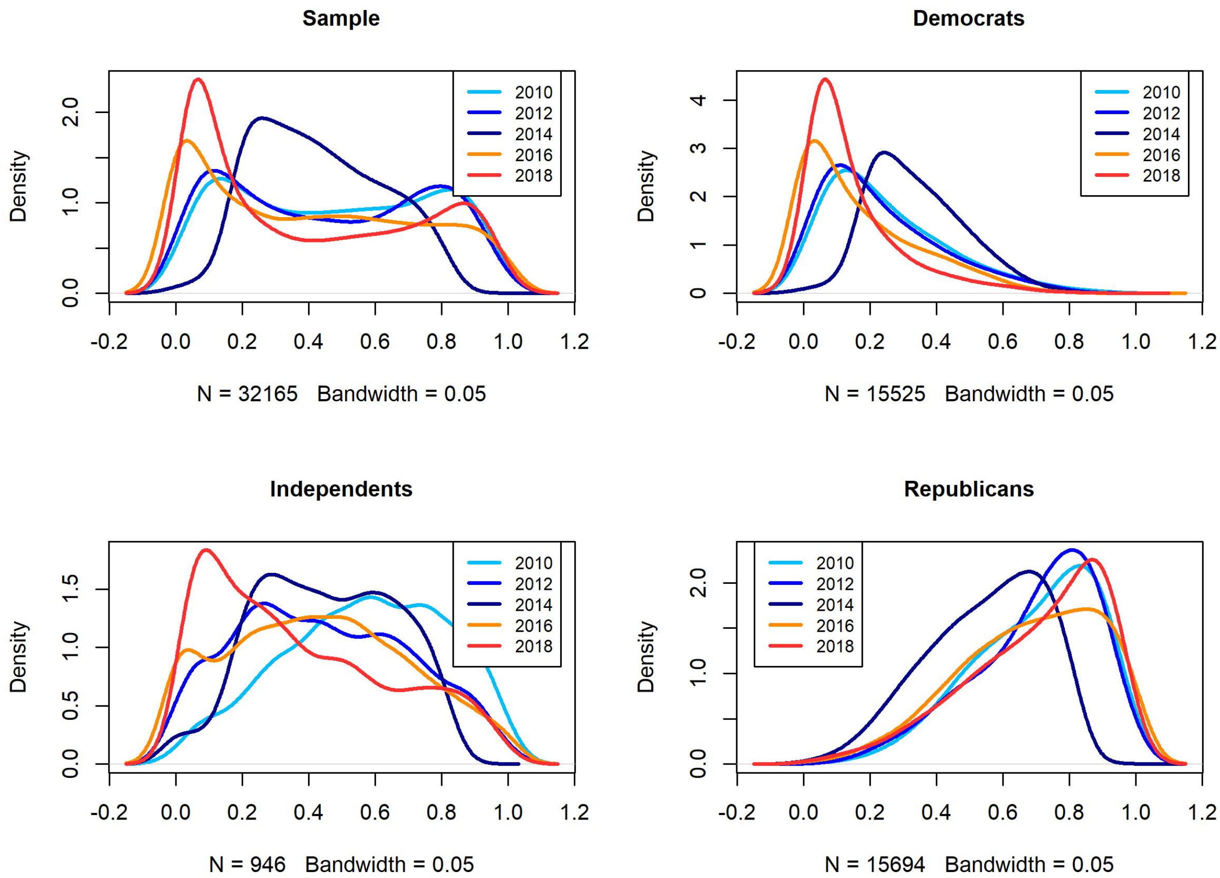
Notes: Counties failing to have at least one interviewee on average are coloured in white.

Table 2.2: Interest for media

	TV	Radio	Newspaper	Internet	Internet > traditional media
Mean	0.78	0.49	0.66	0.29	0.16
Min	0	0	0	0	0
Max	1	1	1	1	1
Standard deviation	0.33	0.41	0.38	0.37	0.37

preceding the administration of the survey. The average value for each media variable represents the mean across the three years considered (2010, 2012, and 2014). For internet use, exposure was measured through a question on whether the individual had consulted a blog within that time frame. The table indicate a strong preference for traditional media, with TV being the most popular, followed by newspapers and then radio. Moreover, only 16% of individuals show a greater interest in internet-based news compared to traditional media. This pattern could be attributed to the relatively high average age of the sample, which is 52 years old. However, it is important to

Figure 2.3: Ideology variable Kernel density - full sample and party groups



note that even traditional media in the US are highly polarized, often reflecting distinct ideological perspectives (Feldman et al., 2014).

2.4 Empirical model and identification strategy

The main equation for our empirical analysis via OLS regressions is the following:

$$\text{Ideology}_{i,t} = \alpha + \beta_1\text{Party} + \beta_2\text{Party} \times \text{TC\_exposure}_{i,t} + \gamma \text{X}_{i,t} + \delta_t + \mu_z + \epsilon_{i,t} \tag{2.2}$$

where $\textit{Party} \times \textit{TC\_exposure} \in$ {Top10Democrat, Top10Republican, Top10Independent, Bottom90Democrat, Bottom90Republican, Bottom90Independent} and $\textit{Party} \in$ {Democrat, Republican, Independent}.

Ideology is the dependent variable of interest at individual level *i*, the political very liberal – very conservative ideology score at time *t*, where T is composed by 9 years and each period is constituted by a six month before survey window.

Party is a set of dummy variables indicating the political party of the U.S. president voted during last presidential election.

Party X *TC_exposure* represents a set of independent (dummy) variables indicating the interaction between tropical cyclone damage percentiles and party affiliation. These dummy variables are assigned a value of 1 when both the condition for each percentile category (bottom 90th or top 10th) and the party affiliation (Democrat, Republican, or Independent) are jointly satisfied; otherwise, they are set to 0. For instance, a Republican affected by a tropical cyclone in the top 10th percentile of the damage distribution will have the dummy variables *Top10Republican*, *Top10*, and *Republican* equal to 1. Similarly, the dummy *Bottom90Independent* will be set to 1 only in the case where both the *Independent* and *Bottom90* dummies are equal to 1 for the individual year. All other combinations of storm percentile (including the absence of any tropical cyclone events) and party affiliation will result in a value of 0.

Vector X is a set of control variables which regards the socioeconomic characteristics of each individual (education, age, gender, family income, religion, race, job status, presence of a health insurance, citizen status, type of housing contract, and membership of a union status).

Equation 2.2 also contains δ_t, a year dummy variable, and μ_z, which is the county dummy variable. Standard errors have been clustered at county level, in order to account for auto-correlation. This is because each county resident has been assigned the same tropical cyclone exposure measure value.

Our empirical analysis aims to test the following claim: for each political group, we investigate whether greater exposure to tropical cyclone events—measured using wind-speed economic damage percentiles (bottom 90% and top 10%)—correlates with increased extremeness in political ideology. Specifically, we test whether Democrat voters tend to become more liberal and Republicans more conservative, indicating a phenomenon of ideological polarization.

Given the importance of controlling for geographical and temporal factors, we include county and year dummies. Controlling for geographic features is critical in natural disaster studies, as it allows us to account for resilience levels, disaster proneness, and the effectiveness of post-disaster government responses, which vary across locations. We included county-level dummies to account for the localized nature of tropical cyclone impacts and damages, as well as to ensure consistency with our independent variable, which is measured at the county level. Year dummies are essential to capture the influence of macroeconomic shocks—such as economic crises, globalization, and automation—on electorate ideology.

Our study exploits the exogenous nature of tropical cyclones, whose origin, timing, trajectory, and intensity cannot be predicted (Wang et al., 2018). Additionally, we rely on scientifically sound and politically independent data, derived from a best-tracks wind model, which is free from biases related to media coverage or public perception.

While it is important to note that our sample includes both cyclone-prone and non-prone areas, we deliberately chose to analyze the entire U.S. in order to generalize our findings on a national scale. This broader approach allows us to extend the same hypotheses to other types of natural disasters across the country. Restricting the sample to areas based solely on cyclone risk could inadvertently exclude nearby regions that may also be affected by cyclones, especially as these events are becoming more intense and shifting geographically towards the western U.S. Partitioning the sample based on geographic boundaries is ultimately a researcher's decision, and such an approach could introduce bias depending on the areas selected. By analyzing the entire U.S. without manipulating the sample, we allow nature to exogenously and randomly assign exposure to cyclones, while controlling for county-level characteristics using fixed effects.

In addition, the timing of the CES survey minimizes the risk of bias related to respondents' holiday periods or their location at the time hurricanes occur. By September, almost all students have returned to their usual places of residence following the summer holiday period,[13] particularly given that the peak of hurricane activity occurs on September 10.[14] Even if some respondents are temporarily away, the material impacts of tropical cyclones ensure that individuals would still

[13]https://www.pewresearch.org/short-reads/2023/08/25/back-to-school-dates-u-s/

[14]https://www.nhc.noaa.gov/climo/: :text=The%20official%20hurricane%20season%20for,%2DAugust%20and%20mid%2DOctober.

experience significant property damage at their primary residence, underscoring the relevance of their reported location. This assumption is further supported by the limited holiday time available to U.S. workers. On average, American workers take 17 holiday days per year, among which the average time spent away from home is only 7 to 8 days.[15] Moreover, 45% of workers do not use their full paid time off.[16] Administered online, the survey explicitly asks respondents to indicate their actual location at the time of the survey, rather than their legally registered address.

In addition, focusing on political ideology rather than voting behavior may more effectively capture political attitudes among disaster-exposed residents who might face barriers to voting, such as relocation or difficulties accessing polling stations due to recent climate hazards (Debbage et al., 2014). Measuring political views one month before the November elections serves as a valuable proxy for voting intentions.

However, several limitations should be acknowledged. First, the need to analyze a large number of U.S. residents and counties affected by tropical cyclones led us to use an unbalanced repeated cross-sectional dataset, which precludes identifying causal effects of cyclones on ideology. Furthermore, U.S. residents affected by natural disasters may be less likely to participate in surveys, introducing selection bias in our dependent variable.

2.5 Results

We turn now our analysis to the description of the results using OLS regression (N=207,229 and T=9) as observable from Table 2.3.

According to Table 2.3, a polarizing phenomenon is observed when individuals experience a tropical cyclone ranked in the top 10 percentile of cyclone damage. Specifically, at this level of exposure, Democrats become, on average, 1.7% points more liberal compared to Democrats not affected by tropical cyclones (a result significant at the 5% level). Meanwhile, Republicans become, on average, 4.5% points more conservative compared to their unaffected counterparts (a

[15] https://www.ustravel.org/system/files/media_root/document/StateofAmericanholiday2018.pdf.

[16] https://www.pewresearch.org/short-reads/2023/08/10/more-than-4-in-10-u-s-workers-dont-take-all-their-paid-time-off/.

Table 2.3: Main results

	Dependent variable: ideology
	(1)
Democrat	-0.400***
	(0.002)
Republican	base
Independent	-0.201***
	(0.004)
Tropical cyclone bottom 90th percentile and Democrat	-0.000
	(0.004)
Tropical cyclone bottom 90th percentile and Republican	0.001
	(0.005)
Tropical cyclone bottom 90th percentile and Independent	0.010
	(0.016)
Tropical cyclone top 10th percentile and Democrat	-0.017**
	(0.009)
Tropical cyclone top 10th percentile and Republican	0.045***
	(0.014)
Tropical cyclone top 10th percentile and Independent	0.004
	(0.040)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	207229
adj. R^2	0.591

Notes: OLS regression model. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. *Standard errors are clustered at county level. Dataset years range from 2010 to 2018. Positive values of wind-speed tropical cyclone damage have been categorized into two intensity levels: the top 10th percentile and the bottom 90th percentile. Prior to the two classes categorization, tropical cyclone variable was a continuous wind-speed cumulative damage variable comprehensive of tropical cyclones. Ideology is a continuous measure ranging between 0 and 1 (from very liberal to very conservative). Democrat, Independent and Republican dummies indicate the U.S. presidential candidate's party voted during the latest pre-survey and pre-tropical cyclone 6 month window election. The set of independent variables consists of dummy variables that take the value 1 when both the percentile of tropical cyclones damage (bottom 90th or 10th) and party (Democrat, Republican or Independent) conditions are met, 0 otherwise.*
The control variables included are: education, age, gender, family income, religion, race, job status, presence of a health insurance, citizen status, type of housing contract, membership of a union status. County dummies and year dummies included.

result significant at the 1% level). This indicates that Republicans' ideological response to tropical cyclone shocks is 2.6 times greater than that of Democrats.

In absolute terms, the 1.7% point shift in Democratic ideology corresponds to 9.4% of the standard deviation of ideology within this political group. For Republicans, the 4.5% point change accounts for 23% of the standard deviation of their ideological score. By contrast, independent individuals show no significant or substantial ideological changes associated with tropical cyclone exposure.

When examining the bottom 90th percentile of the tropical cyclone damage distribution, no evidence of polarization is detected. Individuals across political groups do not exhibit statistically significant or meaningful changes in their ideological patterns, underscoring the role of extreme disaster damage as a key driver of opinion change.

It is important to note that lower values of our ideological score represent more liberal ideologies, while higher values indicate more conservative ones. Given the continuous 0–1 nature of this indicator, the results can be directly interpreted as percentage changes relative to the tropical cyclone-party baseline (no cyclone exposure or differing percentile and party group). For each category of cyclone exposure intensity, a negative coefficient for the tropical cyclone-party interaction signals an increase in liberal values, while a positive coefficient indicates an increase in conservative values.

2.6 Robustness checks

2.6.1 Alternative bottom and top percentiles of tropical cyclone wind damage

First of all, a series of party-related alternative bottom (85th, 80th, 75th and 70th) and top (15th, 20th, 25th and 30th) percentiles have been created to test the robustness of the main results (Table 2.4) and tested over 4 different models. These joint party and tropical cyclone percentile dummies have been created following the same methodology of the main results' independent variables.

Table 2.4: Robustness: alternative bottom and top percentiles

	Dependent variable: ideology			
	(1)	(2)	(3)	(4)
Democrat	-0.400***	-0.400***	-0.400***	-0.400***
	(0.002)	(0.002)	(0.002)	(0.002)
Republican	base	base	base	base
Independent	-0.201***	-0.201***	-0.201***	-0.201***
	(0.004)	(0.004)	(0.004)	(0.004)
Tropical cyclone bottom 85th percentile and Democrat	0.001			
	(0.004)			
Tropical cyclone bottom 85th percentile and Republican	-0.000			
	(0.006)			
Tropical cyclone bottom 85th percentile and Independent	0.011			
	(0.017)			
Tropical cyclone top 15th percentile and Democrat	-0.023***			
	(0.008)			
Tropical cyclone top 15th percentile and Republican	0.035***			
	(0.011)			
Tropical cyclone top 15th percentile and Independent	-0.002			
	(0.028)			
Tropical cyclone bottom 80th percentile and Democrat		0.001		
		(0.004)		
Tropical cyclone bottom 80th percentile and Republican		-0.001		
		(0.006)		
Tropical cyclone bottom 80th percentile and Independent		0.005		
		(0.017)		
Tropical cyclone top 20th percentile and Democrat		-0.014*		
		(0.008)		
Tropical cyclone top 20th percentile and Republican		0.029***		
		(0.010)		
Tropical cyclone top 20th percentile and Independent		0.024		
		(0.023)		
Tropical cyclone bottom 75th percentile and Democrat			-0.001	
			(0.004)	
Tropical cyclone bottom 75th percentile and Republican			-0.001	
			(0.006)	
Tropical cyclone bottom 75th percentile and Independent			0.007	
			(0.018)	
Tropical cyclone top 25th percentile and Democrat			-0.005	
			(0.007)	
Tropical cyclone top 25th percentile and Republican			0.025***	
			(0.009)	
Tropical cyclone top 25th percentile and Independent			0.014	
			(0.021)	
Tropical cyclone bottom 70th percentile and Democrat				-0.001
				(0.005)
Tropical cyclone bottom 70th percentile and Republican				-0.000
				(0.006)
Tropical cyclone bottom 70th percentile and Independent				0.012
				(0.020)
Tropical cyclone top 30th percentile and Democrat				-0.003
				(0.006)
Tropical cyclone top 30th percentile and Republican				0.019**
				(0.008)
Tropical cyclone top 30th percentile and Independent				0.003
				(0.020)
Regional dummies included	yes	yes	yes	yes
Year dummies included	yes	yes	yes	yes
Controls included	yes			
N	207229	207229	207229	207229
adj. R^2	0.591	0.591	0.591	0.591

Notes: OLS regression model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

Starting from the top 15th percentile, it is observable that there is a lower coefficient for the Republicans (and a larger one for the Democrats) compared to the baseline. As for the top 20th percentile, a decrease in magnitude size of Democrat and Republican coefficients is evident with reference to the top 15th percentile. Results are less statistically significant for Democrats (while statistical significance at 1% level is maintained for Republicans). At the top 25th and 30th percentiles results for Democrats are not statistically significant anymore at 10% level and the coefficient of Republicans, still significant, gets progressively smaller in size. All in all, this table confirms the hypothesis of higher occurrence of extreme ideologies across both Democrats and Republicans when particularly damaging tropical cyclones hit the US. At the 25th and 30th percentile we are still in presence of a political polarization phenomena, given the greater divergence in liberal and conservative opinions though, despite being driven by a Republican conservative shift only.

2.6.2 Alternative dependent variable: exclusion of the environmental topic

We explored an alternative specification of the dependent variable by excluding survey questions related to environmental topics. These questions asked respondents to approve or reject potential environmental policies, assess their level of concern about climate change, and indicate their preference for environmental protection over job security (see the "Environment" topic in Tables 2.A.1 and 2.A.2). All other features of the model remain unchanged from the main analysis. In this version, survey questions related to environmental topics are excluded from the measurement of the dependent variable to enhance the focus of the results. Including questions about climate change while studying how hurricanes influence individuals' positions on the political spectrum might reflect effects more closely tied to environmental attitudes rather than broader political shifts. By excluding these questions, the analysis seeks to more accurately capture movements along the political spectrum without mixing them with changes in environmental perspectives.

Table 2.5 presents the results for this robustness check. At the 10th percentile of the distri-

Table 2.5: Robustness: alternative dependent variable - exclusion of the environmental topic

	Dependent variable: ideology
	(1)
Democrat	-0.398***
	(0.002)
Republican	base
Independent	-0.202***
	(0.004)
Tropical cyclone bottom 90th percentile and Democrat	-0.005
	(0.005)
Tropical cyclone bottom 90th percentile and Republican	0.006
	(0.006)
Tropical cyclone bottom 90th percentile and Independent	0.012
	(0.017)
Tropical cyclone top 10th percentile and Democrat	-0.015
	(0.010)
Tropical cyclone top 10th percentile and Republican	0.050***
	(0.014)
Tropical cyclone top 10th percentile and Independent	0.018
	(0.041)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	207229
adj. R^2	0.554

Notes: OLS regression model. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. *Standard errors are clustered at county level. Dataset years range from 2010 to 2018. In this robustness check the environmental component of the indicator is excluded. Positive values of wind-speed tropical cyclone damage have been categorized into two intensity levels: the top 10th percentile and the bottom 90th percentile. Prior to the two classes categorization, tropical cyclone variable was a continuous wind-speed cumulative damage variable comprehensive of tropical cyclones. Ideology is a continuous measure ranging between 0 and 1 (from very liberal to very conservative). Democrat, Independent and Republican dummies indicate the U.S. presidential candidate's party voted during the latest pre-survey and pre-tropical cyclone 6 month window election. The set of independent variables consists of dummy variables that take the value 1 when both the percentile of tropical cyclones damage (bottom 90th or 10th) and party (Democrat, Republican or Independent) conditions are met, 0 otherwise.*
The control variables included are: education, age, gender, family income, religion, race, job status, presence of a health insurance, citizen status, type of housing contract, membership of a union status. County dummies and year dummies included.

bution only Republicans result to change their ideology (becoming more conservative) with a statistical significance of at least at 10% level. Despite not statistically significant, the coefficient of Democrats is negative.

This result highlights that extremization of Democrats' ideology may mostly come from a shift in opinions related with environmental policies and environmental protection, while this does not not seem to hold for Republicans. A polarization phenomenon deriving from a directional change in Republican's opinion and immobility of the rest of population's opinion still remains, though.

2.6.3 Alternative tropical cyclones time window: 12 months

Additionally, we check whether the main results change when considering a different tropical cyclone temporal window. Such window is extended from 6 to 12 months before pre-election survey (see Table 2.6). In this 12-month temporal window, we have some additional counties hit from 7 to 12 months before the surveys (see figure 2.A.3 and 2.B.3 in supplementary information for a comparison across 6- and 12-month time windows counties hit and maximum wind speed experienced).

Results (Table 2.6) appear to be also in this case confirmed in terms of p-values levels, coefficient signs (negative for Democrats and positive for Republicans) and similarity in coefficient magnitudes with respect to the main analysis (Table 2.3). Hence, also in this case a polarising phenomenon emerges in the population at the greatest level of tropical cyclone damage (10th percentile). Again, Independent individuals' ideology is not correlated with tropical cyclone events exposure. All in all, the results highlighted hereby are in line with the main specification results.

2.6.4 Northeast and South regions sample restriction

In this robustness check (see Table 2.7) we use an alternative database, differing in the geographical area covered: we retained as U.S. regions only the Northeast and the South, given the traditional occurrence of hurricanes in this area. We removed from the database the individuals living in Midwest and West US. The number of observations resulted to be reduced by slightly

Table 2.6: Robustness: alternative independent variable: 12 month tropical cyclone window

	Dependent variable: ideology
	(1)
Democrat	-0.400***
	(0.002)
Republican	base
Independent	-0.201***
	(0.004)
Tropical cyclone bottom 90th percentile and Democrat	0.004
	(0.004)
Tropical cyclone bottom 90th percentile and Republican	-0.001
	(0.005)
Tropical cyclone bottom 90th percentile and Independent	0.014
	(0.014)
Tropical cyclone bottom 10th percentile and Democrat	-0.027***
	(0.009)
Tropical cyclone top 10th percentile and Republican	0.058***
	(0.011)
Tropical cyclone top 10th percentile and Independent	-0.043
	(0.036)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	207229
adj. R^2	0.591

Notes: OLS regression model. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$. *Standard errors are clustered at county level. Dataset years range from 2010 to 2018. In this robustness check pre-tropical cyclone time window has been extended up to 12 months before survey administration (in main analysis it was up to 6 months). Positive values of wind-speed tropical cyclone damage have been categorized into two intensity levels: the top 10th percentile and the bottom 90th percentile. Prior to the two classes categorization, tropical cyclone variable was a continuous wind-speed cumulative damage variable comprehensive of tropical cyclones. Ideology is a continuous measure ranging between 0 and 1 (from very liberal to very conservative). Democrat, Independent and Republican dummies indicate the U.S. presidential candidate's party voted during the latest pre-survey and pre-tropical cyclone 6 month window election. The set of independent variables consists of dummy variables that take the value 1 when both the percentile of tropical cyclones damage (bottom 90th or 10th) and party (Democrat, Republican or Independent) conditions are met, 0 otherwise.*
The control variables included are: education, age, gender, family income, religion, race, job status, presence of a health insurance, citizen status, type of housing contract, membership of a union status. County dummies and year dummies included.

less than 50% (N = 110,386). Again, a polarization phenomenon is detected at extremely damaging hurricanes: Democrats are associated with more liberal values and Republicans with more conservative views with respect, compared to the rest of the sample. Results are robust in almost all cases at 5% level. At the top 10th percentile of tropical cyclone damage the coefficient magnitudes of Democrats and Republicans are greater compared to the baseline ones, with Republicans always showing a greater coefficient than Democrats. Independent individuals do not follow any specific pattern of ideology. None of the bottom 90 percentile coefficient dummies is statistically significant at least at 10% level.

2.6.5 Counties only hit once in the 2010-2018 period

Finally, Table 2.8 presents the results, focusing exclusively on counties that were affected only once throughout the entire period covered by our database, following Deryugina (2017). This allows us to account for the potential persistent effects of tropical cyclones, which may not be fully captured by the model.

This robustness check confirms our baseline results, indicating that political polarization remains present. Notably, independents also show a shift toward more conservative positions. While the effects for Republicans and Democrats are larger in magnitude, they are less statistically significant compared to the baseline findings.

2.6.6 Inclusion of more-likely to move individuals

In the next robustness check, only individuals who are more likely to have changed location during the hurricane period are retained. Young individuals under 40 have been found to be the most inclined to travel.[17] Only these individuals are included, and the regressions are re-run.

The results show that for extremely damaging tropical cyclones, polarization occurs, driven by an increase in Republican ideology and a lack of change in Democrat ideology. Overall, even

[17]Tufft, C., Constantin, M., Pacca, M., & Mann, R. (2024, May 29). The state of tourism and hospitality 2024. McKinsey & Company. https://www.mckinsey.com/industries/travel/our-insights/the-state-of-tourism-and-hospitality-2024.

Table 2.7: Robustness: Northeast and South regions restriction

	Dependent variable: ideology
	(1)
Democrat	-0.391***
	(0.005)
Republican	base
Independent	-0.192***
	(0.004)
Tropical cyclone bottom 90th percentile and Democrat	-0.003
	(0.004)
Tropical cyclone bottom 90th percentile and Republican	0.007
	(0.005)
Tropical cyclone bottom 90th percentile and Independent	0.006
	(0.016)
Tropical cyclone top 10th percentile and Democrat	-0.021**
	(0.009)
Tropical cyclone top 10th percentile and Republican	0.050***
	(0.014)
Tropical cyclone top 10th percentile and Independent	-0.000
	(0.040)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	110386
adj. R^2	0.581

Notes: OLS regression model. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. *Standard errors are clustered at county level. Regions retained: Northeast and South. Regions excluded: West and Midwest. Dataset years range from 2010 to 2018. Positive values of wind-speed tropical cyclone damage have been categorized into two intensity levels: the top 10th percentile and the bottom 90th percentile. Prior to the two classes categorization, tropical cyclone variable was a continuous wind-speed cumulative damage variable comprehensive of tropical cyclones. Ideology is a continuous measure ranging between 0 and 1 (from very liberal to very conservative). Democrat, Independent and Republican dummies indicate the U.S. presidential candidate's party voted during the latest pre-survey and pre-tropical cyclone 6 month window election. The set of independent variables consists of dummy variables that take the value 1 when both the percentile of tropical cyclones damage (bottom 90th or 10th) and party (Democrat, Republican or Independent) conditions are met, 0 otherwise.*
The control variables included are: education, age, gender, family income, religion, race, job status, presence of a health insurance, citizen status, type of housing contract, membership of a union status. County dummies and year dummies included.

Table 2.8: Rob. check: counties only hit once in the 2010-2018 period

	Dependent variable: ideology
	(1)
Democrat	-0.200***
	(0.004)
Republican	0.201***
	(0.003)
Independent	base
Tropical cyclone bottom 90th percentile and Democrat	0.010
	(0.006)
Tropical cyclone bottom 90th percentile and Republican	-0.005
	(0.011)
Tropical cyclone bottom 90th percentile and Independent	-0.020
	(0.025)
Tropical cyclone top 10th percentile and Democrat	-0.027*
	(0.014)
Tropical cyclone top 10th percentile and Republican	0.061*
	(0.033)
Tropical cyclone top 10th percentile and Independent	0.053**
	(0.024)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	207229
adj. R^2	0.591

Table 2.9: Rob. check: travelers (below 40 years old)

	Dependent variable: ideology
	(1)
Democrat	-0.136***
	(0.007)
Republican	0.159***
	(0.007)
Independent	0.000
	(.)
Tropical cyclone bottom 90th percentile and Democrat	-0.005
	(0.008)
Tropical cyclone bottom 90th percentile and Republican	-0.049***
	(0.017)
Tropical cyclone bottom 90th percentile and Independent	-0.007
	(0.027)
Tropical cyclone top 10th percentile and Democrat	-0.014
	(0.031)
Tropical cyclone top 10th percentile and Republican	0.063**
	(0.029)
Tropical cyclone top 10th percentile and Independent	0.002
	(0.057)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	25702
adj. R^2	0.479

when controlling for individuals who were more likely to be located in a place different from their declared residence in the CES survey at the time of the hurricane (e.g., due to being on holiday or in another temporary location), the polarization phenomenon still holds, though it is not linked to shifts in both Democrat and Republican ideology.

2.6.7 Non-election years

Finally, this robustness check omits the presidential election years, as factors related to the presidential campaign may interfere with individual opinion formation. I therefore run a robustness check for non-election years only (excluding 2012 and 2016).

Table 2.10: Rob. check: non-election years

	Dependent variable: ideology
	(1)
Democrat	-0.182***
	(0.004)
Republican	0.193***
	(0.004)
Independent	base
Tropical cyclone bottom 90th percentile and Democrat	-0.007
	(0.005)
Tropical cyclone bottom 90th percentile and Republican	0.010
	(0.007)
Tropical cyclone bottom 90th percentile and Independent	0.012
	(0.019)
Tropical cyclone top 10th percentile and Democrat	-0.034***
	(0.010)
Tropical cyclone top 10th percentile and Republican	0.041***
	(0.016)
Tropical cyclone top 10th percentile and Independent	-0.069
	(0.067)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	138760
adj. R^2	0.568

The results are confirmed in this robustness check: a polarization pattern emerges for particularly destructive phenomena, with very similar coefficients for Republicans, while the Democrat coefficient is slightly larger. Results for highly destructive hurricanes are significant at 1% level for both Democrats and Republicans. All in all, the fact that cyclone exposure during certain years can coincide with campaign exposure in election years is not a source of bias.

2.7 Mechanisms

2.7.1 News exposure

The first mechanism considered is demand-driven exposure to news. Individuals affected by extreme events are more likely, due to their heightened concern with causes, attribution, relief efforts, and policy responses, to seek out news through media channels (Miller and Goidel, 2009). However, the media landscape is highly polarized (Levendusky, 2013). Consequently, being affected by a hurricane may lead to an increased demand for news consumption, which can further intensify the polarization of the audience's views (Hoewe and Peacock, 2020; Carmichael et al., 2017).

This mechanism (Table 2.11) is tested using a set of independent dummy variable. These dummy variables take on a value of 1 when three specific conditions are simultaneously met: (1) the respondent falls within a particular damage percentile (either the bottom 90th or 10th percentile), (2) the respondent identifies him/herself within a specific political party (Democrat, Republican or Independent), and (3) the respondent has a high level of interest in news. If none of these conditions are met, the dummy variable takes value 0.

To assess individuals' interest in general news, we used the *newsint* question from the Cooperative Election Study (CES) database. This question measures self-reported interest in public affairs and political news on a 4-point scale, ranging from "hardly at all" to "most of the time." We classified an individual as having a high level of news interest if their response was at least 4, which corresponds to the median value of the sample distribution. The level of interest is determined based on responses to a survey question within the CES database, which specifically investigates the degree of interest in both general public and political news. Among individuals exposed to the top 10 percentile of tropical cyclone damage, 59% have a high interest in news. This percentage increases slightly to 63% for those in the bottom 90 percentile of cyclone damage. Similarly, 61% of individuals not affected by tropical cyclones also show a high interest in news.

The findings indicate that news exposure amplifies political polarization among survey respondents residing in counties with both high levels of news exposure and tropical cyclone damage, regardless of whether the damage falls within the top 10th percentile or the bottom 90th percentile. This effect intensifies with the severity of tropical cyclone damage and is more pronounced among Republicans compared to Democrats. By summing the coefficients for *tropical cyclone x party* and *tropical cyclone x party x low public funds*, we find that for the top 10th percentile of damage, there is an increase of 7.3% points in liberal ideology among Democrats and an increase of 9.6% points in conservative ideology among Republicans. For the bottom 90th percentile of damage, Democrats exhibit an increase of 2.8% points in liberal views, while Republicans show an increase of 4.3% points points in conservative views. These results highlight a statistical significant association among disasters, news consumption, and individual opinions, positioning news exposure as plausible amplifying factor of the political polarization phenomena associated with tropical cyclones.

2.7.2 Granted FEMA funds distribution

The second mechanism investigated concerns the distribution of granted FEMA relief aid. We hypothesize that an unequal distribution of the approved FEMA public fund may fuel political polarization within U.S. society. In situations of severe income and public budget scarcity, coupled with widespread destruction of natural resources and infrastructure, the adverse socioeconomic and distributive impacts caused by hurricanes may not be adequately absorbed. This can exacerbate societal conflicts, competition over resources and ultimately lead to increased polarization (Casal Bértoa and Rama, 2021; Levin, 2014; Roche et al., 2020).

The focus of this second mechanism (Table 2.12) is on a set of independent variables represented by dummy variables. These variables are set to 1 when each conditions combination is met:

Table 2.11: Mechanism: news exposure

	Dependent variable: ideology
	(1)
Democrat	-0.400*** (0.002)
Republican	base
Independent	-0.201*** (0.004)
Tropical cyclone bottom 90th percentile and Democrat	0.037*** (0.006)
Tropical cyclone bottom 90th percentile and Republican	-0.081*** (0.007)
Tropical cyclone bottom 90th percentile and Independent	-0.007 (0.017)
Tropical cyclone bottom 90th percentile and Democrat and high news exposure	-0.065*** (0.007)
Tropical cyclone bottom 90th percentile and Republican and high news exposure	0.124*** (0.008)
Tropical cyclone bottom 90th percentile and Independent and high news exposure	0.030 (0.027)
Tropical cyclone top 10th percentile and Democrat	0.045*** (0.016)
Tropical cyclone top 10th percentile and Republican	-0.049** (0.020)
Tropical cyclone top 10th percentile and Independent	0.004 (0.068)
Tropical cyclone top 10th percentile and Democrat and high news exposure	-0.118*** (0.018)
Tropical cyclone top 10th percentile and Republican and high news exposure	0.145*** (0.028)
Tropical cyclone top 10th percentile and Independent and high news exposure	0.001 (0.089)
Regional dummies included	yes
Year dummies included	yes
Controls included	yes
N	207229
adj. R^2	0.592

Notes: OLS regression model. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Standard errors are clustered at county level. Dataset years range from 2010 to 2018. Positive values of wind-speed tropical cyclone damage have been categorized into two intensity levels: the top 10th percentile and the bottom 90th percentile. Prior to the two classes categorization, tropical cyclone variable was a continuous wind-speed cumulative damage variable comprehensive of tropical cyclones. Ideology is a continuous measure ranging between 0 and 1 (from very liberal to very conservative). The focus of this mechanism table is the set of independent variables consisting of dummy variables that take the value 1 when both the percentile (bottom 90th or 10th), party (Democrat, Republican or Independent) and high level of news interest conditions are met, 0 otherwise. I used a question from the Cooperative Election Study (named "newsint" in the CES database) to assess individuals' interest in general news. An individual has a high level of news if the news interest he has on a 4-classes scale (from hardly at all to most of the time) is at least equal to the median (= 4). News interest variable comes from a survey question in the CES database investigating the level of interest towards general public and political news. Democrat, Independent and Republican dummies indicate the U.S. presidential candidate's party voted during the latest pre-survey and pre-tropical cyclone 6 month window election. The set of independent variables consists of dummy variables that take the value 1 when both the percentile of tropical cyclones damage (bottom 90th or 10th) and party (Democrat, Republican or Independent) conditions are met, 0 otherwise.*
The control variables included are: education, age, gender, family income, religion, race, job status, presence of a health insurance, citizen status, type of housing contract, membership of a union status. County dummies and year dummies included.

the percentile (bottom 90th or 10th), party affiliation (Democrat, Republican or Independent) and a low level of FEMA funds, 0 otherwise.

We utilized data from the open FEMA database[18], aggregating information at the county-year of tropical cyclone level for the Public Assistance (PA) program funds.

FEMA's Public Assistance Program offers supplemental grants to state, tribal, territorial, and local governments, as well as certain private non-profits, to support communities in responding to and recovering from major disasters or emergencies. Following events like hurricanes, tornadoes, earthquakes, or wildfires, these grants help cover the costs of debris removal, life-saving protective measures, and restoring public infrastructure. To access these funds, a formal application must be submitted by the affected entity (state, local authorities, non-profits, or tribal authorities) within 30 days of the disaster declaration issued by the president. The recipient, typically a state, territorial, or tribal government, is responsible for receiving and managing the federal funds under the disaster declaration and distributing them to eligible subrecipients. Emergency work, such as debris removal, must be completed within six months, while permanent repairs (e.g., to roads, public buildings, and utilities) must be finished within 18 months of the disaster declaration, with potential for extensions if necessary.

In our analysis, per capita per knot measures were created, with population data sourced from the U.S. Census Bureau[19] and wind speed exposure information is our county-year independent variable information. Each individual is assigned the county of residence level information. All public funds approved for disbursement associated with a tropical storm or hurricane that occurred within our 6-month window have been included. The low level of public funds is defined as any county-year funding data point below the per capita per knot median value ($ 2.28). Regions hit by hurricanes but receiving no funding are also included in the low funding category.

The results presented in Table 2.12 do not support the aforementioned hypothesis, at least from a correlational perspective. Overall, individuals residing in counties that experienced particularly damaging hurricanes (top 10th percentile) and received limited post-disaster funding do

[18] https://www.fema.gov/openfema-data-page/public-assistance-funded-projects-details-v1.
[19] https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-total.html.

Table 2.12: Mechanism: FEMA funds distribution

	Dependent variable: ideology
Funding type	Public funds per capita per knot
Democrat	-0.400*** (0.002)
Republican	base
Independent	-0.201*** (0.004)
Tropical cyclone bottom 90th percentile and Democrat	-0.021** (0.009)
Tropical cyclone bottom 90th percentile and Republican	0.027** (0.012)
Tropical cyclone bottom 90th percentile and Independent	-0.013 (0.036)
Tropical cyclone bottom 90th percentile and Democrat and low public funds	0.025*** (0.009)
Tropical cyclone bottom 90th percentile and Republican and low public funds	-0.032** (0.013)
Tropical cyclone bottom 90th percentile and Independent and low public funds	0.029 (0.037)
Tropical cyclone top 10th percentile and Democrat	-0.020* (0.010)
Tropical cyclone top 10th percentile and Republican	0.051*** (0.015)
Tropical cyclone top 10th percentile and Independent	-0.089 (0.089)
Tropical cyclone top 10th percentile and Democrat and low public funds	0.004 (0.017)
Tropical cyclone bottom 90th percentile and Republican and low public funds	-0.013 (0.028)
Tropical cyclone bottom 90th percentile and Independent and low public funds	0.138 (0.097)
N	207229
adj. R^2	0.591

Notes: OLS regression model. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. *Standard errors are clustered at the county level. The dataset covers the years 2010 to 2018. Positive values of wind-speed tropical cyclone damage have been categorized into two intensity levels: the top 10th percentile and the bottom 90th percentile. Prior to categorization, the tropical cyclone variable was a continuous wind-speed cumulative damage variable, including tropical cyclones. Ideology is a continuous measure ranging between 0 and 1 (from very liberal to very conservative). The focus of this mechanism table is the set of independent variables consisting of dummy variables that take the value 1 when both the percentile (bottom 90th or 10th), party (Democrat, Republican or Independent), and a low level of FEMA funds conditions are met, 0 otherwise. I used data for public funds from the open FEMA databases, aggregating information at the county level. The low level of public funds is defined as any county-year funding below the per capita per knot median value ($ 2.28). Democrat, Independent, and Republican dummies indicate the U.S. presidential candidate's party voted for during the latest pre-survey and pre-tropical cyclone 6-month window election. The set of independent variables consists of dummy variables that take the value 1 when both the percentile of tropical cyclones damage (bottom 90th or 10th) and party (Democrat, Republican or Independent) conditions are met, 0 otherwise. The control variables included are education, age, gender, family income, religion, race, job status, presence of health insurance, citizenship status, type of housing contract, and union membership status. County dummies and year dummies are included.*

not exhibit increased political polarization. Conversely, in the case of tropical cyclones of lesser magnitude (bottom 90th percentile), there is evidence of a slight decrease in polarization in a few instances. However, given the minimal magnitude of this effect, as indicated by the sum of the coefficients of *tropical cyclone x party* and *tropical cyclone x party x low public funds*, this finding can be regarded as negligible and safely disregarded.

Ultimately, it is not possible to claim that low FEMA funds are associated with political polarization. This may be explained by the fact that funding is at county level, with no guarantee that the individual will effectively benefiting from it, as FEMA information has been aggregated at county level. Another explanation is that, on average, public funding was disbursed approximately 10 months (311 days) after approval. The median disbursement time is 1 year and 1 month (398 days). Only 20% of public funding was reimbursed within 6 months after the end of the tropical cyclone, but a significant portion of them (40%) was disbursed after September, meaning it likely did not reach the counties before the survey was administered (only 12% of funds did). This delay may have been too long for individuals to change their opinions based on the increased funding.

2.8 Concluding remarks

This work has highlighted that extremely damaging tropical cyclone events (including tropical storms and hurricanes) lead to a polarization phenomenon among U.S. residents. A polarizing pattern emerges when individuals reside in counties that experience tropical cyclone damage in the top 10th percentile. Specifically, Democrats become 1.7% points more liberal compared to other U.S. residents, while Republicans become 4.5% points more conservative, with Republicans showing 2.6 times greater responsiveness to tropical cyclone shocks than Democrats.

The change in Democratic ideology, amounting to 1.7% points, represents 9.4% of the standard deviation of ideology within this group. In contrast, the variation for Republicans, at 4.5% points, corresponds to 22.5% of the standard deviation of the dependent variable for this political group.

Independent individuals show no significant ideological shift. However, when tropical cyclone damage is below the 90th percentile, no significant association is observed, underscoring that only extreme tropical cyclone events are linked to more pronounced shifts in public opinion.

We validate our main results by varying the bottom and top percentiles of tropical cyclone wind damage, using different ideological dependent variables, adjusting the pre-survey tropical cyclone occurrence time window (from 6 to 12 months), applying sample restrictions to the Northeast and South regions, including counties only hit once by hurricanes in the entire database period, including in the sample only individuals more likely to change location during hurricanes period and excluding election years.

We investigated two potential mechanisms: the first hypothesizing that being hit by tropical cyclones may increase the demand for news consumption, leading to greater political polarization (Hoewe and Peacock, 2020), and the second suggesting that insufficient public FEMA funds allocated to disaster-exposed counties could exacerbate societal conflicts, competition over resources, and ultimately political polarization (Casal Bértoa and Rama, 2021; Levin, 2014; Roche et al., 2020). We found that high exposure to public affairs and political news likely intensifies political polarization linked to extreme tropical cyclone damage, while no evidence was found to support the role of FEMA fund allocation.

Our results contrast with the literature in which events like temperature anomalies and wildfires primarily affect the preferences of Democrats, but not Republicans (Boudet et al., 2020; Hazlett and Mildenberger, 2020). This difference can likely be explained by the fact that those events are either weather anomalies or localized occurrences (such as wildfires in sparsely populated areas), whereas we contribute new evidence showing how highly destructive events in densely populated U.S. areas, such as tropical cyclones, drive polarization.[20]

In future analyses, it would be valuable to focus on Independents to determine whether this group genuinely does not change its opinion or if opposing forces between Democrat-leaning and Republican-leaning Independents are canceling each other out. Additionally, a promising next step would be to apply Natural Language Processing (NLP) techniques to analyze public opinions sourced from platforms like Twitter. Constructing a panel of U.S. counties could also enable a deeper investigation of causal relationships. Expanding the research to other regions, such as Europe, or to other types of highly destructive events, like floods, would offer valuable insights as well.

[20] https://maps.geo.census.gov/ddmv/map.html

Appendix

2.A Data and descriptive statistics

Figure 2.A.1: Mean ideology across U.S. states (2010-2018)

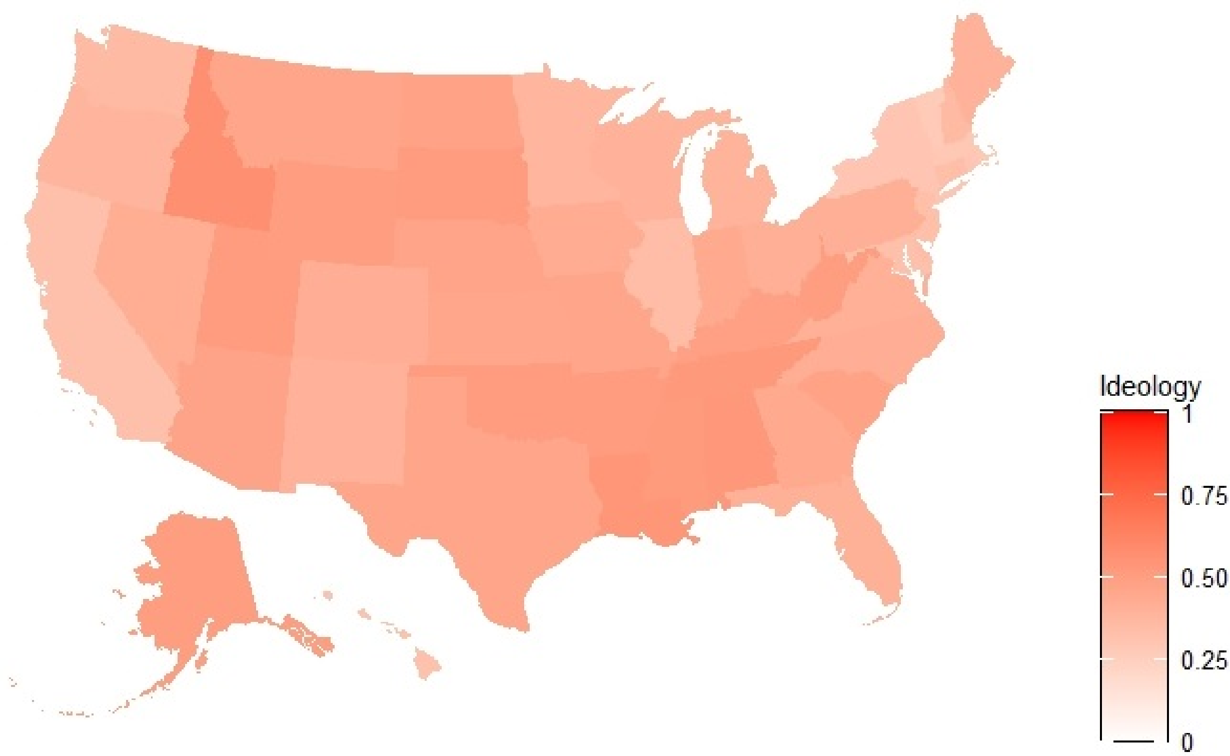
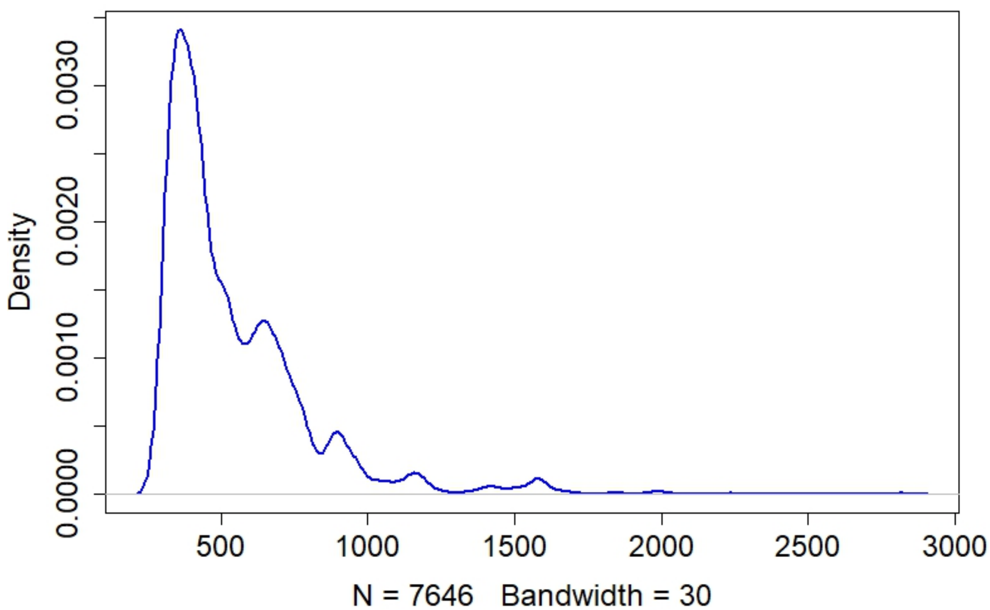


Figure 2.A.2: tropical cyclone Wind speed exposure density



Notes: This kernel density figure represents the wind speed exposure after the computation of the squared wind damage function (see Equation 2.1). Wind speed values equal to zero have been omitted in the computation of density.

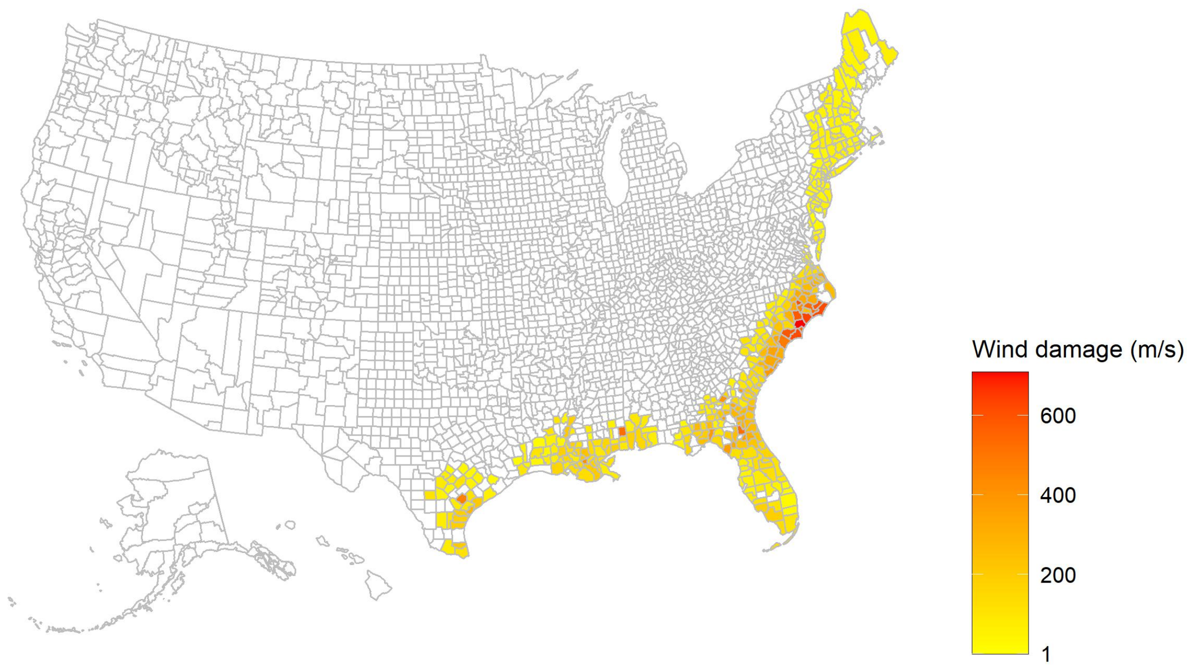
Table 2.A.1: Questions chosen for the ideology indicator and wording example (2010-2013)

Topic	Variable Name	Description	Years	Question Text
Abortion	abortion_scale	Support scale for access to abortion	2010-2013	Which one of the opinions on this page best agrees with your view on abortion? [1 By law, abortion should never be permitted, 2 The law should permit abortion only in case of rape, incest or when the woman's life is in danger, 3 The law should permit abortion for reasons other than rape, incest, or danger to the woman's life, but only after the need for the abortion has been clearly established, 4 By law, a woman should always be able to obtain an abortion as a matter of personal choice].
Environment	enviro_scale	Opposition scale to climate change	2010-2013	From what you know about global climate change or global warming, which one of the following statements comes closest to your opinion? [1 Global climate change has been established as a serious problem, and immediate action is necessary. 2 There is enough evidence that climate change is taking place and some action should be taken. 3 We don't know enough about global climate change, and more research is necessary before taking any actions. 4 Concern about global climate change is exaggerated. No action is necessary. 5 Global climate change is not occurring; this is not a real issue.]
Environment	enviro_vs_jobs	Preference scale between environmental protection and job availability	2010-2013	Some people think it is important to protect the environment even if it costs some jobs or otherwise reduces our standard of living. Other people think that protecting the environment is not as important as maintaining jobs and our standard of living. Which is closer to the way you feel, or haven't you thought much about this?
Immigration	immig_legalize	Grant conditional legal status to undocumented	2010-2013	What do you think the U.S. government should do about immigration? Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years, and not been convicted of any felony crimes.
Immigration	immig_border	Increase border security between US-Mexico	2010-2013	What do you think the U.S. government should do about immigration? Increase the number of border patrols on the US-Mexican border.
Immigration	immig_police	Allow police questioning of suspected undocumented	2010-2013	What do you think the U.S. government should do about immigration? Allow police to question anyone they think may be in the country illegally.
Gay Rights	gaymarriage_ban	Amendment banning gay marriage	2010-2011	Do you support a constitutional Amendment banning Gay Marriage?
Gay Rights	gaymarriage_legalize	Support for legalizing gay marriage	2012-2013	Do you favor or oppose allowing gays and lesbians to marry legally?
Affirmative Action	affirmativeaction	Opposition scale to affirmative action	2010-2013	Affirmative action programs give preference to racial minorities in employment and college admissions in order to correct for past discrimination. Do you support or oppose affirmative action?

Table 2.A.2: Questions chosen for the ideology indicator and wording example (2014-2018)

Topic	Variable Name	Description	Years	Question Text
Abortion	abortion_always	Always allow abortion	2014-2018	Do you support or oppose each of the following proposals? Always allow a woman to obtain an abortion as a matter of choice.
Abortion	abortion_coverage	Employer coverage of abortion	2014-2018	Do you support or oppose each of the following proposals? Allow employers to decline coverage of abortions in insurance plans.
Abortion	abortion_expenditures	Prohibit expenditures for abortion	2014-2018	Do you support or oppose each of the following proposals? Prohibit the expenditure of funds authorized or appropriated by federal law for any abortion.
Environment	enviro_carbon	Allow EPA to regulate carbon dioxide emissions	2014-2018	Do you support or oppose each of the following proposals? Give Environmental Protection Agency power to regulate Carbon Dioxide emissions.
Environment	enviro_mpg_raise	Raise average fuel efficiency	2014-2018	Do you support or oppose each of the following proposals? Raise required fuel efficiency for the average automobile from 25 mpg to 35 mpg.
Environment	enviro_renewable	Require states use a minimum amount of renewable fuels	2014-2018	Do you support or oppose each of the following proposals? Require that each state use a minimum amount of renewable fuels (wind, solar, and hydroelectric) in the generation of electricity even if electricity prices increase a little.
Environment	enviro_airwateracts	Strengthen EPA enforcement of Clean Air and Water acts	2014-2018	Do you support or oppose each of the following proposals? Strengthen the Environmental Protection Agency enforcement of the Clean Air Act and Clean Water Act even if costs U.S. jobs.
Immigration	immig_legalize	Grant conditional legal status to undocumented	2014-2017	What do you think the U.S. government should do about immigration? Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years, and not been convicted of any felony crimes.
Immigration	immig_border	Increase border security between US-Mexico	2014-2017	What do you think the U.S. government should do about immigration? Increase the number of border patrols on the US-Mexican border.
Immigration	immig_deport	Identify and deport illegal immigrants	2014-2017	What do you think the U.S. government should do about immigration? Identify and deport illegal immigrants.
Immigration	immig_report	Withhold funding from police failing to report illegal immigrants	2018	What do you think the U.S. government should do about immigration? Withhold federal funds from any local police department that does not report to the federal government anyone they identify as an illegal immigrant.
Immigration	immig_reduce	Reduce legal immigration by 50 percent	2018	Do you support or oppose each of the following proposals? Reduce legal immigration by eliminating the visa lottery and ending family-based migration.
Immigration	immig_wall	Increase spending on border security, including building a wall	2018	Do you support or oppose each of the following proposals? Increase spending on border security by 25 billion, including building a wall between the U.S. and Mexico.
Guns	guns_bgchecks	Background checks for all gun sales	2014-2018	On the issue of gun regulation, are you for or against each of the following proposals? Background checks for all sales, including at gun shows and over the Internet.
Guns	guns_assaultban	Ban assault rifles	2014-2018	On the issue of gun regulation, are you for or against each of the following proposals? Ban assault rifles.
Guns	guns_permits	Ease ability to obtain concealed-carry permits	2014-2018	On the issue of gun regulation, do you support or oppose each of the following proposals? Make it easier for people to obtain concealed-carry permits.
Health	healthcare_aca	Repeal the Affordable Care Act	2014-2018	Congress considered many important bills over the past few years. Do you support or oppose the legislation in principle? Repeal the Affordable Care Act.

Figure 2.A.3: Mean 6-month window wind speed damage across U.S. counties (2010-2018)



Notes: Counties failing to receive at least one tropical cyclone in the entire period are coloured in white. Tropical cyclone mean wind damage over the period are computed on positive wind values only.

Table 2.A.3: Descriptive statistics for the Democrats

Statistic	N	Mean	St. Dev.	Min	Max
Ideology	104,785	0.228	0.180	0.000	1.000
Tropical cyclone bottom 90th percentile	104,785	0.033	0.178	0	1
Tropical cyclone bottom 10th percentile	104,785	0.003	0.053	0	1
Tropical cyclone damage	104,785	19.155	108.911	0.000	2,235.600
Age	104,785	50.481	15.738	18	96
Education	104,785	4.013	1.456	1	6
Gender: male	104,785	0.435	0.496	0	1
Race: black	104,785	0.169	0.374	0	1
Race: white	104,785	0.692	0.462	0	1
Race: other	104,785	0.139	0.346	0	1
Family income	104,785	6.528	3.181	1	12
Job: employed	104,785	0.548	0.498	0	1
Job: unemployed	104,785	0.052	0.222	0	1
Job: inactive	104,785	0.379	0.485	0	1
Job: other job type	104,785	0.021	0.142	0	1

Table 2.A.4: Descriptive statistics for the Independent

Statistic	N	Mean	St. Dev.	Min	Max
Ideology	12,666	0.426	0.268	0.000	1.000
Tropical cyclone bottom 90th percentile	12,666	0.031	0.174	0	1
Tropical cyclone bottom 10th percentile	12,666	0.004	0.060	0	1
Tropical cyclone damage	12,666	19.202	110.665	0.000	1,667.138
Age	12,666	46.028	15.382	18	93
Education	12,666	3.961	1.416	1	6
Gender: male	12,666	0.556	0.497	0	1
Race: black	12,666	0.045	0.208	0	1
Race: white	12,666	0.785	0.411	0	1
Race: other	12,666	0.170	0.376	0	1
Family income	12,666	6.258	3.151	1	12
Job: employed	12,666	0.599	0.490	0	1
Job: unemployed	12,666	0.058	0.234	0	1
Job: inactive	12,666	0.315	0.465	0	1
Job: other job type	12,666	0.028	0.164	0	1

Table 2.A.5: Descriptive statistics for the Republicans

Statistic	N	Mean	St. Dev.	Min	Max
Ideology	89,778	0.670	0.202	0.000	1.000
Tropical cyclone bottom 90th percentile	89,778	0.035	0.183	0	1
Tropical cyclone bottom 10th percentile	89,778	0.004	0.062	0	1
Tropical cyclone damage	89,778	21.079	116.612	0.000	2,816.494
Age	89,778	55.618	14.686	18	95
Education	89,778	3.650	1.429	1	6
Gender: male	89,778	0.559	0.497	0	1
Race: black	89,778	0.013	0.114	0	1
Race: white	89,778	0.889	0.315	0	1
Race: other	89,778	0.098	0.298	0	1
Family income	89,778	6.769	3.046	1	12
Job: employed	89,778	0.503	0.500	0	1
Job: unemployed	89,778	0.045	0.208	0	1
Job: inactive	89,778	0.431	0.495	0	1
Job: other job type	89,778	0.021	0.144	0	1

Table 2.A.6: List of U.S. states and macro-regions hit (6 months window)

Hit states	South region	Northeast region
Alabama	✓	
Connecticut		✓
Delaware	✓	
Florida	✓	
Georgia	✓	
Louisiana	✓	
Maine		✓
Maryland	✓	
Massachusetts		✓
Mississippi	✓	
North Carolina	✓	
New Hampshire		✓
New Jersey		✓
New York		✓
Pennsylvania		✓
Rhode Island		✓
South Carolina	✓	
Texas	✓	
Vermont		✓
Virginia	✓	

2.1.1 Ideology indicator creation and combined database cleaning

To create the political ideology indicator we consider 26 survey questions, covering various macro topics, from the database. These questions, asked before elections, assess residents' approval or disapproval of potential government policies and their views on several societal issues. The 26 selected questions regard the following topics: abortion, environment, immigration, gay rights, affirmative action, guns, and health. See Tables 2.A.1 and 2.A.2 for the list of questions. During each survey year the total number of topics is always equal five but the topics included vary across years. From 2010 to 2013 the topics included are abortion, environment, immigration, affirmative action, and gay rights. From 2014 to 2018 the topics included are abortion, environment, immigration, health, and guns. Such discontinuity in policy topics is due to the relevance of considering the ideological spectrum as formed by opinions on several policy domains. In order to create the continuous ideology indicator, we first created a 0-1 categorical indicator for each of the five yearly question topics.[21] Subsequently, we summed all five topics' points (ranging between 0 and 5) and divided this score by the number of topics (equal to 5) to obtain the final continuous score ranging from 0 to 1. As result, our final measure of political ideology is an originally created indicator ranging from very liberal to very conservative. This is a continuous indicator which assumes values between 0 and 1, such that the lower the values assumed by the indicator, the greater the liberal political assessment of the individual and such that the greater the values assumed, the higher the conservative political assessment of the individual.

Regarding the data cleaning process for the database, we implemented several key steps. First, we focused on retaining data only from the years 2010 to 2018, out of the full range available from 2006 to 2021. This selection was made to ensure that only the years with relevant policy

[21]The number of points assigned reflects how liberal or conservative the opinion given by the individual is, taking into account the questions of every topic, according to the authors' scientific judgment. For each topic's points computation, we can have two options: a question formed by multiple answers (with more than two options) or several binary-answer questions. In the case where the topic presents a multiple-answer question, we proceed as follows: for 2 possible answers, the points obtainable, according to the selected answer, are (from very liberal to very conservative): 0 or 1. For 3 answers: 0, 0.5, or 1. For 4 answers: 0, 0.33, 0.66, or 1. For 5 answers: 0, 0.25, 0.5, 0.75, or 1. If the topic presents several binary questions, we treat these questions as if they were a multiple-answer question, where the greater the number of conservative answers, the higher the score assigned (following the points attribution explained in the multiple-answer case).

questions were included. Notably, 2018 also marks the last year of available data concerning tropical cyclones, as referenced in Anderson et al. (2020). Second, individuals failing to respond at least at one of the 26 questions have been excluded in the creation of the ideology indicator, so as in the final database. Third, any responses categorized as "prefer not to say" or skipping a question were treated as missing values (NA) for that particular question. Finally, any cases lacking individual identifiers or county codes were also removed from the dataset to maintain data integrity. The final database is unbalanced, given that we rely on repeated cross-sectional information. The individuals answering to the 2006-2021 Cooperative Election Study – CES policy preferences database.[22] are also contained in the Cooperative Election Study (CES) 2006–2021.[23]

[22]CCES Cumulative Policy at https://cces.gov.harvard.edu.
[23]Cooperative Election Study Common Content at https://cces.gov.harvard.edu.

2.B Robustness checks and mechanisms

Figure 2.B.1: Mean alternative ideology (without environment) across U.S. counties (2010-2018)

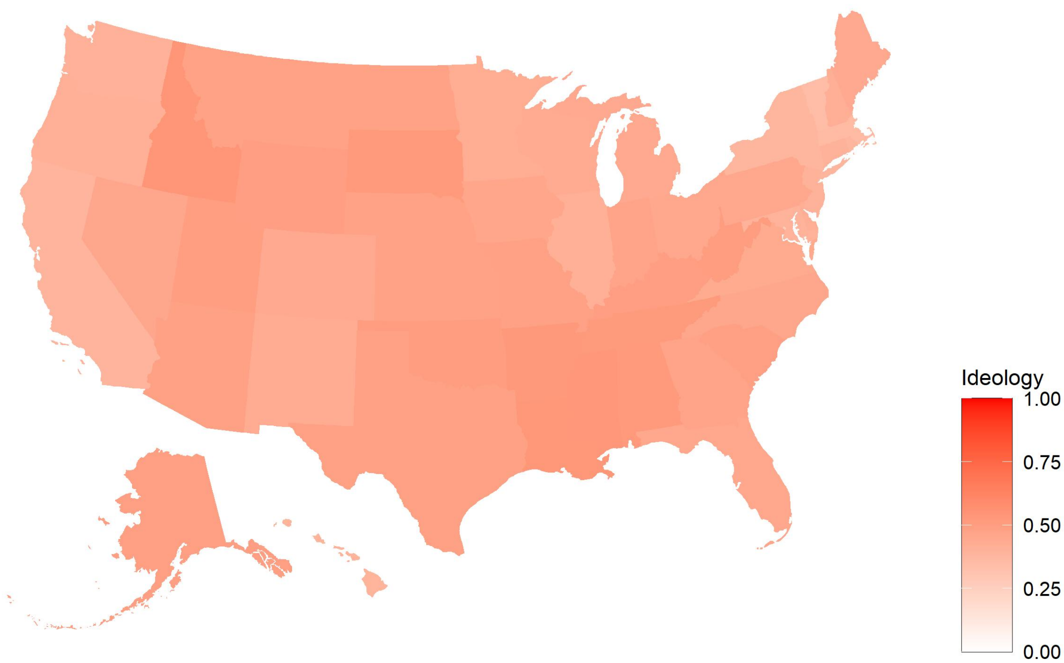


Figure 2.B.2: Mean alternative ideology (abortion, environment, immigration) across U.S. counties (2010-2018)

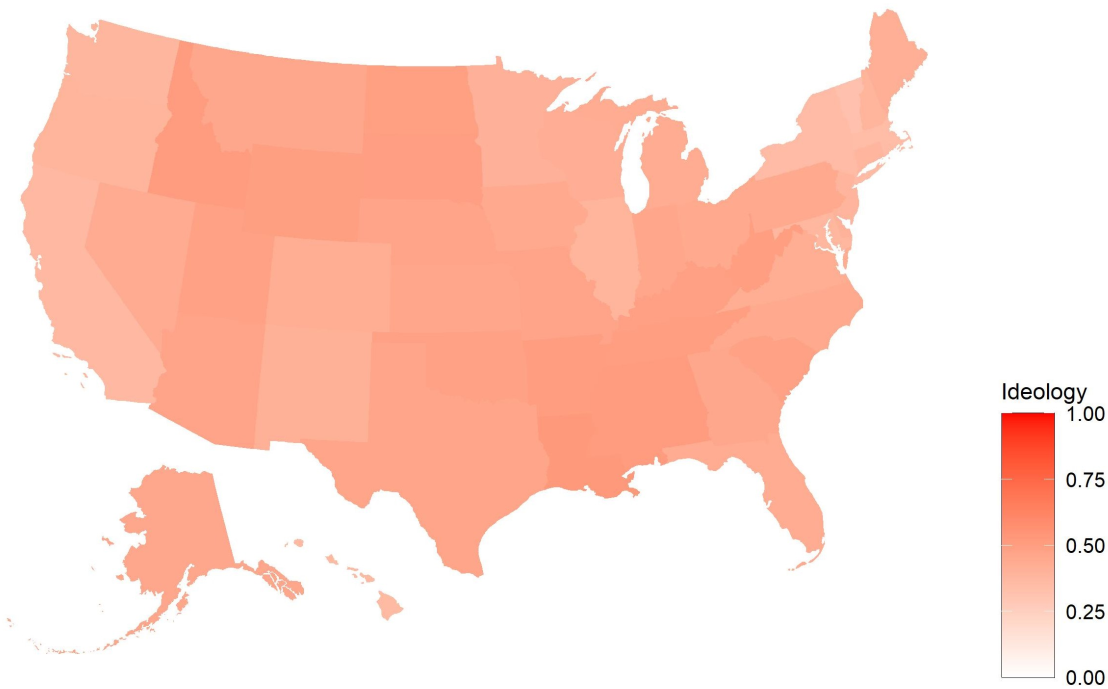
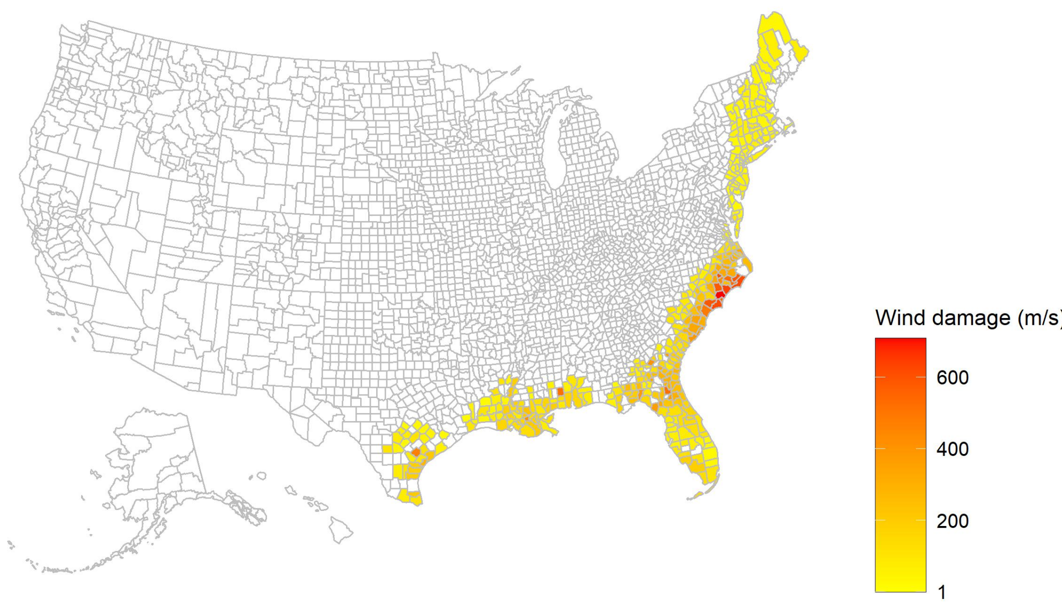


Figure 2.B.3: Mean 12-month window wind speed damage across U.S. counties (2010-2018)



Notes: Counties failing to receive at least one tropical cyclone in the entire period are coloured in white. Tropical cyclone mean wind damage over the period are computed on positive wind values only.

Figure 2.B.4: Mean news interest across U.S. states(2010-2018)

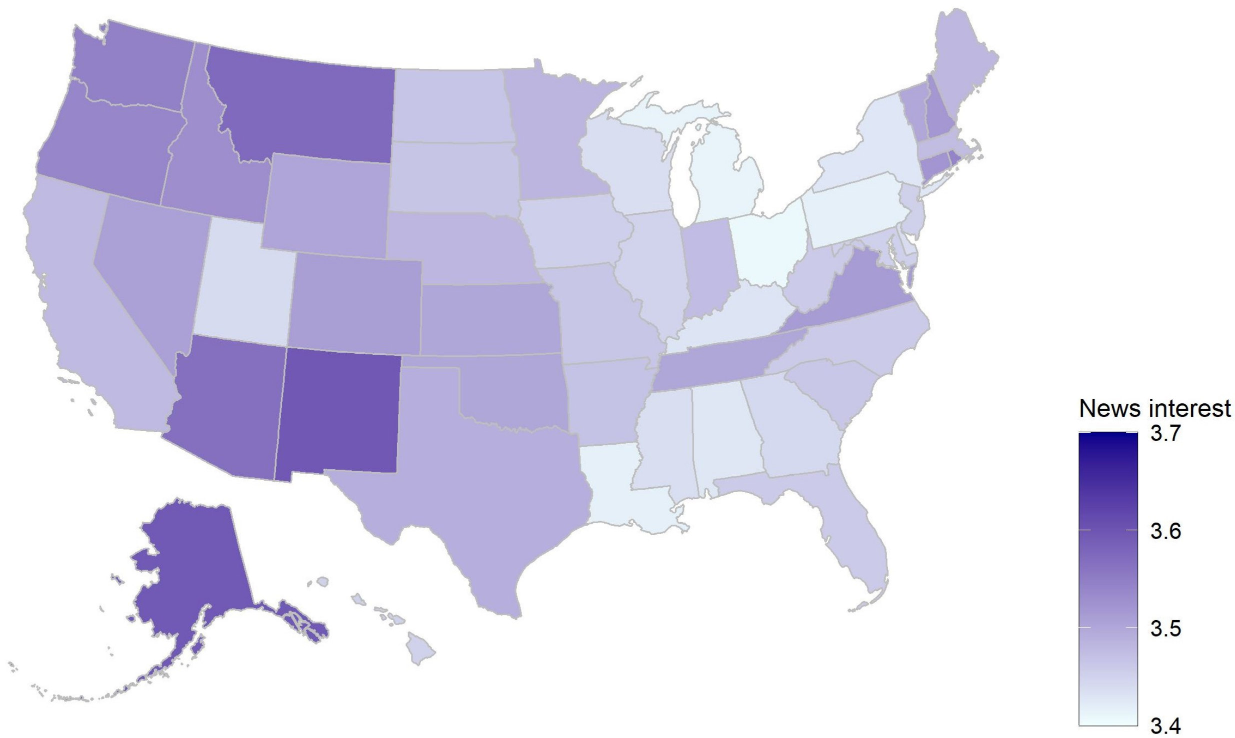
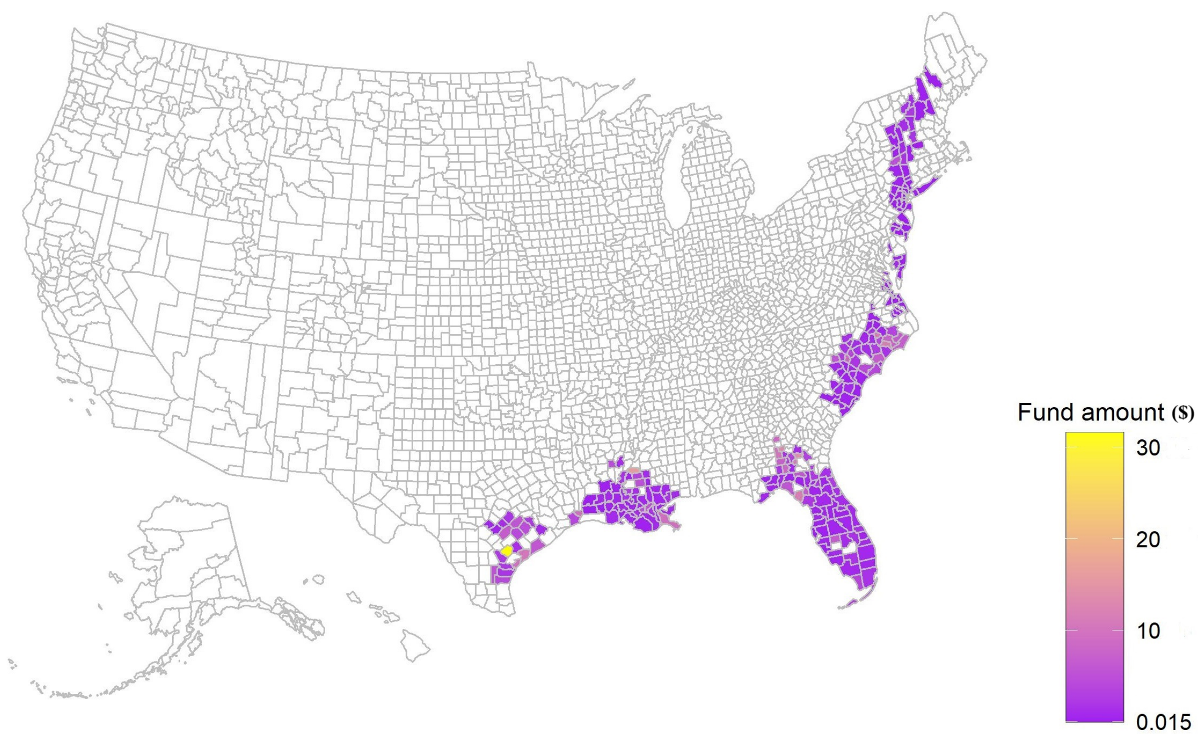
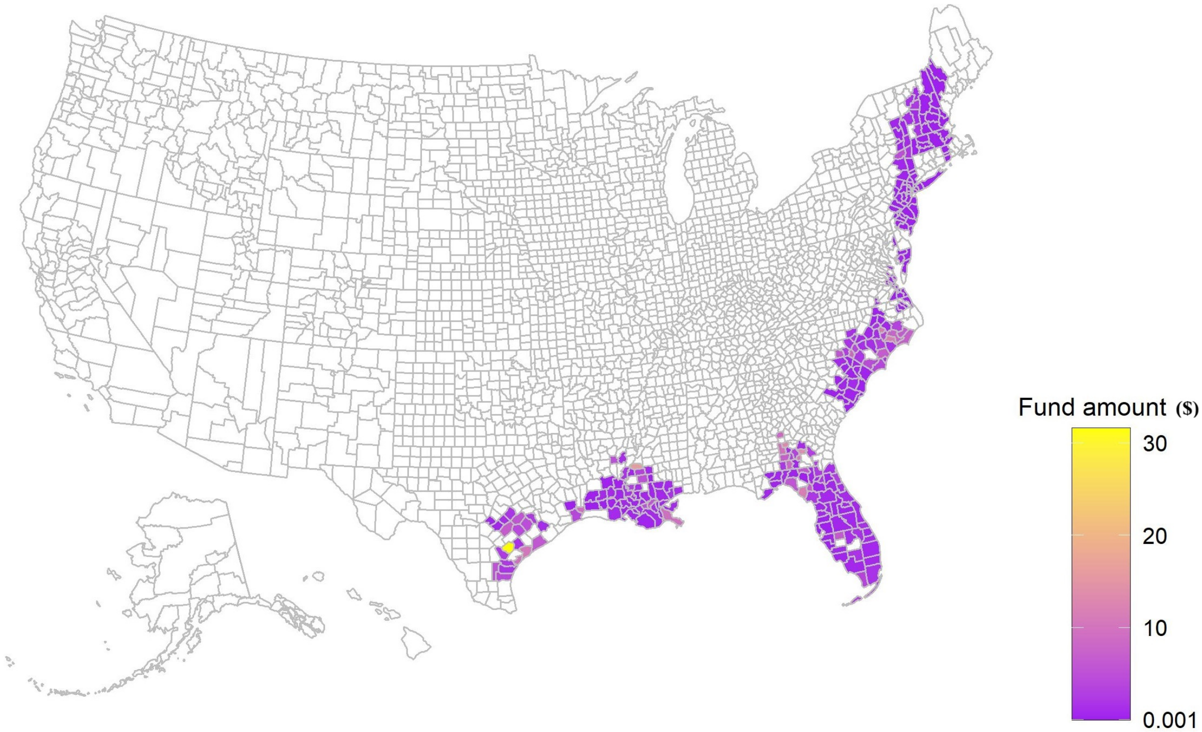


Figure 2.B.5: Mean public funding per capita per knot across U.S. counties (2010-2018)



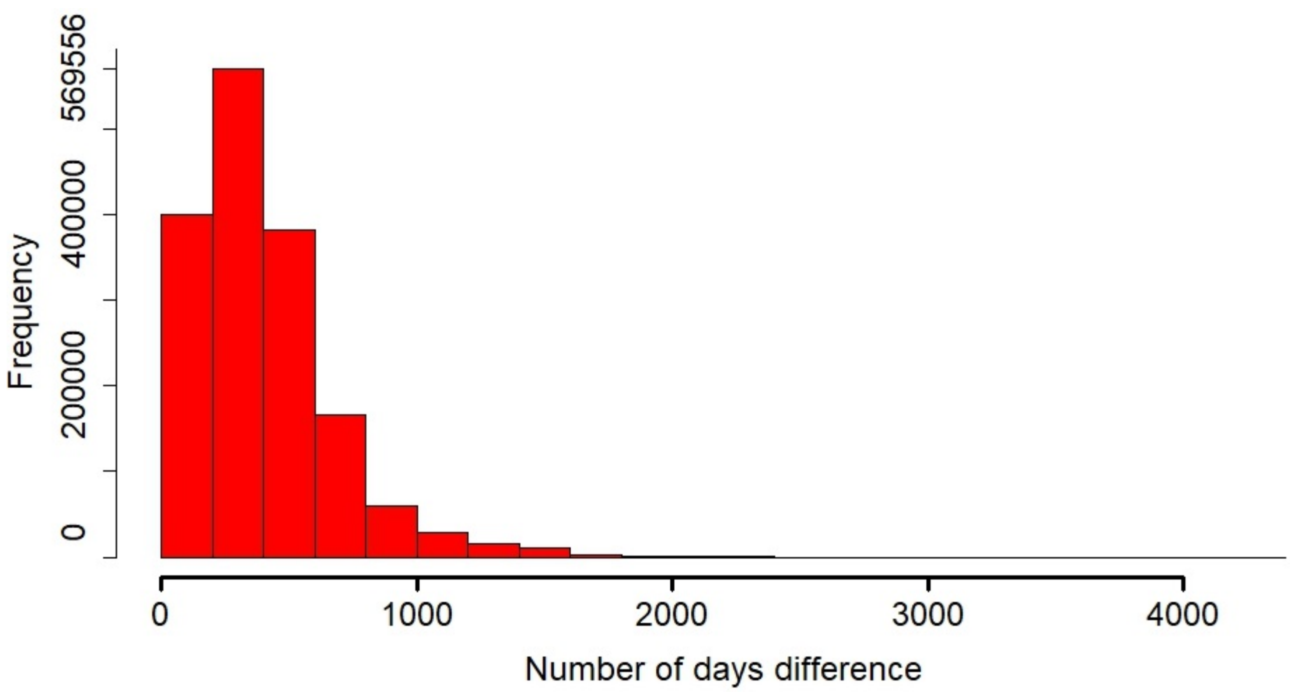
Notes: Counties failing to receive tropical cyclone aids in the entire period are coloured in white.

Figure 2.B.6: Mean total funding per capita per knot across U.S. counties (2010-2018)



Notes: Counties failing to receive tropical cyclone aids in the entire period are coloured in white.

Figure 2.B.7: Number of days between the end of tropical cyclones and the disbursement of public funds



Chapter 3

Breaking news: media exposure and climate change denial in the United States

3.1 introduction

«The earth's rotation is getting closer to the sun», «The media», «Politics», «Equal parts human and nature», «God», «Periods of warming and cooling on the earth have been happening for thousands of years». These are examples of free-text responses from participants in the Climate Change in the American Mind[1] survey who selected "other" as the cause of climate change, indicating that they did not attribute it to either human activity or natural causes.

Climate change denial remains a significant issue in the United States, with only 70% of registered American voters believing in climate change in 2019. Additionally, among those who do believe in climate change, one in five believes it is caused by natural factors.[2] This contrasts with the situation in other developed counties, as the European Union ones, where 93% of individu-

[1] https://osf.io/w36gn/.

[2] https://climatecommunication.yale.edu/publications/politics-global-warming-april-2019/toc/4/.

als consider climate change a serious problem[3]. Despite the fact that there is such an extensive number of articles covering the severity of climate change impacts providing scientific evidence,[4] climate change disinformation is greatly widespread in the U.S. (Treen et al., 2020).

Though a significant body of literature describes the stability of aggregate climate change preferences in the U.S. at the national and state levels (Marlon et al., 2022; Egan and Mullin, 2017), less is known about the factors determining preference stability at the individual level and the role of news as an independent variable (Jenkins-Smith et al., 2020) within the framework of directional motivated reasoning theory (Druckman and McGrath, 2019). This theory posits that individuals process information in a way that aligns with their existing beliefs. Specifically, people seek information with the goal of confirming conclusions they already hold, doing so by (i) choosing information that aligns with their current beliefs (confirmation bias); (ii) evaluating the accuracy of information based on whether it supports their desired conclusion (prior attitude effect); and (iii) rejecting information that contradicts their beliefs (disconfirmation bias) (Druckman and McGrath, 2019).

Inspired by this theory, the present research focuses on whether increased exposure to climate change news is (i) positively related to the stability of climate change opinions in the general population; (ii) linked to a stronger alignment with their political group's views (agreement with "their side");[5] and (iii) negatively associated with the stability of opposing viewpoints (disagreement with "the other side").[6] Points (ii) and (iii) are meant to investigate if climate news are related with a backlash mechanism such that individuals tend to adhere more the opinion of a social group (in this case their supported political party) and disagree more with contrasting points of view.

This micro-level work exploits nationally representative U.S. surveys, namely the Cooperative Election Study (CES) 2010-14 panel database[7] and the Climate Change in the American mind

[3] https://climate.ec.europa.eu/citizens/citizen-support-climate-action$_en$

[4] https://edition.cnn.com/2023/06/06/world/arctic-sea-ice-free-climate-change/index.html.

[5] I identified the major political opinion of Democrats as "accept climate change" (98% of Democrats accept), and that of Republicans as "deny climate change" (57% of Republicans deny).

[6] The opposing viewpoint of Democrats is "deny climate change" (2% of Democrats deny), while that of Republicans is "accept climate change" (43% of them accept).

[7] CCES 2010-2014 Panel Study at at https://cces.gov.harvard.edu.

2008-2022 database.[8] I collected micro-level information for three different points in time (for 2010, 2012, and 2014) and I have aggregated these values by individual through period averages or modes.

The econometric model relies on a cross-sectional database and on probit regressions. There are three independent variables (which are used separately across the regression models). First of all, *opinionated* investigates the stability in opinion about never changing opinion about accepting or denying climate change over the three survey waves. This is a dummy variable coded as 1 if the individual is opinionated and 0 otherwise. Then, *opinionated believer* takes value 1 if the individual believed in climate change across all survey waves (years: 2010, 2012, and 2014), 0 otherwise. Finally *opinionated denier* takes value 1 if the individual denied the existence of climate change over all the 2010/12/14 survey years. The independent variable *climate change news* is measured via a survey question investigating the frequency of exposure to climate change news in the media over the years.

The paper is organized as follows. Section 3.1 is an introductory chapter, while Section 3.2 contains the literature reviewed. Then section 3.3 provides the reader with an overview about the data, while Section 3.4 presents the empirical models and the identification strategy. Sections 3.5 and 3.6 are respectively illustrative of results and robustness checks. Sections 3.7 follows. Finally conclusions (Section 3.8) follow.

3.2 Literature review

3.2.1 The impact of news on climate change denial

There is a well-established strand of literature analyzing the relationship between news exposure and the level of climate change denial, utilizing meta-analyses and descriptive evidence (Drews and Van den Bergh, 2016; Marlon et al., 2022). This research specifically examines factors that reduce climate change denial and increases acceptance, rather than exploring the simultaneous increases in both acceptance and denial that may occur. Drews and Van den Bergh (2016) review

[8] https://osf.io/w36gn/.

various determinants of climate policy support based on the existing literature, highlighting that media coverage of climate issues is a significant factor influencing policy support. They emphasize that the framing and frequency of climate-related content are even more crucial in shaping public support. Other determinants include partisanship, individual values and norms, awareness of climate change, perceptions of policy design (moderated by education), religion, social trust, and the perceived impacts of climate change. Marlon et al. (2022) examine the dynamics of changes in public opinion about climate change in U.S. states from 2008 to 2022, using nationally representative surveys. Their findings reveal an increase in the percentage of individuals who believe in climate change, recognize its human causation, and perceive scientific consensus during this period. However, support for climate policy expanded only in more liberal states, such as California and New York, while remaining relatively stable in others. The authors note that states experiencing the most significant increases in climate change opinions are also those where personal experiences of climate change and perceptions of its harmful effects are most pronounced.

Simultaneously, several studies adopt experimental and empirical approaches to this topic (Bain et al., 2012; Bakaki and Bernauer, 2017; Happer and Philo, 2016). For instance, Bakaki and Bernauer (2017) conduct a survey-embedded experiment revealing that exposure to (positive/negative) information from COP 14 (Conference Of the Parties) increased awareness about climate change among respondents but did not yield a positive effect on climate mitigation support. In a representative sample, Bain et al. (2012) corroborate that positively framing climate action can promote intentions to act among climate change deniers without diminishing the intentions of believers in Australia. Their evidence suggests that framing climate change action as a way to build a more caring and considerate community, while also fostering a more prosperous and technologically advanced society, is particularly effective. Conversely, frames emphasizing the risks associated with climate change are found to be less impactful.

3.2.2 The impact of news on climate change opinion stability

Although some contributions exist, less is known about the extent to which media sustains opinion stability over time (Perse and Lambe, 2016), particularly in reinforcing individuals' views.

While the previous subsection highlighted researches showing that media increase climate change acceptance, fewer investigate how news can similarly reinforce denial. Firstly, Ballew et al. (2022) use nationally representative survey data to investigate the correlation between news exposure and changes in the opinions of U.S. individuals regarding global warming, considering the intensity of change in opinions on a 1 to 5 scale (from greater denial opinion change to greater belief opinion change). They conclude from their empirical analysis that there is a low association between attention to climate news and intensity and direction of opinion change. Only the frequency of watching Fox News (not CNN) correlates with a shift in opinion, increasing the intensity of denial. Secondly, Palm et al. (2017) study the determinants of positive opinion changes about global warming (coded as -1 = less skepticism, 0 = no opinion change and 1 = more concern) using a generalized ordered logit and a large panel dataset for the U.S. (Cooperative Election database 2010-2014). If on the one hand, they use the same database as this manuscript, on the other hand, they do not consider the year 2012 (they study two points in time, 2010 and 2014) and in some cases results suggest farther investigation (e.g. skepticism across Democrats decreased but at the same time there is neither an evidence of an increase in climate concern, nor of a decrease of opinion stability). Finally, Shehata et al. (2022) use a three-wave panel survey (in the 2018–2019 period) in Sweden to study climate change acceptance and denial opinion maintenance. The authors (2022) find that higher trust towards traditional media correlates with opinion stability.

On top of the lack of knowledge in the literature, less is known about the micro level (Jenkins-Smith et al., 2020). Egan and Mullin (2017) analyze national-level climate change preferences by collecting survey data on concern, policy support, and awareness, and they detect significant stability in opinions over the long term, between 1989 and 2016. The authors claim that negative variations in aggregate trends were especially marked during periods of economic crisis, greater unemployment, and inflation. This national opinion stability trend is also evident when analyzing state-level opinion pools.

Finally, there is a lack of recognition regarding societal and job market-related groups that may be more sensitive to news. The literature has primarily focused on partisanship. For example, Jenkins-Smith et al. (2020) finds that Oklahoma Republicans exhibit more inter-temporal instability in their climate change beliefs compared to Democrats. These results were obtained using quarterly panel data on Oklahoma residents over a four-year period (June 2014 - May 2018). Individuals who participated in at least 10 out of 16 surveys were included in the study.

3.2.3 Mechanisms and heterogeneity in opinion formation and stability

In the following section, I will examine various theoretical frameworks that illuminate the mechanisms through which media exposure affects individual beliefs about climate change.

First, there is a body of literature that posits news as essential for changing opinions. A popular approach in climate change communication is the 'Bayesian theory' or 'Information Deficit Model' (Dickson, 2005). This theory suggests that individuals rationally update their pre-existing beliefs based on new information received (Ripberger et al., 2017). It follows that public skepticism toward modern scientific topics, such as the existence of climate change, stems from a lack of knowledge. Consequently, the model argues that the most effective way to persuade skeptics to accept climate change is by providing them with more precise, science-based information (Suldovsky, 2017).

Second, there are theories that challenge this perspective by focusing on how individuals filter information at its source. One of these theories is known as "selective exposure." This concept, prevalent in communication science, highlights individuals' inclination to choose sources that align with their pre-existing attitudes. This tendency can create a bias in the audience composition for a particular message or medium (Knobloch-Westerwick, 2014).

Other important contributions emphasize that individuals not only select the content they wish to be exposed to but also engage in cognitive processes to reject information that contradicts their existing beliefs (Druckman and McGrath, 2019). This process is referred to as "directional motivated reasoning." Directional motivated reasoning, as elaborated by Druckman and McGrath (Druckman and McGrath, 2019), asserts that individuals are driven by specific "directional goals"—preferred conclusions they are inclined to affirm through their information-seeking behaviors. According to this theory, people actively seek out information that reinforces their existing viewpoints while tending to disregard information that contradicts their desired conclusions. This selective information acquisition involves not only choosing sources that support their pre-existing opinions but also assessing the credibility of the information based on its alignment with their goals. Druckman and McGrath's seminal research (Druckman and McGrath, 2019) indicates that various factors motivate the pursuit of these directional goals. These include the desire to align with the values and expectations of one's social groups (such as political affiliations) or social networks (including family, friends, and colleagues), as well as the need to maintain coherence with one's established beliefs, scientific principles, or moral values. The field of global warming Fryer et al. (2018) illustrates how polarization in opinions about climate change and the death penalty is fueled by confirmation bias, which arises from the pre-selection of information and the interpretation of that information based on pre-existing beliefs. Similarly, Zappalà (2023) finds that rural households in Bangladesh who believe that drought events have increased over time tend to overestimate the frequency of their exposure to droughts. This suggests that their pre-existing beliefs about climate trends influence their perception of actual events, leading them to perceive droughts as more frequent than they are. Babutsidze et al. (2023), using a large-scale survey data across multiple European countries in the period from 2002 to 2010, found that while traditional media consumption did not contribute to the polarization of environmental attitudes in Europe, digital media consumption was positively associated with polarization dynamics regarding environmental views. For progressive and green voters, increased internet use was linked to stronger pro-environmental attitudes, whereas for conservative voters, internet use appeared to correlate with more negative environmental views. This suggests that digital media also reinforces ideological differences in environmental opinions. Furthermore, online platforms, with their algorithms and personalized content, may play a key role in shaping individuals' environmental beliefs by exposing them to content that aligns with their pre-existing views, contributing to the deepening of these divides.

Third, another group of theories aligns with the idea of news reinforcing opinions, employing alternative terms such as "boomerang effect" or "reinforcing spirals." The "boomerang effect" refers to the dismissal of information contrary to one's beliefs, thereby strengthening the individual's own opinion (Carmichael et al., 2017). For example, individuals skeptical about climate change might dismiss ostensibly reliable scientific data if it challenges their pre-established convictions (see Hart and Nisbet, 2012). The concept of "reinforcing spirals" describes the tendency for individuals to select news media information that reinforces their pre-existing beliefs, as observed in the case of climate change (see Bolin and Hamilton, 2018). Feldman et al. (2014) conducted an experiment on climate change opinions within the context of media selectivity using a two-wave representative U.S. sample panel database. The authors found that individuals exposed to either conservative or non-conservative media during Wave 1 were more likely to continue consuming the same type of media in Wave 2, which in turn reinforced their certainty in global warming beliefs and policy preferences.

Finally, sociological and communication science literature pays great attention to social networks as platforms where "echo chambers" and "filter bubbles" originate. Echo chambers manifest as collectives of individuals who share similar perspectives and reinforce the group's viewpoint (Sunstein, 2001). In contrast, filter bubbles refer to social media algorithms that suggest content aligning with the user's interests while obscuring conflicting information (Pariser, 2011).

It is also noteworthy that scholars consider various types of heterogeneity when studying the relationship between news and climate change opinion. This includes heterogeneity among senders, receivers, and the framing of climate news content. Regarding the receivers, Schuldt and Roh (2014) found that the terms "global warming" and "climate change" evoke different perceptions among conservatives and liberals. On the sender side, Bohr (2020) argued that conservative and liberal media outlets cover different climate topics, with conservative media tending to focus more on climate scandals, infrastructure, and corporate issues compared to their liberal counterparts. Furthermore, Bolsen and Shapiro (2018) highlighted how climate change discourses can be framed positively or negatively, providing several examples across various topics, including environmental and economic consequences.

Finally, some research does not fully account for heterogeneity in their empirical models. For instance, Bakaki and Bernauer (2017) find that COP 14 information messages influence climate awareness among participants, irrespective of whether the messages were framed as positive or negative.

3.3 Data

3.3.1 Being opinionated as stability

This work uses a set of three dependent variables which will be alternated across various baseline models, all obtained from the Cooperative Election 2010-14 panel database[9] The first dependent variable of this manuscript, called *opinionated*, is a dummy variable which takes value 1 if the individual results to have always either denied or accepted global warming over the three survey waves. The second one, *opinionated believer*, takes value 1 if the U.S. resident declared to always believe in climate change (over the 2010/12/14 surveys), 0 otherwise. Similarly, the last dependent variable, *opinionated denier*, assumes value 1 if the interviewee answered to deny climate change in all of the three even years survey waves, 0 otherwise.

In order to create these dependent variables, firstly, it has been necessary to verify if during every survey year the individual either denied or accepted the existence of climate change. A recoding of a CES survey climate change question[10] has been performed (see Table 3.A.1 in supplementary information). Secondly, the three opinion-related dependent variables have been created starting from the above indicated denial coding, according to Table 3.A.2. Remarkably, 83.22% of individuals are opinionated, with 1 in 4 opinionated individuals being opinionated deniers, and 3 in 4 opinionated being opinionated believers.

Considering the state level percentage of opinionated (in general), opinionated believers and opinionated deniers (see Figure 3.A.1), it is observable that there are more opinionated believers than deniers in the U.S. states. Vermont is the state with the highest percentage of opinionated believers (88%), while Nevada, sharing the border with California, is a state with a considerable amount of opinionated deniers (35.8%).

I also included in the database three alternative opinionated variables (which investigate the

[9]CCES 2010-2014 Panel Study at at https://cces.gov.harvard.edu.

[10]Question number CC10_321 for the year 2010, CC12_321 for 2012 and CC14_321 for 2014.

job vs. the environment topic and have been created starting from a job vs. the environment question in CES). See Tables 3.A.8 and 3.A.9 for visualising the descriptive statistics and coding for these variables. This variable examines whether individuals prioritize environmental protection or job protection. First, I created a dummy variable where a value of 1 indicates that the individual prioritizes job protection over environmental protection (answers 4-5 in the "job_vs_enviro" question coding of the CES 2010-14 panel). Conversely, a value of 0 is assigned if the individual values environmental protection more than job protection (answers 1-3 in the "job_vs_enviro" question coding of the CES 2010-14 panel). Following this, I developed the "jobs vs. the environment" opinion-related variables, categorizing individuals as either "pro-environment" (formerly "opinionated believer") or "pro-job" (formerly "opinionated denier"), using the same methodology as described in the opinionated data section for creating the alternative dependent variable (See Tables 3.A.8 and 3.A.9).

3.3.2 Climate change news exposure

The independent variable *climate news* is a continuous frequency exposure measure. This measure is not included in The Cooperative Election Study (panel) database, prompting the need to consider another data source to impute climate news information onto the survey data of U.S. residents obtained from the Cooperative Election Study. *Climate news* is extracted from the Climate Change in the American Mind 2008-2022 database[11] using a question that investigates the frequency of hearing about climate change in the media (3.A.3). The answers have been coded as numbers from 1 to 4, indicating "never / once a year or less often" to "at least once a week". To impute climate news information from this source into the individual data collected by the Cooperative Election Study, I focused solely on the 2015 data from the Climate Change in the American Mind database, as data is only available from that year onward.

Climate change news is derived as a predicted value using the following steps: (1) identify a set of 7 variables (all categorical) with corresponding values and categories between the Cooperative Election Study (CES) database (the primary database) and the Climate Change in the American

[11] https://osf.io/w36gn/.

Mind (CCAM) database (division, political party, family income, education, gender, race, and age category); (2) in the CCAM database, an OLS regression model is applied where climate change news is regressed onto the 7 individual characteristics, preserving the β and α coefficients; (3) for each of the 7 variables, the corresponding β coefficient from the previous regression is assigned to CES individuals based on the corresponding categories. In the CES panel, the relevant data comes from the mode of 2010, 2012, and 2014, while the 2015 data is used for the CCAM database; (4) the predicted values of climate change news are computed in the CES database by summing α and the various βX values for the 7 characteristics, forming the primary dependent variable.

Looking at the state figures concerning the average value of news exposure by state (Figure 3.A.2), it is remarkable to note that several Western coast (California, Washington, Oregon, Alaska) and Eastern coast (Massachusetts, Connecticut, New Jersey, Maryland) states appear to be especially exposed to climate news (around 7.5 out of 11.2). These are states considered to be typically Democratic, hence the type of news circulating here may more be pro-climate. Yet, there is a greater exposure to climate news also in states which are typically "red" and where the type of news exposure shall be less favourable to climate support (Wyoming, Arizona and Nebraska). South Dakota is the state with lowest climate news exposure (average of 5 out of 11.2).

I also construct an alternative climate news variable (see Tables 3.A.8 and 3.A.9), derived through a Cooperative Election Study-Climate Change in the American Mind data imputation process and extracted climate news information. As regards the procedure to create it, first, to ensure consistency between the datasets, I recode the Climate Change in the American Mind responses to align with Cooperative Election Study categories. Then, I determine the mode across the three Cooperative Election Study survey waves to generate a unified climate news measure for each individual. Second, I extract climate news exposure from the Climate Change in the American Mind database (2008–2022) using a 2015 survey question that asks respondents how frequently they hear about climate change in the media. Responses are categorized on a four-point scale, ranging from 1 ("never" or "once a year or less often") to 4 ("at least once a week"). Third, to impute this climate news exposure into individual data from the Cooperative Election Study. I assign each Cooperative Election Study respondent the average climate news exposure of

Climate Change in the American Mind database respondents who share identical characteristics across key variables: U.S. geographical division, age category, education level, political affiliation, gender, race, and family income. These categories are the same as those used for the primary climate change news dependent variable (see Table 3.A.7).

Additionally, I include in the database two general news indicator: *news interest* and *news media count* (see Tables 3.A.8 and 3.A.9). As regards the first, I used a question from the Cooperative Election Study (CES) to assess individuals' interest in general news. Initially, I ranked respondents based on their self-reported interest in public affairs and government news, which ranged from 1 to 4 (from hardly at all to most of the time) to create a cross-sectional measure. As for the second general news variable, a count of news media exposure, this was created starting from the Cooperative Election Study (panel) database. This variable measures how many different types of media (TV, blogs, newspapers and radio) individuals reported consuming in the 24 hours preceding the survey administration. The scale ranges from 0 (no media exposure) to 4 (exposure to all four types of media).

3.3.3 Final database and descriptive statistics information

The final database for this study includes all individual information, except for the climate change news exposure measure (the independent variable), which is sourced from the Cooperative Election panel database 2010-2014 study[12] (survey years: 2010, 2012, and 2014). Thus, data on the opinion-related dependent variables and individual controls are extracted from this source. The only variable included in the final database from the Climate Change in the American Mind database[13] is the climate change news exposure.

To create a cross-sectional database, information from the 2010, 2012, and 2014 CES databases has been aggregated by individual based on the average or mode. The choice to use these databases for the empirical part of this study is due to their large, representative sample sizes, which have been extensively utilized in the literature (see Palm et al., 2017 and Marlon et al., 2022, for in-

[12]CCES 2010-2014 Panel Study at https://cces.gov.harvard.edu.
[13]https://osf.io/w36gn/.

stance).

I complemented my dataset with individuals information obtained from the Cooperative Election Study panel database, which have been aggregated using the simple average or mode for each individual over the 3-wave period. This regards: family income category, party voted by the individual during last presidential election, education level, religion, age category, race, gender, working status (employed, unemployed, inactive or other), U.S. citizenship dummy, union member status, type of home ownership, health insurance dummy, marital status dummy, parent of children below 18 dummy, mover across states dummy and state dummies. Education is a six-level categorical variable about the highest title achieved ranging from "no high school" to "post grad". Family income is a categorical variable containing 12 different income thresholds. Religion affiliation is a 14-category variable (comprehensive of several religions, as well as agnostic, atheist, and those identifying as 'nothing in particular). Race is a three-value categorical variable (black, white and other race). Party voted indicates the latest presidential party voted (1: Democrat, 2: independent, 3: Republican). Age category is a categorical variable composed of 3 classes (less than 35, between 35 and 54 and older than 55 years old). Working status is composed of several working categories (related to being employed, unemployed, inactive or to having another status). Union takes values from 1 to 3, where 1 represents never having been part of a union, 2 represents having been part of a union in the past, and 3 represents currently being part of one. The housing variable is composed of three categories (tenant/owner/other). Health insurance is a dummy variable indicating whether the individual has health insurance at the time of the interview. Children <18 indicates if the respondent is the parent or guardian of any children under the age of 18. Mover is a dummy assuming value one if the individual ever changed state residence across survey waves. The variables expressed in over-the-period means are union membership, citizenship, health insurance and marital status. All remaining controls are expressed in terms of the mode[14].

[14] The mode was computed while ignoring NA values, unless an individual had NAs for a certain variable across all years (in which case, the mode was assigned as NA). If the individual had three different non-NA values, they were assigned the median. If the individual had one NA and two different non-NA values, they were assigned the non-NA value in position [3]; otherwise, the value in position [2] was used.

Finally, dummy variables are also included for the individual's state of residence. The state of residence is assigned based on the last state the individual lived in (i.e., the state of residence in 2014). Similarly, county dummies are retained in the same manner and will be considered in a subsequent robustness check.

Table 3.A.5 presents the variables and descriptive statistics. The average U.S. resident in this study is a citizen with moderate climate change news interest, who attended at least the first two years of college, has a family income close to \$60,000–\$69,999, and falls into the last age category (older than 55 years). Notably, 8.6% of individuals in the sample do not have health insurance, 55% are male, 65% are married, 16% are parents or guardians of children under 18 years old, and 4.9% changed their state of residence over the three years of analysis.

Finally, Table 3.1 shows the average, minimum, maximum and standard deviation information for the climate change news variable, according if the individual is more interested in traditional media or digital media. To determine whether an individual is more interested in traditional or digital media, I first computed the average consumption of traditional media (TV, radio, and newspapers). Each of these media variables was initially coded as a 0-1 dummy in the survey, where individuals were asked if they had consumed the respective media in the last 24 hours. I then averaged these variables over the three survey years to obtain a one-year aggregated measure. This allowed me to create a single "traditional media" variable by averaging the three 1-point time variables. Additionally, I calculated an "internet media" variable, which represented the average usage of blogs in the last 24 hours across the three survey years. Finally, I constructed an *internet media preferred* dummy variable, which was set to 1 if an individual preferred traditional media less than internet-based media (i.e., they consumed more digital media). If the individual consumed more traditional media, the dummy variable was set to 0. This allowed me to categorize individuals as more interested in either traditional or digital media.

It is noticeable that individuals who prefer the internet as a news source tend to be more exposed to climate change news. This could be attributed to the fact that younger individuals, who are generally more engaged with climate change issues, are also more likely to consume news through digital platforms.

Table 3.1: Baseline climate change news indicator average across individuals more exposed to internet media vs individuals more exposed to traditional media

	More exposed to internet	More exposed to traditional media
Mean	6.54	6.18
Min	1.28	0.95
Max	11.18	11.18
Standard deviation	1.98	2.03

3.4 Empirical strategy

This micro-level analysis employs probit regressions to assess whether individual opinions—classified into three dependent variables: *opinionated*, *opinionated believer*, and *opinionated denier*—are influenced by exposure to *climate news*.

The *opinionated* variable captures non-directional persistence in opinion, identifying individuals who consistently either deny or believe in climate change. In contrast, *opinionated believer* and *opinionated denier* are directional dummy variables that indicate whether an individual persistently believes in or denies climate change, respectively.

The probit analysis does not focus on a single year but instead spans three years (2010, 2012, and 2014), with values aggregated over this period for each individual. The aggregation is performed by taking the mean for all proxies of the main independent variable (climate news) and for continuous, dummy, or ordinal control variables. For purely nominal control variables, the mode is used.

Separate probit regressions are estimated for each dependent variable. The general model specification is:

$$Pr(Y = 1|X) = \Phi(X'\beta) \tag{3.1}$$

where $\Phi(\cdot)$ represents the cumulative distribution function of the standard normal distribution, and Y alternately represents one of the three dependent variables (*opinionated*, *opinionated believer*, or *opinionated denier*), depending on the specific regression. The vector $\mathbf{X}$ includes the main independent variable (climate change news exposure) along with a set of demographic and socio-economic controls, while β denotes the estimated coefficients.

The empirical strategy presents several advantages. First, the main database utilized—the Cooperative Congressional Election Study—is well representative of the U.S. population, encompassing not only U.S. citizens but also, more broadly, U.S. residents. Surveys can provide advantages over online tools for social media content and sentiment analysis, as social media users are often unrepresentative of the overall U.S. population. For instance, the Pew Research Center indicates that Twitter users are primarily Democratic and younger individuals[15]. Moreover, the use of this database allows for a substantial sample size of 9,500 U.S. residents, contributing to the statistical robustness of this study. Additionally, this micro-level work utilizes a vast set of individual controls that capture various dimensions of U.S. resident characteristics.

Furthermore, despite the econometric strategy presented, this study is not exempt from endogeneity issues related to reverse causality, omitted variable bias, and measurement errors. It is important to note that, given the use of a dummy variable as dependent variable of a cross-sectional database, the results cannot be interpreted causally. It is plausible that residents' opinions influence their level of news exposure, leading to reverse causality.

To construct a comprehensive profile of individuals independent of specific time points, I aggregated data from three years (2010, 2012, and 2014) into a single measure. This approach allows for a characterization of individuals' exposure to climate news and their opinions over time, rather than capturing momentary fluctuations. Moreover, even the use of a panel database would not fully resolve omitted variable bias, as data availability constraints limit the possibility of identifying exogenous shocks in news exposure demand or supply. For instance, while natural disasters may cause power outages affecting media coverage, these disruptions typically last only a few days. Additionally, data on changes in TV channel numbering is not publicly available, and the U.S. digital TV switch-over occurred between 2008 and 2009, preceding the first year covered by this study's database.

The analysis has a limitation related to the method used to impute climate change news information from the CCAM databases to CES individuals. This process assumes that individuals with

[15] https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/

the same demographic characteristics in both surveys exhibit comparable responses, introducing the risk of ecological fallacy (Herger, 2020). This statistical bias arises when inferences about individual behavior (from the CES database) are drawn from aggregate data (based on CCAM groupings), incorrectly assuming that relationships observed at the group level hold at the individual level. In any case, it is important to note that the number of CCAM respondents combined for each CES individual is relatively small, with an average of 3.8 individuals. In 25% of cases, a CES respondent is linked to only one CCAM individual, while the median group size is three, the 90th percentile is eight, and the maximum is 23.

3.5 Results

Table 3.2 and Table 3.3 show respectively the probit regression results table and the related average marginal effects table. As for the average marginal effects (Table 3.3), it is possible to claim, interpreting Column 1, that in the full sample of individuals climate news is related with an increase in the probability of being *opinionated*. The higher the interest of the individual for climate change news and the higher the probability of being opinionated (either always denying or believing in climate change). For a unit increase in climate news exposure the probability of being opinionated increases by 1.09% percentage point. This result is significant at 1% level.

This is an absolute change in probability; the relative probability, given the unconditional probability of being opinionated (=1) equal to 83.22%, amounts to 1.3%. A unit change in news interest would lead to have a 84.31% of opinionated U.S. residents.

Columns 2-5 verify if climate news correlates with a confirmation (2-3) and disconfirmation (4-5) bias phenomenon coherent with each political party supported by the individual point of view. Such view is discording across Democrats (acceptance of climate change) and Republicans (denial of climate change). Indeed in our sample the majority (57%) of Republicans can be coded as a denier (looking at the mode of the variable "deny"), while the majority of Democrats (98%) is a "believer".

Columns 2–3 examine whether Democrats and Republicans are more likely to be opinionated

Table 3.2: Main results

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0449***	0.1456***	0.0245**	-0.2132***	-0.0212*
	(0.0086)	(0.0195)	(0.0105)	(0.0449)	(0.0111)
N	9042	4374	4382	3571	4385
Controls added	yes	yes	yes	yes	yes
log-likelihood	-3945.0595	-749.11482	-2939.6838	-156.21413	-2628.5966
pseudo R^2	0.037	0.081	0.008	0.098	0.011
chi2	268.2502	124.3017	46.2368	37.8832	56.7586
p	0.0000	0.0000	0.0007	0.0003	0.0000

Notes: Probit regression models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are present.
The dependent variable "opinionated" (Column 1) is a dummy variable indicating that over all three years of analysis (2010, 2012, and 2014) the individual has maintained the status of climate change denial or, alternatively, climate change believer, without switching opinions. "Opinionated believer" is a dummy variable assuming value 1 in case in all three years of analysis (2010, 2012, and 2014) the individual has maintained the status of climate change believer, 0 otherwise. "Opinionated denier" is a dummy taking value 1 if over all three years of analysis (2010, 2012, and 2014) the individual has maintained the status of climate change denier, 0 otherwise.
The main climate viewpoint for Republicans is "deny climate change" (57% of Republicans), while the primary viewpoint for Democrats is "accept climate change" (98% of Democrats).
Climate change news is derived as a predicted value based on the following steps: (1) identify a set of 7 categorical variables that have consistent values and categories between individuals in the Cooperative Election Study (CES) database (the main database) and the Climate Change in the American Mind (CCAM) database; (2) in the CCAM database, an OLS regression model is applied where climate change news is regressed onto the 7 individual characteristics: division, political party, family income, education, gender, race, and age category and the resulting β and α coefficients are preserved; (3) for each of the 7 variables, the corresponding β coefficient from the previous regression is assigned to the CES individuals, according to their values in the matching categories, where in the CES panel, the matching information comes from the mode across the 2010/12/14 waves, while 2015 data is used for the CCAM database; (4) the predicted values for climate news are computed in the CES database by summing α and the various βX values for the 7 characteristics. This computed value becomes the main dependent variable. The model also includes control variables, expressed as the average (or mode) over the 2010/12/14 period for each individual: religion, working status (employed, unemployed, inactive, or other), U.S. citizenship dummy, union membership status, homeownership type, health insurance dummy, parent of children under 18 dummy, and a dummy for moving across states. The variables that are expressed as period averages include union membership, citizenship, and health insurance. All remaining variables are expressed as mode values. In Columns 2-5, the full sample is split into Democrats and Republicans, based on the mode of the party declared to be voted for by the individual in the 2010/12/14 waves of the CES. The full sample includes Democrats, Republicans, Independents, and neutral/not voters.

Table 3.3: Average marginal effects table for the main results

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0109***	0.0130***	0.0094**	-0.0045***	-0.0072*
	(0.0021)	(0.0018)	(0.0040)	(0.0012)	(0.0038)
N	9042	4374	4382	3571	4385
Controls added	yes	yes	yes	yes	yes

Notes: Average marginal effects for the baseline probit regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The main climate viewpoint (deny vs. accept) of Republicans is "deny climate change" (57% of Republicans). The primary viewpoint of Democrats is "accept climate change" (98% of Democrats).

believers or opinionated deniers. Columns 4–5 assess whether they are more inclined to reject the opposing view—Republicans becoming more opinionated believers and Democrats becoming opinionated deniers—when exposed to increased climate news. Starting with the 'own side' hypothesis, Column 2 shows that Democrats experience an increase in the probability of being an opinionated believer by 1.3 percentage points (significant at the 1% level), while Column 3 indicates that Republicans are more likely to be opinionated deniers, with a 0.94 percentage point increase (significant at the 5% level). On the other hand, when considering disagreement with the 'own side,' greater climate news exposure reduces the probability of being an opinionated denier among Democrats by 0.45 percentage points (significant at the 1% level) and the probability of being an opinionated believer among Republicans by 0.72 percentage points (significant at the 10% level). Conversely, with respect to disagreement with the 'own side,' greater climate news exposure reduces the probability of being an opinionated denier among Democrats by 0.45 percentage points (significant at the 1% level) and reduces the probability of being an opinionated believer among Republicans by 0.72 percentage points (significant at the 10% level).

From this analysis we can conclude that climate change news leads individuals to be more convinced of their own political viewpoint and to shift away from the counterpart opinion, creating an alignment of visions across the individuals belonging to the same party group. This is in line with several effects and hypothesis advanced in the literature (motivated reasoning, reinforcing spirals, boomerang effect...) All in all, in general the relation between climate change news frequency exposure and opinion stability results to be particularly statistically relevant but quantitatively marginal. Individuals opinion on this important societal subject seems indeed to be particularly sticky and grounded into individuals. See the full regression Table 3.B.2 in supplementary information.

3.6 Robustness checks

3.6.1 Inclusion of state dummies

Table 3.4 includes state dummies in the baseline analysis, allowing control for important fixed characteristics shared by all residents within each state, such as geography, climate, and the type and frequency of climate-related disasters. For example, California is particularly prone to wildfires, whereas hurricanes and tropical storms are more frequent in Southeastern coastal states. State dummies were not included in the baseline model, as the dependent variable (climate news) was constructed based on individuals' U.S. division of residence, along with six other characteristics.

Again, this result mimics the baseline result in Table 3.3, where a directional motivated reasoning emerges. There is a positive sign of marginal effect values in Columns 2 and 3, corresponding to the hypothesis of "agreement with one's own side" (climate acceptance for Democrats and denial for Republicans). Conversely, there is a negative sign in Columns 4 and 5, which confirms a tendency to disregard the "other side " (denial for Democrats and acceptance for Republicans). The magnitude and p-value significance levels are similar to the baseline marginal effects results in this case as well.

Table 3.4: Rob. check: state dummies included

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0100***	0.0133***	0.0078*	-0.0070***	-0.0069*
	(0.0022)	(0.0020)	(0.0042)	(0.0019)	(0.0039)
N	9042	3947	4379	2197	4385
Controls	yes	yes	yes	yes	yes
State dummies	yes	yes	yes	yes	yes

Notes: Average marginal effects after probit regressions. In this robustness check I include state dummies (based on the 2014 state of residence. All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

Table 3.5: Rob. check: county dummies included

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0079***	0.0206***	0.0055	-0.0270***	-0.0085*
	(0.0026)	(0.0041)	(0.0050)	(0.0064)	(0.0048)
N	6948	1521	3351	285	3188
Controls	yes	yes	yes	yes	yes
County dummies	yes	yes	yes	yes	yes

Notes: Average marginal effects after probit regressions. In this robustness check I include county dummies based on the 2014 county of residence. All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

3.6.2 Inclusion of county dummies

Concerning a model where county dummies are included (Table 3.5), the results appear to be confirmed, especially for the full sample and the Democrat sample of individuals (results are significant at least at the 1% level). This indicates that higher exposure to climate news generally leads individuals to be more "opinionated" (holding more stable-over-time opinions on the existence of climate change, whether it involves acceptance or denial). The Democrat sample tends to agree more with the main political point of view of this group (acceptance) and to disagree more with the opposite view (denial). For Republicans, the results are not confirmed (at least at the 10% level) for the confirmation bias hypothesis (Column 3).

3.6.3 Alternative econometric technique: complementary log-log regression

Finally, Table 3.6 shows the average marginal effects for the baseline model (same dependent, independent and control variables and robust standard errors) but using a complementary log-log model. This enables to account for the fact that the opinionated variable assumes a small percentage of zeros (17%).

The econometric model is the following

$$\log\left(-\log\left(1 - P(Y = 1 \mid \mathbf{X})\right)\right) = \mathbf{X}\beta \tag{3.2}$$

where $\mathbf{X}$ is a vector of explanatory variables, including the factors discussed in equation 3.1, and β represents the coefficients for each explanatory variable. These β coefficients indicate the effect of each variable on the probability of the occurrence of Y (that alternately represents one of the three dependent variables, opinionated, opinionated believer, or opinionated denier, depending on the specific regression).

Results are corroborated in this case too: climate news frequency is associated with confirmation and disconfirmation bias mechanisms. All results are significant at least at 5% level, besides

Table 3.6: Rob check: complementary log-log regression

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0111***	0.0128***	0.0093**	-0.0047***	-0.0072*
	(0.0021)	(0.0018)	(0.0040)	(0.0013)	(0.0038)
N	9042	4374	4382	3571	4385
Controls added	yes	yes	yes	yes	yes

Notes: Average marginal effects after complementary log-log regression model. All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

Column 5. All in all, this robustness check confirms the baseline results.

3.6.4 Alternative independent climate change news variable

In the next robustness check (Table 3.7), I use an alternative measure of climate change news exposure, derived through a CES-CCAM imputation process (see Section 3.3 for further details on the procedure).

This robustness check confirms the importance of climate news in relation to the directional motivated reasoning (positive sign for "agreement with own story" and negative sign for "disagreement with own story". The marginal effect values are in many cases larger than the baseline case. Despite, this robustness check failed to capture the relation between climate news and opinion stability considering the full sample, Column 5's p-value is greater than in the baseline case (significant at 1% level).

3.6.5 Alternative independent variable: news interest

Table 3.8 refers to a model where, instead of considering climate change news as the independent variable, we consider general public affairs and political news interest. This is a 1 to 4 self-assessment indicator of the interest of the individual for this type of news (this is a 2010/12/14

Table 3.7: Rob check: alternative climate news measure

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news alt.	0.0112 (0.0082)	0.0347*** (0.0059)	0.0424** (0.0171)	-0.0107*** (0.0028)	-0.0663*** (0.0154)
N	9052	4239	4312	3465	4315
Controls added	yes	yes	yes	yes	yes

Notes: Average marginal effects after probit regression models. Instead of considering the climate news independent variable of the baseline model, here I consider an alternative climate change news information deriving from a CES-CCAM climate news extraction extraction and imputation. The procedure is the following. First of all, a climate news information is extracted from the Climate Change in the American Mind 2008-2022 database using a 2015 year question that investigates the frequency of hearing about climate change in the media. The answers have been coded as numbers from 1 to 4, indicating "never" / "once a year or less often" to "at least once a week". To impute climate news information from this source into the individual data collected by the Cooperative Election Study, I focused solely on the data for 2015 in the Climate Change in the American Mind database. My approach involved assigning to CES individuals the average climate news exposure based on the responses of participants in the 2015 Climate Change in the American Mind survey. These participants shared identical values for several key variables, namely: U.S. geographical division, age category, education level, partisanship, gender, race an family income. To identify matching information, I firstly recoded the Climate Change in the American Mind survey responses to align with the values and categories of the CES database and, subsequently, I determined the mode across the three survey waves for the CES database. All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

mean). This variable comes from the Cooperative Election Study panel database.

Considering news interest is important because it is an information directly provided by the individuals of the survey. It can be assumed that the greater exposure to general news, the greater the exposure to climate change news, as well. The climate change topic is indeed generally covered by the media[16]. Having measures for general news, and not just climate-related ones, is important because certain news items can influence climate denial opinions even if they are not explicitly presented to the audience as climate change-related. Examples include earth science news related to the history of global cooling and warming or changes in the earth's proximity to the sun, which may not explicitly mention "climate change".

This indicator produces average marginal effects with greater statistical significance in columns 3 and 5 and bigger marginal effect values in columns 2-5. All in all, when splitting the sample into Democrats and Republicans a directional motivated reasoning theory of preferences emerges and our main baseline conclusions hold also in the presence of a more general news indicator. This ro-

[16] https://scholar.colorado.edu/concern/articles/5m60qt246.

Table 3.8: Rob check: news interest as alternative independent variable

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
News interest	-0.0042	0.0333***	0.2201***	-0.0058***	-0.1894***
	(0.0065)	(0.0042)	(0.0177)	(0.0022)	(0.0127)
N	9409	4396	4437	3587	4440
Controls added	yes	yes	yes	yes	yes

Notes: Average marginal effects after probit regression models. Instead of considering the climate news independent variable of the baseline model I consider one CES question investigating the level of interest towards news. In order to create it, firstly, I considered the self- declared individual level of interest in public affairs and government news on an ascending order scale from 1 to 4 (from hardly at all to most of the time) declared when answering to a question in the Cooperative Election Study (panel) database. Subsequently, to obtain a cross-sectional measure, I averaged the yearly individual news interest values over the 2010/12/14 years for each individual. All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

bustness check confirms that there is a positive correlation between a greater exposure to general news change and a greater positioning of opinion towards the main political point of view the individual belongs to (confirmation bias). There is also a negative relation between the news interest indicator and the maintenance of an opposing view position about the existence of climate change (disconfirmation bias).

3.6.6 Alternative independent variable: news media count

Table 3.9 highlights the results for a model where the independent variable has been substituted with another general news indicator: "news media count". This is a count variable ranging from 0 to 4 of the media listened to/watched by the individual in the last 24 hours and created starting from CES database questions collecting the single media (TV, blog, radio and newspaper) answers. It is a 2010/12/14 years average and is hence a continuous information. Baseline results are confirmed in this robustness check, as well.

Table 3.9: Rob check: news media count as alternative independent variable

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
News media count	-0.0004	0.0209***	0.0746***	-0.0041**	-0.0771***
	(0.0043)	(0.0037)	(0.0082)	(0.0018)	(0.0075)
N	9413	4397	4437	3588	4440
Controls added	yes	yes	yes	yes	yes

Notes: Average marginal effects after probit regression models. Instead of considering the climate news independent variable of the baseline model, I use the variable "news media count" as dependent variable. News media count was obtained from the Cooperative Election Study (panel) database for each year of the panel survey (2010/12/14). This variable counts the number of media the individual listened to/watched over the last 24 hours before the administration of the survey (the possible media types are TV, blog, newspaper and radio). The counter goes from 0 (no media exposure) to 4 (exposed to all media). I have calculated the cross-sectional measure by averaging the individual information over a three-year period for each person. All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

3.6.7 Alternative dependent variable: job vs. the environment opinion

In the last robustness check (Table 3.10) I consider an alternative opinionated dependent variable: instead of using opinion measures based on the acceptance or denial of climate change, I create the opinion-related dependent variables based on a "job vs. the environment" question, which investigates whether the individual values the environment or job protection more. First of all, I created a dummy variable which takes value 1 if the individual gives more importance to job protection compared to environmental protection (answers 4-5 in the "job_vs_enviro" question coding of the CES 2010-14 panel), otherwise, 0 is assigned if environment is more important than job protection (answers 1-3 in the "job_vs_enviro" question coding of the CES 2010-14 panel). Next, the job vs. the environment opinionated, opinionated pro environment (former opinionated believe) and opinionated pro job (former opinionated denier) have been created (refer to Section 3.3.1).

This robustness check confirms the baseline model results: a higher exposure to climate change news is correlated with a greater conformance to the political group point of view (pro environment preservation for the Democrats and pro job protection for the Republicans) and a

Table 3.10: Rob check: job vs. the environment opinion as dep. variable

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated environment	Opinionated job	Opinionated job	Opinionated environment
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0196***	0.0316***	0.0208***	-0.0088***	-0.0121***
	(0.0025)	(0.0033)	(0.0041)	(0.0015)	(0.0029)
N	8611	4131	4219	4105	4218
Controls added	yes	yes	yes	yes	yes

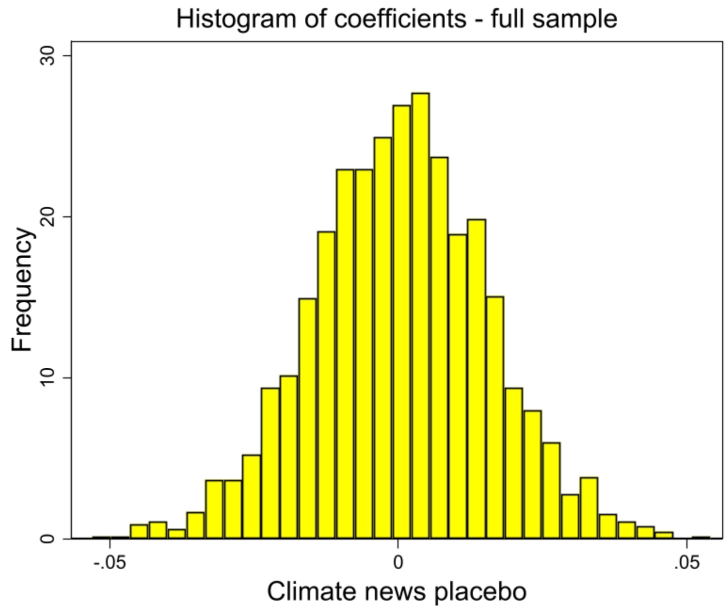
Notes: Average marginal effects after probit regression models. Instead of considering the climate change existence-related question to create the "opinionated" dependent variables I use a job vs. the environment question ("enviro_vs_jobs" question, contained in the CES 2010/12/14 panel). All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

greater disagreement with the contrasting opinion (pro job for Democrats and pro environment for the Republicans). The magnitudes of marginal effects are greater compared to the baseline case.

3.6.8 Placebo test

This extension ensures the robustness of our main analysis by considering randomized subsets of the data, verifying that the statistical method used in this study does not influence the results. To test the stability of my findings, I randomize climate change news information across three samples of individuals: the full sample, Democrats, and Republicans. The procedure is as follows: first, I generate a vector of observed climate change news, which will remain fixed throughout the simulation exercise. Second, I randomly sort the observations using a uniformly generated random variable. Third, I assign the climate change news vector to the randomly sorted observations. Fourth, I estimate equation 3.1 on the newly created dataset. Finally, I retrieve the parameter estimate for the climate change news placebo variable and repeat the simulation exercise 2000 times. The distribution of the climate change news parameter, which follows a normal distribution, is centered around 0. Since the mean is not significantly different from 0, we can conclude that the

Figure 3.1: Density histogram of coefficients - full sample of individuals

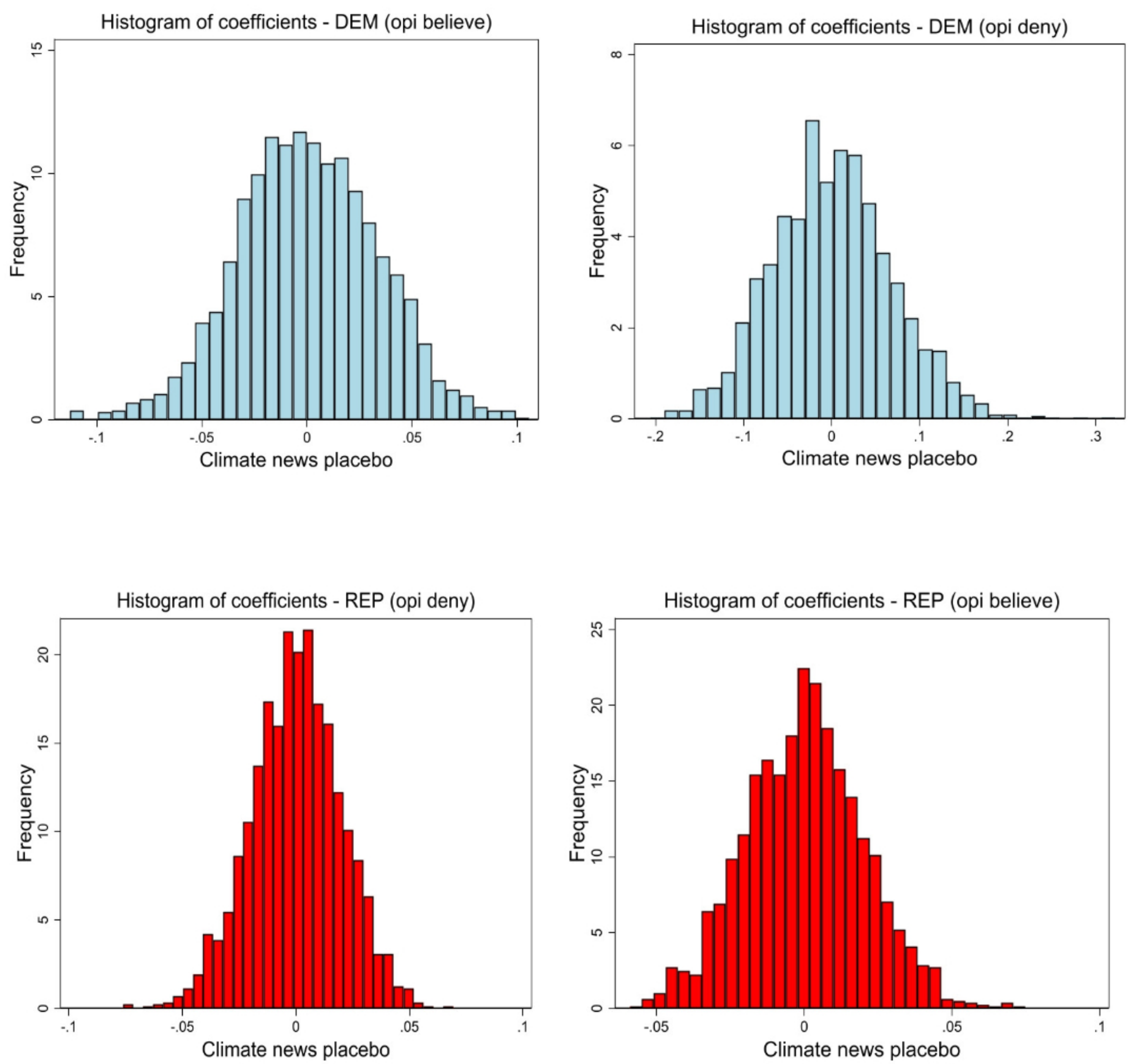


assignment procedure does not deviate from a random assignment of climate change news.

Figure 3.1 shows the histogram density of the coefficients from the 2000 iterations for the full sample (referencing Column 1 in the baseline model, where the dependent variable is "opinionated"). The mean value of the randomized climate news variable's coefficient distribution is 2.8×10^{-4}. The distribution follows a normal shape. Since the distribution of the placebo dependent variable is centered around zero, we can conclude that there is no real effect of the climate news variable when this information is randomized. This reinforces the reliability of our main results.

Figure 3.2 shows the histograms of density for the Democrat sample (see Columns 2 and 3 in the baseline model, where the dependent variables are "opinionated believer" and "opinionated denier," respectively) and the Republican sample (corresponding to Columns 4 and 5 in the baseline model, where the dependent variables are "opinionated denier" and "opinionated believer," respectively). Once again, the mean value of the climate placebo coefficients is 0, and the density plots exhibit a bell-shaped distribution. Overall, when a randomized climate news variable is used, no clear relationship between climate news and opinion is observed.

Figure 3.2: Density histogram of coefficients - Democrat and Republican samples



3.7 Extension

In this section, I investigate whether greater consumption of internet news, compared to traditional media (TV, radio, and newspapers), is associated with a higher probability of being an opinionated individual, particularly focusing on opinionated believers and deniers across Democrats and Republicans.

To assess this, I computed the average consumption of traditional media (TV, radio, and newspapers). These media variables were initially coded as 0-1 dummy variables in the survey, where individuals were asked if they had watched or listened to each type of media in the last 24 hours. These variables were then averaged over the three survey years to obtain aggregated data for each year. A traditional media variable was created by averaging these three years-specific variables. Additionally, I created an internet media variable, which is the average blog usage in the last 24 hours across the three survey waves. Finally, I developed an *internet media preferred* dummy variable, which takes a value of 1 if the individual consumes more traditional media than internet-based media.

Table 3.11: Average marginal effects table with internet preferred to traditional media as independent variable

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Internet media preferred	0.0440*** (0.0112)	0.0370*** (0.0104)	0.1303*** (0.0212)	-0.0046 (0.0043)	-0.1025*** (0.0210)
N	9413	4397	4437	3588	4440
Controls added	yes	yes	yes	yes	yes

I find that greater consumption of internet media, as opposed to traditional media, increases the likelihood of being an opinionated individual (Table 3.11). Among Democrats, the probability of being an opinionated believer increases, while among Republicans, it decreases, though no statistical significance is observed for this group. Similarly, the probability of being an opinionated denier decreases among Democrats and increases among Republicans. Overall, when comparing the magnitude of these coefficients with the baseline ones, it appears that the type of media consumed is a stronger predictor of an opinionated condition than the quantity of climate change news consumed.

3.8 Conclusion

3.8.1 The study's contribution, findings and implications

This study provides empirical validation for the significant role of climate change news in relation to opinion stability during the 2010-2014 period. The findings indicate that greater exposure to climate change news is statistically linked to a higher likelihood of being opinionated, whether in support of or denying climate change, across the full sample. In the baseline model (Table 3.3), a unit increase in climate news exposure increases the relative probability of being opinionated by 1.09 percentage points in the general population. The effect of climate change news on opinion stability aligns with the "directional motivated reasoning" theory, as discussed in the literature review, where individuals seek information that aligns with their social group or pre-existing beliefs, thereby reinforcing their opinion (see Druckman and McGrath, 2019). When individuals are exposed to climate news that resonates with their political affiliation—accepting climate change for Democrats and denying it for Republicans—a greater degree of opinion stability is observed. Conversely, exposure to opposing viewpoints increases instability. Specifically, greater exposure to climate news increases the stability of climate change acceptance among Democrats by 1.3 percentage points and reinforces climate change denial among Republicans by 0.94 percentage points.

The results, which are highly statistically robust, are further corroborated by a variety of robustness checks, including alternative variables, geographic dummies, and placebo tests. However, the effect size remains modest, as multiple individual factors also contribute to opinion stability (Table 3.B.2). Figures 3.1 and 3.2 further confirm the robustness of the main analysis, demonstrating that the statistical method used does not introduce bias regarding climate beliefs when related to climate news exposure. Moreover, greater consumption of internet media, as opposed to traditional media, is a significant predictor of being an opinionated individual. Additionally, in our database, individuals more interested in climate change news tend to be those exposed to internet media rather than traditional media. The internet may drive polarization by creating "echo chambers" where like-minded individuals interact and adopt more extreme viewpoints. Furthermore, the difficulty in verifying online information can lead individuals to rely on pre-existing beliefs, while algorithms create filter bubbles that expose users to content reinforcing their views, further deepening polarization.

3.8.2 Policy-making and research future challenges

The results presented offer insights into several key areas for policy-making and research.

First, it is crucial to examine the relationship between individual opinions and news exposure, particularly in light of emerging AI technologies like AI-generated or modified images and deepfakes. These tools have the potential to dramatically alter how we consume news and can fuel misinformation, even on topics like climate change (see Doss et al., 2023). Society must develop effective strategies to detect and counter fake or misleading information, which poses a significant threat to the scientific consensus on climate change impacts. Second, the role of news in shifting stable skeptical opinions deserves attention. If, as theory suggests, individuals select media based on their pre-existing beliefs and preferences (Knobloch-Westerwick, 2014) and tend to reject information that contradicts their views (Carmichael et al., 2017), the challenge becomes how to break through this resistance. One possible approach could involve subtly introducing positive frames about climate change within the partisan media that individuals already consume. Alternatively, positive climate frames could be gradually embedded in content that initially appears to align with a skeptic's perspective (e.g., in the headline or abstract), thereby engaging them before revealing the contrary message. Finally, developing an original, text-based indicator to assess how climate messages are framed across U.S. states and counties would be valuable. This indicator could focus on the balance between skepticism and pro-environment perspectives, providing a deeper understanding of regional differences in climate communication.

Appendix

3.A Data description

Table 3.A.1: Initial question from which opinionated dummy has been created

From what you know about global climate change or global warming, which one of the following statements comes closest to your opinion?	Dummy denial coding
1. Global climate change has been established as a serious problem, and immediate action is necessary	0
2. There is enough evidence that climate change is taking place and some action should be taken	0
3. We don't know enough about global climate change, and more research is necessary before we take any actions	0
4. Concern about global climate change is exaggerated. No action is necessary	1
5. Global climate change is not occurring; this is not a real issue	1

Table 3.A.2: Opinionated variable coding

Initial denial question coding			Opinion related dependent variables coding		
Denial status dummy			Opinionated	Opinionated believer	Opinionated denier
2010	2012	2014			
1	1	1	1	0	1
0	0	0	1	1	0
0	0	1	0	0	0
0	1	1	0	0	0
1	0	0	0	0	0
1	1	0	0	0	0
1	0	1	0	0	0
0	1	0	0	0	0

Notes: The percentage of deniers has been computed starting from the 2010/12/14 mode of the individual answering a CES question investigating if the individual believes or deny climate change.

Figure 3.A.1: Percentage of opinionated, opinionated believers and opinionated denials per state

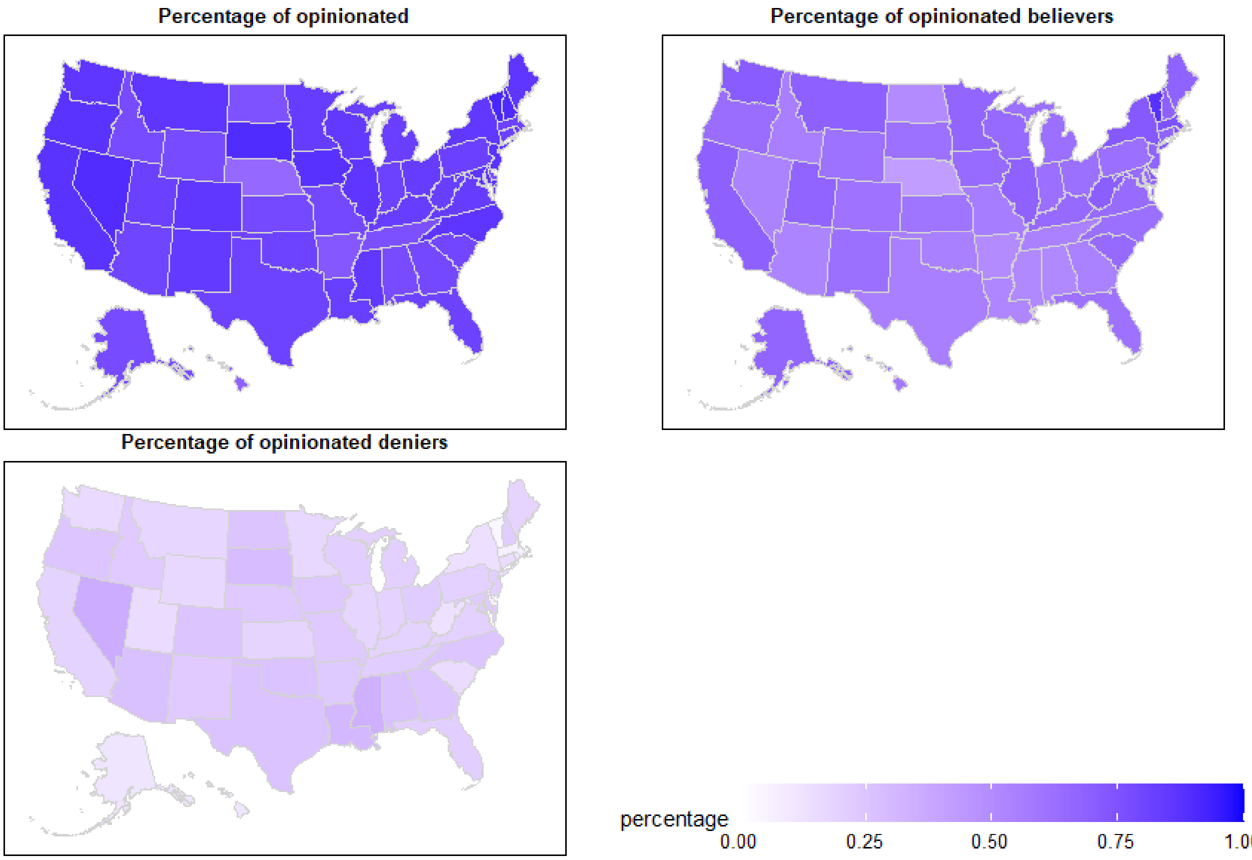


Table 3.A.3: Coding of the climate news variable based on survey answers

News variable	Question text	News coding
Climate news	About how often do you hear about global warming in the media (TV, movies, radio, newspapers/news websites, magazines, etc.) ?	
	1. Never	1
	2. Once a year or less often	1
	3. Several times a year	2
	4. At least once a month	3
	5. At least once a week	4

Table 3.A.4: Coding of the rob. checks general news variables based on survey answers

News variable	Question text	News coding
News interest	Some people seem to follow what's going on in government and public affairs most of the time, whether there's an election going on or not. Others aren't that interested. Would you say you follow what's going on in government and public affairs ... ?	
	1. Hardly at all	1
	2. Only now and then	2
	3. Some of the time	3
	4. Most of the time	4
News media count	In the past 24 hours have you ... - Read a blog. (Yes/no) - Read a newspaper in print or online. (Yes/no) - Watched TV news. (Yes/no) - Listened to a radio news program or talk radio. (Yes/no)	
	1. No media selected	0
	2. One selected	1
	3. Two selected	2
	4. Three selected	3
	5. All selected	4

Figure 3.A.2: Average climate news exposure by state

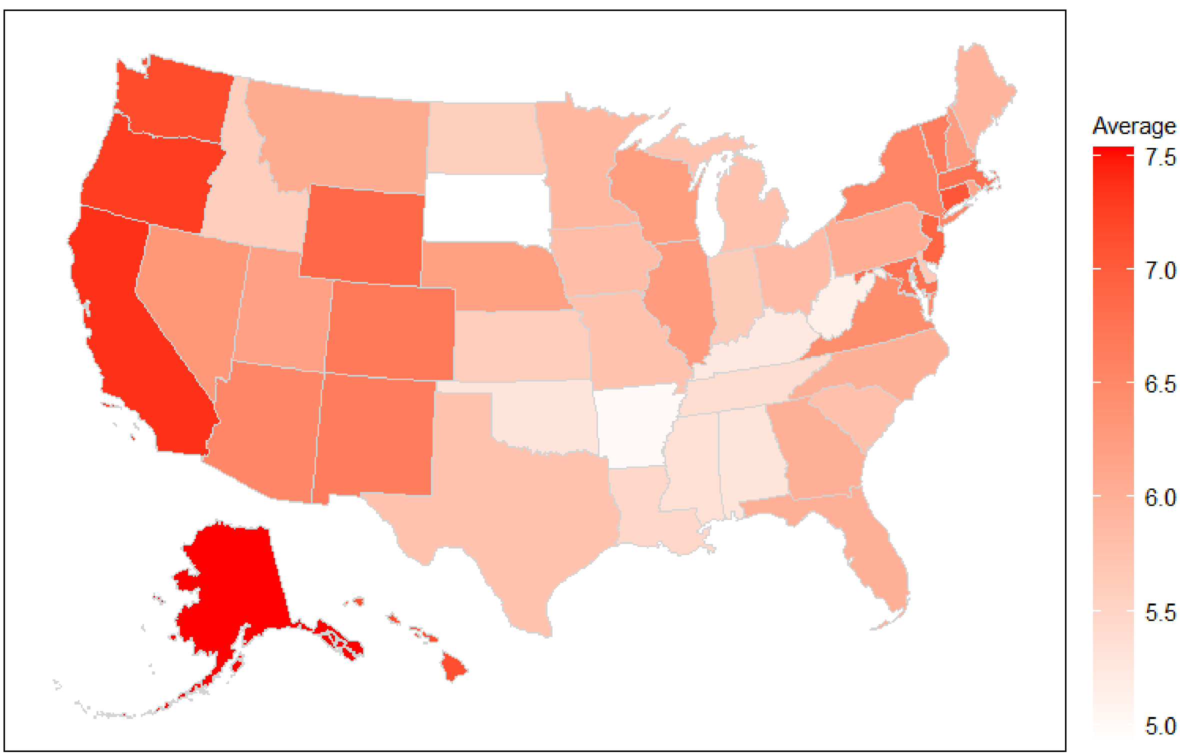


Table 3.A.5: Descriptive statistics for the whole sample

Description	N	Mean	Std. Deviation	Min	Max	Variable type
Opinionated	9430	0.83	0.37	0	1	Dummy
Opinionated Believer	9430	0.63	0.48	0	1	Dummy
Opinionated Denier	9430	0.20	0.40	0	1	Dummy
Climate News	9127	6.24	2.03	0.95	11.18	Continuous
Education	9500	3.9	1.4	1	6	Categorical
Family Income	9500	7.8	3.0	1	12	Categorical
Religion	9500	4.2	4.1	1	12	Categorical
Age Category	9500	2.61	0.57	1	3	Categorical
Gender: Male	9500	0.55	0.50	0	1	Dummy
Race	9500	1.2	0.61	0	1	Categorical
Party Voted	9212	2.0	0.98	1	3	Categorical
Working Status	9500	2.0	1.0	1	4	Categorical
Union	9500	2.6	0.61	1	3	Categorical
Home Ownership Type	9499	1.2	0.46	1	3	Categorical
Citizen	9498	1	0.056	0	1	Dummy
No Health Insurance	9500	0.086	0.23	0	1	Dummy
Married	9500	0.65	0.46	0	1	Dummy
Children <18	9500	0.16	0.34	0	1	Dummy
Mover	9500	0.049	0.22	0	1	Dummy

Table 3.A.6: List of descriptive statistics databases sources and variable codes

Variable	Database	Question code in survey[a]
Opinionated[b]	2010-2014 CES Panel Survey	CC10_321, CC12_321 and CC14_321
Opinionated Believer[b]	2010-2014 CES Panel Survey	CC10_321, CC12_321 and CC14_321
Opinionated Denier[b]	2010-2014 CES Panel Survey	CC10_321, CC12_321 and CC14_321
Climate News	Created starting from a list of questions - see list of variables in Table 3.A.7	
Education	2010-2014 CES Panel Survey	educ
Family Income	2010-2014 CES Panel Survey	faminc
Religion	2010-2014 CES Panel Survey	religpew
Age Category	2010-2014 CES Panel Survey	birthyr
Gender: Male	2010-2014 CES Panel Survey	gender
Race	2010-2014 CES Panel Survey	race
Political party[c]	2010-2014 CES Panel Survey	CC10_317, CC12_317, CC14_317, CC12_410a and CC14_317_2012
Working Status	2010-2014 CES Panel Survey	employ
Union	2010-2014 CES Panel Survey	union
Home Ownership Type	2010-2014 CES Panel Survey	ownhome
Citizen	2010-2014 CES Panel Survey	immstat
No Health Insurance	2010-2014 CES Panel Survey	healthins_6
Married	2010-2014 CES Panel Survey	marstat
Children <18	2010-2014 CES Panel Survey	child18
Mover[d]	2010-2014 CES Panel Survey	countyfips

[a] The survey question code numeric suffixes referring to the year of survey (_10, _12 and _14) have been here omitted where the pre-suffix part remained unvaried over the years.
[b] This variable has been recoded and created starting from this question as specified in Tables 3.A.1 and 3.A.2.
[c] This variable refers to the latest presidential election president's party voted. When it was not possible in the year of election to know the president voted by the individual I considered the answer provided in the subsequent(s) year: if the individual in 2010 did not indicated the president voted in 2008 I will consider his answer to the same question in 2012 or, if not provided, in 2014. Same consideration apply to the 2012 year.
[d] Mover refer to change in state, extracted from county fips information.

Table 3.A.7: List of variables used to create the climate news dependent variable

Variable	Database	Question code in survey
Age category	2008-2022 CCAM cross-sectional survey	age_category
Education	2008-2022 CCAM cross-sectional survey	educ
Gender	2008-2022 CCAM cross-sectional survey	gender
Family Income	2008-2022 CCAM cross-sectional survey	income
Race	2008-2022 CCAM cross-sectional survey	race
Political party	2008-2022 CCAM cross-sectional survey	party
U.S. division	2008-2022 CCAM cross-sectional survey	region9

Table 3.A.8: Descriptive statistics for additional individual variables used in robustness checks and heterogeneity Analyses

Description	N	Mean	Std. Deviation	Min	Max	Variable type
Opinionated about Job vs. the Environment	8911	0.74	0.44	0	1	Dummy
Opinionated Pro-Environment	8911	0.46	0.50	0	1	Dummy
Opinionated Pro-Job	8911	0.28	0.45	0	1	Dummy
Alternative Climate News	9134	3.00	0.49	1	4	Continuous
News Interest	9496	3.60	0.63	1	4	Continuous
News Media Count	9500	2.20	0.91	0	4	Continuous
Internet User	9500	0.29	0.37	0	1	Dummy

Table 3.A.9: List of descriptive statistics databases sources and variable codes

Variable	Database	Question code in survey[a]
Opinionated about Job vs. the Environment [b]	2010-2014 CES Panel Survey	CC10_325, CC12_325 an CC14_325
Opinionated Pro-Environment [b]	2010-2014 CES Panel Survey	CC10_325, CC12_325 an CC14_325
Opinionated Pro-Job [b]	2010-2014 CES Panel Survey	CC10_325, CC12_325 an CC14_325
Alternative Climate News	Created starting from a list of CCAM database questions - see list of variables in Table 3.A.10	
News interest	2010-2014 CES Panel Survey	CC10_325, CC12_325 an CC14_325
News interest	2010-2014 CES Panel Survey	newsint
News media count	2010-2014 CES Panel Survey	CC10_301_1, CC10_301_2, CC10_301_3, CC10_301_4, CC12_301_1, CC12_301_2, CC12_301_3, CC12_301_4, CC14_301_1, CC14_301_2, CC14_301_3, CC14_301_4
Internet User	2010-2014 CES Panel Survey	CC10_301_1

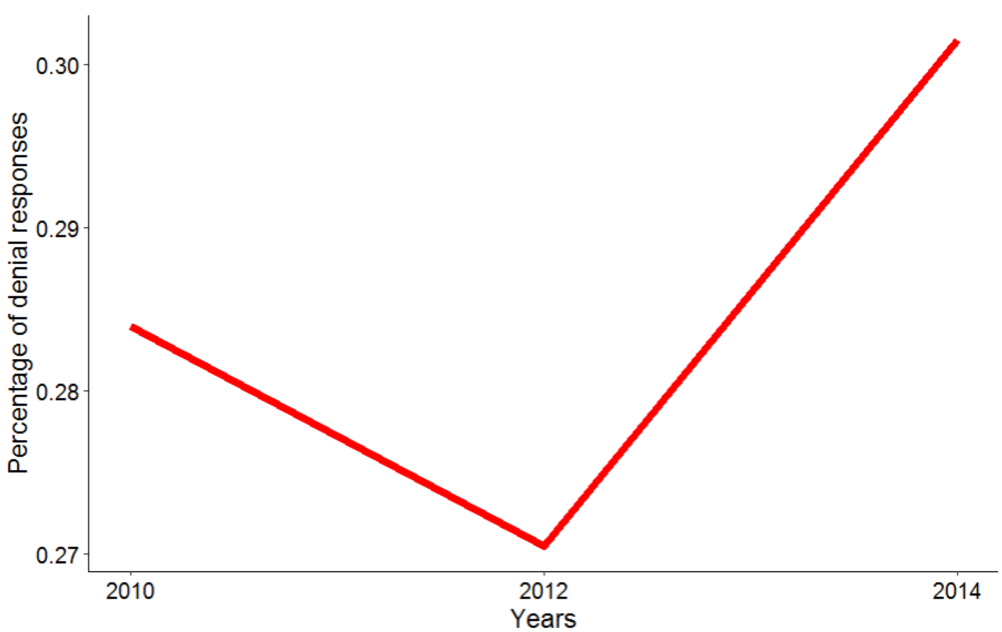
[a] The survey question code numeric suffixes referring to the year of survey (_10, _12 an _14) have been omitted where the pre-suffix part remained unchanged over the years.
[b] This variable has been recoded and created starting from this question following the same climate opinion's coding procedure as specified in Table 3.A.1 and 3.A.2.

Table 3.A.10: List of variables used to create the alternative climate news dependent variable in robustness check

Variable	Question code in CCAM database	Question code in CES database
Age category	age_category	birthyr
Education	educ	educ
Gender	gender	gender
Family Income	income	faminc
Race	race	race
Political party	party	pid3
U.S. division	region9	countyfips

A recoding of the CCAM variables has been performed to align the categories with those in the CES database. The birth year variable in the CES database has been transformed into an age category variable, consistent with the CCAM counterpart.

Figure 3.A.3: Trend over time of the percentage of deniers in the US



3.B Main results

Table 3.B.1: Independent individuals results

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"	Climate news is related with climate opinion stability in disagreement with "own side"
Sample:		Independents	
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier
	(1)	(2)	(3)
Climate news	0.0090 (0.0129)	0.0073 (0.0155)	0.0056 (0.0134)
N	251	249	249
Controls added	yes	yes	yes

Notes: Average marginal effects after probit. In this model I considered the Columns 1, 2 and 3 in the baseline model and restricted the sample only to the independent voters. The main point of view of independent votes is "believe in climate change" (84% of individuals). All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses.

Table 3.B.2: Main results - all controls included

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0449***	0.1456***	0.0245**	-0.2132***	-0.0212*
	(0.0086)	(0.0195)	(0.0105)	(0.0449)	(0.0111)
Religion: protestant	base	base	base	base	base
Religion: roman catholic	-0.0059	0.0439	-0.2088***	-0.2911	0.1847***
	(0.0397)	(0.0934)	(0.0461)	(0.2095)	(0.0477)
Religion: mormon	-0.2946**	-0.1203	-0.1186	0.0000	-0.0168
	(0.1169)	(0.3769)	(0.1251)	(.)	(0.1333)
Religion: eastern or greek orthodox	-0.2530	0.0000	-0.4568	0.0000	0.0805
	(0.2203)	(.)	(0.2884)	(.)	(0.2886)
Religion: jewish	0.5371***	-0.0404	-0.4036***	-0.0809	0.6547***
	(0.1042)	(0.1668)	(0.1402)	(0.3774)	(0.1345)
Religion: muslim	0.0000	0.0000	0.1570	0.0000	0.6004
	(.)	(.)	(0.6239)	(.)	(0.6242)
Religion: buddhist	0.2202	-0.3130	-0.3150	0.2634	-0.0025
	(0.1836)	(0.2392)	(0.3765)	(0.4286)	(0.3996)
Religion: hindu	0.0000	0.0000		0.0000	
	(.)	(.)		(.)	
Religion: atheist	0.9216***	0.5443***	-0.1180	0.0000	0.2599
	(0.1060)	(0.1716)	(0.1829)	(.)	(0.1863)
Religion: agnostic	0.4825***	0.2166	-0.2290*	-0.0383	0.1579
	(0.0770)	(0.1363)	(0.1222)	(0.2370)	(0.1256)
Religion: nothing in particular	0.2898***	0.0494	-0.2514***	-0.2357	0.2718***
	(0.0522)	(0.0976)	(0.0720)	(0.2161)	(0.0724)
Religion: something else	0.4553***	0.9716***	-0.0619	-0.2081	0.0237
	(0.1041)	(0.3644)	(0.1379)	(0.3861)	(0.1478)
Job: employed	base	base	base	base	base
Job: unemployed	0.0025	-0.0915	0.0690	0.0000	0.0441
	(0.0793)	(0.1548)	(0.0922)	(.)	(0.0961)
Job: inactive	0.0004	0.0167	-0.0585	-0.0151	0.0489
	(0.0348)	(0.0751)	(0.0420)	(0.1383)	(0.0440)
Job: other	0.0415	0.2358	0.0888	0.0000	-0.1280
	(0.1181)	(0.3031)	(0.1421)	(.)	(0.1554)
Union: currently part of it	base	base	base	base	base
Union: formerly part of it	-0.2066***	0.1422	-0.0124	-0.1516	-0.0020
	(0.0682)	(0.1262)	(0.0918)	(0.2286)	(0.0965)
Union: not part of it	-0.1894***	-0.0081	-0.0105	-0.2377	0.0850
	(0.0642)	(0.1144)	(0.0873)	(0.2155)	(0.0916)
Own home: own	base	base	base	base	base
Own home: rent	0.2059***	0.1090	0.0188	-0.3295*	0.0157
	(0.0461)	(0.0831)	(0.0614)	(0.1762)	(0.0643)
own home: other contract	0.1183	0.2472	0.0413	0.0000	-0.0391
	(0.1244)	(0.2768)	(0.1574)	(.)	(0.1677)
Us citizen: no	base	base	base	base	base
Us citizen: yes	0.2647	0.0000	0.0000	0.0000	-0.8514
	(0.6328)	(.)	(.)	(.)	(0.7246)
Health insurance: possessed	base	base	base	base	base
Health insurance: not possesed	0.0623	-0.0309	0.1212	-0.0768	-0.0961
	(0.0649)	(0.1198)	(0.0814)	(0.2494)	(0.0850)
Has child: no	base	base	base	base	base
Has child: yes	-0.1059**	-0.3237***	-0.0426	0.0238	0.0427
	(0.0442)	(0.0876)	(0.0532)	(0.1972)	(0.0553)
N	9042	4374	4382	3571	4385
Controls added	yes	yes	yes	yes	yes
pseudo R^2	0.037	0.081	0.008	0.098	0.011
ll	-3.9e+03	-7.5e+02	-2.9e+03	-1.6e+02	-2.6e+03
chi2	268.2502	124.3017	46.2368	37.8832	56.7586
p	0.0000	0.0000	0.0007	0.0003	0.0000

Notes: Probit regression models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are present.

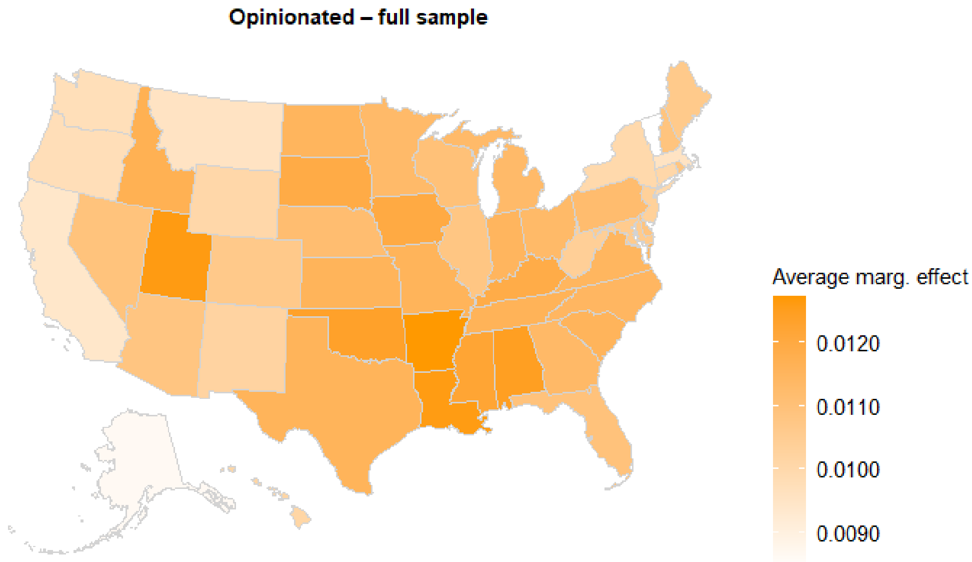
3.C Robustness checks, heterogeneity and extensions

Table 3.C.1: Rob. check: state level controls included

Hypothesis:	Climate news is related with climate opinion stability	Climate news is related with climate opinion stability in agreement with "own side"		Climate news is related with climate opinion stability in disagreement with "own side"	
Sample:	Full	Democrats	Republicans	Democrats	Republicans
Dep. variable:	Opinionated	Opinionated believer	Opinionated denier	Opinionated denier	Opinionated believer
	(1)	(2)	(3)	(4)	(5)
Climate news	0.0101***	0.0124***	0.0084**	-0.0044***	-0.0071*
	(0.0022)	(0.0019)	(0.0042)	(0.0012)	(0.0039)
N	9042	4374	4382	3571	4385
Individual controls	yes	yes	yes	yes	yes
State controls	yes	yes	yes	yes	yes

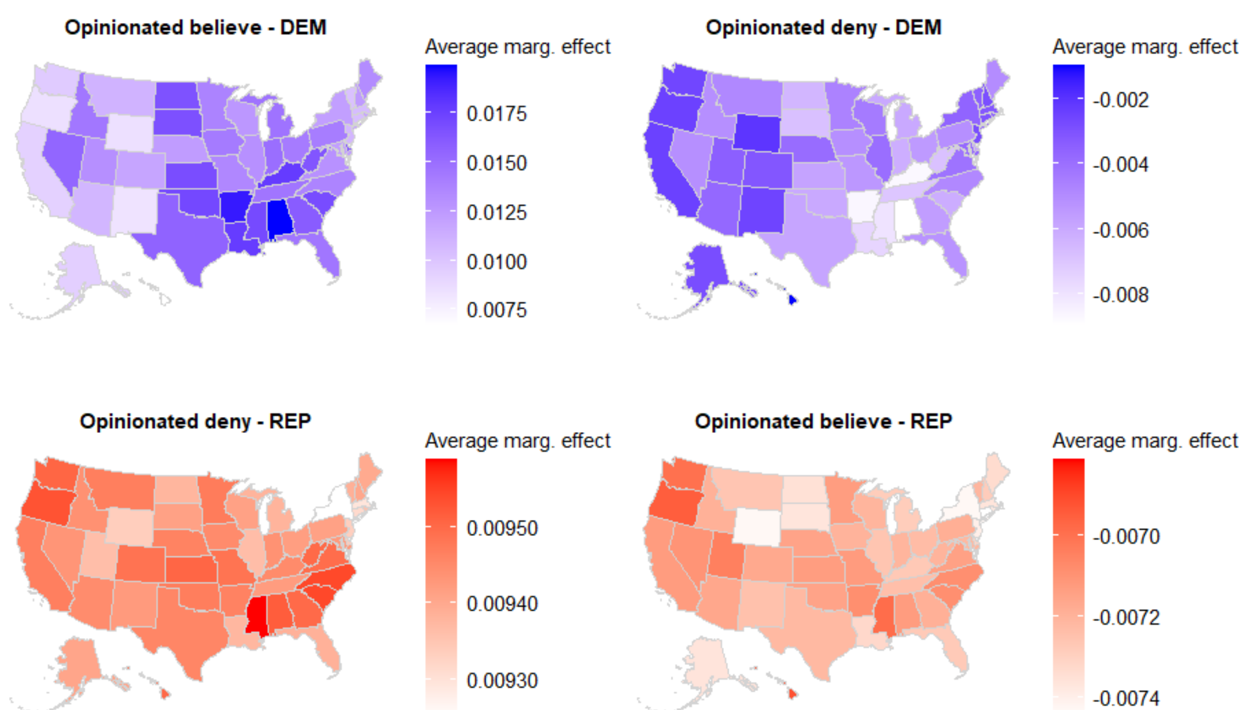
Notes: Average marginal effects after probit regressions. In this robustness I have added several state level average over-the-period controls obtained from the cumulative 2006-2022 Cooperative Election Study database for the years 2010, 2012, and 2014. The state level controls (these are state level averages information) added regard the job status (mean employment, unemployment, inactive or other occupation), presence of a child in family, union membership status, U.S. citizen status and no health insurance possessed status, housing contract typology and region dummies. All other variables are unchanged with respect to the main results model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in parentheses. The results appear to mirror the main results in terms of signs of the coefficients, p-values significance levels and probability changes magnitude. Climate change news increase the probability of being opinionated in the whole sample and to present opinions more in agreement with the main point of view, discarding opposing views.

Figure 3.C.1: Average marginal effect by state for each opinionated dependent variable in the full sample



Notes: This figure represents the average marginal effect of the dependent variable across U.S. states. Results were obtained considering the baseline regression model in Column 1 (as in Table 3.2). After computing individual marginal effects for each model, the state average has been extracted.

Figure 3.C.2: Average marginal effect by state for each opinionated dependent variable across REPs and DEMs



Notes: This figure represents the average marginal effect of the dependent variable across U.S. states. Results were obtained considering the baseline regression model in Columns 2-5 (as in Table 3.2). After computing individual marginal effects for each model, the state average has been extracted.

Conclusion

Summary of results

This dissertation provides new evidence regarding the relationship between tropical cyclones, political preferences, and the economy. It first considers materialistic aspects and then addresses the less visible factors, such as individual opinions. Additionally, it examines the varying distances of impacts, starting with an analysis of direct exposure to tropical cyclones and subsequently exploring more remote and indirect exposure through climate change news.

Chapter 1 has analyzed the significant subnational economic damage caused by direct exposure to tropical cyclones on a global scale, while also evaluating the impacts of tropical cyclone episodes, including all three concurrent hazards: wind, rainfall, and storm surge. This is especially relevant in light of the projected increase in tropical cyclone rainfall and storm surge intensity due to climate change and the only negligible rise in wind speed. The chapter has focused on providing a comprehensive evaluation of how accounting for each of these factors in the model contributes to a more precise tropical cyclone economic growth damage quantification. By collecting information for over a thousand of subnational units in the 1980-2020 period and using spatially modeled tropical cyclone intensity data in a regional fixed-effects panel model, results show that wind is the most damaging hazard to economic growth and that it produces long-term economic impacts. Tropical cyclones can have either a negative or positive marginal effect on gross regional product per capita (GRP PC) growth, depending on the specific hazard. An increase of one standard deviation in wind speed, the 90th percentile of rainfall, and storm surge results in decreases of 1.71, 1.5, and 0.92 percentage points in GRP PC growth, respectively. In contrast, median rainfall has a positive effect, increasing GRP PC growth by 1.39 percentage points for one standard deviation rise in intensity. Furthermore, agriculture is the most damaged sector sector, while low-development regions especially benefit from tropical cyclone rainfall.

Chapter 2 has studied the relationship between the experience of tropical cyclones and political polarization in the U.S. population, with a focus on the less visible psychological changes involved. To achieve this, repeated cross-sectional survey data on hundreds of thousands of individuals has been utilised. Their characteristics and preferences, based on 26 policy questions across various policy fields, as well as modeled data on maximum wind speeds for measuring tropical cyclone damage from 2010 to 2018, have been extracted. In terms of methodology, we conducted Ordinary Least Squares (OLS) regressions with county and year dummies, using standard errors clustered at the county level. This chapter has led to conclude that extremely damaging tropical cyclone events (in the top 10th percentile of damage) correlate with wider political polarization in the U.S. population. Democrats exposed to these episodes experience a 1.7 percentage point increase in liberal ideology, whereas Republicans show a 4.5 percentage point rise in conservative views, reacting 2.6 times more strongly than Democrats. The shift in Democratic ideology represents 9.4% of the standard deviation within this group. In contrast, the adjustment for Republicans accounts for 22.5% of the standard deviation of the dependent variable for this political faction. No polarization is detected when TC damage is below the 90th percentile and among political Independents. It is therefore confirmed, also through a robustness check varying damage percentiles, that only the most extreme events are linked to ideological shifts. Finally, we found that extensive exposure to public affairs and political news may be associated with increased political polarization linked to extreme tropical cyclone damage. However, the specific framing of the news and the exact content to which individuals were exposed remain uncertain.

Chapter 3 examines whether exposure to climate change news is associated with the stability of opinions on the existence of climate change. By collecting data from thousands of individuals during the 2010-2014 period, utilizing U.S. representative sociopolitical and climate change surveys, and performing probit regressions, this chapter provides relevant evidence. This chapter has empirically found that increased exposure to climate change news is associated with greater opinion stability, heightened consistency in individuals' climate change stances and larger disagreement with opposing views. A 1-unit increase in climate news exposure is associated with a 1.09 percentage point increase in the probability of maintaining one's pre-existing opinion on the acceptance or denial of climate change. Moreover, exposure to favorable climate change news increases the probability of being an opinionated believer among Democrats by 1.3 percentage points and the probability of being an opinionated denier among Republicans by 0.94 percentage points. The findings are robust across various validity tests, including a placebo test and different dependent and independent variable modifications.

Societal and policy implications

There are several implications to be summarized stemming from this dissertation, especially in terms of societal resilience and policy recommendations. First of all, chapter 1 has shown, aligning with the literature that wind speed is a major driver of tropical cyclones damage, while also highlighting the relevant contribution of storm surge and extreme levels of rainfall to the adverse economic impacts and the beneficial role of small levels of rainfall. Given the projected intensification of tropical cyclone rainfall and surge (Emanuel, 2005; Estrada et al., 2015) and the fact that the most catastrophic events are compound events, formed by two or more hazards (Zscheischler et al., 2018), this study has presented novel evidence and more precise estimates of the economic growth impacts resulting from the simultaneous inclusion of all concurrent tropical cyclone hazards. According to the results in chapter 1, adaptation and resilience policies for tropical cyclones should primarily focus on reducing wind speed damage. In a secondary phase only, plans should be developed to address the impacts of storm surge and rainfall. Given the climate change-driven intensification of tropical cyclone rainfall and storm surge (with only a modest increase in wind-related damage), and recognizing that coastal areas are uniquely vulnerable to all three hazards examined in this dissertation, it is crucial to progressively increase public expenditure on adaptation measures for tropical cyclone rainfall and storm surge, particularly in coastal regions. In addition, the agricultural sector is the most affected by tropical cyclones (this is in line with Kunze, 2021), so workers and firms in this sector should be prioritized for government aids.

Second, regarding the sociopolitical consequences of tropical cyclones (chapter 2), this dissertation confirms that highly destructive tropical cyclone events in the U.S. are associated with political polarization. This implies that the population may be subject to greater conflicts (Piazza, 2023) and lower societal trust (Lee, 2022). Moreover, if individuals tend to make goal-oriented decisions when financially constrained (Huijsmans et al., 2019), it is possible that the income reduction caused by tropical cyclones may lead individuals to adopt more self-interested behaviors. Moreover, if tropical cyclones are followed by an increase in political polarization, this latter may, in turn, undermine the future societal resilience to tropical cyclones, given that Democrats and Republicans present opposing disaster responses and behaviours, with Democrats generally more likely to evacuate in the emergence of a hurricane than Republicans (Long et al., 2020). Authorities should also be more committed to monitoring post-disaster public and political news and to preventing the spread of disinformation, to mitigate the political polarization effects that news may amplify following tropical cyclones.

Finally, chapter 3 corroborates the importance of studying news in relation to opinion persistence, which some authors identify as a potential cause of political polarization in the U.S. (Fryer et al., 2018). The results of this chapter underline the need for well-designed communication policies that not only promote climate change acceptance but also tailor information strategies to individuals based on their political affiliations. It is essential to consider both the type of message, whether it aligns with or contradicts pre-existing beliefs, and the individual characteristics of the audience. By addressing these factors, it could be possible to mitigate the negative effects of news, such as boomerang effects and the reinforcement of existing viewpoints when individuals encounter opposing messages.

Limitations

This dissertation has a few limitations that must be especially clarified. First, it must be acknowledged that, despite the databases' wide geographical coverage, there are instances where information is lacking for areas of significant interest to the study, resulting in sample bias. The DOSE database (Wenz et al., 2023), comprehensive of subnational economic information and used in chapter 1, excludes, due to data availability, a few regions in the Southeast Asia and underrepresents Africa and South America. The Cooperative Election Study,[17] used for the chapters 2 and 3's analyses, presents no information for many counties in the Great Plains central area of the U.S. Second, chapter 1's analysis examines only the direct economic impacts and does not account for indirect effects such as environmental degradation and social costs, while chapters 2 and 3 have relied on databases and/or econometric techniques that has not allowed for tracking individuals over time, neglecting the ability to establish causal relationships. Third, the use of survey data in this dissertation also presents certain limitations. These include potential biases related to the questionnaire's completion, such as individuals providing false answers, masking extreme opinions, or not paying sufficient attention when responding to questions.

Future research avenues

This dissertation suggests many future research questions to be addressed. To start with, considering the economic growth impacts of tropical cyclones (chapter 1), it would be of great relevance to study the effectiveness of early warning systems, preparedness measures and trade in reducing economic damage and facilitating faster recovery. As climate change is projected to increase both the frequency and intensity of tropical cyclones, it will be crucial to explore how these phenomena impact economic growth in areas that are especially vulnerable. Future studies could also further investigate the socio-economic consequences of tropical cyclones, focusing on their effects on income inequality, education levels, and healthcare access, which are key to assessing

[17] Cooperative Election Study Common Content at https://cces.gov.harvard.edu.

the recovery and resilience of affected areas. Moreover, exploring the possibility of diminishing marginal impacts of cyclone frequency on economic activity, as regions with repeated exposure may develop greater adaptive capacity, would offer important perspectives on disaster impact and long-term recovery. Next, we could apply Natural Language Processing (NLP) techniques to the research questions addressed in chapters 2 and 3. For instance, opinions could be gathered from social networks like Twitter, while data on climate change news volume and framing types could be extracted from newspapers. These data could then be subjected to text and sentiment analysis. A replication of the research from chapters 2 and 3 in different geographical contexts, such as Europe, or in the case of chapter 2, to other extremely devastating disasters, as floods, can also be performed. Additionally, creating a panel of U.S. states/counties would enable the examination of causal mechanisms. Moreover, it may be valuable, using the framework from chapter 3, to conduct an experiment to examine the reaction of individuals from different political groups when exposed to climate-related conflicting information presented in media sources previously selected by the individual. In conclusion, further research and policy commitments are necessary to strengthen societal and economic resilience to the adverse impacts of tropical cyclones and to address the side effects of the increasing divide in public opinion.

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