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1 Introduction

In the scientific community, there is vast consensus that human activity caused the climate to change significantly in recent decades and actions need to be taken immediately to prevent the worst scenarios from materializing. In the general public, however, such widespread support cannot be observed, and is even completely lacking in some parts of the population. The reasons for this divergence are manifold and research has just begun to unravel this puzzle. To a large part, the great heterogeneity in the public seems to be built on the volatile effects of personal weather experiences on climate change perceptions. Individuals reverting to this source of information to make inferences about the climate are prone to attribution biases and other psychological fallacies, failing to grasp the true magnitude and strength of ongoing climate change. In addition, learning from personal experiences with weather is subject to significant moderation by confounders such as the media, social networks or ideology. The latter in particular has been identified to heavily distort how people learn from weather events, emphasizing that how they see climate change is only a reflection of their previously held core beliefs and world views. This makes it increasingly hard to convince skeptical (e.g. conservative) peer groups of the challenges lying ahead. This is what is ultimately needed, however, to be able to win support for powerful policies enacted by governments who can draw on majorities in parliaments, and finally achieve large-scale changes in behavior to fight against climate change.

As the landscape of climate change perceptions is so scattered, researchers have looked to identify common patterns in what can reconcile this lack of consensus.

This paper contributes to this mission by looking into the effects of the 2020 hurricane season on climate change perceptions. Employing Google Trends data in combination with a recent survey on attitudes and behaviors on climate change, the distinct building blocks of how hurricanes can shape beliefs are uncovered, paying particular attention to the perception shifts of the conservative peer group. A sub-analysis on the mediating effect of climate change search behavior completes the empirical strategy. This approach allows to identify distinct drivers of changes in climate change perception, digging deep into individual personal characteristics as well as unique features of the hurricane season.

The rest of the paper proceeds as follows. Section 2 discusses the existing relevant literature. Thereafter, the data sources for the analysis are presented and the construction of the variables that are needed for the analysis is explained. Section 4 states the regressions run in order to investigate the relationship between hurricane activity and climate change perceptions, and Section 5 shows the results of these. Section 6 connects the findings to the literature and Section 7 concludes.

2 Literature Review

2.1 Climate Change Perceptions

Climate change is intensifying. The newest publication of the IPCC[1] projects that only the most optimistic out of five modelled future paths of greenhouse gas emissions will reach the goal of the Paris Climate Agreement to limit global warming to 1.5 degrees compared to pre-industrial levels (Masson-Delmotte et al., 2021). In the other scenarios, scientists project massive adverse ecological, societal and economic impacts following extreme weather events, biodiversity loss, agricultural degradation and inequity considerations (Poertner et al., 2022). These developments call for immediate action to slow down and eventually turn around these processes. Therefore, as a major part of change passes through political decisions, a widespread awareness in the population is needed for governments to win majorities to ultimately legislate powerful policies to combat this harmful behavior. In the face of the ongoing climate crisis and major threats for humanity, it is puzzling to observe that, although scientific research mostly points into one direction, perceptions of climate change and affiliated risks heavily diverge in the population. In fact, a Pew Research Center Study (2009) found that 84 percent of scientists believe the earth is getting warmer because of human activity, while only 49 percent of the general public do. The existence of a divide between the scientific and public consensus is confirmed also by Doran and Zimmerman (2009) and Oreskes (2004). Other studies perform a segmentation of the population, sorting individuals into different categories depending on their level of concern about climate change, describing a divergence in the debate on the importance of envi-

[1]Intergovernmental Panel on Climate Change

ronmental issues (Leiserowitz et al. (2013); Maibach et al. (2011)). There are also large differences between countries on how climate change is perceived as a threat, making the landscape of interventions even more heterogeneous (Pew Research Center (2006); Archibald and Butt (2018)).

How can the expected convergence towards consensus on the threats of climate change, that should be driven by the growing scientific evidence in addition to the increasing number of climatic disasters caused by climate change itself, be reconciled with the apparent mistrust and disbelief observed in the public? The presence of such differences in opinions on climate change urges the question of how climate change perceptions are built up and can be affected. Weber (2010) suggests two allies that contribute to the formation of perceptions of climate change, which can begin to explain why consensus on climate change is so unequal between scientists and the general public. The first is centered around personal experiences of events that may be attributed to a warming of the globe. This way of learning is very affective and intuitive, and a very human and instinctive way of processing information that turns adverse experiences into behavior learned from for the future. It is thus drawn on easily by vast parts of the general public when making inferences about the climate. The second is a more analytical way of gathering information, a statistical process that needs to be trained. This is the method that the scientist community draws on to carve out evidence for climate change and communicate it to the public. The differentiation between two distinct types of learning is confirmed by other studies such as Konisky et al. (2016) or Shao and Goidel (2016). Thus, in order to understand why large parts of the public lack the statistically and scientifically justified level of concern about climate change, it is imperative to understand precisely how personal experiences with weather events shape perceptions of a changing climate.

2.2 Personal Experiences with Weather Events

Sisco (2021) states that affect activation, issue salience and psychological distance are the mechanisms that make personal experiences with weather events such strong drivers of climate change perceptions. This explains in part the variation that is observed in the population regarding belief in climate change, as geographies are hit with different intensities and frequencies by extreme weather. Another issue with using personal experiences of weather events as evidence for climate change lies in the human perception of what constitutes a statistically expected (adverse) weather event (e.g. droughts, heat waves, hurricanes) or a weather event that needs to be attributed to a changing climate. According to Weber (2010), climate change in the meteorological sense is the systematic change in average weather conditions for a region, i.e. a trend that can be observed in random fluctuations and thus easily confused with the occurrence of single disruptive weather events. There is a vast literature that states how perceived weather abnormalities, rather than objective environmental conditions shape belief in climate change (Shao and Goidel (2016); Akerlof et al. (2013)). On top of this attribution bias in relying on weather events as indicator for climate change risks, the psychological theory of classical reinforcement learning also interferes with using personal experiences to make these kind of inferences. It explains how evaluation of risky options under the repeated sampling in decisions from experience gives more weight to recent events than to distant ones (Weber et al., 2004). Rare adverse events have a small probability of happening or having happened recently, thus the concern about them is undershot. In case they do occur, the attention to such rare events shoots up and exceeds the statistically expected correct probability that is warranted by them. The result is a generally low concern about climate change in the population on average in normal times, and an unreasonably strong effect of adverse events on climate change perceptions (Yechiam et al., 2005). All in all, relying on weather events as the public does by its affective nature creates high volatility, unpredictability and inaccuracy in gauging the impact of climate change.

2.2.1 Types of Weather Events

The effect of specific weather phenomena on the perception of climate change is a well-researched field that is growing fast. Temperature abnormalities are recognized as one of the most powerful shifting forces making people worry about the climate (Howe et al. (2019); Brooks et al. (2014); Egan and Mullin (2012); Pianta and Sisco (2020); Lee et al. (2015); Kirilenko et al. (2015)). Other papers investigate how extreme weather events, such as droughts, wildfires or floods, can persuade people to believe in human-made climate change or drive support for climate change policies (Sisco et al. (2017); Konisky et al. (2016); Ray et al. (2017)). One particular stream of papers focuses on hurricanes. Rudman et al. (2013) and Seara et al. (2020) use a similar (case study) approach as they examine how particular tropical storms[2] can change support for climate change mitigating policies. Also Howe et al. (2014) and Lang and Ryder (2016) prove that hurricanes raise attention to climate change and can alter beliefs. Moreover, a note issued in the Yale Program on Climate Change Communication right before

[2]Hurricane Irene and Sandy as well as Irma and Maria, respectively.

the bulk of the hurricanes hit in 2020 discusses the opinions of residents in the five states that are historically hit hard by hurricanes and finds that people are worried more about climate change on average, suggesting that a certain elevated vulnerability due to exposure to hurricanes influences people's worry (Talaty et al., 2020). The effect of hurricanes can be particularly linked to their destructive power and strong impacts on economic and societal life in their aftermath. Given these characteristics, hurricanes perfectly match the before-mentioned dynamics of classical reinforcement learning, creating spikes in attention to climate change that fade out and revert back to the generally low level. Naturally then, one can expect how a record hurricane season as it occurred in 2020 will even amplify this already strong impact. In this regard, Thompson (2020) states how the 2020 season was the most active on record, counting 30 hurricanes and six becoming major category 3+ storms. As such, and in light of the underlying psychology behind personal weather experiences, the 2020 hurricane season makes for an interesting subject of further research into climate change perceptions.

2.2.2 Methodological Approaches

Besides the focus on a particular weather event, studies can also be differentiated according to the means through which the change in perceptions is captured. Among the more classic means are survey responses as in Konisky et al. (2016) or in Howe et al. (2014).[3] In addition, media attention can also be used as sensor to detect how weather events shape public opinion as is done by Pianta and Sisco (2020), that make use of news paper articles. More modern uses of data mining

[3]These use the *CCES* (Cooperative Congressional Election Study, a large cross-section of the American Public) and survey data from *Knowledge Networks*, respectively.

techniques include Twitter data (Sisco et al. (2017); Kirilenko et al. (2015)) or Google Trends data. The latter is increasingly used as it offers a convenient way to measure attention to a given phenomenon in the public in the form of revealed preferences, that stand in contrast to relying on stated preferences as in survey data. In particular, it allows to extract how the population perceives a certain event by creating a time trend scaled from 0 to 100 that displays the relative search activity for up to five keywords in a given period and metropolitan area. How a given sentiment prevails and develops in an area can thus be traced on a very granular level (Lang (2014)). This precise geospatial attribution is of key interest in the climate change literature (Konisky et al. (2016)). Lang and Ryder (2016) show that Google Trends data can be used to detect rises in climate change awareness following tropical cyclones. Also Archibald and Butt (2018) make use of search volume on Google to gauge climate change understanding across countries, discovering a two scale matrix of risk and awareness. Sisco et al. (2021) have shown that climate activist events can push attention to climate change on the Internet more than political events and temperature abnormalities. Google Trends data can be very advantageous in climate change research as it offers the ability to operationalize clear-cut weather events such as hurricanes that can be targeted with precise keyword searches.

2.3 The Role of Moderators

Up to this point, it has been explained how the reliance on personal weather experiences can create a divergence in the public regarding the belief in climate change and the urgency to act, due to psychological biases and an uneven distribution of extreme weather events. By itself, however, this cannot entirely explain the huge existing perception gaps. This is where what Sisco (2021) refers to as moderators come into play. He mentions media attention, event attribution and moderated reasoning (or partisanship) as confounding factors. How a weather event is perceived also depends on these concepts. For example, Sisco et al. (2021) show the mediating effect of the media by proving its significance in communicating the impact of climate marches on climate worry. Of utmost importance in the literature,however, is the effect of partisanship or ideology in interpreting climatic events. The prevalent direction of this relationship is that more conservative individuals fail to correctly attribute weather events to climate change (Goebbert et al. (2012); Howe and Leiserowitz (2013)). Shao and Goidel (2016) use a massive survey of U.S. Golf Coast residents to show that objective conditions have limited explanatory power, party affiliation however plays a powerful role on perceptions of weather patterns. Various other studies confirm how individuals of different political orientations might react distinctively to weather events and characterize it as driving force of how climate change perceptions manifest (Brody et al., 2008; Hamilton and Stampone, 2013; Dunlap and McCright, 2008; Egan and Mullin, 2012; Zaval et al., 2014; Akerlof et al., 2013). On top of impacting personal experiences, moderators such as partisanship and group membership, societal norms or peer networks also influence how individuals gather information from statistical description. According to Weber (2010), attention and trust - the key enablers for learning from statistics - are also heavily influenced by partisanship and the like. Eventually, moderating effects interfere with personal as well as statistical learning experiences and tilt the already heterogeneous landscape of climate change perceptions even more.

2.4 Outlook

In summary, there are various mechanisms that allow to explain the great divide between scientific and public opinion on the necessity to act against climate change. The gaps in opinion of the public on the importance of climate change and its threats are wide and seem hard to overcome. Personal experiences with weather, that in itself pose difficulties to correctly track down changes in the climate, are influenced by a number of mediating effects that create a vastly heterogeneous and unclear picture. Reducing the knowledge gaps to these driving forces that operate behind them, however, allows to understand how these differences can finally be eradicated. Policy and mitigation need to be aware of the above-mentioned dynamics and what constitutes them in order to be able to summon significant agreement to be implemented by governments and executed by citizens. This works when, in combination with research on policy effectiveness, decisions are made keeping in mind the particular necessities of different parts of the population. Sisco (2021) hints at the importance of understanding when in time policy proposals can be effective. It is the duty of research then to dig into these mechanisms to reach the aforementioned goal, i.e. to close these gaps by identifying distinct features of climate change communication that can lead to majorities for action finally tackling climate change. By changing the perception, action can finally take place.

3 Data

3.1 International Climate and Air Pollution Panel (ICAPP)

Three sources of data are used in this paper. The project of the International Climate and Air Pollution Panel (ICAPP) developed a rich data set that was collected to capture attitudes on climate change and air pollution (Sisco et al., 2020b). It combines a survey instrument with additional modules of social media and news reports, as well as weather and air pollution measurements. In this paper, the focus is laid on the survey component. This data was captured over a period from December 2019 to December 2020 in three countries (USA, Italy, China), targeting the six cities of New York, Dallas, Milan, Rome, Beijing and Shanghai and their respective metropolitan areas. A total of 24,824 individuals - some of which were interviewed multiple times making up 27,662 observations - answer questions on attitudes, beliefs and behavior related to climate change and other threats. For the purpose of this analysis the focus will be on the subset of the 9,204 observations in the USA, made up of 4,589 and 4,615 observations in the metropolitan areas of New York City and Dallas, respectively.[4,5]

3.1.1 Dependent Variables

The six dependent variables drawn on in this paper can be subdivided into two categories as shown in Table 1.[6]

[4] In New York, the number of distinct individuals is 4,000 and in Dallas 4,076. Some individuals were interviewed repeatedly to arrive at the stated counts of observations.

[5] See Sisco et al. (2020a) for additional documentation, survey questions, roll-out schedules and target city determination.

[6] The data set is retrieved in *csv* format. After importing it to *STATA 17*, it is cleaned and prepared for analysis. All the relevant variables are re-coded to be in numeric rather than string format.

Table 1. Descriptive Statistics of Key Dependent Variables

	Obs	Mean	SD
Attitudes			
worry	9204	3.57	1.24
certainty	9204	5.69	1.48
futureharm	8859	3.86	1.26
Behaviors			
bvr_you	9204	3.22	1.26
bvr_oth	9204	2.63	1.09
act	2943	1.74	.61

The first set contains questions on attitudes towards climate change. These include the perceived worry about climate change (worry), the certainty that climate change is happening (certainty) and the expected future harm caused by climate change (futureharm). The second set deals with behavioral intentions to combat climate change. One question asks about the willingness to act against climate change (bvr_you) and another elicits how much the respondent thinks other people are taking action against climate change in their city (bvr_oth). In addition, an index is constructed out of a battery of 12 sub-questions asking about a particular behavior (act). These sub-questions could be answered on a three point scale ranging from "No intention to perform" to "Performed recently". Also "Not possible for me" could be ticked. The answers to these twelve sub-questions were summed up to create one variable ranging from 12 to 36, which was then divided by twelve to retain the original scale of the sub-questions. Only individuals that answered to all 12 questions, and did not tick two boxes for one sub-question were included in the construction of the indicator which explains the low number of observations.[7,8]

[7]The construction of the index is partly based on a procedure in Brody et al. (2008), p.79.

[8]Precise wording of the questions and answer categories can be found in Appendix 8.1.

3.1.2 Independent Variables

Another huge advantage of the ICAPP data set is the rich set of socio-demographic characteristics of the respondents that are captured in the survey. The baseline set of controls drawn on in this paper includes data on age, gender, ideology, education and income. These constitute important building blocks of the analysis rendering it more robust, since, as mentioned above, personal experiences with climate events are often mediated and influenced by these individual characteristics.[9] Summary statistics for the US sample can be found in Table 2. The sample is balanced between genders and the three defined age brackets. 47 percent of individuals are in any of the conservative ideology categories, while only 35 percent can be labelled liberal. 58 percent possess a Bachelor's degree or higher, while 34 percent have less than a college degree. A third of the sample has an income between \$15,000 and \$60,000 with a large proportion (14 percent) having an income of \$150,000 or more. Combined, these variables are referred to as Set 1 in later regression analysis.

[9] See for example Brody et al. (2008), p.74-77, for a review of the effects of socio-demographic variables on climate change perception.

Table 2. Descriptive Statistics of First Set of Explanatory Variables (Set 1)

	Obs	Percentage	Cumulative
Age			
18-34	2955	32.11	32.11
35-54	3076	33.42	65.53
55+	3173	34.47	100.00
Gender			
Male	4466	48.52	48.52
Female	4712	51.20	99.72
Other	26	0.28	100.00
Ideology			
Extremely Conservative	854	9.28	9.28
Conservative	1870	20.32	29.60
Somewhat conservative	1583	17.20	46.79
Independent	1671	18.16	64.95
Somewhat liberal	1320	14.34	79.29
Liberal	1304	14.17	93.46
Extremely liberal	602	6.54	100.00
Education			
No degree	158	1.72	1.72
High school	1243	13.50	15.22
Some college, no degree	1710	18.58	33.80
Associate's degree	785	8.53	42.33
Bachelor's degree	2841	30.87	73.20
Professional beyond Bachelor's	305	3.31	76.51
Master's degree	1889	20.52	97.03
Doctorate Degree	273	2.97	100.00
Income in $US			
0 - 14,000	903	9.81	9.81
15,000 - 29,000	1054	11.45	21.26
30,000 - 44,000	966	10.50	31.76
45,000 - 59,000	1090	11.84	43.60
60,000 - 74,000	997	10.83	54.43
75,000 - 89,000	867	9.42	63.85
90,000 - 104,000	623	6.77	70.62
105,000 - 119,000	462	5.02	75.64
120,000 - 134,000	395	4.29	79.93
135,000 - 149,000	554	6.02	85.95
150,000 or more	1293	14.05	100.00
Total	9204	100.00	

Table 3. Descriptive Statistics of Second Set of Explanatory Variables (Set 2)

	Obs	Mean	SD
perc_temp	9204	3.11	1.01
perc_precip	9204	3.17	1.014
climate_social	9204	1.72	.86
climate_news	9204	1.91	.86

In addition to this baseline set of controls, four additional controls are used for robustness checks (Table 3). Two ask about temperature and precipitation as perceived by the respondent. As stated above, perceived rather than objective measurements of weather events influence people's beliefs about climate change.[10] These two controls can help to carve out this effect. Controls are also used for how individuals perceive climate change to be represented in discussions on social media[11] and in the news[12]. Once again drawing on literature, these channels have been found to play a powerful role in mediating the effect of a climatic event on climate change perceptions. These four variables are referred to as Set 2.[13]

3.1.3 Effect of the Two Control Sets on Dependent Variables

In an initial screening of the data, the six dependent variables from Table 1 as represented by y in Regression 1 are regressed on the above mentioned two sets of controls. ζ_c captures city fixed effects.

$$y = \phi' set1 + \psi' set2 + \zeta_c \tag{1}$$

The results displayed in Table 4 are very reassuring and confirm what was found

[10] See Shao and Goidel (2016) for the prevailing effect of perceived rather than objective environmental conditions.

[11] See Sisco et al. (2017) or Kirilenko et al. (2015).

[12] See Pianta and Sisco (2020).

[13] Precise wording of the questions and answer categories can be found in Appendix 8.2.

Table 4. Results of Regression 1

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
Set 1						
Age						
35-54	-0.144***	-0.165***	-0.117***	-0.169***	-0.0840***	-0.0357
	(0.0278)	(0.0341)	(0.0289)	(0.0282)	(0.0253)	(0.0245)
55+	-0.287***	-0.249***	-0.299***	-0.467***	-0.435***	-0.192***
	(0.0295)	(0.0360)	(0.0308)	(0.0299)	(0.0253)	(0.0253)
Gender						
Female	0.0869***	0.110***	0.158***	0.0242	-0.0164	0.0632***
	(0.0234)	(0.0293)	(0.0248)	(0.0234)	(0.0200)	(0.0183)
Other	0.0556	0.320	0.0161	0.0554	-0.470***	-0.0484
	(0.192)	(0.221)	(0.220)	(0.243)	(0.155)	(0.230)
Ideology						
Extremely conservative	-1.388***	-1.703***	-1.379***	-1.058***	-0.0617	-0.187***
	(0.0577)	(0.0762)	(0.0603)	(0.0592)	(0.0544)	(0.0461)
Conservative	-1.241***	-1.413***	-1.314***	-1.099***	-0.197***	-0.158***
	(0.0455)	(0.0496)	(0.0434)	(0.0497)	(0.0474)	(0.0441)
Somewhat conservative	-0.999***	-1.060***	-0.953***	-0.913***	-0.205***	-0.105**
	(0.0455)	(0.0490)	(0.0439)	(0.0504)	(0.0482)	(0.0460)
Independent	-0.688***	-0.736***	-0.549***	-0.697***	-0.229***	-0.101**
	(0.0452)	(0.0484)	(0.0420)	(0.0500)	(0.0476)	(0.0463)
Somewhat liberal	-0.311***	-0.229***	-0.231***	-0.438***	-0.213***	-0.0382
	(0.0438)	(0.0470)	(0.0398)	(0.0503)	(0.0483)	(0.0480)
Liberal	-0.144***	-0.0977**	-0.110***	-0.295***	-0.129***	0.101**
	(0.0435)	(0.0446)	(0.0386)	(0.0499)	(0.0483)	(0.0471)
Education	X	X	X	X	X	X
Income	X	X	X	X	X	X
Set 2						
perc_temp	0.0234**	0.0560***	0.0405***	-0.0145	-0.0919***	-0.0150
	(0.0116)	(0.0139)	(0.0119)	(0.0118)	(0.0105)	(0.00994)
perc_precip	0.0664***	0.0890***	0.0744***	0.0941***	0.125***	0.0753***
	(0.0114)	(0.0138)	(0.0117)	(0.0119)	(0.0102)	(0.0101)
climate_social	0.273***	0.168***	0.204***	0.346***	0.308***	0.231***
	(0.0164)	(0.0201)	(0.0168)	(0.0168)	(0.0147)	(0.0158)
climate_news	0.157***	0.118***	0.111***	0.214***	0.209***	0.113***
	(0.0159)	(0.0194)	(0.0165)	(0.0161)	(0.0134)	(0.0134)
City Fixed Effects						
Dallas	-0.221***	-0.189***	-0.175***	-0.169***	-0.302***	-0.0560***
	(0.0225)	(0.0277)	(0.0236)	(0.0226)	(0.0196)	(0.0176)
Constant	3.603***	5.690***	3.838***	2.991***	1.962***	0.885***
	(0.120)	(0.144)	(0.127)	(0.123)	(0.107)	(0.121)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.288	0.221	0.260	0.305	0.312	0.422

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

in previous studies as mentioned above. The older people are, the less they worry about the climate and the more they refrain from taking action. The effect is stronger for the behavioral categories and especially for the group over 55 years, which can represent a decreasing mobility with age. Females worry more about the climate, although there is no strong effect on behavioral outcomes.[14] With regards to ideology, more conservative individuals worry less about the climate and believe less in climate change. The results for this control are especially strong and unmatched by any other coefficient. They will also become the basis for the interaction analysis following below. Note that the baseline omitted category here is "Extremely liberal", so coefficients display deviations from this subgroup. Being extremely conservative lowers certainty that climate change is happening by 1.703 points on the Likert scale, which is more than one standard deviation in that sample for this outcome variable (1.48, Table 1). Education and income controls are not displayed as their effect is marginal and of no interest for further analysis.[15] The four additional controls have the expected strong effect on the outcome variables. Perceived temperature and precipitation as well as climate change covered in the news and in social media all raise worry about the climate and the willingness to act. Lastly, respondents in Dallas worry less and are less willing to act on climate change than those in New York.

3.1.4 Exploratory Data Analysis

At this stage, with regards to the research question, a preliminary exploratory data analysis is carried out with the goal to identify time varying patterns in the

[14]See e.g. Weber (2016); Shao and Goidel (2016); Konisky et al. (2016) for a review of these effects of socio-demographic variables on climate change perception.

[15]Given the weak effect of education, it looks like in the US there is a more generally stable knowledge base on climate change that does not depend on how educated you are, which is a good thing. Interestingly, this result changes when looking at the whole sample including Italy and China, where climate worry and willingness to act is significantly driven by education. This might hint at different roles of the education system for climate change in different countries.

Table 5. Results of Regression 2

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
January	0.0318	0.0503	-0.0196	0.0815	0.0541	-0.0393
	(0.0553)	(0.0689)	(0.0586)	(0.0555)	(0.0476)	(0.0435)
February	0.0593	0.0918	-0.0632	0.0854	0.0911*	0.0168
	(0.0629)	(0.0784)	(0.0668)	(0.0631)	(0.0542)	(0.0503)
March	0.113**	0.209***	0.121**	0.190***	0.120***	0.0850**
	(0.0519)	(0.0647)	(0.0550)	(0.0521)	(0.0447)	(0.0400)
April	0.135***	0.159**	0.145***	0.131**	0.104**	0.0783**
	(0.0508)	(0.0634)	(0.0538)	(0.0510)	(0.0438)	(0.0393)
May	0.117**	0.0915	0.0913	0.118**	0.0195	0.0730*
	(0.0554)	(0.0691)	(0.0586)	(0.0556)	(0.0477)	(0.0429)
June	0.111**	0.196***	0.140**	0.153***	0.0484	0.106***
	(0.0526)	(0.0656)	(0.0557)	(0.0528)	(0.0453)	(0.0409)
July	0.0200	0.135*	0.0442	0.121*	0.0637	0.0628
	(0.0621)	(0.0774)	(0.0659)	(0.0623)	(0.0534)	(0.0470)
August	0.154***	0.217***	0.139**	0.180***	0.192***	0.112***
	(0.0556)	(0.0693)	(0.0586)	(0.0558)	(0.0478)	(0.0421)
September	0.193***	0.249***	0.210***	0.227***	0.130***	0.0816**
	(0.0546)	(0.0681)	(0.0578)	(0.0548)	(0.0470)	(0.0414)
October	0.0873	0.0134	0.102	0.219***	0.165***	0.0475
	(0.0686)	(0.0856)	(0.0726)	(0.0689)	(0.0591)	(0.0514)
November	0.116**	0.0603	-0.00196	0.142**	0.161***	0.119***
	(0.0555)	(0.0692)	(0.0587)	(0.0557)	(0.0477)	(0.0421)
December	0.0784	0.125*	0.110*	0.119**	0.0534	0.0918**
	(0.0547)	(0.0682)	(0.0579)	(0.0549)	(0.0471)	(0.0429)
Fixed Effects						
Set 1	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Constant	3.505***	5.563***	3.724***	2.853***	1.891***	0.815***
	(0.123)	(0.153)	(0.131)	(0.124)	(0.106)	(0.120)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.290	0.224	0.264	0.307	0.315	0.427

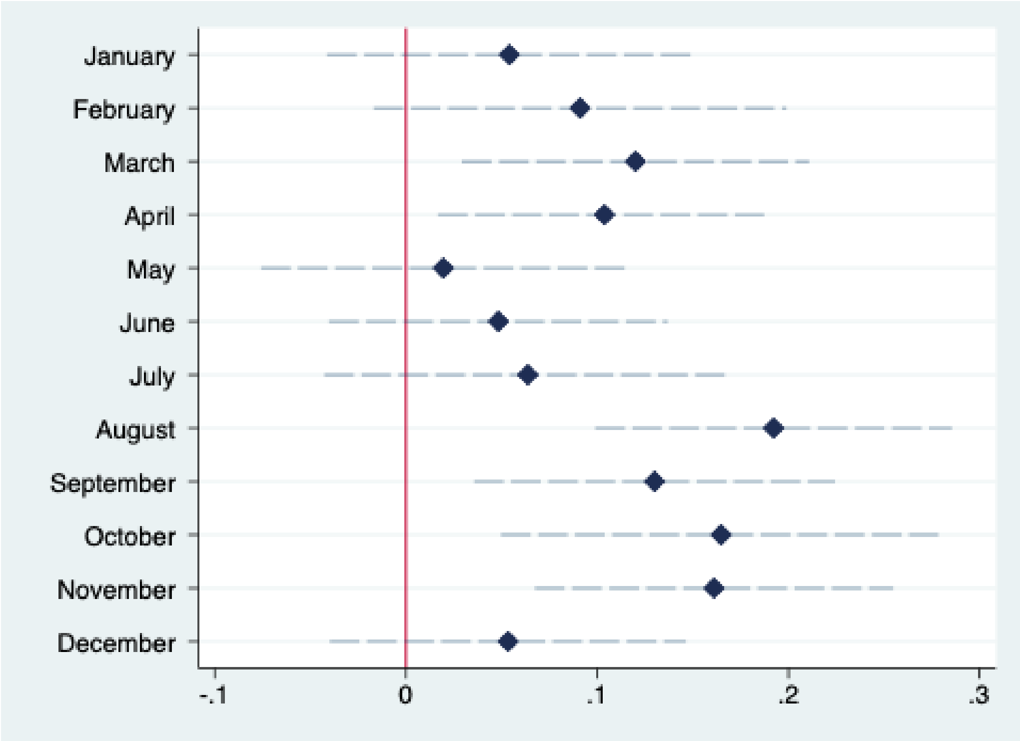
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

data at hand. Therefore, the time dimension of the survey data is exploited and monthly fixed effects (δ_t) are added to Regression (1).

$$y = \phi' set1 + \psi' set2 + \delta_t + \zeta_c \tag{2}$$

The results point to two clusters of significant time spans in the data (Table 5). One is in spring, and the other is precisely during the fall months where the hurricane season takes place. The months from August to November show high significance.

Figure 1. Coefficients of the months of 2020 for variable *bvr_oth* as in Regression 2



Dashed lines show confidence intervals at 95 percent level.

This result holds when adding both sets of controls. The graphic display of these effects confirms the impression that the fall of 2020 had a particularly strong impact on climate change attitudes and behavior (Figure 1).[16]

Another reason to opt for an analysis aiming at the time span covering the second half of the year is the potentially critical effect of the onset of the COVID-19 pandemic in the beginning of the survey period. In February 2020, the novel Corona virus hit the world and led to lockdowns in various economies. Respondents in the survey most certainly were influenced by this global threat, making the analysis of data around March and April particularly noisy.

[16] In Figure 7 of Appendix 8.3 a histogram was used as well to plot the development of one dependent variable over time. The observed trend confirms a spike in worry in the months of August to November.

3.2 International Disaster Database (IDD)

The exploration of the data has yielded that the time span between August and November shows significant increases in climate change worry and willingness to act. Given that this period coincides with the hurricane season, the International Disaster Database (IDD)[17] is used to identify the largest and most destructive hurricanes of the 2020 season that made landfall in the United States.

Table 6. Summary of the 2020 Hurricane Season

Hurricane	Time Span	Damage (US$bn)	Deaths
Hanna	25.7.	1.1	0
Isaias	31.7. - 2.8.	4.8	16
Laura	27.8. - 28.8.	**13**	**33**
Sally	**11-9 - 18.9.**	6.3	8
Delta	7.10. - 11.10.	2.9	4
Zeta	24.10. - 30.10.	3.5	6
Eta	8.11. - 12.11.	1.5	12

There are seven named hurricanes between July 26 and November 12, 2020 that are used in the subsequent analysis (Table 6).[18] Hurricane Laura was the most destructive and deadliest hurricane of that season. Hurricane Sally was the second strongest, but was active for a much longer period as it moved across the continent. Hanna, Laura and Delta moved into Texas, while Isaias became a threat to New York. These characteristics cover the influences mentioned by Howe et al. (2014) who explained how magnitude, duration and proximity of weather events have an effect on perceived threats. This data is used to construct dummy variables identifying the days of the 2020 hurricane season in the data set. Specifically, two variables (*NY_IDD_ind* and *DA_IDD_ind*) are created that equal 1 if one of the seven hurricanes was active that day according to the IDD timeline. *NY_IDD_ind*

[17] See Center for Research on the Epidemiology of Disasters - CRED (2022) for documentation.

[18] More information on their target areas can be found in Table 17 of Appendix 8.4.

assumes values different from zero in the New York sub-sample for the IDD dates, while it is always zero for the data from Dallas. *DA_IDD_ind* works analogously. This setting allows to distinguish between the effects that the hurricanes produced in the different metropolitan areas as they can be used simultaneously in the regressions below. In accordance with Sisco et al. (2021), two more identifiers (*NY_IDD_week* and *DA_IDD_week*) are constructed that equal 1 for the week in which the hurricane occurred in the respective sub-sample. These capture more broadly the effects of a hurricane and build on the assumption that the attention increases already before the hurricane makes landfall and remains high after it passes. Lastly, the identifier is also set up for each hurricane and city separately, to potentially distinguish between diverse effects coming from each hurricane.[19]

3.3 Google Trends

Finally, Google Trends[20] data is used to capture search behavior in the two metropolitan areas.[21] Google Trends offers the possibility to access a time series of keyword search behavior for a given time period and metropolitan area. These time series are scaled from 0 to 100, where 100 is the maximum search activity reached for that keyword in this period and area, and the other data points show the search activity relative to this maximum.[22] There are three main advantages of using

[19] These take the form of *city_hurricane_IDD_ind*, where *city* is either NY or DA, and *hurricane* is one of the seven named hurricanes. Thus, they make up a total of fourteen indicators, seven for each city. See also Table 7 for an overview.

[20] See Google (2022) for documentation.

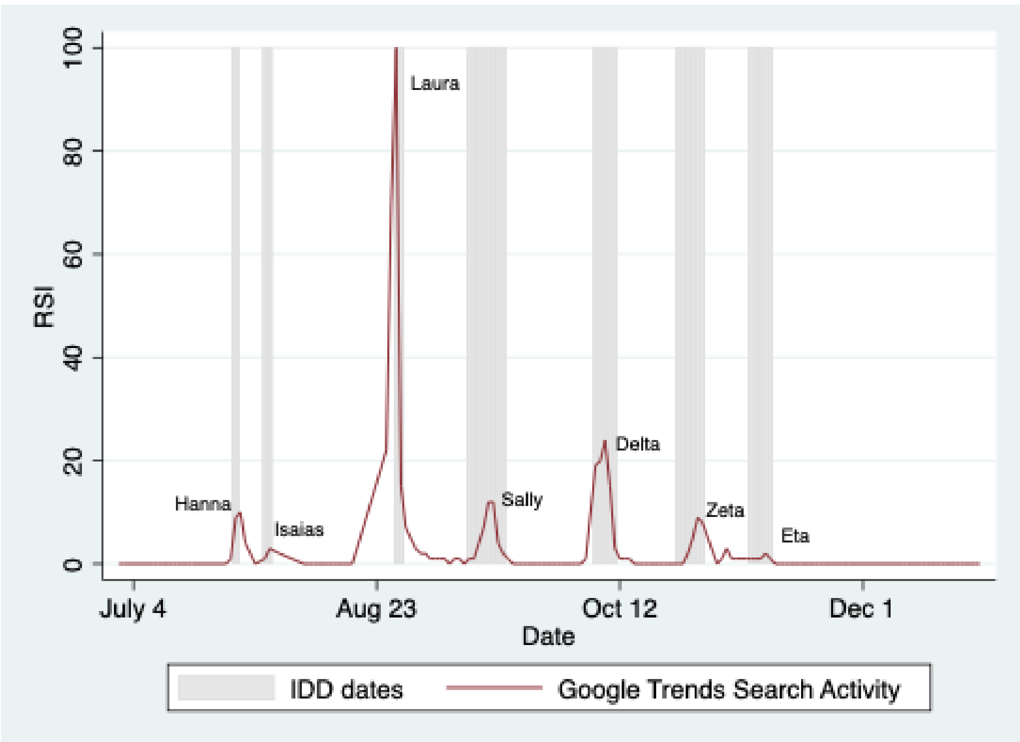
[21] The following procedures are carried out for the two metropolitan areas separately and cover the time period from July 1 to December 31, 2020.

[22] See Lang (2014), p.294-295, and Lang and Ryder (2016), p.627-629, for a detailed discussion of Google Trends data.

Google Trends data as opposed to simply relying on the indicators obtained from the IDD. First, the trends allow for a more nuanced analysis on a daily basis of the effects of a hurricane, accounting for the fact that attention (and potentially worry) peaks on a given day after having built up and before fading out. This climactic shape allows to weigh the days of hurricane activity in a more detailed way than simply tagging them with dummy variables. Second, it captures the relative attention between hurricanes by using the joint interface that allows to input up to five search terms simultaneously. Like this, it can be observed what the relation of the peak search volume of Hurricane Laura was compared to the peak of Hurricane Delta, for example. Again, this is not possible when only tagging each day homogeneously with dummy variables. Lastly, drawing on Google Trends also connects back to the idea of giving more importance to how individuals *perceive* a certain weather event, rather than to the objective conditions. Since the time trends will be used as explanatory variables in the regression analysis below, they can bridge the gap between facts-based events and a sentiment in the population, as has been advertised by Shao and Goidel (2016). In conclusion, there is great advantage in the use of Google Trends data in the subsequent analysis of weather perceptions.

Data is gathered for the seven hurricanes in one data request to harvest these advantages. However, a harmonization procedure is needed to smooth relative search behavior for all seven hurricanes, as it exceeds the maximum comparison of five search terms that can be input in one setting. Data is downloaded for the first five hurricanes of the hurricane season altogether, with Delta being the last (Table 6). Then, data is downloaded for Delta, Zeta and Eta in one additional compound request. These two data sets are then combined and a factor is computed that describes the relation in which the two Delta search trends stand, that were retrieved in both requests. This transformation factor is then applied to Zeta and Eta, that were captured only in the second data retrieval, to arrive at a harmonized time trend. These two trends (*city_season_trend*, where *city* is either NY or DA) are anchored around Hurricane Laura in both cities, which reaches the maximum search volume of 100. This is confirmatory of what was found in the IDD data of Table 6, given Hurricane Laura was the most destructive of that season. Figure 2 shows this anchored time trend for the city of Dallas.[23]

Figure 2. Google Trends of Hurricane Search Activity in Dallas



The shaded grey area marks the dates of the hurricanes from the IDD.

[23]See Appendix 8.6 for a discussion of a potential threat to this identification.

This time trend is then used to create another dummy variable identifying the days in which the anchored time trend is bigger than 1 in each city (*city_season_ind*, where *city* is either NY or DA). These account for a broader interpretation of hurricane exposure than the dummies received from the IDD. For example, one can already see from Figure 2 that in the case of Hurricane Laura, the Google time trend allows for a wider impact of the natural disaster than proclaimed by the IDD, that might be more in line with how the population perceived this hurricane given its strength. The time trend rises well before the hurricane hits as recorded by the IDD (grey area).

In order to get a better understanding of how each hurricane individually impacts attitudes on climate change, the search activity is also downloaded for every hurricane separately, such that it ranges from 0 to 100 in each time series. These trends are called *city_hurricane_trend*, where *city* is either NY or DA and *hurricane* is one of the seven hurricanes from Table 6.

Finally, the day of peak hurricane search behavior is identified for hurricane Laura and Sally, which are the two most destructive hurricanes of the sample. For the four preceding and the four following days around the peak day, separate dummy variables are constructed for each city to investigate how the effect of hurricane exposure builds up and fades out over time. These take the form of *city_hurricane_day_X*, where *city* is either NY or DA, *hurricane* is either Laura or Sally, and X runs from 4^{-} to 4^{+}.

Table 7. Overview of Created Variables from IDD and Google Trends

Variable	Source	Type
Entire Hurricane Season		
city_season_trend	Google	Trend
city_IDD_ind	IDD	Indicator
city_IDD_week	IDD	Indicator
city_season_ind	Google	Indicator
Individual Hurricanes		
city_hurricane_IDD_ind	IDD	Indicator
city_hurricane_trend	Google	Trend
city_hurricane_day_X	Google	Day by day
Climate Change		
city_CC_trend	Google	Trend

The shaded gray variable is used as explanatory variable in the main regression.
City takes either value of NY or DA.
Hurricane takes on one of the seven named hurricanes of the season, except in the case of *city_hurricane_day_X*, where it is either Laura or Sally.

Google search data is also captured for the term "climate change" in each of the two cities individually (*city_CC_trend*).

Table 7 shows a summary of the constructed variables that in its entirety allow to depict the effects of the 2020 hurricane season.

4 Methodology

4.1 Hurricanes and Climate Change Perceptions

In order to identify the effects that the hurricane season had on climate change perceptions, Regression 2 is updated with the anchored time trends as main explanatory variables.

$$y = \beta_1 \ NY\_season\_trend + \beta_2 \ DA\_season\_trend + \phi' set1^{+} + \delta_t + \zeta_c \qquad (3)$$

Monthly fixed effects are captured again by δ_t, and city fixed effects by ζ_c. The dependent variables in Table 1 are represented by y. Control Set 1^{+} is as defined before with the addition of *rep_int* that captures the repeated cross-section characteristic of the survey, in that it identifies interviews that are not the first ones of a given respondent.[24] This helps to control for potential individual fixed effects in the identification and prevent overemphasizing repeatedly interviewed individuals. Control Set 2 is retained for robustness checks. OLS regressions are used and standard errors are robust. Clusters are not applied since the city count is too little.

[24]The variable *rep_int* is equal to 0 if it is the first interview of an individual, and equal to 1 if it is not the first. In the whole sample there are 12 percent repeated interviews. See also footnote 4.

4.1.1 Robustness Checks

The indicator variables that can be found in the top part of Table 7 are used as main explanatory variables in Regression 3.

$$y = \beta_1 \ NY\_IDD\_ind + \beta_2 \ DA\_IDD\_ind + \phi' set1^{+} + \delta_t + \zeta_c \tag{4}$$

$$y = \beta_1 \ NY\_IDD\_week + \beta_2 \ DA\_IDD\_week + \phi' set1^{+} + \delta_t + \zeta_c \tag{5}$$

$$y = \beta_1 \ NY\_season\_ind + \beta_2 \ DA\_season\_ind + \phi' set1^{+} + \delta_t + \zeta_c \tag{6}$$

Also, the additional set of controls is added to Regression 3.

$$y = \beta_1 \ NY\_season\_trend + \beta_2 \ DA\_season\_trend + \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \tag{7}$$

To further investigate the impact of individual fixed effects, Regression 3 is run with the original Control Set 1, and importantly only for interviews that were not a repeated one for an individual (i.e. $rep\_int = 0$).

4.1.2 Individual Hurricane Specifications

In this section, a closer look is laid upon the individual effects of each hurricane. Four models are fitted according to Regression 3 using the individual hurricane trends, the individual hurricane IDD identifiers and the daily dummies for Sally and Laura as described in Table 7 as main explanatory variables.[25]

[25] For full specifications of these models see Regressions 11 to 14 in Appendix 8.5.

4.2 Climate Change Search Behavior as Mediator

So far, it has been investigated how hurricane exposure directly affects attitudes on climate change as captured by the ICAPP survey data. In this section, in a two step approach, climate change search behavior is used to mediate between these two constructs. First, the following regression is run for the two cities separately, to capture the impact that hurricane searches have on climate change search behavior:

$$city\_CC\_trend = \beta \; city\_season\_trend \tag{8}$$

It is worth mentioning here, that the fact that the hurricane trends data (explanatory variable) is now not harmonized to the same scale of the search term "climate change" (dependent variable), should not pose a problem. Given that the hurricane trends are harmonized among themselves and linear regression models are used, a re-scaling would only change the interpretation of the coefficients, not their significance. Importantly, these two regressions are only run for the time period between July 1 and December 31, 2020. In another specification, the *city_season_trend* variables are replaced by the *city_IDD_ind* as in Regression 4. No further controls are employed in these regressions.

Then, the six designated dependent variables are regressed on the two climate search trends in the manner of Regression 3, again restricting the analysis to the time period from July 1 onwards. This is done to see if climate change search trends impact perceptions as elicited in the ICAPP survey.

$$y = \beta_1 \; NY\_CC\_trend + \beta_2 \; DA\_CC\_trend + \phi' set1^{+} + \delta_t + \zeta_c \tag{9}$$

4.3 Distributional Effects for Ideology

In this section, the distributional effects of the impact of hurricanes on self-reported climate change perceptions are examined more profoundly. The literature as referenced above has stated the important moderating effect of ideology in this regard. In line with the strong preliminary findings on this individual characteristic (Table 4), regressions are specified interacting ideology with hurricane activity.

$$\begin{aligned} y = \beta_1 \ (NY\_season\_trend \times cons) + \beta_2 \ (DA\_season\_trend \times cons) \\ + \beta_3 \ NY\_season\_trend + \beta_4 \ DA\_season\_trend + \beta_5 \ cons \\ + \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \quad (10) \end{aligned}$$

The hurricane season trend variables based on Google search data are interacted with an indicator *cons*, that equals 1 if an individual is in one of the three categories adhering to conservative partisanship (Table 2). Control Set 1^{+} (thus including *rep_int*), as well as Control Set 2, month and city fixed effects are included. Following the same structure as in Section 4.1, the *city_season_trend* variables are replaced with the three indicator variables from Table 7. For the *city_IDD_ind* specification, *cons* will also be replaced with *extra_cons*, that equals 1 only for extremely conservative individuals.[26] Lastly, the individual hurricane variables *city_hurricane_IDD_ind* and *city_hurricane_trend* as constructed above are also all interacted with the conservative identifier to differentiate between effects coming from distinct hurricanes.[27]

[26]Note that this is not done for the main specification in this section using *city_season_trend* as the interaction count becomes to little to produce meaningful results in that case.

[27]For full specifications of these models see Regressions 15 to 20 in Appendix 8.5.

5 Results

5.1 Hurricanes and Climate Change Perceptions

The results of the main specification show clearly that for the New York subsample, the presence of hurricane activity significantly alters climate change perceptions. The coefficients for *futureharm, bvr_you* and *bvr_oth* are significant and positive. The effects, however, are rather small.

Table 8. Results of Regression 3

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_season_trend	0.00297	0.000837	0.00497***	0.00574***	0.00575***	0.000895
	(0.00194)	(0.00208)	(0.00175)	(0.00199)	(0.00178)	(0.00146)
DA_season_trend	0.00178	0.00254	0.00189	0.00186	0.000300	0.000101
	(0.00159)	(0.00175)	(0.00167)	(0.00173)	(0.00162)	(0.00118)
Fixed Effects						
Set 1^{+}	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	4.752***	6.658***	4.819***	4.372***	3.152***	1.836***
	(0.111)	(0.133)	(0.117)	(0.118)	(0.104)	(0.140)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.225	0.200	0.226	0.194	0.164	0.229

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

On a day with a hurricane search activity of 10,[28] on average and ceteris paribus, a respondent answers 0.05 points higher on the Likert scale when asked about the future harm coming from climate change in New York. A pattern that emerges and shall remain stable is that Dallas residents experience much weaker effects as a result of hurricane activity. The coefficients are even smaller and not significant.

[28]This search activity is representative when looking at Figure 2, that shows how most hurricanes on the harmonized trend reach such a level at peak.

5.1.1 Robustness Checks

Looking at the specifications using the indicators rather than trend variables as explanatory variables, the results are confirmed. Especially the *NY_IDD_ind* shows high significance.

Table 9. Results of Robustness Checks 4 to 6

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
Regression 4						
NY_IDD_ind	0.166***	0.0501	0.179***	0.316***	0.311***	0.180***
	(0.0571)	(0.0678)	(0.0574)	(0.0576)	(0.0541)	(0.0495)
DA_IDD_ind	0.000361	0.0232	0.0800	0.00313	0.0250	-0.0106
	(0.0621)	(0.0769)	(0.0654)	(0.0643)	(0.0565)	(0.0480)
Constant	4.741***	6.654***	4.813***	4.353***	3.135***	1.820***
	(0.111)	(0.133)	(0.117)	(0.118)	(0.104)	(0.141)
R-squared	0.225	0.200	0.226	0.196	0.166	0.232
Regression 5						
NY_IDD_week	0.128**	0.0453	0.129**	0.221***	0.221***	0.121***
	(0.0539)	(0.0637)	(0.0547)	(0.0566)	(0.0500)	(0.0468)
DA_IDD_week	0.0630	0.0659	0.0924*	0.0509	0.0203	-0.0661
	(0.0524)	(0.0646)	(0.0554)	(0.0554)	(0.0478)	(0.0411)
Constant	4.741***	6.656***	4.814***	4.350***	3.129***	1.810***
	(0.112)	(0.134)	(0.117)	(0.119)	(0.104)	(0.140)
R-squared	0.225	0.200	0.226	0.195	0.165	0.232
Regression 6						
NY_season_ind	0.112**	0.0268	0.113**	0.308***	0.306***	0.191***
	(0.0563)	(0.0673)	(0.0575)	(0.0581)	(0.0534)	(0.0489)
DA_season_ind	0.0133	-0.0100	0.0373	0.0382	0.0340	-0.00969
	(0.0608)	(0.0746)	(0.0626)	(0.0626)	(0.0567)	(0.0480)
Constant	4.743***	6.654***	4.815***	4.348***	3.129***	1.803***
	(0.111)	(0.133)	(0.117)	(0.119)	(0.104)	(0.142)
R-squared	0.225	0.200	0.226	0.196	0.166	0.233
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Observations	9,204	9,204	8,859	9,204	9,204	2,943

Notes: Fixed Effects and Observations are identical for all three regressions.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

On a day of hurricane activity according to the IDD, respondents in the New York sub-sample were 0.316 points on the Likert scale more willing to act against climate change.[29] This is comparable to the difference between being in the oldest age cohort (55+ years) and the center one (35-54 years) and thus a quite sizeable impact.[30] In all of these specifications, also worry about climate change and the index on activity fighting climate change come out significant, contrary to Table 8. Interestingly, the only coefficient in the New York sample that is not significant in either specification is the certainty about climate change happening. Overall, the behavioral variables experience stronger effect magnitudes. Again, Dallas respondents show almost no reaction in the presence of hurricanes. When adding Control Set 2 as suggested in Regression 7, the coefficients of *NY_season_trend* lose some of their significance and strength. This confirms the power of perceived weather and news and social media reports on climate attitudes. The results drawing only on first interviews of the sample are not severely different from the results of the main Regression 3. Individuals being interviewed more than once do not seem to harm the explanatory power of the hurricane season coefficients.[31]

5.1.2 Individual Hurricane Specifications

Table 10 helps to obtain a clearer picture on which hurricanes drive the changes in climate change perceptions.[32] As expected, Laura and Sally have strong effects in the New York sample. On a day where Sally reached its maximum search behavior of 100, willingness to act rises by one Likert scale point in New York on average. That is the difference between wanting to do something against climate change by "a moderate amount" and by "a lot". Referring to Table 6, the results confirm that

[29]For graphic representation of this correlation see Figure 8 in Appendix 8.3.

[30]See Table 4, Column 4, difference between line 1 and 2.

[31]The results of these two regressions can be found in Table 18 and 19 of Appendix 8.4.

[32]Be reminded here that for these disentangled trends the search behavior for each individual hurricane was used, ranging from 0 to 100.

magnitude, financial damage and human fatalities influence how weather events impact climate change perceptions as found by Brody et al. (2008); Sisco et al. (2017) or Howe et al. (2014). The latter makes another point underpinning

Table 10. Individual Hurricanes: Results of Regression 11 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_Hanna_trend	-0.00827***	-0.00697**	-0.00203	-0.00409	-0.00381	-0.00304
	(0.00276)	(0.00354)	(0.00355)	(0.00511)	(0.00510)	(0.00305)
NY_Isaias_trend	-0.00124	0.00444	0.00458	0.00116	0.00242	-0.00373
	(0.00383)	(0.00430)	(0.00413)	(0.00410)	(0.00379)	(0.00311)
NY_Laura_trend	0.00303	0.000493	0.00479***	0.00519***	0.00516***	0.000608
	(0.00196)	(0.00209)	(0.00175)	(0.00199)	(0.00178)	(0.00146)
NY_Sally_trend	0.000372	0.00186	-0.00253	0.0101***	0.00939***	0.0115**
	(0.00339)	(0.00366)	(0.00344)	(0.00373)	(0.00298)	(0.00491)
NY_Delta_trend	-0.00137	0.00453	0.00358	-0.00474	-0.00703	-0.110***
	(0.0130)	(0.00818)	(0.00838)	(0.0139)	(0.0136)	(0.0344)
NY_Zeta_trend	0.0176***	0.0226***	0.0190***	0.0203***	0.0103	0.00507
	(0.00446)	(0.00256)	(0.00228)	(0.00281)	(0.0124)	(0.00459)
NY_Eta_trend	0.00297**	5.27e-06	0.00162	0.00370***	0.00329***	0.00363***
	(0.00132)	(0.00162)	(0.00136)	(0.00138)	(0.00120)	(0.00109)
DA_Hanna_trend	0.00191	0.00118	0.00251	0.00137	0.00337**	0.000225
	(0.00137)	(0.00203)	(0.00172)	(0.00167)	(0.00158)	(0.00130)
DA_Isaias_trend	1.16e-05	-0.000110	-0.000590	-0.00455	-0.00208	-0.00521***
	(0.00263)	(0.00338)	(0.00439)	(0.00386)	(0.00328)	(0.00198)
DA_Laura_trend	0.00197	0.00322*	0.00219	0.00200	0.000162	-0.000114
	(0.00162)	(0.00176)	(0.00169)	(0.00176)	(0.00166)	(0.00120)
DA_Sally_trend	-0.00128	-0.00346	-0.00200	-0.00325	-8.87e-05	0.00176
	(0.00276)	(0.00333)	(0.00270)	(0.00238)	(0.00192)	(0.00225)
DA_Delta_trend	-0.00639	-0.00890	-0.00723	-0.00671*	-0.00550	-0.000708
	(0.00605)	(0.00605)	(0.00541)	(0.00406)	(0.00351)	(0.00353)
DA_Zeta_trend	-0.00997**	-0.00208	-0.00153	-0.00667*	-0.00386	-0.00440***
	(0.00454)	(0.00576)	(0.00299)	(0.00389)	(0.00402)	(0.00135)
DA_Eta_trend	0.00171	0.00266	0.00234	0.00149	-0.000729	0.00107
	(0.00225)	(0.00279)	(0.00229)	(0.00230)	(0.00207)	(0.00221)
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	4.747***	6.650***	4.817***	4.355***	3.146***	1.826***
	(0.112)	(0.133)	(0.117)	(0.118)	(0.104)	(0.139)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.227	0.201	0.227	0.197	0.167	0.236

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the impact of Hurricane Sally, stating how duration of a disastrous weather event increases worry about climate change. Hurricane Sally was particularly slow and hampered the US for an extended time period, aligning with this theory.

It is interesting to see how, besides the strong and disruptive Hurricanes Laura and Sally, the much smaller but late in the season happening Hurricanes Zeta and Eta influence climate change perceptions (cf. Figure 2). On a day of peaking search behavior for Zeta in New York, respondents would on average answer 2.26 points higher on the Likert scale for climate change certainty happening, or 1.9 points more for future harm caused by climate change. Both impacts are well above the respective standard deviations for the outcome variables (1.48 and 1.26, Table 1). This might hint at the idea that the perception that a hurricane season is exceptional and the results of large scale changes in climate is increasing with hurricane count and regardless of individual hurricane strength. Put differently, while earlier in the season strong hurricanes produce attention to weather threats, towards the end of the season the focus is shifted towards the count of hurricanes that the past season has produced and any further (albeit not disruptive) hurricane creates worry about climate change. This interpretation can be sustained by Konisky et al. (2016) who state that perceptions of climate change are affected with increasing frequency of extreme weather events, which in the case of topical storms corresponds to a long hurricane season as was observed in 2020. This finding can also be linked very well to Sisco et al. (2017) who construct a measure of abnormality of weather events based on historical averages and show its importance in attention to climate change. With more and more hurricanes occurring late in the 2020 season (Zeta and Eta being two of them), its abnormality developed into a new US record that might have reinforced the effect of these late hurricanes.

This theory can also be sustained with another interesting finding from Table 10. The two very strong but early Hurricanes Laura and Sally mostly create behavioral changes in the sample, i.e. they increase the willingness to act or make people think others are also acting against climate change. This might be driven by the imagery and proximity of the disastrous effects of those hurricanes and the willingness of the people to get active (potentially even in their neighborhoods) to prevent these disasters from happening in the future. The less destructive hurricanes Zeta and Eta that happened later in the season affected more the attitudinal side of climate change. They increased worry, certainty and concern about future harm from climate change (although Eta also had a behavioral impact). It seems that these storms by raising the number of hurricanes in that season to record levels led to a switch in thinking about climate risks. In Appendix 8.3, Figures 9 and 10 show exemplary graphic correlations between hurricane search trends and the outcome variables. In Table 20 in Appendix 8.4, results are also reported for the individual hurricane dates as stated by the IDD. The pattern remains the same. On days where Hurricane Zeta was active, outcome variables *worry, certainty* and *futureharm* are raised by almost one point each on the Likert scale in New York. Laura, Sally and Eta also have positive and significant effects.

Moving to the analysis of the days on which the hurricanes have an impact on climate change perceptions, one can detect that the effect peaks on the first and second day after the Google search trends reach their maximum in New York. The results for Hurricane Sally from Table 11 are in line with the analysis of Sisco et al. (2017) who find that attention to climate marches sharply concentrates around the days right after the event, and then fades out fast. In Table 21 in Appendix 8.4 results for Hurricane Laura are displayed, which have a similar pattern. Tables 11 and 21 confirm the findings from Table 10 in that mostly behavioral variables

Table 11. Sally Day by Day: Results of Regression 13 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_Sally_day_3^{-}	-0.336	0.130	-0.0407	-0.124	0.169	-0.0349
	(0.394)	(0.377)	(0.202)	(0.217)	(0.581)	(0.0683)
NY_Sally_day_2^{-}	0.222	-0.149	-0.182	0.0988	-0.0270	0.161**
	(0.440)	(0.512)	(0.397)	(0.397)	(0.331)	(0.0767)
NY_Sally_day_1^{-}	-1.008*	-1.083**	-0.953*	-0.700	0.539**	
	(0.544)	(0.535)	(0.492)	(0.508)	(0.215)	
NY_Sally_day_0	-0.557***	-0.264	-0.963	-0.0108	0.532	-0.272***
	(0.136)	(0.322)	(0.779)	(0.528)	(0.553)	(0.0801)
NY_Sally_day_1^{+}	0.156	0.240	0.0941	0.591***	0.312*	0.663***
	(0.183)	(0.184)	(0.162)	(0.153)	(0.179)	(0.137)
NY_Sally_day_2^{+}	0.189	0.283*	0.163	0.607***	0.498***	0.487***
	(0.136)	(0.155)	(0.127)	(0.127)	(0.132)	(0.0974)
NY_Sally_day_3^{+}	0.0357	0.0464	-0.00990	0.218	0.317	-0.0287
	(0.169)	(0.181)	(0.178)	(0.199)	(0.226)	(0.252)
NY_Sally_day_4^{+}	-0.0277	-0.193	-0.114	0.0425	-0.0545	0.570***
	(0.273)	(0.324)	(0.283)	(0.369)	(0.329)	(0.0629)
DA_Sally_day_X			*** not displayed ***			
Fixed Effects						
Set 1^{+}	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	4.754***	6.653***	4.827***	4.368***	3.153***	1.835***
	(0.111)	(0.133)	(0.117)	(0.118)	(0.104)	(0.140)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.226	0.201	0.228	0.197	0.166	0.238

Day 0 is the peak of Goolge Trends search activity.
DA_Sally_day_X dummies are not displayed due to low significance.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

are influenced on these days for these two particular hurricanes. Furthermore, the day by day results in this section strengthen the point of using Google Trends data to capture how hurricane attention evolves. The dummies being mostly significant around the peak of the search behavior show that the Google Trends data gives a good representation of the pile up and fading of worry about climate change related to hurricane activity. Again, in all specifications there are no or even negative effects in Dallas.

5.2 Climate Change Search Behavior as Mediator

The results of Regression 8 and its alternative specification as presented in Table 12 show an interesting pattern. The hurricane season search trend in Dallas has strong effects on climate change search behavior. This relationship is mostly to be interpreted in terms of the sign of the effect, not the strength, as differently harmonized scales are looked into as mentioned before. On days with hurricane exposure as per IDD, relative search volume spikes by 21 percentage points in Dallas. The coefficient for the New York trend is negative which is confusing at first. However, the days with hurricane exposure seem to have a positive albeit not as strong effect here as well.

Table 12. Hurricane and Climate Change Searches: Results of Regression 8

	Trends		IDD Indicators	
	(1)	(2)	(3)	(4)
VARIABLES	NY_CC_trend	DA_CC_trend	NY_CC_trend	DA_CC_trend
NY_season_trend	-0.183***			
	(0.0246)			
DA_season_trend		0.434***		
		(0.00959)		
NY_IDD_ind			10.24***	
			(1.129)	
DA_IDD_ind				20.62***
				(1.393)
Constant	26.17***	19.95***	22.31***	17.20***
	(0.424)	(0.496)	(0.355)	(0.466)
Observations	1,871	1,871	1,871	1,871
R-squared	0.025	0.108	0.068	0.154

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Graphically, this relationship becomes more graspable. Figure 3 shows climate change search behavior for the two metropolitan areas in comparison and the IDD dates of hurricane activity. The green line representing Dallas shows clear spikes where also hurricanes are active. Also New York shows some co-movement which is picked up by the positive coefficient (10.24) in Table 12.

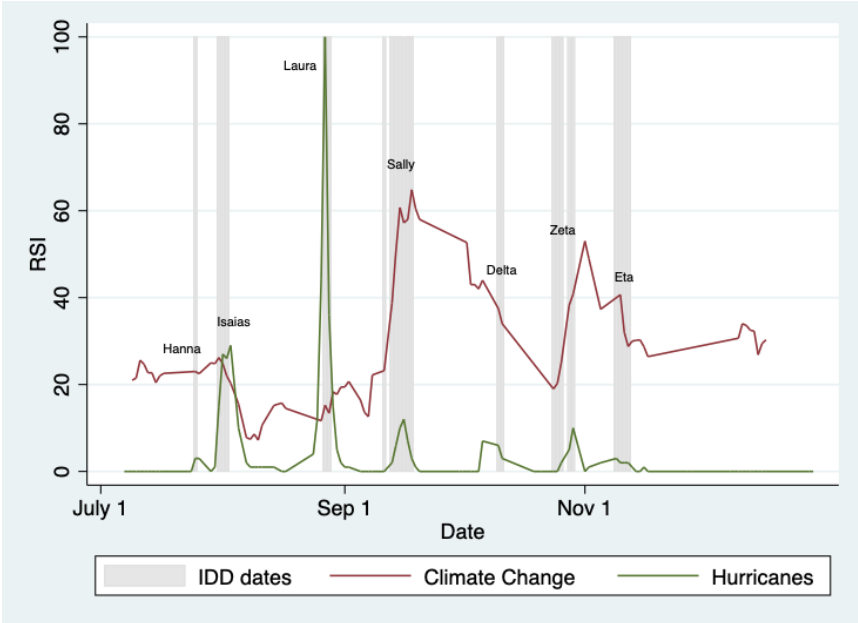
Figure 3. 7-day moving averages of Climate Change Search Activity

The shaded grey area marks the dates of the hurricanes from the IDD.

Figures 4 and 5 make it clear then how strong climate change searches co-move with hurricane search activity in Dallas, but do not do so in New York.[33] One can observe that in New York (Figure 4), although the dates from the IDD correlate with climate change searches, the precise hurricane search trend is not shaped as the climate change trends. This is different from what can be seen in Dallas, and might explain the negative coefficient in Table 12 for New York. It might thus be that that hurricane activity does not immediately translate into climate change search behavior in New York because there is a lag in the transmission as well as other factors and events that drive the searches on climate change. This is

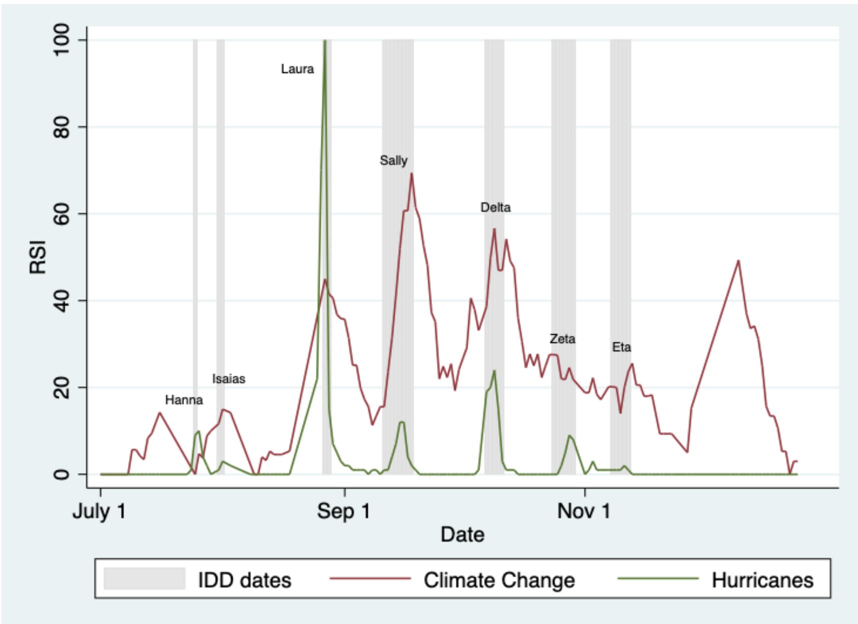
[33]It is worth noting here, again, that the two trends are not harmonized, i.e. relative search volume is higher for climate change than depicted in relation to hurricane searches. Still, the figures give a schematic impression of the correlation.

Figure 4. Climate Change and Hurricane Search Activity in New York



The shaded grey area marks the hurricane activity dates from the IDD

Figure 5. Climate Change and Hurricane Search Activity in Dallas



The shaded grey area marks the hurricane activity dates from the IDD particularly plausible when comparing the effects of Laura, which in Dallas moves very homogeneously with climate change searches, but in New York is not on the same track. In Dallas, hurricane search activity seems to co-move a lot with and be a strong predictor of climate change searches (Figure 5). Another interesting observation is that climate change search behavior peaks late in the season, and, most importantly, not with the presence of by far the strongest hurricane (Laura). This strengthens the theory that was built up before with the help of Table 10 regarding worry about climate change peaking with hurricanes late in the season, and being driven by absolute hurricane count rather than individual strength.

Table 13 then again presents the well-known relationship discovered before: New York respondents react well to movements in the Google Trends search behavior, whereas Dallas shows no responses. The co-movement of answers from the ICAPP with climate change search behavior in the sub-sample of New York is also depicted in Figure 11 in Appendix 8.3 with the example of the outcome variable *bvr_you*.

Overall, climate change search activity seems to bridge quite well between hurricane search activity and responses in the ICAPP survey. There are, however, two takeaways from this sub-analysis. First, the imperfect correlation found in New York in the initial step shows how hurricane search activity might not translate immediately and perfectly into climate change searches. This transmission can be lagged, and there might be drivers other than hurricanes in New York affecting climate change searches. Lang (2014) also describes such a heterogeneous transmission. The almost perfect co-movement in Dallas is very interesting to see nevertheless, and might be due to the greater exposure of Texas to hurricanes as

Table 13. Climate Change Searches and Survey Answers: Results of Regression 9

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_CC_trend	0.00275*	0.00198	0.00115	0.00515***	0.00396***	0.00486***
	(0.00150)	(0.00177)	(0.00149)	(0.00156)	(0.00140)	(0.00131)
DA_CC_trend	-0.000104	0.000597	0.00195	0.000899	0.000895	0.00124
	(0.00120)	(0.00152)	(0.00126)	(0.00123)	(0.00109)	(0.000933)
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	4.259***	6.549***	4.626***	4.145***	2.825***	1.753***
	(0.184)	(0.242)	(0.204)	(0.201)	(0.169)	(0.202)
Observations	3,742	3,742	3,609	3,742	3,742	1,241
R-squared	0.217	0.181	0.208	0.219	0.243	0.313

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

a Southern state as was already pointed out in Talaty et al. (2020). Potentially, in this area hurricanes work more fiercely as main drivers of considerations about climate change due to this proximity.[34] Second, the fact that hurricane searches push climate change searches in Dallas, but the latter do not seem to correlate with attitudes and behavior as elicited by the ICAPP survey, shows that importantly it cannot be inferred with certainty how a person thinks about something just by looking at their search behavior. This issue is already raised by Archibald and Butt (2018) and Sisco et al. (2017) explaining that eventually, googling "climate change" does not imply a certain sentiment about this search term and the impossibility to differentiate between belief and disbelief. Indeed, perceptions as elicited in the ICAPP are of much more explicit nature. What is observed in Dallas could thus only show how people are beginning to make the connection between (increasing strength and magnitude of) hurricanes and climate change, but they do not profoundly change their perceptions and actions as a result of it.

[34]See again also Howe et al. (2014); Brody et al. (2008) on proximity.

5.3 Distributional Effects for Ideology

The results of Regression 10 open room for another stream of interpretations regarding the effect of hurricanes. Table 14 shows how the effect of hurricanes on climate perceptions prominently concentrates among more conservative individuals in New York. One can first detect the confirmation of the previously found result of Table 4: Conservatives on average have a much lower baseline worry and willingness to act than liberals. They are, for example, on average one entire scale point less likely to believe in climate change. In the two lines above *cons*, one can then observe how in this specification Google search trends of the hurricane seasons by itself have a very small effect, if significant, or none at all.

Table 14. Hurricane Searches and Conservatives: Results of Regression 10

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
1.NY_season_trend#1.cons	0.252*	0.350**	0.281**	0.167	0.214**	0.114
	(0.137)	(0.151)	(0.138)	(0.127)	(0.107)	(0.0855)
1.DA_season_trend#1.cons	0.184*	0.172	0.0560	0.0230	0.00240	-0.109
	(0.104)	(0.138)	(0.123)	(0.115)	(0.0847)	(0.0702)
NY_season_trend	0.000991	-0.000605	0.00359**	0.00275	0.00293*	-0.00158
	(0.00191)	(0.00212)	(0.00169)	(0.00183)	(0.00157)	(0.00120)
DA_season_trend	0.00198	0.00333**	0.00221	0.00158	-3.76e-05	-0.000110
	(0.00145)	(0.00164)	(0.00155)	(0.00158)	(0.00142)	(0.000862)
cons	-0.825***	-1.001***	-0.914***	-0.584***	-0.00763	-0.120***
	(0.0237)	(0.0296)	(0.0252)	(0.0235)	(0.0201)	(0.0188)
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	3.058***	5.121***	3.384***	2.342***	1.694***	0.785***
	(0.122)	(0.148)	(0.131)	(0.123)	(0.106)	(0.119)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.263	0.192	0.241	0.288	0.313	0.420

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The top line is the most interesting in Table 14. It shows the interaction effects between hurricane Google search trends and conservatives in New York, highlighting that only for this subgroup the time trends describing hurricane search behavior are highly significant. This effect is very strong on top of that. On a day of hurricane search activity of 10,[35] a conservative would on average be 2.8 points on the Likert scale more afraid of future harm caused by climate change, ceteris paribus. This impact has to be combined with the negative baseline for conservatives, which is minus 0.9 points on the Likert scale. Still, the overall effect is sizeable. Due to the high volatility of the Google Trends data, these results are to be looked at with great caution, however, and below the analysis will draw also on the other specifications. The coefficients found in Table 8 that lacked this interaction were a fraction of those found here, resembling more those of lines 3 and 4 in Table 14. This suggests that it is the conservatives that drive the previously found results and react to hurricane activity in New York. These results hold even when including Control Set 2.

When looking at the interaction using the days of hurricane activity as by IDD (Table 15), the result is confirmed. In this specification, hurricane days in itself are even significantly negative. The interaction with *cons* shows strong effects on the conservative subgroup. Hurricanes then on average push up the worry measurements by about half a scale point. Referring back to Regression 4 in Table 9, one can see that the coefficients detected there for the New York sample were close to averages between the first and third line in Table 15 and thus covering up the fierce effect for the conservatives. It can be seen, that, while conservatives have a much lower baseline worry, they react much stronger to the hurricane activity. Hurricanes can thus be seen as increasingly working to close the perception gap between

[35] Again revert to Figure 2 to observe average search trend sizes.

Table 15. Hurricane Activity by IDD and Conservatives: Results of Regression 15 from Appendix 8.5

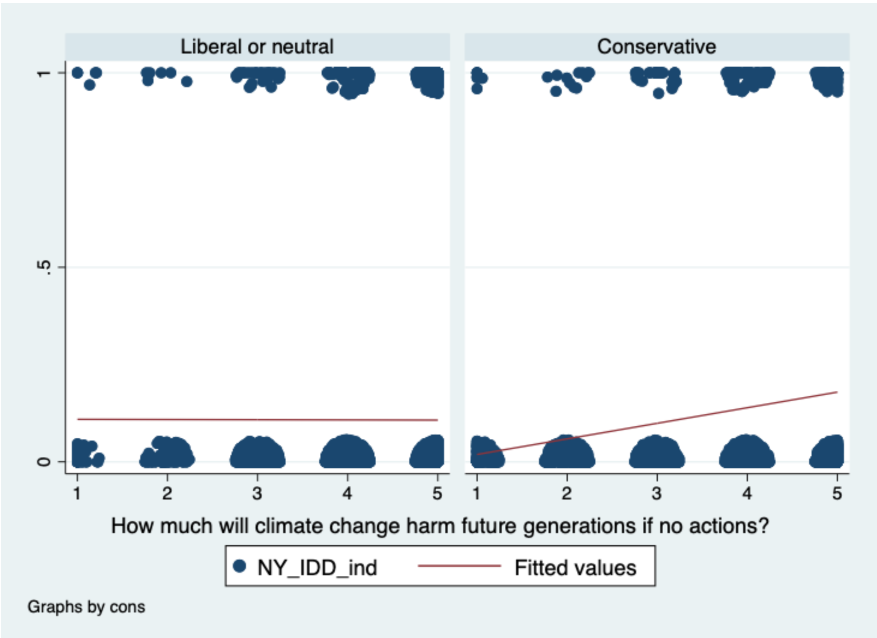
VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
1.NY_IDD_ind#1.cons	0.535***	0.467***	0.578***	0.381***	0.0775	0.113
	(0.0885)	(0.112)	(0.0891)	(0.0904)	(0.0823)	(0.0727)
1.DA_IDD_ind#1.cons	-0.00374	-0.0862	-0.0924	0.0141	-0.0286	-0.124*
	(0.106)	(0.134)	(0.113)	(0.105)	(0.0927)	(0.0698)
NY_IDD_ind	-0.188***	-0.246***	-0.165***	-0.0192	0.0975*	-0.0173
	(0.0631)	(0.0772)	(0.0633)	(0.0648)	(0.0569)	(0.0525)
DA_IDD_ind	-0.00139	0.0827	0.124*	-0.0221	0.00877	0.0310
	(0.0758)	(0.0853)	(0.0732)	(0.0739)	(0.0698)	(0.0565)
cons	-0.844***	-1.009***	-0.935***	-0.602***	-0.00711	-0.121***
	(0.0248)	(0.0308)	(0.0264)	(0.0246)	(0.0208)	(0.0197)
Fixed Effects						
Set 1^{+}	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	3.074***	5.131***	3.401***	2.358***	1.699***	0.784***
	(0.122)	(0.149)	(0.131)	(0.123)	(0.106)	(0.119)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.264	0.193	0.243	0.289	0.313	0.420

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

conservatives and liberals. Another interesting observation is that in these interacted specifications (Table 14 and 15), the outcome variables affected significantly concentrate more on the attitudinal than on the behavioral subgroup, differently from what was discovered before. This is even more surprising, as hurricane activity even seems to change the perception that climate change is happening by almost half a Likert scale point for conservatives, which was hardly moved in the specifications above.

It is also possible to look at these relationships graphically. Figure 6 shows the correlation between days on which hurricanes were active and survey responses for *futureharm*. The basic structure is similar to Figure 8 in Appendix 8.3, although now, the correlation is split for ideologies. One can observe what has been discovered in the regression tables above. Pooling the results for the sample heavily masks the impact that hurricane activity seems to have on conservative individuals. In fact, one can see how conservatives react much stronger in their worry about the climate on days of hurricane exposure than liberals or independents. It is to be noted that, as has been carved out before, this is partly because liberal ideology groups already have a much higher baseline worry about climate change. They are thus potentially not that *surprised* when strong hurricanes hit and a record breaking season takes place.

Figure 6. Correlation between IDD dates and *futureharm* in New York, split by ideologies



Conservatives react much stronger to hurricane activity than other ideologies in New York.

The interaction with extremely conservatives (Table 22 in Appendix 8.4) renders the effect in New York even stronger. Figure 12 in Appendix 8.3 confirms this. The regressions using the *city_IDD_week* and *city_season_ind* variables in the interaction terms displayed in Tables 23 and 24 in Appendix 8.4 underline this further. Finally, it can be observed that, as in Table 10, Laura, Sally, Zeta and Eta are driving these results (Table 16). Again, the hurricane search trends individually do not seem to alter climate change perceptions for the respondents. Only when interacted with *cons* does their significance show, which is once more concentrated among the attitudinal outcomes. In the entire heterogeneity analysis of this section, respondents in Dallas do not seem to offer the same disentanglement as those in New York do. Differences in ideology do not seem to matter much in the Dallas metropolitan area to carve out the effects of hurricanes. In fact, for the whole sub sample, hurricanes do not produce changes in perception. As such, Dallas coefficients are not displayed in Table 16 as they are close to zero and not significant. Table 25 in Appendix 8.4 shows similar results when interacting ideology with the hurricanes according to the IDD dates. Lastly, one exemplary graph shows the correlation of the search trend for Eta with worry about future harm from climate change split for ideologies (Figure 13 in Appendix 8.3.)

All in all, the analysis has shown that the rather weak effect found in the main regression of Table 8 was covered up by the diverse effects of distinct hurricanes and ideologies in two different metropolitan areas. These provide detailed insights into how the 2020 hurricane season affected climate perceptions. The next section will review these findings and tie them back to the literature, as well as suggest links to policy making.

Table 16. Individual Hurricanes and Conservatives: Results of Regression 19 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
1.cons#c.NY_Hanna_trend	0.00604	0.00489	-0.00581	0.00164	0.00937**	0.0515**
	(0.00473)	(0.00566)	(0.00476)	(0.00771)	(0.00467)	(0.0231)
1.cons#c.NY_Isaias_trend	0.00937	0.00347	0.0171**	0.0131	0.00414	-0.00885*
	(0.00711)	(0.00972)	(0.00795)	(0.00856)	(0.00612)	(0.00477)
1.cons#c.NY_Laura_trend	0.00771**	0.00641*	0.0107***	0.00594*	0.00175	0.00192
	(0.00314)	(0.00365)	(0.00307)	(0.00314)	(0.00275)	(0.00199)
1.cons#c.NY_Sally_trend	0.0164***	0.0162**	0.0156**	0.0150**	0.00165	0.0104*
	(0.00616)	(0.00650)	(0.00610)	(0.00611)	(0.00542)	(0.00563)
1.cons#c.NY_Delta_trend	-0.00757	0.00854	-0.000948	-0.0113	-0.0174	-0.0236
	(0.0215)	(0.0168)	(0.0160)	(0.0173)	(0.0137)	(0.0715)
1.cons#c.NY_Zeta_trend	0.0891***	0.118**	0.103***	0.156***	-0.0578*	0.0417
	(0.0344)	(0.0489)	(0.0387)	(0.0388)	(0.0329)	(0.0625)
1.cons#c.NY_Eta_trend	0.00683***	0.00540**	0.00589***	0.00370	0.00382**	0.00234
	(0.00205)	(0.00272)	(0.00218)	(0.00228)	(0.00186)	(0.00178)
NY_Hanna_trend	-0.0103***	-0.00940*	-0.000932	-0.00436	-0.00512	-0.00253*
	(0.00369)	(0.00490)	(0.00350)	(0.00553)	(0.00335)	(0.00143)
NY_Isaias_trend	-0.00602	-0.000291	-0.00258	-0.00324	0.00287	-0.00207
	(0.00417)	(0.00418)	(0.00409)	(0.00402)	(0.00388)	(0.00251)
NY_Laura_trend	-0.00227	-0.00400	-0.00122	-0.000211	0.00135	-0.00309*
	(0.00244)	(0.00262)	(0.00200)	(0.00222)	(0.00192)	(0.00180)
NY_Sally_trend	-0.00997***	-0.00642*	-0.0114***	-0.00210	0.00113	0.00201
	(0.00319)	(0.00335)	(0.00367)	(0.00321)	(0.00336)	(0.00462)
NY_Delta_trend	0.000676	0.000235	0.00224	-0.00212	-3.69e-05	-0.0746*
	(0.00574)	(0.00767)	(0.00620)	(0.00948)	(0.00710)	(0.0400)
NY_Zeta_trend	-0.0736**	-0.0985**	-0.0854**	-0.136***	0.0648**	-0.0384
	(0.0344)	(0.0489)	(0.0387)	(0.0385)	(0.0323)	(0.0619)
NY_Eta_trend	-0.00104	-0.00325*	-0.00173	0.000661	0.000121	0.000933
	(0.00144)	(0.00190)	(0.00142)	(0.00152)	(0.00120)	(0.00119)
cons	-0.842***	-1.008***	-0.934***	-0.604***	-0.0154	-0.124***
	(0.0249)	(0.0309)	(0.0264)	(0.0246)	(0.0209)	(0.0200)
1.cons#c.DA_hurricane_trend			*** not displayed ***			
DA_hurricane_trend			*** not displayed ***			
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	3.080***	5.123***	3.400***	2.353***	1.704***	0.792***
	(0.122)	(0.149)	(0.131)	(0.123)	(0.106)	(0.119)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.266	0.194	0.244	0.291	0.315	0.426

Results for Dallas not displayed due to low significance.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Discussion

Hurricanes have the power to influence people's perceptions on climate change. On days of hurricane activity individuals make connections to threats of a changing climate. This is in line with literature cited on worry about climate change as impacted by extreme weather events (Konisky et al. (2016); Sisco et al. (2017)) and hurricanes in particular (Seara et al. (2020); Rudman et al. (2013); Howe et al. (2014); Lang (2014)). Digging deeper into this correlation, it is found that the magnitude of individual hurricanes (as measured by financial damage, human fatalities or duration) increases the perceived threat of climate change (Brody et al. (2008)). Konisky et al. (2016) make a very important observation on top of that, showing how frequency of an extreme weather event changes climate change attitudes, who is sided by Sisco et al. (2017) referring to abnormality of climatic data.

The hurricane season of 2020 was particularly insightful in all of these regards, as it produced an abnormal (or record) number of hurricanes, while also including some particularly destructive tropical storms (Laura and Sally). According to the 2022 IPCC report (Poertner et al., 2022), tropical cyclones will increase in intensity and frequency with high confidence in the future due to climate change, and seasons such as the one in 2020 will soon become more common. The results found in this analysis show that these hurricanes, in the aftermath of their destructive path, open up some room for policy action. Tierney (2007) and McGee et al. (2009) speak of "windows of opportunity" that are created as a result of destructive weather events and need to be leveraged. People indeed react to the catastrophic and life threatening nature of hurricanes by updating their beliefs on climate change. As could be observed above, however, these effects are very short-lived (Table 11). This matches perfectly with the previously outlined theory on classical reinforcement theory and highly volatile perceptions of threats from climate change, that spike with distinct weather events and revert back to normal. It can be inferred that the time window for policy action is short but existent around hurricane activity. In line with the IPCC, perhaps these opportunities will become more available with increasing frequency of tropical cyclones, in addition to perceptions not reverting back to its generally low level so fast and consistent. A higher total hurricane count seems to effectively alter attitudes and behavior related to climate change in vast parts of the population, which is eventually what is needed to enact meaningful policies. It seems that, in order to really achieve the change needed in the public to fight climate change, it might have to get worse first before it can get better.[36]

The use of Google Trends data in particular proved helpful to account for personal perception of climate change threats. The literature has stated the importance of perceived rather than objective environmental conditions (Shao and Goidel (2016); Goebbert et al. (2012)). Google Trends in this regard can work as a mediator between the two, being based on factual events as recorded by the IDD, but tracking much more intricate sentiments in the population through revealed preferences. This approach to data analysis is of great advantage in the climate change literature (Lang (2014); Lang and Ryder (2016)). The fact that the Google time trends proved to be statistically significant underlines the important role of perceived harm or importance of an (abnormal) weather event.

[36]Let us hope it is not too late by then.

The analysis also offers a precise understanding of how perceptions as captured by Google Trends feed into stated preferences as in the ICAPP survey in different geographical areas due to a detailed attribution of the data to respondents' locations (Konisky et al. (2016)). The sub-analysis on the mediating effect of climate change searches revealed interesting considerations in this regard. New York is much less prone to devastating hurricanes than Dallas; still distant events can impact perceptions in the local population through hearing or reading about it (Reser et al. (2014); Howe et al. (2014)). Residents in Dallas, on the contrary, seem much more skeptical about climate change on average. In Table 8 one could see how respondents in Dallas perceive lower threats by and willingness to act against climate change than compared to New York by roughly the magnitude of being in the center rather than youngest age group, or by moving one category more towards conservative ideologies. This general disbelief and lack of impact on respondents in Dallas is highlighted in the whole analysis. These two distinct subgroups divided by their geographical location, in return, seem to react differently to certain weather events and base their internet searches for climate change on them in diverse ways. Archibald and Butt (2018) observed such geographical divergence already. Different locations with distinct vulnerabilities to certain climate events seem to play a role in forming beliefs on climate change based on weather events (cf. Talaty et al. (2020)). As mentioned, it is still reassuring to see that hurricane activity also raises climate change searches in Dallas. The inconclusive nature of relying on online search data in this regard only allows to hypothesize about such mechanisms (Archibald and Butt (2018); Sisco et al. (2017). More research is needed in this field to understand the transmission of weather events on climate perception in different regions. Case study approaches can potentially create a more detailed picture of what residents of different metropolitan areas perceive as personally harmful climate developments. The analysis can also be extended towards including other weather events, such as wildfires, droughts or heavy rain. Nevertheless, the findings on respondents in Dallas regarding increases in climate change searches with hurricane activity might be a first step towards moving also generally more skeptical geographies towards a switch in attitudes. All in all, Google Trends, while reflecting a subjective perception in the population, offers granular data attributable to distinct regions and can thus be of great help in future studies on climate change.

Finally, this paper is in stark contrast with previous findings on the role of partisanship in mediating weather experiences. Hurricane activity has been shown to predominantly change the attitudes of more conservative individuals towards a more fearful perception. Such a correlation could not be proved so far in other studies to the author's attention. Usually, *Seeing is not Believing* as posited by Shao and Goidel (2016), stating how personal experiences with weather events that should be attributed to climate change are not convincing those that disagree with the existence of the latter to begin with. Individuals holding this disbelief were found to on average adhere more to conservative partisanship (see e.g. Hamilton and Stampone (2013); Konisky et al. (2016) or also Table 8 from this paper) and in turn did not update their belief system in the face of climate events, even struggling to detect their abnormality (Goebbert et al. (2012); Dunlap and McCright (2008); Howe and Leiserowitz (2013)). The findings from this paper strongly oppose this widely agreed on notion. In fact, it shows that conservatives are the only ones that react to hurricanes and display increased levels of worry and belief in climate change. One important explanation for this is that the average level of belief in and willingness to act against climate change in the liberal group is high in the first place. This explains how there is not much *upward movement* left for climate perceptions to react to the perceived threat of hurricanes. Nevertheless, this does not weaken the importance of these findings. Indeed, they can be interpreted as the final convergence on belief in climate change that is taking place as was hypothesized by Weber (2016). Ultimately, with sheer frequency and magnitude, also the deniers as mentioned by Leiserowitz et al. (2013) may be convinced of the luring threat lying ahead of us in the form of climate catastrophes.

This paper could add very well to the notion that moderators do determine the perception of weather events. These included geographies, ideologies and particular characteristics of climate events. It was once again sustained that inferences on climate change based on personal weather experiences are highly heterogeneous and contingent on surrounding factors (Weber (2010); Sisco (2021)). However, with regards to ideology, the direction of this moderating effect was very unexpected and promising for future policy action. Also for the unconvinced, windows of opportunity do open up.

7 Conclusion

This study investigated the effects that the 2020 hurricane season had on climate change perceptions. Google Trends data was used to operationalize the attention that the population payed to a given hurricane. This approach proved very useful and can be built on in the future. More events can be included in the analysis to get an even more complete picture of which events drive climate change perceptions. In this regard, the study at hand can only be seen as part of a greater puzzle that investigated one aspect of how belief in climate change can be manifested. More evidence is also to be gathered on the relationship between climate change search behavior and ultimate belief systems. The transmission seems to be far from linear, and the limits of simply relying on search volume were discussed above. Further research needs to be done in order to understand this chain of causes and effects better. Nevertheless, this paper can spark some definitive hope in the research community as it proves that even climate change skeptical peer groups can ultimately be convinced of the urgency of climate action. This particular finding should be positioned at the beginning of a new research endeavour, investigating whether similar patterns can be found for different weather events, in different locations and time periods. In times of the COVID-19 pandemic and the Russian invasion of Ukraine, it is not getting easier to draw attention to climate change. This study has proven that it is still possible, even for the most remote subgroups. Individuals are not ignorant to weather effects and make a connection to the risks of climate change. Different geographies, ideologies and other factors such as magnitude and frequency mediate this effect. Importantly, however, an effect does prevail. Policy action can happen. There is hope to turn this ship around.

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8 Appendix

8.1 Survey Questions for Independent Variables

The questionnaire states the following explanation:

Climate change refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result.

8.1.1 Attitudinal Questions

worry: How worried are you about climate change?

- Extremely worried
- Very worried
- Somewhat worried
- Not very worried
- Not at all worried

certainty: How likely do you think it is that climate change is happening?

- Extremely likely
- Very likely
- Likely
- About as likely as unlikely
- Unlikely
- Very unlikely
- Extremely unlikely

futureharm: How much do you think climate change will harm future generations of people if we do not take action to stop it?

- A great deal

- A lot
- A moderate amount
- A little
- Not at all
- Don't know

Note that "Don't know" was re-coded to "missing".

8.1.2 Behavioral Questions

bvr_you: How much would you like to take actions to stop climate change?

- A great deal
- A lot
- A moderate amount
- A little
- Not at all

bvr_oth: How much do you think people in your area have recently taken action to stop climate change?

- A great deal
- A lot
- A moderate amount
- A little
- Not at all

act: The index was constructed from the twelve following statements:

1. Invest money in clean energy companies
2. Cut down on your consumption of disposable items whenever possible, e.g. plastic bags from the supermarket, excessive packaging
3. Change some of your light bulbs to high energy-efficiency compact fluorescents (CFLs) or light-emitting diode (LEDs)

4. Insulate your home better to reduce your energy consumption
5. Reward companies that are taking steps to reduce climate changeby buying their products
6. Replace older appliances with more energy efficient new models(e.g., refrigerators, furnaces, dishwashers, and others)
7. Frequently use public transport, cycle or walk rather than using a car
8. Change your housing heating systemto a more eco-friendly model
9. Buy a low emission car
10. Buy eco-friendly itemsfrom the grocery store
11. Choose foods to eat that are more eco-friendly
12. Participate in climate activism(e.g. climate marches, contacting representatives, educating others, etc.)

Each of these could be answered on a three-point scale:

- No intention to perform
- Intent to perform soon
- Performed recently

Also, "Not possible for me" could be answered. The answers to these twelve sub-questions were summed up to create one variable ranging from 12 to 36, which was then divided by twelve to retain the original scale of the sub-questions. Only individuals that answered to all 12 questions, and did not tick two boxes for one sub-question were included in the construction.

The questions are taken from Sisco et al. (2020a).

8.2 Survey Questions for Control Set 2

perc_temp: Thinking about yesterday, do you think that the outdoor temperature in your area was warmer or colder than usual for this time of year?

- Much colder
- Somewhat colder
- About the usual
- Somewhat warmer
- Much warmer

perc_precip: Thinking about the last four weeks, do you think that the precipitation (rain or snow) in your area was more or less than usual for this time of year?

- Much more precipitation
- Somewhat more
- About the usual
- Somewhat less
- Much less precipitation

climate_social: How often did you hear about climate change on social media over the past few days?

- Several times
- Once
- Not at all

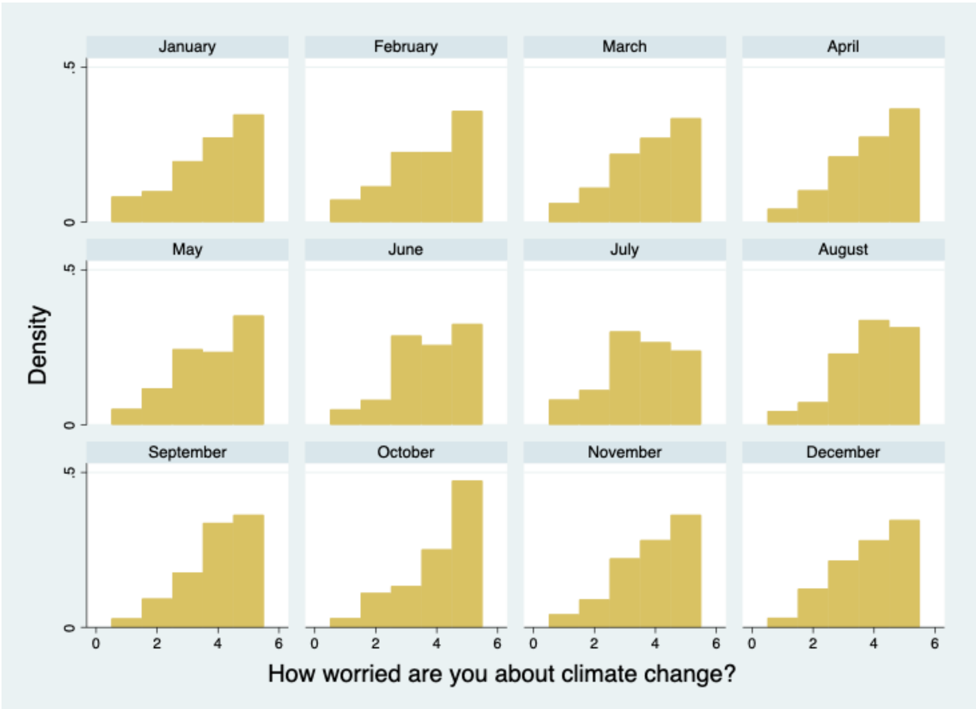
climate_news: How often did you hear about climate change in the news media over the past few days?

- Several times
- Once
- Not at all

The questions are taken from Sisco et al. (2020a).

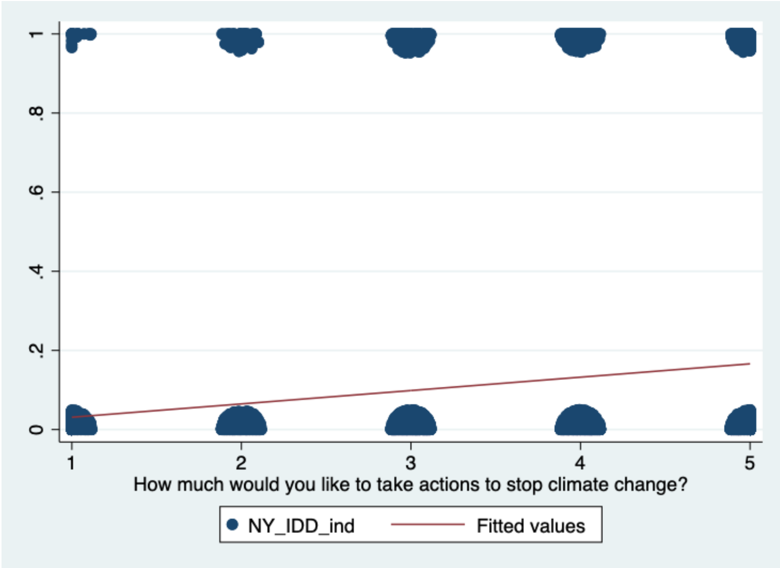
8.3 Additional Graphs

Figure 7. Distribution of answers in New York for variable *worry*



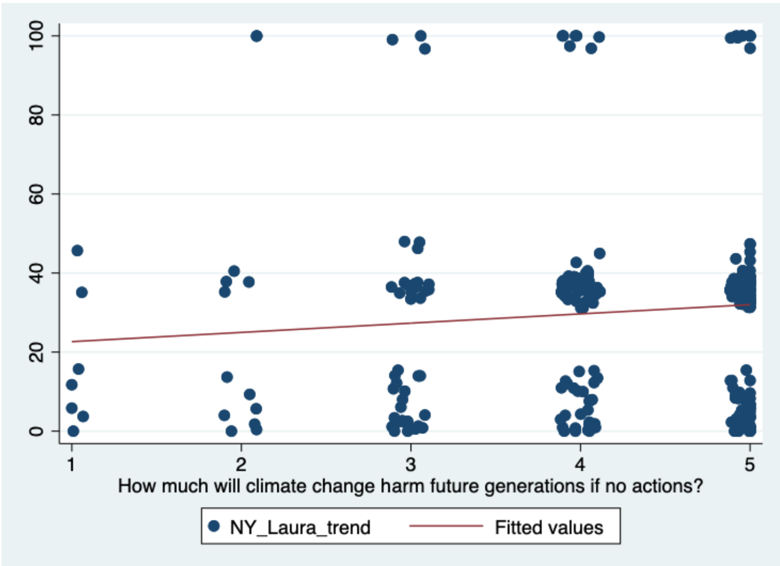
To be noted is the spike in worry from around August to November.

Figure 8. Correlation between IDD dates and variable *bvr_you* in New York



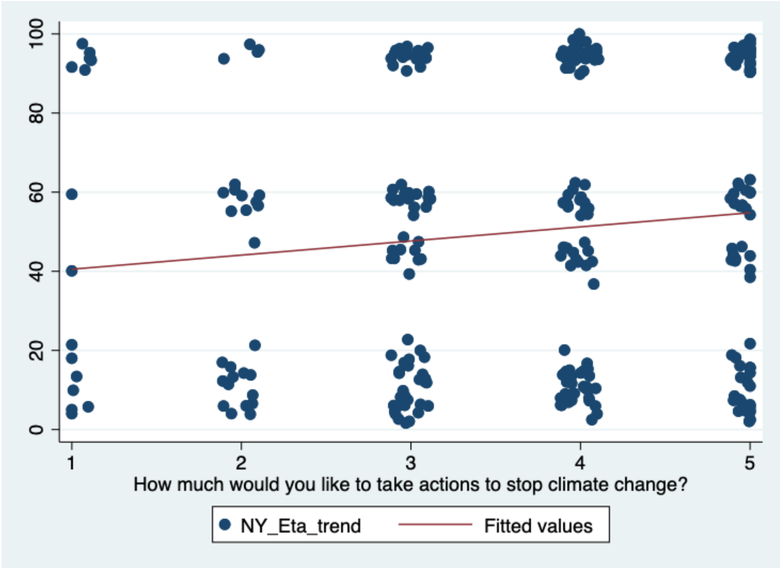
Note how on days with hurricane activity as noted by IDD, willingness to act goes up.

Figure 9. Correlation between Google Trends for Hurricane Laura and *futureharm* in New York



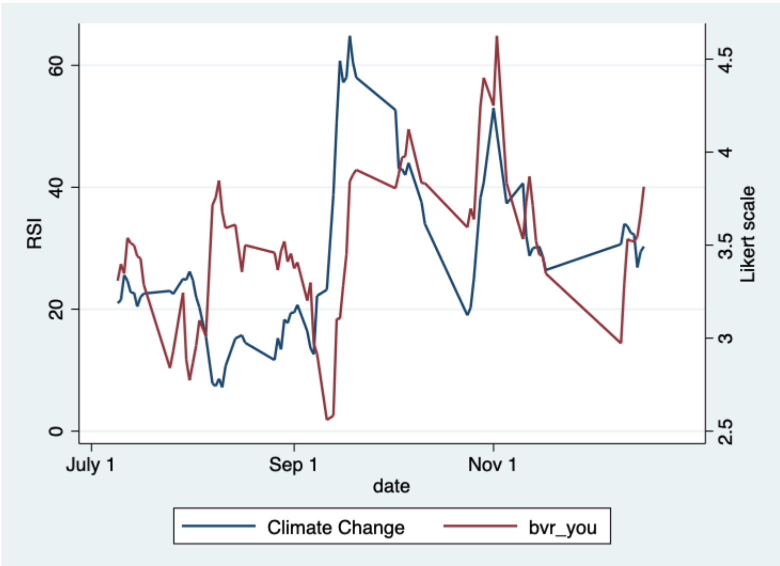
Note how on days with higher hurricane search activity, fear of future harm by CC goes up.

Figure 10. Correlation between Google Trends for Hurricane Eta and *bvr_you* in New York



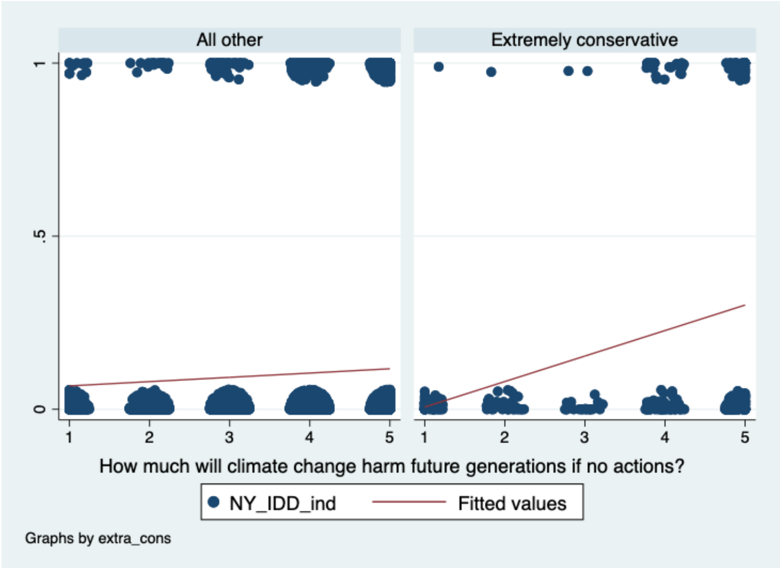
Note how on days with higher hurricane search activity, willingness to act against CC goes up.

Figure 11. Climate Change Search Activity and *bvr_you* in New York



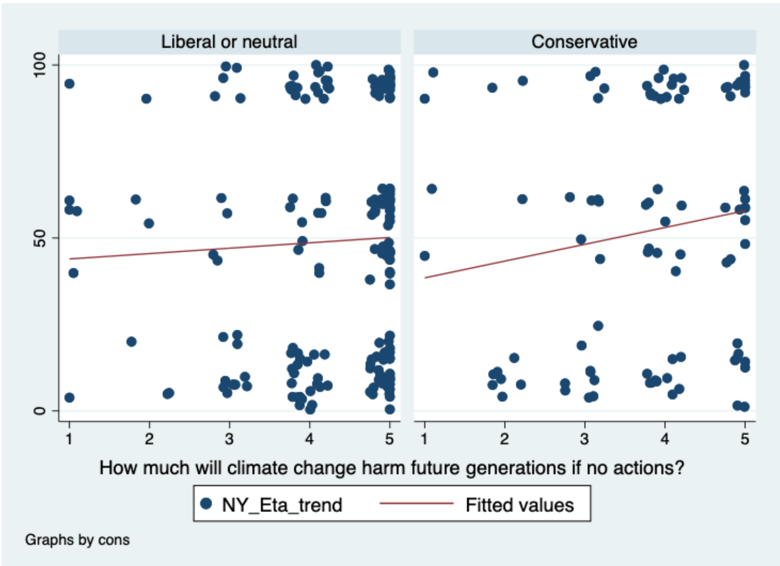
Both variables depicted as 7-day moving averages.

Figure 12. Correlation between IDD dates and *futureharm* in New York, split by ideologies



Extremely conservatives react much stronger to hurricane activity than other ideologies.

Figure 13. Google Trends for Hurricane Eta and *futureharm* in New York, split by ideologies



Conservatives react more to Hurricane Eta than Liberals.

8.4 Additional Tables

Table 17. Areas affected by the Hurricanes of the 2020 Season

Hurricane	States
Hanna	**Texas**
Isaias	North Carolina, South Carolina, **New York**, Maryland, Delaware, New Jersey, Connecticut, Florida, Virginia, Pennsylvania, New Hampshire
Laura	Louisiana, **Texas**, Arkansas, Mississippi
Sally	Alabama, Florida
Delta	Louisiana, **Texas**, Mississippi, Georgia, North and South Carolina
Zeta	Louisiana, Mississippi, Alabama, Northern Georgia, South and North Carolinas
Eta	Florida, North Carolina, Virginia

Table 18. Adding Control Set 2: Results of Regression 7

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_season_trend	0.00118	-0.000472	0.00373**	0.00308*	0.00254	-0.00181
	(0.00189)	(0.00208)	(0.00169)	(0.00177)	(0.00155)	(0.00118)
DA_season_trend	0.00146	0.00265	0.00183	0.00134	-0.000309	-0.000188
	(0.00149)	(0.00168)	(0.00159)	(0.00160)	(0.00142)	(0.000871)
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	3.503***	5.561***	3.721***	2.851***	1.890***	0.809***
	(0.128)	(0.153)	(0.135)	(0.130)	(0.113)	(0.124)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.291	0.224	0.264	0.307	0.316	0.429

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19. Results of Regression 3 when restricting to $rep\_int = 0$

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_season_trend	0.00267	0.000633	0.00420**	0.00657***	0.00531***	0.00112
	(0.00212)	(0.00240)	(0.00200)	(0.00225)	(0.00196)	(0.00153)
DA_season_trend	0.00162	0.00304*	0.00178	0.00154	-0.000895	0.000102
	(0.00172)	(0.00184)	(0.00183)	(0.00187)	(0.00173)	(0.00130)
Fixed Effects						
Set 1	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	4.684***	6.603***	4.799***	4.366***	3.128***	1.840***
	(0.116)	(0.140)	(0.121)	(0.124)	(0.108)	(0.147)
Observations	8,076	8,076	7,782	8,076	8,076	2,583
R-squared	0.213	0.187	0.213	0.196	0.171	0.233

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20. Individual Hurricanes by IDD: Results of Regression 12 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_Hanna_IDD_ind	-0.343	-0.186	-0.303	-0.477	-0.0794	
	(0.619)	(0.275)	(0.635)	(0.439)	(0.632)	
NY_Isaias_IDD_ind	-0.109	-0.0189	0.107	-0.123	0.274*	-0.0965
	(0.171)	(0.175)	(0.179)	(0.170)	(0.165)	(0.137)
NY_Laura_IDD_ind	0.195**	0.00271	0.300***	0.373***	0.380***	0.0471
	(0.0971)	(0.122)	(0.0969)	(0.0994)	(0.0921)	(0.0841)
NY_Sally_IDD_ind	0.122	0.209*	0.0901	0.490***	0.380***	0.486***
	(0.107)	(0.118)	(0.100)	(0.100)	(0.104)	(0.0816)
NY_Delta_IDD_ind	0.206	0.369	0.714*	0.0208	-0.422	
	(0.644)	(0.463)	(0.425)	(0.519)	(0.583)	
NY_Zeta_IDD_ind	0.891**	0.854**	0.912***	0.629	0.442	0.298
	(0.356)	(0.395)	(0.321)	(0.444)	(0.478)	(0.528)
NY_Eta_IDD_ind	0.242**	-0.0259	0.130	0.282***	0.235***	0.150*
	(0.0990)	(0.124)	(0.105)	(0.102)	(0.0889)	(0.0840)
DA_Hanna_IDD_ind	0.0309	-0.212	-0.0817	-0.233	0.388**	-0.118
	(0.214)	(0.388)	(0.307)	(0.224)	(0.157)	(0.136)
DA_Isaias_IDD_ind	0.117	0.403*	0.415	-0.0947	0.205	-0.405***
	(0.221)	(0.227)	(0.364)	(0.354)	(0.229)	(0.0689)
DA_Laura_IDD_ind	0.170	0.227*	0.114	0.158	0.186	-0.0409
	(0.120)	(0.129)	(0.125)	(0.132)	(0.121)	(0.0982)
DA_Sally_IDD_ind	0.0184	-0.0485	0.151	-0.00552	0.0992	0.170*
	(0.128)	(0.164)	(0.136)	(0.133)	(0.119)	(0.0928)
DA_Delta_IDD_ind	-0.575	-0.964**	-0.663*	-0.606**	-0.434*	-0.137
	(0.374)	(0.449)	(0.390)	(0.287)	(0.246)	(0.279)
DA_Zeta_IDD_ind	-0.314*	-0.0998	-0.0169	-0.225	-0.265*	-0.248***
	(0.182)	(0.250)	(0.194)	(0.186)	(0.147)	(0.0933)
DA_Eta_IDD_ind	0.00645	0.0368	0.0998	0.0421	-0.0846	-0.0247
	(0.112)	(0.134)	(0.113)	(0.113)	(0.0983)	(0.0938)
Fixed Effects						
Set 1^+	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	4.740***	6.649***	4.812***	4.353***	3.139***	1.827***
	(0.111)	(0.133)	(0.116)	(0.118)	(0.105)	(0.140)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.226	0.201	0.228	0.197	0.168	0.238

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21. Laura Day by Day: Results of Regression 14 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
NY_Laura_day_3^{-}	-0.0381	-0.288	-0.440	-0.212	0.0821	-0.857***
	(0.286)	(0.287)	(0.284)	(0.468)	(0.400)	(0.0780)
NY_Laura_day_2^{-}	-0.127	0.0219	-0.0893	0.549	0.504	0.727**
	(0.444)	(0.490)	(0.476)	(0.422)	(0.379)	(0.307)
NY_Laura_day_1^{-}	0.117	-0.347	-0.153	0.246	0.176	0.207
	(0.289)	(0.338)	(0.436)	(0.504)	(0.401)	(0.303)
NY_Laura_day_0	0.235	0.131	0.328*	0.159	0.294	-0.0495
	(0.242)	(0.222)	(0.184)	(0.219)	(0.203)	(0.157)
NY_Laura_day_1^{+}	0.171*	-0.0767	0.224**	0.433***	0.393***	0.101
	(0.103)	(0.135)	(0.106)	(0.106)	(0.0985)	(0.0907)
NY_Laura_day_2^{+}	-0.0279	0.0916	-0.117	0.258	0.275*	0.205
	(0.195)	(0.230)	(0.179)	(0.195)	(0.163)	(0.203)
NY_Laura_day_3^{+}	-0.686	-1.617*	-0.904	-1.051	-0.909	
	(0.497)	(0.922)	(0.592)	(0.690)	(0.628)	
NY_Laura_day_4^{+}	-0.0995	0.324	-0.0804	-0.194	0.394	0.422**
	(0.356)	(0.337)	(0.391)	(0.418)	(0.411)	(0.172)
DA_Laura_day_X			*** not displayed ***			
Fixed Effects						
Set 1^{+}	X	X	X	X	X	X
Set 2	-	-	-	-	-	-
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	4.752***	6.659***	4.821***	4.370***	3.150***	1.823***
	(0.111)	(0.133)	(0.116)	(0.118)	(0.104)	(0.141)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.225	0.201	0.227	0.196	0.166	0.232

Day 0 is the peak of Goolge Trends search activity.
DA_Laura_day_X dummies are not displayed due to low significance
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22. Hurricane Activity by IDD and Extremely Conservatives: Results of Regression 16 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
1.NY_IDD_ind#1.extra_cons	0.804***	1.145***	0.921***	0.766***	0.369***	0.164
	(0.136)	(0.188)	(0.121)	(0.112)	(0.0999)	(0.110)
1.DA_IDD_ind#1.extra_cons	-0.161	-0.182	-0.361*	-0.230	0.0518	-0.0287
	(0.181)	(0.269)	(0.201)	(0.177)	(0.129)	(0.0839)
NY_IDD_ind	-0.0862	-0.218***	-0.0635	0.0230	0.0780	0.00301
	(0.0568)	(0.0699)	(0.0592)	(0.0580)	(0.0506)	(0.0455)
DA_IDD_ind	0.0103	0.0514	0.117*	0.00772	-0.00938	-0.0288
	(0.0646)	(0.0805)	(0.0692)	(0.0623)	(0.0542)	(0.0441)
extra_cons	-0.730***	-1.018***	-0.758***	-0.407***	0.0842**	-0.112***
	(0.0493)	(0.0741)	(0.0573)	(0.0462)	(0.0390)	(0.0254)
Fixed Effects						
Set 1^{+}	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	2.715***	4.715***	2.993***	2.086***	1.680***	0.740***
	(0.122)	(0.150)	(0.131)	(0.122)	(0.105)	(0.116)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.189	0.125	0.149	0.248	0.315	0.414

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23. Hurricane Activity by IDD Weeks and Conservatives: Results of Regression 17 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
1.NY_IDD_week#1.cons	0.521***	0.461***	0.487***	0.444***	0.218***	0.207***
	(0.0725)	(0.0895)	(0.0735)	(0.0738)	(0.0665)	(0.0597)
1.DA_IDD_week#1.cons	0.000214	-0.00376	0.0295	0.0141	0.0216	-0.0289
	(0.0738)	(0.0932)	(0.0791)	(0.0737)	(0.0644)	(0.0529)
NY_IDD_week	-0.201***	-0.237***	-0.166***	-0.117*	-0.0376	-0.127***
	(0.0571)	(0.0688)	(0.0579)	(0.0606)	(0.0507)	(0.0476)
DA_IDD_week	0.0460	0.0730	0.0725	0.0124	-0.0351	-0.0828*
	(0.0596)	(0.0715)	(0.0606)	(0.0609)	(0.0538)	(0.0469)
cons	-0.862***	-1.028***	-0.954***	-0.622***	-0.0262	-0.138***
	(0.0264)	(0.0327)	(0.0280)	(0.0261)	(0.0220)	(0.0210)
Fixed Effects						
Set 1^{+}	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	3.087***	5.146***	3.414***	2.370***	1.710***	0.793***
	(0.122)	(0.149)	(0.131)	(0.123)	(0.106)	(0.118)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.266	0.194	0.243	0.290	0.313	0.423

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24. Hurricane Activity by Season Indicators and Conservatives: Results of Regression 18 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
1.NY_season_ind#1.cons	0.477***	0.454***	0.501***	0.365***	0.130*	0.160**
	(0.0831)	(0.105)	(0.0857)	(0.0864)	(0.0776)	(0.0686)
1.DA_season_ind#1.cons	-0.0500	-0.0175	0.0209	0.0456	0.0823	-0.0438
	(0.101)	(0.129)	(0.105)	(0.0979)	(0.0901)	(0.0671)
NY_season_ind	-0.224***	-0.279***	-0.207***	-0.0214	0.0779	-0.0415
	(0.0609)	(0.0752)	(0.0624)	(0.0634)	(0.0550)	(0.0499)
DA_season_ind	0.0142	-0.0104	0.0151	-0.0194	-0.0388	-0.0254
	(0.0720)	(0.0860)	(0.0703)	(0.0718)	(0.0693)	(0.0539)
cons	-0.842***	-1.015***	-0.940***	-0.607***	-0.0172	-0.130***
	(0.0251)	(0.0311)	(0.0267)	(0.0248)	(0.0210)	(0.0200)
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	3.077***	5.140***	3.409***	2.362***	1.704***	0.785***
	(0.122)	(0.149)	(0.131)	(0.123)	(0.106)	(0.119)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.264	0.193	0.243	0.289	0.313	0.421

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25. Individual Hurricanes by IDD and Conservatives: Results of Regression 20 from Appendix 8.5

VARIABLES	(1) worry	(2) certainty	(3) futureharm	(4) bvr_you	(5) bvr_oth	(6) act
1.cons#c.NY_Hanna_IDD_ind	0.385	-0.281	-0.471	-0.407***	0.648*	
	(0.391)	(0.314)	(0.402)	(0.120)	(0.345)	
1.cons#c.NY_Isaias_IDD_ind	0.240	-0.282	0.394	0.00557	0.133	-0.373
	(0.366)	(0.372)	(0.390)	(0.346)	(0.288)	(0.284)
1.cons#c.NY_Laura_IDD_ind	0.443***	0.468**	0.691***	0.348**	0.117	0.0627
	(0.148)	(0.189)	(0.140)	(0.144)	(0.136)	(0.109)
1.cons#c.NY_Sally_IDD_ind	0.679***	0.578***	0.600***	0.467***	-0.0595	0.134
	(0.160)	(0.175)	(0.151)	(0.153)	(0.169)	(0.147)
1.cons#c.NY_Delta_IDD_ind	0.201	0.408	-0.259	-0.695	0.303	
	(0.681)	(0.426)	(0.461)	(0.528)	(0.555)	
1.cons#c.NY_Zeta_IDD_ind	1.345***	1.859***	1.468***	2.074**	-1.274***	
	(0.494)	(0.251)	(0.510)	(1.052)	(0.365)	
1.cons#c.NY_Eta_IDD_ind	0.536***	0.383*	0.481***	0.324*	0.219	0.174
	(0.155)	(0.221)	(0.174)	(0.171)	(0.140)	(0.113)
NY_Hanna_IDD_ind	-0.795***	-0.206**	-0.155*	-0.461***	-0.756***	
	(0.0844)	(0.103)	(0.0903)	(0.0838)	(0.0690)	
NY_Isaias_IDD_ind	-0.252	-0.0545	-0.0875	-0.190	0.234	-0.0609
	(0.183)	(0.179)	(0.180)	(0.179)	(0.168)	(0.113)
NY_Laura_IDD_ind	-0.112	-0.280**	-0.0784	0.0425	0.117	-0.150*
	(0.108)	(0.143)	(0.103)	(0.115)	(0.0991)	(0.0854)
NY_Sally_IDD_ind	-0.394***	-0.189*	-0.333***	0.00166	0.124	0.193
	(0.113)	(0.111)	(0.115)	(0.106)	(0.118)	(0.125)
NY_Delta_IDD_ind	0.000984	0.0268	0.823***	0.458***	-0.663***	
	(0.0855)	(0.105)	(0.0875)	(0.0840)	(0.0720)	
NY_Zeta_IDD_ind	-0.168	-0.616***	-0.225	-1.014	1.266***	0.215
	(0.377)	(0.111)	(0.451)	(1.007)	(0.131)	(0.903)
NY_Eta_IDD_ind	-0.0706	-0.272*	-0.145	0.0236	0.0385	-0.0220
	(0.112)	(0.144)	(0.116)	(0.114)	(0.0917)	(0.0837)
cons	-0.844***	-1.008***	-0.934***	-0.602***	-0.00713	-0.123***
	(0.0249)	(0.0308)	(0.0264)	(0.0246)	(0.0208)	(0.0198)
1.cons#c.DA_hurricane_IDD_ind			*** not displayed ***			
DA_hurricane_IDD_ind			*** not displayed ***			
Fixed Effects						
Set 1+	X	X	X	X	X	X
Set 2	X	X	X	X	X	X
City	X	X	X	X	X	X
Month	X	X	X	X	X	X
Constant	3.073***	5.112***	3.390***	2.346***	1.703***	0.784***
	(0.122)	(0.149)	(0.131)	(0.122)	(0.106)	(0.120)
Observations	9,204	9,204	8,859	9,204	9,204	2,943
R-squared	0.266	0.195	0.245	0.291	0.315	0.425

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

8.5 Additional Regressions

$$
\begin{aligned}
y = \beta_1\ NY\_Hanna\_trend + \beta_2\ NY\_Isaias\_trend \\
+ \beta_3\ NY\_Laura\_trend + \beta_4\ NY\_Sally\_trend \\
+ \beta_5\ NY\_Delta\_trend + \beta_6\ NY\_Zeta\_trend \\
+ \beta_7\ NY\_Eta\_trend + \beta_8\ DA\_Hanna\_trend \\
+ \beta_9\ DA\_Isaias\_trend + \beta_{10}\ DA\_Laura\_trend \\
+ \beta_{11}\ DA\_Sally\_trend + \beta_{12}\ DA\_Delta\_trend \\
+ \beta_{13}\ DA\_Zeta\_trend + \beta_{14}\ DA\_Eta\_trend \\
+ \phi' set1 + \delta_t + \zeta_c
\end{aligned}
\tag{11}
$$

$$
\begin{aligned}
y = \beta_1\ NY\_Hanna\_IDD\_ind + \beta_2\ NY\_Isaias\_IDD\_ind \\
+ \beta_3\ NY\_Laura\_IDD\_ind + \beta_4\ NY\_Sally\_IDD\_ind \\
+ \beta_5\ NY\_Delta\_IDD\_ind + \beta_6\ NY\_Zeta\_IDD\_ind \\
+ \beta_7\ NY\_Eta\_IDD\_ind + \beta_8\ DA\_Hanna\_IDD\_ind \\
+ \beta_9\ DA\_Isaias\_IDD\_ind + \beta_{10}\ DA\_Laura\_IDD\_ind \\
+ \beta_{11}\ DA\_Sally\_IDD\_ind + \beta_{12}\ DA\_Delta\_IDD\_ind \\
+ \beta_{13}\ DA\_Zeta\_IDD\_ind + \beta_{14}\ DA\_Eta\_IDD\_ind \\
+ \phi' set1 + \delta_t + \zeta_c
\end{aligned}
\tag{12}
$$

$$
\begin{aligned}
y = {} & \beta_1\ NY\_Sally\_day\_4^{-} + \beta_2\ NY\_Sally\_day\_3^{-} + \beta_3\ NY\_Sally\_day\_2^{-} \\
& + \beta_4\ NY\_Sally\_day\_1^{-} + \beta_5\ NY\_Sally\_day\_0 + \beta_6\ NY\_Sally\_day\_1^{+} \\
& + \beta_7\ NY\_Sally\_day\_2^{+} + \beta_8\ NY\_Sally\_day\_3^{+} + \beta_9\ NY\_Sally\_day\_4^{+} \\
& + \beta_{10}\ DA\_Sally\_day\_4^{-} + \beta_{11}\ DA\_Sally\_day\_3^{-} + \beta_{12}\ DA\_Sally\_day\_2^{-} \\
& + \beta_{13}\ DA\_Sally\_day\_1^{-} + \beta_{14}\ DA\_Sally\_day\_0 + \beta_{15}\ DA\_Sally\_day\_1^{+} \\
& + \beta_{16}\ DA\_Sally\_day\_2^{+} + \beta_{17}\ DA\_Sally\_day\_3^{+} + \beta_{18}\ DA\_Sally\_day\_4^{+} \\
& + \phi' set1 + \delta_t + \zeta_c \qquad (13)
\end{aligned}
$$

$$
\begin{aligned}
y = {} & \beta_1\ NY\_Laura\_day\_4^{-} + \beta_2\ NY\_Laura\_day\_3^{-} + \beta_3\ NY\_Laura\_day\_2^{-} \\
& + \beta_4\ NY\_Laura\_day\_1^{-} + \beta_5\ NY\_Laura\_day\_0 + \beta_6\ NY\_Laura\_day\_1^{+} \\
& + \beta_7\ NY\_Laura\_day\_2^{+} + \beta_8\ NY\_Laura\_day\_3^{+} + \beta_9\ NY\_Laura\_day\_4^{+} \\
& + \beta_{10}\ DA\_Laura\_day\_4^{-} + \beta_{11}\ DA\_Laura\_day\_3^{-} + \beta_{12}\ DA\_Laura\_day\_2^{-} \\
& + \beta_{13}\ DA\_Laura\_day\_1^{-} + \beta_{14}\ DA\_Laura\_day\_0 + \beta_{15}\ DA\_Laura\_day\_1^{+} \\
& + \beta_{16}\ DA\_Laura\_day\_2^{+} + \beta_{17}\ DA\_Laura\_day\_3^{+} + \beta_{18}\ DA\_Laura\_day\_4^{+} \\
& + \phi' set1 + \delta_t + \zeta_c \qquad (14)
\end{aligned}
$$

$$
\begin{aligned}
y = \beta_1 \; (NY\_IDD\_ind \times cons) + \beta_2 \; (DA\_IDD\_ind \times cons) \\
+ \beta_3 \; NY\_IDD\_ind + \beta_4 \; DA\_IDD\_ind + \beta_5 \; cons \\
+ \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \quad (15)
\end{aligned}
$$

$$
\begin{aligned}
y = \beta_1 \; (NY\_IDD\_ind \times extra\_cons) + \beta_2 \; (DA\_IDD\_ind \times extra\_cons) \\
+ \beta_3 \; NY\_IDD\_ind + \beta_4 \; DA\_IDD\_ind + \beta_5 \; extra\_cons \\
+ \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \quad (16)
\end{aligned}
$$

$$
\begin{aligned}
y = \beta_1 \; (NY\_IDD\_week \times cons) + \beta_2 \; (DA\_IDD\_week \times cons) \\
+ \beta_3 \; NY\_IDD\_week + \beta_4 \; DA\_IDD\_week + \beta_5 \; cons \\
+ \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \quad (17)
\end{aligned}
$$

$$
\begin{aligned}
y = \beta_1 \; (NY\_season\_ind \times cons) + \beta_2 \; (DA\_season\_ind \times cons) \\
+ \beta_3 \; NY\_season\_ind + \beta_4 \; DA\_season\_ind + \beta_5 \; cons \\
+ \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \quad (18)
\end{aligned}
$$

$$y = B_1' \ (\$NY\_trend \times cons) + B_2' \ (\$DA\_trend \times cons) \\ + B_3' \ \$NY\_trend + B_4' \ \$DA\_trend + \beta_5 \ cons \\ + \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \quad (19)$$

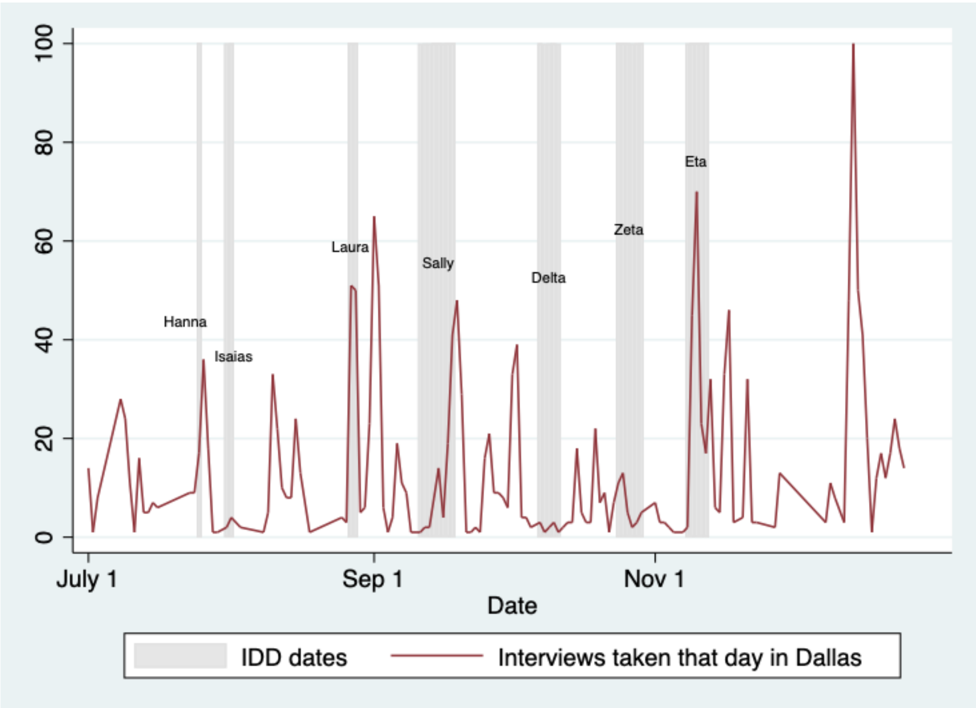
$$y = B_1' \ (\$NY\_IDD\_ind \times cons) + B_2' \ (\$DA\_IDD\_ind \times cons) \\ + B_3' \ \$NY\_IDD\_ind + B_4' \ \$DA\_IDD\_ind + \beta_5 \ cons \\ + \phi' set1^{+} + \psi' set2 + \delta_t + \zeta_c \quad (20)$$

Clarification for Regressions 19 and 20: The regressions are displayed in abbreviated notation. To arrive at Regression 19, one can start from Regression 11. Each of the trend variables is interacted with the *cons* identifier. Then, the trend variables itself are also included in the regression. The control sets are as usual. The same procedure is followed going from Regression 12 to 20.

8.6 Additional Information

In this section attention is raised to a potential complication from the identification strategy. The count of interviews varies substantially throughout the survey period. It is not a smooth timeline where a given number of interviews is conducted on each day. Rather, the number of interviews conducted fluctuates heavily. Figure 14 plots the interviews taken on a given day on the hurricane dates by IDD. This is an issue with relating weather events to survey data that is common in the literature. Hamilton and Stampone (2013) experience very similar patterns in their analysis. In the case of this analysis, the issue is tried to be taken care of by relying on a number of different specifications, employing indicator as well as trend variables and also making the data visible graphically.

Figure 14. Interviews taken per day and hurricane activity in Dallas as per IDD



Hanna, Laura, Sally and Eta with good matches in Dallas.