Different Hazards, Different Responses: Assessments of Flooding and COVID-19 Risks among Upstate New York Residents

John Aloysius Zinda\(^1\)\(^\circ\), James Zhang\(^1\), Lindy B. Williams\(^1\), David L. Kay\(^1\), Sarah M. Alexander\(^1\), and Libby Zemaitis\(^2\)

Abstract
The coronavirus disease 2019 (COVID-19) pandemic and extreme flooding events have recently taken enormous tolls. Drawing on research into differential risk responses across hazards, the authors examine how different social processes surrounding risk from flooding and COVID-19 shape how people respond to each hazard. Data from a household survey of 498 residents in two cities in the northeastern United States reveal that levels of concern and protective measures vary across the two hazards. Whereas climate polarization does not appear to influence flood risk responses, COVID-19 responses appear strongly polarized. However, having a known risk condition can offset Republicans’ doubts about COVID-19. In addition, whereas people of color express greater concern about flooding, white people take more protective measures, and women are more likely than others to take protective measures against COVID-19. Contrasting stakes, immediacy, dread, and polarization surrounding flooding and COVID-19 intersect with social inequalities to produce differing patterns of risk response.

Keywords
risk perception, protective action, floods, COVID-19, political polarization, inequality

The years 2020 and 2021 confronted people around the world with two sources of momentous risk: the novel coronavirus and climate change. The global and uneven impacts of the novel coronavirus (COVID-19) are increasingly well documented (Leach et al. 2021; Robinson et al. 2021), while disasters linked to climate change have proliferated. Tremendous wildfires swept through North America, Australia, and Siberia, devastating landscapes, displacing thousands of people, and shrouding millions in smoke (Kramer and Drew 2021; Pierre-Louis 2020). In 2021, a shocking heat wave hit the Pacific Northwest, followed by catastrophic flooding in China, Europe, and the United States (Fountain 2021; Issai 2021; Ramzy 2021).

What drives differing responses to risks from flooding and COVID-19? Do people who are at risk from both hazards worry about and take protective measures for each? COVID-19 and climate-driven hazards are both objects of intense social and political polarization (Cowan, Mark, and Reich 2021; Gadarian, Goodman, and Pepinsky 2021; Hamilton et al. 2015; Kahan 2015; McCright and Dunlap 2011; Shepherd, MacKendrick, and Mora 2020). Yet these two hazards differ in many aspects known to affect risk perception and response: the parts of people’s lives they threaten, the levels of urgency they provoke, the extent to which they are recognized and familiar, and the public conversations surrounding them (Botzen et al. forthcoming). These differences interact with social inequalities and cultural differences to generate varying responses across contexts.

In this study, we ask how the different social processes surrounding risk from flooding and COVID-19 shape how people perceive and respond to each hazard. Most studies of risk concern a single hazard, evaluating covariation among factors generally expected to influence risk perception or protective measures with regard to that one hazard. Yet different hazards elicit different levels of concern, and these concerns play important roles in motivating actions people take to protect themselves (Douglas and Wildavsky 1982;
differ: four dimensions of risk on which flooding and COVID-19 consequential for how people respond to each. We highlight flooding and COVID-19 show many contrasts that may be Varying Response across Hazards Experience, Exposure, Polarization Different Risks, Different Responses: (Kundzewicz, and Wright 2021).

Using an original data set from a survey of households in two flood-affected cities in the northeastern United States, we examine patterns of concern about and of protective measures taken against flooding and COVID-19 in parallel. Examining these differences can help us understand responses to each hazard on its own as well as yield theoretical insights into more general issues surrounding risk perception and response. It can also contribute to disaster management in multihazard scenarios, a major concern that has intensified during the pandemic (Botzen et al. forthcoming; CONVERGE 2020; Ishiwatari et al. 2020; Simonovic, Kundzewicz, and Wright 2021).

Different Risks, Different Responses: Experience, Exposure, Polarization Varying Response across Hazards

Flooding and COVID-19 show many contrasts that may be consequential for how people respond to each. We highlight four dimensions of risk on which flooding and COVID-19 differ:

- **Stakes**: According to a widely adopted definition, risk is “a situation or event where something of human value . . . is at stake and where the outcome is uncertain” (Rosa, Renn, and McCright 2014:21). A stake is “something of human value.” Stakes vary in magnitude and in kind. For example, COVID-19 brings direct threats to one’s life and the lives of others. Floods do kill, but in most cases, damage to homes and belongings is much more widespread than harm to life.

- **Immediacy**: Depending on how frequent, recent, or memorable its occurrences are, a hazard may appear more or less immediate (Meyer and Kunreuther 2017). At the time of the survey, COVID-19 was an unavoidable, constant object of media attention, an intrusive reality in everyone’s life. Stay-at-home orders such as the one issued by the government of the State of New York likely boosted the immediacy of COVID-19. In contrast, in many locales, flooding is an infrequent occurrence. Although both of the cities surveyed had experienced major floods, the most recent instances were in August 2011, almost 9 years before the survey.

- **Dread**: Dread is an emotion of profound fear that people tend to express about risks that are unfamiliar, poorly understood, delayed in their impacts, uncontrollable, and catastrophic at a wide scale (Slovic 1987). Several of these attributes arguably apply more strongly to COVID-19 than to flooding in these locales.1

- **Polarization**: An issue upon which distinct population segments show sustained divergence of views is polarized (Fiorina and Abrams 2008). COVID-19 is known to be highly politically polarized (Gadarian et al. 2021; Shepherd et al. 2020). As we discuss below, the conduct of public figures, divergent media portrayals, and broader social interactions have fostered contrasting beliefs about the pandemic, with people with conservative worldviews less likely to worry about COVID-19 or take protective measures (Hamilton and Safford 2021; Shepherd et al. 2020). Flooding is often linked to climate change, which also is highly polarized (Bolin and Hamilton 2018; McCright and Dunlap 2011), so we might expect to see partisan polarization on concern and protective measures surrounding flooding as well. Yet some studies suggest that people may focus on the immediate impacts of weather-related hazards rather than climate connections, circumventing otherwise polarizing interactions (Bruine de Bruin, Wong-Parodi, and Morgan 2014; Schwaller et al. 2020).

Given the high stakes, immediacy, and dread that characterize COVID-19, we expect higher overall levels of concern and protective measures regarding COVID-19, consistent with recent findings in another locale (Botzen et al. forthcoming). However, differences across these two hazards may affect not just overall levels of concern and action but their distribution. Hazards with differing stakes provoke varying levels of concern in people with differing relationships to those stakes. Differing levels and directions of polarization arouse concern in differing populations. People take protective measures on the basis of their levels of concern, knowledge of protective measures, and available resources, all of which are uneven across individuals and across hazards. Hence, the people who worry most about flooding may not worry the most about COVID-19, and the people who worry most about either hazard may not be the ones most likely to take protective measures.

Risk Perception and Concern

Analysts commonly define the risk of a hazard as the product of the probability of a hazard occurring and the magnitude (or severity) of consequences (Cordner 2016; Freudenburg 1988; Kahneman and Tversky 1979). Hence, risk perception is commonly measured in terms of one’s evaluation of

1If we worked in places prone to catastrophic floods such as those that tropical storms can bring, we could expect to see different patterns.
hazard probability and severity (Rosa et al. 2014). In this view, risk perception is a cognitive process through which individuals judge the probability and consequences of the hazard occurring. Risk cognition depends on available information about those parameters and the mental processes through which people evaluate that information. Cognitive biases often distort these processes: using mental shortcuts or heuristics to assess risk often leads people to underestimate likely impacts of low-probability events (Tversky and Kahneman 1974). For example, the availability heuristic relies on knowledge of comparable events for risk assessment, so if one has not experienced a catastrophic event, one may underestimate their likelihood (Kahneman and Tversky 1979). Moreover, responses to risk attenuate over time: a person who endured flooding last year is more likely to be concerned about future flood risk than one whose experience was 10 years ago (Kahneman and Tversky 1979; Meyer and Kunreuther 2017). In other words, hazards that appear more immediate tend to arouse greater perceptions of risk. In this framework, risk perception in terms of probability and magnitude depends on a hazard’s recency and stakes as well as how an individual processes past experiences and available information.

However, people perceive risk in terms of not only these calculative dimensions but also the feelings a hazard evokes as they consider the parts of their lives and communities it might affect (Slovic et al. 2004; Terpstra 2011). In social psychology, this phenomenon is known as the “affect heuristic” (Terpstra 2011). In particular, hazards that evoke feelings of dread arouse heightened concern (Slovic 1987). This individual psychological pattern contributes to collective processes that frame hazards and underpin repertoires of emotional response (Auyero and Swistun 2009; Cordner 2016; Douglas and Wildavsky 1982; Leguizamón 2020). In obtaining information about probabilities and consequences as well as constructing narratives of a hazard’s root causes and its stakes—its potential effects on objects of concern—people draw on discussions in the media, official communications and warnings, artifacts like flood insurance rate maps, state-by-state tallies of COVID-19 cases and deaths, emotional involvement in places and homes, and conversations within communities and social networks (Burningham, Fielding, and Thrush 2008; Elliott 2019; Kasper and Kaspereon 1996). Research increasingly suggests that emotional responses to hazards play a key role in motivating both individual protective measures and collective efforts to change policies and seek redress (Bubeck, Botzen, and Aerts 2012; Gotham, Lauve-Moon, and Powers 2017; Meyer et al. 2018; Siegrist and Gutscher 2008). As a result, this study focuses on concern as a measure of perception.

Social status and identity also influence risk perception. For example, women are often more likely than men to perceive environmental risks as probable and worrisome (Davidson and Freudenburg 1996; Gotham et al. 2017; Milnes and Haney 2017; Xiao and McCright 2015), as has been found for many health risks (Anson et al. 1993; Hamilton and Safford 2021; Verbrugge 1985). Similarly, some studies have found that Black and Latinx people tend to express greater environmental risk perceptions than white respondents (Lindell and Hwang 2008; Lindell and Perry 2004). People with greater income and wealth may have more property at stake, which might heighten concern, but also more resources with which to protect themselves, dampening concern. Education is often expected to reduce concern about natural hazards, though findings are mixed (Lindell and Perry 2004).

To sum up, different hazards arouse different levels of concern, and concern toward a given hazard tends to be unevenly distributed. The greater dread and immediacy COVID-19 presents in the context of this study, along with its stakes of health and life as opposed to home and property, may generate higher overall levels of concern. Gendered and racialized processes of risk evaluation may contribute to differences in how people respond to risks with varying stakes, dread, and immediacy.

### Protective Measures

One of the main reasons researchers do so much work to understand risk perception is because of its presumed role in leading people to take measures to protect themselves from hazards (Bubeck et al. 2012). Protective measures include actions taken to prevent exposure altogether, such as moving out of a flood-affected area or quarantining, as well as those that reduce damage in the event of a hazard, like preparing sandbags, making an evacuation plan, purchasing flood insurance, or wearing a mask or receiving a vaccination. Perception of risks plays an important role in motivating people to take protective measures, but this role is by no means simple or direct. Researchers have called the phenomenon of inconsistent relationships between risk perception and protective measures the “risk perception paradox” (Wachinger et al. 2013).

Bubeck et al. (2012) suggested two reasons for the risk perception paradox. The first is a temporal element: cross-sectional studies may misidentify the relationship between risk perception and protective measures. People who become concerned about a risk may subsequently take protective measures, after which they may feel reassured. If interviewed before acting, respondents might report concern but no protective measures, while afterward they might indicate protective measures but less concern. Neither situation reflects the theorized causal connection between concern and action one might expect. Panel studies can address this issue; for example, Qin et al. (2021) used panel surveys to demonstrate that COVID-19 risk perceptions predicted protective measures, while taking protective measures had a negative effect on subsequent risk perceptions.

The second explanation concerns intervening processes posited within protection motivation theory (Bubeck et al. 2012):
Experience of harm from a hazard is a strong predictor of protective measures. Rather, upon recognizing a risk, people evaluate available protective measures and their ability to undertake them effectively. Any given protective measure confronts a person with costs. Hence, people with limited economic resources, relevant skillsets, and available time are less likely to take protective measures if those measures are costly. Protection motivation theory also posits that a person’s beliefs about whether the measure will effectively protect them (response efficacy) and whether they have the capacity to adopt it (self-efficacy) shape decisions about taking protective measures (Poussin, Botzen, and Aerts 2014).

The protective action decision model builds on these insights; in addition to one’s sense of self-efficacy, trust in risk managers, social connections, and social norms all influence decisions regarding protective measures (Lindell and Perry 2004, 2012). Empirical findings on these relationships are mixed (Poussin et al. 2014; Terpstra and Lindell 2013), however, and point to broader conditions that underlie decisions about protective measures. For example, racial disparities in protective measure adoption reveal how people who face discrimination or have limited financial resources are constrained in their ability to protect themselves (Fothergill, Maestas, and Darlington 1999; Fothergill and Peek 2004).

Protective measures may be patterned by the ways differing stakes, immediacy, and dread differentiate concern about flooding and COVID-19; the uneven distribution of resources needed to take protective measures; and socioeconomically differentiated risk responses. Specific differences in the resources necessary to undertake protective measures may also influence the distribution of protective measure adoption. With regard to flooding, homeownership often facilitates or is a prerequisite for many protective measures, as in most cases renters are not permitted to make structural modifications to protect their homes from flooding (Lindell and Hwang 2008).

**Exposure and Experience**

Two factors that often promote risk perception and protective measures are exposure to and experience of hazards. Exposure is the extent to which a given person or group is in a location or condition in which a hazard tends to occur, and hence more or less likely to experience a given hazard (IPCC 2012). A person who works in daily face-to-face contact with many other people in the absence of facemasks may face higher exposure to the risk of contracting COVID-19 pathogen than someone who is able to maintain physical distance and masking. Someone living in a low-lying area near a river or ocean may face greater exposure to floods than someone whose home is on higher ground. We expect exposure to be positively correlated with both concern and protective measures.

Direct experience mediates the effect of exposure. Past experience of harm from a hazard is a strong predictor of both concern about hazards and taking protective measures (Bubeck et al. 2012; Gotham et al. 2017; Haney 2019; Ludy and Kondolf 2012; Meyer et al. 2018; Thistlethwaite et al. 2018). These effects may work through the emotional residues a disaster leaves and spur protective measures. Those who have not experienced a hazard may fail to anticipate the emotional impacts that could accompany the experience (Siegrist and Gutscher 2008).

Nonetheless, experience of a hazard does not always yield an active response. People who make it through an event without great harm may decide that it was not that bad, resulting in reduced concern (Meyer and Kunreuther 2017), while limited resources and self-efficacy, as well as local norms and ways of living can prevent hazard experience from translating into concern or protective measures. As Buringham et al. (2008) asserted, “the problem is how to raise awareness without people having to go through the trauma of an actual event” (p. 233).

Experience and exposure are both conditioned by many factors. In the United States, racially marginalized and lower income people face disproportionate exposure to COVID-19 because of weak health care access, greater employment in occupations considered essential or less conducive to remote work, and accumulated health hazards in their living environments, among other factors (Wrigley-Field et al. 2020). The situation is somewhat more complicated for flooding. On one hand, risk of flooding and histories of riverside land use tend to concentrate socioeconomically disadvantaged people in floodplains (Hardy, Milligan, and Heynen 2017; Liévanos 2020; Lu 2017; Qiang 2019). On the other hand, the cachet of riverside and coastal locations has concentrated wealth at the waterside in many places, both historically and as sites of contemporary gentrification (Gould and Lewis 2017).

Varying patterns of experience and exposure reflect in part the differing stakes of COVID-19, a health hazard, and flooding, which threatens homes, possessions, infrastructure, and personal safety. Recognizing that COVID-19 presents a novel hazard, we operationalize experience as recent severe respiratory illness, which measures experience of a hazard similar to COVID-19.

**Partisan Polarization and Responses to Hazards**

Among attributes that differ across hazards, partisan polarization has become increasingly prominent (McCright and Dunlap 2011; Zanocco et al. 2019). Partisan polarization has been central to public and scholarly discussions surrounding both climate change and COVID-19 (Bolin and Hamilton 2018; Gadarian et al. 2021; Shepherd et al. 2020). Conservative organizations allied with fossil fuel firms have inundated public discourse in the United States with positions doubting the existence and consequences of anthropogenic climate change, while concern about climate change has become steadily more pronounced among political
liberals (Brulle, Carmichael, and Jenkins 2012; Farrell 2016; McCright and Dunlap 2011; Oreskes and Conway 2010). Over time the predominant conservative narrative has shifted from asserting that climate change is not happening to arguing that although it may be happening, the causes are natural (Dunlap, McCright, and Yarosh 2016). Several studies have found interactive effects of partisanship and education surrounding views on climate change: among people who identify as Democrats, increased education brings greater belief in and support for policies targeting climate change, while among Republicans, increased education decreases climate change belief and policy support (Drummond and Fischhoff 2017; Hamilton 2008, 2011; Hamilton et al. 2015; Kahan 2015; McCright and Dunlap 2011). One key mechanism explaining this pattern appears to be selective acquisition of information to confirm one’s own predispositions, resulting in “reinforcing spirals” of self-confirmation (Feldman et al. 2014; Slater 2007; Zhao 2009). Political orientation and education predict media selection, which in turn predicts beliefs about climate change (Bolin and Hamilton 2018).

However, climate polarization may not be immutable. In communities that had experienced wildfire, landslide, flood, tornado, or hurricanes, researchers found that experience of climate-related hazards mediates the effect of partisanship (Zanocco et al. 2019). Among people who had directly experienced a climate-related hazard, the negative effect of conservative ideology on support for climate policy was significantly smaller (see also Javeline, Kijewski-Correa, and Chesler 2019). These findings highlight the importance of direct experience of acute impacts, contrasting with studies that have not found such effects in the contexts of droughts and hot summers (Palm, Lewis, and Feng 2017). Given the links of flooding with climate change, we might expect views around flooding to show similar partisan patterns. One key question is what role partisanship plays in risk perception and adoption of protective measures. The answer may depend on how closely respondents associate flooding with climate change. In a study of people who had recently experienced a major flood in Calgary, researchers observed that participants viewed flooding as causally distinct from global climate change and avoided questions attempting to link the two. If flood risk is not framed in terms of climate change, partisan views might not dominate responses to questions about flood risk (Milnes and Haney 2017).

Partisan divides pertaining to COVID-19 appear similarly entrenched. Among U.S. residents, conservative relative to liberal beliefs and Republican relative to Democratic and other party identifications strongly predict lower levels of concern and protective measures (Cowan et al. 2021; Gadarian et al. 2021; Qin et al. 2021; Shepherd et al. 2020). Polarization developed over time, in response to elite cues as former U.S. president Donald Trump questioned scientific findings and public health responses to the pandemic (Hamilton and Safford 2021). These effects may work at a finer level of political identification than party affiliation. Shepherd et al. (2020) found, for example, that approval of Donald Trump accounts for beliefs concerning COVID-19 above and beyond party affiliation and health vulnerabilities. If cues from the former president are the key mechanism, we might expect them to be transmitted by selective media consumption, as Bolin and Hamilton (2018) found with respect to climate change. However, a study of nationally representative survey data found that consumption of right-wing media did not explain effects of party identification on health behaviors and policy preferences (Gadarian et al. 2021). Finally, it might be the case that as with climate-linked hazards and climate policy preferences, partisan differences around COVID-19 might be muted among people who had recently experienced severe respiratory illnesses.

**Hypotheses**

The varying attributes of hazards feed into social processes generating patterns of concern and protective measures. Differing stakes, immediacy, dread, and polarization affect concern and protective measures directly and through differential exposure and experience. On the basis of these observations, we venture several hypotheses regarding predictors of concern and protective measures across flooding and COVID-19. First, if we posit that concern and protective measures draw from an individual’s general orientation toward risk, we would expect that, controlling for exposure and experience, responses to each hazard would show a similar pattern of correlates. We expect that the effects of exposure and experience will be positively associated with both risk perception and protective measures for each hazard.

**Hypothesis 0a:** Measures of hazard exposure will be positively correlated with perception and protective measures for both flooding and COVID-19.

**Hypothesis 0b:** Measures of hazard experience will be positively correlated with perception and protective measures for both flooding and COVID-19.

Because COVID-19 presents greater stakes, immediacy, and dread than flooding, we expect respondents to be more likely to report concern about and protective measures against COVID-19 than flooding.

**Hypothesis 1:** Respondents will report more concern about and protective measures against COVID-19 than against flooding.

Race, gender, and marital status signify socialization processes and affordances related to social and family roles that influence how people respond to potential hazards, while economic resources shape how people evaluate the costs of protective measures. We expect individuals with higher incomes and who identify as white to be able to take more protective measures against both forms of risk. In the case of
floods, homeownership is necessary to undertake measures that involve modifications of built structures.

Hypothesis 2a: Individuals who report higher incomes will take more protective measures against both risks.
Hypothesis 2b: Individuals who identify as white will take more protective measures against both risks.
Hypothesis 2c: Homeownership will show a positive correlation with protective measures for flooding.

Finally, we offer several hypotheses surrounding partisan polarization. Conservative politics as indicated by Republican party identification may be negatively associated with perception and protective measures for both hazards. If conservative respondents dissociate flooding from climate change, the effect of party identification may only manifest for COVID-19. An additional measure of political orientation, media consumption, may explain the effect of party identification. Finally, experience of a hazard may offset the effect of conservative political inclination.

Hypothesis 3a: For both risks, Democrats will express greater concern and take more protective measures than Republicans.
Hypothesis 3b: Consumption of conservative media will moderate the effect of party identification.
Hypothesis 3c: Experience of a hazard will moderate the effect of political orientation.

Risk perceptions and decisions to adopt protective measures are not only internal psychological processes; they are socially situated. Hence, in our analyses we highlight demographic and socioeconomic attributes that reflect social positions and relationships that shape how people approach risk evaluation.

**Setting and Methods**

**Setting**

This project emerged out of a study of flood risk perception and response in the Hudson River valley in the northeastern United States. An estuarine system, the Hudson River experiences ocean tides and sea level rise extending north of Albany, New York. Flooding has long affected low-lying communities along the river (National Weather Service 2021). Rising water levels and increasingly frequent extreme precipitation events aggravate flood risk.

This study took place in two municipalities with recent and historical flood experience. Troy is a deindustrialized city northeast of Albany with a demographically diverse population of more than 50,000. Some areas of the city have experienced White flight and disinvestment, while other areas are undergoing gentrification. Troy has a long history of flooding, from both the Hudson riverfront and streams that run through the city into the river. A seawall that has protected Troy’s downtown was damaged by Hurricane Irene in 2011, and upgrades to the seawall were completed in 2020. Other parts of the city remain exposed to nuisance and severe flooding.

Kingston has a population half the size of Troy, with a similar racial demography. Rondout Creek, a Hudson River tributary running through on the south side of the city, is a major source of inundations. Kingston experienced serious flooding from Hurricane Irene, which local officials viewed as a wake-up call. As flooding alongside its waterfront has become a regular occurrence every few years, the city has undertaken a variety of projects to address flood risk. These efforts proceed amid concerns about gentrification as a brisk property market erodes housing affordability.

Kingston and Troy were chosen as case studies because of their histories of flooding, risk of future floods, and active efforts to adapt to increased flood risk. Aiming to understand flood concern, private adaptation measures, insurance take-up, and perception of public resilience projects, we designed a questionnaire survey in Spring 2020. As COVID-19 swept across the country, we realized that health risks from the virus as well as the social and economic impacts of the pandemic would influence how respondents answered questions about other hazards. We changed course and redesigned the survey instrument to ask parallel questions about flooding and COVID-19.

**Data**

We worked with the Cornell University Survey Research Institute to design and implement a mail survey of households in Troy and Kingston. The mail survey allowed us to link each questionnaire to an address, enabling us to directly assess measures of flood exposure with greater precision than would be possible an online survey. The questionnaire contained 52 items including question sets regarding views on the respondent’s neighborhood, concern and protective measures surrounding COVID-19, concern and protective measures surrounding flooding, news media consumption, and individual and household attributes (see supplementary materials).

Questionnaires were mailed to 3,750 addresses in a sampling frame maintained by the survey administration organization. The stratified random sample aimed for similarly sized samples in each city, and in both cities the probability of inclusion was higher for households in Census blocks with some or all of their area within the boundaries of zones defined by the Federal Emergency Management Administration as having 1 percent or 0.2 percent annual flood risk. These zones define high and moderate risk areas subject to specific requirements in federal, state, and local flood management policies (FEMA 2018). The questionnaire was mailed in May 2020 and again in July and in August to nonresponding households, with one postcard reminder in
between. By September few or no responses arrived each week, and collection discontinued. We received 499 responses,² with 1 refusal and 362 undeliverable because of bad addresses,³ yielding a response rate of 14.7 percent. In analyses below, we exclude one case with a “don’t know” value for homeownership and one case that was an outlier with excessive leverage.

This study was conducted under a protocol approved by the institutional review board at Cornell University. Each questionnaire began with an informed consent statement and researcher contacts. The raw data set included addresses to which questionnaires were mailed, which were used to obtain flood exposure measures (see the following discussion), then removed from the data set before analysis. All data were stored in a secure server only accessible by members of the research team.

Variables

Outcomes. Concern: Respondents were asked to rate their level of agreement with the following statements: “I am very worried about the possibility of myself or someone in my household getting infected by Coronavirus” and “I am very worried about the possibility of my home being flooded in the future.” Responses were coded on a Likert-type scale: 1 = strongly disagree, 2 = somewhat disagree, 3 = neither agree nor disagree, 4 = somewhat agree, 5 = strongly agree.

Protective measures: To evaluate protective measures taken, for both hazards, we presented respondents with a list of actions they might take to mitigate risk for harm (see Table 1). Each response was coded as a binary variable, with “yes” coded 1 and “no” coded 0. For the set of protective measures for COVID-19 and the set of protective measures for flooding respectively, we created an index using the first component from a polychoric principal-components analysis, a data reduction technique applicable to discrete variables (Kolenikov and Angeles 2009).

Main Predictors

Experience. Flood experience: Respondents were asked whether in the past their homes had faced several types of flooding impacts, such as basement flooding and private property damage. We created an index again using polychoric principal-components analysis.

Prior respiratory illness: For COVID-19, we measure experience of severe respiratory illnesses. This is a binary response to the question

Within the past two years, have you been ill from a respiratory illness such as the seasonal flu or a cold to the point where you had to take at least a few days off from work or other daily activities?

Exposure. Flood Factor: Flood Factor (First Street Foundation 2020) is a tool that estimates a property’s risk for

Table 1. Actions.

| Flooding |
| --- |
| I pay attention to storm flood warnings. |
| I have attended information sessions about flooding. |
| I have learned where the circuit breaker panel is in order to turn off all electricity in my home. |
| I have informed myself about flood insurance. |
| I have planned what to do in case of flooding. |
| I have an emergency kit (e.g., radio with batteries, food, water). |
| I store important documents where I can find them quickly (e.g., identity card). |
| I moved valued items to upper rooms/out of the basement. |
| I store sandbags. |
| I bought protective barriers for the windows, doors, or basement openings of this home. |
| I have made other adaptations or modifications in the structure of my home or property to reduce flood risk. |
| My furnace is in a flood safe location. |
| I have a sump pump. |
| I moved to a less risky house or apartment because of the probability of being affected by floods. |
| I have a plan for making sure any pet I own is safe in the event of a flood. |

| COVID-19 |
| --- |
| I wash my hands or use hand sanitizer more often. |
| I wear a face mask when going outside of my home. |
| I avoid social interaction with people outside of my household. |
| I shop for food less often. |

²There are 279 responses from Kingston and 220 responses from Troy.
³Because of the high rate of undeliverable mailings, we requested the survey provider to make a third mailing, which obtained 12 additional responses. It is possible that problems affecting U.S. Postal Service operations during summer 2020 affected survey delivery.
flooding using data on precipitation, topography, infrastructure, past flood events, and climate change. Using the Flood Factor Web site, we obtained the Flood Factor score for the address to which each questionnaire was sent. Scores range from 1 to 10. Higher scores indicate greater likelihood of flooding.

Risk condition: Having a health condition associated with COVID-19 infection heightens one’s exposure to the risk of contracting COVID-19. To evaluate risk condition, we use the response to the question “Do you or anyone in your household have a health condition that puts you at higher risk for experiencing severe impacts from Coronavirus?”?

Party: Respondents indicated their party affiliations as Republican, Democrat, independent, or other. Our analysis includes binary indicators of identification as Republican and as independent or other.

Media consumption: For each of the following sources, respondents indicated whether they used the source daily, several times a week, occasionally, or never: local TV news, public radio, conservative talk radio, CNN, Fox News, MSNBC, the New York Times, USA Today, and local newspapers. Responses informed a polychoric principal-components analysis, the first component of which we used as an index. Post hoc comparisons show that higher values correspond with consumption of conservative media and lower values with liberal media.

Controls. Age: Respondents were asked their year of birth. We subtracted the response from 2020 to calculate the respondent’s age.

Woman: This is a binary variable with a value of 1 if the respondent identified as a woman or female and 0 otherwise.

Marital status: Marital status includes five categories (single, married, cohabiting, divorced or separated, widowed), converted to dichotomous variables in regression models, with married as reference category.

White: The question “What best describes your racial or ethnic identity?” was followed by the response options “White or Caucasian”; “Black or African-American”; “Hispanic, Latino, or Spanish origin”; “Asian”; “Native American or Alaska Native”; “Middle Eastern or North African”; “Native Hawaiian or Other Pacific Islander”; and “Other”; multiple categories were allowed. More than four fifths of respondents (85.6 percent) chose only white or Caucasian, and respondents are coded 1 if they identified as white only and 0 otherwise.

Education: We measure education with a binary variable with a value of 1 if the respondent reported having attained a bachelor’s degree or beyond and 0 otherwise.

Income: Respondents were asked to report annual household income before taxes by choosing from categories including less than $10,000, $10,000 to $29,999, corresponding $20,000 increments up to $169,999, and $170,000 or more. In analyses we treat this ordinal variable as interval-ratio.

Homeownership: We asked respondents if their homes were rented, owned by someone in the household, or otherwise. This variable is coded 1 for homeowners, 0 for all others.

Time in residence: This variable is the number of years the respondent has lived at their current residence. A longer time in a given residence affords a longer period to observe natural hazards in the home and neighborhood. This variable often correlates positively with hazard experience, risk perception, and protective measures (Lindell and Hwang 2008).

City: We include a binary variable indicating whether the respondent was located in Troy (0) or Kingston (1).

Survey return date: To account for changing situations surrounding the COVID-19 pandemic, we include a count of the number of days between receipt of the first questionnaire returned and the date the respondent’s questionnaire arrived.

Analyses

To estimate descriptive statistics and bivariate tabulations, we calculated survey weights to address unequal sampling proportions across cities and flood zone status and to adjust for nonresponse. As descriptive statistics show (Table 2), unweighted means, weighted means, and means estimated for imputed data sets were similar.

Our core analyses are cumulative odds ordered logistic regression models (Long 2014) predicting concern regarding flooding and COVID-19 respectively and ordinary least squares regression models predicting protective measure indices for flooding and for COVID-19. All use multiply imputed data. Each set of models uses a parallel set of predictors. For each outcome, we include corresponding measures of experience and exposure: Flood Factor score and flood experience for flooding, recent respiratory illness and known risk factor for COVID-19. We include indicators of age, gender, marital status, race, education, income, homeownership, time in residence, city, and the date the survey was returned. A second model introduces party identification, and a third includes the media consumption index. For COVID-19 outcomes, we present a fourth model with an interaction of risk condition and party. Because party does not have significant effects in models predicting flood outcomes, we do not examine the interaction for these outcomes.

As is common in respondent-completed surveys, missing data presented a challenge. Although no variable was missing for more than 10 percent of observations, more than 24.6 percent of the sample (123 of 499) was missing data on at least one variable. We performed multiple imputation in Stata 17 using a chained equations algorithm, appropriate for data including continuous and categorical variables with a non-monotonic missing data structure. To strengthen the imputation process, in addition to the variables described above, we also included household size and indicators of employment and retirement status. The models presented use 20 imputed data sets generated with a
burn-in of 50 iterations. The burn-in allows an adequate number of iterations to ensure convergence. We also conducted analyses using listwise deletion, obtaining substantively identical results (see supplementary materials).

Given the advantages of multiple imputation in countering parameter biases present with listwise deletion and other approaches to missing data (Allison 2001), we present the imputation-based models. Considering the unreliable effects of survey weights on regression estimates (Bollen et al. 2016; Gelman 2007; Solon, Haider, and Wooldridge 2015), we do not present regression models incorporating survey weights.

### Results

As expected, overall rates of concern with regard to COVID-19 were much higher than with regard to flooding (Figure 1). About two thirds of respondents somewhat or strongly agreed that they are very worried about coronavirus infection; a similar proportion somewhat or strongly disagreed that they are very worried about their home being flooded. Furthermore, most respondents reported few flood-related protective measures, while approximately 60 percent reported taking all four measures listed for protecting oneself from COVID-19.

Although overall levels of concern vary markedly, concern regarding flooding and COVID-19 did covary. A linear regression of flooding concern on COVID-19 concern yields a coefficient of 0.148; the pairwise correlation using unimputed data is 0.160. Both are significant at \( p < .001 \). This modest correlation suggests that there might be a common process underlying the propensity to worry about each hazard. In contrast, protective measures indices are not correlated across the two hazards.

### Table 2. Descriptive Statistics.

| Variable                          | Unweighted | Weighted | Imputed |
|----------------------------------|------------|----------|---------|
|                                  | Mean or Percentage | SD | n | Mean or Percentage | SD | n | Mean or Percentage | SE | n | Imputations |
| Flooding concern                 | 2.011 | 1.127 | 376 | 2.015 | .073 | 376 | 1.995 | .051 | 498 | 20 |
| COVID concern                    | 3.721 | 1.133 | 376 | 3.662 | .080 | 376 | 3.730 | .051 | 498 | 20 |
| Flooding protective measures     | .084 | 1.292 | 376 | -.059 | .089 | 376 | -.004 | .059 | 498 | 20 |
| COVID protective measures        | .015 | .809 | 376 | -.006 | .056 | 376 | -.005 | .039 | 498 | 20 |
| Flood Factor                     | 2.715 | 2.840 | 376 | 2.375 | 1.24 | 376 | 2.596 | .123 | 498 | 20 |
| Flood impact index               | .012 | .964 | 376 | -.021 | .042 | 376 | .003 | .032 | 498 | 20 |
| Risk condition                   | 46.3% | 376 | 40.4% | 376 | 45.4% | 376 | 33.6% | 376 | 498 | 20 |
| Respiratory illness              | 34.3% | 376 | 37.4% | 376 | 45.4% | 376 | 33.6% | 376 | 498 | 20 |
| Age (years)                      | 56.976 | 16.824 | 376 | 53.397 | 1.172 | 376 | 58.521 | .753 | 498 | 20 |
| Gender (woman = 1)               | 58.8% | 376 | 59.1% | 376 | 57.8% | 376 | 52.7% | 376 | 498 | 20 |
| Marital status                   | 376 | 376 | 498 | 20 |
| Single                           | 23.7% | 376 | 28.1% | 376 | 23.2% | 376 | 23.2% | 376 | 498 | 20 |
| Married                          | 39.6% | 376 | 32.4% | 376 | 39.1% | 376 | 39.1% | 376 | 498 | 20 |
| Cohabitating                     | 42.5% | 376 | 14.5% | 376 | 11.2% | 376 | 11.2% | 376 | 498 | 20 |
| Divorced or separated            | 13.3% | 376 | 14.8% | 376 | 14.5% | 376 | 14.5% | 376 | 498 | 20 |
| Widowed                          | 10.9% | 376 | 10.3% | 376 | 12.0% | 376 | 12.0% | 376 | 498 | 20 |
| Race (white = 1)                 | 85.6% | 376 | 83.1% | 376 | 84.4% | 376 | 84.4% | 376 | 498 | 20 |
| Education (bachelor’s degree or higher = 1) | 56.1% | 376 | 53.8% | 376 | 52.7% | 376 | 52.7% | 376 | 498 | 20 |
| Income                           | 4.840 | 2.427 | 376 | 4.462 | 1.146 | 376 | 4.620 | .109 | 498 | 20 |
| Homeownership (own = 1)          | 63.0% | 376 | 42.8% | 376 | 62.6% | 376 | 62.6% | 376 | 498 | 20 |
| Time in residence                | 14.492 | 15.815 | 376 | 11.471 | .719 | 376 | 16.105 | .753 | 498 | 20 |
| City (Kingston = 1)              | 53.5% | 376 | 47.4% | 376 | 55.8% | 376 | 55.8% | 376 | 498 | 20 |
| Survey return date               | 28.471 | 16.783 | 376 | 29.395 | 1.359 | 376 | 28.620 | .781 | 498 | 20 |
| Party                            | 376 | 376 | 498 | 20 |
| Democratic                       | 47.6% | 376 | 51.0% | 376 | 46.7% | 376 | 46.7% | 376 | 498 | 20 |
| Independent/other                | 38.8% | 376 | 37.8% | 376 | 40.3% | 376 | 40.3% | 376 | 498 | 20 |
| Republican                       | 13.6% | 376 | 11.2% | 376 | 13.0% | 376 | 13.0% | 376 | 498 | 20 |
| Media consumption                | -.030 | 1.282 | 376 | .022 | .083 | 376 | -.019 | .058 | 498 | 20 |

Note: We include descriptive statistics for imputed data for reference. However, the purpose of data imputation is to generate efficient and unbiased regression parameters (Allison 2001), and it is not well suited for estimating population means and proportions.
To evaluate whether findings in these communities are consistent with national patterns of climate change polarization, we tabulate reported views on climate change by party identification (Figure 2). The vast majority of people identifying as Democrats indicated that climate change is real and caused by humans. Among people who identify as independent or other party, about three quarters chose the same category. In contrast, among Republicans only one fifth identified climate change as anthropogenic. About half indicated a belief that climate change is happening because of natural causes. More than 10 percent indicated no opinion. Polarization is present, but, consistent with recent trends among conservatives, the divide is less over whether climate is changing than around its causes.

Regressions

Our first set of models examines correlates of flood concern (Table 3). As expected, both greater exposure to and experience with flooding are associated with increased odds of higher concern. Across all three models, a one-unit increase in the Flood Factor score of one’s home raises odds of concern by 12 percent, while a one-unit increase in flood experience more than doubles those odds. Identifying as white reduces odds of concern by more than 60 percent. People who had lived in their current residences for a longer time are also less likely to express concern about flooding. Party identification and media consumption do not show significant effects on concern about flooding.

Predictors of concern regarding COVID-19 differ from those for flooding (Table 4). Although reporting a known risk condition more than doubles odds of COVID-19 concern, reporting a recent severe respiratory illness does not have a significant effect. Each year of age brings 2 percent greater odds of higher COVID-19 concern. In the base model, respondents who are divorced or separated have significantly lower odds of COVID-19 concern than married respondents, but the effect of marital status diminishes in models including party identification. Model 2 shows that Republican identification reduces odds of COVID-19 concern by more than half relative to identifying as a Democrat, but with the inclusion of the media consumption index in model 3, the effect of Republican relative to Democratic identification on COVID-19 concern becomes nonsignificant. In model 3, for every unit increase in conservative media consumption, there is a corresponding 30 percent drop in odds of COVID-19 concern. In model 4, relative to Democrats without risk conditions, Republicans with no risk conditions are significantly less likely to show high COVID-19 concern, while both Democrats and independents with risk conditions are more likely to express COVID-19 concern. Republicans with risk conditions do not report significantly different levels of COVID-19 concern from Democrats without one (Figure 3).

In models predicting protective measures for flooding (Table 5), exposure to flooding does not show a significant effect, but the effect of having experienced flooding impacts is significant and positive. Age has a significant negative
effect on protective measures for flooding, although the effect of age loses significance when media consumption is included. In contrast to results in the models predicting flooding concern, White respondents reported significantly more protective measures for flooding, as did homeowners. People who completed the survey later reported more flood preparedness measures. Although we included this variable anticipating an effect of time passage on COVID-19 indicators, it appears that when an additional mailing was sent, people more attuned to flooding responded. In separate analyses excluding these cases, the effect disappears. Party identification and media consumption show no significant effects.

As in models predicting COVID-19 concern, having a known risk condition correlates positively with protective measures against the coronavirus, while having recently experienced a severe respiratory condition does not show a significant effect on COVID-19 protective measures (Table 6). Identifying as a woman also shows a positive relationship with COVID-19 protective measures. In the base model, having a bachelor’s degree or greater is positively associated with COVID-19 protective measures, but this effect of education diminishes in models including party affiliation. The date of the survey is negatively related to COVID-19 protective measures, but just shy of 95 percent confidence in each model. In model 2, Republican identification has a significant negative effect on COVID-19 protective measures relative to being a Democrat. However, in model 3, the media consumption index explains away much of the effect of party on COVID-19 protective measures. Finally, in the last model, relative to Democrats without risk conditions, Democrats with known risk conditions report more protective measures against COVID-19, while Republicans reporting no risk condition also tend to report fewer COVID-19 protective measures. Republicans with risk conditions do not differ significantly from Democrats without risk conditions (Figure 4).

**Discussion**

Our findings show contrasting predictors of risk response, both across COVID-19 and flooding and across risk perception and protective measures pertaining to each hazard. Regarding hypotheses 0a and 0b, we find some support for expected effects of exposure and experience. For flooding, exposure has a significant positive effect on concern but not on protective measures, while experience of flood impacts has a stronger, significant effect on both outcomes. This finding is consistent with research showing the role of direct experience in motivating concern and protective measures (Bubeck et al. 2012; Gotham et al. 2017; Meyer et al. 2018; Thistlethwaite et al. 2018). For COVID-19, experience, measured as recent severe respiratory illness, has a significant effect on concern but not protective measures, while exposure, measured as having a known risk condition, correlates positively with protective measures against the coronavirus.
condition for COVID-19, has a stronger, significant effect on both outcomes. The distinction between exposure and experience in these measures is less clear cut than for the flooding measures. Further exploring relationships between experience and exposure in COVID-19 response will be crucial to targeting public health efforts.

In assessing flooding, we note several differences in the variables that predict concern as opposed to protective measures. The positive relationship between homeownership and flood protection measures is consistent with the much existing research (Bubeck et al. 2012) and with hypothesis 2c, most likely because homeowners have greater agency in taking measures like moving appliances or modifying a built structure. Longer time in residence is linked to reduced concern about flooding but is not correlated with protective measures. This effect may involve endogeneity; people who have experienced flooding damage may be less likely to stay a long time. Meanwhile, people who have lived in a home for a long time may have experienced floods but without substantial damage.

Regarding hypothesis 2a, the effect of income is nonsignificant across models. However, the contrasting relationships of race with concern and protective measures for flooding are striking. Nonwhite respondents are more likely to worry about flooding than respondents who identify as white, consistent with past findings (Lindell and Hwang 2008; Lindell and Perry 2004). Meanwhile, white respondents are more likely than nonwhite respondents to take protective measures, supporting hypothesis 2b. These effects are net of income, education, and homeownership. Racial inequities in exposure and vulnerability to flooding and other hazards are well documented (Bullard and Wright 2009; Fothergill et al. 1999; Liévanos 2020). The negative effect of nonwhite identification on protective measures indicates that racialized barriers are operating above and beyond effects of other aspects of inequality. Flood risk managers should

| Table 3. Ordinal Logistic Regression Models Predicting Flooding Concern. |
|-------------------------|-------------------------|-------------------------|
|                         | Model 1          | Model 2          | Model 3          |
|                         | OR   | SE   | OR   | SE   | OR   | SE   |
| Flood Factor           | 1.123*** | .038  | 1.122*** | .038  | 1.122*** | .038  |
| Flood experience       | 2.283*** | .310  | 2.300*** | .314  | 2.301*** | .315  |
| Age                    | 1.001  | .008  | 1.001  | .008  | 1.001  | .008  |
| Woman                  | 1.340  | .249  | 1.333  | .249  | 1.333  | .249  |
| Marital status         |       |      |       |      |       |      |
| Married (reference)    |       |      |       |      |       |      |
| Single                 | 1.360  | .374  | 1.373  | .378  | 1.374  | .378  |
| Cohabiting             | .982   | .319  | .967   | .315  | .967   | .315  |
| Divorced or separated  | 1.212  | .373  | 1.222  | .377  | 1.222  | .376  |
| Widowed                | 1.477  | .521  | 1.470  | .518  | 1.470  | .519  |
| White                  | .377*** | .098  | .377*** | .098  | .378*** | .099  |
| Bachelor’s degree or higher | .732   | .154  | .725   | .157  | .726   | .163  |
| Income                 | .990   | .051  | .993   | .051  | .993   | .051  |
| Own home               | .799   | .190  | .793   | .190  | .793   | .190  |
| Time in residence      | .980*  | .007  | .980*  | .008  | .980*  | .008  |
| City (Kingston)        | .847   | .160  | .858   | .164  | .858   | .165  |
| Date of survey         | .998   | .005  | .998   | .005  | .998   | .005  |
| Party                  |       |      |       |      |       |      |
| Democratic (reference) |       |      |       |      |       |      |
| Independent/other      | 1.041  | .221  | 1.041  | .231  |
| Republican             | .851   | .273  | .850   | .315  |
| Media consumption index|       |      |       |      |       |      |
| Imputations            | 20    |      | 20    |      | 20    |      |
| n                      | 497   |      | 497   |      | 497   |      |
| Average RVI            | .1024  |      | .1152  |      | .1208  |      |
| Largest FMI            | .1837  |      | .1933  |      | .2555  |      |
| F                      | 5.86   |      | 5.11   |      | 4.80   |      |
| df                     | 15, 27267.0 |      | 17, 25176.6 |      | 18, 24494.6 |      |
| Probability > F        | <.0001 |      | <.0001 |      | <.0001 |      |

Note: FMI = fraction of missing information; OR = odds ratio; RVI = relative variance increased.
*p < .05. **p < .01. ***p < .001.
target policy and outreach in ways that start with the needs and concerns of communities of color.

In assessing predictors of concern and protective measures for COVID-19, we find that age has a significant, positive correlation with concern across models, but not with protective measures. Education has a positive relationship with protective measures until political views are controlled, perhaps because political views moderate the effect of education, as has been found in other politically polarized issue domains (Hamilton 2011). Additionally, respondents who identify as women report significantly more protective measures than others. Many studies of environmental action find that women are more likely than men to engage in proenvironmental behaviors, often because of caregiving and provisioning activities (Kennedy and Dzialo 2015). In particular, women’s involvement in shopping and as guardians of household members’ health often converge to saddle them with the task of ensuring the safety of the products a household consumes (MacKendrick 2018). The significant gender effect for COVID-19 protective measures may reflect related gendered roles in care for the health of family members. Other than gender, measures of inequality largely fail to predict concern about or response to COVID-19.

### Table 4. Ordinal Logistic Regression Models Predicting COVID-19 Concern.

|                        | Model 1 | Model 2 | Model 3 | Model 4 |
|------------------------|---------|---------|---------|---------|
|                        | OR      | SE      | OR      | SE      |
| Risk condition         | 2.552***| .473    | 2.540***| .473    |
| Prior respiratory illness| 1.424   | .269    | 1.457b  | .276    |
| Age                    | 1.020** | .007    | 1.019b  | .007    |
| Woman                  | 1.372   | .241    | 1.308    | .231    |
| Marital status         |         |         |         |         |
| Married (reference)    | .651    | .168    | .642    | .167    |
| Cohabitating           | .948    | .299    | .936    | .297    |
| Divorced or separated  | .563*   | .158    | .591    | .166    |
| Widowed                | .670    | .217    | .671    | .219    |
| White                  | .898    | .219    | .946    | .233    |
| Bachelor’s degree or higher| 1.305   | .262    | 1.214    | .246    |
| Income                 | 1.039   | .051    | 1.046    | .052    |
| Own home               | .772    | .174    | .771    | .175    |
| Time in residence      | .990    | .007    | .992    | .007    |
| City (Kingston)        | 1.096   | .188    | 1.130    | .196    |
| Date of survey         | 1.007   | .005    | 1.007    | .005    |
| Party                  |         |         |         |         |
| Democratic (reference) |         |         |         |         |
| Independent/other      | .803    | .156    | .991    | .199    |
| Republican             | .441**  | .123    | .768    | .238    |
| Media consumption index|         |         | .701*** | .059    |
| Party and risk condition|       |         |         |         |
| Democratic + no risk condition (reference) |         |         |         |         |
| Democratic + risk condition | 2.362** |
| Independent/other + no risk condition | .783    | .204    |
| Independent/other + risk condition | 1.935*  | .567    |
| Republican + no risk condition | .365**  | .137    |
| Republican + risk condition | 1.292   | .526    |

| Imputations | 20 | 20 | 20 | 20 |
| n           | 497 | 497 | 497 | 497 |
| Average RVI | .0293 | .0349 | .0333 | .0365 |
| Largest FMI | .0904 | .0949 | .0951 | .0965 |
| F           | 3.98 | 3.97 | 4.63 | 3.59 |
| df          | 15, 252,191.8 | 17, 207,622.2 | 18, 246,185.6 | 19, 218,165.3 |
| Probability > F | <.0001 | <.0001 | <.0001 | <.0001 |

Note: FMI = fraction of missing information; OR = odds ratio; RVI = relative variance increased.
*p < .05. **p < .01. ***p < .01.
For both concern and protective measures relating to COVID-19, political party has a significant effect, consistent with hypothesis 3a, but media consumption accounts for much of this effect (hypothesis 3b). One explanation could be a “reinforcing spiral” of selective media consumption that intensifies partisan views (Feldman et al. 2014; Slater 2007). Evaluating this possibility would require additional modeling that is outside the scope of this study. Another possible explanation is that, by capturing a finer gradation of political views, media consumption simply provides a more precise measure of political identity.

Having a known risk condition moderates the effect of party identification on COVID-19 concern and protective measures (hypothesis 3c). Although Republicans without risk conditions report less concern and fewer protective measures than Democrats, those with risk conditions report levels of concern and protective measures that are similar to Democrats. This result parallels Zanocco et al.’s (2019) finding that direct experience of climate-linked hazards shrinks the gap between Republicans and Democrats in support for policy interventions to mitigate climate change. It suggests that, at least within the time frame of this survey, personal identification of heightened vulnerability to COVID-19 offsets the effects of partisan polarization. The practical implications are complicated. Research in risk communication stresses the challenge of conveying tangible impressions the impacts a hazard could have to people who have not yet experienced that hazard (Meyer and Kunreuther 2017). Months of news reports chronicling public health efforts surrounding COVID-19 have demonstrated the limitations of public health messaging attempting such persuasion. Similarly, the effect of direct experience on flood risk responses raises a conundrum of how to simulate the emotional impacts of flood losses for people who have not met them firsthand (Burningham et al. 2008; Siegrist and Gutscher 2008).

Partisan polarization is not evident with regard to risk for flooding. This is not to say that the population we studied has transcended polarization around climate change. Consistent with patterns found nationwide (Dunlap et al. 2016), surveyed Republicans are more likely than Democrats or independents to report a belief that changes in climate are due to natural causes. In this context, recognizing and devoting resources to responding to growing flood risk may not cause cognitive dissonance for climate skeptics. This circumstance presents potential openings for adaptation. People who may not agree on causes may still concur about the need to alleviate hazards. Researchers have shown how avoiding explicit discussion of climate change can enable coalitions working to reduce disaster risk to hold together, an approach some call “agnostic adaptation” (Koslov 2019; Prokopy et al. 2015). Although agnostic adaptation facilitates responses to climate-related hazards, it precludes efforts to mitigate greenhouse emissions that are making these hazards worse. Finally, our findings do not speak to which approaches to

Figure 3. Marginal predictions of coronavirus disease 2019 concern by party and risk condition.
adaptation, with their attendant distributions of burdens and responsibilities across different groups of people (Elliott 2019), are preferable.

### Conclusion

Risks of COVID-19 and flooding draw forth differing responses. These differences emerge from the ways the contrasting stakes, immediacy, dread, and polarization of each hazard intersect with social processes shaping risk perception and protective measures. In the contexts participants in this study faced, greater stakes, immediacy, and dread likely contributed to greater overall concern about COVID-19 than flooding. It may be unsurprising to find that the two hazards elicit different patterns of response. This study makes an additional contribution by examining how patterns of perception and protective measures differ. Social differentiation in household resources, gender roles, racial marginalization, and partisan views shapes how individuals respond to these two distinctive threats. Moreover, for each hazard the factors affecting risk perception and protective measures differ because, beyond recognizing risk and feeling concerned about it, protective measures require resources and a sense of efficacy. Several distinctions stand out. In particular, people of color are more likely to express concern about flooding, yet white people take more protective measures. Women are more likely than others to take protective measures against COVID-19. Although climate polarization does not appear to influence flood risk responses, COVID-19 responses appear strongly polarized, but having a known risk condition can offset Republicans’ doubts about COVID-19.

One challenge studies such as this one raise is that individualized analyses of risk perception have an affinity with management approaches that individualize responsibility, obscuring collective sources and responses to risk. We question the appropriateness of such management approaches in the absence of public debate about where responsibility lies and inclusive efforts to mitigate and adapt to risk at varied

### Table 5. Linear Regression Models Predicting Flooding Actions.

|                     | Model 1 |        | Model 2 |        | Model 3 |        |
|---------------------|---------|--------|---------|--------|---------|--------|
|                     | B       | SE     | B       | SE     | B       | SE     |
| Flood Factor        | .030    | .022   | .031    | .022   | .030    | .022   |
| Flood experience    | .438*** | .083   | .425*** | .083   | .430*** | .083   |
| Age                 | -.010*  | .005   | -.010*  | .005   | -.009   | .005   |
| Woman               | -.025   | .117   | -.029   | .118   | -.025   | .118   |
| Marital status      |         |        |         |        |         |        |
| Married (reference) |         |        |         |        |         |        |
| Single              | .025    | .172   | .015    | .172   | .021    | .172   |
| Cohabitating        | .004    | .208   | .035    | .209   | .026    | .208   |
| Divorced or separated| -.102  | .191   | -.108   | .191   | -.125   | .191   |
| Widowed             | .279    | .218   | .308    | .219   | .297    | .219   |
| White               | .359*   | .163   | .372*   | .164   | .391*   | .164   |
| Bachelor’s degree or higher | -.025 | .134   | -.032   | .136   | .019    | .141   |
| Income              | -.018   | .033   | -.018   | .033   | -.016   | .033   |
| Own home            | .586*** | .154   | .595*** | .155   | .603*** | .155   |
| Time in residence   | -.008   | .004   | -.008   | .005   | -.008   | .005   |
| City (Kingston)     | .024    | .121   | .002    | .121   | .024    | .122   |
| Date of survey      | .009**  | .003   | .010**  | .003   | .010**  | .003   |
| Party               |         |        |         |        |         |        |
| Democratic (reference) |       |        |         |        |         |        |
| Independent/other   | -.168   | .129   | -.215   | .134   |
| Republican          | .125    | .186   | -.001   | .208   |
| Media consumption index |     |        |         |        |         |        |
| Imputations         | 20      |        | 20      |        | 20      |        |
| n                   | 497     |        | 497     |        | 497     |        |
| Average RVI         | .0225   |        | .0248   |        | .0241   |        |
| Largest FMI         | .0992   |        | .0962   |        | .0965   |        |
| F                   | 4.95    |        | 4.55    |        | 4.41    |        |
| df                  | 15, 478.5 |      | 17, 476.4 |      | 18, 475.5 |      |
| Probability > F     | <.0001  |        | <.0001  |        | <.0001  |        |

Note: FMI = fraction of missing information; OR = odds ratio; RVI = relative variance increased.

*p < .05, **p < .01, ***p < .01.
levels. Nonetheless, examining individual perceptions and protective measures is vital to identifying patterns across individuals and groups, informing public discussions and disaster management efforts. Knowing who is more or less likely to be concerned and to act in different ways can help risk managers and policymakers target assistance and communication where they are most needed. It can provide a basis for efforts to rectify inequities that put people in harm’s way. To do so well, we must design and interpret analyses in ways that address individuals’ embeddedness in collectivities and networks.

This study’s results give us much to contemplate regarding differential responses to dissimilar hazards, but the study’s design presents several weaknesses. Given the high nonresponse rate, we advise caution in interpreting population estimates. The context of small cities in the U.S. Northeast shapes the patterns we observe. This region experienced its severest wave of COVID-19 in April 2020, earlier than many other places, while the combination of estuarine sea level rise and flash flooding along steep tributary streams contributes to a distinctive flood regime along the Hudson River. We hope researchers will ask similar questions in

| Table 6. Linear Regression Models Predicting Coronavirus Disease 2019 Actions. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
|                                 | Model 1         | Model 2         | Model 3         | Model 4         |
|                                 | B       | SE   | B       | SE   | B       | SE   | B       | SE   |
| Risk condition                  | .265** | .081 | .253** | .080 | .216** | .080 | .117 | .084 |
| Prior respiratory illness       | .115   | .084 | .118   | .084 | .113   | .083 | .117 | .084 |
| Age                             | -.001  | .003 | -.002  | .003 | -.003  | .003 | -.002 | .003 |
| Woman                           | .248** | .078 | .230** | .077 | .227** | .076 | .227** | .078 |
| Marital status                  |        |      |        |      |        |      |        |      |
| Married (reference)             |        |      |        |      |        |      |        |      |
| Single                          | .071   | .117 | .075   | .116 | .061   | .115 | .080 | .116 |
| Cohabitating                    | -.183  | .148 | -.179  | .148 | -.164  | .146 | -.183 | .149 |
| Divorced or separated           | -.015  | .136 | .003   | .136 | .032   | .136 | .003 | .136 |
| Widowed                         | -.064  | .149 | -.050  | .149 | -.042  | .147 | -.051 | .150 |
| White                           | .093   | .118 | .130   | .119 | .103   | .118 | .134 | .120 |
| Bachelor’s degree or higher     | .217*  | .095 | .174   | .096 | .084   | .100 | .173 | .096 |
| Income                          | .022   | .022 | .024   | .022 | .020   | .021 | .025 | .022 |
| Own home                        | -.024  | .103 | -.024  | .103 | -.036  | .102 | -.016 | .104 |
| Time in residence               | .000   | .003 | .001   | .003 | .001   | .003 | .001 | .003 |
| City (Kingston)                 | .140   | .076 | .141   | .076 | .102   | .076 | .139 | .076 |
| Date of survey                  | -.004  | .002 | -.004  | .002 | -.004  | .002 | -.004 | .002 |
| Party                           |        |      |        |      |        |      |        |      |
| Democrat (reference)            |        |      |        |      |        |      |        |      |
| Independent/other               | -.165  | .087 | -.087  | .090 | -.110  | .145 | -.126** | .036 |
| Republican                      | -.320* | .129 | -.110  | .145 | -.126** | .036 | -.126** | .036 |
| Media consumption index         |        |      |        |      |        |      |        |      |
| Party and risk condition         |        |      |        |      |        |      |        |      |
| Democrat + no risk condition     |        |      |        |      |        |      |        |      |
| Democrat + risk condition        |        |      |        |      |        |      |        |      |
| Independent/other + no risk condition |        |      |        |      |        |      |        |      |
| Independent/other + risk condition |        |      |        |      |        |      |        |      |
| Republican + no risk condition   |        |      |        |      |        |      |        |      |
| Republican + risk condition      |        |      |        |      |        |      |        |      |
| Imputations                     | 20     | 20   | 20     | 20   | 20     | 20   | 20     | 20   |
| n                               | 497    | 497  | 497    | 497  | 497    | 497  | 497    | 497  |
| Average RVI                     | .0714  | .0795 | .0816  | .0772 | .1806  | .1941 | .1895  | .1895 |
| Largest FMI                     | .3.46  | 3.53 | 4.07   | 3.18 | 15.474.6 | 17.472.3 | 18.471.4 | 19.471.1 |
| df                              |     |     |     |     |     |     |     |     |
| Probability > F                 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |

Note: FMI = fraction of missing information; OR = odds ratio; RVI = relative variance increased.
*p < .05. **p < .01.
Temporal variation is also important. As noted above, timing is crucial for accurately understanding relationships between risk perception and protective measures. A major theme of research on COVID-19 is that because of changing material and political conditions, findings are time sensitive. Our data were gathered early in the pandemic, at a time when unfamiliarity and unpredictability of the virus were especially pronounced, arguably augmenting dread surrounding COVID-19 relative to flooding. Meanwhile, conservative distrust of science took shape over a span of several months (Hamilton and Safford 2021). Qin et al. (2021) found that conservative views were negatively associated with change in COVID-19 risk perception between February and April 2020, after which the relationship between partisanship and risk perception stabilized. Cowan et al. (2021) found that in November 2020 demographic attributes and trust in institutions could account for patterns of vaccine hesitancy, but by February 2021, the effects of partisan polarization overwhelmed other explaining factors. Flooding presents similar challenges. Had we conducted our survey following the onslaught of Hurricane Ida in 2021, our findings would likely differ. For studying flooding, COVID-19, and other hazards, panel designs are a crucial tool.

In addition to its specific findings concerning COVID-19 and flooding, this study provides insights that may contribute to broader comparative research on COVID-19 and concurrent hazards (Botzen et al. forthcoming; Ishiwatari et al. 2020; McBride et al. 2020; Simonovic et al. 2021). By examining how risk response varies across hazards on the basis of stakes, immediacy, dread, and polarization, we contribute to efforts to understand risks not only in terms of probability and severity but also in terms of their qualitatively differing physical and social content. Furthermore, we show how these differing hazard attributes elicit differing responses across social groups. Comparative work of this sort may enable more responsive hazard management by identifying how people in different situations attune to different aspects of risk (Boudet et al. 2020). We encourage further research examining a broader array of hazards to evaluate how social responses to different risks vary.

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ORCID iD

John Aloysius Zinda https://orcid.org/0000-0002-7124-5916

Supplemental Material

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Author Biographies

John Aloysius Zinda is an assistant professor in the Department of
Global Development at Cornell University. An environmental soci-
ologist, he studies how people create, struggle over, and sometimes
resolve environmental concerns. In work on flooding, examines how
residents and local governments confront changing flood risk. Much of
his work has examined how people and landscapes in rural China
respond to developmental and environmental interventions around
new national parks, afforestation, and agricultural livelihoods.

James Zhang a recent graduate of the Environment and Sustainability
program at Cornell University. He is interested in urban response to
climate change in the housing and transportation sectors.

Lindy B. Williams is a professor emerita in the Department of Global Development at Cornell University. The majority of her
research has focused on family sociology and demographic patterns
trends in Southeast Asia, including causes and consequences of, and barriers to labor migration in Thailand and the Philippines.
Her more recent work addresses issues of flood risk, perception,
and adaptation in the Philippines and upstate New York.

David L. Kay is a faculty member and senior extension associate
with Cornell University’s Department of Global Development. He is trained as an economist, and his career has focused on socioeco-

omics and local policy in the areas of energy, land use,
community development and regional economics. His current
research and extension agenda is broadly concerned with the com-

munity and economic development implications of energy transi-
tions and climate change. As a practicing mediator and educator, he
is particularly interested in building informed decision making capacity in the context of community controversy. He has served on
numerous advisory and governing boards of municipal and New
York State not-for-profit and government organizations concerned
with sustainability, conflict transformation, and municipal land use
planning.

Sarah M. Alexander is a visiting fellow in the Department of
Global Development at Cornell University. Her work explores vari-
rnos aspects of the social worlds of water. This includes work on
the social landscape of flood risk and the impact of trust on in-home
drinking water behavior and perceptions.

Libby Zemaitis is the climate change program coordinator at the
New York State Department of Environmental Protection’s Hudson
River Estuary Program, in partnership with the Water Resources
Institute at Cornell University. Her work supports local govern-
ments in the Hudson Valley to adapt to climate change and build
resiliency through community planning, collaborative design and
state policy leadership. She leads her team to build diverse partners-
ships and fund innovation in ecological and equitable solutions.
Her previous work includes management consulting and leading start-
ups in the cleantech space. She earned her dual MBA and MS in
climate science and policy from Bard College and her BA in geol-
y from Vassar College.