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Never Waste a Crisis: How COVID-19 Lockdowns and Message Sources Affect Household Emergency Preparedness

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Abstract: Public institutions face natural and manmade hazards of increasing frequency and severity. While the costs of disasters can be greatly reduced when individuals prepare, encouraging preparation is difficult for governments given the low salience of such risks. We examine whether the increased salience of *other* types of risks can influence individual willingness to prepare, and whether message impact varies with recipients' levels of trust in their source. We capitalize upon a rare policy experiment—the staged rollout of COVID-19 lockdowns in California—to assess if increases in the salience of the pandemic were associated with greater willingness to store water for earthquake-induced system outages. We find that experiences of a disaster in a different domain (public health) and higher levels of trust in message source both increase willingness to store water. This suggests that public agencies should encourage preparedness during actual emergencies, or "not let a crisis go to waste."

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Introduction

Public institutions face natural and manmade hazards of increasing frequency and severity. Governments can help reduce the potential costs of natural and manmade disasters such as earthquakes, tornados, tsunamis, wildfires, pandemics, and cyberattacks through preparation (Comfort 2005; Drabek 2018; Hede 2017; Kapucu and Van Wart 2006; Logue 1996). For example, they can upgrade infrastructure so that it can better withstand disasters, institute regulations that reduce the number of households that will be impacted by disasters, or create electronic warning systems and evacuation plans. Similarly, governments can prepare for pandemics by requiring excess capacity in hospitals and helping procure necessary equipment. Political science research has found that while voters reward and penalize elected officials for emergency response and relief (e.g., Gasper and Reeves 2011), officials receive less credit for investments in preparedness (Healy and Malhotra 2009), which helps explain insufficient preparation efforts by government agencies.

Fortunately, governments can also reduce the potential costs of natural and manmade hazards by encouraging household preparation (Aldrich and Meyer 2015; Becker et al. 2012; L. K. Comfort, Boin, and Demchak 2010; Naderpajouh et al. 2018). Public water networks, for instance, may be offline for weeks for repairs following a major earthquake (Hudnut et al. 2018), and potentially also following cyberattacks. The extent to which households store potable water, they will be able to better cope with water service disruptions. Analogs exist in other disaster domains, such as acquiring generators or other back-up power sources for electricity outages (Chakalian, Kurtz, and Hondula 2019), cutting vegetation near homes to reduce the spread of wildfires (Cao, Boruff, and McNeill 2016), and wearing masks to mitigate the spread of COVID-19. Unfortunately, levels of household disaster preparation are typically quite low (King 2002).

How can public agencies encourage greater household preparation for natural disasters and other emergencies? Existing social science research suggests that the answers are not straightforward, with most individuals "overestimating their capacity to cope during an emergency" and anticipating reliance on government emergency aid (Levac, Toal-Sullivan, and O`Sullivan 2012, 727). Despite evidence that individual preparation contributes significantly to community resilience in the face of disasters (Buckland and Rahman 1999; Finch, Emrich, and Cutter 2010), research highlights considerable psychological barriers, especially the tendency for individuals to underestimate the likelihood of hazards. The strongest driver of risk assessments across a variety of domains is personal experience (Liberman, Trope, and Stephan 2007), yet the vast majority of the population has not experienced hazards personally. Recent national estimates for experience with any hazard fall below 1/3 of the population (Kaplan and Ba Tran 2021), and individuals report low rates of experience with natural hazards like earthquakes and wildfires in recent surveys (Al-Rousan, Rubenstein, and Wallace 2014; Lovekamp and McMahon 2011; Tkachuck, Schulenberg, and Lair 2018). As a result, most perceive hazards as remote possibilities, which diminishes individual incentives to prepare. Declining trust in political institutions and political polarization can also work against government efforts to encourage household preparation. Political scientists studying American politics have found that the source of a message often matters more for its perceived credibility than the content of the message (Citrin and Stoker 2018; Lenz 2013). In an increasingly polarized information market, individuals' willingness to prepare for disasters in response to public agency messages has become more centered around trust in the actors providing the message rather than the message itself.

In this study, we assess two strategies that may contribute significantly to government efforts to encourage emergency preparedness by the public. First, we examine whether increased cognizance of one hazard is associated with a greater willingness to prepare for *other emergencies,* a phenomenon we refer to as "transitivity." We also investigate the extent to which the effectiveness of messages encouraging preparedness varies with a respondent's reported level of trust in the institution or organization providing the preparation message.

Our data is drawn from a survey with 1,211 California residents administered in March 2020 that assessed the effect of disaster experience and trust in a message source on willingness to store water in preparation for earthquakes. As we explain in greater detail below, earthquakes constitute a prime example of a natural disaster that few individuals have experienced personally, and where rates of household preparation are low. Our survey sample was reflective of the California population, and was timed to leverage the staged rollout of COVID-19 lockdowns—i.e., various types of shelter-in-place orders that restrict household and business activities—in the state. It included both closed-form and open-ended questions, the latter of which allowed us to probe underlying mechanisms connecting experience with an actual disaster, as well trust in a message source, with reported willingness to prepare for an earthquake.

We find that experiencing a COVID-19 lockdown prior to California's statewide order is associated with a higher willingness to store water for an earthquake. In other words, the increased salience of one type of disaster is associated with an increased willingness to prepare for *other* types of disasters, at least in the period immediately following hazard onset. Our study is one of the first demonstrations of the transitivity of risk perceptions and behaviors across domains, in this case, between public health and natural hazards. We also find that higher degrees of trust in the source of a preparation message is associated with a greater willingness to store water in anticipation of an earthquake. Survey responses indicated individuals highly trust the organizations and institutions involved in emergency management, regardless of partisanship, and that college-educated households with children trust these institutions more.

In our paper, we first review research on risk perceptions and communication from political science and political behavior. We then develop hypotheses regarding the transitivity of risk perceptions across hazard domains, as well as the effects of messages from different sources. We present analyses of our experimental and observational data, and review our open-ended survey responses for insights regarding the underlying mechanisms driving our results. We conclude by discussing the implications of our findings for emergency preparedness policy and academic discussions of risk perceptions, and stress the importance of leveraging the current COVID-19 pandemic to help prepare the public for less salient hazards like natural disasters and cyberattacks.

Existing Research on Experience, Trust, and Risk Perceptions

Existing research highlights two main barriers to encouraging preparedness, both rooted in psychology. First, research indicates that individuals tend to underestimate hazard risks. While individual estimates of disaster likelihood are affected by a number of factors, such as beliefs about whether an event would affect an individual or their community (e.g. Eisenman et al. 2007; Scannell and Gifford 2013), the predominant driver of variance in risk perceptions is prior experience with a similar disaster (see Hertwig 2015). Existing research shows that disasters which individuals have not experienced are less accessible as they form risk assessments, leading them to underestimate the probability of disaster occurring (Keller, Siegrist, and Gutscher 2006). In addition, disasters may feel unlikely because individuals do not live where one has previously occurred (O'Neill et al. 2016); a disaster may also seem improbable because one has not occurred recently (Chandran and Menon 2004). More simply, lack of recency and proximity make disasters less “available” to both heuristic (e.g., associative and reflexive) and systematic thought processes (Tversky and Kahneman 1974), leading to underestimated hazard probabilities. If individuals discount disaster likelihoods, it stands to reason that they will be less likely to prepare for such disasters.

While the literature indicates that prior experience may affect individuals’ estimates of the probability of a specific disaster, it remains unclear whether this effect is transitive. Succinctly, does the experience of a disaster or emergency management measures in one domain affect risk perceptions and preparation in other domains? Some research has shown that risk perceptions may vary across different manifestations of a hazard (e.g., climate change-induced flooding versus climate change itself (Stoutenborough, Vedlitz, and Xing 2016)), but no work has yet examined whether experiencing one disaster affects perceptions of risks in entirely distinct domains. Addressing this gap in the literature, we develop a theoretical argument regarding the possibility for the “transitivity” of risk perceptions and emergency preparation in the following section.

Our study is also informed by political science and disaster preparedness literatures on public receptivity to information from different sources. Recent political science research shows that American’s trust in government has declined over the past several decades (Citrin and Stoker 2018; Hetherington 2005), which suggests that any government agency interested in encouraging preparation faces an uphill battle in public information campaigns. Moreover, increasing partisan polarization and media segmentation have contributed to a fragmented political environment in which individuals trust different organizations. This has come to the fore in the ongoing COVID-19 pandemic, where perceptions of and responses to government mandates regarding social distancing and related measures are differently received (e.g. Sibley et al. 2020), and often vary along partisan lines (see Utych 2020). Disaster management research similarly shows that the credibility of the source of public service announcements affects their effectiveness (B. F. Liu, Fraustino, and Jin 2016; B. Liu and Mehta 2017). This occurs across a variety of domains—even for less political areas like flood control (e.g. Poortinga and Pidgeon 2003; Renn and Levine 1991).

While political science research has shown general declines in trust in the government as a whole, little research has examined variation in levels of trust in specific emergency management organizations, and their implications for crafting public service announcements related to disaster preparedness, despite the issues of agency-specific trust and political environment being one of the greatest reported challenges to emergency response organizations (B. Liu and Levenshus 2010). A more granular investigation of how levels of trust in specific organizations affect the efficacy of public service announcements could inform governmental efforts to encourage preparedness, and also contribute to more effective community crisis mitigation (Aldrich 2011).

How to Increase Preparedness: Risk Transitivity and Trusted Message Sources

We extend the literatures described above to offer new propositions regarding the circumstances under which governmental efforts to encourage public preparedness may be effective. First, we propose that experiencing a disaster in one domain may affect individuals' willingness to prepare for other kinds of disasters. Building on research on schematic logics of cognition and risk perception, which suggests that individuals process information through 'mental maps' of the world around them (Crocker, Fiske, and Taylor 1984; Langford 2002), we argue that experiencing a disaster not only increases the salience of that particular hazard, but also heightens the salience of disasters more broadly through a *halo effect*. Individuals could also be expected to *learn by analogy* from local disasters and policy efforts to address them. Behaviors that individuals engage in or observe to cope with an actual disaster as it transpires can encourage individuals to consider preparation in other domains; this could be due either to updated perceived likelihoods of disasters and service outages, or becoming accustomed to preparation activities.

There are clear policy implications to this logic, if it holds. While public agencies can rarely leverage past personal experience with a specific type of emergency (e.g., tsunamis) to encourage households to prepare for future ones—simply because so few individuals have experienced them—they can leverage other, more widespread disasters when they occur. Crises, in other words, may constitute opportunities for encouraging household preparedness across a variety of domains.

It is possible that the risk transitivity logic we outline may not exist or may be offset by countervailing tendencies. Experiencing a crisis could diminish cognitive and financial resources, rendering individuals less responsive to preparation messages by public agencies. In order to arbitrate between these possibilities, we provide an empirical test of the relationship between the perceptions of hazards in one domain (COVID-19 lockdowns) and willingness to prepare for risks in another domain (earthquakes). Meanwhile, we also expect that recommendations sent by credible sources will be more effective for encouraging emergency preparedness. While most research on trust in message sources has focused on non-emergency political messaging (Mondak 1990; Robinson 2010) or the role of peer-to-peer trust in emergency messaging (Patterson, Weil, and Patel 2010), we expect individuals to respond more readily to emergency preparedness announcements from more trusted sources. Depending upon preexisting levels of trust in different institutions, this may or may not translate into specific institutions being more effective messengers than others.

Prior research, to the best of our knowledge, has not examined trust in specific institutions involved with emergency management. We hypothesize that individual characteristics like partisanship, race/ethnicity, and income may be associated with higher levels of trust in emergency management institutions like FEMA and may help explain differences in the efficacy of messages from particular organizations with some groups. For example, Republicans may be less trusting of federal government institutions like FEMA than Democrats, and college-educated and higher-income individuals may place greater trust in government institutions and academic experts.

Research Design

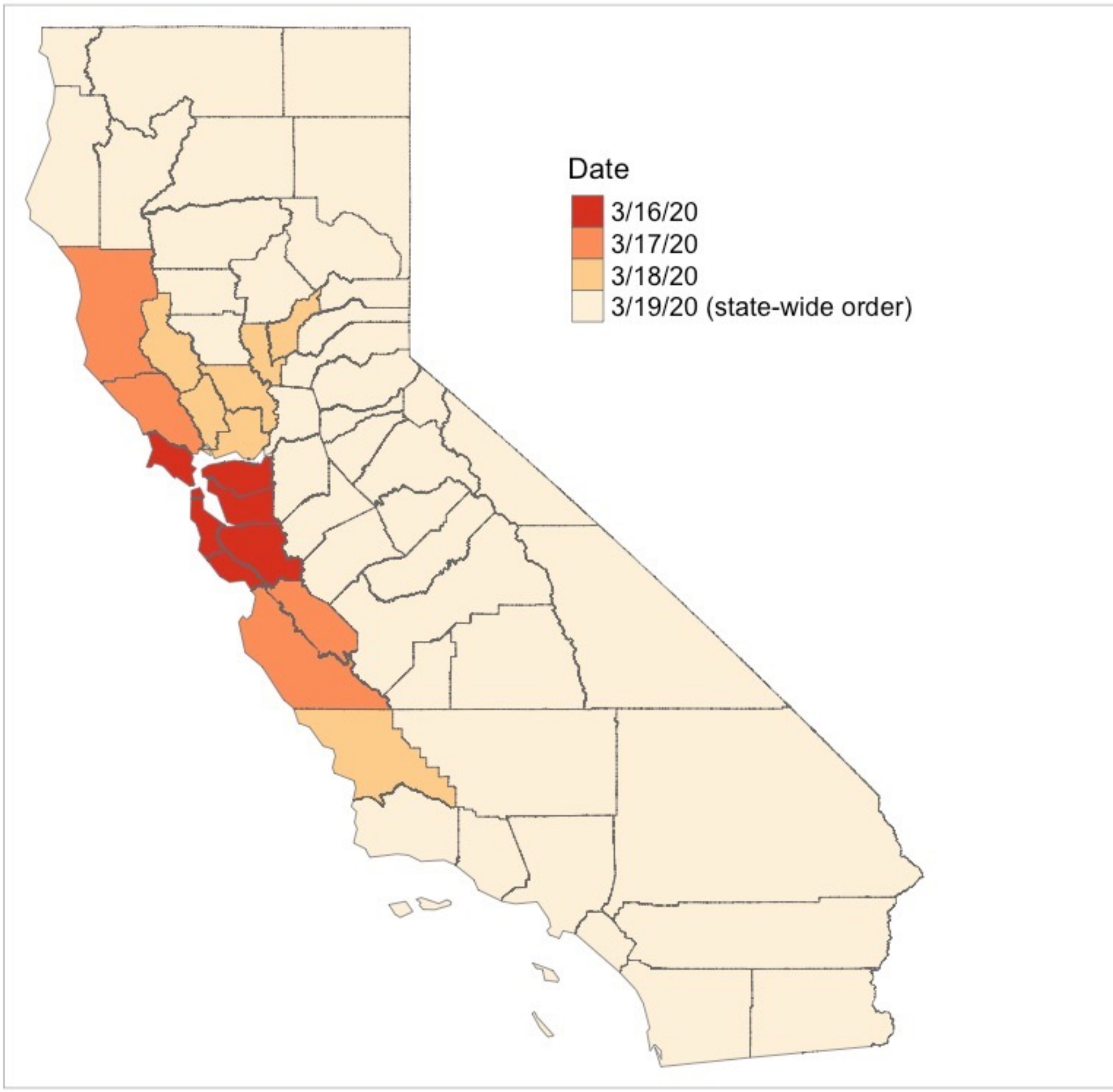
To assess the efficacy of these two approaches to encouraging household emergency preparedness, we focused on potable water storage for household use following a major earthquake. Recent simulation studies of earthquake probabilities in California suggest that, following a major quake, water distribution systems may be offline for weeks before services can be fully restored (Hudnut et al. 2018). Household storage reduces strains upon government efforts to distribute water at public access points or via bottled water deliveries, and allows individuals to better cope with system outages. Entities such as the Red Cross and Ready.Gov generally recommend that households store 1 to 2 gallons per person per day for 3 to 7 days. Our prior December 2019 MTurk survey of California residents suggests that very few (< 1% of 1,423) store these recommended quantities. Increasing household storage thus represents an important problem to solve. It is also one for which the financial and logistical barriers to household action are low relative to measures like constructing tornado shelters or purchasing electricity generators.

Our study examined the efficacy of these two means of encouraging water storage through a survey of California residents that yielded observational and experimental data. First, the study examined the extent to which concrete experience with risk mitigation measures in a *different* domain, COVID-19 lockdown orders, increased individuals' willingness to store the recommended amount of water for earthquakes. Storing the recommended quantities requires space, effort, and some resources to prepare, and as a result, serves as an important case for understanding the drivers of household preparation.

This survey was timed to leverage the staged roll-out of local, COVID-19-related shelter-in-place orders before California's statewide order, which allowed us to examine how differential exposure to COVID-19 lockdowns affected willingness to store recommended quantities of water. Due to the rapid unfolding of the COVID-19 pandemic and the California lockdowns, we recruited respondents through Amazon mechanical Turk (mTurk), a platform that allowed us to prepare and administer our survey within a very short time frame, and which has become an increasingly common platform for social science research (see Berinsky, Huber, and Lenz 2012). As compared to other survey outlets, mTurk allows for rapid survey administration by allowing any eligible individual on the site to take a survey for a pre-determined payment. The platform allows researchers to specify eligibility criteria to allow for a geographically specific sample. Our sample was restricted to California residents, both through a requirement imposed via the mTurk platform and a pre-test screening question. We limited our survey to individuals reliant primarily upon local water providers (rather than household wells) because earthquakes are more likely to disrupt large-scale distribution networks, and we set demographic quotas to obtain sufficient participation by female-identifying and non-white respondents, as well as age cohorts reflective of the CA population (see Note S.1 in the SI). The final sample included 1,211 California residents, with a demographic balance that resembles the state sociodemographic breakdown, as we show in Table S.14 (SI). Notable differences include a skew toward white respondents (50.5% in the sample as compared to 36.8% in California) and higher levels of college education (60.7% in the sample as compared to 33.3% in California) (Table S.14; CA-wide statistics from https://www.census.gov/quickfacts/CA). Such demographic skews are characteristic of other mTurk surveys (Berinsky, Huber, and Lenz 2012), and represent the trade-offs we faced while considering how to best leverage the unique opportunity presented by the staged rollout of lockdowns in California.

The staggered rollout of California's lockdown orders presented a rare opportunity to compare the efficacy of water storage recommendations among individuals who had differential exposure to lockdown policies. During March 2020, counties in the state of California each independently instituted local shelter-in-place (lockdown) orders in response to the COVID-19 pandemic. Six counties in the Bay Area issued orders on March 16, followed by an additional four counties on March 17th, and an additional seven counties on March 18th (see Figure 1). On March 19th, California issued a state-wide order. We deployed our survey within 24 hours of the statewide order, and secured a sample in which approximately half (48.3%) reported having experienced a local lockdown before the statewide order. Because this "prior lockdown" portion of the sample had experienced COVID-19 risk-mitigation measures for a longer period, we assume that the salience of the threat posed by COVID-19 was greater for this population. Individuals had already experienced everyday activities being curtailed, empty streets and public spaces, the presence of some masked individuals in public spaces and stores, and other visible manifestations of health risks posed by the pandemic.

Fig. 1: COVID-19 Lockdown Orders across California Counties by Date Instituted



Note: Green: 3/6/2020. Yellow: 3/17/20. Purple: 3/18/20. Red: 3/19/20 (all other California counties, which did not issue orders prior to the California-wide one).

Our "prior lockdown" measure is perception-based, in line with our proposed theory regarding how perceptions of risks in one domain may affect perceptions and behaviors in other domains. To measure whether respondents had experienced a COVID-19 lockdown prior to the statewide order, we included a screening question: "Was your town or city under a "shelter in place" or "stay at home" order before the state-wide directive on Thursday March 19 at 6:30pm?" Respondents could answer "Yes", "No", or "I don't know." This was worded to capture the effect of actually perceiving a lockdown, rather than the material effect of a lockdown. This approach also helped us address the fact that several towns and cities instituted lockdowns independently from counties (e.g., Berkeley, Fresno, Palm Springs).

Fortunately, the populations that experienced a lockdown prior to the statewide order and those that did not are reasonably comparable. While Bay Area counties imposed their lockdown first, the "prior lockdown" portion of our sample also includes less affluent central California and inland counties that lean more Republican. As reported in Table S.8a (SI), balance tests indicate there are no significant differences in the number of Republicans (31% versus 29%), percentage of non-whites (48% versus 51%), average age, dwelling size, or length of CA residence between the groups. Respondents in each group also trusted institutions such as their city government, the Red Cross, their local water provider, and FEMA at similar levels. There are differences, however, in average income (2019), educational level, employment status (2019), and having children at home. Because of these differences, we include control variables in our analyses.

The survey also included an experiment designed to compare the relative efficacy of storage recommendations from different entities typically involved with emergency and earthquake response: the Federal Emergency Management Agency (FEMA), local city governments, the Red Cross, local water providers, and independent academic experts. The survey also included questions allowing us to assess whether recommendations from more trusted sources were more effective. Respondents were all presented with a message encouraging household water storage in anticipation of an earthquake. We randomly assigned the source of the message, including the five organizations above and a generic recommendation (see Table S.9, SI).

The messages followed this structure: "[Independent academic experts recommend that / It is generally recommended that] individuals store approximately 2 gallons of water, per person, per day, for 3 – 7 days of potential water outages from a major earthquake." As noted above, this follows the consensus recommendations from entities like the East Bay Municipal Utility District, Ready.gov (an official website of the U.S. Department of Homeland Security), and the Red Cross. Our outcome variable was the expressed intent to store the recommended amounts of water for an earthquake. Per our pre-analysis plan (see SI note S.5), our survey experiment was powered to detect a 10% increase in our dependent variable, the respondent's stated willingness to store recommended amounts of water, in response to exposure to messages from different organizations.

Results

COVID-19 Lockdowns and Household Water Storage

We found that the "prior lockdown" group—those that had experienced local lockdowns prior to the statewide order—reported significantly greater willingness to prepare the recommended volumes of water for earthquake-related service outages. Table 1 reports results from a robust logistic regression model predicting whether a respondent would be "very", "extremely", or "definitely" willing to store expert-recommended volumes of water for an earthquake in California. In Model 1, the experience of a pre-statewide lockdown is associated with a ~30% [3.4%, 64.2%] higher likelihood of a respondent reporting this willingness to prepare (with demographic controls, this is associated with a ~ 24% higher likelihood [-2.5%, 57.6%]).

Controlling for the trust in the source of the storage recommendation, a factor we discuss in the next section, does not change the size or significance of this effect.

Table 1: Main Results for Lockdown and Trust in Source on Willingness to Prepare

Explanatory Variables	*Dependent variable: Willing to Prepare Water for Earthquake*			
	Model 1	Model 2	Model 3	Model 4
Prior Lockdown (Binary)	0.264^{**}		0.266^{**}	0.215^{*}
	(0.118)		(0.118)	(0.122)
Trust in Source		0.102^{**}	0.102^{**}	0.081^{*}
		(0.047)	(0.047)	(0.048)
White				-0.143
				(0.126)
Male				-0.094
				(0.123)
Republican (Binary)				0.264^{*}
				(0.135)
Age				-0.014
				(0.033)
Age^2				0.0003
				(0.0004)
College Education				0.205
				(0.135)
Income (Scale)				-0.037
				(0.051)
Children in Residence				0.190
				(0.135)
Employed				0.358^{**}
				(0.153)
Days in Lockdown (Count)				-0.003
				(0.020)
Constant	-0.557^{***}	-0.520^{***}	-0.651^{***}	-0.884
	(0.083)	(0.074)	(0.094)	(0.620)

Observations	1,211	1,211	1,211	1,211
AIC	1623.66	1623.68	1620.60	1615.27

Note: *p<0.1; **p<0.05; ***p<0.01; models estimated with robust standard errors. Standard errors in parentheses below regression coefficients.

Even with a battery of controls, prior lockdown experience remains significant and continues to be positively associated with a willingness to store water (Model 4). The weaker lockdown effect is due in part to the correlation between some of these other predictors and prior lockdown, namely respondents with a college education and respondents with children in their household (see Table S.8b, SI). As evidenced by the insignificant effect of days under lockdown, this effect on preparation appears to be driven strictly by the experience of a local lockdown. Results are consistent without robust standard errors. Results are also similar if the dependent variable is recoded as an ordinal variable reflecting varying levels of willingness to store water, as we report in Table S.2 (SI). We assess concerns regarding demographic skews in our sample through the inclusion of standard demographic control variables and checking that we receive the same results when using propensity score matching, rather than the use of survey weights, which diminish the precision of treatment effect estimates in survey experiments (Miratrix et al. 2018). Our results are consistent in a variety of sub-sample specifications, and when using propensity score matching models, as we discuss later.

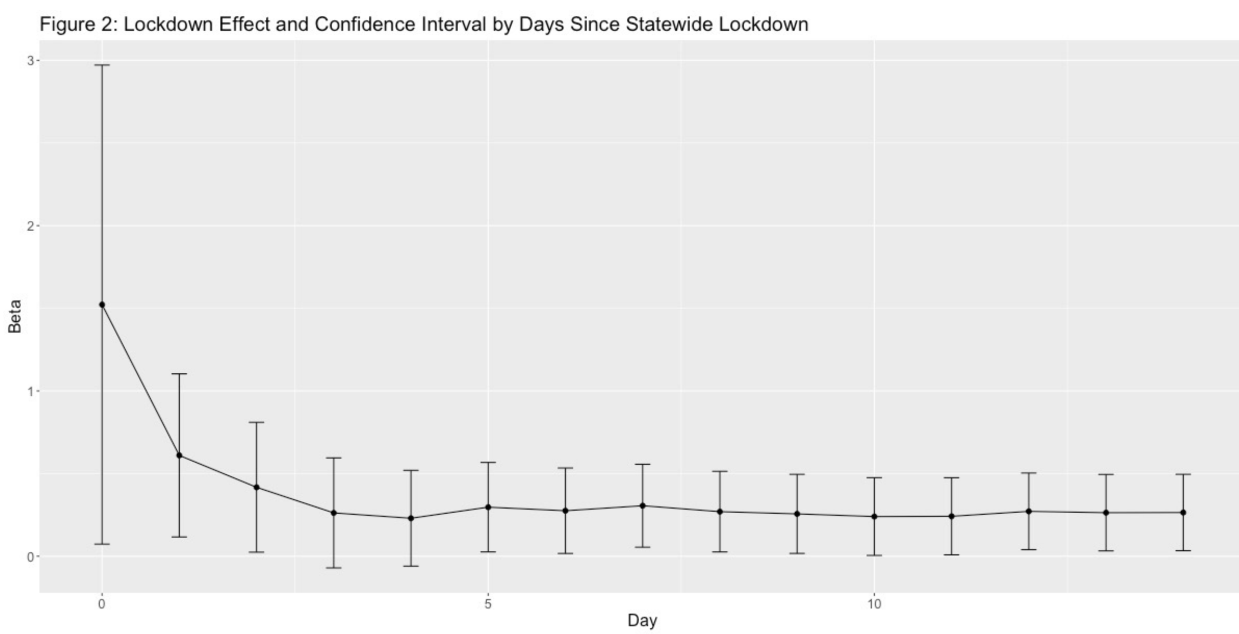
As our survey ran for 14 days following the statewide order, we can test whether these effects were particularly pronounced immediately following the statewide order—when the difference in exposure to lockdown between the prior lockdown and no prior lockdown groups was greatest. Table 2 and Figure 2 below illustrate how the "prior lockdown" effect varies if we subset our data to survey responses received within the first 1, 2, and 3 days of our survey. Effects are larger and statistically significant for the first three days for a model without controls, and over the course of the survey regress to the results in Table 1; effects are similar including controls, but the effect of lockdown loses significance due to the much smaller subset sample size.

Table 2: Effects of Prior Lockdown in Subset Time Windows

	Dependent variable: Willing to Prepare Water for Earthquake		
Explanatory Variables	Day 1	Days 1-2	Days 1-3
Prior Lockdown (Binary)	1.522**	0.610**	0.417**
	(0.739)	(0.252)	(0.200)
Constant	-0.511	-0.735***	-0.646***
	(0.433)	(0.146)	(0.126)
Observations	39	312	449
AIC	53.15	408.83	596.35

Note: *p<0.1; **p<0.05; ***p<0.01; models estimated with robust standard errors. Standard errors in parentheses below regression coefficients.

Fig. 2: Lockdown Effect and Confidence Interval by Days Since Statewide Lockdown



Note: Results on the y-axis include a point estimate for the effect of prior lockdown, with 95% confidence interval bars, based on robust logistic regression models on different subsets of the data. The x-axis reports different cutoff points to subset these data, based on the number of days since the statewide lockdown, until respondents completed the survey. For example, the estimate for Day=3 is drawn from a regression model including only responses collected within the first three days of the survey being live; the estimates pool responses collected at or before that day on the x-axis. The regression model used to estimate these results draws on the independent variables used in the table 1 model 3, predicting willingness to prepare.

In our survey, we also asked individuals whether they had stored goods in preparation for the California COVID-19 lockdowns, and if so, which goods they had obtained and why. We offer quantitative analysis of preparation correlates in Note S.2 and Table S.13, and here explore replies to our optional, open-ended survey questions that suggest some reasons why concrete experience with COVID-19 mitigation measures increased respondents' willingness to store water. One respondent voiced concern that utility workers could contract COVID-19 and thus be unavailable to make needed repairs (#565). Another respondent pointed to a heightened sense of the importance of preparedness: "It wasn't just because of the outbreak. I realized that it's probably a good idea to have some water available for any kind of emergency. This could range from an earthquake to something as simple as plumbing issues in my apartment" (#230; see also #549). This comment suggests that our hypothesized *halo effect,* in which the greater salience of risks in one domain would increase the salience of other risks, is at work in at least some circumstances. Some respondents also purchased water out of fear that other households were "hoarding" water and other essential supplies: "I wasn't expecting (and am still not expecting) any real disruption to supply lines, but the sad fact is that I had to panic-buy supplies because I knew that everyone else was going to do it, and I couldn't take the risk of needing something and finding the stores empty" (#191; also #830, 862, 1043, 1700).

Recommendation Sources and Household Water Storage

Our survey was also designed to allow us to assess the relative efficacy of messages from different institutions and organizations typically involved in disaster relief, which we expected respondents would trust to varying degrees. We asked individuals to characterize the extent to which they trusted members of the general public, FEMA, independent academic experts, their local city government, the Red Cross, and their local water provider. Respondents could choose one of six response options for each organization: “Completely distrust”, “Distrust”, “Somewhat distrust”, “Somewhat trust”, “Trust”, and “Completely trust.”. These were respectively coded on a scale including -3, -2, -1, 1, 2, and 3. We omit a centered 0-value response option in the survey instrument, which compels a respondent to indicate some degree of trust or distrust in a particular organization. Beyond evidence that these middle-value options are disproportionately used by particular demographic groups (Stone 2003), this choice yields a 0-value as a control for respondents who saw a message about water preparation that was not endorsed by a specific organization. We then randomly assigned respondents to a water storage recommendation from one of the five organizations or a general recommendation from an unspecified source.

Contrary to recent literature highlighting declining trust in U.S. governmental institutions (Levi and Stoker 2000), we found reasonably high levels of trust across organizations (Table 3), The mean score for these organizations was close to 1 (“somewhat trust”), above the mean for average respondent trust in the general public; the difference is statistically significant. We observed similar results when we asked respondents to rank these organizations from most to least trusted (Table S.10, SI). Counter to recent work on increasing political polarization in the U.S., we observed few differences between Republicans and Democrats (Kousser 2010; Masket 2004); Republicans are slightly less likely to trust FEMA and their city government, but differences are small, at 0.22 (p = 0.013) and 0.27 (p = 0.002) respectively on our 6 point scale. Rather, college education and having children are associated with higher trust in all organizations (Table S.11, SI).

Table 3: Average Trust in Groups with 95% Confidence Intervals

Group	*2.5%*	*Mean*	*97.5%*

General Public	0.583	0.656	0.730
FEMA	0.981	1.057	1.133
Independent Academic Experts	0.991	1.067	1.143
Local City Government	0.998	1.074	1.151
Red Cross	1.012	1.087	1.162
Water Provider	1.011	1.089	1.167

Perhaps unsurprisingly given the similar degrees of trust respondents expressed in these different organizations, our survey experiment did not show that messages from a particular organization were more effective than those from other sources, or more than a generic recommendation (Table S.6, SI). Given that our survey was powered to detect effect sizes of 0.7 on our 7-point scale reflecting differing levels of willingness to store water (see our pre-analysis plan), we should have been able to detect a reasonably sized effect if one existed. These results suggest that there is no single source to which agencies should delegate messaging campaigns.

Our survey also allowed us to assess the efficacy of messages received from organizations more and less trusted by individual respondents in accordance with our pre-analysis plan (SI). While trust in a particular organization cannot be experimentally manipulated, our survey data allows us to examine the association between an individual's trust in the message source and their post-test willingness to store the recommended amounts of water. The average spread between a respondent's most and least-trusted organization in the Likert scale responses was approximately 2 points, but the spread within our sample ranged over the entire -3 to 3 scale (Figure S.2; see also Table S.7, SI).

We find that trust in the message source is associated with a greater willingness to store water (see Table 1, Models 2, 3, and 4). Model 2 shows that a one-unit shift in the reported level of trust in the message source—i.e. a shift from "somewhat trust" to "trust"—is associated with an approximately 10.7% [1.3%, 21.1%] higher likelihood of reporting that they would be very, extremely, or definitely willing to store the recommended volume of water. These results are consistent in a variety of sub-sample specifications, discussed later in our robustness tests.

Relying on the average spread between most- and least-trusted organizations among respondents, a two-unit shift, this translates to an approximate 21.4% difference in that reported storage likelihood. The size of the effect remains large and significant even with the addition of demographic controls (Model 4). Figure 3 shows that the predicted willingness to store water increases with trust, per our model, and how this varies between our "prior lockdown" and "no prior lockdown" groups in Model 3. Drawing on our raw data, Table 4 shows respondents' average willingness to store water on our 7-point scale, and a 95% confidence interval, according to respondents' trust in the message source. This suggests that our model results are strongly influenced by cases where individuals received messages from sources they "completely trusted".

Fig. 3: Predicted Individual Willingness to Store Water by Trust in Message Source

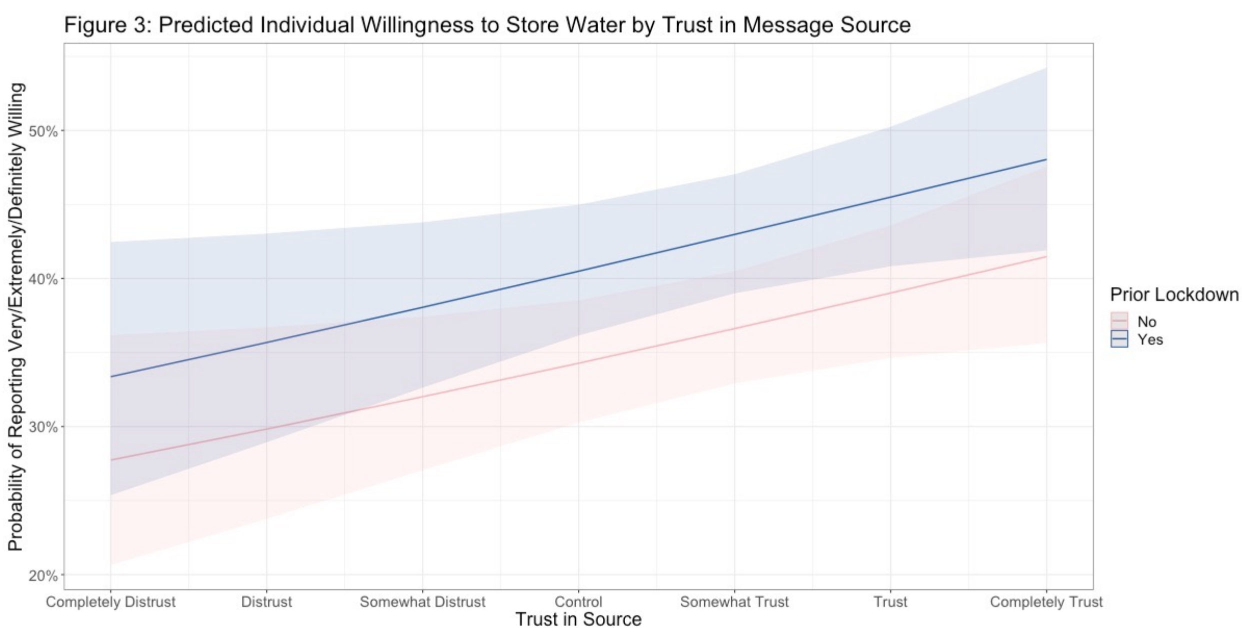


Table 4: Average and 95% Confidence Interval for Willingness to Store by Trust

Trust in Message Source	Proportion Willing	95% Confidence

	to Store Water	Interval
Completely Distrust	0.470	[0.18, 0.75]
Distrust	0.370	[0.24, 0.50]
Somewhat Distrust	0.310	[0.23, 0.40]
Control	0.420	[0.35, 0.49]
Somewhat Trust	0.360	[0.31, 0.41]
Trust	0.400	[0.34, 0.45]
Completely Trust	0.620	[0.51, 0.73]

Following this survey question, we asked respondents why they chose a particular level of willingness to prepare; these responses illustrate the importance of trust in the source of preparation recommendations. Several respondents who received messages from independent academic experts expressed their trust in the scientific origins of these recommendations: "I selected this likelihood because I believe in the recommendations of independent academic experts. This is where I think these recommendations come from" (#167; also #224, 488, 1032). Others who had received a recommendation from FEMA explained that their willingness to prepare was contingent on their trust in that agency, admitting they had previously considered and written off the need to prepare water given the associated difficulties: "With so many people living in my household and with how little space we have, we simply don't have enough space to store even a few gallons of water per person. However, after reading the recommendation from FEMA, it makes me think that maybe I should try to save up water anyway" (#1111; also 699, 1048, 1052, 1206). Overall, it is clear that trust played a role for respondents, best exemplified by response 1,014: "I think I should probably do so if it is recommended by a group I trust."

Aggregate Effects of Lockdown and Trust

These results clearly indicate that lockdowns and trust in a message source are associated with greater individual-level willingness to store water. They also point to potential larger-scale community effects. We drew on our model to simulate the predicted sample-level rates of binary willingness to store under four different scenarios: (a) *no one* under prior lockdown, all individuals receive messages from their *least* trusted sources; b) *all* under prior lockdown, all individuals receive messages from their *least* trusted sources; c) *no one* under prior lockdown, all individual receive messages from their *most* trusted sources; d) *all* under prior lockdown, all individuals receive messages from their *most* trusted sources. Drawing on our respondents' Likert response trust scores for their most and least trusted organizations, we predicted the likelihood of being very likely, extremely likely, or definitely willing to store the recommended volume of water if respondents were to receive a message from either of their most or least trusted source, with or without a prior lockdown. We use this distribution to simulate predicted proportions of the entire sample that would exhibit this willingness to prepare water under those four distinct scenarios.

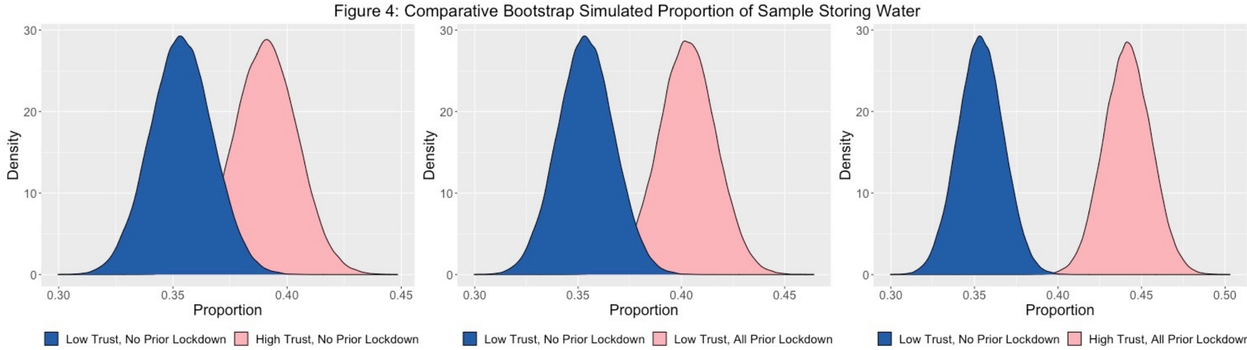
Following the procedure outlined in the online appendix (see Note S.2, SI), we conducted bootstrap simulations of individual likelihood to prepare under different treatment scenarios to estimate the aggregate effects of lockdown and trust in source on our preparation outcome. Below, Table 5 reports the average proportion of the sample which was predicted to prepare water across all 10,000 simulations, and Figure 4 presents the distribution of proportions across all simulations.

Table 5: First Difference Estimates and Confidence Intervals Across Conditions

Simulation Condition	*Proportion Willing To Store Water*	*Difference in Proportion*	*95% Confidence Interval*
No Lockdown, Low Trust	35.37%	-	-
No Lockdown, High Trust	39.06%	3.69%	(3.68%, 3.70%)
All Lockdown, Low Trust	40.29%	4.92%	(4.90%, 4.93%)
All Lockdown, High Trust	44.16%	8.79%	(8.77%, 8.80%)

Fig. 4: Comparative Bootstrap Simulated Proportion of Sample Storing Water

Figure 4: Comparative Bootstrap Simulated Proportion of Sample Storing Water



These simulation results show that receiving messages from trusted sources and prior lockdown experience can potentially trigger large and significant shifts in group-level behavior, even when controlling for demographic variables included in Model 4. Manipulating both of these factors in tandem in our models produces approximately 8.8% higher rates of willingness to store water across the full sample. Furthermore, it makes a difference whether or not an emergency preparedness recommendation comes from a trusted source. However, as noted above, none of the institutions and organizations typically involved in emergency management are consistently trusted more by standard demographic or partisan groups. We ran regressions models to assess whether demographic factors like age, gender, education, and income, as well as partisanship, were associated with trust in each of these organizations and no consistent patterns emerged (Table S.11, SI). We also ran models to assess whether particular groups were more likely to hold discrepant levels of trust across organizations; these analyses also did not yield clear results.

Robustness Tests

We conducted a number of robustness checks of our findings. First, our main results are robust to omitting the 671 out of 1,211 respondents who reported having stored water specifically for the COVID-19 pandemic (Table S.4, SI). Our results remain positive and significant in this sub-sample, suggesting that our lockdown results are not driven by COVID-19 preparation.

Second, our results could be driven by responses from individuals who receive water from small-scale providers, who may engage in storage because they have long been concerned about drinking water quality; California's small-scale water providers typically supply lower-quality water (Dubrovsky et al. 2010; Heaney et al. 2011; National Research Council 1997). To test this possibility, we subset our sample to those who reported receiving water from one of the following large water providers in California: Los Angeles Department of Water & Power (LADPW), San Jose Water (SJJJ), San Francisco Water Power Sewer, San Diego Public Utilities, or the East Bay Municipal Utility District (EBMUD). Within this subset, our lockdown coefficient estimates are slightly larger than in the main models (Table S.5), but given the smaller sample (554), we do not have power to detect significant effects.

Third, we receive very similar results using ordinal logistic regression models (Table S.2, SI). Fourth, our results regarding the effect of "prior lockdown" are consistent when we run our main logistic regression models following propensity score matching (see SI Note S.4 for discussion of our propensity score matching procedure, and Table S.15 for balance for post-matching demographic covariates). As we report in Table S.16, the coefficient estimate for prior lockdown is consistent and remains significant when we run the models on the matched sample. Fifth, one might wonder why our results for trust in the message source are weaker in full models. Here, it appears that strong correlations between certain respondent demographic characteristics (college education and having children in home) and trust in the main institutions involved in emergency management (Table S.11, SI) attenuate the observed relationship between trust in message source and expressed willingness to prepare. This can be addressed in future research through variations on our survey design with a broader battery of messaging organizations and additional open-ended questions.

Sixth and finally, there are natural concerns about mTurk samples, especially possibly fraudulent responses in our sample. In order to address this concern, we replicated our main models on two subsets of responses. As we show in Table S.17 (SI), when we restrict the sample to only the respondents whose latitude and longitude could be confirmed with certainty to be in California, we obtain similar results; while trust loses significance due to power constraints, our estimate for lockdown effects is larger and more significant. Second, as we show in Table S.18 (SI), when we omit respondents who took less than 3 minutes with the survey to limit potential speed-responders, we register similar regression estimates of our main results, allaying potential concerns.

Discussion and Conclusion

Our results suggest important new lines of research on how governments can most effectively encourage household preparation for disasters. First, our study indicates that concrete experience with policies addressing risks in one domain—COVID-19 related lockdowns in our case—can increase willingness to prepare for other types of emergencies. To our knowledge, this is one of the first quantitative studies to demonstrate the existence of such spillover effects, or the transitivity of risk perceptions; we hope that other researchers can test for this spillover dynamic with larger and more balanced samples than we could collect using mTurk in our attempt to leverage the rapid rollout of COVID-19 lockdowns in California.

Future research on disaster experience and its relationship to risks perceptions should also examine the circumstances under which these spillovers occur. It is unclear, for example, if similar dynamics would be observed in different institutional and political settings. It is also unclear from this study if such spillovers would operate across different hazard areas, or if the experience of lockdowns during the COVID-19 pandemic represents a particularly dramatic case. If spillovers *do* operate across multiple domains, the policy implications are clear: public agencies should actively encourage emergency preparedness for a variety of hazards during actual emergencies, despite the fact that they will be more pressed for time and resources during emergency events. Public agencies should never "let a crisis go to waste," as this is when the public will likely be most receptive to messaging. This approach could be impactful across a range of domains, including not only earthquakes, but also tsunamis, volcanic eruptions, and pandemics. At the same time, authorities should be careful to discourage counterproductive behaviors such as hoarding.

Further research is also needed to understand the underlying mechanisms driving the transitivity between different risk domains. We hypothesized that spillovers could stem from a *halo effect,* through which the heightened salience of risks in one domain increased the prominence of risks in other domains. We also proposed that spillovers could occur through *learning by analogy*, namely that risk preparation in one domain could accustom individuals to emergency preparation more broadly. While responses to open-ended questions in our survey suggest such mechanisms may be at work, our study does not provide direct experimental support for either mechanism. Future research could help uncover whether these or alternative processes help explain the transitivity of risk perceptions and risk-mitigation behaviors across domains. Furthermore, future research should explore whether these effects are most pronounced at the onset of crises, or whether "windows of opportunity" are relatively long, as our survey was administered during the immediate rollout of local lockdowns. While our study offers novel and compelling evidence regarding the transitivity of risk perceptions across hazard domains at the very onset of a crisis, we are unable to examine longer-term effects; these could explored in future studies involving repeated surveys of a panel of subjects.

Our findings regarding the efficacy of messages from different emergency management organizations also suggest new research avenues. First, our respondents expressed, on average, reasonably high levels of trust in organizations like FEMA and their local water providers ("somewhat trust")—significantly higher levels than they expressed for members of the general public. These results stand in contrast with research suggesting declining trust in political institutions and experts in the United States (Levi and Stoker 2000). Individuals may perceive public agencies and organizations with specific mandates differently than "government" in general, especially given early descriptive and experimental work around COVID-19 messaging (Boynton et al. 2021; Llewellyn 2020; Mora and Schickler 2020). This indicates that emergency management institutions are reasonably well-positioned to engage in preparedness campaigns. This being said, it is likely possible to identify other organizations more trusted by some groups than those included in our survey, such as faith-based or community organizations.

Meanwhile, our evidence that messages from sources individuals trust most are particularly effective extends existing literature on message source credibility to a new domain: earthquake preparedness. However, our analyses do not suggest turning to specific organizations to target particular subsets of the population. Specific organizations did not appeal to different demographic groups, which would allow for a segmented messaging strategy. Rather, the question that arises is what organizations or institutions could more effectively encourage emergency preparedness among those without a college education or children. Future research should include a broader array of organizations and should also explore how trust in government agencies can be improved.

Future research should also explore how the efficacy of messaging strategies varies with the quality of public services that may be cut off during emergencies. It may be that respondents were more likely to express a willingness to store extra water when they received poor quality or less dependable services. If this is the case, preparedness efforts may yield greater impacts if they target those who rely entirely on water providers delivering higher quality services. Similar differences may be observable in other domains, like preparation for electricity blackouts.

In conclusion, encouraging private emergency preparedness among members of the public is an essential yet difficult task for public agencies. It is one that is becoming increasingly important as climate change raises the frequency and severity of natural hazards like floods and wildfires, and as globalization makes the emergence of pandemics and cyberattacks a part of the "new normal." In this analysis, we have extended research on risk perceptions and disaster preparation encouragement by testing two influences upon individual willingness to prepare – experience with *other* disasters, and trust in message sources. Our results suggest that not only is public trust in emergency response agencies a critical determinant of private preparedness, but also that the best time to encourage this preparation is during an actual, if unrelated emergency. In other words, public agencies charged with emergency response should never waste a crisis.

Data Availability Statement

All data, models, and code generated or used during the study are available in a repository online in accordance with funder data retention policies. See:
https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GT8VK9

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Table of Contents:

Table S1: Main OLS Regression Results for Willingness to Prepare

	Dependent variable: Willingness to Prepare (7 point Scale)	
Explanatory Variables	(1)	(2)
Prior Lockdown (Binary)	0.228^{**}	0.172^{*}
	(0.096)	(0.097)
Trust in Source	0.082^{**}	0.062
	(0.038)	(0.038)
White		-0.226^{**}
		(0.099)
Male		-0.116
		(0.097)
Republican (Binary)		0.256^{**}
		(0.111)
Age		-0.035
		(0.027)
Age^2		0.001^{*}
		(0.0003)
College Education		0.169
		(0.106)
Income (Scale)		-0.001
		(0.041)
Children in Residence		0.204^{*}
		(0.110)
Employed		0.367^{***}
		(0.119)
Days in Lockdown (Count)		-0.013
		(0.016)
Constant	3.906^{***}	4.152^{***}
	(0.075)	(0.496)
Observations	1,211	1,211
Adj. R2	0.007	0.029

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S2: Main Regression Results with Ordinal Logit Model

	Dependent variable: Willingness to Prepare (Factored 7 point)	
Explanatory Variables	(1)	(2)
Prior Lockdown (Binary)	0.256**	0.197*
	(0.101)	(0.103)
Trust in Source	0.086**	0.068*
	(0.039)	(0.040)
White		-0.225**
		(0.106)
Male		-0.116
		(0.104)
Republican (Binary)		0.258**
		(0.117)
Age		0.009**
		(0.005)
College Education		0.160
		(0.112)
Income (Scale)		0.004
		(0.043)
Children in Residence		0.172
		(0.114)
Employed		0.334***
		(0.123)
Observations	1,211	1,211

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S3: Correlation in Main Model Predictors for Demographics and Trust in Source

	Dependent variable: Trust in Source (-3 to 3)
Explanatory Variables	(1)
White	0.025
	(0.077)
Male	-0.059
	(0.077)
Republican (Binary)	0.008
	(0.085)
Age	-0.013
	(0.019)
Age^2	0.0002
	(0.0002)
College Education	0.269***
	(0.085)
Children in Residence	0.269***
	(0.083)
Employed	-0.075
	(0.092)
Income (Scale)	0.015
	(0.032)
Days in Lockdown (Count)	-0.001
	(0.012)
Constant	0.832**
	(0.368)
Observations	1,211
Adj. R2	0.017

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S4: Main OLS and Logit Results Omitting Lockdown Water Preparers

	Dependent variable: Willingness to Prepare Water for Earthquake			
Explanatory Variables	OLS (7 point scale)	OLS (7 point scale)	Logistic (Binary Willingness)	Logistic (Binary Willingness)
Prior Lockdown (Binary)	0.275**	0.225*	0.304*	0.278
	(0.125)	(0.125)	(0.168)	(0.173)
Trust in Source	0.097*	0.079	0.150**	0.134*
	(0.050)	(0.050)	(0.070)	(0.071)
White		-0.226*		-0.196
		(0.132)		(0.184)
Male		-0.116		-0.189
		(0.126)		(0.175)
Republican (Binary)		0.251*		0.260
		(0.146)		(0.192)
Age		-0.030		-0.017
		(0.034)		(0.047)
Age^2		0.001		0.0004
		(0.0004)		(0.001)
College Education		0.126		-0.007
		(0.139)		(0.198)
Income (Scale)		0.023		-0.021
		(0.051)		(0.071)
Children in Residence		0.237		0.360*
		(0.152)		(0.197)
Employed		0.215		0.249
		(0.155)		(0.217)
Constant	3.524***	3.648***	-1.078***	-1.197
	(0.096)	(0.622)	(0.139)	(0.883)
Observations	671	671	671	671
Adj. R2	0.01	0.03		
AIC			831.41	830.94

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S5: Main OLS and Logit Results with Only Urban Water Providers

	Dependent variable: Willingness to Prepare Water for Earthquake			
Explanatory Variables	OLS (7 point scale)	OLS (7 point scale)	Logistic (Binary Willingness)	Logistic (Binary Willingness)
Prior Lockdown (Binary)	0.222	0.103	0.286	0.169
	(0.148)	(0.147)	(0.176)	(0.185)
Trust in Source	0.132^{**}	0.083	0.139^{**}	0.089
	(0.058)	(0.057)	(0.069)	(0.072)
White		-0.128		-0.045
		(0.144)		(0.184)
Male		-0.171		-0.166
		(0.146)		(0.187)
Republican (Binary)		0.478^{***}		0.476^{**}
		(0.165)		(0.209)
Age		-0.096^{**}		-0.096^{*}
		(0.042)		(0.055)
Age^2		0.001^{**}		0.001^{**}
		(0.001)		(0.001)
College Education		-0.023		-0.113
		(0.166)		(0.214)
Income (Scale)		-0.002		-0.044
		(0.061)		(0.078)
Children in Residence		0.613^{***}		0.775^{***}
		(0.164)		(0.204)
Employed		0.378^{*}		0.260
		(0.199)		(0.251)
Constant	4.028^{***}	5.261^{***}	-0.533^{***}	0.763
	(0.122)	(0.770)	(0.150)	(0.996)
Observations	554	554	554	554
Adj. R2	0.01	0.06		
AIC			759.16	743.49

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S6: Willingness to Prepare by Organization Presented (No Results)

	Dependent variable: Willingness to Prepare Water	
Messaging Organization	OLS	Logistic
FEMA	0.099	0.121
	(0.168)	(0.201)
City Gov't	-0.213	-0.199
	(0.172)	(0.204)
Red Cross	-0.183	-0.293
	(0.168)	(0.206)
Academics	-0.000	-0.102
	(0.170)	(0.203)
Water Provider	-0.208	-0.186
	(0.170)	(0.204)
Constant	4.173^{***}	-0.320^{**}
	(0.122)	(0.143)
Observations	1211	1211
Adj. R2	0.001	
AIC		1631.25

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S7: Demographic Drivers of Breadth in Most- and Least-Trusted Scores (Likert)

	Dependent variable: Spread in Most and Least Trusted Scores
Explanatory Variables	(1)
Male	0.046
	(0.081)
White	0.100
	(0.082)
Age	0.011
	(0.021)
Age^2	-0.0002
	(0.0002)
Republican (Binary)	0.056
	(0.089)
College Education	-0.078
	(0.088)
Children in Residence	-0.239^{***}
	(0.090)
English at Home	0.193
	(0.194)
Employed	0.017
	(0.101)
Income (Scale)	-0.024
	(0.035)
Residence Duration	-0.013
	(0.033)
Residence Size (Scale)	-0.021
	(0.048)
Constant	1.921^{***}
	(0.442)
Observations	1,211
Adj. R^2	0.005

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S8a: Balance Table Between Lockdown Groups in Survey Sample

Demographic Indicator	Prior Lockdown	No Prior Lockdown	Difference
Male	0.440	0.500	-0.05*
White	0.520	0.490	0.03
Age	35.320	35.320	0
Republican	0.310	0.290	0.02
College	0.670	0.550	0.12* * *
Children	0.360	0.290	0.08* * *
English	0.970	0.960	0
Employed	0.780	0.710	0.07* * *
Income (Scale)	2.960	2.690	0.27* * *
Residence Duration (Scale)	5.300	5.370	-0.07
Residence Size (Scale)	2.240	2.290	-0.05
Trust: FEMA	0.990	1.120	-0.12
Trust: Red Cross	1.130	1.040	0.09
Trust: Local water provider	1.110	1.070	0.04
Trust: Independent academic experts	1.080	1.060	0.02
Trust: Local city government	1.030	1.110	-0.08

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Note: Each cell of the first two columns reports the average value per condition of its column. For binary variables (including: male, white, republican, college, children, English, employed) this is the proportion of respondents in each condition which code positively on that predictor. For continuous variables (like age) and scale variables (like income, residence duration, and size), this is the average value of that predictor among respondents in the condition per column. The third column reports the difference between these averages across the two groups, with indicators from t-test estimates determining whether they are statistically significant, and at what level.

Table S8b: Logistic Regression Results for Experience of Pre-Statewide Lockdown

	Dependent variable: Experience Prior Lockdown
Explanatory Variable	(1)
Male	-0.250**
	(0.120)
White	0.064
	(0.123)
Age	-0.004
	(0.005)
Republican	0.071
	(0.134)
College	0.368***
	(0.128)
Children	0.281**
	(0.132)
English	-0.073
	(0.323)
Employed	0.208
	(0.141)
Income	0.105**
	(0.050)
Residence Duration	-0.007
	(0.049)
Residence Size	-0.102
	(0.070)
Constant	-0.279
	(0.430)
Observations	1,211
Log Likelihood	-819.595
Akaike Inf. Crit.	1,663.189

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S9: Regression Model for Balance in Assignment to Control

	Dependent variable: Assignment to Control Group	
Explanatory Variable	OLS	Logistic
Male	0.008	0.056
	(0.022)	(0.159)
White	-0.029	-0.208
	(0.023)	(0.163)
Age	0.001	0.007
	(0.001)	(0.007)
Republican (Binary)	-0.009	-0.065
	(0.025)	(0.177)
College Education	0.016	0.125
	(0.023)	(0.172)
Children in Residence	0.023	0.162
	(0.024)	(0.172)
English at Home	0.022	0.174
	(0.059)	(0.456)
Employed	0.002	0.024
	(0.026)	(0.190)
Income (Scale)	0.018^{**}	0.131^{**}
	(0.009)	(0.066)
Residence Duration	0.002	0.017
	(0.009)	(0.067)
Residence Size (Scale)	-0.006	-0.046
	(0.013)	(0.094)
Constant	0.055	-2.450^{***}
	(0.079)	(0.598)
Observations	1,211	1,211
R^2	0.009	
Adjusted R^2	-0.0002	
Log Likelihood		-540.524
Akaike Inf. Crit.		1,105.047
Residual Std. Error	0.373 (df = 1199)	
F Statistic	0.977 (df = 11; 1199)	

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S10: Trust Ranking by Organization (Proportion of Total Sample by Organization-Rank)

Rank	*FEMA*	*City Government*	*Water Provider*	*Red Cross*	*Independent Academic Experts*
1	0.191	0.183	0.211	0.212	0.202
2	0.168	0.208	0.219	0.215	0.191
3	0.223	0.199	0.191	0.174	0.213
4	0.215	0.205	0.192	0.201	0.188
5	0.204	0.205	0.187	0.198	0.206

Note: ranking of 1 means most trusted, ranking of 5 means least trusted. Each cell reports the proportion of respondents who ranked the organization in a column by the rank in that row. Every respondent ranked every organization, presentation was randomized in the survey instrument.

Table S11: OLS Models Predicting Trust in Each Organization

	Dependent variable: Trust in Organizations (-3:3 scale)				
Explanatory Variables	FEMA	Academics	City Gov't	Red Cross	Water Provider
White	0.107	0.107	0.115	0.025	-0.024
	(0.080)	(0.080)	(0.079)	(0.080)	(0.082)
Male	0.143*	0.101	0.061	0.065	0.084
	(0.080)	(0.079)	(0.078)	(0.077)	(0.079)
Republican (Binary)	-0.219**	-0.139	-0.268***	-0.074	-0.077
	(0.092)	(0.092)	(0.092)	(0.088)	(0.089)
Age	-0.002	-0.040**	-0.030	-0.030	-0.006
	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)
Age^2	0.0001	0.001**	0.0004	0.0004*	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
College Education	0.251***	0.369***	0.332***	0.234***	0.394***
	(0.088)	(0.087)	(0.088)	(0.086)	(0.087)
Income (Scale)	0.050	0.006	0.063*	0.083**	0.042
	(0.032)	(0.034)	(0.033)	(0.033)	(0.034)
Children in Residence	0.284***	0.316***	0.303***	0.200**	0.159*
	(0.082)	(0.087)	(0.084)	(0.088)	(0.088)
Employed	-0.239***	-0.130	0.014	-0.039	-0.239**
	(0.092)	(0.093)	(0.096)	(0.096)	(0.097)
Days in Lockdown (Count)	0.003	-0.009	-0.018	-0.018	-0.002
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Constant	0.774**	1.520***	1.209***	1.232***	0.918**
	(0.373)	(0.381)	(0.363)	(0.368)	(0.375)
Observations	1,211	1,211	1,211	1,211	1,211
Adj. R^2	0.024	0.027	0.036	0.02	0.022

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S12: Main Logit Models with Days Under Lockdown Instead of Prior Lockdown

	Dependent variable: Willing to Prepare Water for Earthquake		
Explanatory Variables	(1)	(2)	(3)
Days in Lockdown (Count)	-0.006	-0.006	0.002
	(0.020)	(0.020)	(0.020)
Trust in Source		0.102^{**}	0.079^{*}
		(0.047)	(0.048)
White			-0.139
			(0.126)
Male			-0.106
			(0.122)
Republican (Binary)			0.267^{**}
			(0.135)
Age			-0.017
			(0.033)
Age^2			0.0004
			(0.0004)
College Education			0.226^{*}
			(0.134)
Income (Scale)			-0.032
			(0.051)
Children in Residence			0.204
			(0.134)
Employed			0.374^{**}
			(0.152)
Constant	-0.403^{***}	-0.496^{***}	-0.771
	(0.099)	(0.109)	(0.610)
Observations	1,211	1,211	1,211
AIC	1628.61	1625.59	1616.36

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors in parentheses below regression coefficients.

Note: The effect of days under lockdown as a continuous variable remains insignificant in models specified without the binary prior-lockdown variable, as we report above in table S.12, suggesting that these effects are especially salient in the first few days, but driven by binary experience of a pre-statewide order, and not magnitude of time under lockdown.

Table S13: Robust Logistic Regression Models for Covid-19 Preparation Reporting, by Item Type

	Dependent variable: Reported Preparation Willingness (Model 1) or Preparation for Covid (Other Models)								
Explanatory Variables	Willing: Earthquake Water	Binary: Prepared for Covid	Water for Covid	Food for Covid	Medicine for Covid	Medical Supplies for Covid	Toilet Paper for Covid	Luxury Goods for Covid	Guns or Ammo for Covid
White	-0.137	-0.321**	-0.449***	-0.326***	-0.065	-0.274*	-0.360***	0.406**	0.177
	(0.125)	(0.131)	(0.123)	(0.125)	(0.126)	(0.146)	(0.124)	(0.164)	(0.314)
Male	-0.110	-0.219*	0.093	-0.219*	-0.341***	0.056	-0.332***	-0.086	0.188
	(0.122)	(0.127)	(0.121)	(0.123)	(0.124)	(0.144)	(0.123)	(0.162)	(0.337)
Republican (Binary)	0.268**	0.049	0.121	-0.159	-0.132	0.014	0.042	0.093	0.916***
	(0.135)	(0.145)	(0.135)	(0.137)	(0.138)	(0.160)	(0.136)	(0.177)	(0.338)
Age	-0.018	-0.008	-0.017	0.018	0.008	0.042	0.030	0.084*	0.099
	(0.033)	(0.034)	(0.031)	(0.032)	(0.031)	(0.037)	(0.031)	(0.049)	(0.103)
Age Squared	0.0004	-0.00000	0.0001	-0.0002	-0.0001	-0.001	-0.0003	-0.001**	-0.002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.001)	(0.001)
College Education	0.247*	0.366***	0.013	0.220*	0.182	0.099	-0.057	-0.201	-0.427
	(0.133)	(0.135)	(0.130)	(0.129)	(0.134)	(0.155)	(0.130)	(0.177)	(0.329)
Income (Scale)	-0.031	0.160***	0.076	0.183***	0.028	-0.020	0.020	0.111	-0.125
	(0.051)	(0.054)	(0.050)	(0.051)	(0.051)	(0.060)	(0.050)	(0.068)	(0.127)
Children in Residence	0.225*	0.164	0.483***	-0.086	0.186	0.027	0.048	-0.208	0.506
	(0.134)	(0.145)	(0.133)	(0.137)	(0.135)	(0.159)	(0.134)	(0.184)	(0.332)
Employed	0.368**	0.050	0.047	-0.011	0.157	0.179	0.210	0.055	1.099**
	(0.152)	(0.153)	(0.146)	(0.149)	(0.151)	(0.177)	(0.149)	(0.204)	(0.477)
Days in Lockdown (Count)	0.002	-0.003	-0.007	0.008	0.015	-0.0005	0.007	0.048*	0.063
	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)	(0.024)	(0.020)	(0.026)	(0.045)
Constant	-0.704	0.556	0.013	-0.179	-0.896	-2.064***	-0.904	-3.528***	-5.664***
	(0.609)	(0.638)	(0.590)	(0.604)	(0.604)	(0.711)	(0.588)	(0.914)	(2.119)
Observations	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211	1,211
AIC	1617.26	1503.5	1648.13	1610.95	1590.83	1286.04	1633.82	1072.89	382.91

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S14: Demographic Breakdown of Survey Sample

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
White	1,211	0.505	0.500	0	0	1	1
Male	1,211	0.471	0.499	0	0	1	1
Children	1,211	0.324	0.468	0	0	1	1
College	1,211	0.607	0.489	0	0	1	1
Income	1,211	2.822	1.278	1	2	4	6
Age	1,211	35.318	11.848	18	27	41	83
Residence Duration	1,211	5.337	1.245	1	5	6	6
Employed	1,211	0.746	0.436	0	0	1	1
Student	1,211	0.086	0.280	0	0	0	1
Own Residence	1,211	0.462	0.499	0	0	1	1
Rent Residence	1,211	0.501	0.500	0	0	1	1
Residence: Apartment	1,211	0.317	0.466	0	0	1	1
Residence: House	1,211	0.615	0.487	0	0	1	1
Residence Size	1,211	2.268	0.881	0	2	3	3
External Storage	1,211	0.729	0.445	0	0	1	1
Cars	1,211	0.925	0.264	0	1	1	1
English	1,211	0.964	0.185	0	1	1	1
Republican	1,211	0.301	0.459	0	0	1	1
Prepared Water for Covid	1,211	0.446	0.497	0	0	1	1
Lockdown Before State Order	1,211	0.483	0.500	0	0	1	1
Days in Lockdown by Response	1,211	4.070	2.989	0	1	6	14

Table S15: Diagnostics on Data Balance After Matching

Demographic Indicators	Prior Lockdown	No Prior Lockdown	Difference
White	0.520	0.500	0.02
Male	0.440	0.470	-0.03
Republican	0.310	0.290	0.03
Age	35.320	35.230	0.09
Age Squared	1,388.960	1,381.430	7.54
College	0.670	0.580	0.08***
Income (Scale)	2.960	2.770	0.18**
Children	0.360	0.300	0.06**
Employed	0.780	0.740	0.04

Note: Each cell of the first two columns reports the average value per condition of its column in the data after nearest-neighbor propensity score matching procedures. For binary variables (including: male, white, republican, college, children, employed) this is the proportion of respondents in each condition which code positively on that predictor. For continuous variables (like age) and scale variables (like income), this is the average value of that predictor among respondents in the condition per column. The third column reports the difference between these averages across the two groups, with indicators from t-test estimates determining whether they are statistically significant, and at what level.

Table S16: Main Logit Models for Willingness to Prepare with Matched Data

	Dependent variable: Willing to Prepare Water for Earthquake	
Explanatory Variables	(1)	(2)
Prior Lockdown (Binary)	0.243**	0.212*
	(0.120)	(0.124)
Trust in Source		0.081*
		(0.049)
White		-0.157
		(0.128)
Male		-0.095
		(0.125)
Republican (Binary)		0.257*
		(0.138)
Age		-0.012
		(0.034)
Age Squared		0.0003
		(0.0004)
College Education		0.178
		(0.137)
Income (Scale)		-0.035
		(0.052)
Children in Residence		0.193
		(0.137)
Employed		0.392**
		(0.159)
Days in Lockdown (Count)		-0.006
		(0.021)
Constant	-0.536***	-0.907
	(0.086)	(0.634)
Observations	1,170	1,170
AIC	1573.09	1564.91

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S17: Main Logit Models for Willingness to Prepare with Latitude Longitude Filtering

	Dependent variable: Willing to Prepare Water for Earthquake			
Explanatory Variables	(1)	(2)	(3)	(4)
Prior Lockdown (Binary)	0.270**		0.273**	0.266**
	(0.126)		(0.126)	(0.130)
Trust in Source		0.072	0.074	0.062
		(0.050)	(0.050)	(0.051)
White				-0.324**
				(0.135)
Male				-0.060
				(0.131)
Republican (Binary)				0.172
				(0.145)
Age				0.011
				(0.035)
Age Squared				0.0001
				(0.0004)
College Education				0.087
				(0.143)
Income (Scale)				-0.015
				(0.056)
Children in Residence				0.068
				(0.147)
Employed				0.298*
				(0.162)
Days in Lockdown (Count)				-0.021
				(0.022)
Constant	-0.631***	-0.563***	-0.699***	-1.225*
	(0.089)	(0.078)	(0.101)	(0.656)
Observations	1,079	1,079	1,079	1,079
AIC	1430.44	1432.86	1430.16	1428.42

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Table S18: Main Logit Models for Willingness to Prepare Omitting Short Response Times

	Dependent variable: Willing to Prepare Water for Earthquake			
Explanatory Variables	(1)	(2)	(3)	(4)
Prior Lockdown (Binary)	0.274^{**}		0.274^{**}	0.220^{*}
	(0.119)		(0.119)	(0.124)
Trust in Source		0.090^{*}	0.090^{*}	0.071
		(0.047)	(0.047)	(0.049)
White				-0.116
				(0.127)
Male				-0.086
				(0.124)
Republican (Binary)				0.239^{*}
				(0.137)
Age				-0.011
				(0.033)
Age Squared				0.0003
				(0.0004)
College Education				0.203
				(0.136)
Income (Scale)				-0.046
				(0.052)
Children in Residence				0.185
				(0.136)
Employed				0.338^{**}
				(0.155)
Days in Lockdown (Count)				-0.002
				(0.020)
Constant	-0.569^{***}	-0.517^{***}	-0.651^{***}	-0.929
	(0.084)	(0.074)	(0.095)	(0.623)
Observations	1,191	1,191	1,191	1,191
AIC	1594.72	1596.24	1592.93	1589.45

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses below regression coefficients.

Figure S1: AME Plot for Main OLS Regression Results

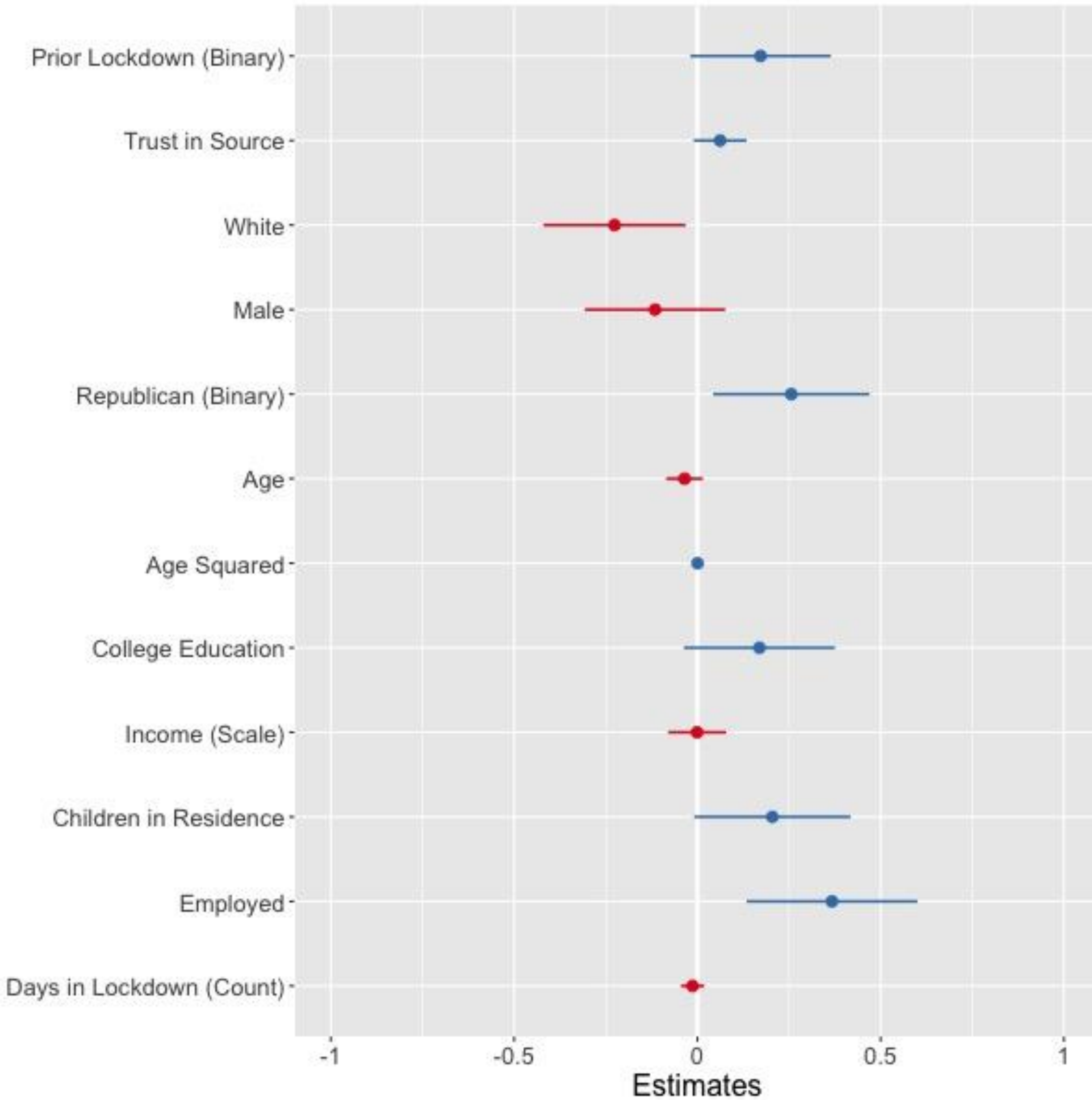
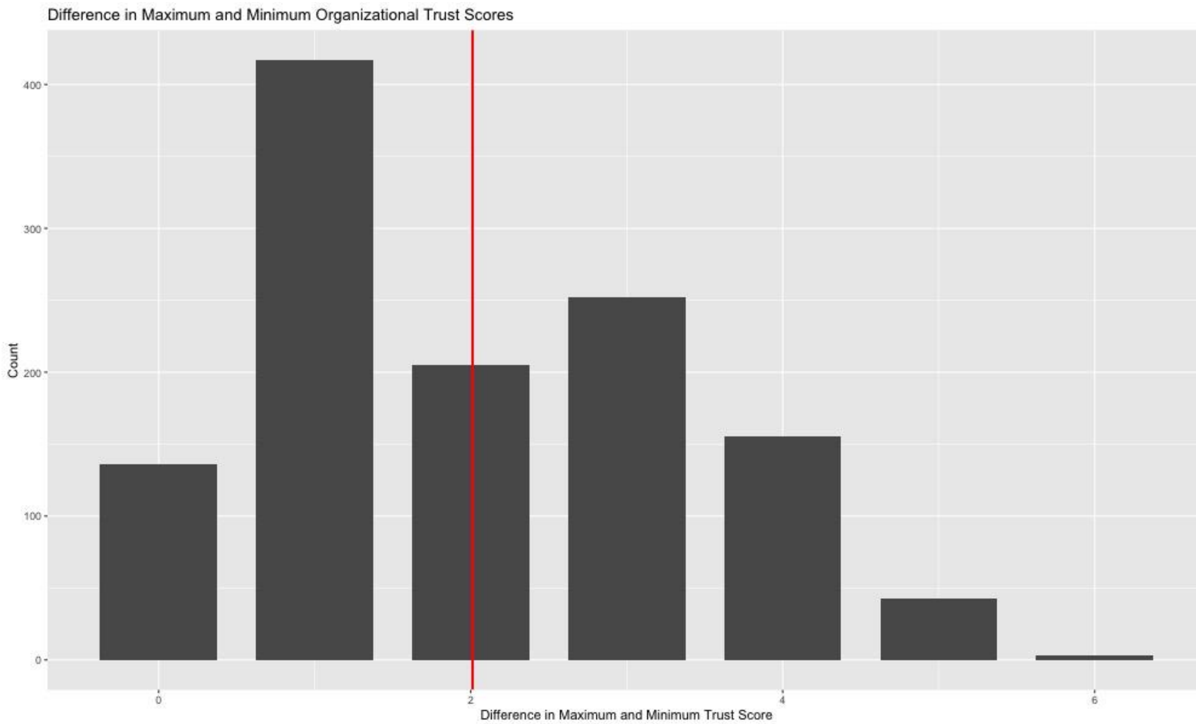


Figure S2: Histogram for Breadth of Difference in Most and Least Trusted Likert Scores



Note S1: Survey Respondent Consent and Pay

Respondents were informed of any potential risks before beginning the survey, and were allowed to end or leave the survey at any time. Respondents were informed that the information could be used for reports in scholarly journals, academic seminars, or research association meetings, and were provided a contact email of the primary investigator to raise any questions or concerns. The survey took approximately 6 minutes and 30 seconds, with a standard deviation of 1 minute and 48 seconds. The first 772 respondents received $1.00 for their response if they completed the survey, and the remaining 439 respondents were paid $1.50 for a complete response; the pay rate was increased to accelerate response collection and we saw no significant impact of the pay rate difference on our main predictor or outcome variables.

Note S2: Demographic Correlates and Extraneous Covid Preparation

Our analysis also suggests that the individual-level characteristics associated with preparedness vary across domains. In our survey, we asked individuals whether they had stored goods in preparation for the California COVID-19 lockdowns.[1] If they responded positively, we asked whether they had obtained canned and dry food, water, medicine, medical supplies, toilet paper, luxury items (like alcohol and tobacco), and/or firearms and ammunition. We also allowed respondents to list other items they had chosen to prepare after the closed-ended question;

[1] See Table S.13 for sociodemographic drivers of COVID-19 preparation.

respondents often listed cleaning supplies and sanitizer, pet food, and entertainment products. College education was not only a significant predictor of willingness to store water for earthquakes; it was also a significant predictor of household storage of a variety goods in response to the COVID-19 pandemic. We found that non-white respondents were significantly more likely to report having prepared water, food, medical supplies, and toilet paper. In contrast, white-identifying respondents were significantly more likely to report having stored luxury goods, like alcohol and tobacco. These results suggest non-white individuals may have worse access to well-stocked stores where they could purchase such goods in their neighborhoods and/or lower expectations of governmental assistance in the event of shortages. Further research should assess the extent to which underlying rates of disaster preparation across different demographic groups vary with the *type* of emergency, as well as how access to staple goods and relationships with public authorities affect rates of preparedness among different segments of the population.

Note S3: Simulation Procedure from Section on Aggregate Effects

We rely on Model 4 from the main results table, including all demographic covariates in this predictive exercise from our survey data. This procedure yields four N-length vectors of predicted probabilities (one for each scenario) that each respondent would be willing to store the recommended amount of water. For each predicted probability p, in each of the four scenarios, we conduct 100,000 Bernoulli trials to simulate a binary outcome indicating whether the respondent would prepare (this yields 1 in p proportion of those trials, and 0 in $(1-p)$ proportion of those trials). For each iteration of Bernoulli trials on the N-length vector, we average the binary outcomes to produce a sample-level proportion of respondents simulated as willing to prepare water. We then estimate the difference in predicted proportions of the sample expressing willingness to prepare water in each of the higher-likelihood scenarios from the simulated proportion in the low-likelihood scenario. This exercise produces an estimate of the total proportion of the sample which would be willing to prepare water under each scenario, a point estimate of the difference between higher-likelihood scenarios and the low-likelihood scenario, and a 95% confidence interval for this difference based on the iterated simulation trials.

Note S4: Propensity Score Matching Procedure for Robustness Tests

We use nearest-neighbor propensity score matching from a logistic regression model predicting prior lockdown with our main demographic covariates, to match treated and untreated survey responses. This procedure matched treated (respondents reporting prior lockdown) and untreated (respondents reporting no prior lockdown) responses as a function of the minimal distance in propensity scores on those demographic covariates predicting prior lockdown using the R package MatchIt (Stuart et al., 2011).

Note S5: Anonymized Pre-Analysis Plan (March 2020)

i. Summary and Rationale

The purpose of this survey experiment is to understand how risk communication from different message sources can affect individuals' propensities to prepare for emergency situations, and how the effect of this intervention varies across individuals experiencing Covid-19 related lockdowns.

We leverage one primary messaging intervention in this survey, premised on trust in message source. The survey includes pre-test questions on respondents' trust in five different organizations, including: local city government, local water providers, FEMA, Red Cross, and independent academic experts. It then presents a message from one of these organizations, randomly selected, regarding risk information about the recommended volume of water individuals should store for emergency situations (2 gallons, per person, per day, for 3 to 7 days).

Beyond this, the survey leverages a natural experiment currently unfolding in California, specifically the various shelter-at-home lockdowns enacted by counties and city governments. We plan to leverage the variance in when and where these lockdowns have been enforced, in order to determine the influence of emergency salience on our primary messaging interventions.

We anticipate that receiving information from more trusted organizations will generally increase self-reported intentions to engage in risk-reducing behaviors, specifically intention to store water in preparation for earthquake-induced service outages. We expect Covid-related lockdowns to increase risk salience for respondents, and thus the amplitude of our messaging interventions, as a feature of the visibility of a currently-unfolding emergency among respondents to our survey.

ii. Study Design

The survey design is as follows:

a. Obtain consent and ensure respondents are 18 years or older;
b. Ask a series of questions to filter respondents who are not appropriate for the study (in this case, individuals who receive well water or are not California residents) and to screen respondents who were not under a lockdown before the state-wide directive on March 19 at 6:30 pm (to ensure balance in natural experiment treatment);
c. Present an introduction explaining water utilities to respondents, the services they provide, and the various natural hazards which they face (such as earthquakes);
d. Ask respondents a series of trust questions on five organizations, including local city government, local water providers, FEMA, Red Cross, and independent academic experts. These are collected first as a 6-point Likert scale for trust in each, and then as a ranking question to solicit comparative trust across those organizations.
e. Ask a series of demographic questions, including traditional batteries such as age, racial identity, gender, education, income, partisanship, and employment. We also ask duration of respondents' residence in California, ZIP code (to use as a covariate for if the respondent is in a lockdown area at time of response), and about the size and membership of their households as control variables for later analysis;

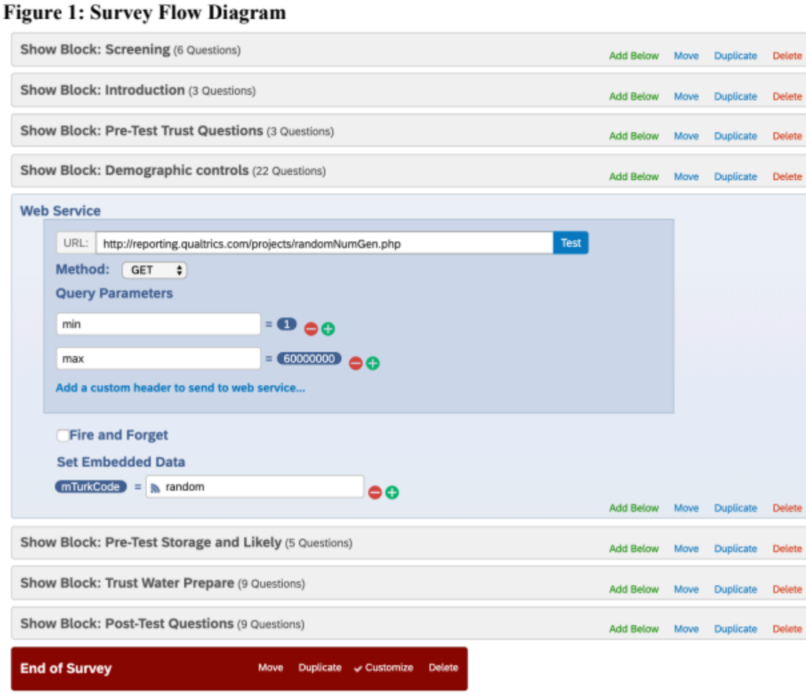
f. Ask individuals how much water they currently have stored for an emergency, how this is stored if any storage is reported, and respondents' perception about the likelihood of a magnitude 6.7 or higher earthquake affecting their water service in the next 5 years;
g. Respondents are then exposed to a message on recommended volumes of water to store for emergency situations, with a message source chosen randomly from one of the above 5 groups, or from a control (with language that this is "generally recommended")
h. Ask a final series of post-test questions, including:
   - the perceived ease of storing this recommended volume of water;
   - whether respondents' obtained emergency supplies for the Covid-19 lockdown;
   - what they chose to store (contingent on positive response to prior question);
   - why they chose to store these items (if they selected water or firearms);
   - how much water they chose to store (if they selected water);
   - on what day their lockdown began;
   - on what day they began working remotely (if they are employed); and
   - on what day their children stopped going to school (if they have children).

iii. Survey Design and Assignment Logic

The survey is designed to evenly allocate respondents across the five organizations of message sources and a control group. As such, with 1,200 respondents, we plan to have 200 respondents in each of these groups. The survey flow diagram can be found below in figure 1.

Figure S3: Survey Flow Diagram

Figure 1: Survey Flow Diagram



iv. Hypotheses

We hypothesize that the trust in message source will have a positive effect on the likelihood of intention to store recommended water:

H1: Respondents exposed to messages from sources in which they have higher prior levels of trust will be more likely to prepare the expert-recommended volume of water for an earthquake than messages from sources in which they have lower levels of prior trust.

An initial pilot survey offers insignificant but supporting evidence of these trends, which showed a positive relationship between trust in message source and support for this outcome measure.

We also hypothesize that this treatment effect will be larger among individuals who experienced a lockdown before the state-wide directive on March 19 at 6:30 pm, as a feature of higher salience in their lived experience of an actual emergency situation:

H1A: Respondents who were in a Covid-related lockdown before the state-wide directive will be more sensitive to the trust intervention than respondents who were only affected by the state-wide directive.

H1B: Respondents who experienced lockdowns for longer periods of time would be more sensitive to the trust intervention than those who experienced lockdowns for shorter periods. We also expect individuals who have children or who have been forced to work at home under the lockdown to be more affected by the interventions, as this amounts to be intensive exposure to the lockdowns.

We also hypothesize that effects may be conditional on background demographics, including gender, race, age, income, and having children. Household factors such as unavailability of storage space should be associated with less proclivity to store water.

v. Data Collection

We will collect data to test these hypotheses through the online survey platform, Amazon mechanical Turk (mTurk). This is the same platform which was used to collect data for a pilot for this experiment. We intend to apply respondent quotas to achieve balance across respondents who did and did not experience a Covid-related lockdown before March 19 at 6:30 pm. We plan to collect responses from 1,200 California residents, and do not plan to impose demographic quotas. We plan to follow this with a second wave survey which tests a broader collection of outcome measures, which will include quotas to achieve a demographically representative sample.

Respondents are restricted by state of residence, to ensure only individuals residing in California may access the survey. This is a critical aspect of the design for ensuring credibility of risk estimates, which are generated for California fault lines and earthquake preparation. We expect to administer this survey beginning Friday, March 20, and to continue this until we have achieved a sample including a reasonable balance of respondents who were and were not under previous Covid-related lockdowns before the state-wide directive.

Respondents will receive $1.00 for completing the survey, which takes approximately 8-10 minutes to complete. This is to achieve a pay rate of approximately federal minimum wage, which is understood to incentivize thoughtful and honest answers from respondents. Respondents are made aware of this value before taking the survey, as well as the stipulations for its receipt, including full completion of the survey and following all listed instructions. We will ensure confidentiality by assigning a random identification code for each respondent. This can be found in the 'Web Service' portion of the survey flow. This code is also used for respondents to submit their pay request following the survey, and for validating responses. Qualtrics data which could conceivably be used to identify respondents will be destroyed.

vi. Sample Size and Power

We have designed this survey to have power over between-respondent effect sizes corresponding to a 10% shift on a 7-point scale (0.7). We base this calculation with data from a previous pilot on intention to store water, with a SD of this outcome at 1.63. For power over 5 groups and a control, we estimate that 1,200 respondents will be larger than necessary for power over this effect size.

vii. Data Analysis

a. Attrition. This is a concern in all survey experiments. We have attempted to reduce this issue by offering a competitive pay rate, as discussed in the previous section.
b. Response Quality. Time spent on the survey is a strong predictor of this, and we will thus use this as an indicator in robustness tests. We have also chosen to include an attention check within the survey instrument to filter out respondents who are not following instructions and randomly entering responses to questions.
c. Balance. As all experimental designs require randomization, we will both strive for and test for balance in our survey data. We have attempted to achieve representativeness with quotas, which can be tailored to ensure concurrent balance. We will also test for balance with t-tests and K-S tests following data collection. Preliminary simulations of survey responses demonstrate that the instrument evenly allocated respondents across treatment domains and organization message source.
d. Outcomes. Assuming that we have avoided attrition, and achieved response quality and balance, we will test the hypotheses on the data in two primary ways. First, we will use basic bivariate t-tests for treatment effects, as in traditional experiments. We will also use linear models with controls to test robustness of these estimates.

viii. Respondent Recourse

Respondents have the ability to communicate with the survey administrators through the survey platform, and are provided the contact information of the PI in the survey. If any respondent experiences discomfort or another negative effect of their participation in the survey, they may use this contact as means of communication with the research team. During the pilot, we received several emails from respondents with primarily positive feedback about the information they received in the survey-taking experience. This contact information is also a means by which respondents can resolve any potential pay discrepancies which may arise during the response validation process, or as a result of a technical flaw in the Amazon mTurk compensation system.

Works Cited

Stuart, E. A., King, G., Imai, K., & Ho, D. (2011). MatchIt: Nonparametric preprocessing for parametric causal inference. *Journal of Statistical Software*.