Natural Disasters and Cooperation under Diversity: Evidence from Hurricane Harvey

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How does diversity affect cooperation after natural disasters? Drawing on an original survey of Houston-area households and two survey experiments, we find that diversity is associated with lower levels of impersonal cooperation—beyond family and friends—before natural disasters and with lower cooperation both before and after disasters. In affected areas, households in more diverse tracts report receiving less help and express lower support for recovery policies. In a policy experiment, affected respondents typically favor more costly recovery measures, but this preference weakens in high-diversity areas. A second experiment uncovers strong post-disaster ingroup biases along partisan and religious lines, while shared membership in civic associations emerges as a critical facilitator of cooperation in diverse settings. Taken together, these findings demonstrate that diversity can impede post-disaster cooperation and illuminate how social identities shape cooperation and recovery efforts.

Introduction

How do natural disasters affect cooperation? A growing literature documents that disasters tend to have a positive impact on prosocial behavior and that social capital facilitates recovery. However, the evidence remains mixed: some studies document positive effects, where exposure to natural disasters elicits higher cooperation (Calo-Blanco et al., 2017; Cassar et al., 2017; Dacy and Kunreuther, 1969; Douty, 1972; Toya and Skidmore, 2014; Schilpzand, 2023); others report mixed or negative effects (Albrecht, 2018; Berrebi et al., 2021; Fleming et al., 2014; Rayamajhee et al., 2024). Much of this research treats disasters as uniform shocks, but whether shocks foster cooperation is likely to depend on features of the social environment in which shocks occur.

We argue that two environmental features affect cooperation after natural disasters: (1) the extent of damage to individuals and communities; and (2) the level of ethnic diversity. Prior research suggests that shocks such as natural disasters foster cooperation and heighten compliance with social norms (Gelfand et al., 2011); diversity, on the other hand, tends to undermine cooperation and the provision of public goods (Alesina et al., 1999; Alesina and Ferrara, 2000; Algan et al., 2016; Costa and Kahn, 2003; Habyarimana et al., 2007; Luttmer, 2001; Miguel and Gugerty, 2005). Yet little attention has been given to how these two features interact affecting cooperation.

Hurricane Harvey, the second-costliest disaster in U.S. history, provides a critical setting to study how exposure to natural disaster and ethnic diversity affect cooperation. Harvey was highly destructive—causing $125 billion in damages, 68 direct deaths, and over 100 indirect deaths (Blake and Zelinsky, 2018)—and struck one of the most ethnically diverse metropolitan areas in the United States. These features allow us to study how variation in both exposure to the shock and ethnic diversity shapes post-disaster cooperation. We study the effect of Hurricane Harvey on cooperation employing observational and experimental data. We draw on three waves of an original panel survey fielded by the Hobby School of Public Affairs at the University of Houston between 2017 and 2020 covering four counties in the Houston area; the 2020 wave included two survey experiments. We merge the survey data with detailed administrative records to construct measures of ethnic diversity and damage levels at the census tract level.

We rely on multiple measures of cooperation, including spontaneous interpersonal assistance during the natural disaster and support for costly recovery and adaptation policies. First, we examine the effect of Harvey on cooperation and show that ethnic diversity moderated responses to the storm, decreasing costly cooperation. Prior to the storm, cooperation with neighbors—but not with friends and family—was significantly lower in census tracts with higher ethnic diversity. Respondents in more diverse areas were less likely to receive help before and after Harvey. This effect was only present in tracts directly affected by the storm.

Second, we examine support for recovery and adaptation policies, a measure of costly cooperation. The policies we analyze are local adaptation measures intended to reduce future flood risk, including flood-control infrastructure, land-use regulations, and building standards designed to reduce vulnerability to future storms. We find that tract-level damage is associated with greater support for adaptation policies in more homogeneous areas. In affected areas, support for these policies decreases as diversity increases. Drawing on data from a conjoint experiment, we further show that while respondents strongly preferred proposals involving lower tax increases, support for costlier policies was higher among respondents personally affected by the storm. Among respondents experiencing damage during Harvey, support for costly policies was lower in more diverse tracts. These findings contribute to recent work showing that losses increase support for climate policies: diversity moderates the relationship between exposure and policy support (Arias and Blair, 2024; Bechtel and Mannino, 2023; Bergquist and Warshaw, 2019).

Having established how diversity and damage interact to shape cooperation, we then analyze patterns of *parochial cooperation* across groups of various identities (Bernhard et al., 2006). Results from a conjoint experiment suggest the existence of ingroup bias, but reveal three noteworthy patterns: (1) gender- and race-based ingroup bias is modest or absent; (2) shared partisanship and religion command a high degree of cooperation, but are invariant to the level of diversity in the community; and (3) in diverse areas, civic associations become important channels of cooperation, a pattern consistent with earlier work on the role of social capital in impersonal and heterogeneous environments.

Our findings contribute to a growing literature on how natural disasters affect cooperation and prosocial behavior. Much work documents positive effects (Calo-Blanco et al., 2017; Cassar et al., 2017; Dacy and Kunreuther, 1969; Douty, 1972; Toya and Skidmore, 2014; Schilpzand, 2023), yet findings remain mixed (Berrebi et al., 2021; Fleming et al., 2014). This might reflect that the effect of natural disasters on cooperation is theoretically ambiguous (Schilpzand, 2023). However, it might also reflect heterogeneity driven by contextual characteristics, such as ethnic diversity. Our results suggest that the effect of disaster exposure on cooperation depends on ethnic diversity, identifying the scope conditions under which natural disasters elicit cooperation.

Earlier work has on natural disasters and cooperation relied on specific events (Aldrich, 2011, 2012a; Calo-Blanco et al., 2017; Chamlee-Wright and Storr, 2009; Storr and Haeffele-Balch, 2012; Storr et al., 2017) and large samples (Berrebi et al., 2021; Cutter, 2016; Toya and Skidmore, 2014; Schilpzand, 2023). Our focus on a highly heterogeneous urban context allows us to take a multi-pronged approach, combining observational and experimental evidence. We contribute to this literature in two main ways. First, despite the variety and sophistication in measuring what might be correlates of cooperation, such as trust (Cassar et al., 2017; Toya and Skidmore, 2014; Schilpzand, 2023) and social cohesion (Calo-Blanco et al., 2017), few studies deal with cooperation explicitly.

We move beyond proxies such as trust and cohesion and examine a wider range of behavioral and policy-relevant measures of cooperation at the interpersonal and societal level: (1) self-reported measures of cooperation and helping behavior, (2) support for costly recovery policies, and (3) cooperation along multiple group identities. The consistency of our results across multiple measures is reassuring and suggestive of construct validity (Adcock and Collier, 2001). Second, we show that diversity differentially affects various forms of cooperation: it is negatively associated with cooperation on average, yet, in the aftermath of Harvey, cooperation is strongly parochial, with different effects for strong and weak ties. By establishing that diversity enables cooperation through civic associations, we help to clarify the role of "bonding" and "bridging" social capital in disaster recovery (Aldrich, 2012a; Aldrich and Meyer, 2015; Chamlee-Wright and Storr, 2009; Rayamajhee and Bohara, 2021; Storr et al., 2017). Together, our findings offer a clearer understanding of how social context shapes cooperative behavior in the face of disasters.

Natural disasters, ethnic diversity and cooperation

Cooperation occurs when an individual incurs a cost to provide a benefit for others (Henrich and Henrich, 2007, p.37). Cooperative interactions can occur on an interpersonal level—helping a friend or a stranger—or in large groups—voting, recycling, paying taxes. While cooperation in small-scale societies can be explained by kinship (McNamara and Henrich, 2017), large-scale cooperation in diverse societies is a puzzle that has motivated a great deal of theoretical and empirical work (Bowles and Gintis, 2011; Henrich and Henrich, 2007; Seabright, 2010).

Natural disasters are a laboratory for testing theories of cooperation. The literature highlights two main findings. First, disasters tend to increase prosocial behaviors, including trust, social cohesion, and helping behavior (Calo-Blanco et al., 2017; Cassar et al., 2017; Dacy and Kunreuther, 1969; Douty, 1972; Schilpzand, 2023). Second, social capital facilitates disaster recovery (Aldrich, 2011, 2012a,b; Aldrich and Meyer, 2015; Chamlee-Wright and Storr, 2009; Cutter, 2016; Rayamajhee and Bohara, 2021; Storr et al., 2017; Townshend et al., 2015).

Researchers, however, have paid limited attention to the social environment in which shocks occur. Social geography shapes inter-group attitudes and behavior (Enos, 2017). The environment in which disasters occur is characterized by two relevant features. First, individuals are affected to different degrees. Second, communities vary in their heterogeneity. We argue that both features influence the likelihood and form of cooperation.

Convergent lines of research indicate that common shocks can promote cooperation. First, an economic argument posits that shocks may increase the marginal value of public goods—this argument has been applied to wars (Besley and Persson, 2009). Individuals affected by disasters are therefore more willing to incur costs that yield future benefits. Second, evolutionary psychologists propose that shocks foster compliance social norms: communities exposed to pathogen stress and natural disasters display stronger norms (Gelfand et al., 2011). In a similar vein, studies document positive effects of disasters on trust (Cassar et al., 2017; Toya and Skidmore, 2014; Schilpzand, 2023), group cohesion (Calo-Blanco et al., 2017), and helping behavior (Kaniasty and Norris, 1995). These arguments imply that storm damage should be associated with greater levels of cooperation, both in terms of interpersonal assistance and contributions to public goods **(H1)**.

Ethnic diversity is another environmental feature affecting individuals' propensity to cooperate. Evidence shows that diversity hinders cooperation and public goods provision (Algan et al., 2016; Alesina and Ferrara, 2000; Costa and Kahn, 2003; Luttmer, 2001; Miguel and Gugerty, 2005). Diversity may reduce cooperation through three mechanisms: (1) divergent preferences (Alesina et al., 1999), (2) ingroup bias (Tajfel, 1974), and (3) limited norm enforcement across groups (Habyarimana et al., 2007). We therefore expect that greater ethnic diversity will be associated with lower levels of cooperation **(H2)**.

Although the literature has studied these forces independently, we propose that they are likely to interact. In diverse settings, weaker norm enforcement increases the likelihood that out-group members may free-ride on the provision of public goods—for example, costly investments for disaster prevention—and on contributions to cooperation efforts in general. Uncertainty about whether others will contribute reduces the expected collective benefits of cooperation. As a result, individuals may refrain from contributing. Thus, we expect diversity to attenuate the positive relationship between disaster damage and collective cooperation **(H3)**.

Yet disasters do not only affect the likelihood of cooperation—they also shape with whom individuals choose to cooperate. Human cooperation is *parochial*—we tend to cooperate more with members of our ingroup (Bernhard et al., 2006; Cappelen et al., 2025; Choi and Bowles, 2007) and are less likely to cooperate with outgroup members. In diverse settings, individuals encounter both ingroup and outgroup members. Research shows that disasters heighten the salience of group boundaries, increasing trust in ingroup members (Schilpzand, 2023) and fostering negative perceptions of outgroups (Chung and Rhee, 2022). In diverse communities affected by disasters, minority groups receive less help (Bolin and Bolton, 1986; Kaniasty and Norris, 1995). This suggests that shocks such as Hurricane Harvey may not uniformly affect cooperation levels, but instead shift patterns of parochial cooperation. We therefore expect that cooperation will become more directed toward ingroup members **(H4)**.

In modern urban settings, however, individuals typically belong to multiple groups defined by both ascriptive traits and voluntary associations—they have both "strong" and "weak" ties (Granovetter, 1973). Because diversity is a source of uncertainty, individuals may use different group traits as heuristics for partner selection. Yet, which identities or ingroups command greater levels of cooperation in the face of shocks? We address this question experimentally by probing ingroup bias across multiple group identities after a storm.

Hurricane Harvey: A costly disaster in a diverse metropolitan area

The Houston Metropolitan Area is the fourth-largest metro area in the US, with more than 7 million residents. It has grown by 25% since 2010, with a population increase of 1.5 million people. It is also one of the most ethnically diverse metro areas in the US, with a population that is 44.5% Hispanic or Latino, 24.1% white, 22.1% Black or African American, and 6.8% Asian (U.S. Census Bureau, 2023). More than 28% of Houston's residents were born outside the United States. Such high levels of diversity and the fact that no ethnic group constitutes a majority make the Houston metro an ideal setting to test the effects of diversity on political behavior.

In the United States, disasters are increasing in frequency and cost. Between 1980 and 2023, the country experienced 403 weather and climate disasters that exceeded $1 billion each in damages, with total costs exceeding $2.9 trillion[1]. Hurricane Harvey, a Category 4 hurricane, was the second-costliest disaster in U.S. history, with a cost of $125 billion and 68 direct deaths and over 100 indirect deaths (Blake and Zelinsky, 2018). It caused widespread damage due to extreme rainfall—the heaviest in U.S. history—totaling 27 trillion gallons of rain, with some areas receiving over 50 inches (Blake and Zelinsky, 2018). It displaced 30,000 people and destroyed more than 200,000 homes and businesses.[2]

The response to Harvey included immediate efforts by local first responders, such as the Texas National Guard, the U.S. Coast Guard, and the Federal Emergency Management Agency (FEMA). Financially, Congress approved $15.25 billion in federal disaster relief, and over 890,000 households registered for FEMA aid. The National Flood Insurance Program (NFIP) paid out more than $8.92 billion in flood insurance claims. Beyond governmental response, Harvey

[1] U.S. Billion-Dollar Disasters: 1980-2024

[2] National Centers for Environmental Information (2025).

triggered grassroots civil society efforts and volunteer operations. Churches and faith communities played a prominent role, providing a wide range of services, including funds and housing assistance (Westfall et al., 2019).[3] Local volunteers and groups, such as the civilian "Cajun Navy," provided assistance such as boat rescues and evacuation.[4] Stephen Flynn, one of the foremost experts on the role of civil society in disaster recovery, described the response to Harvey as "bottom-up, emergent" highlighting the importance of social cohesion and collective action.[5]

Data

Survey data. The Hobby School of Public Affairs at the University of Houston conducted three survey waves in Harris, Fort Bend, Brazoria, and Montgomery counties following Hurricane Harvey. The first wave, fielded by telephone in November–December 2017, interviewed 2,002 adults and oversampled areas expected to have flooded; weights were applied only to correct for the owner–renter imbalance in Harris County. The second wave, conducted by telephone in June–July 2018, included 1,073 respondents, of whom 572 had participated in the 2017 survey and 501 were drawn from a fresh sample; weights corrected for owner–renter balance and racial distribution across all four counties. The third wave, conducted online in May–June 2020, surveyed 1,065 respondents with demographic quotas for county, age, race, and gender, and applied weights for race, sex, age, and party identification. Across the three surveys, the 2017 and 2018 waves shared a phone-based design and emphasis on flood-exposed areas, while the 2020 wave shifted to an online mode with quota sampling. Online Appendix Section A2 provides details on sampling and survey logistics and Table A1 provides descriptive statistics of the survey variables used in the analysis.

[3]"Church Groups Mobilize to Rebuild Houston Homes." *State of Emergency News 21*, July 10 2019.

[4]In all-hands-on-deck response to Harvey, lessons learned from earlier storms," *The Christian Science Monitor*, August 28, 2017.

[5]Harvey brings out 'hidden capacity in civil society' to respond."

Administrative data. To measure ethnic diversity and storm damage, we employ two administrative datasets: the US Census 2016 American Community Survey (ACS) and the City of Houston Open Data website.

1. ***Ethnic diversity***. We calculate measures of ethnic diversity using data from the 2016 American Community Survey (ACS). The ACS provides social and demographic data at the census tract level. We use ACS variables that capture the number of individuals from each ethnic group in each tract: White or Anglo, Black or African American, Hispanic or Latino, Asian, and Other. We construct a standard measure of ethnic fractionalization, which represents the probability that two randomly selected individuals in a given tract belong to different ethnic groups.[6]

2. ***Storm damage***. We obtained census tract-level measures of damage from the City of Houston Open Data website. The data contains count variables of housing units affected by Harvey, based on a range of assessment surveys, including 311 service request calls, 911 incident calls, Solid Waste Management Department debris pickup locations, high water mark data obtained by the Public Works Department Flood Plain Management Office, FEMA individual assistance requests, and data from the National Flood Insurance Program. We collapse these counts into a binary tract-level indicator. The variable $Damage_j$ equals 1 if any housing units in tract j are recorded as affected by Harvey (count > 0) in the administrative data, and 0 otherwise.[7]

[6]Formally, ethnic fractionalization is defined as $1 - \sum_{g=1}^{G} \pi_{gt}^2$, where π_{gt} denotes the share of residents in tract t who belong to ethnic group g, and G is the total number of ethnic groups.

[7]Online Appendix Section A2 provides a detailed analysis of missingness in each variable used in the analysis in the following section.

Results

Cooperation before Harvey

Table 1 reports OLS estimates of the relationship between ethnic diversity and reported cooperation pre-Harvey with different groups in the community. The outcome is whether respondents coordinated preparedness actions with immediate family, extended family, neighbors, or friends prior to the hurricane making landfall in the region. The exact survey question is: "Before Harvey reached Houston, did you coordinate plans for the approaching hurricane with others? With whom did you coordinate?" Although the wording emphasizes coordination, we interpret this behavior as a form of cooperation. We estimate the following equation:

$$\text{Coordination}_{ij}^{k} \;=\; \alpha \;+\; \beta\,\text{Diversity}_{j} \;+\; \mathbf{X}_{ij}\boldsymbol{\gamma} \;+\; \varepsilon_{ij}^{k}, \tag{1}$$

where i denotes a respondent in census tract j, $\text{Coordination}_{ij}^{k}$ is a pre–Harvey binary measure of coordination, k indexes social tie categories (immediate family, extended family, neighbors, or friends). All outcome variables are coded 1 when the response is affirmative, and 0 otherwise. The key explanatory variable, Diversity_{j}, is the tract-level index of ethnic fractionalization. The coefficient of interest, β, captures the association between local ethnic heterogeneity and each form of coordination. $\mathbf{X}_{ij}$ is a vector of individual-level controls. Controls include indicators for partisanship, race/ethnicity, age group, educational attainment, household-income bracket, zipcode fixed effects, an in-town indicator (presence during Hurricane Harvey), and a survey-wave indicator. All models are estimated by weighted least squares using the survey weight, with standard errors clustered at the census-tract level.

All models include zipcode fixed effects and individual-level controls (Party ID, age, education, race, income, years in town, and survey wave). While ethnic diversity is not correlated with coordination with respondents' family or friends, respondents in more diverse areas were significantly less likely to coordinate with neighbors before Harvey (Table 1). A one-unit increase in ethnic diversity is associated with a 21.7 percentage-points (pp) decrease in the likelihood of coordinating with neighbors ($p < 0.05$), conditional on covariates. This is a large effect given the average probability of coordinating with neighbors (12.7%). These results speak to **H2**—diversity is associated with lower cooperation—but only of the more impersonal type, not driven by strong reciprocity or kin obligations. By contrast, cooperation with family and friends remains invariant to the level of diversity.

Table 1: Likelihood of coordinating prior to Hurricane Harvey.

	(1) Immediate Family	(2) Extended Family	(3) Neighbors	(4) Friends
Diversity	-0.0538	-0.218	-0.217**	0.0526
	(0.122)	(0.135)	(0.0890)	(0.149)
Adj. R-squared	0.117	0.104	0.129	0.106
Observations	1381	1381	1381	1381

Notes: Results from OLS models. Controls include respondents' party ID, age, education, race, income, number of years in town, and survey wave. All models include zipcode fixed effects. Survey weights included for all models. Standard errors clustered at the tract level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Cooperation before and after Harvey

Here, we examine whether ethnic diversity shaped patterns of cooperation before and after Hurricane Harvey. Here, the outcome is the answer to the question: "In the days immediately before or after Hurricane Harvey, did you receive any help from family members, friends, or other people who you might know through clubs, churches or organizations you belong to?" We estimate the following equation:

$$\text{Received Help}_{ij} = \alpha + \beta_1 \text{Diversity}_j + \beta_2 \text{Damage}_j + \beta_3 \left(\text{Diversity}_j \times \text{Damage}_j\right) + \mathbf{X}_{ij}\boldsymbol{\gamma} + \varepsilon_{ij}, \tag{2}$$

where i denotes respondents in census tract j, the dependent variable Received Help_{ij} equals 1 if the respondent received assistance before or after Hurricane Harvey and 0 otherwise. Diversity_j denotes the ethnic fractionalization index, Damage_j is binary variable that takes the value of 1 if tract j experienced storm damage. The interaction term $\text{Diversity}_j \times \text{Damage}_j$ allows the diversity effect to differ between damaged and undamaged tracts. $\mathbf{X}_{ij}$ is a vector of controls as in Equation 1, adding an indicator of whether the respondent evacuated before landfall. All models are estimated by weighted least squares with respondent survey weights and standard errors clustered at the census tract level.

Consistent with **H2**, columns 1 and 2 of Table 2 shows that higher ethnic diversity is significantly associated with a lower likelihood of receiving help ($p < 0.05$), conditional on covariates. The coefficient on tract-level damage is negative and noisy, which does not support **H1**. The negative interaction term between damage and diversity indicates that the likelihood of receiving help decreases as diversity increases in tracts that experienced damage. Figure 1 illustrates this conditional relationship: in unaffected tracts, diversity is unrelated to the probability of receiving help, but in affected tracts, higher diversity predicts substantially lower levels of help. In a low-diversity affected tract ($Diversity_j =$ 0.25), damage increases the probability of receiving help by about 9.1 pp. This is a 28% increase relative to the baseline probability of receiving help of 31.9%. In a high-diversity affected tract ($Diversity_j =$ 0.75) the marginal effect of damage is -24 pp, a 75% decrease relative to the baseline. Moving from an affected tract with 25% diversity to one with 75% diversity is associated with a 33 pp decrease in the marginal effect, which is roughly the size

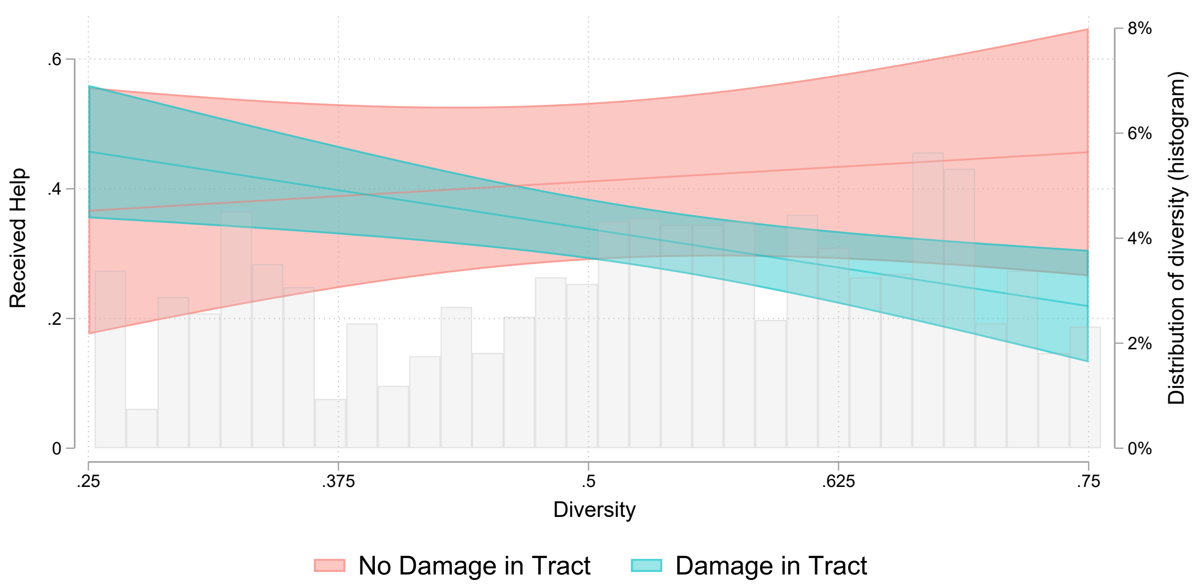
(103%) of the baseline mean. Overall, consistent with **H3**, ethnic diversity is associated with a lower probability of receiving help in more affected areas.

Table 2: Likelihood of receiving help following Hurricane Harvey.

	Received Help		
	(1)	(2)	(3)
Diversity	-0.390**	-0.370**	0.181
	(0.154)	(0.155)	(0.300)
Tract Damage		-0.102	0.256
		(0.0859)	(0.180)
Diversity × Tract Damage			-0.657**
			(0.320)
Adj. R-squared	0.189	0.190	0.193
Observations	1511	1511	1511

Notes: Results from OLS models. Controls include respondents' party ID, age, education, race, income, number of years in town, and survey wave. All models include zipcode fixed effects. Survey weights included for all models. Standard errors clustered at the tract level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure 1: Effect of ethnic diversity on the likelihood of receiving help, conditional on damage.



Notes: Marginal effect of diversity on the probability of receiving help after Harvey, by whether the respondent's district was damaged during the storm. Estimates are based on Model 3 in Table 2. Shaded confidence bands represent 95% intervals. The grey bars in the background indicate the distribution of ethnic diversity across tracts.

Support for recovery and adaptation policies

Here, we examine support for recovery and adaptation policies—a measure of costly cooperation. We construct an index of policy support equal to the average of ten binary survey questions about support for specific policy proposals to protect the Houston area from severe weather events:[8]

$$\text{Policy Support}_{ij} = \frac{1}{10}\left(\text{policy}_{ij}^{(\text{i})} + \text{policy}_{ij}^{(\text{ii})} + \cdots + \text{policy}_{ij}^{(\text{x})}\right), \quad \text{with policy}_{ij}^{(\cdot)} \in \{0, 1\}.$$

We estimate the following equation:

$$\text{Policy support}_{ij} \;=\; \alpha + \beta_1\,\text{Diversity}_j + \beta_2\,\text{Damage}_j + \beta_3\left(\text{Diversity}_j{\times}\text{Damage}_j\right) + \mathbf{X}_{ij}\boldsymbol{\gamma} + \varepsilon_{ij}, \tag{3}$$

where i indexes respondents in census tract j, the dependent variable Policy Support$_{ij}$ is the index described above, Diversity$_j$ is the ethnic fractionalization index, Damage$_j$ is an indicator of whether tract j experienced storm damage, and the interaction term Diversity$_j$ $\times$ Damage$_j$ allows the diversity association to differ between damaged and undamaged tracts, and $\mathbf{X}_{ij}$ is a vector of controls as in the earlier models, including an indicator for evacuation before landfall. All models are estimated by weighted least squares using respondent survey weights, with standard errors clustered at the census tract level.

[8]The items are: (i) a program to buy homes in areas that have repeatedly flooded with local, state, and federal moneys; (ii) construction of a new reservoir to protect the western portion of the Houston area; (iii) greater restrictions on construction in flood plains; (iv) establishment of a regional flood agency with taxing authority to plan for the prevention of regional flooding; (v) denying federally financed flood insurance to homeowners whose homes have flooded three or more times since 2001; (vi) not allowing homes that have flooded three or more times since 2001 to be rebuilt by buying out these homeowners with local and federal moneys; (vii) requiring sellers of homes to fully disclose prior flood damage to their homes and prior flooding in the surrounding neighborhood; (viii) preventing development/construction on native prairies and wetlands in western and northwestern portions of Harris County; (ix) requiring government compensation for homes that are flooded due to the release of water from local reservoirs; and (x) new building codes that require homes built in flood-prone areas to be elevated/raised to avoid flooding.

Consistent with **H1**, greater damage is correlated with higher support for costly recovery policies (Table 3, column 3). This result is consistent with work on how disaster exposure affects support for climate policies (Arias and Blair, 2024; Bechtel and Mannino, 2023; Bergquist and Warshaw, 2019). Notably, diversity increases baseline support for recovery policies. The interaction term indicates that the positive relationship between damage and policy support is weakened in high-diversity tracts, consistent with **H3**. Specifically, relative to a baseline policy-support level of 78.3%, damage is associated with an increase of roughly 7 pp in low-diversity ($Diversity_j$ = 0.25) tracts and a decrease of roughly 6 pp in high-diversity ($Diversity_j$ = 0.75) tracts. This reflects a 13 pp change across the diversity range, about 16% of baseline levels.

While effects vary by individual policies (Online Appendix Section A4.1), the effect appears to be driven by the most fiscally costly policies. Buyouts of homes in risky areas with federal and state funds, arguably the costliest policy, exhibit the largest negative interaction effect. This is consistent with the notion that citizens would oppose costlier policies in diverse areas.

Table 3: Support for recovery policies following Hurricane Harvey.

	Support for Policies (Index)		
	(1)	(2)	(3)
Diversity	0.0288	0.0296	0.216**
	(0.0732)	(0.0737)	(0.0885)
Tract Damage		0.00306	0.136***
		(0.0157)	(0.0485)
Diversity × Tract damage			-0.257***
			(0.0943)
Adj. R-squared	0.117	0.117	0.124
Observations	1383	1383	1383

Notes: Results from OLS models. Controls include respondents' party ID, age, education, race, income, number of years in town, and survey wave. All models include zipcode fixed effects. Survey weights included for all models. Standard errors clustered at the tract level. See Online Appendix Tables A6-A7 for item-level results for each component of the index. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

To further probe this relationship we rely on a conjoint experiment implemented in the third wave of the survey (2020). Respondents were presented with pairs of policy proposals that varied randomly along three dimensions: (1) project type (road infrastructure, loans to rebuild housing, or infrastructure to prevent new flooding), (2) geographic area covered by the policy (all of the Houston area vs. poor residential areas), and (3) the level of tax increase. The original attribute randomized sales and property tax schedules, each anchored to an average household income and an average house value in the Houston metro area (Figure 2).

Figure 2: Policy conjoint experiment: sample scenario.

In each of the following pages, you will be shown profiles from **two different** proposals associated with generating funds for recovery/prevention of natural disasters and your willingness to pay for funding of those programs. For each pair, read each profile carefully and indicate your response. Please consider each pair of profiles independently of the pairs listed on other pages.

Attribute	**Proposal A**	**Proposal B**
Tax Option	1% increase in sales tax (extra $200 tax per year for a household income of $60,000)	0.2% increase in property tax (extra $400 tax per year for a $225,000 house)
To be used for	Build infrastructure to prevent new flooding	Recover road infrastructure affected by Harvey
Project	Poor residential areas	Throughout the Houston area

Which of these two proposals do you prefer?

- ○ **Proposal A**
- ○ **Proposal B**

The original conjoint presented seven tax schedules, spanning from no increase to a three-percent sales-tax increase and 0.3 percent increase in property tax. To test whether respondents are willing to endorse the more costly policy, the tax attribute—regardless of the tax base, sales or property—was recoded as a binary variable which takes the value 1 when the profile shows the highest of the two tax levels in the pair and 0 when it shows the lowest tax level; profiles in which both options display the same tax level are coded as missing. After this transformation, 3,700 profile choices are classified as Higher Tax Increase and 3,700 as Lower Tax Increase, while 1,120 tied profiles are excluded from the analysis.[9] In addition, we included a last attribute for the geographic area of the project (Project) with four levels: *Residential Areas*, *Industrial Areas*, *Commercial Areas*, and *Houston-wide*. We estimate the following linear probability mixed model:

$$\begin{aligned}\text{Choice}_{itp} &= \alpha + b_1\,\text{Use}_p + b_2\,\text{Projects}_p + b_3\,\text{HighTax}_{tp} + b_4\,\text{Affected}_i + b_5\big(\text{Use}_p \times \text{Affected}_i\big)\\ &\quad + b_6\big(\text{Projects}_p \times \text{Affected}_i\big) + b_7\big(\text{HighTax}_{tp} \times \text{Affected}_i\big) + u_t + v_i + \varepsilon_{itp},\end{aligned} \tag{4}$$

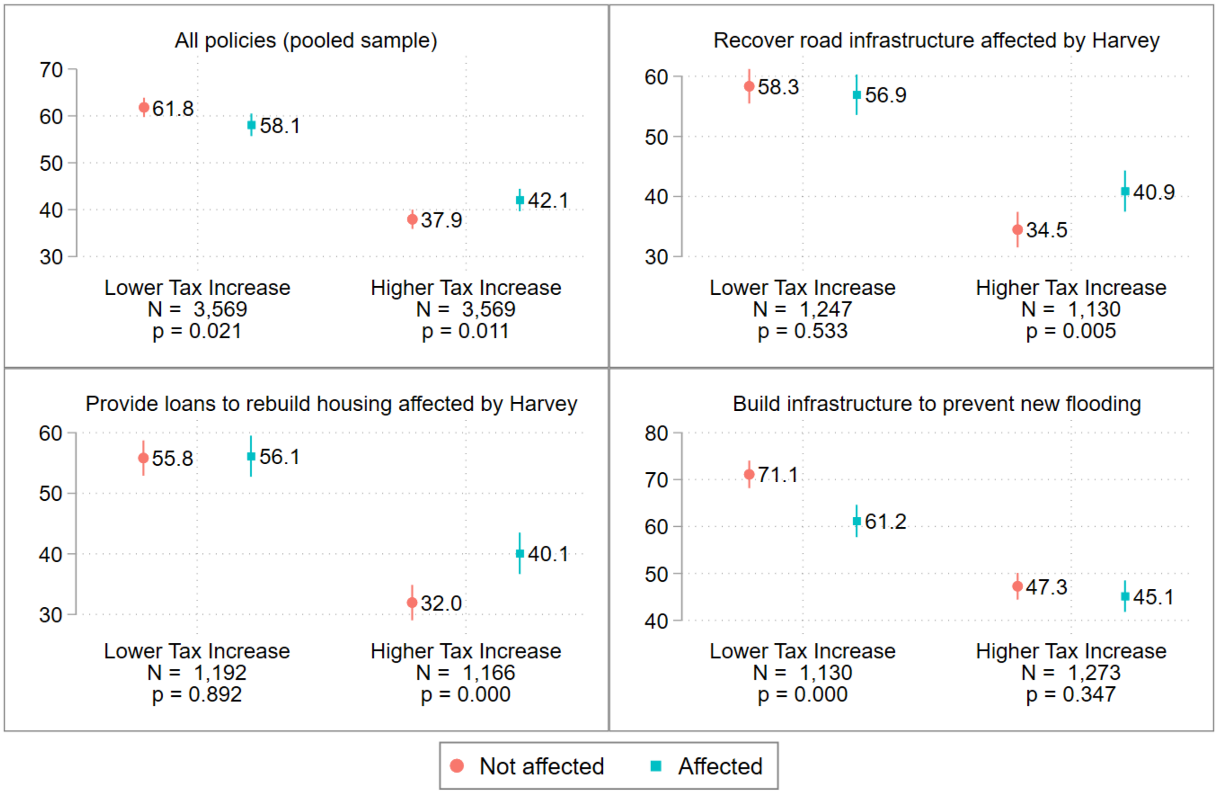
where the dependent variable Choice_{itp} is a binary variable capturing whether profile p evaluated by respondent i in paired trial t was selected.The attribute Use_p denotes the policy type, and Projects_p refers to the target area of the project. The binary variable HighTax_{tp} equals 1 when the profile carries the highest of the two tax levels in the pair and 0 otherwise. We interact each attribute with Affected_i, an indicator that records whether the respondent reported being personally affected by Harvey. The random intercepts u_t and v_i account for unobserved heterogeneity at the trial and respondent levels.

Figure 3 presents the results. In general, respondents were much more likely to support proposals that involved lower rather than higher tax increases—although levels of support for the

[9] 304 observations were excluded due to missingness in the damage survey question.

costlier policy are non-negligible. Building preventive infrastructure against flooding received the highest support. Across all policies (top-left panel), affected respondents are about 4 points more likely to choose the high-tax proposal. Looking at specific policies, the increase is high (+8.1 pp) for housing loans (bottom-left panel) and road recovery (+6.4 pp), but negative and small (-2.2 pp) for flood prevention infrastructure. Affected respondents are on average 3.7 pp less likely to support lower tax increases, with the highest effect coming from building infrastructure against flooding (9.9 pp). Overall, this indicates that being affected by the shock moderately increases the willingness to pay for costly policies across domains.

Figure 3: Predicted margins of choosing high versus low tax increases following Hurricane Harvey conditional on being affected by the storm.



Notes: Points plot are predicted margins of choosing the proposed policy option for respondents affected by Hurricane Harvey (teal squares) and not affected (salmon circles), conditional on (i) the size of the required tax increase (lower vs. higher) and (ii) how the additional revenue would be used. The top-left panel pools all policy earmarks. The top-right panel shows results for recovering damaged road infrastructure, the bottom-left panel for providing loans to rebuild housing affected by Harvey, and the bottom-right panel for building infrastructure to prevent future flooding. Labels below each tax condition report the number of choice tasks (N) and the associated p-value. Vertical bars denote 95% confidence intervals. See Online Appendix Table A8 for the full set of estimates.

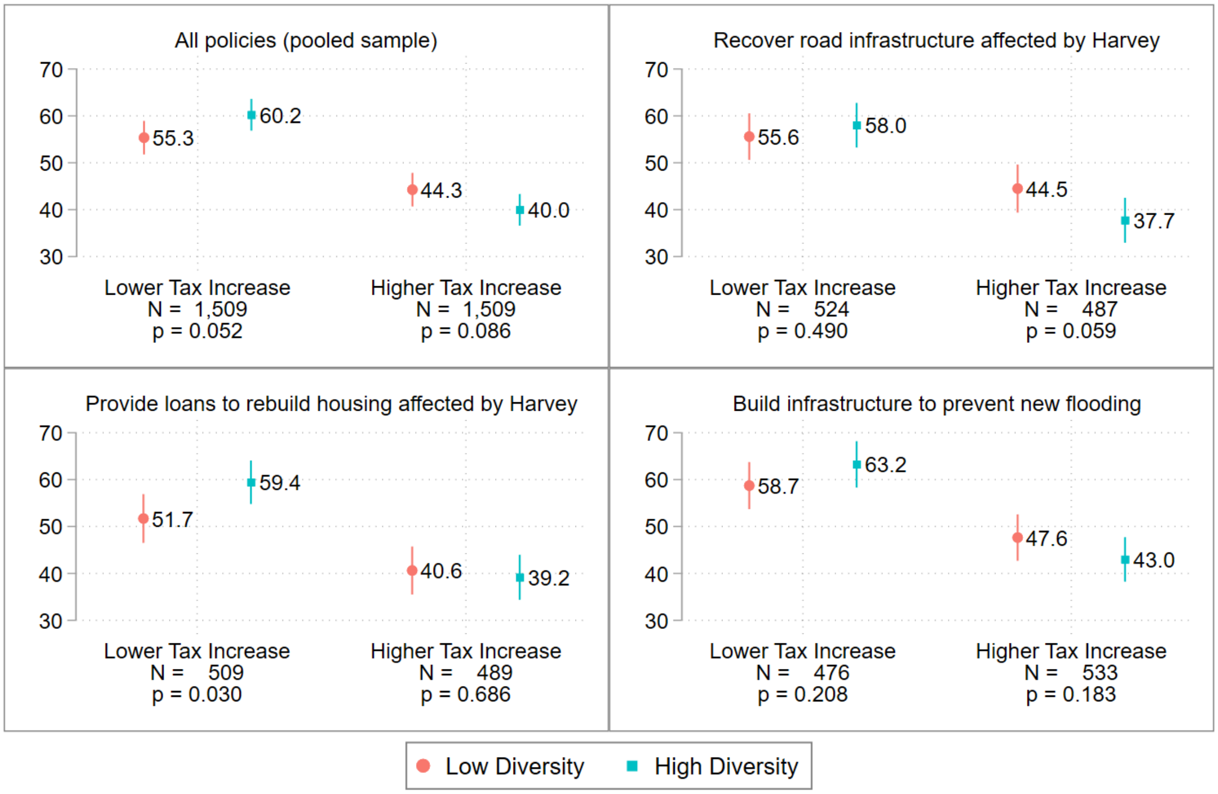
Equation (5) re-estimates the conjoint model for the 373 respondents who reported being affected by Hurricane Harvey (42.3 percent of the full sample).

$$
\begin{aligned}
\text{Choice}_{itp} \; &= \alpha + \beta_1 \, \text{Use}_p + \beta_2 \, \text{Projects}_p + \beta_3 \, \text{HighTax}_{tp} + \beta_4 \, \text{HighDiversity}_i \\
&\quad + \beta_5 \, \text{Use}_p \times \text{HighDiversity}_i + \beta_6 \, \text{Projects}_p \times \text{HighDiversity}_i \\
&\quad + \beta_7 \, \text{HighTax}_{tp} \times \text{HighDiversity}_i + u_t + v_i + \varepsilon_{itp},
\end{aligned}
\tag{5}
$$

where Choice_{itp} equals 1 when profile p is selected in paired trial t by respondent i. The covariates Use_p, Projects_p, and HighTax_{tp} retain their earlier definitions — policy type, project-area type, and high-tax indicator, respectively. The binary variable HighDiversity_i takes the value 1 when the ethnic fractionalization index in respondent i's tract is higher than the sample mean and 0 otherwise.

Across policies, affected respondents living in high-diversity areas are 4.3 pp less likely to choose the high-tax proposal and 4.9 pp more likely to choose the low-tax proposal (Figure 4). This implies that diversity reduces support for high tax policies by almost 9.2 pp (Online Appendix Table A9). Effects for specific policies vary: in the case of road recovery infrastructure, respondents in diverse areas are more likely to choose the higher tax increase—with no effects on the lower tax increase—whereas in the case of housing loans, they are more likely to choose the lower tax increase—with no effects on the higher tax increase. These results provide further evidence supporting **H3**.

Figure 4: Predicted margins of choosing high versus low tax increases following Hurricane Harvey for affected respondents conditional on ethnic diversity.



Notes: Points plot are predicted margins of choosing the proposed policy option for respondents living in low-diversity areas (below-mean ethnic diversity, salmon circles) and high-diversity areas (above-mean, teal squares), conditional on (i) the size of the required tax increase (lower vs. higher) and (ii) how the additional revenue would be used. The top-left panel pools all policy earmarks, the top-right panel shows results for recovering road infrastructure damaged by Hurricane Harvey, the bottom-left panel for providing loans to rebuild housing affected by Harvey, and the bottom-right panel for building infrastructure to prevent future flooding. Labels beneath each tax condition report the number of choice tasks (N) and the associated p-value. Vertical bars denote 95% confidence intervals. See Online Appendix Table A9 for the full set of estimates.

Preferences for cooperation

Here, we study respondents' preferences for cooperation with different hypothetical members of their community three years after Harvey. Each respondent completed paired tasks, choosing the person with whom they would prefer to cooperate. They were presented with the following vignette:

> *Now, let's suppose that you are creating a neighborhood association to provide information and help to people in the neighborhood during future flooding. Which of these two individuals do you prefer to collaborate with?*

In each profile, we randomized the following attributes: (1) race/ethnicity (White, Black, Hispanic); (2) gender (male, female); (3) a photograph and fictitious first name that were aligned with the race–gender cue ("Miguel," "Latonya," "Darnell," "Guadalupe," "Matthew," "Julie"); (4) party identification (Democrat, Republican, Independent); (5) religion (Christian/Protestant, Roman Catholic, nonreligious, Muslim, Jewish); and (6) association membership (American Society for the Prevention of Cruelty to Animals [ASPCA], Mothers Against Drunk Driving [MADD], National Rifle Association [NRA], Rotary International, YMCA). Each race–gender combination was represented by a single photograph and first name (e.g., a particular Black woman, a particular Hispanic man). As a result, our estimates for race and gender ingroup effects reflect responses to these specific exemplars as well as to the broader social categories. While this enhances realism, it also means that the null race and gender ingroup effects should be interpreted with some caution and may not generalize to all possible members of these groups. Figure 5 shows an example of the screen that respondents in our second experiment saw. In addition, Online Appendix A3.1 shows the full set of race–gender profiles, with pictures and names, that were included in our experiment.

Figure 5: Example of paired-choice task in the cooperation experiment.

Notes: See Online Appendix Section A3.1 shows the full set of race–gender profiles.

Cases in which the respondent and the profile share the same value on a given attribute are coded as "ingroup." For each respondent i, task t, and profile p, we recode five binary indicators that equal 1 when the profile matches the respondent's self-report and 0 otherwise: M_{itp}^{gender} (ingroup gender), M_{itp}^{race} (ingroup race), M_{itp}^{party} (ingroup party), M_{itp}^{relig} (ingroup religion), and M_{itp}^{assoc} (ingroup association). "Independent" and "Non-religious" are treated as valid ingroups. For respondents who selected "Other" for race, we set $M_{itp}^{\text{race}} = 0$ for all profiles; likewise, for respondents who did not report gender, we set $M_{itp}^{\text{gender}} = 0$ for all profiles.

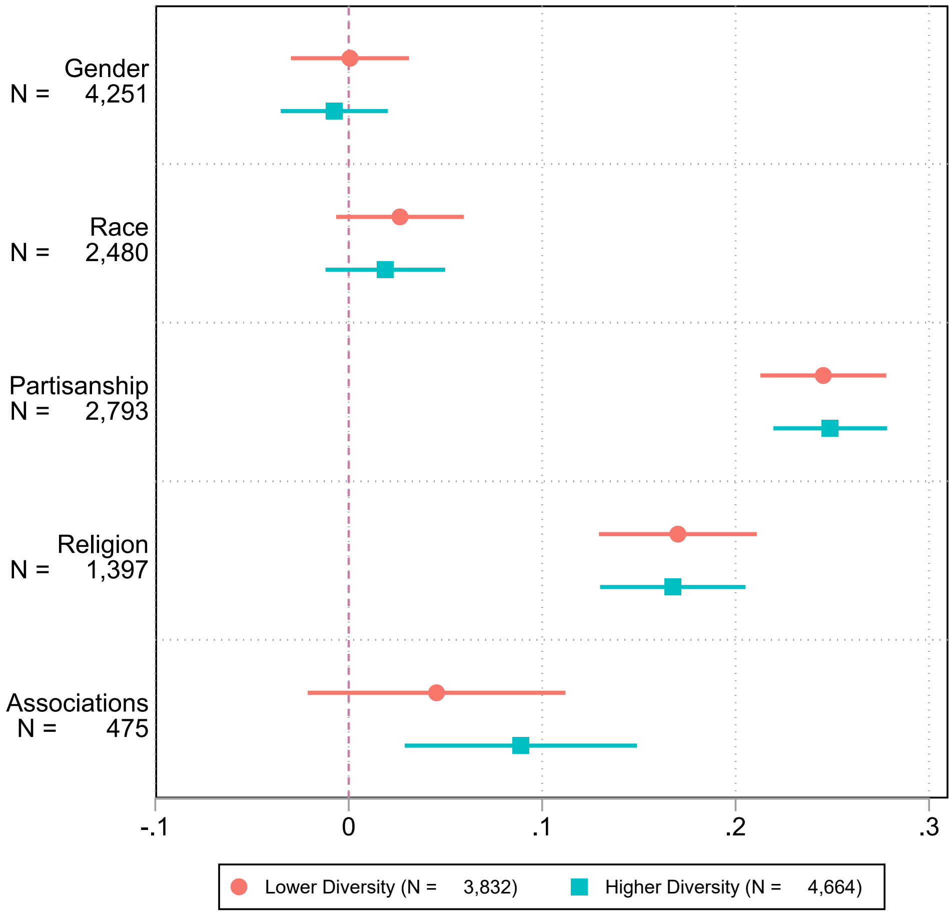
The results show that respondents are more likely to cooperate with members of their ingroup (Figure 6), consistent with **H4**. Yet, not all traits drive parochial cooperation: cooperation with co-partisan and co-religious profiles is high. Notably, effects are zero for gender and race, indicating that these traits are not drivers of parochial cooperation in the face of negative shocks.

We then classify each respondent's census tract as lower diversity if its diversity index is below the sample mean and higher diversity if it is above the sample mean. Let $g_i \in \{\text{Low Diversity}, \text{High Diversity}\}$ denote that status (constant across tasks for respondent i). Our estimation uses one simple specification, run separately for $g_i = \text{Low Diversity}$ and $g_i = \text{High Diversity}$:

$$\begin{aligned} \text{Cooperation}_{itp} = \alpha + b_1\, M_{itp}^{\text{gender}} + b_2\, M_{itp}^{\text{race}} + b_3\, M_{itp}^{\text{party}} + b_4\, M_{itp}^{\text{relig}} + b_5\, M_{itp}^{\text{assoc}} + \varepsilon_{itp} \\ \text{if diversity} = g_i. \end{aligned} \tag{6}$$

We compare b_1–b_5 across $g_i = \text{Low Diversity}$ versus $g_i = \text{High Diversity}$ to assess how cooperation patterns vary with neighborhood diversity. The results show three patterns. First, individuals are not more likely to cooperate with profiles of the same gender or race. Second, cooperation increases sharply for co-partisan (25 pp) and co-religious (17 pp) profiles. These effects are stable across levels of diversity. By contrast, the probability of cooperating with a member of the same civic association becomes significant and almost doubles in magnitude—from 5 pp to about 9 pp—when moving to low- to high-diversity neighborhoods. That is, civic associations become a relevant channel for cooperation in diverse settings. This result is consistent with the voluminous literature on the role of social capital in disaster recovery (Aldrich, 2011, 2012b,a; Chamlee-Wright and Storr, 2009; Storr et al., 2017). Overall, these results suggest that, in the aftermath of shocks, strong ties based on homophily matter irrespective of diversity, while weak ties based on voluntary associations become more important in diverse settings (Storr and Haeffele-Balch, 2012).

Figure 6: Probability of cooperating with individuals of the same ingroup in the event of future flooding.



Notes: Points plot average marginal component effects of each ingroup cue on the probability of cooperation, separately for respondents in low diversity neighborhoods (salmon circles) and high-diversity neighborhoods (teal squares). Horizontal bars denote 95% confidence intervals; the vertical dashed line marks a null effect of zero. Labels on the left report the number of profile evaluations in which the corresponding ingroup cue is present (N), and the legend reports the number of observations in the low and high-diversity subsamples. See Online Appendix Table A10 for the full set of estimates.

Conclusion

We examined how disaster exposure and neighborhood diversity are associated with different forms of cooperation. Our main contribution is to show that disasters do not uniformly affect cooperation—post-disaster cooperation is heterogeneous and shaped by local social conditions.

Using three waves of an original survey and experimental evidence collected prior to and following Hurricane Harvey, we documented how two contextual features—damage levels and ethnic diversity—shape levels and patterns of cooperation.

Using behaviorally anchored measures—receiving help, supporting costly policies, and choosing cooperation partners—rather than proxies such as trust or social cohesion, we documented the following patterns. First, interpersonal cooperation among neighbors is less likely in more diverse census tracts. Second, ethnic diversity moderates responses to shocks: both cooperation and support for costly recovery policies are generally higher in more affected areas, but this pattern is reversed in high-diversity tracts. Finally, examining cooperation patterns three years after the storm with a conjoint experiment, we documented strong ingroup bias across multiple group identities, consistent with prior work (Chung and Rhee, 2022). Although most of these effects are invariant to diversity, in more diverse settings, individuals are more likely to cooperate with members of their own civic-association. This experimental result adds new evidence to observational studies on the role of social capital in disaster recovery (Aldrich, 2011, 2012b,a; Chamlee-Wright and Storr, 2009; Storr et al., 2017).

Together, the findings show that group identities and organizational ties structure post-disaster cooperation in the aftermath of natural disasters. Recognizing this variation helps interpret heterogeneous community responses to shocks. Future research can examine how these dynamics operate in other metropolitan areas and under different types of disasters.

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Conflict of interest. The authors of this manuscript have no competing interests or conflicts of interest to declare.

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Online Appendix

Table of Contents

A1 Descriptive statistics

Table A1 presents descriptive statistics for all variables used in the observational analyses reported in Tables 1–3. Coordination and help measures come from the pre- and post-Harvey behavioral questions, while the ten policy-support variables correspond to the recovery measures detailed in Section A4.1. Individual- and residential-level covariates, along with survey design and tract characteristics, follow the specifications of the main models. Table A2 reports the same set of variables, but restricted to the subset of observations used in the coordination models in Table 1; the means are very similar to those in Table A1, and there are no substantive differences. Descriptive statistics for the analytic samples used in Tables 2 and 3 are likewise similar to those in Table A1 and are therefore not reported.

A2 Survey and sampling details

2017 survey wave. A university-affiliated public affairs research institute conducted a baseline telephone survey in November and December 2017 to understand the experiences of people impacted by Hurricane Harvey and to gauge their support for flood prevention policies. A total of 2,002 respondents aged 18 and older and residing in Harris, Fort Bend, Brazoria, and Montgomery counties were interviewed. The survey was conducted by telephone (50 percent landline, 50 percent cell phone) between November 20 and December 20, 2017. The four counties were divided into eight sampling areas based on whether structures in a given area had a high or low probability of significant flooding. Areas in each county that received two or more feet of rainwater between August 26 and 30 were identified[1] and used to define the high-risk strata. A sample of active landline and cell phone numbers matched to residential household street addresses was purchased from

[1]as having the greater potential for flooding to residential and commercial property.

Table A1: Descriptive statistics for all observations used in the study.

Variable	Obs	Mean	Std. Dev.	Min	Max
Coordination and help before/after Harvey					
Coordinated with immediate family (pre-Harvey)	1995	0.230	0.421	0	1
Coordinated with extended family (pre-Harvey)	1995	0.278	0.448	0	1
Coordinated with neighbors (pre-Harvey)	1995	0.127	0.333	0	1
Coordinated with friends (pre-Harvey)	1995	0.140	0.347	0	1
Received help after Harvey	2495	0.319	0.466	0	1
Support for recovery policies					
Buyouts in repeatedly flooded areas	1814	0.695	0.461	0	1
New reservoir to protect western Houston	1832	0.909	0.288	0	1
Stricter limits on construction in flood plains	1883	0.899	0.302	0	1
Regional flood authority with taxing power	1788	0.721	0.449	0	1
Deny federal flood insurance after repeated flooding	1795	0.486	0.500	0	1
Ban rebuilding homes flooded 3+ times	1806	0.698	0.459	0	1
Require seller disclosure of flood history	1914	0.937	0.242	0	1
Restrict development on prairies/wetlands	1734	0.763	0.425	0	1
Compensate reservoir-release flooding victims	1838	0.808	0.394	0	1
Elevated codes for flood-prone homes	1916	0.894	0.308	0	1
Individual characteristics					
Ethnic diversity (fractionalization index)	1685	0.503	0.159	0.023	0.756
Party identification (1–9)	2503	3.069	2.359	1	9
Race/ethnicity (1–9)	2503	2.191	1.889	1	9
Age category (1–4)	2503	3.089	0.941	1	4
Education (1–9)	2503	4.306	1.709	1	9
Household income (1–9)	2503	4.436	2.710	1	9
Residential characteristics					
ZIP code	2226	77235.240	199.914	77003	77598
In town during Harvey (1–9)	2446	3.092	2.536	1	9
Homeowner	2423	0.808	0.394	0	1
Insurance coverage	2471	0.579	0.494	0	1
Survey design and tract characteristics					
Wave 1 respondent	2503	0.800	0.400	0	1
Survey weight	2503	0.608	0.720	0.001	2.616
Census tract ID	2365	457995.500	158211.100	210400	760502
Damaged tract (indicator)	1679	0.703	0.457	0	1

Table A2: Descriptive statistics for observations used in Table 1.

Variable	Obs	Mean	Std. Dev.	Min	Max
Coordination and help before/after Harvey					
Coordinated with immediate family (pre-Harvey)	1381	0.227	0.419	0	1
Coordinated with extended family (pre-Harvey)	1381	0.266	0.442	0	1
Coordinated with neighbors (pre-Harvey)	1381	0.125	0.331	0	1
Coordinated with friends (pre-Harvey)	1381	0.135	0.342	0	1
Received help after Harvey	1375	0.340	0.474	0	1
Support for recovery policies					
Buyouts in repeatedly flooded areas	1261	0.713	0.453	0	1
New reservoir to protect western Houston	1279	0.905	0.294	0	1
Stricter limits on construction in flood plains	1300	0.898	0.303	0	1
Regional flood authority with taxing power	1236	0.729	0.445	0	1
Deny federal flood insurance after repeated flooding	1252	0.479	0.500	0	1
Ban rebuilding homes flooded 3+ times	1249	0.703	0.457	0	1
Require seller disclosure of flood history	1326	0.935	0.246	0	1
Restrict development on prairies/wetlands	1200	0.768	0.422	0	1
Compensate reservoir-release flooding victims	1275	0.817	0.387	0	1
Elevated codes for flood-prone homes	1322	0.896	0.306	0	1
Individual characteristics					
Ethnic diversity (fractionalization index)	1381	0.501	0.158	0.023	0.756
Party identification (1–9)	1381	3.079	2.383	1	9
Race/ethnicity (1–9)	1381	2.192	1.915	1	9
Age category (1–4)	1381	3.182	0.909	1	4
Education (1–9)	1381	4.252	1.718	1	9
Household income (1–9)	1381	4.421	2.788	1	9
Residential characteristics					
ZIP code	1381	77163.100	171.232	77003	77598
In town during Harvey (1–9)	1381	3.206	2.641	1	9
Homeowner	1381	0.818	0.386	0	1
Insurance coverage	1381	0.538	0.499	0	1
Survey design and tract characteristics					
Wave 1 respondent	1381	1.000	0.000	1	1
Survey weight	1381	0.762	0.812	0.001	2.616
Census tract ID	1381	385948.200	111281.400	210400	556000
Damaged tract (indicator)	1375	0.721	0.448	0	1

Marketing Systems Group in Horsham, PA.[2] Interviews were conducted in English and Spanish by Customer Research International of San Marcos, Texas, and sampling was based on the proportion of households in each county and in areas where flooding was expected to have occurred.

Oversampling of areas where flooding was expected to have occurred produced an imbalance in the share of owner- and renter-occupied households in Harris County. To correct this, we constructed post-stratification weights for the Harris County portion of the sample so that the distribution of renter- and owner-occupied households matched the U.S. Census Bureau's 2016 American Community Survey (ACS) for Harris County, Texas. Respondents in the remaining three counties receive a weight of 1. Demographic measures for the combined four-county sample fall within ACS ranges, so no additional adjustment was implemented. Our observational models also include tract-level measures of storm damage, so differences in flood risk are accounted for directly as covariates rather than through additional sampling weights. The margin of error for the full sample of 2,002 respondents is ± 2.2 percentage points; margins of error for subgroups (e.g., by county or race/ethnicity) are larger. These data, merged with tract-level administrative measures of ethnic diversity and storm damage, form part of the pooled dataset used for the observational analyses of pre-Harvey coordination, mutual help, and support for recovery policies reported in Tables 1–3 of the main text.

2018 survey wave. A second telephone survey was conducted between June 25 and July 31, 2018 with 1,073 respondents in Brazoria, Fort Bend, Harris, and Montgomery counties. Slightly more than half of these respondents ($N = 572$) had participated in the 2017 wave, while the remaining 501 respondents were drawn from a fresh sample in the same counties. The margin of error for the full 2018 sample is ± 3 percentage points; for the Harris County subsample it is ± 3.4 percentage points, with larger margins of error for smaller subgroups.

[2] Street addresses were purchased from Marketing Systems Group in Horsham, PA.

As in 2017, interviews were conducted by telephone (50 percent landline, 50 percent cell phone). The panel component of the sample—those first interviewed in 2017—was drawn from areas expected to have experienced household flooding (areas receiving two or more feet of rainwater between August 26 and 30, 2017). The fresh cross-sectional sample of residential households was randomly selected in each of the four counties. Active landline and cell phone numbers matched to residential street addresses were again purchased from Marketing Systems Group in Horsham, PA. Interviews were administered in English and Spanish by Customer Research International of San Marcos, Texas, with only one phone number per household selected at each address. Because oversampling of flood-prone areas generated an imbalance in the share of owner- and renter-occupied households in Harris County, survey weights were constructed to align the distribution of tenure and race across Brazoria, Fort Bend, Harris, and Montgomery counties with the 2016 ACS. Together with the 2017 baseline, the 2018 wave extends the panel and supplies additional observations for the pooled observational models of coordination before Harvey, help received, and support for recovery policies (Tables 1–3).

2020 survey wave. A third survey wave was fielded online between May 20 and June 23, 2020, using a representative sample of adults (18+) residing in Brazoria, Fort Bend, Harris, and Montgomery counties. In total, 1,065 individuals completed the questionnaire. Data collection was conducted in English and Spanish by Customer Research International (CRI), a survey research firm headquartered in San Marcos, Texas.

Sampling for the 2020 wave relied on demographic quotas for county, age, race, and gender based on 2019 American Community Survey benchmarks. Post-stratification weights were then applied to match the joint distribution of race, sex, age, and party identification in the target population. The margin of error for the full 2020 sample is approximately ± 3 percentage points, and ± 4 percentage points for the Harris County subsample; margins of error for smaller subgroups are larger. This online wave is the vehicle for the two conjoint experiments analyzed in the main text: the policy-preference conjoint on willingness to support costlier recovery measures and the parochial-cooperation conjoint on cooperation across partisan, religious, racial, gender, and associational identities. Results from these experiments appear in the main figures and in the robustness tables of Appendix A and Appendix B.

Sample weights. For the pooled observational analyses in Tables 1–3, we use a single survey-weight variable that stacks the wave-specific design weights. The weights for the 2017 and 2018 waves consist of post-stratification adjustments that align the joint distribution of age and race across Brazoria, Fort Bend, Harris, and Montgomery counties with the 2016 ACS. All models estimated on the pooled 2017–2018 dataset use this unified survey weight, together with an indicator for survey wave.

Missing data in Tables 1, 2, and 3. A key source of missing data in our analyses is the tract-level ethnic diversity index. We construct this measure by geocoding respondents to census tracts based on their self-reported nearest street intersection. Many respondents either declined to provide an intersection, provided descriptions that could not be reliably matched to a specific location, or lived in areas for which we could not assign a tract identifier. In addition, we compute the diversity index only for respondents with non-missing values on the survey variables required for each model, so missingness in the outcomes or in core covariates can also result in a missing diversity score. In practice, the pattern-of-missingness tables (Tables A3, A4 and A5) show that non-disclosure or non-geocodability of the intersection, and the resulting absence of tract-level diversity, is the dominant reason why observations are excluded from the regression samples.

All models in Tables 1, 2, and 3 are estimated on the pooled two-wave survey file. Each specification includes an indicator for the first survey wave and is restricted to respondents with complete information on the relevant outcome, individual covariates, tract identifiers, diversity, and survey weights. Respondents with missing data on any of these components are excluded, so the effective sample sizes reported at the bottom of each table are smaller than the number of records in the combined file.

The missing-value patterns for the coordination models in Table 1 (summarized in Table A3) make this structure clear. Among the observations excluded from these regressions, nearly half have complete data on the coordination outcome and all covariates but lack only the diversity variable. Roughly one out of ten excluded observations are missing the coordination outcome but have non-missing diversity and individual covariates, and another share of similar magnitude are missing both the outcome and tract-level information (tract and ZIP code). The remaining excluded cases are spread across patterns that combine missing diversity with missing geocodes or storm-related covariates such as being in town during Harvey, homeownership, or insurance coverage. Only a very small fraction of excluded observations are complete on these variables and are dropped because of survey design features such as zero weights rather than item nonresponse.

Table A3: Missing-value patterns among observations excluded from the coordination regression models in Table 1.

Pattern	%	Coordination	Diversity	Insurance	In town	Owner	Tract	Zip code
1	<1	1	1	1	1	1	1	1
2	47	1	0	1	1	1	1	1
3	12	0	1	1	1	1	1	1
4	10	0	0	1	1	1	0	0
5	7	0	1	1	1	1	1	0
6	6	0	0	1	1	1	1	1
7	4	1	1	1	1	0	1	1
8	4	0	0	1	1	1	1	0
9	2	1	0	1	1	0	1	1
10	1	0	0	1	0	1	0	0
11	1	0	1	1	0	1	1	1
12	1	1	1	0	1	1	1	1
13	<1	0	0	1	0	1	1	0
14	<1	1	1	0	1	0	1	1
15	<1	0	1	1	0	1	1	0
16	<1	0	0	1	0	1	1	1
17	<1	0	0	1	1	1	0	1
18	<1	1	0	0	1	1	1	1
19	<1	0	0	0	1	1	0	0
20	<1	0	0	1	1	0	0	0
21	<1	0	1	0	1	1	1	0
22	<1	0	0	0	0	1	0	0
23	<1	0	1	0	0	1	1	0
24	<1	1	0	0	1	0	1	1
25	<1	0	0	1	0	0	0	0
26	<1	0	0	1	0	1	0	1
27	<1	0	0	1	1	0	1	0

Notes: 1 indicates non-missing, 0 indicates missing. Percentages indicate the distribution of missing-value patterns among all observations excluded from the coordination regression models. The corresponding regression models are estimated on $n = 1{,}381$ included observations. The following variables exhibit no missing values among the included observations in Table 1: Race, Party identification, Age category, Education, and Income.

The models in Table 2 exhibit similar role for missing diversity (Table A4). Among observations not used in these regressions, around three out of five have complete information on the help outcome and covariates but lack the diversity index only. Much smaller proportions combine missing diversity with missing geocodes or with missing storm-related covariates, and only a very small share are missing the help outcome itself while having an observed diversity score. Thus, for the post-Harvey help outcome, attrition is driven primarily by the inability to construct tract-level diversity rather than by nonresponse on the outcome.

Table A4: Missing-value patterns among observations excluded from the regression models in Table 2

Pattern	%	Help Received	Diversity (elf)	Evacuated	In town	Insurance	Zip code	Owner	Tract
1	<1	1	1	1	1	1	1	1	1
2	59	1	0	1	1	1	1	1	1
3	11	1	0	1	1	1	0	1	0
4	8	1	1	1	1	1	0	1	1
5	4	1	1	1	1	1	1	0	1
6	4	1	0	1	1	1	0	1	1
7	2	1	0	1	1	1	1	0	1
8	1	1	0	1	0	1	0	1	0
9	1	1	1	1	0	1	1	1	1
10	1	1	1	1	1	0	1	1	1
11	1	1	0	1	0	1	0	1	1
12	<1	1	1	1	1	0	1	0	1
13	<1	1	1	1	0	1	0	1	1
14	<1	1	0	1	0	1	1	1	1
15	<1	0	1	1	1	1	1	1	1
16	<1	1	0	1	1	0	1	1	1
17	<1	1	0	1	1	1	1	1	0
18	<1	1	0	1	1	0	0	1	0
19	<1	1	0	1	1	1	0	0	0
20	<1	0	0	1	1	1	1	1	1
21	<1	1	1	1	1	0	0	1	1
22	<1	1	1	1	1	0	0	1	1
23	<1	1	0	0	1	1	1	1	1
24	<1	1	1	0	1	1	1	1	1
25	<1	1	0	1	0	0	0	1	0
26	<1	1	1	1	0	0	0	1	1
27	<1	1	0	1	1	0	1	0	1
28	<1	1	0	1	0	1	0	0	0
29	<1	1	0	1	0	1	1	1	0
30	<1	1	0	1	1	1	0	0	1

Notes: 1 indicates non-missing, 0 indicates missing. Percentages indicate the distribution of missing-value patterns among all observations excluded from the regression models in Table 2. The corresponding Table 2 regressions are estimated on a sample of $n = 1{,}511$ included observations. The following variables exhibit no missing values among the included (used) observations: Race, Party identification, Age category, Education, and Income.

For the policy support models in Table 3, which use an index of support for ten recovery policies, the pattern is similar (Table A5). Among the observations excluded from these regressions, roughly half are missing only the diversity measure, with the policy support index and individual covariates observed. Around one-eighth of excluded observations have a missing policy support index but a non-missing diversity score, and the remainder display various combinations of missing diversity, missing policy items, and missing geocodes. Across all three sets of models, the tables show that item nonresponse on the core demographic covariates is minimal—variables such as race, party identification, age category, education, and income are essentially fully observed among the included cases—whereas the main driver of sample loss is the absence of usable intersection information needed to assign tract-level diversity.

Table A5: Missing-value patterns among observations excluded from the support index regression models in Table 3.

Pattern	%	Policy Support	Diversity	Evacuated	In town	Insurance	Zip code	Owner	Tract
1	<1	1	1	1	1	1	1	1	1
2	47	1	0	1	1	1	1	1	1
3	12	0	1	1	1	1	1	1	1
4	10	0	0	1	1	1	0	1	0
5	7	0	1	1	1	1	0	1	1
6	6	0	0	1	1	1	1	1	1
7	4	1	1	1	1	1	1	0	1
8	4	0	0	1	1	1	0	1	1
9	2	1	0	1	1	1	1	0	1
10	1	0	0	1	0	1	0	1	0
11	1	0	1	1	0	1	1	1	1
12	1	1	1	1	1	0	1	1	1
13	<1	0	0	1	0	1	0	1	1
14	<1	0	1	1	0	1	0	1	1
15	<1	0	0	1	0	1	1	1	1
16	<1	0	1	1	1	0	1	0	1
17	<1	1	1	1	1	0	1	0	1
18	<1	1	0	1	1	0	1	1	1
19	<1	0	0	1	1	1	1	1	0
20	<1	0	0	1	1	0	0	1	0
21	<1	0	0	1	1	1	0	0	0
22	<1	0	1	0	1	1	0	1	1
23	<1	0	1	0	1	1	0	1	1
24	<1	1	0	1	1	0	0	1	1
25	<1	1	1	0	1	1	0	1	1
26	<1	1	1	0	1	1	1	1	1
27	<1	0	0	1	0	0	0	1	0
28	<1	0	1	1	0	1	1	0	1
29	<1	0	0	1	0	1	0	0	0
30	<1	0	0	1	0	1	0	1	0
31	<1	0	0	1	1	1	0	0	0
32	<1	0	1	1	1	1	1	0	1

Notes: 1 indicates non-missing, 0 indicates missing. Percentages indicate the distribution of missing-value patterns among all observations excluded from the support index regression models. The corresponding regressions are estimated on the same set of included observations as the Table 3 models. The following variables exhibit no missing values among the included (used) observations: Race, Party identification, Age category, Education, and Income.

A3 Cooperation conjoint design and attributes

A3.1 Profile images

Figure A1 displays the six profile images used in the conjoint experiment. Each image represents a unique combination of race and gender, which were the only attributes presented visually; all other attributes were presented as text.

Figure A1: Profile images used in the conjoint experiment. Labels correspond to the file names: `Miguel`, `Darnell`, `Guadalupe`, `Julie`, `Latonya`, and `Matthew`. Race and gender are the only attributes presented via images; all other attributes are shown as text.

A4 Additional results and robustness checks

A4.1 Additional results for recovery policies

Tables A6 and A7 estimate separate models for each of the ten individual policy proposals that make up the index used in Table 3. Respondents were asked if they support or opposed the following policies: (1) a program to buy homes in areas that have repeatedly flooded with local state and federal moneys, (2) the construction of a new reservoir to protect the western portion of the Houston area, (3) greater restrictions on construction in flood plains and new building codes, (4) the establishment of a regional flood agency with taxing authority to plan for the prevention of regional flooding, (5) denying federally financed flood insurance to homeowners whose homes have flooded three of more times since 2001, (6) not allowing homes that have flooded three or more times since 2001 to be rebuilt by buying out these homeowners with local and federal moneys, (7) requiring sellers of homes to fully disclose prior flood damage to their homes and prior flooding in the surrounding neighborhood, (8) preventing development/construction on native prairies and wetlands in western and northwestern portions of Harris County, (9) requiring government compensation for homes that are flooded due to the release of water from local reservoirs, and (10) new building codes that require homes built in flood prone areas to be elevated/raised to avoid flooding.

Diversity does not systematically reduce baseline support for recovery policies —in some cases coefficients are positive. However, the negative interaction effect reported in Table 3 is mainly driven by policies that impose fiscal costs. Buyouts of homes in risky areas with federal and state moneys, arguably the costliest policy, display the largest negative interaction. Other policies — e.g., building limits, disclosure of prior flood damage — impose private costs. This result is consistent with the notion that diversity reduces cooperation in terms of costly policies

Table A6: Support for individual policies (I).

	(1) Buyouts	(2) Reservoirs	(3) Restrict building	(4) Regional authority	(5) Deny fed insurance
Diversity	0.344	0.139	0.530***	0.463**	0.252
	(0.248)	(0.157)	(0.195)	(0.223)	(0.261)
Tract Damage	0.268**	0.0956	0.222*	0.0766	0.0471
	(0.131)	(0.0943)	(0.121)	(0.128)	(0.130)
Diversity × Damage	-0.655***	-0.247	-0.409*	-0.136	-0.160
	(0.247)	(0.173)	(0.216)	(0.227)	(0.266)
Observations	1266	1284	1306	1241	1257

Notes: Results from OLS models. Controls include respondents' party ID, age, education, race, income, number of years in town, and survey wave. All models include zipcode fixed effects. Survey weights included for all models. Standard errors clustered at the tract level.. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A7: Support for individual policies (II).

	(1) Rebuilding ban	(2) Seller disclosure	(3) Prevent development	(4) Gov compensation	(5) New codes
Diversity	0.133	0.0414	-0.0672	0.187	0.328**
	(0.238)	(0.122)	(0.246)	(0.207)	(0.155)
Tract Damage	0.0612	0.123*	-0.00432	0.140	0.124
	(0.135)	(0.0690)	(0.127)	(0.117)	(0.0838)
Diversity × Damage	-0.0961	-0.250*	0.0479	-0.226	-0.207
	(0.255)	(0.144)	(0.238)	(0.223)	(0.156)
Observations	1254	1332	1205	1281	1328

Notes: Results from OLS models. Controls include respondents' party ID, age, education, race, income, number of years in town, and survey wave. All models include zipcode fixed effects. Survey weights included for all models. Standard errors clustered at the tract level.. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

A4.2 Conjoint results: affected vs. not affected

Table A8 reports the full set of average marginal component effects (AMCEs) from the mixed-effects conjoint model underlying Figure 3. The coefficients summarize how project type, target area, and tax level affect the probability that a proposal is chosen, separately for respondents personally affected by Hurricane Harvey and those who were not. The estimates show that higher tax increases reduce support overall, but affected respondents are more willing to endorse the costlier options.

Table A8: AMCEs conjoint model for policy preferences: damage vs. not affected.

	(1) Coefficient	Std Err
Housing Loans	-2.524	(1.825)
Flood Prevention	12.777***	(1.818)
Affected	-6.231*	(2.936)
Loans × Affected	1.717	(2.801)
Flood prev × Affected	-8.529**	(2.798)
Industrial Areas	-18.713***	(2.112)
Commercial Areas	-15.934***	(2.087)
Houston-wide	8.638***	(2.096)
Industrial × Affected	10.908***	(3.244)
Commercial × Affected	5.673	(3.227)
Houston-wide × Affected	2.733	(3.246)
High Tax	-23.860***	(1.484)
High Tax × Affected	7.825***	(2.283)
Log likelihood	-37696.872	
AIC	75427.74	
BIC	75544.59	
Observations	7,138	

Notes: Coefficients and standard errors from the mixed-effects conjoint model reported in Figure 3.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A4.3 Conjoint results: Affected respondents by level of diversity

Table A9 presents AMCEs from the conjoint model estimated only among respondents who reported being affected by Hurricane Harvey, with effects allowed to differ between low- and high-fragmentation neighborhoods. These coefficients correspond to the results displayed in Figure 4. The estimates indicate that affected households in more ethnically fragmented tracts exhibit lower support for the high-tax option.

Table A9: AMCEs conjoint model for policy preferences: diversity among affected respondents.

	(1) Coefficient	Std Err
Housing Loans	-3.877	(3.193)
Flood Prevention	3.144	(3.127)
High Diversity	-0.501	(4.577)
Loans $\times$ High Diversity	5.306	(4.354)
Flood prev $\times$ High Diversity	2.096	(4.349)
Industrial Areas	-10.992**	(3.640)
Commercial Areas	-12.789***	(3.658)
Houston-wide	10.560**	(3.657)
Industrial $\times$ High Diversity	5.873	(5.035)
Commercial $\times$ High Diversity	4.376	(5.036)
Houston-wide $\times$ High Diversity	1.294	(5.069)
High Tax	-11.084***	(2.582)
High Tax $\times$ High Diversity	-9.177**	(3.551)
Log likelihood	-16000.577	
AIC	32035.15	
BIC	32137.36	
Observations	3,018	

Notes: Coefficients and standard errors from the mixed-effects conjoint model reported in Figure 4.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A4.4 Conjoint results: Parochial cooperation by level of diversity

Table A10 reports AMCEs for the cooperation conjoint, estimated separately for respondents living in low- and high-diversity neighborhoods; these results correspond to Figure 6. The table shows strong ingroup effects for partisanship and religion in both contexts, with little or no parochialism based on gender or race. Association-based ingroup effects, however, are larger and statistically significant only in high-diversity neighborhoods, reinforcing the notion that civic associations become especially important channels of cooperation in more diverse settings.

Table A10: AMCEs of parochial cooperation by neighborhood diversity.

	(1) Lower Diversity	(2) Higher Diversity
Gender	0.000657	-0.00751
	(0.0156)	(0.0141)
Race	0.0265	0.0189
	(0.0168)	(0.0158)
Partisanship	0.245***	0.249***
	(0.0166)	(0.0150)
Religion	0.170***	0.168***
	(0.0208)	(0.0192)
Associations	0.0454	0.0890***
	(0.0340)	(0.0306)
Log likelihood	-2639.661	-3208.517
AIC	5297.32	6435.03
BIC	5353.58	6493.06
Observations	3,832	4,664

Notes: Entries report average marginal component effects from mixed-effects conjoint models with respondent and trial random intercepts reported in Figure 6. Columns show estimates separately for respondents living in low and high-diversity neighborhoods. Each coefficient gives the ACME of each group cue on the probability of cooperation when the profile shares the respondent's gender, race, partisanship, religion, or association membership, relative to the corresponding out-group baseline. Standard errors in parentheses.