Retrospection, Fairness, and Economic Shocks: How Do Voters Judge Policy Responses to Natural Disasters?*

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Abstract

Which factors explain voters' evaluations of policy responses to economic shocks? We explore this question in the context of mass preferences over the distribution of disaster relief and evaluate three theoretical arguments related to fairness norms that highlight affectedness, need, and political ties. We analyze experimental data from an original survey conducted among American citizens and find that affectedness and need are important drivers of voters' preferred disaster responses. We then compare these patterns with observed disaster relief distributions (1993-2008). The results suggest that observed relief allocations largely mirror the structure of voter preferences with respect to affectedness and need, but not political ties. These findings have implications for an ongoing debate over the electoral effects of natural disasters, voters' retrospective evaluations of incumbent performance, and the extent to which divide-the-dollar politics decisions align with mass preferences.

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I. Introduction

Coping with the changing climatic conditions and the resulting increases in natural disasters on this planet poses a major policy challenge (Obradovicha, Tingley and Rahwana 2018). Even record-shattering disasters such as Hurricanes Katrina or Harvey that cause large human and economic losses (CRED, EM-DAT and UNISDR 2017) do no longer constitute rare phenomena.[1] The policy responses to extreme weather events are ethically salient, economically significant, and politically consequential. First, compensating individuals for experienced disaster damage, which is the preferred response of elected officials (Healy and Malhotra 2009) absorbs significant financial resources. Second, the policy responses entail important divide-the-dollar decisions (Kriner and Reeves 2015) that raise particularly challenging ethical and inequality-related issues as previous research documents that natural disasters place a disproportionate burden on the poor, the elderly, women, and children (Aldrich and Sawada 2015; Neumayer and Pluemper 2007; Kahn 2005). Third, since the policy responses to extreme weather events determine disaster recovery they affect voter evaluations of incumbent performance (Atkeson and Maestas 2012) and electoral outcomes. However, empirical findings regarding the impact of natural disasters on elections are contested and seem contradictory at times. Some studies suggest that voters reward incumbents electorally for the provision of disaster relief (Bechtel and Hainmueller 2011; Gasper and Reeves 2011). Others conclude that the public engages in blind retrospection (Achen and Bartels 2018 2004) by punishing governments for natural disasters although they constitute "random events" that policymakers remain unable to control (Abney and Hill 1966) and even in regions that have received exceptionally high levels of disaster relief (Heersink, Peterson and Jenkins 2017).

These contradictory findings have resulted in an ongoing theoretical and empirical debate over whether citizens' retrospective evaluations of incumbent performance follow reasonable standards (Achen and Bartels 2018; Heersink, Peterson and Jenkins 2017; Ashworth and de Mesquita 2014;

[1]NOAA National Centers for Environmental Information (NCEI). "U.S. Billion-Dollar Weather and Climate Disasters (2017)", accessed February 2, 2017, `https://www.ncdc.noaa.gov/billions/`.

Healy and Malhotra 2013). The importance of this discussion has been further heightened by the fact that previous scholarship has used extreme weather events to estimate an upper bound on the impact of large-scale economic shocks on electoral behavior and political attitudes (Baccini and Leemann 2020; Margalit 2019). Policy responses to major shocks such as natural disasters may also improve or shatter trust in a country's political system (Damico, Conway and Damico 2000). We argue that one important element missing from this literature is that retrospective evaluations of incumbent performance depend on both voter preferences over disaster relief allocations and policymakers' actual allocation decisions. Whether incumbents gain or suffer electorally in the aftermath of extreme weather events hinges on an assessment of the observed policy response benchmarked against voters' preferred distributive decisions. We offer the first analysis of individual preferences over the provision of disaster relief.

Several factors may influence how publics would like policymakers to respond to economic shocks. For example, preferences over the provision of financial assistance could reflect affectedness and need-based conceptions of fairness. These fairness norms imply that the preferred allocation of disaster relief should mirror the distribution of factors related to damage and need. However, distributive preferences may also be influenced by partisan solidarity and electoral considerations. We use data from an original survey conducted on a population-based sample of American citizens (N=2,618) to study the structure of disaster relief preferences. The survey includes a novel resource allocation conjoint design that asks respondents to distribute relief aid to counties affected by a natural disaster. The attributes specified in the experiment capture three theoretically relevant dimensions: affectedness, need, and political ties. This allows us to explore which factors drive citizens' preferred relief allocations and the relative importance of different conceptions of fairness for our understanding of redistribution preferences.

We analyze 20,000 individual-level allocation decisions and find that respondents allocate significantly more disaster relief to counties that experienced higher levels of economic damage and more fatalities. The results also indicate that individuals prefer relief allocations that provide

more relief to poorer regions. In contrast, preferences over disaster relief do not mirror electoral or partisan considerations. We then evaluate the plausibility of our theoretical interpretation of the causal effects as reflecting individuals' conceptions of distributive fairness and subject our results to a large set of additional tests. These include various tests of interactions between policy response features and individual-level characteristics such as personal exposure to natural disasters. The findings suggest that the sensitivity to disaster damage and income characteristics is quite stable across levels of personal disaster exposure as well as partisanship.

Finally, we leverage the results from our experimental conjoint to compare the structure of voter preferences over relief aid and the patterns that characterize policymakers' actual relief allocations along all three theoretically important dimensions: need, affectedness, and political ties. The results suggest that both preferred and observed allocation choices strongly mirror affectedness and, to some extent, need. However, while voters prefer apolitical distributions of disaster relief, policymakers have engaged in politically motivated allocations of relief payments.

This study makes several contributions. First, our results inform ongoing work on retrospective voting and the evaluative standards that voters employ when assessing the policy responses to major economic shocks in the context of life-threatening events such as natural disasters. Second, we present a novel divide-the-dollar conjoint experiment that allows scholarship to gain more detailed insights into mass preferences over public spending decisions and enables comparisons of voters' preferred relief allocations with policymakers' actual allocation decisions. Third, by studying the causal drivers of preferences for disaster relief allocations we hope to offer insights that improve the ability of democratic systems to cope with the increasing number of extreme weather events in ways that are widely perceived as fair and therefore more likely to be sustainable politically.

II. Conceptual Framework

A considerable body of literature has studied the electoral impact of extreme weather events (Abney and Hill 1966; Reeves 2011; Gasper and Reeves 2011; Bechtel and Hainmueller 2011; Chen 2012), the role of political communication in the context of natural disasters (Sood, Stockdale and Rogers 1987; Utz, Schultz and Glocka 2013), and how public and private actors assess disaster damage when deciding about their assistance efforts (Waugh and Streib 2006; Aldrich 2016).[2] So far, however, we do not know which factors drive individual preferences over government responses to natural disasters which arguably entail important divide-the-dollar decisions which figure prominently in formal models of redistribution (Huber and Ting 2013). However, since disaster relief aims to help individuals who have become victims of a life-threatening, exogenous event, the prominent distinction between luck and effort that the literature on preferences for redistribution tends to emphasize (Scheve and Stasavage 2016; Durante, Putterman and van der Weele 2014; Fisman et al. 2015; Brosnan and de Waal 2003) may not offer the most promising theoretical starting point for our conceptual framework. As a consequence, our research question requires us to begin exploring largely unknown territory. However, we can build on existing work on conceptions of distributive justice (Kendrick 1939; Lind and Tyler 1988; Deutsch 1975), equity and the social contract (Rawls 2009), and recent theoretical contributions (Valentini 2013) to develop fairness-based explanations of preferences over the distribution of disaster relief.

When theorizing about how individuals would like to allocate relief aid, an important distributive fairness norm is the polluter-pays or affectedness principle. Whereas the polluter-pays principle applies to situations that require a decision about how to allocate costs, the affectedness principle is relevant when distributing benefits meant to compensate for experienced losses. This fairness norm specifies that the distribution of benefits should be proportional to the experienced losses.[3] In the context of disaster relief programs, financial benefits are explicitly meant to re-

[2] Aldrich (2012) offers a review of the literature on the politics of natural disasters.

[3] This proportionality requirement dates back to ancient philosophical treatments of distributive justice that rely on a geometric approach to determining fair allocations of costs and benefits (Judson 1997).

flect the level of affectedness by compensating for losses due to a natural disaster. According to the Stafford Act relief aid is intended "to alleviate the suffering and damage which result from such disasters [...] by providing Federal assistance programs for both public and private losses sustained in disasters" (Robert T. Stafford Disaster Relief and Emergency Assistance Act, I, Sec. 101, b), (6)). If voters follow an affectedness-based fairness norm we would expect that the level of economic damage will influence how much relief aid publics would like to provide.

Preferences over relief allocations may also be explained by the ability to pay principle. This norm, which is most prominent in the context of tax policy questions and "advocated alike by the scholar in taxation and the common man" (Kendrick 1939, 92), attempts to determine the amount that constitutes an equal sacrifice when requiring individuals to make a contribution. The ability-to-pay logic can be extended to scenarios that require a distribution of benefits where the allocation would also have to account for differences in individual's level of wealth. When theorizing about how voters judge the provision of disaster relief, this fairness norm suggests that the distribution of relief aid should mirror differences in wealth among disaster victims. An important collective goal of relief aid is to help disaster victims to recover and this goal may be served best if the allocation of relief aid mirrors the distribution of wealth, as those who are poorer find it more difficult to meet their immediate survival needs and finance their economic recovery. Consequently, we expect that individuals prefer to allocate more relief aid to regions that are poorer.

Voters may also view the distribution of policy benefits from a political perspective that highlights the role of electoral reciprocity and partisan solidarity. The electoral reciprocity argument builds on the logic of democratic selection and electoral accountability (Downs 1957). To realize the welfare-enhancing effect of democracy citizens have to be willing to electorally reward incumbents that have provided them with policy benefits. This incentivizes policymakers to engage in targeted public spending decisions to maximize their re-election chances. While some believe that political leaders tend to pursue universalistic policies, i.e., policies that cater to the nation

as a whole without favoring particular interests (Cronin and Genovese 2004), others (Kriner and Reeves 2015) have argued that political leaders may engage in partisan particularism by advantaging constituencies that have supported them in the past election.

Voters could subscribe to a universalistic ideal which requires incumbents to be responsive to all citizens irrespective of whether they have supported the incumbent or not. The argument implies that citizens should not be responsive to electoral considerations when deciding about how to allocate disaster relief. However, citizens could also follow an electoral reciprocity logic. Allocating slightly more relief aid to regions that have supported the incumbent in previous elections could be seen as an example of political elites giving back to those who have voted for them. Even if this concern may be less pronounced than factors such as affectedness or need, voters could place some value on maintaining the reciprocal relationship between affected citizens and the incumbent. If this argument has empirical merit, we would expect that individuals prefer relief allocations that reflect the extent to which an affected county has voted for the incumbent in the previous election.

A second political logic that may explain how voters judge distributive policy decisions argues that shared partisan orientation could give rise to in-group solidarity. Party identification is not only a stable and powerful predictor of electoral choice and civic engagement (Dalton 2016), but also offers a shared, loyalty-based identity (Clifford 2017). This could generate partisan solidarity that gives rise to preferential in-group treatment in which voters who identify with a political party would allocate more relief aid to co-partisans. Our design allows us to test both the electoral reciprocity and the partisan solidarity argument.

III. Data and Research Design

To empirically evaluate our theoretical predictions, we develop a novel conjoint experiment (Bechtel and Scheve 2013; Hainmueller, Hopkins and Yamamoto 2014) that asked respondents to make divide-the-dollar decisions (see below). This conjoint was embedded in an online survey fielded to

a population-based quota sample of American citizens (N=2,618) in December 2016. The sample was provided by Respondi and based on their online panel. This panel is constructed by drawing a random sample from the population which is then converted into panels and sub-panels on the basis of known population margins (Respondi 2015). Our survey contains a standard set of sociodemographic questions and several novel question items needed to empirically test the theoretical mechanisms. The full survey instrument is included in the replication archive. The Appendix offers detailed information about these questions (Appendix Tables A.1) and reports descriptive statistics in Appendix Table A.2. In addition, Appendix Table A.3 shows that the distribution of sociodemographic characteristics in our sample closely matches the population margins. Unless stated otherwise, we report results that employ weights although the findings remain unchanged when estimated on the unweighted sample.

A. Experimental Design: Relief Allocation Conjoint and Divide-the-Dollar Decisions

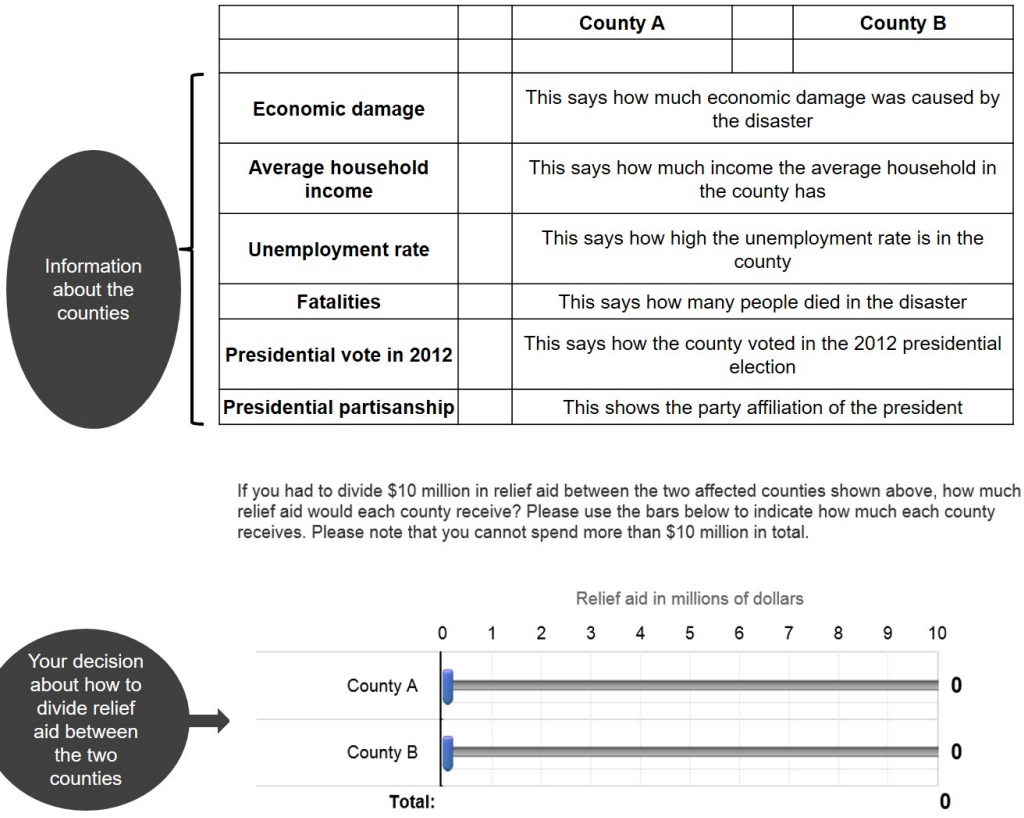
To explore which factors explain individual preferences over the distribution of disaster relief, the conjoint presents respondents with theoretically relevant characteristics of two counties that were affected by a natural disaster. In reality, policymakers (governors and the president) issue county-specific disaster declarations which establish the eligibility of individuals residing in these counties for applying for disaster relief.[4] This turns the distribution of disaster relief into a "divide-the-dollar politics" (Kriner and Reeves 2015) scenario. We mirror this decision developing a novel outcome measure that asks respondents to split a fixed total amount of relief aid between the affected counties. This modification of the standard conjoint design in combination with county-level conjoint scenarios offers two advantages. First, it reflects that budgets are always constrained and this design places a limit on what a respondent can spend in total. Even if disaster relief is often funded by supplemental appropriations, these resources remain ultimately finite. Second, it allows us to perform a more informative comparison with policymakers' actual

[4]See, e.g., `https://www.eda.gov/programs/disaster-recovery/`.

relief allocation choices since this information is only available at the county level.

Figure 1 shows the instructions of the conjoint experiment along with the divide-the-dollar outcome component. Our conjoint task asks each respondent to distribute a total of $10 million in relief aid between two counties and this task was repeated four times. In total, respondents made 20,944 county-level relief spending decisions. The conjoint contained six dimensions derived from the theory: Economic damage and the number of fatalities caused by the disaster, average household income, unemployment rate, presidential partisanship, and a county's vote in the 2012 presidential election. For each dimension we used between two and five different values. We detail and justify these dimensions and values below.

Figure 1: Instructions for the Divide-the-Dollar Conjoint Experiment (Screenshot)



Note: This figure shows the instructions for the conjoint experiment which asked respondents to allocate relief aid between two affected counties. In the conjoint tasks, the values of all attributes were randomized except for presidential partisanship which was randomized across binary comparisons but held constant within each comparison to avoid internally inconsistent hypothetical scenarios. To remove any order effects, the order of the dimensions was randomized across individuals.

B. Selection of Attribute Values in the Divide-the-Dollar Conjoint

Table 1 presents the attribute values for each dimension. We choose the attribute levels to approximate the historically observed county characteristics as closely as possible. To examine the role of affectedness considerations, we include two attributes that capture the most prominent ways of measuring affectedness: Economic damage ($100,000, $1 million, $4 million, $24 million) and the number of fatalities (0, 5). While it is possible for respondents to fully compensate the economic damage whenever disaster losses are $4 million or less (since then the maximum of the total damage for two counties is $8 million), we intentionally include one higher damage level ($24 million) that exceeds the available budget. The purpose of this design is to also observe individual allocation decisions under a more difficult, but also potentially more realistic scenario in which the available resources are not sufficient to compensate the experienced damage in full. The robustness section reports results suggesting that the structure of mass preferences over disaster relief are quite stable even if the available resources only allow for compensating a small fraction of the financial losses.

We also include two attributes widely used to measure wealth and need-based characteristics: the average annual household income in a county ($10,000, $40,000, $70,000, $100,000) and the level of joblessness (3%, 5%, 7%, 9%). Based on data from 1993 to 2008, 25 percent of all counties had an unemployment rate between 0% and 4%. The corresponding value in the conjoint experiment is the 12.5th percentile which in this case amounts to 3%. Due to inflation and income changes we decided to accept slight deviations from the long-term, historically observed values to more closely mirror the more recent distribution of those variables. Finally, to estimate the causal effects of electoral and partisan characteristics, we include presidential partisanship (Democratic, Republican) and the five two-party vote share for Democrats and Republicans to conceptualize swing (50%/50%), core (60%/40%), core stronghold (70%/30%), opposition (40%/60%), and opposition stronghold counties (30%/70%).

The conjoint fully randomizes all values with the exception of those related to presiden-

Table 1: Distributions of Explanatory Variables (Historical Data) and Attribute Levels for the Relief Allocation Conjoint Experiment

Variable/Attribute	**Historical Data**	**Conjoint Attribute Levels**
Economic damage	\$0 - \$456,000	\$100,000
	\$456,000 - \$2,277,000	\$1 million
	\$2,277,000 - \$11,800,000	\$4 million
	\$11,800,000 - max	\$24 million
Fatalities	0	0
	More than 0	5
Average income	\$40,000 - max	\$100,000
	\$34,000 - \$40,000	\$70,000
	\$29,000 - \$34,000	\$40,000
	\$0 - \$29,000	\$10,000
Unemployment rate	0% - 4%	3%
	4% - 5%	5%
	5% - 7%	7%
	7% - max	9%
Presidential partisanship		Democratic
		Republican
Presidential vote in 2012	Swing: $\Delta_v \in$(-5,5)	50% Democrat, 50% Republican
	Core: $\Delta_v \in$[5,25)	60% Democrat, 40% Republican
	Core Stronghold: $\Delta_v \in$[25,100]	70% Democrat, 30% Republican
	Opposition: $\Delta_v \in$[-5,-25)	40% Democrat, 60% Republican
	Opposition Stronghold: $\Delta_v \in$[-25,-100]	30% Democrat, 70% Republican

Note: This table shows the dimensions and values used in the conjoint experiment. Ranges for the variables economic damage, fatalities, income, and unemployment rate are based on the 25%, 50%, and 75% percentile of the empirical distributions of these variables in the historical data. All values are randomly assigned except presidential partisanship which varies randomly between conjoints, but is constant for a given conjoint. Δ_v denotes the two-party vote share difference in percentage points.

tial partisanship as this characteristic theoretically cannot differ between different counties in a contemporaneous setting. Our design avoids such combinations by randomizing presidential partisanship across conjoint comparisons while keeping it constant within each conjoint comparison. This means that whenever a respondent considers two affected counties in a divide-the-dollar conjoint task, presidential partisanship is the same for both of these regions. All other attribute values are fully randomized since an this is generally preferable to estimate causal effects and none of the remaining potential value combinations seem to result in a logically inconsistent or implausible scenario. In addition, we randomize the order of the dimensions between respondents to avoid order effects. However, we keep the order of the dimensions constant within respondents to reduce the complexity of the task (Bechtel and Scheve 2013).

IV. Experimental Results

We estimate the causal effects of the conjoint attributes by regressing the amount of relief aid a respondent allocated to a county on treatment variables that indicate the presence or absence of the randomly assigned attribute values for each of the six attributes. Figure 2 reports the causal effects along with 95% confidence intervals computed from standard errors clustered by conjoint comparison. Dots without error bars represent the reference categories. Since presidential partisanship was kept constant at the conjoint-task level, we report the results separately by government partisanship. Appendix Figure A.1 reports the pooled results using the weighted and unweighted sample. In what follows, we first focus on the causal effects of the conjoint attributes. We then perform various subgroup estimations to evaluate the plausibility of the theoretical mechanisms.

A. The Causal Drivers of Preferences over Disaster Relief

We find that all treatment indicators for the economic damage dimension have positive and significant effects on individuals' relief spending preferences. An increase in damage from $100,000

to $1 million causes an increase in preferred relief aid by about $500,000, which equals 50% of the damage. Larger damages trigger higher amounts of relief aid. For example, experiencing $4 million in damage increases relief aid allocated to a county by $750,000 while large damages of $24 million leads relief aid to increase by $1.2 million. This pattern holds across Republican and Democratic partisanship and is consistent with the affectedness argument. When we conceptualize affectedness as having experienced fatalities, we find that counties that experienced casualties receive about $100,000 more disaster relief than counties without any fatalities. Overall, these sensitivities are consistent with the argument that affectedness-based fairness norms help explain disaster relief preferences.

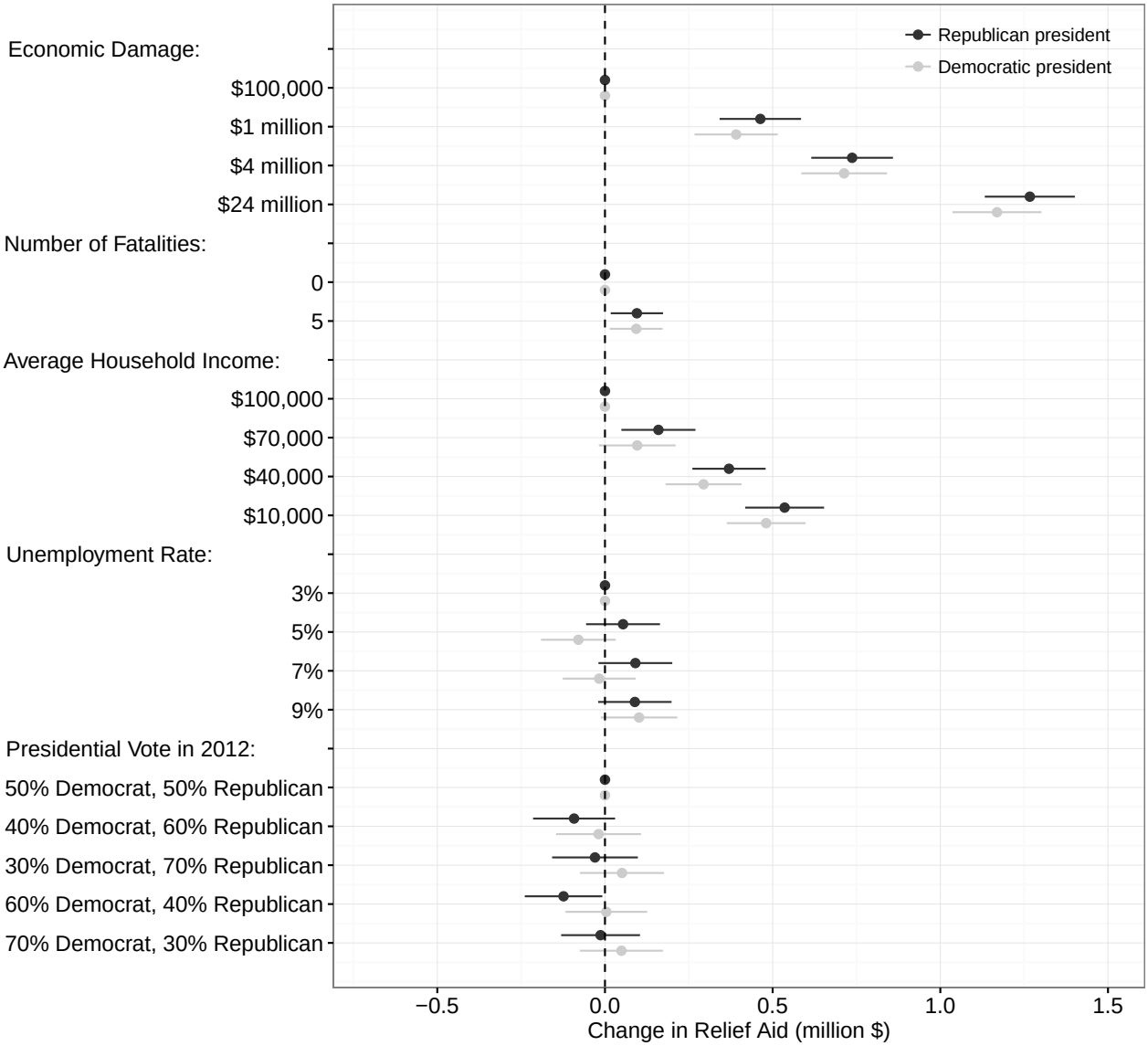
How important are need-related characteristics for understanding voter evaluations of policy responses to natural disasters? The results in Figure 2 suggest that respondents allocate about $4 million more in relief to a county in which households make about $40,000 per year compared to a wealthier county in which the average household income is $100,000. This sensitivity seems to be rooted in the desire to provide support as a function of the level of wealth and not as a function of regional employment conditions since voters do systematically change their preferred relief allocation in response to higher unemployment rates.

When examining the impact of a region's past voting record, we find that almost all effects are statistically indistinguishable from zero. Overall, we individuals tend to prefer relief aid allocations that reflect affectedness and need, while the political orientation of a county does not seem to play an important role in individuals' allocation choices. In the next section we explore which theoretical mechanisms may underlie these treatment effects.

B. Theoretical Mechanisms

We now explore whether variables related to the underlying theoretical mechanisms systematically moderate the treatment effects in ways consistent with the theory. For example, if affectedness-based norms of distributive justice drive allocation preferences, we would expect

Figure 2: The Causal Effects of County Characteristics on Relief Spending Preferences by Presidential Partisanship



Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Baseline levels of relief aid: Republican president = $4.1 million, Democratic president = $4.1 million. N (county-level relief spending decisions) = 20,944.

to the causal effect of economic damage to be stronger among individuals subscribing to an affectedness-based conception of justice. To implement an empirical test of each of the theoretical mechanisms we collect information about whether individuals subscribe to fairness ideas

related to affectedness, need, and political ties. We use this data to reestimate the causal effects of county characteristics by theoretically meaningful subgroups. To avoid priming a specific sensitivity among respondents to the attributes included in our relief aid conjoint, these measures of individuals' fairness norms came after the conjoint experiment. In the robustness section we report additional results that rely on recoded reference categories for these subgroup estimations. Our findings remain unchanged.

Affectedness

Figure 3 shows the causal effects separately for the group of respondents that are relatively more supportive of affectedness-based fairness and the group of respondents that are less supportive of this conception of justice. This split is based on the question: "People sometimes experience negative events and go through difficult times. To what extent do you agree or disagree (1-10) with the following statement: 'Those who are more strongly affected should receive more help than those who are less affected'." This direct question approach seems preferable since – to the best of our knowledge – established and validated indirect measures of the types of fairness norms we are interested in do not yet exist. Therefore, if we had designed a novel indirect question the results would not have been very informative.[5] We also note that the question wording does not make any reference to the attribute names used in the conjoint (e.g., economic damage, fatalities, etc.). To avoid priming respondents in a specific direction, this question was asked later in the survey. Moreover, the conjoint and the questions on support for different types of fairness were separated by several question items on other issues. As Appendix Table A.2 reports, the median response on this question is 8 which indicates that half of our respondents are quite supportive of an affected-based conception of fairness given that the underlying response scale ranges from 1 (completely disagree) to 10 (completely disagree). We convert respondents' answers into a binary

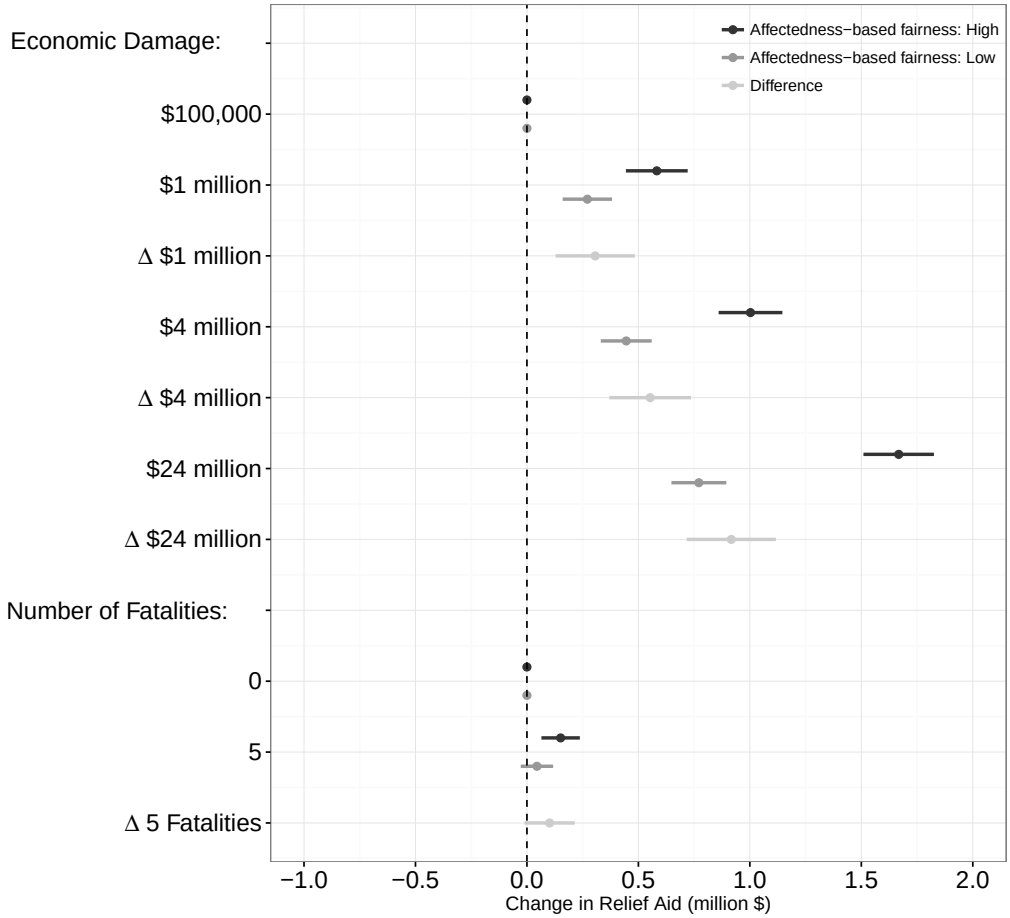
[5]For example, in case of a null finding it would have been unclear whether this is due to the survey item not measuring the relevant construct or whether the null result is valid. Similarly, in case of a significant finding one may question whether the item is really measuring the relevant underlying trait. Employing a direct measure avoids these complications.

indicator based on the median that is 1 for those whose level of agreement with the statement was greater than the median and is zero otherwise. Appendix Table A.4 reports the full estimation results for all attributes.

The results suggest that respondents who are more supportive of a general affectedness-based fairness norm are much more sensitive to the level of economic losses when allocating relief aid. For example, damage in the order of $4 million increases relief aid by $500,000 among individuals who are relatively less supportive of affectedness-based justice. In contrast, the same amount of economic damage increases relief spending allocated to a county by close to $1 million. Thus, the treatment effect doubles when comparing respondents that generally support affectedness-based justice with those that are less supportive of this fairness principle.

We formally test the hypothesis that the treatment effects for the two groups are statistically different from each other by computing effect differences along with the corresponding 95% confidence intervals based on the corresponding variance-covariance matrix. Figure 3 reports these results. We find that respondents who are generally more supportive of affectedness-based fairness provide counties that have experienced $1 million in damage with about $300,000 more relief aid than individuals who are less supportive of this fairness norm. We find similar patterns when examining the effects of higher levels of economic damage. In fact, the difference between the treatment effects becomes larger as disaster damage increases. This heterogeneity in the treatment effects is consistent with the argument that an affectedness-based norm of distributive justice may explain individuals' strong sensitivity to economic damage when allocating relief aid. Figure 3 also shows that we estimate a significant and positive difference when comparing the causal effect of 5 fatalities on relief preferences among *Affectedness-based fairness: High* respondents and *Affectedness-based fairness: Low* individuals. This suggests that individuals who advocate affectedness-based justice in the abstract tend to provide more relief aid to counties that experienced casualties than respondents who are less supportive of this notion of justice.

Figure 3: The Causal Effects of Economic Damage and Fatalities on Relief Spending Preferences by Affectedness-based Fairness



Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Δ reports the difference in the treatment effects between a given attribute level and the reference group. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Baseline levels of relief aid: Affectedness-based fairness: High = \$3.7 million, Affectedness-based fairness: Low = \$4.3 million. N (county-level relief spending decisions) = 20,944. N (respondents) per group = 1,309. The measure of support for affectedness-based fairness is based on the question: "People sometimes experience negative events and go through difficult times. To what extent do you agree or disagree with the following statement: 'Those who are more strongly affected should receive more support than those who are less affected'." Respondents' answers on a 1-10 scale were converted into a binary indicator based on the median. The indicator variable is 1 for those whose level of agreement with the statement was greater than the median and is zero otherwise. Appendix Table A.4 reports the full estimation results for all attributes.

Need

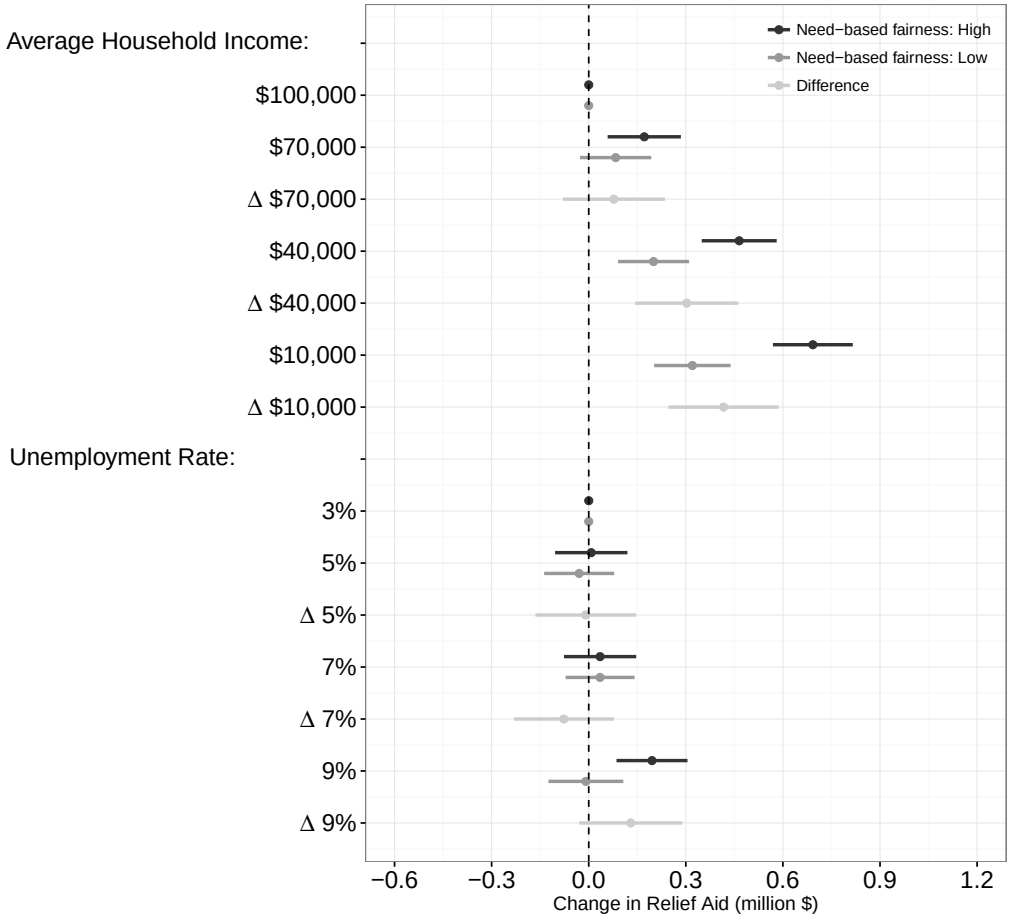
Our main results indicate that voter preferences over disaster relief are sensitive to income differences between affected counties. To explore whether this pattern can be explained by a need-based norm of distributive justice, we again use a direct question wording seeking to measure general agreement with this norm while at the same time avoiding any of the terms used in the conjoint attributes: "People sometimes experience negative events and go through difficult times. To what extent do you agree or disagree with the following statement: "Those who are richer should receive less support than those who are poorer even if they are equally affected". We again split the sample at the median for descriptive statistics) and reestimate the causal effects for both subgroups.[6]

Figure 4 shows the causal effects of need-related factors on the amount of relief aid allocated to a county by our respondents separately for the two groups. We find that the effects of a county's average household income are much stronger among individuals who generally support a need-related notion of distributive justice. For example, individuals subscribing to need-based justice allocate $300,000 more in relief aid to counties with an average household income of $40,000 than individuals who are less supportive of this type of fairness. The heterogeneity in the treatment effects is even larger for very poor counties ($10,000 average household income). Are these effects significantly different from each other when comparing the two groups? Our estimate of the difference in the effects, Δ, which we report with the corresponding 95% confidence interval, suggests that this is the case, as the confidence interval excludes zero. These results support the argument that the sensitivity to a county's level of wealth is driven by a need-based notion of distributive justice.

When examining the effects of a county's economic standing in terms of joblessness, we find that individuals respond very similarly unless the unemployment rate reaches 9%. Given high levels of unemployment, respondents that favor need as a criterion for distributive fairness allocate

[6]We note that the median response to this question is 6 which is quite close to the natural midpoint of 5.5 on the 1 (completely disagree) to 10 (completely agree) answer scale (see Appendix Table A.2).

Figure 4: The Causal Effects of Household Income and Unemployment on Relief Spending Preferences by Need-based Fairness



Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Δ reports the difference in the treatment effects between a given attribute level and the reference group. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Baseline levels of relief aid: Need-based fairness: High = \$4 million, Need-based fairness: Low = \$4.2 million. N (county-level relief spending decisions) = 20,944. N (respondents) per group = 1,309. The measure of support for affectedness-based fairness is based on the question: "People sometimes experience negative events and go through difficult times. To what extent do you agree or disagree with the following statement: 'Those who are richer should receive less support than those who are poorer even if they are equally affected'." Respondents' answers on a 1-10 scale were converted into a binary indicator based on the median. The indicator variable is 1 for those whose level of agreement with the statement was greater than the median and is zero otherwise. Appendix Table A.4 reports the full estimation results for all attributes.

about $150,000 more in relief payments than individuals less supportive of need-based justice. The difference between those two effects fails to reach significance at the 5% level, although it is significant at the 10% level.

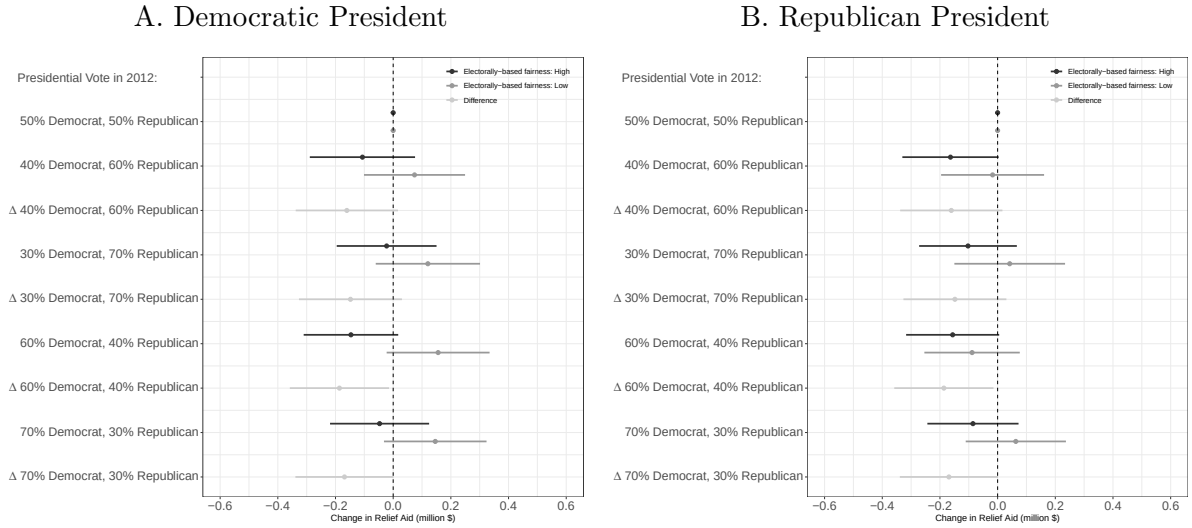
Political Ties: Electoral Reciprocity and Partisan Solidarity

A third explanation for voter preferences over relief aid allocations focuses on the role of political ties. If the electoral reciprocity argument is valid, we would expect voters who are more sympathetic towards this type of fairness norm to allocate more relief aid to counties that have supported the president's party in the previous election. We offer an evaluation of this prediction by first classifying respondents based on their agreement with the statement: "Governments should prioritize the needs of those who voted for them". The question was asked after the divide-the-dollar conjoint and was separated by a set of items that elicited individuals' views on other topics. Respondents' answers on a 1-10 scale were converted into an indicator variable based on the median response.[7] We then further partition our data according to whether the conjoint specified a scenario in which a Democratic or a Republican president was in power. Figures 5A and B report the causal effects along with the differences in the treatment effects (Δ). The estimates reported in Figure 5A indicate that high electoral reciprocators do not systematically allocate more relief aid to Democratic strongholds under a Democratic administration. If anything, such respondents tend to allocate somewhat less relief aid to counties that provided more support for either candidate in the past election which is inconsistent with the electoral reciprocity argument. We find a similar pattern when exploring respondents' relief allocations in conjoint scenarios that featured a Republican president.

An alternate version of the political ties argument assumes that respondents' hold in-group views based on partisanship which could give rise to solidarity among co-partisans. Individuals who identify with a specific party would then allocate more relief aid to regions that are core

[7]The median response to this question is 5, see Appendix Table A.2.

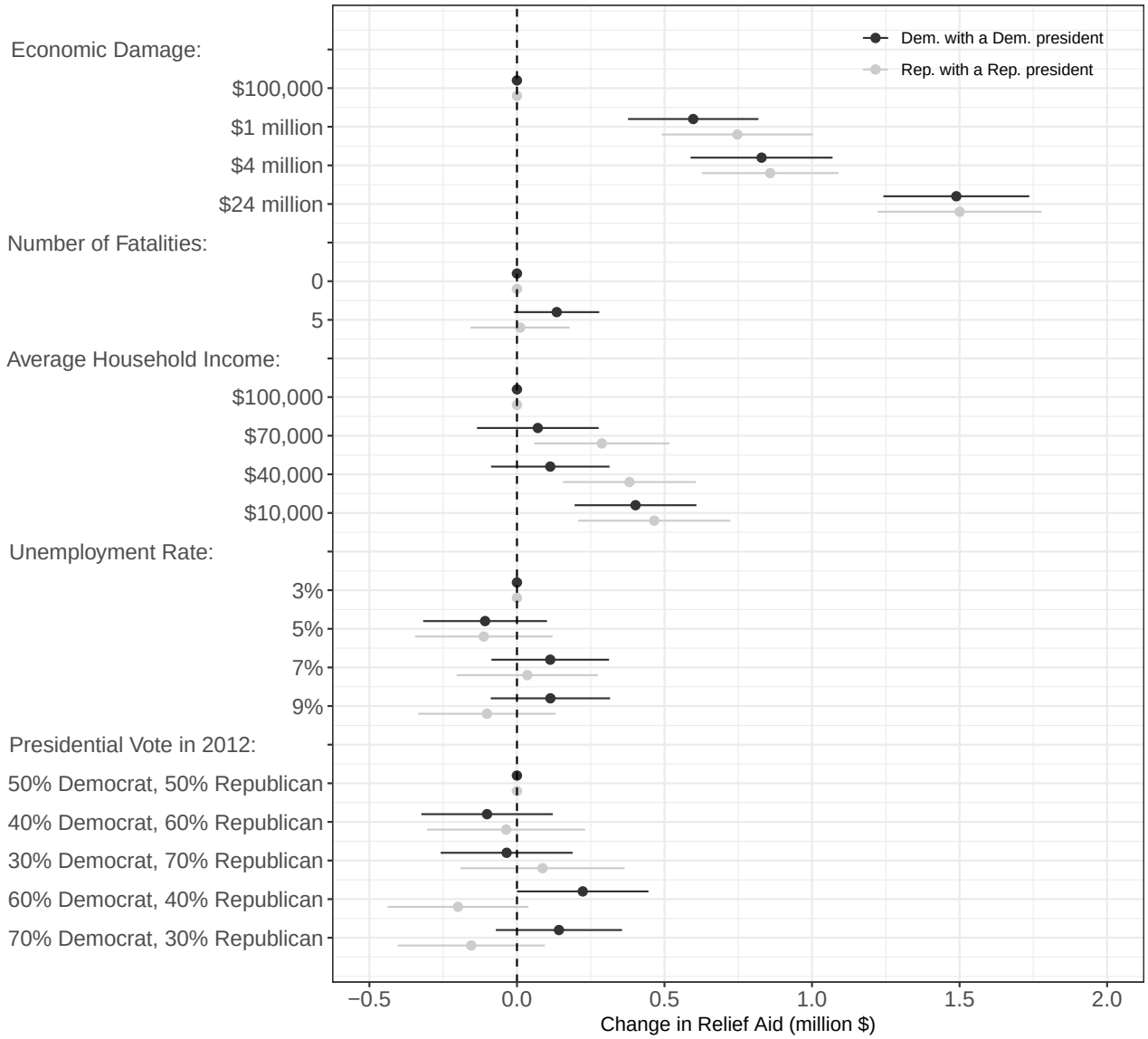
Figure 5: The Causal Effects of Previous Presidential Vote on Relief Spending Choices by Electoral Reciprocity and Government Partisanship



Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Points without confidence intervals indicate the reference category for a given attribute. Δ reports the difference in the treatment effects between a given attribute level and the reference group. Horizontal lines indicate 95% robust confidence intervals. Baseline levels of relief aid: electoral reciprocity low and Republican president=$3.9 million, electoral reciprocity high and Republican president=$4.3 million, electoral reciprocity low and Democratic president=$3.9 million, electoral reciprocity high and Democratic president=$4.4 million. N(county-level relief spending decisions) = 20,944.

supporters of their preferred party. To evaluate this argument we break down the results by respondents' partisan identification and government partisanship. The causal effects of a county's presidential vote reported in Figure 6 indicate that Democratic respondents have a slight preference for favoring Democratic strongholds under a Democratic administration. Republicans do not seem to systematically favor Republican strongholds during times of Republican government partisanship. Overall, the results indicate that even when focusing on political scenarios that should give rise to allocation behavior consistent with partisan solidarity, affectedness and need seem to remain the main concerns.

Figure 6: The Causal Effects of County Characteristics on Relief Spending Preferences by Respondents' Partisan Identification and Government (Presidential) Partisanship



Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Baseline levels of relief aid: Republican with a Republican president = $4.1 millions, Democrat with a Democratic president = $4 millions. N(county-level relief spending decisions) = 20944. N (respondents) = 2,618.

V. Robustness

We subject our results to a large set of robustness tests which Appendix I reports in detail. First, we explore whether the disaster relief preferences of likely voters differ from those of the rest of the adult population. The results in Appendix Figure A.2 indicate that this is not the case. Second, we test if voters' sensitivities depend on whether the available resources are sufficient to fully compensate for the experienced disaster losses. We re-estimate the results for the subset of allocation decisions in which the combined damage in both divide-the-dollar conjoint scenarios was equal to or less than $10 million. As the results in Appendix Table A.6 show, the structure of mass preferences over disaster relief remains quite comparable to the main results reported above. Preferences may be shaped by personal exposure to extreme weather events. Appendix Figure A.3 suggests, however, that the causal effects do not depend on whether a respondent has been personally affected by a natural disaster in the past ten years or not. We find a similar level of homogeneity across levels of attentiveness (Appendix Figure A.4), and time spent on the survey (Appendix Figure A.5). We also explore the existence of racial differences in how voters judge the policy responses to natural disasters. The results in Appendix Figure A.6 suggest that relief allocations of white and non-white respondents are equally sensitive to economic damage and household income. Moreover, the structure of voter preferences over disaster policy responses are quite stable across different regions (see Appendix Figure A.7). We also find that the results are not sensitive to which attribute level is used as the reference category (see Appendix Table A.7).

VI. Comparing Voter Preferences over Relief Spending with Observed Relief Allocations

An important question in research on political representation and the functioning of democracy asks whether redistributive spending choices made by public officials correspond to citizens' preferences. Our data allows us to perform a novel and unusually direct juxtaposition of the structure

of voter preferences and policymakers' actual spending decisions. Clearly, the coefficients from our experimental results and those based on the historical data should not be compared as precisely as two models estimated on the same data. Yet, they offer useful information about whether the empirical patterns are broadly consistent with each other, i.e., whether factors related to affectedness, need, and political ties correlate with relief aid decisions in roughly the same direction. For this comparison we collect county-level data from the Consolidated Federal Funds Report (CFFR) from 1993 to 2008 and identify those spending items that are related to natural disasters. Appendix Tables A.8 and A.9 provide a detailed list of these programs. Our outcome of interest is the amount of relief spending received by a county during a presidential term.[8] This type of temporal aggregation is necessary to evaluate explanations related to government partisanship. We combine this data with information about the occurrence, damage, and associated fatalities of natural disasters from the Spatial Hazard Events and Losses Database for the United States.[9] As others have argued (Kriner and Reeves 2015), there exist many opportunities for elected officials to affect the allocation of relief aid. These include appointing bureaucrats with similar political orientations as well as strategically crafting budget proposals that facilitate electorally profitable spending decisions.

We regress *Relief Aid*$_{c,t}$ received by county c in term t in logs per capita on covariates that capture need-based, affectedness-based, and electoral considerations.[10] Since the outcome variable is log-transformed, the coefficients measure changes in percent (not percentage points). Our predictor variables closely mirror the attributes used in our conjoint experiment. We quantify affectedness in terms of both economic damage and human losses. *Damage* measures the value of economic damage a county has experienced due to natural disasters in million dollars. *Fatalities* counts the number of individuals who were killed by a disaster. To account for need-based

[8]For example, relief aid for county c in 2000 is the sum of relief aid spent in 1997, 1998, 1999, and 2000. Overall, we have four presidential terms (1996, 2000, 2004, 2008).

[9]This data is accessible at `http://hvri.geog.sc.edu/SHELDUS`. If a disaster affects multiple counties, the total damage and associated fatalities are distributed equally across these counties.

[10]For counties that did not receive any payments we add one to the per capita spending measure, divide it by population size and take the natural logarithm.

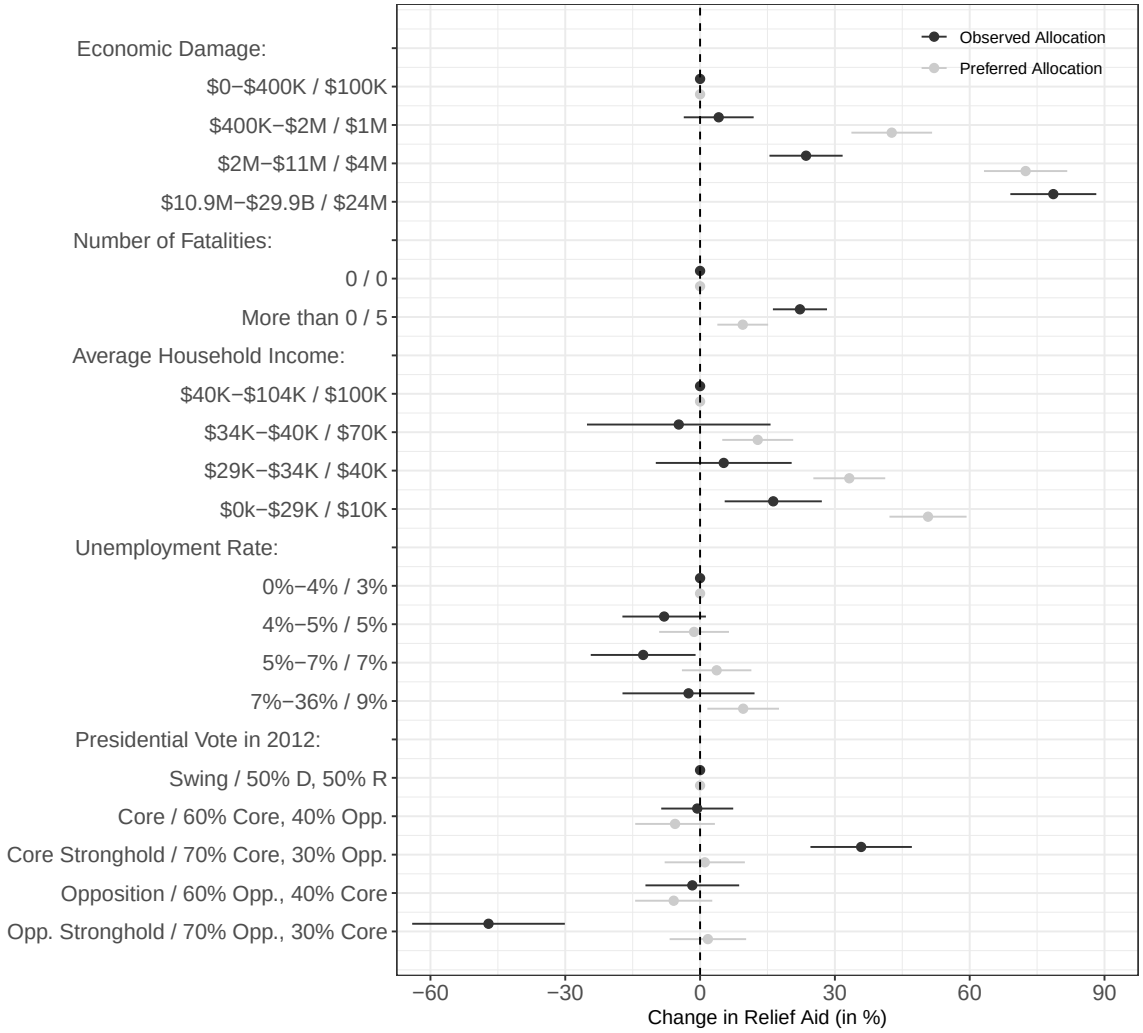
considerations, *Household Income* measures the average household income in the county and *Unemployment Rate* is the county-level share of unemployed individuals. To explore the importance of electoral motivations we classify counties into core, core stronghold, swing, opposition, and opposition stronghold counties based on the two-party vote share difference in the previous presidential election.[11] All regressions include county and period fixed effects, and a set of time-varying sociodemographic and political covariates.

Figure 7 shows the results. We find that disaster damage significantly and positively correlates with the amount of federal relief aid. Compared to the reference group (Economic Damage<$401,000), counties that experienced losses between $2 and $11 million receive about 25% more relief payments. The results also suggest that the allocation of relief aid mirrors the number of casualties. Counties that suffered human losses receive 20% more financial support than counties without fatalities. This patterns seem broadly consistent with the structure of voter preferences over the distribution of relief aid.

The estimates reported in Figure 7 also suggest that poorer regions receive more relief aid which is consistent with a need-based fairness norm that also seems to help explain voter preferences over the allocation of disaster aid. In contrast, we find strongly divergent patterns when examining the correlation between a county's previous voting record and the amount of relief aid it receives. For example, core stronghold counties receive 40% more relief payments than observably similar swing states while opposition strongholds on average receive 40% less relief aid. The former finding is consistent with the core voter model (Cox 2010) which argues that rewarding loyalists offers additional advantages over an allocation that targets swing voters because of its mobilizing and coordination-enhancing effect. The results is also in line with previous empirical work on the relationship between federal grant aid and a county's historical voting record (Kriner

[11] We first compute the two-party vote share difference by subtracting the vote share of the opposition party from the vote share of the presidential party. Counties with an electoral margin between (-)5 and (-)25 percentage points are coded as core (opposition) counties. Counties with an electoral margin greater (less) than (minus) 25 percentage points are coded as core stronghold (opposition stronghold) counties. Counties with a vote share difference of -5 to 5 percentage points are coded as swing counties.

Figure 7: Observed and Preferred Disaster Relief Allocations



Note: This plot reports linear regression coefficients. Horizontal lines indicate 95% robust confidence intervals. For the observed relief allocation results, the dependent variable is the natural logarithm of relief aid received. This model uses county-fixed effects and standard errors clustered at the county-level. Controls include preparedness spending as well as socio-economic and political characteristics. Points without confidence intervals indicate the reference categories. The preferred allocation results are based on the main conjoint estimates. N = 12,424.

and Reeves 2015).

VII. Conclusion

Despite unprecedented increases in wealth and major technological advances, humans continue to be vulnerable to existential threats such as natural disasters. Although most would agree

that resources should be made available to provide assistance to affected individuals and compensate at least some of the experienced losses, political conflict may arise over how these finite resources should be distributed. Moreover, since policymakers seek re-election, one may view policy responses to natural disasters as providing yet another example of "electoral politics as a redistributive game" (Cox and McCubbins 1986) in which incumbents engage in targeted spending decisions to cater to their voter base. At the same time, there may exist a broad consensus among voters as to which principles should guide public spending decisions in response to major shocks and, more importantly, affected and unaffected individuals may disapprove of redistribution decisions that reflect electoral considerations.

We devise a disaster relief conjoint that we embed in a population-based sample of American citizens and find that individuals allocate significantly more relief payments to counties that experienced more damage, had more fatalities, are poorer and have higher unemployment rates. Moreover, our findings show that mass preferences over disaster relief do not or at most weakly reflect the political characteristics of a county. These sensitivities are robust across a large set of subgroups including whether an individual has been personally affected by a natural disaster in the past. When contrasting these results with the observed distribution of federal relief aid, we find a notable degree of congruence. For example, and in line with voter preferences, more affected counties receive significantly more relief aid.The alignment between voter preferences and observed relief distributions could seem surprising since respondents in our survey and policymakers may operate under different incentive structures. Yet, since policymakers seek re-election, there still exists a strong incentive to engage in spending decisions that mirror voter preferences. At the same time, we find that core strongholds receive significantly higher payments, a pattern that contradicts the preferences of voters who seem to favor relief allocations that are not affected by electoral considerations.

There exist several avenues for future research. First, subsequent work may use our approach to generate information about the extent to which governments' actual policy decisions deviate

from voters' preferred policy responses to more accurately model electoral choice. If incongruence between public policy and mass preferences explains variation in voting behavior, it may also improve forecasts of electoral outcomes in the aftermath of extreme weather events which are likely to become increasingly frequent and destructive in the foreseeable future. One could also explore how other factors such as preparedness, private as opposed to public losses, or growth and recovery potential influence individual preferences over disaster responses using the divide-the-dollar conjoint design. Finally, subsequent work may study the extent to which spending preferences over the policy responses to extreme weather events generalize to other types of shocks such as economic crises, pandemics, and conflict.

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Online Appendix

I. Robustness

A. *Personal Affectedness and Preferences over Relief Spending*

Experiencing natural disasters does not only constitute a threat to individuals' economic survival, but can also put them in a life-and-death situation. In this sense, disasters resemble other potentially life-changing experiences that cause economic and social disruption, give rise to powerful emotions such as fear and anger, and can severely traumatize individuals. The mere threat of such experiences can fundamentally alter how individuals perceive the underlying events and their views about them. Consequently, having been directly affected by a natural disaster in the past may also influence citizens' preferences over the allocation of relief aid. We explore the sensitivity of our results to whether a respondent has been personally affected. Overall, 37% of the respondents included in our sample report to have been personally affected at least once since 2006 (see Table A.1 in the Appendix for descriptive statistics on this question). Figure A.3 in the Appendix reports the treatment effects separately for respondents that indicated to have been affected by a disaster in the past ten years and those that did not. The results are very similar for both subgroups.

B. *Disaster Relief Allocations and Partisan Identification*

Given the increasing prevalence of partisan cleavages in public policy attitudes and voting behavior, one may ask to what extent the results differ by respondents' own partisan identification? We estimate our results separately for respondents that self-identified with either the Democratic or the Republican party.[12] Figure **??** in the appendix reports the results. We find that a surprisingly clear consensus exists among Republicans and Democrats when examining the causal effects: They generally agree that the distribution of relief aid should reflect affectedness and need, largely to the same extent. The only clear difference we find relates to the importance of electoral reciprocity. Republicans allocate $250,000 more relief aid to counties that have provided strong electoral support (70% Republican vote share) for the Republican presidential candidate.

C. *Censored Nature of Outcome Variable, Dependence between Relief Allocation Choices, and Attentiveness*

Next, we explore whether our results remain intact when using an estimation technique that accounts for the boundedness of our dependent variable. In our relief conjoint, the outcome variable is bounded on the interval (0,10) since the minimum amount of relief aid respondents can allocate is $0 million and the maximum is $10 million. We therefore estimate the treatment effects using a tobit model which accounts for the boundedness of our dependent variables. The results reported in Figure A.8 suggest that our results remain virtually identical.

As is common in conjoint designs, there exists a built-in dependency between respondents' decisions since individuals make choices based on a binary comparison between two affected counties based on their theoretically relevant characteristics. Moreover, our outcome variable is by definition compositional because the amount spent on one county reduces the amount that can be allocated to the remaining county. We address these issues by estimating the main results using the z-transformed amount of relief aid as our dependent variable. We remove the bounds by computing the relative share of relief aid allocated to county A and county B for each conjoint comparison (e.g. if county A received $3 million and county B received $7 million, the shares are .3 and .7, respectively). We then compute the corresponding z-value using the inverse cumulative distribution function of the standard normal distribution. Figure A.10 in the Appendix shows the results, which are virtually identical to those reported above. In addition, we assess the robustness of our results to only using data from individuals'

[12] This variable is based on the standard survey question: "Is there a particular party you feel closer to than all the other parties?".

spending decision on one of the two counties which means that we reduce the number of observations by 50%. The results in Figure A.11 in the Appendix show that our findings remain unchanged.

Finally, we evaluate the sensitivity of our results to respondents' level of attention as measured by a screener question and the time respondents needed to complete the conjoint component of our survey. As Figures A.4 and A.5 in the Appendix show, our results remain largely unaffected in those robustness tests.

D. Interactions between Affectedness and Need

Voters could be sensitive to both economic damage and poverty levels because they use this information to make inferences about an affected region's population size. For example, if a poor region experiences large economic damage, this could be interpreted to indicate that a large number of individuals was affected by the disaster. This, in turn, may increase voters' preferred amount of relief aid. We test this argument in two ways. We address this question by re-estimating the main results conditional on the level of damage and compare the causal effects of a region's income on respondents' relief allocation choices. Appendix Table A.10 reports the results. We find little to no evidence for the argument that the sensitivity to poverty (as measured by lower average household income) decreases as damage levels increase. Second, we reestimate the effects in a model that includes a full set of interaction terms between income and damage indicators. With one exception, none of these additional coefficients is significantly different from zero. Overall, respondents' sensitivities to damage and economic conditions are unlikely to reflect concerns related to population size.

E. Changing the Reference Groups and Regional Differences

Recent research argues that subgroup estimations from experimental results may be sensitive to which condition is used as the reference category (Leeper, Hobolt and Tilley 2018). We re-estimated the main and subgroup results reported above using the opposite attribute level as the reference group. The results reported in Table A.7 in the Appendix suggest that the subgroup differences are very consistent with our initial subgroup findings on the theoretical mechanisms. Previous work has documented regional differences in environmental policy preferences when comparing the American South with the rest of the United States (Shipan and Lowry 2001). As Appendix Figure A.7 shows, our results for respondents who live in the South are quite similar to those who live in the rest of the United States.[13]

[13]The US Census Bureau defines the Southern United States as Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas.

II. Appendix Tables

Table A.1: Descriptive Statistics: Reported Personal and Household Affectedness

Event	**Myself**	**Other Household members**
Not affected	51%	57%
Closed/restricted roads or (partial) shutdown of public transportation	37%	28%
Shutdown of school/university	23%	20%
Communication problems	26%	20%
Restricted access to food or water	18%	15%
Evacuation	14%	13%
Financial loss	19%	15%
Injury	13%	12%

Note: The table reports the share of respondents who indicated to have been affected by a specific event. The question wording is: "In the past years, natural disasters such as tornadoes, floods, earthquakes, droughts, and other adverse weather events have affected several regions in the United States. We are interested in learning about whether you have experienced or not experienced one or more natural disasters. Please indicate below whether you or members of your household were affected by any of the following events as a consequence of a natural disaster in the past ten years (since 2006). If you or members of your household were not affected please select 'Not affected'. If you were affected, please select all that apply." N = 2,618.

Table A.2: Fairness Norms: Descriptive Statistics (N=2,618)

Variable	Mean	Median	Std. Dev.	Min.	Max.
Affectedness					
Question: Those who are more strongly affected should receive more support than those who are less affected Scale: 1 (completely disagree) - 10 (completely agree)	7.2	8.0	2.7	1	10
Need					
Question: Those who are richer should receive less support than those who are poorer even if they are equally affected Scale: 1 (completely disagree) - 10 (completely agree)	5.7	6.0	2.8	1	10
Electoral Reciprocity					
Question: Governments should prioritize the needs of those who voted for them Scale: 1 (completely disagree) - 10 (completely agree)	4.8	5.0	3.1	1	10

Table A.3: Socio-Demographics of the Target Population, Weighted Sample, and Raw Sample (in %)

	Population	Weighted Sample	Raw Sample
Age: 18-24	12.6	12.7	16.8
Age: 25-44	34.2	34.2	35.0
Age: 45-64	33.9	33.8	30.6
Age: 65+	19.3	19.3	17.5
Gender: Male	48.7	48.7	47.3
Gender: Female	51.3	51.3	52.7
Education: Less than High School	12.2	12.2	10.6
Education: High School Degree	29.6	29.6	28.3
Education: Some College	28.4	28.5	31.6
Education: Bachelor's Degree	19.2	19.2	18
Education: Advanced Degree	10.6	10.5	11.3

Note: The table reports the distribution of socio-demographic characteristics in the population, the raw sample, and the weighted sample. N = 2,618. The population margins are based on the 2016 Current Population Survey, see `http://www.census.gov/cps/data/cpstablecreator.html`.

Table A.4: The Causal Effects of County Characteristics on Relief Spending Preferences: Full Subgroup Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fairness Norm						
		Affectedness		Need		Electoral Reciprocity	
	Main	Low	High	Low	High	Low	High
Damage: \$1 million	0.427***	0.271***	0.583***	0.519***	0.339***	0.534***	0.323***
	(0.046)	(0.057)	(0.071)	(0.063)	(0.066)	(0.068)	(0.061)
Damage: \$4 million	0.724***	0.445***	1.003***	0.817***	0.639***	0.915***	0.536***
	(0.047)	(0.058)	(0.073)	(0.069)	(0.065)	(0.070)	(0.063)
Damage: \$24 million	1.217***	0.771***	1.668***	1.362***	1.078***	1.483***	0.951***
	(0.052)	(0.063)	(0.081)	(0.074)	(0.073)	(0.077)	(0.069)
Fatalities: 5	0.095***	0.045	0.151***	0.061	0.127***	0.053	0.138***
	(0.029)	(0.037)	(0.044)	(0.039)	(0.043)	(0.040)	(0.041)
Income: \$70,000	0.128***	0.120**	0.141**	0.083	0.172***	0.153***	0.103*
	(0.040)	(0.050)	(0.062)	(0.056)	(0.058)	(0.058)	(0.057)
Income: \$40,000	0.332***	0.247***	0.416***	0.200***	0.465***	0.415***	0.245***
	(0.041)	(0.053)	(0.061)	(0.056)	(0.059)	(0.058)	(0.057)
Income: \$10,000	0.507***	0.457***	0.560***	0.320***	0.693***	0.647***	0.367***
	(0.044)	(0.056)	(0.067)	(0.060)	(0.063)	(0.063)	(0.060)
Unemployment Rate: 5%	-0.013	-0.023	-0.012	-0.030	0.008	-0.025	-0.007
	(0.040)	(0.051)	(0.060)	(0.055)	(0.057)	(0.057)	(0.055)
Unemployment Rate: 7%	0.037	-0.031	0.097*	0.035	0.035	-0.026	0.097*
	(0.039)	(0.053)	(0.058)	(0.054)	(0.057)	(0.054)	(0.057)
Unemployment Rate: 9%	0.096**	0.072	0.116*	-0.009	0.196***	0.044	0.132**
	(0.041)	(0.054)	(0.061)	(0.059)	(0.056)	(0.056)	(0.059)
40% Democrat	-0.056	-0.164***	0.067	-0.120*	0.003	0.028	-0.131**
	(0.045)	(0.061)	(0.066)	(0.063)	(0.064)	(0.064)	(0.064)
30% Democrat	0.010	-0.063	0.097	-0.008	0.022	0.081	-0.060
	(0.046)	(0.061)	(0.068)	(0.065)	(0.063)	(0.067)	(0.061)
60% Democrat	-0.059	-0.118**	0.014	-0.093	-0.027	0.033	-0.149**
	(0.044)	(0.055)	(0.068)	(0.061)	(0.062)	(0.063)	(0.060)
70% Democrat	0.017	-0.066	0.108*	-0.033	0.059	0.105*	-0.066
	(0.043)	(0.056)	(0.065)	(0.060)	(0.062)	(0.063)	(0.059)
Constant	4.105***	4.472***	3.728***	4.190***	4.020***	3.889***	4.325***
	(0.060)	(0.080)	(0.089)	(0.084)	(0.087)	(0.086)	(0.084)
Observations	20,944	10,472	10,472	10,472	10,472	10,472	10,472
R-squared	0.055	0.032	0.083	0.062	0.054	0.079	0.036

Note: OLS coefficients shown with robust standard errors clustered by respondent in parenthesis (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Reference categories for the respective attributes: Damage: \$100,000, Fatalities: 0, Income: \$100,000, Unemployment Rate: 3%, 50% Democrat. Since Model 2 is only based on conjoint tasks in which the total damage across the two scenarios was equal to or less than \$10 million, the treatment indicator for the \$24 million attribute level has to be excluded.

Table A.5: The Causal Effects of County Characteristics on Relief Spending Preferences: Subgroup Results by Alternative Measure of Electoral Reciprocity Fairness (Conjoint Experiment)

	(1)	(2)
	Electoral Reciprocity	
	Low	High
Damage: $1 million	0.443***	0.410***
	(0.066)	(0.064)
Damage: $4 million	0.729***	0.720***
	(0.069)	(0.065)
Damage: $24 million	1.214***	1.223***
	(0.075)	(0.072)
Fatalities: 5	0.050	0.139***
	(0.040)	(0.042)
Income: $70,000	0.147***	0.107*
	(0.057)	(0.057)
Income: $40,000	0.371***	0.291***
	(0.059)	(0.057)
Income: $10,000	0.542***	0.470***
	(0.063)	(0.061)
Unemployment Rate: 5%	0.004	-0.034
	(0.056)	(0.056)
Unemployment Rate: 7%	0.022	0.050
	(0.055)	(0.056)
Unemployment Rate: 9%	0.048	0.142**
	(0.056)	(0.059)
40% Democrat	-0.052	-0.058
	(0.065)	(0.063)
30% Democrat	0.044	-0.023
	(0.065)	(0.063)
60% Democrat	-0.062	-0.054
	(0.065)	(0.059)
70% Democrat	0.031	0.005
	(0.064)	(0.059)
Constant	4.107***	4.104***
	(0.086)	(0.085)
Observations	10,472	10,472
R-squared	0.055	0.056

Note: OLS coefficients shown with robust standard errors clustered by respondent in parenthesis (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Reference categories for the respective attributes: Damage: $100,000, Fatalities: 0, Income: $100,000, Unemployment Rate: 3%, 50% Democrat. The alternative measure of support for electoral reciprocity fairness is based on the question: "How strongly do you agree or disagree with the following statement: 'Politics is about voting for those candidates or parties that provide me with the most policy benefits'." Respondents' answers on a 1 (strongly disagree)-10 (strongly agree) scale were converted into a binary indicator using the median as the cutoff. The indicator variable is 1 for those whose level of agreement with the statement was greater than the median and is zero otherwise.

Table A.6: The Causal Effects of County Characteristics on Relief Spending Preferences: Main Results and by Damage Level (Conjoint Experiment)

	(1)	(2)	(3)
	All	Total Damage	
		$10m or less	more than $10m
Damage: $1 million	0.427***	0.554***	0.049
	(0.046)	(0.051)	(0.089)
Damage: $4 million	0.724***	0.908***	0.160*
	(0.047)	(0.054)	(0.083)
Damage: $24 million	1.217***	*Omitted*	1.528***
	(0.052)		(0.087)
Fatalities: 5	0.095***	0.106***	0.063
	(0.029)	(0.035)	(0.046)
Income: $70,000	0.128***	0.155***	0.108*
	(0.040)	(0.050)	(0.061)
Income: $40,000	0.332***	0.348***	0.311***
	(0.041)	(0.053)	(0.060)
Income: $10,000	0.507***	0.553***	0.459***
	(0.044)	(0.056)	(0.062)
Unemployment Rate: 5%	-0.013	0.045	-0.093
	(0.040)	(0.050)	(0.061)
Unemployment Rate: 7%	0.037	0.087*	-0.033
	(0.039)	(0.051)	(0.063)
Unemployment Rate: 9%	0.096**	0.122**	0.069
	(0.041)	(0.052)	(0.062)
40% Democrat	-0.056	-0.088	-0.009
	(0.045)	(0.059)	(0.070)
30% Democrat	0.010	-0.009	0.058
	(0.046)	(0.057)	(0.070)
60% Democrat	-0.059	-0.047	-0.063
	(0.044)	(0.056)	(0.066)
70% Democrat	0.017	0.015	0.032
	(0.043)	(0.056)	(0.068)
Constant	4.105***	4.152***	3.856***
	(0.060)	(0.071)	(0.104)
Observations	20,944	11,862	9,082
R-squared	0.055	0.048	0.118

Note: OLS coefficients shown with robust standard errors clustered by respondent in parenthesis (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Reference categories for the respective attributes: Damage: $100,000, Fatalities: 0, Income: $100,000, Unemployment Rate: 3%, 50% Democrat. Since Model 2 is only based on conjoint tasks in which the total damage across the two scenarios was equal to or less than $10 million, the treatment indicator for the $24 million attribute level has to be excluded.

Table A.7: The Causal Effects of County Characteristics on Relief Spending Preferences: Recoded Reference Groups and Subgroup Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fairness Norm (Approval)						
		Affectedness		Need		Electoral Reciprocity	
	Main	Low	High	Low	High	Low	High
Damage: \$100,000	-1.217***	-0.771***	-1.668***	-1.362***	-1.078***	-1.483***	-0.951***
	(0.052)	(0.063)	(0.081)	(0.074)	(0.073)	(0.077)	(0.069)
Damage: \$1 million	-0.791***	-0.500***	-1.085***	-0.843***	-0.739***	-0.949***	-0.628***
	(0.046)	(0.057)	(0.070)	(0.065)	(0.064)	(0.068)	(0.060)
Damage: \$4 million	-0.493***	-0.326***	-0.665***	-0.545***	-0.438***	-0.568***	-0.415***
	(0.041)	(0.050)	(0.064)	(0.058)	(0.058)	(0.057)	(0.058)
Fatalities: none	-0.095***	-0.045	-0.151***	-0.061	-0.127***	-0.053	-0.138***
	(0.029)	(0.037)	(0.044)	(0.039)	(0.043)	(0.040)	(0.041)
Income: \$100,000	-0.507***	-0.457***	-0.560***	-0.320***	-0.693***	-0.647***	-0.367***
	(0.044)	(0.056)	(0.067)	(0.060)	(0.063)	(0.063)	(0.060)
Income: \$70,000	-0.379***	-0.337***	-0.419***	-0.237***	-0.521***	-0.495***	-0.265***
	(0.042)	(0.053)	(0.067)	(0.058)	(0.061)	(0.061)	(0.058)
Income: \$40,000	-0.175***	-0.210***	-0.144**	-0.120**	-0.228***	-0.232***	-0.123**
	(0.040)	(0.051)	(0.063)	(0.056)	(0.059)	(0.057)	(0.057)
Unemployment Rate: 3%	-0.096**	-0.072	-0.116*	0.009	-0.196***	-0.044	-0.132**
	(0.041)	(0.054)	(0.061)	(0.059)	(0.056)	(0.056)	(0.059)
Unemployment Rate: 5%	-0.109***	-0.094*	-0.128**	-0.021	-0.188***	-0.070	-0.139**
	(0.041)	(0.054)	(0.060)	(0.059)	(0.056)	(0.057)	(0.058)
Unemployment Rate: 7%	-0.059	-0.103**	-0.020	0.044	-0.160***	-0.071	-0.036
	(0.040)	(0.052)	(0.061)	(0.057)	(0.056)	(0.055)	(0.059)
50% Democrat	-0.017	0.066	-0.108*	0.033	-0.059	-0.105*	0.066
	(0.043)	(0.056)	(0.065)	(0.060)	(0.062)	(0.063)	(0.059)
40% Democrat	-0.073	-0.098*	-0.041	-0.087	-0.056	-0.077	-0.065
	(0.046)	(0.059)	(0.070)	(0.063)	(0.066)	(0.066)	(0.064)
30% Democrat	-0.007	0.003	-0.012	0.026	-0.037	-0.024	0.005
	(0.045)	(0.059)	(0.068)	(0.062)	(0.066)	(0.065)	(0.063)
60% Democrat	-0.076*	-0.052	-0.094	-0.060	-0.087	-0.071	-0.083
	(0.043)	(0.057)	(0.065)	(0.061)	(0.061)	(0.061)	(0.061)
Constant	6.037***	5.751***	6.332***	5.892***	6.172***	6.221***	5.847***
	(0.059)	(0.073)	(0.091)	(0.079)	(0.086)	(0.082)	(0.083)
Observations	20,944	10,472	10,472	10,472	10,472	10,472	10,472
R-squared	0.055	0.032	0.083	0.062	0.054	0.079	0.036

Note: OLS coefficients shown with robust standard errors clustered by respondent in parenthesis (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Reference categories for the respective attributes: Damage: \$24 million, Fatalities: 5, Income: \$10,000, Unemployment Rate: 9%, 70% Democrat. Since Model 2 is only based on conjoint tasks in which the total damage in both scenarios was equal to or less than \$10 million, the treatment indicator for the \$24 million attribute level has to be excluded.

Table A.8: Federal Relief Aid Programs

Program ID	Name of Program	Name of Department
10.054	Emergency Conservation Program	DA
10.073	Crop Disaster Program	DA
10.077	Livestock Compensation Program	DA
10.082	Tree Assistance Program	DA
10.09	Supplemental Revenue Assistance Payments Program	DA
10.404	Emergency Loans	DA
10.444	Direct Housing Natural Disaster Loans and Grants	DA
10.445	Direct Housing Natural Disaster	DA
11.477	Fisheries Disaster Relief	DC
12.102	Emergency Rehabilitation of Flood Control Works or Federally Authorized Coastal Protection Works	DA
12.103	Emergency Operations Flood Response and Post Flood Response	DA
14.119	Mortgage Insurance for Disaster Victims	HUD
59.008	Disaster Assistance Loans	SBA
83.516	Disaster Assistance	FEMA
93.003	Public Health and Social Services Emergency Fund	SAMHSA
83.537/97.03	Community Disaster Loans	FEMA
83.538/97.031	Cora Brown Fund	FEMA
83.539/97.032	Crisis Counseling	FEMA
83.541/97.034	Disaster Unemployment Assistance	FEMA
83.543/97.035	Individual and Family Grants	FEMA
83.544/97.036	Disaster Grants - Public Assistance	FEMA
83.545/97.037	Disaster Housing Program	FEMA
83.558/97.048	Federal Disaster Assistance to Individuals and Households	FEMA
83.559/97.049	Disaster Housing Operations for Individuals and Households	FEMA
83.560/97.05	Assistance to Individuals and Households	FEMA
97.088	Disaster Assistance Projects	FEMA

Note: DA = Department of Agriculture, DC = Department of Commerce, HUD = Department of Housing and Urban Development, SBA = Small Business Administration, SAMHSA = Substance Abuse and Mental Health Services Administration, FEMA = Federal Emergency Management Agency.

Table A.9: Federal Preparedness Spending Programs

Program ID	Name of Program	Name of Department
10.904	Watershed Protection and Flood Prevention	DA
10.923	Emergency Watershed Protection Program	DA
12.101	Beach Erosion Control Projects	DA
12.105	Protection of Essential Highways, Highway Bridge Approaches, and Public Works	DA
12.106	Flood Control Projects	DA
12.111	Emergency Advance Measures for Flood Prevention	DA
15.514	Reclamation States Emergency Drought Relief	DOI
83.203/83.505	State Disaster Preparedness Grants	FEMA
83.506	Earthquake and Hurricane Preparedness Grants	FEMA
83.519	Hazard Mitigation Assistance	FEMA
83.520	Hurricane Preparedness Grants	FEMA
83.521	Earthquake Hazards Reduction Grants	FEMA
83.535	Mitigation Assistance	FEMA
83.105/97.023	Community Assistance Program State Support Services Element	FEMA
83.536/97.029	Flood Mitigation Assistance	FEMA
83.548/97.039	Hazard Mitigation Grant	FEMA
83.555/97.045	Cooperating Technical Partners	FEMA
83.557/97.047	Pre-Disaster Mitigation	FEMA
97.07	Map Modernization Management Support	FEMA
97.082	Earthquake Consortium	FEMA
97.092	Repetitive Flood Claims	FEMA
97.11	Severe Loss Repetitive Program	FEMA

Note: DA = Department of Agriculture, DOI = Department of the Interior, FEMA = Federal Emergency Management Agency.

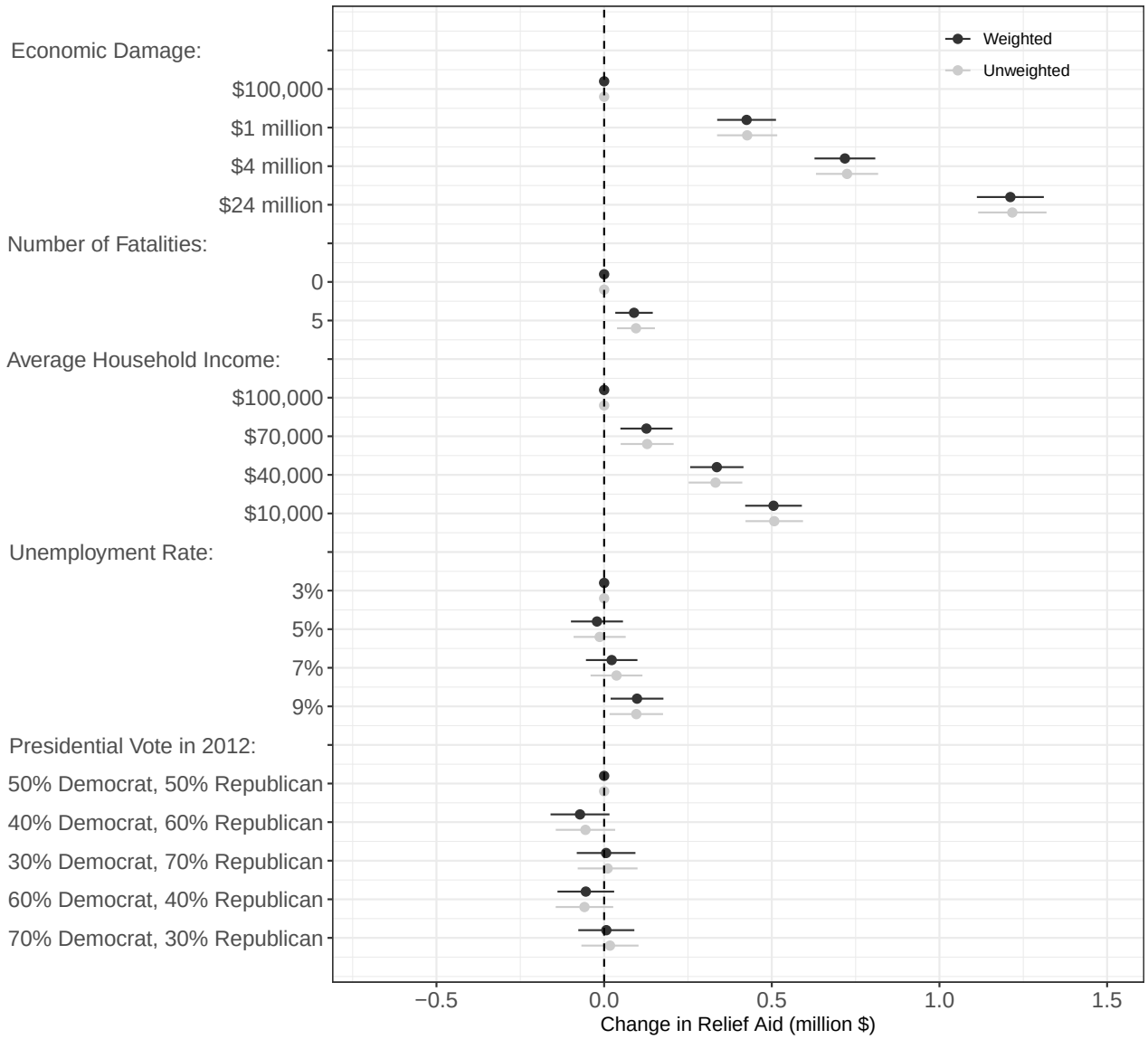
Table A.10: The Causal Effects of County Characteristics on Relief Spending Preferences: Subgroup Results by Damage Levels and Interaction Models

	(1) Main	(2) Damage: $100k	(3) Damage: $1M	(4) Damage: $4M	(5) Damage: $24M	(6) Interaction Terms
Damage: $1 million	0.427***					0.473***
	(0.046)					(0.085)
Damage: $4 million	0.724***					0.719***
	(0.047)					(0.086)
Damage: $24 million	1.217***					1.314***
	(0.052)					(0.089)
Fatalities: 5	0.095***	0.136**	0.067*	0.079	0.105*	0.095***
	(0.029)	(0.058)	(0.040)	(0.055)	(0.058)	(0.029)
Income: $70,000	0.128***	0.259***	0.108*	0.086	0.036	0.260***
	(0.040)	(0.083)	(0.055)	(0.078)	(0.080)	(0.084)
Income: $40,000	0.332***	0.334***	0.352***	0.421***	0.283***	0.337***
	(0.041)	(0.084)	(0.057)	(0.079)	(0.078)	(0.084)
Income: $10,000	0.507***	0.512***	0.564***	0.631***	0.390***	0.511***
	(0.044)	(0.089)	(0.059)	(0.080)	(0.080)	(0.089)
Unemployment Rate: 5%	-0.013	0.062	-0.032	-0.025	-0.048	-0.014
	(0.040)	(0.080)	(0.055)	(0.076)	(0.083)	(0.040)
Unemployment Rate: 7%	0.037	0.159*	0.028	0.027	-0.091	0.036
	(0.039)	(0.081)	(0.054)	(0.076)	(0.083)	(0.039)
Unemployment Rate: 9%	0.096**	0.231***	0.044	0.127	0.045	0.094**
	(0.041)	(0.086)	(0.055)	(0.079)	(0.081)	(0.041)
40% Democrat	-0.056	-0.023	-0.087	-0.137	-0.014	-0.054
	(0.045)	(0.092)	(0.062)	(0.087)	(0.093)	(0.045)
30% Democrat	0.010	0.082	-0.027	0.019	0.035	0.011
	(0.046)	(0.091)	(0.062)	(0.088)	(0.090)	(0.045)
60% Democrat	-0.059	0.040	-0.096	-0.258***	-0.069	-0.058
	(0.044)	(0.096)	(0.061)	(0.085)	(0.089)	(0.044)
70% Democrat	0.017	-0.001	0.035	-0.045	0.007	0.017
	(0.043)	(0.088)	(0.061)	(0.088)	(0.090)	(0.043)
Income $10k X Damage $24m						-0.119
						(0.120)
Income $40k X Damage $24m						-0.050
						(0.116)
Income $70k X Damage $24m						-0.221*
						(0.117)
Income $10k X Damage $4m						0.118
						(0.118)
Income $40k X Damage $4m						0.079
						(0.113)
Income $10k X Damage $4m						-0.177
						(0.114)
Income $10k X Damage $100k						-0.013
						(0.117)
Income $40k X Damage $100k						-0.048
						(0.114)
Income $10k X Damage $100k						-0.125
						(0.116)
Constant	4.105***	3.930***	4.719***	4.860***	5.425***	4.069***
	(0.060)	(0.105)	(0.069)	(0.098)	(0.100)	(0.076)
Observations	20,944	5,157	10,601	5,350	5,186	20,944
R-squared	0.055	0.011	0.013	0.020	0.008	0.056

Note: OLS coefficients shown with robust standard errors clustered by respondent in parenthesis (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Reference categories for the respective attributes: Damage: $100,000, Fatalities: 0, Income: $100,000, Unemployment Rate: 3%, 50% Democrat.

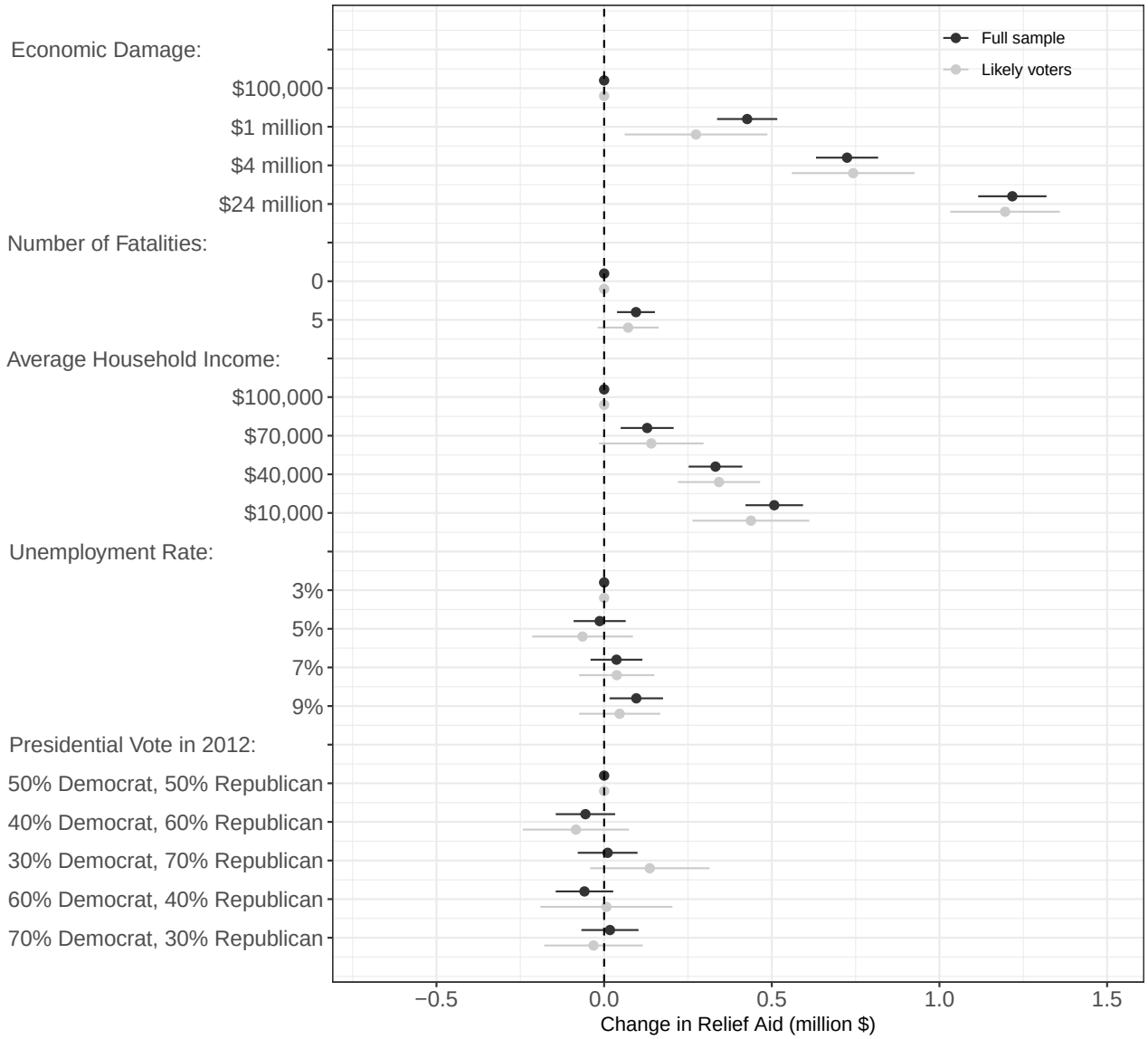
III. Appendix Figures

Figure A.1: The Causal Effects of County Characteristics on Relief Spending Preferences: Weighted vs. Unweighted Sample



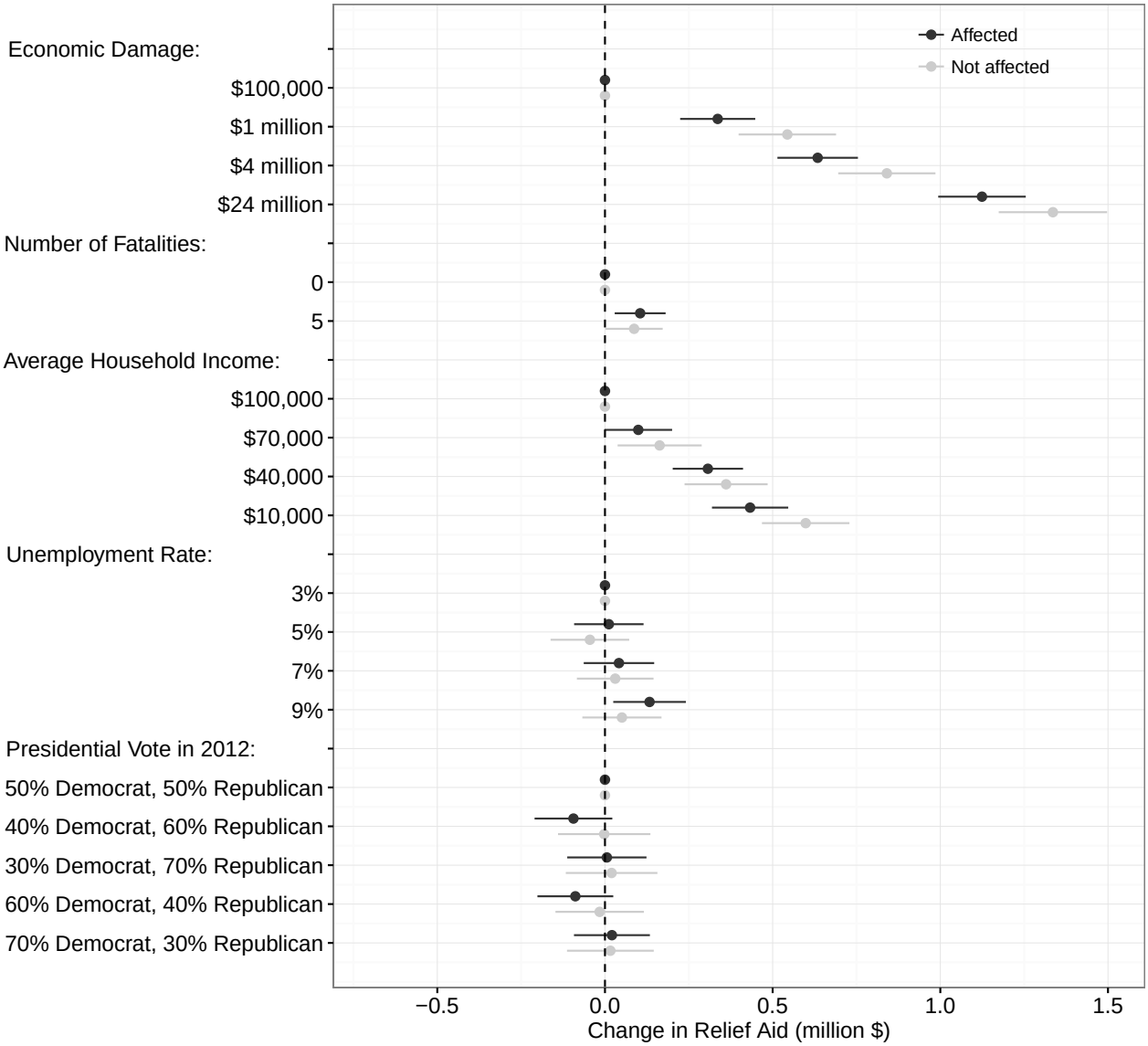
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute.

Figure A.2: The Causal Effects of County Characteristics on Relief Spending Preferences: Likely Voters vs. Adult Population



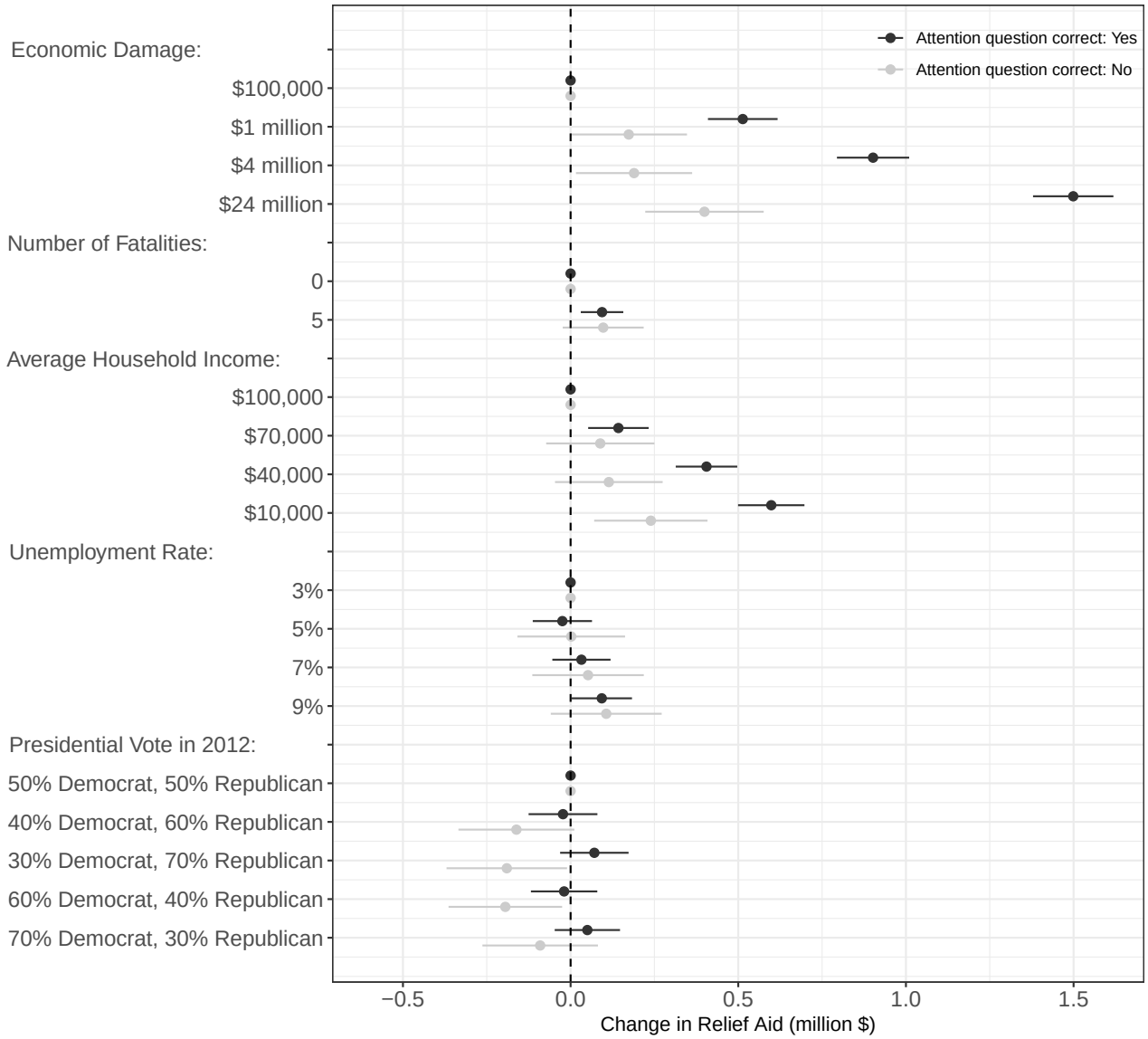
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute.

Figure A.3: The Causal Effects of County Characteristics on Relief Spending Preferences by Personal Affectedness



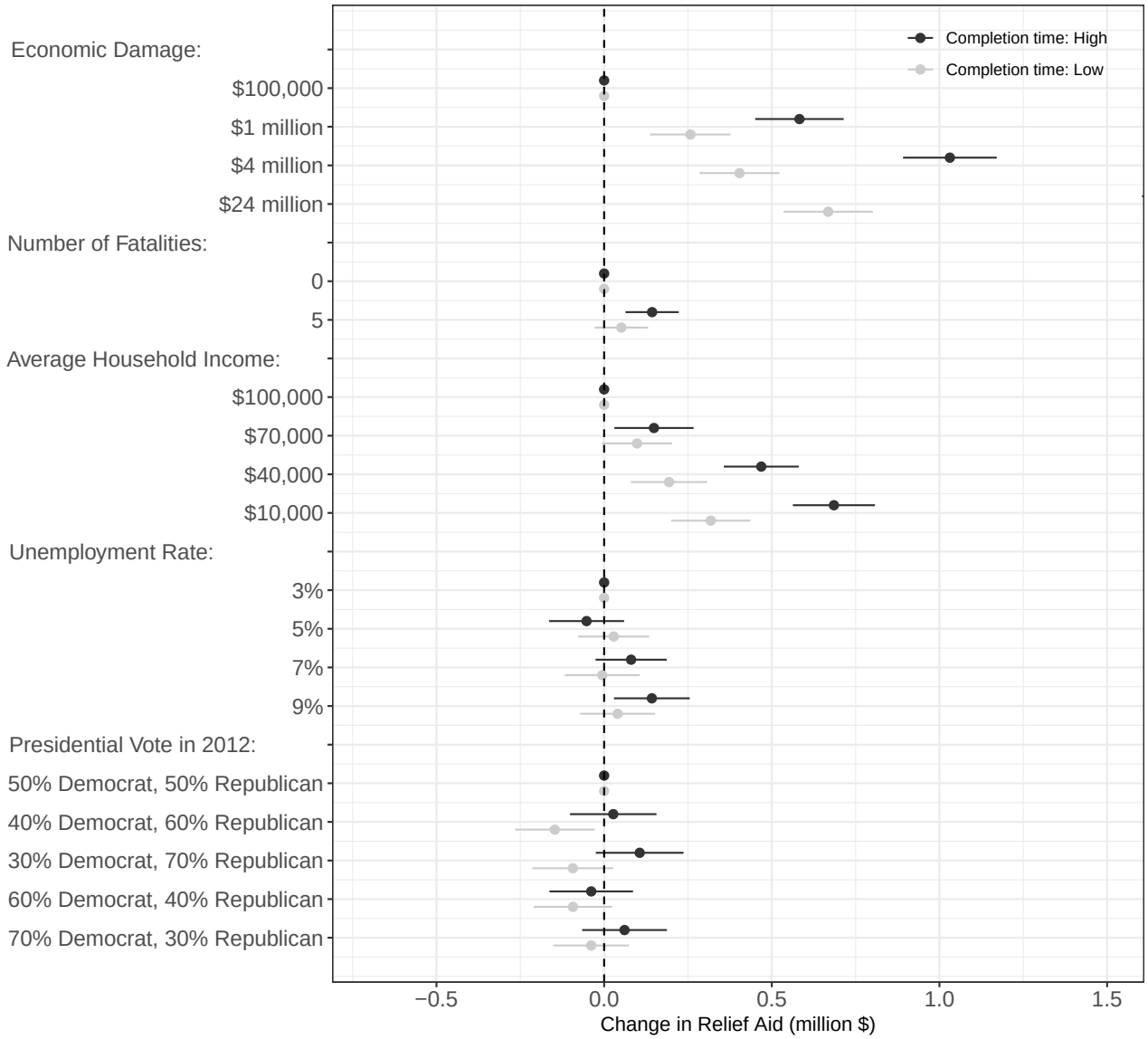
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Baseline levels of relief aid: Affected = $4.2 million, Not affected = $4 million. N(county-level relief spending decisions) = 20,944. N(respondents affected) = 1,488, N(respondents not affected) = 1,130. We classify respondents as "affected" if they were affected by a natural disaster in the past ten years.

Figure A.4: The Causal Effects of County Characteristics on Relief Spending Preferences by Attentiveness



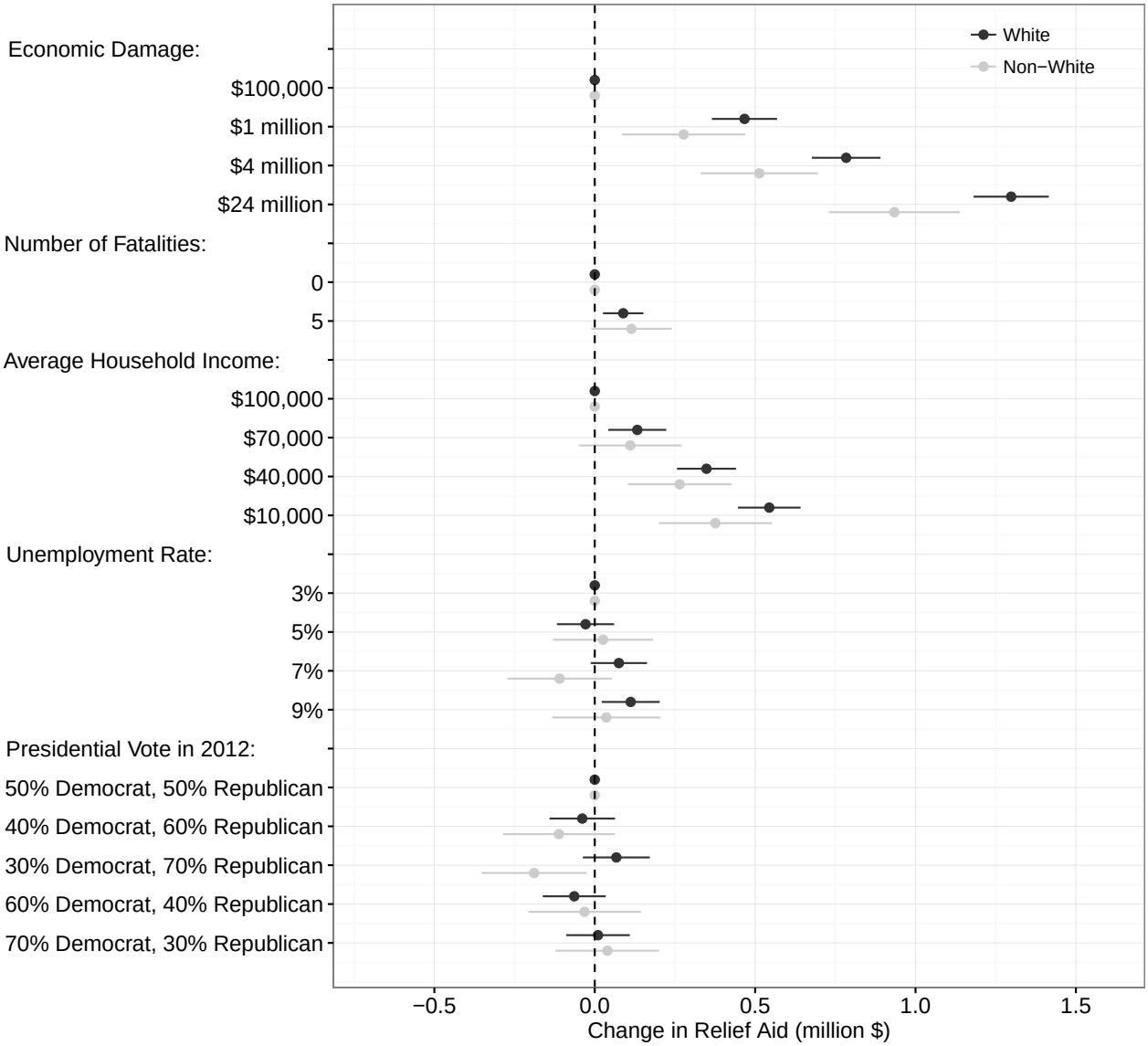
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a tobit regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Attention: High identifies respondents that passed a screener question. Baseline levels of relief aid: Attention: High= \$3.9 million, Attention: Low = \$4.7 million. N(county-level relief spending decisions) = 20,944. N (respondents) per group = 1,309.

Figure A.5: The Causal Effects of County Characteristics on Relief Spending Preferences by Conjoint Completion Time



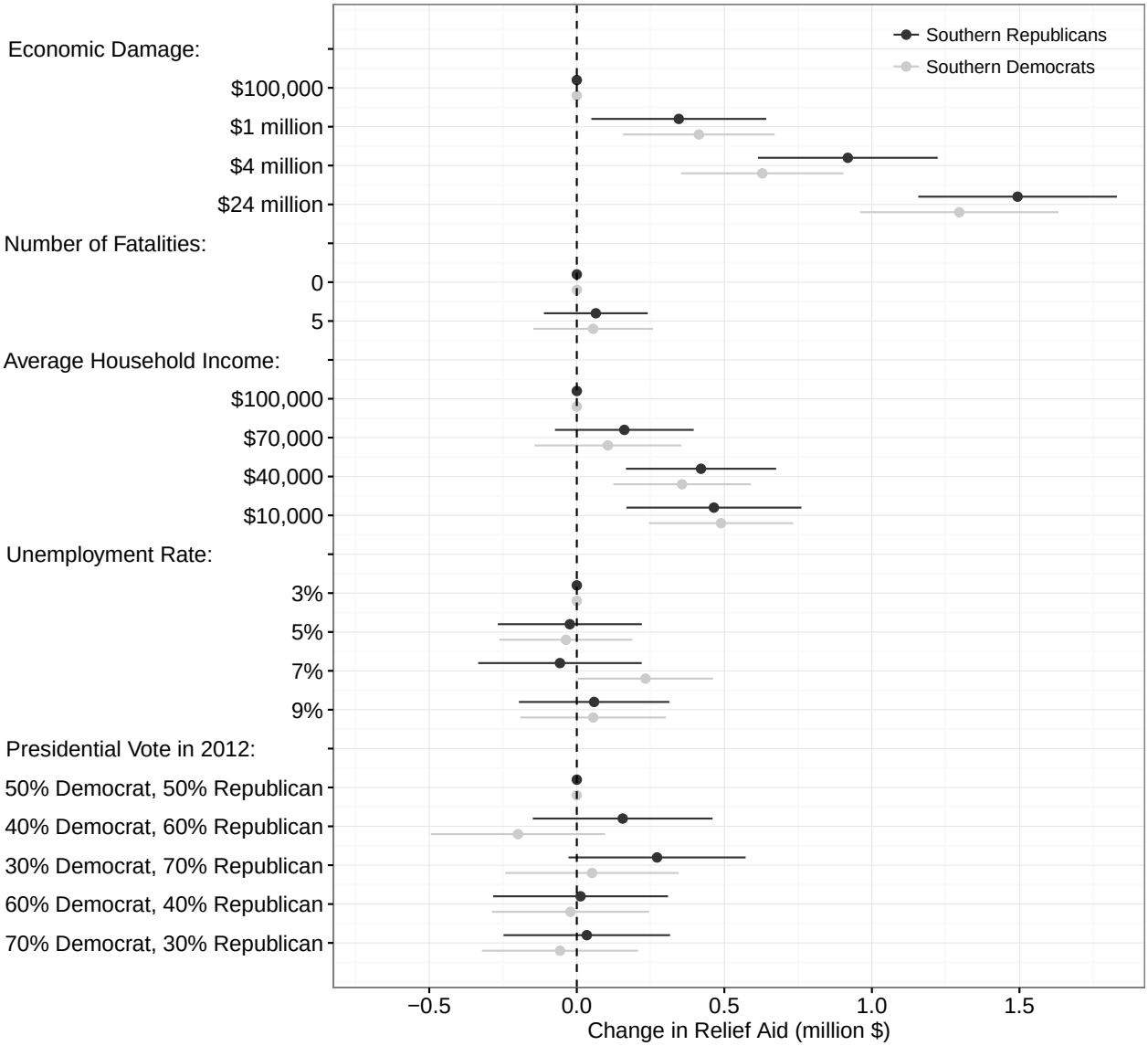
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a tobit regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. *Completion Time: High* identifies respondents who completed the survey faster than the median respondent. *Completion Time: Low* identifies respondents with completion times equal to or greater than the median conjoint completion time (1.6 minutes). Baseline levels of relief aid: Conjoint completion time: High = $4.5 million, Conjoint completion time: Low = $3.7 million. N(county-level relief spending decisions) = 20,944. N (respondents) per group = 1,309.

Figure A.6: The Causal Effects of County Characteristics on Relief Spending Preferences by Race



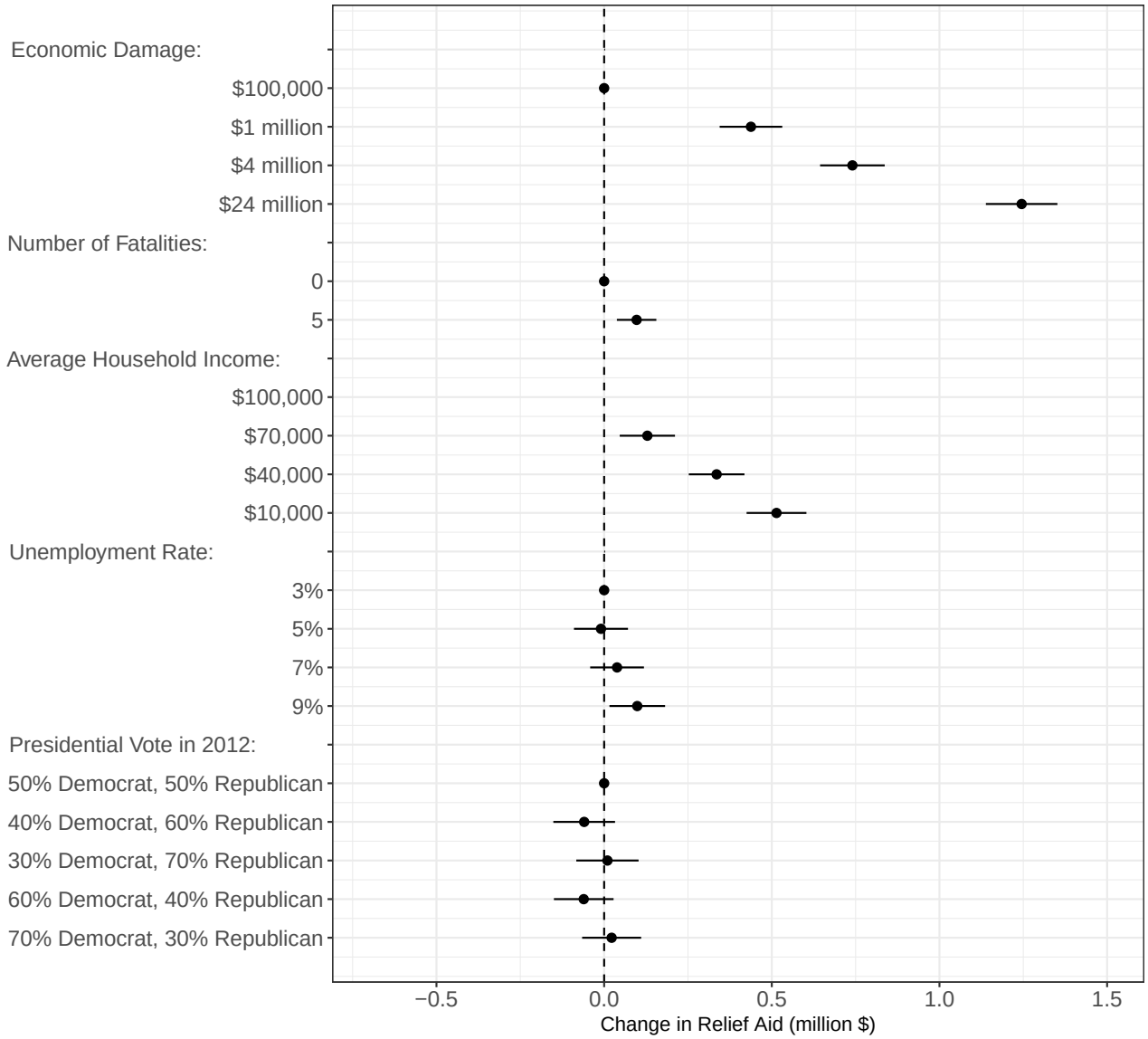
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Baseline levels of relief aid: White = $3.9 million, Non-white = $4.1 million. N(county-level relief spending decisions) = 20,944. N (respondents) = 1,309.

Figure A.7: The Causal Effects of County Characteristics on Relief Spending Preferences by Partisan Identification (Only Southern Central United States)



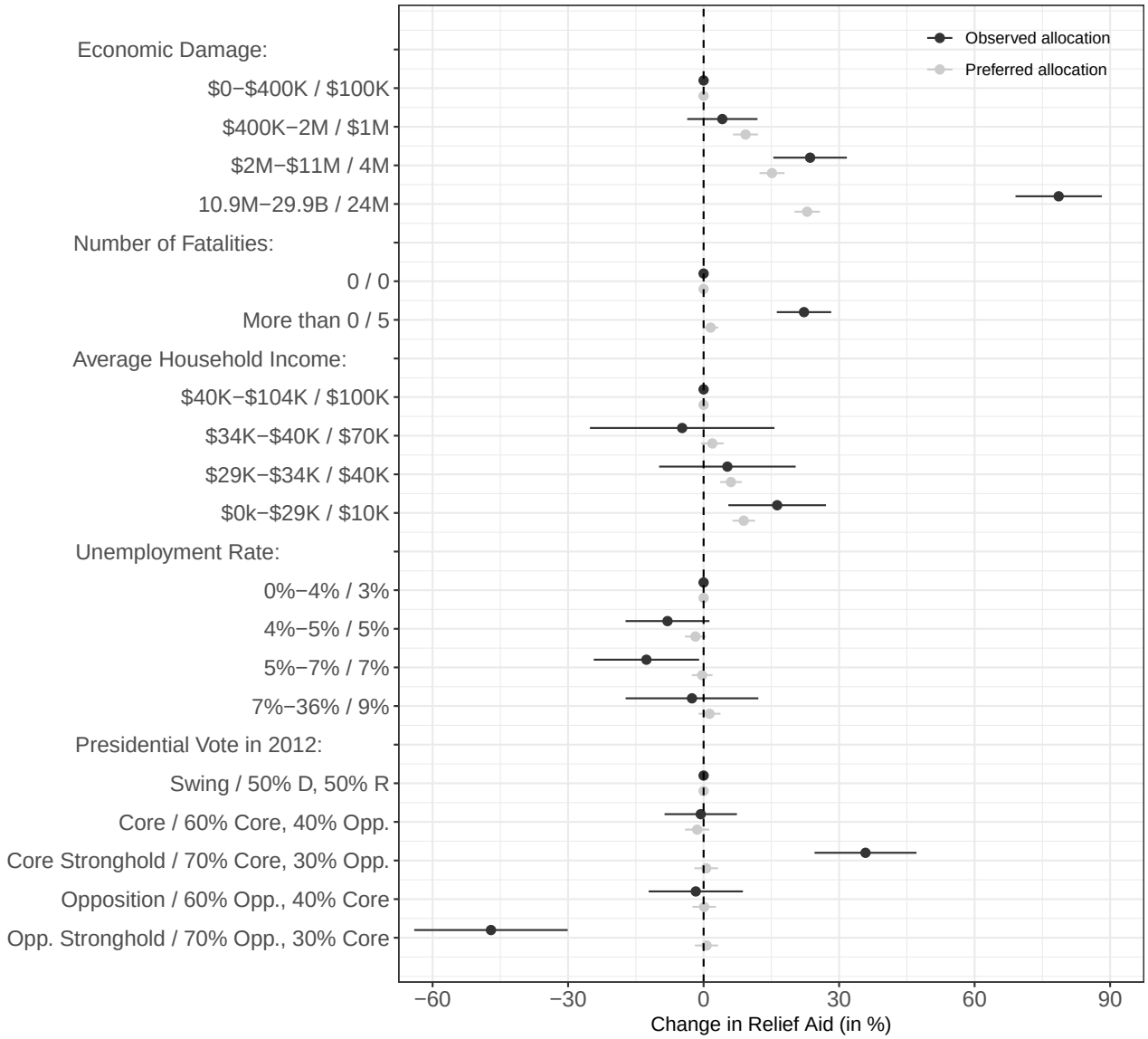
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a linear regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Results are based on all respondents located in the Southern United States according to the definition of the US Census Bureau: Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas. Baseline levels of relief aid: Affected = $4.2 million, Not affected = $4 million. N(Southern Republicans) = 254, N(Southern Democrats) = 268.

Figure A.8: The Causal Effects of County Characteristics on Relief Spending Preferences (Tobit Estimates)



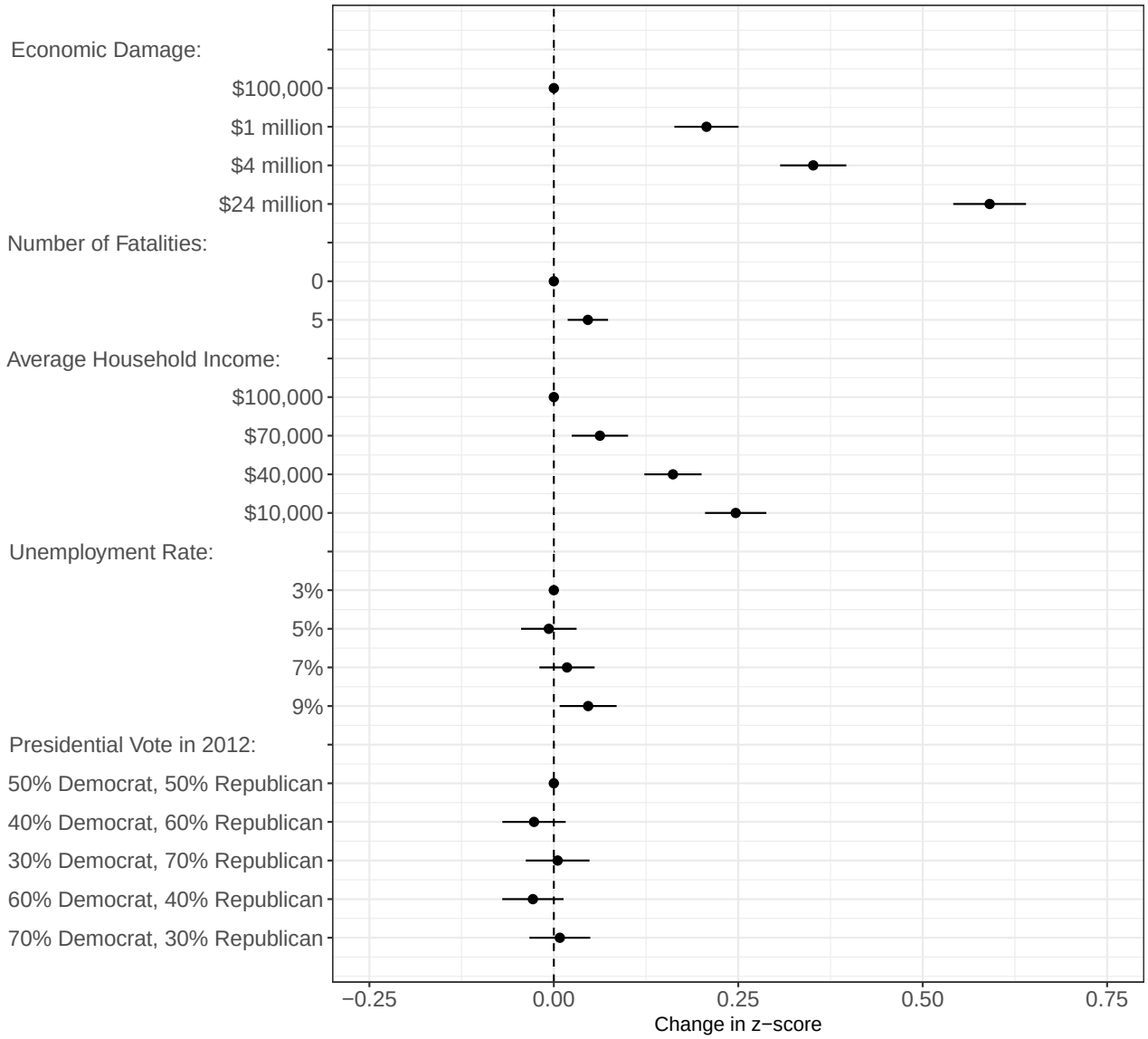
Note: This plot shows the causal effects of randomly assigned attribute values on the amount of relief aid allocated to an affected county. Estimates are based on a tobit regression of *Relief Amount* on indicator variables with standard errors clustered by respondent. Horizontal lines indicate 95% robust confidence intervals. Points without confidence intervals indicate the reference category for a given attribute. Baseline levels of relief aid: $4.1 million. N(county-level relief spending decisions) = 20,944. N (respondents) = 2,618.

Figure A.9: Comparing Observed and Preferred Disaster Relief Allocations (Conjoint: Democratic President)



Note: This plot shows differences in the estimated effects of county-level characteristics on relief aid (in logs). Points without confidence intervals indicate the reference categories. Horizontal lines indicate 95% robust confidence intervals. For the experimental conjoint results the standard errors are clustered by respondent. Experimental data: N(county-level relief spending decisions) = 20,944. N (respondents) = 2,618. Historical data: N = 12,424. Horizontal lines indicate 95% robust confidence intervals; points without lines indicate the reference categories. The experimental estimates are based on scenarios that feature a Democratic president.

Figure A.10: The Causal Effects of County Characteristics on Relief Spending Preferences (z-Transformed Relief Amount)



Note: This plot shows the causal effects of randomly assigned attribute values on the z-transformed amount of relief aid allocated to an affected county. To obtain the z-transformed amount of relief aid we compute the relative share of relief aid allocated to county A and county B for each conjoint comparison (e.g. if county A received \$3 million and county B received \$7 million, the shares are .3 and .7, respectively). We then computed the corresponding z-value using the inverse cumulative distribution function. To avoid infinite values we added .01 when the allocated share of relief aid was 0 and subtracted .01 whenever the allocated share was 1. Estimates are based on a linear regression of *Relief Amount (z-values)* on indicator variables. Horizontal lines indicate 95% confidence intervals based standard errors clustered by respondent. Points without confidence intervals indicate the reference category for a given attribute. Baseline z-score: -0.3. N(county-level relief spending decisions) = 20,944. N (respondents) = 2,618.

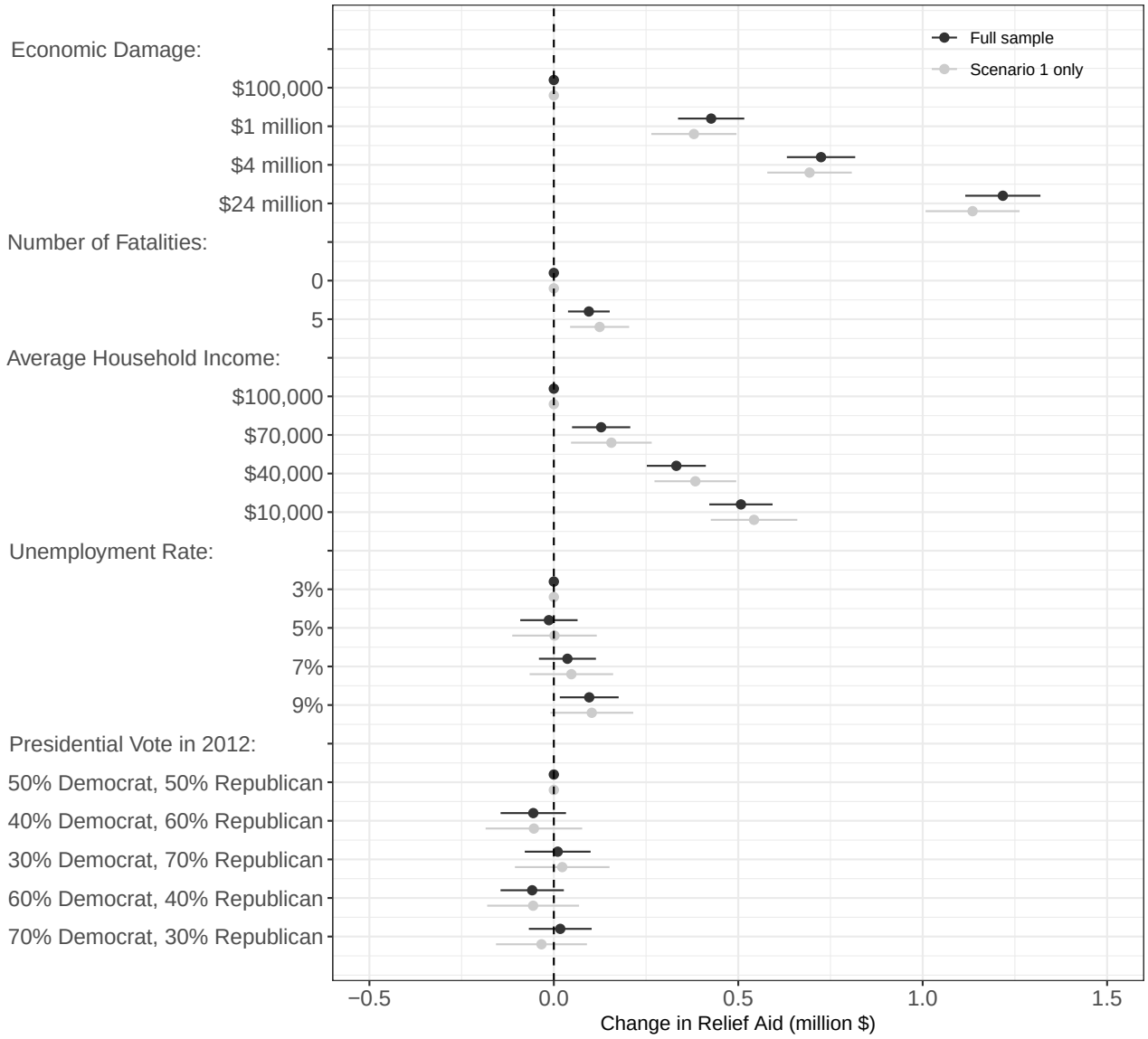



Figure A.11: The Causal Effects of County Characteristics on Relief Spending Preferences (One Spending Decision Only)