Preregistration for
Backyard politics and foreign aid

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1 Introduction

Our project examines how implications of foreign aid projects for the donor country affect public support for foreign aid. Most surveys in foreign aid focus on judgements for appropriateness of flows, overall costs, destinations, etc. However, these foci ignore that much foreign aid, and in particular in the United States, are tied to domestic contractors (firms and NGOs) that subsequently perform the contracted goods and/or services. Since these contractors reside somewhere in the United States, there are tangible benefits that accrue to specific localities. These benefits should also see the engagement of politicians who would like to claim credit (Grimmer, Westwood and Messing 2014).

To understand these issues, we conduct a survey experiment in which we ask respondents to rate hypothetical changes in foreign aid. In one case, procurement changes lead to increased funds that accrue to the locality of the respondent; in others, these changes help some city elsewhere in the United States. Alternatively, we also expose people to cuts in foreign aid contract that can affect the local environment or cities far away. Another aspect we randomize is whether one parliamentarian (i.e. a senator) that represents the locus of the aid change was active in securing funds or in working (and failing) to stop the cut in aid. For the analysis, we ask respondents to evaluate the policy, the two senators representing the state, and several questions that may explain why the local effects generate shifts in support for policy and senators.

This document lays out the analyses that we want to register publicly before we conduct our survey experiment. In the eventual manuscript, there will be dedicated sections in the main body and in the appendix that will feature the results, figures, and tables that we show below. Everything below is based on a pilot run from October 2016. **As some data from this run has been tweaked, every output below is for illustrative purposes only; no substantive inferences ought to be made from this pilot data.**

2 Survey: overview

We recruit survey-takers to evaluate a hypothetical change in foreign aid that (could) have an implication for the respondent's own community. The vignette states that USAID, the main development aid agency, altered a few programs, leading to more contracts for firms in the United States. We randomize where the bulk of the contract value accrues. With probability $\frac{1}{2}$, the affected locale will be the nearest large city, and with equal probability a large city in a random state elsewhere in the United States. As we are also interested in how involvement in this process by senators affects respondents' perceptions, we randomly include a mention that one of the two state senators worked to secure the funds for the company. If a respondent receives the senator mention treatment, we randomly vary which of the two senators is mentioned.

Half of the respondents see a vignette laid out above, while the other sees a mirror version in which contracts got canceled by USAID. If a senator is mentioned, his/her role is described as having worked (but failed) to prevent the cut.

To improve the external validity of our study, we account for the fact that USAID contracts are quite concentrated geographically. In 2015, 93% of the contract count and 95% of positive spending went to ten states (including the District of Columbia). Perhaps unsurprisingly, Washington, DC carried the largest shares, getting 54% of all contracts and 22% of the positive spending volume. As the District of Columbia has no senators who are crucial to our argument, we work only with the top nine states that have representation in the U.S. Senate. These are Virginia, Maryland, Massachusetts, New York, California, Florida, North Carolina, New Jersey, and Texas, as ordered by number of USAID contracts in 2015.

As we are using large cities for where projects take place, we create a data set of large cities in these nine states. We define "large cities" as any city in a state with a population of more than 250,000, as well as the largest city irrespective of population. Across the nine

states, we have 41 such large cities.[1]

After seeing the vignette, each person is asked to evaluate the project and subsequently to provide a feeling thermometer score for each senator representing the respondent's state. Further, we ask several questions that may help explain effects.

3 Survey: details

3.1 Recruitment, sample

We post a job on Amazon's MechnicalTurk (MTurk) platform, seeking participants for a study on public opinion of U.S. government spending. We restrict the job to only voting age people that live in states that were among the ten highest recipients of USAID funds. Amazon determines the worker's location via his/her mailing address. Of course, this is imperfect; in our pilot run, about 3% of respondents selected a state different from the nine states. We exclude these prior to any analysis from the data set.

We plan to spend approximately $1,500 on recruiting subjects via MTurk in late November 2016.

3.2 Aid vignette

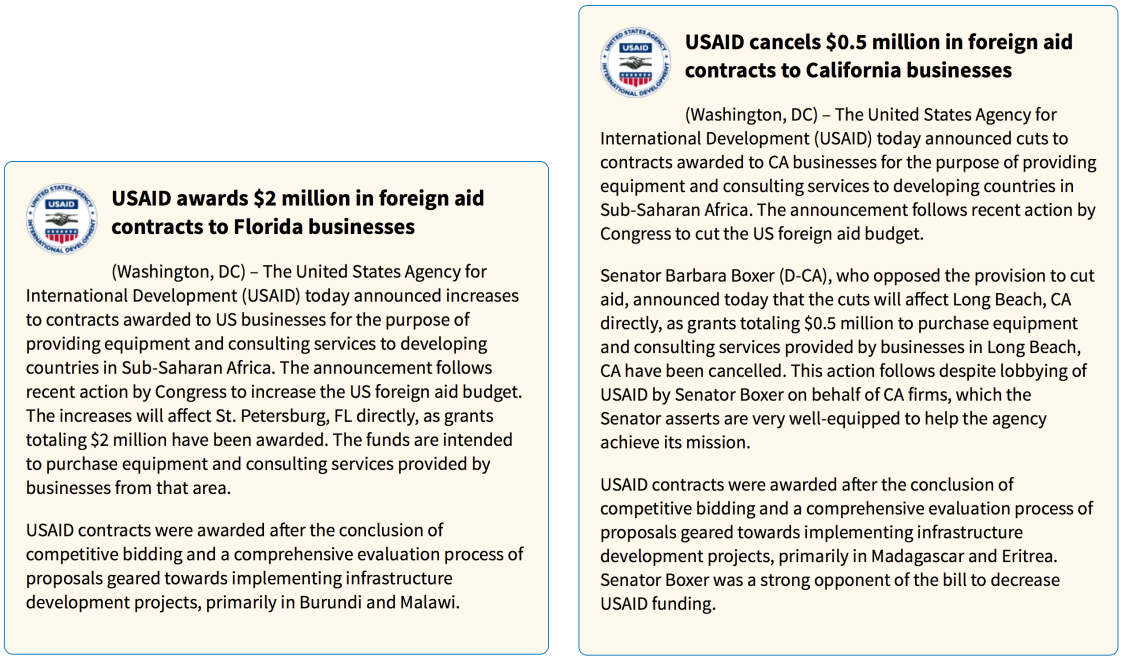
The three main randomizations of interest are the location of the contracts; whether new contracts are awarded or old ones cancelled; and whether a senator (and which of the two) is mentioned as participating in the process.

First, the location is randomized between "local" and "non-local" with equal probability. If the realization is "local," then we find the nearest large city. We use the zipcode package in R and find the nearest city in the respondent's state for each ZIP code.[2] If the ZIP code

[1] See accompanying ZIP_TOP10.csv data set.
[2] See ZIP_TOP10.csv file.

is found in our data set, we use the associated nearest large city. If the user's ZIP code is not found, we approximate the distance via the absolute value between the user's ZIP code and the remaining large cities' ZIP codes (again, conditional on the same state). If the realization of the randomization is "non-local," we pick a random large city from a state that is not the respondent's reported state.

Second, we differentiate between newly awarded contracts and the cancellation of previously awarded contracts. And third, we randomize whether a senator is mentioned: a senator would have worked toward securing or preventing the cut of the funds. The name of the senator is drawn from the two currently representing the state.



USAID awards $2 million in foreign aid contracts to Florida businesses

(Washington, DC) – The United States Agency for International Development (USAID) today announced increases to contracts awarded to US businesses for the purpose of providing equipment and consulting services to developing countries in Sub-Saharan Africa. The announcement follows recent action by Congress to increase the US foreign aid budget. The increases will affect St. Petersburg, FL directly, as grants totaling $2 million have been awarded. The funds are intended to purchase equipment and consulting services provided by businesses from that area.

USAID contracts were awarded after the conclusion of competitive bidding and a comprehensive evaluation process of proposals geared towards implementing infrastructure development projects, primarily in Burundi and Malawi.

USAID cancels $0.5 million in foreign aid contracts to California businesses

(Washington, DC) – The United States Agency for International Development (USAID) today announced cuts to contracts awarded to CA businesses for the purpose of providing equipment and consulting services to developing countries in Sub-Saharan Africa. The announcement follows recent action by Congress to cut the US foreign aid budget.

Senator Barbara Boxer (D-CA), who opposed the provision to cut aid, announced today that the cuts will affect Long Beach, CA directly, as grants totaling $0.5 million to purchase equipment and consulting services provided by businesses in Long Beach, CA have been cancelled. This action follows despite lobbying of USAID by Senator Boxer on behalf of CA firms, which the Senator asserts are very well-equipped to help the agency achieve its mission.

USAID contracts were awarded after the conclusion of competitive bidding and a comprehensive evaluation process of proposals geared towards implementing infrastructure development projects, primarily in Madagascar and Eritrea. Senator Boxer was a strong opponent of the bill to decrease USAID funding.

Figure 1: **Sample realizations of USAID vignette.** The left-hand vignette depicts an increase if aid, some of which go to Floridian businesses in St. Petersburg. In the right-hand vignette, aid is cancel to the detriment of companies in Long Beach, CA. Further, the right-right hand vignette also mentions the involvement of a senator.

Figure 1 shows two sample realizations. In the left-hand example, new contracts are awarded by USAID that pay for services and equipment provided by businesses that were to help implement infrastructure projects in Burundi and Malawi. Notice that no mention

is made that either of the Floridian senators participating in this process. In the right-hand side example, one senator from California, where a cut in aid affected projects, was active. In cases in which a senator is mentioned, his/her activity becomes central to the presented story.[3]

3.3 Main survey questions

Right below the vignette that is presented to the respondent, we ask about the rating for the project: "What do you think about the [cut/ increase] to USAID contracts? Please choose the option below that best reflects your view." The answer options are scaled from 1 – 9, ranging from "Strong opposition" to "Strong support;" 5 is labeled "Neutral."

Below the question for the rating of the project on the same screen, we pose questions that we use for the causal mediation. For each question, we ask "Do you agree or disagree that ...",[4]

- "... the [cut/ increase] to USAID contracts will benefit your friends and family?"
- "... the [cut/ increase] to USAID contracts will benefit the state you live in?"
- "... the [cut/ increase] to USAID contracts will improve the US economy?"
- "... the [cut/ increase] to USAID contracts will improve US national security?"
- "... the [cut/ increase] to USAID contracts will benefit US elites more than ordinary citizens?"
- "... it is a moral imperative to provide foreign aid to help people in poor countries?"

[3]Further, we randomize the volumes ($\{0.5, 1, 2\}$) and the two Sub-Saharan African countries mentioned. The latter are drawn from a list.

[4]The answer options for each question are "Agree" and "Disagree."

On the page following the USAID vignette, the rating of it, and the mediators, we ask for a feeling thermometer evaluation on a scale from 0 through 100. Users have to type in an integer value for each.[5]

3.4 Further questions

We also collected several demographic variables that we ask before a respondent sees a vignette:

- "In what year were you born?"
- "Are you male or female?"
- "Which state do you live in?" The answer to this question will be used to customize other questions; denote this [STATE].
- "In what ZIP code do you currently reside?"
- "What is the highest level of education you have completed?" The answer options are No High School, High School, Some College, 2-year College Degree (Associates), 4-year College Degree (BA, BS), and Post graduate.
- "How many years have you lived in [STATE]?"
- "Would you call [STATE] your home?" Answer options are Yes, No.
- "Would you call yourself a strong Democrat or a strong Republican?" The answer options are "Strong Democrat", "Not very strong Democrat", "Lean Democrat", "Independent", "Lean Republican", "Not very strong Republican", and "Strong Republican". We use this as a 1–7 measure of ideology.

[5]The text is: "We would like to know your feelings towards some political leaders using something we call the feeling thermometer. Please choose a number between 0 and 100 where 50 indicates that you are neutral (not warm or cold) towards the individual, while numbers closer to 100 indicate more warmth, and numbers closer to 0 indicate more coldness. How would you rate [Senator]?"

- "Do you have close friends or family who live outside the United States in countries that could be labelled as 'developing countries'?" Yes, No answer.

- "Do you agree or disagree that the United States is the greatest country in the world?" Answer options are Agree, Indifferent, Disagree.

We also obtain a few further covariates indirectly through a respondent's ZIP code. Specifically, we merge in the median housing value per square foot as well as the percentage of house that have gained in value over the past year. The measures come from Zillow Research.[6]

Before presenting our vignette about a USAID project, we show respondents an introductory screen explaining that they will see two short stories about recent policy changes. The first one is a procurement change in the U.S. Department of Defense which affects a city that is not in the respondent's home state, and with probability $\frac{1}{2}$ will mention a senator who participated in the policy process. We view this vignette as a "brain cleanser" in that it makes people think about changes to contracts while at the same time putting distance between the demographic questions (in particular about whether they call their state home) and our main vignette of interest (USAID).

4 Descriptives of the data

4.1 Checking balance

We check whether the pre-treatment covariates are balanced between the treatment conditions and the control. We calculate the standardized differences-in-means between demographic variables for all treatments against the control case (non-local city and no mentioning

[6]See `http://www.zillow.com/research/`. We impute either value for ZIP codes that users entered but that are not in the Zillow data set.

of a Senator). Further, we perform this comparison separately for aid increases and cuts, as we will analyze these conditions separately. Figure 2 shows the z-scores for the differences in means.

4.2 Location of people and cities

We evaluate the location of the user in two ways, each with pros and cons. First, we rely on the user's self-reported state and ZIP code. The advantage here is that, presumably for many, the self-reported ZIP represents their current home even if the address on file by MTurk is dated. However, self-reporting could result in a false record if users do not want to give out personal information. Second, we look up the longitude and latitude of the respondent's IP address. The advantage in the second method is that IP addresses are not (easily) manipulatable by the user. However, this locator might be cruder and biased if a person is taking the survey while traveling (or otherwise using a virtual private network [VPN]). Therefore, we view the two ways of checking the location as complementary evaluations.

Figure 3 shows two maps, denoting a respondent's location through a semi-transparent dot. The left-hand map shows the location as derived from the IP address; the right-hand side is a mapping of the self-reported ZIP code. Notice that there are users (by IP address) on the Oregon/ Washington border, in Wisconsin, and on the Nebraska/Iowa border, all of which do not appear when we consider the ZIP code-based location; this result speaks to the trade-offs under either metric. Overwhelmingly, however, the two approaches agree that people are in the nine states on which we focus.

For our treatment to work, USAID contract locations that are local and non-local must be different. Figure 4 shows the user-city pairings for local (left column) and non-local (right) treatments, differentiating by using the IP address (top row) and the self-reported ZIP code (bottom). Each start of an arrow indicates the respondent location, and the respective tip the location of the city mentioned in the vignette. Figure 5 plots the resulting histograms

of distances between respondents and the cities that they see.

5 Analyses

Having introduced the data collection, we now lay out our analyses that we preregister with this document. We are interested in the total effect of our two local treatments (local, no-senator-mention & local, senator-mention) on the rating of project (compared to the non-local, no-senator-mention condition) and on the feeling thermometer rating of the two home-state senators; the effect of the treatments that is transmitted through each of our six mediators (indirect effects); and the effect that is not transmitted through them (direct effect).

As we analyze the two change conditions (aid increase/cut) as well as the two outcomes separately, we do not introduce notation that differentiates between the cases. The only substantive difference is that the condition that mentions a senator's name (and when the local treatment applies) implies that only the named senator is treated as local/mentioned; the un-mentioned senator is treated as local only.

All estimates stem from bootstrapping. As we have two outcomes per respondent and vignette realization for the feeling thermometer scores, we apply the cluster-bootstrap (Harden 2011). Finally, for comparability, we rescale the project rating into a 0-100 space to match the feeling thermometer scale.

5.1 Total effects

The total effect is the simplest evaluation. Let's define the three realizations of treatment and controls. For each respondent ($i = 1, \ldots, N$), there are potentially two treatment and one control conditions, which we denote as:

$$T_i = \begin{cases} 0 & \text{if non-local city;} \\ 1 & \text{if local city, no Senator;} \\ 2 & \text{if local city, Senator mentioned.} \end{cases}$$

The total effect is found by simply regressing the evaluation on an intercept and two dummies for the two treatment conditions,

$$Y_i = \alpha_0 + \sum_{j \in \{1,2\}} \alpha_j \mathbf{1}(T_i = j) + \epsilon_{1i}, \tag{1}$$

where $\mathbf{1}(\cdot)$ is the indicator function that takes on 1 if the statement in parentheses is true, and 0 otherwise, and ϵ_{1i} an error term. The coefficients α_1 and α_2 give the treatment effect compared to the control condition ($T_i = 0$). These are the estimates for the total effect.

Using data from the pilot produces Table 1. The first pair of columns gives the effects for the aid increases, the latter pair for cuts.

5.2 Causal mediation

The causal mediation analyses rests on our successful imputation of unobserved and unobservable survey responses so that we can evaluate counterfactuals. To this end, we need to resort to more richly specified regressions. In all subsequent models, let x_i capture covariates taken from the demographics above, including those we obtained from merging ZIP code-level data in. Specifically, these are: Gender dummy; age; a linear version of the ideology measure; dummy for whether one thinks that the United States is the greatest country in the world; whether one has friends or relatives in developing country; a dummy for high school or less as the highest education degree; a dummy for having a B.A./B.S. or above education

degree; the logarithm of the median housing value and the percentage of houses that have increased in value at the given ZIP code.

First, we have to model a persons answers to the mediator questions to predict what they would have answered under an alternative treatment status. As the all mediator questions are binary, we resort to a Bernoulli model and link a linear predictor via the cumulative density of a standard normal distribution (ie. a probit model). Let M_{ki} be i's response to the $k = 1, \ldots, 6$ mediator questions:

$$Pr\left(M_{ki} = 1\right) = \Phi\left(\eta_{0k} + \sum_{j \in \{1,2\}} \eta_{jk} \mathbf{1}(T_i = j) + x_i \iota_k\right), \tag{2}$$

with η_{0k}, η_{1k}, η_{2k}, and ι_k being the coefficient (vectors).

As a short-hand going forward, let $\hat{m}_{ki}\left(T = t\right)$ be the probability that M_{ki} is equal to one if the i^{th} observation's treatment is set to t and the covariate vector x_i remains as observed.

Second, we also need a model that predicts a person's response under alternative treatments as well as under mediator responses that reflect a counterfactual treatment. Again, we regress the rating outcomes on a rich covariate set which includes the treatment indicators, the individual covariates, and the observed responses to the mediator questions:[7]

$$Y_i = \beta_0 + \sum_{k \in \{1,\ldots,6\}} \beta_k M_{ki} + \sum_{j \in \{1,2\}} \gamma_j \mathbf{1}(T_i = j) + x_i \kappa + \epsilon_{2i}, \tag{3}$$

Generally, to obtain the indirect effect under some treatment status $t \in \{1, 2\}$ for the k^{th} mediator for observation i, we need take the respondent's rating under treatment t and the k^{th} mediator taking on its value as if the respondent got treatment t and compare it to the respondent's rating under treatment t and the k^{th} mediator taking on its value as if the

[7]Results from this model for the different outcomes and increase/ cut scenarios using our pilot data are shown in Tables 2 and 3.

respondent got the control condition. Formally and generally, this indirect (δ_{kti}) is obtained via:

$$\delta_{kti} = \mathbf{E}[Y_i|T = t, M_{ki} = \hat{m}_{ki}\left(T = t\right), x_i] - \mathbf{E}[Y_i|T = t, M_{ki} = \hat{m}_{ki}\left(T = 0\right), x_i] \tag{4}$$

$$= \beta_k \ \left[\hat{m}_{ki}\left(T = t\right) - \hat{m}_{ki}\left(T = 0\right)\right]. \tag{5}$$

The subtrahend and minuend of Equation 4 come from Equation 3; we assume that the mediators that are not the k^{th} mediator take on their value observewd under t. As we are interested in average indirect effects, we can simply average across all $i = 1, ..., N$, $\delta_{kt} = \frac{1}{N}\sum_i \delta_{kti}$.

The last quantity of interest is the direct effect (ζ_t). This is the effect of treatment compared to the control condition if all mediators were held at the realizations under the treatment status. Since indirect and direct effects have to sum to the total effect, we simply obtain the direct effect by subtracting all indirect effects from the total effect:

$$\zeta_t = \alpha_t - \sum_k \delta_{kt}. \tag{6}$$

Figures 6 and 7 show the total, direct, and each of the six indirect effects from the pilot data. These are calculated separately for both outcomes and the scenarios of aid increase and cuts.

6 Illustrative figures and tables

The above provides an overview of our study and analyses. In the eventual paper, we will have a dedicated section that presents the analysis output that we preregister; further, ad-hoc analyses will be in a separate section and explicitly denoted as such. In the actual body of the manuscript, we will present the following:

- Table 1
- Figures 6 and 7

All other figures (2, 3, 4, and 5) and tables (2, 3, and 4) will go into a section in the appendix that is also exclusively for preregistered output.

Any adjustments to or deviations from the code will be clearly documented so that readers can judge them.

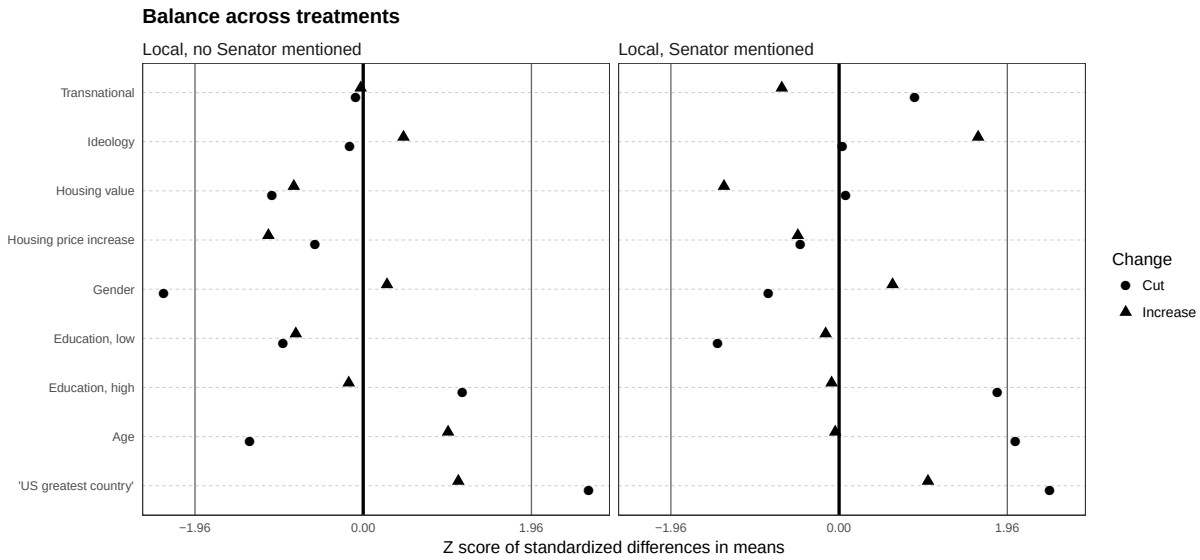


Figure 2: **Covariate balance for treatments compared to control.** The y-axis indicates the covariates, the x-axis the the z-score of the standardized differences in means. In the left-hand panel, the difference is between observations that show the respondent the nearest local city without mentioning a senator and those cases that were non-local. On the right side, the contrast is of local cases that also mentioned the involvement of a senator. Each circle gives the result for the aid increase scenario, the triangle for the aid cuts. *As some data underlying this figure have been tweaked, do not make substantive inferences from this figure.*

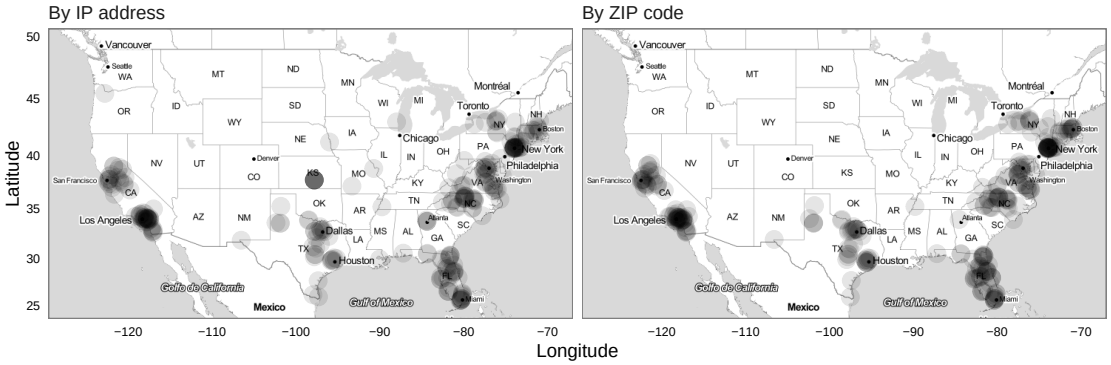


Figure 3: **Map of respondents.** Each semi-transparent circle denotes the location of a respondent in our survey, which is based upon the IP address (left side) and the user-reported ZIP code (right side). *As some data underlying this figure have been tweaked, do not make substantive inferences from this figure.*

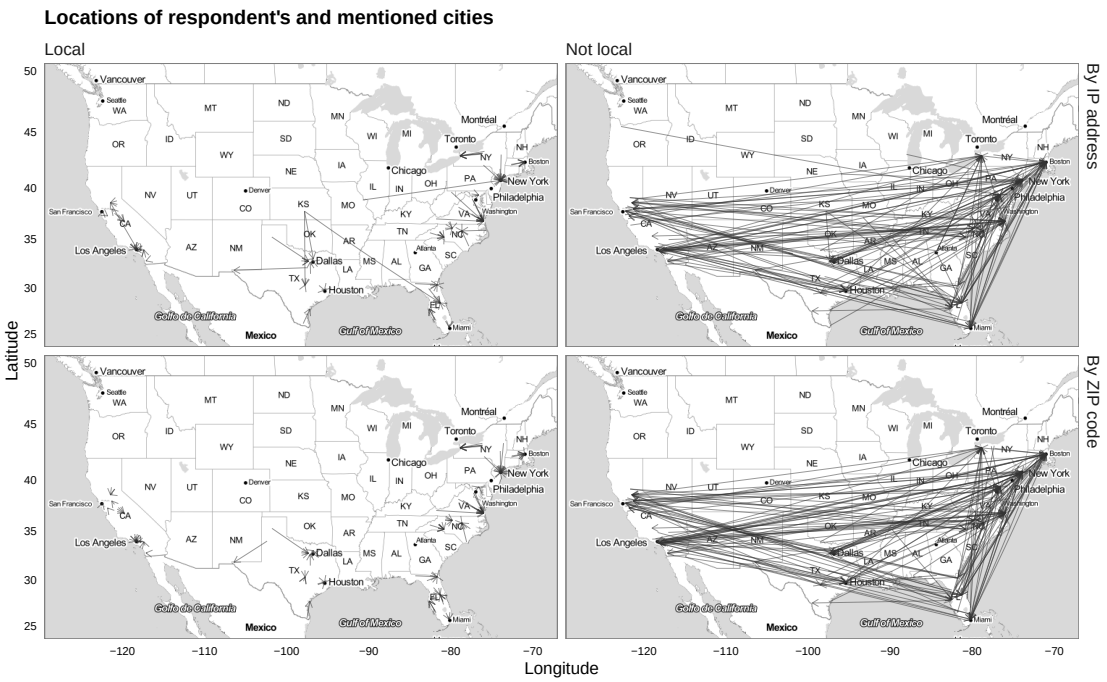


Figure 4: **Locations of respondent–city pairs.** Each panel shows an arrow per respondent. The end of the arrow indicates the location of the user and the tip the city which was affected by the aid change. The top row determines the user's location via the IP address, the bottom through the self-reported ZIP code. The left-hand column shows the pairs for cases with local treatment, the right-hand for those with non-local treatment. *As some data underlying this figure have been tweaked, do not make substantive inferences from this figure.*

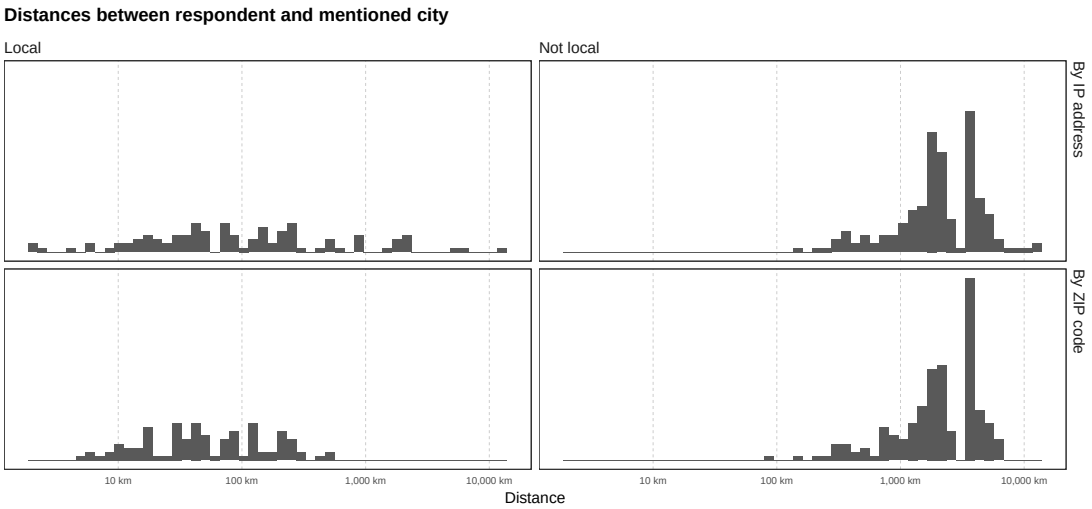


Figure 5: **Histogram of respondent–city distances.** A histogram depiction of the same data underlying Figure 4. Note that the x-axis is scaled logarithmically. *As some data underlying this figure have been tweaked, do not make substantive inferences from this figure.*

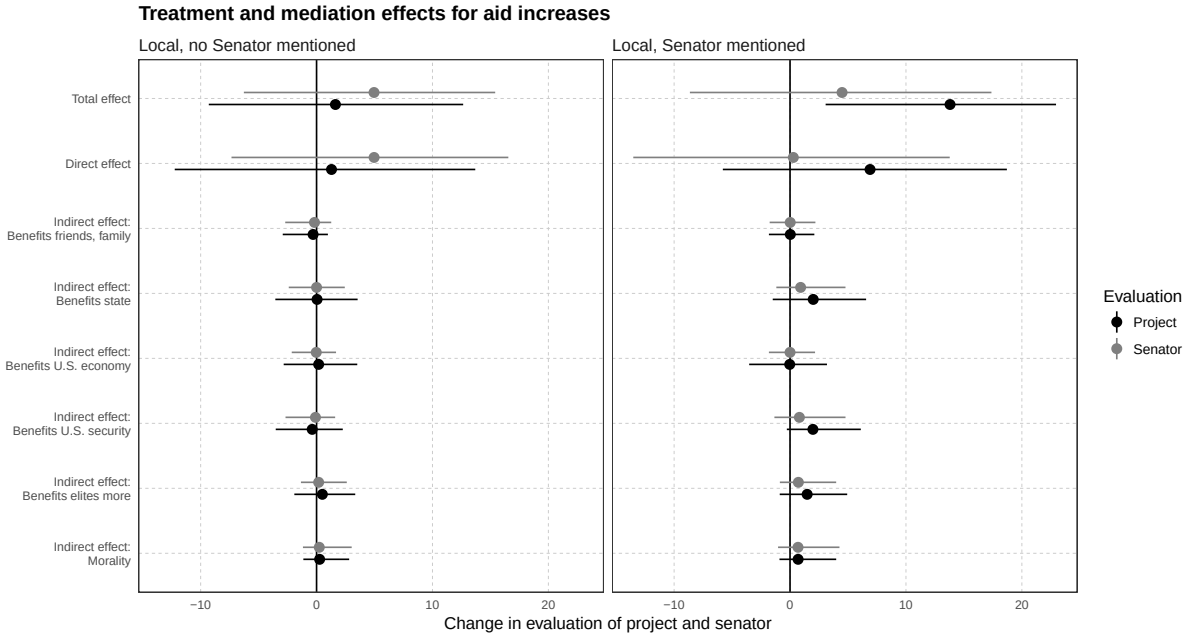


Figure 6: **Causal mediation effects.** The different effects are listed along the y-axis; the x-axis gives the change in the outcome variable. The dots denote the median estimate, the line the 95% confidence interval. The black dots/lines refer to the project ratings, the dark gray to the feeling thermometer score for a senator. The left-hand panel shows the effects when the city is local and no senator is mentioned; the right-hand side for a local including the involvement of a senator. *As some data underlying this figure have been tweaked, do not make substantive inferences from this figure.*

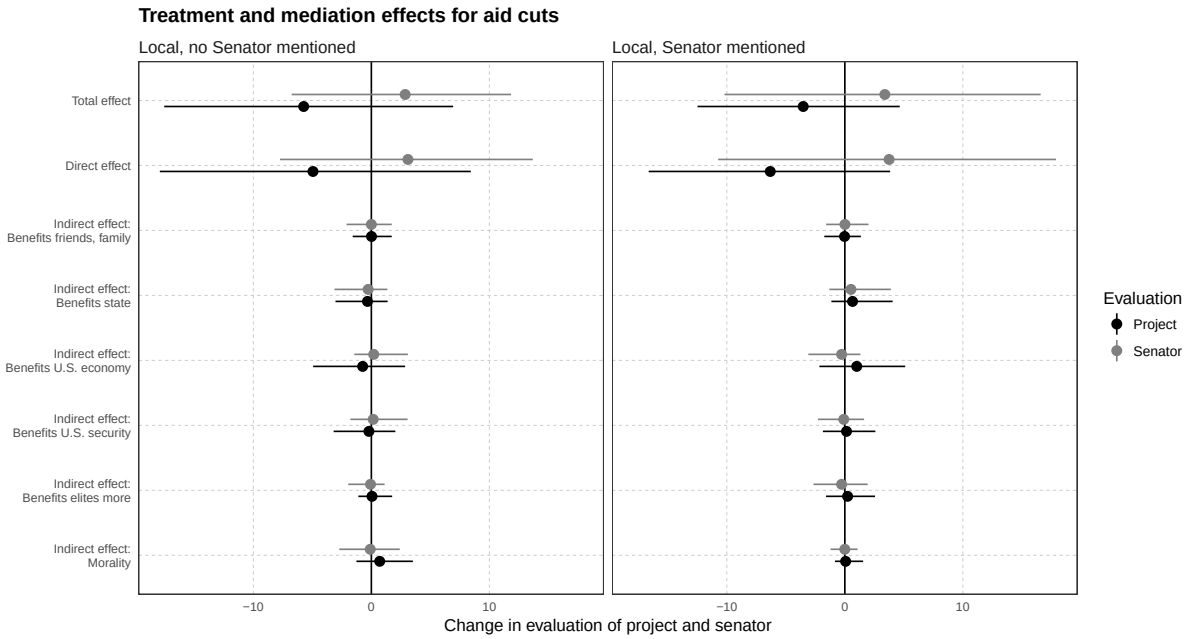


Figure 7: **Causal mediation effects.** The figure is constructed analogously to Figure **??**. *As some data underlying this figure have been tweaked, do not make substantive inferences from this figure.*

	Project	**Senator**	**Project**	**Senator**
	Increase foreign aid		Cut foreign aid	
Local project, no Senator	1.5	5.0	−5.5	2.9
	(−9.3, 12.6)	(−6.3, 15.4)	(−17.6, 6.9)	(−6.8, 11.8)
Local project, Senator	13.6	4.6	−3.6	3.4
	(3.1, 22.9)	(−8.6, 17.4)	(−12.5, 4.6)	(−10.2, 16.6)
Intercept	46.7	42.2	46.2	43.0
	(41.8, 51.3)	(36.6, 47.8)	(41.6, 51.1)	(38.0, 48.1)
Observations	134	268	146	292

Table 1: **Results for treatment effects.** Each single number presents the mean estimate; underneath is the 95% confidence interval. All models were bootstrapped; the Senator-models used the cluster-adjusted bootstrap.

	Friends, family	**State**	**US economy**	**US security**	**Elites**	**Moral**
Local project, no Senator	0.4 (−0.5, 1.1)	0.01 (−0.7, 0.8)	0.1 (−0.7, 0.9)	−0.2 (−0.9, 0.6)	0.2 (−0.5, 1.0)	−0.3 (−1.0, 0.5)
Local project, Senator	−0.1 (−1.2, 0.8)	0.5 (−0.3, 1.3)	−0.02 (−0.9, 0.9)	0.7 (−0.1, 1.7)	0.6 (−0.3, 1.6)	−0.6 (−1.6, 0.3)
Gender	0.3 (−0.3, 0.9)	−0.2 (−0.8, 0.4)	0.2 (−0.3, 0.8)	−0.3 (−0.8, 0.3)	0.4 (−0.2, 0.9)	0.03 (−0.5, 0.6)
Age	0.01 (−0.01, 0.04)	0.000 (−0.03, 0.02)	0.02 (−0.005, 0.04)	−0.01 (−0.03, 0.02)	−0.01 (−0.04, 0.01)	−0.01 (−0.04, 0.02)
Costs	−0.2 (−0.7, 0.2)	0.03 (−0.4, 0.5)	0.1 (−0.3, 0.6)	0.3 (−0.1, 0.7)	0.1 (−0.4, 0.5)	−0.1 (−0.5, 0.4)
Education, high	−0.2 (−1.3, 0.9)	−0.2 (−1.2, 0.9)	−0.1 (−1.2, 0.9)	−0.4 (−1.4, 0.7)	−0.2 (−1.2, 0.8)	1.7 (0.4, 6.6)
Education, low	−0.02 (−1.1, 1.2)	0.2 (−0.8, 1.3)	−0.1 (−1.1, 1.0)	−0.000 (−1.0, 1.0)	−0.1 (−1.2, 1.0)	1.3 (0.1, 6.2)
Ideology	0.1 (−0.1, 0.2)	0.02 (−0.2, 0.2)	−0.2 (−0.4, 0.01)	0.001 (−0.2, 0.2)	−0.2 (−0.4, −0.1)	0.1 (−0.1, 0.3)
Housing value	0.1 (−0.5, 0.5)	−0.2 (−0.7, 0.3)	−0.2 (−0.7, 0.3)	0.4 (−0.1, 0.9)	0.2 (−0.3, 0.7)	−0.5 (−1.0, 0.02)
Housing price increase	0.02 (0.000, 0.1)	0.000 (−0.02, 0.02)	−0.003 (−0.02, 0.02)	0.01 (−0.01, 0.03)	−0.004 (−0.03, 0.02)	−0.01 (−0.04, 0.01)
Transnational	−0.02 (−1.1, 1.0)	−0.6 (−1.7, 0.2)	−0.1 (−0.9, 0.8)	−0.4 (−1.3, 0.5)	−0.5 (−1.4, 0.3)	0.7 (−0.1, 1.6)
'US greatest country'	−0.1 (−0.9, 0.6)	0.3 (−0.3, 1.0)	0.2 (−0.5, 0.9)	0.2 (−0.5, 0.9)	0.1 (−0.5, 0.8)	0.2 (−0.4, 0.8)
Intercept	−3.1 (−7.3, 0.5)	0.4 (−3.4, 4.3)	0.9 (−2.6, 4.4)	−2.7 (−6.5, 0.7)	0.7 (−3.2, 4.3)	2.2 (−3.0, 6.1)
Observations	134	134	134	134	134	134

Table 2: **Results for mediators; aid increase cases only.** Coefficients and 95% confidence intervals from Bernoulli-probit models, regressing each mediator on a full covariate set.

	Friends, family	**State**	**US economy**	**US security**	**Elites**	**Moral**
Local project, no Senator	−0.04 (−0.9, 0.7)	−0.3 (−1.2, 0.4)	−0.2 (−1.0, 0.5)	−0.2 (−1.2, 0.6)	−0.3 (−1.0, 0.4)	−0.8 (−1.6, −0.1)
Local project, Senator	0.05 (−0.6, 0.7)	0.4 (−0.3, 1.0)	0.2 (−0.4, 0.9)	0.1 (−0.6, 0.7)	−0.7 (−1.3, −0.03)	−0.2 (−0.8, 0.5)
Gender	−0.3 (−1.0, 0.3)	−0.2 (−0.8, 0.5)	−0.4 (−1.1, 0.2)	−0.1 (−0.7, 0.5)	−0.1 (−0.8, 0.5)	−0.3 (−1.0, 0.2)
Age	0.02 (0.001, 0.1)	0.02 (−0.01, 0.04)	0.03 (0.005, 0.1)	0.01 (−0.01, 0.04)	−0.01 (−0.03, 0.02)	0.003 (−0.02, 0.03)
Costs	0.01 (−0.4, 0.4)	−0.1 (−0.5, 0.3)	−0.2 (−0.6, 0.2)	−0.1 (−0.5, 0.4)	−0.2 (−0.6, 0.2)	−0.3 (−0.7, 0.1)
Education, high	−0.1 (−1.0, 0.9)	−0.4 (−1.3, 0.4)	0.3 (−0.6, 1.3)	0.2 (−0.7, 1.2)	0.1 (−0.7, 0.9)	−0.03 (−0.9, 0.8)
Education, low	−0.1 (−1.0, 0.9)	−0.2 (−1.1, 0.8)	0.5 (−0.4, 1.5)	0.6 (−0.3, 1.6)	−0.1 (−1.0, 0.7)	−0.01 (−0.9, 0.8)
Ideology	0.2 (0.1, 0.4)	0.1 (−0.03, 0.3)	0.2 (0.04, 0.3)	0.3 (0.1, 0.4)	−0.2 (−0.4, −0.1)	0.01 (−0.1, 0.2)
Housing value	0.1 (−0.4, 0.6)	0.04 (−0.4, 0.5)	0.4 (0.003, 0.9)	0.5 (0.02, 1.0)	−0.2 (−0.7, 0.2)	−0.3 (−0.8, 0.1)
Housing price increase	0.01 (−0.01, 0.03)	0.01 (−0.01, 0.03)	0.01 (−0.01, 0.04)	0.001 (−0.02, 0.02)	0.02 (−0.000, 0.04)	0.02 (−0.002, 0.04)
Transnational	0.6 (−0.1, 1.2)	0.6 (−0.04, 1.3)	0.5 (−0.2, 1.2)	0.7 (0.1, 1.4)	−0.3 (−1.0, 0.4)	−0.2 (−0.8, 0.4)
'US greatest country'	−0.1 (−0.7, 0.4)	−0.2 (−0.7, 0.4)	−0.01 (−0.5, 0.5)	0.4 (−0.1, 0.9)	0.3 (−0.2, 0.8)	0.5 (−0.04, 1.0)
Intercept	−2.9 (−6.6, 0.4)	−2.1 (−5.6, 1.1)	−5.3 (−9.7, −2.1)	−5.0 (−9.3, −1.3)	1.4 (−1.7, 4.6)	0.8 (−2.6, 4.2)
Observations	146	146	146	146	146	146

Table 3: **Results for mediators; aid cut cases only.** Coefficients and 95% confidence intervals from Bernoulli-probit models, regressing each mediator on a full covariate set.

	Project	**Senator**	**Project**	**Senator**
	Increase foreign aid		Cut foreign aid	
M:Friends, family	−5.3	−3.7	−4.0	5.6
	(−16.2, 4.7)	(−16.1, 7.9)	(−16.0, 7.8)	(−8.2, 18.6)
M:State	13.1	7.3	7.3	6.3
	(4.7, 21.8)	(−3.1, 17.6)	(−5.2, 20.1)	(−6.9, 19.9)
M:US economy	10.2	−3.6	16.4	−7.1
	(1.3, 18.8)	(−15.1, 6.8)	(4.9, 27.3)	(−18.8, 4.2)
M:US security	9.9	5.0	8.6	−7.5
	(1.2, 18.4)	(−5.2, 16.0)	(−2.3, 19.1)	(−18.3, 4.4)
M:Elites	9.9	5.8	−1.6	1.7
	(2.0, 17.6)	(−3.4, 15.2)	(−10.0, 6.7)	(−7.8, 10.6)
M:Moral	−5.5	−5.3	−3.3	0.6
	(−14.0, 3.2)	(−15.4, 4.3)	(−11.0, 4.9)	(−8.3, 9.4)
Local project, no Senator	2.2	−0.5	−6.3	3.1
	(−7.6, 11.9)	(−12.7, 11.7)	(−19.1, 5.4)	(−5.7, 12.4)
Local project, Senator	5.4	−2.5	−6.9	4.3
	(−6.7, 16.8)	(−18.1, 11.9)	(−16.6, 2.8)	(−8.7, 17.8)
Gender	−1.1	3.6	−3.8	6.8
	(−8.6, 6.4)	(−6.3, 13.7)	(−12.1, 4.2)	(−4.0, 17.6)
Age	0.2	−0.3	0.1	0.2
	(−0.1, 0.5)	(−0.7, 0.1)	(−0.3, 0.4)	(−0.3, 0.6)
Costs	−2.2	5.1	−0.4	−2.4
	(−8.3, 4.2)	(−2.4, 12.9)	(−6.7, 5.3)	(−8.7, 3.8)
Education, high	3.9	7.2	−5.8	9.2
	(−10.8, 18.0)	(−10.0, 24.1)	(−16.3, 5.5)	(−6.0, 24.1)
Education, low	6.6	1.4	−8.8	4.1
	(−8.0, 20.4)	(−15.1, 18.0)	(−19.9, 2.9)	(−10.4, 19.2)
Ideology	−0.1	−1.9	1.5	−0.8
	(−2.9, 2.5)	(−5.1, 1.4)	(−1.2, 4.2)	(−3.5, 1.9)
Housing value	2.5	7.8	0.7	6.2
	(−3.1, 8.8)	(−0.1, 15.8)	(−4.7, 6.6)	(−1.5, 14.3)
Housing price increase	0.02	0.002	−0.03	−0.3
	(−0.2, 0.3)	(−0.3, 0.3)	(−0.3, 0.2)	(−0.6, −0.02)
Transnational	1.5	1.0	−3.8	0.1
	(−8.4, 12.1)	(−11.8, 13.6)	(−14.7, 7.4)	(−10.9, 11.1)
'US greatest country'	−2.0	11.5	1.7	−1.3
	(−10.6, 7.6)	(0.3, 22.7)	(−5.3, 8.9)	(−10.2, 7.3)
Intercept	8.3	−1.0	38.7	25.8
	(−35.0, 49.8)	(−59.6, 59.9)	(−0.2, 77.4)	(−33.7, 80.4)
Observations	134	268	146	292

Table 4: **Results for treatment effects using full covariate set (including mediators).** Each single number presents the mean estimate; underneath is the 95% confidence interval. All models were bootstrapped; the Senator-models used the cluster-adjusted bootstrap.

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