

# UNIVERSALISM AND POLITICAL REPRESENTATION: EVIDENCE FROM THE FIELD\*

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## Abstract

This paper provides field evidence on the link between morals and political behavior. We create a district-level variable that reflects to what degree charitable giving decreases as a function of (geographic and social) distance, which we interpret as a real-stakes measure of citizens' values on the universalism-particularism continuum. Our measure of district universalism is strongly predictive of local Democratic vote shares, legislators' roll-call voting, and the moral content of Congressional speeches. Spatial heterogeneity in universalism is a substantially stronger predictor of geographic variation in political outcomes than traditional economic variables such as income or education.

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# 1 Introduction

This paper presents field evidence suggesting tight links between political outcomes and spatial variation in the electorate’s values along the universalism-particularism continuum. In recent years, there has been a surge of interest in studying the determinants of voting patterns, likely because the traditional income-based cleavage has become less important in organizing the structure of political conflict (e.g., Guriev and Papaioannou, 2020; Gethin et al., 2022; Danieli et al., 2022). This naturally raises the question of what other factors may drive political divisions. One approach has focused on differences in universalist versus particularist moral orientation. A particularist or communal morality emphasizes group-specific values (loyalty and treating in-group members well), whereas a universalist morality emphasizes equal treatment and impartiality. Arguably, one reason why heterogeneity in universalism is attracting attention in the literature is that many contentious issues (such as immigration, LGBTQ rights, affirmative action, race relations, EU integration, national pride, and “America first”) directly tap into values that relate to people’s moral boundaries. Indeed, recent work has shown that universalist values and preferences are consistently predictive of left-wing policy views and voting (e.g., Graham et al., 2009; Haidt, 2012; Waytz et al., 2019; Enke, 2020; Kivikangas et al., 2021; Enke et al., 2022; Cappelen et al., 2022).

Thus far, this literature has been based on survey- or laboratory-generated data. Most commonly, researchers relate policy views and voting to measures of universalism that are derived from hypothetical survey questions, lab-experimental games or psychological questionnaires. Yet, akin to prominent discussions in behavioral and experimental economics, the use of hypothetical questions (or lab settings) raises important concerns about ecological validity (Levitt and List, 2007; Hatemi et al., 2019).

In this paper, we study the link between universalism and political behavior by focusing exclusively on natural real-stakes decisions. We develop a new measure of district-level universalism that (i) is based on financial choices that voters make in a natural setting and (ii) directly corresponds to theoretical models of universalism (Tabellini, 2008). In these models, universalism is formalized as the *slope* of altruism as a function of social distance – a full universalist exhibits altruism that is invariant to social distance, whereas a particularist’s altruism decreases with distance. Thus, higher universalism means that a given altruism budget is allocated more uniformly across recipients that are socially close or distant.

Motivated by this formalization, we measure a congressional district’s universalism as the slope of charitable donations with respect to distance. We work with large-scale charitable donations data from a non-profit organization, *DonorsChoose*, a crowdfunding platform that allows individuals to donate directly to classroom projects that teachers

across the U.S. post on its website. We obtain access to data on roughly 4 million donations made between March 2000 and October 2016, worth about \$305 million, that cover almost every congressional district in the United States.

For each district, we estimate how much donations decrease as a function of distance to the recipient. Here, “distance” is operationalized in two different ways. First, we estimate the slope of giving with respect to geographic distance, perhaps the most immediate proxy for “social distance” in theoretical models of universalism. Second, we estimate the slope of giving with respect to the Facebook friendship distance between two districts, as captured by friendship links in 2021 (Bailey et al., 2018). We think of this second measure as a rich proxy for social distance that incorporates elements of geographic, ethnic, political, religious, income and educational distance. In this case, heterogeneity in universalism captures that people in some districts primarily donate to places where they have many social ties, while giving in other districts is largely invariant to the presence of social ties. Universalism defined with respect to geographic and friendship distance are highly correlated. Because we view the two indices as each imperfectly capturing the same latent construct, we combine them into a summary measure.

In constructing our measures, we only leverage variation in *to whom* the population in a given district donates (the *slope* of giving), not how much they donate (or receive) overall. While districts differ for many reasons in *how much* they donate or receive on *DonorsChoose*, our analysis nets out these district-specific level effects. Our interpretation of the empirical slope of giving is that it reflects spatial heterogeneity along the universalism-particularism continuum; in Section 3.3, we discuss potential alternative interpretations of this measure and the degree to which they are plausible drivers of our results.

We link our spatial measure to across-district variation in political outcomes, focusing on (i) which legislators get elected to the U.S. House of Representatives and (ii) legislators’ behavior in Congress once elected. We consider three outcomes for the 113th and 114th Congresses (2013-2016):<sup>1</sup> (a) local vote shares; (b) DW-NOMINATE scores of elected representatives; and (c) the universalism of these representatives, computed by applying the extended Moral Foundations Dictionary (Hopp et al., 2021) to congressional speeches.

We find that district-level universalism is strongly correlated with Democratic vote shares in House elections. This across-party result, using our ecological, real-stakes measure of universalism, is consistent with findings from prior work that had documented

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<sup>1</sup>We focus on these congressional terms because it allows us to use the speech data collected by Gentzkow et al. (2019). Many of the donations we use to construct our universalism measure took place during or after these terms. We discuss this issue in more detail in Sections 2 and 3.3.

similar patterns using survey-based universalism measures. The magnitude of the estimated link between universalism and vote shares is surprisingly large. The raw correlation,  $r = 0.50$ , is substantially higher than those of economic variables that are often linked to political behavior, such as median household income and share of population with a college degree. Furthermore, the relationship between district universalism and vote shares is robust to controlling for income, education, White ethnic share, latitude, distance from the coast and state fixed effects.

Next, we show that district universalism is also strongly associated with the behaviors of elected House members. That is, legislators from more universalist districts have more left-leaning DW-NOMINATE scores, even controlling for the legislator's party. This last result is surprising, given the amount of variation in roll-call voting explained by party allegiances.

Finally, we find that legislators from more universalist districts use substantially more universalist moral language in their congressional speeches, even when we focus on within-party comparisons. District universalism is even more predictive of a legislator's speech universalism than the district's Democratic vote share.

***Contribution and related literature.*** Consistent with individual-level survey evidence on the link between measures of universalism and political behavior (Enke et al., 2022; Cappelen et al., 2022), we interpret the correlations reported in this paper as suggesting that a main reason for the large geographic political disagreement in the U.S. is that people differ in *towards whom* they allocate a given altruism budget (rather than differences in the "level" of morality as such). This intuitively resonates with the fact that many policy debates reflect what appear to be different views on one's moral boundaries.

Our contribution is to provide the first evidence on this issue derived from field data. Enke (2020) studies across-county variation in vote shares in presidential elections but relies on a psychological questionnaire to quantify universalism. His results and ours provide converging evidence in the sense that two independent spatial measures of universalism that are constructed based on very different data, are both strongly correlated with local Democratic vote shares. We also link to work on representation that studies the district-level link between voter policy preferences and outcomes (Tausanovitch and Warshaw, 2013). Our paper adds to this literature by studying the values that underlie differences in policy views, ideology and voting, rather than taking policy views as primitives.

Our emphasis on how people spend their altruism budgets also sheds light on whether Democrats or Republicans are more generous, an actively debated topic in the economics of philanthropy literature (e.g. Yang and Liu, 2021). Work in this area has found mixed results (or that both sides donate roughly the same amounts). Our findings indicate that

it may be more fruitful to explore the composition rather than level of giving. This insight contributes to the extensive literature on the determinants of charitable donations (see Gee and Meer, 2020 for a recent survey), in particular work that has documented the importance of proximity – whether social or geographic – in influencing charitable giving (Fong and Luttmer, 2009; Deryugina and Marx, 2021; Xu et al., 2020).

Section 2 develops our new measure of district universalism and explains how we quantify politicians’ universalism. Section 3 presents the results and Section 4 concludes.

## 2 Data and Measurement of Universalism

We wish to study U.S. House races and the subsequent Congressional behavior of Representatives as a function of district universalism. Our unit of analysis is thus a congressional district and the candidates that stand for election.<sup>2</sup>

### 2.1 Estimating District Universalism

**Data.** We create a real-stakes measure that captures the extent to which donations decrease as a function of geographic or social distance. We propose that this serves as a new economic measure for a district’s universalism that directly builds on theoretical models of universalism (Tabellini, 2008; Enke, 2019; Enke et al., 2022). In these models, a person’s degree of universalism is formalized as the degree to which altruism decreases as a function of social distance. Thus, universalism is about the *slope* of generosity rather than its level.

We leverage data from *DonorsChoose*, an American non-profit organization that provides an online “crowdfunding” platform for public school teachers. On one side of the platform, teachers post funding requests for projects such as field trips, classroom furniture, and purchases of basic school supplies or technology. On the other side are potential donors, who visit the website and donate to individual projects. Appendix C.1 provides screenshots and a description of the platform’s layout and functionality. Notably, potential donors’ ability to search through and filter projects based on location is highly salient. The visual ordering of projects on the platform is according to need, which is defined by a combination of (i) time to the project’s expiration; (ii) remaining funds needed; and (iii) general neediness of the school.

The geographic scope of the data is broad and comprehensive: *DonorsChoose* reported in June 2019 that since the platform’s inception in 2000, teachers in 82% of

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<sup>2</sup>We focus on House races for two related reasons. First, our district-level analysis allows for greater statistical power due to the larger number of candidates and races, relative to the Senate. Second, voter universalism varies considerably across districts within states (as reflected in our own data), such that Senate-level analyses eliminate much of the variation of interest.

public schools in the United States had posted 1.4 million projects. We received data that allow us to match all individual donations made on *DonorsChoose* between March 2000 and October 2016 to their recipient projects. These data report the school’s ZIP code and the first three digits of each donor’s ZIP code. We drop observations for which the donor ZIP code is missing. Overall, our data include about 3.9 million donations worth approximately \$305 million.

We provide summary statistics on the *DonorsChoose* data as aggregated by congressional district across all years in the top panel of Table 1. The mean number of donations per donor district in our final dataset is 9,068 (median of 6,133). The average value of donations is just under \$700,000 per district, implying that the average donation is a little under \$80. We note the high dispersion in donations and number of donors across districts. The table also provides a comparison of “blue” versus “red” districts, categorized based on 2012 presidential elections. There are clear differences for both giving and receiving donations: both are considerably higher (especially donations) in blue districts.

We provide a comparison to the universe of charitable donations using IRS data for 2011-2015, which we also show in Table 1. While the value and number of charitable donations made is higher in blue districts also in the IRS data, the differential is less than for *DonorsChoose*. We see this as plausibly reflecting the fact that *DonorsChoose* was founded in New York, and given its tech orientation found considerable support on the West Coast. Notably, receipt of *DonorsChoose* giving is actually *less* skewed towards blue districts than charitable giving overall in the IRS data.<sup>3</sup>

Overall, these summary statistics highlight clear *level* differences in donations made and received in blue versus red districts. As noted above, our interest is in the slope rather than the level of giving, and our empirical analysis will take care to net out level differences.

***Empirical Approach.*** We seek to capture how a district’s donations to another district change as a function of distance. For this analysis, we aggregate individual donation data to the district level and construct a dyadic dataset comprised of all possible donor-recipient district pairs. Appendix C.2 provides details on the matching methodology used.

We estimate the extent to which donations from any given district decline as a function of distance. The top panel of Figure 1 illustrates this approach for two donor districts

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<sup>3</sup>The IRS data on donations received by a charity maps those donations to where the charity is headquartered. For example, *DonorsChoose* is headquartered in New York, and so all donations that happen through the platform are encoded in the IRS statistics as being directed to New York. Note that large cities are both more likely to be the headquarters of national charities, and are also more left-leaning than the general population.

from California. For each donor district, we provide a binned scatter plot of the log donation amount as a function of log geographic distance to the recipient district. Our interest is in the *slope* of this function. In these plots, the donation and distance data are both residualized from donor and recipient fixed effects. That is, as explained below, we hold fixed the level of donations from and to a given district, and only leverage variation in the slope.

Formally, denote the set of districts and its elements by  $x \in X$ . For each donor district  $i$  and recipient district  $j$ , denote a distance measure between the two districts by  $d_{i,j}$  and the log total dollar amount of donations by  $p_{i,j}$ . Further denote by  $S_x \in \{0, 1\}$  an indicator variable for each donor district and by  $R_x \in \{0, 1\}$  an indicator variable for each recipient district. Our estimating equation is then given by:

$$p_{i,j} = \alpha + \sum_x \theta_x [d_{i,j} \times S_x] + \sum_x \gamma_x S_x + \sum_x \beta_x R_x + \varepsilon_{i,j} \quad (1)$$

The primary measure of interest is the vector of  $\theta_x$ , which captures the extent to which donations in a district decline as distance increases.

Importantly, the estimating equation includes donor and recipient fixed effects to control for spatial variation in donation rates for reasons unrelated to universalism. For instance, a given donor district may have disproportionately many users of *DonorsChoose* or be richer on average, hence leading to higher overall donation amounts. Similarly, a given recipient district may post many projects on the *DonorsChoose* website or be very poor, and hence receive many donations. Our specification nets out these level effects. As a result, the estimates of  $\theta_x$  capture how strongly donations decrease as a function of distance, holding fixed how much each district donates and receives. For instance, this means that our estimate of  $\theta_x$  is not mechanically larger in districts that are poorer or have less well-equipped schools.

We interpret the estimate of  $\theta_x$  as a district’s universalism and discuss alternative interpretations and potential confounds in Section 3.3.

***Distance types and resulting universalism measure.*** In the specification presented above, our distance measure is the log geographic distance between two districts’ centroids. A potential problem with interpreting the universalism measure based on this approach is that it might be confounded by heterogeneity in social or economic ties. For example, suppose that left-leaning districts in general had more frequent or stronger social ties to geographically distant districts than right-leaning districts. Left-leaning districts may, for example, have higher mobility, different friendship patterns, and distinct economic interactions and trade patterns relative to right-leaning districts. Ideally, one would like to assess a district’s degree of universalism also based on a more encom-

passing proxy for social distance.

To do so, we compute the slope of donations with respect to the friendship distance between two districts, as constructed from Facebook data made public by Bailey et al. (2018) and updated since the original release. The intuition behind this so-called Social Connectedness Index (SCI) is that it gives the probability that two randomly drawn Facebook users from two districts are friends on Facebook. Formally, it is computed as  $SCI = \text{FB\_Connections}_{i,j} / (\text{FB\_Users}_i * \text{FB\_Users}_j)$ . We work with  $-\log(\text{SCI})$  as our measure of distance. Note that the SCI is a snapshot of friendship distance for 2021, several years after the years we use to calculate our political outcome variables. However, friendships frequencies are quite static, in particular at an aggregated level, so that this is very plausibly a fixed rather than time-varying attribute.<sup>4</sup> We take up timing issues in more detail in our discussion of robustness and interpretation below.

We view the measure of friendship distance as a summary statistic of social distance that aggregates a wide variety of demographic and social dimensions, such as ethnic distance, age distance, ideological distance, income distance, educational distance, and so forth. Loosely speaking, heterogeneity in universalism with respect to friendship distance captures that people in some (more particularist) districts show more favorable treatment toward regions where they have many friends, while people in other (more universalist) districts treat regions with many friends or strangers similarly well. Appendix Figure 6 shows the distribution of geographic and friendship distance in our data.

The right panel of Figure 1 shows an illustration of the construction of universalism with respect to friendship distance for two donor districts from New York. In this example, district NY-21 donates relatively more to places where its residents have more friends and less to places where they have fewer friends.

The measure of friendship distance has several advantages – as well as disadvantages – relative to geographic distance. On one hand, as noted above, districts may differ in their geographic distribution of social ties. On the other hand, the SCI is based on friendship links on a particular platform, which creates a set of selection issues both in who uses the platform as well as how different individuals may choose to create network ties.

Universalism computed with respect to geographic and friendship distance are highly correlated ( $r = 0.73$ ). Because we view each as having a set of advantages relative to the other, we aggregate the geographic-based and the friendship-based universalism

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<sup>4</sup>Via personal communication the study's authors noted that the correlation across years in  $\log(\text{SCI})$  is above 0.99, and that generally "both the underlying object of social connectedness across regions, and the measure of it on Facebook are very stable over time." Please see the data documentation on the SCI for further details, which may be accessed at <https://data.humdata.org/dataset/social-connectedness-index?>.



measures into a composite measure by computing the z-score of the average of the two z-scores. We think of this measure as capturing the analog of the overall slope of giving with respect to social distance in theoretical models of universalism (Tabellini, 2008). Below, we always report robustness checks based on each measure separately. Figure 2 shows the heterogeneity in our composite universalism measure across districts.

**Correlates.** A district’s universalism is correlated with log median household income ( $r = 0.45$ ), share of population with a college degree ( $r = 0.44$ ), log distance to the coast ( $r = -0.52$ ) and share of the population which is White ( $r = -0.37$ ). We control for these variables in our analyses below.

To quantify geographic variation in universalism, previous work has relied on the Moral Foundations Questionnaire (Graham et al., 2013; Haidt, 2012). The universalism measure based on this questionnaire constructed by Enke (2020) exhibits a correlation of  $r = 0.47$  with our measure. Taking into account measurement error, this suggests that these two measures plausibly capture the same underlying concept. We view it as encouraging that the two measures – despite being constructed in different ways and based on very different data – exhibit such a high correlation. We highlight that the main advantages of the measure we use in this paper are (i) its ecological and real-stakes nature and (ii) its tight connection to formal theories of universalism.

## 2.2 Estimating Politician Universalism from Text

**Extended Moral Foundations Dictionary.** The eMFD is a standard analytical tool in moral psychology (Hopp et al., 2021), which is a considerably more sophisticated successor of the original Moral Foundations Dictionary (MFD, see Graham et al., 2009). It consists of a bag-of-words that probabilistically assigns a total of 3,270 terms to different moral categories. Unlike the original MFD, which was constructed purely based on researcher intuitions, the eMFD reflects the result of a crowd-sourced text-annotation task. Hopp et al. (2021) selected a set of 3,000 news articles and then asked 550 online workers on the *Prolific* platform to annotate these texts. Each annotator was tasked with highlighting passages of text that contained content related to one of the moral “foundations” posited by Moral Foundations Theory (Haidt, 2012; Graham et al., 2017) that can be aggregated into the particularism-universalism continuum (Enke, 2020).

Hopp et al. (2021) identify 3,270 terms that were annotated relatively often. For each of these terms, the researchers compute the probability that it was marked as an instance of each moral category. Based on these probabilities (weights), we construct an index of the relative frequency of universalist language. This index is analogous to the one proposed by Enke (2020), except that in the current paper (i) it is applied to

the richer eMFD and (ii) it takes into account the probability weights with which each moral keyword belongs to a particular category.<sup>5</sup>

Formally, denote by  $w_i^f$  the (probability) weight of word  $i$  for category  $f$  and by  $x_i$  the word’s frequency in a text. Denote by  $N$  the number of words in the eMFD and by  $L$  the length of a document.<sup>6</sup> The relative frequency of universalist language in a given text is then given by:

$$\text{Rel. freq. universalist language} = \frac{\sum_i^N x_i(w_i^{\text{univ}} - w_i^{\text{partic}})}{L} \quad (2)$$

To estimate the universalism of members of the U.S. House of Representatives, we work with the congressional speeches dataset provided by Gentzkow et al. (2019). The two most recent Congresses in the dataset are the 113th and 114th Congresses. Given that the 112th Congress was based on a different districting, we work with the two later sessions, for a total of 872 observations for which we can also compute district universalism using contemporaneous data. Appendix Table 5 provides an overview of the most frequently used moral target words in the eMFD that appear in the data.

We calculate the statistic in eq. (2) at the level of a speaker-day and then average at the politician level.<sup>7</sup> Appendix Figure 4 shows a histogram of politician-level universalism, separately by party. Three main patterns emerge. First, Democrats are more universalist, on average. Second, there is also large within-party variation in speech universalism. Third, the measure of candidate universalism derived using this procedure is noticeably distinct from standard ways of quantifying partisan speech. The correlation between candidate universalism and the score of partisanship developed in Gentzkow et al. (2019) is  $r = 0.14$ .

## 3 Results

### 3.1 District Universalism and Two-Party Vote Shares

Figure 3 presents a binned scatter plot that visualizes the correlation between universalism and Democratic vote shares ( $r = 0.50$ ,  $p < 0.01$ ). Columns (1)–(2) of Table 2 provide corresponding regression analyses. The point estimate in the bivariate specification in column (1) implies that a one standard deviation increase in district universalism

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<sup>5</sup>Universalist “foundations” are care/harm and fairness/cheating, and particularist foundations are loyalty/betrayal and authority/subversion.

<sup>6</sup>Throughout, we compute text universalism after removing stop words.

<sup>7</sup>Whenever a legislator was replaced during a Congress, we aggregate the universalism scores of the speeches of both the original and the substitute legislators into a single district-congress speech universalism score. Such replacements are infrequent, occurring in only 9 cases during the 113th Congress, and 3 cases during the 114th Congress.

is associated with an increase in Democratic vote share of around thirteen percentage points. This correlation is robust to the inclusion of controls for median income, share of population with a college degree, White ethnic share, geography and state fixed-effects (column (2)).

Traditional political economy analyses highlight the importance of variation in income (Meltzer and Richard, 1981) and education (Gethin et al., 2022) for electoral outcomes. Yet the correlation between vote shares and universalism that we identify is substantially stronger than those relating vote shares to log median household income ( $r = 0.05$ ) or share of population with a college degree ( $r = 0.14$ ).

While the quantitative magnitude of the link between district universalism and Democratic vote shares is striking, we see these findings as a point of departure rather than the main results of our paper, for two reasons. First, the link between county-level universalism and county vote shares in presidential elections has already been noted (although based only on survey responses) by Enke (2020). Second, the correlation documented above is essentially a between-party comparison. We next consider within-party variation in district universalism and representative behavior.

### 3.2 Behaviors in the U.S. Congress

Despite strong party discipline, legislators' roll-call voting behavior in the Congress as summarized by their DW-NOMINATE score exhibits some within-party variation. Columns (3)–(5) document that district universalism is strongly linked to the DW-NOMINATE score of the district's representative (higher scores reflect higher conservatism). The variance explained in these regressions is as high as in analyses with Democratic vote shares as the outcome.

Column (5) documents that this correlation continues to be statistically significant even when we compare politicians from the same party. While the point estimate is notably lower, this is unsurprising given that there is only modest within-party variation in DW-NOMINATE scores (as reflected in the very high proportion of variance explained in column (5)). We report these results because they show that universalism is correlated with political outcomes above and beyond pure partisanship.

Finally, we study whether district universalism is correlated with the revealed universalism of district representatives, as proxied by the moral content of congressional speeches. This provides a more direct (though still correlational) link between voter preferences and legislator behavior, and may also be less confounded by the party discipline that governs roll-call votes. Columns (6)–(8) of Table 2 present the results. We find a strong correlation between district universalism and the representative's universalism as expressed in congressional speeches. A one standard deviation increase in district

universalism is associated with an increase of speech universalism by 22% of a standard deviation. Interestingly – and in contrast to our results on roll-call votes – this relationship is largely unchanged when we only leverage within-party variation in speech universalism (column (8)). Furthermore, the results are even robust to controlling for a district’s Democratic vote shares in the 2012 presidential election, as a proxy for general partisanship.

### 3.3 Robustness and Alternative Interpretations

Our preferred interpretation of the donations-based measure we construct – the slope of giving with respect to distance – is that it captures variation in moral orientation along the universalism-particularism continuum. This interpretation is consistent with the strong correlation between our measure and the measure of universalism constructed by Enke (2020) based on a large-scale moral psychology survey dataset. That said, we emphasize that our evidence is descriptive in nature, such that there may be alternative district-level attributes that might explain our findings or cloud the interpretation of them.

***Higher mobility in blue districts.*** The slope of donations with respect to geographic distance may be flatter as a result of higher mobility and the resultant stronger social ties and/or familiarity. For example, suppose that people in blue districts exhibit higher geographic mobility, such that they are more likely to have friends in (or to have visited) faraway places. If social ties induce giving, districts that exhibit higher mobility could spuriously appear more universalist when universalism is calculated with respect to geographic distance.

This concern is substantially less relevant when we instead compute universalism with respect to Facebook friendship distance. The reason is that higher mobility in blue districts should be reflected in a higher frequency of friendships with people from geographically distant places (such as we would expect if people went to college or worked in a faraway locale). Importantly, variation in universalism with respect to friendship distance reflects whether people predominantly give to places where they have strong social ties or equally to all places, regardless of their geographic proximity.

Panels A and B of Appendix Table 3 document that the results in Table 2 are very similar when we measure universalism based on geographic distance or Facebook friendship distance separately. The main takeaway from this analysis is that Republican places predominantly give to places where they have strong social ties, while Democratic giving is more invariant to the presence of social ties. To the degree that Facebook friendship patterns are an adequate proxy for the level of familiarity or social ties between districts,

these patterns suggest that differential geographic mobility does not drive the results.

***Uneven distribution of red and blue districts.*** A second concern relates to the uneven geographic distribution of red and blue districts across space, because it implies that very long-range donations are mechanically more likely to originate from (coastal) blue districts. Appendix Table 3 (Panel C) presents robustness checks in which we recode geographic distance as a binary variable, based on a threshold of 50 miles, such that the uneven distribution of districts across space is less relevant. The results are very similar to those presented in our main analysis.

***Incentives and information.*** A third set of concerns relate to preferences for school donations that do not reflect particularist preferences but rather economic incentives or information. A first natural possibility is that donations to nearby schools on the *DonorsChoose* platform do not reflect generosity towards friends and neighbors but, instead, personal incentives to fund the classroom of one's own child. A second, related concern is that variation in local giving reflects differences in how well-informed people are about their local neighborhood schools (or variation in how effective schools are at local fundraising). To address these types of concerns, which generally relate to donors' immediate environment, we re-run all analyses using a geographic distance universalism measure that is constructed after excluding all donations that go to a school in the donor's state of residence. Appendix Table 3 (Panel D) shows that the results are very similar. This shows that variation in what we call universalism reflects not just differences in giving between very-local and very-far-away schools, but also between somewhat-far-away and very-far-away schools.

Another potential concern relates to variation in the neediness of schools, which also may be more distant from (relatively richer) blue districts. First note that the general neediness of a given recipient district is netted out of the analysis through recipient district fixed effects – all of our analyses control for how much money each district receives, so we only look at *from whom* a district receives money. To further address potential concerns about neediness, we note that the vast majority of projects (over 97%) on *DonorsChoose* are from schools that the organization classifies as at least “moderate poverty,” and most are from schools that are classified as high (24.8%) or highest (58.5%) poverty, based on the fraction of students that receive free lunches (the *DonorsChoose* proxy for low-income). That is, most recipient schools serve low-income populations. As shown in Appendix Table 4 (Panel A), our results are virtually unchanged if we limit our analysis to high- and highest-poverty schools.

**Selection into DonorsChoose.** Selection into *DonorsChoose* is not random. We surmise that, at the individual level, it probably correlates with age, income, and technological sophistication. At the district level, we observed in Section 2 that *DonorsChoose* receives considerably more donations from Democratic districts than from Republican ones (relative to the benchmark of charitable donations overall); yet because this level difference gets absorbed in district fixed effects, it is unproblematic per se.

A threat for the interpretation of our results, however, would be *differential* selection into the organization's donor pool that is correlated with propensity to donate to local versus distant charities. To illustrate an extreme case, suppose that the true population average of citizen universalism is the same across all districts but that in blue districts mostly universalists (who donate to faraway schools) and in red districts mostly particularists (who donate to nearby schools) select into the *DonorsChoose* platform. In this case, true district universalism would be uncorrelated with local vote shares, but such a relationship would spuriously appear as a result of differential selection. Since we do not have any information on individual donors, we cannot rule out this possibility, though it is unclear to us why such differential selection should exist.

**Timing of data sources.** Finally, as we noted earlier, there is a mismatch in the timing of the *DonorsChoose* data used to construct our independent variable and the political variables that constitute our outcomes. In particular, we use donations from the entire available *DonorsChoose* history from 2000-2016, whereas the 113th and 114th Congresses that are our focus involve 2012 and 2014 elections, and span the years 2013-2016. Thus, our dependent variables partly predate our independent ones.

We use the entire *DonorsChoose* history in large part because the organization's very rapid growth is such that about half of total donations occur after the 2014 elections, and fewer than a quarter occur before the 2012 elections (see Appendix Figure 5). We note that patterns of *DonorsChoose* giving are quite stable and thus so are the resulting measures of universalism: if we generate universalism measures based on donations until the 114th Congress election and those that come after (a roughly equal split of the sample), the correlation is 0.84. This time stability suggests that differential timing is not a major source of concern.

A further robustness check is to restrict attention to (i) the outcome variables in the 114th Congress and (ii) the subsample of donations made before the 114th Congress, such that the timing of data matches up. We present these results in Panel B of Appendix Table 4. They are similar to the ones reported in the main text, though we note that in our most demanding specifications (once we include state fixed-effects and/or controls for political party), district universalism is no longer significantly correlated with vote shares or speech universalism. While we see this as primarily the result of introducing

noise as a result of our smaller sample, we flag this fragility in the results as one caveat in their interpretation.

## 4 Discussion

We make two contributions in this paper. First, we develop a new, real-stakes and theory-guided measure of district-level universalism that improves on previous measures based on unincentivized surveys. Second, while correlational in nature, our results help to make sense of the large heterogeneity in political outcomes across space, such as the make-up of the U.S. Congress and the voting behavior and speeches of elected Representatives. This geographic variation is widely discussed in popular discourse, but economic variables alone have not been very successful in explaining this spatial heterogeneity. We have shown that variation in universalism (descriptively) explains more than 20% of the variation in vote shares and DW-NOMINATE scores across districts. Our findings thus suggest that a considerable fraction of the geographic political divide may result from disagreement over universalist versus particularist moral ideals.

## Tables and Figures

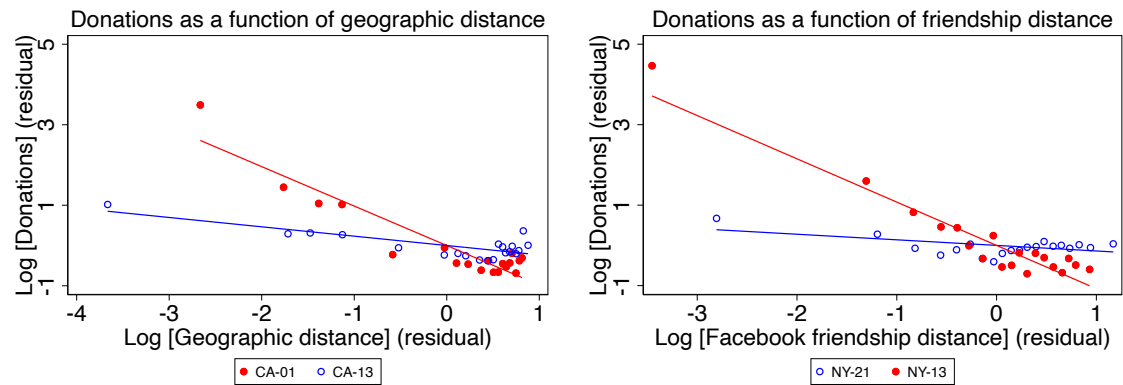


Figure 1: Donations as a function of distance. In the left panel, we illustrate regression equation (1) for two example districts. In the right panel, we show the analogous pattern for a second pair of districts, using Facebook friendship distance. Following equation (1), all variables are residualized of donor and recipient district fixed effects.



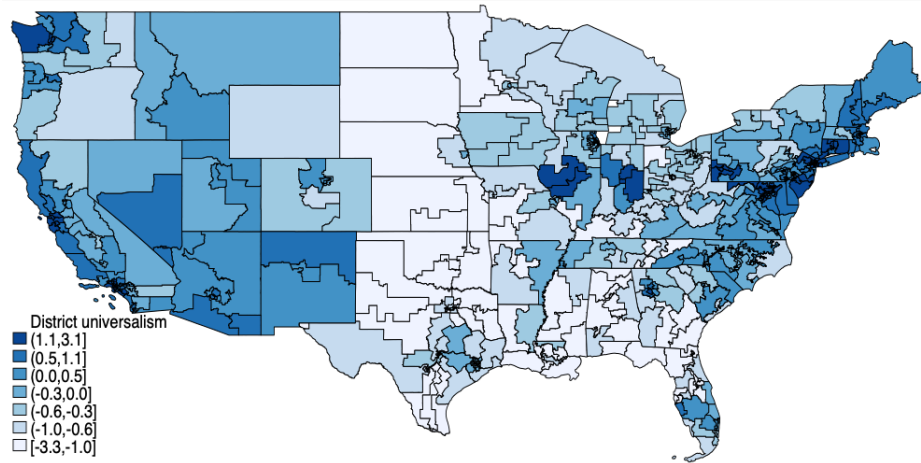


Figure 2: District-level map of composite universalism, computed as the z-score of the average of universalism with respect to geographic and friendship distance.

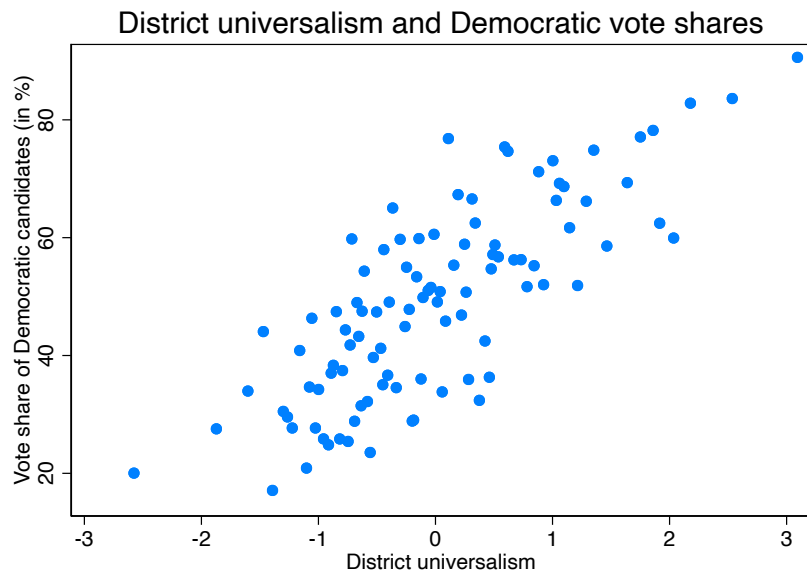


Figure 3: Binned scatter plot of district universalism and summed two-party vote shares of Democratic candidates in U.S. House general elections for the 113th and 114th Congresses.

Table 1: Descriptive statistics

	Mean	Std. Dev.	Blue Mean	Red Mean
<i>DonorsChoose donations, 2000-2016 (thousands)</i>				
Total donated	697.69	2204.90	971.30	346.73
Number of donations	9.07	19.21	11.71	5.68
Number of donors	2.90	1.54	3.34	2.34
Total received	697.69	657.08	835.36	521.11
Number of donations received	9.07	6.94	10.54	7.18
Number of projects	2.76	2.20	3.11	2.30
<i>IRS donations, 2011-2015 (millions)</i>				
Total donations	2502.70	1545.87	2675.96	2280.45
Number of donors	0.50	0.19	0.56	0.42
Total received	3892.03	7057.69	5304.04	2080.80
Total received (education, excl. universities)	524.83	808.43	670.54	337.93
<i>113th House political variables, 2012-2014</i>				
Democratic candidate(s) vote share (%)	48.19	21.94	59.83	33.31
Representative ideology (DW-NOMINATE)	0.08	0.45	-0.20	0.45
Representative speech universalism	0	1	0.16	-0.21
<i>114th House political variables, 2014-2016</i>				
Democratic candidate(s) vote share (%)	44.97	23.98	57.06	29.52
Representative ideology (DW-NOMINATE)	0.10	0.45	-0.18	0.47
Representative speech universalism	0	1	0.15	-0.19
<i>District universalism variables</i>				
District universalism	0	1	0.38	-0.49
District universalism (geographic distance only)	0	1	0.39	-0.50
District universalism (friendship distance only)	0	1	0.33	-0.42
Observations	436		245	191

*Notes.* Summary statistics for main variables used in analysis. Each observation is a Congressional District, and we compute means (and standard deviations) across these districts. The two rightmost columns show summary statistics for “blue” and “red” districts, as defined by vote shares in the 2012 presidential election. Top panel shows data for *DonorsChoose* donations, and second panel shows IRS donations data for comparison. District universalism is computed following equation (1).

Table 2: District universalism and outcomes

	<i>Dependent variable:</i>							
	Dem candidates vote share		Legislator DW-NOMINATE score			Speech universalism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
District universalism	12.8** (0.94)	5.50*** (1.50)	-0.21*** (0.02)	-0.071*** (0.02)	-0.019* (0.01)	0.22*** (0.03)	0.20*** (0.06)	0.18** (0.09)
Log [Median household income]		-22.8*** (5.90)		0.47*** (0.11)	0.14*** (0.05)		-1.10*** (0.39)	-0.97** (0.42)
Share of population with college degree		23.7 (14.40)		-0.81*** (0.26)	-0.22** (0.11)		1.75** (0.78)	1.59* (0.83)
Share pop. White		-84.1*** (6.25)		1.14*** (0.10)	0.23*** (0.05)		0.16 (0.36)	0.93** (0.41)
Latitude		0.0039 (0.77)		-0.025*** (0.00)	0.0048 (0.01)		0.024** (0.01)	0.049 (0.03)
Log [Distance to coast]		-2.28*** (0.76)		0.057*** (0.01)	-0.0021 (0.01)		-0.024 (0.04)	-0.0060 (0.05)
Longitude		-1.61*** (0.59)		0.0027** (0.00)	0.0019 (0.00)		-0.0052* (0.00)	0.021 (0.03)
1 if Democrat					-0.79*** (0.02)			0.68*** (0.12)
Obama 2012 vote share								-0.0038 (0.01)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	No	No	Yes
Observations	870	870	870	870	870	870	870	870
R <sup>2</sup>	0.26	0.60	0.22	0.44	0.94	0.09	0.13	0.29

Notes. Columns (1)–(5) are OLS estimates and columns (6)–(8) WLS estimates, weighted by word count. Robust standard errors (clustered at district level) in parentheses. Dependent variables are for the 113th and 114th Congresses. Democratic vote shares are two-party vote shares. Speech universalism is a z-score. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

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# ONLINE APPENDIX

## A Additional Figures

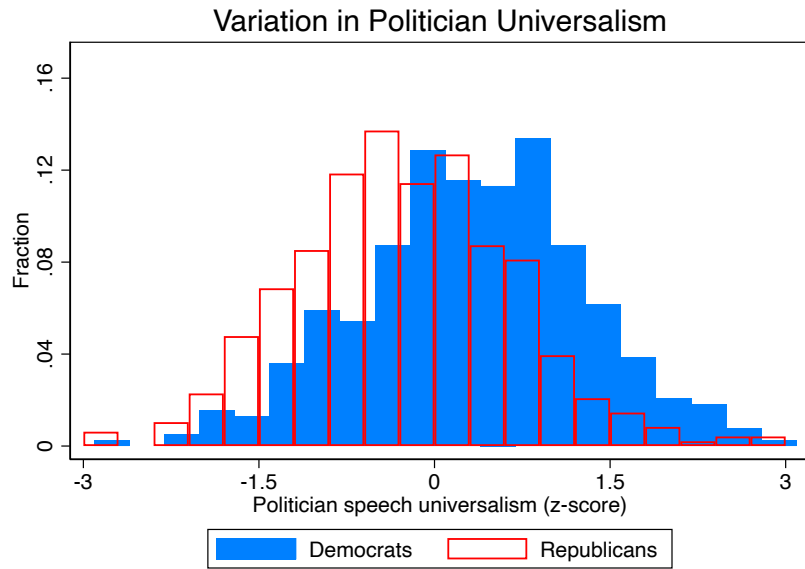


Figure 4: Variation in politician universalism in speeches in the House of Representatives. Data are win-sorized at  $\pm 3$  for readability.



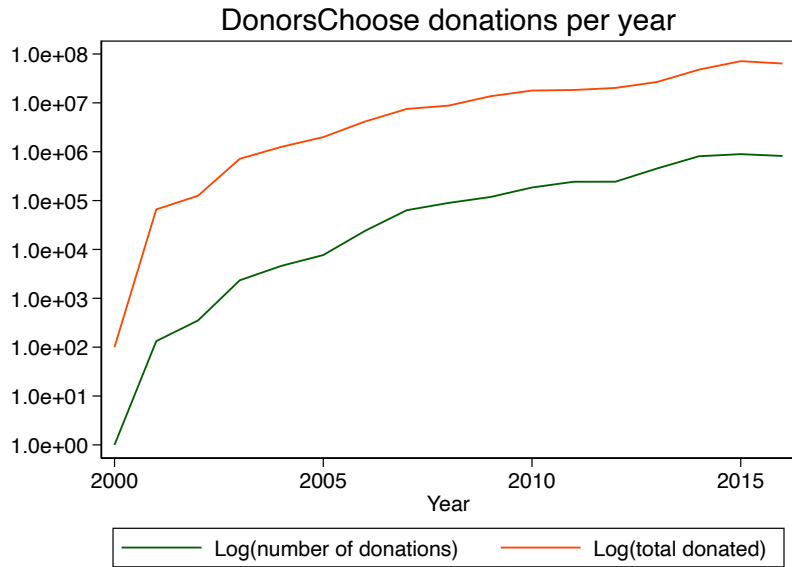


Figure 5: Donations through the *DonorsChoose* platform per year.

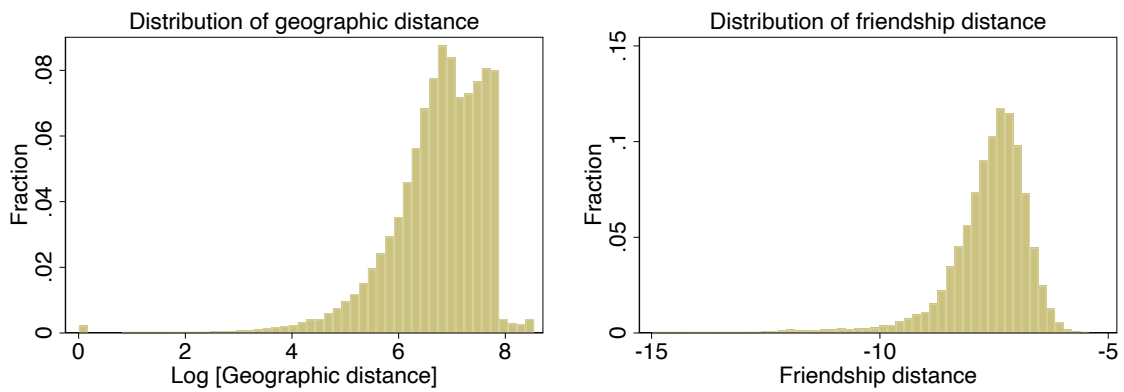


Figure 6: Histogram of the distance between congressional districts. The left panel shows the distribution of log geographic distance, and the right hand panel shows the distribution of friendship distance.

## **B Additional Tables**

Table 3: Robustness checks, part 1

	<i>Dependent variable:</i>							
	Dem candidates vote share		Legislator DW-NOMINATE score			Speech universalism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A</i>								
District universalism (geographic distance)	10.5*** (0.86)	6.47*** (1.04)	-0.20*** (0.02)	-0.071*** (0.02)	-0.016* (0.01)	0.22*** (0.04)	0.19*** (0.05)	0.15*** (0.05)
<i>Panel B</i>								
District universalism (friendship distance)	9.96*** (0.92)	3.94*** (1.06)	-0.20*** (0.02)	-0.050** (0.02)	-0.016** (0.01)	0.21*** (0.04)	0.15** (0.07)	0.16** (0.07)
<i>Panel C</i>								
District universalism (binarized geo. distance)	10.0*** (0.82)	5.92*** (1.32)	-0.19*** (0.02)	-0.077*** (0.02)	-0.025*** (0.01)	0.15** (0.06)	0.15** (0.07)	0.11 (0.07)
<i>Panel D</i>								
District universalism (geo., excl. same state)	9.13*** (0.95)	5.92*** (1.01)	-0.17*** (0.02)	-0.086*** (0.02)	-0.014* (0.01)	0.20*** (0.05)	0.15*** (0.05)	0.10* (0.05)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base controls	No	Yes	No	Yes	Yes	No	Yes	Yes
Democrat dummy	No	No	No	No	Yes	No	No	Yes
Observations	870	870	870	870	870	870	870	870

Notes. Columns (1)–(5) are OLS estimates and columns (6)–(8) WLS estimates, weighted by word count. Robust standard errors (clustered at the district level) in parentheses. Dependent variables are for the 113th and 114th Congresses. Each panel corresponds to a different regression. In panel A, the independent variable is district universalism computed based on geographic distance and in panel B it is computed based on friendship distance. In panel C, geographic distance is binarized based on a cutoff of 50 miles (80 km). Panel D restricts attention to geographic-based universalism using out-of-state donations. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 4: Robustness checks, part 2

	<i>Dependent variable:</i>							
	Dem candidates vote share		Legislator DW-NOMINATE score			Speech universalism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A</i>								
District universalism (high poverty donations sample)	11.1*** (0.89)	6.08*** (1.14)	-0.21*** (0.02)	-0.068*** (0.02)	-0.018** (0.01)	0.22*** (0.04)	0.21*** (0.06)	0.19*** (0.06)
<i>Panel B</i>								
District universalism (pre-114th Congress donations sample)	10.2*** (1.03)	4.49*** (1.20)	-0.20*** (0.02)	-0.041* (0.02)	-0.011 (0.01)	0.25*** (0.06)	0.13** (0.07)	0.11* (0.06)
<i>Panel C</i>								
District universalism (no matched donations sample)	10.7*** (0.91)	5.50*** (1.12)	-0.21*** (0.02)	-0.062*** (0.02)	-0.017** (0.01)	0.22*** (0.04)	0.19*** (0.06)	0.17*** (0.06)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Base controls	No	Yes	No	Yes	Yes	No	Yes	Yes
Democrat dummy	No	No	No	No	Yes	No	No	Yes

*Notes.* Columns (1)–(5) are OLS estimates and columns (6)–(8) WLS estimates, weighted by word count. Robust standard errors (clustered at the district level) in parentheses. Dependent variables are for the 113th and 114th Congresses, except for Panel B. Each panel corresponds to a different regression. Panel A restricts attention high poverty schools. Panel B restricts attention to donations made before the 114th Congress, and dependent variables for the 114th Congress. Panel C excludes donations that have matching funds available. The number of observations is 870 for Panels A and C, and 435 for Panel B.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## C Background on DonorsChoose

### C.1 Visual layout and functionality of the DonorsChoose platform

We ensure our results are not artifacts of the layout or functionality of the DonorsChoose website. To do so, we examined all available screenshots of the platform's layout and functionality since its inception.

Throughout the relevant time period, it is *not* the case that projects are sorted by closest proximity to each donor on the website. Instead, for a significant portion of our sample period, the default sort for projects on the platform was by urgency, which DonorsChoose defines as a combination of the lowest cost to complete, highest economic need, and fewest days left to expiration of the project.

The website's layout also does not vary across space. That is, to the best of our knowledge, at any given time all donors observe the same platform layout regardless of location, and given the default sort, they observe exactly the same projects when they first arrive at the platform. Below, we present a screenshot of the DonorsChoose platform as accessed in June 2019. (The reader may note that one of the projects includes matching funds from Google.org. Approximately 10 percent of listings include such matches; our results are virtually identical if we omit these listings; see Panel C of Table 4.)

Throughout our sample period, the options available to filter and sort projects were constant. Most importantly, the ability to search through and filter projects based on location was and continues to be a salient (usually the highest) option available on the screen. This feature makes a donor's selection of a project based on geography particularly straightforward, and potentially enhances the case for our claim that geographic distance is a relevant metric employed by donors in selecting projects.

### C.2 Additional Notes on Methodology

**Data Cleaning.** Our raw data consist of 6,211,940 individual donations made between March 2000 and October 2016. Beginning in 2007, donations are made to projects in all states in the United States plus the District of Columbia.

In addition to dropping observations with missing geographic or donation data, we exclude donations in which either the donor or the recipient school is located outside of the 50 states and the District of Columbia.

**Aggregation to Congressional District level.** ZIP codes provided in the DonorsChoose data were used to map donors and projects to their respective congressional districts. Note that for reasons of anonymity, donor ZIP codes were truncated at the first three

DonorsChoose.org Find a classroom to support About us Help Sign in

Search topics, teachers & schools near city, state, or zip Search

53,184 projects sorted by most urgent

**SUBJECT**

- Applied Learning
- Health & Sports
- History & Civics
- Literacy & Language
- Math & Science
- Music & The Arts
- Special Needs
- Warmth, Care & Hunger

**SHOW ONLY**

- Match offers
- Never before funded teachers
- Projects with no donations
- More than half of students from low-income households
- Fully funded projects
- Rural schools

**AGE GROUP**

- Grades PreK-2
- Grades 3-5
- Grades 6-8
- Grades 9-12


**REQUESTS FOR**

- Art Supplies
- Books
- Classroom Basics
- Computers & Tablets
- Educational Kits & Games
- Flexible Seating
- Food, Clothing & Hygiene
- Instructional Technology
- Lab Equipment
- Musical Instruments
- Reading Nooks, Desks & Storage
- Sports & Exercise Equipment
- Trips
- Visitors

**PROJECT TYPE**

- Classroom projects
- Professional development

**A Cozy, Comfortable, Reading Corner**




"Help me give my students a warm and cozy classroom reading corner where they can go to sit comfortably and read quietly."

**Mrs. Holcomb**  
Loma Rica Elementary School • Marysville, CA

13 DONORS SO FAR  
~~\$125~~ STILL NEEDED  
\$63 FOR NOW

2X Donations to this project are currently matched, thanks to Google.org.

**Let's Get It Started: Back to School Tools**

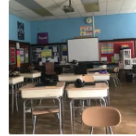


"Help me give my students a stocked classroom with necessary tools to enhance learning."

**Mrs. McDaniel**  
Saks Elementary School • Anniston, AL

13 DONORS SO FAR  
\$82 STILL NEEDED

**Help us Be More Organized**




"Help me give my students a way to organize their materials as we move away from desks and to tables in our classroom"

**Mr. Consaul**  
Nathaniel Hawthorne School 25 • Rochester, NY

8 DONORS SO FAR  
\$73 STILL NEEDED

**I See Me and I See You!**




"Help me give my students a variety of mirror books (reflection of their own identity & culture) and window books (allows students to see other cultures) for our classroom library!"

**Ms. Brown**  
Moulton Elementary School • Des Moines, IA

11 DONORS SO FAR  
~~\$28~~ STILL NEEDED  
\$14 FOR NOW

2X Donations to this project are currently matched, thanks to Google.org.

**Seating for All!**




"Help me give my students a colorful, organized meeting area and bouncy bands to help them focus!"

**Mrs. Correa**  
LEAD Elementary School • San Mateo, CA

13 DONORS SO FAR  
\$80 STILL NEEDED

**Hands-On Learning!**



"Help me give my students more manipulatives (table toys) to help them practice a wide variety of

11 DONORS SO FAR

Figure 7: Screenshot of DonorsChoose platform in June 2019. Note the ability to search for projects near any given geographical location at the top of the page, the options available to the donor with which to filter projects, and the “Double Your Impact” promotion applied to the topmost project presented. Additional options available with which to filter projects included the project’s target age group, request type (e.g., art supplies, books, classroom basics, etc.), project type (classroom projects or professional development), and buckets for amount needed (\$50 and under, \$100 and under, etc.).

digits, which added a layer of uncertainty to congressional district (CD) mappings, beyond the usual fuzziness of ZIP-to-CD mappings. Thus, through data provided by the United States Census Bureau, every donation was first mapped to the area formed by all possible *full* ZIP codes corresponding to the truncated ZIP code from DonorsChoose, and then in turn to a given CD based on all congressional districts overlap with that area. Because this mapping is not one-to-one, when aggregating donations to relevant source CDs, all observations were weighted by the degree of a fuzzy match to relevant CDs. For example, if based on the provided ZIP code a donation could have originated from either MA-2 or MA-3, this donation would appear twice in our merged data once all donations were mapped to donor congressional districts. In turn, each of these two observations would then be weighted by the share of the 3-digit ZIP code area population in each of these congressional districts when aggregating donation statistics by pairs of donor and recipient CDs. An analogous aggregation procedure was used for other variables in our analysis which were not provided at the CD level.

### C.2.1 Social Distance Data

Data on the social connectedness and the “relative probability of friendship” between pairs of counties in the United States was obtained from Facebook. The construction of these data is covered in Bailey et al. (2018). The Social Connectedness Index (SCI) reflects the aggregate number of Facebook friendship links within or between counties. The “relative probability of friendship” normalizes for county populations by dividing the SCI by the product of the number of Facebook users in each of the two counties.

We aggregate this “relative probability of friendship” data to the congressional district level by using the aggregation procedure described in Bailey et al. (2021). Since mappings from county to congressional district are not one-to-one, the aggregation from county to this geographic level accounts for the possibility of a fuzzy match, by weighting observations by the share of the county population in each possible congressional district that a given county could map to.

This aggregation from county-pair SCIs and relative probabilities of friendship forms our measure of “friendship distance.”. Specifically, we define the social distance between a donor in geographic entity  $i$  and a recipient in a geographic entity  $j$  of the same level as  $-\ln(\text{rel. prob. of friendship}_{i,j})$ .

## D Most common eMFD words in Congressional speeches data

Table 5: 20 most frequent eMFD words in congressional speeches

Ranking	Term	Frequency
1	people	114479
2	time	99601
3	president	99435
4	speaker	86166
5	going	64816
6	work	61930
7	states	60363
8	country	58531
9	want	57966
10	act	56262
11	senator	53195
12	know	51902
13	support	51841
14	house	51201
15	need	50814
16	state	50044
17	committee	48681
18	new	48471
19	government	48054
20	think	47174