

UNIVERSALISM AND POLITICAL REPRESENTATION: EVIDENCE FROM THE FIELD^{*}

Benjamin Enke

Raymond Fisman

Luis Mota Freitas

Steven Sun

May 12, 2023

Abstract

This paper provides field evidence on the link between morals and political behavior. We develop a theory-guided real-stakes measure of each U.S. district's values on the universalism-particularism continuum, which reflects the degree to which charitable giving decreases as a function of social distance. District universalism is strongly predictive of local Democratic vote shares, legislators' roll-call voting, and the moral content of Congressional speeches. These results hold in both across- and within-party analyses. Overall, spatial heterogeneity in universalism is a substantially stronger predictor of geographic variation in political outcomes than traditional economic variables such as income or education.

^{*}Enke: Harvard University and NBER; enke@fas.harvard.edu. Fisman: Boston University; rfisman@bu.edu. Freitas: Global Priorities Institute, University of Oxford; luis.motafreitas@economics.ox.ac.uk. Sun: Harvard College; stevensun@college.harvard.edu.

1 Introduction

This paper presents field evidence suggesting tight links between political outcomes and spatial variation in the electorate’s values along the moral 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 these divisions. Among the candidate explanations is heterogeneity in moral orientation, which in turn has led to efforts to develop frameworks to understand and measure the values that might underlie social and moral disagreement. One prominent approach has focused on differences in universalist versus particularist orientation. A particularist or communal morality emphasizes relationship-specific obligations (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 entirely survey-based. Most commonly, researchers link 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. As highlighted by Levitt and List (2007), to the extent that lab and naturally-occurring environments differ on dimensions such as observability and contextual cues, there is no strong a priori reason to expect a tight connection between decisions in surveys (or experiments) and ecological behavior. For instance, in our context one concern is that the heterogeneity in universalism present in surveys does not necessarily reflect variation in deep values but rather heterogeneity in virtue signaling. Similarly, people may “reverse engineer” their stated values in surveys and experiments to comply with what they perceive to be the party line (Hatemi et al., 2019).

In this paper, we study the link between moral universalism and political behavior by focusing exclusively on real-stakes decisions. We develop a new measure of district-level universalism that is (i) 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 using 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 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 the geographic distance to the recipient. Importantly, we only leverage variation in *to whom* the population in a given district donates, 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 and only focuses on the slope of giving as a function of distance. Thus, for example, our measure does not depend on how close people live to schools that are more needy.

While geographic distance is a natural proxy for the “social distance” formalized in theoretical models of universalism, it has the drawback that it does not capture other aspects of distance and familiarity. For example, residents of districts with high geographic mobility may donate more to distant schools because they have previously lived in the recipient area. We thus leverage as a comprehensive summary measure of social distance the Facebook friendship distance between two districts (Bailey et al., 2018). We think of this measure as a rich proxy for social distance that incorporates elements of geographic, ethnic, political, religious, income and educational distance. When defined based on friendship distance, 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. Hence, we combine the two indices into a summary measure of district universalism. We use this spatial measure to shed light on 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. In contrast to previous work on universalism, we seek to explain not only across- but also within-party variation in roll-call voting and political language.

The spatial heterogeneity in political outcomes that we study has attracted consider-

able public attention because it is seen as contributing to political gridlock and affective polarization. Focusing on U.S. House races in particular entails the significant practical advantage that we can analyze a large number of races, unlike prior research on universalism that has focused on studying a few specific case studies (in particular, recent presidential elections; Enke, 2020).

We consider three outcomes: (a) local vote shares, (b) DW-NOMINATE scores of elected representatives, and (c) the universalism of these representatives. DW-NOMINATE scores measure the ideological position of congress members, based on their roll-call voting behavior. To quantify politician universalism, we apply the extended Moral Foundations Dictionary (Hopp et al., 2021) to speeches in Congress and campaign tweets in U.S. House races.

We find that district-level universalism is highly predictive of 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 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 predictive of the behaviors of elected House members. That is, legislators from more universalist districts have more left-leaning DW-NOMINATE scores. Moreover, universalism is significantly correlated with roll-call voting 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.

To better understand the mechanisms behind the link between district universalism and electoral outcomes, we examine whether universalist districts elect more universalist legislators. 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 substantially more predictive of a legislator’s speech universalism than the district’s average Democratic vote share. This finding strongly suggests that district universalism exerts an independent effect on representatives’ behavior that goes beyond partisanship.

In our final set of results, we provide some exploratory analyses to shed light on why universalist districts have more universalist representatives. There are two primary margins of selection: (i) more universalist candidates run in more universalist districts; and (ii) conditional on the set of candidates, more universalist districts elect more uni-

versalist candidates. We cannot evaluate these two possibilities using the congressional speech data, since it includes only election winners. To measure the universalism of all candidates, we extract and analyze the language used in the campaign tweets of the near-universe of candidates in the 2022 U.S. House general elections. We find that district universalism is strongly predictive of tweet universalism within the set of election winners, but not so in the set of election losers. This suggests that the main margin of selection is that more universalist districts elect more universalist candidates.

Contribution and related literature. We provide the first evidence derived from field data on the link between universalism and voting. Enke (2020) studies across-county variation in vote shares in presidential elections but relies on a hypothetical psychological questionnaire to quantify universalism. Moreover, in contrast to previous work, our focus is on documenting, across a large number of races, that universalism explains not only across- but also within-party variation in outcomes. In doing so, we also link to work on representation that studies the district-level link between voter policy preferences and outcomes (Tausanovitch and Warshaw, 2013). This work shows that districts in which people hold more left-wing policy views (e.g., on redistribution or immigration) have higher Democratic vote shares. Our paper adds to this literature by studying the values (or utility functions) that underlie differences in policy views, ideology and voting, rather than taking policy views as primitives.

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. This intuitively resonates with the fact that many policy debates reflect what appear to be different views on one’s moral boundaries. 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.

In this spirit, our work also connects to the literature that has linked experimental or survey measures of social preferences such as inequality aversion or equity-efficiency preferences to political views (e.g. Fisman et al., 2017; Kerschbamer and Müller, 2020; Epper et al., 2020). Consistent with individual-level survey evidence (Enke et al., 2022; Cappelen et al., 2022), we highlight that a key component of cross-partisan differences is not only heterogeneity in how people view “self versus other” tradeoffs, but instead the slope of prosociality as a function of social distance (“us versus them”).

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.¹

2.1 Estimating District Universalism

Data. We propose a new economic (real-stakes) 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 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. Appendix C.2 reports summary statistics. Overall, our data include about 4 million donations worth approximately \$305 million. The mean number of donations per district in our final dataset is 9,068 (median of 6,133).

Empirical Approach. Our universalism measure captures how a district’s donations to another district change as a function of distance. For this analysis, we aggregate indi-

¹We 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.

vidual donation data to the district level and construct a dyadic dataset comprised of all possible donor-recipient district pairs. Appendix C.3 provides details on the matching methodology used. In this dyadic dataset, the donation amount in each cell is computed from 21 donations, on average.

We estimate a district’s universalism as (the negative of) the extent to which donations from a given donor district decline as a function of distance. The left panel of Figure 1 illustrates this approach for two donor districts 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 θ_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 universalism, θ_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 universalism is not mechanically lower in districts that are poorer or have less well-equipped schools.

To address concerns of measurement error in the estimation of district-level universalism, θ_x , we shrink these coefficients to the sample mean by their signal-to-noise ratio; see Appendix C.3.1. Universalism is measured very precisely at the district level due to the large underlying sample of donations, so the shrinkage does not meaningfully impact our results – the correlation between the raw and shrunk measures is $r > 0.99$.

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 with respect to a more encompassing proxy for social distance.

To generate a proxy for social distance, we use friendship distance as constructed from Facebook data by Bailey et al. (2018). 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 $-\log(SCI)$ as our measure of distance.

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. In working with this measure, universalism captures that giving depends less on friendship distance. In other words, compared to a universalist district, a particularist district gives relatively more to places where people have many friends, and less to places where they have fewer friends. Loosely speaking, heterogeneity in universalism with respect to friendship distance captures that people in some (particularist) districts show more favorable treatment toward regions where they have many friends, while people in other (universalist) districts treat regions with many friends or strangers equally well.

The measure of friendship distance is attractive for various reasons. First, as noted above, districts may differ in their geographic distribution of social ties. Second, districts are unevenly distributed across space – for example, those along the coast will, by definition, have a larger geographic distance to some districts than those in the Midwest. The friendship distance measure takes this into account because (unlike geographic distance) the SCI measure is naturally bounded by $[0, 1]$.

The right panel of Figure 1 shows an illustration 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.

Universalism computed with respect to geographic and friendship distance are highly correlated ($r = 0.73$). We aggregate the geographic-based and the friendship-based universalism measures into a composite measure by computing the z-score of the average

of the two z-scores. 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, though we note that some of them may be seen as bad controls.

To quantify geographic variation in universalism, previous work has relied on the Moral Foundations Questionnaire (Graham et al., 2013; Haidt, 2012). The universalism measure constructed by Enke (2020) exhibits a correlation of $r = 0.52$ with our measure. Taking into account measurement error, this suggests that these two measures plausibly capture the same underlying concept, though 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). It 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” prescribed by Moral Foundations Theory (Haidt, 2012; Graham et al., 2017) that can be aggregated into the particularism-universalism distinction (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.²

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.³ The relative frequency of universalist language in a given text is then given by:

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

We calculate this statistic at the level of a text and then average at the politician level. Because this index is more precisely estimated for some politicians than for others (some give longer and more frequent speeches than others), we apply a standard Bayesian shrinkage to this raw index and shrink it to the sample mean using an observation's signal-to-noise ratio, using a method that is identical to the approach we use to shrink district universalism to the sample mean (see Appendix C.3.1).

We apply this procedure to two corpuses of political text: congressional speeches and campaign tweets. These two datasets serve different purposes. Congressional speeches allows us to link a district's universalism to legislators' behavior in the policy-making process. By construction, however, this dataset only allows us to estimate the universalism of House race winners. Campaign tweets, by contrast, allow us to analyze all candidates in a race.

Appendix Table 8 provides an overview of the most frequently used moral target words in the eMFD that appear in the two datasets.

The measure of candidate universalism derived using this procedure is noticeably distinct from standard ways of quantifying partisan speech. For example, in the Congressional speeches data described below, the correlation between candidate universalism and the score of partisanship developed in Gentzkow et al. (2019) is $r = 0.20$.

Congressional speeches. 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 Congress. 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.

For each of these legislators, we compute the relative frequency of universalist lan-

²Universalist "foundations" are care/harm and fairness/cheating, and particularist foundations are loyalty/betrayal and authority/subversion.

³Throughout, we compute text universalism after removing stop words—frequent words that convey little content.

guage, averaged across all days on which the legislator spoke.⁴ Appendix Figure 5 shows a histogram of politician-level universalism, separately by party. Two main patterns emerge. First, Democrats are more universalist, on average. Second, there is also large within-party variation in speech universalism.

Campaign tweets. To quantify the moral content of politicians’ campaign messaging, we rely on their tweets because the vast majority of candidates in U.S. House races in recent years have made use of Twitter. Because Twitter’s Academic API only allows researchers to access the most recent 3,200 Tweets of each user, we focus on the 2022 House races. As a result, we do not necessarily observe the same candidates both on Twitter and in the Congressional speeches dataset.

Candidate Twitter handles were pulled manually using the Google search engine and Ballotpedia, a U.S. politics website where candidates often provide links to their Twitter accounts. Out of 1,056 candidates in the 2022 U.S. House elections, we obtain Twitter handles for 865 of them. Out of the 853 Democrats and Republicans candidates, we obtain Twitter handles for 796. Missing candidates are almost always those with very small vote shares. Tweets were scraped on four separate occasions: November 26th, 2022, December 26th, 2022, February 18th, 2023, and March 22nd, 2023. We clean the text by removing mentions (for example, @RepAOC), links, numbers, emojis, and stop words. We then remove tweets that have no words, such as tweets that are only links or pictures. The resulting dataset consists of 2,471,613 tweets, including 1,344,595 tweets from 400 Democrats and 1,035,948 tweets from 396 Republicans.

There are two types of Twitter accounts: “campaign” accounts and “official” accounts; the latter are limited to current representatives, usually incumbents. Out of 865 candidates with at least one Twitter account, 503 only have a campaign account, 24 only have an official account and 338 have both. To avoid a loss of data, we compute the universalism index described above separately for each account type and then average the z-scores of these two measures to arrive at a summary measure for each politician. In those cases in which only one account type is used, we use the universalism index from that account. All results discussed below are robust to working only with campaign accounts.

Appendix Figure 5 shows a histogram of politicians’ tweet universalism. Again, Democrats are more universalist, on average. Because the Twitter data include both election winners and losers, this pattern illustrates that the average cross-party differences in the

⁴Whenever a legislator was replaced during a congress, we aggregated 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.

congressional speeches data (for which we only observed the winners) do not just reflect differences in “selection” but also underlying across-party differences.

Finally, because the Twitter data are for the 118th Congress (rather than the 113th and 114th, as in the analyses described above), we must account for redistricting in generating our district-level universalism measure. We thus produce a second district-level universalism index akin to the one in Figure 1, for the later district boundaries.

3 Results

3.1 District Universalism and Two-Party Vote Shares

We begin by analyzing what we refer to as the *congressional data*, which contains the two-party vote shares as well as the DW-NOMINATE score and the speech universalism of the district’s representative, for each district and Congress (113th and 114th).

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)–(3) of Table 1 provide corresponding regression analyses. The point estimate in the bivariate specification in column (1) implies that a one standard deviation increase in district universalism 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 and geography (see column (2)) and also state fixed-effects (column (3)).

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 by Enke (2020) (though this earlier work measured universalism based purely on survey responses rather than the theory-guided real-stakes measure we use). 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 (4)–(7) 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 (6) documents that this correlation continues to be statistically highly 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 (6)). We report these results because we believe that – as in the analyses of speeches reported below – they show that universalism is relevant for political outcomes above and beyond pure partisanship. At the same time, we highlight that controlling for the legislator's party affiliation is almost surely a bad control given that party membership and universalism are tightly linked. The relationship is similar in column (7) when we additionally control for state fixed effects (though only marginally significant).

Finally, we study whether universalist districts elect more universalist representatives, as proxied by the moral content of congressional speeches. This provides a more direct link between voter preferences and legislator behavior, and may also be less confounded by the party discipline that governs roll-call votes. Columns (8)–(11) of Table 1 present the results. We find a strong link 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 25% 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 (columns (10) and (11)). Furthermore, the results are even robust to controlling for a district's average Democratic vote shares in recent presidential elections, as a proxy for general partisanship. This correlation again suggests that universalism is relevant for both (i) understanding differences in partisanship and (ii) variation in outcomes *conditional* on partisanship.

Overall, we interpret the results in this section as strongly suggesting that a district's degree of universalism is relevant for understanding the large heterogeneity in the make-up of the U.S. Congress, including the nature of within-party variation in roll-call voting and Congressional speeches.

Robustness checks. A first concern given our research question is 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 Tables 2 and 3 document that the results in Table 1 are very similar when we measure universalism based on geographic distance or Facebook friendship distance, rather than our composite measure. The robustness check that uses Facebook friendship distance alone is particularly informative, because it shows that the results using geographic distance are not simply driven by the fact that Democratic districts have closer social connections to faraway places (e.g., due to migration).

Appendix Table 4 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 above.⁵

Finally, a potential concern 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 related concern is that there is across-district variation in how well-informed people are about their local neighborhood schools (or variation in how effective schools are at local fundraising). To address these concerns, we redo all analyses described above 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 5 shows that the results are very similar.

3.3 Why Do Universalist Districts Have Universalist Representatives?

Two different selection mechanisms could give rise to the link between district universalism and legislators’ universalism: (i) more universalist candidates might run in more universalist districts; and (ii) conditional on the set of candidates, more universalist districts might elect more universalist candidates. We cannot explore this distinction using congressional speech data because we only observe election winners.

To study potential selection mechanisms, we turn to an analysis of campaign tweets in 2022 House races. We look, in particular, at the relationship between candidate and district universalism for district winners versus losers.⁶ Intuitively, if selection operates

⁵We note that one coefficient of interest – on speech universalism – is no longer significant ($p < 0.14$) when we control for whether the legislator is a Democrat.

⁶An open question is whether politicians strategically target a district’s universalism. In the analyses above, we have treated a politician’s universalism – as reflected in speeches and tweets – as a fixed trait. However, it is conceivable that some or all of the use of specific moral language is strategic in nature. To explore this possibility, albeit in a suggestive manner, we consider variation in tweet universalism over time as Election Day approaches. The idea behind this test is that as the election gets closer, candidates should be more focused on convincing the median voter in their district than, for example, winning primaries.

through who selects to run ((i) above), then both winner and loser tweet universalism should be correlated with district universalism. If voters select more universalist candidates ((ii) above) then we expect a stronger relationship between candidate universalism and district universalism for winners relative to losers. Figure 4 shows the link between candidate and district universalism separately for winners and losers of House elections. In the sub-sample of winners there is a clear positive relationship ($r = 0.33$, $p < 0.01$), while this relationship is absent within the set of losers. In Appendix Table 6, we present regression results that confirm these relationships.

We do not wish to over-interpret the entire absence of a relationship in the set of losers, for two reasons. First, candidates who lost the primary elections of the winning party, who might be a more relevant set of losers, were not included in this analysis. Second, candidate universalism is substantially more noisily estimated in the Twitter data than in campaign speeches (tweets are shorter than speeches). However, we do take these results to suggest that the evidence favors the second type of selection described above (universalist districts electing universalist candidates) rather than the selection of candidates into races.

4 Discussion

We make three 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, our results help to make sense of the large geographic 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.

This would suggest that, if moral language is partly strategic, we should see Democrats and Republicans converge to each other within each district. Appendix Figure 6 plots the average tweet universalism of all Republicans and Democrats, respectively, separately for each campaign month. In a within-district analysis, we see strong convergence in universalism for Democrats and Republicans over time. We interpret this result as indicative (though not definitive) evidence that variation in moral language reflects, at least in part, strategic considerations.

Tables and Figures

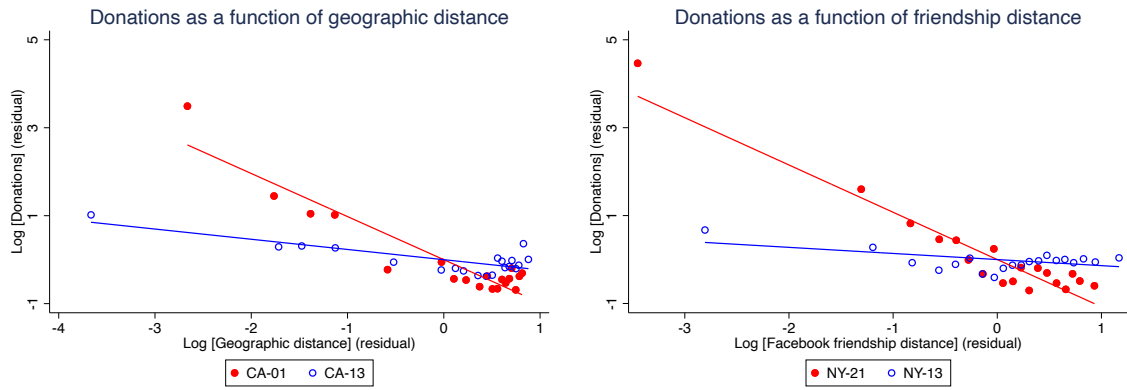


Figure 1: Donations as a function of distance. In the left panel, we illustrate regression equation (1) for two example districts. In the right panel, we show the analogous pattern for a second pair of districts, using Facebook friendship distance. All variables are residualized of donor and recipient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

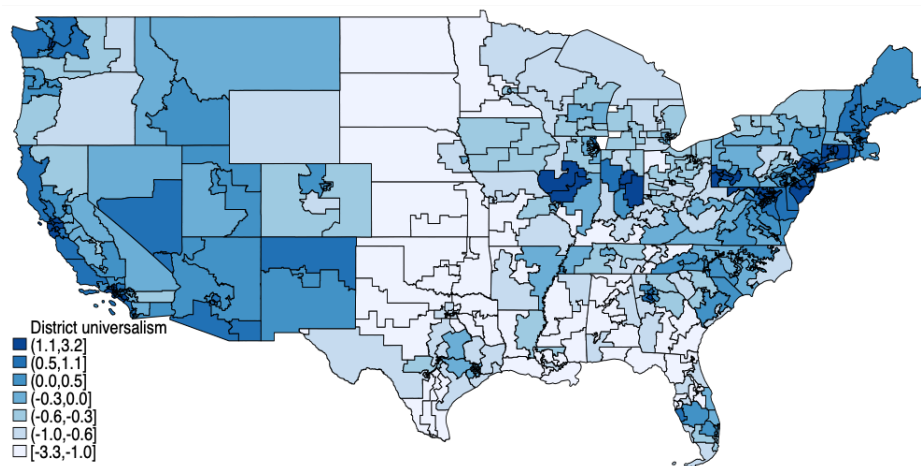


Figure 2: District-level map of composite universalism, computed as the z-score of the average of universalism with respect to geographic and friendship distance.

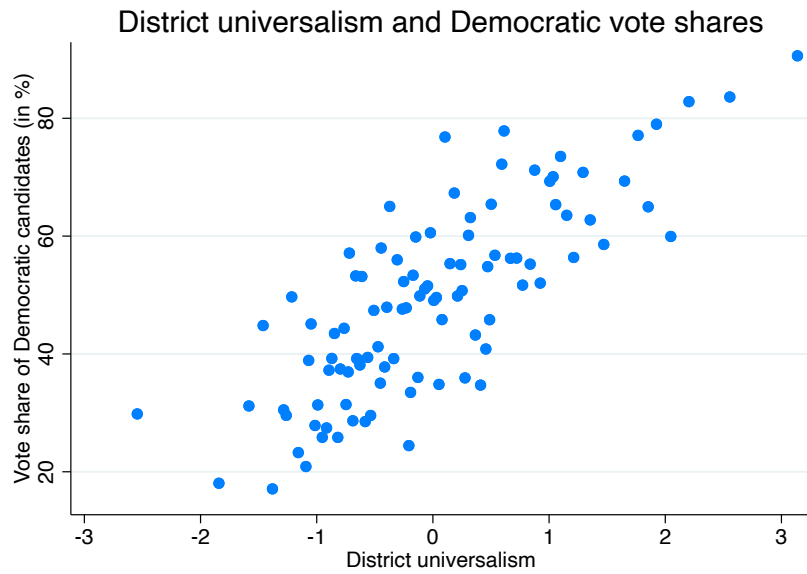


Figure 3: Binned scatter plot of district universalism and summed two-party vote shares of Democratic candidates in U.S. House general elections for the 113th and 114th Congress.

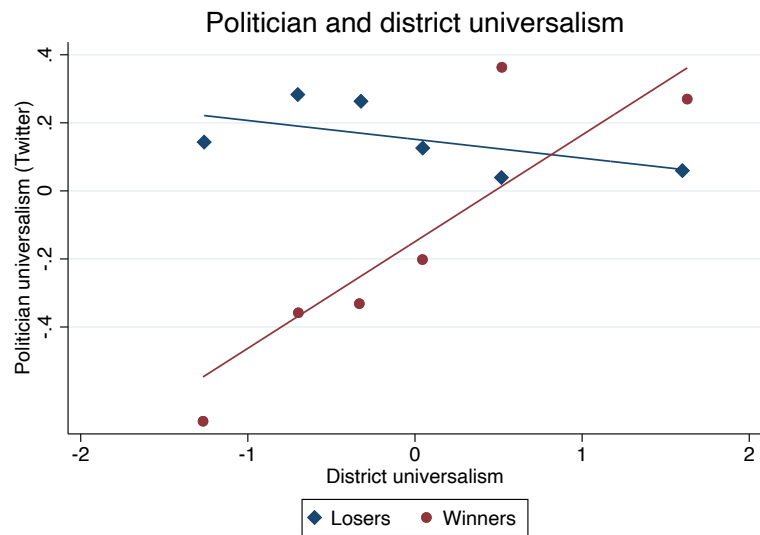


Figure 4: Politician and district universalism, separately for election winners and losers. The figure shows partial correlations that control for fixed effects for the number of candidates in each race. Data for 118th Congress.

Table 1: District universalism and outcomes (113th and 114th Congress)

	Dependent variable:										
	Dem candidates vote share			Legislator DW-NOMINATE score				Speech universalism			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
District universalism	12.8*** (0.94)	6.89*** (1.19)	5.44*** (1.50)	-0.21*** (0.02)	-0.070*** (0.02)	-0.019** (0.01)	-0.019* (0.01)	0.25*** (0.04)	0.22*** (0.07)	0.21*** (0.08)	0.23** (0.11)
Log [Median household income]		-26.0*** (5.40)	-22.8*** (5.90)		0.47*** (0.11)	0.13*** (0.04)	0.14*** (0.05)		-1.23*** (0.44)	-0.94** (0.46)	-1.13** (0.47)
Share of population with college degree		33.1** (13.61)	23.8* (14.40)		-0.81*** (0.26)	-0.16 (0.10)	-0.22** (0.11)		1.99** (0.88)	1.39 (0.98)	1.90* (0.98)
Share pop. White		-64.5*** (5.29)	-84.1*** (6.24)		1.14*** (0.10)	0.16*** (0.04)	0.23*** (0.05)		0.20 (0.41)	0.97** (0.48)	0.89 (0.56)
Latitude		0.92*** (0.22)	0.0011 (0.77)		-0.025*** (0.00)	-0.0070*** (0.00)	0.0048 (0.01)		0.027** (0.01)	0.0052 (0.01)	0.062 (0.04)
Log [Distance to coast]		-2.18*** (0.51)	-2.27*** (0.76)		0.057*** (0.01)	0.013*** (0.00)	-0.0021 (0.01)		-0.028 (0.04)	0.0092 (0.04)	-0.0094 (0.06)
Longitude		-0.060 (0.05)	-1.60*** (0.59)		0.0027** (0.00)	-0.000073 (0.00)	0.0019 (0.00)		-0.0059* (0.00)	-0.0045 (0.00)	0.020 (0.03)
House rep. democrat						-0.80*** (0.01)	-0.79*** (0.02)			0.74*** (0.17)	0.79*** (0.16)
Avg. Democratic vote share										-0.0027 (0.01)	-0.0070 (0.01)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Observations	870	870	870	870	870	870	870	866	866	866	866
R ²	0.26	0.47	0.60	0.22	0.44	0.93	0.94	0.09	0.14	0.21	0.30

Notes. Columns (1)–(6) are OLS estimates and columns (7)–(9) WLS estimates, weighted by word count. Robust standard errors (clustered at district level) in parentheses. Democratic vote shares are two-party vote shares. Speech universalism is a z-score. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

References

- Bailey, Michael, Abhinav Gupta, Sebastian Hillenbrand, Theresa Kuchler, Robert Richmond, and Johannes Stroebe**, “International Trade and Social Connectedness,” *Journal of International Economics*, March 2021, 129, 103418.
- , **Rachel Cao, Theresa Kuchler, Johannes Stroebe, and Arlene Wong**, “Social Connectedness: Measurement, Determinants, and Effects,” *Journal of Economic Perspectives*, 2018, 32 (3), 259–280.
- Cappelen, Alexander W, Benjamin Enke, and Bertil Tungodden**, “Moral universalism: Global evidence,” 2022.
- Chetty, Raj and Nathaniel Hendren**, “The impacts of neighborhoods on intergenerational mobility II: County-level estimates,” *The Quarterly Journal of Economics*, 2018, 133 (3), 1163–1228.
- Danieli, Oren, Noam Gidron, Shinnosuke Kikuchi, and Ro’ee Levy**, “Decomposing the Rise of the Populist Radical Right,” *Working Paper*, 2022.
- Enke, Benjamin**, “Kinship, cooperation, and the evolution of moral systems,” *The Quarterly Journal of Economics*, 2019, 134 (2), 953–1019.
- , “Moral values and voting,” *Journal of Political Economy*, 2020, 128 (10), 3679–3729.
- , **Ricardo Rodríguez-Padilla, and Florian Zimmermann**, “Moral Universalism and the Structure of Ideology,” *Review of Economic Studies*, 2022.
- Epper, Thomas, Ernst Fehr, and Julien Senn**, “Other-regarding preferences and redistributive politics,” Technical Report, Working Paper 2020.
- Fisman, Raymond, Pamela Jakiela, and Shachar Kariv**, “Distributional preferences and political behavior,” *Journal of Public Economics*, 2017, 155, 1–10.
- Gentzkow, Matthew, Jesse M Shapiro, and Matt Taddy**, “Measuring group differences in high-dimensional choices: method and application to congressional speech,” *Econometrica*, 2019, 87 (4), 1307–1340.
- Gethin, Amory, Clara Martínez-Toledano, and Thomas Piketty**, “Brahmin left versus merchant right: Changing political cleavages in 21 Western Democracies, 1948–2020,” *The Quarterly Journal of Economics*, 2022, 137 (1), 1–48.

- Graham, Jesse, Jonathan Haidt, and Brian A. Nosek**, “Liberals and Conservatives Rely on Different Sets of Moral Foundations,” *Journal of Personality and Social Psychology*, 2009, 96 (5), 1029.
- , —, **Matt Motyl, Peter Meindl, Carol Iskiwitch, and Marlon Mooijman**, “Moral Foundations Theory: On the Advantages of Moral Pluralism Over Moral Monism,” *Working Paper*, 2017.
- , —, **Sena Koleva, Matt Motyl, Ravi Iyer, Sean P. Wojcik, and Peter H. Ditto**, “Moral Foundations Theory: The Pragmatic Validity of Moral Pluralism,” *Advances in Experimental Social Psychology*, 2013, 47, 55.
- Guriev, Sergei and Elias Papaioannou**, “The political economy of populism,” 2020.
- Haidt, Jonathan**, *The Righteous Mind: Why Good People are Divided by Politics and Religion*, Vintage, 2012.
- Hatemi, Peter K, Charles Crabtree, and Kevin B Smith**, “Ideology justifies morality: Political beliefs predict moral foundations,” *American Journal of Political Science*, 2019, 63 (4), 788–806.
- Hopp, Frederic R, Jacob T Fisher, Devin Cornell, Richard Huskey, and René Weber**, “The extended Moral Foundations Dictionary (eMFD): Development and applications of a crowd-sourced approach to extracting moral intuitions from text,” *Behavior research methods*, 2021, 53, 232–246.
- Kerschbamer, Rudolf and Daniel Müller**, “Social preferences and political attitudes: An online experiment on a large heterogeneous sample,” *Journal of Public Economics*, 2020, 182, 104076.
- Kivikangas, J Matias, Belén Fernández-Castilla, Simo Järvelä, Niklas Ravaja, and Jan-Erik Lönnqvist**, “Moral foundations and political orientation: Systematic review and meta-analysis,” *Psychological Bulletin*, 2021, 147 (1), 55.
- Levitt, Steven D and John A List**, “What do laboratory experiments measuring social preferences reveal about the real world?,” *Journal of Economic perspectives*, 2007, 21 (2), 153–174.
- Meltzer, Allan H and Scott F Richard**, “A rational theory of the size of government,” *Journal of Political Economy*, 1981, 89 (5), 914–927.
- Tabellini, Guido**, “The Scope of Cooperation: Values and Incentives,” *Quarterly Journal of Economics*, 2008, 123 (3), 905–950.

Tausanovitch, Chris and Christopher Warshaw, “Measuring constituent policy preferences in congress, state legislatures, and cities,” *The Journal of Politics*, 2013, 75 (2), 330–342.

Waytz, Adam, Ravi Iyer, Liane Young, Jonathan Haidt, and Jesse Graham, “Ideological differences in the expanse of the moral circle,” *Nature Communications*, 2019, 10 (1), 1–12.

Yang, Yongzheng and Peixu Liu, “Are conservatives more charitable than liberals in the US? A meta-analysis of political ideology and charitable giving,” *Social Science Research*, 2021, 99, 102598.

ONLINE APPENDIX

A Additional Figures

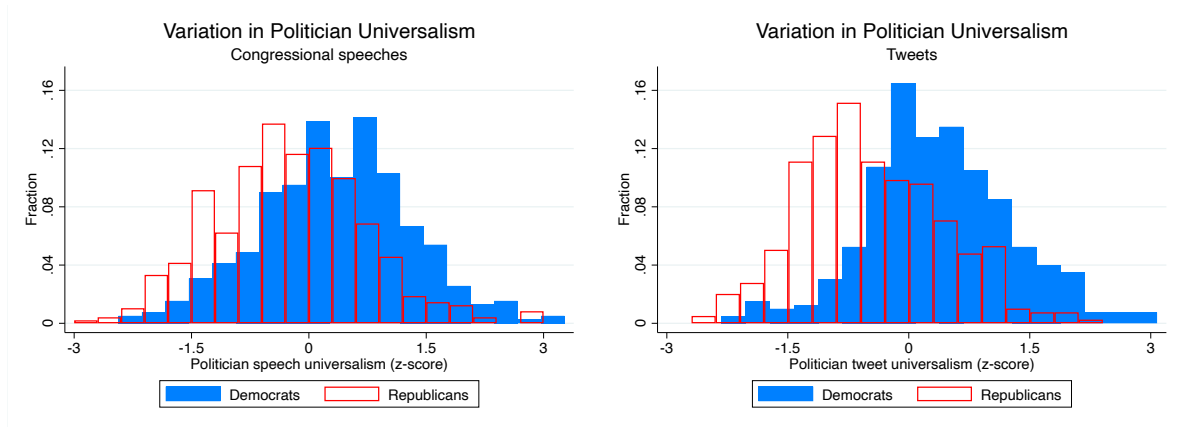


Figure 5: Variation in politician universalism in speeches in the House of Representatives (left panel) and candidate universalism in campaign tweets (right panel). Both panels are winsorized at ± 3 for ease of readability.

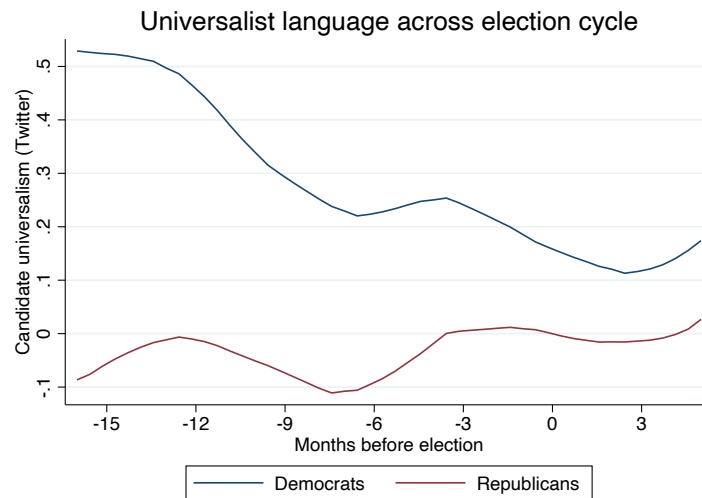


Figure 6: Cross-party differences in candidate universalism on Twitter as a function of proximity to the general election, net of district fixed effects.

B Additional Tables

Table 2: Robustness checks with universalism variable based on geographic distance (113th and 114th Congress)

	Dependent variable:							
	Dem candidates vote share		Legislator DW-NOMINATE score			Speech universalism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
District universalism (geographic distance)	10.5*** (0.86)	6.46*** (1.06)	-0.20*** (0.02)	-0.071*** (0.02)	-0.016* (0.01)	0.25*** (0.04)	0.21*** (0.06)	0.17*** (0.06)
Log [Median household income]		-22.9*** (5.36)		0.48*** (0.10)	0.13*** (0.04)		-1.28*** (0.45)	-0.97*** (0.47)
Share of population with college degree		30.3** (12.84)		-0.85*** (0.25)	-0.17* (0.10)		2.17** (0.90)	1.57 (0.97)
Share pop. White		-64.5*** (5.05)		1.17*** (0.10)	0.17*** (0.04)		0.078 (0.38)	0.88** (0.39)
Latitude		0.76*** (0.20)		-0.025*** (0.00)	-0.0073*** (0.00)		0.028** (0.01)	0.0091 (0.01)
Log [Distance to coast]		-1.21** (0.50)		0.055*** (0.01)	0.013*** (0.00)		-0.029 (0.04)	-0.00073 (0.04)
Longitude		-0.051 (0.05)		0.0021* (0.00)	-0.00019 (0.00)		-0.0048 (0.00)	-0.0039 (0.00)
1 if Democrat					-0.80*** (0.01)			0.67*** (0.13)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	870	870	870	870	870	866	866	866
R ²	0.21	0.46	0.19	0.44	0.93	0.09	0.14	0.20

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

Table 3: Robustness checks with universalism variable based on friendship distance (113th and 114th Congress)

	<i>Dependent variable:</i>							
	Dem candidates vote share		Legislator DW-NOMINATE score			Speech universalism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
District universalism (friendship distance)	9.96*** (0.92)	3.92*** (1.06)	-0.20*** (0.02)	-0.049** (0.02)	-0.016** (0.01)	0.24*** (0.05)	0.17** (0.08)	0.19** (0.08)
Log [Median household income]		-19.9*** (5.50)		0.45*** (0.11)	0.13*** (0.04)		-1.22*** (0.44)	-0.87* (0.45)
Share of population with college degree		29.7** (13.48)		-0.83*** (0.26)	-0.16 (0.10)		2.16** (0.89)	1.28 (0.94)
Share pop. White		-64.4*** (5.17)		1.16*** (0.10)	0.15*** (0.04)		0.15 (0.43)	1.13*** (0.41)
Latitude		0.88*** (0.22)		-0.026*** (0.00)	-0.0072*** (0.00)		0.032** (0.01)	0.0057 (0.01)
Log [Distance to coast]		-2.06*** (0.47)		0.064*** (0.01)	0.014*** (0.00)		-0.050 (0.04)	-0.0010 (0.04)
Longitude		-0.14*** (0.05)		0.0031*** (0.00)	0.000058 (0.00)		-0.0077** (0.00)	-0.0059* (0.00)
1 if Democrat					-0.81*** (0.01)			0.73*** (0.12)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	870	870	870	870	870	866	866	866
R ²	0.19	0.43	0.19	0.44	0.93	0.08	0.13	0.21

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

Table 4: Robustness checks with binarized geographic distance variable (113th and 114th Congress)

	Dependent variable:							
	Dem candidates vote share		Legislator DW-NOMINATE score			Speech universalism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
District universalism (binarized distance)	10.1*** (0.82)	5.34*** (1.37)	-0.19*** (0.02)	-0.068*** (0.02)	-0.024*** (0.01)	0.17** (0.07)	0.15* (0.08)	0.12 (0.08)
Log [Median household income]		-27.6*** (5.90)		0.55*** (0.11)	0.16*** (0.04)		-1.46*** (0.48)	-1.10** (0.51)
Share of population with college degree		33.6** (13.04)		-0.88*** (0.25)	-0.17* (0.10)		2.44*** (0.90)	1.73* (0.97)
Share pop. White		-58.0*** (6.03)		1.08*** (0.11)	0.12*** (0.04)		0.22 (0.45)	1.05** (0.45)
Latitude		1.10*** (0.21)		-0.029*** (0.00)	-0.0081*** (0.00)		0.042*** (0.01)	0.018* (0.01)
Log [Distance to coast]		-2.08*** (0.48)		0.064*** (0.01)	0.014*** (0.00)		-0.065* (0.04)	-0.027 (0.04)
Longitude		-0.18*** (0.05)		0.0037*** (0.00)	0.00026 (0.00)		-0.0092*** (0.00)	-0.0073** (0.00)
1 if Democrat					-0.80*** (0.01)			0.70*** (0.12)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	870	870	870	870	870	866	866	866
R ²	0.20	0.44	0.18	0.44	0.93	0.03	0.12	0.19

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

Table 5: Robustness checks with geographic distance variable excluding same state donations (113th and 114th Congress)

	Dependent variable:							
	Dem candidates vote share		Legislator DW-NOMINATE score			Speech universalism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
District universalism (excl. same state)	9.13*** (0.95)	5.87*** (1.00)	-0.17*** (0.02)	-0.085*** (0.02)	-0.013* (0.01)	0.22*** (0.06)	0.16*** (0.06)	0.11* (0.06)
Log [Median household income]		-25.5*** (5.38)		0.53*** (0.11)	0.14*** (0.04)		-1.38*** (0.46)	-1.04** (0.49)
Share of population with college degree		39.7*** (12.73)		-0.96*** (0.25)	-0.20** (0.10)		2.61*** (0.91)	1.93* (1.01)
Share pop. White		-66.8*** (4.99)		1.18*** (0.10)	0.18*** (0.04)		-0.036 (0.38)	0.79** (0.39)
Latitude		0.96*** (0.19)		-0.027*** (0.00)	-0.0079*** (0.00)		0.038*** (0.01)	0.017 (0.01)
Log [Distance to coast]		-1.67*** (0.48)		0.057*** (0.01)	0.015*** (0.00)		-0.055 (0.04)	-0.024 (0.04)
Longitude		-0.041 (0.05)		0.0017 (0.00)	-0.00019 (0.00)		-0.0053 (0.00)	-0.0045 (0.00)
1 if Democrat					-0.80*** (0.01)			0.68*** (0.13)
Congress FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	870	870	870	870	870	866	866	866
R ²	0.16	0.46	0.15	0.46	0.93	0.06	0.13	0.19

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

Table 6: Candidate tweet universalism of election winners and losers (118th Congress)

	<i>Dependent variable:</i> Candidate tweet universalism			
	Winners	Losers	All	
	(1)	(2)	(3)	(4)
District universalism	0.31*** (0.06)	0.0020 (0.08)	0.18*** (0.05)	0.0020 (0.08)
District universalism \times 1 if winner				0.30*** (0.09)
1 if winner				-0.25*** (0.08)
Observations	409	432	841	841
R^2	0.10	0.00	0.03	0.07

Notes. OLS estimates, robust standard errors (clustered at district level) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Background on Donors Choose

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.

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.

[Find a classroom to support](#)
[About us](#)
[Help](#)
[Sign in](#)

near

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.).

C.2 Summary Statistics

Category	Statistic
Number of donations (overall)	3,958,705
Number of donors (overall)	1,265,589
Number of projects (overall)	1,203,259
Average donation amount (overall)	\$76.96
Median donation amount (overall)	\$25
Average number of donations by a CD to a recipient CD	20.80
Median number of donations by a CD to a recipient CD	4
Max number of donations by a CD to a recipient CD	11,701
Min number of donations by a CD to a recipient CD	0
Average donation amount by a CD to a recipient CD	\$1,600.21
Median donation amount by a CD to a recipient CD	\$143.06
Max donation amount by a CD to a recipient CD	\$1,259,881.46
Min donation amount by a CD to a recipient CD	\$0
Average total number of donations by a CD	9,068
Median total number of donations by a CD	6,133
Max total number of donations by a CD	245,891
Min total number of donations by a CD	1,194
Average total donation amount by a CD	\$697,692.10
Median total donation amount by a CD	\$334,298.60
Max total donation amount by a CD	\$24,278,288.33
Min total donation amount by a CD	\$56,997.79

C.3 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 digits, which added a layer of uncertainty to 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 all possible *full* ZIP codes corresponding to the truncated ZIP code from DonorsChoose, and then in turn to a given CD based on all possible congressional districts that each one of these possible full ZIP codes could map to. 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.

C.3.1 Bayesian Shrinkage

Our raw regression coefficients θ_i form unbiased but imprecise estimates of universalism. To reduce measurement error and generate more precise estimates of this parameter, we “shrink” our estimates toward the mean $\bar{\theta}$ of the average across CDs, producing a shrunk coefficient θ_i^s that is a weighted average of θ_i and $\bar{\theta}$:

$$\theta_i^s = w_i \theta_i + (1 - w_i) \bar{\theta}. \quad (3)$$

As in Chetty and Hendren (2018), the weights w_i are selected to minimize the mean-squared prediction error, so that

$$w_i = \frac{\text{Var}(\theta_i) - E[se_i^2]}{\text{Var}(\theta_i) - E[se_i^2] + se_i^2}.$$

$\text{Var}(\theta_i)$ represents the variance of the raw coefficients across CDs, and se_i the standard error of the coefficient for CD i .

C.3.2 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

Table 8: 20 most frequent eMFD words in congressional speeches and Twitter datasets

Ranking	Congressional speeches		Twitter	
	Term	Frequency	Term	Frequency
1	people	114479	people	147823
2	time	99601	thank	132456
3	president	99435	day	121791
4	speaker	86166	great	121579
5	going	64816	need	120531
6	work	61930	time	117335
7	states	60363	support	116429
8	country	58531	new	115816
9	want	57966	work	113041
10	act	56262	help	111810
11	senator	53195	house	104364
12	know	51902	act	101395
13	support	51841	vote	95292
14	house	51201	president	91653
15	need	50814	families	84498
16	state	50044	proud	83479
17	committee	48681	like	82746
18	new	48471	health	82428
19	government	48054	country	79314
20	think	47174	community	76554