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Nonprofit Partisanship

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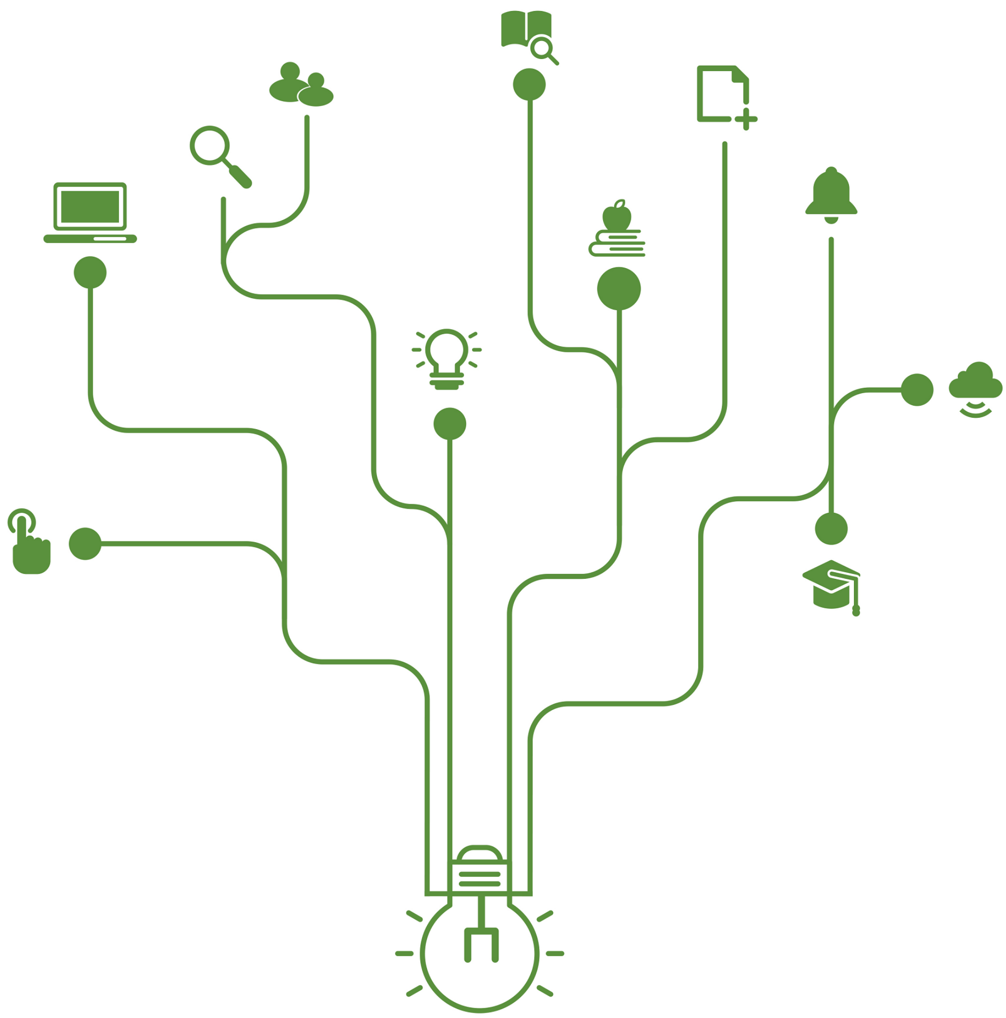

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Nonprofit Partisanship[1)]

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Abstract

We establish a novel measurement of nonprofit organization ideology using semantic text analysis and validate it with a large-scale online experiment. On average, health- related nonprofits as well as education-related organizations, including US universities, are the most left-leaning group. Religion-related nonprofits, on the other hand, are the most conservative. We then examine whether "rage donations" for selected lib- eral nonprofits right after the Trump elections documented by the media hold true more generally across different sectors over different presidential elections. We find no evidence that expected shifts in ideology of a government systematically influence donations differently depending on nonprofit ideology.

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Introduction

In November and December of 2016 after Donald Trump was elected as the U.S. President, there were reports on the media on “rage donations” towards progressive causes (Walters, 2016). The ACLU’s donation website crashed the day after election as visitors increased by 7,000%: 120,000 contributions, of more than $7.2 million came pouring in that week (cf. 354 donations for a total of $27,800 after Barack Obama’s win in 2012 during comparable period). Six weeks since the election, Planned Parenthood received forty times the normal rate and 70% of the donors had never given to planned parenthood before.

Conklin and Foshee (2019) argue that such behavior is not new: for the past four presi- dential election years (2004, 2008, 2012, 2016), nonprofits that were politically aligned with the losing presidential candidate received a drastic spike in giving compared with those aligned with the winner. Their approach, however, was to single out 37 organizations that were known of their partisanship and compare their annual donations the year before and the year of the presidential elections.

This research examines whether such shift in donations for the limited sample hold more generally. In other words, do expected shifts in ideology of a government influence donations to nonprofit organizations differently depending on their varying ideologies? Answering this question will contribute to the literature on motivation behind giving. While there is an inconclusive literature on how individual ideology affects private donations- some find that conservatives tend to donate more, while others find the opposite (Allan and Scruggs, 2004; Feldman and Zaller, 1992; Bielefeld et al., 2005; Brooks, 2006; Karlan and List, 2007). Whether donation behavior respond to political or ideological competition has not yet been studied much. One exception is Paarlberg et al. (2019). Based on individual and household income tax returns at the county-level for 2012 and 2013, they find that political ideology and electoral competition affect private donations: as the proportion voting Republican in non- Republican-dominated counties increases, the predicted levels of charitable giving decreases. In contrast, as the proportion voting Republican increases in Republican-dominated counties, charitable contributions increase.

Our study also give us a new angle in thinking about social welfare consequences of parti- san governments. If citizens actively choose what public goods to be provided by donating to or setting up nonprofit organizations to countervail government influence (Rose-Ackerman, 1997), one may not have to be too worried about the elected government being too partisan. The key contribution of our paper is a novel measurement of nonprofit organization ideology. More than 170,000 nonprofit organizations are categorized in Section 501(c)(3) of the Internal Revenue Code of the U.S., including the universe of organizations with greater than $50 million in assets, are ranked on a liberal to conservative scale based on how their mission statements align with speeches by members of Congress.

To the best of the authors' knowledge, there has been no attempt to directly measure partisanship of nonprofits, though news sources do occasionally generate list of "liberal" or "conservative" organizations for selected sectors (Langbert, 2018; Overberg and Adamy, 2019). To estimate the ideology of nonprofits, we use semantic text analysis to classify non-profits based on their mission statements. Language has been often used to analyze the ideology of the subject since language can be assumed to reflect the user's psychological states and preferences (Preo¸tiuc-Pietro et al., 2017). For instance, the Laver et al. (2003) political position measure applies a naive Bayes method based on the relative frequencies of reference texts. Gentzkow and Shapiro (2010) compare the text from newspapers to the congressional speeches to construct a media slant index. Baker et al. (2016) provide an index for economic policy uncertainty from texts of major newspapers. For a summary ofthe textual analysis toolkit, please see Gentzkow et al. (2019).

Here, following Gentzkow and Shapiro (2010), we first identify words and phrases that are used more often by one party than the other based on the congressional record of the 112th, 113th and 114th congress (January 3, 2011 - January 3, 2017) obtained from Stanford SSDS (Gentzkow et al., 2018).

For instance, we identify "Obamacare" as highly Republican language while Democrats often use "affordable care act" instead. Other examples include "illegal immigrants", "tax increase", "American people" as phrases often chosen by Republicans and "climate change", "tax cut", "gun violence" as Democratic-leaning phrases. We then collect the mission state- ments of nonprofit organizations from their Form 990 filings and a US charity evaluator CharityNavigator.org. The assumption is that organization's ideology is reflected in the mission statement text as it comes directly from the organization to describe its goals and programs. We adopt the naive Bayes method based on words and two-word phrases to con- struct the ideology ranking by measuring the similarity between the language used in the mission statement and the congressional speeches of Democrats or Republicans.

The calculated ideology score ranking is validated with a large scale online experiment based on Amazon Mechanical Turk which lets the survey takers read the mission statement from a sub-sample of the nonprofits, rate their perceived ideology, and decide how much of their payment they want to donate. The survey takers generate ratings consistent with our semantic measure which gives us confidence in our ratings across the entire set of US non profits. We also find consistency between our rankings and some lists of left-wing and right-wing nonprofit organizations from other sources.

Our ranking suggests some groups of nonprofit organizations are more partisan than others. On average, health-related nonprofits are the most left-leaning group. Education-related organizations, including US universities, are also left-leaning. This is consistent with both intuition and evidence from previous studies. For example, Langbert (2018) shows top liberal arts college faculties are mostly Democrats. A 2016 Gallup poll shows more doctors consider themselves as Democrats as opposed to Republicans (Overberg and Adamy, 2019). On the other hand, religion-related nonprofits are the most conservative.

We find no evidence that presidential elections have affected donors to donate more to organizations at the other side of the ideological spectrum.

Data

This section describes the data used for our partisanship metric. Section 2.1 describes the congressional speech data and the preprocessing procedure. Section 2.2 describes the mission statement data from nonprofit organizations. The details of our online survey is discussed in Section 2.3.

Congressional Record Data

We use the congressional record of the 112th, 113th and 114th congress (January 3, 2011-January 3, 2017) obtained from Stanford SSDS (Gentzkow et al., 2018) to identify words and phrases used more frequently by one party than the other. This includes all speeches spoken on the floor of both House and Senate of Congress. Gentzkow et al. (2018) download and parse the text of the congressional speeches and the information of congress members from thomas.loc.gov and polidata.org.

To reduce the noise in the text data, we apply a standard preprocessing procedure introduced by Bird et al. (2009). This step is very similar to Gentzkow and Shapiro (2010). We first remove all procedural speeches, for instance, speeches by the Clerk, since they are mostly functional and not relevant to the content of the congressional debate. Next, we remove a set of procedural words[5] suggested by Gentzkow et al. (2018) and a list of very common words in English called the "stopwords".[6] The words are then reduced to their linguistic roots with a stemming algorithm by Porter et al. (1980). The stemming algorithm ensures that words and phrases in different grammatical forms are regarded as equivalent. For instance, we treat "children" and "child" as the same word. After the stemming, we apply the commonly employed bag-of-words method to represent a document by a word list and a two-word phrase list.[7]

We collect 233,805 speeches from the congressional record, excluding the procedural speeches and speeches by independent congressmen. 51.9% of them are from Democrats and 48.1% from Republicans. Table 1 shows the word count for congressional speeches. Demo- cratic and Republican speeches are very similar in their word count. A congressional speech on average contains 260 words. The number of two-word phrases contained in each document is the word count less one because two-word phrases are constructed by concatenating the consecutive words. This can create strange and meaningless phrases. We address this issue

Table 1: Word Count of Congressional Speeches

Description	Mean	sd	Pct01	Pct25	Median	Pct75	Pct99
Democratic	263.21	457.12	3	17	74	324	2,142
Republican	260.94	534.44	3	18	66	279	2,583

Notes: For each congressional speech, we count the number of words it contains. Please note that the number of two-word phrases in each document is the total word count less one because we construct two-word phrases by concatenating consecutive words.

in Section 3.2.

Nonprofit Organization Data

We focus on the charitable organizations described in Section 501(c)(3) of the Internal Rev- enue Code that files Form 990 with Internal Revenue Service (IRS).[8] Section

5) Examples include "absent", "adjourn", "chairman", etc. These commonly-used words in congressional speeches are mostly procedural. The full list is available at https://stacks.stanford.edu/file/druid: md374tz9962/codebook.pdf

6) 2This includes "me", "to", "is", etc. They are frequently used in English but very unlikely to be partisan. A full list is available at http://snowball.tartarus.org/algorithms/english/stop.txt

7) For example, to process the sentence "This is an example to illustrate text processing", we first remove the very common English words "this", "is", "an", "to". We then trim the remaining words to their stems and obtain "example illustrate text process". Finally we obtain a word list "example", "illustrate", "text", "process", and a bigram list "example illustrate", "illustrate text", "text process". For more details, please see Gentzkow et al. (2019).

8) Definition from IRS (available at: https://www.irs.gov/charities-non-profits/charitable-org anizations) The exempt purposes set forth in section 501(c)(3) are charitable, religious, educational, sci- entific, literary, testing for public safety, fostering national or international amateur sports competition, and preventing cruelty to children or animals.

501(c)(3) allows for federal tax exemption of non-profit organizations that are organized and operated exclu- sively for charitable purposes. A 501(c)(3) organization must file its annual return with the Internal Revenue Service (IRS) to maintain their tax-exempt status. Depending on the size of assets and revenue, the required filing for large public organizations is Form 990.[9] Form 990 requires the organization to describe its mission or most significant activities in text in a short document called the mission statement.

The mission statement is the main input for our partisan measure. This statement briefly describes the goals of the organization in text. The language in mission statements is compared to the congressional record after the preprocessing procedure described in Section

2.1. We obtain the mission statements for Section 501(c)(3) organizations from two sources. First, we collect the mission statements from the electronically filed Form 990 data pub-lished by the IRS.[10] Missing the paper-filed 990 forms are a concern but over 60% of all Form 990 returns are filed electronically as of 2016, and the IRS has mandated e-filing for large organizations since 2010.[11] We download all electronic filings for tax year 2018 published by IRS from its AWS server. This data set includes 172,625 organizations. Table 2 shows the distribution of the length of the mission statements. An average mission statement from the AWS dataset has 25 words. However, a number of mission statements contain only several words, for instance, “education”, “community betterment”. It is difficult for them to reflect the ideology of the organization accurately.

To alleviate the issue of short mission statement, we also download mission statements of nonprofit organizations from CharityNavigator.org, a leading charity evaluator in the US. Charity Navigator provides mission statements for charities rated by them. They do not cover all organizations but they focus on large public charities with at least 7 years of operation and at least $1 million revenue.[12] We collect mission statements for all 9,288 Section 501(c)(3) organizations rated by Charity Navigator. These mission statements are

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The term charitable is used in its generally accepted legal sense and includes relief of the poor, the distressed, or the underpriv- ileged; advancement of religion; advancement of education or science; erecting or maintaining public buildings, monuments, or works; lessening the burdens of government; lessening neigh- borhood tensions; eliminating prejudice and discrimination; defending human and civil rights secured by law; and combating community deterioration and juvenile delinquency.

9) Private foundations are required to file 990-PF. Organizations with gross receipts less than $200,000 and assets size less than $500,000 can choose to file the short forms 990-N and 990-EZ. Please see https: //www.irs.gov/charities-non-profits/form-990-series-which-forms-do-exempt-organizations- file-filing-phase-in for more details.

10) Available at https://registry.opendata.aws/irs990/

11) Please see https://www.irs.gov/newsroom/irs-makes-electronically-filed-form-990-data-available-in-new-format, and https://www.irs.gov/e-file-providers/e-file-for-charities-and- non-profits for details.

12) Only charities meeting certain criteria are rated by Charity Navigator. The criteria include at least $1 million revenue in 2 years and operating for at least 7 years. Please see https://www.charitynavigator.o rg/index.cfm?bay=content.view&cpid=32 for details.

based on the Form 990 filings but they also include text from organization's websites, annual report and brochure. The text comes entirely from the organization. The Charity Navigator data significantly increases the length of the mission statement. As shown in Table 2, a mission statement downloaded from CharityNavigator.org consists of 96 words on average. The partisan ranking produced by this set of mission statements is thus more accurate.

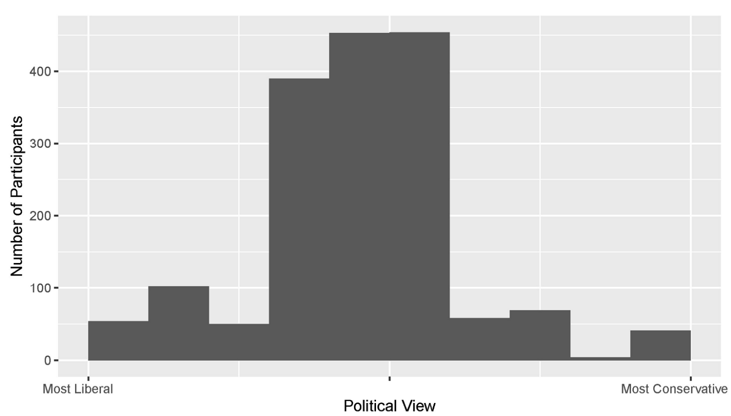
In addition to mission statements, we also collect the Form 990 financial statement data from 1985 to 2017. This includes the annual total revenue, total donation, government grants and other financial data reported on Form 990. Please note that the the IRS started to publicize all e-filed Form 990 since 2010. Prior to that, we can only download a sample of all 990 forms every year provided by the IRS. This sample focuses on larger organizations with a sampling rate ranging from 1% for small-asset organizations to 100% for large-asset (greater than $50 million) organizations. The IRS also uses this sample to produce their tax-exempt organization statistics and report.[13]

Table 2: Word Count of Mission Statements

Description	Mean	sd	Pct01	Pct25	Median	Pct75	Pct99
Charity Navigator	95.96	34.54	17	77	100	119	163
AWS 990 Data	25.30	24.79	2	11	20	32	127

Notes: For each mission statement, we count the number of words it contains. Please note that the number of two-word phrases in each document is the total word count less one because we construct two-word phrases by concatenating consecutive words.

Figure 1: Political Views of Survey Participants



Notes: For each major category, we calculate the average percentile rank by taking the simple average across the percentile ranks of all nonprofit organizations in this category.

13) Please see https://www.irs.gov/statistics/soi-tax-stats-charities-and-other-tax-exempt-organizations-statistics.

Online Survey Data

In addition to the textual analysis, we also conduct an online survey via Amazon Mechanical Turk (MTurk). We ask the survey participants to read the mission statements and rate the ideology of the organizations. We select a sample of 16,963 mission statements. This includes all mission statements from the Charity Navigator data set and a random sample from the AWS data focusing on longer statements. The average length for the sample is 85 words.

The participants are asked to read a mission statement and rate the perceived ideology of the organization from 1 (most liberal) to 6 (most conservative). There are 1,677 participants in our survey. To ensure the survey participants are not biased, we ask them to report their self-identified political standing from 1 (most liberal) to 6 (most conservative) before reading the mission statement. Figure 1 shows the distribution of the average self-reported political standing for all survey participants. The distribution leaning slightly left but the overall political standing of our survey participants is not heavily biased.

Measuring Ideology

Our partisanship measure use Congressional speeches to identify the language features that distinguish Democrats from Republicans. We then compare the charity's mission statement text to the Congressional speeches to measure the organization's ideology. We apply the generative naive Bayes method to rank the charity ideology. To reduce the noise of our measure, we incorporate language feature selection and document length normalization into the naive Bayes method. Section 3.1 describes the basic idea of our method. Section 3.2 discusses the approaches to select the relevant words and phrases and Section 3.3 addresses document length normalization.

Naive Bayes

Our partisanship measure is constructed by the generative naive Bayes method. This is a proven method widely used in text classification (please see Murphy 2012 for a textbook treatment). The goal is to rank the ideology of nonprofit organizations by the probability that that organization's mission statement was spoken by a Republican[14] lawmaker. An

14) The probability for an organization's mission statement to be Democratic and Republican sum to one if we ignore

organization is ranked as more conservative if its mission statement has a higher probability of soundling like a Republican lawmaker and more liberal if this probability is lower.

Our main ideology measure is based on two-word phrases, or bigrams because they can capture more information than single words. Having said that, we also consider an alternative method using single words, or unigrams. We compare the result of both methods in Section 4. For ease of exposition, we use w to represent a word or a two-word phrase from a document. The key assumption for naive Bayes method is that every unigram or bigram, w, in a text document is chosen independently according to some probability distribution P(w|p) depending on the party affiliation p of the author, either Democrats D, or Republican R. Suppose a preprocessed mission statement mi from some nonprofit organization i consists of distinct words or phrases $w_1^i, w_2^i, ..., w_N^i$, with frequencies $x_1^i, x_2^i, ..., x_N^i$. Let $x^i = \sum_{k=1}^N x_k^i$ denote the total word count of the mission statement. By the independence assumption, the probability to produce mission statement mi conditional on the author's ideology p_i is

$$\mathbb{P}(m_i|p_i) = \frac{x^i!}{\prod_{k=1}^N x_k^i!} \cdot \prod_{k=1}^N \mathbb{P}(w_k^i|p_i)^{x_k^i}.$$

We can then use Bayes formula to write down the probability for this mission statement to be Republican (R) as

$$\begin{aligned}\mathbb{P}(p_i = R|m_i) &= \frac{\mathbb{P}(p_i = R)\mathbb{P}(m_i|R)}{\mathbb{P}(p_i = R)\mathbb{P}(m_i|R) + \mathbb{P}(p_i = D)\mathbb{P}(m_i|D)} \\ &= \frac{\mathbb{P}(p_i = R) \cdot \prod_{k=1}^N \mathbb{P}(w_k^i|R)^{x_k^i}}{\mathbb{P}(p_i = R) \cdot \prod_{k=1}^N \mathbb{P}(w_k^i|R)^{x_k^i} + \mathbb{P}(p_i = D) \cdot \prod_{k=1}^N \mathbb{P}(w_k^i|D)^{x_k^i}}. \qquad (1)\end{aligned}$$

As we can see from the formula, the order of word occurrence is irrelevant in naive Bayes since the combinatorial terms cancel out completely in the second equality. The next step is to estimate the conditional probability P(w|p) for any w to be chosen in the mission statement given the ideology p. This information is extracted from the Congressional record. We use the empirical multinomial distribution constructed from the

middlegrounds. One can also construct a measure with the probabilities to be Democratic. This is equivalent to ours except that the ranking is reversed.

Congressional speeches P^(w|p) to estimate P(w|p). Specifically, we use the Laplace-smoothed relative frequency of win speeches of party p as P(w|p) in Equation 1[15]. For each mission statement, we can apply Equation 1 to estimate its probability those words were uttered by a Republican with prior belief P(p = R) = P(p = D) = 0.5. The ranking for nonprofit organization ideology is thus obtained by ranking these probabilities.

Language Feature Selection

The naive Bayes method described in 3.1 is in its most primitive form. All words and two- word phrases are considered in the Bayes formula. However, this introduces noise into the measure by including rare words and meaningless two-word phrases. The problem of noisy language features is more prevalent for two-word phrases since we form them by joining consecutive words ignoring whether the resulted phrase is meaningful. This can create strange terms such as "receive receive" that are unlikely to be indicative and distort our ideology measure. To alleviate this problem, we introduce language feature selection. The idea is to select words and phrases that are more relevant to ideology and partisanship. Only the selected words and phrases can enter Equation 1 and affect the ideology ranking. We consider two different methods: the data-driven Chi-squared selection and the theory- driven moral word selection. Our main method uses the Chi-squared score to select two-word phrases. We also present the result for alternative methods of Chi-squared selected words |

Chi-Squared Selection

Our first and main approach is to identify words and bigrams that are more likely to be partisan-relevant based on the Pearson's Chi-squared statistic. This method is used in Gentzkow and Shapiro (2010) and has proven to be effective. The Chi-squared statistic for each word or bigram w is defined as

$$\chi_w^2 = \frac{(f_w^R f_{\neg w}^D - f_w^D f_{\neg w}^R)^2}{(f_w^R + f_w^D)(f_w^R + f_{\neg w}^D)(f_w^D + f_{\neg w}^R)(f_{\neg w}^D + f_{\neg w}^R)} \tag{2}$$

15) If we use the relative frequency to estimate P(w|p) directly, it might happen that some w appears only in the speeches of one party but not the other, leading to P^(w|p) = 0 for some w and p. This is problematic since the zero value wipes out the information obtained from other unigrams or bigrams. To solve this problem, we estimate P(w|p) after adding one more occurrence for all distinct unigrams and bigrams in the congressional records, that is, we use $(f_w^p + 1)/(L_p + V_p)$, where f_w^p is the frequency of w in speeches of party$_p$, L_p is the total word length of speeches of party p, and Vp is the number of distinct words in speeches of both parties. This is typically described as Laplace smoothing.

where f_w^p denotes the frequency of w in speeches of party p, and f_w^p denotes the frequency of words or phrases other than w in speeches of party p. The Chi-squared statistic is a test statistic for the null hypothesis that w is used symmetrically by Democrats and Republicans. A larger Chi-squared value indicates that the distribution of w is more likely to be correlated with party affiliation. We calculate the Chi-squared value for all words and two-word phrases in the congressional record and select the words and phrases whose Chi-squared values above the 80th percentile.

Table 3 and 4 show the most partisan words and phrases used more often by congressional Democrats and Republicans, ranked in a descending order by the value of their Chi-squared statistic. Many of the selected words and phrases are known to be highly relevant to partisan discourse. For instance, regarding the health care act, Democrats tend to say “affordable care act” while Republicans use the word “Obamacare”. Survey results show that mentioning “Obamacare” polarizes people more compared to “affordable care act”, which provides sup- port for the underlying partisan purpose of this difference (Dropp, 2017). On environmental issues, “climate change”, “pollution”, “oil companies” are identified as highly Democratic by our approach while “American energy” is identified as highly Republican. This is again consistent with the Republican consultant Frank Luntz’s advise to use words like “energy” instead of “oil drilling” for their partisan impact (Luntz, 2007).

Moral Keywords

The second approach to language feature selection is to actively select the keywords guided by the moral foundation theory. The moral foundations theory tries to reduce the panoply of human values by seeking the anthropological and evolutionary roots of morality (please see Haidt and Joseph 2004; Haidt 2007; Haidt and Graham 2007; Graham et al. 2009). The theory defines five sets of moral foundations as follows: [direct citation]

Table 3: Most Democratic Words and Phrases

Words		
republican	women	gun
investment	student	climate
cut	pollution	violence
education	vote	communication
family	public	children
Vermont	clean	college
infrastructure	work	million
Rhode	island	nomination
food	poverty	proceed
loan	protect	equal
Two-Word Phrases		
climate change	middle class	tax
cut gun violence	Rhode Island	tax
break		
minimum wage	student loan	African
American public health		affordable
care	voting right	
care act	immigration reform	unemployment
insurance senate proceed		senate republican
	carbon pollution congressional black	
black caucus	clean energy	
civil right	head start	comprehensive
immigration background check		work family
million American		
oil company	right act	New York

Notes: We compute the Chi-squared statistic for each word and phrase in the congressional record. This table shows the most partisan words and phrases used more often by congressional Democrats ranked by their Chi- squared value.

Table 4: Most Republican Words and Phrases

Words			
	Obamacare	spend	administration
	regular	Obama	trillion
	president	mandatory	Washington
	government	debt	bureaucrat
	Islam	revise	illegal
	amnesty	law	Wyoming
	constitution	actual	freedom
	taxpayer	Iran	promise
	suspend	regulatory	extraneous
	God	Christian	unborn
Two-Word Phrases			
	care law	member legislation	consent member
	revision extend	extend remark	Obama administration
	White House	day revision	move suspend
	legislation day	remark include	include extraneous
	suspend rule	extraneous material	federal government
	raise tax	rule pass	president health
	president Obama	job creator	tax increase
	American people	material bill	American energy
	radical Islam	illegal immigrants	senate necessary
	trillion debt	balanced time	Muslim brotherhood

Notes: We compute the Chi-squared statistic for each word and phrase in the Congressional record. This table shows the most partisan words and phrases used more often by Congressional Republicans ranked by their Chi- squared value.

1. Harm/care: basic concerns for the suffering of others, including virtues of caring and compassion.
2. Fairness/reciprocity: concerns about unfair treatment, inequality, and more abstract notions of justice.
3. Ingroup/loyalty: concerns related to obligations of group membership, such as loyalty, self-sacrifice and vigilance against betrayal.
4. Authority/respect: concerns related to social order and the obligations of hierarchical relationships, such as obedience, respect, and proper role fulfillment.
5. Purity/sanctity: concerns about physical and spiritual contagion, including virtues of chastity, wholesomeness and control of desires.

Graham et al. (2009) find that liberals tend to rely more on harm and fairness values, while conservatives emphasize more on the other three categories. They also create a set of 295 moral keywords relevant to each category of moral foundations[16). and show that liberals and conservatives use the moral keywords in a different manner by counting the occurrences in religious sermons. Recent studies provide further evidence that the moral keywords are highly relevant in ideological narratives (Sagi and Dehghani, 2014; Enke, 2018). As a result, restricting our attention to the moral keywords is a plausible alternative of word selection. We hence consider another ideology measure by applying the naive Bayes method with only the moral keywords.

Document Length Normalization

Another improvement to our method is document length normalization. Section 2 shows that the mission statements are highly heterogeneous in length. The length of the statement should not be ideologically relevant. But our method can disproportionately favor longer mission statements since they have a higher chance to match the partisan words and phrases in Congressional speeches. For example, a long mission statement is ranked more Democratic than a short one if it has more left-leaning partisan words even though the short statement has a higher density of such words.

Our solution is to normalize the document length. Let *mi* be the mission statement of nonprofit organization i after preproceessing. It consists of distinct words or phrases w_1^i, w_2^i, ... w_N^i with frequencies x_1^i, x_2^i, ... , x_N^i. We normalize the length of the document

16) available from: https://moralfoundations.org/other-materials/

$x^i = \sum_{k=1}^{N} x_k^i$ to the average length across all mission statement $\bar{x}$ by adjusting the frequencies proportionally to $\bar{x}/x^i \cdot x_k^i$ for $k = 1, 2, ..., N$. The adjustment term $\bar{x}/x^i$ penalizes the frequencies of words and phrases according to the document length. After the length normalization, we apply Equation 1 to rank the ideology with the adjusted frequencies[17)]

$\bar{x}/x^i \cdot x_k^i$ Our method is supported by the machine learning literature. Singhal et al. (2017) compare different text length normalization strategies. Kim et al. (2002) adopt a normalization method similar to ours under a naive Bayes context. They also point out the importance of length normalization if the purpose is to give appropriate Bayes scores for all documents.

Validation Exercise

To get a sense of the types of mission statements generated by our method, consider these two mission statements for two different Planned Parenthoods which make up nearly all of the E42 Family Planning non-profits with more than $50 million in assets. For analysis purposes, we divide non-profits into quintiles. Not surprisingly, most Planned Parenthoods fall into quintile 1 (Most Liberal) under our measure. For example, Planned Parenthood LA's mission statement reads as follows:

To provide convenient and affordable access to a comprehensive range of quality reproductive health care and sexual health information through patient services, education, and advocacy.

By contrast, one of the few large Planned Parenthood's that our metric classifies as conservative (quintile 5) is Planned Parenthood Mar Monte, also in California, but in the much more conservative part of the State.

The mission of Planned Parenthood Mar Monte, Inc is to ensure that every individual has the knowledge, opportunity, and freedom to make every child a wanted child, and every family a healthy family.

Notably, this mission statement uses terms like freedom, opportunity and family. Hence its conservative classification. While we acknowledge that this is probably a misclassification by our algorithm, it also makes sense that this particular Planned Parenthood, with a focus on Central California and Northern Nevada, areas that

17) We allow for fractional frequency counts in Equation 1. Multinomial distribution usually requires integer counts but fractional counts are widely used in textual analysis.

traditionally vote Republican, would choose a mission statement that is more attractive to conservative donors.

Table 5 shows the most partisan mission statements in the Charity Navigator sample by our bigram approach. The most liberal organizations focus on typical left-wing issues such as LGBT right and clean energy. On the other hand, we see a religion-related organization and free market advocate on the most conservative side.

Table 5: Most Partisan Mission Statements

Most Liberal Mission Statements

Equality Florida Institute

Equality Florida Institute is a part of Equality Florida, the largest civil rights organization dedicated to securing full equality for Florida's lesbian, gay, bisexual, and transgender (LGBT) community. Through education, grassroots organizing, coalition building, and lobbying, we are changing Florida so that no one suffers harassment or discrimination on the basis of their sexual orientation or gender identity.

Acadia Center

Acadia Center is a non-profit organization committed to advancing the clean energy future. Through research and advocacy, it works to empower consumers and offer real-world solutions to the climate crisis for all.

Most Conservative Mission Statements

Open Doors USA

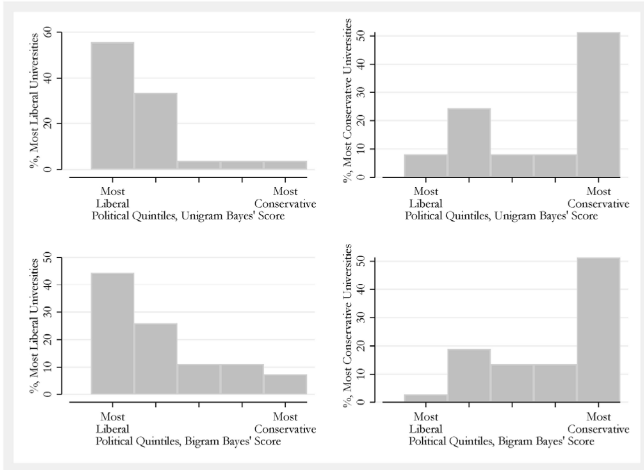
For 60 years, Open Doors has worked in the world's most oppressive countries, empowering Christians who are persecuted for their beliefs. Open Doors equips persecuted Christians in more than 60 countries through programs like Bible & Gospel Development, Women & Children Advancement and Christian Community Restoration. As a result, Open Doors has specialized in helping Christians who are persecuted for their faith. However, we work with persecuted Christians to reach out to non-Christians, even their persecutors, so that they can reach them with the message of Christ.

FreedomWorks Foundation

The mission of FreedomWorks Foundation is to educate and empower Americans with the principles of individual liberty, small government, and free markets.

Notes: This table shows the most liberal and the most conservative mission statements by our bigram Bayes' scores in the Charity Navigator sample. Please refer to Section 3 for more detail.

Figure 2: Most Liberal and Most Conservative Universities



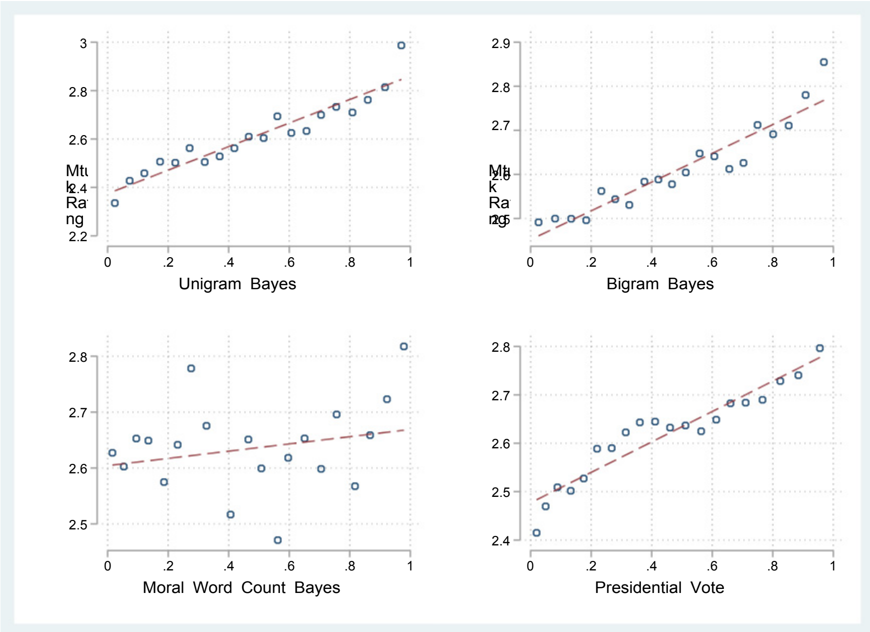
Notes: This figure shows the political quintiles of the most liberal and the most conservative universities and colleges in our Charity Navigator sample. We obtain the a list of most liberal and most conservative universities in 2018 from Niche.com and PrincetonReview.com. 61 from the most liberal list and 66 from the most conservative list show up in our data. We present the histograms of their political standings.

In addition to looking at specific mission statements, We also obtain a list of universities and colleges rated as the most liberal and the most conservative in 2018 by Niche.com and PrincetonReview.com and report their political quintiles by our partisan measures in Figure2. Our measures are mostly consistent with the external ideology ratings

We also compared the results of our text analysis based metrics with the mean partisanship ratings from Amazon Mturk workers. (We also did a revealed preference analysis where we gave the Mturk Workers the opportunity to donate a fraction of their earnings to the charities they were rating. We then compared their revealed preference donation choices with their own stated partisanship affiliation to construct a revealed preference estimate of partisanship for each organization. This analysis yielded similar results.)

Figure 3 presents binscatter plots of our unigram bayes' score, the bigram Bayes' score, the moral word count Bayes' score, against the Amazon MTurk rating. We also add a binscatter plot between the MTurk raings and the inferred partisanship of each organization based on the 2012 presidential Republlican vote share within the zipcode that they filed their taxes in, as this was a commonly used method to assess partisanship in prior work. As we can see in Figure 3, all of these measures (except for Moral Word Counts) does a fairly good job matching the MTurk worker rating, but we can also see from the correlation Table

Figure 3: Binscatter: Partisanship Measures vs MTurk Rating



Notes: Binscatter plots of our Bayes' Score ratings of non-profit mission statements based on Congressional Record Data against the mean rating of those non-profit mission statements by MTurk raters. The fourth graph plots the MTurk rating against the presidential vote share of the zip code in which the non-profit is based.

6 between the different measures, that each metric is capturing something different.

Results

The remainder of the results will use our normalized bigram metric of partisanship. Unigram measures look fairly similar. Figure 4 plots the percent share of donations to each quintile of partisanship for "Big" organizations (with assets over $50 million in a given year). The shading of the graph represents control of Congress, with darker shadings of red and blue indicating party control of both Congress and the Presidency.

Figure 5 breaks down donations into subsectors between the years 2006 and 2017. We highlight in blue and in red, 2008 and 2016 because those were presidential election years. Note there are dramatic increases in donations for different ideological quintiles in election years, but also we often observed large movements both before and after election years.

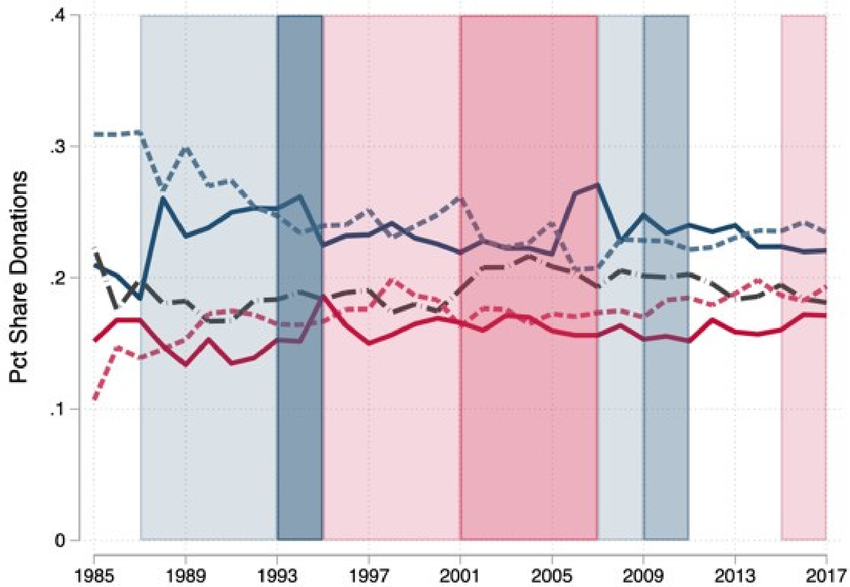
One of the largest spikes can be observed in 2017 in the Civil Rights category. This spike is almost entirely due to some regional chapters of the ACLU. Our metric places these organizations as somewhat more conservative than the median. There are two reasons, the first is that roughly 80% of organizations are considered "liberal" according to our Bayes'

Table 6: Correlation Between Metrics

	Mturk Rating	Presidential Vote Share	Unigram Bayes Score	Bigram Bayes Score	Moral Word Bayes Score
Mturk Rating	1.0000				
Presidential Vote Share	0.1757	1.0000			
Unigram Bayes Score	0.2266	0.1663	1.0000		
Bigram Bayes Score	0.1667	0.1304	0.4059	1.0000	
Moral Word Bayes Score	0.0485	0.0093	0.2647	0.2022	1.0000

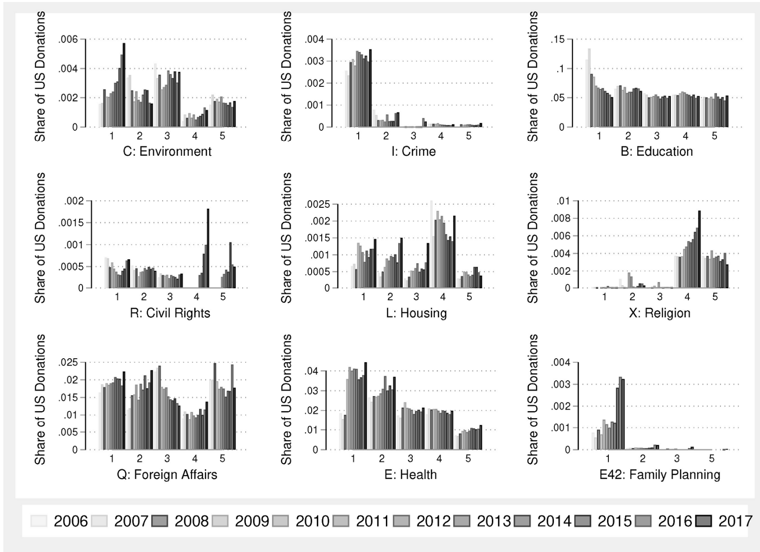
Notes: We compute the ideology rankings by different methods and report the correlation between the percentile rankings.

Figure 4: Percent Share of Total Donations by Political Quintile



Notes: This figure shows the percent share of total donations by political quintile of non-profit organizations across years. Shaded areas represent control of Congress, dark shaded areas indicate control of Congress and the Presidency. Dark blue is most liberal, Dark red is most conservative.

Figure 5: Percent Share of Total Donations by Political Quintile and NTEE Cat- egory



Notes: Share of total US donations by NTEE category and political quintile (from 1 - most libreal to 5 most conservative) between 2006 to 2017. 2008 and 2016 are highlighted as presidential election years.

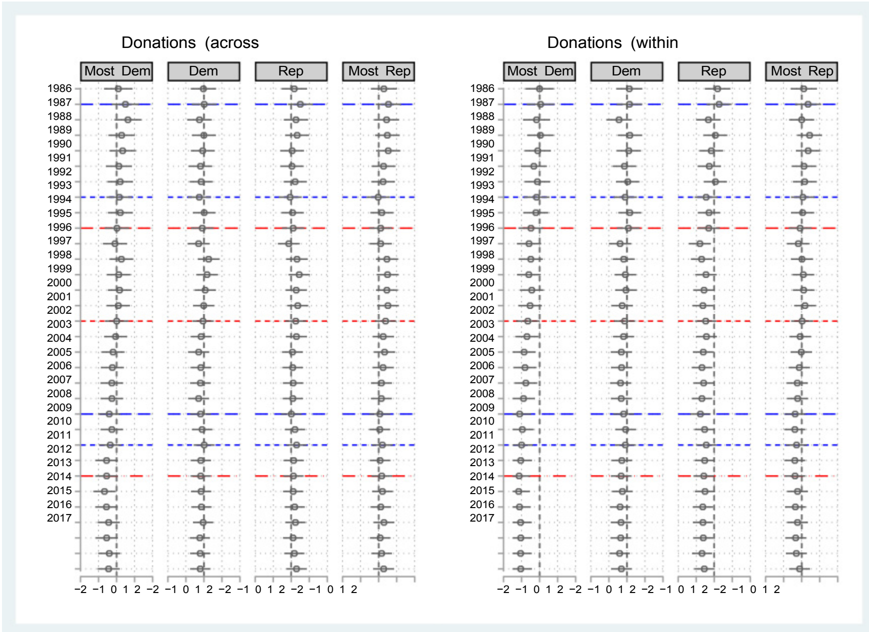
standard. In other words, 80% of our organizations have mission statements that sound more like a Democratic politician than a Republican politician. So the ACLU in the 4th quintile is still somewhat liberal. Also, the ACLU, with its focus on civil liberty and bill of rights is arguably more conservative (relatively speaking) than most other organizations in the category.

Other things to note, Family Planning organizations (mostly Planned Parenthood) did see dramatic increases in 2016, and 2017, but we see that those increases started before the Trump election in 2015 as well. Also, relatively conservative religious donations and relatively liberal environmental donations both saw large increases in 2017, but both were part of a trend that began years earlier as well.

Finally, we follow the analysis of Andreoni and Payne (2011) and others, by estimating a regression model of the log of donations on year by quintile fixed effects and organizational fixed effects. Each parameter estimate represents the percent difference of donations to those organizations relative to a median organization.

While parameters were largely zero, we do see a trend toward median partisanship orga- nizations beginning in the year 2000, especially if we classify organizations relative to their own NTEE Subgroup (e.g. we can say that the most liberal organizations within groups like

Figure 6: Atypical Donation to Political Charities Relative to the Median Quintile



Notes: Atypical donation to political charities relative to the median quintile. These are coefficients of year by quintile fixed effects (with 95% confidence intervals), in regressions of the log of donations received on organization fixed effects.

Health or Environment, saw their donations fall relative to the median organization in their group in the years after 2000. We also saw similar declines for somewhat more conservative organizations within each subgroup as well.)

Discussion and Conclusion

These results are all still somewhat preliminary so we will try not to infer too much. The main purpose of this exercise is to take advantage of recent advances in text analysis techniques which have recently become more broadly accepted, to offer a new way to categorize the partisanship of non-profits. We take advantage of the fact that mission statements of non- profits are publicly available as part of IRS tax forms to construct a partisanship metric for non-profit organizations. We validate this metric by comparing our metric to that of Amazon Mturk workers, and to measures based on presidential vote share. We hope our measure will be a useful tool for future work on non-profits that requires a measure of political positioning.

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