The Tangled Web of Policy Support: Foundations and Environmental NGOs

Adam Joseph Ramey

NYU, Abu Dhabi

Lawrence S. Rothenberg

University of Rochester

Abstract[*]

It has long been recognized that foundation support is a crucial element for NGOs, particularly for those championing the environment. However, exactly how foundations and NGOs match, or whether NGOs tailor their organizations to appeal to foundations, has been understudied. We address these issues by compiling a dataset of foundation support of environmental NGOs and specifying a statistical model of donating using Item Response Theory. Estimating this model using Correspondence Analysis, we find two key spatial dimension—ideology and focus—and evidence consistent with the idea that environmental NGOs moving in space to accommodate foundations do better.

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Introduction

At least since the publication of Walker's (1991) seminal work, scholars have been sensitive to the key role that foundations may play in the financial lives of interest groups or non-governmental organizations (NGOs).[1] Even for groups typically thought of in the public mind as membership organizations, foundation dollars are frequently an important complement to other revenue streams for organizational creation and maintenance (on the possible differences between creation and maintenance, see Nownes and Cigler 1995). For example, although certainly not a typical case, in 2011 the Environmental Defense Fund received 50% of its revenues, almost $49 million dollars, from foundations; roughly $42 million dollars came from contributions and membership dues, with the remaining $4 million or so generated by bequests and government grants (EDF 2011).

Yet, despite widespread acknowledgement of the importance of foundation support for the NGO community's size and composition, recent years have witnessed little additional investigation into the interrelationships and dynamics between such philanthropic sources and organized groups. Almost paradoxically, this absence of scholarly investigation has occurred despite the number of foundations operating in the last two decades more than doubling and, even with the economic downturn of the early 21st century, the amount of real dollars that foundations provide increasing by roughly one-third in the last ten years (Lawrence and Mukal 2011), and rising roughly four-fold from the year (1985) for which most data were collected for Walker's study. Yet, in particular, we lack knowledge about what makes a good match between a foundation and a group (but see Lowry 1999). Nor do we definitively understand

[1] While Walker and many others employ the term patron, we will simply talk in terms of foundations (a key subset of patron dollars), as the patron data which we draw on involves foundation contributions exclusively (for a further discussion of the use of the term patron, see Nownes 1995a).

whether, or to what degree groups adjust their own agendas or methods in order to procure foundation support (but see Brulle and Jenkins 2005).

In thinking about these issues of matching and adjustment (and foreshadowing our analytic approach), for example, we may conceptualize interest groups and foundations as roughly analogous to candidates seeking election and voters deciding whom to support respectively. Corresponding to candidate behavior, it is imperative that groups appeal to their supporters. However, just as election-seekers have multiple constituencies with whom they desire to curry favor (primary and general election voters, campaign contributors, etc.), so do group leaders (e.g., foundations, individual members, group activists and board members to enumerate a few). Conversely, in the spirit of citizen-candidate models, just as candidates may have their own personal preferences (e.g., Osborne and Slivinski 1996, Besley and Coate 1997), so may leaders and others active in the internal operation of the organizations that they represent have their own policy preferences which they wish to advance (e.g., Rothenberg 1992, Lowry 1997, Hewitt and Brown 2000). Ultimately, analogous to voters, foundations implicitly vote with their dollars by deciding whom and what they support, and they may focus on their spatial correspondence with groups or their matches along some other valence dimensions.

In this spirit, our analysis seeks to take a step toward disentangling relationships between groups and foundations by taking advantage of the increased availability of data on foundation giving and advances in statistical methodologies. Specifically, we use available databases to compile data for eight years of foundation giving,[2] employ statistical techniques in the form of Item Response Theory (IRT; on this methodology

[2] Our actual data go through the end of 2012. However, due to delays in the digitization of information on IRS 990 forms (the primary source), we restrict our focus to 2003-2010.

generally, see Hambleton, Swaminathan, and Rogers 1991; Johnson and Albert 1999; Baker and Kim 2004; for political science applications, see Clinton, Jackman, and Rivers 2004; Spirling and Peress 2010) that have previously been applied to the study of decision-making (such as voting over candidate choices, roll calls, judicial cases, or bureaucratic commission decision-making), but not to the decisions of foundations, and then use an estimation procedure, Correspondence Analysis (CA; e.g., Greenacre 1984, 2005, 2007; Ter Braak 1985; Lowe 2008; Bonica 2012), that helps us get around problems of parametric estimation.

Specifically, we investigate the interactions between environmental NGOs (ENGOs) receiving foundation monies and those foundations deciding on the grants by initially putting both sets of actors in a common dimensional space—using a variant of IRT for ideal point estimation—and then specifying a statistical model of the determinants of foundation contributions and estimating it using CA.[3] This allows us to gain insights into aspects of the relationship between foundations and NGOs that we have heretofore been unable to investigate and disentangle.

Our results are notable in a number of important respects. First, despite seemingly great diversity—particularly with respect to ENGOs—and no institutional rules and structures analogous to formal political institutions, foundations and environmental groups are both extremely well-categorized on two dimensions when we estimate a fully structural IRT model. On the one hand, there does seem to be ideological matching, as we might expect, between foundations and ENGOs. But, additionally, there is a dimension that we label as *focus*, which involves whether there is

[3] Although, beginning with analyses of the U.S. Congress, it is typical to label a first dimension as ideological or liberal-conservative (e.g., Poole and Rosenthal 1997), in our case this interpretation is more nuanced, so for now we simply talk about a common space on which foundations and ENGOs are jointly placed.

a match on breadth between foundation and group. Furthermore, our model specifying that theses dimension act jointly is superior to alternatives, including one where these dimensions are specified as additive. Additionally, we find evidence that is at least consistent with groups adjusting their actions with time to better get the funds that they need to maintain themselves as organizations and potentially impact policy. Thus, besides saying that foundations matter, we now delineate how this process operates.

The remainder of our analysis is as follows. We begin with a brief literature review regarding foundation support of NGOs generally and ENGOs specifically, followed by a more thorough discussion of ENGOs. We then overview the data on foundations and ENGOs, specify our statistical theory of foundation giving, and present the results from our IRT/CA estimation. We conclude by discussing implications from our analysis and future research directions.

Literature Review[4]

As mentioned, discussion of the analysis of foundation/patron support for interest groups typically commences with Walker's (1991) seminal work. Walker argued that national interest groups are quite dependent on help from patrons who are not formal group members, with foundations being extremely prominent among them. This revenue stream has a large impact, he asserted, on both which interests were represented in the group universe and how these NGOs went about their business. Most obviously, patrons were found as helping promote public or citizen interests that

[4] Here we focus on scholarship more or less directly related to claims made by political scientists and those in allied disciplines studying interest group decision-making. There is also another, largely unrelated, literature by students of the philanthropic and non-profit sectors who examine foundations specifically, which we only mention here in passing for parsimony. For example, some look at factors such as the financial efficiency of groups requesting support (e.g., Ashley and Faulk 2010), while others discuss issues such as whether foundations coopt groups or merely help them build their capacity (e.g., Delfin and Tang 2008).

might otherwise have fallen prey to the logic of collective action à la Olson (1965), which is consistent with the view of a number of later scholars that the interest group system can be described as neopluralistic (e.g., Gray and Lowery 2004) and that citizen groups are influential (e.g., Berry 1999). Also, Walker claimed that foundation support discouraged conflict and litigation, as foundations preferred to put their monies elsewhere (see also Brulle and Jenkins 2005, for a further discussion on the limiting effects of foundations).

Walker's analysis has had a large impact in that it is now conventional wisdom in textbooks on organized interests that patrons matter. Nonetheless, subsequent investigations into foundation activities vis-à-vis organized interests have been relatively sparse. Most notably, Nownes and his coauthors authored a series of papers, much of which questioned some of Walker's specific claims, such as whether patrons matter more for organizational creation or maintenance (Nownes 1995a, b, 1996; Nownes and Cigler 1994, 1995; Nownes and Neeley 1996a,b; see, also, Imig and Berry 1996). Others have focused on differences between foundations: Notably, Lowry (1999) claimed a distinction between company-sponsored foundations on the one hand—which he found to be primarily goodwill oriented—and independent foundations, which are claimed to be sensitive to a group's program activities, governance structure, and political activities, which themselves may be endogenous to group leader choices.

While jointly these analyses produce important additional insights into how foundations and groups function, as foreshadowed above, it is also notable that none have brought to bear techniques developed in the last several decades that social scientists typically use to measure preferences. Gaugingideal points would seem theoretically fundamental for understanding how groups and foundations interact in the complex environment in which they operate. Put differently, we might think that foundations donate to groups with the same preferences and, if foundation preferences are fixed, it will be NGOs with the same preferences which will prosper from the former's largess.[5] In turn, this should have significant policy impacts. Key, then, is understanding how widely distributed foundation preferences are in the aggregate, and which groups do or do not fit their profiles. Alternatively, it may be that foundations choose based on other group characteristics—a number of which are intuitive (e.g., region, policy focus, etc.)—and that preference matching is not the be all and end all of foundation support.

Why Environmental NGOs?

ENGOs are an obvious candidate for the analysis which we have in mind for several reasons. The first is obviously numerical; environmental groups are the single largest subgroup of public regarding interest groups. There are literally thousands of ENGOs (although, admittedly, our analysis covers only a modest subset of them given that only a small, but extremely important, subset receive substantial foundation support). Furthermore, environmental groups have been one of the most rapidly growing parts of the voluntary interest group universe over the last decades (e.g., Baumgartner 2005).

Second, environmental groups receive substantial foundation support.[6] While such support was only minimal at the beginning of the modern environmental movement, it has grown many times over through the years (Brulle and Jenkins 2005).

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[5] There would be relatively little reason for foundations to alter their preferences in the short-term, but given a need for resources and a desire for policy impact, groups might certainly have an incentive to change where they stand ideologically, although group leaders certainly maintain they do not do so (e.g., Nownes 1994).

[6] Many environmental groups also receive funding from other sources beyond individuals, such as governments and corporations. Nevertheless, as mentioned, foundations' support for ENGOs is quite important.

By 2010, foundation grants for the “environment and animals” (using the Foundation Center’s criteria) totaled almost $1.4 billion dollars for the year, with the top 50 foundations giving roughly two-thirds of this amount.

Third, environmental groups are extremely diverse—there are many “shades of green,” to use Hoffman’s (2009) term. ENGOs would seem to differ in their ideological dispositions, whether they specialize in specific environmental issues or not, their area focus (local, national, or international), and their tactics (Bosso 2005). Of course, not all such groups are likely attractive candidates for foundation support (although, as we will document, there is more variety in groups receiving foundation dollars than one might otherwise guess).

Hence, we have a rather complicated group system, with many ENGOs occupying rather different niches in the group universe. Such groups often compete for dollars, and their survival, or at least their organizational health, are very much at stake (e.g., Bosso 2005, Asproudis 2011). At the same time, foundations are clearly committed to the environmental arena, allocating vast sums of money in the aggregate. As such, examining ENGOs would seem an ideal arena for teasing out the nuanced relationships between foundations and organizations.

Data

Overview

We gathered data on every foundation donation to all environmentally-oriented groups during the years 2003-2010. While emanating from a number of sources, the majority of this information is taken from the Foundation Directory’s online database, which provides identifying information for every ENGO receiving at least $1,000 in any given year from a not-for-profit foundation. Not surprisingly, some groups receive money from only one or two foundations, whereas others are supported by many. In total, 4027 foundations gave to 185 ENGOs over the eight-year period.

Table 1 displays the top 10 donors and the top 10 recipients across these years. Somewhat predictably, the top 10 recipients (i.e., 10 out of 185) receive about 56% of all disbursements over the time period. Indeed, even someone with a cursory knowledge of ENGOs will recognize the names on the list. This core group dominates not only the total amount of receipts, but also numbers of grants: They are not just drawing a few large grants, but are attracting myriad substantially-sized contributions. By contrast, the top 10 foundations control a substantial but lesser percentage of the overall financial pie, accounting for less than one-third of all grant dollars provided. This is encouraging, since it facilitates our desire to see if ENGOs go about matching on one or more dimensions with foundations.

[Table 1 about here]

Moving on to foundation disbursements, although the mean per grant is roughly constant over time, the distribution of grant amounts changes. Figure 1 provides a so-called violin plot (a combination of a boxplot and a kernel density plot) that displays the distribution of grants by year (given a few extremely large grants, we log grant amounts for visualization). We see that the average grant hovers around 10 on the logarithmic scale, which translates to about $22,000. However, as indicated, there are some extremely large outliers, particularly in the period just before the economic downturn in the latter part of the first decade of the 2000's. Shifting attention from the distribution of amounts per grant to the distribution of grants in total (i.e., the full amount disbursed across all cross-sectional units), we observe a different pattern. As seen in Figure 2, the total dollar amount in grants climbs steadily through the recession's start (and corresponding stock market plummet) in 2008 and, from there on, the amount in grants takes a huge dive.[7]

[Figures 1 and 2 about here]

Types of ENGOs

Another source of variation in our contribution data is the type of ENGOs themselves. It is hard not to recognize from Table 1 that certain kinds of ENGOs (e.g., those who might be buying or preserving large parcels of land) might be favored. To parse groups, we use the National Center for Charitable Statistics' coding system of groups by expertise and action for NGOs, the National Taxonomy of Exempt Entities (NTEE). When contribution data by NTEE classification is broken down (Table 2), we see that the two most dominant categories—which are quite different from one another—are D30, "Wildlife Preservation/Protection," and C01, "Alliance/Advocacy Organizations." D30 organizations are engaged in what we might call "environmental action," using many contribution dollars to promote environmental change and protection directly, while the C01 organizations are advocacy groups, often devoting their funds to ideas and pushing for changes in statutes, regulations, and behavior.

[Table 2 about here]

This distinction provides a potentially important insight regarding the process by which foundations and groups match spatially. For example, some foundations may develop a niche around a particular area covered by the NTEE and, in deciding which groups to support, they look within it and find ENGOs whose mission roughly corresponds to their own. We will explore this idea further using our spatial model below.

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[7] In future work, this temporal variation should be an asset as we can examine shifting ENGO behavior after the shock from the crisis to see if adaptation helped groups weather the financial storm.

Does "Where" Matter? The Importance of Geography

Before turning to how foundations choose ENGOs to allocate funds, for a number of reasons it is worth surveying where funds are geographically distributed. First, in contrast to many political choice models, geography rather than policy preferences may be behind the politics of "who gets what." Specifically, at least some ENGOs may be strongly prone to apply for, and foundations disposed to give, grants based on geographic proximity. In a related vein, surveying the geographic distribution of funds can provide clues for interpreting any spatial dimensions produced by our statistical model. If money seems to be funneling from big foundations in one location to "high impact" ENGOs in another, then a geographic coding of the data will help us make sense of the data.

For examining money's geographic flow, we use social network analysis, mapping the geographic linkages of our contribution data pooled over years. Figure 3 provides a so-called directed graph, with the particular map arrangement due to Fruchterman-Reingold (1991). Here, each social network pair consists of the geographic locations of the foundation and the recipient, each node denotes a state or a country, and each edge connecting them is weighted based on the frequency that money flows between these two locations. Most "central" locations are placed in the graph's center.

[Figure 3 about here]

Not surprisingly, as evidenced by the thicker lines (outlying locations that only have one or two financial exchanges are light and barely visible) much money flows between New York, California, and Washington, D.C./Virginia. More interestingly, arrows point from New York to D.C., suggesting that the bulk of receipts are to D.C.-based ENGOs. The strength of our patterns suggest that a primary or secondary dimension extracted from our statistical model may, indeed, be geographic, e.g., national/international (note the presence of many other nations at the outer edges of Figure 3) vs. regional.[8]

A Statistical Model of Foundation Contributions

Model Structure

Our statistical foundation contribution models belongs to a family of models stemming from IRT (on our specific model, see Bock and Aitkin 1981). This modeling approach considers individual behavior as a function of latent attributes, such as ability, intelligence, ideology, etc., and IRT represents a methodology for measuring these constructs. Originally, IRT was typically applied to data generated from questions in which individual test-takers answered a number of binary (e.g., yes/no, true/false) or ordinal (e.g., choose one out of five) queries. A latent trait measure was then extracted by assuming that the questions varied in both difficulty and ability to discriminate between individuals. Subsequently, IRT has been proven applicable to a wider variety of contexts. For example, Clinton, Jackman, and Rivers (2004) demonstrate that traditional spatial ideal point models in political science and IRT are mathematically equivalent, allowing the latter's employment for studying legislator ideology in Congress.

However, analyzing foundation giving patterns requires modification of existing IRT models given that our key variable of interest—the amount a foundation provides to a group in a given year—is continuous rather than discrete. This differs from other spatial models involving dollars, such as those pertaining to financial contributions (Bonica 2011, 2012**)**, because in the latter contributions typically arrive in standard-sized blocks (e.g., $500 or $1000 units) that can be treated as discrete.

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[8] As this does not turn out to be the case, and our CA analysis makes assessing geographic effects somewhat difficult, we plan on exploring the role of geographic proximity in greater detail in subsequent work.

To begin, suppose that we have a set of foundations indexed by i, where $i = 1,2, \ldots, N$, who are choosing how much money to provide to a set of groups, indexed by $j = 1,2, \ldots, J$, in a given year, $t = 1,2, \ldots, T$ (Table 3 summarizes our model's parameters). Denote the amount that a foundation gives to a group in a given year as y_{ijt}. For computational convenience we add one (to deal with issues of zero contributions in logs), so that we examine the $\ln(1 + y_{ijt})$.

[Table 3 about here]

We assume that each foundation and each group has a position in some D-dimensional space, $d = 1,2, \ldots, D$, which we denote by ν_i^d for foundations and θ_{jt}^d for groups. Note that only group positions are indexed by time, meaning that groups can move about in space, potentially searching for more money, while foundations are static (i.e., fixed). Although the latter assumption is essential for model identification, it is reasonable given that we are analyzing an eight-year span.[9]

The amount that a foundation provides to a group is a function of spatial proximity, which may have several dimensions, and various non-spatial factors. Specifically, we assume that foundations want to provide more to spatially closer groups. We capture closeness via a quadratic utility model as $-\left(\nu_i^d - \theta_{jt}^d\right)^2$, so that this expression (and expected contributions) are maximized when the group and the foundation are identically located. As the group-foundation match lessens and closeness' value decreases, the amount of money provided should decline quadratically. We further assume that the effect of each dimension is additive and independent, so

[9] Put differently, if we could allow foundations to vary over this period, we would expect very stable ideological estimates, so our assumption should not be costly; by contrast, if we were using a far longer period, the probability of foundations changing positions would be considerably greater, for example, as a function of changes in direction prompted by leadership or disruptions from the external world.

that in the utility function we sum over the quadratic differences across dimensions (we will examine whether this assumption is warranted in our empirical analysis).

Beyond spatial factors, we also allow for some foundations just being more likely to give out more funds than others, and for some groups just being more likely to receive more funds than their counterparts. We capture these propensities using random effects, β_i for foundations and γ_j for groups, which are both assumed to be Normally-distributed.

Additionally, we want to allow for the possibility of fixed factors having an across-the-board impact on contribution amounts. For example, being located in the same geographic location as a foundation may increase the funds that any group receives. Thus, we control for these covariates and group them together in a vector $\boldsymbol{x_{ijt}}$, which is $K\times1$, where K is the number of covariates. The coefficient on this vector, $\boldsymbol{\eta}$, captures the effects of non-policy factors on the contribution decision. For our analysis we control for two factors: a global mean baseline and shared geographic location. Specifically, we suppose that there is a baseline contribution amount and that foundations and groups in the same location may be more likely to match, irrespective of spatial considerations. Thus, $\boldsymbol{\eta}$ consists of a global intercept and a slope for a same-location dummy variable.

Putting these pieces together, each foundation's contribution decision is given by

$$\ln(y_{ijt}+1) \;= -\textstyle\sum_d\left(\nu_i^d-\theta_{jt}^d\right)^2+\beta_i+\gamma_j+\boldsymbol{\eta}'\boldsymbol{x_{ijt}}+\varepsilon_{ijt},$$

where $\varepsilon_{ijt}\sim N(0,\sigma^2)$. The Likelihood is given by

$$\pi(\xi|\boldsymbol{y},\boldsymbol{x}) \propto \Pi_{\mathrm{i}}\Pi_j\Pi_d\Pi_t f\left(\ln(1+y_{ijt})\,\middle|\nu_i^d,\theta_{jt}^d,\beta_i,\gamma_j,\eta;\sigma^2\right)f\left(\nu_i^d\right)f(\theta_{jt}^d)f(\beta_i)f\left(\gamma_j\right)f(\boldsymbol{\eta}),$$

where $\xi = \left(\boldsymbol{\nu_i^d}, \boldsymbol{\theta_j^d}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\eta}\right)$ and $f\left(y_{ijt} \middle| \nu_i^d, \theta_{jt}^d, \beta_i, \gamma_j, \eta; \sigma^2\right)$ is the log-Normal distribution centered at $-\sum_d \left(\nu_i^d - \theta_{jt}^d\right)^2 + \beta_i + \gamma_j + \boldsymbol{\eta}'\boldsymbol{x_{ijt}}$ with variance σ^2.

Estimation: From Maximum Likelihood to Correspondence Analysis

Typically, parameters for the model above should be estimable in batches (e.g., global, then foundation-specific, then group-specific) by Maximum Likelihood methods using zig-zag estimation (Heckman and Macurdy 1980, Poole and Rosenthal 1997). Unfortunately, given that receiving a grant is a relatively rare event, there is a preponderance of zeroes in our data, so such estimation is computationally unstable and produces unreliable estimates. To ameliorate these problems, we use CA, which has been shown to approximately estimate our derived parametric model very reasonably (Ter Braak 1985) and to deal quite nicely with sparse data matrices (Greenacre 1984).

To estimate via CA, we begin with a contingency table and seek to decompose the row and column variables along various dimensions, also known as *principal axes* (Greenacre 1984). In the context of our model, this involves cross-tabulating foundation contributions (rows) with ENGOs (columns) in a given year. Let $\boldsymbol{Y^t}$ be a contingency table of contributions in year t, given by $\ln(1 + y_{ijt})$, with dimensions $N \times J$. We define a correspondence matrix, $\boldsymbol{Z} = \frac{\boldsymbol{Y^t}}{\sum_{\mathrm{ij}} \ln 1 + y_{ijt}}$, which is just the contingency table divided by the sum of all of its elements. Denote the row and column marginal sums of $\boldsymbol{Z}$ as vectors $\boldsymbol{r}$ and $\boldsymbol{c}$ respectively.

Actual estimation is then performed as a Singular Value Decomposition (SVD) of the matrix of standardized residuals of the correspondence matrix, given by

$$\boldsymbol{S} = \left[diag\{\boldsymbol{r}\}^{-\frac{1}{2}}\right] (\boldsymbol{Z} - \boldsymbol{rc}') \left[diag\{\boldsymbol{c}\}^{-\frac{1}{2}}\right].$$

The SVD decomposes this matrix into three matrices, $\boldsymbol{U}, \boldsymbol{\Sigma}, \boldsymbol{V}$, such that $\boldsymbol{S} = \boldsymbol{U\Sigma V}'$, $\boldsymbol{U}'\boldsymbol{U} = \boldsymbol{V}'\boldsymbol{V} = \boldsymbol{I}$, the identity matrix. This decomposition then yields *D*-dimensional ideal points of both the foundations and the groups. Foundation ideal points are given by

$$\boldsymbol{\nu}_i = (\nu_i^1, \nu_i^2, \dots, \nu_i^D) = \left[diag\{\boldsymbol{r}\}^{-\frac{1}{2}}\right]\boldsymbol{U\Sigma},$$

and ENGO ideal points by

$$\boldsymbol{\theta_{jt}} = \left(\theta_{jt}^1, \theta_{jt}^2, \dots, \theta_{jt}^D\right) = \left[diag\{\boldsymbol{c}\}^{-\frac{1}{2}}\right]\boldsymbol{V\Sigma}.$$

Note that, although these expressions may seem a bit obtuse, the foundation and group ideal points are simply the *row-singular* and the *column-singular* vectors respectively.

Using CA makes our estimation problem akin to solving a Singular Value problem. Happily, as computer scientists and statisticians have spent decades perfecting fast, efficient, techniques to perform such estimation, our model estimates in seconds. Specifically, we use the R package **ca**, developed by CA pioneer Michael Greenacre and Oleg Nenadic (2007).

Limitations of Data and Model

Before examining the CA results, two practical data issues deserve mention, as does a brief discussion of what an alternative model might look like.

The first data issue pertains to applying CA to our structural model. In our derivation of CA, we omit reference to model covariates since, while the CA technique embeds fixed and random effects (see Ter Braak 1985), it does not allow for incorporating spatial covariates. While we accept this tradeoff, we will also conduct secondary analyses with our data controlling for both CA-generated ideology estimates and non-spatial covariates.

The second issue pertains to our data's sparseness. While we have noted that CA has been shown to be robust to sparse data and/or outliers, there are peculiarities in our data warranting *some* degree of adjustment. For example, it is not uncommon for a foundation to give an extremely generous grant to *one* ENGO and then never appear again in the data, leading to a matrix with thousands of zeros and one multi-million-dollar grant. This one donation, in turn, will severely impact the row and column means. To remedy this, we restrict our analysis by only including: (1) foundations providing funds to *at least 10* groups during the eight years covered (i.e., roughly one contribution per year); and (2) ENGOs that receive funds from at least *one foundation per year* for *all years* in our dataset (this cuts the number of ENGOs from nearly 200 to 129; relaxing this assumption would likely eliminate our ability to examine the dynamics of groups adapting to the foundation landscape).

Finally, we should say a few words about one obvious model that some might claim would better fit foundation giving. Specifically, our spatial model notwithstanding, the most likely alternate scenario is what we might call *quality-matching*¸ where foundations provide more to higher quality and lower risk ENGOs in a manner akin to how investors put more money into higher quality and less risky firms. ENGOs that more efficiently use resources or are more prominent and, presumably, trustworthy, will match with foundations. If q_{jt} is the perceived quality of group j at time t, then we should expect that an increase in q_{jt} is associated with a strict increase in $\ln y_{ijt}$. However, happily, quality-matching is merely a group-year fixed effects model that is nested within our existing model. Thus, rather than having to fit a non-nested quality model, we can assess the relative model fit between it and our more expansive model; if our model outperforms the nested quality model, then it suggests that non-quality spatial factors are in play.

Results: Why Makes Foundations Give?

Model Estimates and Interpretation

We estimate a two-dimensional ($D = 2$) CA model on the data discussed above. To obtain dynamic ideal points for the ENGOs, we column-stack the yearly contingency matrix and perform CA on the resulting matrix. Specifically, we perform CA on the matrix $\boldsymbol{Y} = [\boldsymbol{Y_1}\ \boldsymbol{Y_2} \ldots \boldsymbol{Y_T}]$, where $\boldsymbol{Y_t}$ is just the $N \times J$ contribution matrix for year t. After removing outliers, we are left with $N = 163$ foundations, $J = 129$ ENGOs, and a total of 729 ENGO-year pairs (data from 2003-2010). Thus, our estimation results contain 163 two dimensional ideal points for foundations (i.e., one per foundation) and 729 such ideal points for ENGOs (i.e., one for each year the ENGO is included).

As with any model generating ideal points, we first want to assess the substantive meaning of the dimensions of the underlying space. Given our large number of foundations and group-year pairs, a scatterplot of ideal points will not be illuminating. We instead present ideal point estimates for the ten most left-of-center and the ten most right-of-center foundations on the first dimension (Table 4; note that left-of-center and right-of-center do not necessarily correspond to left and right ideological leanings).

[Table 4 about here]

We can see that the ten most negative foundations both have fairly similar estimated positions and are disproportionately representative of major oil and gas companies (ExxonMobil and BP). Examining these foundations using public data and resources such as www.sourcewatch.org reveals that all tend to donate to right-wing think tanks and causes. For example, the Alcoa and ExxonMobil Foundations regularly give to the American Enterprise Institute, a right-of-center policy think tank,[10] while the F.M. Kirby foundation routinely donates to the Media Research Center, a conservative media "watchdog" group looking for liberal bias in mainstream news sources.[11] Conversely, in the top 10 right-of-center foundations we find The Streisand Foundation and the V. Kann Rasmussen fund. The former is led by Hollywood icon Barbara Streisand, an unabashed liberal, while the latter donates to institutions such as the Center for Media and Democracy, a left-wing counterpart to the Media Research Center.[12] Thus, it appears that the first dimension is ideological, with the left side of zero denoting conservative foundations/groups and the right side liberal ones.

What about the second dimension? Table 5 replicates Table 4 substituting second dimension scores. Right away, we notice that the ten most right-of-center foundations are all "big name" foundations (e.g., the Ford Foundation, the UPS Foundation, GE, and MacArthur) while, on the other extreme, are foundations that are known by few individuals. Examining further suggests that this dimension likely discriminates between "big focus" and "small focus." Groups loading positively will have a large, national or global focus, and thus tend to work with the largest and most powerful foundations. Conversely, smaller ENGOs with more local or parochial interests will load on the negative side of the dimension.

[Table 5 about here]

Having identified the dimensions, we turn to examining in more depth the juxtaposition of foundation and group ideal points. Figures 4 and 5 show plots of such ideal points and (like the tables above) only focus on the 10 most extreme

[10] http://www.rightwingwatch.org/content/american-enterprise-institute
[11] http://www.sourcewatch.org/index.php?title=Media_Research_Center
[12] http://www.groupsnoop.org/Center+for+Media+and+Democracy

foundations/groups on each respective dimension. Since presenting ideal points for each group across multiple periods is too cumbersome, we present the averages across all years covered for each groups. We see in Figure 5 that there is definitely some clustering on the dimensions. For example, the Georgia Conservancy and Ducks Unlimited load negatively on the first dimension, suggesting that they appeal to conservative-leaning foundations (to reiterate, this does not mean that they espouse conservative policies but merely that they appeal to more conservative foundations, e.g., by engaging in noncontroversial land conservation). Groups like CERES (which focuses on sustainability leadership for progressive businesses) and the Alliance for Nuclear Accountability load on the liberal side. Looking at the second dimension, we see that both Ducks Unlimited and CERES are loaded together on the positive side of the axis; though these groups differ ideologically, both have a broad-based focus (while the former might seem narrow, its conservation efforts are national). On the negative side of the second dimension, we witness a clustering of smaller, narrower, groups, including the Powder River Basin Council and the Northern Plains Resource Council.

[Figures 4 and 5 about here]

Model Fit: Do Ideology and/or Focus Matter?

Given we have extracted what appears to be two meaningful dimensions and distinctions in the data, we turn to the question of whether our model substantially improves estimation of foundation support. This requires appropriate (non-spatial) baseline model(s) for benchmarking as well as a spatial model where the Euclidean distances from dimensions are separated rather than combined.

One possible alternative is that the contributions constitute white noise, i.e., the data are distributed randomly. Though intuitive, this clearly constitutes a straw man and, for this reason, we eschew it for a slightly higher bar. Instead we use three more credible baselines, each building in more structure than the last.

The first is a linear mixed effects model taking the data's hierarchical nature as given and modeling the different levels using random effects for foundations, ENGOs, and year. Under this model, foundation contributions vary based on both the recipient's and donor's identities and are subject to temporal fluctuations. However, employing random effects and nothing more essentially models these differences as idiosyncratic (e.g., as neither ideological nor geographic). The second adds a fixed-covariate dummy for whether or not the foundation and the ENGO are in the same geographic location, capturing the idea that being geographically proximate might lead to a higher expected grant. The model also accounts for three other geographic components gathered from the social network analysis. Recall that we discovered that a considerable amount of money was flowing from New York and California foundations to Washington, D.C.-based ENGOS. To account for this, we include three dummies, two for foundations in New York and California and one for ENGOs in Washington, D.C., all of which should be positive. The third involves adding separately the Euclidean distances between the foundation and the ENGO on the first and second dimensions, allowing for the possibility that distance on the first dimension matters more than distance on the second, and that the two distances do not have a joint impact.

Finally, we compare the results for the former three models with those for our full structural model, which includes the total Euclidean distance for both dimensions, $\sqrt{\sum_d \left(\nu_i^d - \theta_{jt}^d\right)^2}$. We believe that this specification is the truest representation of the structure derived from our model, as it assumes that the distances across all relevant dimensions work together rather than separately.

Due to the large number of estimated random effects, we summarize the results from all four models in terms of the fixed coefficient parameters and the model fit statistics: the log-likelihood, BIC, and AIC (Table 6).[13] We see that, no matter which fit statistic we examine, our full structural model (the fourth column) significantly outperforms all the alternatives. Indeed, an Analysis of Variance of the four models shows that the more structure built into the model, the better the model does statistically.

[Table 6 about here]

Substantively, the main variables of interest—the two spatial dimensions of ideology and focus—work precisely as we would expect. In the separate distance model (the third column in Table 6), the ideology dimension has a larger coefficient than that for focus, suggesting that ideological divergence is punished more than the divergence in big vs. small focus. In the full structural model where the two dimensions are presumed to have a joint effect ("Structural with Total Distance"), cumulative distance has a large substantive effect.

Given our logarithmic dependent variable, an example for the full structural model is illuminating. When the ideological distance is zero—a perfect match—the expected mean grant amount is $\exp(\$10.411) = \$32{,}223$. Increasing distance to first one and then two units, the expected grant amount declines to $\exp(\$10.411 - \$0.36) = \$23179$ and $\exp(\$10.411 - 2\times\$0.36) = \$16{,}171$ respectively, the latter cutting the expected contribution from perfect matching in half.

Does Spatial Shift affect Contributions?

13 AIC and BIC are similar means of comparing the relative fit of models, with the principal difference between them being how the number of parameters are treated if one model has more than the other. Lower AIC and BIC values imply a better fit.

We now turn to one of our central interests, whether or not spatial shifts by ENGOs from year to year effect the contribution amounts garnered. To examine this, we compute the difference in spatial distances from year $t-1$ to year t separately for each dimension, d: $\sqrt{\left(\nu_i^d-\theta_{jt}^d\right)^2}-\sqrt{\left(\nu_i^d-\theta_{jt-1}^d\right)^2}$, where a negative [positive] distance means that the group is closer to [further from] the foundation this year than last. Naturally, if spatial shifts matter, being more divergent this year should lead to a lower grant this year, even controlling for the amount received last year (which would seem to work against finding any effect). Hence, the coefficient on these independent variables should be negative and statistically significant.

Table 7 reports the results from a log-Normal mixed effects model regressing contributions this year on contributions last year, the difference in ideology from year-to-year, and our location controls. Again, we have random effects for foundations and ENGOs. Interestingly, the coefficient on the first dimension shifts is negative and significant (as expected), but that for the second dimension is insignificant. Though unexpected, there is an intuitive explanation for this: when ENGOs shift ideologically, it can help them (or hurt them), but repositioning focus may not impact grants on a year-to-year basis because payoffs will probably be in the somewhat longer-term.

How much do ideological shifts matter? Figure 6 shows predicted grant amounts from our model assuming all factors remain constant except for the first dimension. In this example, we assume that an ENGO received a grant of $10,000 last year; growing four points closer to a foundation then leads to an expected grant of $12,000, while a four-point divergence leads to an expected grant of just over $9,000. These differences are fairly large relative to the previous year's grant amount, ranging from a 20% increase to a 10% decrease in funding. Note that if an ENGO was exceptionally successful in the previous year, for example bringing in over a million dollars), differences between convergence and divergence can amount to hundreds of thousands of dollars (!).

[Table 7 about here]

[Figure 6 about here]

Discussion and Conclusion

Scholars have for multiple decades emphasized the importance of foundation support for the growth and survival of NGOs, with ENGOs being a primary focus of attention. Now, with data more readily available, and statistical theories and techniques far better developed, we are positioned to go beyond simply saying that foundations are relevant to exploring more deeply what makes a good match between an ENGO and a foundation.

Our analysis suggests that two factors make such a match. Probably to no one's surprise, even given the fact that ENGOs at least will have ideological ideal points that are far more truncated than distributions of voters or legislators, ideological matches do matter both statistically and substantively. However, there is a second dimension, which we have called focus that matters as well. Therefore, entrepreneurial group leaders will have two dimensions on which to adjust their group's actions in order to cull the financial favors of foundations, presumably while balancing the demands of other constituencies such as organizational members and their own policy preferences. Furthermore, as we have shown, these dimensions interact so that we can think of their being a total distance, and leaders will do best if they understand this.

Additionally, as we have seen, we do find evidence that ENGOs that move toward foundations do better. While we do not want to push our interpretation beyond what the data can sustain, it is at least consistent with strategic ENGO leaders seeing where foundations are in space and move accordingly. This, in turn, suggests that foundations, or those who are thinking of entering the foundation universe, may be very well-positioned to influence the ENGO community should they create a foundation, increase their funding, or move where they fit on either of our two dimensions.[14]

There are many ways that our analysis can be extended. The easiest is to allow for time to expand the temporal scope of our analysis which will allow us to produce estimates in which we will have more confidence. More ambitiously, we might extend this type of analysis to other types of NGOs, of which education groups would appear to be the most obvious candidate. Furthermore, we might try to integrate data about other players, such as the policy preferences of citizen-members of ENGOs or characteristics about their leaders or structures that might be relevant.

[14] To reiterate, we do not allow for strategic foundation movement on the estimated dimensions for our eight-year period.

Figure 1: Average and Distribution of Grants by Year (Logged US Dollars)

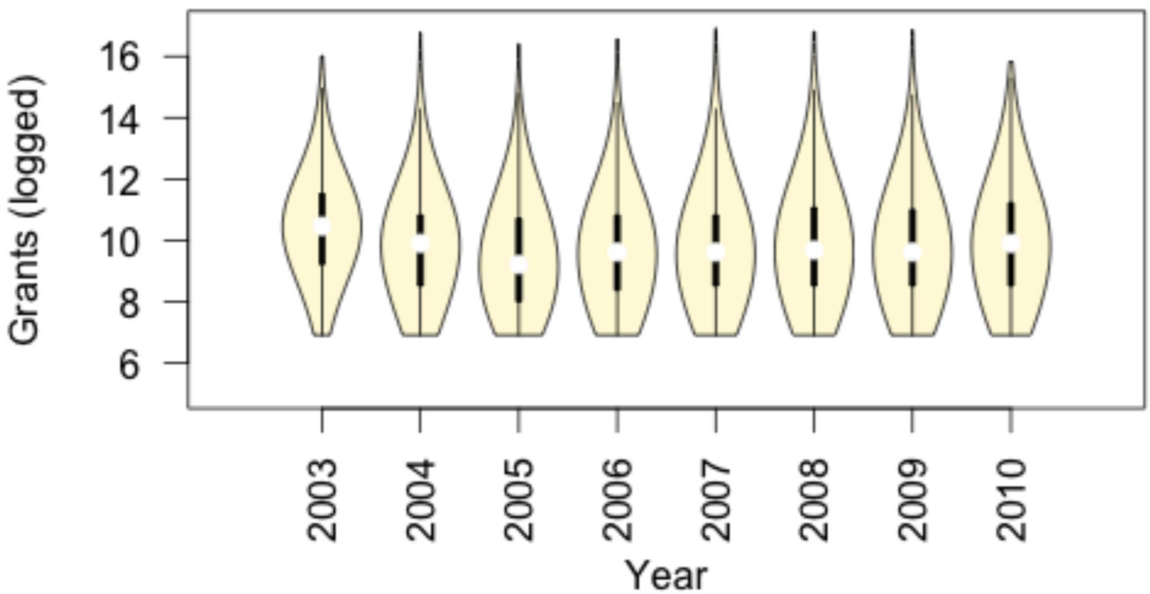


Figure 2: Trends in Aggregate Foundation Funding to ENGOs

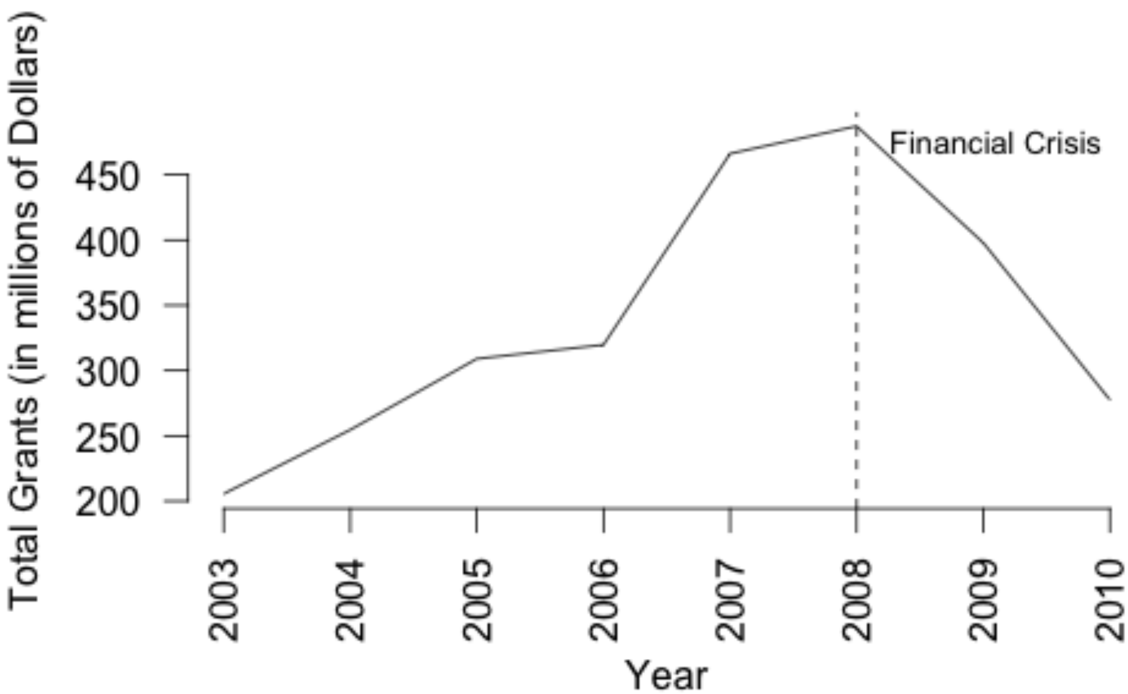


Figure 3: Geographic Contributions Network

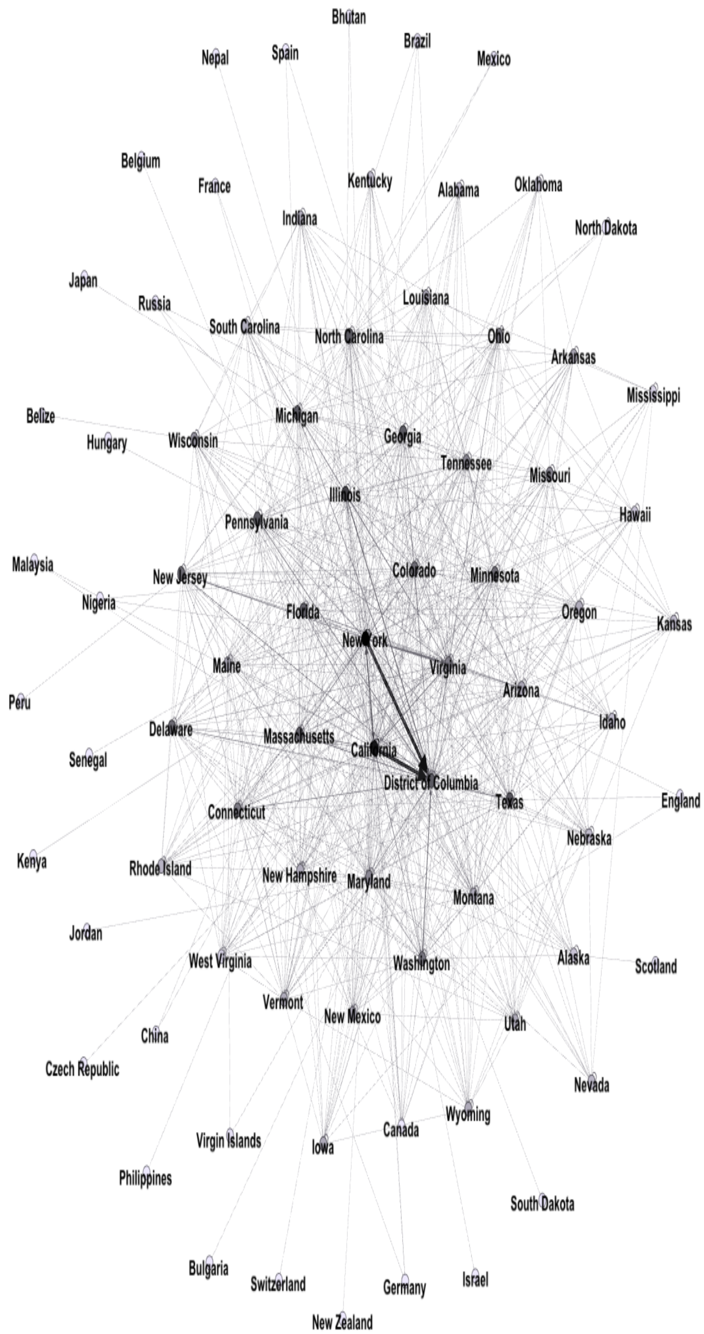


Figure 4: Foundation Ideal Points
(Ten Most Extreme on Each Dimension)

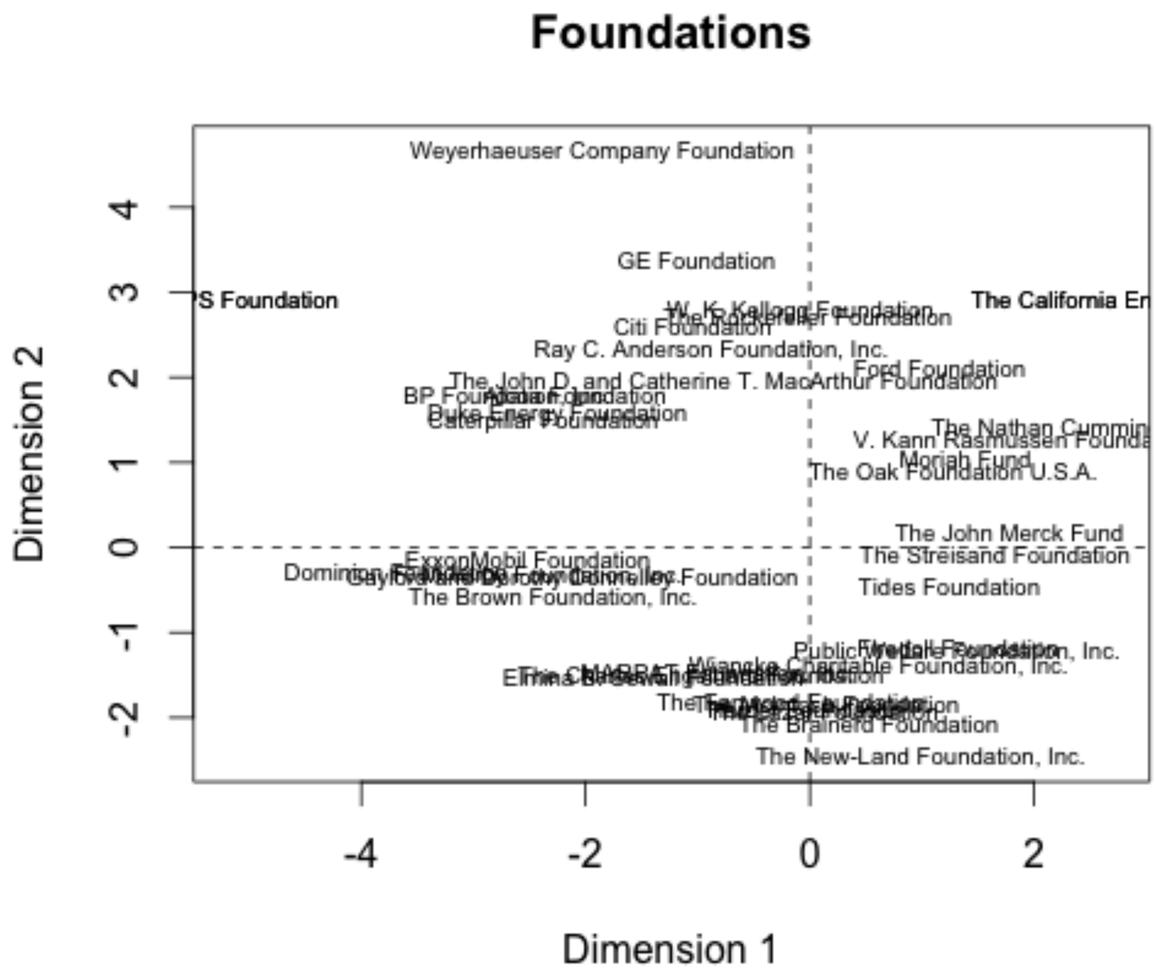


Figure 5: Group Ideal Points
(Ten Most Extreme on Each Dimension)

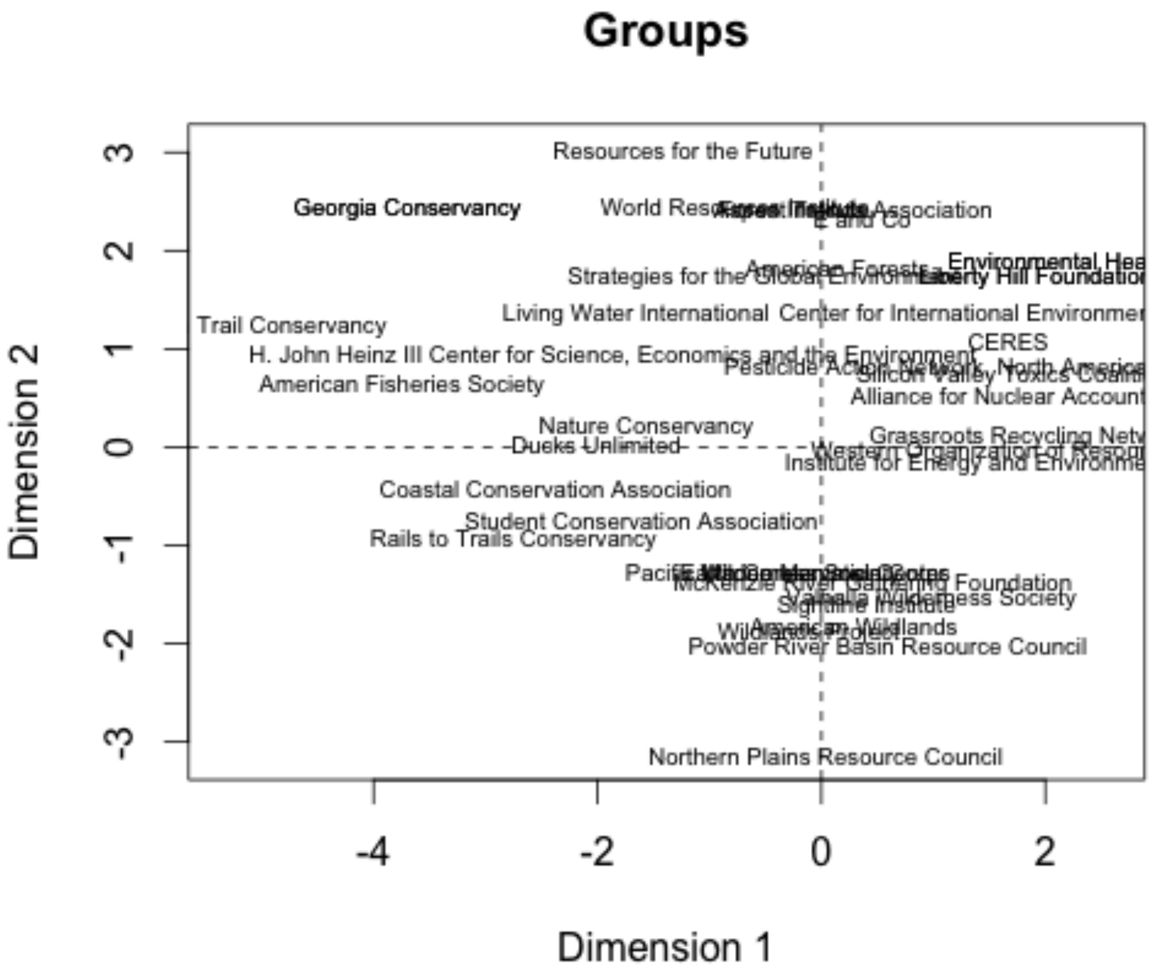
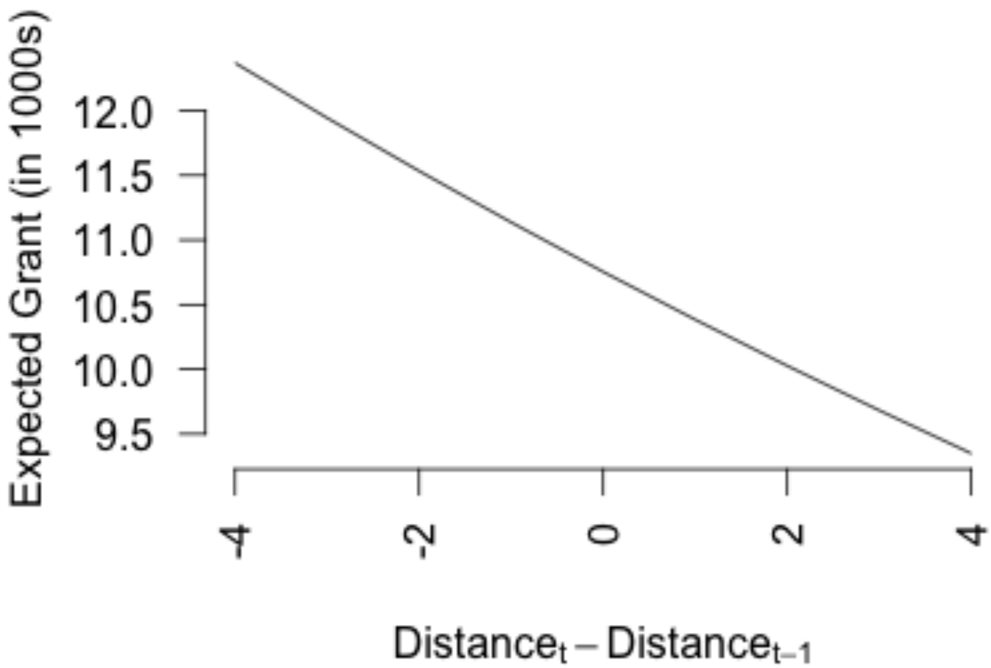


Figure 6: Expected Grants by Ideological Shifts



Note: Predicted values are generated assuming that an ENGO received a grant last year of $10,000, did not reposition its focus ("big" vs. "small"), and was not from the same geographic location as the giving foundation. Negative distances in this picture imply converging ideological proximity; positive distances indicate growing divergence.

Table 1: Top Ten Donors and Recipients, 2003-2010

Top 10 Foundation Donors	**Total Disbursements**
Gordon and Betty Moore Foundation	$155,534,592
The Pew Charitable Trusts	$117,858,000
Energy Foundation	$110,182,307
The David and Lucile Packard Foundation	$107,816,716
The William and Flora Hewlett Foundation	$107,144,880
The Robert W. Wilson Charitable Trust	$80,104,397
Doris Duke Charitable Foundation	$69,897,580
The Marisla Foundation	$68,378,464
Charles Stewart Mott Foundation	$56,425,466
Ford Foundation	$53,748,666

Percentage of Total: 32.7%

Top 10 ENGO Recipients	**Total Receipts**
Nature Conservancy	$371,482,216
Wildlife Conservation Society	$234,020,037
Aspen Institute	$210,620,963
World Wildlife Fund	$161,178,434
Trust for Public Land	$157,446,182
Alliance for Climate Protection	$148,433,136
Natural Resources Defense Council	$141,353,655
National Parks Conservation Association	$65,213,199
Ducks Unlimited	$62,480,546
Oceana	$58,138,463

Percentage of Total: 56.8%

Table 2: Receipts by NTEE Code

NTEE Code	Description	Total Receipts
D30	Wildlife Preservation/Protection	246345360
C01	Alliance/Advocacy Organizations	162845340
C99	Environmental Quality, Protection, and Beautification N.E.C.	86594714
C05	Research Institutes and/or Public Policy Analysis	68331451
C30	Natural Resource Conservation and Protection	53857644
C60	Environmental Education and Outdoor Survival Programs	47909146
T30	Public Foundations	24397289
K25	Farmland Preservation	17038405
C32	Water Resource, Wetlands Conservation and Management	15603563
D20	Animal Protection and Welfare	14845627
U05	Research Institutes and/or Public Policy Analysis	13851562
C36	Forest Conservation	12451564
S99	Community Improvement, Capacity Building N.E.C.	12177546
U50	Biological, Life Science Research includes Marine Biology, Physiology, Biochemistry, Genetics, Biotechnology, etc.	7402068
C50	Environmental Beautification	7286782
Q05	Research Institutes and/or Public Policy Analysis	6630853
C27	Recycling	3807100
D01	Alliance/Advocacy Organizations	2496580
O50	Youth Development Programs	2309430
D31	Protection of Endangered Species	1201000
C34	Land Resources Conservation	986250
W05	Research Institutes and/or Public Policy Analysis	925000
C35	Energy Resources Conservation and Development	413000
U40	Engineering and Technology Research, Services	96000

Table 3: Summary of Model Parameters

	Foundation Parameters	Group Parameters
Index	$i = 1,2,\ldots,N$ $d = 1,2,\ldots,D$	$j = 1,2,\ldots,J;$ $t = 1,2,\ldots,T;$ $d = 1,2,\ldots,D$
Spatial Location	ν_i^d	θ_{jt}^d
Time-varying ideal point?	No	Yes
Random Effects	β_i	γ_j
Fixed covariate(s)	η	η

Table 4: Ten Most Left-of-center and Right-of-center Foundations (D1)

Foundation	State	First Dimension	Second Dimension
The UPS Foundation	Georgia	-5.180428344	2.921953823
Dominion Foundation	Pennsylvania	-3.692483455	-0.289837799
BP Foundation, Inc.	Texas	-2.700651918	1.781918903
ExxonMobil Foundation	Texas	-2.513338003	-0.128925933
F. M. Kirby Foundation, Inc.	New Jersey	-2.422532618	-0.326012935
Caterpillar Foundation	Illinois	-2.377965169	1.476912764
The Brown Foundation, Inc.	Texas	-2.289184972	-0.57379304
Duke Energy Foundation	North Carolina	-2.250468448	1.559820233
Gaylord and Dorothy Donnelley Foundation	Illinois	-2.120029737	-0.351662582
Alcoa Foundation	Pennsylvania	-2.092714389	1.799191781
Tides Foundation	California	1.244391563	-0.436984691
The Oak Foundation U.S.A.	Maine	1.278135695	0.91831418
Public Welfare Foundation, Inc.	District of Columbia	1.309579475	-1.20961345
Firedoll Foundation	California	1.321976249	-1.159876404
Moriah Fund	District of Columbia	1.387745578	1.044313316
The Streisand Foundation	California	1.652392988	-0.062900323
The John Merck Fund	Massachusett s	1.779604866	0.185034135
V. Kann Rasmussen Foundation	New York	1.899228944	1.275498987
The California Endowment	California	2.674624439	2.91481816
The Nathan Cummings Foundation	New York	2.713478717	1.393234231

Table 5: Ten Most Left-of-center and Right-of-center Foundations (D2)

Foundation	State	First Dimension	Second Dimension
The New-Land Foundation, Inc.	New York	0.98871267	-2.469242597
The Brainerd Foundation	Washington	0.526030238	-2.056570774
The Lazar Foundation	Oregon	0.120657449	-1.918294059
Harder Foundation	Washington	-0.039695056	-1.887660143
The McIntosh Foundation	District of Columbia	0.147475778	-1.842516034
The Fanwood Foundation	New York	-0.170166982	-1.801843683
The Charles Engelhard Foundation	New York	-0.967676161	-1.512027793
Elmina B. Sewall Foundation	Maine	-1.395016686	-1.500599392
MARPAT Foundation, Inc.	Maryland	-0.823110129	-1.477298387
Wiancko Charitable Foundation, Inc.	Washington	0.613967587	-1.391992169
Weyerhaeuser Company Foundation	Washington	-1.85099701	4.669071135
GE Foundation	Connecticut	-1.010446241	3.388533206
The UPS Foundation	Georgia	-5.180428344	2.921953823
The California Endowment	California	2.674624439	2.91481816
W. K. Kellogg Foundation	Michigan	-0.082464044	2.76864412
The Rockefeller Foundation	New York	-0.018802205	2.714995877
Citi Foundation	New York	-1.044409204	2.595473453
Ray C. Anderson Foundation, Inc.	Georgia	-0.879064597	2.318446008
Ford Foundation	New York	1.155907534	2.109177885
The John D. and Catherine T. MacArthur Foundation	Illinois	-0.771369642	1.979761927

Table 6: Predicting Grant Amounts

Model/ Variable	Baseline (Random Effects Only)	Baseline with Covariates	Structural with Separate Dimensions	Structural with Total Distance
Intercept	10.185***	10.043***	10.211***	10.411***
	(0.134)	(0.152)	(0.157)	(0.167)
Same Location		0.053***	0.057***	0.064***
		(0.000)	(0.000)	(0.000)
NY Donor		0.570	0.686*	0.646*
		(0.292)	(0.305)	(0.305)
CA Donor		0.504	0.556	0.536
		(0.315)	(0.330)	(0.330)
DC Recipient		0.057***	0.048***	0.049***
		(0.000)	(0.000)	(0.000)
1st Dimension. Distance			-0.063***	
			(0.000)	
2nd Dimension Distance			-0.146***	
			(0.000)	
Total Distance				-0.360***
				(0.000)
Log-Likelihood	-963272208.540	963043711.195	-938760661.782	-933301856.729
Deviance	1926544417.080	1926087422.390	1877521323.563	1866603713.458
AIC	1926544423.080	1926087436.390	1877521341.563	1866603729.458
BIC	1926544444.376	1926087486.082	1877521405.453	1866603786.249

N	8945	8945	8945	8945

Note: **Results are from a log-Normal mixed effects model, with all random effects suppressed and standard errors in parentheses. ***p<0.001, **p<0.01, *p<0.05**

Table 7: Does Spatial Change Matter?

	Model Coefficients
Intercept	7.453***
	(0.055)
Grant (Lagged 4th Root)[15]	0.183***
	(0.003)
$\boldsymbol{Distance_t - Distance_{t-1}}$ First Dimension	-0.035*
	(0.021)
$\boldsymbol{Distance_t - Distance_{t-1}}$ Second Dimension	0.007
	(0.019)
Same Location	0.159 ***
	(0.044)
Log-Likelihood	-5402
Deviance	10804
AIC	10820
BIC	10869
N	3723

***Note:* Results are from a log-Normal mixed effects model, with all random effects suppressed and standard errors in parentheses. ***p<0.001, **p<0.01, *p<0.05**

[15] Due to skewedness in the grant lag distribution and our inability to take the logarithm of zero, we opt to take the 4th root of the lagged grant amount. Other specifications do not affect the results.

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