Social Science Research 42 (2013) 1750–1764

Contents lists available at ScienceDirect

Social Science Research

journal homepage: www.elsevier.com/locate/ssresearch

Understanding selection bias, time-lags and measurement bias in secondary data sources: Putting the *Encyclopedia of Associations* database in broader context

Shaun Bevan [a,*], Frank R. Baumgartner [b], Erik W. Johnson [c], John D. McCarthy [d]

[a] *Mannheim Centre for European Social Research (MZES), University of Mannheim, Germany*
[b] *Department of Political Science, University of North Carolina, Chapel Hill, United States*
[c] *Department of Sociology, Washington State University, United States*
[d] *Department of Sociology and Criminology, Pennsylvania State University, United States*

ARTICLE INFO

Article history:
Received 1 January 2013
Revised 9 April 2013
Accepted 12 August 2013
Available online 22 August 2013

Keywords:
Secondary data
Measurement
Associations
Interest groups
Social movements

ABSTRACT

Secondary data gathered for purposes other than research play an important role in the social sciences. A recent data release has made an important source of publicly available data on associational interests, the *Encyclopedia of Associations (EA),* readily accessible to scholars (www.policyagendas.org). In this paper we introduce these new data and systematically investigate issues of lag between events and subsequent reporting in the *EA*, as these have important but under-appreciated effects on time-series statistical models. We further analyze the accuracy and coverage of the database in numerous ways. Our study serves as a guide to potential users of this database, but we also reflect upon a number of issues that should concern all researchers who use secondary data such as newspaper records, IRS reports and FBI Uniform Crime Reports.

1. Introduction

Our aims in this paper are twofold. The first is to describe a systematic data set we have assembled that will allow researchers to track, over an extended period, the national associations in the US that make up what political scientists call the interest-group system or the associational universe. The source of that data is the *Encyclopedia of Associations,* a publication that was not originally assembled for research, but which has extensive research value nonetheless. The second is to situate the potential biases that we enumerate and assess in the EA into a broader context of problems of bias that have been investigated in the use of other widely used data sets, including FBI Uniform Crime Reports, IRS 990 filings, and newspaper reports of protest. We call such data secondary, in that is not initially collected by researchers for their own purposes, but distinguish it from the typical use of the term to describe survey data that is used by researchers who did not collect the survey data themselves. We begin by introducing the EA data set, then describe our assessment of its biases, and conclude with a discussion of the lessons we believe our efforts teach, comparing and contrasting our assessments of the EA with similar efforts to assess biases in newspaper, IRS and FBI crime data.

* Corresponding author. Address: University of Mannheim, MZES, D-68131 Mannheim, Germany. Fax: +49 621 181 2845.
E-mail address: shaun.bevan@gmail.com (S. Bevan).

0049-089X/$ - see front matter © 2013 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.ssresearch.2013.08.003

2. The encyclopedia of associations

Since 1956 Gale Research (which became part of Thomson Learning in 1984, and a part of Cenage Larning in 2007) has published an annual volume listing US voluntary associations active at the national level: the *Encyclopedia of Associations (EA)*.[1] The *EA* is intended to act much like a trade directory that potential members and other interested parties can use to locate information about groups of interest. This directory is the publisher's best attempt in any given year to capture the total number of national-level voluntary associations operating in the United States. The annual nature and consistently meticulous search process used by the compilers of the *EA* make it an excellent resource for the creation of a time-series dataset on national-level voluntary associations.

For each organization listed, the *EA* provides contact information, an abstract describing its activities, information about its membership size, staff, budget, and details such as whether it publishes magazines, holds annual conventions, etc. The *EA* is organized into 16 sections including Trade and Business, Health, Agriculture, Environment, Public Affairs, Social Welfare, among others, and each group is associated with a keyword that further highlights the main focus of its activities. Hundreds of highly detailed keywords are used. The 16 sections used to organize the Sections of the *EA* have been used in a consistent manner since 1959, with only minor changes to the subject names over time.[2]

The *EA's* empirical value has been demonstrated previously by other research, generally[3] within specific areas of interest, e.g., the women's and civil rights movements (Minkoff, 1995, 1997), gay/lesbian movement (Nownes, 2004) labor unions (Martin et al., 2006), human rights (Walker et al., 2010) and the environment (Johnson et al., 2010; Johnson and Frickel, 2011). Many scholars are interested in tracking populations of associations within policy sectors or issue-domains (Aldrich and Ruef, 2006; Davis et al., 2005; Hannan and Freeman, 1989; McCarthy and Zald, 1977; Minkoff and McCarthy, 2009; Perrow, 1992; Walker, 1983, 1991), and they use a variety of methods to do so. Important sources of data include general organizational directories like the *EA* and *Yearbook of International Associations* (see e.g. Boli and Thomas, 1997; Smith and Wiest, 2012), as well as domain specific directories (e.g. Edwards, 1994), IRS 990 forms (Brulle et al., 2007), activist biographies (Rosenthal et al., 1985), newspaper reports (Soule and King, 2008), and combinations of secondary sources and qualitative methods to build systematic enumerations of organizations within a defined geographical area (e.g. Andrews and Edwards, 2005; Kempton et al., 2001).

Despite the variety of strategies employed to identify relevant populations of social change organizations, limitations of data access have largely restricted previous analyses to single topics or to a single population or community of organizations. Building comprehensive knowledge from case studies one issue-domain at a time is a limited route to generalizable theory. Whereas information on commercial establishments, trade unions, and registered political parties, for example, is relatively plentiful and readily accessible, the lack of available data for systematic research on the characteristics and dynamics of broad associational populations has been the subject of repeated lament in social movements and interest group literatures (Gray and Lowery, 2000; Knoke, 1986; Lowery, 2012; McCarthy and Castelli, 2002; Schlozman and Tierney, 1986; Walker 1991). By aggregating and making available the full data associated with the entire set of organizations listed in the *EA* (Gale Research, 1970–2005), we aim to spur more comprehensive assessments of the population dynamics of US voluntary associations.

In 2012 the Policy Agendas Project (PAP; see www.policyagendas.org) made available annual counts of associations present per year in each of the PAP topic categories. The PAP also makes available time-series databases relating to national government activities of all types from 1948 to present. By linking the EA database with those of the PAP, we allow scholars to study the linkages between growth and development of the voluntary sector with that of government. As government has become more active in education policy, have more education-related associations formed? Or, were associations leading indicators, preceding government activities in various fields? The PAP database also provides a cross-walk through its issue codes to a database composed of all reports of protest in the *New York Time* between 1960 and 1995, inclusive (http://www.stanford.edu/group/collectiveaction/cgi-bin/drupal/), allowing for the first time systematic analyses of public protest, the formation of voluntary associations, newspaper coverage, and government activity not just for a single issue-domain, but in all areas of public policy.

Our intent here is to assess the quality of the database and to bring front-and-center what we have learned about the apparent lag between the time when a group forms and the time when it is reported in these published volumes. The lessons we have learned throughout our efforts to create a high quality database from an existing published source, we believe, should have broad resonance for any scholars interested in using secondary data of any type.

2.1. Creating a database

We began the daunting project of compiling a time-series database covering 35 years and more than 20,000 records per year by looking at two sections of the database: Labor Unions, and Public Affairs. The Labor Union section had fewer than 300 records and focusing on it allowed us to understand the logistics and difficulties of the large task we were undertaking.

[1] Before 1974, volumes were published less regularly. Today, the printed version still appears each year, but many university libraries offer an electronically searchable database that is continuously updated: *Associations Unlimited*. The *EA* can be thought of as an annual snap shot of this database.

[2] The only major change in the 1970–2005 time period is the addition of a section on Fan Clubs in 1987.

[3] A bibliography including all social science journal articles using the source in some way generated from an exhaustive search of the JSTOR database is available (see Baumgartner and McCarthy, 2009).

Moving to the Public Affairs section allowed us to cover many politically relevant organizations, but still to be focused on fewer than 2000 groups in each volume rather than the full complement of organizations included in the *EA*. By beginning with a focus on two sections of the larger database we were able to draw some important lessons, which we incorporated as we expanded the project to the entire contents of the *EA.*

2.2. Accuracy and coverage

Several studies have addressed the issue of selection bias in the types of organizations included in the *EA* (e.g. Brulle et al., 2007; Johnson and Frickel, 2011, appendix A; Walker et al., 2011). We review this literature here, and our modest contribution, before moving onto the poorly understood issue of the lagged data-structure present in these data.

In the most authoritative test of potential selection bias in the *EA*, Martin et al. (2006) compared the *EA* coverage of labor unions with the universalistic catalog provided by the US Department of Labor, which requires all labor unions to register with them and makes this information available to the public. They found that the *EA* included 95% of all labor unions having more than 10,000 members. Coverage was lower among very small unions, just 50% in the case of unions with fewer than 5000 members. Budgetary and staff data showed a similar pattern: coverage was near universal among large groups and lower for groups with fewer resources.

Other sections of the *EA* do not benefit from the presence of an official registry of national groups, so we cannot carry out a similar analysis of inclusion in the *EA* as a percentage of a national universe of known groups. We have strong reasons to believe, however, that the high level of coverage for large groups as well as the more spotty coverage of small or ephemeral groups is a general rule (see also Brulle et al., 2007; Minkoff, 1999).[4] In later sections, we note how long it takes before a new organization is listed for the first time in the *EA*. This information about lag structures further corroborates the labor union analysis suggesting that large and stable groups are very highly covered whereas smaller groups, those without staff, and those that were only recently formed, are more likely to be missed. Scholars concerned with different elements of the US voluntary sector may have different reactions to this bias in coverage. For those interested in the impact of associations on public policy, it is certainly better to have high coverage of large (and presumably more influential) groups rather than small groups with no staff. For those interested in a fuller analysis of population dynamics, in particular the early stages of organizational life, the bias against small, new, and poor groups may be more problematic. For the typical user of the PAP, who may be interested in groups with the potential to affect public policy, omitting small groups with few resources is certainly preferable to missing the large, rich ones. Very few of these appear to be omitted from the *EA*.

3. Understanding lag structures

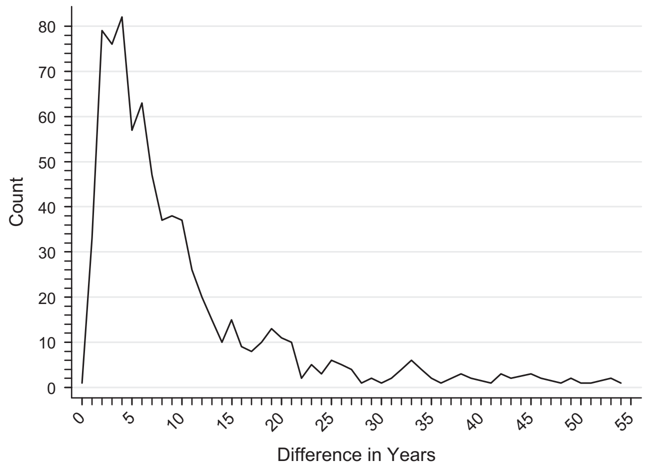
In a perfect world all new associations would be instantly recognized by the publisher of the *EA*, changes to association descriptions would be made in real time, and associations that fail would be removed from the directory immediately. Even in this hypothetical perfect world new associations and changes to the descriptions for existing associations could occur an entire year before being listed in a new volume of the *EA,* creating a lag between the event and its report. Here we pay careful attention to the delays between when an event occurs (e.g., a new organization is formed; it changes its budget, areas of activity, or staff size; or it goes out of existence) and when this new event is recorded in the annual *EA.* Understanding these delays is fundamental for scholars interested in time-series models of policy dynamics.

Available evidence suggests that the rules and procedures applied by *EA* editors to data collection are mostly consistent over time, with the reasonable exception of technological driven changes in search and information gathering procedures. Organizations are identified for inclusion primarily through scouring mass-media, with organizations then contacted directly with requests to provide the information necessary to complete *EA* entries. Minkoff found during her research in the 1980s that editors relied heavily on mass media (especially newspaper) accounts to initially identify organizations, and that once an organization was identified it typically took one additional year to contact the organization, assemble and publish relevant data (D. Minkoff, personal communication, March 28, 2013). This reliance on mass media coverage to initially identify organizations for inclusion in the *EA* existed both in earlier and, based on our conversations with *EA* staff, later time periods as well. The spread of digital media and new search technologies in recent years may be expected to reduce search costs and thus organizational listing lags (Minkoff, 2002). From our own statistical analyses we find that, on average, the printed volumes reflect events that occurred four years in the past for the time period covered by our data.

3.1. The lag between actions and their reporting

One bit of information recorded about each group listed in the *EA* is the date it was created. We can compare this reported creation date with the year when the organization first appears in the annual publication to assess lag structures. If a group reports being created in 1972 but does not appear in the *EA* before the 1980 edition, then we can say the lag is 8 years. About

[4] Brulle et al. (2007) further suggest that groups located in or near Washington D.C. are over-represented in the *EA* data, though Martin et al. (2006) did not find this for labor unions. Bias in coverage favoring groups proximate to national policy makers enhances our confidence that policy-relevant national groups are largely listed within its pages.



	Mean	Median	Mode	Min	Max
All groups	10.5	6	4	0	129
Excluding groups with more than 10 years of lag	5	5	4	0	10

Fig. 1. Count of differences between date first included and reported creation date.

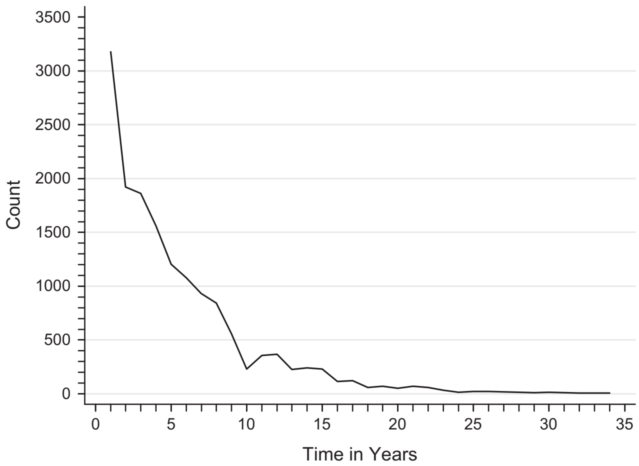
90% of the groups listed in the *EA* include information on their creation-year. Fig. 1 shows the delay between creation and first listing, and the table below provides summary statistics.

Fig. 1 shows the difference between founding dates and first inclusion is typically about 4 years but there is a fat right tail to the distribution, with one group being listed in the directory 129 years after it was created.[5] Our assessment is that these extreme outliers result from two processes. First, they result from the fact that many national associations were founded well before the *EA* began compiling its listing. Second, we suspect they stem also from changes in the purpose of the groups rather than deficiencies in the data collection process. This is the case with the group joining the directory 129 years after its founding, which was founded in 1865, but which originated as a state and later regional association. Recall that the *EA* is a directory of *national-level* voluntary associations. Many groups start out as local or regional groups and then, through merger, acquisition, or simple organizational transformation, become active on the national level years later. When asked to report the year they were *created*, they may well list the earliest relevant year, which might be when the largest parent organization was formed or during a period when the group was active only in a single state or region, and was therefore not eligible for inclusion in the *EA*. We do not always know exactly when a group shifted from being regional to having a national character, but our assessment of those groups with long delays in Fig. 1 suggests that most correspond to this process. Shifts in organizational scope are common as groups grow. This is why we present two sets of summary data: one for all groups listed and one excluding those groups with more than 10 years' delay. The truncated distribution corresponds better to the delay from creation of a group to its first listing in the *EA*, we believe.

With these possible reasons for a lag between a group's reported founding date and its year of first inclusion in mind, Fig. 1 can be understood more fully. What we can call the data collection lag is related to the process of surveying the landscape and identifying new organizations. The shifting scope of existing organizations (e.g. from a state-wide to national focus) may occur at any time in an organization's life-cycle. The results in Fig. 1 are therefore a combination of the effects of the search process and the selection criteria. These two factors result in a Poisson distribution, making the use of the mean or median values a poor estimate of the expected difference between when a group is first included in the *EA* and when it first met the inclusion criteria. Even when only considering those groups with a ten year difference or less the mean and median values are inappropriate. It is safe to assume that as the number of years difference increases the percentage of differences due to the search process decreases, while the percentage of differences due to changes in organizational scope increases. The best single estimate of the difference between first inclusion and first eligibility is the mode: 4 years. Group counts based on the edition with a copyright year of 1990 therefore reflect group formations, deaths, and mergers from 1986, on average.[6] As the figure makes clear, there is considerable variation around this average. Thus, we see an inherent measurement ambiguity

[5] Fig. 1 is based on the Public Affairs section of the *EA*. The number of groups per PAP topic code in the Public Affairs section correlates at more than 0.95 with the number of groups with that same topic code in the overall *EA* for the cases of civil rights, defense, government operations, and foreign affairs. Therefore we feel confident extrapolating from our more detailed analysis of the Public Affairs section.

[6] A comparison of the most recent edition of the *EA* used in our analyses (copyright 2002) with the full dataset shows no significant differences over time in updating lag. The data for 2002 demonstrate the same second spike at 4 years as is displayed in Fig. 1. However, it is around this time that organizational web sites become commonplace (only a small percentage of our groups report websites in 2002, compared to near universal coverage in 2013). Future research should examine whether data-entry lags decrease in the most recent time period. More timely updating is exactly the intent of Associations Unlimited, the online and continuously update version of the hard-copy published *EA*.



	Mean	Median	Mode	Min	Max
All groups	5.5	4	1	1	34
Excluding groups with more than 10 years of lag	3.9	3	1	1	10

Fig. 2. Group updating time, continuing groups.

relating to the original data collection process: some events are recorded in the database with a six-year lag, some after two years, and so on, with four years the typical case.

3.2. Updating an annual volume

We can assess lag structures in additional ways: by looking at how such information as budgets, staff sizes, and membership is reported from year to year for the same group, and by looking at what happens to listings after groups go defunct. It is clear from this analysis that while the compilers of the *EA* do their best to contact each group every year, in the absence of new information they continue to publish the most recent information previously reported. Thus, some percentage of what is listed as information for year$_t$ is actually about year$_{t-x}$, where x is a range of years, not a single value.

We provide here some examples of organizational updates that illustrate our concern. The American Political Science Association, for example, lists a membership of 2300 in the 1981 edition, 2400 in 1983 through 1987, then 2200 members in each volume from 1990 through 2003. The American Civil Liberties Union lists 275,000 members, 125 staff, and a budget of $20 million in each volume from 1998 through 2003. Our point is not that the directory is inaccurate, but that updates may or may not be made on an annual basis, depending on whether the group in question responded to the publisher's inquiries or whether updated information was available for the publisher to update using public sources. Fig. 2 gives our assessment of how many years separate any changes in the numeric resources (that is, either budget, staff, or membership size) in the Public Affairs section of the *EA*. Note that this figure likely *overestimates* update lag, because we are unable to distinguish between the failure to update an organizational listing and instances where updates are made but there are no changes reported.[7]

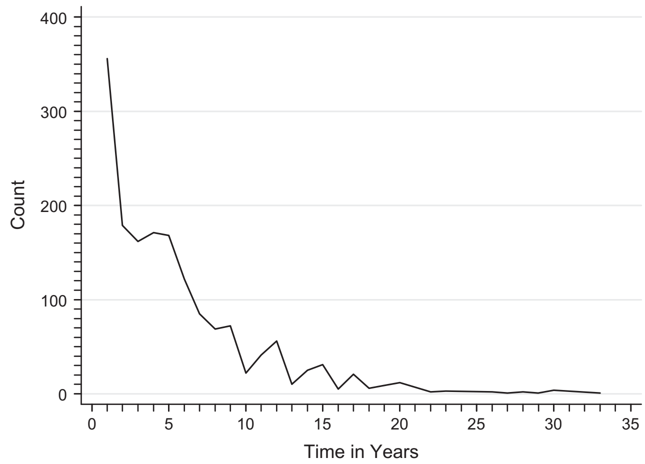
As Fig. 2 shows the compilers of the *EA* update resource information for most groups quite regularly; the modal category is every year. However, some groups clearly do not respond to the repeated requests they receive from the *EA* staff, and the distribution tails off to the right with some information remaining in print decades after it was last updated. The data in Fig. 2 indicate that updates follow a Weibull distribution and the mean and median values are therefore meaningful. The summary statistics reported in Fig. 2 indicate that group information is updated every 4 years on average with half of the groups being updated more frequently, but with some being updated much more rarely.

Fig. 2 is limited to those groups that continued in existence past the last year of observation. In Fig. 3 we present identical information for those groups that went out of existence. One might expect that for failing groups[8], we might see a longer period of inactivity before the compilers finally decided that the group no longer existed or received clear evidence of the group's demise.

The results in Fig. 3 are quite similar to the results for continuing groups in Fig. 2 in the shape of the distribution, but there are some small differences. While the modal category for updates is again after a single year, a second peak in the data is found at the 4 year mark. Additionally, the proportion of updates occurring after more than 3 years is slightly higher with

[7] However, as our update measures are a combination of staff, budget and membership numbers it is unlikely that these values would remain unchanged for five years in the majority of associations.

[8] By failing we mean groups that were removed from the EA. In this sense a failure may mean several things the most common of which is the failure of the group outright, but also includes a group changing into a corporation or reverting back to a regional or even state association. However, all of these failures are by defition a failure for the group as a national-level voluntary association (see Bevan, 2013).



	Mean	Median	Mode	Min	Max
All groups	5.4	4	1	1	33
Excluding groups with more than 10 years of lag	3.9	4	1	1	10

Fig. 3. Group updating time, failed groups.

failing groups. Still, whether we look at continuing groups, failing groups, or the first appearance of newly created groups, Figs. 1–3 and the associated statistical summaries make clear that 4 years is the average lag from an event affecting a group and that information being reflected in the *EA*.

4. Imputing annual counts from five-year observations

Based on the analysis above, as we moved to create a comprehensive time-series of these large annual volumes, we determined that we could estimate the numbers of groups existing each year by PAP topic category reasonably accurately by assessing counts in the *EA* on the basis of five-year increments.[9] We lost little in terms of measurement accuracy, since the entries are typically not updated annually in the first place. The PAP database relating to the *EA* therefore has an indicator variable coded 1 for those years where we compiled the data directly from the *EA* and coded 0 for those years which are estimates. Here we explain how we imputed the annual counts from the observations based on the five-year intervals.

Using an extended version of the PAP coding scheme (see Table 1) research assistants classified each association by topic. In order to create a consistent time series, we faced the task of linking the entry for a given organization, say the National Association of Manufacturers, in one year to the same organization in another year. We found that the purpose of an organization changed only very rarely, and such items as the creation date remained unchanged across all editions of the *EA*. So by matching each group to its entry in previous editions, we were able to create a single panel dataset. Creating this panel dataset was a time- and resource-intensive task, but the choice to code every five years was based on an investigation of the *EA* that revealed that less than 10% of all associations contained in the *EA* survive for fewer than five years. A five year sampling procedure assures that the vast majority of associations (greater than 90%) are captured in the *EA* dataset. Further, among organizations with significant staff, budget, and presence, virtually all survive for at least five years. The five year sampling process therefore produces a workable dataset of national-level voluntary associations in the US.

Table 1 presents the extension of the traditional PAP topic coding system, breaking apart Topic 12 (law and crime as topic 12, but with family-oriented organizations in their own category 11); sub-setting from public affairs groups (topic 20) those that were purely single issue-ideological groups (topic 32), and sub-setting from the general "culture" topic 23 those groups based on arts (topic 40), culture (41), and shared hobbies (42). The table shows the number of organizations in each of these extended topic areas for the 2005 edition of the *EA*. By consulting the PAP website users can easily see the number, per PAP topic category, for each year from 1970 to 2005.[10]

While we believe the use of a five-year sampling procedure appropriately captures the population of groups contained in the *EA* it also makes necessary the imputation of data for the years not directly observed. We make use of our precise knowledge of the overall number of groups in each volume to improve on a simple linear interpellation.[11] We count the precise

[9] For the labor union and public affairs sections, with which we started, we gathered information for each year, and the analysis above is based on the public affairs section of the dataset. After seeing these patterns, and the high cost of data collection in terms of person-hours, we determined it was better to complete the project based on observations at 5-year intervals.

[10] Yearly adjusted counts of national organizations by *EA* topic category are available from the Policy Agendas Project (PAP) website: http://www.policyagendas.org/page/datasets-codebooks#EA_of_associations.

[11] See Honaker and King (2010) for a more general discussion of how to impute time series cross-sectional data. In this case, given the clear effect that the overall number of groups has on the *EA* dataset, we are confident that the method we discuss here performs well.

Table 1
EA dataset extended topic codes and PAP equivalents.

EA topic	PAP topic	Abbreviation	Name	Number listed, 2005
1	1	Economy	Macroeconomics, taxes, and the economy	83
2	2	Civil	Civil Rights, Minority Issues and Civil Liberties	848
3	3	Health	Health	2822
4	4	Agriculture	Agriculture	987
5	5	Labor	Labor, Employment, and Immigration	418
6	6	Education	Formal Education System	1214
7	7	Environment	Environment	566
8	8	Energy	Energy	184
10	10	Transport	Transportation	790
11[b]	12	Family	Family Issues	401
12	12	Law	Law and Crime Issues	507
13	13	Social	Social Welfare	467
14	14	Housing	Community Development and Housing Issues	192
15	15	Commerce	Banking, Finance, and Domestic Commerce including Business and Corporate Issues	2883
16	16	Defense	Defense	656
17	17	Science	Telecommunications, Mass Media, Space, Science and Technology	1151
18	18	Trade	Foreign Trade	156
19	19	Foreign	International Affairs and Foreign Aid	1321
20	20	Gov't	Federal Government, Public Policy Generally	424
21	21	Lands	Public Lands and Territories, Indian Affairs, Forest Management, and Government Dams, Water, and Irrigation Projects	151
24[a]	24	State	State and Local Government and Policy	98
26[a]	26	Weather	Weather and Natural Disasters	16
27[a]	27	Fire	Fires	10
29[a]	29	Sport	Sports and Recreation	795
30[a]	30	Death	Death Notices	22
31[a]	31	Church	Churches and Religion	943
32[b]	20	Ideological	Ideological, Social Cause, and Political Groups	611
40[b]	23	Arts	Performing, Fine and Creative Arts	1193
41[b]	23	Culture	Culture, Heritage and History	1480
42[b]	23	Hobbies	Hobbies, Collectors, Amusements and Clubs	940
99[b]	99	Other	Other and Miscellaneous	95

Note that the PAP website lists all data with the traditional PAP codes but that the extended codes are available by downloading the full data file. N's listed refer to the most recent, 2005, edition.
[a] An addition from the New York Times Codebook.
[b] An addition from the EA Codebook.

number in each annual volume, by *EA* section, and make that information available on the PAP web site. However, the *EA* sections do not correspond perfectly to the PAP topic codes, so our extrapolations are designed to calculate these estimates. The linear count of groups by issue is calculated for the missing data points by averaging the change in counts between each coded year. For example, if there are 100 groups in year_t and 120 groups in year_{t+5} the growth of 20 groups is average over the four missing years producing imputed values of 104, 108, 112, 116 in order. We then transpose these annual counts of groups into percentages of each annual total. Since we know the actual total number, we adjust the estimated number of groups per topic code by multiplying the estimated percentage of the annual total by the *actual* total for that year. The resulting measure combines the linear imputation of group percentages by issue with the known count of groups and provides greater variance for the group count series based on real data. The resulting series by issue is presented in Fig. 4 in a stacked count graph.

Fig. 4 shows the dramatic changes that have taken place in the associational universe in the US from 1970 to 2005. Trade associations have always been an important element of the total, but their share has declined steadily as a proportion of the universe of national associations. Health, education, and environmental groups have grown quickly, while labor groups have stagnated. We do not elaborate on these substantive trends here (see Jordan et al., 2012), but the key take away is that this new database allows an analysis of change across the full range of national associations in the US over time.

Several scholars, as we have observed, have studied the growth of groups in a single issue domain or in a small number of related domains (e.g. Hannan and Freeman, 1989; Chong, 1991; Hansen, 1991; Minkoff, 1995, 1997; Nownes, 2004; Johnson and Frickel, 2011; Soule and King, 2008). Yet, surprisingly no scholar has systematically studied the growth of the group system in the United States over time despite the large body of work that considers that general process (e.g. Olson, 1965; Walker, 1983; Hannan and Freeman, 1989; Perrow, 1992; Aldrich and Ruef, 2006). The creation of the *EA* dataset and the imputations calculated from it will, we hope, help to change that by allowing for far more comprehensive investigations of groups across policy issues (e.g. Bevan, 2013).

5. Lessons from similar secondary data sources for assessing bias in the *EA*

In any area of research, scholars using secondary data collected for other purposes must be concerned with its quality and potential biases. In this section we organize discussion around the quality of the source data as well as two sources of bias that are the focus of social science survey research more generally (it can be useful to think of the *EA* and similar directories as the result of a yearly organizational survey administered by the publisher): *sampling bias* and *measurement bias*. We seek to place bias contained in the *EA* within a broader perspective by focusing especially on how it compares with other secondary sources with similar attributes, but about which scientists know more. Knowledge from similar research communities on other popular sources of secondary data (such as the FBI Uniform Crime Reports, IRS 501(c)3 registrations and media), has heretofore failed to inform our understanding of increasingly popular organizational directory resources (including not just the *EA*, but also, e.g. the *Yearbook of International Associations* and the *Directory of British Associations*). These data sources are increasingly important within sociology, political science, and other social science research on a broad range of nonprofit organizations (including politically oriented groups), yet there is surprisingly little attention given to sources of potential bias in these directories. Research on organizational survey methodologies has similarly remained unconnected to the analysis of these organizational directories.

The reflections we offer concerning the *EA* database are meant not only to elucidate these issues for potential users of this valuable new resource, but to allow us the opportunity for a bit broader discussion of how to assess the quality of any similar secondary database. There are no doubt many other research communities working with other data sources collected for purposes beyond basic research. What is striking to us, however, is how investigations of bias in the sources we discuss here have run parallel to one another with almost no reference to researchers in other substantive domains who have considered very similar issues of bias.

5.1. Source quality

5.1.1. What was the original purpose for which the data was collected?

The first and most important question in using secondary data is also the most obvious, but is often overlooked. The purpose of the data and audience it was intended for play a large role in the data generating process. This can lead to inclusions or exclusions of potentially important observations, and introduce systematic biases in a secondary data source. Identifying these biases is a necessary first step in accounting for or correcting them.

Research on newspaper reporting of protest events is particularly instructive here. Media traces, particularly newspaper reports, have been widely used by researchers to study protest events (Earl et al., 2004). News reporters and editors very selectively determine what news items are published, governed by what systematic observers of the media have dubbed "news values." Media gatekeepers are most certainly not influenced by the concerns of researchers who use their products, and the dimensions of selectivity of events to be covered (selection bias) and the content of media descriptions of those events (measurement of description bias) have been the focus of research aimed at delineating the biases in news products (e.g. McCarthy et al., 1996; Oliver and Myers, 1999; Oliver and Maney, 2000) demonstrating empirically the central role of news values in creating these biases.

In the case of the *EA*, the goal of the creators of the original volumes has consistently been to create a comprehensive list of national-level voluntary associations in the United States. The *EA* serves as a reference text for libraries and schools, as well as a source for businesses such as printers and event organizers seeking to identify potential clients. This suggests a strong motive for comprehensiveness exists for its creators at least when it comes to large and established groups. That

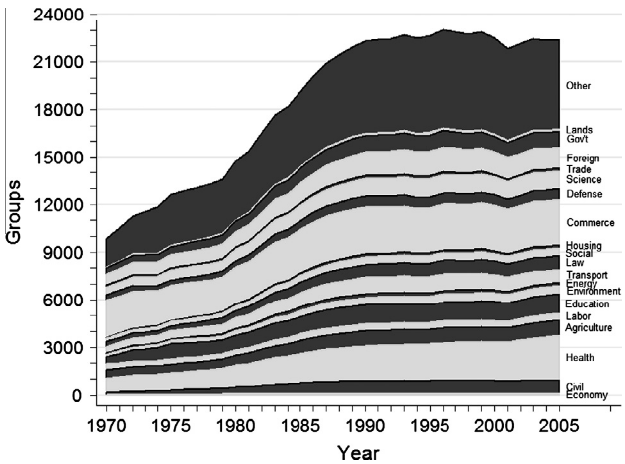


Fig. 4. Imputed group densities by issue, 1970–2005.

the *EA* also lists information on name changes and group mergers, allowing users to trace individual groups over time as they evolve and change, suggests a strong motive for accuracy in these details. One popular alternative source of information on national non-profit associations is the Internal Revenue Service's 990 registration and reporting system, which has become increasingly comprehensive in recent decades and now requires all 501(c) nonprofit organizations to register and submit annual financial reports that also include additional information on those organizations' mission and annual activities. These reports are now finding wide use by researchers interested in the rapidly growing nonprofit sector in the US (e.g. Saxton and Benson, 2005). While this elaborate system was not established to gather data for researchers of nonprofit organizations, its evolution has been, in part, guided by such concerns through the efforts of the National Center for Charitable Statistics (NCCS, 2010a). Since the system is a voluntary reporting one, questions have been raised about the accuracy of information provided by nonprofits to the IRS (measurement bias) as well as the timeliness of registration (lag in reporting, a subcategory of selection bias), each of which will be discussed below.

Beginning in the 1920s the Federal Bureau of Investigation started collecting information about "crimes known" to the police. The mature FBI Uniform Crime Report (UCR) is the aggregation of reports from every police jurisdiction in the US on at least the seven major individual crimes (homicide, aggravated assault, forcible rape, burglary, robbery, theft and auto theft). The reporting system has achieved high rates of compliance, typically receiving reports from almost all jurisdictions annually. These official crime reports are often used to evaluate police performance among neighborhoods at the local level, and when made public provide opportunities to assess police performance between cities. These realities place heavy pressure upon police district commanders and agencies to underreport crimes (Mosher et al., 2002).

5.1.2. What is the reputation of the data source creator(s)?

The credibility of the data source is an important proxy indicator of quality. Established academic researchers and research institutions (e.g. NORC, Michigan's Institute for Social Research/ICPSR, Gallup, etc.), for instance, have reputations to consider and can be expected to strive to produce the highest quality data possible that can, once archived, be used by other researchers. On the other hand, businesses (especially those dominated by short-term economic incentives) may produce data that is designed to suit their needs or frame the data in a way that serves those needs best.[12]

In the case of the *EA* the publisher, Gale Research (founded in 1954, purchased by the Thomson Corporation in 1985, Cenage Learning in 2007), has throughout its history been focused on creating high quality reference sources and databases for sale to libraries and educational institutions. Founded by Frederick Gale Ruffner in 1954, the company quickly gained a sterling reputation for this task, building off the success of the *EA.* Gale Research is today responsible for producing a wide variety of reference texts beyond the *EA,* as well as respected online historical, newspaper and various other databases. Given its long-standing market niche as a producer of high-quality library reference works, the publisher can be expected to value the strength of its reputation and to strive to create as accurate and useful reference texts as possible. Furthermore, as a result of what we have determined is a common and consistent work culture at the publisher the same basic rules and principles have governed the gathering of data, except for reasonable changes in the search and information gathering procedures with the advent of new and emerging technologies. Personal meetings between a senior author of this article and the senior staff of Thompson / Gale responsible for compiling the *EA* made clear the high standards that the publisher sets as a continuing goal. Over the decades, compilers have developed considerable expertise and they appear to value their reputation for compiling high quality information. Were this reputation to be degraded, or should a rival publisher offer a more complete directory, considerable profit to the firm would be lost.[13]

Among US researchers of protest events, the *New York Times* has been the primary source of data in large part because it is the premier national newspaper, with a reputation for objective reporting, an important rationale for its wide use as a research tool. The public availability of a comprehensive data set on protest events constructed from its reports[14] has quickened the pace of such research in recent years, and, as a result, we know most about biases in its coverage and reporting. The IRS has achieved a strong reputation for assembling information from tax records, although recent cuts in its agency funding are thought by some to have reduced its ability to audit reports, and, in general, its auditing attention to nonprofit reporting appears to be driven primarily by complaints from citizens and watchdog organizations. It does not yet possess a mechanism to enforce the recent registration requirement that all nonprofit organizations, even the smallest with minuscule budgets, register. The NCCS has a strong reputation as a vendor of statistical information on the nonprofit sector, including its management of the 990 data bases. The FBI devotes extensive resources to its UCR data gathering efforts, and is widely recognized to be doing a good job in monitoring local jurisdictions cooperation and encouraging compliance with its rigid reporting protocols.

5.2. Measurement bias

Measurement bias refers to the degree of accuracy of measures of the concepts they are intended to reflect. The publishers of the *EA* primarily rely on survey responses from representatives of individual groups to compile their volumes. The use of survey data from groups themselves means that the description of an association contained in the *EA* may be slanted toward representing the best public face of an association. One association in the dataset called the *Salt Institute,* for instance, states

12 See Lewis (2011) for stark evidence of this pattern by financial institutions leading up to and following the 2008 financial collapse.

13 The firm currently charges $1037 for the print version of Volume 1, and $2663 for Volumes 1–3.

14 http://www.stanford.edu/group/collectiveaction/cgi-bin/drupal/.

that its primary goal is to educate the public about the health benefits from a healthy sodium intake as well as the many common and uncommon uses for salt in our everyday lives. In reality the goal of the *Salt Institute* is not public education, but to promote the use of salt so that the many companies that are members of the group can expand their sales volume and thereby make greater profits. Research assistants in charge of coding the *EA's* entries were aware of this incentive to misrepresent a group's primary goals in the text of group abstracts and were trained to deal with them by using the implied meanings of the group abstracts rather than the literal meanings when appropriate. Thus we aimed to have groups like the *Salt Institute* be properly coded as commerce associations rather than health-focused ones. The *EA* dataset therefore represents an educated assessment of the primary public face of national-level voluntary associations over time.

Newspaper reports about the size of protest events are typically disputed by activist organizers who complain that they underestimate the number of demonstrators present, a reflection of the extent of support for the dissident message they intend to communicate (McPhail and McCarthy, 2004). While there are very few systematic assessments of such claims, one study suggests that newspaper reports are generally rather accurate in their reports of what journalists call "hard news," that is the basic details about when and where an event occurred, its primary message, and the number of demonstrators present (McCarthy et al., 1998), lending credence to claims that measurement error in such reports is probably a trivial concern.

The wide use of IRS 990 filing information has prompted a spate of studies of the accuracy of financial information provided by the filings of tax-exempt nonprofits (Froelich et al., 2000; Yetman et al., 2009; Fischer et al., 2002). And, while discrepancies are revealed between voluntary reports and independent audits of samples of nonprofits, these appear, in general, to be relatively minor, leading the authors of one widely cited study to "conclude that the IRS 990 Return can be considered an adequate and reliable source of financial information for many types of investigations..." (Froelich et al., 2000, p. 232). We have been unable to locate studies assessing the accuracy of other forms of information included in the 990 returns.

5.3. Selection bias

Selection bias refers to biases in the inclusion of cases (individuals, organizations or events) in a data base. Newspaper selection bias has been widely studied by scholars of protest events and consistently demonstrates that large events are much more likely to be covered and smaller events much less likely to be covered. This finding mimics what we know about larger associations being more likely to be included in the *EA*, and about large nonprofit associations being almost universally registered and filing annual 990 reports while very small ones are far less likely to be registered and if so, less dutiful in filing annual reports.

Protest event selection bias studies have also investigated variation in patterns of bias between newspaper sources and mixed media sources, including comparisons of local with national sources, local with other local sources, and print with television sources. The empirical results of these many studies have been mixed, sometimes showing major differences in source bias and sometimes relatively minor differences.[15] One strategy designed to generate more comprehensive event catalogs is the use of multiple news sources, a strategy that has become far more feasible with the wide availability of media source data in electronically searchable form (e.g. Schrodt, 2012).

Data bases typically are fraught with selection biases, many of which are intentional. As a result, alternative sources used for enumerations of organizational populations rarely include identical cases. That is, alternative sources can be expected to exhibit variable patterns of selection bias. The strategy of adopting multiple sources to triangulate a more comprehensive catalog of events in newspapers can be applied to the study of non-profit associations. It is likely that an enumeration strategy relying on a discrete number of broadly representative sources is the most feasible route towards a more comprehensive data-collection strategy. Clearly, the EA would be an important source for populations of national associations in the US.

Oftentimes, selection biases are the intentional result of explicit filtering rules. The intended coverage of the *EA* is every national-level voluntary association in the US active during the year of publication, for instance. Scholars interested in local groups, international groups, or non-membership lobbying organizations will find no useful information here. Knowing the intended coverage of a data source is a fundamental aspect of assessing its potential usefulness. Rules for including and excluding an observation from the data play an important role in the creation of a secondary data source and should be well noted by any researcher interested in using it.

Two main criteria must be met for an association to be included in the *EA*. The first is that an association is active at the national level, not just in certain regions or localities. The second criterion is that the association be a voluntary association, defined as an association whose membership joins by choice for some common goal or goals other than profit. Following these two criteria the publishers include a wide variety of groups from the Sierra Club to the United Autoworkers Union to Bobs International (an association comprised of people with the forename Robert that holds an annual national convention with awards that include the best shish ka-Bob). Despite including all groups matching the publisher's definition of a national-level voluntary association by following these two criteria the publisher excludes the vast majority of formal organizations in the United States namely local/state groups and businesses. It is with these two criteria that the publisher of the *EA* has done a consistent job of documenting national-level voluntary associations over time.

[15] One study in particular suggests that source selection bias makes newspaper protest event data highly unreliable for studying cross-community or time series patterns or protest (Ortiz et al., 2005).

A number of studies have compared different sources with regards to their coverage of associations and scholars have complained that different data sources lead to widely varying estimates of the number of groups. Scholars using various sources such as IRS Form 990s and enumerations of groups in a given locality (typically in a single issue domain such as the environment) sometimes identify numbers of groups that are very different from what would be found relying exclusively on the *EA* (Andrews and Edwards, 2005; Brulle et al., 2007; Carmichael et al., 2012). A particularly harsh critique of the *EA* as a comprehensive source of environmental advocacy organizations compares it with a variety of other listings of US national environmental organizations (Brulle et al., 2007; Carmichael et al., 2012), arguing that its lack of comprehensiveness renders it a poor resource for studying national environmental organizations. Two subsequent studies have addressed the question of selection bias in the *EA*, one for environmental organizations (Johnson and Frickel, 2011) and another for subcategories of advocacy groups (women's, human rights, and civil rights) (Walker et al., 2010). Each makes a strong case for how to take known selection biases into account when interpreting models, and for the *EA* as a particularly valuable resource when analysts are interested in temporal change. While IRS data are more comprehensive in terms of the total volume of organizational listings, this source omits politically active groups that do not qualify for tax-exempt status. More troubling for analysts interested in temporal change is that, while the official selection criteria for the IRS's 990 registration and reporting system may have changed little over time, the registry has clearly grown increasingly comprehensive. In contrast, the publishers of the *EA* have maintained relatively stable selection criteria for 50+ years and the resulting data is thus more suitable for over time analyses.

We believe that much of the current debate over representativeness in the *EA* overlooks the reality that any directory or survey misses information on population members. For instance, a review of articles published in *Nonprofit and Voluntary Sector Quarterly* from 1996–2001 found that published studies employing mail surveys of non-profit organizations had an average return rate of 42% (Hager et al., 2003).[16] The issue, we think, is less about comprehensiveness than it is differences in intended coverage and what is known about the biases in selection onto the lists that are used so that we can take those selection biases into account when performing and interpreting analyses. That is, understanding the rules that allow a group to be listed or not is fundamental to knowing whether the database is useful for one's purpose.

Probably the most dramatic example of a secondary data set beset with serious and well investigated selection bias issues, but nevertheless still in wide use by researchers, is the FBI Uniform Crime Reports (UCR). Beginning with two classic critiques of official crime statistics (Kitsuse and Cicourel, 1963; Black, 1970) researchers have identified a wide variety of factors that affect the rate at which crimes are reported by citizens and police. Key issues of bias in these data include variable rates of citizen reporting of crimes to police (selection bias) and how local police policies and organizational structure affect what gets recorded and passed onto the FBI (selection and measurement bias respectively). For example, one widely cited study concludes "...official crime rates are a function of [police] organizational structures related to (1) formal complaint investigation; (2) hierarchical control of crime processing; and (3) dispatching routines" (McCleary et al., 1982, p. 361). And, a more recent study looking at the size of a police force controlled for population size of a jurisdiction, shows that "each additional officer is associated with roughly five Index crimes that previously would have gone unreported" (Levitt, 1998, p. 61).

The result of this stream of research is a detailed portrait of the extensive biases contained in official crime statistics, such as the UCR (see Mosher et al., 2002 for a summary). Despite this, criminologists and policy analysts continue to routinely use the reports to study major crime rates over time and across communities. Criminologists who use these data are well aware of selection bias problems, but there are few other such comprehensive time series sources of data on crime across American communities available.[17] UCR users work around data limitations by drawing on multiple sources (e.g. UCR official stats and unofficial victim surveys) in an attempt to triangulate their data (e.g., Gove et al., 1985; Schwartz et al., 2009). These users recognize that, while the UCR cannot tell us the exact amount of crime (it is not 100% comprehensive), it does accurately depict changes in relative characteristics over time (e.g. male v. female crime, the relative incidence of different crime types). The selection bias issues we have identified in the *EA* pale in comparison to those confronted by criminologists.

IRS Form 990s list all groups that fall under a certain element of the tax code. They include local groups (which are indistinguishable from those with a regional or national orientation), groups that have many spin-offs for tax purposes, and groups without members. These IRS data do not include information on many other groups, however, since organizations are not required to register with the government unless they seek formal non-profit status, and many (especially in the case of politically active groups) do not do so (Edwards, 1994; McCarthy et al., 1991). Biases contained within the *EA* privilege the types of organizations that are most central to the theoretical concerns of social movement and interest group scholars, those that are large and more politically active (as indicated by an inclusion bias towards groups located close to the nation's capital). Relying on newspaper reports of groups would generate a much smaller list than what we have here, as the vast majority of the groups listed in the *EA* are utterly unworthy of extensive national news coverage (Amenta and Caren, 2010).

Our point is that differences in the number of groups observed by different methods of observation are not necessarily a sign of spotty or poor data collection practice; it could easily be because of different rules of coverage. Assessments of how well a given dataset measures its intended organizational universe must be made with reference to another observation of the same range universe, not by comparison with a database with a different intended coverage. Assessment of the labor

[16] There is some evidence that non-response bias is less of a concern for surveys of organizations than it is for surveys of individuals (Smith, 1997).

[17] See Maxfield (1999) for a description of the alternatives and a comparison between them.

union section of the *EA* (Martin et al., 2006) suggests that coverage for large, stable groups is virtually complete. It is less complete, however, for smaller and ephemeral groups. More important for some users, however, the *intended coverage* of the *EA* may not match what is needed.

5.3.1. Reporting lag: a sub-category of selection bias

Lags in reporting are another source of selection bias. The date of publication can serve as important signal not only about the content of the data source, but also quality. Many primary and secondary data sources are updated months or years after new activity. For example, budgets printed in the same year as they were issued are often estimates and revised numbers are published in the following year. This question on the date of publication often requires a broader look and analysis of the data than noting the copyright year in a published volume or the publication date of survey data. Surveys for instance take time to run and publishing a book of any sort also requires time. Field work dates and the point that data gathering stopped to finish a manuscript can both have large effects on the interpretation of data.

The question of when the data published or more importantly what was the observation point is especially important for time-series data. The data contained in the *EA* is in effect the best information available to the publisher at the time of publication. However, like any published volume there is a lag between event and publication due to the delays involved in data collection and publishing. The details of this lag and why it is a concern were discussed extensively in a previous section.

Similar issues of lags in the formal registration of a nonprofit organization with the IRS confront researchers using that data set for studying them. NCSS cautions users of its database, stating "The IRS Business Master Files include a field (RULEDATE) indicating when registered nonprofit organizations obtained formal recognition of their tax exempt status by the IRS (in other words, when the IRS approved their applications for exempt status). NCCS typically uses this as a proxy for when an organization was created. However, one should understand its origins and flaws before determining how best to use it in one's research" (2010b). This problem is directly analogous to the lag structure we assess in the *EA* data set. It is not uncommon for there to be a significant lag between when organizations are created and when they apply for formal nonprofit status. We have not been successful in locating equivalent analyses for the IRS data base.

Protest event researchers also confront similar lags in the reporting of protest events. They typically frame narrow time windows around events seeking to locate reports, but often events are not reported for months and sometimes even years after they occurred. Widening the research time window can raise the costs of data collection considerably. The creators of the Dynamics of Collective Action data set were able to address this problem by examined all daily issues of the *New York Times* for a 35 year period, bundling all reports of an event no matter when they were made and centering them, on the date which they occurred. (See http://www.stanford.edu/group/collectiveaction/cgi-bin/drupal/ for a description of this element of their data collection methodology.)

6. Discussion

No primary or secondary data set is without its biases. An important goal of the user of any dataset is to determine the sources and the structure of its biases. The more we know about these biases the more we can adjust for them in our analyses and calibrate the amount of confidence to place in the patterns revealed by our analyses. This principle has motivated the extensive and careful work we have done to learn as much as we can about the *EA*. The *EA* database is a valuable tool for social science scholars interested in a range of substantive processes, and we trust future analysts will extend our inquiry into the structure and sources of *EA* bias and look into other secondary datasets as well.

Among the most serious biases we have identified in the *EA* database is its undercount of small associations and its lag structure. The *EA* systematically under represents small, understaffed, or ephemeral associations. For larger, significant associations the coverage is quite comprehensive. This has important implications for users; for some purposes the missing cases are relatively unimportant, but for other types of analysis this bias is prohibitive.

We focus on the less well understood, but significant, lag between new actions (such as the creation of an organization) and when these actions are reported in the dataset. This is our most important lesson: if the year of publication is 2005, the actions refer, on average, to 2001. But there is some inherent variance even here, so that some events listed as 2005 actually refer to 2002, 2000, etc., with 2001 being the single most common year.

The largest hurdle in using the *EA* dataset, therefore, is the establishment of the lag between the *EA's* copyright year and the year it represents. Detailed analyses of the differences between group founding dates and first inclusion and of the average length of time it takes to update existing associations offer strong insights. Combined these analyses demonstrate that the data in the *EA* most closely matches the group system 4 years prior to the publication date. The nature of the *EA* makes it impossible to determine when every group was founded and failed. The 5 year sampling procedure employed by the project adds to this problem, but the lag structure of the *EA* itself means that problems with establishing the lag structure would exist whether the data was gathered every year, every 5 years or every 10. Calculating group counts by topic instead of focusing on the details of individual groups leads to more reliable aggregate values over time. This information will allow an analyst to take into account of lag structure in future analyses. Comparing the bias structures we have identified in the *EA* with those in three other widely used secondary data sets, we believe, puts them in the broader context of equivalent biases confronted by other research communities, and, in sum increasing our confidence in it.

While hesitant to make overly broad claims for data-sources not directly examined here, we believe our findings regarding the lag-structure of *EA* data has important implications for the large research literature relying not just on the *EA* but other similar organizational directories commonly employed as secondary data: including the *Yearbook of International Organizations* (e.g. Beckfield, 2010; Boli and Thomas, 1997; Frank et al., 2000; Smith and Wiest, 2012), *Directory of British Associations* (see Halpin and Jordan, 2012), and *Associations Canada* (e.g. Abelson and Carberry, 1998; Handy et al., 2008; Quarter et al., 2001). It is likely that all of these sources contain some sort of listing lag, although specifying the exact nature of that lag structure across these different data sources will require additional scholarly research.

The lagged structure of information contained within organizational directories, including that which we specify for the case of the *EA*, is more or less likely to be problematic depending on how information is accessed and used. A lagged data structure is relatively unproblematic for analyses which rely exclusively on organizational founding and mortality information contained in the *EA* to generate yearly organizational counts, as in classic organizational ecology models (e.g. Johnson and Frickel, 2011; Minkoff, 1997; Nownes, 2004; Walker et al., 2011). The lagged data structure is likely to be more problematic when the focus is on the precise timing of organizational change (e.g. Johnson, 2006; Minkoff, 1999), especially at the individual level. For aggregated counts of how many groups are active across various policy domains, as is the purpose of the PAP *EA* data release, the source is likely to be highly accurate, but they reflect a distributed lag of ± four years and this lag must clearly be understood by any user interested in time-series dynamics. While this has clear implications for time series models the same concerns hold for other quantitative and qualitative studies that also consider the relationship between a group or groups and other factors such as policy agendas, protests, public opinion, events and more. Without an accurate understanding of a group lifespans analyses run a very real risk of making inappropriate causal inferences.

More generally, our detailed analysis of the nature of errors of omission in the *EA* is not meant to discourage its use. On the contrary, we believe the database to be of great use to a wide range of political scientists, sociologists, and other academic audiences. But before scholars make use of secondary data resources, or any other, they should clearly understand the nature of any discrepancy between the social process "out there" in society, and its reflection in the archived records of the publisher of the dataset. While our theories tend to be about the social processes, our tests typically relate to the archived record. Some slippage between these two is typically inevitable, but all too often it is assumed to be limited, unbiased, and trivial. More often, it is an empirical matter that can be estimated directly and therefore understood.

Acknowledgments

The *Encyclopedia of Associations* data was gathered by Frank R. Baumgartner and John McCarthy through the National Science Foundation, "Collaborative Research: Database Development for the Study of Public Policy," Grant Number SBR 0111611. Erik Johnson and Shaun Bevan served as lead Research Assistants on the project sequentially. The Policy Agendas Project data were originally collected by Frank R. Baumgartner and Bryan D. Jones, with the support of National Science Foundation Grant Numbers SBR 9320922 and 0111611, and are distributed through the Department of Government at the University of Texas at Austin. Neither the NSF nor the original collectors of the data bear any responsibility for the analysis reported here.

References

Abelson, Donald E., Carberry, Christine M., 1998. Following suit or falling behind? A comparative analysis of think tanks in Canada and the United States. Canadian Journal of Political Science/Revue canadienne de science politique 31 (3), 525–555.
Aldrich, Howard, Ruef, Martin, 2006. Organizations Evolving, second ed. Sage Publications, Thousand Oaks, CA.
Amenta, Edwin, Caren, Neal, 2010. Making the news: movement organizations. Media Attention, and the Public Agenda American Sociological Review 75, 841–866.
Andrews, Kenneth, Edwards, Bob, 2005. The organizational structure of local environmentalism. Mobilization: An International Journal 10 (2), 213–234.
Baumgartner, Frank R., McCarthy, John D., 2009. An Annotated Bibliography of Articles Using the Encyclopedia of Associations. <http://www.unc.edu/≃fbaum/papers.htm>.
Beckfield, Jason, 2010. The social structure of the world polity. American Journal of Sociology 115 (4), 1018–1068.
Bevan, Shaun, 2013. Continuing the collective action dilemma: the survival of voluntary associations in the United States. Political Research Quarterly 66 (3), 545–558.
Black, Donald J., 1970. Production of crime rates. American Sociological Review 35, 733–748.
Boli, John, Thomas, George M., 1997. World culture in the world polity: a century of international non-governmental organization. American Sociological Review 62, 171–190.
Brulle, Robert J., Turner, Liesel, H., Jenkins, J. Craig, Carmichael, Jason, 2007. Measuring SMO populations: a comprehensive census of U.S. Environmental Movement Organizations. Mobilization 12(3), 195–211.
Carmichael, Jason.T., Craig Jenkins, J., Brulle, Robert.J., 2012. Building Environmentalism: The Founding of Environmental Movement Organizations in the United States, 1900–2000. The Sociological Quarterly 53 (3), 422–453.
Chong, Dennis, 1991. Collective Action and the Civil Rights Movement. University of Chicago Press, Chicago, IL.
Davis, Gerald F., Doug McAdam, W., Scott, Richard, Zald, Mayer N., 2005. Social Movements and Organization Theory. Cambridge University Press, New York.
Earl, Jennifer, Martin, Andrew, McCarthy, John D., Soule, Sarah A., 2004. The use of newspaper data in the study of collective action. Annual Review of Sociology 30, 65–80.
Edwards, Bob, 1994. Semiformal organizational structure among social movement organizations: An analysis of the U.S. Peace Movement. Nonprofit and Voluntary Sector Quarterly 23 (4), 309–333.
Fischer, M., Gordon, T., Kraut, M., 2002. An examination of differences between financial information provided on form 990 and audited financial Statement data of U.S. private colleges and universities. Academy of Accounting Finances 6 (1), 87–104.
Frank, David John, Hironaka, Ann, Schofer, Evan, 2000. The nation-state and the natural environment over the twentieth century. American Sociological Review 65, 96–116.

Froelich, K.A., Knoepfle, T.W., Pollak, T.H., 2000. Financial measures in nonprofit organization research: Comparing IRS 990 return and audited financial statement data. Nonprofit and Voluntary Sector Quarterly 29 (2), 232–254.
Gale Research, 1970–2005. EA: National Organizations of the U.S., vols. 12–40. Gale Research, Detroit.
Gove, Walter R., Hughes, Michael, Geerken, Michael, 1985. Are uniform crime reports a valid indicator of the index crimes? An affirmative answer with minor qualifications. Criminology 23 (3), 451–502.
Gray, Virginia, Lowery, David, 2000. The Population Ecology of Interest Representation: Lobbying Communities in the American States. University of Michigan Press, Ann Arbor.
Hager, Mark A., Wilson, Sarah, Pollak, Thomas H., Rooney, Patrick Michael, 2003. Response rates for mail surveys of nonprofit organizations. Nonprofit and Voluntary Sector Quarterly 32 (2), 252–267.
Halpin, Darren, Jordan, Grant (Eds.), 2012. The Scale of Interest Organization in Democratic Politics. Palgrave, London.
Handy, Femida, Mook, Laurie, Quarter, Jack, 2008. The interchangeability of paid staff and volunteers in nonprofit organizations. Nonprofit and Voluntary Sector Quarterly 37 (1), 76–92.
Hannan, Michael T., Freeman, John H., 1989. Organizational Ecology. Harvard University Press, Cambridge, MA.
Hansen, John Mark, 1991. Gaining Access: Congress and the Farm Lobby, 1919–1981. The University of Chicago Press, Chicago.
Honaker, James, King, Gary, 2010. What to do about missing values in time-series cross-section data. American Journal of Political Science 54 (2), 561–581.
Johnson, Erik W., 2006. Changing issue representation among major United States environmental movement organizations. Rural Sociology 71 (1), 132–154.
Johnson, Erik W., Frickel, Scott, 2011. Ecological threat and the founding of U.S. national environmental movement organizations, 1962–1998. Social Problems 58 (3), 305–329.
Johnson, Erik W., Agnone, Jon, McCarthy, John D., 2010. The contingent impact of U.S. environmental movement organizations and activities on agenda setting and law passage. Social Forces 88 (5), 2267–2292.
Jordan, Grant, Baumgartner, Frank R., McCarthy, John, Bevan, Shaun, Greenan, Jamie, 2012. Tracking interest-group populations in the US and UK. In: Halpin, Darren, Jordan, Grant (Eds.), The Scale of Interest Organization in Democratic Politics. Palgrave, London.
Kempton, Willet, Holland, Dorothy C., Bunting-Howarth, Katherine, Hannan, Erin, Payne, Christopher, 2001. Local environmental groups: a systematic enumeration in two geographical areas. Rural Sociology 66 (4), 557–578.
Kitsuse, John I., Cicourel, Aaron V., 1963. A note on the uses of official statistics. Social Problems 11 (2), 131–139.
Knoke, David, 1986. Associations and interests groups. Annual Review of Sociology 12, 1–21.
Levitt, Steven D., 1998. The relationship between crime reporting and police: implications for the use of uniform crime reports. Journal of Quantitative Criminology 14 (1), 61–81.
Lewis, Michael, 2011. The Big Short. W.W. Norton, New York.
Lowery, David, 2012. Interest organization populations: the demands of the scale of analysis and the theoretical purposes of counting. In: Halpin, Darren, Jordan, Grant (Eds.), The Scale of Interest Organization in Democratic Politics: Data and Research Methods. Palgrave MacMillan, pp. 44–66.
Martin, Andrew W., Baumgartner, Frank R., McCarthy, John, 2006. Measuring association populations using the EA: evidence from the field of labor unions. Social Science Research 35 (3), 771–778.
Maxfield, Michael.G., 1999. The national incident-based reporting system: Research and policy applications. Journal of Quantitative Criminology 15 (2), 119–149.
McCarthy, John D., Castelli, Jim, 2002. The necessity for studying organizational advocacy comparatively. In: Flynn, Patrice, Hodgkinson, Virginia (Eds.), Measuring the Impact of the Nonprofit Sector. Kluwer Academic/Plenum Publishers, New York, pp. 103–122.
McCarthy, John D., Zald, Mayer N., 1977. Resource mobilization and social movements: a partial theory. American Journal of Sociology 82, 1212–1241.
McCarthy, John D., Britt, David W., Wolfson, Mark, 1991. The institutional channeling of social movements in the modern state. Research in Social Movements, Conflict and Change 13, 45–76.
McCarthy, John.D., McPhail, Clark., Smith, Jackie., 1996. Images of protest: dimensions of selection bias in media coverage of Washington demonstrations, 1982 and 1991. American Sociological Review 61, 478–499.
McCarthy, John D., McPhail, Clark, Smith, Jackie, Crishock, Louis J., 1998. Electronic and print media representations of Washington, D.C. Demonstrations: a demography of description bias. In: Rucht, Dieter, Koopmans, Ruud, Neidhardt, Friedhelm (Eds.), Acts of Dissent: New Developments in the Study of Protest. Sigma, Berlin, pp. 90–112.
McCleary, Richard, Neinstedt, Barbara C., Erven, James M., 1982. Uniform crime reports as organizational outcomes: three time series experiments. Social Problems 29 (4), 361–372.
McPhail, Clark, McCarthy, John D., 2004. Who counts and how: estimating the size of protests. Contexts 3 (3), 12–18.
Minkoff, Debra, 1995. Organizing For Equality: The Evolution of Women's and Racial-Ethnic Organizations in America, 1955–1985. Rutgers University Press, New Brunswick, NJ.
Minkoff, Debra, 1997. The sequencing of social movements. American Sociological Review 62, 779–799.
Minkoff, Debra, 1999. Bending with the wind: organizational change in american women's and minority organizations. American Journal of Sociology 104 (6), 1666–1703.
Minkoff, Debra, 2002. Macro-organizational analysis. In: Klandermans, Bert, Staggenborg, Suzanne (Eds.), Methods of Social Movement Research. University of Minnesota Press, Minneapolis, pp. 260–285.
Minkoff, Debra C., McCarthy, John D., 2009. Reinvigorating the study of organizational processes in social movements. Mobilization: An International Journal 10 (2), 289–308.
Mosher, Clayton J., Miethe, Terance D., Phillips, Dretha M., 2002. Mismeasure of Crime. Sage Publications.
National Center for Charitable Statistics, 2010a. Number of Nonprofit Organizations in the United States, 1999–2009. <http://nccsdataweb.urban.org/PubApps/profile1.php> (accessed 03.02.11).
National Center for Charitable Statistics, 2010b. Using the Ruling Date (RULEDATE) for Research. <http://nccsdataweb.urban.org/knowledgebase/detail.php?linkID=762&category=83&xrefID=3433> (accessed 12.11.10).
Nownes, Anthony J., 2004. The Population ecology of interest group formation: mobilizing for gay and lesbian rights in the United States, 1950–98. British Journal of Political Science 34 (1), 49–67.
Oliver, Pamela A., Maney, Greg M., 2000. Political processes and local newspaper coverage of protest events: from selection bias to triadic interactions. American Journal of Sociology 106, 463–505.
Oliver, Pamela E., Myers, Daniel J., 1999. How events enter the public sphere: conflict, location, and sponsorship in local newspaper coverage of public events. American Journal of Sociology 105, 38–87.
Olson, Mancur, 1965. The Logic of Collective Action: Public Goods and the Theory of Groups. Harvard University Press, Cambridge, MA.
Ortiz, David G., Myers, Daniel J., Walls, Neil, 2005. Were do we stand with newspaper data? Mobilization 10, 397–419.
Perrow, Charles, 1992. A society of organizations. Theory and Society 20, 725–760.
Quarter, Jack, Sousa, Jorge, Richmond, Betty Jane, Carmichael, Isla, 2001. Comparing member-based organizations within a social economy framework. Nonprofit and Voluntary Sector Quarterly 30 (2), 351–375.
Rosenthal, Naomi, Fingrutd, Meryl, Ethier, Michel, Karant, Roberta, McDonald, David, 1985. Social movements and network analysis: a case study of nineteenth-century women's reform in New York state. American Journal of Sociology 90 (5), 1022–1054.
Saxton, Gregory D., Benson, Michelle A., 2005. Social capital and the growth of the nonprofit sector. Social Science Quarterly 86, 16–35.
Schlozman, Kay L., Tierney, John T., 1986. Organized Interests and American Democracy. Harper and Row, New York.
Schrodt, Phillip A., 2012. Precedents, progress and prospects in political event data. International Interactions 36 (4), 546–569.

Schwartz, Jennifer, Steffensmeier, Darrell, Zhong, Hua, Ackerman, Jeff, 2009. Trends in the gender gap in violence: re-evaluating NCVS and other evidence. Criminology 47, 401–425.
Smith, Jackie, 1997. Nonresponse bias in organizational surveys: evidence from a survey of groups and organizations working for peace. Nonprofit and Voluntary Sector Quarterly 26 (3), 359–368.
Smith, Jackie, Wiest, Dawn, 2012. Social Movements in the World-System. Russell Sage Foundation, New York.
Soule, Sarah A., King, Brayden G., 2008. Competition and resource partitioning in three social movement industries. American Journal of Sociology 113 (6), 1568–1610.
Walker, Edward T., John D. McCarthy, and Frank R. Baumgartner. 2011. Replacing Members with Managers? Mutualism among Membership and Non-Membership Advocacy Organizations in the U.S. American Journal of Sociology 116(4), 1284–1337.
Walker Jr., Jack L., 1983. The origins and maintenance of interest groups in America. American Political Science Review 77, 390–406.
Walker Jr., Jack L., 1991. Mobilizing Interest Groups in America. University of Michigan Press, Ann Arbor, MI.
Walker, Edward T., McCarthy, John D., Baumgartner, Frank, 2010. Replacing members with managers? Mutualism among membership and non-membership advocacy organizations in the United States. American Journal of Sociology 116 (4), 1284–1337.
Yetman, Michelle H., Yetman, Robert J., Badertscher, Brad, 2009. Calibrating the reliability and publically available nonprofit taxable activity disclosures comparing IRS 990 and IRS 990-T data. Nonprofit and Voluntary Sector Quarterly 38, 95–116.