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Cross-Survey Analysis to Estimate Low-Incidence Religious Groups

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Abstract

Population-based surveys are of limited utility to estimate rare or low-incidence groups, particularly for those defined by religion or ethnicity not included in the U.S. Census. Methods of cross-survey analysis and small area estimation, however, can be used to provide reliable estimates of such low-incidence groups. To illustrate these methods, data from 50 national surveys are combined to examine the Jewish population in the United States. Hierarchical models are used to examine clustering of respondents within surveys and geographic regions. Bayesian analyses with Monte Carlo simulations are used to obtain pooled, state-level estimates poststratified by sex, race, education, and age to obtain certainty intervals about the estimates. This cross-survey approach provides a useful and practical analytic framework that can be generalized both to more extensive study of religion in the United States and to other social science problems in which single data sources are insufficient for reliable statistical inference.

Keywords

cross-survey analysis, population estimation, low-incidence groups, Jewish population, multilevel models, hierarchical Bayesian analysis

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The study of rare or low-incidence population groups presents a number of methodological challenges, particularly when the groups are religious minorities. In the United States, the census does not collect data on religious identification (PL 94-521 1976), and general population surveys typically include too few respondents for reliable inference. To address concerns associated with the study of low-incidence groups, the present article describes the application of hierarchical Bayesian methods to pool multiple sources of survey data. As a focal exemplar, the size and characteristics of the Jewish population in the United States are estimated. Along with adding knowledge about a specific minority group, this study provides a practical analytic framework that can be generalized to more extensive study of religious and ethnic identity in the United States, to the study of other small social groups, and to other social science problems in which single data sources are insufficient for reliable statistical inference.

Several methods exist to estimate rare populations. One of the most common is to oversample the groups of interest. Another approach is to use social network measures, for example, asking respondents to list those whom they know in the low-incidence group and using this list as the basis for inferring group size (Kadushin et al. 2006; Zheng, Salganik, and Gelman 2006). A third method is to pool data across multiple samples to increase the effective sample size (Smith 2005). Each of these methods has utility but is not without limitations. Recent advancements in methods of small area estimation (SAE) and Bayesian analysis (Lohr and Prasad 2003; Pfeffermann 2002; Rao and Yu 1994) offer an alternative means to study low-incidence groups in a way that obviates many of the limitations of existing methods. With SAE methods, multiple sources of data are combined to estimate small areas or groups. When data sources are complex surveys, however, one must account for both the clustering of respondents within surveys and the representativeness of the samples across surveys. In the present study, this is accomplished through cross-survey analysis methods that standardize poststratification across the sample of surveys to be combined.

There is substantial theoretical and practical interest in use of this method to study religious minorities in the United States. Religious orientation has been associated with a host of social behaviors, including voting and involvement in politics (Gelman 2008; Mattis 2001; Olson and Carroll 1992; Shriver 1985), family life, health behavior, and social capital (Sheerkat and Ellison 1999). A major challenge is how best to estimate the prevalence of particular religious groups (e.g., Pew Research Center 2007; 2008; Smith 2002; 2005; Stevens-Arroyo 1998). The small size of many of the groups makes study of these populations highly problematic. Jews, Mormons, and Muslims, for example, are estimated to be less than 1 to 4 percent of the total U.S. population (Pew Research Center 2008). The practical difficulties of studying such rare groups at national and subnational levels require a new approach, one that goes beyond standard methods such as oversampling and incorporates the latest methods of small area estimation and extends them to address the unique challenges of combining data across complex surveys.

Existing Measures of the Jewish Population in the United States

The standard method, albeit expensive, to overcome limitations of small sample sizes associated with low-incidence groups is to include very large sample sizes and oversamples of the groups of interest. This was the key strategy used in the National Jewish Population Survey (NJPS) (Kotler-Berkowitz et al. 2004) and, on a smaller scale, in the Survey of Heritage and Religious Identification (Groeneman and Tobin 2004). The NJPS included an oversample of approximately 4,500 Jewish respondents and yielded an estimate of 3.04 million adults in U.S. households (1.5 percent) who identify their current religion as Jewish. The estimate is higher if one includes additional estimates for those not living in households and those who identify as Jewish in ways other than by current religion (e.g., culturally or by upbringing). The NJPS is perhaps the most widely referenced source of data on the Jewish community in the United States. Its population estimates, however, are dubious. The 2000–2001 NJPS had a very low response rate (less than 20 percent) and was plagued by a host of administrative and methodological problems, ranging from lost data to screening procedures (Kadushin, Phillips, and Saxe 2005). Furthermore, the survey provides insufficient data with which to compare this group to other similarly sized religiously or ethnically defined groups in the United States. The lack of such comparative data limits the utility of these data for broader social scientific understanding of this group.

A more recent attempt to improve estimation of small, religiously defined groups by increasing the overall sample size and including oversamples is the U.S. Religious Landscape Survey (Pew Research Center 2008). This survey obtained an overall sample size of just over 35,000 and included an oversample of approximately 500 people in order to increase the number of respondents in three low-incidence groups—Buddhists, Hindus, and Orthodox Christians. The response rate was also less than 30 percent. Although the inclusion of oversamples improved the study's utility, the samples yield large standard errors for the study of and comparisons among subgroups.

The problems with existing sources of data reflect the broader challenges associated with general population surveys. Response rates are now significantly lower than in the past (Groves et al. 2004; Massey, O'Connor, and Krotski 1998; Smith 1994). Declines in response rates are especially problematic for estimation of rare populations. Such estimates are highly sensitive to disparities between responders and nonresponders; as well, there may be interactions with survey-level characteristics. For example, those for whom religion is most important might be more likely to participate in surveys that focus on issues of religion than those that focus on health or politics. This would lead to bias in estimates depending on the purpose of the survey. Similarly, factors such as interest and involvement can interact with variables involved in poststratification. Younger respondents are more difficult to reach (Keeter et al. 2006), and those who are reached may be more likely to be religious (Phillips 2006). This would lead to an overestimation of the prevalence of some religious groups. Typically, there are too few cases overall and within subgroups associated with interactions among poststratification variables to be able to describe the groups with a high degree of reliability. Furthermore, the costs of oversampling in this context, and oversampling multiple small groups simultaneously in order to provide comparative data, are prohibitive to most ordinary social scientists and government agencies.

One can circumvent reliance on single surveys and oversamples by pooling data across multiple surveys. For example, the American Religious Identification Survey (ARIS) (Kosmin, Mayer, and Keysar 2001; U.S. Census Bureau 2010) consists of a sample of approximately 50,000 respondents aggregated across 50 random digit dial (RDD) omnibus telephone surveys. The omnibus surveys were part of a twice-weekly RDD telephone survey conducted for a number of independent clients and designed to assess topics ranging from advertising awareness to product usage. At the end of these surveys, respondents were asked their religion. The ARIS yielded an overall estimate that was somewhat lower than the NJPS: 1.3 percent of the U.S. adult population (2.7 million) identified as Jewish by religion. The overall response rate, taking into account residential versus nonresidential numbers, was also low, 18 percent. Whether the estimate from this survey should hold precedence over estimates observed in other surveys such as the NJPS or the HARI is unclear. Those interested in studying the Jewish population are left unsure of which survey provides the "true" estimate of the underlying population.

In contrast to the ARIS, Smith (2005) combined several samples from the General Social Survey (GSS) to estimate that 1.8 percent of all U.S. adults identify their current religion as Jewish. Similar to the ARIS, the number of Jewish respondents in a single administration of the survey was too few for meaningful analysis. Compared with typical commercial omnibus surveys, the GSS has much higher response rates owing in part to its general interest topics. This particular aggregation may, in fact, reflect a more accurate estimate of the population. One must assume, however, that there are no significant changes in population, demographics, and variance distributions over time.

Analytic Approach: Cross-Survey Meta-Analysis and Hierarchical Bayesian Analysis

Combining data across multiple studies to increase the power to explain and predict variability associated with small effects (small groups in this case) is the premise of traditional meta-analysis. Most meta-analytic reviews focus on the estimation of effects in terms of associations between independent and dependent variables and include weights and adjustments to account for variance distributions associated with each data source. There are few examples of the use of these methods to estimate the prevalence of rare populations, with the exception of epidemiological studies of rare diseases. For example, the U.S. General Accounting Office (1998) used meta-analytic methods to estimate the prevalence of Alzheimer's disease. This study combined estimates of prevalence by age and sex across 18 independent studies of neighborhood or small town samples. None consisted of representative samples that would generalize to the entire U.S. population. A pooled estimate of prevalence across these multiple independent samples was used to estimate the national rates. Similarly, Jorm and colleagues used meta-analytic methods to estimate the prevalence of dementia (Jorm and Jolley 1998; Jorm, Korten, and Henderson 1987). Estimates by demographic groups such as age, sex, and ethnicity were obtained for subsets of surveys that reported summary statistics for each of these groups. Studies had to report summary statistics for both the overall population and the demographic subgroups of interest in order to be included. This approach limits one's ability to examine key features of rare populations other than those reported or summarized in the original reports. Furthermore, the reliance on summary statistics in conventional meta-analytic methods (Hedges and Olkin 1985) inhibits the ability to simultaneously examine variance at both the survey and respondent levels.

A separate approach to combine multiple sources of data is small-area estimation (Lohr and Prasad 2003; Pfeffermann 2002; Rao and Yu 1994). This method is similar to traditional meta-analysis in that data are pooled across different sources to improve estimation of small geographic areas or groups. The primary difference is that raw data are combined rather than only summary statistics. One application of SAE methods is the National Health Interview Survey, which was designed with a sample size appropriate to produce a picture of health behavior of the entire U.S. population. Data from this survey, on their own, cannot be used to estimate county or city levels because the number of respondents at any of these lower levels is too few, and the errors around the estimates too large, to draw reliable inferences. One can, however, borrow information from other sources of data to improve estimation at the county level (Malec et al. 1997). Hierarchical Bayesian methods with Markov chain Monte Carlo simulations are frequently used to combine data in this way (Ghosh et al. 1998).

Application of SAE methods to pool data across multiple national surveys is exemplified by Park, Gelman, and Bafumi (2004) in their analysis of national polling data. Park and colleagues combined data from CBS/*New York Times* polls to obtain state-level estimates of voting behavior. Standard demographic variables—such as census region, sex of respondent, ethnicity, age, and education—that were used to create survey weights in the CBS/*New York Times* polls were included as fixed and random effects in hierarchical Bayesian analyses. States, nested within regions, was included as a factor. A sample of simulations based on the final model was used to calculate estimates poststratified to U.S. Census distributions for demographic variables in the model.

Similar methods were used by O'Hara et al. (2006) to estimate the prevalence of low-income, uninsured women in need of screening for breast and cervical cancer. The effort built on the Census Bureau's Small Area Health Insurance Estimates (SAHIE) program. Data from multiple surveys were combined with administrative data to develop model-based population estimates by age, race, and income for states and counties.

The application of hierarchical Bayesian methods to study small, religiously defined groups overcomes many of the challenges associated with single surveys. Although there is no definitive source of data on the religious composition of the total U.S. population, a wealth of data have been collected for purposes other than the estimation of religious groups that include assessment of respondents' religious identification. This includes political polls as well as surveys of health and social behavior. When combined, these data can be used to study the social composition of religious groups.

A key challenge when pooling survey data is to understand the sources of variability introduced by methodological differences among the surveys.

Most national surveys use complex sample designs in which respondents are selected from geographic clusters. Such surveys vary in the representativeness of their samples and rely on weights that take into account sample design effects, with further adjustments for distributions of demographic variables. There is little consistency in how sampling and weighting are implemented across surveys. Nevertheless, one can adjust for nonrepresentativeness on key demographic variables by combining the modeling approach described by Park et al. (2004) with poststratification methods. This is done by including in hierarchical models the demographic variables that are related to the likelihood of identifying as Jewish and are over- or underrepresented across the sample of surveys relative to their distribution in the total U.S. adult population. The variability associated with clustering of respondents within surveys is examined directly through the use of hierarchical models. Any variability in survey estimates that remains after poststratification variables are included can then be examined by including survey-level characteristics in the analysis.

Method

Major data repositories were searched to identify studies conducted between 1998 and 2005 that included assessment of religious identification or affiliation. These archives included the Inter-University Consortium for Political and Social Research (ICPSR) and the American Religion Data Archive (ARDA). In addition, poll archives at the Odum Institute, Roper Center, and Gallup were searched. Keywords for searching each of the databases were: religion; relig∗; Protestant[1]; Catholic; Jewish; denom∗; religious preference; religious id∗. Results were screened using the following criteria: The study had to include (1) a nationally representative sample of the U.S. adult population, (2) information to classify respondents by current religious identification, and (3) baseline demographic information (sex, race, education and age).[2]

This search strategy yielded 146 independent surveys. The present analyses focus on a critical mass of 50 of these surveys that were pooled into a single data set.[3,4] The pooled data set consisted of individual-level data with demographics and current religion recoded into a standard format across all surveys. In addition, the data set included survey characteristics such as response rates and sampling methods.

Sample. The full sample consists of 240,247 respondents across 50 surveys.[5] Some surveys were conducted as part of ongoing series, such as the American National Election Study (ANES), the General Social Survey

(GSS), and Pew Research surveys on Religion and Public Life (see Table 1 and Appendix Table A1).

The surveys were conducted for a broad range of purposes (see Table 2). Most were designed to assess general issues, such as politics and social life (60 percent). A third focused specifically on issues of religion (34 percent). More than half of the surveys (54 percent) consisted of single-administration, cross-sectional samples. The remaining surveys were part of trend studies with independent samples across time. All surveys were RDD telephone surveys, with the exception of the ANES,[6] the GSS, and the Arts and Religion survey (Wuthnow 1999), which were in-person interviews. All are multistage probability surveys that use some version of the Mitofsky-Waksberg RDD sampling method (see Brick and Tucker 2007). The primary deviation from full probability is in the selection of respondents within households. Twenty percent of the surveys used the Kish method of listing all members of the household and then randomly selecting one.

The average response rate across surveys was 34 percent (18 percent). About 12 percent of the surveys reported response rates of 60 percent or greater, whereas 24 percent had response rates less than 25 percent. More than half of the surveys provided detail on final dispositions with which response rates could be calculated directly. Six surveys provided no information on response rate. For these six surveys, a conservative estimate of 10 percent is included, which is consistent with the lower end of response rates obtained by polling agencies.

Results

First, the range of observed estimates of the Jewish population across the 50 surveys is described. Variance in these estimates at the survey level is then examined. This is followed by Bayesian analyses to obtain a set of simulations for regression coefficients of the likelihood that respondents identified as Jewish on demographic and geographic variables to be used in poststratification.

Distribution of Percent Jewish Across Surveys

Estimated prevalence of respondents who identify as Jewish by current religion was first calculated using available weighting and primary sampling unit information for each survey. These estimates with 95 percent confidence intervals are displayed in Figure 1.

Most estimates hover around 1.6 percent. Two or three of the surveys yield higher estimates, but none are outside the 95 percent confidence

Table 1. Surveys Included in the Sample of 50

	Year	Sample size		Year	Sample size
American National Election Study			**General Social Survey**		
	1998	991		1998	2,747
	2000a	1,006		2000	2,750
	2000b	801		2002	2,698
	2004	1,212		2004	2,745
Pew			**ABC/*Washington Post* polls**		
Civic and political health	2002	3,246	Church abuse	2004	979
Biennial media consumption	1998	3,002	Church scandal	2002	1,168
	2000	3,142	Vatican	2002	1,166
	2002	3,002	**ABC News polls**		
	2004	3,000	Islam	2003	957
GOP and religion	2004	1,512	Bishops	2002	951
Immigration survey	2006	2,000	Religion poll	1997	733
Religion and politics	2000	5,427	Pedophilia	2002	960
Religion post 9-11	2001	1,414	**Annenberg Election Survey**		
Religion and public life	2001	1,985		2000	56,224
	2002	1,948		2004	77,946
	2003	1,940	**Other**		
	2005	1,964	American perceptions of aging	2000	3,000

(continued)

Table 1. (continued)

	Year	Sample size		Year	Sample size
Values update	2003	2,430	American perception of artists	2002	948
War tracking			Exercising citizenship	2002	981
Wave 1	2003	3,486	Social capital benchmark	2000	2,928
Wave 2	2003	1,660	Exploring religious America	2002	1,922
			Genetic testing	2000	1,749
State of the First Amendment			Heritage and religious identity	2000	9,872
	1997	983	Religion and diversity	2002	2,813
	1999	949	American evangelicals	2004	861
	2000	922	Multi-investigator study	1998	1,046
	2001	953	American public opinion: U.S. foreign policy	2002	2,736
	2002	939	Arts and religion	1999	1,477

a. Face-to-face sample.
b. Random digit dial sample.

Table 2. Methodological Characteristics Across the 50 Surveys

	Number of surveys	Percent of surveys		Number of surveys	Percent of surveys
Primary purpose			**Survey shop**		
Religion	17	34	University affiliated	16	32
Politics	20	40	ISR[a]/NORC[b]	8	16
Social life	10	20	University of Connecticut	5	10
Other	3	6	UC Berkeley	1	2
Design			University of Maryland	1	2
Cross-section	27	54	University of Indiana	1	2
Trend	23	46	PSRA[c]	13	26
Mode of administration			Abt SRBI, Inc.	7	14
Telephone	42	84	TNS Intersearch	7	14
In-person	8	16	Other	7	14
Response rates			**Respondent selection**		
AAPOR 3[d] (mean, *SD*)	34	18	Kish	10	20
Final dispositions	29	58	Hagan-Collier	20	40
			Last/first birthday	13	26
			”Random adult”	6	12

a. Institute for Social Research.
b. National Opinion Research Center.
c. Princeton Survey Research Association.
d. American Association for Public Opinion Research Response Rate 3.

intervals for most of the other surveys. Similarly, one survey appears to yield a rather low estimate, but it too remains in the 95 percent confidence interval for several of the other surveys. There are a number of ways in which these surveys differ, including methods of weighting and the factors included to calculate survey weights. Thus, it is difficult to draw conclusions about the range of estimates observed without first examining the nature of the variability associated with the surveys. Because the goal is to estimate prevalence and examine the characteristics of those who identify as Jewish, the variability associated with surveys is examined through hierarchical models with individuals' data nested within surveys.

Clustering of Respondents Within Surveys

The basic model is represented by a simple intercept-only logistic regression (see Table 3). The first columns present the log-odds that a respondent is

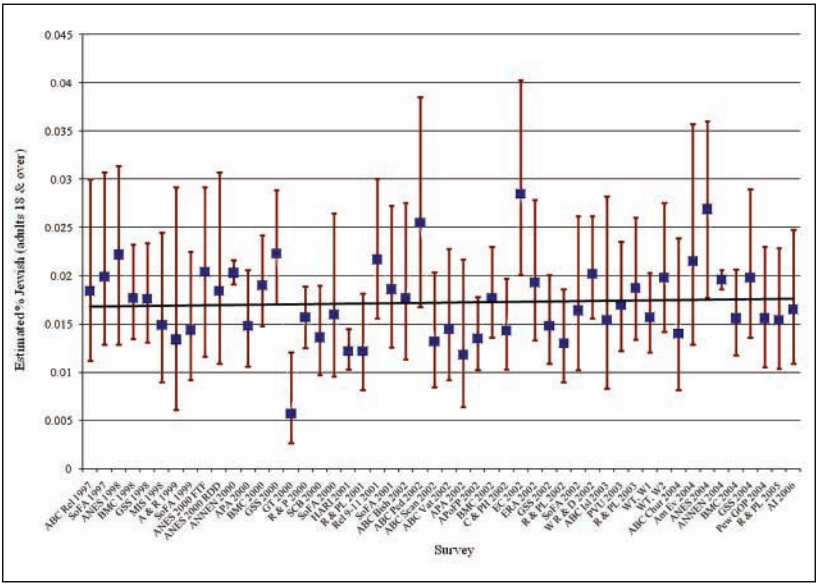

Figure 1. Distribution of weighted estimates of Jewish population across 50 surveys

Jewish across all surveys, ignoring clustering of respondents within surveys. The log odds of –3.9 corresponds to approximately 2 percent of the adult population in the United States, which is somewhat higher than estimates obtained in most surveys when analyzed individually.

The last two sets of columns in Table 3 display results from a standard multilevel model using the LMER package in R (Bates 2005) and a hierarchical Bayesian analysis implemented in WinBUGS using R2WinBUGS (Gelman 2007; Park et al. 2004; Park, Gelman, and Kaplan 2006). The Bayesian and R2WinBUGS methods were preferred for theoretical and practical reasons, not least of which was the efficiency of model fitting and postmodel processing. The two methods are compared to confirm that they yield similar estimates because results from standard methods such as LMER are used as starting values to speed convergence of the Bayesian models. For both models, the constant-only model can be specified as a two-level model. The level 1 model represents the likelihood a respondent identifies as Jewish by religion:

$$ln(p_{ij}/(1 - p_{ij}) = \beta_{0j},$$

Table 3. Results, Including Log Likelihood Functions and Variance Components for Constant-Only Models

			Hierarchical models			
	Logistic		R-lmer		WinBUGS	
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Intercept	–3.872	0.015	–3.929	0.028	–3.953	.03
invlogit	.0204		.0193		.0188	
AIC[a]	46978.63				46954.80	
Variance components					tau	80.10
Level 2 = survey			0.0129		1/tau	0.0125
ICC			0.004			0.004
MOR			1.114			1.112

Note: AIC = Akaike's Information Criterion; ICC = intraclass correlation; MOR = median odds ratio; *SE* = standard error.
a. For WinBUGS model, DIC rather than AIC is reported.

where j denotes surveys, and i denotes respondents within surveys. The coefficient β varies across surveys and is represented by a level 2 model:

$$\beta_{0j} = \gamma_{00} + \mu_{0j}$$

As expected, both methods yield similar estimates. Intercepts, which represent the likelihood a respondent is Jewish, are approximately –3.9. Variance estimates are essentially identical. Intraclass correlations (ICCs) of .004 indicate that only a small proportion of the total variance is explained by the clustering of respondents within surveys. The ICC in this context is equivalent to tests of homogeneity of study effects in the context of meta-analysis (Hox 2002). The median odds ratio (MOR) provides an interpretation of the variance estimate as an odds ratio (Larsen et al. 2000). The observed values of 1.1 indicate that given any two randomly chosen surveys, the odds of a respondent identifying as Jewish in the survey with the highest likelihood are nearly equivalent to the odds of identifying as Jewish in the survey with the lowest likelihood, which supports the observation that very little variability exists between the surveys.

Poststratification

In the context of survey analysis and population estimation, one must consider whether the respondents in the surveys are representative of the target population before generalizing the observed estimates to population estimates. The 50 surveys differ in a number of ways, including methods of respondent selection and response rates. Most of the factors related to survey design ultimately affect external validity and the representativeness of the samples. The analysis of cross-survey estimation, therefore, begins by examining factors related to sample characteristics.

RDD surveys typically overrepresent college-educated and white non-Hispanic groups (Keeter et al. 2006). The overall distributions of demographics in comparison to the prevalence in the U.S. population are displayed in Table 4.[7] Also included is the proportion of missing data.

Overall, the white non-Hispanic and college-educated groups are overrepresented. White non-Hispanics comprise 78 percent of all respondents compared with 72 percent in the general population. More than 35 percent of the sample has a four-year college degree or greater, compared with 24 percent in the general population. There are also small differences in the representation by census regions. These differences are attributable to the disproportionate representation of particular states. For example, California is underrepresented across the sample of 50 surveys (9.8 percent) compared with 11.8 percent of the total population in the continental United States. New York (6 percent) and Illinois (3.7 percent) are also underrepresented (6.8 percent and 4.4 percent, respectively).

Individual surveys typically adjust for disproportionate representation through weighting procedures. A majority of the surveys (60 percent) account for disproportionate sampling solely through the use of poststratification weights. Among these, there is variability in what variables and demographic groups are used in poststratification. Fewer than 15 percent of the surveys include weights based solely on factors related to the probability of selection introduced by their sampling strategies (e.g., geographic areas, number of eligible respondents, and number of phone lines). The lack of consistency in how survey weights are created requires application of methods that account for factors related to the disproportionate representation of respondents in a way that is comparable, or standardized, across all surveys. Given the small amount of missing data for the standard demographics of sex, race, education, and age, all nonmissing data are included. For key geographic variables, however, where there are substantially more missing data, distributions and estimates for surveys that include these variables are first compared with surveys that did not include these variables.

Inclusion of Sex, Race, Education, and Age

The observed distributions of Jewish respondents across the full sample of 50 surveys by sex, race, education, and age are displayed in Table 5. A higher

Table 4. Percentages of Respondents Within Basic Demographic Categories Across All Surveys Compared With the Census

	50 surveys	Percentage missing[a]	Census
Sex		0.004	
Male	44.9		48.1
Female	55.1		51.9
Race		1.5	
White, non-Hispanic	78.0		72.0
Black, Hispanic, other	22.0		28.0
Education		0.8	
College graduate	35.4		24.3
Non–college graduate	64.6		75.7
Age		1.2	
18–24 years	9.5		13.0
25–34 years	17.6		18.5
35–44 years	21.2		21.1
45–54 years	20.4		18.9
55–64 years	14.2		12.4
65+ years	17.1		16.1
Region		4.9	
Northeast	19.0		19.7
Midwest	24.6		23.2
South	36.2		35.5
West	20.3		21.6
Metro status		18.1	
Nonmetropolitan	21.7		21.6
Metropolitan	78.3		78.4

a. The percentage missing represents the amount of missing data list-wise—for the variable listed and all variables preceding it in the table.

proportion of Jewish respondents are white non-Hispanic and college educated. In addition, there are a higher proportion of Jewish respondents in the older compared with younger age groups.

Logistic regressions of the likelihood a respondent is Jewish on the age, sex, race, and education of the respondent were run. A completely pooled analysis across the 50 surveys was run, as well as unpooled models, one with survey as a factor in a generalized linear model (GLM) and the other with survey as a level of clustering in a hierarchical model (see Table 6).[8]

Inclusion of survey as a grouping factor did not affect estimates of the fixed effects. None of the surveys significantly differed from the reference category. When one takes into account demographic covariates, however, the amount of

Table 5. Distribution of Jewish Respondents by Sex, Race, Education, and Age

	Count	Percentage within subgroup
Sex		
Male	2,288	2.17
Female	2,528	1.94
Race		
White, non-Hispanic	4,527	2.49
Black, Hispanic, other	256	0.50
Education		
College graduate	3,270	3.95
Non–college graduate	1,534	1.01
Age		
18–24 years	343	1.55
25–34 years	611	1.48
35–44 years	816	1.64
45–54 years	1,094	2.30
55–64 years	794	2.40
65+ years	1,104	2.76

variability associated with the clustering of respondents within surveys is reduced to nearly zero, indicated by the ICC of .001 and MOR near 1.0.

A Bayesian analysis was conducted, and a sample of approximately 1,000 simulations postconvergence were saved and used to create poststratified estimates (cf., Park, Gelman, and Bafumi 2004). Starting values were based on the results from the GLM model. A summary of the distribution of model coefficients across simulations is displayed in Table 7. Average values for the estimated logit and standard deviation for each variable in the model closely approximate the coefficients obtained using GLM. In addition, the table includes the estimated R-hat, a measure of convergence for each of the parameters in the model (Park et al. 2006). Values of R-hat of 1 indicate convergence.

The estimates for each simulation were used in the calculation of poststratified estimates in combination with data from the 2002 Current Population Survey March Supplement (CPS). The estimated percentage Jewish in each demographic group was obtained by substituting the 48 possible combinations of sex, race, education, and age into the resulting equation for each simulation, yielding a $48 \times 1{,}000$ matrix of likelihood estimates, which were then converted to proportions (see Table 8). These proportions were then multiplied by the corresponding CPS population count for each cell to obtain estimated Jewish population counts. Summing across the estimated cell counts for each simulation yields an estimate of the total Jewish population,

Table 6. Logistic Regression of Current Religion Jewish on Sex, Race, Education, and Age of Respondent With and Without Survey Cluster Information

	GLM logistic		GLM survey as factor[a]		LMER logistic	
	B	*SE*	*B*	*SE*	*B*	*SE*
Intercept[b]	–3.19***	0.04	–3.21***	0.04	–3.23***	0.05
Sex	–0.05	0.03	–0.05	0.03	–0.05	0.03
Race	–1.41***	0.06	–1.40***	0.06	–1.58***	0.04
Education	–1.58***	0.04	–1.58***	0.04	–1.40***	0.06
Age 18–24 years	0.08	0.11	0.09	0.11	0.08	0.11
Age 25–34 years	–0.09	0.05	–0.09	0.05	–0.09	0.05
Age 45–54 years	0.28***	0.05	0.28***	0.05	0.28***	0.05
Age 55–64 years	0.36***	0.05	0.37***	0.05	0.36***	0.05
Age 65+ years	0.48***	0.06	0.49***	0.06	0.48***	0.06
Education × Age 18–24	0.74***	0.13	0.74***	0.13	0.74***	0.13
Education × Age 65+	0.40***	0.07	0.40***	0.07	0.40***	0.07
AIC	42,747.69		42,749.23		42,781.33	
Variance components						
Survey					0.009	
ICC[c]					0.001	
MOR					1.09	

Note: AIC = Akaike's Information Criterion; GLM = Generalized Linear Model; ICC = intraclass correlation; LMER = Linear Mixed Effects Models for R; MOR = median odds ratio; *SE* = standard error.
a. For brevity, coefficients for the 49 dummy variables for survey are omitted. The survey with the largest sample size, the 2004 Annenberg Election Survey, is the reference category.
b. The intercept represents the reference group on all demographic covariates: male, white non-Hispanic, college graduates, using two categories of sex (0 = male, 1 = female), two categories of race (0 = white non-Hispanic, 1 = other), and two categories of education (0 = college graduate, 1 = not a college graduate).
c. ICC is based on Level 1 variance estimate of 2/3 (Hox 2002).
*p < .10. ***p < .001.

with certainty intervals based on the distribution across the 1,000 simulations. The overall population is estimated to be 1.7 percent, with a 95 percent certainty interval ranging from 1.66 percent to 1.75 percent. This corresponds to an estimated 3,542,000 adults (95 percent confidence interval, 3,444,771–3,636,757).

Inclusion of Census Regions, States, and Metropolitan Status

Surveys define their primary sampling units (PSUs) differently; thus, a direct comparison of PSUs is difficult. Furthermore, only two sets of

Table 7. Node Statistics for Bayesian Logistic Regression, Summary of 1,000 Simulations Postconvergence

	Mean	*SD*	R-hat
(Intercept)	–3.19	0.04	1.04
Female	–0.05	0.03	1.04
Nonwhite	–1.41	0.06	1.01
Non–college graduate	–1.58	0.04	1.02
Age 18–24 years	0.08	0.10	1.02
Age 25–34 years	–0.08	0.06	1.02
Age 45–54 years	0.28	0.04	1.01
Age 55–64 years	0.36	0.05	1.01
Age 65+ years	0.48	0.05	1.02
Education × Age 18–24	0.74	0.11	1.01
Education × Age 65+	0.40	0.08	1.02
Deviance	42,731.20		

Note: *SD* = standard deviation.

surveys—ANES and GSS—provide respondent-level PSU information. In both cases, public use files include proxies for the PSU, which can be used to estimate variance. Despite the variability in methods, all of the surveys are designed to provide adequate representation by geographic regions and metropolitan areas. Thus, sample characteristics for surveys that include and exclude key geographic variables of census region, state, and metropolitan area were examined (see Appendix Table A2).

Surveys that omitted geographic information, particularly the four surveys that did not include information on census region, tended to yield lower estimates of the Jewish population. All surveys overrepresented women, with the exception of surveys that excluded metropolitan status. Surveys that included geographic information also overrepresented the white non-Hispanic population and college graduates. All of these demographic variables are included in the model and poststratification.

Bayesian analyses were run for subsets of surveys based on available geographic information to obtain population estimates poststratified by demographic characteristics and by corresponding geographic variables (see Appendix Table A3). The inclusion of geographic variables in poststratification yielded higher estimates of the Jewish population than models that did not include these variables. With the inclusion of census region, there are an estimated 3.7 million (1.76 percent) Jewish adults in the United States. With the inclusion of states nested within regions, there are an estimated

Table 8. Estimated Proportion of Jewish Adults by Demographic Group, With 95% Certainty Intervals

	White, non-Hispanic				Black, Hispanic, and other			
	Non–college graduate		Non–college graduate		College graduate		College graduate	
	Prop	95% CI	Prop	95% CI	Prop	95% CI	Prop	95% CI
Male								
18–24 years	1.90	1.65–2.15	4.28	3.54–5.08	0.47	0.40–0.55	1.08	0.86–1.34
25–34 years	0.78	0.70–0.86	3.65	3.34–3.99	0.19	0.16–0.23	0.92	0.80–1.06
35–44 years	0.85	0.77–0.93	3.97	3.71–4.29	0.21	0.18–0.24	1.00	0.88–1.14
45–54 years	1.11	1.01–1.22	5.17	4.84–5.52	0.27	0.24–0.32	1.32	1.15–1.50
55–64 years	1.21	1.09–1.33	5.61	5.21–6.01	0.30	0.25–0.35	1.43	1.25–1.65
65+ years	2.02	1.83–2.22	6.23	5.71–6.75	0.50	0.43–0.58	1.60	1.37–1.85
Female								
18–24 years	1.81	1.58–2.05	4.09	3.40–4.86	0.45	0.38–0.53	1.03	0.82–1.28
25–34 years	0.74	0.66–0.81	3.49	3.20–3.79	0.18	0.16–0.21	0.88	0.75–1.02
35–44 years	0.81	0.74–0.88	3.79	3.53–4.07	0.20	0.17–0.23	0.95	0.83–1.10
45–54 years	1.06	0.96–1.15	4.94	4.61–5.28	0.26	0.22–0.30	1.25	1.10–1.43
55–64 years	1.16	1.04–1.26	5.36	4.98–5.77	0.28	0.24–0.33	1.37	1.19–1.58
65+ years	1.92	1.75–2.11	5.95	5.45–6.51	0.48	0.41–0.56	1.52	1.30–1.77

Note: CI = certainty interval; prop = proportion.

3.9 million (1.86 percent) Jewish adults. Distributions by state indicate that the largest percentages of Jewish adults are concentrated in New York, New Jersey, and the District of Columbia, with additional concentrations in Maryland and Massachusetts. Although there was a significant relationship between metropolitan status and likelihood of identifying as Jewish, inclusion of metropolitan status as a poststratification variable did not affect estimates at the national, regional, or state levels. Overall, there were greater proportions of Jewish adults in metropolitan than nonmetropolitan areas, and this difference was most pronounced in the Northeast.

Discussion

The present analyses demonstrate the utility of combining data from multiple surveys to estimate the distribution of small religious groups throughout the United States. Regional and state-level estimates were generated as well as estimates by age, sex, race, and educational attainment. Pooled estimates indicate that the number of adults in the United States who identify as Jewish by current religion is upwards of 3.9 million, or 1.86 percent of all U.S. adults. There were substantial differences by region, with the largest proportion of Jews living in the Northeast. Jews were also more likely to reside in metropolitan areas. Most important, there were substantial differences across the 48 demographic groups included as poststratification variables. Among white non-Hispanics, a greater proportion of those with college degrees or greater were likely to identify by religion as Jewish. In addition, those aged 45 years and older were more likely than younger respondents to identify as Jewish.

The overall estimate of 1.86 percent, derived through the pooling of many sources of nationally representative data poststratified by state, age, sex, race, and education, was consistent with Smith's (2005) review of a limited set of GSS data, which yielded an overall estimate of 1.8 percent. The key difference is that our pooled sample of 50 surveys allows for better estimation of the characteristics of the population, including differences among subgroups by age, education, and regional and state distributions. In addition, the use of hierarchical models allows one to examine heterogeneity of the multiple independent samples prior to pooling.

Had there been additional survey-level variance, heterogeneity could be modeled and estimates could be adjusted accordingly. Other survey-level factors that could be examined that may affect estimates of other groups, or of other characteristics of these groups (e.g., political orientation), include whether (1) question wording influences identification; (2) certain religious groups are more or less likely to participate depending on the primary topics of the survey—religious, political, social, and health; (3) surveys that are conducted in-person rather than over the phone yield a different likelihood of identification for some groups; (4) there are differences between surveys with high and low response rates; (5) other sampling variables such as household size and number of phones affect estimates[9]; and (6) there are changes over time in the geographic and demographic distribution of the population. Although the majority of surveys in the current sample were clustered around the year 2000, an eight-year span was represented across the full sample of surveys. The lack of significant variability at the survey level suggests that little would be gained in overall population estimation with the inclusion of year of survey administration. The addition of more surveys within all years would improve the ability to detect and describe interactions associated with population shifts over time.

One of the benefits of this approach is that the model-based estimates of the size of different religious groups can serve as a critical source of external data for those conducting single surveys. For standard demographics such as age, race, sex, and education, investigators typically rely on the U.S. Census to determine the representativeness of their samples and to create poststratification weights. Because the census does not include religion, there is no single source of data for determining the representativeness of samples in terms of religious identification. This is critically important for surveys that seek to examine religion and the influence of religion on social behavior more broadly. The methods presented here represent the best means to estimate the size of these groups and, with additional analysis and data, can be extended to update group estimates over time. Furthermore, these analyses can be extended to the study of other similarly sized groups in a manner that allows for direct comparisons between groups using the same data source. This approach greatly reduces costs and burdens associated with the collection of multiple, independent oversamples of small populations.

Many of the surveys assessed similar core social data, such as political orientation, party affiliation, marriage, and the importance of religion. With reliable methods to combine across surveys, outcomes such as these can be studied across a broader range of religious groups. With single surveys, the reliability of inferences associated with these sorts of questions for groups other than the most predominant groups such as Catholic and mainline Protestant are highly unreliable. Pooling data across multiple sources is the only way investigators can examine characteristics and behavior of these groups in meaningful detail. With additional data on household composition, as well as inclusion of surveys of youth, these results can be extended to examine population characteristics more broadly.

The analyses presented here represent a leap in method designed to maximize the utility of the abundance of survey data in the public domain. The techniques described have a number of applications to studying rare populations, although the utility of the information is necessarily limited by the questions asked in surveys. Thus, the present analyses focused on the Jewish population in terms of religious identification. Jews, however, also identify by ethnicity or culture. Kosmin et al. (2001) included a broader set of questions about identity. Those investigators found that of all adults who could be classified as Jewish either by religion or culture, about half (53 percent) self-identified as Jewish when asked about their religion. This compares to nearly 80 percent of the Jewish respondents in the NJPS survey (Kotler-Berkowitz et al. 2004). In our sample of 50 surveys, only 5 surveys included identification of Jewish by both ethnicity and religion. Of the 13,500 respondents in these 5 surveys, only 346 self-identified either ethnically or religiously as Jewish. Of these, 77 percent self-identified as Jewish when asked about their religion.

One could extrapolate to our full sample and conclude that there are an additional 23 percent who identify ethnically but not religiously as Jewish. Many of those in this very small sample of 81 of 13,500 people, however, would not be considered Jewish by the larger Jewish community because although they may identify with their family heritage of Judaism, they also self-identified with religions considered to be incompatible with being Jewish (e.g., Protestantism). Thus, one might conclude that there is an additional 10 percent beyond our estimate of 1.86 percent, or upwards of 2.1 percent of adults in the United States, who identify as Jewish (i.e., 4.39 million). With additional surveys and samples that include such distinctions, it will be possible to examine this group in greater detail.

As with all population estimates that rely on survey responses, there is the threat of undercount given the possibility that some groups may be more or less likely to participate in surveys and some may be more or less likely to reveal their religious affiliation (O'Neil 1979). We expected that we would be able to examine this possibility by comparing estimates within surveys of high response rate to those of low response rate. The lack of survey-level variance after poststratification by basic demographics suggests that nonresponse biases likely have more to do with sociodemographic characteristics, as has been-reported elsewhere (Keeter et al. 2006), than with religious identification. Future analyses, using additional surveys with high and low response rates and conducted for different purposes, can explore this possibility. If surveys that minimize nonresponse and yield high response rates result in higher estimates of one group than do surveys with low response rates, one would be able to conclude that, indeed, that group is likely underrepresented. One could also examine whether there are differences between surveys that are conducted in different languages, particularly for the assessment of religious groups that are known to have experienced large influxes of recent immigration (e.g., Muslims from Arab and South Asian countries; Jews from the former Soviet Union; Hispanic Catholics and Protestants from Mexico).

Conclusion

The diversity of religious groups in the United States and their influence on social life and social policy require practical application of methods that facilitate both the understanding of groups that are relatively small and the comparison of those groups with other similarly sized and larger groups. Short of a change in law that would allow the collection of religious identification in the U.S. Census, the combination of multiple data sources described in the present article offers the best cost-effective alternative. These methods maximize the utility of existing sources of data while also attending to differences in the sources that can affect population estimates that result. The evidence provided from this investigation may only scratch the surface of the utility of this approach, yet it highlights the feasibility of cross-survey analysis for the estimation of population groups not represented in the U.S. Census.

Authors' Note

The online appendices are available at http://smr.sagepub.com/supplemental

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Notes

1. *Protestant* and *Catholic* were included as search terms because they are the most common categories. If a survey reports these, there are usually data available to identify Jewish respondents.
2. Education is included as a proxy for socioeconomic situation given its strong association with income and the lack of comparable income data across surveys (Arrow, Bowles, and Durlauf 2000).
3. Surveys with the largest sample sizes were included, with two notable exceptions. The NJPS was excluded because it did not include basic demographic variables in the screener where religious identification was assessed. The ARIS was not released until the analyses reported here had been completed. Furthermore, there is insufficient information on the 50 independent samples that comprise this data set. Of the remaining surveys with modest sample sizes of around 1,000 respondents or fewer, a subset of surveys was included, primarily those archived in the ARDA. The ARIS and other surveys, including restricted samples such as the follow-up sample of the NJPS, can be added in subsequent analyses.
4. A number of other surveys were also excluded because of differences in sampling frames. To minimize the number of variables changing at the same time, analyses were limited to only those surveys that drew samples from the same underlying target population of all adults aged 18 years and over. Surveys of special populations, including special populations defined by age (e.g., the National Survey of Family Growth, the Health & Retirement Survey, the Panel Study of Income Dynamics), were excluded here. Future work will focus on the integration of special population data with general population surveys.
5. A majority (88 percent) of the surveys were of the continental United States, including the District of Columbia. Of the remaining surveys that included both the continental and non-continental United States (Alaska and Hawaii), only cases in the continental United States were included in these analyses.
6. In 1998 and 2000, the ANES included both telephone and in-person interviews. The two samples are included separately for 2000. In 1998, only 290 respondents were initially contacted for in-person interviews, compared with 991 by telephone. Given the small number of respondents contacted for in-person interviews, only the telephone sample for this year is included.
7. Race and education were simplified to two categories based on preliminary analyses that demonstrated that the greatest variability in the likelihood a respondent was Jewish was between the broad categories of white non-Hispanic and nonwhite and college educated and non–college educated.

8. Age by education interactions were also included based on analyses of all possible two-way interactions in each of the 50 surveys.
9. Too few surveys provided sufficient data on household size, number of eligible respondents, and number of phone lines to be able to include these factors.

References

Arrow, Kenneth, Samuel Bowles, and Steven Durlauf, eds. 2000. *Meritocracy and Economic Inequality*. Princeton, NJ: Princeton University Press.

Bates, Douglas. 2005. ''Fitting Linear Mixed Models in R.'' *R News: The Newsletter of the R Project* 5:27–30.

Brick, J. Michael and Clyde Tucker. 2007. ''Mitofsky-Waksberg: Learning From the Past.'' *Public Opinion Quarterly* 71:703–16.

Gelman, Andrew. 2007. ''Struggles with Survey Weighting and Regression Modeling.'' *Statistical Science* 22:153–64.

Gelman, Andrew. 2008. *Red State, Blue State, Rich State, Poor State: Why Americans Vote the Way They Do*. Princeton, NJ: Princeton University Press.

Ghosh, Malay, Kannan Natarajan, T. W. F. Stroud, and Bradley P. Carlin. 1998. ''Generalized Linear Models for Small-Area Estimation.'' *Journal of the American Statistical Association* 93:273–82.

Groeneman, Sid and Gary Tobin. 2004. ''The Decline of Religious Identity in the United States.'' San Francisco, CA: Institute for Jewish and Community Research.

Groves, Robert M., F. J. Fowler, Mick P. Couper, James M. Lepkowski, Eleanor Singer, and R. Tourangeau. 2004. *Survey Methodology*. New York: Wiley.

Hedges, L. V. and Ingram Olkin (1985). *Statistical Methods for Meta-Analysis*. New York, NY: Academic Press, Inc.

Hox, Joop J. 2002. *Multilevel Analysis: Techniques and Applications*. Mahwah, NJ: Lawrence Erlbaum.

Jorm, A. F and D. Jolley. 1998. ''The Incidence of Dementia: A Meta-Analysis.'' *Neurology* 51:728–33.

Jorm, A. F., A. E. Korten, and A. S. Henderson. 1987. ''The Prevalence of Dementia: A Quantitative Integration of the Literature.'' *Acta Psychiatrica Scandinavica* 76:465–79.

Kadushin, Charles, Peter D. Killworth, H. Russell Bernard, and Andrew A. Beveridge. 2006. ''Scale-up Methods as Applied to Estimates of Heroin Use.'' *Journal of Drug Issues* 36:417–40.

Kadushin, Charles, Benjamin Phillips, and Leonard Saxe. 2005. ''National Jewish Population Survey 2000–01: A Guide for the Perplexed.'' *Contemporary Jewry* 25:1–32.

Keeter, Scott, Courtney Kennedy, Michael Dimock, Jonathan Best, and Peyton Craighill. 2006. ''Gauging the Impact of Growing Nonresponse on Estimates from a National RDD Telephone Survey.'' *Public Opinion Quarterly* 70:759–79.

Kosmin, Barry A., Egon Mayer, and Ariela Keysar. 2001. ''American Religious Identification Survey.'' New York: Graduate Center of the City University of New York.

Kotler-Berkowitz, Laurence, Steven M. Cohen, Jonathon Ament, Vivian Klaff, Frank Mott, and Danyelle Peckerman-Neuman. 2004. ‘‘The National Jewish Population Survey 2000–01: Strength, Challenge and Diversity in the American Jewish Population.’’ Rev. ed. New York: United Jewish Communities.

Larsen, Klaus, Jorgen Holm Petersen, Esben Budtz-Jorgensen, and Lars Endahl. 2000. ‘‘Interpreting Parameters in the Logistic Regression Model With Random Effects.’’ *Biometrics* 56:909–14.

Lohr, Sharon L. and N. G. Narasimha Prasad. 2003. ‘‘Small Area Estimation With Auxiliary Survey Data.’’ *Canadian Journal of Statistics* 31:383–96.

Malec, Donald, J. Sedransk, Christopher L. Moriarity, and Felicia B. LeClere. 1997. ‘‘Small Area Inference for Binary Variables in the National Health Interview Survey.’’ *Journal of the American Statistical Association* 92:815–26.

Massey, James T., Dan O’Connor, and Karol Krotski. 1998. ‘‘Response Rates in Random Digit Dialing (RDD) Telephone Surveys.’’ Pp. 707–12 in *1997 Proceedings of the Survey Research Methods Section, American Statistical Association*. Arlington, VA: American Statistical Association.

Mattis, Jacqueline S. 2001. ‘‘Religion and African American Political Life.’’ *Political Psychology* 22:263–78.

O’Hara, Brett, Joana Turner, Mark Bauder, Steven Riesz, and David Waddington. 2006. ‘‘Initial Assessment of Small Area Estimation of the Number of Eligible Women for the CDC’s NBCCEDP.’’ Atlanta, GA: Centers for Disease Control and Prevention.

O’Neil, Michael J. 1979. ‘‘Estimating the Nonresponse Bias Due to Refusals in Telephone Surveys.’’ *Public Opinion Quarterly* 43:218–32.

Olson, Daniel V. A. and Jackson W. Carroll. 1992. ‘‘Religiously Based Politics: Religious Elites and the Public.’’ *Social Forces* 70:765–86.

Park, David K., Andrew Gelman, and Joseph Bafumi. 2004. ‘‘Bayesian Multilevel Estimation with Poststratification: State-Level Estimates from National Polls.’’ *Political Analysis* 12:375–85.

Park, David K., Andrew Gelman, and Noah Kaplan. 2006. ‘‘R2WinBUGS: Running WinBUGS From R.’’ *Political Methodologist* 14:5–10.

Pew Research Center. 2007. ‘‘Muslim Americans: Middle-class and Mostly Mainstream.’’ Washington, DC: Pew Research Center. Retrieved August 29, 2008 (http://pewresearch.org/assets/pdf/muslim-americans.pdf).

Pew Research Center. 2008. ‘‘U.S. Religious Landscape Survey.’’ Washington, DC: Pew Research Center. Retrieved August 29, 2008 (http://religions.pewforum.org/pdf/report2-religious-landscape-study-full.pdf).

Pfeffermann, Danny. 2002. ‘‘Small Area Estimation: New Developments and Directions.’’ *International Statistical Review* 70:125–43.

Phillips, Benjamin. 2006. ‘‘Numbering the Jews: Evaluating and Improving American Jewish Population Studies.’’ PhD dissertation, Department of Sociology, Brandeis University, Waltham, MA.

Public Law 94-521, HR 11337, 90 Stat 2459 (1976).

Rao, J. N. K. and Mingyu Yu. 1994. ‘‘Small-Area Estimation by Combining Time-Series and Cross-Sectional Data.’’ *Canadian Journal of Statistics* 22:511–28.

Sheerkat, Darren E. and Christopher G. Ellison. 1999. ‘‘Recent Developments and Current Controversies in the Sociology of Religion.’’ *Annual Review of Sociology* 25:363–94.

Shriver, Peggy L. 1985. ‘‘Religion’s Very Public Presence.’’ *Annals of the American Academy of Political and Social Science* 480:142–53.

Smith, Tom W. 1994. *Trends in Non-Response Rates*. Chicago, IL: National Opinion Research Center.

Smith, Tom W. 2002. ‘‘Religious Diversity in America: The Emergence of Muslims, Buddhists, Hindus, and Others.’’ *Journal for the Scientific Study of Religion* 41:577–85.

Smith, Tom W. 2005. *Jewish Distinctiveness in America*. New York: The American Jewish Committee.

Stevens-Arroyo, Anthony M. 1998. ‘‘The Latino Religious Resurgence.’’ *Annals of the American Academy of Political and Social Science* 558:163–77.

U.S. Census Bureau. 2010. *Statistical Abstract of the United States: 2010*. 129th ed. Washington, DC: U.S. Census Bureau. (http://www.census.gov/compendia/statab/2010/tables/10s0075.pdf), accessed April 6, 2010.

U.S. General Accounting Office. 1998. *Alzheimer’s Disease: Estimates of Prevalence in the United States*. Washington, DC: U.S. General Accounting Office.

Wuthnow, Robert. 1999. *Arts and Religion Survey*. Princeton, NJ: Gallup Organization.

Zheng, Tian, Matthew J. Salganik, and Andrew Gelman. 2006. ‘‘How Many People Do You Know in Prison? Using Overdispersion in Count Data to Estimate Social Structure in Networks.’’ *Journal of the American Statistical Association* 101:409–23.

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