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ABSTRACT

Problems associated with low response rates to surveys are considered, drawing from the literature on the methodology of survey research. A series of analyses are presented which were designed to examine the efficacy of Astin and Molm's procedure to adjust for nonresponse biases. Data were obtained form the Cooperative Institutional Research Program survey of 1987 incoming students and the 1991 followup survey. Data were analyzed for 209,627 students at 390 institutions. After separating the data into respondents (21 percent) and nonrespondents (79 percent), attention was directed to how distributions and relationships change due to nonresponse. The efficacy of the Astin and Molm procedure was examined using univariate and joint distributions and multiple regressions. It is concluded that the Astin and Molm procedure for adjusting for patterns of nonresponse is very effective in reducing biases in univariate distributions. The effectiveness of this weighting procedure is less clear in adjusting the results of correlation and regression analyses. The analyses did not reveal a situation where the weighted results were clearly less preferable than the unweighted one. Although the Astin and Molm technique is designed for use in longitudinal research, related methods of weighting can be implemented for cross-sectional surveys. (Contains 27 references.) (SW)

Working with low survey response rates: The efficacy of weighting adjustments

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Jean Endo
Editor
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Among survey researchers, obtaining a high response rate is akin to reaching nirvana. Although the figure that defines a high response rate is somewhat dependent upon the eye of the beholder, one trend is not: Americans are increasingly less likely to be willing to respond to surveys[1] (Groves, 1989; Steeh, 1981). This trend is quite troubling since surveys play a central role in the data collection activities of most institutional research efforts (Grosset, 1995; Schiltz, 1988; Cote, Grinnell, & Tompkins, 1986).

Within the context of higher education research, an example of declining response rates is provided by a series of national longitudinal follow-up surveys of college students conducted by the American Council on Education and the Cooperative Institutional Research Program (CIRP). As can be clearly seen in Table 1, there has been a pronounced decline in response rates since the early 1960s, and response rates appear to be continuing their decline at the rate of a few percentage points a year Although the national CIRP surveys provide a good way of documenting this decline due to their continuity, the response rate issue affects many single-institution research projects as well (see for example Cabrera, Castañeda, Nora, & Hengstler, 1992, who report a response rate of 19 percent).

Although telephone and face-to-face surveys are commonly used in large-scale public opinion research (Groves, 1989; Davis & Smith, 1991), mail surveys are more commonly used within higher education settings (Grosset, 1995; Dillman, 1991; Schiltz, 1988; Cote, Grinnell, &

[1]Based on data from the General Social Survey, Davis & Smith (1992) disagree with this point but acknowledge that declining rates of survey cooperation may be masked by improved field procedures in the GSS.

Tompkins, 1986) and will serve as the focus of this paper. This is an important distinction when considering the issue of nonresponse, since mail surveys have, on average, a much lower rate of response than that associated with other modes of data collection. Although this has long been recognized, the mail survey has continued to be popular in many settings due to low costs and ease of administration (Grosset, 1995; Dillman, 1991).

Although there is a wealthy literature available to institutional researchers that suggest ways to dramatically improve response rates in mail survey (e.g., Dillman, 1978, 1983, 1991; Cote, Grinnell, & Tompkins, 1986; Smith & Bers, 1987), we also need to have methods of dealing with data generated by survey efforts when the rates of response are below -- and sometimes well below -- 100 percent. One long-standing procedure for accomplishing this is the use of weighting techniques to compensate for errors in survey coverage and unit (as opposed to item) nonresponse, with the weight representing the inverse of the probability of being sampled and responding, respectively (Kalton, 1983; Oh & Scheuren, 1983; Rossi, Wright, & Anderson, 1983).

Within the field of higher education, Astin and Molm (1972) have described a method of dealing with survey nonresponse in cases where researchers have information on the characteristics of individual respondents (as is the case with longitudinal research efforts). This method, which has been used for many years in the CIRP follow-up surveys, employs multiple regression to calculate the likelihood that a student will return a completed survey. Using this information, it is possible to produce a weighting factor that consists of the inverse of a student's computed probability of response. This weighting factor thus adjusts the analyses by giving "the greatest weight to the responses of those students who most resemble the non-respondents" (Higher Education Research Institute, 1992).

Although the Astin and Molm procedure has been employed for many years, it should be noted that it was developed at a time when response rates to follow-up surveys employing similar administration modes were two to three times what they currently are (see Table 1). Thus, it may be that the Astin and Molm (and similar) weighting adjustments may no longer be as effective at compensating for nonresponse. Set within this context, then, this paper has several main goals. At the outset, I review the analytical challenges associated with low response rates by drawing upon the general literature on the methodology of survey research. I then present a series of analyses designed to examine the efficacy of the Astin and Molm procedure as a general method for adjusting for nonresponse biases, and conclude with a set of recommendations to consider in order to improve the quality of survey research within the context of institutional research.

Problems associated with survey nonresponse

In understanding the problems associated with nonresponse to mail surveys, it is important to recognize that response rate is different from response error or bias. It may be that a survey which yields a very low response rate, say 10 percent, does a fairly good job of representing the population from which the mailout sample was originally drawn. This would be the case if the 10 percent who responded to this hypothetical survey are quite similar to the 90 percent who failed to respond. It is not often the case, however, that respondents are a perfectly random subset of those to whom surveys were originally mailed (although in many situations this is an untestable proposition), which leads to the problem of nonresponse bias (Dillman, 1991).

The effect of nonresponse bias is manifested in different ways for different statistics, but can be fairly easily visualized by examining the nonresponse bias associated with a sample mean. For a particular variable (Y), the sample mean is calculated as follows:

$$\overline{Y} = p_r\overline{Y}_r + p_n\overline{Y}_n$$

where p_r and p_n represent the proportions of respondents and nonrespondents, respectively (following Davis & Smith, 1991). Put another way, the nonresponse bias is "a function of the percentage of the sample not responding to the survey and the difference on the statistic between respondents and nonrespondents" (Groves, 1989, p. 134), or

$$\text{nonresponse bias} = \text{response rate} * (\overline{Y}_r - \overline{Y}_n)$$

From these equations it is clear that the extent to which $\overline{Y}_r$ and $\overline{Y}_n$ are different from one another will be directly related to how well the mean among respondents ($\overline{Y}_r$) represents the true mean in the sample ($\overline{Y}$). More complex statistics are affected by nonresponse bias as well, but in a less intuitively obvious way. In the case of a simple regression under assumptions of normality, the relationship between the standardized regression coefficient in the original sample (β) and that which is estimated from survey respondents (β^*) is:

$$\beta^* = \beta \frac{V^*(y)/V(y)}{1 - \rho^2[1 - V^*(y)/V(y)]}$$

where $V^*(y)$ is the variance of the dependent variable in the original sample, $V(y)$ is the variance of the dependent variable among survey respondents, and ρ^2 is the coefficient of determination for the regression model among survey respondents (from Goldberger, 1981, cited in Groves, 1989). It is important to note that while response rate plays a straightforward role in the case of sample means, the nonresponse bias is simply the function of variances in the original and respondent samples and of model fit.

In most cross-sectional surveys it is impossible to precisely know the degree to which statistics may be biased by nonresponse due to the simple fact that little is known about the characteristics of nonrespondents. Although it is common in such surveys to compare respondents and nonrespondents across known population characteristics (such as basic demographic information, or within the context of research on students grade point average), the reality is that "even when one can be confident that no differences exist on these [types of] variables, one still does not know whether differences exist on those variables of interest that led to the decision to conduct the survey" (Dillman, 1991, p. 299). This has led to the response rate being seen as a proxy for nonresponse bias despite the lack of correspondence between these two concepts (Dillman, 1991; Groves, 1989).

The Astin and Molm (1972) procedure exploits the fact that additional information is available on those to whom follow-up surveys were sent, regardless of their later response status. In the context of the CIRP follow-up surveys, the nonresponse weights are generated by regressing a variable denoting the final survey response status (1 = respondent, 0 = nonrespondent) upon a large number of variables derived from the CIRP freshman survey and an independent survey of college registrars. By employing regression it is possible to generate weights based on a large number of student characteristics (many of which may be related to one another) (see HERI, 1992). Although this should in theory produce more precise weights for individuals, it is conceptually similar to other weighting procedures which usually rely on a limited number of variables to create stratification cells (Rossi, Wright, & Anderson, 1983). Given the general similarity between these approaches to weighting, the results shown below should be applicable with little modification to a wide variety of survey projects of both longitudinal and cross-sectional design.

Methodology

In undertaking this study, I use data collected as part of the Cooperative Institutional Research Program (CIRP), a continuing program of research that is sponsored by the American Council on Education and the Higher Education Research Institute (HERI) at the University of California, Los Angeles. The CIRP freshman survey program annually collects a broad array of student background information using the Student Information Form (SIF; see Astin, Panos, & Creager, 1966), and is designed to longitudinally assess the impact of college on students. The data for this study are primarily drawn from the 1987 SIF administered to incoming students and the 1991 Follow-up Survey of 1987 Freshmen. In addition to these data, further information about each student was requested through an institution's CIRP representative, and included information on degree earned, number of years competed at the freshman institution, and whether or not the student was still enrolled. The registrar's survey had a response rate of 68 percent, and these data are an important supplement for the purposes of creating nonresponse weights since this information is provided on an unbiased subset of the original follow-up sample (HERI, 1992).

Sample

The Student Information Form (SIF) was distributed to campuses in the Spring and Summer of 1987 for distribution to college freshmen during orientation programs and in the first few weeks of fall classes. As part of the 1987 freshman survey, the 289,875 students at 562 participating colleges and universities completed the SIF. To reduce the possibility of bias due to errors in survey coverage, survey respondents at 172 institutions were excluded from the SIF normative population because of a low rate of return from their college as a whole (usually below 75%). This left 209,627 students at 390 institutions in the national normative population (Dey, Astin, & Korn, 1991).

The Follow–up Survey (FUS), when linked with freshman SIF data, is designed to assess a wide–range of student experiences and undergraduate achievements and to provide a longitudinal database for studying how different college environments influence student development. A sample of SIF respondents in the normative population was drawn using a stratified, random sampling procedure designed to ensure an adequate representation of student respondents from different types of higher education institutions (HERI, 1992). The stratification scheme classified institutions by type and selectivity into one of 23 cells, a sample of 27,111 students was drawn from institutions in the CIRP national norms (i.e., those institutions whose response rates to the freshman survey were judged representative of their entering freshman class). This sample size was selected based upon earlier Follow–up Survey response rates and was designed to yield a minimum of 175 respondents in each stratification cell.

The Follow–up Survey instrument was sent to students in June, 1991. A second wave of follow–up surveys was mailed to non–respondents in mid–August, 1991. The response rate to the FUS averaged 20.7 percent.

Analysis

In order to examine the influence of nonresponse on results, and the effectiveness of weighting procedures to eliminate this influence, the data for specific analyses are drawn only from the freshman survey. It is important to remember that the freshman survey data contain full information on all students to whom a survey was sent regardless of whether or not they later responded to the follow-up survey. As such, my analysis be limited to those variables which appear on either the freshman or registrars' survey. By partitioning these data into respondents (21 percent) and nonrespondents (79 percent) we can examine how distributions and relationships change due to nonresponse. Moreover, by having full data from the freshman survey, we can see how well the correct values for the entire sample are reproduced by weighting the respondent data.

In order to examine the efficacy of the Astin and Molm procedure I conducted several analyses which are representative of the kinds of analyses one might see in studies of college impact. Specifically I present information on univariate and joint distributions, as well as two multiple regressions (one of which is longitudinal in nature, and relies on the subset of data from the registrar's survey for the outcome variable). This mixture of analyses is important since nonresponse may strongly bias certain statistics associated with a particular set of variables, while other statistics based on the same variables may be relatively unaffected.

Results

Before addressing the issue of the effectiveness of Astin and Molm's technique for correcting for nonresponse bias, it is important to first understand the extent to which different characteristics predict the likelihood of a student returning a follow-up survey. This is important information for it is these characteristics which reveal the ways in which student follow-up samples tend to be biased. Table 2 shows the 10 strongest positive and 10 strongest negative correlations between student characteristics (measured in 1987) and response status on the 1991 follow-up survey (1 = yes, 0 = no). These results show that the two strongest correlates of survey response are high school grades and academic self-rating, which suggests that students who tend to do well in educational settings are also those who tend to return surveys (HERI, 1992). Other variables in Table 2 which reinforce this interpretation are years studying foreign language in high school, scholarly orientation (Astin, 1993), expectation of earning a bachelor's degree, self-rating and years of high school study in math, and intending to improve study skills during college. This is a critical relationship to note since student retention is an important area of research, and this suggests that follow-up surveys will be biased towards those likely to have success in college.

Student race is another characteristic which predicts survey response. African American students are much less likely than average to return a survey, while white students are more likely than average. In direct percentages, this translates to a response rate among African Americans of 8.8 percent versus 23.1 among white students. Although it might be tempting to attribute the low rate of response among African American students to a hostile educational climate within predominantly white campuses, the fact that the response rate among African American students was 11.2 percent in white colleges versus 7.6 in historically black colleges suggests that this problem is very complex. The disparity in response rates among students of different races is troubling, and an area in need of future study.

A final pattern in Table 2 which is worthy of note relates to six of the top ten negative correlates with response. Taken together, these items show that students who are entrepreneurial and oriented toward economic success are less likely to return follow-up surveys than are other students. Although this pattern may be related to differential patterns of academic ability (these students, as a group, are less likely to be oriented toward academic success), it stands as a reminder that there are many possible -- and somewhat subtle and unexpected -- patterns of nonresponse which can lead to biased samples.

Table 3 shows comparative information on respondents (column 2) and nonrespondents (column 3) to the follow-up survey, as well as the complete original sample (column 1) and the weighted results based upon respondents only (column 4). Panel A in Table 3 shows the univariate distributions of two variables -- high school grades and degree aspirations -- while Panel B shows the correlation between these two variables. The data on the distribution of high school grades is very different for the respondents and nonrespondents. Whereas 24 percent of all freshmen reported a high school grades of A- or better, the corresponding figure for the follow-up respondents is 50 percent higher (36 percent). The equivalent proportion among nonrespondents is closer to the proportion for the entire population (21 versus 24 percent) which mathematically has to be the case since 4 out of 5 students in the freshman population are follow-up nonrespondents. The bias associated with the aspirations for various degrees is somewhat less pronounced yet still evident. A comparison of columns 1 and 4 for both variables shows that the weighting procedure suggested by Astin and Molm is effective in reducing the bias in the distribution of responses for each these variables relative to that which is found in the complete sample.

Turning now to Panel B we see the effect on nonresponse bias on joint distributions, measured here by Pearson's *r*. By correlating the two variables considered in Panel A we can examine the extent to which variables which are individually biased influence their joint relationship. In the original sample, the correlation between high school grades and degree aspirations is modest ($r = .2507$). The same is true of the correlations shown in columns 2 through 4 to the extent that these correlations are essentially equivalent (and certainly statistically equivalent) › the original, correct value shown in column 1. This suggests that even when individual variables are noticeably biased, their relationships with one another tend not to be strongly influenced. Earlier methodological studies have come to similar conclusions (Astin & Panos, 1969).

In order to consider the effectiveness of the Astin and Molm procedure in a multivariate context, I conducted two multiple regression analyses which are shown in Table 4. The first analyses predicts a student's degree aspiration from high school grades and demographic variables. The overall predictability of the dependent variables was similar across the three samples (around 11 percent of the variance in degree aspirations was explained by the set of independent variables), and while there are a few differences across the regressions all variables are significant predictors in each of the three samples. In comparing the unweighted and weighted results to those from the original sample it is hard to identify which comes closest to replicating the original, correct results. For example, if we compare across samples using the metric results we see that the regression coefficients in the unweighted sample tend to be slightly closer to the original values, while the constant is closer to the original in the weighted sample.

Turning now to the longitudinal analysis shown in Table 4, there is less consistency across samples in terms of predicting the number of full years of college completed as reported by college registrars. Given that this variable is one which is likely to be heavily biased by the patterns described in Table 2 this is perhaps not too surprising. Both of the respondent samples (unweighted and weighted) suggest that degree aspirations are unrelated to the number of years of college completed even though this is significant in the original sample. A similar pattern is found for the student race variable. The weighted results fail to show that parental income is a significant predictor, while the unweighted results incorrectly identify gender as a significant negative predictor. As with the regression predicting degree aspirations it is unclear whether one regression -- unweighted or weighted -- is to be preferred over the other (although the weighted results produce a Multiple R value which is slightly closer to that produced in the original, correct regression). Several college impact researchers using other CIRP dataset have not shown a tendency to prefer unweighted or weighted analyses, and have characterized the substantive differences between these two approaches as trivial (e.g., Pascarella, Ethington, & Smart, 1988; Pascarella, Brier, Smart, & Herzog, 1987).

Discussion and Implications

These results show that the Astin and Molm procedure for adjusting for patterns of nonresponse is very effective in reducing biases in univariate distributions. The effectiveness of this weighting procedure is less clear in adjusting the results of correlation and regression analyses, perhaps in part because these statistics appear to be less systematically affected by bias introduced by nonresponse patterns. Moreover, the analyses did not reveal a situation where the weighted results were clearly less preferable than the unweighted one. This suggests that the application of carefully designed weights is a generally effective method for reducing nonresponse bias. Although we cannot be certain that this pattern of results will hold for all analyses under all conditions, previous research seems to suggest that this is indeed the case (Pascarella, Ethington, & Smart, 1988; Pascarella, Brier, Smart, & Herzog, 1987; Astin & Panos, 1969).

The first and most important approach in working with low survey response rates is avoiding low survey response rates. The literature on survey research is abundant with good information and suggestions on the topic of improving response rates to surveys (Dillman, 1991; Cote, Grinnell, & Tompkins, 1986; Smith & Bers, 1987). While this literature should become a working part of the library of any institutional researcher doing survey research, we need to recognize that achieving very high response rates will probably continue to remain problematic (especially given the amount of resources available to most institutional researchers to conduct surveys of students and faculty). Given these constraints, adjustments of this sort appear to be a fairly effective methods of dealing with survey nonresponse.

Although the Astin and Molm technique is designed to be used in longitudinal research, related methods of weighting can be implemented for cross-sectional surveys and are routinely employed for this and related purposes (Groves, 1989; Madow, Olkin, & Rubin, 1983; Rossi, Wright, & Anderson, 1983). This can be created by defining a number of stratification cells based upon characteristics which are 1) known or suspected to be related to nonresponse bias, and 2) which are available for the population from which the original (mail-out) sample was drawn. Once this is done, developing weights to adjust the returned-survey sample to the original sample is straightforward (by taking the reciprocal of the ratio of respondents to original sample within the stratification cell). Although this sort of post-stratification adjustment may be somewhat less precise than that which can be obtained through more complex weighting schemes, they nonetheless should be useful in reducing obvious sources of nonresponse bias in cross-sectional surveys. It should, however, be noted that all weighting adjustments have subtle and complex implications for the analytic (as opposed to more descriptive) uses of survey data (Skinner, Holt, & Smith, 1989; Rubin, 1987). Although I have not addressed these issues here, it is important to recognize that such issues will become increasingly important as the quality of survey research improves within higher education settings.

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Table 1
Trends in response rates to national ACE/CIRP student surveys: 1961 – 1991

Student cohort	Response rate	Source
1961 – 1962	58	Astin, 1968
1961 – 1965	60	Astin & Panos, 1969
1966 – 1974 (multiple)	65 to 40	Astin, 1977
1971 – 1980	40	Astin, 1982
1983 – 1987	26	HERI, 1989
1985 – 1989	23	HERI, 1991
1987 – 1991	21	HERI, 1992

Table 2
Top correlates of nonresponse in the 1991 HERI follow-up survey

Postive correlates	*r*	Negative correlates	*r*
High school grades	.180	Race: African American	-.122
Self-rating: Academic ability	.131	Life goal: Be successful in business of my own	-.091
Race: White	.115	View: There should be laws prohibiting homosexual relationships	-.084
Years of HS study: Foreign language	.107	Hours per week: Partying	-.082
Orientation: Scholar	.094	Life goal: Be very well-off financially	-.081
Parent's status: Married, living together	.092	Reason for college: Improve study skills	-.078
Sex: Female	.091	Orientation: Status striver	-.077
Expectation: Will earn BA degree	.084	Life goal: Be an expert on finance and .nmerce	-.072
Self-rating: Mathematical ability	.082	Reason for college: To be able to make more money	-.072
Years of high school study: Math	.079	View: The chief benefit of college is to increase earning power	-.071

Table 3
Effect of nonresponse on univariate and joint distributions

	Complete sample	FUS nonrespondents	Follow-up survey Unweighted	Follow-up survey Weighted
A. Univariate distributions				
High school grades				
A or A+	12.1%	10.2%	19.0%	12.0%
A-	12.3	11.2	16.8	12.2
B+	20.2	19.1	23.6	21.1
B	20.9	20.9	20.1	23.1
B-	16.0	17.1	11.6	15.8
C+	9.5	10.7	5.1	8.5
C or less	8.9	10.4	3.8	7.2
Degree aspirations				
Post-master's	26.4	25.7	29.2	26.9
Master's	37.8	37.4	39.5	38.6
Bachelor's	30.0	30.5	28.2	30.4
Associate's	5.7	6.4	3.2	4.0
B. Joint distributions				
	r	r	r	r
High school grades & degree aspirations	.2507	.2468	.2377	.2529
Proportion of sample	1.00	.79	.21	.21

Table 4
Comparison of two sets of unweighted and weighted regressions

Dependent variable	Complete sample	Unweighted results	Weighted results
Degree aspriations (1987)			
Standardized regression coefficients			
High school grades	.25	.23	.25
Parental income	.07	.07	.11
Parental education	.18	.16	.12
Student race: White	-.16	-.13	-.10
Student sex: Female	-.02	-.05	-.08
Metric regression coefficients			
High school grades	.12	.12	.13
Parental income	.02	.02	.03
Parental education	.09	.08	.06
Student race: White	-.34	-.33	-.23
Student sex: Female	-.03	-.08	-.13
Intercept	4.28	4.45	4.28
Multiple R	.35	.33	.33
R^2	.12	.11	.11
Adjusted R^2	.12	.11	.11
Number of full years completed (Registrar's survey)			
Standardized regression coefficients			
Degree aspirations (1987)	.05	.02 ○	.00 ○
High school grades	.29	.24	.28
Parental income	.08	.05	.03 ○
Parental education	.12	.08	.08
Student race: White	-.04	-.03 ○	-.03 ○
Student sex: Female	.00 ○	-.05	-.03 ○
Metric regression coefficients			
Degree aspirations (1987)	.08	.03 ○	.00 ○
High school grades	.23	.18	.23
Parental income	.03	.02	.01 ○
Parental education	.10	.05	.07
Student race: White	-.17	-.13 ○	-.12 ○
Student sex: Female	.00 ○	-.11	-.08 ○
Intercept	1.70	3.08	2.47
Multiple R	.36	.28	.30
R^2	.13	.08	.09
Adjusted R^2	.13	.07	.09

Note: All regression coefficients significant at $p < .01$ except for those noted with ○.