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WORKING WITH LOW SURVEY RESPONSE RATES: The Efficacy of Weighting Adjustments

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National data show a continuing decline in the willingness of people to respond to surveys. This trend is troubling given the central role that survey research plays in collecting data for institutional research purposes. This paper examines the effectiveness of a weighting procedure described by Astin and Molm for adjusting survey results to correct for nonresponse bias. Using data from a Cooperative Institutional Research Program (CIRP) follow-up survey, the results indicate that the weighting procedure is highly effective at reducing nonresponse bias in univariate distributions. The effectiveness of the weighting procedure in adjusting correlation and regression analyses is less clear. This may be due in part to the observation that even when individual variables are noticeably biased, their relationships with each other tend not to be.

Among survey researchers, obtaining a high response rate is akin to reaching nirvana. The figure that defines a high response rate is somewhat dependent on the eye of the beholder, but one trend is not: Americans appear increasingly reluctant to respond to surveys (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, and Tompkins, 1986).

Within the context of research on higher education, an example of declining response rates is provided by a series of national longitudinal 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 percent-

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TABLE 1. Response Rates of National ACE/CIRP Student Surveys: 1961–1991

Survey Years	Response Rate (%)	Source
1961–1962	58	Astin, 1968
1961–1965	60	Astin and Panos, 1969
1966–1974 (multiple)	65–40	Astin, 1977
1971–1980	40	Astin, 1982
1983–1987	26	HERI, 1989
1985–1989	23	HERI, 1991
1987–1991	21	HERI, 1992

Note: Each of the surveys mentioned above used a longitudinal design to follow up cohorts of students who were originally surveyed on college entry. Response rates shown are those associated with the follow-up component of the survey project; response rates for the base-year surveys are much higher due to on-campus administration and do not show a decline.

age points a year. The national surveys conducted by the CIRP provide a good way of documenting declining response rates due to their continuity over a 30-year period, but low response rates affect many single-institution research projects as well (see, for example, Cabrera et al., 1992, who report a response rate of 19 percent).

Telephone and face-to-face surveys are commonly used in large-scale public opinion research (Groves, 1989; Davis and Smith, 1992), but mail surveys are more common in higher education settings (Grosset, 1995; Dillman, 1991; Schiltz, 1988; Cote, Grinnell, and Tompkins, 1986) and 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 survey data collection. Even though this limitation has long been recognized, the mail survey has continued to be popular in many settings due to low cost and ease of administration (Grosset, 1995; Dillman, 1991).

There is a wealthy literature available that suggests ways to improve response rates in mail surveys (e.g., Dillman, 1978, 1983, 1991; Cote, Grinnell, and Tompkins, 1986; Smith and Bers, 1987), but we also need to have methods of dealing with data generated by survey efforts when response rates are below—and sometimes well below—100%. One longstanding 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 and Scheuren, 1983; Rossi, Wright, and 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 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 is the reciprocal 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). This means that respondents whose predicted likelihood of response was .50 would receive a weight of 2, while those with a response probability of .25 would receive a weight of 4.

The Astin and Molm procedure has been employed in CIRP follow-up studies for many years, but it should be noted that it was developed at a time when response rates to follow-up surveys were much higher on average (see Table 1). Thus, it may be that the Astin and Molm weighting approach is less effective at compensating for nonresponse due to its reliance on linear (as opposed to logistic) regression techniques (Dey and Astin, 1993). Set within this context, then, this paper has several main goals. First, I review the analytical challenges associated with low response rates by drawing upon the general literature on survey research methodology. 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 bias, 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 bias. It may be that a survey that yields a very low response rate, say 10%, does a fairly good job of representing the population from which the mail-out sample was originally drawn. This would be the case if the 10% who responded to this hypothetical survey were quite similar to the 90% who failed to respond. However, it is not often the case that respondents are a perfectly random subset of those to whom surveys were originally mailed, and this creates 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 can be calculated (following Davis and Smith, 1992) as:

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

where p_r and p_n represent the proportions of respondents and nonrespondents, respectively. This equation shows that the extent to which $\bar{Y}_r$ and $\bar{Y}_n$ are different from one another will be directly related to how well the mean among respondents ($\bar{Y}_r$) represents the true mean in the sample ($\bar{Y}$). This indicates that the nonresponse bias of a mean will thus be "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).

More complex statistics are affected by nonresponse bias as well, but in less obvious ways. 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; Groves, 1989). Unlike the straightforward role that response rate plays in the case of sample means, the nonresponse bias of a regression estimate is a 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. It is common in such surveys to compare respondents and nonrespondents across known population characteristics (such as basic demographic information, or perhaps grade-point average within the context of research on students); 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. 229). 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 described above 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) on a large number of variables derived from the CIRP freshman survey and a parallel 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 each other) (see HERI, 1992). This approach is conceptually similar to other weighting procedures that use stratification cells to generate corrective weights (Rossi, Wright, and Anderson, 1983), so the results shown below should be applicable with little modification to other longitudinal and cross-sectional survey projects.

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, and 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 completed at the freshman institution, and whether or not the student was still enrolled. The registrar's survey had a response rate of 68%, and these data are an important supplement for the purpose 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 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, 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, and 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), and these individuals were sent an FUS in June 1991. A second wave of follow-up surveys was mailed to nonrespondents in mid-August 1991, yielding a final response rate of 20.7%.

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 follow-up survey was sent *regardless* of whether or not they eventually returned it. Thus, my analyses will be limited to those variables that appear on either the freshman or registrars' survey. By partitioning these data into respondents (21%) and nonrespondents (79%) we can examine how observed 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 conducting this study I performed analyses that are representative of the kinds of approaches one might see in studies of college impact. Specifically, I present analyses of univariate and joint distributions, as well as two multiple regressions. One of the multiple regressions is based on unbiased longitudinal data derived from the parallel registrar's survey. The mixture of analyses used is important since nonresponse bias may strongly affect certain statistics associated with a particular set of variables, while other statistics based on the same variables may be relatively unaffected.

RESULTS

Before examining the effectiveness of Astin and Molm's technique for correcting for nonresponse bias, it is useful to first understand the extent to which different characteristics predict the likelihood of a student returning a follow-up survey. This is important information since these characteristics 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

TABLE 2. Top Correlates of Response in the 1991 HERI Follow-up Survey

Positive 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
Parents' status: Married, living together	.092	Reason for college: Improve study skills	−.078
Sex: Female	.091	Orientation: Status striver	−.077
Expectation: Will earn B.A. degree	.084	Life goal: Be an expert on finance and commerce	−.072
Self-rating: Mathematical ability	.082	Reason for college: To be able to make more money	−.072
Years of high school study: Math	.079	Views: The chief benefit of college is to increase earning power	−.071

Note: All correlation coefficients significant at $p < .01$.

survey response are high school grades and academic self-rating, which suggests that students who do well in educational settings are also those who tend to return surveys (HERI, 1992). Other variables in Table 2 that 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. Taken together, these findings suggest that follow-up responses will be biased toward those likely to have success in college.

Table 2 also shows that students of different races return surveys at different rates. On average, African American students are less likely to be survey respondents, with white students being more likely to respond. Even though these correlations do not appear to be especially strong, these relationships are associated with large differences in response rates. Given in percentages, for example, the response rate among African Americans was 8.8% versus 23.1% for white students. The disparity in response rates from students of different races is troubling, and an area in need of study.

A final pattern in Table 2 worthy of mention relates to 6 of the top 10 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 success (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 that 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 on 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% of all freshmen reported high school grades of A− or better, the corresponding figure for the follow-up respondents is 50% higher (36%). The equivalent proportion among nonrespondents is closer to the proportion for the entire population (21% versus 24%), which mathematically has to be the case since four out of five 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

TABLE 3. Effect of Nonresponse on Univariate and Joint Distributions

	Complete Sample	FUS Nonrespondents	Follow-up Survey	
			Unweighted	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 and degree aspirations	.2507	.2468	.2377	.2529
Proportion of sample	1.00	.79	.21	.21

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 of these variables.

Turning now to Panel B we see the effect of nonresponse bias on joint distributions, measured here by Pearson's *r*. In the original sample, the correlation between high school grades and degree aspirations is modest ($r = .2507$). The correlations shown in columns 2 through 4 are essentially equivalent (and certainly statistically equivalent) to the original, correct value shown in column 1. This suggests that even when individual variables are noticeably biased, their relationships with each other tend not to be. Earlier methodological studies have come to similar conclusions (Astin and Panos, 1969).

In order to consider the effectiveness of the Astin and Molm procedure in a multivariate context, I conducted the multiple regression analyses shown in Table 4. The first analysis 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% of the variance in degree aspirations was explained by the limited set of independent variables employed). Although there are a few differences across the regressions, all of the independent variables significantly predict degree aspirations 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 that a student completed. Given that this variable is likely to be heavily biased by the nonresponse patterns described in Table 2, this is not too surprising. Both of the respondent samples (unweighted and weighted) suggest that degree aspirations upon entry are unrelated to the number of years of college completed even though this relationship 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 not obvious whether one regression—unweighted or weighted—is to be preferred over the other (although the weighted results produce a multiple *R* value slightly closer to that produced in the original, correct regression). Researchers using other CIRP data sets have come to similar conclusions and, finding only trivial differences between weighted and unweighted results, used both approaches (e.g., Pascarella, Ethington, and Smart, 1988; Pascarella et al., 1987).

TABLE 4. Comparison of Two Sets of Unweighted and Weighted Regressions

Dependent Variable	Complete Sample	Unweighted Results	Weighted Results
Degree aspirations (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 asterisk.

DISCUSSION AND IMPLICATIONS

The results show that the Astin and Molm weighting procedure is very effective in reducing nonresponse bias in univariate distributions, even when response rates are low. Since many survey projects are conducted to generate information on basic distributions, the effectiveness of this procedure is an important finding. Although response weights developed using fewer predictor variables than were used here may be somewhat less effective, this finding suggests that weighting adjustments should be employed when examining univariate distributions and statistics.

The advantage of using the Astin and Molm weighting procedure is less clear in adjusting correlation and regression analyses, perhaps in part because these statistics appear to be less obviously affected by nonresponse bias. Although the analyses did not reveal a situation where the weighted results were clearly less preferable than the unweighted ones, the advantage of using such weights was not particularly clear either. Although we cannot be certain that this pattern will be true for all analyses under all conditions, previous research seems to suggest that this pattern is common (Astin and Panos, 1969; Pascarella, Ethington, and Smart, 1988; Pascarella et al., 1987).

Thinking more broadly about the issue of working with low response rates, an important point not to be overlooked is that the first and most important suggestion is to avoid low response rates in the first place. The literature on survey research is abundant with good information and suggestions for improving survey response rates (Dillman, 1991; Cote, Grinnell, and Tompkins, 1986; Smith and Bers, 1987). This literature should become a working part of the library of any institutional researcher doing survey research, but we need to recognize that achieving very high response rates will continue to remain challenging (especially given the limited resources usually available to most institutional researchers to conduct surveys of students and faculty). Adjustments of the sort described by Astin and Molm appear to be fairly effective in 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, and Rubin, 1983; Rossi, Wright, and Anderson, 1983). A number of stratification cells are defined based on characteristics known or suspected to be related to nonresponse bias and 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 and accomplished by taking the reciprocal of the ratio of respondents to original sample within each stratification cell. Although this sort of poststratification adjustment may be somewhat less precise than that which can be obtained through more complex weighting schemes, it should nonetheless 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, and Smith, 1989; Rubin, 1987). Although such issues have not been addressed here, it is important to recognize that they will become increasingly important in improving the quality of survey research within higher education settings.

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