Correcting for Survey Nonresponse

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Abstract

All surveys with less than full response potentially suffer from nonresponse bias. Simple weighting can only correct for selection based on any observables whose distribution is known in the population. Variables such as gender, race, income, and region satisfy this requirement because they are available from the U.S. Census, but often they will not account for all forms of selection. We offer a direct way of correcting for selection based on unobservables. We can classify survey responders by their ‘response propensity’. Proxies for response propensity include the number of attempted phone calls, indicators of temporary refusals, and interviewer-coded measures of cooperativeness. We can then learn about the population of non-responders by extrapolating from the low-propensity responders. We apply our new estimator to correct for nonresponse bias in the American National Election Studies. We find that our method is successful in reducing nonresponse bias.
1 - Introduction

In an ideal world, a survey would consist of a random sample of the population. Each individual in the population of interest would have an equal chance of being interviewed, or at minimum, this probability would be known. If this were the case, simple averages could be used to estimate most quantities of interest. But these assumptions are almost always violated.

Survey methodologists have devised fairly effective methods for generating a random sample of households. Random digit dialing can produce a representative sample of phone lines. By adjusting for the number of phone lines in a household, we can obtain a representative sample of households. By adjusting for the size of the household, we can obtain a representative sample of adults. The missing link is that not every selected adult will be reachable and willing to participate.

Along with less than complete response comes the possibility of nonresponse bias- the responding portion of the population differs from the non-responding portion. Under these conditions, simple averages produce biased estimates of the population parameters of interest. Weighting the data such that the distribution of observables in the sample matches the distribution in the population is often used to correct for nonresponse bias. However, this technique will produce biased estimates as well if there is selection on unobservables. We will develop an approach that directly corrects for selection on unobservables. Our approach classifies survey responders by their ‘response propensity’, and extrapolates from the low propensity respondents to the nonrespondents.
We apply our ‘variable response propensity’ estimator to correct for nonresponse bias in the American National Election Studies. This dataset allows us to test our estimator in an environment where the “truth” is known, from election results and the voter validation studies. The ANES also provides multiple useful measures of response propensity- the number of calls or visits to a household, whether there was an initial refusal, interviewer coded measures of cooperativeness, etc.

In the years we study, the ANES overestimates turnout by 9 to 12\%\textsuperscript{1}. If we weight by demographic characteristics, the discrepancy drops to between 6 and 9\%. Our results indicate that our approach is quite successful in reducing nonresponse bias. Our estimator almost always provides a better estimate than a demographic-weighted proportion. Some of the measures of response propensity almost completely eliminate nonresponse bias. The number of calls to a household is the least effective measure. Interviewer coded measures of cooperativeness and interest in the interview are the most successful.

Contrarily, the ANES provides a fairly accurate sample of the vote shares received by Presidential candidates. The performance of estimator for the vote shares of these Presidential candidates indicates that our estimator is not only able to correct for nonresponse bias when it is present, but that it will also suggest a negligible correction when non-response bias is absent.

2 – Nonresponse Bias

\textsuperscript{1} These estimates are after measurement error is corrected for. The discrepancy with self-reported voter turnout is about twice as large.
Survey researchers have become increasingly worried about nonresponse bias, in a large part due to decreasing response rates. Efforts to compensate for a decreasing willingness of households to participate include making multiple calls, attempting to convert initial refusers, and providing cash incentives to respondents or interviewers (Curtin, Presser, and Singer, 2000). Increased effort can indeed lead to increased response rates (Keeter, Miller, Kohut, Groves, and Presser, 2000), yet the evidence is quite mixed as to whether marginal increases in response rates will actually reduce nonresponse bias.

Keeter et. al. (2000) found that most variables of interest yielded similar estimates in their rigorous and non-rigorous surveys. Curtin, Presser, and Singer (2000) found that excluding late responders from the analysis did not lead to many differences in estimates of the Index of Consumer Sentiment. Groves and Peytcheva (2006) performed a meta-analysis of 59 surveys, and determined that there is a very weak relationship between nonresponse rates and nonresponse bias. However, a number studies have found that significant differences exist between early and late responders (Ellis, Endo, and Armer, 1970; Hawkins, 1975; Stinchcombe, Jones, and Sheatsley, 1981; Fitzgerald and Fuller, 1982), suggesting that in these cases, stopping the surveys earlier would have led to increased nonresponse bias.

Marginal increases in response rates may not appreciably reduce nonresponse bias, and nonresponse bias may still be present even in the most rigorously conducted survey. Direct methods for diagnosing and correcting for nonresponse bias are essential.

The most common approach is weight by observables (Groves, Dillman, Eltinge, and Little, 2002; Groves, Fowler, Couper, Lepkowski, Singer, and Tourangeau, 2004)\(^2\).

\(^2\) An alternative approach (Fuller, 1976) consists of bounding the proportions of nonrespondents between zero and one. This can be used to generate confidence intervals...
In order to implement this correction—two conditions must be met. First, we must be able to identify and measure those variables that determine selection into the group of respondents. Second, the distribution of these variables in the population of interest must be known. For example, it is well known that the elderly are more likely to participate in surveys (Brehm, 1993). To correct for this fact, one could weight the young more heavily when computing sample averages.

Simple weighting is extremely useful, but has its limitations. It cannot correct for selection on unobservables. A political survey may over-represent households that are interested in politics. Consequently, the survey may overestimate the proportion of American adults who vote, attend a campaign event, read the newspaper, etc. One could not easily correct this problem using weighting since the proportion of adults who are interested in politics would not be independently known.

Increasing distrust of the media by conservatives may mean that participation in political surveys is correlated with ideology. As many political variables of interest will be correlated with ideology as well, this will introduce non-response bias into items such as presidential approval and voting intentions. If demographic weighting cells do not perfectly capture ideology (and there is little reason to think that they will), weighting by demographics will not succeed in eliminating nonresponse bias.

To correct for selection on ideology, we may consider weighting by party identification (which is a good proxy for ideology). The difficulty is that the distributions that account for nonresponse bias. In practice, this leads to confidence intervals that are too large to be useful.

Throughout the paper, we will use ‘observables’ as shorthand for variables that are observable in the survey and whose distribution is known in the population, and ‘unobservables’ for variables which are not measured in the survey, or for which reliable weighting targets do not exist.
of ideology and party identification are not known for the population of interest\(^4\). Unlike gender and race, which are inherently stable over time, ideology is not (Newport, 2006). Hence, even if one believes that exit polls provide a correct estimate of party identification among the voting population at a point in time, weighting by party identification could not easily be applied to correct for selection on ideology in public opinion polls conducted months or years later.

**Models of Survey Nonresponse**

Insight into understanding and correcting for nonresponse bias (and selection on unobservables in particular) can be obtained from the continuum of resistance model and the classes model. The continuum of resistance model (Endo et. al., 1970; Filion, 1975, 1976; Hawkins, 1975; Dunkelberg and Day, 1973; Fitzgerald and Fuller, 1982; Traugott, 1987) posits that voters differ in their response propensity. Those in the population with low response propensity are less likely to respond. We can infer the variables of interest for the nonrespondents by extrapolating from the low propensity respondents.

The ‘classes’ model (O’Neil, 1979; Stinchcombe et. al., 1981; Smith, 1984) instead posits that there are groups of respondents who resemble the nonrespondents. For example, refusers may resemble temporary refusers and un-located individuals may resemble hard-to-locate individuals.

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\(^4\) One suggestion that has been put forward is to construct weighting targets based on rolling averages of party identification from recent polls. This suggestion has recently been adopted by Rasmussen. If party identification changes more slowly over time than presidential approval, this approach could conceivably reduce sampling error in presidential approval (for example). This approach cannot eliminate non-response bias.
The continuum model has primarily been used to theorize about nonresponse bias rather than correct for it. Filion (1975, 1976) provides a rare attempt to use this model to reduce nonresponse bias. Since he does not provide a test of his method, it is difficult to know if his method is effective. The classes model has been applied to correct for nonresponse bias as well (O’Neil, 1979; Fitzgerald and Fuller, 1982; Lin and Schaeffer).

The continuum and classes models share something in common. Both suggest extrapolating from the population of respondents to the population of non-respondents. Both provide alternatives to the implicit extrapolation being performed when summarizing the population using the mean of the achieved sample. Using the achieved sample mean implicitly extrapolates from all respondents to the nonrespondents. The classes model suggests extrapolating from a subset of respondents to the non-respondents. The continuum model suggests an extrapolation based on response propensity.

Our method provides a direct way of correcting for selection on unobservables that, in the spirit of the continuum of resistance model, extrapolates based on response propensity. Methods for correcting for selection on unobservables exist in the literature (Filion, 1975, 1976; Drew and Fuller, 1980, 1981; Potthoff, Manton, and Woodbury, 1991). Unlike any of these methods, our method easily integrates with demographic weighting, so that selection on both observables and unobservables can be corrected for. Moreover, unlike previous work, we will choose an application where the truth is known, so that we can gauge the effectiveness of our method.

however, since each of the surveys used in the rolling average would itself be subject to the same nonresponse bias.
In order to implement our method, we must be able to measure response propensity. Surveys currently offer a number of useful measures of response propensity. The numbers of calls (or visits) and whether the individual was a temporary refuser are the most prevalent measures in the literature. These measures have the advantage of being (in principle) available for every survey. Both measures have drawbacks—callback procedures may not be systematic enough to provide reliable measures and typically the temporary refusers are a small fraction of the respondents.

Interviewer coded measures of the respondent’s cooperativeness and interest in the interview, though available less readily, may be useful as well. Some surveys send persuasion letters to initial non-respondents. Whether such a letter was sent can be used as a measure. Other surveys offer increasing cash incentives to initial non-respondents, so that the amount of cash received could measure response propensity. Self reports of willingness to participate in future surveys and measures based on the degree of item nonresponse provide other possible measures.

3 – Theory

In this section, we derive the variable response propensity estimator, which can potentially correct for selection based on observables and unobservables. Our correction method will require specifying a joint statistical model of the outcome variable and response propensity, which we will now describe. Suppose that $y_n$ is an outcome variable, $x_n$ and $z_n$ are vectors of regressors, and $\epsilon_n$ and $\eta_n$ are disturbance terms. We
assume that \( \varepsilon_n \) and \( \eta_n \) are jointly normally distributed with mean 0 and variance 1, and have correlation \( \rho \).

We will consider the case where \( y_n \) is a binary variable (e.g. whether the respondent approves of the president). The outcome equation is given by
\[
y^*_n = \alpha' x_n + \varepsilon_n \quad \text{where} \quad y_n = 1 \text{ if } y^*_n < 0 \text{ and } y_n = 0 \text{ otherwise.}
\]
The selection equation is given by
\[
r^*_n = \beta' z_n + \eta_n.
\]
We let \( r_n \) denote the response category where \( r_n = R + 1 \) indicates nonresponse. We assume that \( r_n = 1 \) if \( r^*_n < \theta_1 \), \( r_n = 2 \) if \( \theta_1 < r^*_n < \theta_2 \), …, \( r_n = R \) if \( \theta_{R-1} < r^*_n < \theta_R \) and \( r_n = R + 1 \) if \( r^*_n > \theta_R \). Thus, \( (y_n, x_n, z_n) \) are only observed if \( r_n \leq R \). We let \( N \) denote the number of observations for which \( r_n \leq R \) and let \( N_{\text{miss}} \) denote the number of observations for which \( r_n = R + 1 \). Here, \( r_n \) is a measure of response propensity (e.g. the number of callbacks, whether the respondents initially refused, etc.). We assume that \( R \geq 2 \), or that there are at least two categories of respondents.

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5 Surveys such as the American National Election Studies induce cooperation of initial refusers by offering increasing monetary incentives.
6 As with the binomial probit model, the assumption that the disturbance terms have variance 1 is without loss of generality.
7 This technique can, of course, be extended to continuous, ordered categorical variables, and unordered categorical variables.
8 The technique we present can be extended to deal with continuous variables, ordered categorical variables, and unordered categorical variables. The variable response propensity estimator we introduce consists of two simultaneous equations. The outcome equation is a binomial probit and the selection equation is an ordered probit. Considering a continuous outcome variable simply changes the outcome equation to a linear model. Considering an ordered categorical variable changes the outcome equation to an ordered probit. Considering an unordered categorical variable changes the outcome equation to a multinomial probit or multinomial logit.
We assume for simplicity that each unit in the population has an equal probability of entering the selected sample of $N + N_{\text{miss}}$ individuals. Individuals differ in their probability of entering the achieved sample of $N$ respondents.

For simplicity, we will also assume that $x_n$ and $z_n$ are discrete random variables. Suppose that $x_n = \bar{x}_j$ and $z_n = \tilde{z}_k$ with probability $p_{j,k}$, for $j = 1, \ldots, J$ and $k = 1, \ldots, K$. We let $p_j^x = \sum_{k=1}^{K} p_{j,k}$ and $p_k^z = \sum_{j=1}^{J} p_{j,k}$ denote the marginal distributions of $x$ and $z$. Our quantity of interest is $\mu = E[y]$ (which could be the president’s approval rating or the proportion of individuals who attended a campaign event). This quantity is equal to,

$$
\mu = E[y] = \sum_{j=1}^{J} \sum_{k=1}^{K} p_{j,k} P(\alpha' \bar{x}_j + \epsilon_n \leq 0) = \sum_{j=1}^{J} \sum_{k=1}^{K} p_{j,k} \Phi(-\alpha' \bar{x}_j) = \sum_{j=1}^{J} p_j^x \Phi(-\alpha' \bar{x}_j)^{11}
$$

Our goal then is to obtain a good estimator of $\mu$, the population proportion. Ideally, we would like to obtain an unbiased estimator of $\mu$, or if this is not possible, a consistent estimator.$^{12}$

**The Unweighted Sample Proportion**

The simplest estimator we could consider is the unweighted sample proportion,

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$^9$ Stratified sample may introduce unequal selection probabilities. It is certainly possible to deal with unequal selection probabilities within this framework.

$^{10}$ It is standard practice to weight by discrete random variables.

$^{11}$ Here, $\Phi$ denotes the standard normal cumulative distribution function.

$^{12}$ An estimator $\hat{\theta}$ of a population parameter $\theta$ is consistent if it converges to the population parameter in large samples. We denote this using $\hat{\theta} \xrightarrow{\text{prob.}} \theta$. 

10
\[ \hat{\mu}_i = \frac{1}{N} \sum_{n=1}^{N} y_n \]

This estimator will be a consistent estimator of \( \mu \) only under very strong assumptions.

We would require that \( x_n \) and \( z_n \) are independent and that \( \epsilon_n \) and \( \eta_n \) are independent. In other words, we would need that the selection of respondents is completely independent of the outcome.

To see that this is the case, we first characterize the expected value of the estimator,

\[
E[\hat{\mu}_i \mid r_n \leq R] = E \left[ \frac{1}{N} \sum_{n=1}^{N} y_n \mid r_n \leq R \right] = E[y_n \mid r_n \leq R] = P(\alpha' x_n + \epsilon_n \leq 0 \mid \beta' z_n + \eta_n \leq 0)
\]

\[
= \frac{P(\alpha' x_n + \epsilon_n \leq 0, \beta' z_n + \eta_n \leq 0)}{P(\beta' z_n + \eta_n \leq 0)} = \frac{\sum_{j=1}^{J} \sum_{k=1}^{K} p_{j,k} P(\alpha' \tilde{x}_j + \epsilon_n \leq 0, \beta' \tilde{z}_k + \eta_n \leq 0)}{\sum_{k=1}^{K} p_{k}^\prime P(\beta' \tilde{z}_k + \eta_n \leq 0)}
\]

Next, notice that,

\[
P(\alpha' \tilde{x}_j + \epsilon_n \leq 0, \beta' \tilde{z}_k + \eta_n \leq 0) = \int_{-\infty}^{0} \left[ \phi(t - \alpha' \tilde{x}_j) \Phi \left( \frac{-\beta' \tilde{z}_k - \rho(t - \alpha' \tilde{x}_j)}{\sqrt{1-\rho^2}} \right) \right] dt
\]

\[
P(\beta' \tilde{z}_k + \eta_n \leq 0) = \Phi(-\beta' \tilde{z}_k)
\]

Hence,

\[
E[\hat{\mu}_i \mid r_n \leq R] = \frac{\sum_{j=1}^{J} \sum_{k=1}^{K} p_{j,k} \int_{-\infty}^{0} \left[ \phi(t - \alpha' \tilde{x}_j) \Phi \left( \frac{-\beta' \tilde{z}_k - \rho(t - \alpha' \tilde{x}_j)}{\sqrt{1-\rho^2}} \right) \right] dt}{\sum_{k=1}^{K} p_{k}^\prime \Phi(-\beta' \tilde{z}_k)}
\]

In general, \( E[\hat{\mu}_i \mid r_n \leq R] \neq \mu \), indicating that the estimator will be biased. Since \( \hat{\mu}_i \) will converge to \( E[\hat{\mu}_i \mid r_n \leq R] \) in large samples, this indicates that \( \hat{\mu}_i \) will in general
be inconsistent. However, in the special case where $\rho = 0$ and $p_{j,k} = p_j^*p_k^*$ (i.e. $x$ and $z$ are independent), we have,

$$P(\alpha'\tilde{x}_j + \varepsilon_n \leq 0, \beta'\tilde{z}_k + \eta_n \leq 0) = \Phi(-\alpha'\tilde{x}_j)\Phi(-\beta'\tilde{z}_k)$$

so that,

$$E[\widehat{\mu} | r_n \leq R] = \frac{\sum_{j=1}^{J} \sum_{k=1}^{K} p_j^*p_k^*\Phi(-\alpha'\tilde{x}_j)\Phi(-\beta'\tilde{z}_k)}{\sum_{k=1}^{K} p_k^*\Phi(-\beta'\tilde{z}_k)} = \frac{\sum_{j=1}^{J} p_j^*\Phi(-\alpha'\tilde{x}_j)}{\sum_{k=1}^{K} p_k^*\Phi(-\beta'\tilde{z}_k)} = \mu$$

Consequently, the estimator is consistent and unbiased when both observables and unobservables from the outcome and selection equations are independent. More generally, this estimator is not consistent. Consequently, the estimator is rarely used.

**The Weighted Sample Proportion**

Define, $\widehat{\theta}_j = \frac{\sum_{n=1}^{N} 1\{x_n = \tilde{x}_j\}y_n}{\sum_{n=1}^{N} 1\{x_n = \tilde{x}_j\}}$. Then the weighted sample proportion is given by,

$$\hat{\mu}_2 = \sum_{j=1}^{J} p_j^*\widehat{\theta}_j$$. Notice that,

$$E\left[1\{x_n = \tilde{x}_j\}y_n \mid r \leq R\right] = P(x_n = \tilde{x}_j, \alpha'\tilde{x}_j + \varepsilon_n \leq 0 \mid \beta'\tilde{z}_n + \eta_n \leq 0)$$
\[
\frac{P(x_n = \tilde{x}_j, \alpha' \tilde{x}_j + \varepsilon_n \leq 0, \beta' z_n + \eta_n \leq 0)}{P(\beta' z_n + \eta_n \leq 0)}
\]

Hence, the law of large numbers and the continuous mapping theorem imply that,

\[
\hat{\theta}_j = \frac{1}{N} \sum_{n=1}^{N} 1\{x_n = \tilde{x}_j\} y_n \xrightarrow{\text{prob.}} \frac{P(x_n = \tilde{x}_j, \alpha' \tilde{x}_j + \varepsilon_n \leq 0, \beta' z_n + \eta_n \leq 0)}{P(x_n = \tilde{x}_j, \beta' z_n + \eta_n \leq 0)}
\]

which further implies that,

\[
\hat{\mu}_2 \xrightarrow{\text{prob.}} \sum_{j=1}^{J} p_j^* \left\{ \frac{K}{\sum_{k=1}^{K} p_{j,k} \Phi(-\beta' \tilde{z}_k)} \right\}
\]

As the right-hand side does not necessarily equal \( \mu \), this weighted sample proportion is not in general consistent.

Suppose, however, that \( \varepsilon_n \) and \( \eta_n \) are uncorrelated. In this case,

\[
\hat{\mu}_2 \xrightarrow{\text{prob.}} \sum_{j=1}^{J} p_j^* \left\{ \frac{\Phi(-\alpha' \tilde{x}_j) \sum_{k=1}^{K} p_{j,k} \Phi(-\beta' \tilde{z}_k)}{\sum_{k=1}^{K} p_{j,k} \Phi(-\beta' \tilde{z}_k)} \right\} = \sum_{j=1}^{J} p_j^* \Phi(-\alpha' \tilde{x}_j) = \mu
\]

Hence, the estimator will converge to the true parameter of interest if the unobservables are uncorrelated. This is equivalent to saying that we can fully control for selection using observables.
The Variable Response Propensity Estimator

We present an estimator that is consistent even when \( \varepsilon_n \) and \( \eta_n \) are correlated. We will proceed by estimating the underlying model for \((y_n, r_n)\) using maximum likelihood. Computing the likelihood function requires characterizing the following probabilities,

\[
P(y_n = 0, r_n = r, x_n = \tilde{x}_j, z_n = \tilde{z}_k) = p_{j,k} \int_{\alpha \leq 0, \theta \leq 0, \beta' z_k + \eta \leq 0} \phi(\varepsilon, \eta) d\varepsilon d\eta
\]

\[
P(y_n = 1, r_n = r, x_n = \tilde{x}_j, z_n = \tilde{z}_k) = p_{j,k} \int_{\alpha \leq 0, \theta \leq 0, \beta' z_k + \eta \leq 0} \phi(\varepsilon, \eta) d\varepsilon d\eta
\]

\[
P(r_n = R + 1) = \sum_{k=1}^{K} p_{\tilde{z}_k} \int_{\beta' \tilde{z}_k + \eta \geq \theta_k} \phi(\varepsilon, \eta) d\varepsilon d\eta
\]

Combining these, we can write the log-likelihood as,

\[
l(\xi) = \sum_{n=1}^{N} \sum_{r=1}^{R} 1\{r_n = r, y_n = 0\} \log \int_{\alpha \leq 0, \theta \leq 0, \beta' \tilde{z}_k + \eta \leq 0} \phi(\varepsilon, \eta) d\varepsilon d\eta
\]

\[
+ \sum_{n=1}^{N} \sum_{r=1}^{R} 1\{r_n = r, y_n = 0\} \log \int_{\alpha \leq 0, \theta \leq 0, \beta' \tilde{z}_k + \eta \leq 0} \phi(\varepsilon, \eta) d\varepsilon d\eta
\]

\[
+ N_{\text{miss}} \log \sum_{k=1}^{K} p_{\tilde{z}_k} \int_{\beta' \tilde{z}_k + \eta \geq \theta_k} \phi(\varepsilon, \eta) d\varepsilon d\eta
\]

where \( \xi = (\alpha, \beta, \rho, \theta) \) denotes the model parameters\(^{13}\).

The likelihood function above does not admit a closed-form expression. In particular, evaluating the likelihood involves computing rectangles of the normal distribution. We compute these integrals using the GHK method, which computes these

\(^{13}\) We normalize \( \theta_R = 0 \) for identification purposes.
integrals using simulation methods. The GHK method has been successfully applied to estimate multinomial probit, multivariate probit, and panel probit models (Geweke, Keane, and Runkle, 1994) and is used in popular statistics packages such as Stata and Limdep.

Relying on the fact that maximum likelihood estimators are consistent when the model is identified and certain regulatory conditions are satisfied, we have that

\[ \hat{\alpha} \xrightarrow{\text{prob}} \alpha. \]

Now, recall that \( \mu = P(\alpha' x_n + \varepsilon_n < 0) = \sum_{j=1}^{J} p_j \Phi(-\alpha' \tilde{x}_j) \). This suggests that we estimate \( \mu \) using \( \hat{\mu}_3 = \sum_{j=1}^{J} p_j \Phi(-\hat{\alpha}' \tilde{x}_j) \). Since \( \hat{\alpha} \xrightarrow{\text{prob}} \alpha \), the continuous mapping theorem implies that \( \Phi(-\hat{\alpha}' \tilde{x}_j) \xrightarrow{\text{prob}} \Phi(-\alpha' \tilde{x}_j) \) and \( \hat{\mu}_3 \xrightarrow{\text{prob}} \mu \). Thus, the variable response propensity estimator will be consistent, even if there is selection based on unobservables.

We can obtain a standard error estimate for \( \hat{\mu}_3 \) using the delta method (Green, 2001). Notice that, 

\[ \frac{\partial \hat{\mu}_3}{\partial \alpha} = -\sum_{j=1}^{J} p_j^* \phi(-\hat{\alpha}' \tilde{x}_j) \]

so that the standard error is given by,

\[ se(\hat{\mu}_3) = \sqrt{\frac{1}{n+\hat{V}_a} \sum_{j_1}^{J} \sum_{j_2}^{J} p_{j_1}^* p_{j_2}^* \phi(-\hat{\alpha}' \tilde{x}_{j_1}) \phi(-\hat{\alpha}' \tilde{x}_{j_2}) \tilde{x}_{j_1} \Phi'_{\alpha} \tilde{x}_{j_2}} \]

where \( \hat{V}_a \) is the usual maximum likelihood estimator for the variance of \( \hat{\alpha} \).

Our framework shares much in common with Heckman’s (1979) sample selection model. Both frameworks assume that the variables of interest are unobserved for certain values of the selection variable. There is an important difference. Heckman’s model requires an exclusion restriction for identification purposes. Our model does not require an exclusion restriction because the response variable (by assumption) contains more that
two categories. Conditional on selection, we observe multiple values of response propensity.

**Summary**

We considered three estimators of the population proportion—the unweighted sample proportion, the weighted sample proportion, and the variable response propensity estimator. The unweighted sample proportion is consistent only when selection into the sample is unrelated to the outcome variable. The weighted sample proportion is consistent when there is no selection based on unobservables. The variable response propensity estimator is consistent even when there is selection on unobservables.

**4 – Evaluating the Estimator**

In this section, we provide a brief Monte Carlo study of the variable response propensity estimator. We suppose that the variables \( x \) and \( z \) each take on the values 0, 1, and 2. This allows us to characterize the joint distribution of \( x \) and \( z \) using a 3 by 3 matrix. We considered two choices for this matrix, 

\[
p_1 = \begin{bmatrix} 0.05 & 0.10 & 0.05 \\ 0.10 & 0.20 & 0.10 \\ 0.10 & 0.20 & 0.10 \end{bmatrix}
\] and 

\[
p_2 = \begin{bmatrix} 0.10 & 0.20 & 0.10 \\ 0.05 & 0.05 & 0.20 \\ 0.10 & 0.10 & 0.10 \end{bmatrix}
\]. In the first case, \( x \) and \( z \) are independent and in the second
case, \( x \) and \( z \) are dependent. We also considered two values for the correlation term, \( \rho_1 = 0.0 \) and \( \rho_2 = 0.8 \). In the first case, there is no selection on unobservables, and in the second case, there is. We chose the values \( \alpha = [0, 1, 0.5] \) and \( \beta = [0.5, 2.5, -0.5] \). We let \( R = 3 \) and \( \theta = [-1.5, 0.5, 0.0] \). These values are somewhat arbitrary, but we note that they generate non-response rates of between 70% and 80%, which are the non-response rates we would expect in many public opinion polls. We selected \( N_{\text{tot}} = N + N_{\text{miss}} = 3000 \). This yield samples sizes of between 800 and 1,000. All calculations are preformed using \( S = 100 \) Monte Carlo replications.

There are four cases we will consider. When \( (p, \rho) = (p_1, \rho_1) \), selection is completely random. When \( (p, \rho) = (p_2, \rho_1) \), there is correlation in the observables only. When \( (p, \rho) = (p_1, \rho_2) \), there is correlation in the unobservables only. When \( (p, \rho) = (p_2, \rho_2) \), there is correlation in both the observables and the unobservables.

Table 1 displays the results of our simulations. These simulations comport with what we found in Section 3. We compare each of the 3 estimators- \( \hat{\mu}_1 \) (the unweighted sample proportion), \( \hat{\mu}_2 \) (the weighted sample proportion), and \( \hat{\mu}_3 \) (the variable response propensity estimator)- to \( \hat{\mu}_0 \), the infeasible full sample proportion\(^{15} \).

[ Table 1 About Here ]

The unweighted sample proportion only yields reasonable estimates when selection is completely random. The weighted sample proportion gives reasonable

\(^{14}\) This is consistent with other work on survey nonresponse (Rosenbaum and Rubin, 1983; Little, 1986; Bethlehem, 1988).
estimates when selection is based on observables only. The variable response propensity estimator does seem to effectively correct for selection on unobservables. While the unweighted and weighted sample proportions often yield estimates that are more than two standard deviations away from the full sample proportion, the variable response propensity estimator is typically within two standard deviations.

We must be cautious here- the Monte Carlo results do not prove that our estimator is capable of correcting for selection based on unobservables because the Monte Carlo simulations assume that the model used to derive the variable response propensity estimator is in fact correct. In particular, the Monte Carlo results don’t really test the fundamental assumption we are making- that non-respondents resemble low propensity responders more than high propensity respondents. What our Monte Carlo results do show is that under these assumptions, the estimator we propose behaves well. Moreover, when selection based on unobservables is present, the conventional estimators behave poorly.

5 – Application to the National Election Studies

In this section, we consider an application of the variable response propensity estimator. In searching for an application, we considered a number of factors. First, the survey should include as many measures of response propensity as possible. Second, the survey should include quantities that are known from other sources, so that the

\[ y_a \]

is infeasible in any real application because we don’t observe \( y_a \) for non-respondents, but is a useful benchmark in our simulation study.
performance of the method can be evaluated. Third, the survey should suffer from significant nonresponse bias, and some of this bias should persist after weighting by demographics characteristics. The voter turnout and Presidential candidate choice items in the 1980, 1984, and 1988 American National Election Studies provides the ideal test case, meeting the conditions outlined above.

*Estimating Voter Turnout*

Our first goal is to use validated voter turnout in the ANES survey to infer the turnout rates in the 1980, 1984, and 1988 U.S. Presidential elections. The ANES includes a pre-election and a post-election component (using the same respondents). The voter turnout item is reported for respondents who participated in both the pre- and post-election surveys. The total response rates for the post-election survey vary between 61% and 63% for the years we consider. Most nonresponse in the ANES is attributable to refusal to participate in the pre-election or post-election surveys, as opposed to noncontact and other sources.

In Table 2, we report the actual turnout rates. We also report simple proportions based on self-reported and validated turnout. Self reported turnout overestimates actual turnout by between 19 and 20%. Using validated turnout reduces the discrepancy to

---

16 It is well known that self-reported voter turnout in the ANES suffers from misreporting (Burden, 2000; Katz, 2000). Using the validated turnout item allows us to isolate the problem of nonresponse bias from the problem of measurement error.
17 Response rates for the pre-election survey varied between 61.2% and 63.1%. The ANES does not attempt re-contact nonrespondents when conducting the post-election survey. Response rates for the post-election survey varied between 86.9% and 87.5%.
18 It is possible to disentangle the sources of survey nonresponse in 1988 using the auxiliary nonresponse file.
between 9 and 12%. We take the validated turnout rates as our starting point because it allows us to isolate the problem of nonresponse bias from the problem of measurement error.

A first step in the correction process is to use simple weighting. We construct 32 demographic cells based on race, gender, age, and educational attainment. Race is divided into two categories (black and other), age is divided into four categories (18-29, 30-44, 45-59, and 60+) and educational attainment is divided into 3 categories (less than high school, high school, and some college). To obtain weights for these targets, we relied on demographic data from the U.S. Census\(^\text{19}\).

The weighting targets indeed differed from the values found in the ANES. The most significant differences were that the ANES included a higher proportion of older and highly educated individuals. In Table 2, we report a demographics-weighted proportion. The weighted proportion overestimates turnout by between 6 and 8%. Weighting by demographic characteristics succeeds in reducing nonresponse bias, but it does not eliminate it completely.

More sophisticated methods of correcting for nonresponse bias require measuring response propensity. We considered five different measures- the number of calls or visits to the household, whether a persuasion letter was sent, whether the household initially refused, and interviewer coded measures of interest in the interview and cooperativeness\(^\text{20}\).

\(^{19}\) We used cross tabs for educational attainment which are available at http://www.census.gov/population/www/socdemo/past-educ.html.
In Figure 1, we graph turnout against three measures of response propensity. For cooperativeness and interest, we see strong monotonic relationships. Low propensity respondents vote at lower rates indicating that corrected estimates would lead to lower estimates of turnout\textsuperscript{21}. For number of calls, the relationship between turnout and response propensity is much weaker, suggesting that corrections based on the number of calls will lead to smaller corrections.

Before we consider the variable response propensity estimator, we consider a simpler correction based on the classes model. The difficulty of applying this method as described in Stinchcombe et. al. (1981) to the ANES data is that we cannot separate refusals from non-contacts\textsuperscript{22}. Because of this limitation, we will instead lump all nonrespondents together. Table 3 reports estimates based on the classes model, for all five measures of response propensity. These measures lead to an improvement over the weighted proportions reported in Table 2, but do not fully correct for nonresponse bias\textsuperscript{23}.

Finally, we compute results for the variable response propensity estimator. In the first step, we estimate the parameters of the model using maximum likelihood. We consider a similar specification for latent voting propensity and latent response propensity. We estimate the model,

---

\textsuperscript{20} See Appendix I for further description of the variables.
\textsuperscript{21} These same patterns persisted after we controlled for demographic characteristics.
\textsuperscript{22} Only the 1988 ANES included a supplementary dataset with further information on nonrespondents.
\textsuperscript{23} One may initially think that it provides an ‘unfair’ comparison to employ weighting in the variable response propensity estimator, but not the classes estimator. Employing weights to match the weighting targets in the achieved sample in the classes estimator would lead to an extrapolated sample that no longer matched those weighting targets. One the advantages of our approach is that it provides a way to deal with this problem.
\[ y_n^* = \alpha_1 + \alpha_2 \text{Educ2}_n + \alpha_3 \text{Educ3}_n + \alpha_4 \text{Female}_n + \alpha_5 \text{Black}_n \]
\[ + \alpha_6 \text{Age2}_n + \alpha_7 \text{Age3}_n + \alpha_8 \text{Age4}_n + \varepsilon_n \]
\[ r_n^* = \beta_1 + \beta_2 \text{Educ2}_n + \beta_3 \text{Educ3}_n + \beta_4 \text{Female}_n + \beta_5 \text{Black}_n \]
\[ + \beta_6 \text{Age2}_n + \beta_7 \text{Age3}_n + \beta_8 \text{Age4}_n + \eta_n \]

where \( \text{Educ2}_n \) and \( \text{Educ3}_n \) are dummy variables summarizing education and \( \text{Age2}_n \), \( \text{Age3}_n \), and \( \text{Age4}_n \) are dummy variables summarizing age. The variable response propensity estimator also requires selecting weighting targets. We used the same weighting targets as we did for the demographics-weighted proportion.

For space considerations, we only report the full estimation results for the cooperation measure. These results are reported in Table 4. Looking at the outcome equation, the results indicate that older and more educated respondents were far more likely to vote in the Presidential elections we analyze. Blacks were less likely to vote in 1984 and 1988. The coefficients on Female are statistically insignificant. Looking at the selection equation, we find that older and more educated respondents are more likely to have been deemed cooperative by the interviewers. This is consistent with our earlier finding, which suggested that weighting by age and education significantly affected the estimates of turnout.

[ Table 4 About Here ]

The parameter \( \rho \) captures the correlation between the unobservables in the two equations. The coefficients range between 0.23 and 0.27, and are highly statistically significant in the years we analyze. This indicates that selection based on unobservables is in fact a serious problem, which must be corrected for.
We report the variable response propensity estimates in Table 5. The results for number of calls are mixed. Although the correction is in the right direction in 1988 (relative to the weighted proportion), the estimator yields a small correction in 1980 and 1984. The results for letter are somewhat better. In both cases, the estimate is substantially closer to the truth. Using cooperation or interest, we almost completely eliminate nonresponse bias. The results for refusal conversion are more mixed, but once again offer an improvement over the weighted proportion.

[ Table 5 About Here ]

Relative to the estimates reported in Table 3, the variable response propensity estimator offers an improvement as well. The classes model assumes that non-respondents resemble low propensity respondents, while in fact, non-respondents tend to be more extreme than low propensity respondents.

**Estimating the Presidential Candidates’ Vote Shares**

Estimating the share of voters voting for each of the presidential candidates provides a further test of our method. In this case, the “truth” is known from election results. The ANES provides accurately measures of the Presidential candidate’s vote shares, indicating that little nonresponse bias is present. Hence, if our method is to be effective, it should lead to only small changes in the estimated vote shares.

Here, we are making inferences on a subset of respondents- those that voted in the Presidential race. Hence, the population of American adults no longer provides appropriate weighting targets. We use the relationship between voting and demographics
present in the ANES data to provide appropriate weighting targets for this subset of the population.

In each case, we categorize voters as voting for the Democratic candidate, the Republican candidate, or another candidate. We provide four different types of estimates—the simple proportion, the weighted proportion, the classes estimator, and the variable response propensity estimator. Both the classes estimator and the variable response propensity estimator use cooperativeness as the measure of response propensity. Our results are displayed in Tables 6 and 7.

The simple proportion never differs significantly from the true proportion, indicating that little if any non-response bias is present. Moreover, the four estimators never differ by as much as one standard deviation from each other. The results in Tables 6 and 7 demonstrate that the variable response propensity estimator correctly diagnoses the lack of non-response bias. The estimates for the correlation in unobservables ($\rho$) are small in magnitude and never differ significantly from zero. Hence, we have further reason to believe that the variable response propensity estimator is able to diagnose and correct for nonresponse bias.

6 – Discussion

While methods for correcting survey estimates to account for selection on observables are widely used, methods for correcting for selection on unobservables are
far less prevalent. We derived a new estimator that is capable of correcting for selection based on both observables and unobservables.

We used our estimator to correct for nonresponse bias in the American National Election Studies. Our results indicated that the procedure preformed quite well. Estimates of voter turnout from the ANES are severely biased, even after measurement error is corrected for using the voter validation studies. Our method never leads to worse estimates than the demographics-weighted average, and usually provides a substantial improvement.

We found that interviewer coded measures of response propensity were the most successful, while number of calls was the least successful. This result is not altogether surprising- most of the nonresponse in the ANES is caused by refusal, rather than failure to contact. Hence, nonrespondents are better characterized as similar to uncooperative respondents rather than hard to locate respondents.

A limitation of our findings is that academic surveys such as the ANES present somewhat of an easy case, in comparison to most public opinion polls. The ANES pre-selects respondents for inclusion in the sample, and the survey is conducted over a long time period, minimizing the number of non-contacts. In contrast, most public opinion polls are less systematic about who enters the sample. Rather than pre-selecting a set of individuals and attempting to contact all of them, individuals are continually selected as the survey proceeds. All contact stops once a target number of respondents is reached. As a result, different levels of effort were made to contact different selected individuals.

Public opinion polls are designed with two concerns in mind- maximizing response rates and minimizing cost. The literature has found that marginal increases in
response rates do not seem to reduce nonresponse bias. Our results suggest that the cost-benefit analysis should be reconsidered. Survey researchers will obtain more accurate estimates by shifting the focus from marginal increases in response rates to constructing the sample in a more systematic way. This will allow survey researchers to better diagnose nonresponse bias and correct for it. Even when surveys are conducted in a relatively un-systemic way, we believe that response propensity is an important diagnostic for nonresponse bias.

References


Appendix I – Construction of the Datasets

All respondents that participated in the post survey were included except a small number of respondents that had missing values for age. 2, 20, and 3 observations were excluded in 1980, 1984, and 1988, respectively.

**VotedReported:** Equal to 1 if the voter reported voting, 0 otherwise.

**VotedValidated:** Equal to 1 if the voter was validated as having voting, 0 if the voter was validated as not voting or not registered. If the observation could not be validated, VotedValidated is equal to VotedReported. Most of the cases were effectively validated.

**PresVote:** Equal to 0 if VotedValidated is equal to 0 or the respondent indicated that they did not vote for the presidential candidate, 1 if VotedValidated is equal to 1 and the respondent reported voting for the Democratic presidential candidate, 2 if VotedValidated is equal to 1 and the respondent reported voting for the Republican presidential candidate, and 3 if VotedValidated is equal to 1 and the respondent reported voting for another presidential candidate.

**Calls:** Available in 1980 (V800038), 1984 (V840057), and 1988 (V880055). The number of calls or visits to the household.

**Letter:** Available in 1980 (V800026, V800034) and 1988 (V880028, V880054). Indicator of whether a persuasion letter was requested or sent in either the pre- or the post-election study.

**Cooperation:** Available in 1980 (V800725), 1984 (V840712), and 1988 (V880554). Interviewer coded measure of the respondent’s cooperativeness.
**Interest:** Available in 1980 (V801189), 1984 (V841115), and 1988 (V880558).

Interviewer code measure of the respondent’s interest in the interview.

**Conversion:** Available in 1984 (V840038 and V840056) and 1988 (V880027 and V880053). Indicator of whether there was a refusal conversion in either the pre- or the post-election component.

Definitions for the demographic variables are straightforward.
### Appendix II – Tables and Figures

#### Table 1 – Monte Carlo Results

<table>
<thead>
<tr>
<th></th>
<th>Unweighted Sample Proportion (μ₁)</th>
<th>Weighted Sample Proportion (μ₂)</th>
<th>Variable Response Propensity Est. (μ₃)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bias</td>
<td>RMSE</td>
<td>Bias</td>
</tr>
<tr>
<td>Random Selection</td>
<td>0.001</td>
<td>0.015</td>
<td>0.001</td>
</tr>
<tr>
<td>Correlation in Observables</td>
<td>-0.041</td>
<td>0.043</td>
<td>0.000</td>
</tr>
<tr>
<td>Correlation in Unobservables</td>
<td>0.194</td>
<td>0.194</td>
<td>0.193</td>
</tr>
<tr>
<td>Correlation in Observables and Unobservables</td>
<td>0.133</td>
<td>0.133</td>
<td>0.194</td>
</tr>
</tbody>
</table>

24 Bias and RMSE (root mean squared error) are measured relative to the infeasible full sample mean.
Table 2 – Simple Estimators\textsuperscript{25}

<table>
<thead>
<tr>
<th></th>
<th>1980</th>
<th>1984</th>
<th>1988</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Voter Turnout</td>
<td>52.8%</td>
<td>53.3%</td>
<td>50.3%</td>
</tr>
<tr>
<td><strong>Simple Estimators</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-Reported Turnout</td>
<td>71.3% (1.2%)</td>
<td>73.6% (1.0%)</td>
<td>69.6% (1.1%)</td>
</tr>
<tr>
<td>Simple Proportion (Validated)</td>
<td>62.0% (1.3%)</td>
<td>64.8% (1.1%)</td>
<td>59.8% (1.2%)</td>
</tr>
<tr>
<td>Weighted Proportion (Validated)</td>
<td>59.0% (1.3%)</td>
<td>61.8% (1.1%)</td>
<td>57.7% (1.2%)</td>
</tr>
</tbody>
</table>

\textsuperscript{25} Standard errors are in parentheses.
Table 3 – Corrected Estimates Based on Classes Model\(^{26}\)

<table>
<thead>
<tr>
<th></th>
<th>1980</th>
<th>1984</th>
<th>1988</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Voter Turnout</td>
<td>52.8%</td>
<td>53.3%</td>
<td>50.3%</td>
</tr>
<tr>
<td><strong>Corrected Estimates (Classes)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Calls</td>
<td>60.2% (1.6%)</td>
<td>62.3% (1.0%)</td>
<td>55.7% (1.2%)</td>
</tr>
<tr>
<td>Letter</td>
<td>59.7% (2.2%)</td>
<td>-</td>
<td>55.1% (1.5%)</td>
</tr>
<tr>
<td>Cooperation</td>
<td>55.2% (1.8%)</td>
<td>60.3% (1.4%)</td>
<td>54.5% (1.6%)</td>
</tr>
<tr>
<td>Interest</td>
<td>53.2% (1.5%)</td>
<td>58.7% (1.3%)</td>
<td>52.1% (1.5%)</td>
</tr>
<tr>
<td>Conversion</td>
<td>-</td>
<td>61.8% (2.1%)</td>
<td>57.8% (3.4%)</td>
</tr>
</tbody>
</table>

\(^{26}\) Standard errors are in parentheses.
Table 4 – Coefficient Estimates

<table>
<thead>
<tr>
<th>Outcome</th>
<th>1980</th>
<th>1984</th>
<th>1988</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant</td>
<td>Female</td>
<td>Black</td>
</tr>
<tr>
<td>Equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.937*** (0.123)</td>
<td>-0.074 (0.072)</td>
<td>0.006 (0.112)</td>
</tr>
<tr>
<td></td>
<td>-0.899*** (0.104)</td>
<td>0.096 (0.061)</td>
<td>-0.287** (0.097)</td>
</tr>
<tr>
<td></td>
<td>-0.971*** (0.111)</td>
<td>-0.020 (0.064)</td>
<td>-0.401*** (0.097)</td>
</tr>
<tr>
<td>Selection</td>
<td>Constant</td>
<td>Female</td>
<td>Black</td>
</tr>
<tr>
<td>Equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.439*** (0.093)</td>
<td>0.118 (0.067)</td>
<td>0.067 (0.089)</td>
</tr>
<tr>
<td></td>
<td>-0.380*** (0.078)</td>
<td>0.048 (0.058)</td>
<td>-0.007 (0.085)</td>
</tr>
<tr>
<td></td>
<td>-0.283*** (0.084)</td>
<td>0.115 (0.061)</td>
<td>0.036 (0.084)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rho</td>
<td>0.227*** (0.062)</td>
<td>0.258*** (0.049)</td>
<td>0.265*** (0.056)</td>
</tr>
</tbody>
</table>

27 Standard errors are in parentheses. One star indicates significance at the 5% level, two stars indicates significance at the 1% level, and three stars indicates significance at the 0.1% level.
Table 5 – Corrected Estimates using Variable Response Propensity\(^{28}\)

<table>
<thead>
<tr>
<th></th>
<th>1980</th>
<th>1984</th>
<th>1988</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Voter Turnout</td>
<td>52.8%</td>
<td>53.3%</td>
<td>50.3%</td>
</tr>
<tr>
<td><strong>Corrected Estimates (VRP)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Calls</td>
<td>60.4% (3.7%)</td>
<td>59.5% (3.2%)</td>
<td>53.9% (3.3%)</td>
</tr>
<tr>
<td>Letter</td>
<td>56.7% (5.0%)</td>
<td>-</td>
<td>52.8% (3.8%)</td>
</tr>
<tr>
<td>Cooperation</td>
<td>54.5% (3.8%)</td>
<td>56.2% (3.2%)</td>
<td>51.4% (3.4%)</td>
</tr>
<tr>
<td>Interest</td>
<td>52.5% (3.7%)</td>
<td>55.7% (3.1%)</td>
<td>50.9% (3.3%)</td>
</tr>
<tr>
<td>Conversion</td>
<td>-</td>
<td>56.9% (4.2%)</td>
<td>58.6% (4.8%)</td>
</tr>
</tbody>
</table>

\(^{28}\) Standard errors are in parentheses.
### Table 6 – Vote Share of Democratic Presidential Candidate

<table>
<thead>
<tr>
<th></th>
<th>1980</th>
<th>1984</th>
<th>1988</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Actual Vote Share</strong></td>
<td>41.0%</td>
<td>40.6%</td>
<td>45.6%</td>
</tr>
<tr>
<td><strong>Simple Estimators</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simple Proportion</td>
<td>38.7% (1.7%)</td>
<td>40.8% (1.4%)</td>
<td>46.5% (1.6%)</td>
</tr>
<tr>
<td>Weighted Proportion</td>
<td>38.1% (1.7%)</td>
<td>41.1% (1.4%)</td>
<td>46.3% (1.6%)</td>
</tr>
<tr>
<td><strong>Corrected Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classes</td>
<td>37.5% (1.8%)</td>
<td>40.2% (1.3%)</td>
<td>45.9% (1.5%)</td>
</tr>
<tr>
<td>Variable Response Propensity</td>
<td>37.6% (4.5%)</td>
<td>40.4% (3.9%)</td>
<td>47.1% (4.3%)</td>
</tr>
<tr>
<td><strong>Parameter Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rho</td>
<td>0.029 (0.068)</td>
<td>0.048 (0.054)</td>
<td>-0.029 (0.058)</td>
</tr>
</tbody>
</table>

---

29 Standard errors are in parentheses.
Table 7 – Vote Share of Republican Presidential Candidate$^{30}$

<table>
<thead>
<tr>
<th></th>
<th>1980</th>
<th>1984</th>
<th>1988</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Vote Share</td>
<td>50.7%</td>
<td>58.8%</td>
<td>53.4%</td>
</tr>
<tr>
<td><strong>Simple Estimators</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simple Proportion</td>
<td>52.2% (1.7%)</td>
<td>58.2% (1.4%)</td>
<td>52.5% (1.6%)</td>
</tr>
<tr>
<td>Weighted Proportion</td>
<td>53.1% (1.7%)</td>
<td>57.9% (1.4%)</td>
<td>52.8% (1.6%)</td>
</tr>
<tr>
<td><strong>Corrected Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Classes</td>
<td>52.1% (1.8%)</td>
<td>58.9% (1.3%)</td>
<td>53.4% (1.5%)</td>
</tr>
<tr>
<td>Variable Response</td>
<td>52.5% (4.8%)</td>
<td>58.1% (3.9%)</td>
<td>52.0% (4.3%)</td>
</tr>
<tr>
<td>Propensity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Parameter Estimates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rho</td>
<td>0.022 (0.067)</td>
<td>-0.021 (0.049)</td>
<td>0.029 (0.056)</td>
</tr>
</tbody>
</table>

$^{30}$ Standard errors are in parentheses.
Figure 1 – Turnout by Response Propensity

Number of Calls

Cooperation

Interest

39