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Unit Nonresponse in a Presidential Election Day Survey: An Initial Multilevel Exploration Using Fully Conditioned Imputed Data

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Overview

This study uses a novel approach to explore the nexus between voter and interviewer characteristics as predictors of nonresponse. The study uses data from a nationally representative election day survey conducted in Mexico by an independent survey research firm in 2006.

Abstract

This analysis focuses on understudied aspects of nonresponse in a context where limited information is available from refusals. In particular, this study examines social and psychological predictors of nonresponse in fast-paced face-to-face surveys; namely, election day surveys—popularly known as exit polls. Exit polls present unique challenges to study nonresponse since the population being sampled is fleeting and several conditions are beyond the researcher's control. If sample voters choose not to participate, there is no practical way of contacting them to collect information in a timely manner. Under a proof-of-concept approach, this study explores a unique dataset that links information on respondents, nonrespondents, and interviewer characteristics, as well as precinct-level information. Using this information, we generate model-based plausible information for nonrespondents (i.e., imputed data) to examine nonresponse dynamics. Results from multilevel regression analyses are consistent with hypothesized relationships, suggesting that this approach may offer a way of studying nonresponse where limited information exists.

Acknowledgement

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Introduction

A pressing question in the election day survey literature for nearly two decades is why sample voters refuse to participate in exit polls (Frankovic, 2003; Frankovic, Panagopoulos, & Shapiro, 2009; Merkle & Edelman, 2000, 2002; Merkle, Edelman, Dykeman, & Brogan, 1998; Mitofsky, 1991; Mitofsky & Edelman, 1995); however, most of the efforts aimed at reducing nonresponse have been more oriented to developing good survey practices and less oriented to development of substantive theory. For instance, the World Association for Public Opinion Research (WAPOR) made available to the research community a set of general guidelines to conduct and evaluate exit polls, stressing the importance of ethical principles and good practices (WAPOR, 2006, p.575). Additionally, *Elections and Exit Polling* edited by Scheuren and Alvey (2008) describes experiences and current practices in the international field of exit polling.

Despite major efforts developed from the practitioner's perspective (WAPOR, 2006) and scholarly concerns on exit poll nonresponse (e.g., Biemer et al., 2003; Merkle & Edelman, 2002), little is known about the socio-psychological mechanisms that can help us understand why some people leaving voting stations refuse to be interviewed in an exit poll while others accept to participate. As nonresponse trends have been increasing across different types of surveys (e.g., Brick & Williams, 2013)—with exit polling not being the exception (Biemer et al., 2003)—there is a greater need to find ways of studying nonresponse. Exit polling, however, poses its own challenges.

Unlike other data collection methodologies, exit polls present unique complexities to study nonresponse. The population being sampled is fleeting; that is, persons who have just voted are constantly streaming past. Further, conditions encompassing the survey request on election day may inhibit participation, including the presence of "scrutineers" (also known as poll watchers) or lawyers who may interfere with interviewing, polling place officials (who may be uncooperative), or simply bad weather, which may have an effect on survey-taking conditions. If sample voters choose not to participate, there is no practical way of contacting them at a later point in time to collect information.

In survey designs that do not rely on interviewers to gain cooperation, respondents' decisions to participate can be made *after* the survey request has been put forward, whereas in modes in which interviewers are a key component, the decision to participate can conceivably be made even *before* the request has been completely presented (Stoop, 2005). For instance, in a mail survey, a person may choose not to participate after looking at the questionnaire and perceiving that it is lengthy, or even after having started the answering process, if the form is difficult to complete.

In fast-paced surveys that rely on interviewers to gain cooperation (such as exit polls), it is possible that respondents' decisions to participate are made even before a survey request is fully set forth. In election day surveys, the decision to participate may not be based on survey length, content or other questionnaire features; instead, given the brief interaction that characterizes an exit polling request, the decision may depend almost entirely on the social and psychological attributes of the sample person, and on features of the requestor: namely, respondent and interviewer characteristics.

To date, exit polling studies have remained silent for the most part on individual-level mechanisms that may explain the effects of interviewer and respondent interactions on nonresponse. Part of the difficulty in evaluating nonresponse mechanisms is the lack of suitable data—which dictates modeling choices. The present study looks at unique exit polling data and links information of respondents, nonrespondents, and interviewer characteristics, as well as precinct-level information. Consequently, these data are deemed appropriate for a proof-of-concept study. Under this approach, we generate model-based plausible information for nonrespondents (i.e., imputed data) to examine nonresponse dynamics. Particularly, we explore social and psychological predictors of nonresponse by focusing on the effect of interviewer and respondent characteristics.

Theoretical Framework

Building on social isolation theories introduced by Groves and Couper (1998) for household surveys, Merkle and Edelman (2002) have posited that voters who tend to be excluded or isolated from society are less likely to participate than voters who are more involved in society. People who do not share the mainstream culture, or who do not feel the influence of the dominant norms, tend to ignore or minimize the social interactions with the larger group; consequently, they feel less compelled to participate in social surveys (Brehm, 1993; Dillman, 1978; Dillman, Smyth, & Christian, 2008; Goyder, 1987; Groves & Couper, 1998; Moreno & Parás, 2010).

Although the act of voting is itself a form of participation in a societal event, in the context of exit polling, social isolation theories have been put forward to explain nonresponse (Merkle & Edelman, 2002). That is, while social isolation might not entirely explain nonresponse, it may represent a useful theoretical formulation with which to understand mechanisms of participation in election day surveys (2002, p. 246). However, empirical analyses provide inconclusive evidence to support the theory (Groves & Couper, 1998; Merkle & Edelman, 2002).

In addition to socio-structural elements (i.e., social isolation theories), the literature has proposed that psychological factors can influence survey response. Researchers who are associated with the cognitive aspects of the survey methodology (CASM) paradigm have provided theoretical frameworks to further understand respondent cognitive tendencies, perception of interviewers, and decision-making processes in the responding task (Schwarz, 2007; Tourangeau, Rips, & Rasinski, 2000; Willis, 2008).

Under the CASM paradigm, scholarly work has shed light on how cognitive functioning is critical to explain any decision-making process (Schwarz, 2000). Importantly, in the survey methodology literature, cognitive abilities are related to comprehension and communication dynamics, and they have been regarded as essential ingredients in the survey response process (Schwarz, 2007; Sudman, Bradburn, & Schwarz, 1996; Tourangeau, 1984). Further, the literature suggests that there is a link between socio-psychological and socio-structural aspects; namely, there is a connection between social isolation, demographic characteristics (e.g., age, gender, marital and socioeconomic status) and cognitive functioning (Crooks, Lubben, Petitti, Little, & Chiu, 2008; DiNapoli, Wu, & Scogin, 2014; Giuli et al., 2012). Consequently, it is hypothesized that cognitive elements, in conjunction with social elements, are key predictors in the decision-making process of exit polling participation.

Hypothesized Predictors of Nonresponse

Given that respondents are primarily the ones who made the decision to participate, socio-psychological and demographic metrics at the individual level receive special attention in this study. Bivariate and multivariate analyses—both at a single- and multilevel—include voter characteristics: namely, respondent age, education, gender, socioeconomic status, telephone service, and TV ownership. As previous research on survey nonresponse suggests, interviewers play a significant role in the decision to participate (Pickery & Loosveldt, 2001; Pickery, Loosveldt, & Carton, 2001). Consequently, the empirical analyses also include interviewer characteristics (namely, age, gender, and education) as well as contextual information (i.e., ruralness). The conceptual nexus between predictors (voter and interviewer characteristics) and nonresponse is presented in a set of hypotheses as follows.

Hypothesis 1: Voter Age

The absence of shared norms between the larger group of the society and subgroups has been investigated as a mechanism to understand survey participation. In particular, age has been suggested to be an indicator of social isolation (Gergen & Back, 1966; Glenn, 1969). Arguably, as people age they become gradually less engaged in activities from the dominant group (Gergen & Back, 1966).

Cognitive abilities related to working memory, language processing, and comprehension decrease as people age. The erosion of these cognitive skills effectively reduces people's ability to engage in social activities and ultimately in any responding process (Schwarz, 1999; Schwarz, Knauper, & Sudman, 1998). Furthermore, as people age they are less likely to be involved in societal activities and become more socially isolated (Gergen & Back, 1966; Glenn, 1969), which makes them less likely to participate in surveys (Groves & Couper, 1998).

Merkle and Edelman (2000, 2002), Stevenson (2006), Brown and colleagues (2004), and the Edison/Mitofsky report (2005) suggest that older voters are less likely than younger voters to participate in exit polls. Additionally, information from self-reported intentions to participate in an exit poll, as measured via an opt-in web-based survey panel, supports the same notion (Panagopoulos, 2013). Consequently, the first derived hypothesis is as follows:

> *H1: Older voters are more likely than younger voters to refuse to participate in an exit poll.*

Hypothesis 2: Voter Education

Education has long been used in the survey methodology literature as a proxy for cognitive skills (e.g., Ceci, 1991; Kaminska, McCutcheon, & Billiet, 2010; Krosnick & Alwin, 1987). Scholarly work suggests that people with higher levels of education are better equipped to engage in cognitive challenges; namely, those with higher levels of education are more likely to "optimize" their performance in the answering process (Krosnick, 1991; Krosnick & Alwin, 1988; Narayan & Krosnick, 1996). Surprisingly, current studies suggest that education does not seem to be related with exit poll participation. Using aggregate-level data, Merkle and Edelman (2000) found that precincts with more educated voters do not exhibit higher rates of participation. Further, Panagopoulos (2013) did not find any relationship between levels of education and self-reported intentions to participate in an exit poll. Thus, the second hypothesis is presented:

> *H2: Sample voters with higher levels of education are less likely than voters with lower levels of education to refuse cooperation in election day surveys.*

Hypothesis 3: Voter Age by Voter Education

Overall, age and education—as main effects—have been linked with activities that demand cognitive skills, such as the ability to provide answers in a survey (e.g., Belli, Weiss, & Lepkowski, 1999; Holbrook, Cho, & Johnson, 2006). While respondent age and education have been examined as factors that play a role in the decision-making process of participation, little is known about their interactive effects in the exit polling literature.

It is hypothesized that the effect of age in conjunction with voter's education has an impact on the decision to participate in exit polls. The age-education interaction can be used to explain why differential participation patterns attributable to education may exist. Presumably, a lessened cognitive capacity due to aging could be offset by higher levels of education. In other words, if higher levels of education are likely to play a role in the decision to participate in an exit poll, the effect is expected to occur depending on the voter's age. Then, the third hypothesis is derived:

> *H3: Among older voters, more highly educated voters are less likely to refuse cooperation in an exit poll relative to lower educated voters; whereas among younger voters, higher educated voters are equally likely to refuse to participate as lower educated voters.*

Hypothesis 4: Voter Education and Interviewer Education

The survey methodology literature has put forth that survey cooperation and data quality are higher when interviewer and respondents share background characteristics (Bateman & Mawby, 2004; Cannell, Miller, & Oksenberg, 1981; Schaeffer, 1980; Schuman & Converse, 1971). This has been widely investigated in the form of "interviewer effects" (e.g., Biemer, 2001; O'Muircheartaigh & Campanelli, 1999; Olson, 2006). Yet little is known regarding the combined effect of respondent and interviewer background in exit poll participation.

Based on Groves and Couper's (1998) argument that respondents are more likely to comply with requests from liked others (i.e., one person liking another person or organization), Merkle and Edelman (2002) argue that similarity of background may partially account for nonresponse in exit polls. A key element in Merkle and Edelman's (2002) conceptualization is that similarity of background increases liking. In this study, it is hypothesized that interviewer education is reflected in social and behavioral mannerisms and interviewer appearance; consequently, respondents' perceptions of interviewers are likely to have an effect on participation. In other words, the interaction between respondent education and interviewer education helps account for nonresponse.

> *H4: Voters with higher levels of education are less likely (relative to voters with lower levels of education) to refuse participation when approached by an interviewer with a higher level of education as opposed to a lesser educated interviewer. Voters with lower levels of education are*

equally likely to refuse cooperation to an interviewer with a higher level of education relative to an interviewer with a lower level of education.

Hypothesis 5: Voter Socioeconomic Status

Groves and Couper (1998) have proposed that social and psychological aspects of underclass groups (i.e., people who do not feel part of the mainstream group in society) have modified their attitudes toward social requests, suggesting that those who do not share the norms of the society are less likely to be engaged in social exchanges, including social surveys. While Merkle and Edelman (2002) have suggested that social isolation also helps explain nonresponse in exit polls, they hypothesized a weaker effect in exit polls (relative to household surveys). According to Merkle and Edelman (2002), voters in an election are already participating in a societal event.

Studies have found limited evidence to support the notion that social isolation is a likely explanation for nonresponse. Using respondent race as a proxy measure for isolation, Merkle and Edelman (2002) did not find evidence to support the hypothesis. In household surveys, Groves and Couper (1998) did not find support for the social isolation hypothesis using socioeconomic status as a proxy measure. In this study, the social isolation hypothesis is investigated using socioeconomic status. That is, it is hypothesized that underclass voters (as measured in self-reports to the question of socioeconomic class) are less likely than voters who do not see themselves as part of a lower socioeconomic class, to participate in exit polls.

H5: Voters selected into the sample who regard themselves as low-level socioeconomic class are more likely than selected voters who regard themselves as middle or middle-upper class to refuse to participate.

Hypothesis 6: Voter Ruralness

Studies have found that helpful behavior—actions that aim to help others—tends to be higher in rural areas relative to urban areas (Amato, 1983, 1993; House & Wolf, 1978; Wilson & Kennedy, 2006), especially when helping actions are more informal and require spontaneous behavior (Amato, 1983). Consequently, it is possible that ruralness can have an effect on requests to participate in an exit poll. In previous exit polling research, using data from five state-level gubernatorial exit polls in Mexico, Bautista et al. (2006) found significant evidence to propose that ruralness interacts with voter's age. In this study, it is hypothesized that people who live in rural areas are less likely to refuse an invitation to participate in election day surveys relative to sample voters living in urban areas. Particularly, older voters living in rural areas are disproportionately less likely to refuse cooperation in exit polls than older voters living in urban areas.

> *H6: Sample voters who live in rural areas are less likely than those living in urban areas to refuse to participate. Particularly, older voters living in rural areas are less likely than older voters living in urban areas to refuse.*

Hypothesis 7: Voter Social Connectedness

Researchers have reported that people who do not interact with society are less likely to participate in a survey (Groves & Couper, 1998). Literature on social isolation has proposed that contact with others, whether immediate communication with friends and family, or even indirect interaction with others by means of mass media, is likely to have an impact on social participation (Atchley, 1969; A. Brown, 1974; Cumming & Henry, 1961; Lemon, Bengtson, & Peterson, 1972; Maras, 2006). It is hypothesized that sample voters with fewer means of communicating and interacting with society are more likely to refuse when asked to participate in an exit poll. Channels of communication such as television and telephone service can be predictors of exit polling nonresponse.

> *H7a: Voters who own a TV set are less likely than voters who do not own a TV set to refuse participation.*
> *H7b: Voters who have telephone service are less likely than voters with no telephone service to refuse participation.*

Hypothesis 8: Voter Gender

Studies on gender norms have suggested that gender roles in society and social context are likely to influence a person's behavior (Correll, 2007; Eagly, 1987; Eagly & Steffen, 1984; Wood & Eagly, 2002). Studies have hypothesized that, due to gender differences, women tend to experience more social pressure for establishing and maintaining social interactions (e.g., relationship with neighbors, friends, child care, and other activities) than men (Groves, 1990; Groves & Couper, 1998). Yet the empirical survey methodology literature on differential survey nonresponse patterns shows mixed results on this hypothesis (Groves & Couper, 1998; Lindström, 1983; Smith, 1983).

Equivocal results have also been found in exit polling participation regarding gender differences. Merkle and Edelman (2000, 2002) found that even though women exhibited slightly higher levels of cooperation in 1992, 1994, 1996, and 1998, these differences did not reach statistical significance at traditional levels.

Brown et al. (2004) found that there is no difference in nonresponse patterns in the Wilfrid Laurier University exit poll in Canada.

Conversely, Stevenson (2006) found that the difference between women and men was statistically significant in the 2004 Brigham Young University (BYU) Utah colleges exit poll. Bautista et al. (2006) found that women were significantly more likely than men to participate in two state-level exit polls in Mexico; however, such differences disappear after accounting for urbanicity. In light of the hypothesized relationship, the next hypothesis is derived.

H8: Men are more likely than women to choose not to participate in an exit poll.

Hypothesis 9: Voter Age by Interviewer Age

It has been hypothesized that respondents' self-perceived physical vulnerability influences the process of exit poll participation. Merkle and Edelman (2002) have proposed that fearful voters are less likely than confident voters to answer positively to an exit poll request. Merkle and Edelman's "fear and suspicion of strangers" hypothesis builds on concepts that relate to lack of trust in unfamiliar people and fear of crime. This theoretical framework has been developed and adopted from nonresponse studies in the context of household surveys (Couper & Groves, 1996; Groves & Couper, 1998; House & Wolf, 1978; Stoop, 2005). The essential premise in the argument is that respondents modify their behavior toward persons who appear to be a threat in any way (Groves & Couper, 1998).

Merkle and Edelman (2002) study the "fear of strangers" by looking at bivariate analyses between interviewer and respondent age on nonresponse, proposing that fear of strangers partially accounts for exit polling nonresponse. This argument suggests that older voters are less likely to participate in exit polls than younger voters due to the perceived physical vulnerability. The theoretical implication of Merkle and Edelman's (2002) study is that the fear of strangers mechanism occurs as a result of an interaction (in the social and statistical sense) in the exit polling process, and not only as a consequence of the main effect, in this case, respondent's age alone. As a result, the last hypothesis is presented:

H9: Older voters who are interviewed by younger interviewers are more likely to refuse in an exit poll relative to older voters interviewed by older interviewers. However, younger voters are equally likely to participate in an exit poll irrespective of the interviewer's age.

Data and Methods

Respondent age and gender (as well as race, in the case of the United States) have been traditionally the only variables considered to conduct analysis on exit polling nonresponse (Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2000, 2002). Other individual-level variables have been hypothesized to help account for nonresponse (for instance, socioeconomic characteristics, education or access to communications); however, they have been historically excluded from analyses, due to the fact that they are unavailable to researchers.

Previous studies have approximated the relationship between demographic characteristics and nonresponse by means of comparing aggregate-level data to exit polling data. For example, indirect methods have compared Current Population Survey figures on education to Voter News Service results (Merkle & Edelman, 2000; Mitofsky & Edelman, 1995; Popkin & McDonald, 1998; Teixeira, 1998). Other approaches have estimated the relationship between proportion of college educated voters and response rates at the precinct level (Merkle & Edelman, 2000). Needless to say, these aggregate-level data examinations have limited the examination of individual-level mechanisms of nonresponse in exit polls.

To bridge the gap between theory and a more comprehensive empirical study of nonresponse, this study adopts a proof-of-concept approach. That is, the study introduces a different approach that seeks to explore the hypothesized relationships with model-based data that generates plausible data for nonrespondents, and discusses some of the results to advance our knowledge in the field of election day surveys. Namely, an imputation model is developed to assign approximate data to individual cases whose demographic information would be otherwise unknown (Little & Rubin, 2002). Consequently, based on 1) individual demographic data observed among respondents and nonrespondents, and 2) demographic composition of sample precincts derived from population data, an imputation model allows one to generate likely results on the social and psychological mechanisms that predict nonresponse.

Imputation models appear to be an increasingly attractive method for handling missing data in statistical analysis (Carpenter & Kenward, 2012; Kaplan, 2014; Kropko, Goodrich, Gelman, & Hill, 2014; Little & Rubin, 2002; Raghunathan, Lepkowski, Van Hoewyk, & Solenberger, 2001; Royston, 2007; Schafer, 1997; Van Buuren, 2012; White, Royston, & Wood, 2011). More interestingly, recent studies in the survey methodology literature have begun to explore the effect of unit nonresponse (i.e., when a sample member entirely refuses to participate in the study), through imputation methods in household and online surveys (Peytchev, 2012; Zhang, 2014). In this study, imputation methods are explored to approximate plausible values of non-observed values (i.e., refusals) in election day surveys.

Exit Poll Data

The data for this study come from an exit poll conducted in the 2006 Mexican presidential election by Parametría SA de CV. The exit poll was conducted at 200 precincts. A voting station in 1 of the 200 precincts did not open on election day and was excluded from the sample, leaving 199 precincts available for analysis. In the 2006 exit poll, a total of 14,630 exit voters were randomly selected; only 7,764 of them complied with the interview, and 6,866 refused to participate. Traditionally, exit polling designs do not produce data to calculate usual American Association for Public Opinion Research (AAPOR) response rates; however, an approximation of AAPOR's response rates is given by an adaption of Slater and Christensen's (2002) RR5, yielding an overall response rate of 53 percent.

A mixed-mode data collection method was used in the exit poll, mainly due to literacy limitations in the target population. The interviewing process was divided into three parts. First, the interviewers approached exiting voters to request participation in the exit poll. Upon acceptance of the request, they conducted a face-to-face interview asking for questions about demographic data and political opinions. Second, a black-and-white reproduction of the official ballot was handed out to interviewers to be filled out in secret and dropped in a portable "ballot box." Finally, the interview ended with some more demographic questions in a face-to-face mode. Field representatives wore clothing (vest, cap, and portable ballot box) featuring Parametria's logo as well as an identification badge.

The target population was defined as Mexican voters age 18 and older who cast a ballot in the 2006 presidential election. The sampling frame was the listing of all precincts in the country, as determined by the Federal Electoral Institute. The sample was drawn using a two-stage sampling process. Precincts, also known as "electoral sections," were considered as primary sampling units.

The sample frame was ordered according to the number of registered voters—an implicit stratification strategy. The first precinct was randomly selected and the subsequent precincts were selected systematically, such that the probability of selecting a person in any given precinct varies inversely with the size of each electoral section (i.e., probability proportional to size). In a second stage, voters were selected within each of the precincts with approximately 73 sample voters per precinct. In each precinct, every *k-th* person was interviewed. The systematic interval *k* did not vary across precincts.[1] One

[1] The lack of variation in the systematic interval could have led to reaching sample voters more quickly in larger precincts. While this could reduce the quality of the analyzed sample (i.e., certain demographic groups potentially could have voted earlier in the day, thus giving lower chances of participation of groups voting later in the day), it is assumed that any possible effects occurred at random.

interviewer was assigned per precinct. On average, 39 voters were interviewed per interviewer after refusals.

Eligibility problems are believed to be minimal. This is because, in Mexico, once the voter has dropped the official electoral ballot into the voting box, the voting station official inks the voter's right thumb with indelible liquid so the voter cannot vote twice. Hence, when eligibility was in doubt, exit poll interviewers asked the interviewee to show the inked right thumb as a proof of voting. Early and absentee voting is not allowed in Mexico, therefore this source of coverage problem is not considered.

Due to the difficult nature of gathering self-reported information from persons who refuse to participate in exit polls, interviewers marked to the best of their ability whether refusals appeared to be younger or older than 40 years, and whether they were male or female. That is, two broadly defined categories are defined for sex and age on election day (i.e., male vs. female and <40 vs. 40+). Exit voters' ages are binary-coded as less than 40 years ("young") versus 40 years or more ("old"). Information is available at two levels in the 2006 data used for analysis: 1) information on voters who accepted the survey request (i.e., respondents, n=7,764) and 2) interviewers' field reports containing information on nonrespondents' demographic characteristics (age and sex), n=6,866.

Refusals counted by interviewers on election day were appended as individual observations onto the respondent file. A binary variable was created to indicate acceptance or not to the exit poll. Importantly, this individual-level variable (i.e., "refusal") serves as a dependent variable in logistic regression models. This categorization results in a new respondent-level dataset consisting of 14,630 cases (=7,764 respondents + 6,866 nonrespondents).

While there are available data for respondents and nonrespondents on age and gender, there is incomplete information for voter education, socioeconomic status, TV ownership, and telephone service. These incomplete data are filled-in based on an imputation model (see Imputation Methods section).

Additionally, interviewer socio-demographic characteristics (age, gender, and education) were obtained from a brief survey conducted among field staff after the completion of the exit poll. This information is linked to voter-level data to explore hypothesized interviewer effects on nonresponse. The consequence of linking voter-level information with interviewer-level information is a hierarchical dataset, where voters are nested within interviewers. Different from existing studies on exit polling data—and based on existing literature on analysis methods for hierarchical data (e.g., Hox, de Leeuw, & Kreft, 1991; O'Muircheartaigh & Campanelli, 1999; Rabe-Hesketh & Skrondal, 2012; Snijders & Bosker, 2012)—this study considers multilevel models (also known as "mixed effects" models) to explore hypotheses.

As described in the Imputation Methods section, multiple datasets were generated with imputed values (Graham, Olchowski, & Gilreath, 2007; Little & Rubin, 2002), creating a total of 30 imputed datasets, *m*=30. Nonetheless, in this study, only results from one imputation (*m*=1) are analyzed. This is because the study aims to provide a focused and initial discussion of multilevel regression models (to account for the fact that voters are nested within interviewers), without having to introduce a discussion on combination of results from different imputations as recommended in the literature (Little & Rubin, 2002). A more robust analysis using multilevel regression modeling with multiply imputed datasets (m=30) is conducted elsewhere (Bautista, 2015).

Auxiliary Data for Imputation

As detailed in the section on Imputation Methods, imputation methods are used in this research as proof-of-concept to estimate plausible values for voters who chose not to participate in the 2006 exit poll. External data for the imputation process come from aggregate-level data provided by Mexico's Federal Electoral Institute (IFE, 2009). Particularly, the national electoral commission combined precinct-level census data collected by the National Institute of Statistics and Geography with geographic information related to the electoral precinct for the period of 2005-2006. These data provide information for population distribution of age, education, and health care access. These precinct-level data are used to impute data in the 2006 exit poll.

Missingness in the Data

Table 1 shows the level of missingness in the exit poll data on voter and interviewer characteristics, considering item and unit nonresponse. Overall, data in Table 1 show that voter age and gender have a negligible level of missing data (0.27 and 0.05 percent, respectively). However, levels of missingness for education, socioeconomic status, TV ownership, and telephone service are non-negligible (46.93, 48.18, 46.93, and 46.94 percent, respectively). Ruralness does not have missing data since rural/urban characteristics are derived from the sampling frame.

Table 1. Level of Missingness in Data from 2006 Exit Poll

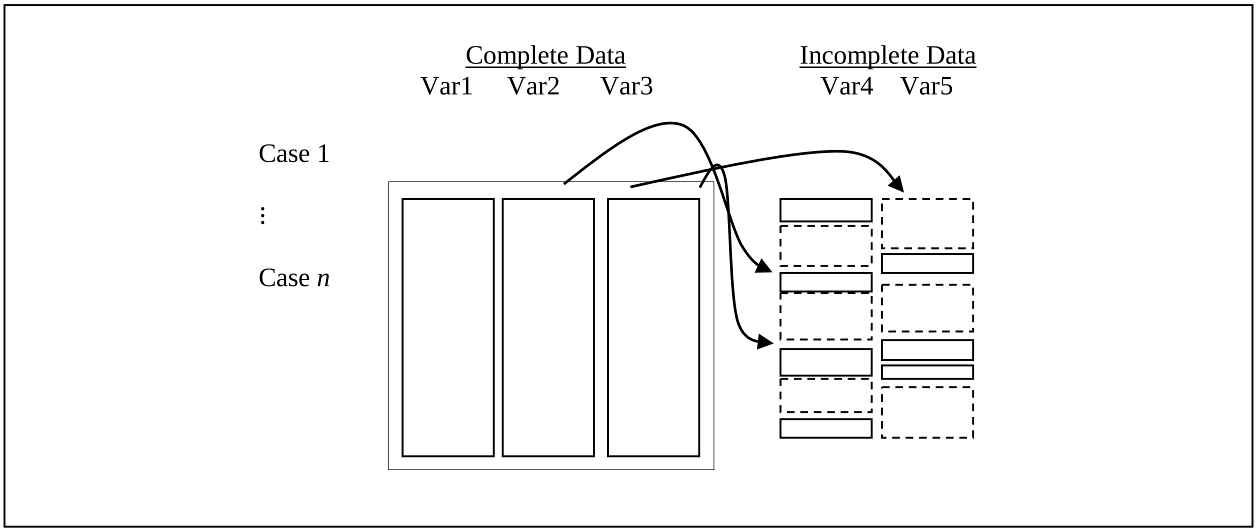
	Missing Cases	Total Cases	Percent Missing
Voter Characteristics			
Age	40	14,630	0.27
Gender	7	14,630	0.05
Education	6,866	14,630	46.93
Socioeconomic status	7,049	14,630	48.18
TV ownership	6,866	14,630	46.93
Telephone service	6,868	14,630	46.94
Interviewer Characteristics			
Education	9	199	4.52
Age	4	199	2.01
Gender	14	199	7.04
Ruralness	0	199	0.00

Imputation Methods

This section offers details of imputation methods implemented in the present study. Overall, imputation can be broadly understood as a model-based procedure devised to deal with missing data whose purpose is to approximate missing data from the distribution that originates with the full data distribution. Particularly, imputation provides plausible values for each missing observation, conditional on observed data (Rubin, 1976, 1977, 1987). Single imputation methods assign only one fixed datum to each person's missing value (m=1), while multiple imputation produces a set of $m > 1$ plausible values for each missing observation. These values are generated using the available information and take into account the covariation among variables in the full data matrix.

The generation of imputed datasets does not introduce changes to the observed data matrix, but assigns different reasonable values for the missing data. Under this view, it is assumed that the missingness in the data is at random, given observed covariates. Figure 1 shows an intuitive way of displaying the mechanism of imputation using complete data.

Figure 1. Missing Data Completion Using Multiple Imputation



Model-based imputation methods assume that data-missingness depends on the observed variables and that it is missing at random (MAR). That is, the missing data mechanisms are expected to be ignorable, conditional on the observed data. Formally,

$$P(R|D_{obs}) = P(R|D)$$

where R is an indicator for missing data, D_{obs} is the observed data, and D is all the data—namely, $D \in \{D_{obs}, D_{miss}\}$.

Consequently, the imputation procedure approximates the original or true distribution of each variable given the observed and auxiliary data. In this study, since data for imputation of missing values are derived from the underlying distribution of the data, imputation models assume that refusals are missing data at random given the full set of covariates (i.e., internal and external data). Put differently, the respondents and nonrespondents are not systematically different within segments of the population, which makes analysis possible.

Fully Conditional Methods for Imputation

The literature discusses several methods for multiple imputation including a joint multivariate normal approach (which has been adopted in numerous studies), but the present study adopted a fully conditional specification (FCS) approach. This is because recent empirical research suggests that the FCS approach tends to produce better imputations for categorical data compared to a joint multivariate normal approach (Kropko et al., 2014). The chosen FCS procedure is also discussed in the literature as multivariate imputation using chained equations (MICE) (Abayomi, Gelman, & Levy, 2008; Kennickell, 1991; Raghunathan et al., 2001; Schenker et al., 2006; Van Buuren, 2007; Van Buuren, Boshuizen, & Knook, 1999; Van Buuren, Brand, Groothuis-Oudshoorn, & Rubin, 2006).

FCS is implemented by means of an iterative process where missing values are imputed conditionally and subsequently on the available data. Namely, it starts by imputing the variable with the lowest level of missingness with prediction equations (i.e., chained equations) using all available data, and then proceeds to impute the next variable with the lowest level of missingness.

Subsequent imputations use predicted values from the previous iteration as well as observed values from the rest of the variables. This process is sequentially repeated until all missing data have been predicted. Conveniently, Stata's routine `mi impute chain` (version 13) allows the user to customize the specification of chained equations by declaring whether an imputed variable is categorical or continuous in nature (StataCorp, 2013).

Formally, the process of sequential univariate imputation modeling (i.e., iteratively imputing data) can be described as one equation for each imputation variable ($Y_1,\ldots,Y_j$) and a set of complete predictors ($\boldsymbol{X}$) with FCS (StataCorp, 2013, p.7). Consequently, imputed values are drawn as follows:

$$Y_1^{(t+1)} \sim g_1\left(Y_1 |\, Y_2^{(t)}, \ldots, Y_j^{(t)}, \boldsymbol{X}, \phi_1\right)$$

$$Y_2^{(t+1)} \sim g_2\left(Y_2 |\, Y_1^{(t+1)}, Y_3^{(t)}, \ldots, Y_j^{(t)}, \boldsymbol{X}, \phi_2\right)$$

$$(\ldots)$$

$$Y_j^{(t+1)} \sim g_j\left(Y_j |\, Y_1^{(t+1)}, Y_2^{(t+1)}, \ldots, Y_{j-1}^{(t+1)}, \boldsymbol{X}, \phi_j\right)$$

where t=0,1…T (iterations) reaches convergence when t=T and where ϕ_j is defined as model parameters with a uniform prior. As can be seen from the equations above, imputation models include all variables as predictors except the one being imputed. Models are estimated iteratively until all variables have been fully imputed.

A convenient way of representing the FCS probability model on the complete data (i.e., observed and missing values) for the 2006 dataset is as follows (Model A):

$$(Y_{A1}\ Y_{A2}\ Y_{A3}\ Y_{A4}\ Y_{A5}\ Y_{A6}\ Y_{A7}\ Y_{A8}\ Y_{A9}\ \ Y_{A10}\ \ Y_{A11}\ \ Y_{A12}\ \ Y_{A13}\ \ Y_{A14}\ \ Y_{A15}\ \ Y_{A16}) = (X_{A1}\ X_{A2}\ X_{A3}\ X_{A4}\ X_{A5}\ X_{A6}\ X_{A7}\ X_{A8}\ X_{A9}\ X_{A10}\ X_{A11}\ X_{A12}\ X_{A13}\ X_{A14}\ \ X_{A15})$$

Table 2 shows the description of "dependent"[2] variables used in the 2006 model ($\boldsymbol{Y_A}$, A=1…16). Also, Table 2 shows the regression model used for each imputation variable (see Regression Method column). Similarly, Table 3 shows the set of "independent" variables used in the 2006 model ($\boldsymbol{X_A}$, A=1…14).

Table 1. Dependent Variables for Imputation in the 2006 Regression Method

Model A (2006)	Description	Categories	Regression Method
Y_{A1}	Interviewer gender	Female, Male	Logit
Y_{A2}	Interviewer age	Less than 20 years, 21-30 years, 31-40 years, 41 years or more	Ordinal logit
Y_{A3}	Interviewer education	(Less than high school, High school graduate, College)	Ordinal logit
Y_{A4}	Interviewer noted conflict at voting station	Yes, No	Logit
Y_{A5}	Number of exits at voting station as noted by interviewer	One exit, More than one exit	Logit
Y_{A6}	Interviewer experience	Yes, No	Logit
Y_{A7}	Interviewer average interviewing time	Five minutes or less, More than 5 minutes	Logit
Y_{A8}	Distance from station as reported by interviewer	10 meters or less (30 feet), More than 10 meters	Logit
Y_{A9}	Voter age	Less than 40 year, 40 years or more	Ordinal logit
Y_{A10}	Voter gender	Female, Male	Logit
Y_{A11}	Voter education	Less than high school, High school, College	Ordinal logit
Y_{A12}	Voter socioeconomic status	Low, Middle-low, Middle, Middle-high/High	Ordinal logit
Y_{A13}	Voter telephone service	Yes, No	Logit
Y_{A14}	Voter TV ownership	Yes, No	Logit
Y_{A15}	Voter time of voting	Before 1:00pm, After 1:00pm	Logit
Y_{A16}	Voter party preference	PAN, PRI, PRD, Other	Multinomial logit

[2] These are not dependent variables in the traditional modeling sense, as the imputation model is an iterative process where dependent variables become independent variables after imputation for the next imputation model.

Table 2. Set of Independent Variables for Imputation Model in the 2006 Dataset

Dependent Variables	Description	Categories
X_1	Cluster indicator variables	Yes, No
X_2	Nonresponse	Yes, No
X_3	Proportion of actual votes for PAN, PRI, PRD and Other Party at the precinct level in the 2006 election	Continuous
X_4	Type of PSU	Rural, Nonrural
X_5	Proportion of adult population with primary education (6 years) or less	Continuous
X_6	Proportion of adult population with lower secondary education (3 years)	Continuous
X_7	Proportion of adult population with upper secondary education (3 years)	Continuous
X_8	Proportion of adult population with college education (4 years)	Continuous
X_9	Proportion of adult population beneficiary of the Mexican Social Security Institute (IMSS)	Continuous
X_{10}	Proportion of adult population beneficiary of the Institute for Social Security and Services for State Workers (ISSSTE)	Continuous
X_{11}	Proportion of adult population beneficiary of the health programs provided by Mexican Petroleums (PEMEX), Secretary of National Defense (SEDENA), or Secretary of the Mexican Navy (SEMAR)	Continuous
X_{12}	Proportion adult population with other publicly funded health coverage	Continuous
X_{13}	Proportion adult population with privately funded health coverage	Continuous
X_{14}	Proportion adult population with no health coverage	Continuous
X_{15}	Proportion of female adult population	Continuous

As variables in Table 3 show, the FCS models used in this study attempt to 1) maintain population proportions by means of external data and 2) preserve existing relationships in the data through the imputation process by means of primary data. Namely, the imputation model includes variables representing the structure of the data (for instance, specification of clusters, population distribution of vote, population distribution of education). Furthermore, the imputation models keep variables that are presumed to be correlated at the first level (for example, voter age and voter education) and at the second level (for instance, interviewer age and interviewer education). Importantly, the outcome variable for substantive analysis (i.e., nonresponse) is also included in the imputation model.

The current literature recommends at least 10 iterations for chain (per imputation) (StataCorp, 2013; Van Buuren, 2007, 2012; Van Buuren et al., 2006). In this study, each filled-in dataset was estimated with 15 iterations for a robust “chain” to converge to a stationary distribution. The software used for FCS imputation (Stata, version 13) allows for specification of the distribution for each imputation variable (e.g., logit, ordinal logit, or multinomial). Nonetheless, the fact that imputation variables are categorical introduces the possibility of "perfect prediction." That is, covariates can potentially perfectly predict to one another (Agresti, 2013; Albert & Anderson, 1984).

The issue of perfect prediction has been documented in the literature, and a practical solution known as "data augmentation" has been suggested (White, Daniel, & Royston, 2010; White et al., 2011). This strategy consists of adding a few extra observations with negligible weights during the sequential process to avoid perfect prediction. The data augmentation solution is readily available from Stata's official command for imputation `mi impute chain` (StataCorp, 2013), and it was adopted for this study to minimize possible issues of non-convergence.

Data Before and After Imputation

To assess the quality of the imputed data, Table 4 shows demographic characteristics of voters and interviewers before and after imputation. As can be seen, the distribution of variables for voters remains consistent across socio-demographic characteristics after imputation. Only education shows a negligible difference of 1 percentage point between the two distributions; particularly, the observed differences around 1 percentage point are for categories Secondary education or less (=64.1-65.2 percent) and College (=19.2-18.2 percent). Differences for the rest of the variables are less than 1 percentage point.

For interviewers, item nonresponse was also imputed (i.e., when interviewers failed to provide an answer to a particular item in the post-election questionnaire). The maximum difference is in the order of 2.5 percentage points for gender (=44.3-46.7 and =55.7-53.3 percent). The rest of the interviewer data remain nearly identical.

Table 3. Distribution of Voter and Interviewer Characteristics before and after Imputation of Item and Unit Nonresponse Data (Frequencies and Column Percentages)

	Before Imputation		After Imputation	
	Frequency	Percent	Frequency	Percent
Voter Characteristics				
Gender				
0 Female	7,205	49.3	7,206	49.3
1 Male	7,418	50.7	7,424	50.8
	14,623	100	14,630	100
Age				
0 Less than 40 years	7,101	48.7	7,119	48.7
1 40 years or more	7,489	51.3	7,511	51.3
	14,590	100	14,630	100

	Before Imputation		After Imputation	
	Frequency	Percent	Frequency	Percent
Education				
1 Secondary education or less	4,977	64.1	9,536	65.2
2 High school	1,293	16.7	2,438	16.7
3 College	1,494	19.2	2,656	18.2
	7,764	100	14,630	100
Socioeconomic Status				
1 Low	2,435	32.1	4,790	32.7
2 Middle-low	2,002	26.4	3,889	26.6
3 Middle	2,768	36.5	5,228	35.7
4 Middle-high/High	376	5.0	723	4.9
	7,581	100	14,630	100
TV Ownership				
0 No	705	9.1	1,382	9.5
1 Yes	7,059	90.9	13,248	90.6
	7,764	100	14,630	100
Telephone Service				
0 No	3,116	40.1	5,968	40.8
1 Yes	4,646	59.9	8,662	59.2
	7,762	100	14,630	100
Interviewer Characteristics				
Gender				
0 Female	82	44.3	93	46.7
1 Male	103	55.7	106	53.3
	185	100	199	100
Education				
1 Less than high school	25	13.2	25	12.6
2 High school graduate	116	61.1	121	60.8
3 College	49	25.8	53	26.6
	190	100	199	100
Age				
1 Less than 20 years	61	31.3	61	30.7
2 21-30 years	80	41.0	82	41.2
3 31-40 years	30	15.4	31	15.6
4 41 years or more	24	12.3	25	12.6
	195	100	199	100
Contextual Characteristics				
Ruralness (Variable not subjected to imputation)				
0 Nonrural	138	69.4	138	69.4
1 Rural	61	30.7	61	30.7
	199	100	199	100

Results

To provide a first view of results of hypothesized relationships, H1 through H9 are analyzed with traditional bivariate and multivariate methods. In a subsequent analysis of this section, these relationships are reconsidered with multilevel regression methods to better account for clustering effects due to “nesting” effects of sample persons within interviewers.

Bivariate Analysis of Voter and Interviewer Characteristics

Table 5 displays bivariate relationships between variables of interest and exit polling participation. As mentioned before, data for nonrespondents on education, socioeconomic status, TV ownership, and telephone service were imputed based on a fully conditional model-based approach designed to deal with missing data. Age and gender data were primarily collected by interviewers either as self-reported information or by observation alone; consequently, age and gender data are subject to minimal imputation.

Data in Table 5 suggest that gender seems to be related to exit polling participation; namely, men (45.9 percent) are slightly less likely to refuse than are women (48 percent) at conventional significance levels ($\chi^2(1)=6.54$, $p<.05$). While the gender difference is statistically significant, the difference is not large. For voter age, Table 5 indicates that younger persons (defined as voters age less than 40 years) and older persons (voters age 40 years or more) refused to participate at nearly the same rate (46.8 vs. 47.1 percent), as these percentages are not statistically different ($\chi^2(1)=0.11$, $p>.05$).

Table 1. Exit Polling Response by Voter Socio-Demographic Characteristics (Row Percentages)

	Response	Nonresponse
Voter Gender		
0 Female	52.0	48.0
1 Male	54.1	45.9
	Pearson χ^2 (1) = 6.54 Pr = 0.011	
Voter Age		
0 Less than 40 years	53.2	46.8
1 40 years or more	52.9	47.1
	Pearson χ^2 (1) = 0.11 Pr = 0.740	
Voter Education		
1 Secondary education or less	52.2	47.8
2 High school	53.0	47.0
3 College	56.3	43.8

	Response	Nonresponse
	Pearson χ^2 (2) = 13.74 Pr = 0.001	
Voter Socioeconomic Status		
1 Low	52.3	47.7
2 Middle-low	52.4	47.6
3 Middle	54.2	45.8
4 Middle-high/High	53.8	46.2
	Pearson χ^2 (3) = 4.40 Pr = 0.222	
TV Ownership		
0 No	51.0	49.0
1 Yes	53.3	46.7
	Pearson χ^2 (1) = 2.59 Pr = 0.108	
Telephone Service		
0 No	52.2	47.8
1 Yes	53.7	46.3
	Pearson χ^2 (1) = 2.97 Pr = 0.085	
Ruralness		
0 Nonrural	52.2	47.8
1 Rural	55.3	44.7
	Pearson χ^2 (1) = 10.66 Pr = 0.001	

As suggested by a simple chi-square test ($\chi^2(2)=13.74$, $p<.001$) on the distribution of voter education (Table 5), college educated voters (43.8 percent) seem to be significantly less likely to refuse compared to voters with high school (47 percent) or with secondary education or less (47.8 percent). In terms of socioeconomic status, there appears to be no statistical difference between voters who are characterized as low class (47.7 percent), middle-low class (47.6 percent), middle class (45.8 percent), and middle-high or high class (46.2 percent) under conventional testing levels ($\chi^2(3)=4.40$, $p>.05$).

Table 5 also displays a distribution of response rates across TV ownership and telephone service. Voters with telephone service appear to be as likely to refuse (46.3 percent) as voters with no telephone service (47.8 percent), under a conventional chi-square test ($\chi^2(1)=2.97$, $p>.05$). Likewise, voters who own a TV set seem to be statistically as likely to refuse (46.7 percent) as voters who are not TV owners (49 percent) ($\chi^2(1)=2.59$, $p>.05$). The data also suggest that ruralness seems to be related to exit polling participation. The level of nonresponse in rural areas (44.7 percent) is significantly lower than in nonrural areas (47.8 percent) at conventional statistical levels ($\chi^2(1)=10.66$, $p<.001$).

Table 6 displays the interactive bivariate effects of voter age and voter education on nonresponse. These data suggest that the nonresponse rate of voters with college education is 46.7 percent when voters are less than 40 years old; however, the nonresponse rate decreases for the same group (college educated voters, 39.1 percent) when they are older than 40 years. Also, the data suggest that among younger voters (defined as less than 40 years old) the difference between the lower educated group (i.e., secondary education or less) and the higher educated group (i.e., college) is approximately 2 percent (=48.8-46.7 percent), whereas among older voters (defined as 40 years or more) this difference is approximately 8 percent (=47.1-39.1 percent).

Table 2. Exit Polling Response by Voter Age and Voter Education (Row Percentages)

	Response	**Nonresponse**
When Voter Age=0 (Less than 40 years)		
Voter Education		
1 Secondary education or less	51.2	48.8
2 High school	58.0	42.0
3 College	53.3	46.7
	Pearson χ^2 (2) = 20.89 Pr = 0.000	
When Voter Age=1 (40 years or more)		
Voter Education		
1 Secondary education or less	52.9	47.1
2 High school	43.9	56.1
3 College	60.9	39.1
	Pearson χ^2 (2) = 54.50 Pr = 0.000	

Data in Table 7 indicate that the effect of voter age on nonresponse changes depending on levels of interviewer age. Approximately one half (50.8 percent) of the oldest voting group (i.e., voters age 40 years or more) refused to participate when approached by a younger interviewer (i.e., a person age 20 years or less). Importantly, such percentage decreases (46.8 percent) when the contact is made by a slightly older interviewer (i.e., a person between the age of 21 and 30), and further decreases (42.6 percent) when the interviewer is even older (i.e., between 31 and 40 years). Nonresponse remains under one half (45.1 percent) when the interviewer is in the oldest category (i.e., 41 years or more).

Table 3. Exit Polling Response by Voter Age and by Interviewer Age (Row Percentages)

	Response	Nonresponse
When Interviewer Age=1 (<=20 years)		
Voter Age		
0 Less than 40 years	50.3	49.7
1 40 years or more	49.2	50.8
	Pearson χ^2 (2) = 0.54 Pr = 0.462	
When Interviewer Age=2 (21-30 years)		
Voter Age		
0 Less than 40 years	54.9	45.1
1 40 years or more	53.2	46.8
	Pearson χ^2 (2) = 1.75 Pr = 0.185	
When Interviewer Age=3 (31-40 years)		
Voter Age		
0 Less than 40 years	55.8	44.2
1 40 years or more	57.4	42.6
	Pearson χ^2 (2) = 0.628 Pr = 0.428	
When Interviewer Age=4 (41 years or more)		
Voter Age		
0 Less than 40 years	51.3	48.7
1 40 years or more	54.9	45.1
	Pearson χ^2 (2) = 2.41 Pr = 0.120	

Table 8 suggests that the levels of nonresponse vary for college educated voters across levels of interviewer education. Particularly, approximately 1 in every 2 college educated voters (49.5 percent) refused to participate when they were approached by interviewers with lower levels of education (i.e., with less than high school). This percentage reduces as the level of education increases among interviewers. When college educated voters are approached by interviewers whose level of education is high school, only 42.6 percent refused to participate. Similarly, when college educated voters are approached by interviewers with comparable levels of education (i.e., college), only 44.2 percent declined to participate.

Table 4. Exit Polling Response by Voter Education and by Interviewer Education (Row Percentages)

	Response	Nonresponse
Interviewer Education=1 (Less than high school)		
Voter Education		
1 Secondary education or less	49.9	50.1
2 High school	51.2	48.8
3 College	50.5	49.5
	Pearson χ^2 (2) = 0.22 Pr = 0.892	
Interviewer Education=2 (High school grad)		
Voter Education		
1 Secondary education or less	51.9	48.1
2 High school	51.2	48.8
3 College	57.4	42.6
	Pearson χ^2 (2) = 17.50 Pr = 0.000	
Interviewer Education=3 (College)		
Voter Education		
1 Secondary education or less	54.4	45.6
2 High school	58.4	41.6
3 College	55.8	44.2
	Pearson χ^2 (2) = 3.40 Pr = 0.183	

Table 5. Exit Polling Response by Voter Age and Ruralness (Row Percentages)

	Response	Nonresponse
When Rural=0 (Nonrural)		
Voter Age		
0 Less than 40 years	53.2	46.8
1 40 years or more	51.3	48.7
	Pearson χ^2 (2) = 3.88 Pr = 0.049	
When Rural=1 (Rural)		
Voter Age		
0 Less than 40 years	53.2	46.8
1 40 years or more	57.0	43.0
	Pearson χ^2 (2) = 5.87 Pr = 0.015	

Data displayed in Table 9 indicates that older voters in rural contexts are less likely to refuse (43 percent) compared to older voters in urban areas (48.7 percent). Levels of nonresponse do not seem to change for younger voters at different levels of ruralness. For younger voters (i.e., persons age less than 40 years), the nonresponse rate is 46.8 percent for both rural and nonrural contexts. With these bivariate analyses from Table 5 through Table 9 in mind, we now turn to exploring these data with multivariate regression tools, to control for voter characteristics that might have an influence on nonresponse.

Multivariate Analysis of Voter Characteristics

To estimate main effects and interaction terms of respondent characteristics on nonresponse, net of other factors, two single-level multivariate regression models are estimated. Voter gender (1=Male, 0=Female), age (1=40 years or more, 0=Less than 40 years), education (1=Secondary education or less, 2=High school, 3=College), socioeconomic status (1=Low, 2=Middle-low, 3=Middle, 4=Middle-high/High), TV ownership (1=Yes, 0=No), telephone service (1=Yes, 0=No), and ruralness (1=Rural, 0=Nonrural) are regressed on exit polling nonresponse.

Given the dichotomous nature of the dependent variable (1=Nonresponse, 0=Response), logistic regression models were fit to the data. Regression results (logits and standard errors) from two models (Model A and Model B) are displayed in Table 10. Model A excludes interaction terms between voter age and voter education, as well as the interaction between voter age and ruralness. Model B shows the same model including interaction terms.

Table 6. Logistic Regression Model for Predictors of Nonresponse

	Model A		Model B	
Pr (Y=Refusal|x_i)	Coefficient	Standard Error	Coefficient	Standard Error
Voter Gender				
1 Male	-0.079*	(0.03)	-0.078*	(0.03)
Voter Age				
1 40 years or more	-0.013	(0.03)	-.00004	(0.05)
Voter Education				
2 High school	-0.049	(0.05)	-0.259***	(0.06)
3 College	-0.179***	(0.05)	-0.064	(0.07)
Voter Socioeconomic Status				
2 Middle-low	-0.007	(0.05)	-0.009	(0.05)
3 Middle	-0.059	(0.05)	-0.061	(0.05)
4 Middle-high/High	-0.008	(0.09)	-0.004	(0.09)
TV Ownership				
1 Yes	-0.115	(0.06)	-0.120	(0.06)
Telephone Service				
1 Yes	-0.046	(0.04)	-0.044	(0.04)

Pr (Y=Refusal|x_i)	Model A		Model B	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Ruralness				
1 Rural	-0.224***	(0.04)	-0.119*	(0.06)
Voter Age by Voter Education				
1 40 years or more # 2 high school	-	-	0.582***	(0.10)
1 40 years or more # 3 college	-	-	-0.303**	(0.09)
Voter Age by Ruralness				
1 40 years or more # 1 rural	-	-	-0.192*	(0.08)
Constant	0.18**	(0.07)	0.178*	(0.07)

Table 10 (Model A and Model B) shows that men are significantly less likely to refuse than women (logit=-0.079, SE=0.03; logit=-0.078, SE=0.03). In both models, the odds of refusing to participate versus accepting the request are approximately 7.5 percent lower [=(exp(-0.079)-1)*100] for men relative to women, net of other factors. In terms of voter age, the analysis suggests that after accounting for other demographic characteristics, the difference in nonresponse between younger and older voters is not statistically significant (Model A and Model B).

While age does not appear to significantly predict nonresponse in Model A or Model B, it appears that the size of the regression coefficient in the model with interaction terms (i.e., Model B, logit-.00004, SE=0.05) is smaller than the size of the coefficient in the model with no interactions (i.e., Model A, logit=-0.013, SE=0.03). Broadly interpreted, this suggests that interaction terms of age introduced in Model B (i.e., age by education and age by ruralness) help to partially account for the variability in the dependent variable. It also suggests that voter age seems to play an indirect role, as opposed to a direct role, in nonresponse. These interaction terms are discussed later in this section.

In terms of education, Model A in Table 10 indicates that the odds of refusing to participate versus accepting the request are 16.4 percent lower [=(exp(-0.179)-1)*100] for voters with a college education relative to voters with a secondary education or less. In Model B, however, where education interacts with age, these data indicate that the odds of refusing to participate are just 6.2 percent lower (and are not significant) for voters with a college education relative to voters with a secondary education or less. This suggests that education also tends to have an indirect effect on exit polling nonresponse depending on voter age.

In terms of socioeconomic status, Model A and Model B (Table 10) indicate that voter socioeconomic status does not seem to be a significant predictor of nonresponse. There is no statistically significant difference between voters in the reference category (i.e., Low socioeconomic status) and any of the other categories (Middle-low, Middle, or Middle-high/High). In terms of TV ownership, Model A (logit=-0.115, SE=0.06) and Model B (logit=-0.120, SE=0.06) indicate that the odds of refusing are approximately 11 percent lower for voters who are TV owners relative to voters who are not. While this relationship occurs in the expected direction, it is not significant at conventional levels.

Telephone service does not seem to predict exit polling nonresponse as well. Model A and Model B (Table 10) suggest that although the odds of refusing to participate are 4.5 percent lower for voters with telephone service than for voters with no telephone service (as hypothesized), the relationship does not appear to reach statistically significant levels. Model A and Model B also present results on the relationship between ruralness and nonresponse. The model with no interaction terms (Model A) indicates that the odds of refusing to participate are statistically significant, and they are 20.1 percent [=(exp(-0.224)-1)*100] lower for voters living in rural areas than for voters living in nonrural areas—which is consistent with the corresponding hypothesis. Model B (with interaction terms) indicates that the relationship seems to be statistically significant, but the odds of declining cooperation are 11.2 percent [=(exp(-0.119)-1)*100] lower for rural voters versus nonrural voters.

Given that the effect of voter education is expected to vary across levels of voter age, as previously mentioned in this section, in Model B (Table 10), an interaction term between voter age and voter education is included. When the odds ratio of refusing to participate is calculated for college educated voters (vs. voters with secondary or less) among older voters, the corresponding odds ratio equals to 0.69 [=exp(-0.064)*exp(-0.303)]. The fact that the resulting odds ratio of the interaction term is less than 1 suggests that the odds of the higher educated group to refuse are less than the odds of the lower educated group to refuse, when voters are age 40 years or more. In other words, among older voters (40 years or more), college educated voters seem to be less likely to refuse (at conventional statistical levels) compared to their lower educated counterparts, net of other variables.

Model B includes an interaction term between age and ruralness to explore whether the effect of voter age varies across levels of ruralness. When the odds ratio for older voters versus younger voters in rural areas is calculated [exp(-0.00004) * exp(-0.192)], the corresponding odds ratio equals to 0.83. The fact that the odds ratio is less than 1 suggests that the odds of the older group refusing are less than the odds of the younger group to refuse when they live in rural areas. Put differently, among voters living in rural areas, it seems less likely that older voters would refuse to participate compared to younger voters, controlling for other factors.

Thus far, conventional multivariate methods have shed light on hypothesized relationships using model-based data for non-observed data; however, multilevel models can take this exploration one step further. That is, while results from single-level multivariate logistic regression models are helpful to control for the simultaneous effect of different voter-level characteristics, there is a need to develop a categorical model that allows us to model variability of voter-level characteristics across levels of interviewer characteristics. In other words, the fact that voters are nested within interviewers motivates the need for a multilevel model. Consequently, the next step in the analysis is to determine whether the previously described multivariate relationship between voter characteristics and nonresponse is likely to hold when accounting for interviewer characteristics.

The Need and Set-Up of Multilevel Modeling

Consistent with multilevel terminology, in this study respondent-level variables are referred to as Level 1 information, and interviewer-level variables as Level 2 information. This is because respondents (L1) are "nested" or grouped within interviewers (L2). Traditionally, logistic regression modeling for binary data assumes that responses in the outcome variable are conditionally independent given covariates; however, multilevel models for clustered binary data account for the fact that responses are dependent even after controlling for other variables (Hox, 2010; Luke, 2004; Rabe-Hesketh & Skrondal, 2012; Snijders & Bosker, 2012).

Before estimating a multilevel model, one needs to establish whether L2 information (i.e., interviewers) helps explain part of the total variability in the dependent variable (in this case defined as 1=Nonresponse, 0=Response) (Snijders & Bosker, 2012). Consequently, an "empty model" is estimated first, which is a regression model with only the dependent variable included—no predictors, hence the name—and a grouping indicator (L2), which in this case is the interviewer.

To ease interpretation of a multilevel "empty model," a conventional single-level empty model (i.e., a constant-only model with no L2 information and no L1 predictors) is presented first, and then the results of a second-level (or multilevel) empty model. A single-level logit model for nonresponse yields a constant term or "intercept" equal to -0.122 (Table 11). This constant term or intercept is the initial distribution of the outcome variable (i.e., nonresponse). In other words, given that the probability of refusing is 0.4693 [=6,866 nonrespondents divided by 14,630 sample voters], the odds of this event are 0.4693/(1-0.4693)= 0.884. If we calculate the logit (i.e., the log of the odds) of the event, this produces the constant term -0.123 [=log(0.884)] that is displayed in Table 11.

To assess whether L2 information (interviewer-level data) is needed to help explain the expected distribution of the outcome variable (nonresponse), L2 data or "grouping" information is added to the model. Table 11 (Multilevel Empty Model column) shows a no-predictors model with a constant of -0.474. As can be seen from Table 11, the constant coefficient has changed from -0.123 to -0.474. This is because—unlike single-level models that estimate population-average probabilities (i.e., estimation for groups, for example, men vs. women)—multilevel models estimate subject-specific or conditional probabilities (i.e., estimation for individuals with specific characteristics, for example, a person with a TV set) accounting for nesting information. Importantly, the fact that the variance component associated to the random intercept (i.e., 1.285) is more than twice its standard error (0.15) suggests that there is significant variation among L2 units (i.e., interviewers).

The estimated intraclass correlation coefficient (ICC=0.280) shown in Table 11 suggests that approximately 30 percent of the variance can be attributed to the influence of L2 components. The L2 constant-only model (i.e., Multilevel Empty Model column) provides a likelihood ratio test for the null hypothesis that the between-cluster variance is zero compared to a single-level constant-only model (χ^2=2,391.61, p<.05), which indicates that a multilevel model (also known as mixed model) is needed.

Table 7. Single-Level and Multilevel Empty Model for Predictors of Nonresponse

Predictors (x)	Single-Level Empty Model		Multilevel Empty Model	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
Fixed Effects				
Constant	-0.123*	(0.17)	-0.474*	(0.08)
Random Effects				
Variance (Constant)			1.285	(0.15)
Intraclass Correlation			0.280	(0.23)

Likelihood ratio test vs. single-level logistic regression: (χ^2=2,391.61, p<.05)

To conduct a better statistical testing of the hypothesized relationships about respondent and interviewer effects on nonresponse described earlier in this section, respondent-level (L1) as well as interviewer-level (L2) predictors need to be included simultaneously in the multilevel model. As discussed in the Data and Methods section, multilevel models are explored with a single-imputation dataset (m=1) in the rest of the paper. Thus, Table 12 presents five mixed effects regression models starting with a random intercept model (Model 0). Additional terms are added successively to explore data while adjusting standard errors for nesting effects (i.e., random slopes models, Model 1 though Model 4).

Briefly described, a random intercept model (Model 0, single imputation) estimates L1 characteristics controlling for L2 variation. Since interviewers can have different effects on nonresponse, this first model (i.e., Model 0) lets the voters' baseline probability be different across interviewers. Successive models (Model 1 through Model 4, single imputation) add "random slopes," which allows for modeling of the influence of specific L2 variables on the outcome variable.

One can think of "random slope models" as regression models with cross-level interaction effects (L1*L2). With cross-level terms, voter characteristics are treated as random variables at the interviewer level. This is to say that coefficients for voter characteristics in estimated models depend on higher-level variables (in this case, interviewers). Also, these cross-level terms allow one to see how interviewers influence nonresponse. In other words, not only does the inclusion of cross-level interaction effects allow one to account for differences across interviewers to estimate better fixed effects, but it also allows modeling such differences as random effects. Accounting for interviewer variation is important to estimate "net" voter and interviewer effects because, for example, an interviewer may be able to elicit more cooperation due to voters in his/her pool whose demographic characteristics make them more likely to participate, whereas a different interviewer may achieve better response rates regardless of voter characteristics.

While models in Table 12 are presented in logit units (i.e., the log of the odds), some of these results are selectively discussed in terms of odds ratios—similar to the discussion above for single-level multivariate models displayed in Table 10. Consequently, it is important to keep in mind that odds ratios derived from logit models in Table 10 will be conditional odds ratios for 1) a voter holding other predictor variables constant and for 2) a voter with the same or an average interviewer (i.e., an interviewer with similar random effects).

Mean-Centering of Predictor Variables in Multilevel Models

Given that the common interpretation of regression coefficients (both fixed effect and random effect models) typically assumes that everything else is held constant (including random effects), L1 and L2 predictors are mean centered on the overall mean of each variable. The literature on regression analyses discusses how different mean centering strategies can have an impact on estimated intercept and slope parameters in multilevel models. That is, while different approaches can be adopted (e.g., grand-mean centering vs. group-mean centering), in general, mean centering techniques make coefficients more interpretable in a multilevel context (Algina & Swaminathan, 2011; Bauer & Curran, 2005; Enders & Tofighi, 2007; Hofmann & Gavin, 1998; Snijders & Bosker, 2012).

In this study, dichotomized variables were grand-mean centered prior to multilevel modeling: voter gender (1=Male, 0=Female), age (1=40 years or more, 0=Less than 40 years), education (1=College, 0=Otherwise), and TV ownership (1=Yes, 0=No). Voter socioeconomic status was not included in multilevel regression models since bivariate analysis suggests that there is no significant variation in the distribution of nonresponse across its levels (Table 5). Furthermore, socioeconomic status did not appear to be a significant predictor in conventional multivariate regression models (Table 10).

Interviewer characteristics were also grand-mean centered: that is, education (1=College, 0=Otherwise), age (1=41 years or more, 0=Less than 40 years), and gender (1=Male, 0=Female). Likewise, ruralness (1=Rural, 0=Nonrural) was grand-mean centered. Mean centering of binary variables allows us to interpret the mean of each variable as the proportion of cases in the sample; for instance, the proportion of voters in the rural group versus the proportion of voters in the nonrural group.

Results of Multilevel Analysis

Random Intercept Model (Model 0)

Table 12 shows the first random intercept model (Model 0, single imputation). This model suggests that voter gender and education seem to have a direct impact on nonresponse (voter gender logit=-0.100, SE=0.04, p <0.05; voter education logit=-0.246, SE=0.05, p <0.05). For gender, it means that a female voter is more likely to refuse than a male voter. For education, it means that a lower educated voter would be more likely to refuse than a higher educated voter, after accounting for variation across interviewers.

Despite the fact that voter age seems to increase the chances of refusing (as suggested by the positive sign of its logit coefficient), the main effect does not reach statistically significant levels (voter age logit=0.041, SE=0.04, p>.10). Yet age appears to significantly interact with education (voter age # voter education logit=-0.451, SE=0.10, p<.001). When analyzing education alone, the coefficient suggests that the odds ratio of a college educated voter refusing to participate compared to a lower educated voter is .78 to 1 [=exp(-0.246)]. However, when the same odds ratio is calculated for an older voter (by means of an interaction term), the odds ratio is .49 to 1 [exp(-0.246)*exp(-0.459)]. The fact that the odds ratio of refusing cooperation decreased for an older college educated voter suggests that education is likely to make an important difference among older voters, net of interviewer effects.

In terms of TV ownership, fixed effects in Model 0 suggest that—as hypothesized—there is a negative relationship between TV ownership and nonresponse (i.e., a person who owns a TV set seems to be less likely to refuse); however, corresponding standard errors indicate that the relationship is not likely to be statistically significant. Moreover, the relationship between TV ownership and nonresponse does not seem to reach statistical significance in any of the models in Table 10.

Random effects in Model 0 (single imputation) indicate that there is significant variability around the constant term (variance of constant=1.294, SE=0.15, p<.001). This suggests that some of the variation in the dependent variable (nonresponse) is likely to be explained by L2 information—the interviewer. Nonetheless, Model 0 does not provide information on which particular interviewer characteristics are likely to have an effect on nonresponse. Thus, additional random slope models are estimated in Model 1 through Model 4, where specific interviewer characteristics are included as predictors of nonresponse.

Table 8. Mixed Effects Logistic Regression Models for Predictors of Nonresponse (Single-Imputed Data)

Predictors	Model 0		Model 1		Model 2		Model 3		Model 4	
Pr (Y=Refusal|x_{ij})	Random intercept model		Random intercept and random slope model (Interviewer Education)		Random intercept and random slope model (Interviewer Education and Interviewer Age)		Random intercept and random slope model (Interviewer Education, Interviewer Age and Interviewer Gender)		Random intercept and random slope model (Intv'r Education, Intv'r Age, Intv'r Gender, and Ruralness)	
	Coef.	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**
Fixed Effects										
Voter Age	0.041	(0.04)	0.022	(0.06)	0.022	(0.06)	0.027	(0.06)	0.034	(0.06)
Voter Education	-0.246***	(0.05)	-0.262**	(0.09)	-0.260**	(0.09)	-0.260**	(0.09)	-0.348***	(0.10)
Voter Gender	-0.100**	(0.04)	-0.106**	(0.04)	-0.106**	(0.04)	-0.090	(0.05)	-0.088	(0.05)
Voter Age # Voter Education	-0.451***	(0.10)	-0.459***	(0.11)	-0.453***	(0.11)	-0.452***	(0.11)	-0.496***	(0.11)
Voter TV Ownership	-0.010	(0.07)	-0.016	(0.07)	-0.016	(0.07)	-0.016	(0.07)	-0.017	(0.07)
Interviewer Education	--	--	-0.218	(0.14)	-0.214	(0.14)	-0.222	(0.14)	-0.215	(0.14)
Interviewer Age	--	--	--	--	0.076	(0.23)	0.114	(0.23)	0.094	(0.23)
Interviewer Gender	--	--	--	--	--	--	0.216	(0.14)	0.241	(0.14)
Ruralness	--	--	--	--	--	--	--	--	-0.276	(0.19)
Voter Age # Interviewer Education	--	--	0.015	(0.13)	0.005	(0.13)	-0.016	(0.13)	0.003	(0.12)
Voter Age # Interviewer Age	--	--	--	--	-0.296	(0.17)	-0.291	(0.17)	-0.319	(0.17)
Voter Age # Ruralness	--	--	--	--	--	--	--	--	-0.282*	(0.13)
Voter Educ # Interviewer Education	--	--	-0.075	(0.18)	-0.078	(0.18)	-0.079	(0.18)	-0.074	(0.18)
Voter Educ # Interviewer Age	--	--	--	--	-0.165	(0.24)	-0.157	(0.24)	-0.148	(0.24)
Voter Educ # Ruralness	--	--	--	--	--	--	--	--	-0.563*	(0.27)
Voter Gender # Interviewer Gender	--	--	--	--	--	--	0.011	(0.10)	0.022	(0.10)
Voter Gender # Ruralness	--	--	--	--	--	--	--	--	0.010	(0.12)
Constant	-0.488***	(0.08)	-0.486***	(0.09)	-0.486***	(0.09)	-0.484***	(0.09)	-0.495***	(0.09)
Random Effects	--	--			--	--				
Var(Voter Age)	--	--	0.313***	(0.06)	0.304***	(0.06)	0.310***	(0.06)	0.296***	(0.06)
Var(Voter Education)	--	--	0.504***	(0.13)	0.501***	(0.13)	0.496***	(0.13)	0.457***	(0.13)
Var(Voter Gender)	--	--	--	--	--	--	0.176***	(0.05)	0.175***	(0.05)
Var(Constant)	1.295***	(0.15)	1.332***	(0.16)	1.336***	(0.16)	1.354***	(0.16)	1.345***	(0.16)
Cov(Voter Education, Voter Age)	--	--	0.131	(0.07)	0.125	(0.07)	0.129	(0.07)	0.106	(0.07)
Cov(Voter Gender, Voter Age)	--	--	--	--	--	--	-0.083*	(0.04)	-0.084*	(0.04)
Cov(Constant, Voter Age)	--	--	0.054	(0.09)	0.053	(0.09)	0.077	(0.09)	0.061	(0.09)
Cov(Voter Gender, Voter Education)	--	--	--	--	--	--	-0.041	(0.06)	-0.059	(0.06)
Cov(Constant, Voter Education)	--	--	0.054	(0.13)	0.055	(0.13)	0.063	(0.13)	0.068	(0.13)
Cov(Constant, Voter Gender)	--	--	--	--	--	--	-0.147	(0.08)	-0.149	(0.08)

* *p*<.05, ** *p*<.01, *** *p*<.001 # Interaction

First Random Slope Model (Model 1)

The first random slope model (Model 1, single imputation) incorporates interviewer education as a predictor of nonresponse. The effect of voter age and voter education on nonresponse may vary across levels of interviewer education. Therefore, interviewer education is included as a main effect in Model 1 as well as the two corresponding cross-level interaction terms: 1) voter age by interviewer education and 2) voter education by interviewer education. Although random effect parameters in Model 1 suggest significant variation of voter age and voter education across levels of interviewer education (voter age variance=0.313, SE=0.06, p<.001; voter education variance=0.504, SE=0.13, p<.001), interviewer education—as a main fixed effect—does not seem to have a significant influence on nonresponse (interviewer education logit=-0.218, SE=0.14, p>.05).

Model 1 indicates that none of the two cross-level interaction terms are likely to be statistically significant (voter age # interviewer education logit= 0.015, SE=0.13, p>.10; voter education # interviewer education logit= -0.075, SE=0.18, p>.10). Furthermore, the inclusion of interviewer education (and its corresponding cross-level interactions) does not seem to fundamentally change the significant interaction between voter age and voter education previously found in Model 0.

Second Random Slope Model (Model 2)

The second random slope model (Model 2, single imputation) includes an additional interviewer characteristic as a predictor of nonresponse: namely, interviewer age. In Model 2, both voter age and voter education vary across levels of interviewer education and across levels of interviewer age. The inclusion of interviewer age in Model 2 adds two more cross-level interaction terms: 1) voter age by interviewer age and 2) voter education by interviewer age. Random effects in this model suggest that there is significant variation of voter age and voter education across levels of both interviewer education and interviewer age (voter age variance=0.304, SE=0.06, p<.001; voter education variance=0.501, SE=0.13, p<.001).

Despite variation in random effect parameters, the fixed effect coefficients in Model 2 indicate that neither interviewer education nor interviewer age is likely to be a significant predictor of nonresponse (interviewer education logit=-0.214, SE=0.14, p>.10; interviewer age logit=0.076, SE=0.23, p>.10). Nonetheless, the model suggests that interviewer age significantly interacts with voter age. While Model 2 indicates that interviewer age appears to help offset the effect of voter age, the relationship does not reach statistical significance (voter age # interviewer age logit=-0.296, SE=0.17, p<.05).

Particularly, Model 2 indicates that the odds ratio of an older voter refusing participation compared to a younger voter is approximately 1.02 [=exp(0.022)] (i.e., slightly higher chances to refuse for an older voter), but when an older voter is approached by an older interviewer, the odds ratio for refusing is reduced to 0.76 [=exp(0.022)* exp (-0.296)] but with no statistical significance. Though interviewer age seems to interact with voter age, interviewer age does not seem to interact with voter education (voter education # interviewer age logit=-0.165, SE=0.24, p>.05).

Third Random Slope Model (Model 3)

The third random slope model (Model 3) adds interviewer gender as a third L2 predictor of nonresponse. In this model, voter gender varies randomly across levels of interviewer gender. Consequently, the corresponding cross-level interaction term is added: that is, voter gender by interviewer gender. The random effect parameters of this model indicate that there is significant variation of voter gender across interviewer gender (voter gender variance=0.176, SE=0.05, p<.001). Similar to previous random slope models (Model 1 and Model 2), fixed effect terms in Model 3 suggest that the chances of refusing participation for a male voter compared to a female voter are lower; however, the relationship is not likely to be statistically significant (voter gender logit=-0.090, SE=0.05, p<.05).

Also, Model 3 (single imputation) suggests that a male interviewer is not significantly more likely to produce higher nonresponse relative to a female interviewer (interviewer gender logit=0.216, SE=0.14, p>.05). Likewise, the non-significant cross-level interaction term suggests that there is no systematic nexus between voter gender and interviewer gender (voter gender # interviewer gender logit=0.011, SE=0.10, p>.05). Interestingly, the non-significant main effect of interviewer gender appears to become relevant once ruralness is taken into account in the fourth model (Model 4), although not at traditional statistical significance levels.

Fourth Random Slope Model (Model 4)

The fourth random slope model (Model 4, single imputation) includes the effect of ruralness on nonresponse. This is the most complex model where the regression equation lets voter age, voter gender, and voter education have random variation across levels of interviewer education, interviewer age, and ruralness at the same time. Random effect parameters of this model suggest that there is significant variability of voter characteristics across interviewer characteristics and across levels of ruralness (voter age variance=0.296, SE=0.06, p<.001; voter education variance=0.457, SE=0.13, p<.001; voter gender variance=0.175, SE=0.05, p<.001).

Since ruralness is included in the model as main effect, three corresponding cross-level interactions are also included: 1) voter age by ruralness, 2) voter education by ruralness, and 3) voter gender by ruralness. Fixed effect parameters in Model 4 indicate that while ruralness may not necessarily be a direct predictor of nonresponse, it is likely to have a significant interaction with voter age. In previous models (Model 1 through Model 3), voter age does not seem to directly predict nonresponse, but it appears to interact with voter education and interviewer age. Thus, not surprisingly, in Model 4, voter age is also likely to interact with ruralness.

Particularly, fixed effects in Model 4 suggest that an older voter has a 3 percent increase in the odds of refusing participation [1.03=exp(0.034)] than a younger voter; yet for an older voter living in a rural area, the possibility of refusing is 22 percent less likely to occur [0.78=exp(0.034)*exp (-0.282)] compared to a younger voter. In other words, it appears that an older voter is significantly less likely to refuse compared to a younger voter when the voter is living in a rural area.

Model 4 also indicates that the effect of voter education on nonresponse is likely to be larger when the voter is living in a rural area. In other words, the odds ratio of refusing participation for a higher educated voter relative to a lower educated voter is .71 to 1 [=exp(-0.348)]. The odds ratio becomes statistically lower (0.4 to 1 [=exp(-0.348)*exp(-0.563)]) when the same higher educated voter (vs. a lower educated voter) lives in a rural area.

Unlike the immediately previous model (Model 3), where ruralness is not accounted for (and which suggested no direct effect of interviewer gender), the model that takes into account ruralness (Model 4) indicates that interviewer gender may matter. Namely, coefficients in Model 4 suggest that a male interviewer has a 27 percent increase in the odds of producing a refusal [1.27=exp(0.241)] when compared to a female interviewer, but the statistical test does not reach significance at conventional levels (i.e., $p<.05$). In terms of voter gender and ruralness, Model 4 does not suggest an interaction between the two (i.e., voter gender # ruralness logit=0.010, SE=0.12, $p>.10$).

To offer a succinct view of results from analyses conducted in this section, a summary of main findings follows. These findings are presented in light of existing studies on exit polling nonresponse.

Findings

Nonresponse in election day surveys has been a concern over the past two decades in the methodological literature, yet empirical research on individual mechanisms of refusals has been scant. Scholars have discussed different theories to explain exit polling nonresponse, but data on nonrespondents are practically nonexistent due to the fact that election day surveys are conducted in transient populations (i.e., voters leaving voting stations as they cast their votes), making it almost impossible to develop follow-up procedures in a timely manner.

Unlike traditional approaches that have relied on community-level data to establish differences across respondents and nonrespondents, this study offers an alternative method to understand the socio-psychological mechanisms of nonresponse using individual-level data. Using model-based data with a fully conditional approach, plausible values are generated for nonrespondents on key characteristics: namely, education, socioeconomic status, TV ownership, and telephone service. Under this novel and practical approach, a proof-of-concept study with a single-imputed dataset was conducted to investigate hypothesized relationships. These model-based data were explored with bivariate, multivariate, and multilevel models.

Finding 1: Voter Age

Building on existing socio-psychological literature for survey methodology (Groves & Couper, 1998; Schwarz, 1999; Schwarz et al., 1998), H1 hypothesized that as voters age, they experience a cognitive decline, become less engaged in societal events, and ultimately become socially isolated. Presumably, lessened cognitive abilities affect people's capacity to engage in social activities, including election day surveys. Nonetheless, as pointed out by Merkle and Edelman (2002), participation in an election already indicates participation in a societal event. This means that age may not be necessarily a direct predictor of exit polling participation.

Previous empirical research has found that older voters tend to participate at lower rates than younger voters in exit polls (Brown et al., 2004; Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2000, 2002; Stevenson, 2006). Results from this study, however, suggest that voter age—as main effect—does not appear to directly predict exit polling participation when controlling for other voter and interviewer characteristics. Instead, the analysis suggests that voter age plays an indirect effect on nonresponse.

To be specific, initial explorations suggest that the effect of the voter's age on nonresponse is mediated by different factors. Particularly, the effect depends on 1) whether the exit poll takes place in a rural context, 2) the interviewer's age, and 3) the voter's level of education. Findings about these interactions—which were proposed as part of the set of hypotheses—are summarized in their corresponding sections below.

Finding 2: Voter Education

Drawing on cognitive theories and aspects of survey methodology, H2 hypothesized that more educated voters are more capable than lower educated voters to process cognitive demands and engage in cognitive challenges (Ceci, 1991; Kaminska et al., 2010; Krosnick, 1991; Krosnick & Alwin, 1987, 1988; Narayan & Krosnick, 1996). Consequently, it was hypothesized that voters with higher levels of education are less likely than lower educated voters to decline an invitation to participate in an exit poll.

Previous research on exit polling nonresponse has either used aggregate-level demographic estimates to compare against exit polling demographic data at the precinct level, or used self-reported intentions of exit polling participation collected in telephone and opt-in web-based surveys (Merkle & Edelman, 2000; Panagopoulos, 2013). These approaches in the literature have not been able to provide support to the hypothesis on education effects.

The present study (using individual-level approximate values for nonrespondents' educational attainment from a single imputation) suggests that voter education is likely to have an effect on nonresponse. Analyses indicate that education—as a main effect and net of other L1 and L2 factors—may be a plausible mechanism responsible for exit polling nonresponse. Particularly, higher educated voters are less likely to refuse cooperation relative to lower educated voters. Furthermore, this study suggests that the influence of education is stronger in rural contexts.

Finding 3: Voter Age by Voter Education

H3 hypothesized that both voter age and voter education are socio-demographic characteristics associated to the ability to perform demanding cognitive skills, including the ability to answer surveys. Thus, it was hypothesized that a lessened cognitive capacity due to aging could be offset by higher levels of education. The literature reviewed revealed a dearth of knowledge about this important interaction term, largely because data on voter education for nonrespondents are typically not available.

Using individual-level plausible data on voter education for nonrespondents and consistent with expectations, results suggest that among older voters, highly educated voters would be less likely to refuse an invitation to cooperate compared to lower educated voters. However, among younger voters, highly educated voters are just as likely to refuse as lower educated voters. In other words, education is likely to make an important difference among older voters but not necessarily among younger voters, net of other voter and interviewer predictors.

Finding 4: Voter Education and Interviewer Education

Building on interviewer effects literature, H4 hypothesized that exit poll cooperation is higher when voters and interviewers share background characteristics (Bateman & Mawby, 2004; Cannell et al., 1981; Schaeffer, 1980; Schuman & Converse, 1971). Theoretically, individuals are more likely to comply with requests from liked others (Groves & Couper, 1998). Consequently, it was hypothesized that voters with higher levels of education (relative to voters with lower levels of education) are less likely to refuse if an interviewer with higher levels of education makes the request to participate. However, voters with lower levels of education are as likely to refuse cooperation irrespective of the interviewer's levels of education.

Analyses from this study do not to support the hypothesized interaction between voter education and interviewer education. Interviewer education—either as a main effect or moderator effect—does not seem to have an effect on nonresponse. In previous sections, it was discussed that voter education as a main effect appears to be a significant predictor of nonresponse; however, the non-significant interaction term between voter education and interviewer education suggests that the influence of voter education on nonresponse does not depend on the level of the interviewer's education, net of other voter and interviewer variables.

The non-significant interactivity between voter education and interviewer education found in this study may be due to several reasons. First, it may mean that the similarity of background hypothesis is not helpful to explain nonresponse in the context of exit polls. However, a more plausible explanation involves the way exit polls are implemented. Typically, field representatives conducting exit polls are encouraged (and some instances required) to dress in a particular manner for a standardized appearance.

In the case of the analyzed 2006 exit poll data, surveyors were instructed to wear white clothing (i.e., vest, cap, bag, and portable ballot box) featuring the survey agency logo and an identification badge. Thus, it is possible that sample voters were not immediately able to form a judgment on the interviewer's educational background with standardized clothing as it would be possible with other more visible characteristics of interviewers, such as age or gender. Results from this study leave room for future experimental research in exit polls.

Finding 5: Voter Socioeconomic Status

Social and psychological theories have proposed that underclass groups do not feel part of the mainstream group in society. Conceptually, those who do not share the norms of the society are less likely to engage in social exchanges, and they tend to modify their attitudes toward social requests, including participation in surveys (Groves & Couper, 1998). In H5 we hypothesized that voters who regard themselves as low-level socioeconomic class may be more likely than voters who regard themselves as middle- or middle-upper class to refuse cooperation.

Neither bivariate analysis nor single-level multivariate analyses offered supporting evidence for this theoretical notion. In light of non-significant results from preliminary analyses, unnecessary complexity in the multilevel regression models was circumvented and socioeconomic status was not included. The lack of significant results for the “underclass” hypothesis suggests that this concept may not be as predictive as anticipated in the literature. That is, voters already participating in a societal event (i.e., an election) may not feel completely excluded from society, and their socioeconomic status is not likely to play a role on refusing participation. Nonetheless, further exploration of socioeconomic status in more robust multilevel models (with multiple imputed data) are presented elsewhere (Bautista, 2015).

Finding 6: Voter Ruralness

Theories of social participation have proposed that spontaneous actions aimed to help others (i.e., helpful behavior) are more likely to occur in rural contexts (Amato, 1983, 1993; House & Wolf, 1978; Wilson & Kennedy, 2006). Also, previous empirical research on exit polling suggests that ruralness is a moderator variable for the effect of voter age on nonresponse (Bautista et al., 2006). Consequently, H6 hypothesized that voters living in rural areas are less likely than city dwellers to refuse participation. Furthermore, it was hypothesized that older voters living in rural areas are disproportionally less likely than older voters living in non-urban areas to refuse cooperation.

As expected, the analysis indicates that ruralness mediates the effect of voter age. Specifically, results suggest that while voter ruralness is not a direct predictor of nonresponse, ruralness seems to interact with voter age, net of other voter and interviewer variables. In other words, an older voter appears to be less likely to refuse an invitation to participate compared to a younger voter when the voter is living in a rural area. Also, results suggest that ruralness interacts with voter education. That is, a higher educated voter appears to be even less likely to refuse participation (compared to a lower educated voter) when the voter lives in a rural context.

Finding 7: Voter Social Connectedness

H7 hypothesized that voters with reduced social connectedness are less likely than voters with better social connectedness to accept a request to participate in an exit poll. Particularly, it was hypothesized that TV owners are less likely than non-owners to decline participation. Similarly, it was hypothesized that voters with a telephone are less likely to refuse compared to voter with no access to a telephone.

Results from single-level bivariate and multivariate analyses indicate that telephone service is not likely to be related to nonresponse. Consequently, telephone service was not included in multilevel models to avoid unnecessary complexity. Nonetheless, the effect of access to telephone service should be re-examined with more robust models (multiply imputed data).

Similar to single-level results, multilevel models suggest that TV ownership is not predictive of nonresponse. Consequently, results from this study suggest that the social connectedness hypothesis may not be helpful to explain nonresponse among people already participating in a societal event (i.e., an election).

Finding 8: Voter Gender

While empirical analyses in the exit polling literature show mixed results on the effect of voter gender on nonresponse, hypotheses of gender roles in society—as applied to survey participation—propose that women are less likely than men to decline an invitation to participate in a survey (Groves, 1990; Groves & Couper, 1998). Consequently, H8 hypothesized that women are less likely than men to refuse cooperation in an exit poll.

Although the direction of regression coefficients suggests that male voters tend to be more likely to cooperate than female voters, net of voter and interviewer factors, this relationship does not appear to be statistically significant. In terms of interviewer gender, the theoretical framework was agnostic regarding such direct effects on nonresponse. Results suggest that a male interviewer tends to be more likely to produce refusals that a female interviewer, but the relationship is not statistically significant. Despite trends in main effects of voter and interviewer gender, there is no significant interaction between voter gender and interviewer gender. In other words, a male interviewer who tends to produce refusals does not appear to make a male voter who tends to participate, less likely to participate. Bautista (2015) furthers the exploration of gender effects with more robust models (i.e., multiply imputed data).

Finding 9: Voter Age by Interviewer Age

Drawing on theories proposing that fear and suspicion of strangers is one of the primary mechanisms responsible for survey nonresponse (Merkle & Edelman, 2002), H9 hypothesized that fearful voters (defined as older voters) are less likely than confident voters (defined as younger voters) to answer positively to an exit poll request when approached by a person who appears to be threating in any way (in this case, defined as a younger interviewer). Thus, it was proposed that older voters who are interviewed by younger interviewers are more likely to refuse cooperation relative to older voters interviewed by older interviewers. However, younger voters are equally likely to participate in an exit poll irrespective of the interviewer's age.

Results from this initial examination indicate that this appears to be the case. The analysis conducted suggests that older voters who are interviewed by younger interviewers seem to be more likely to refuse cooperation in an exit poll relative to older voters interviewed by older interviewers. In other words, when a vulnerable voter (older voter) is approached by a non-threatening interviewer (older interviewer) the chances of refusing seem to reduce, although with marginal statistical significance, net of other voter and interviewer factors.

Discussion

The examination of datasets in the present study provides insights into the socio-psychological theories of nonresponse in exit polls. It points to the importance of studying individual-level mechanisms of nonresponse. The proof-of-concept approach allowed us to approximate information from nonrespondents that otherwise would be unknown. Importantly, this approach allowed us to expand modeling choices and offered a different perspective to explore hypothesized relationships.

These results identified trends previously unknown in the exit polling literature (for instance, a possible direct and indirect effect of voter education and the mediating effects of voter age on exit polling nonresponse). Results obtained in this initial analysis (based on one imputation only, m=1) are consistent with theoretical expectations—suggesting that this approach may offer a viable solution to examine nonresponse in exit polls. However, the reader is referred to a more robust examination, where an expanded view on the analysis of exit polling nonresponse with multiply imputed data (m=30) and with additional predictors at the voter and interviewer level is presented (see Bautista (2015)).

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