AN EXAMINATION OF SOURCES OF ERROR IN EXIT POLLS: NONRESPONSE AND MEASUREMENT ERROR

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AN EXAMINATION OF SOURCES OF ERROR IN EXIT POLLS:

NONRESPONSE AND MEASUREMENT ERROR

by

René Bautista

A DISSERTATION

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AN EXAMINATION OF SOURCES OF ERROR IN EXIT POLLS:

NONRESPONSE AND MEASUREMENT ERROR

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This dissertation 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 participate, there is no practical way of contacting them to collect information in a timely manner. Using a proof-of-concept approach, this study explores a unique dataset that links information of respondents, nonrespondents, interviewer characteristics, as well as precinct-level information. Using this information, model-based plausible information is generated for nonrespondents (i.e., imputed data) to examine nonresponse dynamics. These data are then analyzed with multilevel regression methods. Nonresponse hypotheses are motivated by literature on cognitive abilities, cognition and social behavior.
Results from multiply imputed data and multilevel regression analyses are consistent with hypothesized relationships, suggesting that this approach may offer a way of studying nonresponse where limited information exists. Additionally, this dissertation explores sources of measurement error in exit polls. It examines whether the mechanisms likely to produce refusals are the same mechanisms likely introduce error once survey cooperation is established. A series of statistical interaction terms in OLS regressions —motivated by social interactions between interviewers and respondents— are used to explore hypothesized relationships. Overall, this research finds that cognitive mechanisms appear to account for voter nonresponse, whereas social desirability mechanisms seem to explain exit polling error.
DEDICATION

To Erika Martinez, without whom this dissertation would simply not exist.

To my children Alan Ernesto, Valeria and Adela, who by constantly asking me “Dad, can we play?” kept me focused on the end goal. I love them very much.
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CHAPTER 1: INTRODUCTION

Unlike other types of social surveys, surveys conducted the day of the election using “a sample of voters exiting a collection of polling places” (Scheuren & Alvey, 2008, p. 4), also known as exit polls, may have a strong influence on many people’s trust in the democratic system. Exit polls have vigorously monitored many electoral processes around the world and rapidly have become critical instruments to develop political accountability. Exit polls have helped journalists and scientists to understand the “mandate” of elections (Frankovic, 2008; Hilmer, 2008; Lavrakas, 2007; Mitofsky, 2004); however, they have also been a source of controversy in electoral results (Moore, 2006; Tello-Díaz, 2006). As Welch, Gruhl, Comer and Rigdon (2009, p. 59) observe, “Election Day exit polls are ubiquitous and controversial features of media coverage.”

As election day surveys become relevant measurement instruments in democratic societies, survey methodologists face the challenge of better understanding voters’ exit polling participation (Edelman & Tucker, 2008; Feinberg, 2007; Mitofsky, 1991, 2004, 2006; Mitofsky & Edelman, 2002). There is an increasing need in the field to understand predictors of participation and accuracy in exit polls. Consequently, critical survey design elements of exit polls need to be studied (Frankovic, 2008; Lavrakas, 2007; Scheuren & Alvey, 2008).

In particular, exit polling elements such as interviewer and respondent characteristics as well as election day factors have been a subject of interest in the research literature (Biemer et al., 2003; Edison Media Research and Mitofsky International, 2005; Frankovic, 2008; Merkle & Edelman, 2000; Traugott, Highton, & Brady, 2005). For instance, after the 2000 United States Presidential election, when mainstream broadcasters mistakenly announced the winner of
Florida’s 25 electoral votes (Frankovic, 2003; Mitofsky, 2003; Mitofsky & Edelman, 2002; Welch et al., 2009), the Research Triangle Institute (RTI) conducted in 2003 a methodological review of the procedures and operations used by the Voter News Service (VNS) to estimate the outcome of the election (Biemer et al., 2003; Mitofsky, 2003). RTI’s 2003 investigation expressed concerns about the decline of average state-level response rates in U.S. exit polls: 60% in 1992, 55% in 1996, and 51% in 2000 (Biemer et al., 2003; Mitofsky, 2003).¹ RTI’s recommendations included launching an ongoing research program to increase exit poll response rates and to enhance the quality of the interviewers’ behavior. Overall, the ultimate concern of unit nonresponse (i.e., people who choose not to participate in a survey) in RTI’s report is about the potential bias that can be introduced into a survey estimate.

The importance of exit polls is well illustrated in the 2000 and 2006 Mexican Presidential elections, where exit polls played an important role in the credibility of the electoral result. In particular, in the year of 2000, after a 70-year period of the same party in power (Institutional Revolutionary Party, PRI), media-sponsored exit polls contributed to the stability of the country on election night by projecting correctly, and in a timely manner, the victory of the challenger party. Contrary to the stability provided by exit polls in the year of 2000 in Mexico, in the 2006 Presidential election, exit polls were a source of great confusion on election night and afterwards (Bautista, Morales, Abundis, & Callegaro, 2008e; Schedler, 2007; Tello-Díaz, 2006). In 2006, the official count took several weeks to be delivered and the final outcome was with a margin difference of roughly a half of one percentage point. While the media-sponsored exit polls conducted in 2006 did not call results at the end of the election day, party-sponsored exit polling

¹ABC reported further national-level response rates based on Edison Media Research documents: 53% in 2004 and 44% in 2008 (Langer, 2009).
results filled the vacuum with opposing projections of the winner. It was unclear what led to conflicting results in the announced party-sponsored exit polls (Tello-Díaz, 2006).

There are other instances that help illustrate the role of exit polls in democracies around the world. For example, in the 1992 British General election, exit polls also played a major role when they failed to correctly project the composition of the English Parliament amidst a major economic recession (Butler & Kavanagh, 1992; Payne, 2003). In the 2004 Ukrainian Presidential election, exit polling projections were at the center of the single most controversial election in Ukraine’s history when the country was deciding between a more pro-European orientation and development of democracy, or a more pro-Russian orientation with a more authoritarian government (Bautista, Callegaro, Paniotto, Kharchenko, & Scheuren, 2008; Hesli, 2006).

Likewise, in the 2004 Venezuelan referendum on the continued tenure of President Hugo Chavez, exit polls played a significant role in the middle of social division and political distrust. Exit polling results generated the impression that the official outcome was going to be different than what, in the end, it turned out being (McCoy, 2006).

Common to politically intense situations like these is that exit polling results have been—to a considerable extent—even more contentious due to methodological limitations of exit polls themselves. As mentioned before, a driving force in the controversy over exit polls is the number of voters who refuse to participate, and the differential response patterns collected among those who accepted to participate.

Despite the fact that there is some evidence suggesting that the exit polling error may not necessarily be a function of exit polling response rates (Bautista, Callegaro, Vera, & Abundis, 2007; Blumenthal, 2005a; Merkle & Edelman, 2000, 2002; Mitofsky, 2005), it is unclear why some selected voters do not accept a request to participate in an exit poll survey. Available
studies suggest that some voter characteristics tend to correlate with nonresponse. Particularly, older voters seem to refuse to participate more often than younger voters (Merkle & Edelman, 2002); however, it is unknown whether voter education is also likely to have an effect on nonresponse; or if voter education offsets the effect of age.

The limited research conducted on nonresponse error in the context of exit polls leaves a great deal of uncertainty about the causes and effects of nonresponse in election day surveys. In addition to nonresponse, election day factors, respondent and interviewer effects also have been characterized as a source of errors in exit polls. The evidence about the effects of such sources of error on exit polling accuracy is sparse and mainly concentrated in studies of the United States (Lindeman & Brady, 2006).

The present study is an attempt to contribute to our understanding of sources of error in exit polls; particularly, nonresponse and measurement error. This research is based on the examination of exit polling collected in Mexico in 2006 and 2009 (survey design elements of such exit polls are described in Chapter 3). Election day survey principles and strategies in Mexico are remarkably similar to exit polling methodologies used in other democracies, which follow pioneering methodologies developed by Warren Mitofsky (Mitofsky, 1991, 1993, 1994, 2000). Consequently, it is reasonable to discuss and build on the existing exit polling literature developed in countries around the world, mainly in the United States.

In spite of differences related to cultural, educational and governance-system aspects across democracies, exit polling methodologies are commonly characterized by three stages (Scheuren & Alvey, 2008 p. 10):

1) Interviewer-respondent phase (i.e., approaching and interviewing of every k-th voter leaving from voting stations),
2) interviewer/data-entry personal phase (i.e., transmission of collected data from the field to the data entry facilities by means of speedy communication technologies) and,

3) data analysis phase (i.e., preparation of statistical results to be presented at the end of the election day).

These three stages were present in the Mexican exit polls analyzed in this dissertation, adding to the external validity of the research. Thus, the identification of systematic sources of error in the 2006 and 2009 Mexican election day surveys will hopefully shed light on the mechanisms of measurement error and nonresponse in exit polls.

To establish to what extent exit polling estimation is accurate, a quality measure has been typically used in the literature. This measure of accuracy has often been referred to as “Signed Error” and more recently as “Within Precinct Error” (WPE) (Bautista et al., 2007; Edison Media Research and Mitofsky International, 2005; Liddle, 2005; Lindeman, Liddle, & Brady, 2006; Merkle & Edelman, 2000, 2002). This precinct-level metric (detailed in Chapter 6, Section “A Note on Within Precinct Error”) is essentially calculated by taking the difference between the exit poll estimate of vote choice and the official count at the precinct level. Available data for this research makes it possible to estimate such a measure in the Mexican case.

Researchers have used the WPE to investigate the effect of election day factors, respondent characteristics, and interviewer effects on exit polling accuracy. Nonetheless, these studies have been limited to bivariate analyses. A literature review (Chapter 2) reveals a dearth of multivariate studies devoted to understand the determinants of Within Precinct Error in exit polls. The few multivariate studies dedicated to understand nonresponse and measurement error in vote choice surveys have been mostly conducted in the context of pre-election surveys. The purpose and design of pre-election surveys differ from those in exit polls (i.e., exit polls focused
on self-reported immediate past behavior, while pre-election surveys measure future intention).

Despite differences between pre-election surveys, or other surveys (i.e., household surveys) and exit polls, the literature review will examine useful findings in the survey literature to help layout the theoretical framework. That is, this study will build the theoretical framework based on relevant research in the survey methodology field.

The overarching goal of the current research is to contribute to the understanding of sources of nonsampling error in exit polls. This investigation will provide a unique perspective of such sources of error by making use of exit polling datasets available for analysis from the Mexican case. Importantly, the analysis will link information of respondents, nonrespondents, interviewers, election day factors, external demographic information, and actual outcomes. Linked information is briefly introduced as part of the research objectives (in the section immediately below) and further detailed through this study.

**Research Objectives**

This investigation stems from previous methodological research on exit polls (Bautista, Callegaro, Vera, & Abundis, 2006; Bautista et al., 2007; Bautista, Morales, Abundis, & Callegaro, 2008a; Edelman & Tucker, 2008; Frankel, 2002; Merkle & Edelman, 2000, 2002; Merkle, Edelman, Dykeman, & Brogan, 1998; Mitofsky & Edelman, 1995, 2002). The general focus is on examining sources of nonsampling error in election day surveys, with a specific focus on nonresponse and measurement error. The “Total Survey Error” paradigm informs the general approach of the present study (Biemer & Lyberg, 2003; Groves, 1989; Krosnick et al., 2002; Merkle & Edelman, 2000; Weisberg, 2005a, 2005c).
The vast majority of studies on nonresponse and measurement error have focused on household, telephone, mail, and internet-based surveys (e.g., Biemer & Trewim, 1997; Dillman, Smyth, & Christian, 2008; Fricker, Galesic, Tourangeau, & Yan, 2005; Groves, Dillman, Eltinge, & Little, 2002; Groves & Peytcheva, 2008; Keeter, Miller, Kohut, Groves, & Presser, 2000; Moreno & Parás, 2010; Olson, 2006). A more limited number of studies have examined sources of error in the context of election day surveys (Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2002; Merkle et al., 1998; Mitofsky & Edelman, 1995). Consequently, this study adds evidence from the exit polling perspective to a developing literature suggesting that nonsampling error could be partly explained by norms and expectations governing human interactions taking place at the moment of contact and interviewing. More specifically, sources of error in exit polls are likely to be the product of an interaction between interviewers’ characteristics and voters’ cognitive abilities and perceptions.

While the major objective of this research is to examine sources of error in exit polls, it is recognized that the notion of sources of error can be fairly broad (Groves, 1989); therefore, a specific focus on two sources is proposed for this research: nonresponse and measurement error. Such focus is expressed in three specific objectives.

**Objective I: Nonresponse Error**

The first objective is to examine the reasons that lead some participants to refuse to participate in an exit poll interview. The aim is to identify the likely socio-psychological mechanisms of nonresponse in election day surveys by focusing on the effect of respondent and interviewer characteristics, and election day factors on participation. Given that voter and interviewer characteristics serve as proxy measures to study hypothesized effects due to
cognitive factors (as it will be discussed through this investigation), this dissertation will examine voter characteristics such as age, education, gender, voter socioeconomic status, voter TV ownership, voter telephone service, voter time of day for voting, and voter ruralness. Likewise, interviewer characteristics considered for analysis are age, education, gender, previous exit polling experience and average interview length.

Election day factors are also considered for this objective as there might be elements beyond the researcher control having an effect on nonresponse. These factors refer to interviewer distance from voting station, whether interviewer monitored more than one exit at the voting station, and whether the interviewer had problems with election officials. Additionally, type of election (i.e., Congressional or Presidential) is considered in analysis. Given the hierarchical nature of the data (i.e., voters nested within interviewers), the analyses take into consideration multilevel models (also known as mixed models).

**Objective II: Measurement Error**

The second objective is to investigate the relationship that exists between nonresponse, measurement error and the Within Precinct Error (WPE). The focus is on the nexus between WPE and nonresponse accounting for election day factors, interviewer and respondent characteristics. Importantly, the primary goal is to investigate whether psychological and behavioral mechanisms governing interpersonal relations (i.e., social desirability hypotheses) are likely to account for measurement error.

Further, election day factors as well as interviewer and respondent characteristics that were described in Objective I are also used in Objective II. However, additional concepts are considered to investigate measurement error as part of the second objective. These additional concepts include interviewer political preference, whether the interviewer thinks that the
meaning of questions in the exit poll questionnaire are clear and whether the interviewer has
doubts on how to apply exit poll questionnaires,

Furthermore, concepts explored as part of this objective are related to operational aspects
that may occur during the actual data collection process in the field and that are not completely
covered or anticipated before the exit poll; namely, whether the interviewer preferred his or her
own script to interact with voters during the process, and whether the interviewer received
training prior to the exit poll. Likewise, it is considered whether the interviewer had previous
experience in households and exit poll surveys, whether the interviewer noticed conflicts at the
voting station on election day, and whether the interviewer was asked by poll worker or party
representative to stop any exit polling activity or asked to show an interviewing permit.

**Objective III: Statistical Adjustments – Multiple Imputation**

This objective is twofold. First, it explores whether innovative statistical strategies (i.e.,
imputation methods) would have any discernible impact on the estimation of vote choice
compared to traditional statistical methods (i.e., list-wise deletion and class weighting), in the
presence of nonresponse. Ultimately, the aim is to determine if multiple imputation helps
improve accuracy of exit polls relative to a complete-case analysis approach (i.e., list-wise
deletion) and relative to a class-weighting approach.

The second purpose of this objective is to assess whether a statistical approach based on
imputations of each missing datum corresponding to sample voters who chose not to participate
in the exit poll helps *approximate* the relationship between unobserved data and available
information. This approach will make extensive use of demographic information corresponding
to nonrespondents that was recorded by observation alone (i.e., age and gender) and information
from actual respondents (i.e., age, education, gender, socioeconomic status, ownership of a TV set, access to telephone service, access to a cellular phone, ownership of a computer, access to internet service, time of day for voting, party preference).

Also, external sources of information given at the aggregate level are used to approximate values for nonrespondents; namely, proportion of actual votes for major parties, educational attainment of the adult population (i.e., proportion of the population with primary education, lower and upper secondary education and college education), proportion of the adult population with health coverage and distribution of gender in the adult population.

**Significance of the Study**

Despite the limited research on exit polling methodology, exit polls have proven to be influential in both emergent and advanced democracies, and are used extensively around the world (e.g., Bautista, Callegaro, et al., 2008; Frankovic, 2008; Hilmer, 2008; Hofrichter, 1999; Lavrakas, 2007; Mitofsky, 2004; Moon, 1999; Warren, 2003; Wright, 2004). Common to countries having democracy as their system of governance is that public opinion research has helped develop political accountability. In consequence, exit polls have become an extremely valuable asset to collect information on actual voters. Not only are exit polls a powerful tool to help project the winner of elections on election night, they also are powerful instruments to help us understand why voters say they cast the ballots the way they do on election day (Frankovic, 2003, 2008; Mitofsky, 1991).

To this point in history, exit polling remains the fastest and most reliable method for gathering information on actual voters’ opinions, attitudes and choices on election day, even after incorporating other supplementary data collections methods such as landline and cell phone
surveys (Eagly & Steffen, 1984; McDonald & Thornburg, 2012). Overall, exit polls have a good record for accuracy in their predictions. Nonetheless, such a good record does not mean exit polls are flawless mechanisms to estimate electoral outcomes (Mitofsky, 2006; Moore, 2006). On the contrary, there are sources of error not fully understood that can jeopardize the accuracy of exit polling results on election night.

In the context of election day surveys, progress has been made in showing that response rates are related to respondent and interviewer characteristics, as well as to election day factors at the precinct level. Particularly, empirical studies indicate that voter age and voter gender seem to be related to nonresponse. Also, interviewer age and education have been hypothesized to have an effect on nonresponse (Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2000, 2002; Stevenson, 2006). What it is unclear to date, however, is the socio-psychological mechanisms at the individual level that explains nonresponse and measurement error.

The lack of such knowledge is an important problem, because by understanding and evaluating such mechanisms, we may be able to begin to understand the effects of nonresponse in exit polls. In addition, survey researchers will be able to modify existing survey methodologies to improve exit polling accuracy. The findings of this research will contribute to a growing literature on exit polling methodology, with a goal of helping exit poll researchers adjust current methodologies, and creating more effective strategies to gather high quality exit polling data.
Significance of Objective I: Nonresponse

Overall, nonresponse may be more of a problem to the extent that sample persons who refuse to participate represent a larger number relative to those who do participate, and to the extent that nonrespondents differ from respondents on the statistic of interest (Groves, 1989; Groves & Peytcheva, 2008). The consequence of nonresponse could conceivably represent predictable systematic departures of the estimated value from the “true” value (i.e., bias), or variations over expected realizations of the estimates in multiple trials under the same survey conditions (i.e., variance) (Groves, 1989, 2006; Groves & Couper, 1998; Leslie Kish, 1965; Lessler & Kalsbeek, 1992).

When the probability of accepting the survey request is related to the statistic of interest, the survey estimate corresponding to those who accepted the request could be different from values that correspond to those who refused to participate, introducing bias to a survey statistic (Groves, 2006; Groves, Presser, & Dipko, 2004; Messonnier, Bergstrom, Cornwell, Teasley, & Cordell, 2000). In the context of exit polls, the relationship between nonresponse (i.e., the probability of declining an exit polling request) and vote choice has not been fully understood.

The limited research available on election day surveys has examined the relationship between election day factors, interviewer and respondent characteristics, and response rates at the aggregate level. Particularly, voter age and voter gender as well as interviewer age have been found to be likely predictors of nonresponse (Merkle & Edelman, 2000, 2002; Merkle et al., 1998). Nonetheless, there is clearly a limitation on studies using multivariate modeling devoted to explore nonresponse and its covariates at the micro level (i.e., the voter level). A methodical, multivariate study of the mechanisms of nonresponse in exit polls is needed to better understand and predict nonresponse.
**Significance of Objective II: Measurement Error**

Measurement error refers to departures of “estimates” from “true parameters” due to specific aspects of the survey design. When a systematic correlation of errors between units of observation exists because of factors such as interviewers, coders, questionnaire features, question wording, mode of data collection, timing, sponsorship, subject matter, among others, a bias may be observed in a statistic of interest. Furthermore, even if no systematic correlation of errors exists between sample members (as a by-product of survey design elements that can potentially change the estimates in one direction), the sole presence of measurement error may yield to an increase of variance in a survey estimate, under the same survey conditions (Alwin, 2007, 2010; Biemer & Lyberg, 2003; Biemer & Trewim, 1997; Groves, 1989; Groves, Fowler, et al., 2004; O'Muircheartaigh, 1977; O'Muircheartaigh & Campanelli, 1999).

Sources of measurement error can be studied by comparing survey estimates (i.e., data from self-reports) with measures of quality or “gold standards.” There are relatively few opportunities to gain access to population-based “gold standards.” Usually quality measures take the form of re-interviewing methods of sample members, previously validated surveys, theoretical or mathematical representations of the estimates of interest, and external records of actual results (Alwin, 2010; Biemer & Lyberg, 2003; O'Muircheartaigh, 1977; Peytchev & Peytcheva, 2007; Ypma, 2007). In the context of exit polls, researchers have taken advantage of official results of the election at the precinct level as a way to generate population-based “gold standards” (Edison Media Research and Mitofsky International, 2005; Mitofsky, 1991).

A very limited number of studies in the literature of exit polls have examined sources of measurement error such as interviewer and respondent characteristics, election day factors in reference to the **Within Precinct Error (WPE)**. Although a more extensive elaboration of WPE is
provided in Chapter 6, where WPE data are analyzed, here the formula is briefly introduced. WPE has typically been described as the difference of differences between the leading candidate in the exit poll and the actual vote for sample precincts. In its basic form, the WPE equation in the literature is as follows:

\[
WPE = (D_v - R_v) - (D_p - R_p)
\]

Where \(D_v\) and \(R_v\) represent actual vote percentages of the two main contenders (e.g., Democrats and Republicans), and \(D_p\) and \(R_p\) represent percentages derived from exit polling results. This measure has also been referred to as “signed error” because WPE can take positive or negative values to indicate over- or sub-estimations using exit polling results (Bautista et al., 2007; Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2002).

For the most part, the known relationships of measurement errors with the WPE are limited to bivariate analyses (Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2000; Merkle et al., 1998). A thorough multivariable examination of the factors that jointly explain WPE is needed to better understand mechanisms that predict exit polling error.

**Significance of Objective III: Imputation Methods**

Total (unit) nonresponse (i.e., the refusal by a sample person to participate in a survey) represents a challenge to survey statisticians to the extent that it may introduce bias or increase the variance in a survey estimate (Groves, 1989, 2006; Leslie Kish, 1965; Lessler & Kalsbeek, 1992). Traditionally, statistical nonresponse adjustments seek to reduce the bias due to nonresponse but at the expense of increasing the variance (Brick & Kalton, 1996; Kalton, 1983; Kalton & Flores-Cervantes, 2003; Kalton & Kasprzyk, 1982; cf. Little & Vartivarian, 2005).
Nonresponse weighting methods typically are based on class or cell weighting; that is, respondents and nonrespondents are classified into several groups using auxiliary information (e.g., socio demographic characteristics) such that respondents are weighted up or down to account for the lack of information that was not obtained from nonrespondents on the statistic of interest (Kalton & Flores-Cervantes, 2003). These adjustment methods rely on the assumption that nonrespondents are fundamentally not different from respondents in the statistic of interest given the auxiliary information—a notion that corresponds to the “Missing at Random” assumption (MAR) discussed by Little and Rubin (2002). Due to the assumptions made by class weighting methods on nonresponse adjustments, such methods can be regarded as deterministic in nature (Kalton, 1983).

In the context of exit polls, weighting methods have been typically used to compensate for nonresponse. However, stochastic methods such as multiple imputation have not been used or investigated to compensate for nonresponse in the context of exit polls. Multiple imputation, originally proposed by Donald Rubin (1976, 1977, 1987), is a model-based approach to account for nonresponse that assigns plausible values for missing data conditional on observed data. Unlike traditional weighting methods, multiple imputation methods take into account the uncertainty associated with the fact that actual data from nonrespondents were not collected.

Multiple imputation techniques can help generate approximate values of what the data might have been had they been observed. A model-based simulation of missing data to study correlates of nonresponse and measurement errors would help us to better understand likely causes of such missingness. Consequently, an examination of alternative adjustment methods such as multiple imputation would (i) help account better for nonresponse in survey estimates
and (ii) help approximate the relationship between refusals and predictors to explore plausible mechanisms responsible for nonresponse.

**Political Context**

Election day surveys in Mexico have largely performed a political function more than a media-related function. In other democracies, such as the United States, the media have shaped the role of exit polling. There are key political events that frame the development of exit polls in Mexico (Bautista, Morales, et al., 2008a). In 1988, in the era in which the Institutional Revolutionary Party (PRI) dominated Mexican politics, the Gallup organization and its Mexican partner Instituto Mexicano de Opinión Pública tried to carry out an exit poll on election day. However, political pressures from government-controlled electoral authorities prevented the realization of what would have been the first exit poll in the country. Five days before election day, the executive secretary of the Mexican Federal Electoral Commission sent a letter prohibiting such exit poll on the grounds that it would violate Constitutional article 41, which establishes that people have the right to vote in secret (Domínguez & McCann, 1996; Mitofsky, 1994, 2004).

Paradoxically, in 1989—just a year later and under the auspice of the PRI-ruled government—the first exit poll ever was conducted in Mexico. It was believed that the then-governing Institutional Revolutionary Party (PRI) would lose the gubernatorial election in the northern State of Baja California, which would hold elections in July of 1989. On election day, PRI-controlled government’s exit poll briefed to a few decision makers that the gubernatorial PRI candidate had been defeated. Hence, after assessing the cost of tampering with electoral
results, the party decided to acknowledge its defeat. Since its founding in the late 1920s the PRI had never lost an election.

Later that year the Governor of the southern State of Guerrero hired a Mexican firm to conduct an exit poll during the PRI’s primary election to select the Mayoral candidate for Acapulco. Traditionally, party leaders selected PRI’s candidates without asking its base. Hence, a primary election and an exit poll were up to that time unprecedented practices. Apparently using exit poll information, the Guerrero Governor tried to foresee the winner of the Acapulco primary election to timely forge political alliances before the actual tally was released (Moreno, 1996).

In 1991 the TV broadcaster Televisa commissioned to the Gallup Organization an exit poll for the Congressional elections. Nevertheless, the Televisa-Gallup exit poll went practically unnoticed, not only because midterm elections elicit less attention than Presidential elections, but also because in those years the media were perceived as instruments of government control—setting aside that PRI won the elections by a landslide. It was not until 1994 when exit polls and quick counts\(^2\) were publicly discussed within the context of electoral reforms. Also in that year, better electoral rules were instituted, a newly created electoral commission was endowed with more autonomy and the media industry started gaining more credibility.

After proving their relevance in politics—and not just their novelty—exit polls received extensive attention from journalists. For the 1994 Presidential election the media sincerely undertook the idea of conducting an exit poll, though no single media had enough authority to

\(^2\) A “quick count” is a sampling procedure conducted right after the close of voting. Unlike exit polls, which rely on self-reported information, quick counts are based on actual votes. Election results are projected from a sample of voting stations using recorded votes on election day.
credible conduct it. The sponsorship of the National Chamber for the Radio and Television Broadcasting (CIRT) was necessary to make the project legitimate. Mitofsky International and two other Mexican firms, BIMSA and Indemerc-Louis Harris, were hired to conduct the project for that occasion (Beltrán, 2007; Mitofsky, 2004). Although the Institutional Revolutionary Party (PRI) won the election by a wide margin, blurring the immediate benefits of exit polls, CIRT exit poll represented a big step, in that it showed the media were speedily becoming independent.

In the 1997 Mexico City Mayoral election, the largest TV networks declared the leftist — and perhaps the most powerful opposition figure to the PRI at the time — winner of the race on the basis of exit polling data. Mitofsky International along with Mexican polling agency Consulta were hired for this election by broadcaster Televisa to project the results (Beltrán, 2007). Nevertheless, it would not be until the 2000 Presidential Election when exit polling became a critical element in providing credibility to election night results. The legitimacy of the political system, the authority and independence of the electoral institutions were all at stake. A variety of media-sponsored exit polls and quick counts released timely and accurate results, announcing that the once-undefeatable PRI had lost the Presidency by more than six percentage points. Such announcement brought stability and certainty on election night (Fröhling, Gallaher, & Jones III, 2001).

**Period of Study (2006-2009)**

In the 2006 Presidential election the situation was quite different. In the weeks preceding the election, polls had showed a fierce race between the conservative National Action Party
(PAN) and the leftist Party of the Democratic Revolution (PRD), while Institutional Revolutionary Party (PRI) was trailing a relatively distant third. On election night 2006, media exit polls indicated a very tight race and broadcasters preferred not calling winner based on exit poll data; they waited for quick count results, which later confirmed the tight scenario between the two frontrunners. In the end, the media did not call results. As a matter of fact, it took weeks until the official count was delivered, with PAN being the winner by a margin of roughly a half percentage point (Tello Díaz, 2006).

Although the media played a responsible role on election night 2006 acknowledging the limitations of exit polls and quick counts, a number of party-sponsored exit polls filled the vacuum on election night. Presidential candidates proclaimed themselves winners of the election based on their own exit polls. Therefore, contrasting numbers about the two frontrunners candidates were shown. The discrepancy between exit polling results and the official count, and the tight difference in the actual outcome (0.56%) was seen by the losers of the election—without direct evidence—as indicative of fraud (Aparicio, 2006; Schedler, 2007).

Despite the fact that some party-sponsored exit polls were controversial in 2006, exit polls have clearly proven useful in the Mexican democracy. In the 2006 Presidential election, a total of eight exit polls and quick counts were conducted by a dozen of survey agencies, which results were reported by nine mainstream media (Beltrán, 2007). In that year, there was a high demand of information not only concerning election results, but also on election procedures such as evaluation of voting station workers on aspects such as training, courtesy, and knowledge. In response to this latter form of information demand, Parametría, a Mexico-city based polling company, conducted a country-level syndicated exit poll.
In 2006, a major newspaper in the country, a political party, and the Federal Electoral Institute (IFE) were among the stakeholders who shared resources to help cover the costs associated with Parametría’s exit poll. Importantly, the syndicated exit poll led to a scholarly interest to further develop a data collection method and data analysis strategy introduced by Mitofsky (2000) to the field of exit poll which accommodates different exit polling questionnaires as part of one data collection process. Such data collection and data analysis strategy are reported elsewhere (Bautista, Morales, et al., 2008a).

In 2009, Congressional elections were held in the country along with several local elections; notably, six gubernatorial elections. On election day, media-sponsored exit polls helped confirmed for the mid-term elections what pre-election polls had previously anticipated: slow but steady resurgence of PRI. During the first half of PAN’s presidential term, PAN progressively lost support amidst of a ferocious war on drugs in the country. PRI capitalized on the lack of support to the President’s militarized approach, regained the public’s sympathy, and ultimately translated opinions into votes. PRI moved up from third to first political force in Congress and won five out of six gubernatorial races that year. Exit polls correctly predicted the outcome of the Congressional election, lessening uncertainties among political actors and the public on the reconfiguration of the political arena.

Parametría’s exit polls represent the main source of data for the present study. Parametría is a non-partisan independent agency which collected data useful for this research. That is, as part of their data collection fieldwork on election day, they gathered data on nonrespondents, and also information from field personnel who participated in exit polls. These data are detailed in the next chapter.
Dissertation Structure

This dissertation is organized into eight chapters. This introductory chapter lists the three major research objectives and the significance of the study. It also presents a contextual description of the data analyzed, it offers a historical note on election day surveys in Mexico (which is where the exit poll data come from for this study) with a focus on contextualization of the period of study (2006-2009). Chapter 2 discusses the existing literature concerning the three main objectives detailed above. Overall, Chapter 2 provides a literature review of nonresponse, measurement error and statistical approaches to handle nonresponse.

To develop a theoretical framework for the study of nonresponse, the review of literature in Chapter 2 focuses on cognitive aspects, cognition and social isolation theories, and on empirical studies conducted in the area of exit polling. The chapter reviews how voter and interviewer characteristics may relate to nonresponse. Furthermore, the chapter reviews previous studies on measurement error with a focus on psychological mechanisms about interviewer behaviors and expectations as well as interviewer effects. It also reviews empirical studies published on exit polling error.

Additionally, Chapter 2 reviews four statistical approaches available to handle nonresponse; namely, complete-case analysis (also known as list-wise deletion), class weighting, single imputation and multiple imputation. Importantly, the chapter provides a review of conceptual notions in the social science that have illuminated the analysis of situations where limited data are available. Insights from this chapter helps understand why multiple imputation is a preferred method for analysis of nonresponse.
Chapter 3 presents data and methods used in the research. This chapter explains sources of data and it also details analysis methods. Explicitly, the chapter describes imputation methods adopted to approximate values of nonrespondents and methods to account for the hierarchical nature of the data (i.e., respondents nested within interviewers).

Chapter 4, 5 and 6 are written as stand-alone papers (which leads to some inevitable minor repetition across chapters). When considered together, these chapters attempt to illuminate our understanding of a single story; namely, what are the mechanisms through which we can understand nonresponse and measurement error in exit polls. Particularly, Chapter 4 and 5 may be seen as a sequel, whereas Chapter 6 may be read more independently. All three chapters have an introduction, set of hypotheses, data and methods, analysis and results.

To be specific, Chapter 4 is devoted to an initial empirical investigation of hypothesized patterns of nonresponse using single-imputed data. The chapter starts with an overview of nonresponse patterns using bivariate and multivariate analysis and then introduces multilevel models to explore nonresponse hypotheses. The purpose of this strategy is to assess whether multilevel models are helpful to analyze exit polling data without having to discuss issues of multiple imputation. A set of preliminary findings from multilevel models based on a single imputation are included in the chapter.

Chapter 5 seeks to expand knowledge on mechanisms of nonresponse. The chapter reassesses preliminary findings from the previous chapter but this time using multiply imputed data. Importantly, Chapter 5 adds new hypotheses derived from the literature and analyzes more data. The purpose is to assess whether multilevel models based on multiple imputations could be used to understand mechanisms of nonresponse in the presence of limited information. Chapter 5
provides conclusions on hypothesized nonresponse mechanisms, acknowledges limitations and outlines possible lines for future research.

Unlike Chapter 4 and 5, Chapter 6 focuses on response error and explores hypothesized mechanisms that can account for exit polling error. In this chapter, the pool of voters who chose to participate is analyzed using Ordinary least-squares (OLS) regression and no imputations are performed. At the end of the chapter, main findings and limitations are discussed.

Lastly, Chapter 7 provides an integrated view of the three previous chapters. It provides a summary of main findings and how these findings help advance our knowledge in the field of exit polling, relative to previous studies. It also discusses some of the limitations. Because potential readers may have different training and background (whether as academics or practitioners), the chapter is presented in a non-technical manner. The chapter may serve as an abbreviated reading of the present dissertation.
CHAPTER 2: LITERATURE REVIEW

The exit polling literature has discussed nonresponse and measurement error almost since it is inception (Mitofsky, 1991); however, the focus of the exit polling literature has been more on developing good practices and less oriented to development of 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). Further, “Elections and Exit polling” edited by Scheuren and Alvey (2008) describes experiences and current practices in the international field of exit polling. Despite these two remarkable efforts, little is known about the mechanisms that can help us understand why some people leaving voting stations refuse to participate in the exit poll while others participate, and about various elements that jeopardize exit polling accuracy.

This chapter establishes a theoretical framework for exit polls, based on the existing election day survey literature. It provides a guide to the empirical work conducted in the present research. Importantly, this chapter provides an overview of the existing literature focusing on nonresponse and measurement error.

Nonresponse

A pressing question in the election day survey literature for nearly two decades is why sample voters refuse to participate in exit polls. In data collection methods that do not rely on interviewers, respondents’ decision to participate can conceivably be made
after the survey request has been put forward, where as in modes in which interviewers are present, the decision to participate can conceivably be made even before the request has been completely presented (Stoop, 2005). For example, a sample person may choose not to participate in a mail or web survey after inspecting the questionnaire and perceiving that it is a lengthy form or it has unreadable typography. A person may even choose not to participate after having started the answering process; for instance, a person may feel the language or some terminology is confusing, find that skip patterns are difficult to follow, information is hard to remember, or simply the survey topic is boring.

In data collection modes that rely on interviewers to gain cooperation and in which interactions occur in a very fast pace, such as exit polls, the decision to participate is likely to be made even before the request for participation is fully set forth. That is, the selected person may not use elements such as survey length, content of the questionnaire, or skip patterns as key factors in the decision-making process.

As Mitofsky and Brennan (1993) put it: “One of the things that we know is that most of the refusals we’re getting occur prior to the introduction of the questionnaire. That is, it’s not a case of people looking over the ballot, thinking that it’s too complicated, or that the lettering is too small, or whatever else, and then refusing. They’re refusing to participate right up front, the moment they’re approached.”

The decision to participate in an exit poll is likely to be made based on elements and conditions available at the onset of the interaction. These immediate elements are likely to include the sample person’s own social and psychological attributes and features of the requestor; namely, respondent and interviewer characteristics.
As a way to understand nonresponse in exit polls, Merkle and Edelman (2002) hypothesized that voters who tend to be excluded or isolated from the society are less likely than voters who are more involved in the society to participate. Merkle and Edelman’s (2002) argument builds on social isolation theories, which are rooted in theories of social engagement and social exchange.

Such theoretical approach in the survey research literature proposes that people who do not share the mainstream culture, or that 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 et al., 2008; Goyder, 1987; Groves & Couper, 1998).

Although the act of voting is in itself a form of participation in a societal event, in the context of exit polling, social isolation theories have been found helpful in understanding 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). In addition to socio-structural elements (i.e., social isolation theories), the literature has proposed that psychological factors can influence survey response. For instance, researchers have offered a number of different theories regarding survey response in a movement known as Cognitive Aspects of Survey Methodology (CASM). These theories have been helpful to 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 movement, 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, cognitive elements in conjunction with social elements are likely to play an important role in the decision making process of exit polling participation. In the following sections of this chapter related to nonresponse, we review the existing literature on the theorized social and psychological elements, identify current gaps in knowledge, and point out research needs.

**Social Isolation, Cognition and Participation**

**Voter Age**

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

Similarly, the psychological literature suggests that as people age they are more likely to experience a decline in several cognitive aspects including performance of working memory, language processing —whether visually or aurally— and comprehension. These cognitive limitations may effectively impede competence in communicative skills among older adults, which means a limitation in the ability to answer survey questions (Schwarz, 1999). While it is often conjectured that older people are less likely to accept an invitation to participate in surveys, Glenn (1969) and Groves and Couper (1998) have pointed out that the statistical relationship between age and survey participation, may not hold when other control variables are taken into account.

For the analysis of exit polls conducted during the 1990s in the United States, Merkle and Edelman (2000, 2002) examined age. They found that in the 1992 and 1996 exit polls, people aged 60 years and above were more likely than younger voters to refuse participation. In the 2003 Wilfrid Laurier University exit poll (Brown, Docherty, Ellis-Hale, Henderson, & Kay, 2004) and the 2004 BYU/Utah Colleges exit polls (Stevenson, 2006), voter age also seems to be related to survey participation. Likewise, in the 2004 Presidential exit poll conducted by Edison/Mitofsky (2005) older voters were less likely to take a survey than younger voters. Nevertheless, in the case of the Edison/Mitofsky exit poll (2005), survey participation is analyzed by age without other controlling variables, which leaves uncertainty on the results.

In a study about exit polling participation, Panagopoulos (2013) found consistent results with the theorized relationship in a multivariate regression analysis. Panagopoulos (2013)
examined self-reports on the intention to participate in an exit poll, collected in an opt-in web-based survey panel (i.e., YouGov/Polimetrix panel) for the 2008 U.S. Presidential Election. Panagopoulos (2013) indicates that age is negatively related to self-reported intentions to participate in an exit poll. This relationship is statistically significant among the group of voters who plan to vote at the voting station on the day of the election, but it is not statistically significant among respondents who report to be early voters or absentee voters. However, when both groups are pooled together for analysis (i.e., “precinct voters” and “early/absentee voters”), Panagopoulos (2013) finds that the relationship between age and participation is statistically significant.

To further confirm conclusions derived from the online survey, Panagopoulos (2013) fitted a regression model of similar self-reported metrics on data collected in a nationwide post-election telephone survey, conducted by CNN/ORC in November 2006. Such analysis shows a negative and statistically significant relationship between age and self-reported intentions to participate in an exit poll, net of other factors. While the relationship is consistent with theory, the data in the Panagopoulos’s (2013) study are self-reports gathered from a non-probability web survey and from a probability telephone survey, leaving uncertainty on these results in a population of actual election day voters.

**Voter Education**

In the survey research literature, education has been widely recognized as an important factor to explain the lack of answers to specific questions in a questionnaire —namely, item nonresponse— but less frequently education has been used to predict unit nonresponse (v. gr.,
In the literature, education has been used as proxy for cognitive skills (Ceci, 1991; Krosnick, 1991, 2002; Krosnick & Alwin, 1987, 1988; Krosnick et al., 2002; Narayan & Krosnick, 1996). Presumably, those with higher levels of education have better cognitive tools to “optimize” on their performance of various tasks — as opposed to “satisfice” — including the ability to answer questions (Krosnick et al., 2002). Theoretically, more educated groups of the population have more elements than low educated groups to engage in tasks that are cognitively more demanding, such as participating in a survey (Groves & Couper, 1998).

The study of the relationship between respondent education and unit nonresponse can be challenging, especially in the context of exit polls, where is nearly impossible to gather actual demographic characteristics from nonrespondents. In contexts other than exit poll, the correlation between unit nonresponse and demographic characteristics has been studied using indirect approaches. For example, Johnson, Cho, Campbell and Holbrook (2006) used community-level metrics to assess nonresponse effects in telephone surveys, finding that population metrics such as poverty levels are associated with nonresponse.

In the context of exit polls indirect approaches have also been used. For instance, Merkle and Edelman (2000) used aggregate-level data to conduct an analysis for the 1996 American exit poll to test whether more educated voters are more likely to participate in exit polls. They found no relationship between precinct-level response rates and precinct-level percentage of each of the
voter education categories (i.e., less than high school, high school graduate, college graduate and postgraduate).

Using self-reports on the intention to participate in an exit poll, Panagopoulos (2013) found that education is not related to metrics of exit poll participation, net of other factors, among respondents from the non-probability internet survey and the probability telephone survey. Panagopoulos (2013) and Merkle and Edelman’s (2000) obtained consistent results (i.e., no direct relationship between education and nonresponse); however, conclusions in these studies are not derived from an actual population of sample voters on election day.

**Interaction of Voter Age and Voter Education**

Age and education are typically used as proxies for cognitive functioning and they are likely to play a role in the response process (e.g., Belli, Weiss, & Lepkowski, 1999; Holbrook, Cho, & Johnson, 2006; Kaminska, McCutcheon, & Billiet, 2010; Krosnick, 1991). Age and education may, or may not, have an effect on survey participation in exit polls as main effects, but it is likely that an interaction between the two, may also produce effects. Consequently, it is not far-fetched to posit that the effect of respondent age on nonresponse could change at different levels of respondent education. Nonetheless, given the difficulty to collect individual-level educational attainment among nonrespondents, this interactivity has not been explored in the context of exit polls.
Interaction of Voter Education and Interviewer Education

Although the empirical exit polling literature suggests no consequence overall of respondent education (as main effect) on nonresponse in exit polls (Merkle & Edelman, 2000; Panagopoulos, 2013), theoretical accounts suggest that a connection (in the form of an interaction term) might exist between respondent education and interviewer education to account for nonresponse. This interaction term is proposed based on what Merkle and Edelman (2002) refer to as “similarity of background” hypothesized.

In the context of household surveys, it has been theorized that survey cooperation is higher when interviewer and respondent have similar demographic characteristics and lower cooperation when the backgrounds are different (Bateman & Mawby, 2004; Cannell, Miller, & Oksenberg, 1981; Schaeffer, 1980; Schuman & Converse, 1971). However, there is a gap in the exit polling literature on how the effect of the respondent’s education on nonresponse may change depending on the level of the interviewer’s education.

In general, the “similarity of background” hypothesis has been typically investigated in the form of “interviewer effects” on data quality; that is, how background characteristics of interviewers can potentially have an impact on respondents’ perceptions and ultimately how this dynamic modifies survey responses (Biemer, 2001; O’Muircheartaigh & Campanelli, 1999; Olson, 2006; Whitehead et al., 1993).

As previously mentioned, given the difficulty to directly observe some demographic characteristics (such as education) from nonrespondents in general, recent studies in the survey methodology literature have proposed some alternatives (Peytchev, 2012; Zhang, 2014); specifically, it has been proposed to approximate non observed data based on imputation
methods (Little & Rubin, 2002; Little & Rubin, 1987; Rubin, 1976, 1977). A revision concepts about data imputation is presented later in this chapter (Section “Statistical Approaches to Study Nonresponse and Measurement error”). Briefly defined, the imputation approach involves model-based simulations of plausible data; this approach might be helpful to test several hypotheses in the context of exit polls. Such an alternative has not been attempted in the context of election day surveys.

**Respondent Ruralness**

In the limited literature on exit polls, ruralness has been hypothesized to have an effect on nonresponse, especially when interacting with other demographic variables. In the analysis of five statewide gubernatorial exit polls in Mexico conducted during 2004 and 2005, Bautista and colleagues (2006) found that older Mexican voters are less likely to participate than younger Mexican voters, regardless of voter sex. Particularly, the study suggests that older voters living in rural areas are less likely than older voters living in urban areas to participate in exit polls. If one assumes that ruralness in Mexico is indicative of less exposure to survey requests, analyses from Bautista et al. (2006) seem to be consistent with presumptions of social isolation.

**Respondent Social Connectedness**

The literature has long suggested that social participation; particularly among older people, is defined by social activity, which includes having contacts with friends and relatives, communication, and connection with the society in general (Atchley, 1969; Cumming & Henry, 1961). Furthermore, empirical research suggest that socially isolated persons tend to have a
reduced social network, primarily in terms of family components (Crooks et al., 2008; Giuli et al., 2012).

The main channel of communication with the society is not reduced to a face-to-face interaction, telephone and even letter exchanges also represent important channels of communication (A. Brown, 1974). Also, independent activities such as reading or watching television may be indicative of social activity (Lemon, Bengtson, & Peterson, 1972). Therefore, it seems reasonable to put forward that survey measures other than age alone, such as telephone and television ownership, might be indicators of social isolation. Nevertheless, there is a gap in the literature examining the relationship between social involvement measures and survey participation in the context of exit polling.

### Roles in Society

#### Voter Gender

Gender has been hypothesized to have an effect on social participation. Gender studies have proposed that gender roles in society modifies individual behaviors (Correll, 2007; Eagly, 1987; Eagly & Steffen, 1984; Wood & Eagly, 2002). In the survey research literature it has been hypothesized that women are more likely than men to participate in surveys (Groves & Couper, 1998). This argument suggests that women tend to experience more social pressure for establishing and maintain social interactions (e.g., relationship with neighbors, friends, child care, and other activities) than men (Groves, 1990; Groves & Couper, 1998).

Although women are hypothesized to be more engaged in social interactions — and consequently more likely than men to cooperate in surveys — the research literature on
differential response rates between men and women has found mixed results (Groves & Couper, 1998; Lindström, 1983; T. W. Smith, 1984). In the context of election day surveys, Merkle and Edelman’s (2000, 2002) found that while response rates for women are slightly higher than response rates for men, differences are not consistently significant across years.

Stevenson’s study (2006) of the 2004 BYU/Utah colleges exit poll, and Bautista et al.’s study (2006) of five state-level exit polls in Mexico, indicate that women were more likely than men to participate. Nonetheless, in the Bautista et al.’s (2006) study, such association disappears after accounting for urbanicity. Using data from the Wilfrid Laurier University exit poll, Brown and colleagues (2004) found that women are as likely as men to participate.

Interestingly, using self-reports from an non-probability online panel Panagopoulos’s (2013), found that in the combined pool of “precinct voters” and “early/absentee” voters, women seem to be more likely than men to self-report participation; however, using self-reports from a probability telephone survey, such relationship does not hold. In any case, the existing studies in the exit polling literature suggest an equivocal relationship between gender and response rates.

Fear of Strangers

Interaction of Voter Age and Interviewer Age

The literature posits that fear of strangers may help to explain nonresponse in exit polls. This argument proposes that fearful voters are less likely than unafraid voters to participate in an exit poll (Merkle & Edelman, 2002). The 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. Such theoretical framework has been developed and adopted from nonresponse studies.
in the context of household surveys (Groves & Couper, 1998; House & Wolf, 1978; Stoop, 2005). The essential premise in the argument is that sampled respondents modify their behavior toward persons that appear to be a threat in any way (Groves & Couper, 1998).

The idea of vulnerability has been studied in the survey methodology literature with mixed results. Part of the literature suggests that crime rates can account for the decline in response rates (House & Wolf, 1978). Other studies, however, suggest that vulnerable groups such as women and the elderly are as likely to comply with survey requests as other groups, after controlling variables (Groves & Couper, 1998; Smith, 1983). Merkle and Edelman (2002) tested the “fear of strangers” hypothesis using data corresponding to the 1992, 1994, 1996 and 1998 U.S. exit polls.

Looking at the effects of interactions between interviewer and respondent age on nonresponse, Merkle and Edelman (2002) argue that “fear of strangers” may explain part of the exit polling nonresponse, suggesting that older voters are less likely to participate in exit polls than younger voters due to the perceived physical vulnerability. The key element implied in 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.

**Measurement Error**

The quality of surveys can be influenced by a variety of survey-design factors frequently referred to as “essential survey conditions” (Alwin, 2010; Biemer & Lyberg, 2003; Frankovic,
Panagopoulos, & Shapiro, 2009; Groves, Fowler, et al., 2004; Hansen, Hurwitz, & Bershad, 1961; Lessler & Kalsbeek, 1992; O'Muircheartaigh, 1977). These factors include the topic of the survey, question wording, length of the questionnaire, the data collection method, timing, sponsorship, faulty memory, political climate, interviewer characteristics, interviewer behaviors (whether conscious or unconscious), interviewer actions (whether indicated by training or unforeseen), respondent reactions (whether to the topic, the sponsor, or to the interviewer appearance), and others (Biemer & Lyberg, 2003).

Provided that cooperation is obtained from the respondent, all these factors can produce deviations from the “true value” that each person is assumed to have. Departures of responses from the “true value” are known as “response errors,” “observational errors,” or “measurement errors” (Alwin, 2007; Biemer & Lyberg, 2003; Biemer & Stokes, 1991; Biemer & Trewim, 1997; Bound, Brown, & Mathiowetz, 2001; Groves, 1989; Groves, Fowler, et al., 2004; Hansen et al., 1961; Krosnick et al., 2002; O'Muircheartaigh, 1977).

**Interviewers, Respondents and Data Quality**

Interviewer behaviors are hypothesized to have important effects on data quality and be a likely cause of measurement error. In particular, the literature indicates that interviewer behaviors are driven by interviewers’ expectations and preferences; that is, expectations make interviewers modify, consciously or not, their own behaviors in such a way that they exert an influence on respondents’ behaviors, and consequently on answers (Cannell et al., 1981; Hyman, Cobb, Feldman, Hart, & Stember, 1954; Kahn & Cannell, 1957; Katz, 1942; Olson & Bilgen,
Since the sample $i$-th respondent is part of the $j$-th interviewer pool, respondents are subject to the $j$-th “interviewer effect” (Biemer & Lyberg, 2003; Biemer & Trewim, 1997; Groves, 1991; Leslie Kish, 1962; O'Muircheartaigh, 1977; O'Muircheartaigh & Campanelli, 1999; Olson & Bilgen, 2011). Thus, if the interviewer systematically communicates — intentionally or not — his or her expectations, or repeatedly display some behaviors to respondents, the interviewer may modify respondents’ answers on vote choice.

**Interviewer Similarity Expectations**

Canell, Miller and Oksenberg (1981) building on the pioneering work of Hyman, Cobb, Feldman, Hart and Stember (1954) describe three types of interviewer expectations that may arise during an interview, as follows.

a) Role expectations, which refers to situations where interviewers expect certain responses from respondents based on the respondent demographic profile.

b) Attitude structure expectations, which refers to situations where interviewers expect consistency on the respondent answers throughout the interview. And,

c) Probability expectations, which refers to situations where interviewers expect responses based on what the interviewer believes is the current opinion of the target population (Cannell et al., 1981, p. 391).

Interviewer expectations are closely connected to several factors including interviewers’ beliefs, interviewing experience, ideology, preferences, and group membership (Boyd &
Westfall, 1955; Cahalan, Tamulonis, & Verner, 1947; Durrant, Groves, Staetsky, & Steele, 2010; Kahn & Cannell, 1957; Katz, 1942; Olson & Bilgen, 2011; Olson & Peytchev, 2007; Rice, 1929; Singer et al., 1983).

Since elements such as beliefs, ideology, preferences, and group membership serve as basis for interviewer expectations, it is possible that a particular type of interviewer expectation exists in the context of exit polling; namely, “similarity expectations.” “Similarity expectations” are here defined as situations where an interviewer expects respondents’ self-reported vote choice to be similar to his or her own political preference.

Although interviewing techniques have been suggested in the survey methodology literature to reduce the effects of interviewers such as standardizing interviewing procedures (e.g., Fowler, 1995; Fowler & Mangione, 1990), there are aspects that are not always controlled and minimized by survey researchers (Biemer & Lyberg, 2003; Groves & Couper, 1998). This is the case of interviewer expectations.

“Interviewer training now typically stresses the importance of appearing neutral and accepting toward all responses. Questionnaire wording and administration have been standardized; nondirective probing procedures have been developed. It is probable that these improvements have reduced the potential for interviewers to influence adversely the validity of data through their personal attitudes and beliefs. There remains one important exception: Respondents sometimes modify answers in reaction to the appearance of the interviewer” (Cannell et al., 1981, p. 392)
The effect of interviewer expectations may not be completely eliminated from the interviewing process. This might be especially problematic in face to face surveys, where full standardization of the interaction between respondent and interviewer is not always achieved (Beatty, 1995; Houtkoop-Steenstra, 2000; Suchman & Jordan, 1990). Consequently, similarity expectations are the link to understand interviewer partisanship associated with interviewer effects.

**Interviewer Party**

The presumptions of effects due to interviewer political preferences fit squarely in the overall theoretical framework of interviewer expectations, and particularly in the similarity expectations framework. In the current literature, Butterworth (2006) refers to the concept of “interviewer party” and posits that interviewers’ party identification has an influence on Within Precinct Error (WPE).

Arguably, interviewers with a defined political orientation are more likely than interviewers whose political preferences are not defined, to modify peripheral aspects of the interviewing process. As Finkel, Gutenbock, and Borg put it, “On certain kinds of survey items, individuals react in part to the social pressure of the interview situation and tend to respond based on their expectations of the interviewers’ preference” (Finkel, Gutenbock, & Borg, 1991, p. 315).

Butterworth’s study (2006) is based on a post-election questionnaire presumably conducted among exit poll interviewers in the United States after the 1996 Presidential exit poll. This study, however, provides no details on statistical testing to allow a meaningful
interpretation of empirical results on what the effect of interviewer partisanship would be on exit polling accuracy.

Edison/Mitofsky (2005) indicate that a post-election telephone survey was conducted among interviewers after the 2004 U.S. exit poll, unfortunately, empirical results are very limited in the report thus no firm conclusions can be derived. In a post-election examination like Edison/Mitofsky’s (2005) study, it would have been desirable to collect and report data on interviewer political preference. As analyst blogger Mark Blumenthal expresses it: “It would seem logical to ask the interviewers about their partisan leanings, especially in a post-hoc probe, but the [Edison/Mitofsky] report makes no mention of any such measure” (2005c para. 7).

Needless to say, a gap remains in the literature on the relationship between interviewer party and exit polling accuracy.

**Respondent Cognitive Burden**

The notion of interviewer effects on responses due to the interviewer behavior and expectations is consistent with “cognitive script” theories (Abelson, 1976, 1981; Groves, Cialdini, & Couper, 1992; Groves & Couper, 1998; Schank & Abelson, 1977) and respondent’s cognitive burden (Groves, 1989; Tourangeau, 1984). Cognitive script theories suggest that pre-existing psychological structures are imposed to the received information in order to reduce cognitive burden. In other words, people try to comprehend situations through prototypical circumstances.
The “cognitive script” hypothesis suggests that as information is gathered, organized and understood, people use “cognitive scripts” to identify the appropriate behavior and engage in different situations, including interacting with unfamiliar persons. For example, interactions with medical doctors, mail carriers, charity or sale requestors, political or religious petitions, and so on, are situations in which developed “cognitive scripts” shape the nature of social interactions (Groves & Couper, 1998 p. 220; Tourangeau, 1984 p. 75).

In the context of interviews, respondents are likely to use available cognitive scripts along with surrounding visual cues such as clothes, facial expressions, demographic characteristics, behaviors, materials, devices, activities, and other helpful hints to comprehend the intention of requestor, and to behave accordingly (Bateman & Mawby, 2004; Bischoping & Schuman, 1992; Finkel et al., 1991; Groves & Couper, 1998).

**Respondent Reactions to Peripheral Aspects**

The literature has long established that errors are specific to a particular variable (Groves, 1989); that is, error mechanisms may not affect equally all of the questions in a survey. Thus, the effect of peripheral aspects such as interviewer appearance might be more relevant for a set of survey participants and for certain metrics.

In the context of exit polling, it is seems logical to theorize that sample voters may modify their answers to vote choice due to the perceived intentions of the interviewer, especially in “highly intense elections where interviewers may be perceived (correctly or incorrectly) as favoring one or another candidate or party” (Frankovic, 2008, p.575). This interviewer effect is likely to occur because respondents tend to maximize available heuristics including the
“appearance of the interviewer” (Cannell et al., 1981 p. 392), “peripheral aspects of the options” (Groves & Couper, 1998 p. 32), and suppositions on the requestor’s intentions, as a way of reducing cognitive burden to comprehend the situation.

**Position of Power and Dominance in Society**

The literature on human interactions suggests that the perceived position of power and dominance in society is likely to have an effect on how people interact and behave. Studies have hypothesized that individual self-perceived status and perceived social status of others affect the dynamic of social relationships. That is, people less established in society (“powerless”) are presumably more likely to be impacted by the influence of others, relative to those with a better social position (“empowered”), especially in politically charged contexts (Blaydes & Gillum, 2013; Ross & Mirowsky, 1984).

In that regard, it has been proposed that younger, less educated and lower social status populations are more likely to be worried about impression management and self-presentation than those with more authority in society (i.e., older people, more educated and with higher social status) (Blaydes & Gillum, 2013; Davis, Couper, Janz, Caldwell, & Resnicow, 2010). Under this argument, it could be hypothesized that differential response patterns among survey participants may be due to the pressured perceived from interviewers.

This hypothesized psychological mechanism may be helpful to understand a tendency of some respondents to modify answers that are perceived to be socially acceptable to others (for example, younger, low-educated voters may experience pressure from an older high-educated interviewer, when reporting their vote choice). This mechanism implies that an interviewer-
respondent interaction occurs in the social and statistical sense. However, no available studies exist in the exit polling literature to assess the hypothesis.

**Interviewer Characteristics**

Interviewer characteristics have been hypothesized to play a direct role in explaining measurement error of self-reported vote choice, independent from other factors. For instance, Finkel, Guterbock and Borg (1991) analyzed the effect of interviewers in the context of the 1989 Virginia gubernatorial election. Using data from a pre-election survey, they studied a more observable characteristic of interviewer appearance — race of the interviewer. In Finkel et al.’s study (1991) white respondents are more likely to express support for a black candidate to a black interviewer than to a white interviewer. Likewise, white respondents are more likely to express support for a white candidate when interviewed by a white interviewer than when interviewed by a black interviewer.

While a relationship between interviewer characteristics and data quality has also been acknowledged in exit polls (Edison Media Research and Mitofsky International, 2005), it has not been well understood. A very few studies in the exit polling literature, which will be discussed in the following sections, have been conducted to assess how other aspects such as interviewer age, gender and education may affect exit polling estimates.
Interviewer Age

Interviewer age has been hypothesized in the exit polling literature as a visual cue used by respondents to judge the tasks implied in the answering process. Researchers posit that respondents, regardless of age, are more likely to take more seriously the reporting task when the request comes from an older person than when it comes from a younger person (Blumenthal, 2005c; Brown et al., 2004; Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2002; Stevenson, 2006).

Among several interviewer demographic characteristics examined in the 1992 and 1996 exit polls in the United States, age was related to response rates. In particular, survey cooperation—measured at the precinct level—increases as interviewer age increases, controlling for other factors (Merkle & Edelman, 2000, 2002). Importantly, Merkle and Edelman (2002) found a significant interaction between interviewer age and voter age. This interaction shows that younger voters are equally likely to cooperate with either younger or older interviewers, but older voters are much more likely to cooperate with older interviewers than with younger interviewers.

In the 2003 Wilfrid Laurier University exit poll in Ontario (Brown et al., 2004) and the BYU/Utah Colleges exit poll (Stevenson, 2006), older voters seem to be less likely to cooperate with young interviewers, while younger voters are more likely to cooperate. Apparently, young interviewers experienced fewer refusals from young respondents because younger interviewers were able to build better rapport with younger sample voters than with older voters (Brown et al., 2004; Stevenson, 2006). Although the body of interviewers in these surveys was primarily constituted by college students—thereby limiting the ability to generalize conclusions—their results seem to be in line with other findings in the literature.
In the Edison/Mitofsky’s (Edison Media Research and Mitofsky International, 2005) report, younger interviewers had higher levels of nonresponse than older interviewers, on average. Likewise, younger interviewers had a higher Within Precinct Error (WPE) in favor of the Democrat candidate than older interviewers. Although findings reported by Edison/Mitofsky (2005) are consistent with those reported by Merkle and Edelman (2002), suggesting that older interviewers experienced fewer refusals and lower levels of WPE, in the Edison/Mitofsky’s (2005) report the relationship between interviewer age and nonresponse as well as the relationship between interviewer age and WPE, are reported without control variables, limiting the strength of the conclusions.

Interestingly, Edison/Mitofsky (2005) report that interviewers age 18 to 24 represented more than one third of the fieldwork force (35%) and those age 25 to 34 represented almost one sixth (15%); which means that a half of the fieldwork team (50%) was under the age of 34. Interestingly, these findings are consistent with thoughts from some analysts that have speculated about the effect of having a sizable number of young interviewers in the 2004 Presidential exit poll in the United States:

“What assumptions might a voter make about a college student approaching with a clipboard? Would it be crazy to assume that student was a [John] Kerry supporter? If you were a Bush voter already suspicious of the media, might the appearance of such an interviewer make you just a bit more likely to say no, or to walk briskly in the other direction? Would it be easier to avoid that interviewer if they were standing farther away? What if the interviewer were forced to stand 100 feet away, among a group of electioneering Democrats –
would the Bush voter be more likely to avoid the whole group?” (Blumenthal, 2005c para. 12).

**Interviewer Gender**

Interviewer gender has been also discussed as a visual cue to respondents; however, the literature suggests that effects of such demographic characteristic on participation and accuracy disappear once age is accounted for (Edison Media Research and Mitofsky International, 2005). Analyses on the relationship between interviewer sex and WPE indicates that male interviewers are slightly more likely to have a higher WPE than female interviewers; however, when male and female interviewers are divided into two age groups (i.e., older or younger than 35 years) respectively, the relationship between interviewer sex and WPE disappears (Traugott et al., 2005).

In analyses for the 1992 and 1996 U.S. exit polls conducted to understand correlates of nonresponse at the precinct level, Merkle and Edelman (2002) found that interviewer gender is not statistically significant to predict response rates, net of other interviewer characteristics. The only strong predictor of nonresponse at the precinct level was age. Similarly, in the 2003 Wilfrid Laurier University exit poll (Brown et al., 2004), there was no relationship between interviewer sex and participation. In the Wilfrid Laurier University exit poll, nonetheless, the body of interviewers was made of students and the poll was conducted only in 10 voting stations selected mainly because of their proximity to the University campus. Therefore, the range of variation of interviewer characteristics is not as wide as the range corresponding to the 1992, 1996 and 2004 U.S. exits polls.
Interviewer Education

Interviewer education is presumably another interviewer characteristic that may have an effect on the interviewer appearance and behavior. However, the magnitude and direction of a potential interviewer education effect on exit polling accuracy is unclear. In the Edison and Mitofsky report (2005), as interviewer education increases the WPE increases as well, but in the middle education categories the WPE slightly decreases and then, increases again for the upper category of education, suggesting a nonlinear relationship. Nevertheless, the analysis is limited since no control variables are included in this bivariate relationship. In turn, Merkle and Edelman (2002) found that education is positively related to response rates at the precinct level in the 1992 U.S. exit poll net of other factors; however, they found that these results do not hold for the 1996 U.S. exit poll (Merkle & Edelman, 2002), leaving uncertainty on effects due to interviewer education.

Interviewer Skills, Attitudes and Behaviors

Interviewer Attitudes toward Interviewing

Interviewer actions are influenced by their perception and attitudes towards the task (Singer et al., 1983). Some studies suggest that as interviewers become more familiarized or “confident” with the interviewing tasks, they unknowingly start to modify their behaviors, and replace training with other elements (Olson & Peytchev, 2007). Presumably, as interviewers go through their workload they become less careful on the way they administer questionnaires. Interviewers who increase the pace at which interviews are conducted are more likely to
introduce measurement error relative to interviewers that do not increase the pace (Fowler, 1991; Olson & Peytchev, 2007; Pickery & Loosveldt, 2001).

When interviewers start to replace their training with other elements acquired during the data collection process they deviate from the standardized interviewing protocol; consequently, they start paying less attention to instructions, increase the pace of interviews and ultimately increase the level of error in a survey estimate (Fowler, 1991, 1995; Fowler & Mangione, 1990; Olson & Peytchev, 2007; Van der Zouwen, Dijkstra, & Smit, 1991).

In the context of exiting polls, interviewer expectations and attitudes might be affected by their confidence in their own interviewing skills and experiences acquired in the field, and the pressure to collect complete interviews on election day. Conceivably, interviewers who report at the time of post-exit poll debriefing that there were no problems with the survey instrument (e.g., no faulty phrasing of questions or design problems in questionnaire), or who did not have doubts on how to proceed on election day, are presumably interviewers who become overconfident on the exit polling task. Thus, interviewers who become overconfident presumably are more likely to introduce measurement error. Nonetheless, this hypothesis has not been explored in the exit polling literature.

**Intervewer Experience**

Interviewer experience defined as the overall experience gained in respondent’s lifetime has been identified as a desirable survey design element. In the literature, experience is a variable that tends to correlate with data quality (Cannell, Marquis, & Laurent, 1977; Gfroerer et al., 1997; Krosnick et al., 2002; Singer et al., 1983). However, empirical analyses of the effect of
interviewer experience on exit polling accuracy are scarce. Unlike regular survey agencies, exit polling vendors have a fewer contracts a year. Thus, exit interviewers have fewer opportunities to gaining exposure to the exit polling technique (Merkle & Edelman, 2002). Further, exit poll interviewers work with little or almost no supervision compared to other kinds of surveys (e.g., telephone or household surveys), slowing the possibility of monitoring interviewers’ performance in their assignments (Weisberg, 2005a).

Edison/Mitofsky (2005) reports that in the 2004 exit poll, 339 out of 1,473 interviewers had previously worked as exit interviewers. Out of these 339 Edison/Mitofsky interviewers, only 214 worked for the company during the 2004 Presidential primary elections. This means that less than a quarter of the Edison/Mitofsky fieldwork team had exit polling experience for the 2004 Presidential election and less than a sixth had a recent exit polling experience. Edison/Mitofsky does not provide, however, analysis on the relationship between interviewer experience and Within Precinct Error (WPE) or response rates (Edison Media Research and Mitofsky International, 2005).

In the analysis of the 1992 and 1996 exit polls in the United States, Merkle and Edelman (2002) found no relationship between interviewer experience and response rates at the precinct level, net of other factors. They measured interviewer experience as a composite index of three variables: number of telephone surveys worked on, number of in-person surveys worked on and number of exit polls worked on.

It is possible that such nonsignificant relationship is due to the fact that the interviewing experience acquired in telephone or household surveys is not automatically an asset on exit polling, or that the 1992 and 1996 exit interviewers did not have much of experience in exit
polling—just as the Edison/Mitofsky interviewers did not have for the 2004 election—which means that there is not enough variability to estimate the effect of interviewing experience.

Interestingly, in the 2004 BYU/Utah Colleges exit polls (Stevenson, 2006), exit interviewers with previous job experience involving activities that required human interaction such as retail sales, door-to-door sales, waiter/waitress experience, and telemarketing/surveys had a positive relationship with exit polling participation. In that study, however, it was not investigated if such experience had an impact on exit polling accuracy. Moreover, although most of these experiences imply strength in communicative skills and abilities to deal with people, they are not a direct measure of exit polling experience, thus limiting the scope of any potential conclusion.

**Interviewer Training**

Interviewer training has been theorized to increase the standardization of interviewers’ performance and behavior, thus reducing the potential bias and variance in the survey estimates (Fowler, 1991; Groves & Couper, 1998). Relevant skills are taught or reinforced during the exit polling training process, including the ability to approach voters using a methodical sampling selection and persuade them of accepting the survey request, computational skills as interviewers are expected to tally collected questionnaires, count misses and refusals, record refusals’ demographic characteristics, and call in the results to the data center on the telephone.

Edison/Mitofsky (2005) reports that the training process for the 2004 Presidential exit poll included providing the interviewer with a manual. They also conducted a 20-minutes rehearsal/training telephone call seven days prior to election day. In such telephone call, some of
the practicalities of the interviewing and reporting process were highlighted. Nevertheless, there was no assurance that the training provided to interviewers would be effective; especially when interim events could jeopardize interviewers’ ability to remember details and instructions. For instance, during the 2008 Presidential primary elections there were some concerns about the elapsed time between the date in which the training session was conducted and the exit poll:

“The real issue with the timing though is how close Iowa and New Hampshire are to the Christmas and New Years holidays. That will, I believe, raise some issues, because you can't just call up and train people on Christmas Eve or Christmas Day or New Year's Eve or New Year's Day, and we still need them to show up in Iowa two days after the start of the year. So that's one thing that we are going to keep an eye on. But we are going to start training earlier than usual, and hopefully people will still remember what they learned after they eat a lot on Christmas Eve and drink a lot on New Year's Eve so that they are ready to go on January 3” (interview with Joe Lenski in Kohut, 2006a).

Edison/Mitofsky reports (2005) that interviewers who described themselves as “somewhat/not very well trained” are slightly more likely to have higher levels of error (i.e., WPE) than interviewers who feel they are “very well” trained. Thus, interviewers less familiarized with the exit polling technique are more likely to have higher levels of WPE. Nevertheless, the data analyzed in the Edison/Mitofsky do not provide statistical analysis to determine if the difference observed is statistically significant.

In the 2004 BYU/Utah College exit polls, the training was conducted in-person for almost an hour and included “a mixture of lecture, demonstration, and role playing”
In Stevenson’s (2006) study, interviewer training was not specified as a predictor of exit polling acceptance. Thus, no statistical association was attempted between interviewer training and levels of errors.

In the 1997 exit poll in the United Kingdom, an experiment was conducted to evaluate the effect of interviewer training (Moon, 1999). In Moon’s study (1999), half of the interviewers had a “personal briefing” and the other half did not. The researchers found no differences between the two conditions; however, they noticed that briefing interviewers was a reassuring factor for the research team and the client.

In the 1992 and the 1997 British exit poll, the research team provided a BBC-produced instructional video to interviewers to show important aspects to the interviewing process. The idea was to show the interviewer the process of recruiting exit voters and administering the questionnaires so they could be aware of potential difficulties (Moon, 1999). A similar strategy was adopted in the United States. In the 2008 Presidential primary exit polls, a training video was distributed among interviewers. The aim was to improve interviewers’ knowledge on the exit polling technique (Joe Lenski in Kohut, 2007). Although there is no conclusive evidence in the literature showing the effect of interviewer training on participation or exit polling accuracy, exit pollsters acknowledge that it is a critical factor (interview with Warren Mitofsky in Kohut, 2006c).
**Election Day Factors**

In the exit polling literature, interview environment factors are typically referred to as election day factors. Such elements include timing of the day in which voters attend voting stations, length of the interview, problems with precinct officials and party representatives, number of exits at the voting station, and distance of the interviewer from the voting station (Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2002). In the literature, these factors have been hypothesized to have an impact on nonresponse and measurement error. Although election day factors are usually beyond the researchers control, these contextual elements are presumed to reduce interviewers’ ability to persuade exit voters to participate in a survey (Merkle & Edelman, 2002).

**Time of Voting**

Time of voting has been associated with people having restricted schedules. For example, voters with fixed work agendas are more likely to vote in the morning than in the afternoon in the United States (Busch & Lieske, 1985; cf. Fuchs & Becker, 1968; Klorman, 1976). Presumably, morning voters are more reluctant to cooperate because of the pressure they have to return to work (Stevenson, 2006). Nonetheless, such theoretical account (i.e., busy people during weekdays) excludes elections conducted in weekends.

An alternative explanation on the effect of timing of voting posits that interviewers gain experience as they conduct exit polling interviews over the course of the day, thus afternoon
voters may seemingly be more likely to cooperate (Brown et al., 2004). If this is indeed the case (i.e., interviewers acquiring exit polling experience throughout the day), exit polling experience may become an asset. Consequently, measurement error is expected to decrease as the timing of the day progresses.

An additional explanation posits that the higher level of cooperation among afternoon voters observed in some studies could be partially due to the fact that the majority of older voters—who have an overall tendency to refuse to participate, as discussed earlier in this chapter—have already cast their ballots by mid-afternoon (Brown et al., 2004; Merkle & Edelman, 2000). Although it seems that time of voting has an effect on participation or even quality of response, there are no studies testing for a systematic effect accounting for other factors.

**Length of Interview**

Length of the interview tends to have a negative impact on response rates (Mitofsky, 1991; Moon, 1999) and potentially on data quality. Ideally, exit polls should be able to accommodate lengthy questionnaires, since it is the only opportunity to interview actual voters, right after they have cast their ballots. In practice, a long questionnaire may harm response rates and may lead to survey fatigue.

In several experiments, Mitofsky (1991) has found that the larger the exit poll questionnaire, the lower the response rates. In particular, for three types of questionnaires, large, medium and small (i.e., 8.5 x 11 in., 5.2 x 8.5 in., and 4.2 x 5.2 in., respectively), Mitofsky (1991) mentions that the corresponding response rates are approximately 60%, 80% and 90%. The small size version asks for vote choice only, the medium version includes up to 25
questions—if the front and back pages are used—, and the large size can accommodate up to double the number of questions included in the medium size format.

Moon (1999) mentions that the size of the questionnaire does not have an impact on the reliability of questions. Interestingly, Mitofsky (1991), on his part, found that the smallest questionnaire used in several experiments—with highest response rate— it is also the one with the highest exit polling bias. He suggests that the small version loses legitimacy in the voters’ eyes. In any case, these two pieces in the literature imply that the while reliability of exit polling questions might not be affected by lengthy interviews, the validity of answers may be at stake.

A practical strategy developed in the United States to accommodate as many questions as possible in an exit poll questionnaire without undermining the response rate or the validity of the questions, has been to create several mid-size questionnaires containing different questions to be administered on election day (Mitofsky & Edelman, 1995). This strategy has been further developed in countries other than the United States (Bautista, Morales, et al., 2008a) to cope with the trade-off between length of the interview and response rates.

Creative ways of combining mid-size questionnaires have been proposed in the literature to fit comprehensive multivariate regression models. For example, a Planned-Missingness Multiple-imputation (PM-MI) exit poll was designed implemented in Mexico on election day. Such design used several versions of exit polling questionnaires that later on were combined as if the questions had been asked in the same questionnaire (Bautista, Morales, et al., 2008a). However, the effect of survey length on data quality has not been further explored.
Problems with Precinct Officials and Party Representatives

Evidence from the literature suggests that problems with poll watchers, political party representatives, poll workers and others may have an impact on response rates and data quality. Merkle and Edelman (2002) show that problems with precinct officials have a negative impact on response rates. They further suggest that problems with precinct officials may explain distant interviewing positions. In a similar fashion, Edison/Mitofsky (2005) reports that interviewers who experienced problems with officials have higher WPE and higher levels of nonresponse.

Problems experienced by interviewers with people other than precinct officials (i.e., poll watchers, political party representatives, lawyers, police, and so on) seem to be not related to participation. Edison/Mitofsky (2005) points out that there are not differences in WPE and response rates between interviewers who experienced and who did not experience such types of problems in the 2004 exit poll. Likewise, Bautista and colleagues (2006) in the Mexican context did not find evidence to believe that problems with people other than precinct officials have an impact on response rate.

Interviewer Distance to Exit

Merkle and Edelman (2002) found evidence in the 1992 and 1996 American exit polls showing that interviewing position is related to participation in exit polls. Likewise, Frankovic (1992) reports that in studies conducted by CBS News, distance seems to harm accuracy of exit polling estimates. The further away the interviewer stands from the voting station, the lower the response rate is. Similarly, Edison/Mitofsky (2005) reports that interviewer distance had an effect on both response rates and exit polling precision in the 2004 exit poll in the U.S.; this is apparently the case when interviewers stand more than 100 feet away from the polling place.
Consistently, in a 2005 gubernatorial exit poll in Mexico, Bautista et al. (2006) found that distance from polling stations had a significant impact on refusals.

**Statistical Approaches to Study Nonresponse and Measurement Error**

Statistical sampling methods aim to collect complete information from a selected target population. Nonetheless, the survey research literature has long recognized that it is not always possible to collect data from all units in the sample, or for all items included in a survey instrument (e.g., Biemer & Lyberg, 2003; Cochran, 1963; Groves, 2006; Lessler & Kalsbeek, 1992; Lohr, 2009). A typical approach is to conduct statistical analysis using only a subset of cases for which information is complete. Although such an approach is attractive because it is the default method in commercial statistical software (i.e., listwise deletion), it is limited as it does not offer any insights on nonrespondents. Consequently, different techniques have been discussed in the literature to replace missing data with plausible values (e.g., Brick & Kalton, 1996; Frankovic et al., 2009; Little & Rubin, 2002; Raghunathan, 2004).

Particularly, the literature on missing data discusses four potential ways of analyzing data with missing cases; namely, (i) complete-case data (also known as list-wise deletion), (ii) class weighting based on demographic population controls (sometimes also referred to as cell weighting or post-stratification), (iii) a single imputed dataset, and (iv) multiply imputed data (Brick & Kalton, 1996; Kalton, 1983; Kalton & Flores-Cervantes, 2003; Kalton & Kasprzyk, 1982; Little & Rubin, 2002; Little & Rubin, 1987). The following sections offers a literature review of these approaches.
Complete Case Data

Complete-case analysis (i.e., *list-wise deletion*) has been traditionally default in commercial statistical packages (Raghunathan, 2004). With this approach, point and variance estimation is conducted using only the set of complete cases (i.e., respondents) and information from unobserved cases (i.e., nonrespondents) is null. While *list-wise deletion* facilitates statistical analysis as it simply ignores data missingness for variables of interest, it becomes problematic when data are not missing at random (Rubin, 1987).

Complete-case analysis might produce accurate estimations but for a population different from the intended one (Rubin, 1976). In other words, the main risk with list-wise deletion is producing inefficient and biased estimated coefficients, since fewer cases are employed and relevant information is excluded (King, Honaker, Joseph, & Scheve, 2001). Therefore, any analysis conducted using *only* information from *respondents* is adopting a *complete case* approach, and it is effectively ignoring the group of *nonrespondents*.

Class Weighting

Weighting methods are typically based on *class* or *cell weighting*; that is, respondents and nonrespondents are classified into several groups using auxiliary information (for example, age and gender) such that respondents are weighted up or down (Kalton, 1983; Raghunathan, 2004). This is adjustment is conducted based on population controls to account for the lack of information not observed from nonrespondents in the statistic of interest (Kalton & Flores-Cervantes, 2003).
Weighting adjustment methods rely on the assumption that nonrespondents are fundamentally not different from respondents in the statistic of interest given the auxiliary information—a notion that corresponds to the “Missing at Random” assumption (MAR) described by Little and Rubin (2002). Due to the processes made in class weighting, such methods can be regarded as deterministic; that is, the statistical corrections due to nonresponse entirely depend on an adjustment of sample totals versus control totals (Kalton, 1983).

**Single Imputation and Multiple Imputation**

Conversely, single- and multiple-imputation approaches are non-deterministic since they rely on assigning plausible values *imputing* to missing values that were not collected (Little & Rubin, 2002; Rubin, 1987, 1996). Nonetheless, unlike weighting and single imputation methods, multiple imputation takes into account the uncertainty associated with the fact that actual data from nonrespondents were not collected. Consequently, multiple imputation methods can be regarded as stochastic in nature.

In the imputation framework, missing data are assumed to come from a *distribution* that is modeled exploiting available information to recreate the *correlation structures* of the analyzed data. For data imputation, auxiliary information can come from variables offered in the original dataset, external sources, survey design variables and other types of metadata. All this information may serve to characterize an *underlying distribution* of the data producing a plausible complete dataset (Little & Rubin, 2002; Rubin, 1987).
Compared with the list-wise deletion approach, class weighting and single imputation are theoretically superior since they take some practical steps to address data missingness. Nonetheless, there are practical shortcomings due to variance underestimation that is likely to occur when only a specific set of population controls are used in class weighting, or when just one sampled value from the estimated distribution is considered in the imputation process (Little, 1992; Weisberg, 2005c).

While class weighting could be regarded as a single imputation process (i.e., class weighting and single imputation attempt to account for missing information), they evade the fact that there is uncertainty associated to the unobserved data. Particularly, the literature indicates that a single imputation is likely to produce smaller standard errors. This is because simple imputation increases the sample size without incorporating the uncertainty associated with the fact that the estimation process utilizes predicted values as if they were true (unobserved) values. Therefore, the variance that is estimated when using a single imputation may be severely underestimated (Little & Rubin, 2002; Little & Rubin, 1987).

In the literature, multiple imputation is said to be model-based since it relies on modeling multiple predicted values to approximate an overall distribution of the population data (Little, 1988; Little & Rubin, 2002). Put differently, this method relies on assigning one plausible value from the corresponding underlying distribution to each missing value, and the process of assigning one possible value is conducted multiple times. This permits incorporating the uncertainty surrounding each missing datum, which is crucial to approximate the asymptotic variance in practice. The multiple imputation approach for analysis is superior to the previously described three approaches (i.e., list-wise deletion, class weighting and single imputation) since it
accounts for missing data while acknowledging uncertainty in the data (Little & Rubin, 2002; Rubin, 1987, 1996).

**Missing Data as Limited Information**

Situations where information is incomplete is not uncommon in empirical settings. Asides from the statistical approaches detailed above, economic and social sciences have developed related perspectives grounded in econometrics that deal with these situations, by explicitly incorporating the missing data in the estimation process. In particular, econometricians have conceived them as cases of limited or absent information. Specifically, the problem of limited information refers to observing a non-random subset of data generated through a process—not explicitly modeled—governing elements that are both observed and not observed. In other words, the statistical process is observed for the variable of interest that has an *incidentally truncated distribution* (Greene 2003).

For this reason, models that address this problem are sometimes referred to as “incidental truncation models”, of which Heckman’s (1979) “selection model” is perhaps the best-known example. Heckman was interested in studying female labor supply; particularly, he wanted to estimate the average wage of women using data collected from a population of women where housewives *did not* participate in the job market. Therefore, observed wages were truncated by the decision of these women to opt out of the market.

The solution proposed by Heckman (1979) is a two-step estimation procedure. On the first step, a “selection equation” is estimated, which is then used to compute a selection

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3 Heckman was awarded the 2000 Nobel Prize in Economics for this specific contribution.
parameter. On the second step, the “outcome equation” is estimated incorporating the estimated selection parameter. Since its inception, it has been a workhorse of labor economics studies (Puhani, 2000).

Heckman’s approach is related to Tobin’s (1958) censored regression model. Tobin was concerned with explaining the relationship between household income and household purchase of durable goods. Yet, when looking at the data it became clear that there were many households with exactly zero expenditure on these types of goods. According to his reasoning, an unobserved (or latent) variable must determine expenditures in durable goods. When this latent variable exceeds a specific value, households start purchasing these goods and the behavior can be observed. Tobin’s (1958) model is conceptually equivalent to the notion proposed by Heckman (1979). Hence, the problem is tackled by exploiting the unobserved population to infer the distribution of the full population in order to analyze it.

Key aspects of society have been investigated using Heckman’s (1979) and Tobin’s (1958) approaches. For instance, they have been used to study the number of extramarital affairs (Fair, 1978), the number of hours worked by a woman in the labor force (Greene & Quester, 1982), the number of arrests after release from prison (Witte, 1980), household expenditure on commodity goods (Jarque, 1987). Interestingly, Amemiya (1985) has done extensive work expanding and classifying these types of models.

It should be clear by now that the problem known in the econometrics literature as limited information corresponds to what is known in the statistics literature as a missing data problem that was described above (Rubin, 1977, 1987). As the observed and unobserved populations may

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4 Tobin was awarded the 1981 Nobel Prize in Economics for his contributions to the “analysis of financial markets and their relations to expenditure decisions, employment, production and prices”, many of which depended on his censored regression models.
differ in missing patterns, they cannot be ignored. Accordingly, missing data mechanisms are
discussed in terms of “ignorability” (Rubin, 1976, 1977, 1987). Conceptually, once ignorability
has been achieved (i.e., bringing data closer to be missing at random), it may be possible to
characterize the full distribution of interest by assigning plausible values to the missing data
(Gelman & Hill, 2006). The analysis, then can be done to understand both observed and
unobserved data (Little & Rubin, 2002; Little & Rubin, 1987; Rubin, 1996).

In essence, both the statistics and econometric literature tackle this problem by using
available information to model the mechanism governing the missingness and extend the
analysis to encompass missing data in the full data analysis. We shall return to the application of
these approaches in Chapter 3 where data and methods are presented. However, prior to detailing
the proposed methodological framework, a contextual note about the data is in order.
CHAPTER 3 : DATA AND METHODS

Primary Data

Primary data for this study come from two nationwide exit polls conducted by Parametría SA de CV in Mexico. The first exit poll was conducted for the 2006 Presidential election and the second exit poll was conducted for the 2009 Congressional election. Contextual information about these elections has been provided in Chapter 1 “Political Context.” In both exit polls, the target population was defined as Mexican citizens age 18 and older who cast a ballot in the 2006 Presidential election and the 2009 Congressional election, correspondingly. The 2006 and 2009 exit polls share a similar sampling plan and data collection strategy, and they are described as follows.

Sampling strategy

The sampling frame for each election year was designated to be the listing of all precincts in the country, as determined by the electoral authority — the Federal Electoral Institute (IFE) at that time. The sample was drawn using a two-stage sampling process. Precincts, also known as “electoral sections,” were considered as primary sampling units (PSUs). The sample frame was ordered according to the number of registered voters — an implicit stratification strategy. The first precinct was randomly selected and 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). The number of registered voters in each PSU was used as an approximate measure of size.

In a second stage, voters were selected within each of the precincts and the design aimed to have the same number of sample voters per precinct. The strategy followed in the first and second stage was designed to be a self-weighting sample in respect to the target population to facilitate computation of results on election night. At the second sampling stage, 73 sample voters were selected on average per precinct in 2006 and 53 sample voters per precinct in 2009. In each precinct every k-th person was interviewed. The systematic interval “k” did not vary across precincts in both years. One interviewer was assigned per precinct. On average, 39 voters were interviewed per interviewer after refusals in 2006, and 31 voters were interviewed per interviewer after refusals in 2009.

The 2006 exit poll consisted of 200 precincts. A voting station in 1 of the 200 selected 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 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%. Interviewers completed a post-exit poll questionnaire with demographic questions as well as other aspects related to election day elements. This post-exit poll questionnaire is described later in this chapter.

In 2009, the exit poll sample consisted of 75 precincts. One of the 75 precincts did not open its corresponding voting station on election day. In 5 of the 75 precincts, interviewers failed
to collect information on nonrespondents. In 3 of the 75 precincts, interviewers did not answer the post-exit poll questionnaire. These 9 precincts (out of 75) were excluded from analysis due to lack of useable data, leaving 66 precincts available for statistical analysis. Overall, in the 2009 exit poll, a total of 3,906 exit voters were randomly selected; only 2,511 of them complied with the interview and 1,395 refused to participate, yielding an overall response rate of 64% — calculated using Slater and Christensen’s (2002) RR5. The adjusted response rate after excluding nine unusable precincts is 62% (i.e., 2,223 respondents out of 3,557 contacted voters).

In the 2006 Presidential exit poll as well as the midterm 2009 Congressional election, voter eligibility is believed to be less of an issue. This is because once the voter has dropped the official electoral ballot into the voting box, the voting station official inks, with indelible liquid, the voter’s right-thumb thus 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 was not allowed in Mexico at the time for Congressional elections, therefore this source of coverage problem is not considered.

**Data Collection Method**

The 2006 Presidential exit poll and the 2009 midterm Congressional exit poll followed the same data collection methodology. A mixed mode data collection method was used in these exit polls, 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 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. Interviewers wore white clothing (vest, cap and portable ballot box) featuring Parametría’s logo as well as an identification badge.

Interviewers called a toll free number four times over the course of the day the election at scheduled hours to communicate collected data. Data entry personnel at the data center facility took telephone calls in order to enter information by means of *ad hoc* computer software. Interviewers also collected available information obtained on election day such as actual outcomes — as reported by voting station officials at the end of the election — for the purpose of providing information to conduct “quick counts” (i.e., which are projections of winner based on actual tallies from the sample of precincts). Interviewers were administered a post-exit poll questionnaire to collected information about irregularities observed through the day as well as demographic characteristics.

**Post-Election Questionnaire among Interviewers**

In the 2006 and 2009 exit polls, a self-administered post-election questionnaire was completed by interviewers. Field staff provided information on age (measured as a continuous metric), gender and educational attainment (less than high school, high school graduate and college graduate). Also, other information was collected in the debriefing questionnaire; particularly, whether wording of survey items was clear in the questionnaire and whether they had questions or doubts on how to apply the exit poll.

Additionally, interviewers where asked whether they thought it was better to read the standard introduction as it appeared at the beginning of the questionnaire or to use an
introduction crafted by themselves, whether they had voted for a particular political party had they had the opportunity to vote on election day, whether they ever applied a questionnaire in a household or exit poll survey before, and how long each questionnaire took on average to complete. They also reported distance from the voting station exit and whether they noticed conflicts of any kind at the voting stations.

In 2006 and 2009, the electoral commission (i.e., Federal Electoral Institute (IFE) at that time) asked survey agencies to submit application letters to express their intention to conduct exit polls, along with proposed methodology and materials. The election commission stamp-marked application letters upon receipt. These marked letters served as proof of legitimacy or “permits” that survey agencies gave to field representatives to show on request at precincts. Consequently, in the post-election questionnaire, interviewers were asked whether precinct officials or party representatives requested a “permit” to conduct interviews. Also, interviewers were asked if a precinct officials or a party representative asked them to stop interviewing. A list of complete questions administered to interviewers is displayed in Appendix 1.

External Data

Official Election Results for the 2006 Presidential and 2009 Congressional

As shall be discussed in Chapter 6, measurement error can be estimated by comparing survey data with actual data. Actual voting results available at the precinct level for the set of sampled PSUs (i.e., “electoral sections”) are used as “gold standard” data (i.e., independent data). The 2006 and 2009 election official results were retrieved from the official web-based
compendium published by Mexico’s election commission (IFE, 2012). Actual voting results for all sample precincts included in analyses were successfully matched for both elections.

**Auxiliary Data for Imputation**

As introduced in the next section and further discussed through Chapters 4 and 5, 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 and 2009 exit polls. 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 (INEGI) 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. While these data are provided for the 2005-2006 period, they are used to impute data in both the 2006 and the 2009 exit polls. This is deemed reasonable because no major changes in the demographic structure of the population were observed from the year of 2006 to 2009.

**Imputation Methods**

Chapter 4 and 5 provide an analysis of hypothesized relationships in nonresponse using imputed data. Consequently, this section offers details of imputation methods implemented in the present study. As discussed in the literature review in Chapter 2, 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 the full data distribution.
Particularly, it 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 persons’ 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 \( m > 1 \) data sets 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 3-1 shows in an intuitive way of displaying the mechanism of imputation using complete data.

![Figure 3-1. Missing Data Completion Using Multiple Imputation](image)

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), 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, Goodrich, Gelman, & Hill, 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, Lepkowski, Van Hoewyk, & Solenberger, 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 \textit{conditionally} and \textit{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 \texttt{mi impute chained} (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 ($X$) with fully conditional specifications (StataCorp, 2013, p.7). Consequently, imputed values are drawn as follows:

\[
Y_1^{(t+1)} \sim g_1(Y_1, Y_2^{(t)}, \ldots, Y_j^{(t)}, X, \phi_1)
\]

\[
Y_2^{(t+1)} \sim g_2(Y_2, Y_1^{(t+1)}, Y_3^{(t)}, \ldots, Y_j^{(t)}, X, \phi_2)
\]

\[
(\ldots)
\]

\[
Y_j^{(t+1)} \sim g_j(Y_j, Y_1^{(t+1)}, Y_2^{(t+1)}, \ldots, Y_{j-1}^{(t+1)}, X, \phi_j)
\]

Where $t=0,1\ldots T$ (iterations) reaches convergence when $t=T$ and where $\phi_j$ is defined as model parameters with a uniform prior. As it can be seen from 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 fully conditional specification (FCS) probability model on the complete data (i.e., observed and missing values) for the 2006 dataset is as follows (Model A):

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

Likewise, the FCS probability model for the 2009 is conveniently described as (Model B):

\[
(Y_B Y_{B1} Y_{B2} Y_{B3} Y_{B4} Y_{B5} Y_{B6} Y_{B7} Y_{B8} Y_{B9} Y_{B10} Y_{B11} Y_{B12} Y_{B13} Y_{B14} Y_{B15} Y_{B16} Y_{B17} Y_{B18} Y_{B19})
= (X_B X_{B1} X_{B2} X_{B3} X_{B4} X_{B5} X_{B6} X_{B7} X_{B8} X_{B9} X_{B10} X_{B11} X_{B12} X_{B13} X_{B14} X_{B15})
\]

Table 3-1 shows the description of “dependent”\(^5\) variables used in the 2006 model \(Y_A, A=1\ldots16\) as well as “dependent” variables used in the 2009 model \(Y_B, B=1\ldots19\). Also, Table 4-1 shows the regression model used for each imputation variable (see column “Regression Method”). While each the 2006 and 2009 models were estimated separately, the parametrization of the FCS regression for both models is similar. Similarly, Table 3-2 shows the set of independent variables used in the 2006 model \(X_A, A=1\ldots14\) and independent variables used in the 2009 model \(X_B, B=1\ldots15\).

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\(^5\) 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>
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<tr>
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</thead>
<tbody>
<tr>
<td>$Y_{A1}$</td>
<td>$Y_{B1}$</td>
<td>Interviewer gender</td>
<td>Female, Male</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A2}$</td>
<td>$Y_{B2}$</td>
<td>Interviewer age</td>
<td>Less than 20 years, 21-30 years, 31-40 years, 41 years or more</td>
<td>Ordinal logit</td>
</tr>
<tr>
<td>$Y_{A3}$</td>
<td>$Y_{B3}$</td>
<td>Interviewer education</td>
<td>(Less than High School, High School Graduate, College)</td>
<td>Ordinal logit</td>
</tr>
<tr>
<td>$Y_{A4}$</td>
<td>$Y_{B4}$</td>
<td>Interviewer noted conflict at voting station</td>
<td>Yes, No</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A5}$</td>
<td>$Y_{B5}$</td>
<td>Number of exits at voting station as noted by interviewer</td>
<td>One exit, More than one exit</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A6}$</td>
<td>$Y_{B6}$</td>
<td>Interviewer experience</td>
<td>Yes, No</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A7}$</td>
<td>$Y_{B7}$</td>
<td>Interviewer average interviewing time</td>
<td>Five minutes or less, More than 5 minutes</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A8}$</td>
<td>$Y_{B8}$</td>
<td>Distance from station as reported by interviewer</td>
<td>10 meters or less (30 feet), More than 10 meters</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A9}$</td>
<td>$Y_{B9}$</td>
<td>Voter age</td>
<td>Less than 40 year, 40 years or more</td>
<td>Ordinal logit</td>
</tr>
<tr>
<td>$Y_{A10}$</td>
<td>$Y_{B10}$</td>
<td>Voter gender</td>
<td>Female, Male</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A11}$</td>
<td>$Y_{B11}$</td>
<td>Voter education</td>
<td>Less than High School, High School, College</td>
<td>Ordinal logit</td>
</tr>
<tr>
<td>$Y_{A12}$</td>
<td>$Y_{B12}$</td>
<td>Voter socioeconomic status</td>
<td>Low, Middle-Low, Middle, Middle-high/high</td>
<td>Ordinal logit</td>
</tr>
<tr>
<td>$Y_{A13}$</td>
<td>$Y_{B13}$</td>
<td>Voter telephone service</td>
<td>Yes, No</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A14}$</td>
<td>$Y_{B14}$</td>
<td>Voter TV ownership</td>
<td>Yes, No</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A15}$</td>
<td>$Y_{B15}$</td>
<td>Voter time of voting</td>
<td>Before 1:00pm, 1 After 1:00pm</td>
<td>Logit</td>
</tr>
<tr>
<td>$Y_{A16}$</td>
<td>$Y_{B16}$</td>
<td>Voter party preference</td>
<td>PAN, PRI, PRD, Other</td>
<td>Multinomial logit</td>
</tr>
<tr>
<td>NA</td>
<td>$Y_{B17}$</td>
<td>Voter personal computer ownership</td>
<td>Yes, No</td>
<td>Logit</td>
</tr>
<tr>
<td>NA</td>
<td>$Y_{B18}$</td>
<td>Voter access to internet</td>
<td>Yes, No</td>
<td>Logit</td>
</tr>
<tr>
<td>NA</td>
<td>$Y_{B19}$</td>
<td>Voter access to cellular phone</td>
<td>Yes, No</td>
<td>Logit</td>
</tr>
</tbody>
</table>
Table 3-2. Set of Independent Variables for Imputation Model in the 2006 and 2009 Dataset

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Description</th>
<th>Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>Cluster indicator variables</td>
<td>Yes, No</td>
</tr>
<tr>
<td>$X_2$</td>
<td>Nonresponse</td>
<td>Yes, No</td>
</tr>
<tr>
<td>$X_3$</td>
<td>Proportion of actual votes for PAN, PRI, PRD and Other Party at the precinct level in the 2006 election</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_4$</td>
<td>Type of PSU</td>
<td>Rural, nonrural</td>
</tr>
<tr>
<td>$X_5$</td>
<td>Proportion of adult population with primary education (6 years) or less</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_6$</td>
<td>Proportion of adult population with lower secondary education (3 years)</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_7$</td>
<td>Proportion of adult population with upper secondary education (3 years)</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_8$</td>
<td>Proportion of adult population with college education (4 years)</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_9$</td>
<td>Proportion of adult population beneficiary of the Mexican Social Security Institute (IMSS)</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_{10}$</td>
<td>Proportion of adult population beneficiary of the Institute for Social Security and Services for State Workers (ISSSTE)</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_{11}$</td>
<td>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)</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_{12}$</td>
<td>Proportion adult population with other publicly-funded health coverage</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_{13}$</td>
<td>Proportion adult population with privately-funded health coverage</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_{14}$</td>
<td>Proportion adult population with no health coverage</td>
<td>Continuous</td>
</tr>
<tr>
<td>$X_{15}$</td>
<td>Proportion of female adult population</td>
<td>Continuous</td>
</tr>
</tbody>
</table>
As variables in Table 3-2 show, the fully conditional specification (FCS) models used in this study attempt to (i) maintain population proportions by means of external data and (ii) 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 “chain” to converge to a stationary distribution. The software used for FCS imputation (Stata v.13) allows to specify 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, Royston, & Wood, 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.

Number of Multiply Imputed Datasets

As mentioned before, model specification for each imputation variable is different because it depends on the type of imputation variable (logit, ordinal logit or multinomial logit). This imputation iterative process is repeated multiple times ($m>1$) to generate $m$ filled-in datasets. In theory, between 3 and 10 imputations ($m$) are needed to approximate asymptotic properties of the estimated coefficients (Little & Rubin, 2002; Little & Rubin, 1987; Schafer & Olsen, 1998). In practice, however, this number depends critically on the degree of missingness in the data being analyzed (Graham, Olchowski, & Gilreath, 2007). Relying on Monte Carlo simulations, Graham and colleagues (2007) indicate that the appropriate number of imputations depend on the degree of missingness in the dataset. Thus, the higher the fraction of missing information in the data, the higher the number of imputations required to approximate the same asymptotic properties.

Graham et al. (2007) empirically investigated Rubin’s (1987) theorized statistical efficiency for different rates of missing information of the statistic of interest. In their study, the authors found that the number of imputations ($m$) needed to achieve acceptable levels of efficiency is higher than the previously theorized number (i.e., between $m=3$ and $m=10$). Graham and colleagues (2007) indicate that the number of imputation depends on (a) the missing information fraction —which ranges from 0.10 to 0.9 in their study— and (b) the level of statistical power falloff the researcher is willing to accept (whether <5%, <3% or <1%).
Graham et al. (2007) conclude that for true missing rates of 0.10, 0.30, 0.50, 0.70 and 0.90, the adequate number of imputed datasets ($m$) is approximately 20, 20, 40, 100 and >100, respectively (Graham et al. 2007, p. 212). Therefore, considering theoretical background, empirical research, computational capabilities available at this point in history, and considering that the level of missingness in the present study for variables is on average less than 0.50, a set of $m=30$ imputed datasets are produced for analysis.

**Methods for Analyzing Multiply Imputed Data**

The analysis of multiply imputed data requires two steps: the first step consists of analyzing each dataset separately to estimate coefficients of interest (for example, means or regression coefficients) and associated measures of variability (for example, standard errors). In a second step, the results of each dataset (i.e., point estimates and covariances) are combined using a set of rules commonly referred to as “Rubin rules” (Little & Rubin, 2002; Rubin, 1976, 1996).

The combining rules establish that coefficients of interest are produced by averaging out point estimates across imputed datasets. The variances associated to point estimates however, are estimated with two components: (a) the *within imputation* variance (essentially, an average of the variances across imputations) and (b) *between imputation* variance (essentially the variance across variances). This last term accounts for estimation uncertainty and corrects for the underestimation observed in single-imputations.
Specifically, Little and Rubin (2002) indicate that after the process of filling-in datasets, each dataset is analyzed using complete-data methods that would be used in the absence of nonresponse. First, a complete-data point estimate of the quantity of interest $\hat{\theta}_m$, with data $m$ (where $m=1, 2\ldots M$), is calculated. This is a conditional draw from the underlying distribution, instead of simple conditional mean. Likewise, $W_m$ is the corresponding standard error estimated with data $m$ (where $m=1, 2\ldots M$), under a given imputation model. The combined estimate for the quantity of interest (assuming $m>1$) is the average of individual point estimates:

$$\bar{\theta}_M = \frac{1}{M} \sum_{m=1}^{M} \hat{\theta}_m.$$ 

According to Little and Rubin (2002), the averaging over $M$ imputed datasets increases efficiency relative to a single dataset with conditional draws imputed. Therefore, the variance associated to the estimate depends on two components. They are defined as:

1) the within-imputation variance:

$$\bar{W}_M = \frac{1}{M} \sum_{m=1}^{M} W_{mj}$$

2) the between-imputation variance:

$$B_M = \frac{1}{D-1} \sum_{m=1}^{M} (\hat{\theta}_m - \bar{\theta}_M)^2$$

Finally, the total variability associated to $\bar{\theta}_M$ is defined as:

$$T_M = \bar{W}_M + \frac{M+1}{M} B_M$$
Calculations of the total variability for estimates (i.e., standard error) for the present study were conducted using Stata 13’s imputation routine \texttt{mi estimate} (StataCorp, 2013).

**Distribution of Univariate Statistics Before and After Imputation**

Table 3-3 compares univariate statistics of binary-coded variables from the 2006 and the 2009 data for voter characteristics. These variables will be analyzed in Chapter 4 and 5. Additionally, Table 3-3 shows how original, non-imputed data (i.e, complete-case data) compares to \textit{multiply imputed data} for 2006 and 2009 \((m=30)\). As it can be seen, the overall univariate distributions for imputed data for each of the respondent characteristics in 2006 and 2009 remain close to non-imputed data, and observed differences are negligible. In both years, the largest difference between complete-case data and multiply imputed data is approximately 1%.

Specifically, Table 3-3 shows that the univariate distribution of voter gender and voter age are similar in 2006 and 2009 with the number of cases almost evenly distributed (approximately 50%) across categories (i.e., men vs. women, and “less than 40 years” vs. “40 years or more”). In terms of education, approximately 19% of voters in 2006 report to be college graduates, whereas in 2009 approximately 23% report to be college educated in 2009, a difference of approximately four percentage points between the two years.

Data in Table 3-3 indicates that the distribution of voter’s time of day for voting is similar in 2006 and 2009, with more than half of voters (approximately 56%) showing up at polling stations during morning or early afternoon hours (i.e., before 1:00 PM) than to afternoon or
evening hours (after 1:00 PM). In terms of TV ownership, approximately one in ten voters report having a TV set, with a higher percent in 2009 (95%) than in 2006 (91%).

Cellular service and internet services are measures available only for the 2009 exit poll. Data for that year indicates that about two in every three voters have access to cellular service (64%) whereas only one in every three voters have access to internet service (30%). Measures for socioeconomic status show that in 2006 and 2009, less than half of voters are classified as middle, middle-high or high (versus otherwise), with fewer voters classified as such in 2006 (41%) than in 2009 (47%).

Table 3-4 displays data related to interviewer characteristics and contextual factors from 2006 and 2009. The data show that the percent of younger interviewers (i.e., less than 40 years) is higher in 2006 (88%) compared to 2009 (79%). Also, the data reveal that the percent of male interviewers is higher in 2009 (61%) relative to 2006 (56%). The distribution of educational attainment is similar in both years; namely, in 2006 approximately 26% of interviewers have a college degree while in 2009 approximately 27% are college educated. In both years, about half of the interviewers (48%) report having previous exit polling experience.

In 2006, slightly more than one half of the interviewers (53%) report an average interview length of 5 minutes or more. Regarding interviewing position at the voting station, the data show that in 2006 approximately 30% of respondents positioned themselves more than 10 meters away (~30 feet) from the polling place; however, in 2009 50% of the interviewers stood more than 10 meters away. In 2006, about 17% of interviewers reported problems with election officials while approximately 27% of interviewers reported problems with officials in 2009. In
both years, slightly over one fourth of interviewers (27%) reported two or more exits at the voting station.
Table 3-3. Distribution of Voter Characteristics Before and After Imputation of Item and Unit Nonresponse Data

<table>
<thead>
<tr>
<th>Voter Characteristics</th>
<th>2006 Exit poll Complete-Case</th>
<th>2006 Exit poll Multiply imputed ((m=30))</th>
<th>2009 Exit poll Complete-case</th>
<th>2009 Exit poll Multiply imputed ((m=30))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent</td>
<td>S.E.</td>
<td>Percent</td>
<td>S.E.</td>
</tr>
<tr>
<td>Gender</td>
<td>N=14,623</td>
<td></td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>0 Female</td>
<td>49.3</td>
<td>(0.41)</td>
<td>49.3</td>
<td>(0.41)</td>
</tr>
<tr>
<td>1 Male</td>
<td>50.7</td>
<td>(0.41)</td>
<td>50.7</td>
<td>(0.41)</td>
</tr>
<tr>
<td>Age</td>
<td>N=14,590</td>
<td></td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>0 Less than 40 years</td>
<td>48.7</td>
<td>(0.41)</td>
<td>48.7</td>
<td>(0.41)</td>
</tr>
<tr>
<td>1 40 years or More</td>
<td>51.3</td>
<td>(0.41)</td>
<td>51.3</td>
<td>(0.41)</td>
</tr>
<tr>
<td>Education</td>
<td>N=7,764</td>
<td></td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>0 Less than College</td>
<td>80.8</td>
<td>(0.45)</td>
<td>81.3</td>
<td>(0.39)</td>
</tr>
<tr>
<td>1 College</td>
<td>19.2</td>
<td>(0.45)</td>
<td>18.7</td>
<td>(0.39)</td>
</tr>
<tr>
<td>Voters’ time of day for voting</td>
<td>N=7,745</td>
<td></td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>0 Before 1:00 PM</td>
<td>57.2</td>
<td>(0.56)</td>
<td>57.1</td>
<td>(0.55)</td>
</tr>
<tr>
<td>1 After 1:00pm</td>
<td>42.8</td>
<td>(0.56)</td>
<td>42.9</td>
<td>(0.55)</td>
</tr>
<tr>
<td>Telephone service</td>
<td>N=7,762</td>
<td></td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>40.1</td>
<td>(0.56)</td>
<td>41.0</td>
<td>(0.52)</td>
</tr>
<tr>
<td>1 Yes</td>
<td>59.9</td>
<td>(0.56)</td>
<td>59.0</td>
<td>(0.52)</td>
</tr>
<tr>
<td>TV ownership</td>
<td>N=7,764</td>
<td></td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>9.1</td>
<td>(0.33)</td>
<td>9.3</td>
<td>(0.36)</td>
</tr>
<tr>
<td>1 Yes</td>
<td>90.9</td>
<td>(0.33)</td>
<td>90.7</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Socio Economic Status</td>
<td>N=7,581</td>
<td></td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>0 Otherwise</td>
<td>58.5</td>
<td>(0.57)</td>
<td>59.1</td>
<td>(0.54)</td>
</tr>
<tr>
<td>1 Middle-high/high</td>
<td>41.5</td>
<td>(0.57)</td>
<td>40.9</td>
<td>(0.54)</td>
</tr>
</tbody>
</table>

NA: Not available
Table 3-4. Distribution of Interviewer Characteristics and Contextual Factors Before and After Imputation of Item and Unit Nonresponse Data

<table>
<thead>
<tr>
<th>Interviewer Characteristics</th>
<th>2006 Exit poll</th>
<th>2009 Exit poll</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Complete-Case</td>
<td>Multiply imputed (m=30)</td>
</tr>
<tr>
<td></td>
<td>Percent</td>
<td>S.E</td>
</tr>
<tr>
<td><strong>Interviewer Characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Less than 40 years</td>
<td>87.7 (2.36)</td>
<td>87.5 (2.38)</td>
</tr>
<tr>
<td>1 40 years or More</td>
<td>12.3 (2.36)</td>
<td>12.5 (2.38)</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Female</td>
<td>44.3 (3.66)</td>
<td>44.9 (3.58)</td>
</tr>
<tr>
<td>1 Male</td>
<td>55.7 (3.66)</td>
<td>55.1 (3.58)</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Less than College</td>
<td>74.2 (3.18)</td>
<td>73.7 (3.21)</td>
</tr>
<tr>
<td>1 College</td>
<td>25.8 (3.18)</td>
<td>26.3 (3.21)</td>
</tr>
<tr>
<td><strong>Exit polling experience</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>51.3 (3.61)</td>
<td>51.5 (3.59)</td>
</tr>
<tr>
<td>1 Yes</td>
<td>48.7 (3.61)</td>
<td>48.5 (3.59)</td>
</tr>
<tr>
<td><strong>Average interview length</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Five minutes or less</td>
<td>46.6 (3.62)</td>
<td>46.4 (3.58)</td>
</tr>
<tr>
<td>1 More than 5 minutes</td>
<td>53.4 (3.62)</td>
<td>53.6 (3.58)</td>
</tr>
<tr>
<td><strong>Contextual elements</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interviewer distance from exit</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 10 meters (30 feet) or less</td>
<td>69.9 (3.31)</td>
<td>69.9 (3.30)</td>
</tr>
<tr>
<td>1 More than 10 meters</td>
<td>30.1 (3.31)</td>
<td>30.1 (3.30)</td>
</tr>
<tr>
<td><strong>Interviewer problems with election officials</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>82.4 (2.75)</td>
<td>82.6 (2.72)</td>
</tr>
<tr>
<td>1 Yes</td>
<td>17.6 (2.75)</td>
<td>17.4 (2.72)</td>
</tr>
<tr>
<td><strong>Number of exits monitored by interviewer</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 One exit</td>
<td>72.4 (3.23)</td>
<td>72.8 (3.20)</td>
</tr>
<tr>
<td>1 Two or more</td>
<td>27.6 (3.23)</td>
<td>27.2 (3.20)</td>
</tr>
</tbody>
</table>
Chapter 4 and 5 consider the use of multilevel models in the analysis of data. While those chapters discuss motivation, hypotheses and results of models in detail, this section offers a methodological description of regression equations. As previously mentioned in this chapter, there is one interviewer per precinct — and precincts are primary sampling units (PSUs). This means that voters are nested within interviewers. Given the hierarchical structure in the data, information is explored with a two-level multivariate analysis, as recommended in the literature (Gelman & Hill, 2006; Hox, de Leeuw, & Kreft, 1991; Luke, 2004; O'Muircheartaigh & Campanelli, 1999; Pickery, Loosveldt, & Carton, 2001; Rabe-Hesketh & Skrondal, 2012; Snijders & Bosker, 2012).

While the design of the analyzed exit polling data does not entirely allow to disentangle cluster variance from interviewer variance — as it might be possible in interpenetrated designs (e.g., O'Muircheartaigh & Campanelli, 1999) — this study assumes that variation due to interviewers is still captured in the design thereby allowing valid inferences. In that sense, multilevel models can help account and investigate “interviewer effects” — which are described in Chapter 4 and 5. In other words, in exit polls sample voters are typically in the same j-th interviewer pool at each precinct; as a result, respondents are expected to experience the j-th “interviewer effect” (Biemer & Lyberg, 2003; Biemer & Trewim, 1997; Groves, 1991; Hox et al., 1991; Leslie Kish, 1962; O'Muircheartaigh, 1977; O'Muircheartaigh & Campanelli, 1999; Olson & Bilgen, 2011; Pickery et al., 2001).

Chapter 4 discusses five logistic multilevel models to explore predictors of nonresponse and Chapter 5 introduces five additional models. Table 3-5 outlines five models estimated in
Chapter 4 (i.e., Model 0 to Model 4) and five additional models (i.e., Model 5 to Model 9) estimated in Chapter 5. Table 3-5 also shows the number of imputations used to conduct multilevel analysis (whether \(m=1\) or \(m=30\)) as well as the source of data used for regression estimation (2006 or 2009).

<table>
<thead>
<tr>
<th>Model</th>
<th>Data Source (Year)</th>
<th>Number of imputations ((m))</th>
<th>Model Specification</th>
<th>Level-1 predictors (Voter)</th>
<th>Level-2 predictors (Interviewer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 0 (M0)</td>
<td>2006</td>
<td>1</td>
<td>Random intercept</td>
<td>No predictors</td>
<td>No predictors</td>
</tr>
<tr>
<td>Model 1 (M1)</td>
<td>2006</td>
<td>1</td>
<td>Random intercept - random slope</td>
<td>Age, education, gender, age by education, TV ownership</td>
<td>Education</td>
</tr>
<tr>
<td>Model 2 (M2)</td>
<td>2006</td>
<td>1</td>
<td>Random intercept - random slope</td>
<td>Same as above</td>
<td>Education and age</td>
</tr>
<tr>
<td>Model 3 (M3)</td>
<td>2006</td>
<td>1</td>
<td>Random intercept - random slope</td>
<td>Same as above</td>
<td>Same as above plus gender</td>
</tr>
<tr>
<td>Model 4 (M4)</td>
<td>2006</td>
<td>1</td>
<td>Random intercept - random slope</td>
<td>Same as above</td>
<td>Same as above plus ruralness</td>
</tr>
<tr>
<td>Model 5 (M5)</td>
<td>2006</td>
<td>30</td>
<td>Random intercept - random slope</td>
<td>Same as above</td>
<td>Same as above</td>
</tr>
<tr>
<td>Model 6 (M6)</td>
<td>2006 &amp; 2009</td>
<td>30</td>
<td>Random intercept - random slope</td>
<td>Same as above plus type of election (Congressional vs. Presidential)</td>
<td>Same as above</td>
</tr>
<tr>
<td>Model 7 (M7)</td>
<td>2006 &amp; 2009</td>
<td>30</td>
<td>Random intercept - random slope</td>
<td>Same as above plus voter age by type of election</td>
<td>Same as above</td>
</tr>
<tr>
<td>Model 8 (M8)</td>
<td>2006 &amp; 2009</td>
<td>30</td>
<td>Random intercept - random slope</td>
<td>Same as above plus voter socioeconomic status and voter time of day for voting but excluding selected L1*L2 interactions</td>
<td>Same as above plus exit poll experience, average interview length, distance from polling place, interviewer monitored more than one exit, interviewer problems with election officials</td>
</tr>
<tr>
<td>Model 9 (M9)</td>
<td>2006 &amp; 2009</td>
<td>30</td>
<td>Random intercept - random slope</td>
<td>Same as above plus voter socioeconomic status and voter time of day for voting but including selected L1*L2 interactions</td>
<td>Same as above</td>
</tr>
</tbody>
</table>
More formally, regression equations for models discussed in Chapter 4 (Model 0 to Model 4) and Chapter 5 (Model 5 to Model 9) shown in Table 3-6, 3-7 and 3-8. Model 0 through Model 9 are two-level logistic regression models with dependent variable (nonrespondent) $y_{ij} \sim Bernoulli(\varphi_{ij})$ and $Logit(\varphi_{ij}) = \eta_{ij}$ (top part in Table 3-6). The same level-1 equation (L1) is used for all five models (middle part in Table 3-6), whereas level-2 equations (L2) are specified differently for each of the models (bottom part in Table 3-6).

In the L1 equation (Table 3-6), $\beta_{0j}$ is the constant term for the $j$-th cluster; $\beta_{1j}, \ldots, \beta_{5j}$ are regression coefficient for the $j$-th cluster, $A$ represents voter age, $E$ is voter education, $A \# E$ is an interaction term of voter age by voter education, $G$ is voter gender and $T$ is voter TV ownership. Additionally, L2 equations display each cluster’s constant term and slope (for instance, $\gamma_{00}$ and $\gamma_{10}$, respectively) plus a residual term (e.g., $U_{0j}$) that captures the variability of the relationship between predictors and dependent variable across $j$-units (i.e., cluster deviations). In Table 3-6, $IE$ is interviewer education, $IA$ is interviewer age, $IG$ is interviewer gender, and $R$ is ruralness.

Likewise, Table 3-7 and Table 3-8 show L1 and L2 equations for Model 6 and 7 as well as Model 8 and Model 9, respectively. These tables include additional parameters for L1 equations; that is, $C$ (whether Congressional or Presidential), $SES$ (socioeconomic status), $Time$ (whether voters’ time of day for voting was before or after 1:00 pm) and $Phone$ (voter telephone service). Additional parameters for L2 equations are $Experience$ (Interviewer exit poll experience), $Length$ (whether interview length average was less or more than 5 minutes), $Distance$ (whether interviewer distance from polling place was less or more than 10 meters), $Exits$ (whether interviewer monitored more than one exit) and $Problems$ (whether interviewer had problems with either election officials).
Table 3-6. Multilevel Equations for Model 0 through Model 4 and Number of Analyzed Imputations

<table>
<thead>
<tr>
<th>Model 0</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>(m=1)</td>
<td>(m=1)</td>
<td>(m=1)</td>
<td>(m=1)</td>
<td>(m=1)</td>
<td>(m=30)</td>
</tr>
</tbody>
</table>

Dependent variable \(y_{ij}\) (nonresponse \(\varphi_{ij}\)):

\[ y_{ij} \sim Bernoulli(\varphi_{ij}) \text{ and } Logit(\varphi_{ij}) = \eta_{ij} \]

Level 1 equation:

\[ \eta_{ij} = \beta_{0j} + \beta_{1j}(A) + \beta_{2j}(E) + \beta_{3j}(G) + \beta_{4j}(A#E) + \beta_{5j}(T) \]

Level 2 equations:

\[
\begin{align*}
\beta_{0j} &= \gamma_{00} + \gamma_{01}(IE) + U_{0j} \\
\beta_{1j} &= \gamma_{10} + \gamma_{11}(IE) + U_{0j} \\
\beta_{2j} &= \gamma_{20} + \gamma_{21}(IE) + U_{0j} \\
\beta_{3j} &= \gamma_{30} \\
\beta_{4j} &= \gamma_{40} \\
\beta_{5j} &= \gamma_{50}
\end{align*}
\]

Same as Model 4

Same as Model 4

Same as Model 4

Same as Model 4

Same as Model 4

Table 3-7. Multilevel Equations for Model 6 and Model 7 and Number of Analyzed Imputations

<table>
<thead>
<tr>
<th>Model 6</th>
<th>Model 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>(m=30)</td>
<td>(m=30)</td>
</tr>
</tbody>
</table>

Dependent variable \(y_{ij}\) (nonresponse \(\varphi_{ij}\)):

\[ y_{ij} \sim Bernoulli(\varphi_{ij}) \text{ and } Logit(\varphi_{ij}) = \eta_{ij} \]

Level 1 equation:

\[ \eta_{ij} = \beta_{0j} + \beta_{1j}(A) + \beta_{2j}(E) + \beta_{3j}(G) + \beta_{4j}(A#E) + \beta_{5j}(T) + \beta_{6j}(SES) \]

Level 2 equations:

\[
\begin{align*}
\beta_{0j} &= \gamma_{00} + \gamma_{01}(IE) + \gamma_{02}(IA) + \gamma_{03}(IG) + \gamma_{04}(R) + \gamma_{05}(C) + U_{0j} \\
\beta_{1j} &= \gamma_{10} + \gamma_{11}(IE) + \gamma_{12}(IA) + \gamma_{13}(R) + U_{0j} \\
\beta_{2j} &= \gamma_{20} + \gamma_{21}(IE) + \gamma_{22}(IA) + \gamma_{23}(R) + U_{0j} \\
\beta_{3j} &= \gamma_{30} + \gamma_{31}(IG) + U_{0j} \\
\beta_{4j} &= \gamma_{40} \\
\beta_{5j} &= \gamma_{50} \\
\beta_{6j} &= \gamma_{60}
\end{align*}
\]
Table 3-8. Multilevel Equations for Model 8 and Model 9 and Number of Analyzed Imputations

<table>
<thead>
<tr>
<th>Model 8</th>
<th>Model 9</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Dependent variable $y_{ij}$ (nonresponse $\varphi_{ij}$):  

\[ y_{ij} \sim \text{Bernoulli}(\varphi_{ij}) \text{ and } Logit(\varphi_{ij}) = \eta_{ij} \]

Level 1 equation:

\[ \eta_{ij} = \beta_{o7} + \beta_{1j}(A) + \beta_{2j}(E) + \beta_{3j}(G) + \beta_{5j}(\text{SES}) + \beta_{6j}(\text{Time}) \]

\[ \eta_{ij} = \beta_{o7} + \beta_{1j}(A) + \beta_{2j}(E) + \beta_{3j}(G) + \beta_{5j}(\text{SES}) + \beta_{6j}(\text{Phone}) + \beta_{7j}(\text{Time}) \]

Level 2 equation2:

\[ \beta_{0j} = \gamma_{00} + \gamma_{01}(\text{IE}) + \gamma_{02}(\text{IA}) + \gamma_{03}(\text{IG}) + \gamma_{04}(\text{R}) + \gamma_{05}(\text{C}) + \gamma_{06}(\text{Experience}) + \gamma_{07}(\text{Length}) + \gamma_{08}(\text{Experience} \# \text{Length}) + \gamma_{09}(\text{Distance}) + \gamma_{10}(\text{Exits}) + \gamma_{11}(\text{Problems}) + U_{0j} \]

\[ \beta_{1j} = \gamma_{10} + \gamma_{11}(\text{IE}) + \gamma_{12}(\text{IA}) + \gamma_{13}(\text{R}) + U_{0j} \]

\[ \beta_{2j} = \gamma_{20} \]

\[ \beta_{3j} = \gamma_{30} \]

\[ \beta_{4j} = \gamma_{40} \]

\[ \beta_{5j} = \gamma_{50} \]

\[ \beta_{6j} = \gamma_{60} \]

\[ \beta_{7j} = \gamma_{70} \]
Estimation of Multilevel Models with Multiply Imputed Data

Stata’s official commands `melogit` (StataCorp, 2013) is primarily used to estimate multilevel categorical regression models. For additional verification of results, Stata’s command `xtlogit` was also used. Furthermore, Stata-based user-written routine `gllamm` (Rabe-Hesketh & Skrondal, 2012) is used to supplement analysis. All these modules produce extremely similar results for multilevel models and negligible dissimilarities are due to slightly different approaches in the use of adaptive quadrature algorithms (Rabe-Hesketh & Skrondal, 2012). The main practical difference is how routines display information in their output. For instance, `xtlogit` provides random-effect parameters as standard deviations whereas `gllamm` and `melogit` displays parameters as variance.

When used together, Stata’s commands `mi estimate` and `melogit` (StataCorp, 2013) allows for a simultaneous estimation of multilevel logistic coefficients on different multiple-imputed datasets ($m=30$) and combination of regression results using Rubin’s rules (Little & Rubin, 2002) described earlier in this chapter. For instance, the basic Stata code to conduct such analysis is: `mi estimate, melogit [depvar] [L1 equation] || [L2 equation], covariance (unstructured).`
CHAPTER 4 : AN INITIAL EXPLORATION OF NONRESPONSE BASED ON MULTILEVEL MODELS WITH FULLY CONDITIONED SINGLE-IMPUTED DATA

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 et al., 2009; Merkle & Edelman, 2000, 2002; Merkle et al., 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 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’ decision to participate can be made after the survey request has been put forward, where as 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 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, 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 than voters who are more involved in society to participate. 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 et al., 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 analysis 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 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 et al., 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 et al., 1996; Tourangeau, 1984). Further, the literature suggests that there is 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 et al., 2008; DiNapoli et al., 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 multi-level— 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 et al., 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 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 reduce 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 make 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 an opt-in web-based survey panel, supports the same notion (Panagopoulos, 2013). Consequently, the first derived hypothesis is as follows:

\[ H1: \text{Older voters are more likely than younger voters to refuse to participate in an exit poll} \]

**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 et al., 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:

\textit{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.}

\textbf{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, et al., 1999; Holbrook et al., 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 have 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.

\textit{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 et al., 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, 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 helps also 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 (SES) as proxy measure. In this study, the social isolation hypothesis is investigated using SES. 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 voters’ 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 et al., 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 television 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 maintain social interactions (e.g., relationship with neighbors, friends, child care, and other activities) than men (Groves, 1990;
Yet the empirical survey methodology literature on differential survey nonresponse patterns shows mixed results on this hypothesis (Groves & Couper, 1998; Lindström, 1983; T. W. 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 on nonresponse patterns in an exit poll 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 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 that 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 account 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 that 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 (CPS) figures on education to Voter News Service (VNS) 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 discuss 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 (i) individual demographic data observed among respondents and nonrespondents, and (ii) demographic composition of sample precincts based on population data, an imputation model allows to generate likely results on the social and psychological mechanisms that predict nonresponse.
As discussed in the literature review (Chapter 2) and further detailed in Chapter 3 (methodology chapter), imputation models appear to be an increasingly attractive method for handling missing data in statistical analysis (Carpenter & Kenward, 2012; Kaplan, 2014; Kropko et al., 2014; Little & Rubin, 2002; Raghunathan et al., 2001; Royston, 2007; Schafer, 1997; Van Buuren, 2012; White et al., 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.

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. As described in Chapter 3, data for the present chapter was collected in a nationwide exit poll in Mexico in 2006 conducted in a Presidential election. Thus, information is available at two levels in the 2006 data used for analysis: 1) information on voters that 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. Importantlty, this individual-level variable (i.e., “refusal”) serves as 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).
Information on nonrespondents was gathered using two broadly defined categories for sex and age on election day (i.e., male vs. female and <40 vs. 40+), the respondents’ information are binary-recoded accordingly; that is, exit voters’ age are binary-coded as less than 40 years (“young”) vs. 40 years or more (“old”). Consequently, there are available data for respondents and nonrespondents on age and gender, but there is incomplete information for voter education, socio economic status, TV ownership and telephone service. These incomplete data are filled-in based on an imputation model (see Chapter 3, Section “Imputation Methods”).

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 et al., 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 Chapter 3 (Section “Imputation Methods”), multiple datasets were generated with imputed values (Graham et al., 2007; Little & Rubin, 2002), creating a total of thirty imputed datasets, \( m=30 \). Nonetheless, in this chapter only results from one imputation \( m=1 \) are analyzed. This is because the chapter aims to provide a focused 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 is conducted later in Chapter 5.

**Missingness in the Data**

Table 4-1 shows the level of missingness in the data on voter and interviewer characteristics, considering item and unit nonresponse. Overall, data in Table 4-1 shows that voter age and gender have a negligible level of missing data (0.27% and 0.05%, 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%, respectively). Ruralness does not have missing data since rural/urban characteristics are derived from the sampling frame.

<table>
<thead>
<tr>
<th>Table 4-1. Level of Missingness in Data from 2006 Exit Poll</th>
<th>Missing Cases</th>
<th>Total Cases</th>
<th>Percent Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voter Characteristics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>40</td>
<td>14,630</td>
<td>0.27</td>
</tr>
<tr>
<td>Gender</td>
<td>7</td>
<td>14,630</td>
<td>0.05</td>
</tr>
<tr>
<td>Education</td>
<td>6,866</td>
<td>14,630</td>
<td>46.93</td>
</tr>
<tr>
<td>Socio Economic Status</td>
<td>7,049</td>
<td>14,630</td>
<td>48.18</td>
</tr>
<tr>
<td>TV ownership</td>
<td>6,866</td>
<td>14,630</td>
<td>46.93</td>
</tr>
<tr>
<td>Telephone Service</td>
<td>6,868</td>
<td>14,630</td>
<td>46.94</td>
</tr>
<tr>
<td>Interviewer Characteristics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>9</td>
<td>199</td>
<td>4.52</td>
</tr>
<tr>
<td>Age</td>
<td>4</td>
<td>199</td>
<td>2.01</td>
</tr>
<tr>
<td>Gender</td>
<td>14</td>
<td>199</td>
<td>7.04</td>
</tr>
<tr>
<td>Ruralness</td>
<td>0</td>
<td>199</td>
<td>0.00</td>
</tr>
</tbody>
</table>
To assess the quality of the imputed data, Table 4-2 shows demographic characteristics of voters and interviewers before and after imputation. As it can be seen, the distribution of variables for voters remains consistent across socio demographic characteristics after imputation. Only education shows a negligible difference of one 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%) and “College” (=19.2%-18.2%). 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 two and a half percentage points for gender (=44.3-46.7 and =55.7-53.3). The rest of interviewer data remain nearly identical.
Table 4-2 Distribution of Voter and Interviewer Characteristics Before and After Imputation of Item and Unit Nonresponse Data (Frequencies and Column Percentages)

<table>
<thead>
<tr>
<th>Voter Characteristics</th>
<th>Before Imputation</th>
<th></th>
<th>After Imputation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Frequency</td>
<td>Percent</td>
<td>Frequency</td>
<td>Percent</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Female</td>
<td>7,205</td>
<td>49.3</td>
<td>7,206</td>
<td>49.3</td>
</tr>
<tr>
<td>1 Male</td>
<td>7,418</td>
<td>50.7</td>
<td>7,424</td>
<td>50.8</td>
</tr>
<tr>
<td></td>
<td>14,623</td>
<td>100</td>
<td>14,630</td>
<td>100</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Less than 40 years</td>
<td>7,101</td>
<td>48.7</td>
<td>7,119</td>
<td>48.7</td>
</tr>
<tr>
<td>1 40 years or More</td>
<td>7,489</td>
<td>51.3</td>
<td>7,511</td>
<td>51.3</td>
</tr>
<tr>
<td></td>
<td>14,590</td>
<td>100</td>
<td>14,630</td>
<td>100</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Secondary Education or Less</td>
<td>4,977</td>
<td>64.1</td>
<td>9,536</td>
<td>65.2</td>
</tr>
<tr>
<td>2 High School</td>
<td>1,293</td>
<td>16.7</td>
<td>2,438</td>
<td>16.7</td>
</tr>
<tr>
<td>3 College</td>
<td>1,494</td>
<td>19.2</td>
<td>2,656</td>
<td>18.2</td>
</tr>
<tr>
<td></td>
<td>7,764</td>
<td>100</td>
<td>14,630</td>
<td>100</td>
</tr>
<tr>
<td>Socio Economic Status</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Low</td>
<td>2,435</td>
<td>32.1</td>
<td>4,790</td>
<td>32.7</td>
</tr>
<tr>
<td>2 Middle-Low</td>
<td>2,002</td>
<td>26.4</td>
<td>3,889</td>
<td>26.6</td>
</tr>
<tr>
<td>3 Middle</td>
<td>2,768</td>
<td>36.5</td>
<td>5,228</td>
<td>35.7</td>
</tr>
<tr>
<td>4 Middle-high/high</td>
<td>376</td>
<td>5.0</td>
<td>723</td>
<td>4.9</td>
</tr>
<tr>
<td></td>
<td>7,581</td>
<td>100</td>
<td>14,630</td>
<td>100</td>
</tr>
<tr>
<td>TV ownership</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>705</td>
<td>9.1</td>
<td>1,382</td>
<td>9.5</td>
</tr>
<tr>
<td>1 Yes</td>
<td>7,059</td>
<td>90.9</td>
<td>13,248</td>
<td>90.6</td>
</tr>
<tr>
<td></td>
<td>7,764</td>
<td>100</td>
<td>14,630</td>
<td>100</td>
</tr>
<tr>
<td>Telephone service</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>3,116</td>
<td>40.1</td>
<td>5,968</td>
<td>40.8</td>
</tr>
<tr>
<td>1 Yes</td>
<td>4,646</td>
<td>59.9</td>
<td>8,662</td>
<td>59.2</td>
</tr>
<tr>
<td></td>
<td>7,762</td>
<td>100</td>
<td>14,630</td>
<td>100</td>
</tr>
<tr>
<td>Interviewer Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Female</td>
<td>82</td>
<td>44.3</td>
<td>93</td>
<td>46.7</td>
</tr>
<tr>
<td>1 Male</td>
<td>103</td>
<td>55.7</td>
<td>106</td>
<td>53.3</td>
</tr>
<tr>
<td></td>
<td>185</td>
<td>100</td>
<td>199</td>
<td>100</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Less than High School</td>
<td>25</td>
<td>13.2</td>
<td>25</td>
<td>12.6</td>
</tr>
<tr>
<td>2 High School Graduate</td>
<td>116</td>
<td>61.1</td>
<td>121</td>
<td>60.8</td>
</tr>
<tr>
<td>3 College</td>
<td>49</td>
<td>25.8</td>
<td>53</td>
<td>26.6</td>
</tr>
<tr>
<td></td>
<td>190</td>
<td>100</td>
<td>199</td>
<td>100</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Less than 20 years</td>
<td>61</td>
<td>31.3</td>
<td>61</td>
<td>30.7</td>
</tr>
<tr>
<td>2 21-30 years</td>
<td>80</td>
<td>41.0</td>
<td>82</td>
<td>41.2</td>
</tr>
<tr>
<td>3 31-40 years</td>
<td>30</td>
<td>15.4</td>
<td>31</td>
<td>15.6</td>
</tr>
<tr>
<td>4 41 years or more</td>
<td>24</td>
<td>12.3</td>
<td>25</td>
<td>12.6</td>
</tr>
<tr>
<td></td>
<td>195</td>
<td>100</td>
<td>199</td>
<td>100</td>
</tr>
<tr>
<td>Contextual Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ruralness (Variable not subjected to imputation)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Nonrural</td>
<td>138</td>
<td>69.4</td>
<td>138</td>
<td>69.4</td>
</tr>
<tr>
<td>1 Rural</td>
<td>61</td>
<td>30.7</td>
<td>61</td>
<td>30.7</td>
</tr>
<tr>
<td></td>
<td>199</td>
<td>100</td>
<td>199</td>
<td>100</td>
</tr>
</tbody>
</table>
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 4-3 displays bivariate relationships between variables of interest and exit polling participation. As mentioned before, data for nonrespondents on education, socio-economic 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 4-3 suggest that gender seems to be related to exit polling participation; namely, men (45.9%) are slightly less likely to refuse than are women (48%) 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 4-3 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%), as these percentages are not statistically different ($\chi^2(1)=0.11, p>.05$).
As suggested by a simple chi-square test ($\chi^2(2)=13.74, p<.001$) on the distribution of voter education (Table 4-3), college educated voters (43.8%) seem to be significantly less likely to refuse compared to voters with high school (47%) or with secondary education or less (47.8%). In terms of socioeconomic status, there appears to be no statistical difference between voters who are characterized as low class (47.7%), middle-low class (47.6%), middle-class
and middle-high or high class (46.2%) under conventional testing levels ($\chi^2(3)=4.40$, $p>.05$).

Table 4-3 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%) as voters with no telephone service (47.8%), 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%) as voters who are not TV owners (49.0%), ($\chi^2(1)=2.59$, $p>.05$). The data also suggest that ruralness seems to be related to exit polling participation. The level of nonresponse in rural areas (44.7%) is significantly lower than in nonrural areas (47.8%) at conventional statistical levels ($\chi^2(1)=10.66$, $p<.001$).

Table 4-4 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% when voters are less than 40 years old; however, the nonresponse rate decreases for the same group (college educated voters, 39.1%) 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% (=48.8%-46.7%), whereas among older voters (defined as 40 years or more) this difference is approximately 8% (=47.1%-39.1%).
Table 4-4 Exit Polling Response by Voter Age and Voter Education (Row Percentages)

<table>
<thead>
<tr>
<th>Voter Education</th>
<th>Response</th>
<th>Nonresponse</th>
</tr>
</thead>
<tbody>
<tr>
<td>When Voter Age=0 (Less than 40 years)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Secondary Education or Less</td>
<td>51.2</td>
<td>48.8</td>
</tr>
<tr>
<td>2 High School</td>
<td>58.0</td>
<td>42.0</td>
</tr>
<tr>
<td>3 College</td>
<td>53.3</td>
<td>46.7</td>
</tr>
<tr>
<td>Pearson $\chi^2 (2) = 20.89$ Pr = 0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>When Voter Age=1 (40 years or More)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Secondary Education or Less</td>
<td>52.9</td>
<td>47.1</td>
</tr>
<tr>
<td>2 High School</td>
<td>43.9</td>
<td>56.1</td>
</tr>
<tr>
<td>3 College</td>
<td>60.9</td>
<td>39.1</td>
</tr>
<tr>
<td>Pearson $\chi^2 (2) = 54.50$ Pr = 0.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Data in Table 4-5 indicate that the effect of voter age on nonresponse changes depending on levels of interviewer age. Approximately one half (50.8%) of the oldest voting group (i.e., voters aged 40 years or more) refused to participate when approached by a younger interviewer (i.e., a person aged 20 years or less). Importantly, such percentage decreases (46.8%) 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%) when the interviewer is even older (i.e., between 31 and 40 years). Nonresponse remains under one half (45.1%) when the interviewer is in the oldest category (i.e., 41 years or more).
Table 4-5 Exit Polling Response by Voter Age and by Interviewer Age (Row Percentages)

<table>
<thead>
<tr>
<th>When Interviewer Age=1 (&lt;=20 years)</th>
<th>Response</th>
<th>Nonresponse</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voter Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Less than 40 years</td>
<td>50.3</td>
<td>49.7</td>
</tr>
<tr>
<td>1 40 years or More</td>
<td>49.2</td>
<td>50.8</td>
</tr>
<tr>
<td>Pearson $\chi^2 (2) = 0.54$ Pr = 0.462</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| 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 $\chi^2 (2) = 1.75$ 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 $\chi^2 (2) = 0.628$ 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 $\chi^2 (2) = 2.41$ Pr = 0.120 |         |             |

Table 4-6 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%) 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% refused to participate. Similarly, when college educated voters are approached by interviewers with comparable levels of education (i.e., college), only 44.2% declined to participate.
### Table 4-6 Exit Polling Response by Voter Education and by Interviewer Education (Row Percentages)

<table>
<thead>
<tr>
<th>Interviewer Education=1 (Less than High School)</th>
<th>Response</th>
<th>Nonresponse</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voter Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Secondary Education or Less</td>
<td>49.9</td>
<td>50.1</td>
</tr>
<tr>
<td>2 High School</td>
<td>51.2</td>
<td>48.8</td>
</tr>
<tr>
<td>3 College</td>
<td>50.5</td>
<td>49.5</td>
</tr>
<tr>
<td>Pearson $\chi^2 (2) = 0.22$ Pr = 0.892</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Interviewer Education=2 (HS 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 $\chi^2 (2) = 17.50$ 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 $\chi^2 (2) = 3.40$ Pr = 0.183         |          |             |

### Table 4-7 Exit Polling Response by Voter Age and Ruralness (Row Percentages)

<table>
<thead>
<tr>
<th>When Rural=0 (Nonrural)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Voter Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Less than 40 years</td>
<td>53.2</td>
<td>46.8</td>
</tr>
<tr>
<td>1 40 years or More</td>
<td>51.3</td>
<td>48.7</td>
</tr>
<tr>
<td>Pearson $\chi^2 (2) = 3.88$ Pr = 0.049</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>When Rural=1 (Rural)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Voter Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Less than 40 years</td>
<td>53.2</td>
<td>46.8</td>
</tr>
<tr>
<td>1 40 years or More</td>
<td>57.0</td>
<td>43.0</td>
</tr>
<tr>
<td>Pearson $\chi^2 (2) = 5.87$ Pr = 0.015</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Data displayed in Table 4-7 indicates that older voters in rural contexts are less likely to refuse (43%) compared to older voters in urban areas (48.7%). 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% for both rural and nonrural contexts. With these bivariate analyses from Tables 5-3 through Table 4-7 in mind, we now turn to explore 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 4-8. 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 4-8 Logistic Regression Model for Predictors of Nonresponse

| Pr (Y=Refusal|x_i)                  | Model A        | Model B        |
|-----------------------------------|----------------|----------------|
|                                   | 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)         | -0.00004       | (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 Socio Economic 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)         |
| 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)         |

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

Table 4-8 (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 vs. accepting the request are approximately 7.5% 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, \( \logit = -0.0004, \ SE = 0.05 \)) 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) helps 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 4-8 indicates that the odds of refusing to participate vs. accepting the request are 16.4% lower \( \left[ (\exp(-0.179) - 1) \times 100 \right] \) for voters with college education relative to voters with 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% lower (and are not significant) for voters with college education relative to voters with secondary education or less. This suggests that education tends to play also an indirect effect on exit polling nonresponse depending on voter age.

In terms of socioeconomic status, Model A and Model B (Table 4-8) 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 SES) 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% 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 B (Table 4-8) suggest that although the odds of refusing to participate are 4.5% 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 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% \(=(\exp(-0.224)-1)*100\) 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% \(=(\exp(-0.119)-1)*100\) lower for rural voters vs. 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 4-8) an interaction term between voter age and voter education is included. When the odds ratio of refusing to participate is calculated for college educated voter (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 aged 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 odd ratios for older voters vs. younger voters in rural areas are calculated \([\exp(-0.00004) \times \exp(-0.192)]\) 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 to refuse are less than the odds of 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 are 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 level-2 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); in this case, the interviewer.

To ease interpretation of a multilevel “empty model,” a conventional single-level “empty model” (i.e., a constant-only model with no level-2 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 4-9). 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 4-9.

To assess whether level-2 information (interviewer level data) is needed to help explain the expected distribution of the outcome variable (nonresponse), level-2 data or “grouping” information is added to the model. Table 4-9 (column “Multilevel Empty Model”) shows a no-predictors model with a constant of -0.474. As it can be seen from Table 4-9, 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 than its standard error (0.15) suggests that there is significant variation among level-2 units (i.e., interviewers).

The estimated intraclass correlation coefficient (ICC=0.280) shown in Table 4-9 suggests that approximately 30% of the variance can be attributable to the influence of level-2 components. The level-2 constant-only model (i.e., Multilevel Empty Model) provides a likelihood ratio test for the null hypothesis that the between-cluster variance is zero compared to a single-level constant-only model ($\chi^2=2,391.61, p<.05$), which indicates that a multilevel model (also known as mixed model) is needed.

<table>
<thead>
<tr>
<th>Predictors (x)</th>
<th>Single-level Empty Model</th>
<th>Multilevel Empty Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed Effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.123 *</td>
<td>-0.474 *</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.08)</td>
</tr>
<tr>
<td><strong>Random Effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance (Constant)</td>
<td>1.285</td>
<td>0.280</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.23)</td>
</tr>
</tbody>
</table>

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

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 “Data and Methods” from this chapter, multilevel models are explored
with a single-imputation dataset \( m=1 \) in the rest of the chapter. Thus, Table 4-10 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 level-1 characteristics controlling for level-2 variation. Since interviewers can have different effects on nonresponse, this first model (i.e., Model 0) let the voters’ baseline probability to 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 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 to model 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 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 4-10 are presented in logit units (i.e., the log of the odds), some of these results are selectively discussed in terms odd ratios — similar to the discussion above for single-level multivariate models displayed in Table 4-8. Consequently, it is important to keep in mind that odds ratios derived from logit models in Table 4-10 will be conditional odds ratios for (i) a voter holding other predictor variables constant and for (ii) 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 common interpretation of regression coefficients (both fixed effect and random effect models) typically assume 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 (i.e., 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 4-3).
Furthermore, SES did not appear to be a significant predictor in conventional multivariate regression models (Table 4-8).

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 4-10 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 4-10.

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 4-10 Mixed Effects Logistic Regression Models for Predictors of Nonresponse (Single-Imputed Data)

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Model 0</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pr (Y=Refusal</td>
<td>x_0)</td>
<td>Random intercept model</td>
<td>Random intercept and random slope model (Interviewer slope)</td>
<td>Random intercept and random slope model (Interviewer Education, Interviewer Age)</td>
<td>Random intercept and random slope model (Interviewer Education, Interviewer Age, Interviewer Gender and Ruralness)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
</tr>
<tr>
<td>Voter Age</td>
<td>0.041</td>
<td>(0.04)</td>
<td>0.022</td>
<td>(0.06)</td>
<td>0.022</td>
</tr>
<tr>
<td>Voter Education</td>
<td>-0.246 ***</td>
<td>(0.05)</td>
<td>-0.262 **</td>
<td>(0.09)</td>
<td>-0.260 **</td>
</tr>
<tr>
<td>Voter Gender</td>
<td>-0.100 **</td>
<td>(0.04)</td>
<td>-0.106 **</td>
<td>(0.04)</td>
<td>-0.106 **</td>
</tr>
<tr>
<td>Voter Age # Voter Education</td>
<td>-0.451 ***</td>
<td>(0.10)</td>
<td>-0.459 ***</td>
<td>(0.11)</td>
<td>-0.453 ***</td>
</tr>
<tr>
<td>Voter TV ownership</td>
<td>-0.010</td>
<td>(0.07)</td>
<td>-0.016</td>
<td>(0.07)</td>
<td>-0.016</td>
</tr>
<tr>
<td>Interviewer Education</td>
<td>--</td>
<td>--</td>
<td>-0.218</td>
<td>(0.14)</td>
<td>-0.214</td>
</tr>
<tr>
<td>Interviewer Age</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.076</td>
</tr>
<tr>
<td>Interviewer Gender</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Ruralness</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Voter Age # Interviewer Education</td>
<td>--</td>
<td>--</td>
<td>0.015</td>
<td>(0.13)</td>
<td>0.005</td>
</tr>
<tr>
<td>Voter Age # Interviewer Age</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.296</td>
</tr>
<tr>
<td>Voter Age # Ruralness</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Voter Educ # Interviewer Education</td>
<td>--</td>
<td>--</td>
<td>-0.075</td>
<td>(0.18)</td>
<td>-0.078</td>
</tr>
<tr>
<td>Voter Educ # Interviewer Age</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>-0.165</td>
</tr>
<tr>
<td>Voter Educ # Ruralness</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Voter Gender # Interviewer Gender</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
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<tr>
<td>Voter Gender # Ruralness</td>
<td>--</td>
<td>--</td>
<td>--</td>
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<td>--</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.488 ***</td>
<td>(0.08)</td>
<td>-0.486 ***</td>
<td>(0.09)</td>
<td>-0.486 ***</td>
</tr>
<tr>
<td>Random Effects</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Var(Voter Age)</td>
<td>--</td>
<td>--</td>
<td>0.313 ***</td>
<td>(0.06)</td>
<td>0.304 ***</td>
</tr>
<tr>
<td>Var(Voter Education)</td>
<td>--</td>
<td>--</td>
<td>0.504 ***</td>
<td>(0.13)</td>
<td>0.501 ***</td>
</tr>
<tr>
<td>Var(Voter Gender)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Var(Constant)</td>
<td>1.295 ***</td>
<td>(0.15)</td>
<td>1.332 ***</td>
<td>(0.16)</td>
<td>1.336 ***</td>
</tr>
<tr>
<td>Cov(Voter Education, Voter Age)</td>
<td>--</td>
<td>--</td>
<td>0.131</td>
<td>(0.07)</td>
<td>0.125</td>
</tr>
<tr>
<td>Cov(Voter Gender, Voter Age)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Cov(Constant, Voter Age)</td>
<td>--</td>
<td>--</td>
<td>0.054</td>
<td>(0.09)</td>
<td>0.053</td>
</tr>
<tr>
<td>Cov(Voter Gender, Voter Education)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Cov(Constant, Voter Education)</td>
<td>--</td>
<td>--</td>
<td>0.054</td>
<td>(0.13)</td>
<td>0.055</td>
</tr>
<tr>
<td>Cov(Voter Gender, Voter Gender)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

* 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 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 main effect in Model 1 as well as the two corresponding cross-level interaction terms: (i) voter age by interviewer education and (ii) 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 predictor of nonresponse; namely, interviewer age. In this model (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: (i) voter age by interviewer age and (ii) 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
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 vary 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 indicates 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 suggests 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 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 to 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: (i) voter age by ruralness, (ii) voter education by ruralness and (iii) 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% 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% 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 rural areas. 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 \([\exp(-0.348) \times \exp(-0.563)]\)) 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 suggests that a male interviewer has a 27% 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, the next section presents a summary of main findings. 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 inexistent 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
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 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, socio economic status, TV ownership, telephone
service. Under this novel and practical approach, a proof-of-concept study 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, lessen 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 chapter, however, suggest that voter age—as main effect—does not appear to directly predict exit polling participation, controlling for other voter and interviewer characteristics. Instead, the analysis suggests that voter age plays an indirect effect on nonresponse.

To be specific, results suggest that the effect of the voter’s age on nonresponse is mediated by different factors. Particularly, the effect depends on (i) whether the exit poll takes place in a rural context, (ii) the interviewer’s age and (iii) 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, we anticipated 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 play 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 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 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 levels 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 to 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 results leave room for future experimental research in exit polls.

**Finding 5: Voter Socioeconomic Status**

Social and psychological theories have proposed that under class 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 circumvented and socioeconomic
status was not included. The lack of significant results for the “under-class” 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, we shall return to a further exploration of SES in more robust multilevel models (with multiple imputed data) in Chapter 5.

**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 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 telephone are less likely to refuse compared to voter with no access to 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 will be re-examined with more robust models (multiply imputed data) in Chapter 5.

Similar to single-level results, multilevel models suggests that TV ownership does not seem be predictive of nonresponse. Consequently, results from this chapter 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 shows 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 suggest 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 does not appear to be statistical significance. Despite trends in main effects of voter and interviewer gender, there appear to be 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. Chapter 5 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 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 that appears to be threatening 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 chapter 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 that is, 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. Chapter 5 offers more empirically robust examinations of this hypothesis.

Discussion

The examination of data sets 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. Our 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). While results obtained in this chapter (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— a more robust examination is offered in the next chapter. Consequently, Chapter 5 offers 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.
CHAPTER 5: A FURTHER EXPLORATION OF NONRESPONSE BASED ON
MULTILEVEL MODELS WITH FULLY CONDITIONED MULTIPLY IMPUTED
DATA

Introduction

To cast light on probable causes of nonresponse in exit polls — where information on voters who choose not to respond is limited — a proof-of-concept method was introduced in Chapter 4. The method relies on model-based imputations for approximating values of missing voters. Specifically, the previous chapter discussed estimation methods appropriate to analyze nested data (i.e., voters nested within interviewers), because such approach allows to simultaneously model respondent and interviewer effects.

In Chapter 4 the focus was on providing details about multilevel regression methods without introducing a discussion on combination of results from different multiple-imputed datasets (Little & Rubin, 2002; Rubin, 1976, 1977). In the present chapter, however, a more detailed discussion of imputation methods is offered. This is because the goals of Chapter 5 are:

a) To conduct a more robust multilevel analysis using multiply imputed data to assess whether multilevel patterns on nonresponse that appear to be significant in Chapter 4 ($m=1$), hold across a set of different imputed datasets ($m=30$).

b) To introduce another set of hypothesized predictors of nonresponse (adding voter characteristics, interviewer characteristics and election day factors).

c) To include additional data in the multilevel analysis (i.e., adding data from the 2009 Congressional election) in order to conduct a more robust empirical analysis.
As discussed in Chapter 3 (Section “Number of Multiply Imputed Datasets”), the imputation literature suggests that it is important to generate missing data *multiple* times since imputed data drawn from a given estimated distribution in likely to change in every imputation attempt (Little & Rubin, 2002; Little & Rubin, 1987; Rubin, 1976). In other words, more than one dataset is necessary to account for the uncertainty associated with the fact that data were not originally observed (Brick & Kalton, 1996; Graham et al., 2007; Little & Rubin, 2002; Rubin, 1987). Prior to conducting multilevel modeling with multiply imputed data, we compare univariate statistics of an important variable in exit polls (vote choice), calculated based on different methods to handle nonresponse. This examination will provide insights as to the usefulness and possible limitations of multiple-imputed datasets.

**An Initial Empirical Examination of Multiply Imputed Data**

This section offers an initial empirical illustration of how traditional approaches used to handle nonresponse (i.e., list-wise deletion, class weighting and single imputation) compare to a more innovative method (i.e., multiple imputation). Specifically, Table 5-1 and 5-2 display descriptive statistics for vote intention, which is the variable with the highest level of missingness in the 2006 and 2009 data (as shown in Table 5-3, later in this chapter).

While vote intention is not utilized to predict nonresponse in multilevel models, it helps to exemplify and assess different methods to account for nonresponse in exit polls. More importantly, self-reported vote choice for the 2006 Presidential election and the 2009 midterm Congressional election are compared to their corresponding official results. Table 5-1 and 5-2
present estimates of vote intention for the 2006 and 2009 data using each one of the approaches (complete-case, class weighting, single- and multiple-imputation).

Class weighting estimation is conducted based on two voter characteristics; namely, age and gender, because these are the only two available variables for respondents and nonrespondents. Single and multiple imputation models are based on information and models detailed in Chapter 3 (Section “Imputation Methods”).

In Table 5-1 and 5-2, the complete-case column (i.e., list-wise deletion approach) generates point estimates and variances directly from non-missing observations; that is, respondents only. The single and multiple imputation columns show point estimates and variances that substitute missing values with one \((m=1)\) or many \((m=30)\) plausible values for them, respectively. Table 5-1 compares these four methods to the actual results for the 2006 Presidential election. As one would expect, the point estimates for class weight, single and multiply imputed data are not very different from one another. In fact, the differences occur in terms of standard errors across methods (Raghunathan, 2004).

With the exception of results for the Party of the Democratic Revolution (PRD), these imputation-based estimates represent a slight yet noticeable improvement on point estimates from the complete case estimation, as they render point estimates that are closer to the outcome of the election (Table 5-1). Class weighting results offer a slightly improvement in terms of point estimates over complete-case results, but it does not provide more cases for analysis as it does not fill-in plausible values for nonrespondents.

On the contrary, given that class weighting depends on available demographic information (i.e., age and gender) for adjustment, those cases that have missing information are
not included in class weighting calculations. This can be seen in Table 5-1 by comparing the number of cases under “Complete case” (N=6,761) vs. “Class Weighting” (N=6,733). In other words, since some respondents do not report age, the number of cases available for class weighting purposes decreases.

<table>
<thead>
<tr>
<th>Vote Choice</th>
<th>Official results</th>
<th>Complete-case approach</th>
<th>Class weighting</th>
<th>Single Imputation (m=1)</th>
<th>Multiple Imputation (m=30)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N=6,761</td>
<td>N=6,733</td>
<td>N=14,630</td>
<td>N=14,630</td>
<td></td>
</tr>
<tr>
<td>National Action Party (PAN)</td>
<td>35.9 (0.58)</td>
<td>35.2 (0.58)</td>
<td>36.4 (0.40)</td>
<td>36.5 (0.57)</td>
<td></td>
</tr>
<tr>
<td>Institutional Revolutionary Party (PRI)</td>
<td>22.3 (0.54)</td>
<td>26.7 (0.54)</td>
<td>25.3 (0.36)</td>
<td>25.4 (0.52)</td>
<td></td>
</tr>
<tr>
<td>Party of the Democratic Revolution (PRD)</td>
<td>35.3 (0.58)</td>
<td>33.6 (0.58)</td>
<td>33.6 (0.39)</td>
<td>33.4 (0.53)</td>
<td></td>
</tr>
<tr>
<td>Other/Void</td>
<td>6.5 (0.25)</td>
<td>4.6 (0.26)</td>
<td>4.6 (0.17)</td>
<td>4.7 (0.24)</td>
<td></td>
</tr>
</tbody>
</table>

In terms of variance estimates, Table 5-1 shows two expected patterns (1) single imputation-based standard errors are smaller than multiple imputation-based standard errors, and (2) single imputation-based standard errors are smaller than complete case-based standard errors. The first pattern occurs because single standard errors are based on substantially more observations (i.e., original data from respondents plus imputed values from nonrespondents) compared to complete-case standard errors.

Nonetheless, it is important to recall that standard errors from a single imputed dataset ignore the uncertainty in the imputation process, because single-imputation estimation essentially treats imputed values as if they were observed values. In contrast, standard errors from multiply
imputed datasets are wider than their single imputation counterparts as they do account for imputation variability. Put differently, the estimates in the multiple imputation column acknowledge that there are many plausible values that can help approximate non-observed values.

Table 5-2 presents similar results for estimates for the 2009 Congressional election. It is interesting in this case to note that the information available in the imputation model does not yield a substantial improvement in the point estimates; that is, percentages based on single or multiple imputations show negligible differences with regard to complete-case point estimates. The only noticeable differences are for class weighting; however, as mentioned before, class weighting does not approximate values for nonrespondents based on an imputation model.

Most importantly, patterns in estimated standard errors displayed in Table 5-2 follow the same pattern as those in Table 5-1. Explicitly, while single imputation-based estimates for standard errors may seem to be more efficient at a first look, their size reflects an underestimation in true variability derived from assuming plausible imputed values as true values. The correction made on standard error estimates from multiple imputed data through the “Rubin rules” (Little & Rubin, 2002) allows them to reflect variability more accurately than the other two methods.
Table 5-2. Percent and Standard Errors for Vote Choice under Different Imputation Approaches for 2009 Congressional Data

<table>
<thead>
<tr>
<th>Vote Choice</th>
<th>Official results</th>
<th>Complete-case approach</th>
<th>Class weighting</th>
<th>Single Imputation ($m=1$)</th>
<th>Multiple Imputation ($m=30$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N=1,685</td>
<td>N=1,685</td>
<td>N=3,557</td>
<td>N=3,557</td>
<td></td>
</tr>
<tr>
<td>National Action Party (PAN)</td>
<td>28.0</td>
<td>30.6 (1.05)</td>
<td>29.8 (1.11)</td>
<td>30.0 (0.73)</td>
<td>30.5 (1.02)</td>
</tr>
<tr>
<td>Institutional Revolutionary Party (PRI)</td>
<td>36.8</td>
<td>35.4 (1.09)</td>
<td>37.3 (1.18)</td>
<td>35.8 (0.77)</td>
<td>35.4 (1.10)</td>
</tr>
<tr>
<td>Party of the Democratic Revolution (PRD)</td>
<td>12.2</td>
<td>16.0 (0.84)</td>
<td>14.6 (0.86)</td>
<td>15.6 (0.58)</td>
<td>16.1 (0.89)</td>
</tr>
<tr>
<td>Other/Void</td>
<td>23.0</td>
<td>18.0 (0.88)</td>
<td>18.4 (0.94)</td>
<td>18.6 (0.62)</td>
<td>18.0 (0.85)</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Overall, results from Tables 6-1 and 6-2 indicate that multiple imputation provide reasonable data to estimate results. A comparison of four different methods (i.e., complete-case, class weighting, single- and multiple-imputation) to actual election results provides further evidence to suggest that multiple imputation gives a way of approximating plausible values for nonrespondents without compromising accuracy in results.

An Expanded Perspective on Predictors of Nonresponse

To continue exploring predictors of nonresponse from a multilevel modeling perspective, the rest of the chapter will be devoted to both (i) re-assess two key findings from Chapter 4 using a more robust approach (i.e., examining multiply filled-in datasets ($m=30$)), and (ii) evaluate additional hypotheses motivated by theoretical accounts in exit polls yet to be explored, using pooled data from 2006 and 2009. A total of ten hypotheses are investigated in the following sections, and they are divided into three themes, as follows.
a) The first two hypotheses (i.e., H1 and H2) examine two interactive concepts that appear to be significant in Chapter 4; that is, (i) the interaction between voter age and voter education and (ii) the interaction between voter age and interviewer age.

b) H3 through H6 are new hypotheses that seek to expand understanding of respondent and interviewer effects on nonresponse. Concretely, H3 explores whether the type of election (Congressional vs. Presidential) has an effect on nonresponse, H4 focuses on voter socioeconomic status, and H5 and H6 focus on aspects related to interviewer characteristics (interviewer experience in exit polling, interviewer average interviewing length), and other respondent characteristics (respondent time of day for voting).

c) The third set of hypotheses (i.e., H7-H10) seek to explore contextual aspects of exit polls, also known as “election day factors” — which may not always be under the researchers’ control. These factors are interviewer distance from the voting station, whether the interviewer monitored more than one exit and problems with election officials.

Re-assessing Initial Nonresponse Hypotheses

To layout the groundwork for a more robust exploration of nonresponse patterns that appear to be significant in Chapter 4, key findings from said chapter are considered once again briefly. Initial examinations of respondent characteristics with a single imputed file (i.e., 2006 exit polling data) suggest that voter age is not likely to be significant as a main effect, but it is significant as an interactive term. Put differently, the effect of age on nonresponse is likely to
change depending on the voter’s level of education. Higher levels of education seem to reduce nonresponse among older voters, but higher levels of education do not seem to lessen nonresponse among younger voters. Other respondent characteristics such as gender or TV ownership do not seem to have a systematic effect on nonresponse.

Additionally, exploratory work conducted with a single imputed file in Chapter 4 suggests that not all interviewer characteristics (i.e., interviewer education, gender and age) equally contribute to nonresponse. Initial patterns suggest that only interviewer age seems to be a moderating factor for a specific respondent characteristic (voter age). That is, an older voter being approached by a younger interviewer seems to be more reluctant to participate, compared to an older voter being approached by an older interviewer. Further, a younger voter seems to be equally likely to participate in an exit poll whether he or she is approached by an older or younger interviewer. The other two interviewer characteristics (i.e., gender and education) do not seem to mediate the effect of any other voter characteristic; namely, voter age, voter education or voter gender.

**Hypothesis 1: The Interaction of Voter Age and Voter Education**

Imputed data drawn from a single distribution ($m=1$) for the 2006 Presidential election provided initial evidence to support the hypothesis that a lessened cognitive capacity due to aging could be offset by higher levels of education to explain refusals. The primary goal of H1 in this chapter is to assess whether multiple imputed datasets ($m=30$) also support the notion of this interaction.
H1: Older voters with higher levels of education are less likely to refuse relative to older voters with lesser education. Younger voters with higher levels of education are equally likely to refuse compared to younger voters with lesser education.

Hypothesis 2: The Interaction of Interviewer Age and Voter Age

An initial multilevel analysis based on a single imputed dataset from the 2006 Presidential election provided initial evidence to support the nexus between interviewer and voter age, consequently, the goal of H2 in this chapter is to evaluate whether multiple imputed datasets \((m=30)\) offer empirical evidence to support the hypothesized conditional effect (i.e., the impact of voter age on refusals changes at different levels of the interviewer age).

H2: Older voters approached by younger interviewer are more likely to refuse relative to older voters approached by an older interviewer. However, interviewer age is not likely to have an effect on nonresponse among younger voters.

Exploring More Plausible Nonresponse Hypotheses

Hypothesis 3: The Effect of Type of Election on Nonresponse

Initial multilevel analyses conducted in Chapter 4 (with a single imputed dataset) indicate that hypothesized relationships seem to find empirical support in a Presidential election (i.e., data
from 2006). Nonetheless, it remains to be explored whether similar patterns are likely to occur also in other elections; in this case, in a Congressional election (i.e., data from 2009). Consequently, it is hypothesized that voters who show up to cast their ballot in a Presidential election are equally likely to refuse cooperation as voters who show up to cast their ballot at midterm elections.

It is expected that voter and interviewer effects discussed in Chapter 4 for a Presidential election (i.e., voter age, voter education, interviewer education, interviewer age and ruralness) also occur in midterm elections (Congressional), across a set of multiple-imputed datasets ($m=30$). If the patterns are not the same across elections, it would suggest that the group of voters who show up at Congressional elections may have different socio-psychological characteristics (for instance, different levels of motivation to participate), and may not experience the same social pressure when interacting with interviewers, as Presidential voters. As it will be explained in the methodological section of this chapter, the 2006 and 2009 datasets are pooled together and an indicator variable (Congressional vs. Presidential election) is used to test whether there is a difference between the two elections.

$H3$: Congressional voters as likely to refuse as Presidential voters after accounting for voter and interviewer demographic characteristics.

**Hypothesis 4: Social Connectedness**

Theories of social isolation suggest that people having weaker ties with society are less interested in cooperating with societal events, including survey requests (Couper, Singer, &
Kulka, 1998; Goyder & Leiper, 1985; Groves et al., 1992; Groves & Couper, 1998). In the context of household surveys, Groves and Couper (1998) hypothesized that people disengaged from society tend to be less cooperative with survey requests relative to those more integrated with society.

Under this theoretical view, people with lower socioeconomic status would be less integrated to the mainstream norms, and consequently less likely to answer a survey, relative to those with a higher status (Groves & Couper, 1998). In the same fashion, Merkle and Edelman (2002) hypothesized that in exit polls, people who tend to be less connected with society at large would be less likely to accept survey request. Merkle and Edelman (2002), however, hypothesized a weaker effect in exit polls (compared to household surveys) since voters in an election are already participating in a societal event.

Groves and Couper (1998) did not find support for the social isolation hypothesis using as proxy measure socioeconomic status. Similar to Groves and Couper’s (1998) results, Merkle and Edelman (2002) did not find evidence to support using as proxy measure voter race. Consistent with previous studies, initial single-level bivariate and multivariate analyses with single imputed data (m=1) introduced in Chapter 4 suggest that neither socioeconomic status nor TV ownership seem to be related to survey participation.

Nonetheless, in an attempt to explore the social isolation hypotheses in exit polls with a more robust approach (i.e., multilevel data with multiply imputed data, m=30), this chapter examines voter socioeconomic status. Consequently, it is hypothesized that:

\[ H4: \text{Voters with lower SES are less likely to refuse cooperation relative to voters with higher SES.} \]
Hypothesis 5: Interviewer Experience in Exit Polling

Overall, in the survey methodology literature, interviewer experience has been found to correlate with survey data quality (Cannell et al., 1977; Gfroerer et al., 1997; Krosnick et al., 2002; Singer et al., 1983). Nonetheless, studies on the effect of interviewer experience are scarce in the field of election day surveys (Merkle & Edelman, 2002). Using a composite index of three variables to represent interviewer experience at the precinct level (that is, number of telephone surveys worked on, number of in-person surveys worked on and number of exit polls worked on), Merkle and Edelman (2002) found no relationship between interviewer experience and response rates. It is possible that such non-significant relationship is due to the fact that the interviewing experience acquired in telephone or household surveys is not automatically an asset on exit polling, or that aggregate level data may not be helpful to reveal dynamics that occur at the individual level.

Interestingly, using individual-level information, Stevenson (2006) found that interviewers with previous job experience involving activities that required human interaction such as retail sales, door-to-door sales, waiter/waitress experience, and telemarketing/surveys had a positive relationship with exit polling participation. While most of these job experiences studied by Stevenson (2006) do imply strength in communicative skills and abilities to deal with people, they are not a measure of exit polling experience.

Given that the literature suggests that individual interviewer experience may help to predict refusals in exit polls, it is hypothesized that:
H5: Interviewers with previous exit polling experience are less likely (relative to interviewers with no exit polling experience) to produce refusals.

Hypothesis 6: Interviewer Average Interview Length

Scholars have hypothesized that interviewer actions are influenced by their perception and attitudes towards the interviewing task (Cannell et al., 1981; Singer et al., 1983). Apparently, as interviewers start feeling confident about interviewing, they unknowingly start to modify their behaviors, and depart from established research protocols (Olson & Peytchev, 2007). Under this view, as interviewers go through their workload they become less careful in the way they administer questionnaires.

Available studies indicate that interviewers who increase the pace at which interviews are conducted are more likely to introduce error relative to interviewers who do not increase the pace (Cannell et al., 1981; Fowler, 1991; Hox, 1994; Olson & Peytchev, 2007; Pickery & Loosveldt, 2001). As Olson and Peytchev (2007, p. 274) put it: “Faster interviews could lead to lower response quality because the respondent is not able to devote adequate time to the response formation process.”

In this study, it is hypothesized that interviewers whose average interviewing time (for completed interviews) is shorter than the average time, become overconfident in their interviewing skills, they pay less attention to instructions, and tend to dismiss contacting and recruiting protocols. Therefore, it is hypothesized that “faster” interviewers are more likely than “slower” interviewers to experience refusals.
In the 2006 and 2009 datasets, interviewers reported that the minimum time they took to conduct an interview was one minute, the maximum time was fifteen minutes, and the average time it took to conduct an interview was about five minutes. Using average interview length (less than five minutes vs. more than five minutes) as proxy measure to categorize overconfident (i.e. faster) vs. careful (i.e., slower) staff, it is proposed hypothesize that,

\( H6a: \) Faster interviewers (i.e., whose average interview length is less than five minutes) are more likely than slower interviewers (i.e., interviewers whose average interview length is more than five minutes) to experience higher refusal rates.

Furthermore, in the context of exit polling, interviewer expectations and attitudes toward the task might be affected also by previous experience, as hypothesized in H5. That is, prior experience conducting exit polls may influence interviewers’ perceptions of the interviewing tasks. Consequently, it is also hypothesized that previous exit polling interviewing help offset the effect of overconfidence.

\( H6b: \) Among interviewers with prior exit polling experience, faster interviewers (i.e., those whose average interview length is less than five minutes) are as likely as slower interviewers (i.e., interviewers whose average interview length is more than five minutes), to experience higher refusal rates. However, among interviewers with no prior exit polling experience, faster interviewers are more likely than slower interviewers, to experience higher refusal rates.
Hypothesis 7: Respondent Time of Day for Voting

Time of day at which voters cast their vote on election day has been hypothesized to affect election outcomes (Busch & Lieske, 1985; Fuchs & Becker, 1968; Klorman, 1976) and on exit polling estimates (Stevenson, 2006). Particularly, Busch and Lieske (1985) hypothesized that turnout rates vary across subgroups over the course of the day; namely, housewives and retirees would be more likely to show up at voting stations in the early- and mid-afternoon. Under this view, these groups would want to avoid wait time due to long lines typically found in early morning or late afternoon (Spencer & Markovits, 2010). Conversely, professionals would be more likely to show up in the early morning and factory workers in the late afternoon due to work schedules (Busch & Lieske, 1985).

In the context of exit polling, Stevenson (2006) found that afternoon hours tend to produce higher cooperation rates compared to morning hours. This suggests that morning voters—who are presumably voters with busier schedules—are more likely to refuse than late afternoon voters. Interestingly, the literature also suggests that time of voting can be due to interviewers effects; that is, interviewers may feel more confident as the day progresses, thus afternoon voters may seemingly be more likely to cooperate (Brown et al., 2004).

Additionally, the literature suggests that higher levels of cooperation observed among afternoon voters (relative to morning voters) could be partially due to the fact that the majority of older voters—who presumably have an overall tendency to refuse to participate (Merkle & Edelman, 2002)—have already cast their ballots by mid-afternoon (Brown et al., 2004; Merkle & Edelman, 2000). Consequently, it is hypothesized that:
Hypothesis 8: Interviewer Distance from Exit

The exit polling literature reports that position of interviewer at the voting station is likely to have an impact on refusals; namely, the farther the interviewers are from the voting booth, the more likely they are to elicit refusals (Edison Media Research and Mitofsky International, 2005; Frankovic, 1992; Merkle & Edelman, 2002; Stevenson, 2006). While interviewers’ distant position from the polling place may cause difficulty for identifying actual voters (which may affect interviewers’ motivation to persuade exit voters), Merkle and colleagues (2002) suggests that it is possible that as voters start moving away from the voting station they start preparing for the next order of business in their day.

H8: Interviewers whose location from the voting station is more 10 meters (~30 feet) are more likely (relative to interviewers whose location from the voting station is less than 10 meters (~30 feet) to produce refusals.

Hypothesis 9: Interviewer Monitored More than One Exit at Voting Station

The literature indicates that interviewers have difficulties in reaching voters on election day due to multiple exits (Bautista et al., 2006; Edison Media Research and Mitofsky
Interviewers are tasked with several activities during the day, including keeping up with a selection rate (i.e., contacting every \( kth \) voter), keeping track of nonrespondents, handing out questionnaires, calling the data center to transmit results periodically, among other activities. Consequently, adding one more activity (i.e., monitoring multiple exits) may lessen interviewer motivation to persuade voters to participate in an exit interview.

\[
H9: \text{Interviewers who monitor more than one exit are more likely (relative to interviewers who monitor just one exit) to experience higher rates of refusals.}
\]

**Hypothesis 10: Interviewer Problems with Election Officials on Election Day**

The literature reports problems with election officials or party representatives on election day response may have an effect on cooperation. Particularly, Merkle and Edelman (2002) show that problems with precinct officials have a negative impact on response rates, further suggesting that problems with precinct officials may explain distant interviewing positions. Similarly, Edison/Mitofsky (2005) indicate that there appear to be differences in response rates due to such types of problems. Bautista and colleagues (2006) in a Mexican exit poll also found evidence to suggest that problems with election officials have an impact on response rate. Consequently, it is hypothesized that unfriendly election officials may cause interviewer legitimacy to decrease, thus lessening interviewer confidence.
H10: Interviewers who experience problems with election officials are more likely than those interviewers who do not experience problems with election officials to experience a higher rate of refusals.

Data and Methods

As detailed in Chapter 3, data for this study come from two nationwide exit polls conducted in Mexico in 2006 and 2009 for a Presidential and Congressional election, respectively. Relevant metrics for analysis are interviewers’ demographic data (i.e., age, gender and education), interviewer characteristics (i.e., exit polling experience and average time spent in each interview) as well as contextual information related to exit polling on election day (i.e., distance from the voting station exit, number of exits and problems with officials). Importantly, this chapter considers multilevel analysis based on multiply imputed datasets. Furthermore, this section provides a revision of the level of missingness in the data and a comparison of key univariate statistics before and after imputation procedures.

Missingness in the Data

Table 5-3 displays level of missingness in the data in the 2006 and 2009 exit polls, whether due to unit nonresponse (i.e., refusals) or item nonresponse (i.e., lack of an answer to a particular survey item). Overall, voter gender and voter age have the lowest level of missing data in both years, having less than a half of a percentage point or zero percent; that is voter gender
(0.05% and 0.00%) and voter age (0.27% and 0.14%), in 2006 and 2009 respectively. However, voter education has a non-negligible level of missingness with approximately 47% of the data missing in 2006, and 38% in 2009.

These levels of missing data are similar for voters’ time of day for voting, telephone service and TV ownership in both years (approximately 47% in 2006 and 38% in 2009). Socioeconomic status has approximately 48% of missing data in 2006 and 39% in 2009. Vote choice is the variable with the highest level of missing data in both years with a little over 50% in both years (54% and 53%).

<table>
<thead>
<tr>
<th>Table 5-3. Level of Missingness in Data from 2006 and 2009 Exit Poll</th>
</tr>
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<tbody>
<tr>
<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td>Voter Characteristics</td>
</tr>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Education</td>
</tr>
<tr>
<td>Voters’ time of day for voting</td>
</tr>
<tr>
<td>Telephone Service</td>
</tr>
<tr>
<td>TV ownership</td>
</tr>
<tr>
<td>Socio Economic Status</td>
</tr>
<tr>
<td>Vote choice</td>
</tr>
<tr>
<td>Interviewer Characteristics</td>
</tr>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>Education</td>
</tr>
<tr>
<td>Exit polling experience</td>
</tr>
<tr>
<td>Average interview length</td>
</tr>
<tr>
<td>Contextual elements</td>
</tr>
<tr>
<td>Interviewer distance from exit</td>
</tr>
<tr>
<td>Interviewer problems with election officials</td>
</tr>
<tr>
<td>Number of exits monitored by interviewer</td>
</tr>
<tr>
<td>Ruralness</td>
</tr>
</tbody>
</table>
Interviewer characteristics present a relatively low level of missingness in the data for both years; that is, the level of non-observed data ranges from two to seven percentage points for all variables in both years. Particularly, interviewer age has the lowest level of missing data with approximately 2% in 2006 and no missing data in 2009 (0%). The missingness level for interviewers’ gender is higher in 2006 (approximately 7%) relative to 2009 (approximately 3%), and interviewer education is approximately 5% in 2006 and no missing data in 2009 (0%). Other interviewer attributes such as exit polling experience and average interview length have 4% or less of missing data in 2006 and 0% in 2009.

Contextual elements also have a lower level of missing data; namely, interviewer distance from exit, interviewer problems with election officials and number of exits monitored by interviewer have about 3.5% or less of missing data in 2006 and 0% percent of missing data in 2009. Ruralness does not have missing data since rural/urban characteristics are derived from the sampling frame in both years.

As shown earlier in this chapter (Section “An Initial Empirical Examination of Statistical Approaches for Missing Data”) and in Chapter 3 (Section “Distribution of Univariate Statistics Before and After Imputation”), differences between original data and multiply-imputed data used in multilevel models seem to be negligible, which gives credence to the plausibility of imputed data. Further, to ease interpretation of regression coefficients with dichotomous variables for multilevel models —where it is typically assumed to hold everything else constant— variables were centered on the overall mean of each variable.

As discussed in Chapter 4 (Section “Mean-centering of Predictor Variables in Multilevel Models”), different mean centering strategies can have different impact on estimated intercepts
and slope parameters in multilevel models. As detailed in Chapter 4, grand-mean centering is adopted instead of group-mean centering thus making coefficients more interpretable in multilevel models. Consequently, mean-centered binary variables allow interpretation of the mean of each variable as the proportion of cases in the sample.

Results

Multilevel Regression Models Based on a Single vs Multiple Imputations

This section presents results from multilevel models or “mixed effects” models (i.e., fixed and random effects) for regressions fitted with multiply imputed data using Presidential and Congressional data. The “fixed effect” part can be thought of as the comparison of means across levels of a given predictor (for instance, the mean value of the Congressional group relative to the mean value of the Presidential group). Alternatively, fixed effects can be thought of as the conditional effect estimated for the i-th voter holding other predictors constant at their mean within the same or average j-th interviewer.

The “random effect” components are helpful to understand to what extent Level-2 or random factors (i.e., interviewers) explain the variability in the dependent variable (i.e., nonresponse). Not only do random parameters help to account for this source of variability in the regression model, but they provide an explicit estimate for the variability. Put differently, unlike the information provided by fixed effects for Level-1 units (i.e., how the mean effect for the i-th voter changes across levels of the factor), random effects show the variance of i-th voter means across values of level-2 factors (i.e., the j-th interviewer).
Contrasting Multilevel Models Based on Single and Multiply Imputed Data

This section presents regression models with a focus on multilevel models estimated on multiply imputed data. Table 5-4 compares the random effects model introduced in Chapter 4 as Model 4 (estimated on the basis of a single imputation with 2006 data) with Model 5 (estimated on the basis of 30 imputed datasets with 2006 data). For the sake of a side-by-side comparison with Model 5 (i.e., 2006 data, multiple imputation), Model 4 (i.e., 2006 data, single imputation) from Chapter 4 is displayed again in Table 5-4. Importantly, Model 5 is empirically superior to Model 4 due to the fact that Model 5 considers regression outcomes across multiple imputed datasets.

In Model 5, regression coefficients and standard errors from 30 different imputations are averaged following “Rubin rules” (Little & Rubin, 2002; Rubin, 1976, 1996). As previously discussed, multiple imputations help to account for the uncertainty created by missing data. Therefore, a more empirically robust interpretation of respondent and interviewer effects with the 2006 data is possible with Model 5. Multilevel regression parameters in Model 5 (multiple imputation) are identical to Model 4 (single imputation); namely, voter age, voter gender and voter education vary across levels of interviewer education, interviewer age and ruralness. Consequently, Model 5 includes corresponding cross-level interaction terms as well.
Table 5-4. Mixed Effects Logistic Regression Models for Predictors of Nonresponse: Single \((m=1)\) vs Multiply \((m=30)\) Imputed 2006 Data

<table>
<thead>
<tr>
<th>Predictors</th>
<th>2006 Data</th>
<th>Presidential Exit Polling Data</th>
<th>2006 Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 4 ((m=1))</td>
<td>Coef.</td>
<td>SE</td>
</tr>
<tr>
<td><strong>Fixed Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pr ((Y=\text{Refusal}</td>
<td>x_0))</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Voter Age</td>
<td>0.034</td>
<td>(0.06)</td>
<td>0.063</td>
</tr>
<tr>
<td>Voter Education</td>
<td>-0.348</td>
<td>***</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Voter Gender</td>
<td>-0.088</td>
<td>(0.05)</td>
<td>-0.109</td>
</tr>
<tr>
<td>Voter Age # Voter Education</td>
<td>-0.496</td>
<td>***</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Voter TV ownership</td>
<td>-0.017</td>
<td>(0.07)</td>
<td>0.042</td>
</tr>
<tr>
<td>Interviewer Education</td>
<td>-0.215</td>
<td>(0.14)</td>
<td>-0.113</td>
</tr>
<tr>
<td>Interviewer Age</td>
<td>0.094</td>
<td>(0.23)</td>
<td>-0.074</td>
</tr>
<tr>
<td>Interviewer Gender</td>
<td>0.241</td>
<td>(0.14)</td>
<td>0.230</td>
</tr>
<tr>
<td>Ruralness</td>
<td>-0.276</td>
<td>(0.19)</td>
<td>-0.176</td>
</tr>
<tr>
<td>Voter Age # Interviewer Education</td>
<td>0.003</td>
<td>(0.12)</td>
<td>0.011</td>
</tr>
<tr>
<td>Voter Age # Interviewer Age</td>
<td>-0.319</td>
<td>(0.17)</td>
<td>-0.374</td>
</tr>
<tr>
<td>Voter Age # Ruralness</td>
<td>-0.282</td>
<td>*</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Voter Educ # Interviewer Education</td>
<td>-0.074</td>
<td>(0.18)</td>
<td>0.004</td>
</tr>
<tr>
<td>Voter Educ # Interviewer Age</td>
<td>-0.148</td>
<td>(0.24)</td>
<td>-0.274</td>
</tr>
<tr>
<td>Voter Educ # Ruralness</td>
<td>-0.563</td>
<td>*</td>
<td>(0.27)</td>
</tr>
<tr>
<td>Voter Gender # Interviewer Gender</td>
<td>0.022</td>
<td>(0.10)</td>
<td>-0.025</td>
</tr>
<tr>
<td>Voter Gender # Ruralness</td>
<td>0.010</td>
<td>(0.12)</td>
<td>0.025</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.495</td>
<td>***</td>
<td>(0.09)</td>
</tr>
</tbody>
</table>

| **Random Effects** | | | | | | | | | | | |
| Var(Voter Age) | 0.296 | *** | (0.06) | 0.297 | *** | (0.06) | | | | |
| Var(Voter Education) | 0.457 | *** | (0.13) | 0.580 | *** | (0.16) | | | | |
| Var(Voter Gender) | 0.175 | *** | (0.05) | 0.170 | *** | (0.05) | | | | |
| Var(Constant) | 1.345 | *** | (0.16) | 1.337 | *** | (0.16) | | | | |
| Cov(Voter Education, Voter Age) | 0.106 | (0.07) | 0.086 | (0.08) | | | | | | |
| Cov(Voter Gender, Voter Age) | -0.084 | * | (0.04) | -0.080 | * | (0.04) | | | | |
| Cov(Constant, Voter Age) | 0.061 | (0.09) | 0.033 | (0.09) | | | | | | |
| Cov(Voter Gender, Voter Education) | -0.059 | (0.06) | -0.003 | (0.07) | | | | | | |
| Cov(Constant, Voter Education) | 0.068 | (0.13) | -0.116 | (0.16) | | | | | | |
| Cov(Constant, Voter Gender) | -0.149 | (0.08) | -0.102 | (0.08) | | | | | | |

* \(p<.05\), ** \(p<.01\), *** \(p<.001\), # Interaction
Random Slope Model for 2006 (Model 5)

Results from Model 5 (multiple imputation) in Table 5-4 suggest that voter gender does not appear to have a systematic effect on survey cooperation. Neither results observed in Model 4 (single imputation) nor results from 30 different models using data from 2006 (voter gender logit=−0.109, SE=0.05, p>.05) indicate an effect. In terms of age, Model 5 (multiple imputation) offers consistent results relative to Model 4 (single imputation); that is, voter age does not seem to be in itself a predictor of nonresponse (voter age logit=−0.063, SE=0.06, p>.05). Instead, voter age seems to interact with voter education.

Unlike Model 4 (single imputation) where voter education appears to predict nonresponse, Model 5 (multiple imputation) suggests that voter education is not likely to directly predict nonresponse. Rather, Model 5 indicates that voter education plays an indirect role and it is likely to be conditional on voter age. Specifically, Model 5 suggests that the odds ratio of refusing cooperation for an older voter (compared to a young voter) is nearly the same; approximately 1.07 to 1 [=exp (0.063)]. However, such odds ratio seems to decrease for a college educated voter, as suggested by the interaction term (that is,.65 to 1 [=exp(0.063)*exp(-0.479)]).

Consistent with results from Model 4 (single imputation), Model 5 (multiple imputation) suggests that voter TV ownership is not likely to be related to nonresponse. Regression coefficients for TV ownership from Model 4 (logit=−0.017, SE=0.07, p>.05) and Model 5 (logit=0.042, SE=0.11, p>.05) do not appear to be significantly different from zero.
In terms of interviewer characteristics, Model 5 (multiple imputation) is consistent with Model 4 (single imputation) in suggesting that interviewer education (logit=-0.113, SE=0.18, \( p > .05 \)), interviewer age (logit=-0.074, SE=0.26, \( p > .05 \)) and interviewer gender (logit=0.230, SE=0.16, \( p > .05 \)) are not likely to account for nonresponse directly. Similarly, ruralness (logit=-0.176, SE=0.20, \( p > .05 \)) does not seem to directly predict nonresponse.

Nonetheless, Model 5 (multiple imputation) suggests that some interviewer characteristics as well as ruralness are likely to be mediators. Particularly, the effect of interviewer age seems to be conditioned on voter age. As mentioned before, the odds ratio of refusing cooperation for an older voter compared to a younger voter is approximately 1.07 to 1 \( [=\exp(0.063)] \); however, when this older voter is approached by an older interviewer (versus a younger interviewer), the odds ratio of refusing cooperation is likely to decrease and become approximately .73 to 1 \( [=\exp(0.063)\times\exp(-0.374)] \).

Model 5 (multiple imputation) indicates that while ruralness is not likely to predict nonresponse directly, it seems to interact with voter age as suggested by the corresponding interaction term (logit=-0.281, SE=0.13, \( p < .05 \)). As previously mentioned, the odds ratio of refusing cooperation for an older voter (compared to a younger voter) is about 1.07 to 1. When this older voter is in a rural context, the odds ratio of refusing cooperation decreases to be approximately .80 to 1 \( [=\exp(0.063)\times\exp(-0.281)] \).

While Model 4 (single imputation) suggests that voter education may interact with ruralness, Model 5 (multiple imputation) does not provide evidence to support this notion. The interaction term is not likely to be statistically significant at traditional levels (logit=-0.060, SE=0.33, \( p > .10 \)). Furthermore, results from Model 5 indicate that voter gender is not likely to
interact with ruralness. Likewise, voter gender and interviewer gender are not likely to have an interactive relationship as the interaction term is not likely to be significant (logit=-0.025, SE=0.10, \( p > 0.05 \)).

Overall, Model 5 (multiple imputation) is consistent with Model 4 (single imputation) for three interactive relationships: (i) voter age and voter education, (ii) voter age and interviewer age and (iii) voter age and ruralness. Conversely, Model 5 does not support the notion of voter education as main effect on nonresponse.

**Examining Further Hypotheses with Multilevel Models Based on Multiply Imputed Pooled Data**

Table 5-5 and 5-6 display results from four multilevel regression models (i.e., Model 6 to Model 9) estimated based on pooled data from the 2006 and 2009 exit polls. Table 5-5 displays fixed effects and Table 5-6 shows random effects. These four models were fit to multiply imputed data sets \( m=30 \). Regression results for each of the models (Model 6 to Model 9) were averaged using “Rubin rules” (Little & Rubin, 2002; Rubin, 1976, 1996) as detailed in Chapter 3 (Section “Methods for Analyzing Multiply Imputed Data”). While Model 6 (multiple imputation) and Model 7 (multiple imputation) are specified with a similar parameterization as Model 5 (multiple imputation), Model 6 and Model 7 introduce a new parameters: type of election (Congressional vs Presidential) and an interaction between type of election and voter age, respectively. Similarly, Model 8 and 9 include additional voter and interviewer characteristics (as presented in Table 5-5) that are discussed along with results below.
Random Slope Model for 2006 and 2009 (Model 6 and Model 7)

Fixed effects results (Model 6) suggest that there appears to be no difference in nonresponse patterns between Congressional and Presidential voters. While the regression coefficient indicates a negative relationship between type of election and nonresponse (logit=-0.244, SE=0.16, \( p > .05 \)), this relationship (i.e., Congressional voters susceptible to refuse at higher rates than Presidential voters) is not likely to be statistically significant. These results do not seem to change in Model 7 when interaction terms of type of election by voter characteristics (age, education and gender) are included. The main effect for type of election remains almost unaltered in Model 7 (logit=-0.246, SE=0.16, \( p > .05 \)).

Consistent with fixed effects from Model 5 (multiple imputation using 2006 data only), Model 6 and 7 (multiple imputation estimated with pooled data from 2006 and 2009) suggest that voter age and voter education are not likely to be direct predictors of nonresponse. Nonetheless, unlike results from Model 5 —where the regression coefficient of voter gender was not likely to be significant (logit=-0.109, SE=0.05, \( p > .05 \)) — the coefficients in Model 6 (logit=-0.128, SE=0.04, \( p < .05 \)) and Model 7 (logit=-0.117, SE=0.05, \( p < .05 \)) suggest that voter gender is likely to have a direct effect on nonresponse.

When regression analyses are conducted with pooled data from 2006 and 2009, Table 5-6 (random effects) suggests that in Model 6 and 7 there is a significant level of variability of voter education and voter age across interviewers (i.e., \( \text{Var(Voter Age)}=0.26, \text{SE}=0.05 \) and \( \text{Var(Voter Education)}=0.46, \text{SE}=0.13 \)). Notwithstanding, it seems the interaction voter age by voter education may not be consistent across interviewers, as suggested by fixed effects (Table 5-5).
The magnitude of the interactive effect between voter age and voter education observed in Model 5 (logit=-0.479, SE=0.15, \( p<.001 \)) decreases and loses significance in Model 6 and 7. Namely, Model 6 suggests that voter education is not likely to consistently offset the effect of voter age (logit=-0.034, SE=0.12, \( p>.05 \)) across interviewers. Furthermore, when this interaction term (i.e., voter age by voter education) is recalculated in Model 7 with two additional interaction terms (i.e., (i) voter age by type of election and (ii) voter education by type of election), the estimated results are nearly identical for the age-by-education interaction (logit=-0.035, SE=0.12, \( p>.05 \)).

To further assess whether the effect of voter characteristics depends on the type of election (Congressional vs. Presidential), Model 7 includes an additional interaction term: voter gender by type of election. Fixed effect results from Model 7 suggest none of the terms interacting with type of election is likely to be significant; namely, (i) voter gender by type of election, (ii) voter age by type of election and (iii) voter education by type of election.

Interestingly, the interaction between voter age and interviewer age — which was not statistically significant in Model 4 (single imputation for 2006) but statistically significant in Model 5 (multiple imputation for 2006) — appears to reach statistical significance in Model 6 (multiple imputation) and Model 7 (multiple imputation), once the 2006 and 2009 data are pooled.

Consistent with fixed effects from Model 5 (multiple imputation with 2006 data only), Model 6 and 7 (multiple imputation estimated with pooled data from 2006 and 2009), TV ownership does not seem to predict nonresponse. In terms of ruralness, Model 6 and 7 do not appear to support the notion observed in Model 5 where ruralness is likely to interact with voter
age. The interaction term for voter age by ruralness in Model 6 (logit=-0.171, SE=0.12, \( p > .05 \)) and Model 7 (logit=-0.168, SE=0.12, \( p > .05 \)) are not likely to be significant.

Overall, Model 7 and 8 suggest that (i) voter age and voter education do not appear to consistently interact across different interviewers, (ii) voter age is likely to interact with interviewer age, (iii) voter gender is likely to play a role in nonresponse and, (iv) the type of election (whether Congressional or Presidential) is not likely to change nonresponse patterns.
### Table 5-5. Fixed Effects Coefficients from Multilevel Logistic Regression with Multiply Imputed Pooled Data (2006 and 2009)

| Pr (Y=Refusal|x_{ij}) | Model 6          | Model 7                  | Model 8                  | Model 9                  |
|-----------------------|------------------|-------------------------|-------------------------|-------------------------|
|                       | (Type of election: Congressional vs. Presidential Election) | (Voter Age # Type of election) | (Voter Age # Type of election, Voter SES, excluding selected L1#L2 interactions) | (Voter Age # Type of election, Voter SES, including selected L1#L2 interactions) |
| Fixed Effects         | Coef.  SE        | Coef.  SE               | Coef.  SE               | Coef.  SE               |
| Voter Age            | 0.065 (0.05)     | 0.057 (0.06)            | 0.071 (0.05)            | 0.072 (0.05)            |
| Voter Education      | 0.042 (0.11)     | 0.016 (0.12)            | 0.038 (0.10)            | 0.055 (0.11)            |
| Voter Gender         | -0.128 * (0.04)  | -0.117 * (0.05)         | -0.127 ** (0.04)        | -0.127 ** (0.04)        |
| Voter Age # Voter Education | -0.034 (0.12)   | -0.035 (0.12)           | -0.034 (0.12)           | -0.034 (0.12)           |
| Voter TV Ownership   | -0.004 (0.10)    | -0.004 (0.10)           | --                      | 0.009 (0.10)            |
| Voter Socioeconomic Status | --          | --                      | --                      | 0.013 (0.05)            |
| Voter Telephone Service | --              | --                      | --                      | 0.013 (0.05)            |
| Voter Time of Day for Voting | --          | --                      | --                      | 0.013 (0.05)            |
| Interviewer Education | -0.194 (0.15)   | -0.195 (0.15)           | -0.223 (0.15)           | -0.221 (0.15)           |
| Interviewer Age      | -0.057 (0.20)    | -0.057 (0.20)           | -0.066 (0.20)           | -0.048 (0.20)           |
| Interviewer Gender   | 0.192 (0.14)     | 0.192 (0.14)            | 0.210 (0.14)            | 0.214 (0.14)            |
| Interviewer Exit Polling Experience | --          | --                      | 0.162 (0.14)            | 0.163 (0.14)            |
| Interviewer Average Interview Length | --          | --                      | -0.076 (0.13)           | -0.078 (0.13)           |
| Intv’r Exit Poll Experience # Average Intrv Length | --          | --                      | -0.024 (0.26)           | -0.022 (0.26)           |
| Interviewer Distance from Polling Place | --          | --                      | 0.018 (0.15)            | 0.018 (0.15)            |
| Interviewer Monitored More than One Exit | --          | --                      | 0.246 (0.15)            | 0.243 (0.15)            |
| Interviewer Problems with Election Officials | --          | --                      | 0.264 (0.18)            | 0.262 (0.18)            |
| Ruralness            | -0.173 (0.17)    | -0.172 (0.17)           | -0.190 (0.16)           | -0.192 (0.17)           |
| Congressional election | -0.244 (0.16)   | -0.246 (0.16)           | -0.286 (0.16)           | -0.282 (0.16)           |
| Voter Age # Interviewer Education | 0.067 (0.11)   | 0.067 (0.11)            | --                      | 0.069 (0.11)            |
| Voter Age # Interviewer Age | -0.310 * (0.14) | -0.313 * (0.14)         | -0.301 ** (0.13)        | -0.309 * (0.13)         |
| Voter Age # Ruralness | -0.171 (0.12)    | -0.168 (0.12)           | -0.166 (0.11)           | -0.168 (0.12)           |
| Voter Age # Congressional election | --          | --                      | 0.031 (0.12)            | --                      |
| Voter Education # Intv’r Education | 0.004 (0.17)   | 0.003 (0.17)            | --                      | 0.005 (0.17)            |
| Voter Education # Intv’r Age | -0.181 (0.21)  | -0.202 (0.22)           | --                      | -0.177 (0.21)           |
| Voter Education # Ruralness | 0.063 (0.30)   | 0.078 (0.30)            | --                      | 0.068 (0.30)            |
| Voter Educ # Congressional election | --          | 0.112 (0.20)            | --                      | --                      |
| Voter Gender # Intv’r Gender | -0.047 (0.09) | -0.044 (0.09)           | --                      | -0.047 (0.09)           |
| Voter Gender # Ruralness | 0.025 (0.10)    | 0.018 (0.10)            | --                      | 0.026 (0.10)            |
| Voter Gender # Congressional election | --          | --                      | --                      | --                      |
| Constant              | -0.444 *** (0.08) | -0.443 *** (0.08)       | -0.478 *** (0.07)       | -0.476 *** (0.07)       |

* p<.05, ** p<.01, *** p<.001; # Interaction
Table 5.6. Random Effects Coefficients from Multilevel Logistic Regression with Multiply Imputed Pooled Data (2006 and 2009)

<table>
<thead>
<tr>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Type of election: Congressional vs. Presidential Election)</td>
<td>(Voter Age # Type of election)</td>
<td>(Voter Age # Type of election, Voter SES, excluding selected L1#L2 interactions)</td>
<td>(Voter Age # Type of election, Voter SES, including selected L1#L2 interactions)</td>
</tr>
<tr>
<td>Coef.</td>
<td>SE</td>
<td>Coef.</td>
<td>SE</td>
</tr>
<tr>
<td>Pr (Y=Refusal</td>
<td>x_{ij})</td>
<td>Coef.</td>
<td>SE</td>
</tr>
</tbody>
</table>

**Random Effects**

| Var(Voter Age) | 0.263 *** (0.05) | 0.263 *** (0.05) | 0.261 *** (0.05) | 0.260 *** (0.05) |
| Var(Voter Education) | 0.462 *** (0.13) | 0.453 *** (0.13) | 0.465 *** (0.13) | 0.460 *** (0.13) |
| Var(Voter Gender) | 0.123 *** (0.04) | 0.123 *** (0.04) | 0.124 *** (0.04) | 0.120 *** (0.04) |
| Var(Constant) | 1.120 *** (0.12) | 1.119 *** (0.12) | 1.080 *** (0.11) | 1.080 *** (0.11) |
| Cov(Voter Education, Voter Age) | 0.034 (0.06) | 0.034 (0.06) | 0.032 (0.06) | 0.030 (0.06) |
| Cov(Voter Gender, Voter Age) | -0.059 (0.03) | -0.059 (0.03) | -0.060 (0.03) | -0.060 (0.03) |
| Cov(Constant, Voter Age) | 0.041 (0.07) | 0.042 (0.07) | 0.015 (0.07) | 0.010 (0.07) |
| Cov(Voter Gender, Voter Education) | 0.011 (0.05) | 0.013 (0.05) | 0.008 (0.05) | 0.010 (0.05) |
| Cov(Constant, Voter Education) | -0.121 (0.11) | -0.119 (0.11) | -0.115 (0.11) | -0.120 (0.11) |
| Cov(Constant, Voter Gender) | -0.049 (0.06) | -0.051 (0.06) | -0.046 (0.06) | -0.050 (0.06) |

* * p<.05, ** p<.01, *** p<.001; # Interaction
Random Slope Model for 2006 and 2009 (Model 8 and Model 9)

To further expand knowledge about the effect of voter and interviewer characteristics on nonresponse, Models 8 and 9 based on multiply imputed datasets displayed in Table 5-5 (fixed effects) and Table 5-6 (random effects) add additional predictors. Model 9 is considerably more complex than Model 8 as it accounts for more cross-level interaction terms; namely, voter age by interviewer education, voter education by interviewer education, voter education by interviewer age, voter education by ruralness, voter gender by interviewer gender and voter gender by ruralness. The interactivity between type of election and voter characteristics (age, education and gender) is excluded from Model 8 and 9 as Model 7 indicates that these interactions are not likely to be significant.

Model 8 includes voter socioeconomic status (SES), which is used as a proxy measure for social isolation. Although exploratory single-level models presented in Chapter 4 indicated that voter SES is not likely to be related to nonresponse, it has not been tested in a multilevel model. In models prior to Model 8, TV ownership served as proxy for social isolation, but results suggest that this metric is not likely to be significant. Consequently, in Model 8 TV ownership is excluded to allow for a clearer interpretation of SES; however, in Model 9 TV ownership is reintroduced again to have a more comprehensive model.

While the negative sign of SES occurs in the expected direction (i.e., higher levels of SES elicit lower levels of nonresponse), results in Model 8 (logit=−0.021, SE=0.06, p>.05) and Model 9 (logit=−0.016, SE=0.06, p>.05) suggest that SES is not likely to be statistically significant. Similarly, in Model 9 Voter TV ownership does not appear to be significantly different from zero (logit=0.009, SE=0.06, p>.05). An additional metric to approximate social isolation was
included in Model 9; namely, voter telephone service. Consistent with previous metrics, telephone service do not appear to be statistically significant (logit=-0.028, SE=0.06, p>.05).

Models 8 and 9 introduce a measure to approximate the time of the day in which voters show up at the voting station (i.e., before or after 1:00pm). Although the sign of “Time of Day for Voting” occurs in the expected direction (i.e. a positive coefficient thus an afternoon voter would have a tendency to refuse more often relative to a morning voter), results in Model 8 (logit=0.013, SE=0.05, p>.05) and Model 9 (logit=0.013, SE=0.05, p>.05) indicate that the effect is not likely to be significant.

Model 8 and 9 introduce interviewer characteristics that are not included in previous models; namely, interviewer’s exit polling experience, interviewer’s average length of interview, interviewer’s distance from polling place, interviewer’s monitoring of more than one exit, and interviewer’s problems with election officials on election day. While signs occur in an expected direction (e.g., problems with election officials, monitoring more than on exit and distant positioning from the voting station increases the number of refusals), none of these predictors seem to reach statistical significance, independent of other factors.

In Models 8 and 9 the sign of the coefficient for sample composition (Congressional vs. Presidential) continues to be negative, as in Model 6 and 7. This indicator variable does not appear to reach significance neither in Model 8 (logit=-0.286, SE=0.16, p>.05) nor in Model 9 (logit=-0.282, SE=0.16, p>.05), controlling for other factors.

Consistent with Model 5 (multiple imputation with 2006 data), and Model 6 and 7 (multiple imputation with 2006 and 2009 data), the interaction term in Model 8 and 9 (multiple imputation with 2006 and 2009 data) for voter age by interviewer age appears to be statistically
significant (logit=-0.301, SE=0.13, p<.05 and logit=-0.309, SE=0.13, p<.05, correspondingly).

Particularly, Model 9 indicates that the odds ratio of refusing cooperation for an older voter (compared to a younger voter) is about 1.07 to 1 \([=\exp(0.072)]\); however, when this older voter is approached by an older interviewer, the odds ratio of refusing cooperation decreases to be approximately .79 to 1 \([=\exp(0.072)\times\exp(-0.309)]\).

Unlike Model 4 (single imputation with 2006 data) and Model 5 (multiple imputation with 2006 data), the interaction term for voter age by voter education in Models 6 to 9 (multiple imputation with 2006 and 2009 data) do not appear to be statistically significant. In theory, a three-way interaction term in Models 6 to 9 (that is, voter age by voter education by type of election across interviewers) would help understand whether the interactivity between voter age and voter education depends on the type of election (i.e., Congressional vs Presidential). In practice, however, a 3-way multilevel interaction term with multiply imputed data \((m=30)\) requires considerably large computing capabilities, even with available technology at this point in history. In other words, given that (a) the influence of voter age could change at higher levels of voter education, (b) vary across interviewers, (c) vary across elections and (d) vary across multiply imputed data \((m=30)\), the iterative process needed to achieve convergence in a maximum likelihood estimation for such effect is not easily attainable with today’s commercial statistical packages. Consequently, a 3-way interaction term for multiply imputed data in a conditional multilevel model should be conducted in future research\(^6\).

\(^6\) Simpler multilevel analyses (results not shown) suggest that a 3-way interaction is not close to reach statistical significance, however.
Despite the absence of a 3-way term for voter age by voter education by type of election, Model 8 suggests that: (i) voter gender is likely to have an effect on nonresponse, (ii) voter age is not likely to predict nonresponse but it is likely to be mediated by interviewer age, (iii) Congressional voters have a marginal trend to cooperate relative to Presidential voters but it is not likely to be systematic.

A summarized discussion of results from analyses conducted in this section is presented next. Similar to the discussion of findings in Chapter 4, these findings are presented in light of the literature on survey methodology and exit polling nonresponse.

Findings

Finding 1: The Interaction of Voter Age and Voter Education

Building on theoretical foundations from the survey methodology literature, H1 hypothesized that voter age and voter education are characteristics associated to the ability of performing cognitive tasks, including the ability to answer questions (Ceci, 1991; Kaminska et al., 2010; Krosnick, 1991; Krosnick & Alwin, 1987, 1988; Narayan & Krosnick, 1996). Also, building on empirical results from exploratory analysis conducted in Chapter 4 with a single imputed dataset, H1 hypothesized that voter age and voter education are likely to have a conditional relationship in exit polls across multiple imputed datasets. This is to say that higher levels of education are likely to have an effect on exit polling nonresponse among older voters but not necessarily among younger voters.
Results from multilevel regression models conducted with multiply imputed plausible data give credence to the notion that voter age and voter education alone are not likely to directly explain nonresponse. Instead, these findings suggest an interesting conditional pattern consistent with what was hypothesized, thus the effect of voter age on nonresponse may change depending on levels of voter education (i.e., a lessened cognitive capacity due to aging could be offset by higher levels of education). Interestingly, while the effect of voter age is likely to depend on voter education in a Presidential election, such interaction term seems to lose statistical significance when combined with data from a Congressional election. Nonetheless, more research is needed to confirm this notion in other types of elections.

Finding 2: The Interaction of Interviewer Age and Voter Age

Building on theoretical foundations from the survey methodology literature and empirical results from regression analyses in Chapter 4, H2 hypothesized that fearful voters are less likely than confident voters to answer positively to an exit poll request. The literature on nonresponse studies for household surveys suggests that the lack of trust in unfamiliar people and fear of crime make older sample members likely to modify their behavior toward persons that appear to be a threat in any way (Couper & Groves, 1996; Groves & Couper, 1998; House & Wolf, 1978; Stoop, 2005). Similarly, exit polling literature hypothesizes that “fear and suspicion of strangers” hypothesis may be a mechanism to explain nonresponse (Merkle & Edelman, 2002).

Results from multilevel regression models conducted in this chapter are congruent with the expected behavior on this notion. Specifically, models using data from 2006 as well as all models using pooled data (2006 and 2009) consistently indicate that older voters asked to
participate by a younger interviewers are more likely to refuse cooperation, compared to older voters asked to participate by older interviewers.

**Finding 3: The Effect of Type of Election**

H3 hypothesized that exit polling nonresponse patterns may be different depending on the type of election; namely, Congressional vs. Presidential. Particularly, if the patterns are not the same across elections, it would suggest that the group of voters who show up at Congressional elections may have different socio-psychological characteristics (for instance, different levels of motivation to participate), and may not experience the same social pressure when interacting with interviewers, as Presidential voters.

Based on multilevel regression analysis of pooled data (Congressional and Presidential elections), results suggest a marginal gap in favor of Congressional voters (i.e., Congressional voters seem to be more cooperative than Presidential voters); however, this trend is not likely to reach traditional levels of significance. More research in necessary to investigate the effect of type of election on nonresponse.

**Finding 4: Social Connectedness**

On the basis of social isolation theories, Groves and Couper (1998) hypothesized that people disengaged from society tend to be less cooperative with survey requests relative to those
more integrated with society. Under this view, “social and psychological” aspects of “underclass” groups do not necessarily share the norms of the society are less likely to be engaged in social exchanges, including social surveys (Groves & Couper, 1998).

Similarly, Merkle and Edelman (2002) suggested that the social isolation framework may also explain nonresponse in exit polls. Nonetheless, they hypothesized a weaker effect in exit polls (compared to household surveys) since voters in an election are already participating in a societal event. Interestingly, Groves and Couper (1998) did not find support for the social isolation hypothesis using socioeconomic status as proxy measure. Likewise, Merkle and Edelman (2002) did not find evidence to support this notion using voter race as proxy measure.

Results from multiply imputed plausible data in the present study (using pooled data in multilevel regressions) also do not find empirical evidence to support the notion of social isolation as an explanation for nonresponse in exit polls. In regression models, voter TV ownership, socioeconomic status and telephone service were used as proxy measures of social isolation. Consistent with previous findings reported in the literature (Groves & Couper, 1998; Merkle & Edelman, 2002), none of these variables appear to be statistically significant to account for nonresponse in exit polls.

**Finding 5: Interviewer Experience in Exit Polling**

H5 hypothesized that interviewers with previous exit polling experience would be less likely to produce refusals. Studies for surveys other than exit polls have found that interviewer experience tends to correlate with survey data quality (Cannell et al., 1977; Gfroerer et al., 1997; Krosnick et al., 2002; Singer et al., 1983).
The few studies that have looked at the effect of exit polling interviewer experience on election day survey indicate that there is no immediate connection. Merkle and Edelman (2002) used a composite index of three variables to represent interviewer experience at the precinct level (number of telephone surveys worked on, number of in-person surveys worked on and number of exit polls worked on). The authors found no relationship between interviewer experience and response rates.

In the present study, exit polling experience was analyzed in multilevel regression models (controlling for voter and interviewer characteristics) which also suggest that exit polling experience is not likely to be a direct predictor of nonresponse. In other words, while there is no supporting evidence in favor of the hypothesized relationship (i.e., exit polling experience reduces refusals), empirical results are consistent with previous findings in the literature, where interviewer experience in a previous exit poll is not likely to improve survey participation. This leaves room for future experimental studies.

**Finding 6: Average Interview Length**

H6 hypothesized interviewers whose average interview length is less than five minutes are more likely (compared to interviewers whose average interview length is more five minutes) to produce refusals. The literature suggests that interviewer actions are influenced by their perception and attitudes towards the interviewing task (Singer et al., 1983). Also, it suggests that as interviewers start feeling confident about the interviewing task, they inadvertently start to modify their behaviors, and depart from established protocols (Olson & Peytchev, 2007).
Similarly, studies report that interviewers who increase the pace at which interviews are conducted are more likely to introduce error relative to interviewers that do not increase the pace (Fowler, 1991; Olson & Peytchev, 2007; Pickery & Loosveldt, 2001). In election day surveys, interviewer expectations and attitudes might be affected by confidence in their own interviewing skills. A proxy measure to capture interviewer overconfidence is the average time the interviewer reports spending in each interview; thus, interviewers whose average interviewing time is shorter are likely to be overconfident on their interviewing skills and more likely to produce refusals.

Results suggests that interview length, as a measure for interviewer overconfidence, is not likely to directly account for nonresponse in exit polls. While the effect of the relationship occurs in the expected direction (i.e., interviewers who spend less than five minutes are more likely to produce more refusals compared to those who take more than five minutes), it does not seem to be systematic.

**Finding 7: Respondents Time of Day for Voting**

H7 hypothesized that time of day at which voters show up at the voting station may have an impact on election outcomes, nonresponse patterns and exit polling results (Busch & Lieske, 1985; Klorman, 1976; Stevenson, 2006). This is because presumably certain demographic groups have a tendency to avoid long files (Spencer & Markovits, 2010). Furthermore, the limited studies in the literature of exit polling suggest that afternoon hours tend to produce higher cooperation rates compared to morning hours (Stevenson, 2006).

Results from multiply imputed plausible data in multilevel models do not provide empirical evidence supporting the notion that time of day is likely to account for nonresponse in
exit polls. It is possible that with a categorization other than the one used in the present study i.e., before and after 1:00 pm), more granular patterns could be observed. This hypothesis should be further investigated in future research.

**Finding 8: Interviewer Distance**

H8 hypothesized that interviewers whose location from the voting station is more 10 mts (~30 feet) are more likely (relative to interviewers whose location from the voting station is less than 10 mts (~30 feet) to produce refusals. The existing literature reports that position of interviewer at the voting station is likely to have an impact on refusals; namely, the farther the interviewer is from the voting booth the more likely s/he is to elicit refusals (Edison Media Research and Mitofsky International, 2005; Frankovic, 1992; Merkle & Edelman, 2002; Stevenson, 2006).

While these analyses occur in the expected direction (i.e., with a positive sign indicating that as distance increases, refusals increase), the relationship does not appear to be significant at conventional statistical levels. Since distance has been a consistent finding in the literature, one possible explanation for this lack of significance may be due to the limited distance considered in the categorization of the metric (i.e., 10 meters/ ~30 feet) provided by interviewers in the post-election questionnaire.

Given that multilevel models based on multiple imputation are more easily estimated and interpretable with binary variables (in this study, grand-mean centered), it seems that different cut-off points for distance should be explored in future analyses; for instance, 15 (~50 feet), 20 (~65 feet) or 25 (~80 feet) meters. Alternatively, a continuous metric of distance could be
explored in multilevel models in the future with optimized computing routines programmed to
deal with continuous variables.

**Finding 9: Interviewer Monitored More than One Exit at Voting Station**

H9 hypothesized that interviewers who monitor more than one exit are more likely
(relative to interviewers who monitor just one exit) to elicit refusals. The existing literature
suggests that interviewers have difficulties in reaching voters on election day due to multiple
exits (Bautista et al., 2006; Edison Media Research and Mitofsky International, 2005; Frankovic,

Overall, interviewers perform several tasks on election day (for instance, keeping up with
a selection rate of the k\textsuperscript{th} voter, recording information by observation from nonrespondents,
handing out questionnaires, assisting voters who accepted the invitation to participate, calling
the data center to transmit results). It is possible that adding one more activity (i.e., monitoring
multiple exits) may lessen the interviewer’s motivation to persuade voters to participate in an
exit interview. Even though regression coefficients point to the expected direction (that is, as the
number of exits being monitored increases so does refusals), the relationship does not seem to
reach significance levels. Consequently, future research should further investigate this
relationship.
Finding 10: Interviewer Problems with Election Officials on Election Day

Studies in the literature suggest that problems with precinct officials have an impact on response rates (Bautista et al., 2006; Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2002). It is possible that unfriendly election officials may cause interviewer legitimacy to decrease, thus lessening interviewer motivation. Consequently, H10 hypothesized that interviewers who experience problems with election officials are more likely (compared to interviewers who do not experience problems with election officials) to produce refusals. Furthermore, Merkle and Edelman (2002) posit that problems with precinct officials may be related to distant interviewing positions. This proposition would imply an interaction term.

Regression coefficients from analyses in this study suggest that there is directional relationship between problems with officials and refusals; however, results do not seem to reach statistical significance to empirically support the notion. It is possible that using data from other election day surveys the relationship reaches significance. Also, since previous studies suggest an interaction terms between problems with officials and distance of the interviewer, future research using multilevel models should include the hypothesized interactivity.

Discussion

This chapter aimed to address a paramount problem inherent to election day surveys: while a well-defined population is surveyed on election day (i.e., exit voters), not all of them choose to participate when approached. As a result, researchers have had near to nil information about those respondents not included in the data. It, therefore, becomes important to understand
some of the mechanisms behind nonresponse in election day surveys, and to elucidate if these reasons are similar to those explaining nonresponse in other types of surveys. In order to do that, this chapter relied on methods that can plausibly inform our knowledge of these topics.

Imputation methods based on a fully conditional specification (FCS) approach are used to approximate plausible values for nonrespondents. This approximation is adopted as proof of concept because on typical election day surveys, it is not feasible to conduct follow-up studies of nonrespondents. Initial comparisons of actual parameters (i.e., election results) with traditional ways of handling nonresponse in exit polls (namely, complete-case analysis and class weighting) versus imputation methods, suggest that imputation methods may be a practical means to approximate values for nonrespondents, and therefore enable some insight about their behavior.

Using individual-level and aggregate-level information, multiple imputation methods in particular, help to fill in values that otherwise would be unknown, while acknowledging the uncertainty associated to the fact that data were not actually observed. Put differently, auxiliary data help characterize an underlying distribution of the data producing a plausible complete dataset.

This approximation of unobserved data allows modeling of hypothesized socio-psychological mechanisms of survey participation among voters. Data derived from imputation models are used to fit multilevel models that help examine voter effects and interviewer effects, simultaneously. Given the nested structure in the exit poll data (i.e., voters nested within interviewer), it is critical to model any hypothesized relationship using a two-level multivariate analysis. In other words, given that sample voters are typically in the interviewer pool they experience the $j$-th “interviewer effect.”
Considering the limited alternatives available to researchers to understand mechanisms of nonresponse at this point in time, findings from this *proof-of-concept* approach provide encouraging results to investigate voter and interviewers effects. Furthermore, the fact that some of these results conform to previous research and no counterintuitive results were found, enhances our confidence in the directional nature of the *proof-of-concept* approach.

These methods and their results, while encouraging at this stage, need to further be investigated with different exit polls as well as in contexts different from exit polls. A promising advantage of these methods—explored here as *proof of concept*—is that their nature enables them to potentially make use of larger auxiliary datasets (e.g., “big data”) to enrich the approximation, and ideally in situations where population parameters can serve as gold standards.
CHAPTER 6: PREDICTORS OF WITHIN PRECINCT ERROR

Introduction

Chapter 4 and 5 discussed likely causes of nonresponse; however, there is another critical indicator in exit polls that is relevant to election day surveys known as Within Precinct Error (WPE). WPE has been used to assess prediction accuracy and it is sometimes loosely referred to as “exit poll bias” (Mitofsky, 2003, p.48). Consequently, this chapter seeks to investigate hypothesized mechanisms responsible for measurement error or “exit poll error”.

The quality of survey answers can be influenced by a variety of survey-design factors such as mode of data collection, topic of the survey, questionnaire length, sponsorship and others elements frequently referred to as “survey conditions” (Biemer & Lyberg, 2003). Likewise, other conditions that may not be entirely under the researcher control may have an impact on data. For example, interview timing, political climate, respondent memory erosion, interviewer characteristics, interviewer appearance, interviewer behaviors (whether conscious or not) and interviewer actions (whether indicated by training or entirely unforeseen) (Alwin, 2010; Biemer & Lyberg, 2003; Bound et al., 2001; Frankovic et al., 2009; Groves, Fowler, et al., 2004; Hansen et al., 1961; Lessler & Kalsbeek, 1992; O'Muircheartaigh, 1977).

Provided that sample individuals accept an invitation to participate in a survey and provide responses, all these factors may produce deviations from the “true value” that each person is assumed to have. These departures from the “true value” are known as “response errors,” “observational errors,” or “measurement errors” (Alwin, 2007; Bautista, 2012; Biemer &

As survey respondents are typically clustered under interviewers, they are likely subject to the \( j \)-th “interviewer effect” (Biemer & Lyberg, 2003; Biemer & Trewim, 1997; Groves, 1991; Leslie Kish, 1962; O'Muircheartaigh, 1977; O'Muircheartaigh & Campanelli, 1999; Olson & Bilgen, 2011). In other words, the interviewer can potentially communicate in a systematic way—intentionally or not—his or her expectations about respondent answers. If interviewers repeatedly display some behaviors to respondents, the interviewer may modify respondents’ answers on key information such as vote choice. Consequently, it is critical to explore potential predictors for response error in election day surveys.

While a more complete description of WPE is provided later in this chapter, a basic conceptualization of WPE (also known as “signed error”) refers to the difference between the percentage margin between the leading candidate in the exit poll and the actual vote in sample precincts (Bautista et al., 2007; Edison Media Research and Mitofsky International, 2005; Liddle, 2005; Lindeman et al., 2006; Mitofsky, 1991).

In the methodological literature, there is a limited number of studies conducted on WPE to investigate the effect of respondent characteristics, interviewer effects and election day factors. Also, available studies are mainly focused on the case of the United States (Lindeman & Brady, 2006). Furthermore, existing studies are limited to bivariate analyses leaving uncertainty on the effects of predictors after accounting for other variables (Edison Media Research and Mitofsky International, 2005).
A literature review conducted in Chapter 2 reveals a dearth of multivariate research on factors that may have an impact on WPE. The few studies that have investigated the relationship between WPE, interviewer and respondent characteristics as well as nonresponse are primarily bivariate. This means that it is unknown the effect of independent factors on WPE after accounting for other variables (Bautista et al., 2007; Merkle & Edelman, 2002; Mitofsky, 1991).

This chapter seeks to examine hypothesized predictors of error in exit polls using statistical methods that go beyond bivariate analysis. The chapter investigates the joint effects of predictors including nonresponse rates, respondent and interviewer socio-psychological characteristics, as well as contextual elements that occur on election day (e.g., problems with party representatives or poll workers, number of exits at voting station). These hypothesized relations are described as part of the theoretical framework on interviewer effects developed in the section below.

**Theoretical Framework**

In the survey methodology literature, interviewer behaviors and expectations are hypothesized to have important effects on data quality (Biemer, 2010; Biemer & Trewim, 1997; Cannell et al., 1981; Davis et al., 2010; Dykema, Lepkowski, & Blixt, 1997; Fowler, 1991; Hox et al., 1991; Van der Zouwen et al., 1991). Theoretically, interviewer’s expectations make them modify —consciously or not— their own behaviors and appearance in such a way that they exert an influence on respondents’ behaviors. As a consequence, respondents’ answers are also modified (Cannell et al., 1981; Hyman et al., 1954; W. Johnson & Delamater, 1976; Kahn &
Interviewer expectations are closely connected to several factors including interviewers’ beliefs, interviewing experience, ideology, preferences, and group membership (Boyd & Westfall, 1955; Cahalan et al., 1947; Durrant et al., 2010; Kahn & Cannell, 1957; Katz, 1942; Olson & Bilgen, 2011; Olson & Peytchev, 2007; Rice, 1929; Singer et al., 1983; H. L. Smith & Hyman, 1950). While methods have been suggested to reduce the effects of interviewers such as standardizing interviewing procedures (e.g., Fowler, 1995; Fowler & Mangione, 1990), there are aspects that are not always controlled and minimized by survey researchers such as expectations (Biemer & Lyberg, 2003; Cannell et al., 1981; Groves & Couper, 1998).

Studies have suggested that the effect of interviewer expectations may not be completely eliminated from the interviewing process (Cannell et al., 1981). This is a cause for concern in face to face surveys (such as election day surveys), where full standardization of the interviewing process is not always achieved (Beatty, 1995; Houtkoop-Steenstra, 2000; Suchman & Jordan, 1990).

The notion of interviewer effects due to the interviewer behavior and expectations is connected with respondent “cognitive script” theories and respondent cognitive burden (Abelson, 1976, 1981; Groves, 1989; Groves et al., 1992; Groves & Couper, 1998; Schank & Abelson, 1977; Tourangeau, 1984). Cognitive script theories suggest that pre-existing psychological structures are imposed to the received information in order to reduce cognitive burden. This means that individuals try to comprehend situations through stereotypical circumstances.
According to cognitive script theory, as information is gathered, organized and understood, people use “cognitive scripts” to identify the appropriate behavior and engage in different situations, including interacting with unfamiliar persons (e.g., interactions with medical doctors, mail carriers, charity or sale requestors) (Groves & Couper, 1998 p. 220; Tourangeau, 1984 p. 75). In the context of in-person interviews, respondents are likely to use available cognitive scripts along with visual cues (e.g., clothes, facial expressions, demographic characteristics, materials, devices) to comprehend the intention of the requestor, and to behave accordingly (Bateman & Mawby, 2004; Bischoping & Schuman, 1992; Finkel et al., 1991; Groves & Couper, 1998).

In the context of exit polling, sample voters may modify their answers to vote choice based on the perceived intention of the interviewer (Frankovic, 2007). This may be even more relevant in “highly intense elections where interviewers may be perceived (correctly or incorrectly) as favoring one or another candidate or party” (Frankovic, 2008, p.575). Nonetheless, researchers have acknowledged that “the effects of interviewer-related error (…) on the measurement accuracy of exit polls is yet to be understood as well as it needs to be, and continued research into these topics is needed (…)” (Lavrakas, 2008 p. 252).

Consequently, while direct measures of interviewer effects may not be easily achieved in exit polls (e.g., an experimental design is desirable), some proxy measures may be helpful in understanding such effects. In this study it is hypothesized that interviewer effects are likely to occur because respondents tend to maximize available heuristics including the “appearance of the interviewer”, “peripheral aspects of the options”, and suppositions on the requestor’s intentions, as a way of reducing cognitive burden to deal with the interviewing (Cannell et al., 1981; Groves & Couper, 1998).
Predictors of Within Precinct Error

As exit poll accuracy is hypothesized to change due to the influence of the interviewer, characteristics of interviewers receive particular attention in this study; namely, demographic information (age, gender, education), confidence on interviewing skills (clear understanding of survey questions, doubts and training), interviewing experience (in household surveys and exit polls), interviewing length, compliance with researcher protocol, and interviewer political preference.

Information collected by interviewers describing contextual elements on election day are also key factors to examine hypotheses; namely, interviewer distance from the voting station, requests received from election officials and party representatives, conflicts observed at the election precinct, and number of exits in the voting station.

While information about respondent characteristics at the precinct level serve as control variables in regression models, these aggregate-level information also help to understand how voter information is related to interviewer effects. Thus, demographic variables included in the present analysis are proportions of voters in the $j$-th pool of respondents recruited by interviewers; namely, age, gender, education and socio-economic status. Importantly, nonresponse is also included as a predictor of exit poll error.
Hypotheses

Hypothesis 1: Refusals as Predictor of Exit poll Error

While recognized as an imperfect measure of data quality, nonresponse has been discussed in the literature as source of error in social surveys and particularly as source of bias (Groves, 1989, 2006; Groves & Lyberg, 2010; Groves & Peytcheva, 2008). Conceivably, nonrespondents could be systematically different from respondents introducing error (i.e., bias) in the estimated value relative to the “true” value. Alternatively, if respondents and nonrespondents are not entirely different, one might expect only an increase in variance over expected realizations of the estimate in multiple trials under the same survey conditions but not necessarily bias (Cochran, 1963; Frankel, 2013; Groves, 1989; Groves et al., 2006; Groves et al., 2002; Leslie Kish, 1965; Lessler & Kalsbeek, 1992; Lohr, 2009; Singer, 2006).

In the context of exit poll, nonresponse has been hypothesized as possible cause of systematic error (Frankovic, 2008; Frankovic et al., 2009; Merkle & Edelman, 2002; Merkle et al., 1998; Mitofsky, 1991, 2006; Mitofsky & Brennan, 1993; Mitofsky & Edelman, 1995, 2002). Published studies, however, indicate that the relationship between exit poll error and nonresponse is not likely to be significant (Bautista et al., 2007; Merkle & Edelman, 2000, 2002). Nonetheless, empirical exit polling studies assessing this relationship are limited to a bivariate relationship leaving uncertainty in results. Building on existing literature, in this study it is hypothesized that, independent from other factors:

\textit{H1: Nonresponse is not likely to be a predictor of Within Precinct Error.}
Hypothesis 2: Effect of Voter Characteristics

Interviewer effects have been extensively discussed in the literature in the form of social desirability. Social desirability is an important mechanism explaining differential response patterns among survey participants. This psychological mechanism indicates that there is a tendency of respondents to modify answers that are perceived to be socially acceptable to others, in this case, the interviewer. Social desirability is even more likely to occur in cases when sensitive information is asked, including political questions (Anderson, Silver, & Abramson, 1988; Aquilino & Sciuto, 1990; Belli, Traugott, Young, & McGonagle, 1999; Catania et al., 1996; De Maio, 1984; Finkel et al., 1991; Flores-Macias & Lawson, 2008; Krysan & Couper, 2003; Nederhof, 1985; Presser & Stinson, 1998; Schaeffer, 1980; Schuman & Converse, 1971; Schuman & Hatchett, 1974).

Scholars have hypothesized that position of power and dominance in society may have an effect on how people interact. Particularly, studies in the literature suggests that people less established in society (i.e., “powerless”) are more likely to be impacted by the influence of others relative to those with a better social position (“empowered”), especially in politically charged contexts (Blaydes & Gillum, 2013; Ross & Mirowsky, 1984). Presumably, younger, less educated and lower social status populations are more likely to be worried about impression management and self-presentation than those with more authority in society (i.e., older people, more educated and with higher social status) (Blaydes & Gillum, 2013; Davis et al., 2010). Presumably, those better positioned to accomplish personal goals in society have a better sense of control over their own life (Mirowsky, 1995; Wolinsky & Stump, 1996).
Consequently, it is hypothesized that when the pool of respondents is mainly comprised of “powerless” respondents (i.e., younger, lower educated, with lower social status and living in a rural context), the level of WPE increases. Alternatively, if the pool of respondents consists of more “empowered” respondents (e.g., more educated voters, people with more experience in life (older person), with a higher socio economic status and living in urban areas), the influence of the interviewer on vote choice responses decreases; therefore, WPE is expected to decrease.

Explicitly,

\[ H2a: \text{As the proportion of older respondents increases, the level of WPE decreases.} \]

\[ H2b: \text{As the proportion of college educated increases, the level of WPE decreases.} \]

\[ H2c: \text{As the proportion of respondents with a higher socio economic status increases, the level of WPE decreases.} \]

\[ H2d: \text{As the proportion of older respondents increases, the level of WPE decreases.} \]

\[ H2e: \text{Rural areas are more likely to produce higher levels of WPE relative to non-rural areas.} \]

**Hypothesis 3: Interviewer Age**

Interviewer age has been hypothesized in the exit polling literature as a visual cue used by respondents to judge the tasks implied in the survey request. Presumably, respondents are more likely to take the reporting task more seriously when the request comes from an older person than when it comes from a younger person (Blumenthal, 2005c; Brown et al., 2004;
Under this logic, interviewer age serves as a cue that would help respondents decide whether to provide a candid answer or not. Presumably, older interviewers may look more professional than younger interviewers. Particularly, Edison/ Mitofsky (2005) found that older interviewer tend to have lower levels of WPE. The report suggests that age and WPE are associated even after controlling for interviewer gender and interviewer education; however, no statistical testing has been provided to determine whether the relationship is significant (Edison Media Research and Mitofsky International, 2005).

It is also hypothesized that the effect of interviewer age depends on the age of the respondent, given that presumably older interviewers are more likely to put pressure on younger respondents compared to older respondents. Consequently, it is hypothesized that:

\[ H3a: \text{As interviewer age increases, WPE decreases, independent from other factors.} \]

\[ H3b: \text{Among younger respondents, as the age of the interviewer increases, the level of exit polling error increases; whereas among older respondents, as the age of the interviewer increases, the level of error decreases.} \]
Hypothesis 4: Interviewer Education

Interviewer education has been hypothesized as another interviewer characteristic that may have an effect on the interviewer appearance and behavior (Edison Media Research and Mitofsky International, 2005). Nonetheless, the magnitude and direction of a potential interviewer education effect on exit polling accuracy has remained elusive in published studies. Particularly, in the Edison and Mitofsky report (2005), as interviewer education increases the WPE increases as well, but in middle education categories the WPE slightly decreases and then, increases again for the upper category of education.

The bivariate relationship reported in the Edison/Mitofsky study (2005) suggests a nonlinear pattern and appears to hold even after accounting for interviewer age. However, the report does not provide any statistical testing to assess whether the relationship between interviewer age and interviewer education is indeed likely to occur. Furthermore, existing literature do not provide elements to evaluate a joint effect of interviewer education and interviewer age on another equally important variable (i.e., respondent age), to predict exit polling error.

In this study it is hypothesized that there is a joint effect of interviewer education, interviewer age and respondent age. In other words, the interviewer age-education interaction varies across levels of respondent age. This joint effect can be hypothesized because social desirability mechanisms are likely to vary across demographic groups (i.e., younger vs. older voters). For instance, a young respondent (presumably less established in society) may experience more social pressure from an older, college-educated interviewer than from an older interviewer with no high school diploma. However, an older respondent with average levels of
education (presumably more established in society) may avoid disclosing voting preferences to a lower educated, older interviewer (who may appear to be less trustworthy) compared to an older interviewer with college-level education (who may appear to be more trustworthy).

Consequently, in this study, it is hypothesized that:

**H4a:** Interviewers with a high school diploma are less likely to increase the level of MWPE relative to interviewers with no high school diploma. Likewise, interviewers with college-level education are less likely to decrease MWPE relative to interviewers with no high school diploma.

**H4b:** When younger respondents interact with interviewers with less than high school, as the age of interviewer increases, the level of exit polling error decreases.

**H4c:** When younger respondents interact with interviewers with high school diploma, as the age of interviewer increases, the level of exit polling error decreases.

**H4d:** When younger respondents interact with interviewers with a college education, as the age of interviewer increases, the level of exit polling error increases.

**H4e:** When older respondents interact with interviewers with less than high school, as the age of interviewer increases, the level of exit polling error increases.

**H4f:** When older respondents interact with interviewers with high school diploma, as the age of interviewer increases, the level of exit polling error decreases.

**H4g:** When older respondents interact with interviewers with a college education, as the age of interviewer increases, the level of exit polling error decreases.
Hypothesis 5: Interviewer Gender

The literature suggests that gender of the interviewer is related to WPE (Edison Media Research and Mitofsky International, 2005). Interestingly, the exit polling literature suggests that the direct effect of gender disappears once interviewer age is accounted for. Particularly, Edison/Mitofsky (2005) shows that male interviewers are slightly more likely to have a higher WPE than female interviewers; but when male and female interviewers are divided into two age groups (i.e., older or younger than 35 years), the relationship between interviewer gender and WPE disappears (Blumenthal, 2005c; Traugott et al., 2005). Notwithstanding, available studies do not provide statistical testing to assess the relationship.

In this study, it is hypothesized that interviewer gender serves as a visual cue to respondents. Particularly, male interviewers are more likely to put social pressure on respondents than female interviewers, independent from the age of the interviewer. Consequently, it is proposed that:

\[ H5: \text{Male interviewers are more likely than female interviewers to increases levels of MWPE, independent from other factors.} \]

Hypothesis 6: Interviewer Attitudes toward Interviewing

The literature in survey methodology indicates that interviewer actions are influenced by their perception and attitudes towards the task (Singer et al., 1983). Some studies suggest that to the extent that interviewers feel confident with the interviewing tasks, they unknowingly start to modify their behaviors, and replace training with other elements (Olson & Peytchev, 2007).
Studies suggest that when interviewers start to replace training with elements acquired during the data collection process, they deviate from the standardized interviewing protocol. Consequently, interviewers begin to pay less attention to instructions, increase the pace of interviews and ultimately increase the level of error in a survey estimate (Fowler, 1991, 1995; Fowler & Mangione, 1990; Olson & Peytchev, 2007; Van der Zouwen et al., 1991).

In the context of exit polls, interviewer expectations and attitudes might be affected by their confidence in their own interviewing skills and experiences acquired in the field, and the stress to collect interviews on election day. Conceivably, interviewers who report at the time of post-exit poll debriefing that there were no problems with the survey instrument (e.g., no faulty phrasing of questions or design problems in questionnaire), or who did not have doubts on how to proceed on election day, or who preferred their own opening script to approach voters, are more likely to become overconfident on the exit polling task. Thus, they become more likely to introduce error in the measures. Explicitly,

**H6a**: Interviewers who believe that there were no problematic questions in the questionnaire are more likely to have an impact on WPE relative to those interviewers expressing that there were problematic survey items.

**H6b**: Interviewers who did not have doubts on how to proceed are more likely to have an impact on WPE, relative to those who had doubts.

**H6c**: Interviewers who preferred to use their own interviewing script are likely to have an impact on WPE relative to those who used the standardized interviewing script.
Hypothesis 7: Interviewer Party

In the existing literature, Butterworth (2006) refers to the concept of “interviewer party” and suggests that interviewers’ party identification has an influence on Within Precinct Error (WPE). Arguably, interviewers with a defined political orientation are more likely than interviewers whose political preferences are not defined, to modify the interviewing process. Butterworth’s study (2006) is based on a post-election questionnaire apparently conducted among exit poll interviewers after the 1996 U.S. Presidential exit poll.

Butterworth’s study (2006), however, provides no details on statistical testing to allow a meaningful interpretation of empirical results on what the effect of interviewer partisanship would be on exit polling accuracy. Similarly, Edison/Mitofsky (2005) indicate that a post-election telephone survey was conducted among interviewers, unfortunately, empirical results are very limited in the study thus no firm conclusions can be derived.

In this study, we hypothesize that:

H7: Interviewers expressing a defined political preference for any of the major political parties in the election are likely to have an impact on WPE relative to interviewers expressing a preference for a non-major political party.

Hypothesis 8: Interviewer Training

In the literature, interviewer training has been described as a tool to standardize interviewers’ performance and behavior, and as a way to reduce potential bias and variance in
the survey estimates (Fowler, 1991; Groves & Couper, 1998). During typical training sessions in exit polls, relevant skills are taught or reinforced, including the ability to approach voters using a methodical sampling selection and persuade them of accepting the survey request, computational skills (as interviewers are expected to tally collected questionnaires), count misses and refusals, record refusals’ demographic characteristics, and call in the results to the data center on the telephone, among others.

Edison/Mitofsky reports (2005) that interviewers who described themselves as “somewhat or not very well trained” are slightly more likely to have higher levels of error (i.e., WPE) compared to interviewers who reported they were “very well” trained. Nonetheless, the data analyzed in the Edison/Mitofsky study do not provide statistical testing to determine if the difference observed is statistically significant.

Interestingly, in a 1997 exit poll in the United Kingdom an experiment was conducted to evaluate the effect of interviewer training (Moon, 1999). In Moon’s study (1999), half of the interviewers had a “personal briefing” and the other half did not. The researchers found no statistically significant differences between the two conditions; however, they noticed that briefing interviewers was a reassuring factor for the research team and the client. Although there is no conclusive evidence in the literature showing the effect of interviewer training on participation or exit polling accuracy, exit pollsters acknowledge that it is a critical factor (interview with Joe Lenski in Kohut, 2006a; interview with Warren Mitofsky in Kohut, 2006c). Based on experimental findings from the literature (Moon, 1999), it is hypothesized that exit polling training does not directly predict levels of error. Namely,
**H8:** Interviewers who received training prior to the exit poll are equally likely to have an impact on WPE relative to interviewer with no training prior to the exit poll.

**Hypothesis 9: Interviewer Experience**

Interviewer experience has been regarded as a desirable survey design element in the survey methodology literature given its correlation with data quality (Cannell et al., 1977; Gfroerer et al., 1997; Krosnick et al., 2002; Singer et al., 1983). However, little is known on the effect of interviewer experience in exit polling error. Survey agencies typically have fewer exit polling contracts a year relative to other survey projects such as telephone or household surveys. Thus, field representatives have fewer opportunities to gain experience in exit polls (Merkle & Edelman, 2002).

Edison/Mitofsky (2005) reports that in the 2004 exit poll, 339 out of 1,473 interviewers had previously worked as exit interviewers. Out of these 339 interviewers, only 214 worked for the company during the 2004 Presidential primary elections. This means that less than a quarter of the Edison/Mitofsky fieldwork team had exit polling experience for the 2004 Presidential election and less than a sixth had a recent exit polling experience. Edison/Mitofsky (2005), however, does not provide analysis on the relationship between interviewer experience and Within Precinct Error (WPE).

In this study, it is hypothesized that:

**H9a:** Interviewers with previous household interviewing experience are less likely to have an impact on WPE relative to those with no previous household interviewing experience.
H9b: Interviewers with previous exit polling experience are less likely to have an impact on WPE relative to those with no previous exit polling experience.

**Hypothesis 10: Length of Interview**

Studies in the literature suggest that length of the interview tends to have a negative impact on participation and potentially on data quality, as it may increase respondent cognitive burden (Galesic, 2006; Groves, Singer, Corning, & Bowers, 1999; Krosnick, 1999; Lynn, 2014; Sharp & Frankel, 1983). In exit polls, researchers typically need to accommodate as many questions as possible since it is the only opportunity to interview actual voters. However, lengthy interviews may lead to survey fatigue and harm data quality in exit polls (Mitofsky, 1991; Moon, 1999).

Based on experimental work, Mitofsky (1991) indicates that the lengthier the exit poll questionnaire, the lower the response rates. Conversely, Moon (1999) finds that the size of the questionnaire does not have an impact on the reliability of questions. Interestingly, Mitofsky (1991), indicates that the smallest questionnaire used in several experiments—which achieves the highest response rate—it is also the one with the highest exit polling bias. Mitofsky (1991) argues that the small questionnaire version is likely to be perceived as less legitimate than the longer version. Taken together, existing studies suggest that although reliability might not be affected by interview length, the validity of answers may be at stake (Mitofsky, 1991; Moon, 1999).
In this study, length of interview (measured as the average number of minutes reported by interviewers spent on each interview) is hypothesized to have an effect on quality of data. Given the theoretical framework on interviewer effects introduced earlier in this chapter, a lengthier interview may be seen as an extended process where the interviewer keeps respondents engaged to provide answers. Thus, while spending more time with voters may help increase the legitimacy of the study, it may lead to an increase likelihood of interviewer effects.

Consequently, it is hypothesized that as the average time spent on interviews increases, the level of WPE is also likely to increase.

\textit{H10: As the average interview time increases so does Within Precinct Error.}

\textbf{Hypothesis 11: Election Day Factors}

Contextual situations of the interview or “interview setting” have been suggested as a possible source of measurement error in social surveys (Biemer & Lyberg, 2003). Adverse interviewing conditions in exit polls—which are typically beyond the researcher control (also known as election day factors) — have been hypothesized to have an impact on interviewer performance and consequently on accuracy (Edison Media Research and Mitofsky International, 2005; Frankovic et al., 2009; Merkle & Edelman, 2002; Stevenson, 2006). Several situations may represent a challenge to interviewers on election day, including problems with poll workers or political party representatives, distance of interviewers from voting stations, number of exits that need to be monitored, inclement weather, conflicts at the precinct, among others.
Considering that interviewers are tasked with various activities during the day (e.g., keeping up with a selection rate, keeping track of nonrespondents, handing out questionnaires, calling the data center to transmit results every given time interval, reporting to supervisors), election day factors may have an impact on performance and data quality. Interviewers may feel pressured to collect response in unfriendly settings; consequently, interviewers may engage in unscripted behaviors (e.g., providing unsolicited clarification on questions or instructions).

Interview distance to exit has been documented as an adverse interviewing situation in exit polls. Merkle and Edelman (2002) found evidence to suggest that interviewing position is related to participation in exit polls. Likewise, Frankovic (1992) reports that in studies conducted by CBS News, distance harms accuracy of exit polling estimates. Edison/Mitofsky (2005) reports that interviewer distance had an effect on exit polling precision in the 2004 U.S. exit poll. According to the Edison/Mitofsky’s (2005) report, this becomes clearer when interviewers stand more than 100 feet away from the polling place.

Problems with precinct officials has also been found to have a negative impact in exit polls. Merkle and Edelman (2002) show that problems with officials have a negative impact on response rates, even suggesting that problems with precinct officials may explain distant interviewing positions. Edison/Mitofsky (2005) reports that there is a tendency of interviewers who experienced problems with polling station officials to have higher levels of WPE and nonresponse but not with people other than precinct officials (i.e., poll watchers, political party representatives, lawyers, and police). Nonetheless, the Edison/Mitofsky’s (2005) report does not provide statistical testing to establish whether contextual elements are systematically associated with error, after controlling for other factors.
In this multivariate study, it is hypothesized that:

**H11a:** As interviewer distance to the voting station increases, the level of Within Precinct Error also increases.

**H11b:** Interviewers who are asked for an exit polling permit by a polling place worker, are more likely to have an impact on WPE, relative to those that are not asked for an exit polling permit.

**H11c:** Interviewers who are asked for an exit polling permit by a political party representative, are more likely to have an impact on WPE, relative to those that are not asked for an exit polling permit.

**H11d:** Interviewers who are asked to stop exit polling by a polling place worker, are more likely to have an impact on WPE, relative to those that are not asked to stop.

**H11e:** Interviewers are asked to stop exit polling by a political party representative, are more likely to have an impact on WPE, relative to those that are not asked to stop.

**H11f:** Interviewers who noted conflicts at the polling station are more likely to have an impact on WPE, relative to those who did not note conflicts.

**H11g:** Interviewers who needed to monitor more than one exit at the polling stations, are more likely to have an impact on WPE, relative to those who monitored just one exit.
Data and Methods

As detailed in Chapter 3, data from this study come from two exit polls conducted in Mexico in 2006 and 2009. Different from Chapter 4 and 5, this chapter considers actual election results at the precinct level. Precinct-level information was retrieved for all parties; however, to ease analysis, only the three major parties in the country were considered individually; namely, Institutional Revolutionary Party (PRI), National Action Party (PAN) and Party of the Democratic Revolution (PRD). Other parties as well as blank or void ballots were grouped as “Other.”

As shall be seen below, exit poll error is calculated at the precinct level (hence the name “Within Precinct Error”). Accordingly, metrics representing respondent characteristics are also calculated at the precinct level. Specifically, proportions of male, older (i.e., respondent age 40 or older), educated (i.e., college educated), and middle or upper class respondents, are considered for analysis. These quantities serve as predictors of Within Precinct Error (dependent variable) in regression analyses.

Traditional analysis of WPE in the literature have used bivariate methods to investigate the relationship between error and potential predictors (i.e., nonresponse, interviewer characteristics, respondent characteristics and election day factors). To go one step further, this study is based on multiple regression analysis to jointly estimate the effect of hypothesized predictors on WPE. Given that the dependent variable (WPE) is continuous, conventional Ordinary Least Square regression (OLS) is deemed appropriate for hypothesis testing.
A Note on Within Precinct Error

Ideally, measurement error should be calculated at the individual level by comparing reported answers to external records. In practice, however, this is not always possible (Biemer, 2001; Biemer & Stokes, 1991; Olson, 2006). Given that voting is anonymous in democracies around the world (i.e., voting systems are designed to avoid linking preferences to any personal record), it is nearly impossible to compare consistently exit polling answers against actual preferences at the individual level. Instead, exit polls are typically validated through precinct-level records using a metric referred to as “signed difference” or “Within Precinct Error” (Merkle & Edelman, 2000, 2002; Mitofsky, 1991, 2003; Mitofsky & Edelman, 2002; Mosteller, 1949).

For the case the U.S. case, the basic notion of the “signed difference” is expressed as follows:

\[
\text{Signed Error}_{\text{Precinct}} = (D_v - R_v) - (D_p - R_p)
\]

Where \(D_v\) and \(R_v\) represent the actual results of vote for the two major political parties in a race (in the case of the United States, the Democratic Party and the Republican Party), respectively. \(D_p\) and \(R_p\) represent the estimated proportions based on exit polls in a given precinct.

This measure of exit polling bias has been further adapted to account the potential effect from differential “sampling rates” within each of the sample precincts (Liddle, 2005; Lindeman et al., 2006). Arguably, differential sampling rates or “sampling propensities” of voters to accept the survey request, and differential propensities of interviewers to select or approach sample
voters are not accounted for in the traditional signed error computation (Liddle, 2005; Lindeman et al., 2006).

Interestingly, Liddle (2005) has suggested the inclusion of a term in the traditional exit polling bias computation to represent the differential sampling rates of the voting groups (in the case of the United States, Democratic and Republican voters). Such additional term is expressed as follows:

\[
\alpha = \frac{D_D}{D_V} \frac{R_P}{R_V} = \frac{S_D}{S_R}
\]

Where \(S_D\) and \(S_R\) represent the “achieved” sampling rate for Democratic and Republican voters, respectively. In other words, \(S_D\) and \(S_R\) are the number of exit polling responses relative to the actual voters at the precinct level, for each group respectively. Noticeably, when \(S_D\) and \(S_R\) are equal, then \(\alpha\) equals 1. Departures from unity indicate differential in response probabilities for sample voters in each group at the precinct level (Blumenthal, 2005i; Liddle, 2005; Lindeman et al., 2006).

The inclusion of \(\alpha\) in the traditional WPE computation would account for some of the potential confounding due to achieved “sampling rates” (Liddle, 2005). When \(\alpha\) is included in the calculation of WPE, it is expressed as follows (Bautista et al., 2007; Liddle, 2005):

\[
\text{WPE} = 2 \times \left[ \frac{D_V^2(1 - \alpha) - D_v(1 - \alpha)}{D_v(1 - \alpha) - 1} \right]
\]

As Lindeman, Liddle and Brady (2006) have noted, the \(\alpha\) term may also change due to administrative errors in the official vote count, since \(\alpha\) is a ratio of poll responses to the counted votes. Some authors have gone even further to suggest the possibility of alterations in the official outcome as the potential driver of increases in the Within Precinct Error. See for instance (Freeman & Bleifuss, 2006). In the present study, administrative errors are assumed to occur at random and not as a consequence of deliberate manipulation.
Bautista et al. (2007) used a modification of this WPE representation to analyze five statewide exit polls in Mexico. Bautista and colleagues (2007) replaced the Democrat piece with the winner party of in each state and the Republican Party component with the second place. The top two parties in each race were used in order to compute the measure that is referred to as Modified Within-Precinct Error or MWPE. Given the convenience of the MWPE metric, this approach has been adopted in other multi-party systems to estimate exit poll error (Bagić & Lamza Posavec, 2008; Kwak & Choi, 2014). Consequently, the following definition is adapted for the present study (for an algebraic explanation see Bautista et al., 2007):

\[ \text{MWPE} = 2 \times \left[ \frac{F_v^2(1-\alpha) - F_v(1-\alpha)}{F_v(1-\alpha) - 1} \right] \] and \[ \alpha = \frac{A_F}{A_S}, \]

where \( F_v \) is defined as actual voting proportion of the winning party or “first place” (defined by number of votes) in the race. \( A_F \) represents the achieved sampling rate for the first place and \( A_S \) is the achieved sampling rate for the second place. Consequently, the Modified Within Precinct Error can be interpreted as the difference between the leading party and the closest party.

In the 2006 Presidential Election the winning party was PAN and the second place was PRD. In the 2009 Congressional Election the first place was PRI and the second place was PAN. Consequently, in 2006 a negative sign means response error in favor of PAN (vs. PRD), and in 2009 a negative sign means response error in favor of PRI (vs. PAN). For regression analysis, however, the absolute value of MPWE as the interest is focused on predictors of error in either direction.
Levels of Missing data

Table 1 displays the level of missing data in variables of interest. As it can be seen, Modified Precinct Error has 5 missing cases in 2006 and 4 in 2009. This is because in these precincts no votes were recorded for the first or second place party. It would make no sense to impute data for actual votes. Consequently, calculations are not possible for \( \alpha \) in the WPE methodology described above and those precincts are not included in the analysis.

Also, information in Table 6-1 shows that some interviewers did not provide complete information for demographic characteristics in the post-election questionnaire (i.e., age, gender and education). Nonetheless, the level of data missingness is relatively low; that is, approximately 2\% for age in 2006 (and 0\% in 2009), approximately 7\% for gender in 2006 and 3\% in 2009, and 4.5\% for education in 2006 (with 0\% in 2009). Considering that the average level of missing data in demographic characteristics (i.e., age, gender and education) is approximately 3\% and given the lack of external auxiliary information on interviewer characteristics, it is deem of little value imposing a probability model on the complete data to generate imputed values.
Table 6.1. Level of Missingness in Data from 2006 and 2009 Exit Polls at Precinct Level

<table>
<thead>
<tr>
<th></th>
<th>2006 Exit Poll</th>
<th>2009 Exit Poll</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Missing cases</td>
<td>Total cases</td>
</tr>
<tr>
<td>MWPE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of refusals</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Voter Information</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Older Voters</td>
<td>0</td>
<td>199</td>
</tr>
<tr>
<td>Proportion of College Educated Voters</td>
<td>0</td>
<td>199</td>
</tr>
<tr>
<td>Proportion of Middle or Upper Class Voters</td>
<td>0</td>
<td>199</td>
</tr>
<tr>
<td>Proportion of Male Voters</td>
<td>0</td>
<td>199</td>
</tr>
<tr>
<td>Rural (Yes)</td>
<td>0</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Information</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interviewer Age</td>
<td>4</td>
<td>196</td>
</tr>
<tr>
<td>Interviewer Gender</td>
<td>14</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Education</td>
<td>9</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Thinks Meaning of Questions is Clear</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Doubts</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Thinks Meaning of Questions is Clear</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Prefers Own Script to Approach Voters</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Interviewer Political Preference</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Interviewer Training</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Experience in HH Surveys</td>
<td>6</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Experience in Election Day Surveys</td>
<td>6</td>
<td>199</td>
</tr>
<tr>
<td>Length of Average Interview</td>
<td>8</td>
<td>199</td>
</tr>
<tr>
<td>Election Day Factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interviewer Distance</td>
<td>6</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Asked for Permit by Poll Worker</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Asked for Permit by Party Representative</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Asked to Stop by Poll Worker</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Asked to Stop by Party Representative</td>
<td>5</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Noticed Conflicts at Voting Station</td>
<td>6</td>
<td>199</td>
</tr>
<tr>
<td>Interviewer Monitor More than One Exit</td>
<td>7</td>
<td>199</td>
</tr>
</tbody>
</table>

Other variables with interviewer characteristics have also relatively low levels of data missingness. On average, approximately 2% of the data are missing for questions answered by interviewers in the post-election questionnaire. Some questions are not available in both years; for example, the question on whether the interviewer prefers his or her own script to approach voters and the question on political preference, are only available in the 2009 dataset. Likewise, the question on whether the interviewer thinks the meaning of questions in the questionnaire was
clear, and whether the interviewer was asked to stop exit polling activities by poll worker or a party representative, are only available in the 2006 dataset.

**Descriptive Statistics**

Table 6-2 shows univariate statistics (sample size, mean, standard deviation, minimum and maximum) of continuous variables used for analysis. Particularly, it shows an average MWPE of -0.004 in 2006 and -0.057 in 2009. A negative sign in 2006 means an overestimation error in favor of PAN (first place party) vs. PRD (second place party) in the order of less than one half of a percentage point (-0.4%=-0.004*100). A negative sign in 2009 means an average overestimation error in favor of PRI (first place) vs. PAN (second place) in the order of approximately six percentage points (-5.7%=-0.057*100).

In 2006, the minimum value of MWPE indicates that the largest overestimation in favor of PAN in a precinct is of approximately 68 percentage points (= -0.682*100) whereas the maximum value indicates that the largest overestimation of PRD in a precinct is about 98% (=0.983*100). In 2009, the minimum value of MWPE indicates that the largest overestimation in favor of PRI is in the order of 83 percentage points (= -0.832*100) and the maximum value indicates that the largest overestimation in favor of PAN in a sample precinct is of approximately 62 percentage points (= 0.620*100).

The average absolute MWPE (i.e., the statistical bias can go in either direction) was also calculated for each exit poll. On average, the mean absolute MWPE per precinct is approximately 20% (=0.204*100) in 2006 and 22% (=0.220*100) in 2009. The minimum and
maximum value for the 2006 exit poll indicates that the smallest bias in a sample precinct is of 0% and the largest bias is approximately 98% (=0.983*100). Likewise, the minimum absolute value in 2009 indicates the smallest bias in a sample precinct is less than one half of a percentage point (0.004*100) and the largest bias is of approximately 83 percentage points (0.832*100).
Table 6-2. Descriptive Statistics for Continuous Metrics at the Precinct Level from the 2006 and 2009 Exit Polls

<table>
<thead>
<tr>
<th>Metric</th>
<th>2006 Exit Poll</th>
<th>2009 Exit Poll</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean</td>
</tr>
<tr>
<td>MWPE</td>
<td>194</td>
<td>-0.004</td>
</tr>
<tr>
<td>Abs(MWPE)</td>
<td>194</td>
<td>0.204</td>
</tr>
<tr>
<td>Refusal Rate</td>
<td>199</td>
<td>0.412</td>
</tr>
<tr>
<td>Proportion of Older Respondents</td>
<td>199</td>
<td>0.516</td>
</tr>
<tr>
<td>Proportion of College Educated Respondents</td>
<td>199</td>
<td>0.181</td>
</tr>
<tr>
<td>Proportion of Middle or Upper Class Respondents</td>
<td>199</td>
<td>0.408</td>
</tr>
<tr>
<td>Proportion of Male Respondents</td>
<td>199</td>
<td>0.508</td>
</tr>
<tr>
<td>Interviewer Age (Male)</td>
<td>195</td>
<td>27.287</td>
</tr>
<tr>
<td>Length of Average Interview (Minutes)</td>
<td>191</td>
<td>6.927</td>
</tr>
<tr>
<td>Interviewer Distance (Meters)</td>
<td>193</td>
<td>11.399</td>
</tr>
</tbody>
</table>
On average, the refusals rate per precinct is approximately 41% (S.D. 22%) in 2006 and 36% (S.D. 17%) in 2009. Table 6-1 also shows proportions for respondent characteristics in the sample of precincts. In both elections, approximately half of respondents are older respondents on average (40 years old or older) (2006: M=0.52, S.D.=0.10; 2009: M=0.51, S.D.=0.11), one fifth of respondents are college educated (2006: M=0.18, S.D.=0.19; 2009: M=0.21, S.D.=0.20), approximately four in every ten respondents are middle or upper class respondents (2006: M=0.41, S.D.=0.27; 2009: M=0.45, S.D.=0.26), and about half of respondents were male respondents (2006: M=0.51, S.D.=0.09; 2009: M=0.52, S.D.=0.09).

Additionally, Table 6-2 shows that interviewers are on average 27 years old in the 2006 election (M=27.3, S.D.=10.09), and approximately 30 years in the 2009 election (M=30.31; S.D.=10.58). The mean value of the variable used to measure length of average interview is approximately 7 minutes (M=6.93; S.D.=3.13) in 2006 and approximately 6 minutes in 2009 (M=6.04; S.D.=2.38).

Table 6-3 shows descriptive statistics of categorical variables related to type of precinct and interviewer characteristics. Approximately a third of sample precincts are rural in the 2006 dataset (30.65%) while about a fifth of sample precincts are rural in 2009 (19.7%). Of the 2006 interviewers, 56% were male and 44% were females. Of the 2009 interviewers, 61% were male and 39% were female. In 2006, the percent of interviewers who did not have a high school diploma was 13%, 61% had a high school diploma, and 26% had a college degree. In 2009, about 20% had less than high school, 53% had a high school diploma, and 27% had a college degree.
Table 6-3. Descriptive Statistics for Categorical Metrics at the Precinct Level from the 2006 Exit Poll
(Type of Precinct and Interviewer Information)

<table>
<thead>
<tr>
<th></th>
<th>2006 Data</th>
<th></th>
<th>2009 Data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Percent</td>
<td>N</td>
<td>Percent</td>
</tr>
<tr>
<td><strong>Type of Precinct</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Otherwise</td>
<td>138</td>
<td>69.35</td>
<td>53</td>
<td>80.3</td>
</tr>
<tr>
<td>1 Rural</td>
<td>61</td>
<td>30.65</td>
<td>13</td>
<td>19.7</td>
</tr>
<tr>
<td>Total</td>
<td>199</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Information</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Interviewer Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Women</td>
<td>82</td>
<td>44.32</td>
<td>25</td>
<td>39.06</td>
</tr>
<tr>
<td>1 Men</td>
<td>103</td>
<td>55.68</td>
<td>39</td>
<td>60.94</td>
</tr>
<tr>
<td>Total</td>
<td>185</td>
<td>100</td>
<td>64</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Less than High School</td>
<td>25</td>
<td>13.16</td>
<td>13</td>
<td>19.7</td>
</tr>
<tr>
<td>1 High School Grad</td>
<td>116</td>
<td>61.05</td>
<td>35</td>
<td>53.03</td>
</tr>
<tr>
<td>2 College</td>
<td>49</td>
<td>25.79</td>
<td>18</td>
<td>27.27</td>
</tr>
<tr>
<td>Total</td>
<td>190</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Thinks Meaning of Questions is Clear</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>52</td>
<td>26.8</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>1 Yes</td>
<td>142</td>
<td>73.2</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Total</td>
<td>194</td>
<td>100</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><strong>Interviewer Doubts</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>173</td>
<td>89.18</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td>1 Yes</td>
<td>21</td>
<td>10.82</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>194</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Prefers Own Script to Approach Voters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>NA</td>
<td>NA</td>
<td>52</td>
<td>82.54</td>
</tr>
<tr>
<td>1 Yes</td>
<td>NA</td>
<td>NA</td>
<td>11</td>
<td>17.46</td>
</tr>
<tr>
<td>Total</td>
<td>NA</td>
<td>NA</td>
<td>63</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Political Preference</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Other</td>
<td>NA</td>
<td>NA</td>
<td>9</td>
<td>14.29</td>
</tr>
<tr>
<td>1 PAN</td>
<td>NA</td>
<td>NA</td>
<td>11</td>
<td>17.46</td>
</tr>
<tr>
<td>2 PRI</td>
<td>NA</td>
<td>NA</td>
<td>7</td>
<td>11.11</td>
</tr>
<tr>
<td>3 PRD</td>
<td>NA</td>
<td>NA</td>
<td>36</td>
<td>57.14</td>
</tr>
<tr>
<td>Total</td>
<td>NA</td>
<td>NA</td>
<td>63</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Training</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>5</td>
<td>2.58</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1 Yes</td>
<td>189</td>
<td>97.42</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>194</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Experience in HH Surveys</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>48</td>
<td>24.87</td>
<td>4</td>
<td>6.35</td>
</tr>
<tr>
<td>1 Yes</td>
<td>145</td>
<td>75.13</td>
<td>59</td>
<td>93.65</td>
</tr>
<tr>
<td>Total</td>
<td>193</td>
<td>100</td>
<td>63</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Experience in Election Day Surveys</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>99</td>
<td>51.3</td>
<td>34</td>
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<tr>
<td>1 Yes</td>
<td>94</td>
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<td>48.48</td>
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<tr>
<td>Total</td>
<td>193</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
</tbody>
</table>
Table 6-3 also shows that 7 in 10 interviewers (73.2\%) thought that the meaning of questions in the questionnaire was clear in the 2006 exit poll. This variable is not available in the 2009 dataset. In 2006, just 1 in 10 interviewers (10.8\%) expressed they had questions on how to apply the questionnaire, while in 2009 none of the 2009 interviewers reported having doubts about the interviewing task. In 2009, 2 in 10 interviewers (17.5\%) indicated they prefer their own script to approach voters instead of the standard protocol. This question was not included in the 2006 post-election questionnaire.

In the 2009 post-election questionnaire, 57\% of interviewers indicated that they would had voted for PRD, 17\% would had voted for PAN, 11\% for PRI and 14\% for other party, had they had the chance to vote on election day.\textsuperscript{8} The question on electoral preference was not included in the 2006 post-election questionnaire.

In 2006, nearly all interviewers (97.4\%) reported going through training prior to the exit poll and in 2009 all interviewers reported receiving training. In 2006, 7 in 10 interviewers (75.1\%) reported having conducted household interviews before. In 2009, 9 in 10 interviewers reported experience in household surveys. About half of the interviewers reported having previous experience in exit polls (48.7\% in 2006 and 48.5\% in 2009).

\textsuperscript{8} In 2009, field representatives traveled from Mexico City to randomly selected precinct locations (as dictated by the sample design). The chance of assigning a field representative to her own precinct is minimal.
Table 6-4. Descriptive Statistics for Continuous Metrics at the Precinct Level from the 2006 Exit Poll
(Election Day Factors)

<table>
<thead>
<tr>
<th></th>
<th>2006 Data</th>
<th></th>
<th>2009 Data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Percent</td>
<td>N</td>
<td>Percent</td>
</tr>
<tr>
<td><strong>Interviewer Asked for Permit by Poll Worker</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>69</td>
<td>35.57</td>
<td>35</td>
<td>53.03</td>
</tr>
<tr>
<td>1 Yes</td>
<td>125</td>
<td>64.43</td>
<td>31</td>
<td>46.97</td>
</tr>
<tr>
<td>Total</td>
<td>194</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Asked for Permit by Party Representative</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>121</td>
<td>62.37</td>
<td>38</td>
<td>57.58</td>
</tr>
<tr>
<td>1 Yes</td>
<td>73</td>
<td>37.63</td>
<td>28</td>
<td>42.42</td>
</tr>
<tr>
<td>Total</td>
<td>194</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Asked to Stop by Poll Worker</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>167</td>
<td>86.08</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>1 Yes</td>
<td>27</td>
<td>13.92</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Total</td>
<td>194</td>
<td>100</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><strong>Interviewer Asked to Stop by Party Representative</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>167</td>
<td>86.08</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>1 Yes</td>
<td>27</td>
<td>13.92</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Total</td>
<td>194</td>
<td>100</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td><strong>Interviewer Noticed Conflicts at Voting Station</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>159</td>
<td>82.38</td>
<td>48</td>
<td>72.73</td>
</tr>
<tr>
<td>1 Yes</td>
<td>34</td>
<td>17.62</td>
<td>18</td>
<td>27.27</td>
</tr>
<tr>
<td>Total</td>
<td>193</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
<tr>
<td><strong>Interviewer Monitor More than One Exit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 No</td>
<td>139</td>
<td>72.4</td>
<td>48</td>
<td>72.73</td>
</tr>
<tr>
<td>1 Yes</td>
<td>53</td>
<td>27.6</td>
<td>18</td>
<td>27.27</td>
</tr>
<tr>
<td>Total</td>
<td>192</td>
<td>100</td>
<td>66</td>
<td>100</td>
</tr>
</tbody>
</table>
Data in Table 6-4 show that two thirds of field representatives (64.4%) were asked to show an interview permit by an election official in 2006. In 2009, only half of interviewers were asked to show an interview permit (46.9%). In 2006 and 2009, about 1 in 4 interviewers were asked by a party representative to display the previously mentioned permit (37.6% and 42.4%, respectively).

In 2006, 1 in 10 interviewers were asked to stop interviewing either by an election official (13.9%) or a party representative (13.9%). These questions are not available for the 2009 dataset. Of the 2006 interviewers, about 18% noticed conflicts at the voting station, whereas 27% of the 2009 interviewers noticed problems. Approximately 27% of interviewers in both elections had to monitor more than exit on election day.

Results

Multiple Regression Analysis

Table 6-5 and 6-6 display coefficients and standard errors from linear regression models estimated by single-level ordinary least squares for the 2006 and 2009 exit polls, respectively. Regression coefficients describe hypothesized relationships, where the dependent variable is the absolute value of the Modified Within Precinct Error (i.e., abs(MWPE)). To facilitate comparison of Table 6-4 and 6-5, the same set of predictors are displayed in tables; however, some variables are not available (NA) for one of the years, as displayed also in Table 6-1.

The set of models included in Table 6-5 (i.e., M1 through M3) and in Table 6-6 (i.e., Model 4 through Model 6) differ from each other in how they incorporate interaction terms.
Particularly, Models 2 and 3 as well as Models 5 and 6 consider two additional predictors: (i) a two-way interaction term for interviewer age and proportion of older respondents in the $j$-th pool assigned to the respondent (ii) a three-way an interaction term between interviewer age, interviewer education and proportion of older respondents in the $j$-th pool assigned to the interviewer.

Coefficients in Table 6-6 reveal no statistically significant patterns when regressing hypothesized predictors on the dependent variable for the year of 2009. It is seems quite possible that the limited number of cases available for regression analysis in 2009 (n=55) does not provide enough statistical power to detect systematic patterns of multiple variables jointly. Conversely, Table 6-5 relies on a dataset that is approximately 3 times larger (n=164) than the 2009 data to test hypothesized relationships.

While pooling datasets might be a practical way of increasing sample size, it is deemed inappropriate in this study. As explained in section “A Note on Within Precinct Error”, calculations of MWPE depend on the difference between first and second place in a particular election. The winner and the second place were not the same in both years (i.e., Congressional vs. Presidential election). Therefore, due to sample size considerations (limited cases in 2009), the section focuses on patterns from the 2006 dataset.

**Evidence for Direct and Indirect Effects**

Regression coefficients from Model 1 (Table 6-5) suggests that refusals are not statistically related to the absolute value of MWPE ($b=-0.0177$, S.E.=0.065, $p>.05$). This
relationship does not appear to reach statistical significance in Model 2 (b=-0.0171, S.E.=0.065, \( p>.05 \)) or Model 3 (b=-0.0127, S.E.=0.067, \( p>.05 \)), independent from other factors. Model 1 also indicates that as the proportion of older voters in the \( j \)-th pool of respondents increases (that is, as “respondent age” increases), the absolute level of WMPE decreases (b=-0.3178, S.E.= 0.139, \( p<.05 \)) — independent from interviewer age and other factors.

An interaction term between the proportion of older voters in the \( j \)-th pool of respondents (loosely referred to as “respondent age”) and interviewer age is included in Model 2. This interaction term does not appear to be statistically significant (b=-0.0066, S.E.=0.016, \( p>.05 \)). Also, after the inclusion of such interaction term (M2), the direct effect of respondent age appears to be no longer significant (b=-0.1475, S.E.=0.423, \( p>.05 \)).
Table 6-5. Multiple Linear Regression Model for Predictors of Modified Within Precinct Error at Precinct Level in 2006

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>SE</td>
<td>Coef</td>
<td>SE</td>
<td>Coef</td>
<td>SE</td>
</tr>
<tr>
<td>Refusal Rate</td>
<td>-0.0177</td>
<td>0.065</td>
<td>-0.0171</td>
<td>0.065</td>
<td>-0.0127</td>
<td>0.067</td>
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<tr>
<td>Rural (Yes)</td>
<td>-0.0354</td>
<td>0.037</td>
<td>-0.0349</td>
<td>0.037</td>
<td>-0.0264</td>
<td>0.036</td>
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<tr>
<td><strong>Voter Demographic Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion of Older Respondents</td>
<td>-0.3127</td>
<td>* 0.141</td>
<td>-0.1475</td>
<td>0.423</td>
<td>-3.8531</td>
<td>** 1.438</td>
</tr>
<tr>
<td>Prop of College Educated Respondents</td>
<td>-0.2192</td>
<td>* 0.090</td>
<td>-0.2180</td>
<td>* 0.090</td>
<td>-0.2234</td>
<td>* 0.089</td>
</tr>
<tr>
<td>Prop of Middle or Upper Class Resp</td>
<td>0.0679</td>
<td>0.068</td>
<td>0.0700</td>
<td>0.069</td>
<td>0.0590</td>
<td>0.068</td>
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<tr>
<td>Proportion of Male Respondents</td>
<td>-0.0402</td>
<td>0.165</td>
<td>-0.0469</td>
<td>0.167</td>
<td>-0.1131</td>
<td>0.174</td>
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<td><strong>Interviewer Demographic Characteristics</strong></td>
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<tr>
<td>Interviewer Gender (Male)</td>
<td>0.0529</td>
<td>0.028</td>
<td>0.0525</td>
<td>0.028</td>
<td>0.0491</td>
<td>0.028</td>
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<tr>
<td>Interviewer Age (Years)</td>
<td>-0.0042</td>
<td>0.004</td>
<td>-0.0006</td>
<td>0.010</td>
<td>-0.0546</td>
<td>* 0.023</td>
</tr>
<tr>
<td>Intv’r Educ (Ref: Less Than H School)</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>High School Graduate</td>
<td>-0.0707</td>
<td>0.139</td>
<td>-0.0654</td>
<td>0.140</td>
<td>-1.9089</td>
<td>* 0.770</td>
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<tr>
<td>College Graduate</td>
<td>-0.1428</td>
<td>0.154</td>
<td>-0.1488</td>
<td>0.155</td>
<td>-3.1126</td>
<td>** 0.962</td>
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<tr>
<td><strong>Two-way Interaction Terms</strong></td>
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<td></td>
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<tr>
<td>Intv’r Educ (Ref: Less High School)</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>High School Graduate # Intv’r age</td>
<td>0.0031</td>
<td>0.004</td>
<td>0.0028</td>
<td>0.005</td>
<td>0.0571</td>
<td>* 0.025</td>
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<tr>
<td>College Graduate # Intv’r age</td>
<td>0.0047</td>
<td>0.005</td>
<td>0.0050</td>
<td>0.005</td>
<td>0.1067</td>
<td>* 0.036</td>
</tr>
<tr>
<td>Interviewer Age # Prop Older Resp</td>
<td>---</td>
<td>---</td>
<td>-0.0066</td>
<td>0.016</td>
<td>0.1000</td>
<td>* 0.044</td>
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<tr>
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<tr>
<td>H School Graduate # Prop Older Resp</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>3.7048</td>
<td>* 1.526</td>
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<tr>
<td>College Graduate # Prop Older Resp</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>5.6535</td>
<td>** 1.805</td>
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<tr>
<td><strong>Three-way Interaction Terms</strong></td>
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<tr>
<td>Intv’r Educ (Ref: Less High School)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H School Grad # I age # Prop Older R</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>-0.1067</td>
<td>* 0.048</td>
</tr>
<tr>
<td>College Grad # I age # Prop Older R</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>-0.1891</td>
<td>** 0.064</td>
</tr>
<tr>
<td><strong>Interviewer Attitudinal and Behavioral Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intv’r Thinks Questions are Clear (Yes)</td>
<td>-0.0027</td>
<td>0.033</td>
<td>-0.0012</td>
<td>0.033</td>
<td>0.0029</td>
<td>0.032</td>
</tr>
<tr>
<td>Intv’r Has Doubts on Survey Qs (Yes)</td>
<td>0.0729</td>
<td>0.043</td>
<td>0.0738</td>
<td>0.043</td>
<td>0.0872</td>
<td>0.043</td>
</tr>
<tr>
<td>Intv’r Prefers Own Script (Yes)</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Intv’r Political Preference (Ref: Other)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interviewer Prefers PAN</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Interviewer Prefers PRI</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Interviewer Prefers PRD</td>
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<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Interviewer Training (Yes)</td>
<td>0.0338</td>
<td>0.079</td>
<td>0.0315</td>
<td>0.079</td>
<td>0.0224</td>
<td>0.079</td>
</tr>
<tr>
<td>Intv’r Experience in HH Surveys (Yes)</td>
<td>0.0024</td>
<td>0.033</td>
<td>0.0034</td>
<td>0.033</td>
<td>-0.0052</td>
<td>0.033</td>
</tr>
<tr>
<td>Intv’r Experience in Exit Polls (Yes)</td>
<td>-0.0157</td>
<td>0.029</td>
<td>-0.0160</td>
<td>0.029</td>
<td>-0.0218</td>
<td>0.029</td>
</tr>
<tr>
<td>Length of Average Interview (Minutes)</td>
<td>-0.0036</td>
<td>0.004</td>
<td>-0.0039</td>
<td>0.004</td>
<td>-0.0046</td>
<td>0.004</td>
</tr>
<tr>
<td><strong>Election Day Factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intv’r Distance (Meters)</td>
<td>0.0025</td>
<td>** 0.001</td>
<td>0.0025</td>
<td>** 0.001</td>
<td>0.0025</td>
<td>** 0.001</td>
</tr>
<tr>
<td>Poll Worker Asked for Permit (Yes)</td>
<td>0.0221</td>
<td>0.030</td>
<td>0.0221</td>
<td>0.030</td>
<td>0.0227</td>
<td>0.03</td>
</tr>
<tr>
<td>Party Rep Asked for Permit (Yes)</td>
<td>-0.0353</td>
<td>0.032</td>
<td>-0.0347</td>
<td>0.033</td>
<td>-0.0235</td>
<td>0.032</td>
</tr>
<tr>
<td>Poll Worker Asked to Stop (Yes)</td>
<td>0.0501</td>
<td>0.046</td>
<td>0.0511</td>
<td>0.046</td>
<td>0.0653</td>
<td>0.046</td>
</tr>
<tr>
<td>Party Rep Asked to Stop (Yes)</td>
<td>-0.0128</td>
<td>0.045</td>
<td>-0.0126</td>
<td>0.045</td>
<td>-0.0157</td>
<td>0.045</td>
</tr>
<tr>
<td>Conflicts at Poll Station (Yes)</td>
<td>0.0536</td>
<td>0.038</td>
<td>0.0545</td>
<td>0.039</td>
<td>0.0415</td>
<td>0.039</td>
</tr>
<tr>
<td>More than One Exit (Yes)</td>
<td>-0.0004</td>
<td>0.031</td>
<td>-0.0015</td>
<td>0.031</td>
<td>0.0099</td>
<td>0.031</td>
</tr>
<tr>
<td>Constant</td>
<td>0.4450</td>
<td>* 0.209</td>
<td>0.3598</td>
<td>0.293</td>
<td>2.2475</td>
<td>** 0.743</td>
</tr>
</tbody>
</table>

*Pr(Y=abs(MWPE)|x)*

N = 164

*p<.05, **p<.01, ***p<.001, # Interaction*
Table 6-6. Multiple Linear Regression Model for Predictors of Modified Within Precinct Error at Precinct Level in 2009

|                        | Pr (Y=abs(MWPE)|x) | Model 4 | Model 5 | Model 6 |
|------------------------|----------------|---------|---------|---------|
|                        |                | Coef    | SE      | Coef    | SE      | Coef    | SE      |
| Refusal Rate           |                | 0.1943  | 0.214   | 0.1841  | 0.219   | 0.2602  | 0.249   |
| Rural (Yes)            |                | -0.0323 | 0.077   | -0.0286 | 0.078   | -0.0137 | 0.083   |
| **Voter Demographic Characteristics** | | | | | | | |
| Proportion of Older Respondents | | 0.1162  | 0.276   | 0.5245  | 1.082   | 1.7157  | 1.994   |
| Prop of College Educated Respondents | | -0.3661 | 0.221   | -0.3350 | 0.238   | -0.3232 | 0.253   |
| Prop of Middle or Upper Class Resp | | 0.1176  | 0.139   | 0.1237  | 0.142   | 0.0727  | 0.151   |
| Proportion of Male Respondents | | 0.0510  | 0.371   | 0.0350  | 0.379   | 0.2073  | 0.442   |
| **Interviewer Demographic Characteristics** | | | | | | | |
| Interviewer Gender (Male) | | -0.0458  | 0.055   | -0.0508 | 0.057   | -0.0420 | 0.061   |
| Interviewer Age (Years) | | -0.0051  | 0.006   | 0.0033  | 0.022   | 0.0371  | 0.039   |
| Intv’r Educ (Ref: Less High School) | | | | | | | |
| High School Graduate | | -0.0491  | 0.257   | -0.0077 | 0.282   | 0.8510  | 1.428   |
| College Graduate | | -0.0567  | 0.374   | -0.0076 | 0.400   | 2.8046  | 2.335   |
| **Two-way Interaction Terms** | | | | | | | |
| Intv’r Educ (Ref: Less Than H School) | | 0.0018  | 0.008   | 0.0008  | 0.008   | -0.0405 | 0.045   |
| High School Graduate # Intv’r age | | 0.0002  | 0.013   | -0.0015 | 0.014   | -0.1233 | 0.088   |
| College Graduate # Intv’r age | | ---     | ---     | -0.0151 | 0.039   | -0.0810 | 0.069   |
| Interviewer Age # Prop Older Resp | | ---     | ---     | ---     | ---     | -1.6662 | 2.530   |
| Intv’r Educ (Ref: Less High School) | | | | | | | |
| H School Graduate # Prop Older Resp | | ---     | ---     | ---     | ---     | -6.3112 | 4.912   |
| College Graduate # Prop Older Resp | | ---     | ---     | ---     | ---     | 0.0809  | 0.082   |
| **Three-way Interaction Terms** | | | | | | | |
| Intv’r Educ (Ref: Less High School) | | 0.0000  | 0.000   | 0.0000  | 0.000   | 0.0000  | 0.000   |
| H School Grad # I age # Prop Older R | | ---     | ---     | ---     | ---     | 0.0820  | 0.190   |
| College Grad # I age # Prop Older R | | ---     | ---     | ---     | ---     | 0.2704  | 0.190   |
| **Interviewer Attitudinal and Behavioral Characteristics** | | | | | | | |
| Intv’r Thinks Questions are Clear (Yes) | | NA     | NA      | NA      | NA      | NA      | NA      |
| Intv’r Has Doubts on Survey Qs (Yes) | | 0.0000  | 0.000   | 0.0000  | 0.000   | 0.0000  | 0.000   |
| Intv’r Prefers Own Script (Yes) | | -0.0819 | 0.082   | -0.0854 | 0.083   | -0.0436 | 0.090   |
| Intv’r Political Preference (Ref: Other) | | | | | | | |
| Interviewer Prefers PAN | | 0.0678  | 0.098   | 0.0702  | 0.100   | 0.1032  | 0.116   |
| Interviewer Prefers PRI | | 0.0267  | 0.088   | 0.0268  | 0.089   | 0.0051  | 0.093   |
| Interviewer Prefers PRD | | 0.1047  | 0.089   | 0.1007  | 0.091   | 0.1025  | 0.093   |
| Interviewer Training (Yes) | | 0.0000  | 0.000   | 0.0000  | 0.000   | 0.0000  | 0.000   |
| Intv’r Experience in HH Surveys (Yes) | | -0.1028 | 0.108   | -0.0978 | 0.110   | -0.1223 | 0.114   |
| Intv’r Experience in Exit Polls (Yes) | | 0.0600  | 0.056   | 0.0543  | 0.059   | 0.0195  | 0.066   |
| Length of Average Interview (Minutes) | | 0.0227  | 0.014   | 0.0232  | 0.014   | 0.0197  | 0.015   |
| **Election Day Factors** | | | | | | | |
| Intv’r Distance (Meters) | | 0.0002  | 0.002   | 0.0003  | 0.002   | -0.0003 | 0.002   |
| Poll Worker Asked for Permit (Yes) | | -0.0199 | 0.064   | -0.0246 | 0.066   | -0.0633 | 0.072   |
| Party Rep Asked for Permit (Yes) | | -0.0137 | 0.076   | -0.0098 | 0.078   | -0.0229 | 0.084   |
| Poll Worker Asked to Stop (Yes) | | NA     | NA      | NA      | NA      | NA      | NA      |
| Party Rep Asked to Stop (Yes) | | NA     | NA      | NA      | NA      | NA      | NA      |
| Conflicts at Poll Station (Yes) | | 0.0712  | 0.066   | 0.0698  | 0.067   | 0.0741  | 0.070   |
| More than One Exit (Yes) | | -0.0399 | 0.078   | -0.0360 | 0.080   | -0.0314 | 0.088   |
| Constant | | 0.2000  | 0.343   | -0.0328 | 0.690   | -0.6766 | 1.243   |

N = 53

*p<.05, **p<.01, ***p<.001, # Interaction
A set of higher-order terms were added to Model 3 to jointly account for (i) the proportion of older voters in the \( j \)-th pool of respondents, (ii) interviewer age and (iii) interviewer education. With these additions, the direct effect of proportion of older voters in the \( j \)-th pool of respondents (\( b=-3.8531, \, S.E.=1.438, \, p<.01 \)) becomes significant again (M3), suggesting both an interactive relationship (i) between age of respondent and interviewer age, and (ii) between age of respondent and interviewer education.

There appears to be a statistically significant interaction between interviewer age and respondent age in Model 3 (\( b=0.1000, \, S.E.=0.044, \, p<.05 \)). In an attempt to ease interpretation of two-way interaction coefficients, Figure 6-1 provides a convenient visualization tool. Although the variable used to measure proportion of older voters in the \( j \)-th pool of respondents (respondent age) is continuous in nature, the variable is divided into three groups for plotting purposes. Thus, Figure 6-1 compares precincts where the percent of older voters (i.e., 40 years old or above) is 25% or less (that is, a pool of younger respondents), with precincts where the percent is 50% (a pool of average age voters) and with cases where the percent of younger voters is 75% (a pool of older respondents).

As it can be seen, within the pool of younger voters, as interviewer age increases, MWPE is likely to increase (Figure 6-1). Within the pool of average age voters, the age of the interviewer does not appear to have an effect. Contrary to the trend among younger voters, within the pool of older respondents, as the age of the interviewer increases, MWPE is likely to decrease.
Figure 6-1. Adjusted Predictions of Effects (2-Way Interaction Term)
Besides an interactive relationship between interviewer age and respondent age, there are other elements that can help account for MWPE. Table 6-5 (Model 1) indicates that as the proportion of college educated voters in the \( j \)-th pool of respondents (loosely referred to as “respondent education”) increases, the level of exit poll error decreases (\( b = -0.2192, \text{S.E.} = 0.090, p < .05 \)). Importantly, respondent education alone seems to predict levels of error in all models. In other words, respondent education is not interacted with any other elements (Model 1 through Model 3) and it helps to directly account for MWPE.

Yet interactive terms were tested to assess a potential relationship between respondent education and interviewer education. Namely, an interaction term was further explored as part of the regression equation (models not shown). While said interaction term was not statistically significant, it did not change any of the results shown in Model 3. Therefore, such interaction term as well as other higher-order terms involving respondent education were excluded from analysis.

Table 6-5 indicates that while interviewer education seems to be neither a direct predictor of MWPE nor a moderator of respondent education (Model 1 and 2), it may interact with both interviewer age and respondent age (Model 3). Particularly, Model 3 indicates that the two-way interviewer education-interviewer age interaction is statistically significant. Likewise, the two-way interviewer education-respondent age appears to be significant.

Furthermore, Model 3 suggests that the two-way interactivity (interviewer education by interviewer age) is likely to change depending on respondent age. It appears that this three-way interaction term (i.e., interviewer education by interviewer age by proportion of older voters in the \( j \)-th pool of respondents) is statistically significant. To facilitate interpretation of this high-order interaction term, Figure 6-2 provides a visual representation to inspect these trends.
Figure 6-2. Adjusted Predictions of Joint Effects (3-Way Interaction Term)
Specifically, Figure 6-2 displays trends for three groups based on the proportion of older voters (i.e., respondents aged 40 or more) in the $j$-th pool of respondents; namely, 25%, 50% and 75%. As it can be seen, among the pool of younger voters (i.e., 25%), when the interviewer has less than high school, as interviewer age increases, the level of MWPE decreases. When the interviewer has a high school diploma, interviewer age does appear to have an obvious effect. However, for college-educated interviewers, as the age increases, the level of MWPE increases.

Among average age voters (i.e., 50%), when the interviewer has no high school diploma, as interviewer age increases the level of MWPE decreases (which is consistent with the trend observed in the pool of younger respondents). When the interviewer has a high school diploma, interviewer age does appear to have a clear effect (which is also consistent with younger voters). However, for college-educated interviewers, as interviewer age increases, the level of MWPE increases but not as much as it does for younger voters.

Among older voters (i.e., 75%), Figure 6-2 suggests that for interviewers with less than high school, as interviewer age increases the level of MWPE increases—a trend occurring in the opposite direction compared to younger voters. When the interviewer has a high school diploma, interviewer age does appear to have a clear effect, which is consistent with average age and younger voters. However, for college-educated interviewers, as interviewer age increases, the level of MWPE decreases—which happens in the opposite direction as the trend observed among younger voters).

None of the variables regarding interviewer attitudinal and behavioral characteristics, Table 6-5 seem to significantly predict MWPE (whether the interviewer reports having doubts on how to apply questionnaires on the day of the election, having doubts on how to proceed on election day), after accounting for higher-order interaction terms.
Related to interviewer behavior characteristics, it is important to note, however, that the metric used to represent interviewer training shows low level of variation; namely, 97.5% of the 2006 interviewers reported receiving trained, as previously described in the “Descriptive Statistics” section. It could be possible that the lack of variability partially explains why this characteristic does not seem to predict variance of MWPE.

Table 6-5 indicates that distance of the interviewer from the exit station is the only contextual element (i.e., election day factor) that seems to significantly predict MWPE, independent from other factors. Particularly, Model 1 suggests that as distance increases, the level of MWPE increases ($b=0.0025$, S.E.$=0.001$, $p<.01$). This effect remains statistically significant in the rest of the 2006 models (M2 and M3), after accounting for interactive relationships. Other factors do not appear to reach statistical significance or marginal significance at conventional levels.

Findings

Finding 1: Effect of Refusals

A very limited empirical literature exists on the relationship between nonresponse and MWPE (Bautista et al., 2007; Merkle & Edelman, 2000, 2002). This work has produced some findings suggesting that nonresponse is not necessarily associated with exit polling error. Available studies, however, rely on bivariate analysis and do not offer a view on independent effects. In this study, H1 hypothesized that refusal rates are not likely to predict MWPE, after accounting for other possible explanations. As expected, results indicate that refusals rates are not likely to explain levels of exit polling error. This suggests that voters who choose not to
participate in an exit poll are not likely to systematically introduce error to exit polling estimates, independent from other factors.

**Finding 2: Effect of Voter Characteristics**

H2 hypothesized that people with less established positions in society are more likely to be impacted by the influence of others compared to those more established in society (Blaydes & Gillum, 2013; Ross & Mirowsky, 1984). Specifically, when the pool of j-th respondents is mainly comprised of younger respondents, lower educated, with lower social status and living in a rural context, the level of WPE increases relative pool of respondents comprised of older, higher educated and higher status respondents, and living in urban contexts.

Results from this study provide evidence to support hypothesized relationships for respondent age and respondent education, but not for respondent social status or respondent gender. Namely, as the proportion of older (i.e., 40 years or more) and educated voters (college-level education) increases in the j-th pool of respondents assigned to an average interviewer, the level of MWPE decreases, apart from other effects. Furthermore, respondent age seem to interact with interviewer age and interviewer education, but respondent education does not appear to interact with any interviewer characteristic. Interaction terms are briefly described below as part of this section.
Finding 3: Interviewer Age

H3 hypothesized that interviewer age is used as visual cue by respondents to assess the level of effort they need to put on the responding tasks. The hypothesized direct effect predicts that respondents are more likely to take the answering process more seriously —and provide more candid answers— when the request comes from an older person than when it comes from a younger person (Blumenthal, 2005c; Brown et al., 2004; Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2002; Stevenson, 2006). Additionally, in this study it was hypothesized that the effect of interviewer age may change depending on the age of the respondent.

Consistent with expectations, results from the present study support the notion that the effect of interviewer age varies depending on respondent’s age. While results indicate that interviewer age alone is not likely to predict exit polling error, a significant interaction term indicates that interviewer age has a differentiated effect based on the age of the respondent.

Among older respondents, as the age of the interviewer increases, the level of exit polling error is likely to decrease. This suggests that older respondents are likely to take more seriously the answering task and report more truthful responses when interacting with an older interviewer. Conversely, among younger respondents, as the age of the interviewer increases, the level of exit polling error increases. This suggests that younger respondents may experience more social pressure when interacting with an older interviewer than when interacting with a younger interviewer.
Finding 4: Interviewer Education

H4 hypothesized that interviewer education influences interviewer appearance and behavior, affecting systematically the pool of j-th respondents. Studies in the literature report an association between interviewer education and error; however, the direction and significance of a potential education-of-interviewer effect has remained elusive (Edison Media Research and Mitofsky International, 2005). Particularly, Edison/Mitofsky (2005) indicates that as interviewer education increases, WPE increases as well, but in middle education categories the WPE slightly decreases and then, increases again for the upper category of education.

Interestingly, based on bivariate analysis, Edison/Mitofsky (2005) indicates that interviewer age does not appear to moderate the influence of interviewer education on WPE. Nevertheless, Edison/Mitofsky (2005) does not provide statistical testing for the results. Consequently, H4 hypothesized that interviewer education has an effect on exit polling error. More importantly, it was hypothesized that interviewer education interacts with interviewer age, and that this two-way interaction term further interacts with respondent age.

Results suggest that interviewer education itself is not likely to predict levels of error (which is similar to the finding on interviewer age as simple effect). Instead, results show that the relation of interviewer education and exit polling error seems to be moderated by interviewer age and respondent age — which is consistent with hypothesized notions. The trend of education-of-interviewer effect appears to impact younger vs. older voters differently depending on the age of the interviewer (for a detailed description of this influence, see Section “Evidence for Direct and Indirect Effects” where trends in Figure 6-2 are discussed).
Overall, results support the hypothesis of differentiated social desirability mechanisms across demographic groups (i.e., younger vs. older voters). Young respondents (who are presumably more worried about impression management and self-presentation than older respondents) may experience more social pressure from an older, college-educated interviewer than from an older, lower educated (i.e., less than high school) interviewer—who may be perceived with lack of authority.

In opposition, an older respondent with an average educational attainment (presumably more established in society due to experience in life than a young person) may avoid disclosing voting preferences to an older, lower educated interviewer—such interviewer may appear to lack authority to said respondent. On the other hand, older voters may be more willing to disclose voting preferences to an older voter with college-level education—such interviewer may be perceived as a more legitimate agent to the said interviewer.

**Finding 5: Interviewer Gender**

Available studies suggest that male interviewers are more likely than female interviewers to increase levels of MWPE. Although existing studies do not provide significance testing, it appears that the effect of gender disappears once interviewer age is accounted for (Edison Media Research and Mitofsky International, 2005). Consequently, H5 hypothesized that interviewer gender serves as a visual cue to respondents in exit polls, and male interviewers are more likely to put social pressure on respondents than female interviewers.

Results from this study indicate that gender does not appear to increase MWPE relative to female interviewers, after other aspects are accounted for. Consequently, interviewer gender is
not likely to serve as visual cue for respondents, and it may not be entirely predictive of error as other interviewer characteristics.

**Finding 6: Interviewer Attitudes toward Interviewing**

Building on existing literature, H6 hypothesized that interviewer expectations might be shaped by their confidence in their own interviewing skills and experiences acquired in the field (Fowler, 1991, 1995; Fowler & Mangione, 1990; Olson & Peytchev, 2007; Van der Zouwen et al., 1991). It was hypothesized that interviewers who report at the time of post-exit poll debriefing that there were no problems with the survey instrument, or who did not have doubts on how to proceed on election day, or who preferred their own opening script to interact with voters (instead of following standardized procedures), are more likely to become overconfident on the exit polling task. Overconfident interviewers were hypothesized to be more likely to introduce error than non-overconfident interviewers.

Overall, results from this investigation do not provide support for the overconfidence hypothesis. Although the concept of interviewer perceptions and attitudes toward the task is a possible conceptual explanation to explain exit polling error, multivariate analysis indicate that measures used to operationalize these constructs do not yield statistically significant results.

The variable on whether interviewers had questions or doubts on how to apply the exit poll was not statistically significant. It was expected that interviewers expressing no doubts were overconfident interviewers, and more likely to introduce error. This suggests that this variable may not be helpful in representing interviewer overconfidence effects, or that said concept is not a predictor of exit polling error.
Finding 7: Interviewer Party

Studies in the literature suggest that interviewers with a defined political orientation are more likely than interviewers whose political preferences are not defined, to modify their expectations in the interviewing process (Butterworth, 2006). Based on data from post-election questionnaires, researchers have tried to understand the relationship between interviewer party and error (Butterworth, 2006; Edison Media Research and Mitofsky International, 2005). Nonetheless, available studies do not provide enough information to determine if such a relationship is likely to occur.

Consequently, H7 hypothesized that an interviewer’s stated political preference is likely to have an impact on exit polling error. Unfortunately, this study is not able to test this hypothesis in the regression models for the year of 2006. The question on interviewer preference is only available in the post-election questionnaire for the year of 2009. As explained in Section “Multiple Regression Analysis,” the 2009 data do not seem to offer enough statistical power to reliably test hypothesized relationships. Consequently, this important hypothesis remains to be tested in future studies.

Finding 8: Interviewer Training

Building on existing exit polling literature, H8 hypothesized that interviewer training provided prior to the exit poll is not likely to have an impact on error. Edison/Mitofsky reports (2005) that “somewhat or not very well trained” trained interviewers are slightly more likely to
have higher levels of error compared to “very well” interviewers. Importantly, a study conducting experimental work in the United Kingdom reports no statistically significant differences between interviewers randomly assigned to a “personal briefing” condition prior to the exit poll vs. no briefing (Moon, 1999).

Results from the present study suggest that interviewer training does not seem to decrease error. While these results may suggest that interviewer is not a critical factor in accounting for error, the more probable explanation lies in constraints on the variable used. The metric utilized to represent interviewer training shows a very low level of variation. As mentioned in Section “Results,” the overwhelming majority of interviewers (approximately 98%) indicated receiving training prior to the day of the election. In any case, results about interviewer training leave room for uncertainty and future experimental research is needed.

**Finding 9: Interviewer Experience**

H9 hypothesized that previous interviewer experience, whether in household or election day surveys, provides elements to better prepare interviewers to conduct exit polls. The literature suggests that interviewer experience tends to correlate with data quality (Cannell et al., 1977; Gfroerer et al., 1997; Krosnick et al., 2002; Singer et al., 1983). Little is known on the effect of interviewer experience in exit polls since survey agencies typically have fewer exit polling contracts a year compared to other types of surveys (e.g., telephone surveys). Thus, interviewers have fewer opportunities to gain experience in exit polls (Merkle & Edelman, 2002).
Results from this study do not provide evidence to support the hypothesis of interviewer experience. While the signs of coefficients occur in the expected direction for previous exit polling experience (i.e., interviewers with previous exit polling experience may decrease error), the associated statistical testing does not allow a clear result.

**Finding 10: Length of Interview**

Studies on the literature suggests that lengthy interviews may lead to survey fatigue and harm data quality in exit polls (Mitofsky, 1991; Moon, 1999). Consequently, H10 suggested that as the average time spent on interviews increases so does the level of exit polling error. Particularly, it was hypothesized that when interviewers spend more time with voters, it increases the possibility of interviewer effects. Nonetheless, results from this study do not provide evidence to support the hypothesized notion. While results are not significant in this analysis, they provide a framework for possible future experimental research in this area.

**Finding 11: Election Day Factors**

Situations that frequently are beyond the researchers’ control having hypothesized to have an impact on interviewer performance and consequently on accuracy (Edison Media Research and Mitofsky International, 2005; Frankovic et al., 2009; Merkle & Edelman, 2002; Stevenson, 2006). H11 hypothesized that interview setting (commonly referred in the literature as election day factors) increases measurement error.
Particularly, the following elements were hypothesized to increase error levels: (i) distance of interviewer from the exit, (ii) whether a poll worker asked for an interviewing permit, (iii) whether a party representative asked for an interviewing permit, (iv) whether a poll worker asked to stop interviewing activities, (vi) whether a party representative asked to stop interviewing activities, (vii) if there were conflicts at the polling station, and (viii) number of exits at the polling station.

Results from this study partially support the notion of interview setting effects. Only interviewer distance significantly predicts levels of error; that is, as interviewer distance to the voting station increases, the level of Within Precinct Error also increases, independent for other possible factors.

**Discussion**

The present chapter offers some theoretical insights appear supported by available data for analysis. In particular, it finds that aspects often thought to be predictive of error in exit polls, such as refusals, are not as powerful as it has been theorized in the literature. Perhaps, this shortcoming is due to a more constrained framework previously used to study exit polls.

In particular, this study provides an insight for researchers interested in the field of exit polls: studying exit polls is a dynamic endeavor. Explicitly, when thinking about sources of error in exit polls, a researcher needs to consider the *simple* effect of both interviewer and respondent characteristics, as well as their *joint* effects. Therefore, a deeper understanding of sources of
error in exit polls comes from acknowledging the interaction between an interviewer who has very specific characteristics, and the characteristics of the interlocutor.

The findings on this chapter suggest that looking at unconditional effects for social desirability effects across subgroups might be masking the more interesting dynamics of the interaction. In particular, the chapter illustrates that even while two-way interactions may be illuminating, three-way interactions can provide a much richer description of a not entirely understood effect. Specifically, the conditional nature of the relationship between age and education of both interviewers and respondents have enabled a richer understanding of error in exit polls to a degree that had not been shown in the literature previously.

The implications of these findings go beyond the academic literature. Practitioners engaged in exit polling may also need to consider procedures to better match demographic characteristics of interviewers and interviewees. To the extent that these interactions help understand the sources of error, minimizing mismatches between interviewers and their potential respondents in a precinct may also contribute to reduce error in exit polls.

In addition, these findings show as well that the sources of error in exit polls may not reside exclusively in contextual factors (or “election day factors”), and a much simple answer has been overlooked. Exit polling is a process where two human beings interact with one another; as such, they are bounded by social rules. Hence, psychosocial mechanisms may be brought to bear on the understanding of sources of error.
CHAPTER 7: CONCLUSIONS

The present dissertation is informed by the “Total Survey Error” paradigm (Biemer, 2010; Groves, 1989; Groves & Lyberg, 2010), with a specific focus on nonresponse and measurement error. Particularly, this dissertation aimed to gain understanding on nonresponse in exit polls and exit polling error. This study had three objectives. First, to investigate likely socio-psychological mechanisms of nonresponse in election day surveys by studying voter and interviewers characteristics as well as election day factors.

The second objective of this dissertation was to investigate whether psychological and behavioral mechanisms governing interpersonal relations are helpful to explain response error (i.e., “exit polling error”), after accounting for nonresponse and election day factors. This is important because the objective aimed to explore whether the mechanisms likely to produce refusals prior to the interview are the same mechanisms likely introduce error once survey cooperation is established.

The third objective fulfills two purposes related to the feasibility of using multiple imputation methods (Little & Rubin, 2002) in analysis of exit polling nonresponse. Namely, the first purpose was to explore whether model-based multiple imputation methods used to approximate information from voters who chose not to participate, can help improve exit polling estimates relative to traditional methods (i.e., list-wise deletion, class weighting and single imputation). The second purpose was to explore whether this model-based statistical approach helps recreate the relationship between unobserved data and available information.

These objectives were fulfilled throughout previous chapters by analyzing data from two exit polling datasets conducted in Mexico in 2006 and 2009. To achieve the first objective (i.e.,
study of nonresponse predictors), a proof-of-concept analysis was introduced as a series of logistic multilevel models conducted using multiply imputed data. To achieve the second purpose (i.e., predictors of response error or “exit polling error”), an analysis of interaction terms between respondent and interviewer characteristics in multiple linear regressions was conducted.

To accomplish the third objective (i.e., assessment of multiple imputation methods to improve exit poll estimates as well as to study predictors of nonresponse), a series of univariate comparisons for imputed and non-imputed respondent characteristics was conducted. Importantly, the proposed proof-of-concept methodology used to explore predictors of nonresponse helped illuminate how an analysis between multiply imputed data and observed data can be conducted to cast light on previously unexplored relationships. While there are limitations to these results (which are discussed below), findings were consistent with expectations, overall. Major findings and implications are presented as follows.

Findings and Implications

Nonresponse

**Finding 1: Voter Age and Voter Education**

Previous studies have suggested 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). In addition, studies using educational attainment reported at the precinct level (Merkle & Edelman, 2002) as well as telephone and web-based survey data (Panagopoulos, 2013), suggest that voter education does...
not seem to be related with exit polling participation. Yet the possible joint effect of voter age and voter education on nonresponse—based on individual-level data—has not been documented before.

Using a *proof-of-concept* multivariate analysis, results suggest that voter age and voter education alone are not likely to directly account for exit polling nonresponse. Rather, the effect of voter age on nonresponse appears to change depending on levels of voter education. Consistent with a hypothesized conditional relationship derived from cognitive theories (e.g., Ceci, 1991; Krosnick, 1991; Krosnick & Alwin, 1987, 1988; Narayan & Krosnick, 1996), a lessened cognitive capacity due to aging to engage in a demanding activity (in this case, an exit poll) appears to be offset by higher levels of education.

Specifically, results suggest that among older voters, highly educated voters are 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 practical terms, this means that education is likely to make an important difference among older voters but not necessarily among younger voters. While this relationship seems to hold up in a Presidential election, it is less clear whether the same pattern occurs in a Congressional election. If supported in future studies, these exploratory patterns suggest that practitioners may consider investigating and developing responsive procedures aimed to persuade less educated and aging sample voters to participate in an exit poll.

**Finding 2: Interviewer Age and Voter Age**

Studies in the exit polling literature have found evidence for an interaction between interviewer and respondent age; that is, older voters seem to react more favorably to older
interviewers while younger interviewers do not seem to react more favorable to an interviewer of the same age (Merkle & Edelman, 2002). These findings led Merkle and Edelman (2002) to hypothesize that older voters may not feel comfortable interacting with younger interviewers. Presumably, when younger interviewers approach older members of the population, older persons may feel more fearful and physically vulnerable than younger persons, and consequently would be more likely to refuse (Groves & Couper, 1998).

Consistent with the “fear and suspicion of strangers” hypothesis (Groves & Couper, 1998; Merkle & Edelman, 2002), results from this study (i.e., interaction between interviewer age and voter age) indicate that older voters who were approached by younger interviewers seem to be more likely to refuse cooperation in an exit poll relative to older voters approached by older interviewers. In practical terms, this means that when a vulnerable voter (older voter) is contacted by an interviewer perceived to be non-threatening (older interviewer) the chances of refusing seem to reduce.

This finding has noteworthy implications for exit pollsters as it suggests that practitioners may consider two aspects to increase participation in exit polls. Namely, (i) researchers may consider interviewer-respondent matching protocols based on age, and (ii) researchers may consider the development of non-threatening approaching scripts and use of effective visual cues to persuade older voters who may be fearful, whether due situational aspects (i.e., interaction with interviewers) or more general aspects (i.e., low literacy levels).

**Finding 3: Interviewer Education and Voter Education**

Previous studies in the literature have hypothesized that similarity of social background between interviewers and sample members may increase liking and therefore increase survey
cooperation (Groves & Couper, 1998). However, empirical studies in the field of exit polling have found insufficient evidence in favor of the notion (Merkle & Edelman, 2002). Specifically, using interviewer race and racial composition of precincts as proxy measures for similarly, Merkle and Edelman (2002) did not find an effect.

In this study, the similarity of background hypothesis was explored by analyzing an interaction between interviewer and voter education. Consistent with Merkle and Edelman’s (2002) finding, the present examination does not provide enough evidence to support the similarity hypothesis. Interviewer education —either as a main effect or moderator effect— does not appear to affect survey participation.

While the lack of significant results may seem to be in conflict with the similarity hypothesis, there is a plausible alternative explanation—at least for the present analysis. In the analyzed exit polls, field staff were instructed to wear standard clothing (i.e., white vests, white cap, white bag and portable ballot box featuring the survey agency logo) and an identification badge. It is possible that voters approached by exit polling staff dressed up as interviewers (wearing standardized clothing), were not immediately able to form a judgment about the interviewer’s educational background based on visual cues, as it would be possible with other more visible characteristics (such as age, for example). Consequently, results from this study call for future experimental research in exit polls to better assess the similarity hypothesis based on social background.

**Finding 4: Voter Socio-economic Status**

While previous studies have hypothesized that people disengaged from society tend to be less cooperative relative to those more integrated with society with household survey requests,
there has been no conclusive evidence to support the notion (Groves & Couper, 1998). Merkle and Edelman (2002) hypothesized a similar but weaker effect in exit polls (compared to household surveys), since voters in an election are already participating in a societal event. Using socioeconomic status as proxy measure for isolation, Groves and Couper (1998) did not find support for the social isolation hypothesis in household surveys. Similarly, Merkle and Edelman (2002) did not find evidence to support the hypothesis when studying voter race, as proxy measure in exit polls.

Results from this study are in line with previous studies; that is, voter socioeconomic status does not appear to influence the decision to participate in an exit poll. Importantly, in this study other possible proxy measures for social isolation were also explored (i.e., TV ownership and telephone service); however, none of them seem to affect the likelihood of participation. The lack of significant results may be attributable to Merkle and Edelman’s (2002) observation that voting is a form of political participation with society itself. Consequently, the social isolation hypothesis may not be helpful to understand nonresponse. Needless to say, future research should attempt to confirm this finding.

**Finding 5: Voter Gender**

Gender studies have hypothesized that due to gender roles in the society, women tend to experience more social pressure for establishing and maintain social interactions (e.g., relationship with neighbors, friends, child care, and other activities) than men (Groves & Couper, 1998). However, empirical examinations have produced mixed results (Groves, 1990; Groves & Couper, 1998; Lindström, 1983).
Although some studies in the field of exit polls report that women appear to be more likely than men to participate (Panagopoulos, 2013; Stevenson, 2006), other empirical studies have found an elusive relationship between gender and participation (Bautista et al., 2006; Brown et al., 2004; Merkle & Edelman, 2000, 2002). Analyses from the present study suggest that male voters seem to be more likely than female voters to participate in an exit poll, independent from interviewer gender, and other factors.

This result, while contrary to that expected by theories of gender role in survey participation (Groves & Couper, 1998), is consistent with alternative studies suggesting that men tend to play a dominant role in the society motivated by economic factors; for example, as head of families or religious groups, or through better access to education and labor opportunities (Farré, 2013). This well could be the case for developing countries where women’s empowerment is less clear than in industrialized countries.

Therefore, it seems plausible that differences exist between gender roles, but not in the direction of the hypothesized relationships derived from the literature mainly produced in the U.S., which may not fit cultural behaviors of the target population in this study (Mexican voters). In any case, this research suggests that voter gender itself is likely to be an important element to understand nonresponse. These results provide a guide toward future research in exit polls with a focus on multinational and multicultural contexts.

**Finding 6: Interviewer Traits**

Although the survey methodology literature indicates that prior interviewing experience tends to correlate with data quality (Cannell et al., 1977; Gfroerer et al., 1997; Krosnick et al., 2002; Singer et al., 1983), studies in the field of exit polling suggest that previous interviewing
experience in general is not necessarily an asset on exit polling (Merkle & Edelman, 2002).
Results from this study are consistent with previous exit polling findings; that is, there appears to be no evidence suggesting that survey participation is likely to increase when field staff has prior interviewing experience.

Additionally, the survey methodology literature has hypothesized interviewer actions are presumed to be influenced by their perception and attitudes towards the interviewing task (Cannell et al., 1981; Olson & Peytchev, 2007; Pickery & Loosveldt, 2001; Singer et al., 1983), it was hypothesized that “faster” interviewers are less careful than “slower” interviewers in persuading individuals to participate in an exit poll. Analysis of average interview length as proxy measure to identify overconfident (i.e., faster) vs. careful (i.e., slower) field staff indicate that interviewer overconfidence is not likely to account for nonresponse. If future studies confirm these exploratory findings, practitioners may have more elements to decide on how to staff exit polls and pay attention to other more relevant aspects.

**Finding 7: Election Day Factors**

Contextual elements have been hypothesized to have an effect on survey participation (Edison Media Research and Mitofsky International, 2005; Merkle & Edelman, 2002). Even when some of the elements hypothesized to have an impact are usually beyond the researchers’ control—including inclement weather conditions (Edison Media Research and Mitofsky International, 2005)—there seems to be aspects that are related to nonresponse. Particularly, it has been documented that interviewers’ distance position from the polling place, problems with election officials, and number of exits at the station, are likely to have a systematic effect on survey participation (Edison Media Research and Mitofsky International, 2005; Frankovic, 1992; Merkle & Edelman, 2002; Stevenson, 2006).
Specifically, problems with unfriendly precinct officials may explain distant interviewing positions (Merkle & Edelman, 2002); thus, lessening interviewers’ motivation, legitimacy and ability to persuade exit voters. Likewise, interviewers monitoring multiple exits may become less motivated to persuade voters to participate in an exit interview (Bautista et al., 2006; Edison Media Research and Mitofsky International, 2005; Frankovic, 1992; Merkle & Edelman, 2002).

While in the expected direction, non-significant difference were found (i) between interviewers distantly positioned from the voting station (i.e., more than 10 meters ~30 feet) compared to those more closely positioned (i.e., less than 10 meters), (ii) interviewers who experienced problems with unfriendly election officials compared to interviewers reporting no problems with officials, and (iii) interviewers who monitored one exit vs. those who monitored more than one exit at the voting station.

As explained earlier in this chapter, nonresponse patterns where explored using a proof-of-concept approach; namely, multilevel models based on multiple imputation. In these models, effects are more easily estimated with binary variables. Consequently, future research is necessary to determine if different cut-off points for variable are likely to produce significant results; for example, distance coded as more or less than 15 meters (~50 feet), 20 meters (~65 feet) or 25 meters (~80 feet).

Nonetheless, if these exploratory patterns are confirmed in further analysis (non-significant effects of elements out of the researcher’s control), these results may open the door to hypothesize that once other important aspects of the survey invitation process have been taken into consideration; namely, the interviewer-respondent interaction based on age, or key cognitive
aspects such as voter age and education (and the corresponding interaction term), external factors may not be as powerful predictors of nonresponse as previously thought.

**Measurement Error**

**Finding 8: Effect of Nonresponse**

Nonresponse has been discussed in the literature as potential source of error —either as bias or variance— in social surveys (Groves, 1989, 2006; Groves & Lyberg, 2010; Groves & Peytcheva, 2008), as well as a source of bias in exit polls (Frankovic, 2008; Frankovic et al., 2009; Merkle & Edelman, 2002; Merkle et al., 1998; Mitofsky, 1991, 2006; Mitofsky & Brennan, 1993; Mitofsky & Edelman, 1995, 2002). Limited studies based on bivariate analysis indicate that the relationship between exit poll error and nonresponse is not likely to be significant (Bautista et al., 2007; Merkle & Edelman, 2000, 2002).

Consistent with expectations, results from this study suggest that refusals alone do not appear to increase exit polling error (i.e., Within Precinct Error). In other words, the group of voters who chose not to respond do not appear to systematically introduce error into the measurement process. As previously discussed, nonresponse seem to be primarily explained by cognitive factors of voters (i.e., age and education) as well as cognition factors (i.e., older voters being more fearful of younger interviewer than of older interviewers), beyond anything else.

Yet there remains the question of why those who choose to participate may not provide candid answers to the vote choice question. Thus, this study hypothesized that social desirability mechanisms could be the likely explanation (De Maio, 1984; Finkel et al., 1991; Flores-Macias & Lawson, 2008; Krysan & Couper, 2003; Presser & Stinson, 1998). This psychological
mechanism was investigated by examining interviewer-respondent interactions. Main findings of such analysis are discussed in the rest of this section.

**Finding 8: Interviewer and Voter Interactions**

This study hypothesized that there is tendency of respondents to modify answers that are believed to be socially acceptable to others who are perceived to have a position of power and dominance (Biemer & Lyberg, 2003; Biemer & Trewim, 1997; Blaydes & Gillum, 2013; Davis et al., 2010; Groves, 1991; O'Muircheartaigh, 1977; O'Muircheartaigh & Campanelli, 1999; Olson & Bilgen, 2011; Ross & Mirowsky, 1984). Results from this study are consistent with hypothesized relationships. Overall, respondent age seems to interact with interviewer age and interviewer education, but respondent education does not appear to interact with any interviewer characteristic.

Specifically, among older respondents, as the age of the interviewer increases, the level of exit polling error is likely to decrease. This suggests that older respondents are likely to take more seriously the answering task; consequently, they report more truthful responses when interacting with an older interviewer. This mechanism is similar to what was noted for nonresponse (older voters seem to react more favorably to older interviewers). However, different from patterns observed in nonresponse, among younger respondents, as the age of the interviewer increases, the level of exit polling error increases.

This finding suggests that younger respondents may experience more social pressure when interacting with an older interviewer than when interacting with a younger interviewer. Also, results from this investigation indicate that interviewer education alone is not likely to predict levels of error (similar to the case of interviewer age as simple effect). Rather, the
relation of interviewer education and exit polling error seems to be moderated by both interviewer age and respondent age.

Interestingly, the interactive analysis of interviewer education with interviewer age and respondent age (i.e., three-way interaction term) cast light on social desirability mechanisms that have not been documented before in exit polls. Namely, young respondents (who are presumably more worried about impression management and self-presentation than older respondents) may experience more social pressure during the interviewing process from an older, college-educated interviewer than from an older, lower educated (i.e., less than high school) interviewer —who may be perceived with lack of authority.

Conversely, an older respondent with an average educational attainment (presumably more established in society due to experience in life than a young person) may be less willing to report voting preferences to an older, lower educated interviewer —such interviewer may appear to lack authority to said respondent. In turn, older respondents may be more willing to disclose voting preferences to an older interviewer with college-level education because said interviewer may be perceived as a more legitimate agent. Under this interpretation, interviewer education appears to play a more important role in the measurement error process than in the nonresponse process. It is possible that once survey cooperation has been granted, respondents could start making some judgments about the interviewer’s level of education by noticing subtle mannerisms or behaviors during the interaction (for instance, the way the interviewer speaks), despite standardized uniforms wore the day of the election.

There is a clear need for other studies to validate these results. It would be premature to generalize from these results as the analysis is based on data from one country. Nonetheless,
patterns seem to be consistent with theoretical expectations. Importantly, the implications of these findings seem to be more complex than those for nonresponse (which could be less consequential since there is no likely systematic effect of refusals on nonresponse). In practical terms, this means that interviewer-respondent matching protocols would need to be carefully studied and prepared to help reduce measurement error. In any event, results from the present study offer guidance for crafting research agendas in future studies.

**Finding 9: Election Day Factors**

Similar to the analysis of contextual effects on nonresponse, several election day factors were hypothesized to have an effect on exit polling error. Specifically, the following elements were hypothesized to increase error levels: (i) distance of interviewer from the exit, (ii) whether a poll worker asked for an interviewing permit, (iii) whether a party representative asked for an interviewing permit, (iv) whether a poll worker asked to stop interviewing activities, (vi) whether a party representative asked to stop interviewing activities, (vii) if there were conflicts at the polling station, and (viii) number of exits at the polling station.

Results suggest that only interviewer distance appears to predict exit polling error, independent from other factors. In practical terms it means that distance may not be entirely relevant for refusals, but it seems to be an important factor for measurement error. Merkle and colleagues (2002) have suggested that it is possible that as voters start moving away from the voting station, they start preparing for the next order of business in their day. It is possible that as interviewers ask about political answers in a distant site from the polling station, voters may rely more on peripheral aspects of the interviewing process (i.e., interviewer characteristics as
described earlier in previous findings for measurement error) when trying to decide whether truthful answers should be reported. Consequently, practitioners may consider developing better strategies to conduct the interview as close as possible to the voting setting, or find ways to increase respondent motivation and minimize possible interviewer effects in these situations.

**Discussion**

Understanding the mechanisms likely to cause a person to refuse an invitation to participate in an exit poll is critical to survey research. By understanding the basic processes that govern refusals in fast-paced surveys, such as exit polls (where there is minimal contact at the moment of the participation solicitation), researchers may begin to understand the possible consequences of nonresponse on the accuracy of exit polling results. Using a novel approach for approximating non-observed data for voters who chose not to respond the day of the election, this dissertation conducted a *proof-of-concept* analysis that allowed us to explore nonresponse in further detail than had been possible in the previous literature. Plausible nonresponse mechanisms that have not been fully understood before (that is, voter cognitive abilities as well as perception of interviewers) were explored. Overall, results corresponded largely with expectations. Instances where unanticipated trends were observed have been discussed as part of the findings.

Furthermore, this dissertation brought to light complicated interrelationships previously unknown on response error in exit polls. It appears that mechanisms likely to produce refusals prior to the interview are not the same mechanisms likely introduce error when survey
cooperation is established. The interaction of interviewer and respondent characteristics seem to produce errors that may not be entirely obvious from either source alone.

Overall, observed patterns from this study seem to be congruent with hypothesized mechanisms derived from the literature based largely on data from U.S. elections. For the study of nonresponse, not only does the considered imputation method adopted in this dissertation provide promising building blocks for future exploration of exit polling information, it also provides a way to exploring nonresponse patterns beyond exit polls in situations characterized by absence of data, and where external and rich sources of information might exist; for instance, paradata, administrative records, survey design data, organic data or “big data.”

Also, the adoption of an interactive model in this dissertation for the study of exit polling error offers a framework to go one step further in the study of measurement error. Traditionally, only main effects tend to be considered in analysis and to a lesser extent interaction terms; but this dissertation suggests that incorporating the conditional nature of these variables through statistical interaction terms is key to understanding the particularities of measurement error in instances where there is a social interaction between interviewers and respondents. While it is clear that more research is necessary, these results should provide guidance for future studies.
## Appendix 1. Information Collected Among Interviewers in 2006 and 2009

<table>
<thead>
<tr>
<th>Question (Original Spanish Version in Italics)</th>
<th>Applied in Election</th>
</tr>
</thead>
<tbody>
<tr>
<td>Did precinct officials at the voting station where you applied your questionnaires request a “permit” to conduct exit polls?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿El presidente o algún funcionario de casilla donde usted aplicó sus encuestas le solicitó o no su “permiso” para levantar encuestas?</td>
<td></td>
</tr>
<tr>
<td>Did any representative of any political party request your “permit” to conduct exit polls?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Algún representante de algún partido político le solicitó o no su “permiso” para levantar encuestas?</td>
<td></td>
</tr>
<tr>
<td>Did precinct officials at the voting station ask you not to conduct the exit poll?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿El presidente o algún funcionario de casilla le pidieron que no aplicara encuestas?</td>
<td></td>
</tr>
<tr>
<td>Did any representative of any political part ask you not to conduct the exit poll?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Algún representante de algún partido político le pidió que no aplicara encuestas?</td>
<td></td>
</tr>
<tr>
<td>Did you notice any conflict of any kind, at the voting station in which you conducted the exit poll?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Hubo conflictos de algún tipo en la casilla donde usted aplicó sus encuestas?</td>
<td></td>
</tr>
<tr>
<td>Was there more than one exit at the voting station where you conducted the exit poll?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Había más de una salida en la casilla donde usted levantó encuestas?</td>
<td></td>
</tr>
<tr>
<td>Was the question wording clear enough in the questionnaire?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿La redacción de las preguntas en el cuestionario era lo suficientemente clara?</td>
<td></td>
</tr>
<tr>
<td>Did you have doubts on how to apply the exit poll on election day?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Usted tuvo dudas o no sobre la forma en cómo aplicar las encuestas durante el día de la elección?</td>
<td></td>
</tr>
<tr>
<td>Did you receive any training before conducting the exit poll?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Usted recibió o no capacitación antes de aplicar las encuestas?</td>
<td></td>
</tr>
<tr>
<td>Have you ever applied a questionnaire in an exit poll before?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Antes de esta ocasión, había usted aplicado cuestionarios en una encuesta de salida?</td>
<td></td>
</tr>
<tr>
<td>Question (Original Spanish Version in Italics)</td>
<td>Applied in Election</td>
</tr>
<tr>
<td>---------------------------------------------------------------------------------------------------------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>Approximately, how long have you been working as exit polling interviewer? (Months) (Years)</td>
<td>No</td>
</tr>
<tr>
<td>¿Aproximadamente, cuánto tiempo tiene usted trabajando como encuestador? (Meses) (Años)</td>
<td>Yes</td>
</tr>
<tr>
<td>Have you ever applied a questionnaire in a household survey before?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Antes de esta ocasión, había usted aplicado cuestionarios en una encuesta en vivienda?</td>
<td>Yes</td>
</tr>
<tr>
<td>Have you ever applied a questionnaire in a telephone survey before?</td>
<td>No</td>
</tr>
<tr>
<td>¿Antes de esta ocasión, había usted aplicado cuestionarios en una encuesta telefónica?</td>
<td>No</td>
</tr>
<tr>
<td>Could you tell me please how long did it take you to conduct each questionnaire on average? (Minutes)</td>
<td>Yes</td>
</tr>
<tr>
<td>Me podría decir ¿cuál fue el tiempo promedio que tardo en aplicar la encuesta? (minutos)</td>
<td>Yes</td>
</tr>
<tr>
<td>Approximately, which was the shortest time a questionnaire took to be completed? (Minutes)</td>
<td>Yes</td>
</tr>
<tr>
<td>Aproximadamente ¿cuál fue el menor tiempo de aplicación de cuestionario? (minutos)</td>
<td>No</td>
</tr>
<tr>
<td>Approximately, which was the longest time a questionnaire took to be completed? (Minutes)</td>
<td>Yes</td>
</tr>
<tr>
<td>Aproximadamente ¿cuál fue el mayor tiempo de aplicación de cuestionario? (minutos)</td>
<td>No</td>
</tr>
<tr>
<td>Approximately, how far from the voting station exit were you standing while conducting exit polls? (Meters)</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Aproximadamente a cuántos metros de distancia estaba usted de la salida de la casilla mientras aplicaba las encuestas? (metros)</td>
<td>Yes</td>
</tr>
<tr>
<td>What is your highest educational attainment?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Cuál es su grado máximo de estudios?</td>
<td>Yes</td>
</tr>
<tr>
<td>How old are you?</td>
<td>Yes</td>
</tr>
<tr>
<td>¿Cuántos años cumplidos tiene?</td>
<td>Yes</td>
</tr>
<tr>
<td>Approximately, how long have you been working as interviewer in general? (meses) (años)</td>
<td>Yes</td>
</tr>
</tbody>
</table>
## Appendix 1 (Continued). Information Collected Among Interviewers in 2006 and 2009

<table>
<thead>
<tr>
<th>Question (Original Spanish Version in Italics)</th>
<th>Applied in Election</th>
</tr>
</thead>
</table>
| In order to gain cooperation from sampled voters, which of the two following strategies do you believe works best?  
- Read the standard introductory script provided in questionnaire  
- Use your own introductory script created by yourself | No  Yes |

Para pedirle a las personas que participen en la encuesta de salida, ¿cuál de las siguientes dos estrategias cree que funciona mejor  
- Leer la introducción estándar que viene al inicio del cuestionario  
- Utilizar una introducción hecha por usted mismo |

If you have had the opportunity to vote today, which party would you have voted for?  
Si usted hubiera podido votar el día de hoy, ¿por qué partido hubiera votado? | No  Yes |
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