Voter Turnout Overreports: Measurement, Modeling and Deception

Voter Turnout Overreports: Measurement, Modeling and Deception

A Dissertation Presented

by

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DEDICATION

A la memoria de mis abuelos Gilberto Cuevas Cuevas, Isabel M. Gerena Toledo, y Bienvenida González Pérez; y a mi abuelo Edelmiro Molina Ríos. Fueron ustedes quienes inspiraron en mí pasión por la política y atesoramiento del derecho democrático al voto.

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ABSTRACT

VOTER TURNOUT OVERREPORTS:
MEASUREMENT, MODELING AND DECEPTION

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American politics scholarship has in great measure dedicated itself to the study of democratic participation in elections. Texts that are considered the cannon on electoral participation have extended our knowledge of the factors that increase/decrease turnout, however, this work has relied on self-reports of turnout in surveys. The use of self-reported turnout is problematic because a non-trivial proportion of survey respondents say they went out to vote when they actually did not, meaning they overreport turnout. Overreports of voter turnout are false reports of participation in elections by nonvoters when responding to political surveys.

Appropriately, scholars of voting behavior have dedicated a great deal of research to the study of this phenomenon by conducting vote validation studies. This work has engendered important questions about the study of overreporting and how it affects the study of voter turnout. There are four major questions in the literature which I address throughout the dissertation: 1) How accurate is vote validation?, 2) Do overreports bias statistical models of turnout?, 3) What is the correct way to measure and model

overreporting?, and 4) What is the cognitive mechanism through which overreports occur?

The first chapter describes the phenomenon of voter turnout overreports in surveys and how they affect estimations of turnout in political polling, and derives a social desirability theory of overreporting from the vote validation literature. Chapter 2 presents analysis of the persistence and prevalence of overreporting in the Cooperative Congressional Election Study of 2008 2010, 2012, and 2014. Also, a comprehensive look at the demographic, social and political characteristics of voters, nonvoters and over-reporters using data from the 2014 and 2012 CCES. Chapter 3 constitutes the first original contribution to the study of overreporting by proposing a new way of modeling the likelihood of overreporting through multinomial logistic regression analysis. Most Importantly, in Chapter 4, I test the social desirability theory of overreporting, namely analysis of response latency data from the 2014 and 2012 CCES studies. Finally, the conclusion of this dissertation summarizes the main findings of previous chapters and presents analysis of the bias induced by overreports in statistical models of turnout.

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LIST OF ABBREVIATIONS

ACDM	Activation-Construction-Decision Model
ANES	American National Election Study
BIDR	Balanced Inventory of Desirable Responding
CCES	Cooperative Congressional Election Study
ICT	Item Count Technique
IM	Impression Management
OLS	Ordinary Least Squares
RDD	Random Digit Dialing
SD	Self-Deception
SDR	Socially Desirable Responding
USEP	United States Election Project
VAP	Voting Age Population
VEP	Voting Eligible Population

CHAPTER 1

INTRODUCTION

American politics scholarship has in great measure dedicated itself to the study of democratic participation in elections. Verba, Brady and Schlozman, in Voice and Equality (1995), gave us insights into the demographic characteristics that make an individual more likely to turn out to vote in conjunction with a theory that focuses on the social and material resources people need to participate. Rosenstone and Hansen (1995) found that strategic mobilization efforts on behalf of parties, candidates, activists and groups are central to getting people to go out to vote. And, Meredith Rolfe's (2012) social theory of political participation illuminated the importance of social network influence on motivating individuals to turnout. These authors have extended our knowledge of the factors that increase and decrease voter turnout in American elections, however, their work has relied on self-reports of electoral participation in surveys.

The use of self-reported turnout in political science is problematic because a non-trivial proportion of survey respondents say they went out to vote when they actually did not, meaning they overreport turnout. Since the 1950's survey researchers have found that respondents often make inaccurate reports about their voting behavior. These inaccurate reports have resulted in the overestimation of turnout in surveys, where the rate of participation measured by public opinion polls far exceeds that of official records. If we took survey respondents at their word we would have thought turnout in 2012 was 73%, when the actual rate was just 58.6%.[1] Appropriately, scholars of voting behavior

[1] Weighted percent of all respondents in the 2012 CCES who reported that they "definitely voted in the General Election". McDonald, Michael. (2014). National General Election VEP Turnout Rates, 1789-Present. The United States Elections Project. http://www.electproject.org/national-1789-present

have dedicated a great deal of research to the study of this phenomenon by conducting vote validation studies. Vote validation itself is the process of matching publicly available voter records to survey data. Survey researchers can match respondent's public records to their questionnaire responses and verify whether a person's claim to participation is accurate or not. Table 1.1 illustrates how the study of overreporting in political science has identified a wide ranging amount of overreporting in survey research across various interview methods and over many survey years. Discrepancies between self-reported turnout and turnout records found in research on overreporting have ranged from 7% to 23% (See Table 1.1), showing that reporting participation in lieu of non participation is a significant occurrence in surveys. For over half a century survey research in the United States has missed the mark when estimating participation in elections, and the consistent finding of overreporting in surveys means that everything we think we know about why people go out to vote might be incorrect.

Overreports of voter turnout are false reports of participation in elections by nonvoters when responding to political surveys. These false reports of turnout are problematic for American politics scholarship because political scientists overwhelmingly use surveys to measure the quantity, quality and equality of participation in politics (Rosentsone & Hansen, 1993; Verba, Brady & Schlozman, 1995; Dawson, 1995; Desipio, 1998; Leighley, 2001). If one of the main goals of this sub-discipline is to identify the factors that stimulate or depress engagement in democratic politics, its mission is complicated by the use of survey data that is contaminated with overreports. Statistical models of electoral participation based on self-reported turnout will almost certainly be inaccurate because overreports of turnout would bias the resulting estimations. For example, a factor that has a statistically significant effect on increasing a person's likelihood of voting in a model based on self-reported turnout might have the opposite effect or no effect in a model based on validated vote. Thus, overreports obstruct the accuracy of the scientific study of participation, which is arguably the most important activity in representative democracy.

Table 1.1 Overreports in National Surveys by Mode of Administration

Authors (year)	**Survey Mode**	**Election Year**	**Overreports as Reported**
Parry & Crossley (1950)	Face-to-face	1948	13%
Katosh & Traugott (1981)	Face-to-face Face-to-face	1976 1978	11% 12%
Sigelman (1992)	Face-to-face	1978	12.8%
Burden (2000)	Face-to-face Face-to-face	1970-1980 1972-1984	10-12% 17.7-20.3%
Belli, Traugott, Beckman (2001)	Face-to-face Face-to-face Face-to-face Face-to-face Face-to-face Face-to-face Face-to-face	1964 1978 1980 1984 1986 1988 1990	14.2% 12.8% 10.7% 9.0% 8.1% 10.1% 7.8%
Bernstein et al. (2001)	Face-to-face Face-to-face Face-to-face Face-to-face Face-to-face Face-to-face & Telephone Face-to-face & Telephone	1972 1976 1980 1984 1988 1992 1996	18% 19% 18% 21% 20% 20% 23%
Berent, Krosnick, Lupia (2011)	Telephone	2008-2009 Panel	12.7%
Ansolabehere & Hersh (2012)	Telephone Telephone Telephone Online	1980 1984 1988 2008	9.4% 9.9% 9.9% 15.8%

Table shows the survey mode, election year, and rate of overreporting found in a selection of vote validation studies.

Voter Turnout Overreports in Survey Research

The initial drive towards the verification of self-reports of turnout in surveys started with the 1949 Denver Validity Study (Parry and Crossley, 1950). Using both aggregate and individual level data sources the authors recorded what they called “invalidity,” finding that a startling number of “respondents exaggerated their participation in elections” (p. 72). Many other scholars have followed suit by exploring which factors are most related to overreporting, including individual level characteristics, political attitudes, and electoral context. Table 1.2 lists seven factors the most commonly predict the likelihood of engaging in overreporting in twelve vote validation studies. Findings show that high education is a significant predictor of overreporting in nine studies, followed by partisan strength and interest in politics. Beliefs in political efficacy, racial identity, age and income are also important factors that results in and increased incidence of overreporting among others not listed. In addition to those listed high salience elections have resulted in higher rates of overreporting in surveys (Karp & Brockington, 2005; Górecki, 2011).

This work has engendered important questions about the study of overreporting itself and how overreporting affects the study voter turnout. I have identified four major debates in the literature: 1) How accurate is vote validation?, 2) Do overreports of voter turnout bias statistical models of turnout?, 3) What is the correct way to measure and model overreporting?, and 4) What is the cognitive mechanism through which overreports occur? I will address each of these debates in this dissertation by either discussing existing evidence or presenting my own research to answer these questions. The main goal of my dissertation is to make original contributions to the third and fourth debates, namely how to best measure and model overreporting and what is the cognitive mechanism involved in overreporting.

Table 1.2 Factors Predicting Turnout Overreports in Past Research

	Education	**Strong Partisanship**	**Political Interest**	**Political Efficacy**	**Race**	**Age**	**Income**
Abramson & Clagget, 1984, 1986, 1991	✓				✓		
Anderson & Sliver, 1986	✓						
Anderson, Silver, Abramson, 1988	✓		✓	✓	✓		
Ansolabehere & Hersh, 2012	✓	✓	✓			✓	✓
Ansolabehere & Hersh, 2010	✓	✓	✓			✓	✓
Belli, Traugott, Beckman 2001	✓	✓	✓	✓	✓	✓	
Bernstien, Chadha, & Montjoy, 2001	✓	✓					
Granberg & Holmberg, 1991		✓	✓				
Presser & Traugott, 1992	✓			✓			
Silver, Anderson & Abramson,1986	✓	✓	✓	✓			
Stoké & Stark 2007		✓	✓	✓	✓	✓	
Traugott & Katosh 1979				✓	✓	✓	✓
Total	**9**	**7**	**7**	**6**	**5**	**5**	**3**

Table shows the characteristics most associated with overreporting in a selection of vote validation studies.

The debate about the accuracy of vote validation is continually revived in political science. Initial inquiries into possible problems with vote validation and the measurement of overreporting stemmed from the consistent finding that Black Americans overreport more than whites (Anderson & Silver,1986; Abramson & Claggett, 1992). Most recently, Berent, Krosnick and Lupia (2016) tested the accuracy of vote validation using government records and computer based matching through an algorithm. They argue that the turnout rates resulting from vote validation only give the illusion of more accuracy and that we should trust turnout self-reports more than validated turnout. Furthermore, they argue that vote validation conducted by and purchased from private voter file companies cannot be independently evaluated and are thus untrustworthy.

However, the Cooperative Congressional Election Study (CCES) has relied on a private voter file vendor, Catalist, for validation for almost a decade. Using Catalist data, Ansolabehere and Hersh (2010) conducted a study of the quality of public record keeping finding low rates of missing information, a small amount of obsolete records and low incidence of discrepancies between the number of "voters recorded as voting and ballots counted" (p. 2). In their 2012 study, Ansolabehere and Hersh described how Catalist obtains their data, how they manage that data and provide a detailed description of the CCES's "commercial validation procedure" or matching process. Moreover, their analysis of overreports of voter turnout found that public registration and turnout record keeping throughout the United States had little to do with the incidence of turnout overestimation in surveys. The authors attribute a small percentage of overreports to measurement error (4-6%) and suggest that the rest is caused by falsehoods reported by respondents. What's more, they argue that:

> "If poor record-keeping was the main culprit, one would not expect to find consistent patterns across years and survey modes of the same kinds of people misreporting. Nor would one expect to find that only validated non-voters misreport." (Ansolabehere & Hersh, 2012: p. 7).

In order to bolster confidence in Catalist matching of the CCES, its principal investigators, Stephen Ansolabehere and Brian Schaffner, purchased vote validation from a second private vendor in 2014. Of the total 56,200 respondents in the 2014 CCES 51% were matched to a record in both Catalist and the other voter file, while Catalist matched 70% of respondents to a record. More importantly, Catalist and the other vendor agreed 96% of time in their classification of voters and nonvoters of those who were matched by both companies. This evidence contradicts the claims made by Berent and colleagues that suggest that vote validation has a high rate of misclassification. Catalist has matched between 70 and 84% of CCES respondents from 2008 to 2014 using only matches with high confidence scores, while Berent et al. (2016) achieved an overall 43% match under their definition of strict standards.

Understandably, some political scientists will resist conclusions that may bring the veracity of self-reports in surveys into question, because those conclusions will put their own past research into question. Berent, Krosnick and Lupia (2016, 2011) strongly disagree with claims that individuals are lying about their political behavior in surveys even though research in and outside of political science shows that individuals misrepresent (lie about) both their attitudes and behaviors when answering questionnaires (Tourangeau & Yan 2007). Proposing that survey respondents sometimes lie about their voting behavior is not a call to wipe the slate clean with respect to the accumulated knowledge However, the very nature of scientific inquiry requires the recognition of problems or flaws in past research in order to improve. In the case of voter turnout overreports, evidence of mistaken or intentional misrepresentation of a respondent's voting behavior will hopefully lead to advances in survey methodology and knowledge about participation. Additionally, consistent overestimation of turnout in survey research suggests that there is something happening during survey administration which results in overreports, not during vote validation. I will continue to address this debate throughout this dissertation.

The second debate regarding the effects that overreports may have on statistical modeling of turnout is related to the first debate. Implicit in the opposition to vote validation of survey data is the argument that overreporting is inconsequential to conclusions made about what makes people turnout. Nonetheless, multiple validation studies have found that overreports do bias the coefficients in statistical models of turnout (Cassel 2003, 2004; Ansolabehere & Hersh, 2012). For example, Presser and Traugott (1992) carried out the first panel study on misreports of electoral participation using Michigan Election Panel data from 1972, 1974 and 1976. Their main finding contradicts the hypothesis set forth in *The American Voter* (Campbell et al, 1960), which states that those who misreport are previous habitual voters. It is habitual nonvoters who overreported turnout most often. More specifically, they were concerned with identifying those who lie about their electoral behavior in order to find the true factors leading to voter mobilization. With this goal in mind they compared a self-reported vote model to a validated vote model using four variables to predict participation 1) interest in public affairs, 2) political efficacy, 3) income, and 4) education while pooling data from all three waves of the panel study. They found that though all four variables were significant predictors for self-reported vote, only interest in public affairs and income were predictive of validated vote. These results reinforce the perspective that survey results based on self-reported turnout lead to inaccurate conclusions about democratic participation in elections. Later in this dissertation I will present data to further support this conclusion by comparing regression models based on self-reported turnout to models based on validated turnout.

The third debate, that surrounding the measurement of overreporting stems from consistent findings that show higher proportions of overreporting among Black survey respondents. Silver and Anderson (1986) sought to debunk the conclusion that Black Americans were more likely to overreport by providing a detailed study of what they considered is the proper methodology to measure the validity of self-reported vote. In replicating previous validation studies while using their measure of validity they found that the miss-measurement of overreports had led to erroneous conclusions about the relationship between race and overreporting. They suggest that the first step should be to identify the nonvoters within a survey in order to then calculate the proportion of nonvoters who falsely said they turned out to vote. In their view, only nonvoters can overreport thus this is the only group to be included in analysis of the tendency to overreport. Still, many other studies have measured overreporting as the proportion of nonvoters among those who reported turning out to vote. Neither approach is inaccurate in measuring the proportion overreporting, but have important consequences for statistical modeling. The first approach results in a model that predicts the likelihood of overreporting given that a respondent is already a nonvoter. The second results in a model that predicts the likelihood that a turnout report is false, an overreport, given a respondent reported turnout. Both approaches fail to account for respondents' probability of turning out to vote as a factor that then affects the probability of overreporting. I will address measurement and modeling of overreporting in Chapters 2 and 3 to illustrate the extent to which there are commonalities between over-reporters and voters or nonvoters.

Finally, the fourth debate involves identifying the cognitive mechanism through which voter turnout overreports occur. This debate requires theory building and is what ultimately animates the research presented in this dissertation. Some scholars suggest that overreports are the result of memory failure and that survey respondents easily forget whether they voted or not (Abelson, Loftus & Greenwald, 1992; Stocké & Stark, 2007).[2] In that same vein, a group of scholars led by Robert Belli have examined the effect elapsed time between an electoral event and a survey interview on memory of participation. Belli and colleagues find that both memory and social desirability bias are at play in the occurrence of overreports (Belli et al., 1999; Belli et al., 2001, Belli et al., 2006). Having said that, overreporting is most frequently attributed to socially desirable responding. I discuss the relationship between overreporting and this form of response bias in the sections that follow.

The Social Desirability Assumption

In spite of the many and varied advances in the study of overreports little is known about the cognitive mechanism through which respondents engage in overreporting. Most vote validation scholars attribute overreports of voter turnout to social desirability bias. Parry and Crossley (1950) suggested that "social pressures" (p. 70) were to blame for the phenomenon. Silver and Anderson (1986) claim that respondents overreport because "voting is a socially desirable behavior" (p. 775). Katosh and Traugott (1981) argue that "a variety of social psychological pressures [are] known

[2] A few articles have focused on underreports of voter turnout, which argue that these rarely occurring reports are causes by memory failure (Adamany & Du Bois, 1974; Adamany & Shelley, 1980).

to result in systematic overreports of eligibility and participation" (p. 519) in elections. Karp and Brockington (2005) also assert that respondents "have a strong incentive to offer a socially desirable response" (p. 825) with regards to their voting behavior. Still, very few have engaged in research to directly test this assumption.

Some researchers have set out to develop ways to diminish the occurrence of turnout overreports by creating new question wording mainly based on the assumption that overreports are the result of socially desirable responding. Presser (1990) failed to reduce overreports with the use of two preemptive questions, the first treatment asking if the respondent knew where their polling place is located and the second treatment asking about past voting behavior. Both treatments bring factual information to the forefront of peoples' mind before answering the vote self-report question. Belli et al. (1999) designed an experimental question that addresses both memory failure and social desirability bias by providing "face-saving response options" that could "mitigate the need to claim having voted because of social desirability concerns" (p. 92). They found that the experimental condition significantly reduced overreporting the more time had passed since the election. Belli, Moore and Van Hoewyk (2006) emulate this study by conducting a new survey experiment where they test three vote reporting questions over a three-month period. They also find that questions providing face-saving response options reduce self-reports of turnout supporting the notion that overreports are caused by socially desirable responding. Yet another study builds on the use of face-saving response alternatives for the vote self-report question while eliminating the previously used lengthy preambles to the question finding positive results in the reduction of overreports (Duff et al., 200). Hanmer, Banks and White (2014), using Catalist validation, find that a “bogus pipeline” treatment question has greater effects in reducing overreports and increasing vote report accuracy than the subtle treatments used by the authors mentioned above. The approach makes respondents aware that voting is a matter of public record and that survey researchers have the ability to verify their response to the vote self-report question.

The problem with these attempts to reduce overreporting, successful or not, is that they sought to treat the disease without having a clear diagnosis. Belli et al. (1999) reduced reported turnout by 8.9% when comparing the total reported turnout in their control group versus their experimental group. Belli, Moore and Van Hoewyk (2006) reduce overreports by 4.6%, while Duff et al. reduce them by 8%, and Hanmer, Banks and White (2014) do so by 7.6%. These are good innovations in the measurement of self-reported vote, but they come nowhere near fully eliminating the problem of overreporting. Though these scholars and I agree that socially desirable responding is the likely cause of false reports of turnout, survey methodologists should base the creation of new questionnaire items on research that identifies the mechanism through which overreporting occurs.

Two sets of authors have gone beyond speculation about SDR being responsible for overreports by testing this assumption directly (Holbrook & Krosnick, 2010; Comsa & Postelnicu; 2012). The item count technique (ICT) or list experiment is one of many techniques developed to reduce and detect SDR in relation to sensitive questionnaire items. It is designed to allow individuals to anonymously report attitudes and behaviors that may or may not be in line with social norms. Respondents are split into an experimental and a control group, and then are “asked to report the number of items on list that fit a particular criterion" (Holbrook & Krosnick, 2010: p.44). The criterion in this case is the respondent's behavior, thus respondents in the control and the experimental group are asked to state how many of the behaviors listed are true for them. The control groups in these studies were given, in most cases, lists of four (4) behaviors and were asked to report how many of them were indicative of their own behavior. The experimental groups were given the same list of behaviors with the addition of an item stating the action of turning out to vote in an election, for example: "Voted in the Presidential election held on November 7, 2000" (Holbrook & Krosnick, 2010: p. 47). The mean number of behaviors reported in the control condition is subtracted from the mean number of behaviors reported in the experimental condition resulting in "the proportion of people given the longer list who said they performed the added behavior" (Holbrook & Krosnick, 2010: p. 44).

Judging whether the ICT was successful or not is simple. The respondents in the control group are given a traditional vote report question, which will likely result in an overestimation of turnout. Comparison of the proportion of reported vote from the ICT is compared to that from the control group. If the proportion of reported turnout from the ICT is lower than that resulting from a traditional vote report question one can infer that SDR with regard to the turnout question has been reduced. The ICT successfully reduced reports of turnout in face-to-face interviews and Random Digit Dial (RDD) telephone surveys, but not in online surveys. Holbrook and Krosnick (2010) applied the ICT to multiple survey modes finding mixed results. In their RDD telephone survey they reduced reports of turnout by 19%, their subsequent online surveys were less successful with no reduction in their first online survey, a 1.4% reduction in the second, and a 3.1%

in final one. Comsa and Postelnicu (2012) reduced reports of turnout in their face-to-face survey by 10.5%. However, the ICT technique is not without faults because it can fail at its main purpose of providing concealed reporting of undesirable behavior like non voting as explained by the following quote:

> "ICT can produce a ceiling and floor effect because of the limited number of statements that are used, and implicitly it is possible for the interview to identify the items selected by respondents when they indicate the minimum or the maximum number of statements" (Comsa and Postelnicu, 2012: p. 3).

The ICT is also limited because it can only provide aggregate values, but cannot identify individuals who voted or not. Consequently, the ICT can measure the overreport rate among the experimental group, but cannot identify exactly who engaged in overreporting.

Together the creation of new question wording and the application of the ICT to self-reports of turnout provide somewhat supporting evidence for the widely held assumption that voter turnout overreports are the result of SDR. Regrettably, these forays into the study of overreporting in connection to SDR reveal almost nothing about the mechanism or mental process that respondents who are nonvoters engage in when they falsely report participating in elections. Though it is valuable to find supporting evidence for the role of SDR in overreporting but the accomplishments of these studies are equal to those of the studies that identified the central correlates of overreporting, because neither identify the mechanism of overreporting. Once the mechanism is identified researchers may be able develop more effective ways of extracting more accurate self-reports.

Socially Desirable Responding: A Complex Construct

Socially desirable responding (SDR) is one of many forms of response bias in surveys. Response biases in general result in a "systematic tendency to answer questionnaire items on some basis that interferes with accurate self-reports" (Paulhus, 2002: p. 49), but SDR specifically produces a "tendency to give overly positive self-descriptions" (p. 50). Holtgraves (2004) gives a more descriptive definition saying; "Social desirability refers to a tendency to respond to self-report items in a manner that makes the respondents look good rather than to respond in an accurate and truthful manner" (p. 161). Tourangeau and Yan (2007) hold that socially desirable responding occurs when individuals are asked questions about sensitive topics like voting. Sensitive questions can elicit answers that are socially undesirable or reveal that individuals have not complied with social norms, like the democratic norm of voting. Consequently, respondents might engage in socially desirable responding to make themselves look good to others or to themselves.

Socially desirable responding has been found to manifest itself in more than one way, meaning all deceptive responses are not created equal. Though many operationalizations and typologies of SDR have been developed (Damarin & Messick, 1965; Sackheim & Gur, 1979), a two factor typology of impression management and self-deception has been most commonly used by social psychologists to theorize and measure SDR. Impression management (IM) is "the tendency to give favorable self-descriptions to others" and self-deception (SD) is "the tendency to give favorably biased but honestly held self-descriptions" (Paulhus & Reid, 1991). In 1984 Paulhus developed the Balanced Inventory of Desirable Responding (BIDR) to assess individual differences in SDR which includes an Impression Management Scale and a Self-Deception Scale which were built on previous work that has focused on "distinguishing self-deception, where the respondent actually believes his or his positive self-reports, from impression management, where the respondent consciously dissembles" (p.599). Furthermore, Paulhus and John (1998) explain that self-deception correspondents to egoistic bias, which reveals an "exaggerated self-worth with regard to social and intellectual status" (Paulhus & John, 1998; p. 1041); while impression management corresponds to moralistic bias, which reveals an "exaggerated self-positivity of being a good person or a good citizen" (p. 1046).

Clearly, awareness of engaging in SDR, on behalf of the respondent, is central to distinguishing between self-deception and impression management style SDR. Paulhus (2002) uses the words "deliberate exaggeration" and "deliberate minimization" to describe impression management. In his early work he was resistant to attributing intentionality to impression management, but now has come to conclude that impression management is characteristically conscious. Other authors have all spoken to the intentionality of impression management. Holtgraves (2004) describes SDR's two factor typology affirming that "impression management, refers to a tendency to purposely tailor one's answers to create a positive social image; it is other-deception… The other factor, termed self-deception, refers to an honest but overly positive self-presentation…" (p 161). Further stating that "impression management (conscious, deliberate, deception of others) and self-deception (nonconscious deception of one-self) "(p. 163). Li and Bagger (2007) explain that "[s]elf-deception is an unintentional propensity to portray oneself in a favorable light, manifested in positively biased but honestly believed self-descriptions… Impression management, in contrast, indicates a tendency to intentionally distort one's self-image to be perceived favorably by others" (p. 526-527).

A Social Desirability Theory of Overreporting

The widely held assumption that voter turnout overreports are caused by SDR has important implications for understanding this phenomenon in political survey research. The definitions and typologies of SDR reveal that there are complexities that validation scholars have not taken into account when studying overreporting or attempting to reduce its occurrence. The first implication of the SDR assumption is that if overreports are caused by SDR, then they themselves are deceptive answers to the vote self-report question because these responses provide false information about the respondents' true behavior. This implication stems from knowing that the social psychology literature defines SDR as a response bias that results in deception because it produces false/deceptive reports of attitudes and behaviors in the process of responding to survey questionnaires.

Validation scholars have been very careful not to say that overreports are in effect lies about going out to vote. Saying that respondents are lying or being deceptive can imply that a moral judgment is being made by the researcher on the respondent. Still, using the words deception, lie, or falsehood to describe overreports is entirely accurate. More importantly, understanding that SDR results in deception becomes an advantage in an academic perspective. It opens up a variety of possibilities with respect to the study of overreporting because psychologists have extensively studied human lying and deception. The existing literature on this phenomenon along with its theories and methodologies then becomes a new tool box for political science to make sense of overreporting.

The second implication of the SDR assumption is that overreporting must be equivalent to one of the two main types of SDR; that is, overreporting must correspond to either self-deception or impression management. The existing literature on SDR suggests that overreporting is equivalent to impression management because this type of SDR is induced by an exaggerated view of being a good citizen. If overreporting occurs due to impression management what occurs in the survey administration process is the following. Nonvoters responding to a post-election survey are given a vote self-report question, their memory of non-participation becomes available in their minds, but also thoughts about group and societal costs and benefits regarding the democratic norm of voting. Nonvoters then decide to falsely report participation in the election they were asked about in order to appear as if they conform to the democratic norm of voting. They decide to give a socially desirable response to make themselves look like good citizens. I qualify the considerations the nonvoters evaluate before overreporting as "group and societal costs and benefits" because moralistic bias is related to "affiliation, belonging, intimacy, love, connectedness, approval, and nurturance" (Steenkamp et al., 2010: p. 200).

The argument that overreporting is equivalent to impression management is further supported by Rolfe's (2012) social theory of political participation. Central to her theory is the "social meaning meaning of voting," where "voting is a fundamental act of the American citizen" (p. 43). Rolfe explains that "[b]ecause the social meaning of voting is uncontested, a failure to vote may be excusable as an accident, but it cannot be justified without casting doubt on one's good standing as an American citizen" (p. 43). More importantly, she finds the nonvoters also recognize the importance of voting and the communal nature of voting in American elections. As I mention before, self-deception is motivated by the need to improve one's self-image while impressions management is about improving one's social image. Consequently, falsely reporting turnout, overreporting, responds to the social meaning of voting which is align with the descriptions of what motivates impression management.

Dissertation Overview

This first chapter described the phenomenon of voter turnout overreports in survey research and how they have affected turnout estimations throughout the history of political polling. A summary of the political science literature on overreporting was presented by highlighting the four main debates surrounding voter turnout overreports: "1) How accurate is vote validation?, 2) Do overreports of voter turnout bias statistical models of turnout?, 3) What is the correct way to measure and model overreporting?, and 4) What is the cognitive mechanism through which overreports occur?" While this dissertation engages these main debates, research in this dissertation seeks to make original contributions to the third and fourth debates. The first and second debates will be addressed throughout.

Chapter 2 will present analysis of the the persistence and prevalence of overreporting in the CCES studies of 2008 2010, 2012, and 2014 (See Appendix A for filed dates and response rates). Also, a comprehensive look at the demographics, political attitudes and levels of political engagement of voters, nonvoters and over-reporters using data from the 2014 and 2012 CCES. Another debate among political scientists is derived from the first, second and third debates which are all related to measurement questions whether 'over-reporters' are more similar to voters or nonvoters. Comparing the descriptive statistics of all three types of respondents will provide a first chance of observing the level of accuracy in the vote validation process, it hints as to whether overreporting affect predictive models of turnout, and provides the scaffolding for Chapter 3.

Chapter 3 constitutes the first original contribution to the study of overreporting by proposing a new way modeling the likelihood of overreporting through multinomial logistic regression analysis. The new approach proposed improves predictive models of overreporting by simultaneously estimating the probability of turning out to vote and that of overreporting. This is the proper methodology for examining the correlates of overreporting, and offers a more definitive view of the similarities and difference between voters and over-reporters.

Most Importantly, I will test the assumption that overreporting is caused by socially desirable responding using new data and methods to do so in Chapter 4. Using response latency data from the 2014 and 2012 CCES studies I demonstrate that residents who overreport turning out to vote intentionally misrepresent their voting behavior. Using the CCES in testing this hypothesis constitutes a hard case for finding social desirability bias in self-reports of voter turnout because self-administered, computer based and online surveys have been found to increase reports of sensitive information (Kreuter et al, 2008).

Finally, the conclusion of this dissertation will summarize the main findings of previous chapters, and present how overreports bias statistical models of turnout.

CHAPTER 2

WHO OVERREPORTS TURNOUT?

Identifying overreports of turnout in surveys and the factors related to its occurrence is the first step in understanding this form of response bias. This task sheds light on the incidence of overreporting, its prevalence over time, and the characteristics of those who overreport in comparison to voters and nonvoters. Explaining the processes through which overreporting can be detected in survey research brings clarity to the debate regarding the accuracy of vote validation, and how to best measure overreporting. Also, finding differences between the dominant characteristics of over-reporters, voters and nonvoters is the first benchmark for concluding whether overreports affect predictive models of turnout. Showing whether over-reporters are more like voters or nonvoters contributes to settling this third debate.

Overreports can be identified indirectly at the aggregate level and directly at individual level, depending on the resources available to researchers. Both modes of identifying of overreporting require the comparison of two sets of data 1) reported turnout in surveys and 2) publicly recorded or estimated turnout. In this chapter, I first present aggregate comparisons of self-reported turnout and recorded turnout to illustrate trends of turnout overestimation mainly in the Cooperative Congressional Election Study (CCES). Second, I focus on individual level measurement of overreporting in the CCES because it allows for precise estimation in descriptive inference, and in correlational analysis in later chapters. I compare validated voters, nonvoters and over-reporters on their demographic characteristics, political attitudes and levels of political engagement.

Together aggregate and individual level analysis of overreporting will answer the question "Who overreports?"

Measuring Voter Turnout Overreports

The comparison of aggregate survey and public data immediately reveals the discrepancy between the proportion of people who reported going out to vote with that recorded by governmental institutions tasked with administering elections. This is the simplest way to identify the occurrence of overreporting in surveys, but this discrepancy is best defined as overestimation of turnout. The comparison of aggregate data from disparate sources is possible because survey samples are, for the most part, the equivalent to a small snapshot of the population under study thanks to the development and use of representative sampling. Consequently, if the survey sample holds the same or very similar characteristics to the population being studied, like adult U.S. citizens eligible to vote, then the survey sample should have the same proportion of turnout than the population. However, this is rarely the case.

Table 2.1. CCES Reported Turnout and United States Election Project VEP Turnout

General Election Year	USEP VEP Estimated Turnout	CCES Reported Turnout	*Difference*
2014	36.7%	69.6%	***32.9***
2012	58.6%	74.5%	***15.9***
2010	41.8%	59.9%	***18.1***
2008	62.2%	68.2%	***6.0***

Rows compare two aggregate turnout estimations, the percent of United States Election Project estimated turnout based on Voting Eligible Population (VEP) and weighted percent of self-reported turnout in the CCES among all citizen respondents.

Early validation studies identified the overestimation of turnout by comparing aggregate level data to document the discrepancy between turnout estimations in surveys and publicly recorded turnout (Clausen, 1968). To illustrate this method, I compare reported turnout in four consecutive CCES surveys to turnout estimates from the United States Election Project[3]. The CCES is a biennial online large sample survey administered through YouGov since the year 2006, which includes a pre-election and post-election questionnaire. CCES samples since the year 2010 have exceeded 50,000 respondents. Quantities for reported turnout in the CCES are the result of the weighted proportion of citizen respondents who said they definitely voted in the 2014, 2012, 2010 and 2008 CCES surveys, proportions are estimated from the full sample of respondents in the CCES subsequent estimates are derived from subsets. The United States Election Project (USEP) "is an information source for the United States electoral system" (McDonald, 2016), it has sourced official state-by-state estimates for every election year since 2000 to determine national turnout levels based on the Voting Eligible Population (VEP).[4] The VEP is the quantity of interest here because the calculating the turnout based on the voting age population (VAP)[5] uses a denominator that is larger and skews the estimated rate of participation downward which then results in an inaccurate representation of turnout in the United States. To be sure, though the U.S. Census Bureau makes official estimates of national turnout those estimates are based on the Current Population Survey while the USEP data is not based on surveys. For this reason, the USEP data cannot be

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[3] McDonald, Michael. (2017). "Home", *United States Elections Project*. URL: http://www.electproject.org. Accessed January 23, 2017.

[4] "…voting-eligible population is constructed by adjusting the voting-age population for non-citizens and ineligible felons, depending on state law." McDonald, Michael. (2017). "Voter Turnout: FAQ", *United States Election Project*. URL: http://www.electproject.org/home/voter-turnout/faq/sold. Accessed: Jan. 23, 2017.

[5] VAP turnout: 33.2% in 2014, 53.6% in 2012, 37.8% in 2010, and 56.9% in 2008. McDonald, Michael. (2017). "Voter Turnout Data," *United States Election Project*. URL: http://www.electproject.org/home/voter-turnout/voter-turnout-data. Accessed: March 7, 2017.

contaminated with response bias, like overreporting, and is treated here as an accurate assessment of national turnout in U.S. elections.

Reported turnout in the CCES exceeds turnout estimations published by the USEP, especially in the year 2014 when turnout hit a historic low. Evidently, the CCES has not made accurate estimations of voter turnout in any of the years under analysis, having overestimated turnout by 6.0 to 32.9 percentage points (See Table 2.1). Yet, the American National Election Study overestimated turnout in the 2008 and 2012 presidential elections by larger margins than the CCES when compared to the amounts calculated by the USEP, a difference of 15.8 percentage points in 2008 and 19.4 percentage points in 2012.[6] The discrepancy between reported turnout in the CCES and that estimated by the USEP is a strong indication that overreporting occurred in the administration of the CCES. Nevertheless, the discrepancy found between reported turnout and official estimates does not necessarily indicate the exact amount of overreporting that occurred among CCES respondents. This is especially true since the sampling method employed in the CCES is not probability sampling, but a sample matching methodology that results in large samples of over 50,000 respondents in each year of the study with the exception of the 2008 CCES, which has a sample of almost 32,800 respondents (Ansolabehere & Schaffner, 2014; 2012; 2010, Ansolabehere, 2008). Moreover, sample selection bias is assuredly a factor in the incidence of overreporting within all surveys that measure turnout because surveys are voluntary and most volunteer respondents are already likely to be politically engaged, which results in "inflated rates of participation" (Ansolabehere & Hersh, 2012). Thus, direct comparison of respondents'

[6] The ANES estimates 78% turnout in both 2008 and 2012. http://www.electionstudies.org/nesguide/toptable/tab6a_2.htm Accessed: March 7, 2017.

reports of turnout with their individual records of participation is the best method for identifying the incidence of overreporting within each survey year. Samples may report higher turnout that actual because of sample composition rather than because of overreporting.

More precise aggregate and individual level identification of turnout overreports can be achieved with the use of vote validation, a main feature of CCES data. Respondents are matched to public records of registration and participation that show exactly who participated and who did not while revealing who overreported participation. Determining whether turnout self-reports in the CCES are accurate or not requires the use of nationwide state and county registration and voting records to measure the validity of these survey responses. For this reason, the CCES entered a partnership with Catalist LLC, a progressive political and marketing data vendor, which conducts the matching of respondents to their vote file. The CCES purchases vote validation from Catalist because there is no publicly administrated national level voter file. Private firms like Catalist have built a commercial business around compiling voter registration records that are then sold to political parties and interest groups for the purposes of political mobilization.

Catalist voter registration and turnout records are of the highest quality (Ansolabehere and Hersh, 2012). Catalist purchases voter registration records from each state and county election administration office several times a year. It then cleans those records and makes them uniform, since the format varies from state to state and county to county. Their team compares old and new files to retain past records of individuals who have been dropped from new registration records. They also take note of missing and duplicate data; and whether individuals have moved or have died by crosschecking with public records from the Post Office and the Social Security Administration. Most importantly, Catalist obtains commercial data from marketing firms and appends it to the voter file allowing them to fill-in possible missing data or data that is not requested during the voter registration process in some states.

Table 2.2 CCES Respondents by Catalist Match Status

CCES Survey Year	Total Respondents	Matched to Catalist	Not Matched
2014	**56,200** **100%**	39,415 70%	16,785 30%
2012	**54,535** **100%**	43,342 80%	11,193 20%
2010	**55,405** **100%**	42,916 78%	12,489 22%
2008	**32,795** **100%**	27,444 84%	5,351 16%

Rows present weighted total and percent of CCES respondents matched and not matched to the Catalist voter file.

Validation is carried out in the Spring following the survey when YouGov shares the identifying information of every CCES respondent with Catalist. The firm sends the records of the respondents to YouGov, which then de-identifies the records and finally delivers their validated registration and participation to the CCES attached to the survey data. In the process of matching respondents to the voter file, Catalist favors precision over coverage in order to avoid false positives, meaning that if a match is ambiguous Catalist does not match the record at all. As a result, Catalist does not match every CCES respondent to a voter file record. However, a great majority are matched, between 70 to 84 percent of CCES respondents have been matched by Catalist from 2008 to 2014. Lower proportions of respondents were matched to Catalist in midterm elections which also happen to have larger samples, 2010 with 22% not matched and 2014 with 30% not matched (See Table 2.2). The larger rate of unmatched respondents in the 2014 CCES has been attributed by YouGov to an increase incomplete address information provided by respondents, which is necessary for the matching process.

Berent, Krosnick and Lupia (2016, 2011) argue that vote validation data is flawed and that it does not provide a more faithful representation of survey respondents' (non)participation in elections. In their 2016 study, the authors acknowledge that nationally representative surveys tend to overestimate turnout by wide margins and that this overestimation has led to interest in vote validation of turnout self-reports in surveys. Using registration and turnout records from six states (CA, FL, NY, NC, OH, and PA) they conduct a matching procedure for the 2008-2009 ANES Panel Study. Using three matching algorithms with three levels of criteria to match respondents to government records (strict stringency, moderate stringency and least stringency). The more stringent algorithm resulted in the lowest number of matches, 46.5% of respondents from the six states under study were matched, while the least stringent algorithm resulted in the highest number of matches, 77.4% of respondents were matched in this algorithm. In their view the results from this study put into question the reliability of all vote validation matching procedures, even though they do not report any false matches in their study.

Berent at al. (2016) say that self-reports of turnout are more trustworthy than vote validation data. First, because among those who are matched to a voter file record self-reports are highly accurate, and this is taken as evidence that turnout overestimation cannot be the result of intentional lying. In line with their finding, CCES respondents who are matched to validation data have high rates of accuracy in their self-reports. I find that on average 90% of matched respondents between 2008 and 2014 accurately report their turnout or nonvoting. Still, on average 10% of matched respondents overreport in the CCES (See Table B.1 in Appendix B). This rate of overreporting is cause for concern because these respondents can bias statistical models of turnout. The second and related reason is that they find that most vote validation scholars assume that non matched respondents are nonvoters. This is not the case in my research, I do not assume that non matched individuals are nonvoters, but assume that non matched respondents who say they did not vote are being honest about their nonparticipation. For example, in the 2014 CCES only 9% of those who said they were not registered to vote were matched to an active voter registration record; they represent 0.01% of the whole 2014 CCES sample. To be clear, only respondents with a confirmed record of nonvoting who said they turned out to vote are classified as over-reporters or liars. Also, non matched respondents who report turning out to vote are excluded form this analysis because there is no way to confirm or refute their reports. Third, Berent and colleagues argue that the variation across states in record keeping and missing information in government records increases the rate of what they call "failure-to-match." However, Catalist draws from multiple information sources in addition to government registration records to build a comprehensive record for every individual in their voter file. Consider for a moment the higher rate of non matches in the 2014 CCES. As I explain above, this occurred due to missing address information about respondents in the survey data not because of missing information in the Catalist voter file.

It is Berent, Krosnick and Lupia's view that "failure-to-match" gives an illusory sense of accuracy by lowering the rate of turnout in surveys and bringing it closer to official estimates, but that survey respondents are in and of themselves more likely to turnout out and we should expect higher rates of participation in survey samples.

However, Catalist vote validation of the CCES is quite successful, having a matching rate of over 70% in four consecutive studies, and turnout rates among matched respondents in the CCES are still far from official estimates. The description of the Catalist matching process provided above suggests that the data matched to the CCES is reliable, and here I treat it as such. What's more, the CCES has verified the quality of the Catalist matching process by comparing it to vote validation purchased from a second voter file. Matching from the two different firms yielded highly consistent results, 96% agreement in matching to be exact, thus strengthening confidence in the vote validation data used in this dissertation.

Table 2.3 CCES Respondents by Vote Validation Status and Reported Turnout

CCES Survey Year	**Total**	**Validated Voters**	**Nonvoters**	**Over-Reporters**
2014	**40,713**	26,648 66%	10,296 25%	3,769 9%
2012	**41,242**	30,050 73%	7,116 17%	4,077 10%
2010	**46,118**	25,439 56%	16,803 36%	3,876 8%
2008	**24,337**	17,401 72%	6,25 17%	2,916 12%

Columns show weighted total and percent by CCES year of validated nonvoters, nonvoters who honestly reported non-participation and validated nonvoters who overreported turnout. Percentages are rounded up to the nearest integer.

Determining the rate of overreporting in each CCES involves important decisions about how to interpret the available data, which includes registration self-reports, turnout self-reports and vote validation data. I start by describing who are nonvoters, then proceed to identify over-reporters among them, and finally identify validated voters using Catalist validation data, all after restricting the data to those respondents who completed the post election wave of the CCES. The result is one variable with three values measuring both actual and reported (non)participation in an election. I only conduct analysis of respondents who completed the post election wave because the focus of this research is on reports of turnout, which occur after the election. This process excludes a considerable number of respondents from the analysis here presented, on average 14% of all CCES respondents do not complete the post election questionnaire. Also, all unmatched respondents who reported turning out to vote are eliminated from this analysis because the validity of their turnout reports cannot be determined.[7] These steps reduce the 2014 CCES sample from 56,200 to 40,713 respondents, the 2012 sample from 55,353 to 41,242, the 2010 sample from 55,405 to 46,118, and the 2008 sample from 32,795 to 24,337 individuals (See Table 2.2 for total CCES respondents and Table 2.3 for subset totals).

Defining who among CCES respondents are nonvoters involves three steps. First, all post election respondents who self-reported that they were not registered to vote are classified as nonvoters. These self-reported non-registered respondents are not asked the turnout self-report question; they are considered honest nonvoters because in all states but North Dakota registration is a requirement for participation in elections and unregistered people in North Dakota are still asked the self-reported vote question. Second, all respondents who reported that they did not go out to vote, not matter their match status, are classified as honest nonvoters. The vote self-report question asks respondents to identify the statement that best describes their behavior during the General Election of the

[7] Although unmatched respondents are likely to be nonvoters because lack of a voter file record can be interpreted as a sign that a respondent is not registered to vote. I do not classify unmatched respondents who report turnout as over-reporters because I cannot say with confidence that they are nonvoters, especially since the vote validation matching rate decreased markedly in the 2014 CCES when compared with other years (See Table 2.2).

year in which they are being interviewed. Five statements are presented; four describe nonvoting in the election in question and one final statement describes participation including the date of the election (See Image 2.1). I categorize all respondents who chose one of the four alternatives to report non-participation as nonvoters because the "social meaning of voting" (Rolfe, 2012) suggests that there is little incentive to report non-participation. I assume that those who say the did not go out to vote for whatever reason are honest about being nonvoters. [8] Third, all matched respondents with no record of voting are also labeled nonvoters. There are lower rates of reported non-participation in the studies that were administered during presidential election years, namely 2008 and 2012.

Image 2.1 CCES Vote Self-Report Question Wording

Which of the following statements best describes you?

I did not vote in the election this November.
I thought about voting this time, but didn't.
I usually vote, but didn't this time.
I attempted to vote but did not or could not.
I definitely voted in the General Election on November 6.

Having determined who among all CCES post election respondents were nonvoters, I then identify those nonvoters who falsely reported turnout: over-reporters. I categorized matched respondents who said they "definitely voted", but had no record of

[8] To be sure, this does not include validated voters who underreported their participation, meaning respondents who reported that they did not turn out to vote while having a validated record of voting.

voting as over-reporters. I only include matched respondents in this category because lack of a voter file record does not represent certainty that a respondent is not registered to vote. Results show that overreports in each CCES survey since 2008 constitute between 8 to 12% of respondents who answered the vote self-report question, excluding unmatched reported voters. This represents an average 10% rate of overreporting for these four consecutive CCES studies. The 2008 CCES has the highest incidence of overreporting with 12% of all post election respondents and 42% of all nonvoters falsely reporting participation. The lowest incidence of overreporting occurred in the 2010 CCES with only 8% of all post election respondents overreporting turnout, which represents a 19% rate of overreporting among nonvoters in that year. Though overreports among respondents in the CCES post election wave occur at a relatively low rate the occurrence of overreporting among nonvoters is substantial, ranging from 19 to 42%.

Validated voters among CCES post election respondents are identified by using vote validation data and are labeled validated voters.[9] A great majority of participants in the CCES are validated voters, between 56 and 73% of post election respondents. Historically presidential elections have higher levels of turnout which is reflected in the rate of validated voters in both the 2008 and 2012 CCES studies, 72% and 73% respectively. Turnout estimated from the above described subsets of CCES data is still larger than turnout among the U.S. population when compared with the VEP turnout estimates from the USEP.

[9] This does include validated voters who underreported their participation. Drawing on past research (Ansolabehere & Hersh, 2012) I assume that underreports of voter turnout are caused by human error—respondents clicked on the wrong answer.

Table 2.4 Validated Nonvoters by Self-Reported Turnout in the CCES

CCES Survey Year	Total Validated Nonvoters	Honest Nonvoters	Over-Reporters
2014	**14,065**	10,296 73%	3,769 25%
2012	**11,192**	7,116 64%	4,077 36%
2010	**20,679**	16,803 81%	3,876 19%
2008	**6,936**	4,019 58%	2,916 42%

Columns show weighted total and percent of nonvoters among CCES matched respondents by self-reported turnout to identify honest nonvoters and over-reporters.

Over-Reporters: More like Voters or More like Nonvoters?

This section gives a comprehensive look at the demographics, political attitudes and level of political engagement of validated voters, nonvoters and over-reporters in the 2014 and 2012 CCES cross sectional surveys. These two studies provide a snap shot of self-reported and validated turnout in the most recent midterm and presidential elections. The purpose of presenting the characteristics of these groups side-by-side is to, first, identify the dominant characteristics of each group and, second, evaluate whether over-reporters are more like voters or nonvoters. Past research would suggest that higher levels of education, income, and political interest along with strong partisanship will be shared characteristics among voters and over-reporters. Figures will show that over-reporters have similarities with both validated voters and nonvoters, but in various instances over-reporters are distinct from these two groups. All statistics presented correspond to CCES post election respondents, excluding unmatched reported voters. Those referred to as 'voters' are respondents with a confirmed record of voting (or validated voters). Those referred to as nonvoters are all respondents who reported they did not go out to vote.

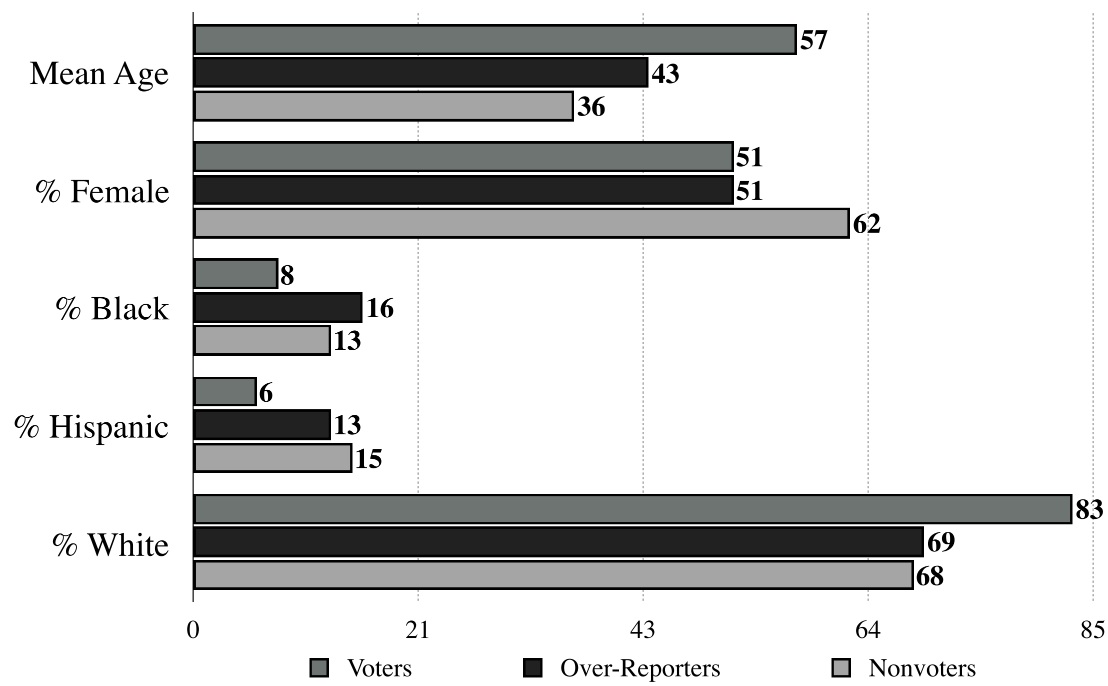
Finally, over-reporters are respondents with no record of voting who reported they definitely went out to vote.

Age, Gender, Race and Ethnicity

Basic demographic characteristics like age, gender, race and ethnicity have been found influence an individual's likelihood of participating in elections and multiple forms of political activity (Rosenstone & Hansen, 1993; Verba, Brady & Schlozman, 1995). It is well known that voters tend to be older while nonvoters tend to be younger, this is also true for CCES validated voters and nonvoters. CCES data includes year of birth of each respondent. Subtracting year of birth from the year of the survey creates a continuous variable for age that will allow to determine the mean age of voters, nonvoters and over-reporters, the mean age for all post election respondents in the 2014 and 2012 CCES was 50 years of age (See Table B.2 in Appendix B). The mean age of validated voters in the 2014 CCES was 57 years of age, which is 21 years older than that of over-reporters with a mean age of 43, and 14 years older than that of nonvoters with a mean age of 36. The mean age of validated voters in the 2012 CCES was 53 years of age, which is 8 years older than that of over-reporters with a mean age of 45, and 11 years older than that of nonvoters with a mean age of 42. Overall, over-reporters in the CCES were closer in age to honest nonvoters than they were to validated voters. Furthermore, as previous literature on voting has established, voters were older than nonvoters including over-reporters (See Figures 2.1 & 2.2).

Women make up 53% of all respondents in both the 2014 and 2012 CCES studies (See Appendix B). Women respondents in the CCES surpassed the electoral participation of men in both 2014 and 2012, where 51% of voters in 2014 and 53% of voters in 2012 were women. Also, these CCES studies show high rates of participation among women themselves, 62% of women voted in 2014 and 73% in 2012. While a majority of validated voters in the CCES were women an even greater proportion of nonvoters were women, 62% in 2014 and 54% in 2012. Over-reporters, on the other hand, have an almost even gender distribution in both CCES surveys with 51% in 2014 and 50% in 2012 being women (See Figures 2.1 and 2.2). This suggests that gender may not have significant relationship with the incidence of overreporting.

Figure 2.1
CCES 2014 Voters, Nonvoters and Over-Reporters by Age, Gender, Race & Ethnicity

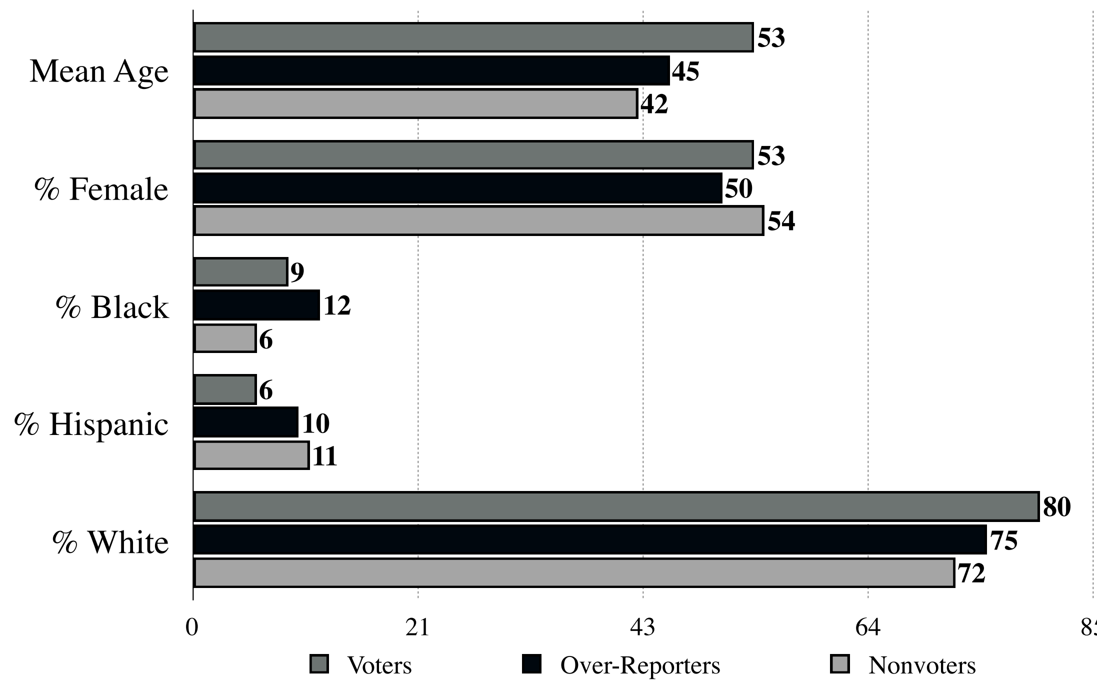


Note: Bars represent weighted percent of CCES validated voters, honest nonvoters and over-reporters in the 2014 midterm election by age, gender, and race and ethnicity.

Now, I summarize the distribution of race and ethnicity of individuals in the full samples of the 2014 and 2012 CCES studies before presenting the proportion of Whites, Blacks and Hispanics among voters, nonvoters and over-reporters. CCES respondents self-report their racial identity in the pre-election questionnaire having the opportunity to choose from multiple categories, including White, Black and Hispanic, even though this last category is an ethnolinguistic designation not a racial one. A total 11% and 9% of post election respondents self-identified as Black in the 2014 and 2012 CCES respectively, while Whites constituted a majority of respondents with 77% in 2014 and 78% in 2012. Because some individuals may identify themselves by both their racial and ethnic identity an additional questionnaire item follows the race question asking about Hispanic, Latino or Spanish identity or heritage. I use this follow up question to complement those who directly reported being Hispanic in the race question to better identify all Hispanics in the CCES. Having added both groups, 9% and 8% of all post election respondents self-identified as Hispanic in 2014 and 2012 respectively (See Appendix B).

The distribution of race among voters, nonvoters and over-reporters suggests that membership in different racial groups is associated with the rate of participation in elections and the likelihood of engaging in over-reporting among CCES respondents. Blacks made up a greater proportion of over-reporters in the CCES than voters and nonvoters. While 16% of over-reporters in 2014 were Black respondents, only 8% of voters and 13% nonvoters in that survey year were Black. In a similar pattern, 12% of over-reporters in the 2012 CCES identify as Black while 9% of all voters and 6% nonvoters also identified as Black. Over-reporters appear to be more similar to voters than nonvoters in 2014 and more similar to voters in 2012 (Figures 2.1 and 2.2). Over-reporting among Blacks was slightly higher in the 2014 midterm election, 16% overreported, than in the 2012, 13%. Fifty-three percent of Black post election respondents in the CCES went out to vote in 2014, while 75% voted in the 2012 presidential election. The higher rate of participation in the 2012 election among Black respondents could be attributed to co-racial mobilization caused by President Obama's running for re-election.

Figure 2.2
CCES 2012 Voters, Nonvoters and Over-Reporters by Age, Gender, Race & Ethnicity



Note: Bars represent weighted percent of CCES validated voters, honest nonvoters and over-reporters in the 2012 presidential election by age, gender, and race and ethnicity.

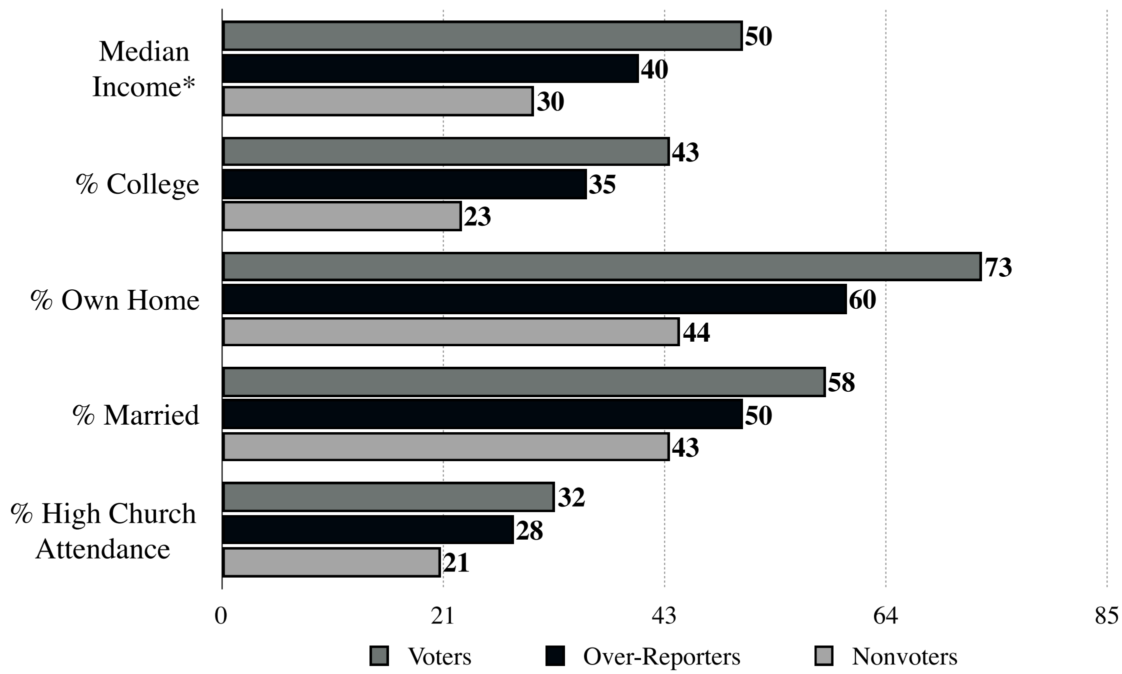
Hispanics comprise a grater proportion of honest nonvoters than over-reporters and validated voters in the CCES. In 2014, 15% of nonvoters, 13% of over-reporters and only 6% of voters were Hispanic (See Figure 2.1). The 2012 CCES presents a similar distribution with self-identified Hispanics amounting to 11% of nonvoters, 10% of over-reporters and 6% of voters (See Figure 2.2). Again, like with the comparison of the proportion of Black respondents, over-reporters were more similar to nonvoters than voters with regard to this pan-ethnic category. Turnout among Hispanics was substantially lower than that of Black respondents in the CCES, by 9 and 14 percentage points, with 44% of Hispanics going out to vote in 2014 and 61% in 2012. However, the rate of overreporting among Hispanics was similar to that among Black respondents differing by only 3 and 2 percentage points, with 13% in 2014 and 10% in 2012 of Hispanics overreporting turnout.

Because Whites constitute a majority of the respondents in the CCES they also constitute a majority of voters, nonvoters and over-reporters. Still, a noticeably larger proportion of validated voters were White when compared to the proportion of White respondents among nonvoters and over-reporters. Eighty-three percent and 80% of voters were White in the 2014 and 2012 CCES respectively, while 68% and 72% of honest nonvoters were White, and 69% and 75% of over-reporters. These statistics continue to show that over-reporters are more similar to nonvoters when it comes the distribution of race within those categories. The rate of overreporting among Whites was lower than that among Blacks and Hispanics in the CCES with 8% of Whites overreporting in 2014 and 9% in 2012. This suggests that being part of these two underrepresented groups in the United States, Blacks and Hispanics, is associated with a respondent's likelihood of overreporting turnout when answering political surveys. However, this does not mean that individuals from these groups are naturally more dishonest. My own past research shows that linked fate and shared identity with down ballot candidates could explain the higher incidence of overreporting among Black and Hispanic respondents.[10]

[10] In my paper "The Effect of Co-Ethnicity and Shared Race on Voter Turnout Overreports" presented at the 2015 Southern Political Science Association Annual Meeting in New Orleans I showed how shared racial and ethnic identity between Latino and Black respondents and their congressional candidates was a significant predictor of overreporting.

Socioeconomic Status, Marital Status and Church Attendance

Figure 2.3
CCES 2014 Voters, Nonvoters and Over-Reporters by
Socioeconomic Status, Marital Status and Church Attendance

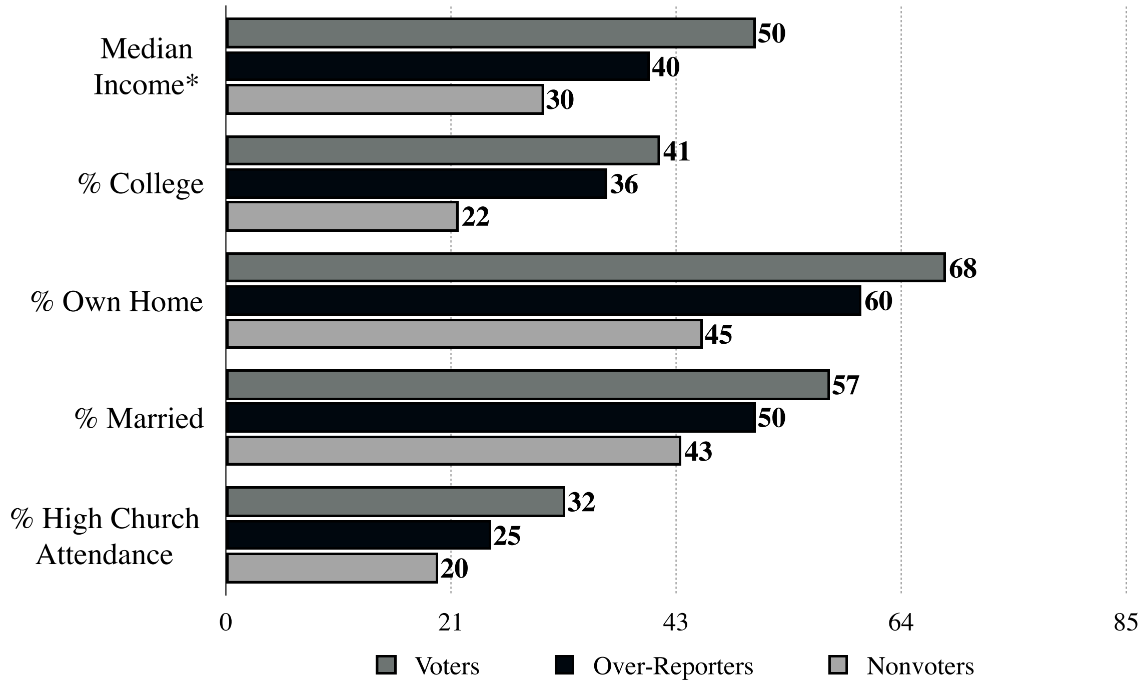


Note: Bars represent weighted percent of CCES validated voters, honest nonvoters and over-reporters in the 2014 midterm election by income, education, home ownership, marital status and church attendance. *Numbers are in thousands.

High levels of socioeconomic status in the form of education and income have been found to increase rates of participation in elections and political activity in general (Rosenstone & Hansen, 1993; Verba, Brady & Schlozman, 1995). Home ownership, marital status and religiosity have also been associated with varying levels of electoral turnout (Verba, Brady & Schlozman, 1995). However, income and education have been found to increase a nonvoter's likelihood of overreporting (Abramson & Claggett, 1984, 1986, 1991; Anderson & Sliver, 1986; Anderson, Silver, Abramson, 1988; Ansolabehere & Hersh, 2012).

Figure 2.4

CCES 2014 Voters, Nonvoters and Over-Reporters by
Socioeconomic Status, Marital Status and Church Attendance



Note: Bars represent weighted percent of CCES validated voters, honest nonvoters and over-reporters in the 2012 presidential election by income, education, home ownership, marital status and church attendance. * Numbers are in thousands.

The education questionnaire item in the CCES has six categories, four of which measure some form of college education attainment ranging from "some college" to "2 years" to "4 years" to "Post-grad." I combine these four categories into one that identifies all CCES respondents who have attended college or obtained a college degree. Thirty-eight and 37% of CCES respondents have gone to college, in 2014 and 2012 respectively (See Appendix B). The CCES asks its respondents to report "family income" instead of individual income, meaning the full income in the respondents' household. This survey item includes sixteen alternatives that represent a range of dollar amounts, for example the first alternative represents those with a family income of $10,000 or less and the sixteenth alternative represents those with $500,000 or more. Since this is not a continuous variable I cannot identify the true average or true median family income of voters, nonvoters and over-reporters in the CCES. Still, I can identify the the median family income category for each of the three subgroups of interest in this analysis.

I find that over-reporters are more similar to voters in their distribution of education attainment in 2014. Of course, a greater proportion of validated voters in both 2014 and 2012 have attended college, meaning they have "some college" education or received undergraduate and postgraduate degrees. Forty-three percent of validated voters in the 2014 CCES attended college, and 41% in 2012. Nonvoters had the smallest proportion of respondents who have attended college, as is expected, with 23% in 2014 and 22% in 2012. Over-reporters were closer to voters than nonvoters in the 2014 CCES with 35% having attended college, 8 percentage points less than voters and 12 more than nonvoters. Likewise, over-reporters in the 2012 CCES were more similar to validated voters. Over-reporters in 2012 differ from voters by only 5 percentage points, but differ from nonvoters by 14 percentage points in the proportion of respondents who have attended college (See Figures 2.3 and 2.4). This establishes a trend that suggests that higher levels of education attainment are related to an individual's likelihood of overreporting turnout in addition to the likelihood of turning out to vote.

I found distinct median income categories for over-reporters when in comparison with voters and nonvoters in both election studies under analysis. To be sure, family income is reported by respondents by choosing one alternative among a total of sixteen, alternatives represent a range of dollar amounts. Voters in both the 2014 and 2012 CCES surveys have higher family incomes than nonvoters and over-reporters having "$50,000 to $59,999" as their median category. Nonvoters had "30,000 to $39,999" as their median family income category, lower than that of voters and over-reporters. Finally, over-reporters fell between voters and nonvoters with “40,000 to $49,999” as their median family income category, making them distinct from voters and nonvoters in this respect (See Figures 2.3 and 2.4). Cleary, higher levels of socioeconomic status are related to the likelihood of participation of CCES respondents, but also the likelihood overreporting given non-participation.

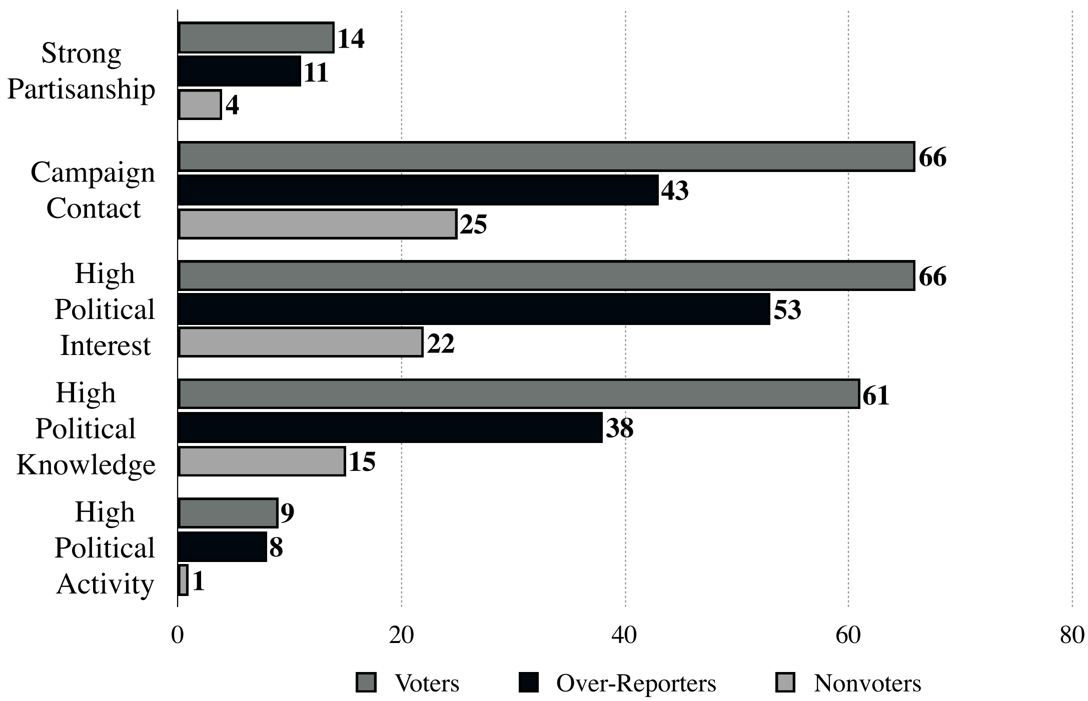
Having described the distribution of demographics characteristics of education and income I go on to describe the type of household that is dominant among voters, nonvoters and over-reporters. I focus on home ownership, marital status and religiosity, particularly the percent of respondents who owned their home, were married, and attended church “once a week” and “more than once a week,” all factors that have been found to be related to high levels of participation in politics (Rosenstone & Hansen, 1993; Verba, Brady & Schlozman, 1995). A majority of CCES post election respondents were homeowners with 65% in 2014 and 63% in 2012; most were also married, 54% in both 2014 and 2012. Still, 29% of CCES respondents in 2014 and 2012 report high church attendance (See Appendix B). However, there were very high rates of electoral participation among those in each of these categories. Seventy-four percent of homeowners, 71% of married respondents and 72% of respondents with high church attendance went out to vote in 2014. Somewhat higher rates of participation were found for 2012 CCES respondents in these categories; 79% of homeowners, 76% of married respondents and 73% of respondents with high church attendance. This increase of participation is to be expected in a presidential year election.

As the quantities above indicate, a larger proportion of voters should be homeowners, married and church goers. Seventy-three percent of voters in 2014 are homeowners and 68% in 2012. Over-reporters in 2014 and 2012 had the same proportion of homeowners among them (60%). Thus, the proportion of homeowners among over-reporters in 2014 and 2012 is closer to that among voters. Married respondents make up 58% of voters in 2014 and 57% of voters in 2012, while in both survey years 50% of over-reporters said they were married at the time, whereas 43% of nonvoters in 2014 and 2012 were married. Over-reporters are practically equidistant to voters and nonvoters differing 8 and 7 percentage points in terms of marital status in both election years. Finally, the proportion of respondents who have high church attendance among over-reporters differs with that among nonvoters by 7 and 5 percentage points in the 2014 and 2012, respectively. Also, the rate of high church attendance among over-reporters differs from that among voters by 4 percentage points in 2014 and 7 percentage points in 2012. Church goers in 2014 make up 32% of voters, 21% of nonvoters and 28% of over-reporters; and in 2012, they make up 32% of voters, 20% of nonvoters and 25% of over-reporters (See Figures 2.3 and 2.4). In this case, over-reporters are most similar to voters in 2014 and most similar to nonvoters in 2012 when it comes to church attendance.

Political Attitudes and Engagement

Partisan strength, campaign contact and political engagement can also affect an individual's likelihood of participation in elections. More specifically, persons who have strong opinions in politics tend to care more about the outcomes of elections which can influence their political behavior and how they answer political surveys. Also, individuals who are contacted by candidates, political campaigns and/or organizations tend to be more likely to participate in elections (Green, Gerber & Nickerson, 2003; Green & Gerber, 2015). Additionally, individuals who report high interest in politics, have high levels of political knowledge and already participate in politics are likely to be voters, because these characteristics indirectly measure political efficacy.[11]

Figure 2.5
CCES 2014 Voters, Nonvoters and Over-Reporters by
Partisan Strength, Campaign Contact & Political Engagement



Note: Bars represent weighted percent of CCES validated voters, honest nonvoters and over-reporters in the 2014 midterm election by campaign contact, high political interest, high political knowledge, and high political activity.

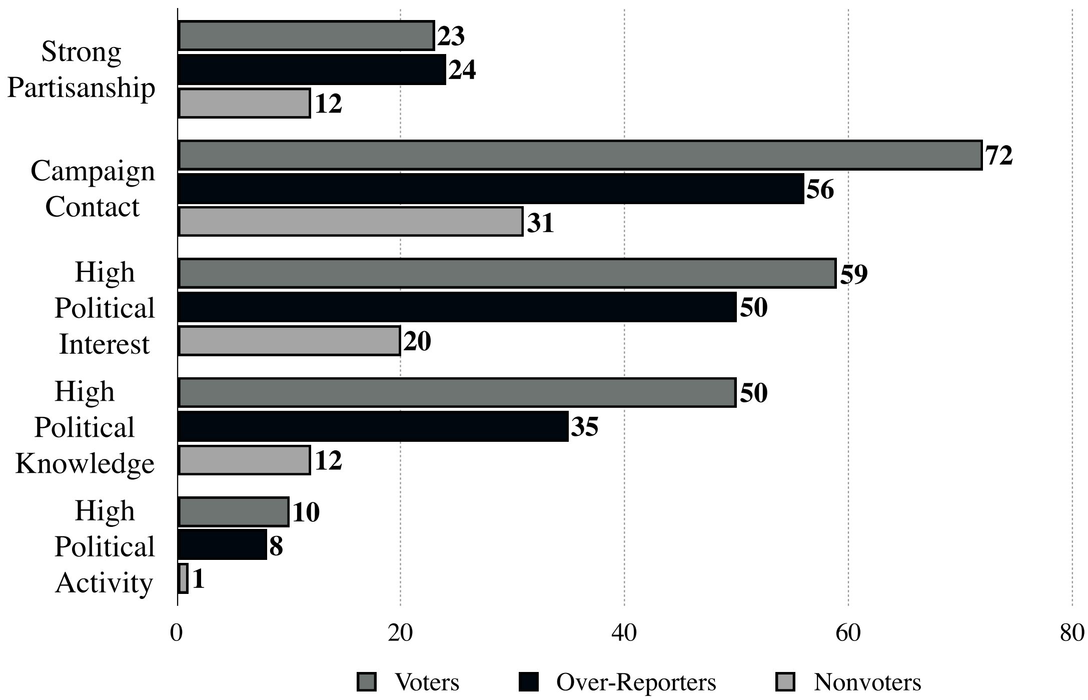
The CCES measures the strength of partisan identification with a 7-point partisanship question where respondents can place themselves along a spectrum that goes from “strong Democrat” to “strong Republican.” Together those who identify with either

[11] “In their landmark study, The Voter Decides (Campbell et al., 1954:18) the concept is defined as: “the feeling that individual political action does have, or can have, an impact upon the political process, i. e., that it is worth while to perform one's civic duties. It is the feeling that political and social change is possible, and that the individual citizen can play a part in bringing about this” (Balch, 1974).

one of these extremes are classified as strong partisans. In 2014, 12% of CCES post election respondents were strong partisans and 21% in the 2012 CCES (See Appendix B). Despite the smaller proportion among the respondents under analysis, rates of electoral participation among strong partisans were high in both 2014 and 2012, 82% and 79% respectively. More importantly, over-reporters appear to be more similar to voters with regard to strength of partisanship, differing from voters by only 3 percentage points in 2014 and 1 percentage point in 2012. Fourteen percent of voters in 2014 and 23% of voters in 2014 were strong partisans, while 11% of over-reporters in the midterm election and 24% in the presidential election were also strong partisans. Nonvoters have the smallest proportion of strong partisans with 4% in 2014 and 12% in 2012 (See Figures 2.5 and 2.6).

I measure political engagement with four variables 1) campaign contact, 2) interest in politics, 3) an index of political knowledge, and 4) an index of political activity. Fifty-three percent of all respondents in the 2014 CCES were contacted by a candidate or campaign, and 63% in the 2012 CCES. Additionally, 53% of CCES respondents in 2014 reported having high interest in politics, and 51% in 2012 (See Appendix B). The political knowledge index measures how many correct identifications a respondent can make of the party of their members of Congress, the majority party of the House of Representatives and that of the Senate. I use the values of 5 and 6 correct answers together to identify respondents with high political knowledge. They made up 46% of all CCES respondents in 2014 and 41% in 2012 (See Appendix B). The political activity index joins three questionnaire items from the CCES: 1) attending a local political meeting, 2) putting up a political sign and 3) working for a candidate or campaign. This index provides a count of how many of these political activities a respondent has performed, 7% of all post election respondents in 2014 and 8% in 2012 reported engaging in two or three (See Appendix B).

Figure 2.6
CCES 2012 Voters, Nonvoters and Over-Reporters by
Partisan Strength, Campaign Contact & Political Engagement



Note: Bars represent weighted percent of CCES validated voters, honest nonvoters and over-reporters in the 2012 presidential election by high political knowledge, contact by a candidate or campaign and high political activity.

Those with high levels of political engagement had higher rates of electoral participation in both 2014 and 2012. Eighty-one percent of respondents who experienced contact by a political campaign went out to vote in 2014 and 83% in 2012. Eighty-one percent of those who reported high interest in politics turned out in 2014 and 84% in 2012. Of those with high political knowledge 85% turned out in 2014 and 87% turned out in 2012. Those with high engagement in political activity had the highest rates of turnout with 84% in 2014 and 88% in 2012.

CCES respondents with high levels of political engagement tend to be more like voters than nonvoters overall. A greater proportion of voters reported having been contacted by political campaigns with 66% in 2014 and 72% in 2012. In this case, over-reporters are closer to nonvoters in 2014 with regard to the proportion of respondents who were contacted by a campaign. Forty-three percent of over-reporters in 2014 were contacted and 25% of nonvoters, a difference of 18 percentage points. In 2012, over-reporters were closer to voters than nonvoters. Fifty-six of over-reporters, 31% of nonvoters and as mentioned above 72% of over-reporters were contacted. With regard to high interest in politics over-reporters were closer to voters than nonvoters in both 2014 and 2012. Over-reporters in 2014 had a proportion of 53% high political interest respondents and 50% in 2012, while the proportion of among voters was of 66% in 2014 and 59% in 2012. A smaller proportion of nonvoters were respondents with high interest in politics with 22% both in 2014 and 20% in 2012.

Greater similarity between over-reporters and voters continues with regard to political knowledge and political activity. A substantial proportion of CCES validated voters have high knowledge about politics, 61% in 0214 and 50% in 2012. Only 15% of nonvoters in 2012 and 12% in 2012 have high political knowledge. Over-reporters are distinct in 2014, but closer to voters in 2012. Thirty-eight percent of over-reporters in 2014 and 35% in 2012 had high levels of political knowledge. Finally, small proportions of voters, nonvoters and over-reporters have engaged in high political activity. Only 9% of voters and 8% of over-reporters in 2014, and 10% of voters and 8% of over-reporters in 2012 engaged in high political activity, 1% of nonvoters in both survey years engaged in high political activity (See Figures 2.5 and 2.6)

How much Overreporting and by whom?

The Catalist vote validation data that accompanies CCES survey data provided for the precise measurement of the proportion of true voters, honest nonvoters and over-reporters in four studies. Description of the Catalist matching procedure along with high matching rates, and high overlap with matching provided by a second source indicate that vote validation can be very accurate and conducted with rigor. At the same time understating the how vote validation is implemented provides evidence to counter the arguments of those who question the accuracy of vote validation. This data also allowed for detailed analysis of the dominant demographics, political attitudes and levels of political engagement of voters, nonvoters and over-reporters. Over-reporters were most similar to voters than nonvoters, but this similarity was characterized by substantial gaps. Over-reporters were sufficiently distinct from both voters and nonvoters to suggest that turnout models that are based on self-reported turnout will result in biased results.

Overreporting of voter turnout is not only a possibility in political surveys, like the CCES, it is expected. The consistent rates of overreporting in four consecutive biennial CCES surveys supports the conclusion that overreporting regularly occurs in political surveys no matter the salience of the election during which they are conducted. Though the sampling frame of the CCES already results in higher rates of estimated turnout than those of official estimates overreporting also impedes the accurate estimation of turnout among survey respondents. Between 8% and 12% of post election respondents in the CCES over-reported their participation in the general elections of 2008 through 2014. Overall, overreporting occurred at quite similar rates in CCES samples. However, overreporting did not occur uniformly among CCES nonvoters with rates of overreporting that ranged from 19% to 42%. This suggests that measurement of overreporting is best performed by simultaneously identifying validated voters, honest nonvoters and over-reporters among all respondents within a survey sample.

Over-reporters hold similarities to voters and nonvoters on almost the same numbers of characteristics (See Table 2.5). They were most similar with voters on eight characteristics, particularly on education, homeownership, partisan strength, political interest and political activity. Additionally, over-reporters were most similar to voters with respect to campaign contact in presidential election, and with respect to Black racial identification in the 2012 presidential election. Over-reporters were most similar with nonvoters on seven characteristics particularly on the subject of age, White racial identification, Hispanic ethnicity, and church attendance. They were also most similar to nonvoters regarding campaign contact and Black racial identification in the 2014 midterm election, and most similar to nonvoters on political knowledge in the 2012 presidential election. Finally, those who overreport are distinct with respect to median income and marital status overall, but also distinct on the matter of political knowledge in the 2014 midterm. These simultaneous similarities of over-reporters with both voters and nonvoters show that overreporting should be recognized as a significant source of bias in the study of voter turnout. What's more, further study of overreporting is necessary to understand this phenomenon, chiefly on what is the cognitive mechanism through which overreporting occurs.

The findings in this chapter provide the scaffolding for the subsequent chapters in this dissertation. Having concluded that the measurement of overreporting must occur alongside the measurement of validated turnout and nonvoting indicates that regression modeling of overreporting should also occur along with modeling the probability of turning out to vote or not. I present a new approach to regression modeling of overreporting in the next chapter, and compare this new approach to past approaches. Furthermore, the conclusion that identification of the cognitive mechanism through which overreporting occurs is the basis for the fourth chapter in this dissertation.

Table 2.5 Similarity of Over-reporters with Voters and Nonvoters in the CCES along Demographics, Socioeconomic Status, Type of Household, and Political Factors

	More Like Voters	**More Like Nonvoters**	**Distinct**
Mean Age		✓	
% Female	✓		
% White		✓	
% Black	✓ presidential	✓ midterm	
% Hispanic		✓	
% College	✓		
Median Income			✓
% Homeowners	✓		
% Married			✓
% Church Goers		✓	
% Strong Partisans	✓		
% Campaign Contact	✓ presidential	✓ midterm	
% High Political Interest	✓		
% High Political Knowledge		✓ presidential	✓ midterm
% High Political Activity	✓		
Total	**8**	**7**	**3**

Columns indicate whether over-reporters in the 2014 and 2012 CCES studies are more similar to voters, more similar to nonvoters or distinct from both voters and nonvoters.

CHAPTER 3

MODELING VOTER TURNOUT OVERREPORTS

This chapter continues the task of engaging the debate of how to correctly measure overreporting, and directly addresses how to correctly model overreporting. Vote validation studies typically model the occurrence of voter turnout overreports using logistic regression analysis, a method that is most appropriate for use with dichotomous dependent variables. The most common dichotomous measurement of overreports restricts analysis to all respondents who are confirmed nonvoters and then identifies those who falsely reported that they turned out to vote. Studies that use this dichotomous measurement exclude validated voters from analysis, risk contamination with selection bias, and fail to recognize that respondents' underlying probability of participating in an election could influence their probability of reporting participation. Furthermore, dichotomous measurement of overreporting impedes comparison of over-reporters with both voters and nonvoters, a necessary task to determine whether overreports are likely to bias predictive models of self-reported turnout.

In Chapter 2, I proposed the simultaneous estimation of the proportion of over-reporters, voters and nonvoters in surveys, which allowed for comparison of all three subgroups across multiple demographic, social and political characteristics in descriptive inference. Now, I propose that statistical modeling of overreports should be implemented using multinomial logistic regression for a multi category dependent variable with three outcomes: 1) validated voters, 2) honest nonvoters, and 3) over-reporters. This research design includes all subgroups of interest, eliminates possible contamination with selection bias, and estimates both the probability of participation in an election and the probability of reporting participation.

I use 2014 and 2012 Cooperative Congressional Election Study (CCES) survey and Catalist vote validation data to measure and model overreports of voter turnout (Ansolabehere & Schaffner, 2014; 2012). I will compare dichotomous measurement to multi category measurement of overreports to examine whether different methods of measurement can affect descriptive inference. Then, I compare results from logistic and multinomial logistic regression analysis of overreporting to address the possible role of selection bias in the results of logit modeling. I will also compare plots of the marginal effects for all three outcomes in the 2014 and 2012 multinomial logistic models of overreporting. This will bring my discussion of the similarities between over-reporters and voters to a close.

Selection Bias

Selection bias in social science research occurs when the researcher does not select the observations under study independent of the outcome of interest, therefore selection is not random. When the observations under study are not randomly selected or are selected on the basis of a particular outcome, then statistical analysis can result in biased inference about social phenomena, in this case political phenomena. More specifically, the presence of selection bias in statistical modeling "yield[s] biased and inconsistent estimates of the effects of the independent variables" (Winship & Mare, 1992: p. 328) on the dependent variable. Selection bias in statistical modeling can cause the researcher to underestimate or overestimate the importance of a particular variable or set of variables in predicting an outcome.

Dubin and Rivers (1989)[12] illustrate the problem of selection bias using an example from political science: analysis of vote choice/preference. Most studies of vote choice would restrict their analysis to only voters, but nonvoters also have preferences. Excluding nonvoters from analysis leaves researchers with a self-selected sample that precludes them from observing “the relationship between demographic characteristics and political preferences in the population as a whole” (p.360). The authors explain that:

> “If turnout and preference are unrelated there should be no bias in estimating a model of preference based on the subsample of voters whose preference is observed. To the degree that there are common factors determining both turnout and preference, turnout is a source of selection bias” (p. 383).

More specifically, excluding nonvoters from analysis “is likely to produce misleading conclusions” (p. 383) about vote preference. You cannot make generalizations about vote preference to the whole population when you have restricted data analysis to a self-selected sample.

Selection bias is a potential problem with traditional logistic regression modeling of overreporting. Engagement in overreporting is dependent on whether a survey respondent participated or not in the election under study. Consequently, restricting statistical analysis of overreporting to the population of nonvoters within a survey, as Anderson and Silver (1986) suggest, does not account for the individual respondent’s probability of turning out to vote (or not) before estimating their probability of overreporting turnout. Logistic regression analysis of overreporting based on

[12] Dubin and Rivers (1989) also describe an example of selection bias in econometrics: “For example, in analyzing the relationship between schooling and earnings, we only have earnings data for those who are employed. Labor-force participation is voluntary. Some people choose not to work, others are unable to find work they considerable acceptable. The employed sample is unlikely to be a random subset of the entire population and there is no reliable way to impute earnings to those who are unemployed” (p. 361).

dichotomous measurements would provide estimates that are conditional on nonparticipation; therefore, those estimates could be contaminated with selection bias.

Selection bias is a topic of research in social science onto itself, particularly in the disciplines of economics and sociology (Berk, 1983, Heckman, 1990). Scholars of selection bias have affirmed that it is naturally occurring in social processes and that its presence should not deter scholars from conducting research, and they have developed models that correct for its effect on correlational analysis (Winship & Mare, 1992). Heckman's two-stage model is the most widely used approach for correcting selection bias. However, in the case of modeling the likelihood of overreporting this approach is not appropriate. Why? Because vote validation literature has demonstrated that factors that determine the likelihood of turning out to vote also more or less determine the likelihood of reporting turnout. And, Heckman's correction assumes that the factors that determine the outcome at the first stage are unrelated to the outcome at the second stage (Heckman, 1990), here participation versus nonparticipation at the first stage, then reporting participation versus reporting nonparticipation at the second stage.

A truly unbiased model of overreporting would include both voters and nonvoters, and would simultaneously estimate a respondent's probability of participating in an election and their probability of falsely reporting turnout. For this reason, I propose multinomial logistic regression as the correct approach for modeling overreports in order to exclude possible selection bias from the results. Multinomial logistic regression is used to predict the probabilities of the different possible outcomes of a categorical dependent variable with multiple categories that cannot be ordered in a meaningful way (Menard, 2002). With this method I can estimate the effect of traditional predictors of turnout on three categorical outcomes 1) voting, 2) nonvoting, and 3) over-reporting.

Measuring Overreports

I use 2014 and 2012 CCES survey and Catalist vote validation data to measure and model overreports of voter turnout in surveys. Again, the CCES is biennial large sample online survey that includes a pre election and post election wave questionnaire. The 2014 CCES had a little over 56,000 respondents and the 2012 CCES had approximately 54,500 respondents. During the post election wave these respondents are asked to report their registration status and whether they turned out to vote in the general election under study. In addition to these self-reports of registration and turnout the CCES includes vote validation conducted by the progressive political data firm Catalist. Self-reports and vote validation data allow for the identification of validated voters, honest nonvoters and over-reporters in both the 2014 and 2012 CCES.

I use the available self-report and validation data to compare the typical dichotomous measurement of overreports to my multi category measurement. Vote validation studies have implemented validity checks on reported turnout by various means, but there are two typical dichotomous methods of identifying overreports of voter turnout is survey research. The first and least common method identifies the proportion of actual nonvoters among all respondents who reported turning out to vote.[13] The second and most common method identifies the proportion of respondents who claimed to have turned out to vote among all nonvoters in a survey. In their essay "Measurement and

[13] This method is used in Chapter 4, because it is the most appropriate method for the analysis carried out there. Otherwise, the best practice is to estimate the proportion of validated voters, honest nonvoters and over-reporters among all survey respondents in a post election questionnaire.

Mismeasurement of the Validity of the Self-Reported Vote," Anderson and Silver (1986) argue that this second method of estimating the rate of overreporting turnout in surveys is the correct one. They maintain that this measurement reflects the true "propensity of respondents in a given survey to overreport voting" (p.771). Moreover, they propose that overreports should be estimated from the "population at risk" of overreporting, namely nonvoters. Here is their logic:

> "Voting is a socially desirable behavior. Many people who do not engage in this desirable behavior claim that they do, but almost no one who in fact performs this desirable behavior denies it. Since it is nonvoters who risk being socially stigmatized by failing to conform to the social norm, it is nonvoters who are the appropriate population at risk for calculating the extent of [overreporting]." (p. 775)

Table 3.1 Over-reporters Among Nonvoters in the CCES

CCES Survey Year	Total Nonvoters	Honest Nonvoters	Over-Reporters
2014	**14,065** **100%**	10,296 73%	3,769 25%
2012	**11,192** **100%**	7,116 64%	4,077 36%

Columns show weighted total and percent of nonvoters among CCES matched respondents by self-reported turnout to identify honest nonvoters and over-reporters.

This dichotomous mode of measurement affects descriptive inference concerning the incidence of overreporting in surveys. The rate of overreporting in the 2014 and 2012 CCES studies is of 25% and 36% respectively (See Table 3.1) when specified as false self-reports of turnout among nonvoters. Honest nonvoters are defined in this research as the sum of respondents who reported that they were not registered to vote in the post election wave of the CCES along with validated nonvoters and non-matched respondents who reported nonparticipation. Over-reporters are defined as validated nonvoters who reported that they definitely turned out vote. In the case of this definition of overreporting, there is a higher rate of overreporting among nonvoters during the presidential election than during the midterm election, differing by twelve percentage points. However, the multichotomous measurement of electoral participation and participation reports that I propose deflates the observed rate of overreporting in both CCES studies bringing the proportion of overreports among all post election respondents within one percentage point of each other, 9% in 2014 and 10% in 2012. The rate of overreporting is only slightly higher in the presidential election year study than in the midterm. As excepted there is a larger rate of turnout in the presidential election with 73% turnout in 2012, seven percentage points higher that in 2014. Here validated voters are all post election respondents with a confirmed record of voting. Evidently, simultaneous estimation of the proportion of validated voters, honest nonvoters and over-reporters provides a more complete picture of actual participation and reported participation than dichotomous measurement of overreporting.

Table 3.2 CCES Respondents by Vote Validation Status and Reported Turnout

CCES Survey Year	**Total**	**Validated Voters**	**Honest Nonvoters**	**Over-Reporters**
2014	**40,713** **100%**	26,648 66%	10,296 25%	3,769 9%
2012	**41,242** **100%**	30,050 73%	7,116 17%	4,077 10%

Columns show weighted total and percent by CCES year of validated nonvoters, nonvoters who honestly reported non-participation and validated nonvoters who overreported turnout. Percentages are rounded up to the nearest integer.

Modeling Overreports of Voter Turnout

Statistical modeling through the use of regression analysis allows researchers to describe the relationship between a variable of interest and a set of predictor variables. In this chapter, I seek to describe the relationship between overreporting turnout, the variable of interest, and traditional predictors of voter turnout, a set of predictor variables.

Descriptive inference in Chapter 2 allowed a comparison of voter, nonvoters and over-reporters across demographic, social and political characteristics that revealed somewhat greater commonalities between over-reporters and voters than with nonvoters. However, the need to estimate the effect that these factors have on predicting a respondent's probability of engaging in overreporting is not nullified by the identification of the dominant characteristics of over-reporters. Regression results can help researchers identify the key predictors of a certain outcome, like overreporting, and distinguish between the predictors of the outcome of interest and those of other outcomes, like voting and nonvoting.

Vote validation scholarship has engaged in statistical modeling of overreports using both Ordinary Least Squares (OLS) (Ansolabehere & Hersh, 2012[14]) and logistic regression analysis (Belli, Traugott & Beckman, 2001; Górecki, 2011; Brenner, 2012). Of course, OLS regression is not the most appropriate method to model overreporting because the dependent variable is often not continuous, and there is no assumption of a linear relationship between the dependent variable and its predictors.

Dichotomous methods of measuring overreports have determined the way overreports haven been statistically modeled in political science. The dependent variable is constructed as an indicator variable that assigns a value of zero (0) to honest nonvoters and a value of one (1) to over-reporters. Statistical models that use this dependent variable thus estimate the likelihood that a nonvoter reported turning out to vote instead of being honest about their nonparticipation. Logistic regression analysis is used when the outcome variable of interest is categorical, particularly for dichotomous variables like

[14] Ansolabehere and Hersh (2012) report results of logistics regression analysis in the appendix of their published article and OLS regression results in the body of the paper.

those usually used to estimate overreporting in the existing vote validation literature; therefore, most vote validation scholars model overreports using logistic regression analysis (Belli, Traugott & Beckman, 2001; Górecki, 2011; Brenner, 2012).

Nevertheless, I argue that dichotomous measurement is not the correct method for estimating the incidence of overreporting in a survey, nor is logistic regression analysis of overreporting the correct function for statistically modeling the relationship between overreporting and traditional predictors of voter turnout. I propose estimation of how the joint probability of being in one of three groups depends on thirteen (13) variables through multinomial logistic regression; the groups are validated voters, nonvoters or over-reporters. I create a categorical variable with three values going from 0 to 2 that represents each group. As I mention before, validated voters are all post election respondents with a confirmed record of voting. These respondents are given a value of zero (0). Nonvoters or honest nonvoters include all self-reported nonregistered respondents and all self-reported nonvoters, either matched or unmatched, and a given a value of one (1). Over-reporters are the reference category and are given a value of two (2); over-reporters are all post election validated nonvoters who self-reported turning out to vote.

I include thirteen independent variables in the predictive models of overreporting that I present in this chapter. These are the same thirteen demographic, social and political factors that where used in Chapter 2 for descriptive inference, and are all considered common predictors of voter turnout and political participation. Describing the size and significance of their effect on the likelihood of being an over-reporter is ultimately pertinent to discussing how overreports of voter turnout can bias predictive models of turnout.

I include three demographic variables that measure age, gender and race. These three factors have been identified as significant predictors of electoral participation in the past (Rosenstone & Hansen, 1993; Verba, Brady, Schlozman, 1995). It is a well know fact that the older a person is the more likely they are to participate in elections. Age is coded as a continuous variable generated from CCES respondent's reported year of birth. Subtracting the year in which the study was conducted from year of birth results in respondents' age, all CCES respondents are 18 years of age or older. Gender is measured with a dichotomous variable where female is the indicator (female=1, male=0). In the past, men where found to participate in politics that women, however, women now turnout to vote at higher rates than men. Race is also a dichotomous variable because white Americans generally turnout to vote more than all other non-white Americans. Self-identified white respondents were given a value of zero (0) and all other "non-white" respondents were given a value of one (1).

Resource models of turnout particularly emphasize the importance of socioeconomic status as something that can foretell whether an individual will turnout to vote or not. Family income and education are used here as indicators of socioeconomic status. Family income is a multi category variable with sixteen values where each category represents an income range; it starts with "less than $10,000" and ends with "more than $500,000." Education is a variable that measures CCES respondents' level of educational attainment with six category variable. Education categories include "no high school," "high school graduate" and four additional categories that measure differing levels of college education.

Additional social characteristics including homeownership, marital status and religiosity are also factors that American political science finds to be related to political participation. Here I code homeownership as a dummy variable where homeowners are given a value of one (1) and all other respondents including renters are given a value of zero. Marital status is represented as a dichotomous variable recoded from the "marital status" question where "married" is the indicator. Religiosity is measured with self-reports of church attendance, a variable with six categories. I recoded the original variable to give frequent churchgoing the highest value, described as "more than once a week" among the response alternatives.

Finally, I also include five political characteristics that are also traditionally related to voter turnout, these are: partisan strength, campaign contact, interest in politics, political knowledge and political activity. Strong partisanship is thought to be an indicator of how much a person cares about the outcomes of elections, something that can motivate individuals to participate in elections. I recode the seven-point party identification item from the CCES into a dummy variable where both strong Democrats and strong Republicans are given value of one (1) and all other respondents are given a value of zero (0). Campaign contact measures reception of mobilization efforts and pressure to participate; this is also a dummy variable representing contact (1) versus no contact (0).

The following three variables represent measures of self-motivated political engagement. Interest in politics seeks to asses how closely a CCES respondent follows what is happening "in government and public affairs." This variable has four values and was recoded to give following politics "most of the time" the highest value and "hardly at all" the lowest value. Political knowledge is a count variable that indicates how many correct identifications a respondent was able to achieve for six questions regarding partisanship of their corresponding federal and state level elected public officials in addition to identifying the majority party of each chamber of Congress at the time of the survey. Values for this variable range from 0 to 6. The last variable included in my model specification is political activity. This is also a count variable with values ranging from 0 to 3 that represents the number voluntary political activities a respondent carried out in the time preceding the election under study. The three activities are attending a local political meeting, putting up a political sign, and working for a candidate or campaign.

The existing literature on overreporting has found commonalities between the predictors of overreporting and those of voter turnout. I estimate statistical models of overreporting with two different, but comparable, probability functions using the above described independent variables. The results from these estimations demonstrate why multinomial logistic regression is the correct method for modeling overreports and why overreports are a source of bias in the prevailing literature on voter turnout.

Results

Figure 3.1 presents a visual representation of the estimated coefficients for the effect of the independent variables in the models on overreporting in two plots. These coefficients were estimated from multinomial logistic and logistic regressions that predict the probability of being an over-reporter in the 2014 and 2012 CCES. Again, the multinomial logistic regression estimates membership in three groups validated voters, honest nonvoter and over-reporters. The coefficients in the logistic and multinomial logistic regressions presented here are comparable estimates because they both show log odds of being an over-reporter versus and honest nonvoter, consequently no transformation needs to made to the raw results in order to make direct comparisons. At first glance both plots give the impression that the size and direction of the effect of each independent variable resulting from both methods are practically the same, and this is nearly the case. However, there are six instances in 2014, and other five instances in 2012 where the results from the logistic model differ from those the multinomial logistic model. Those cases include the effect of age, church attendance, political interest, political knowledge and political activity in 2014, and the effect of age, race, family income, political knowledge and political activity in 2012.

There are two contrasting results that standout in the models estimated for the 2014 CCES, the coefficients for non-white race and those for church attendance. In the case of the effect of non-white race on overreporting, the size of the effect was virtually the same, but the significance level is higher in the multinomial logit model than in the binomial logit model, a $p<0.05$ level and a $p<0.1$ level of significance respectively. Church attendance represents a more extreme case, where this variable is not a statistically significant predictor of overreporting in the logit model, but is a significant predictor in the multinomial logit model at the $p<0.05$ level. There are four variables for which the significance level of their effect on the probability of being an over-reporter is the same in both multinomial logistic and binomial logistic regression models in the 2014 CCES, significant at the $p<0.01$ level, but the size of their effect is somewhat larger in the logit model than in the multinomial logit model.[15] The differences between the results of the multinomial logit and binomial logit model of overreporting are even less apparent for the data from the 2012 CCES.[16] It is of note that while the dummy variable measuring the impact of non-white race on the probability of being an over-reporter was significant in both the logit and multinomial logit models for 2014 it is not a significant predictor in 2012, a factor that has been consistently found to be a key predictor of overreporting (Traugott & Katosh, 1979; Abramson & Claggett, 1984, 1986, 1981; Anderson, Silver & Abramson, 1988).

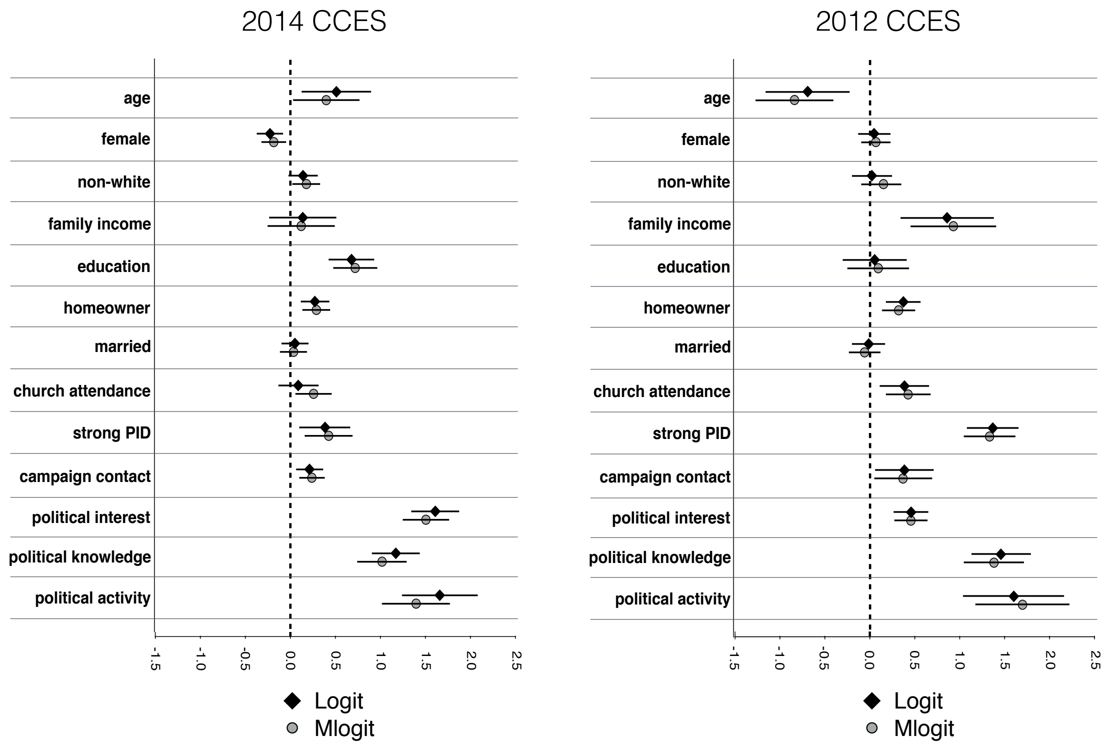
Though the differences between the estimates resulting from the proposed multinomial logit model and those from the traditional binomial logit model of overreporting in Figure 3.1 appear to be very small, the overall cumulative differences support my argument that logit modeling may be contaminated with selection bias. The shifts in the size and statistical significance of the effect of church attendance in the models for 2014 particularly evince how different modeling methods can impact the relationships observed between the outcome of interest and a set of predictor variables. Furthermore, the multinomial logit model ensures that selectivity is not a source of bias in statistical models that are meant to help us further understand the phenomenon of

[15] The coefficient for the effect of age in on predicting overreporting is greater in logit regression than in the multinomial logit regression differing by 0.112 decimal points. The effect of interest in politics is larger by in the logit model by 0.103 decimal points, that of political knowledge by 0.151 decimal points, and that of political activity by 0.260 decimal points (See Table A.3 in the Appendix). These differences are not significant.

[16] The effect of non-white race though not significant is 0.128 decimal points larger in the multinomial logit model. One factor, political knowledge, despite maintaining the same high level of significance in both models the coefficient in the logit model is 0.076 decimal points larger than that in the multinomial logit model. Also, three additional variables had substantially larger effects on the probability of overreporting in the multinomial logit regression then in the binomial logit regression while maintaining a $p<0.01$ level of significance. The coefficient for the effect of age is 0.145 decimal points larger, that of income is 0.069 decimal points larger, and that of political activity is 0.096 decimal points larger (See Table A.4 in the Appendix). These differences are not significant.

overreporting. Thus, even if large selection bias is not observed, it is still important to estimate the most correct model.

Figure 3.1
Coefficient Plots of Logistic and Multinomial Logistic Regressions
Predicting Overreporting in the 2014 & 2012 CCES

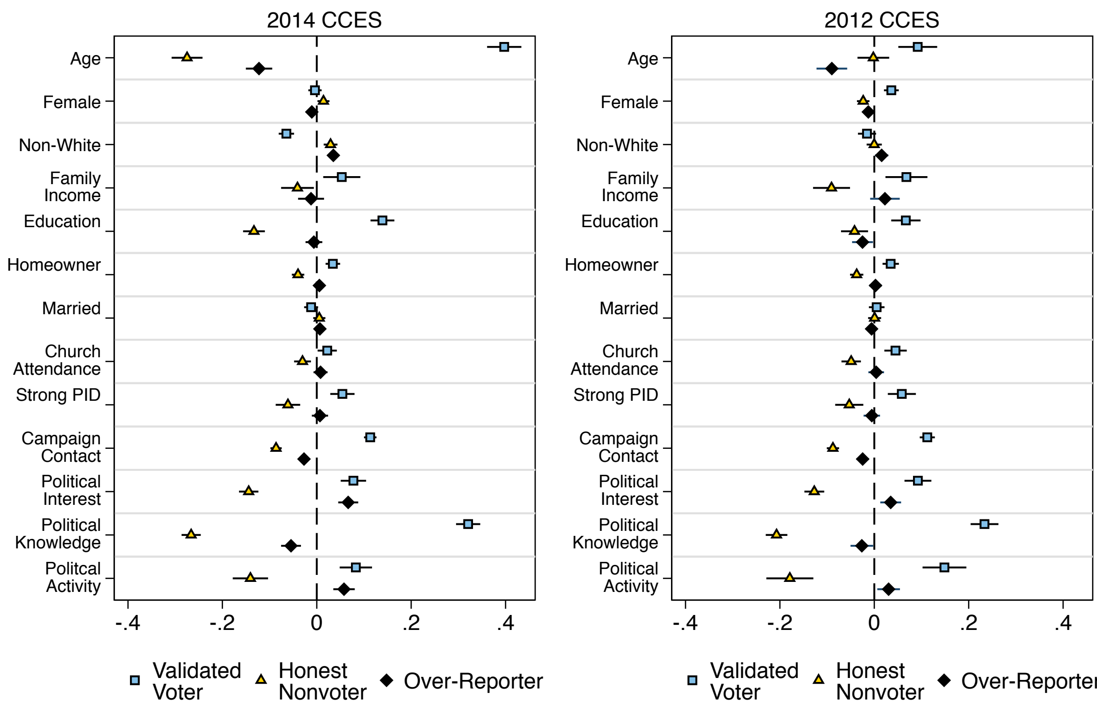


Note: Plots present the estimated coefficients with 95% confidence intervals from weighted logistic and multinomial logistic regressions predicting the probability of being an over-reporter in the 2014 and 2012 CCES.

The key predictors of becoming an over-reporter which are consistent across 2014 and 2012 can be identified in figure 3.1, these are: age (positive in 2014 and negative in 2012), homeownership, strong partisanship identity, campaign contact, interest in politics, political knowledge, and political activity. Five of these seven key predictors are political characteristics, which suggests that heightened awareness of the democratic norm of voting is at play in the incidence of overreporting. Moreover, this evidence supports the social desirability theory of overreporting articulated in this dissertation because heightened awareness and internalization of the social meaning of voting (Rolfe, 2012) is a clear motivation for falsely reporting turnout. Some other characteristics were impactful, but were impactful only either in the midterm 2014 CCES or impactful in the 2012 presidential year CCES. For example, female gender had a significant negative effect on the likelihood of overreporting in the 2014 CCES but not in the 2012 CCES. Also, non-white race and education had a positive significant effect on becoming an over-reporter in the midterm election but not in the presidential election. Family income and church attendance had positive and significant effects on the likelihood of overreporting in the 2012 CCES.

Figure 3.2 presents a graphical representation of average marginal effects for all three outcomes of becoming a validated voter, honest nonvoter and over-reporter in the multinomial logit regressions for the 2014 and 2012 CCES. The data points in both years show that over-reporters occupy a middle ground between voters and honest nonvoters. Still, the average marginal effects of the independent variables predicting membership among over-reporters follow a pattern that is most similar to that of the effects for nonvoters. Overall, the marginal effects for becoming an over-reporter are consistently closer to those of becoming a nonvoter in both survey years under study in five instances. The cases of consistent similarity between over-reporters and nonvoters across both survey years are age, non-white race, marital status, campaign contact and political knowledge. The same is true in only four instances where the marginal effects of becoming an over-reporter are closer to those of becoming a voter; these are: homeownership, church attendance, political interest, and political activity. What's more, in 2014 seven out of thirteen times results for overreporting are closer to those of nonvoting, and eight out of thirteen times in 2012.

Figure 3.2
2014 & 2012 CCES Multinomial Logistic Regression
Average Marginal Effects for Validated Voter, Honest Nonvoter and Over-reporter



Note: Plots show marginal effects with 95% confidence intervals for becoming either a Validated Voter, Honest Nonvoter or and Over-Reporter in the 2014 and 2014 CCES.

The fact that over-reporters occupy a middle ground between validated voters and honest nonvoters suggests that members of this group have a higher probability of going out to vote than that of honest nonvoters, but not high enough to make them go to the polls on Election Day. Moreover, the consistent similarity between the data points for over-reporters and nonvoters in Figure 3.2 show that overall survey researchers should not expect members of this group to turnout in the first place. Yet, the heightened underlying probability of turning out to vote among over-reporters could be one of the reasons why they falsely report participation in elections. As Ansolabehere and Hersh

(2012) explain, self-reports of turnout may actually be more representative of the population of those who think of themselves as voters rather than representative of those who are actual voters. This is to say, that despite being unlikely to turnout to vote, over-reporters seem to think of themselves as voters.

It is noteworthy that female gender has no importance to predicting turnout, nonvoting or over-reporting in 2014, though it is a significant predictor of turnout in 2012. Another interesting finding that regarding marital status, being married has no impact on any of the three outcomes predicted in the multinomial logit models for 2014 and 2012. At the same time, the are multiple factors that appear to be more impactful on the likelihood of being a validated voter and that of being an honest nonvoter than on probability of being an over-reporter. For example, family income has a greater influence on the likelihood of turning out to vote and that of nonvoting than on the likelihood of overreporting. More importantly, age, campaign contact, political interest, political knowledge and political activity are of import in predicting overreporting in both 2014 and 2012. These are the key predictors of overreporting turnout in the CCES.

Conclusion

The results presented in this chapter contradict any existing allegations that over-reporters are "just like voters" and that survey researchers need not be concerned with overreporting. Of course, if the traditional predictors of turnout had the same statistical relationships with the probability of voting and that of over-reporting, then research on the phenomenon of overreporting would not continue to be a relevant area of study today. The use of multinomial logistic regression modeling allowed for a comparison of the effects of these predictors on over-reporting, nonvoting and voting. Joint estimation of the probability of participation and that of reporting participation was necessary to identify the key predictors of overreporting, and to definitively demonstrate that over-reporters are a distinct group that shares characteristics with both voter and nonvoters.

Interestingly, the political characteristics included in the models were the most important factors in predicting overreporting. Campaign contact, political interest, political knowledge and political activity can all be considered indirect measurements of heightened awareness and internalization of the democratic norm of voting and its social meaning. This suggests that avoidance of social stigmatization for not participating in a socially desirable behavior like voting could be the cause of overreporting surveys. Furthermore, since over-reporters are not “just like voters” it is necessary to continue to study why overreporting occurs; more specifically, to identify what is the cognitive mechanism through which it occurs. The following chapter directly examines the social desirability theory of overreporting using new data and methods to detect deception in false reports of turnout.

CHAPTER 4

OVERREPORTING TAKES TIME

Overreports of voter turnout provide false information to survey researchers. A number of respondents present themselves as voters, when they are actually nonvoters, causing scholars of voting behavior to overestimate participation in elections. I demonstrated this trend in the second chapter of this dissertation by presenting rates of overestimation in the CCES using both aggregate and individual level data to show that overreporting occurs consistently in four consecutive biennial studies. In this fourth chapter, I examine the merits of the *social desirability theory of overreporting* outlined in the first chapter. I directly test the first implication drawn for the widely held assumption that overreporting is caused by socially desirable responding (SDR). That is, if overreports are caused by SDR, then they themselves are the result of deception on behalf of survey respondents. I also extrapolate conclusions from the analysis here presented regarding the second implication of the social desirability assumption of overreporting. That overreporting must be equivalent to one of two main types of SDR, impression management or self-deception.

Vote validation scholars, for the most part, have attributed overreporting to social desirability bias, but have focused almost entirely on measuring the incidence of overreporting, and identifying the individual level factors that make survey respondents falsely report participation in elections without seeking to further understand the deceptive nature of turnout overreports (Parry and Crossley, 1950; Clausen, 1968; Silver and Anderson, 1986; Katosh and Traugott, 1981; Karp and Brockington, 2005). Some scholars suggest that overreports are the result of memory failure and that survey respondents easily forget whether they voted or not (Adamany & Du Bois, 1974; Abelson, Loftus & Greenwald, 1992; Stocké & Stark, 2007; Belli, Traugott & Beckman, 1999; Belli, Moore & Van Hoewyk, 2006). Also, others argue that overreporting is an artifact of poor record keeping and not a result of misreporting, intentional or otherwise (Abramson & Claggett, 1992; Cassel, 2003 & 2004; Berent, Krosnick & Lupia, 2011 & 2016), even though Ansolabehere and Hersh (2010) have found that public registration and turnout record keeping throughout the United States has little to do with turnout overestimation in surveys. In spite of with these alternative explanations, most studies of overreporting suggest that SDR is the cause of this particular form of response bias. For this reason, this chapter is concerned with finding evidence to support, or refute, the assumption that social desirability bias is to blame for the phenomenon of voter turnout overreports.

SDR, a form of response bias in surveys, at its core has one fundamental purpose; it allows survey respondents "to give overly positive self-descriptions" (Paulhus, 2002: p. 50) regarding their attitudes and behaviors when answering questionnaires. Similarly, overreports of turnout help nonvoters present themselves in a positive light by appearing to fulfill the democratic norm of voting. Ultimately, the result of both overreporting and SDR is the collection of untruthful self-descriptions in surveys, which at the same time bias survey data. It seems obvious to assume that SDR is what causes overreporting because "the social meaning of voting is uncontested" and failing to participate in elections is a violation of a fundamental act of democratic citizenship (Rolfe, 2012). However, the literature on SDR provides methods for identifying social desirability bias in association with particularly sensitive questions, and political scientists should never leave things to conjecture. Moreover, if the goal is to create more accurate measurements of turnout based on self-reports researchers must understand whether overreporting is actually associated with SDR, and, if so, whether overreporting fits one of the two main types of SDR. The first type, *impression management* is "the tendency to give favorable self-descriptions to others", and the second, *self-deception* is "the tendency to give favorably biased but honestly held self-descriptions" (Paulhus & Reid, 1991). These two types of SDR differ mainly in intentionality, one is intentional other-deception while the other is unconscious self-deception.

Having said that, how can one empirically determine whether overreports are tantamount to responses born from deception? I borrow methods and frameworks from the lie detection and deception literature to ascertain the deceptive nature of overreporting. Response latencies, the time it takes to answer a question in a survey, have proven to be helpful indicators in detecting deception, and cognitive social psychology has found a consistent causal link between deceptive responses and lengthier response times (Mayerl et al., 2005; Vendemia, Buzan & Green, 2005; Verschuere et al., 2011; Walczyk et al., 2003; Walczyk et al., 2009). Additionally, self-deceptive responses have been found to have similar response latencies to those of honest responses, while other-deceptive responses have significantly longer latencies than both self-deceptive and honest responses (Holtgraves, 2004).

The research question in this chapter is: Does overreporting turnout require higher cognitive effort manifested as lengthier response latencies for the vote self-report question? I answer this question by using response latency data from the 2012 and 2014 CCES to measure the cognitive effort it takes to report turning out to vote. I use the

Catalist voter file data included in the CCES to identify over-reporters and carry out Ordinary Least Squares (OLS) regression analysis to estimate the effect of overreporting on response latencies. Results show that response latencies associated with the vote self-report question are significantly longer among over-reporters than among validated voters who honestly report participation. Higher levels of cognitive effort in turnout overreports evinces the intentionality of these false responses and supports the notion that overreports are the result of SDR. I also address the possible role of memory failure as the source of lengthier response latencies.

Response Latencies and Deception

Response latencies measure the time it takes individuals to answer individual questions within surveys. Researchers can use these measurements as indicators of "the information processing involved in answering survey questions" (Mulligan et al., 2003: p. 292). In other words, response latencies signal the level of cognitive effort involved in responding to questionnaire items. Mayerl (2013) explains that "response latencies are used as a proxy measure of spontaneous versus thoughtful responses" (p. 2), and that some response effects, like SDR, require high cognitive effort resulting in longer response latencies. Political science has most often used response latencies to test relationship between the speed of answers and strength of attitudes (Huckfeldt & Levine et al., 1999; Huckfeldt & Sprague et al., 2000; Mulligan et al., 2003; Burdein et al., 2006). Though political science has not used response latency measures in relation to reports of political behavior, cognitive social psychology has well established that deception reliably increases response latencies when answering multiple question types

(Mayerl et al., 2005; Vendemia, Buzan & Green, 2005; Verschuere et al., 2011; Walczyk et al., 2003; Walczyk et al., 2009).

Why does deception increase response latencies? Telling the truth is easier and deception/lying is more cognitively taxing because truth telling is the human default. Again, lying results in longer response times because lying requires more thought processing, while truth telling is spontaneous. Verschuere and colleagues (2011) demonstrated that the human default is truth telling in an experiment using a design similar to that of the Implicit Association Test (Greenwald, McGhee & Schwartz, 1998). Subjects were assigned to two treatment conditions, frequent truth and frequent lie, and a control condition. The control condition required equal proportions truth and lie responses. Participants were instructed to answer yes/no questions that appeared on a computer screen by hitting two keys on a computer keyboard, one key for a "yes" response and one for a "no" response. The color in which questions appeared on the screen indicated whether they were to lie or not. They found that respondents in the "frequent truth condition" had significantly longer response latencies for responses that required them to lie. That is, while the average response latency for truth responses under this condition was approximately 1.35s the average for their lie responses was of approximately 1.70s, a difference of 0.35s. More importantly, they found a significant difference between truth and lie response latencies in the control condition. Their average truth response latency was of approximately 1.55s while their average lie response latency was 1.75s, a difference of 0.20s. That deceptive responses had lengthier latencies in the control condition indicates that under normal circumstances we can already expect deception to result in increased response latencies.

The Activation-Decision-Construction model (ADCM) is a cognitive model of deception that maps the process and structure of lying (Walczyk et al., 2003). This model explains why providing deceptive answers should take longer than answering honestly, arguing that deceptive responses involve three cognitive events. First, there is an activation component where the respondent receives the stimuli, meaning the question is read or heard, which activates information stored memory. The second event involves the decision to lie or not, whether or not to report the information activated in memory. Then third, once the respondent has decided to deceive, they must construct the lie. Hence, engaging in these three cognitive processes has a direct effect on increasing the time it takes to answer a question.

In their study, Walczyk and colleagues (2003) conducted two experiments. The first had two experimental conditions where participants were either instructed to answer honestly or lie when asked factual yes/no and open-ended questions. This experiment was designed to asses the effect of memory activation and response construction on response latencies. Participants in the lie condition had response times that were an average 0.23s longer for yes/no questions and an average 0.23s longer for open-ended questions than those of participants in the truth condition. The second experiment included a third condition where participants were instructed to answer honestly except when asked questions they "might normally lie about if asked by a stranger" in order to asses the decision component of lying. Results show that participants freely deciding to lie on sensitive questions had an average response latency that was 0.15s longer for yes/no lies and 0.34s longer for open-ended deceptive responses. This means that the mere decision to lie results in an increase in the length of response latencies.

Memory Failure and Turnout Overreports

Multiple vote validation studies explore the role of memory failure in augmenting the incidence of turnout overreports in surveys. Belli, Traugott and Beckman (2001) state that “it has yet to be firmly established whether respondents are being intentionally deceptive or whether the misreporting is due to memory confusion about one's actual voting behavior in the most recent election” (p. 494). They argue that both cognitive factors, social desirability bias and memory failure, can be involved in the occurrence of overreporting. In a previous paper, Belli and Traugott (1999) along with other scholars find that overreporting “is predicted to become more pronounced with increases in elapsed time between the election and the interview” (p. 93). More specifically, they find that overreporting increases from the first week to the second week after the election and state that this finding is evidence that memory failure is one of the cognitive processes at play. What’s more, Belli, Moore and Van Hoewyk (2006) propose “that these two processes [social desirability and memory failure] operate concurrently when a respondent is queried about their voting behavior” (p. 752). The cognitive effort demanded by searching one’s memory of a particular event, like voting in an election, might grow as the time elapsed from the event itself also grows in addition to the increased effort generated by social desirability concerns. Consequently, the time it takes for respondents in a survey to report whether they voted or not in an election could increase the further away from the election the interview is conducted.

Expectations

I apply the ADCM model and the memory failure perspective to analysis of self-reports of turnout and in doing so set expectations for the effect of overreporting on the response latencies associated with the turnout question. When respondents are asked whether they went out to vote in an election their memory is activated, and information about participation or non-participation will become available in their minds. Increases in the time elapsed between the election and the survey administration will slow the process of searching for memory of the event. Individuals who actually went out to vote will have little incentive to lie, so they will use the memory of voting to report participation, and nonvoters will decide whether to lie about going out to vote. Once they have decided to be deceptive having chosen to present themselves to the researchers as voters they will falsely report that they "definitely voted in the General Election." Those who choose to be honest about their non-participation will go on to make an honest report.

The turnout question provides a closed set of response alternatives; this eliminates the need to engage in the third cognitive process of lie construction outlined by the ACDM model. Necessarily, survey respondents who overreport turnout should have longer response latencies than those who honestly report participation because the decision to deceive, on its own, has been found to lengthen response times.

Nevertheless, the ADCM model does not account for self-deception. Self-deceptive answers do not fit this model, but the literature on SDR provides a framework that fills this gap. Using an experimental design and response latencies Holtgraves (2004) found that socially desirable responses take longer than honest answers, but that "…participants scoring high on the trait of self-deception were generally faster at making these judgments [deciding whether to lie or not] than participants scoring low on self-deception" in the Self-deception Scale of the Balanced Inventory of Desirable

Responding.[17] Consequently, self-deceptive responses should emulate the ease of providing honest answers, because respondents who engage in this type of SDR believe they are responding honestly to survey questions when making an inaccurate report.[18] Response latencies of self-deceptive responses should not be significantly different from the response latencies associated with honest responses. Thus, finding a significant difference between the response latencies of accurate and false turnout self-reports would show that overreports are likely associated with intentional other-deception.

Data and Methods

I test my hypotheses using the 2012 and 2014 CCES surveys (Ansolabehere & Schaffner, 2013; 2015a), which I already describe in Chapter 2 along with the Catalist vote validation matching process, these are the only CCES datasets with that include response latency data. It is worth repeating that these studies have 54,535 respondents in 2012 and 56,200 respondents in 2014, and include both a pre-election and a post-election questionnaire that are administered in close proximity to the election. The pre-election questionnaire asks respondents about their political attitudes regarding a wide range of issues and about their vote preferences in the up coming election. The post-election has a shorter set of items asking mostly about voting behavior and vote choices in the election that just occurred. Additionally, there is vote validation data regarding both registration and participation of its respondents in the corresponding General Election of the year the survey was conducted. Using data from an online self-administered survey like the CCES

[17] In 1984 Paulhus developed the Balanced Inventory of Desirable Responding (BIDR) to assess individual differences in SDR by including an Impression Management Scale and a Self-Deception Scale in survey instruments.

[18] For example, in episode 102 of the TV show Seinfeld, Jerry gets into a situation were he has to take a polygraph. When Jerry asks George Costanza for advice on how to beat the lie detector test George says: "Jerry, just remember. It's not a lie… if you believe it."

constitutes a hard case for finding any social desirability effects on voter turnout self-reports because online surveys have been found to increase report of sensitive information and reduce the rate of socially desirable responses to sensitive questions (Kreuter et al., 2008).

The analysis in this chapter will be focused on respondents who said they "definitely voted" in the General Election of 2012 and 2014. In order to create more accurate response latency measures I have created subsets of these two datasets. First, I eliminate from my analysis all respondents who were not matched to the Catalist voter file for a total 43,342 in the 2012 CCES and 39,415 matched respondents in the 2014 CCES. Second, I exclude all remaining respondents from the state of Virginia because this state does not make records of participation in elections publicly available, reducing the sample to 42,158 for 2012 and to 38,392 for 2014. Finally, I keep only those who said they "definitely voted in the General Election," making the final total for analysis a sample of 32,846 for the 2012 CCEs and 29,424 for the 2014 CCES (See Table 4.1).

Table 4.1 CCES Respondents by Match Status and Self-Reported Turnout

CCES	Total Sample	Matched Respondents	Matched Respondents Who Reported Turnout
2012	**54,535**	42,158	32,846
2014	**56,200**	38,392	29,424

Weighted total of 2012 and 2014 CCES respondents, Catalist matched respondents, and matched respondents who reported they "definitely voted" in the General Election.

The vote self-report question is the second question presented to participants in the CCES post-election survey right after being asked whether they are registered to vote or not, which is a prerequisite for being presented with the vote self-report question.[19] Respondents who gave the same response to the same vote self-report question, but were found to be either honest or deceptive in their answer are the best comparison groups for the analysis of response latencies and the detection of intentionality in deceptive answers. Honest nonvoters are not included in this analysis because question construction has been found to affect response latencies (Yan & Tourangeau, 2007; Mayerl, 2013). The CCES uses similar question wording could increase the cognitive load of reporting non-participation because honest nonvoters must choose between four alternatives, while those who choose to report participation have only one alternative to do so (See Image 4.1). Here in lies the logic for keeping only respondents who self-reported turning out to vote.

Image 4.1
CCES Vote Self-Report Question Wording

Which of the following statements best describes you?

I did not vote in the election this November.
I thought about voting this time, but didn't.
I usually vote, but didn't this time.
I attempted to vote but did not or could not.
I definitely voted in the General Election on November 6.

[19] Though studies have found that overreporting also occurs in relation to voter registration (Fullerton, Dixon & Borch, 2007) this topic is outside the scope of this current research. In total, 88% of 2012 CCES post-election participants reported being registered to vote and 94% in 2014, while only 85% and 92% had validated records of voter registration.

Having described the subjects included in this analysis I turn to the description of the data used to measure response times associate with the vote self-report question. Since the CCES is an online survey, part of the available data is the measurement of the time it takes for each individual to answer the survey. Every question or group of questions in the CCES pre-election and post election questionnaires has a unique page within the online survey. YouGov, the polling firm that administers the CCES survey, tracks how much time it takes for each respondent to move from one question to the next in seconds and milliseconds. In essence, page timing data is measuring the period during which the survey question becomes visible to the respondent, the respondent reads the question, formulates an answer, makes a report and then moves on to the rest of the survey. These page timing measures are unobtrusive to the respondent because it is a feature embedded into the online survey instrument and respondents are unaware it is happening.

It is noteworthy that respondents to the CCES self-administer the survey and have no limits to the length of time they can take to answer the full survey. What’s more, Schaffner and Ansolabehere (2015) in their study of distractions during survey administration found that 45% of respondents in the CCES 2010-2014 Panel Study said they engaged in activities like doing chores, taking a break, dealing with children, and talking on the phone, among others. As a result, there certainly are outliers having extremely long response latencies within the page timing data of the CCES. They also find that these frequent distractions and interruptions during the completion of the survey do not affect the quality of the data collected by the CCES. However, latencies of minutes, hours or even days cannot be used as valid measurements of cognitive effort for single answer questions in surveys. Consequently, I implement trimming of page timings to create a more accurate assessment of respondents' thought process when answering the vote self-report question (Ratcliff, 1993).

Table 4.2 CCES Vote Self-Report, Placebo and Baseline Page Timings

CCES		Vote Self-Report Timing	Placebo/Party Id Timing	Baseline Timing
2012	**Mean**	**9.270s**	**5.218s**	**6.782s**
	Min.	0.658s	0.678s	2.076s
	Max.	24.601s	15.489s	15.488s
2014	**Mean**	**9.682s**	**4.620s**	**6.925s**
	Min.	0.292s	0.551s	1.688s
	Max.	27.920s	14.161s	16.299s

Weighted mean for three (3) page timing measures: vote self-report timing, party identification timing, and baseline timing in the 2012 and 2014 CCES for respondents who said they "definitely voted in 2012 and 2014. Baseline is the calculated average timing from items presented in Table 2.

The vote self-report question has its own unique page in the survey, meaning the page timing data for this question measures response latencies for this question alone. Trimming strengthens the validity of any inference made regarding the connection between response latencies and intentionality of deceptive answers (Fazio, 1990; Ratcliff, 1993; Mayerl, 2013). I trim the dependent variable, the vote self-report page timing, by eliminating all values above the 95th percentile.[20] This page timing measure has a mean of 9.270s and 9.682s, in 2012 and in 2014 respectively (See Table 4.2). Before trimming, the vote self-report page timing had a mean of 15.680s in 2012 and a mean of 23.692s in 2014. The first column of plots from the left in Figure 4.1 shows the distribution of observations for the vote self-report timing after trimming and includes a reference line indicating the mean timing for this question. The plot reveals higher frequencies around

[20] Total trimmed = 1,411 observations in the 2012 CCES and 1,039 observations in the 2014 CCES.

the 6 second mark for reporting turnout with fewer observations the higher the response timing becomes.

According to the social psychology literature, the ideal design for the analysis of response latencies includes a control measure of baseline response speed (Fazio, 1990; Mayerl et al., 2005; Mayerl, 2013). This baseline is commonly operationalized as the calculated mean of response latencies of filler questions, meaning questions unrelated to the item of interest. Baseline response timing "controls for a wide range of disturbing factors", like age and question construction, and is necessary for the proper interpretation of response latencies "as a proxy measurement of mental processes" (Mayerl, 2013: p. 4). This measure on its own shows us how long it typically takes each individual in the study to answer questions of similar construction to that of the item of interest, in this case questions similar to that of the vote self-report. But in statistical modeling, including baseline timing as a control allows for the detection of differences in response times to the turnout question controlling for typical individual response latencies.

Table 4.3 CCES Questions Used to Create Baseline Timing

Question	2012 Mean Timing	2014 Mean Timing
All things considered, do you think it was a mistake to invade Iraq?	7.263s	8.491s
Would you say that OVER THE PAST YEAR the nation's economy has...?	8.409s	9.470s
Did a candidate or political campaign organization contact you during the 2010 election?	6.854s	7.233s
Have you ever run for elective office at any level of government (local, state, or federal)?	5.204s	5.421s

CCES question wording for page timings used in the baseline timing measure and weighted mean timing (after trimming) for respondents who were matched to the Catalist voter file and said they "definitely voted" in 2012 and 2014.

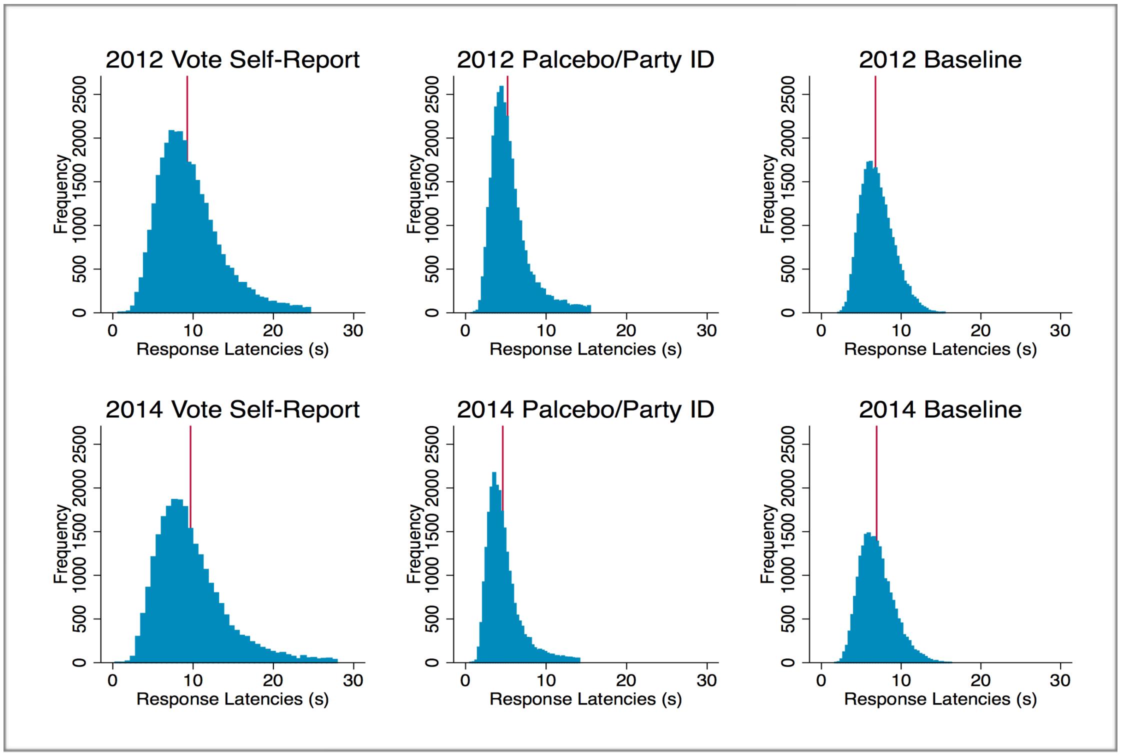
Table 4.4 Reported Voters by Week of Survey Administration

Week of Survey Administration	2012 CCES	2014 CCES
1	7,048 22%	11,417 39%
2	19,349 59%	10,483 36%
3	4,183 13%	3,794 13%
4	1,938 6%	3,514 12%
5	328 1%	216 0%
Total Reported Turnout	**32,846 100%**	**29,424 100%**

Weighted total of matched respondents who said the "definitely voted" by time elapsed for the day after Election Day measured in weeks (7 days).

I use the mean of page timings for four single-answer questions with similar construction to that of the vote self-report question, two from the pre-election and two from the post-election questionnaires in both CCES surveys (See Table 4.3). I apply the same trimming technique I used with the dependent variable, vote self-report timing, to the individual times included in the baseline timing by eliminating all observations above the 95th percentile. Since the CCES allows respondents to skip through questions some of the times included in the baseline timing have values of zero seconds. These values of zeroes seconds represent non responses which I also trim from the individual items included in the baseline. Trimming creates a total of 6,797 missing observations in the 2012 CCES model, and 3,714 missing observations result from trimming the times in the baseline for the 2014 CCES model. The mean of the baseline timing for 2012 CCES respondents who answered the vote self-report question is 6.782s and 7.654s for those in the 2014 CCES (See Table 4.3). The distribution of observations for the baseline has a similar shape to that of the vote self-report timing, however, higher frequencies are found closer to the mean when compared to the distribution of the vote self-report timing (See Figure 4.1).

Figure 4.1
CCES Page Timing Distribution of Vote Self-Report, Placebo and Baseline



As I mention above the CCES is conducted in close proximity to Election Day, suggesting that it is unlikely that respondents forget whether they went out to vote or not. Still, vote validation studies have found that memory is a cognitive factor in the incidence of overreporting in survey (Belli, Traugott & Beckman, 1999; Belli & Traugott, 2001; Belli et al. 2006), which demonstrates that time elapsed between the election and the moment of survey administration may affect response latencies for the vote self-report question. The post-election wave started to be administered to respondents the day after the General Election, November 7th in 2012 and November 5th in 2014. Using the date in which respondents started post-election wave I determined whether respondents who said they "definitely voted" answered the question in within the five (5) weeks following the election to measure time distance from the election. The variable indicates whether respondents started to respond to the post-election questionnaire in the 1st week after the election or the 2nd week and so forth until the 5th week after the election. I use the start date of the post-election wave of the CCES because the turnout self-report question is the second item in the questionnaire. Additionally, trimming of extreme values from the page timings of the turnout self-report question increases the certainty that this question was answered during week for which it is coded. Table 4.4 shows that the bulk of self-reported voters started to respond to the CCES question in the first two weeks of the election. Though "week of administration" may not affect those who participated early on it might significantly affect response latencies for those who participated later on.

Table 4.5. CCES Voters and Over-reporters among Reported Voters

	2012 CCES	**2014 CCES**
Total Respondents Who Reported Turning Out to Vote	**32,846** **100%**	**29,424** **100%**
Validated Voters	28,852 88%	25,739 87.5%
Over-reporters (Validated Nonvoters)	3,994 12%	3,685 12.5%

Weighted total and percentage of 2012 and 2014 CCES respondents who were matched to the Catalist voter file and reported they "definitely voted" in the either the 2012 or 2014 General Election by vote validation status.

The OLS regression models in the following section include only four variables, three of which I have described in detail above. The dependent variable of interest is the vote self-report page timing or response latency, the control variable in the model is the baseline page timing, and the variable for week of survey administration measures the effect of memory. The independent variable is a dummy that distinguishes between self-reported voters who actually went out to vote, validated voters, and those who did not, over-reporters. Self-reported voters who are validated voters were given a value of zero (0) and self-reported voters who are validated nonvoters or over-reporters were given a value of one (1). A great majority of those who reported voting in the both 2012 and 2014 are validated voters, meaning most of those who said they voted when answering the CCES actually voted. However, in 2012 12% of those who said they definitely voted are validated nonvoters and 12.5% in 2014; that is, 3,994 respondents overreported turnout in the 2012 CCES and 3,685 in 2014 CCES (See Table 4.5).

Results

Table 4.6 2012 CCES OLS Model for Vote Self-Report and Placebo Timing by Overreporting

2012	Vote Self-Report Response Timing	Party ID Response Timing
Overreporting	0.325*** (0.118)	-0.212*** (0.0579)
Week of Admin.	0.0177 (0.0362)	0.0340 (0.0219)
Baseline Response Timing	1.037*** (0.0198)	0.502*** (0.0119)
Constant	1.909*** (0.143)	1.629*** (0.0921)
Observations	**26,737**	**26,410**
R-squared	**0.320**	**0.214**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 4.6 and 4.7 show the results of OLS regression modeling to test whether response latencies for vote self-report question are significantly longer when delivered by over-reporters than when delivered by validated voters. Overreporting turnout out in the both the 2012 and 2014 General Election results in a significant increase in the length of response latencies for the vote self-report question; that is, overreporting turnout involves a significantly increased level of cognitive effort than honest reports of turnout. Moving from honest reports of turnout to false reports results in an increase of 0.325 seconds in 2012 and 0.733 seconds in 2014, or between approximately 3 tenths and 7 tenths of a second in the length of response latencies of self-reported turnout controlling for baseline timing and week of survey administration (See Tables 4.6 and 4.7). This effect is comparable to results found in the literature on lie detection where most studies reported average response latency increases of between 0.20s and 1s for deceptive answers in experimental settings. With a mean response latency of 9.270s for the vote self-report question in 2012 (See Table 4.1), overreporting turnout would increase that timing to 9.325s; and with a mean of 9.682s in 2014 overreporting turnout would increase that timing to 10.415s, a substantial increase.[21]

The significant positive relationship between overreporting and its corresponding response latencies suggests that overreports are in fact deceptive responses because falsely reporting participation requires higher cognitive effort than honest reports. Response latencies are also helpful in determining intentionality in overreporting. Social psychology studies of deception show that deceptive responses require more cognitive effort than honest responses then leading to longer response times; however, self-deceptive responses have shorter response latencies and look more like honest answers. Consequently, the finding that overreports cause a significant increase in response

[21] Please note that the response latencies or page timings in the CCES include the complete process of reading the survey question and providing an answer while most of the cited experiments only include the latency recorded after being read the question. For this reason, response latencies in this current study will be noticeable longer that those in past studies.

latencies of turnout self-reports suggests that nonvoters who overreport do so intentionally.

Table 4.7 2014 CCES OLS Model for Vote Self-Report and Placebo Timing by Overreporting

2014	Vote Self-Report Response Timing	Party ID Response Timing
Overreporting	0.733*** (0.121)	-0.115* (0.0659)
Week of Admin.	0.102*** (0.0343)	0.0379* (0.0221)
Baseline Response Timing	0.979*** (0.0199)	0.429*** (0.00961)
Constant	2.302*** (0.154)	1.486*** (0.0857)
Observations	**21,320**	**20,925**
R-squared	**0.266**	**0.218**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The fact that overreports provide false information to researcher is a well known problem in survey administration, but this new piece of evidence uncovers the mechanism through which respondents engage in overreporting. Nonvoters who overreport decide to present themselves as voters by lying about their actual voting behavior; they are not forgetful or falsely believe that they went out to vote when they did not. If overreports were the result of unconscious self-deception there would be no significant difference between the response latencies of voter and nonvoters who reported turnout, yet this is not the case.

Some might argue that respondents who overreport turnout could be significantly different from actual voters and that they might take longer to answer all questions in surveys. Though baseline timing should be sufficient to control for timing differences across individuals, I include a placebo test that measures the effect of being an over-reporter on the page timing for the party identification question. This question is part of the post-election questionnaire administered to subjects in the CCES and comes shortly after the vote self-report question. It is a single answer question with multiple alternatives, but differs from the vote self-report question in that overreporting should be unrelated to the response timing for this question.

I applied trimming to the party identification question page timing by eliminating all values above the 95th percentile, in the same manner that I trimmed extreme values from the response latencies of vote self-report question. The party identification timing has a mean of 5.218 in 2012 and 4.620s in 2014 after trimming (See Table 4.1). The distribution of observations for this page timing is plotted in Figure 4.1, most observations can be found around the 3 second mark. Using OLS regression to measure the effect of being an over-reporter on the placebo timing while controlling for baseline timing and week of survey shows that overreporting does not result in longer response latencies associated with the party identification question. In fact, over-reporters take significantly less time to report their party identification when compared to validated voters by 0.212s in 2012 and by 0.115s in 2014 (See Tables 4.6 and 4.7).

The placebo test is a good indicator of validity of the results found in the initial model because overreporting affects the response latencies of the vote self-report question, but does not affect the response latencies of the party identification question. A greater amount of cognitive effort was expended by over-reporters when delivering false turnout self-reports than when stating their partisanship. Evidently those who overreport have little trouble stating their party identity, but think more about what response to giving a false response about their participation in elections. The negative relationship between overreporting and the response latencies for party identification demonstrates that these respondents are using information readily available in their minds. In contrast, the positive relationship between overreporting and turnout response latencies show that nonvoters who overreport choose not use the information most readily available in memory to then give survey researchers a deceptive answer.

The placebo model demonstrated that overreporting is unrelated to the page timings of the party identification question, but the variable measure week of survey administration had differing results for the 2012 and 2014 CCES models. In 2012, the time elapsed between Election Day and the week of interview did not have a significant effect on increasing the length of remorse latencies for the vote self-report question while it had a highly significant positive effect 2014. Though week of administration significantly increased response latencies in 2014 the size of the effect, 0.102s or one tenth of a second, was not greater than that of overreporting, 0.733s or seven tenths of a second. Thus, overreporting is the main source of heightened cognitive effort in self-reports of voter turnout, measured in the form of response latencies, not memory lapses resulting from time of interview.

Conclusions

In this chapter I explore the deceptive nature of overreporting to better understand the cognitive mechanism through which turnout overreports occur in process of survey administration. As discussed, overreporting electoral participation in surveys is thought to be caused mostly by socially desirable responding (SDR) and memory failure. SDR, as a form of response bias, causes individuals to provide inaccurate self-reports that manifest in two types of deception. Those are self-deception and other-deception. These two forms of SDR differ mainly in whether the respondent consciously or unconsciously delivers a deceptive response to a survey question. Vote validation scholars who have attributed overreporting to social desirability bias have failed to explore the implications of this claim, while the merits of memory failure have been well documented.

The first implication of the social desirability assumption is that overreports are deceptive responses, and the second is that overreports might be either self-deceptive or other-deceptive. I use response latencies to address these implications to demonstrate that overreports are responses born from deception and to determine the intentionality of false reports of turnout. Social psychology studies of deception and lie detection show that deceptive responses require more cognitive effort than honest responses, that cognitive effort can be measured using response latencies, and that honest responses on average have shorter response latencies that deceptive ones. Furthermore, self-deceptive responses have been found to have similar response latencies to those of honest responses, that is, they are not intentional.

I find that overreporting turnout significantly increases the length of response latencies associated with the vote self-reports question controlling for baseline timing and time elapsed from the election, as week of interview. My findings support the widely held assumption that overreports of voter turnout are the result of socially desirable responding because lengthier response latencies are related to greater cognitive effort in deceptive answers. Greater cognitive effort in overreporting leads me to conclude that overreports are deception. Also, OLS modeling shows that overreporting requires a substantially and significantly more cognitive effort than truthful reports of turnout, demonstrating that the one involves intentional deception while the other involves simply reporting facts stored in memory. This gives credence to my second argument, that turnout overreports are equivalent to an impression management type of SDR. If overreports were self-deception there would be no significant difference between the response latencies for honest and false reports of voting, this is not the case. Over-reporters are engaging in conscious other-deception when they falsely report turning out to vote.

The knowledge generated in this chapter and in the preceding chapters are the foundation for the concluding chapter that follows. Having presented evidence in chapters 2 and 3 that over-reporters are sufficiently different from voters in particular I address the bias that overreports bring to statistical modeling of turnout.

CHAPTER 5

OVERRPORT BIAS IN TURNOUT MODELS

Throughout this dissertation I have presented an accumulation of evidence to show that overreports of voter turnout can bias statistical models of turnout. I did so by discussing the distribution of demographic, social and political characteristics among over-reporters in comparison with the distribution of those same characteristics among validated voters and honest nonvoters. Distributions for over-reporters were distinct from those for validated voters and nonvoters, with a trend toward similarities with validated voters. Additional evidence was presented through the discussion of the observed statistical relationship between overreporting and traditional predictors of turnout that resulted from a multinomial logistic model. The relationships between overreporting and predictors of turnout resembled those of nonvoting and predictors of turnout. Then, I showed that overreports were associated with lengthier response latencies for the turnout self-report question, which led to the conclusion that overreports occur due to intentional deception because of social desirability considerations. This suggests that survey researchers should be skeptical of self-reports of voter turnout. Furthermore, political scientists should continue to work towards creating new methods to reduce the incidence of overreporting and to correct for overreport bias in the study of turnout.

By way of conclusion, in this final chapter, I compare turnout models for the 2014 and 2012 Cooperative Congressional Election Study (CCES) to showcase the discrepancies between models that use self-reported turnout as their dependent variable and models that use validated turnout. Discrepancies regarding the size of the statistical relationship between predictors and both dependent variables will produce my final points evidence in response to the vote validation literature's debate on whether overreports bias models of turnout. I also present a possible method of correcting for overreport bias that is rooted in the *social desirability theory of overreporting* that is at the center of this dissertation. Using 2016 CCES UMass Module data I show how a six item version of the Balanced Inventory of Desirable Responding (BIDR) could help respond to whether overreports are akin to a self-deception type of socially desirable responding (SDR) or an impression management (other-deception) type of SDR.

Self-Reported Turnout Versus Validated Turnout

The study of voter turnout in American politics relies almost completely on self-reports of (non)participation in elections collected from survey research. Self-reports of turnout are problematic because a considerable proportion of survey respondents falsely report turning out to vote. Overreports interfere with the accurate measurement of participation in elections and the assessment of what can be done to increase and expand democratic political participation. This interference is reflected in the overestimation of turnout rates in surveys and in biased coefficients of turnout models, as I will demonstrate in this section.

Past vote validation research has engaged in similar comparison of turnout models as the comparison carried out in this chapter. Two studies conclude that overreports do not bias conclusions about which factors are the most important predictors of turnout and two additional studies conclude the opposite. Using 1978 ANES data Katosh and Traugott (1981) find no major changes in the relationship between independent variables and turnout when using validated turnout instead of self-reported turnout. As a consequence, they state that political science has not "suffered a catastrophic loss of any of the substantial body of knowledge about voting behavior" (1982: p. 534). In agreement with this study, using 1976 ANES data, Sigelman (1982) finds no great differences between models fitted using self-reported turnout and validated turnout, and touts the results as "very good news for students of voting" (p. 55). Still, more recent studies take an opposing view (Bernstein, Chadha & Montjoy, 2001; Cassel, 2003). Bernstein et al. (2001) show that overreporting matters and "distorts standard explanations of voting, increasing the apparent importance of independent variables that are related in the same direction to both overreporting and voting, while sharply decreasing the apparent importance of independent variables related in opposing directions to those two variables" (p. 41). In her 2003 study, Cassel compared logistic regressions of self-reported and validated turnout models for 1984 to 1988 presidential elections using ANES data. She concludes that overreports "bias the effect of one in five independent variables in a presidential turnout equation and one in four in a midterm one" (p. 88) either by depressing or inflating their effect. Furthermore, Cassel instructs turnout scholars to forewarn their readers about possible overreport bias in their studies when using any of the identified variables with depressed or inflated effects.[22]

In order to illustrate how overreports can bias statistical models of turnout I carry out logistic regression modeling for self-reported turnout and validated turnout in the 2014 and 2012 CCES. Self-reported turnout is defined here as all matched CCES respondents who selected "I definitely voted in the General Election on November #" as their response to the turnout question in the post election wave of the survey; all other

[22] "Studies of self-reported voting participation that include one or more of these independent variables or other untested independent variables should inform readers how overreporting bias affects, or may affect, their conclusions" (p. 89).

respondents who reported nonparticipation and those who reported being non-registered are self-reported nonvoters. Validated turnout includes all post election CCES respondents with a confirmed record of voting from Catalist, self-reported nonvoters who were not matched to Catalist and all respondents with a confirmed record of nonparticipation. The values for self-reported voters do not include unmatched self-reported voters. Table 5.1 shows totals and percentage of self-reported voters and validated voters in the 2014 and 2012 CCES along with the total and percentage of the discrepancy between these two groups, namely overreports.

Table 5.1 Self-Reported and Validated Turnout in the 2014 and 2012 CCES

	Self-Reported Turnout	**Validated Turnout**	***Overreport Rate***
2014	30,417 75%	26,648 66%	*3,769* *9%*
2012	34,127 83%	30,050 73%	*4,077* *10%*

Columns show the weighted percent of self-reported and validated turnout among post election respondents, and the difference between these quantities for the 2014 and 2012 CCES studies.

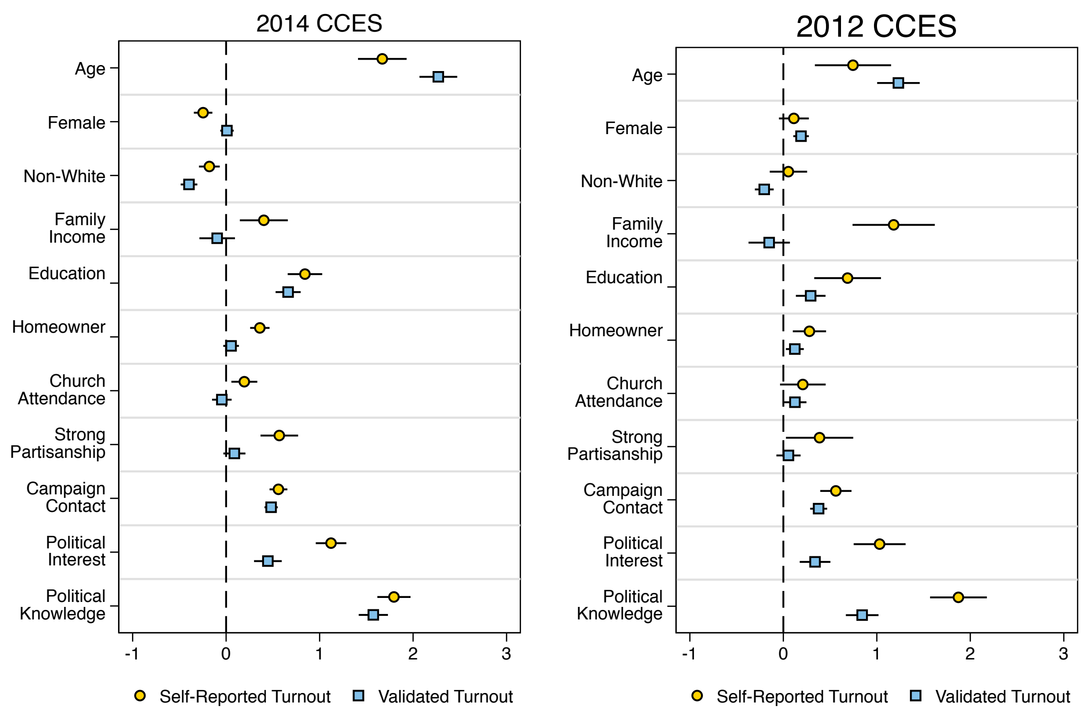
I use ten independent variables that are traditional predictors of voter turnout in the self-reported turnout models and validated turnout models. [23] These include three demographic variables, a continuous variable for age, a dummy variable for gender where female is the indicator, and another dummy variable for race where the indicator is being non-white. Age is a consistent predictor of participation in election, the older the individual the more likely to participate (Rosenstone & Hansen, 1993; Verba, Brady & Schlozman, 1995). I include female gender as a predictor because in the past women were les politically active, but now they are as active or more active than men (Leighley

[23] Marital status is excluded from the analysis in this chapter because results in Chapter 3 show that this is not a significant predictor for validated turnout, nonvoting or overreporting.

& Nagler, 2014). Non-white race is a particularly important addition because non-whites tend to participate at lower rates (Rosenstone & Hansen, 1993; Verba, Brady & Schlozman, 1995), but they also tend to be more likely to overreport turnout, particularly Black Americans (Silver & Anderson 1986; Abramson & Claggett, 1992). Two variables measure socioeconomic status; a measure of family income with sixteen categories staring with "less than $10,000" and ending in "$500,000 or more," and a six category measure of education that has "no high school" as its lowest value and "post-grad" as its highest. Two additional variables measure social connectedness, a homeownership dummy and a six category variable measuring the frequency of a respondent's church attendance. Education, family income, homeownership and church attendance are integral factors to resource models of turnout and has been found to predict participation (Verba, Brady & Schlozman, 1995).

Finally, four variables measure political characteristics. These include two indicator variables, one that measures strong partisanship, and another that measures campaign contact. Also, two variables that measure political engagement, these are: a four category measure of interest in politics, and a count variable that represents political knowledge with seven values. Individuals with strong party identity are general more invested in the outcome of an election and will be motivated to participate. External mobilization efforts like campaign contact have also proven to mobilize voters to the polls (Rosenstone & Hansen, 1993; Gerber & Green, 2015). High levels of political interest have consistently predicted political engagement in voting (Verba, Brady & Schlozman, 1995), and so have high levels of political knowledge (Galston, 2001). All variables were standardized to a zero to one scale and models within each year were estimated on the same sample.

Figure 5.1
Logit Model Coefficient Plots of Validated Turnout and
Self-Reported Turnout in the 2014 and 2012 CCES



Note: Plots show estimated logit coefficients with 95% coefficients intervals from two logistic regression models of turnout in both the 2014 and 2012 CCES, these are a self-reported turnout model and a validated turnout model.

Findings in the studies conducted by Bernstein et al. (2001) and Cassel (2003) allow me to set expectation for the comparison of logistic regressions for self-reported turnout and validated turnout in the CCES. Previous research found no significant difference in the effect of age on self-reported and validated turnout. Still, results from Chapter 3 show a strong relationship between age and validated turnout, but not with overreporting, which could depress the effect of age on self-reported turnout. I expect a significantly larger effect of age on validated turnout than on self-reported turnout. Female gender should have a positive but non significant effect on turnout. Non-white race should have a larger negative effect on validated turnout than on self-reported turnout. The importance of education should be overestimated in the self-reported turnout model, but the coefficient should not be significantly different. I also expect a large difference in the effect of family income, homeownership and church attendance on turnout, where the effect will be inflated in the self-reported turnout model. The effect of all four political variables should be inflated in the self-reported turnout model, particularly political interest and political knowledge.

Figure 5.1 plots logistic regression coefficients estimated in the self-reported and validated turnout models for the 2014 and 2012 CCES. The data points of the validated turnout models show that using self-reported turnout results in both the overestimation and underestimation of the effect of multiple variables on turnout. Eight variables in the 2014 CCES show a substantial shift in the size and significance of their effect on predicting participation in the validated turnout model when compared to the self-reported turnout model. The logit coefficient for age is significantly larger in the validated turnout model by 0.59 decimal points. The impact of age on participation was depressed in the self-reported turnout model. Similarly, the negative effect of non-white race was also depressed in the self-reported turnout model by 0.21 decimal points. There is a marked difference in the effect of family income on self-reported turnout and validated turnout. Family income has a positive and significant effect on predicting participation in the self-reported turnout model, but it is not a significant predictor in the validated turnout model. The same is true for church attendance. In the self-reported turnout model being female has a negative and significant effect on participation. However, the validated turnout model shows that gender does not make a person more or less likely to participate. Additionally, the positive impact of homeownership, partisan strength, interest in politics was inflated in the self-reported turnout model, where the size of the effect of these variables on validated turnout is significantly smaller. These results show an underestimation of the effect age and non-white race, and an overestimation of the effect of female gender, family income, homeownership, church attendance, partisan strength, and interest in politics in the self-reported turnout model.

Six variables in the 2012 CCES show notable changes in the size and significance of their effect in the validated turnout model when compared to the self-reported turnout model. Female gender has a positive and significant effect on validated turnout, while it was non significant for self-reported turnout thought he difference in the size of the coefficient is not significant. Similarly, the effect of non-white race changed from being positive and non significant to negative and significant. The positive effect of four variables on electoral participation show substantial shifts in the size of their effects in the self-reported turnout model and the validated turnout model. Family income, strong partisanship, interest in politics, and political knowledge have significantly larger coefficients in the self-reported turnout model than in the validated turnout model. These results show an underestimation of of the effect of female gender and non-white race and an overestimation of the impact of family income, strong partisanship, interest in politics and political knowledge on increasing the likelihood of participating in electoral events when the participation is measured with self-reported turnout (See Appendix B for regression Tables B.3 & B.4).

The results from comparing turnout models in both 2014 and 2012 show a consistent underestimation of the importance of age in predicting electoral participation, particularly in 2014. The negative effect of non-white race was consistently underestimated in both survey years, while the effect of female gender was also misestimated. There is also a consistent overestimation of the predictive power of family income, strong partisanship, and political interest. For the most part, the coefficients in each model follow a similar pattern, but there are marked discrepancies in the level of statistical significance and the size of the effect that traditional predictors of electoral participation had on self-reported turnout and validated turnout. The results presented in this section show that overreports do bias statistical models of turnout that are based on self-reported turnout. Overreports lead to both overestimation and underestimation of the impact of demographic, social and political factors on predicting turnout. More importantly, the fact that the discrepancies are most remarkable among political factors adds to the evidence already presented throughout this dissertation to support the notion that overreports are associated with socially desirable responding. Furthermore, this reinforces the claim that social desirability bias is related to overreports because survey respondents who recognize that there is a social meaning of voting provide responses that give the impression of conforming to the democratic norm of participation.

Self-Reported Turnout and Social Desirability

In this section I present correlational analysis using Delroy L. Paulhus's (1991) Balanced Inventory of Desirable Responding (BIDR) to identify statistical relationship between self-reports of turnout and socially desirable responding. In the first chapter of this dissertation I explain how vote validation scholarship, for the most part, has assumed that social desirability bias is at play in the occurrence of voter turnout overreports. Very few scholars test this assumption, and those who do so use the same method, the item count technique (ICT) or list experiment (Holbrook & Krosnick, 2010; Comsa &

Postelnicu, 2013). The use of the ICT provides a strong signal that social desirability and overreports are related, but it does not allow for a more nuanced understanding of how overreporting is related to the complex construct that is SDR.

SDR is a form of response bias that “refers to the systematic tendency to give overly positive answers that make the respondent look good” (Bobio & Manganelli, 2011: p. 117). Two typologies dominate the literature on SDR and are typically used to measure and theorize this form of response bias, these are: self-deception and impression management (other-deception). Self-deception “refers to an unconscious tendency to provide honest but positively biased self-reports with the aim of protecting positive self-esteem; it is a predisposition to see oneself in a favorable light…” (p.118). Impression management “refers to the habitual and conscious presentation of a favorable public image” (Bobio & Manganelli, 2011: p. 118), and “signifies a tendency to give inflated self-descriptions to an audience: a conscious dissimulation of responses to create a socially desirable image” (Hart et al., 2015: p. 2). Both types of SDR are forms deception, but differ in who is targeted by the deception. The first has the purpose of enhancing one’s self-image while the second has the purpose of enhancing one’s social image.

The BIDR was created to measure and control for SDR in statistical analysis of data collected from self-report studies. The BIDR is a 40-item instrument developed to assess individual differences in SDR, and for this purpose it includes a Self-Deception Scale (20-itmes) and an Impression Management Scale (20-items) (Paulhus, 1991). The BIDR is typically administered to respondents as a form with a list of 40 statements, and respondents are asked to give each statement a number value from 1 to 7 to indicate how true the statement is. Though this instrument allows for the measurement of both dimensions of SDR its length is not practical for surveys that have time constraints. For this reason, Hart et al. (2015) conducted research to develop and test a short version of the BIDR that reduces the original 40-item questionnaire to a 16-item instrument that can be used more widely in survey research. I took this exercise further by conducting a pilot study in June of 2016 that included the16-item version of the BIDR developed by Hart and colleagues in order to identify six items that could efficiently measure the underlying constructs assessed in both the Self-Deception (SD) Scale and the (IM) Impression Management Scale (See Appendix D for a report on the pilot study and the factor analysis employed to select the BIDR items used here).

The scales within the BIDR have been used to identify SDR in many studies of self-reports. Randal and Fernandes (1991) used the BIDR in correlational analysis of self-reports of ethnical behavior finding higher correlations with the IM Scale than with the SD Scale. Another example of the use of the BIDR is a study conducted to identify SDR in sexuality self-reports, where self-reports of interpersonal sexual behavior and intrapersonal sexual behavior were highly correlated with the IM Scale, while sexual orientation was not correlated with either scales in the BIDR (Meston, Hieman, Trapnell and Paulhus, 1998), Furthermore, using the BIDR social psychologists have found that many types of behavioral and attitudinal self-reports in online and computer based surveys are correlated to both the IM Scale and SD Scale (Booth-Kewley et al., 1992; Risko, Quilty & Oakman, 2006; Booth-Kewley et al., 2007) .

In this dissertation, particularly chapters 1 and 4, I articulate a *social desirability theory of overreporting* where I argue that overreports are evidence of SDR in self-reports of turnout, that they are deception or falsehoods about voting, and that they must be equivalent to an impression management type of SDR, not self-deception. I argue that overreports are impression management because of they respond to the need to generate a positive social image and because voting is a social act that has an uncontested social meaning (Rolfe, 2012). The best test for this theory would be to conduct correlational analysis in a multinomial logit model between overreporting and the BIDR scales, however this is not possible because the 2016 CCES has not been validated at this time

The University of Massachusetts Amherst Department of Political Science purchased one CCES module in the 2016 CCES with 2,500 respondents and shared survey time with a second UMass module with a sample of 1,000 respondents for a total sample of 3,500 participants. A great majority of the combined UMass Module participants completed the post election wave questionnaire, a total 2,757 respondents (79%); this is where respondents report registration and (non)participation in the election under study. Almost all post election respondents reported their registration status and turnout; only 5 post election respondents did not report either. Eighty-three percent of post election respondents self-reported that they definitely went out to vote on November 8, 2016. Nonvoters are comprised of all self-reported non-registered respondents and self-reported nonvoters for a total 18% (See Table 5.2).

Table 5.2 Self-Reported Turnout in the 2016 CCES UMass Module

Total	**2,752**
Voter	2,271 83%
Nonvoter	481 18%

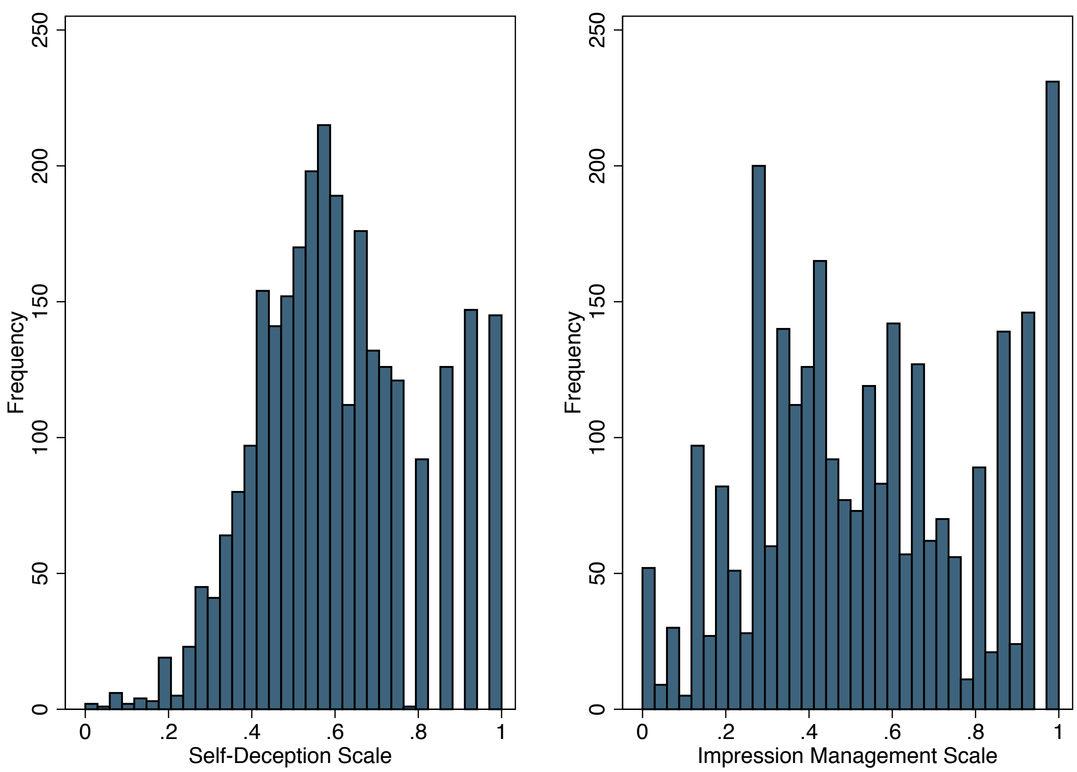
Quantities show the weighted total of post election respondents and the total and percentage of self-reported voters and nonvoters in the 2016 CCES UMass Module.

Table 5.3 Six Item BIDR in the 2016 CCES UMass Module

Instructions: On a scale of Not True to Completely True indicate how each of these statements best describes you.	
SD Scale	1. Its hard for me to shut off a disturbing thought. 2. I'm very confident in my judgments. 3. I am a completely rational person.
IM Scale	4. There have been occasions when I have taken advantage of someone. 5. I have said something bad about a friend behind their back. 6. I sometimes tell lies if I have to.

Table shows wording for the six BIDR items included in the 2016 CCES UMass Module and indicates the three items that measured self-deception and the three items that measured impression management.

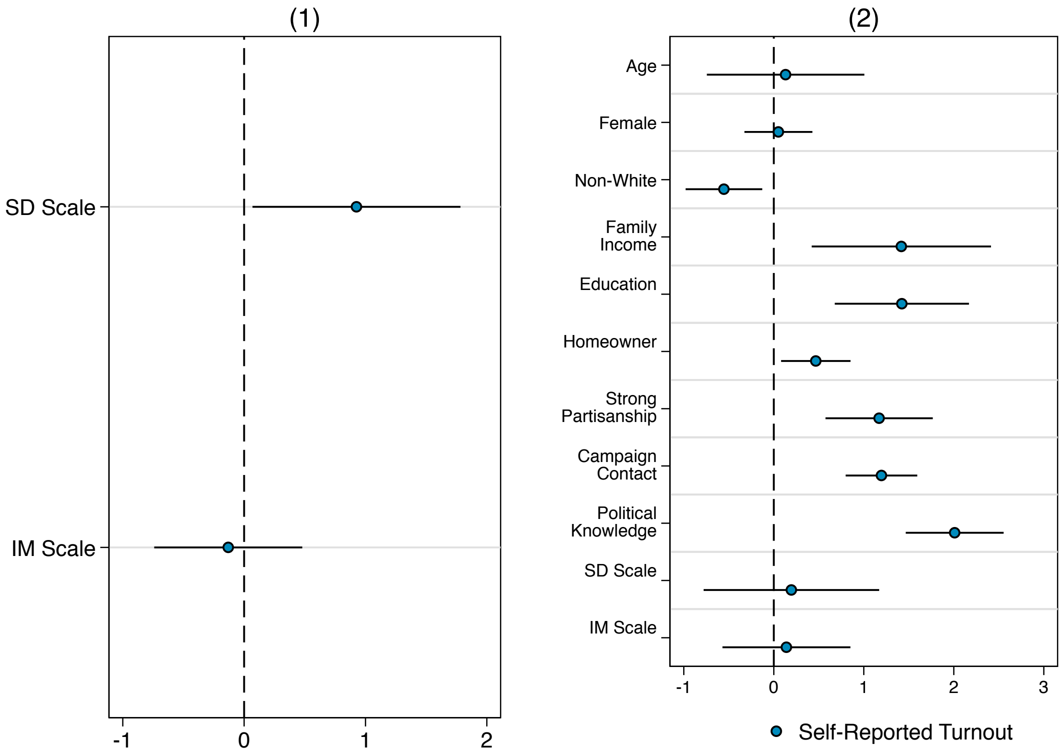
Figure 5.2
Frequency Histograms for the Self-Deception and Impression Management Scales in the Post Election 2016 CCES UMass Module



I included six BIDR items in the 2016 CCES UMass Amherst Module, three items served as a mini SD Scale and another three items served as a mini IM Scale. The six items or statements were presented to CCES respondents on one questionnaire page on the online survey. Next to each item there was a seven-point scale where respondents were asked to indicate how each of the statements best described them, where “not true” had a value of one (1) and “completely true” had a value of seven (7) (See Table 5.3 for item wording). The scores for items 1, 4, 5 and 6 listed in Table 5.4 are negatively keyed items. These items require reversing their values before employing the continuous scoring procedure commonly used in coding the scales within the BIDR. In addition to reverse coding the negatively keyed items extreme responses with a value of 6 or 7 had one point added. Finally, the three SD Scale items and the three items in the IM Scale were summed, averaged and rescaled to a 0 to 1 scale. Though factor analysis could be used to generate a variable for the latent construct measured by each scale, the coding employed here has been extensively tested for validity and reliability (Li & Bagger, 2007; Li & Li, 2008; Bobbio & Manganelli, 2011; Kam, 2013).

Figure 5.2 shows histograms of the frequency of observations within the SD Scale and IM Scale among post election respondents in the 2016 CCES UMass Module. The mean value for self-deception is 0.6 and the mean value for impression management is 0.5. These average values indicate that post election respondents in this survey module tend to score high on the construct of self-deception, while the distribution for impression management has resembles a normal curve where respondents are mostly grouped around the mean value for the IM Scale.

Figure 5.3
Logit Model Coefficient Plots of Self-Reported Turnout by the BIDR
in the 2016 CCES UMass Module



Plot (1) in Figure 5.3 show results for a simple logistic regression for self-reported turnout in the 2016 CCES UMass Modules using both BIDR scales as independent variables. The coefficient for self-deception has positive and significant effect on reporting turnout, while the coefficient for impression management is negative and non significant. These results show that those who said they definitely went out to vote on November 8 have a tendency towards self-deception. However, as the histogram for the SD Scale in Figure 5.2 shows most respondents in the 2016 UMass Modules tend to score high on self-deception, and Table 5.2 show that a great majority of respondents in this survey module report themselves as voters. These previous findings suggest that these results may not retain these values when controlling for other factors. Plot (2) in Figure

5.3 presents results for a logistic regression of self-reported turnout by the BIDR scales controlling for age, female gender, family income, homeownership, strong partisanship, campaign contact, and political knowledge. In this second model both the SD Scales and the IM Scale had no significant effect on predicting self-reported voting. I suspect that using the full 16-item BIDR could have yielded more conclusive results, and that vote validation data could also give a better picture about the relationship between overreporting and social desirability bias.

Conclusion

The research presented in this dissertation has sought to address the four major debates surrounding the vote validation literature: 1) How accurate is vote validation?, 2) Do overreports of voter turnout bias statistical models of turnout?, 3) What is the correct way to measure and model overreporting?, and 4) What is the cognitive mechanism through which overreports occur?

There are two camps in the debate regarding the accuracy of vote validation. One camp argues that vote validation provides an accurate assessment of turnout that uses publicly available record. Also, that vote validation procedures for matching survey data to voter file records can be performed with rigor and high quality standards (Ansolabehere and Hersh, 2010, 2012). The other camp argues against the use of vote validation. Those who shares this view claim that voter file matching is not accurate, that public registration and turnout records used in the process are not well kept, and that validation results in a high rate of misclassification. In the case of Berent et al. (2011, 2016), the authors argue that the lowered rate of turnout estimated from vote validation only give the illusion of accuracy. It is their view that voter turnout self-reports are more trustworthy that validate turnout.

I share the view of the fist camp, that vote validation is a more accurate assessment of voter turnout. In chapters 1 and 2, I describe the Catalist matching procedure used to validate the CCES to demonstrate that vote validation in the CCES is sound. In that description I show that Catalist has high standards for creating their own private file from public records. Catalist purchases registration and voting records from all 50 states in the United States multiple times a year in order to keep their records up to date. They also clean and standardize their data into a uniform record for all individuals. Catalist also complements their vote file data with marketing data to fill in any gaps there may be in any individual's record that might make the matching process more difficult. Finally, Catalist uses a proprietary matching algorithm that result in a probability score for which they only classify CCES respondents as matched if they have a high probability score.

The debate concerning overreport bias in statistical model of turnout was addressed in chapters 2, 3 and in this final chapter. The analysis of descriptive statistics in Chapter 2 showed that over-reporters share characteristics with both voters and nonvoters. However, over-reporters are also distinctive in that they do not match the demographic, social and political characteristics of either voters or nonvoters. Chapter 3 presented statistical modeling of overreports that compared the effect that traditional predictors of turnout had on the probability of becoming an over-reporter, a voter or a nonvoter. Using multinomial logit regression, I found that over-reporters occupy a middle ground between voters and nonvoters, but that the marginal effects of the predictors on overreporting followed a similar pattern to that or their effect on nonvoting. The findings in chapters 2 and 3 lay the foundation for the analysis presented here in Chapter 5, because they show that over-reporters are not just like voters and survey researchers should expect overreports to bias research on turnout. The comparison of validated and self-reported turnout logit models presented at the beginning of this chapter shows that overreports do bias statistical models of turnout. Overreports lead to the underestimation and overestimation of the impact of that multiple characteristics have on predicting the probability of turnout out to vote.

Measurement and modeling of overreports was addressed in chapters 2 and 3. In Chapter 2, I discuss different ways of assessing turnout overestimation in survey research and the measurement of overreports at the individual level using vote validation data. I present overreport estimations using both a dichotomous and multi category measurement, then giving preference to the multi category measurement in order to compare over-reporters to voters and nonvoters. I find that the multichotomous measurement of overreport provides a more comprehensive and consistent look at this phenomenon. In Chapter3, I explain how traditional logit modeling of overreports is not ideal because exclusion of voters form the analysis may introduce selection bias. I propose that multinomial logit regression modeling is the appropriate approach for identifying the key predictors of overreporting, finding that political factors are the most impactful in predicting engagement in overreporting. These results fit the social desirability theory of overreporting proposed in this dissertation, especially since these results from the multinomial logit model suggest that heighted awareness of the democratic norm of voting and its social meaning are related to overreporting.

I have also engaged in addressing the fourth debate about which is the mental process that that occurs when survey respondents overreport. Many vote validation scholars an d survey research are engaged in the development of new methods and questionnaire wording that might reduce the incidence of overreporting and collect more accurate self-report of turnout. However, I propose that it is necessary to identify the cognitive mechanism through which overreport occur before creating effective techniques that will gather unbiased self-report of political participation. In Chapter 4, I test a hypothesis derive from the virtually untested assumption that overreports are caused by socially desirable responding. The hypothesis is that if overreports are caused by SDR, the overreports are equivalent to deception. Using response latency data and methods from the lie detection and deception literature from the discipline of social psychology I found that overreports require more cognitive effort than honest reports of turnout, even when controlling for the possibility of memory failure. The significant statistical relationship between overreports and longer response latencies is evidence that over-reporters intentionally lie about their about their non-participation.

This dissertation is not the final word on the study of voter turnout self-reports, vote validation and overreporting. It represents some of the fundamental methodological questions that scholars of voter turnout should be engaged with when using survey data in their research of democratic participation in elections. More work needs to be done on the role of social desirability bias in overreporting, and more techniques need to be developed in order to curtail the bias introduced by overreports to the study of turnout. Finally, I hope that the work shown here will engender further research on this topic.

APPENDIX A

COOPERATIVE CONGRESSIONAL ELECTION STUDY

CCES 2008:

The 2008 CCES was conducted online by YouGov/Politmetrix using a matched sample design. YouGov/Polimetrix interviewed a nationally representative sample of 32,800 respondents. The response rate was 47%, having initially contacted 105,895 individuals. The Pre-Election wave was conducted between October 8 and November 3, 2008; and the Post-Election wave was conducted after the General Election between November 5 and December 7, 2008.

Stephen Ansolabehere, 2010, "CCES, Common Content, 2008", hdl:1902.1/14003, Harvard Dataverse, V6, UNF:5:7eeaUMPVCcKDNxK6/kd37w==

CCES 2010:

The 2010 CCES was conducted online by YouGov/Politmetrix using a matched sample design. YouGov/Polimetrix interviewed a nationally representative sample of 55,400 respondents. The response rate was 40% having initially contacted 196,235 individuals. The Pre-Election wave was conducted between October 1 and November 1, 2010; and the Post-Election wave was conducted after the General Election between November 4 and December 7, 2010.

Stephen Ansolabehere, 2012, "CCES Common Content, 2010", hdl:1902.1/17705, Harvard Dataverse, V3

CCES 2012:

The 2012 CCES was conducted online by YouGov using a matched sample design. YouGov interviewed a nationally representative sample of 54,535 respondents. The response rate was 35% having initially contacted 264,457 individuals. The Pre-Election wave was conducted between October 1 and November 5, 2012; and the Post-Election wave was conducted after the General Election between November 7 and December 13, 2012.

Ansolabehere, Stephen; Schaffner, Brian, 2013, "CCES Common Content, 2012", hdl:1902.1/21447, Harvard Dataverse, V8, UNF:5:Eg5SQysFZaPiXc8tEbmmRA==

CCES 2014:

The 2014 CCES was conducted online by YouGov using a matched sample design. YouGov/Polimetrix interviewed a nationally representative sample of 56,200 respondents. The response rate was 40% having initially contacted 196,235 individuals. The Pre-Election wave was conducted between October 1 and November 3, 2014; and the Post-Election wave was conducted after the General Election between November 5 and December 8, 2014.

Schaffner, Brian; Ansolabehere, Stephen, 2015, "CCES Common Content, 2014", doi:10.7910/DVN/XFXJVY, Harvard Dataverse, V3, UNF:6:WvvlTX+E+iNraxwbaWNVdg==

CCES 2016 UMass Module:

The 2016 University of Massachusetts Module was purchased as part of the 2016 CCES. Documentation on response rates, and field dates have not been published at this time.

Ansolabehere, Stephen; Schaffner, Brian F., 2017, "CCES Common Content, 2016", doi:10.7910/DVN/GDF6Z0, Harvard Dataverse, V1, UNF:6:XRWBSCTbPDuGIDvAN1TOzQ==

Schaffner, COOPERATIVE CONGRESSIONAL ELECTION STUDY, 2010: University of Massachusetts Amherst CONTENT. Release: 2017. Amherst, MA. http://cces.gov.harvard.edu

APPENDIX B

ADDITIONAL DESCRIPTIVE STATISTICS TABLES

Table B.1 CCES Respondents by Vote Validation Status and Reported Turnout

CCES Survey Year	Total	Validated Voters	Nonvoters	Over-Reporters
2014	36,688	25,739 70%	7,265 20%	3,685 10%
2012	40,616	34,468 85%	2,143 5%	4,005 10%
2010	41,090	25,197 69%	12,269 30%	3,623 9%
2008	23,528	17,221 73%	4,058 17%	2,250 10%

Rows show Catalist matched CCES respondents, excluding Virginians, by validation status and self-reported turnout. Columns show weighted total and percent by CCES year of validated nonvoters, validated nonvoters who honestly reported non-participation and nonvoters who overreported turnout.

Table B.2 CCES Demographics, Socioeconomic Status and Political Engagement

CCES Year	2014	2012
Mean Age	50	50
% Female	53%	53%
% Black	11%	9%
% Hispanic	9%	8%
% White	77%	78%
% College	38%	37%
Median Income	$50,000 - $59,999	$40,000 - $49,999
% Homeowners	65%	63%
% Married	54%	54%
% Church Goers	29%	29%
% Strong Partisans	12%	21%
% Campaign Contact	53%	63%
% High Political Interest	53%	51%
% High Political Knowledge	46%	41%
% High Political Activity	7%	8%

Columns show weighted values for all respondents who answered the turnout self-reports question in the 2014 and 2012 CCES studies, excluding Virginias and unmatched self-reported voters.

Table B.3
Logistic and Multinomial Logistic Regressions Predicting Overreporting in the 2014 CCES

2014 CCES	**Logistic Regression Model**	**Multinomial Logistic Regression Model**	
		Validated Turnout	**Overreport**
Age	0.505*** (0.194)	2.688*** (0.141)	0.393** (0.187)
Female	-0.225*** (0.0729)	-0.0927* (0.0535)	-0.184*** (0.0708)
Non-White	0.138* (0.0828)	-0.347*** (0.0620)	0.175** (0.0775)
Family Income	0.135 (0.188)	0.383*** (0.148)	0.118 (0.188)
Education	0.671*** (0.128)	1.155*** (0.0955)	0.711*** (0.123)
Homeowner	0.268*** (0.0795)	0.324*** (0.0562)	0.285*** (0.0778)
Married	0.0489 (0.0769)	-0.0638 (0.0542)	0.0340 (0.0765)
Church Attendance	0.0853 (0.113)	0.236*** (0.0758)	0.254** (0.101)
Strong Partisanship	0.380*** (0.143)	0.504*** (0.107)	0.420*** (0.134)
Campaign Contact	0.209*** (0.0756)	0.812*** (0.0507)	0.235*** (0.0724)
Political Interest	1.592*** (0.133)	1.050*** (0.0928)	1.489*** (0.130)
Political Knowledge	1.158*** (0.136)	2.427*** (0.0977)	1.007*** (0.140)
Political Activity	1.641*** (0.211)	1.043*** (0.152)	1.381*** (0.190)
Constant	-3.347*** (0.149)	-3.303*** (0.114)	-3.271*** (0.142)
Observations	**13,990**	**34,498**	**34,498**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.4
Logistic and Multinomial Logistic Regressions Predicting Overreporting in the 2012 CEES

2012 CCES	Logistic Regression Model	Multinomial Logistic Regression Model	
		Validated Turnout	Overreport
Age	-0.686*** (0.235)	0.196 (0.163)	-0.831*** (0.220)
Female	0.0442 (0.0906)	0.254*** (0.0645)	0.0642 (0.0841)
Non-White	0.0202 (0.114)	-0.0288 (0.0784)	0.148 (0.102)
Family Income	0.848*** (0.262)	0.838*** (0.192)	0.917*** (0.240)
Education	0.0511 (0.180)	0.457*** (0.137)	0.0906 (0.173)
Homeowner	0.367*** (0.0985)	0.359*** (0.0683)	0.315*** (0.0941)
Married	-0.0145 (0.0941)	0.00476 (0.0671)	-0.0595 (0.0892)
Church Attendance	0.379*** (0.138)	0.469*** (0.101)	0.419*** (0.126)
Strong Partisanship	0.378** (0.166)	0.527*** (0.143)	0.363** (0.163)
Campaign Contact	0.452*** (0.0983)	0.902*** (0.0650)	0.450*** (0.0924)
Political Interest	1.351*** (0.146)	1.170*** (0.107)	1.316*** (0.146)
Political Knowledge	1.440*** (0.166)	2.069*** (0.119)	1.364*** (0.168)
Political Activity	1.582*** (0.283)	1.683*** (0.238)	1.678*** (0.263)
Constant	-2.658*** (0.175)	-1.944*** (0.116)	-2.604*** (0.163)
Observations	**7,331**	**34,270**	**34,270**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.5 Self-Reported vs. Validated Turnout Models, 2014 CCES

2014 CCES	Self-Reported Turnout	Validated Turnout
Age	1.671*** (0.133)	2.270*** (0.103)
Female	-0.246*** (0.0506)	0.00916 (0.0368)
Non-White	-0.179*** (0.0568)	-0.397*** (0.0454)
Family Income	0.404*** (0.131)	-0.0954 (0.0972)
Education	0.843*** (0.0942)	0.664*** (0.0685)
Homeowner	0.361*** (0.0531)	0.0535 (0.0428)
Church Attendance	0.195*** (0.0708)	-0.0457 (0.0535)
Strong Partisanship	0.569*** (0.103)	0.0885 (0.0603)
Campaign Contact	0.560*** (0.0485)	0.481*** (0.0364)
Political Interest	1.123*** (0.0835)	0.447*** (0.0756)
Political Knowledge	1.795*** (0.0906)	1.575*** (0.0797)
Constant	-1.601*** (0.1000)	-2.386*** (0.0845)
Observations	**37,969**	**37,969**

Standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

Table B.6 Self-Reported vs. Validated Turnout Models, 2012 CCES

2012	Self-reported Turnout	Validated Turnout
Age	0.745*** (0.208)	1.231*** (0.116)
Female	0.113 (0.0816)	0.190*** (0.0425)
Non-White	0.0545 (0.102)	-0.204*** (0.0515)
Family Income	1.180*** (0.225)	-0.151 (0.113)
Education	0.688*** (0.182)	0.293*** (0.0809)
Homeowner	0.279*** (0.0907)	0.123** (0.0491)
Church Attendance	0.209* (0.125)	0.124** (0.0628)
Strong Partisanship	0.388** (0.184)	0.0550 (0.0662)
Campaign Contact	0.562*** (0.0855)	0.378*** (0.0464)
Political Interest	1.030*** (0.142)	0.339*** (0.0837)
Political Knowledge	1.873*** (0.155)	0.843*** (0.0891)
Constant	-0.197 (0.137)	-0.794*** (0.0876)
Observations	36,396	36,396

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.7 Self-Reported Turnout by BIDR Scales, 2016 CCES UMass Module

2016	**Self-Reported Turnout**
SD Scale	0.926** (0.437)
IM Scale	-0.131 (0.311)
Constant	1.071*** (0.267)
Observations	**2,758**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.8 Self-Reported Turnout by BIDR Scales with Controls, 2016 CCES UMass Module

2016	Self-Reported Turnout
SD Scale	0.195 (0.497)
IM Scale	0.140 (0.362)
Age	0.131 (0.446)
Female	0.0511 (0.193)
Non-White	-0.554** (0.217)
Family Income	1.417*** (0.508)
Education	1.423*** (0.380)
Homeowner	0.467** (0.197)
Strong Partisanship	1.170*** (0.304)
Campaign Contact	1.196*** (0.203)
Political Knowledge	2.010*** (0.277)
Constant	-1.596*** (0.390)
Observations	**2,483**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX C

ALTERNATE RESPONSE LATENCY ANALYSIS: INCLUDING NON MATCHED RESPONDENTS & UNIFORM TRIMMING ACROSS SURVEY YEARS

In this appendix I present results for the OLS models predicting vote self-report response latencies by overreporting with a less restrictive subset of respondents, and with a uniform cut point for trimming the vote self-report response latencies in both the 2012 and 2014 CCES. The results presented here constitute robustness checks on the model presented in this body of the dissertation, in order to test whether significant findings presented still hold under alternative specifications.

The first robustness check addresses the analysis in Chapter 4, which only included respondents who were matched to the Catalist voter file by using a more inclusive model. Not matched respondents are persons for which Catalist found no record and can be interpreted as nonvoters; however, there is some likelihood that a non trivial amount of not matched respondents could be actual voters. This means that nonvoters in the CCES can be defined in two ways, first as matched respondents with no record of turnout and second as any respondent with no record of voting or registration, which includes not matched respondents. The first definition of who nonvoters are was used in the chapter because it provides the most precise identification of nonvoters within the CCES. Here I use the second and looser definition of nonvoters still finding a significant effect of overreporting on increasing the length of response latencies for the vote self-report question.

The CCES includes a dichotomous variable named “matched” that identifies all respondents who were matched by Catalist to a record, being matched to a record is not predicated on being registered to vote. Independent download of the 2014 CCES dataset and tabulation of the "matched" variable will corroborate the 30% rate of not matched respondents. The CCES sample has almost consistently grown in each of its iterations since 2008. In 2014 the CCES was at its largest and had the largest rate of not matched respondents of any CCES survey conducted since 2008 (See Table C.1). Still, Catalist uses a proprietary algorithm for matching, they purchase new records multiple times a year, continuously update their records, and clean and standardize their data (Ansolabehere and Hersh, 2010). Catalist's data management and customized proprietary algorithm has resulted in high rates of matches with high levels of certainty.

Table C.1 CCES Respondents by Catalist Match Status

CCES Survey Year	Total Respondents	Matched to Catalist	Not Matched
2014	**56,200** **100%**	39,415 70%	16,785 30%
2012	**54,535** **100%**	43,342 80%	11,193 20%
2010	**55,405** **100%**	42,916 78%	12,489 22%
2008	**32,795** **100%**	27,444 84%	5,351 16%

Rows present weighted total and percent of CCES respondents matched and not matched to the Catalist voter file.

The 2012 CCES had a total 54,535 respondents and 80% (43,342) of these respondents were matched to the Catalist voter file, while the 2014 CCES had 56,200 respondents 70% (39,415) were matched, the remaining 20% and 30% are not matched (See Table C.1). The not matched respondents will be considered nonvoters in this alternate analysis. The subset of respondents included in the analysis excludes respondents for the state of Virginia because voting records are not available for public use. Also, only respondents who reported that they "definitely voted in the General Election" are used to compare response latencies of honest voters and over-reporters. A total 38,377 respondents in the 2012 CCES reported that they went out to vote and 75% of those self-reported voters are validated voters. Under the new definition of nonvoters in this appendix 25% of the respondents in the analysis are classified as over-reporters. There are a total 37,722 respondents in the 2014 CCES who are self-reported voters, but only 68% to them are validated voters. With the inclusion of not matched respondents the rate of overreporting in 2014 is of 32% (See Table C.2)

Table C.2 CCES Self Reported Voters by Validation Status

CCES	Total Reported Turnout	Validated Voters	Over-reporters (Nonvoters)
2012	**38,377** **100%**	28,852 75%	9,525 25%
2014	**37,722** **100%**	25,739 68%	11,984 32%%

Weighted total and percentage of 2014 CCES respondents who reported they "definitely voted" in the 2014 General Election by vote validation status.

Table C.3 shows descriptive statistics for the baseline and vote self-report page timings after trimming. The quantities differ only slightly from those in the paper paper because of the inclusion of not matched respondents in this alternate analysis.

Table C.3 CCES Vote Self-Report, Placebo and Baseline Page Timings

CCES		Vote Self-Report Timing	Baseline Timing
2012	**Mean**	**9.249s**	**6.748s**
	Min.	0.579s	2.045s
	Max.	24.954s	15.488s
2014	**Mean**	**9.715s**	**6.866s**
	Min.	0.292s	1.471s
	Max.	29.531s	17.756s

Weighted mean for three (3) page timing measures: vote self-report timing, party identification timing, and baseline timing in the 2012 and 2014 CCES for respondents who said they "definitely voted in 2012 and 2014. Baseline is the calculated average timing from items presented in Table 2.

Table C.4 2012 CCES OLS Models Matched vs. Not Matched, Standard Trimming

2012 CCES	Excludes Not Matched Respondents	Includes Not Matched Respondents
Overreporting	0.325*** (0.118)	**0.154** **(0.0754)**
Week of Admin.	0.0177 (0.0362)	**0.00625 (0.0337)**
Baseline Response Timing	1.037*** (0.0198)	**1.048*** **(0.0184)**
Constant	1.909*** (0.143)	**1.871*** **(0.131)**
Observations	**26,737**	**30,669**
R-squared	**0.320**	**0.319**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

OLS regression models for the effect of overreporting on the vote self-report response latencies show statistically significant results with the same direction as in the more restrictive sample models presented in the paper. The level of significance is lower for the 2012 model, but overreporting continues to be the driving force for increased cognitive effort in responding to the vote self-report question. Results differ in the magnitude of the effect, with a change from an effect of 0.325s to an effect of 0.154s in the 2012 model that includes not matched respondents (See Table C.4). While overreporting also continued to have significant effect of increasing response latencies for the 2014 vote self-report question the size of the effect was much smaller when not match respondents were included in the analysis with an increase increase of 0.471s, almost five tenths of a second (See Tables C.5).

Thought the magnitude of the effect of overreporting is smaller among the models conducted with these less restrictive sample subsets it is clear that falsely reporting participation in elections significantly increases the length of response latencies for the turnout self-report no matter how the subset under analysis is defined. The main conclusion stays the same, overreporting turnout requires greater cognitive effort than honest reports. This evidence continues to support the assumption the overreports are the result of deception and in the form of socially desirable responding.

Table C.5 2014 CCES OLS Models Matched vs. Not Matched, Standard Trimming

2014 CCES	Excludes Not Matched Respondents	Includes Not Matched Respondents
Overreporting	0.733*** (0.121)	**0.471*** (0.0747)**
Week of Admin.	0.102*** (0.0343)	**0.113*** (0.0334)**
Baseline Response Timing	0.979*** (0.0199)	**0.998*** (0.0185)**
Constant	2.302*** (0.154)	**2.181*** (0.143)**
Observations	**21,320**	**28,188**
R-squared	**0.266**	**0.256**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The second robustness check addresses trimming of the dependent variable, namely the response latency for the vote self-report question. In Chapter 4 of this dissertation I use the value at the 95th percentile as the trimming point to eliminate extreme values for the response latency measure. However, because the vote self-report question retains the same question wording and questionnaire placement in the CCES post election survey one could select a non arbitrary trimming point. I use the rounded maximum value for the time it takes to answer this question in the 2012 CCES found in Table C.3, 25s, as the trimming point for the dependent variable in both survey years. I use this alternate trimming for models that exclude not matched respondents and models that include them in the subset under analysis.

Table C.6 2012 CCES Vote Self-Report Response Timing Trimmed at 25s

2012 CCES	Excludes Not Matched Respondents	Includes Not Matched Respondents
Overreport	0.168*** (0.0582)	**0.162*** (0.0584)**
Baseline timing	1.043*** (0.0197)	**1.042*** (0.0197)**
Week of Admin.	0.00198 (0.0355)	**0.00221 (0.0355)**
Constant	1.896*** (0.141)	**1.903*** (0.141)**
Observations	**27,532**	**27,533**
R-squared	**0.320**	**0.319**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The models with a 25s cut off point for trimming the dependent variable continue to hold the same statistically significant relationship between overreporting and lengthier response latencies controlling for baseline timing and week of self-administration of the post election survey (see Tables C.6 & C.7). OLS regression results for 2012 with the 25s trimming point have almost identical coefficients for the effect of overreporting on the vote self-report response timing when not matched respondents are included or excluded from analysis. This is not the case for 2014 where the coefficient for the model including not matched respondents with the 25s trimming point is somewhat lower than the size of the effect of overreporting when not matched respondents were excluded.

Finally, the robustness checks presented in this appendix show that the results in the body of the dissertation hold under alternative specifications. These consistent finding that overreporting has positive and significant relationship with lengthier response latencies for the vote self-report question allows me to say with confidence that overreporting requires more cognitive effort than honestly reporting participation.

Table C.7 2014 CCES Vote Self-Report Response Timing Trimmed at 25s

2014 CCES	Excludes Not Matched Respondents	Includes Not Matched Respondents
Overreport	0.337*** (0.120)	**0.218***** **(0.0697)**
Baseline Timing	0.766*** (0.0171)	**0.764***** **(0.0154)**
Week of Admin.	0.0554* (0.0323)	**0.0589**** **(0.0299)**
Constant	3.615*** (0.137)	**3.622***** **(0.126)**
Observations	**25,057**	**33,096**
R-squared	**0.247**	**0.239**

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX D

BIDR SCALE PILOT STUDY

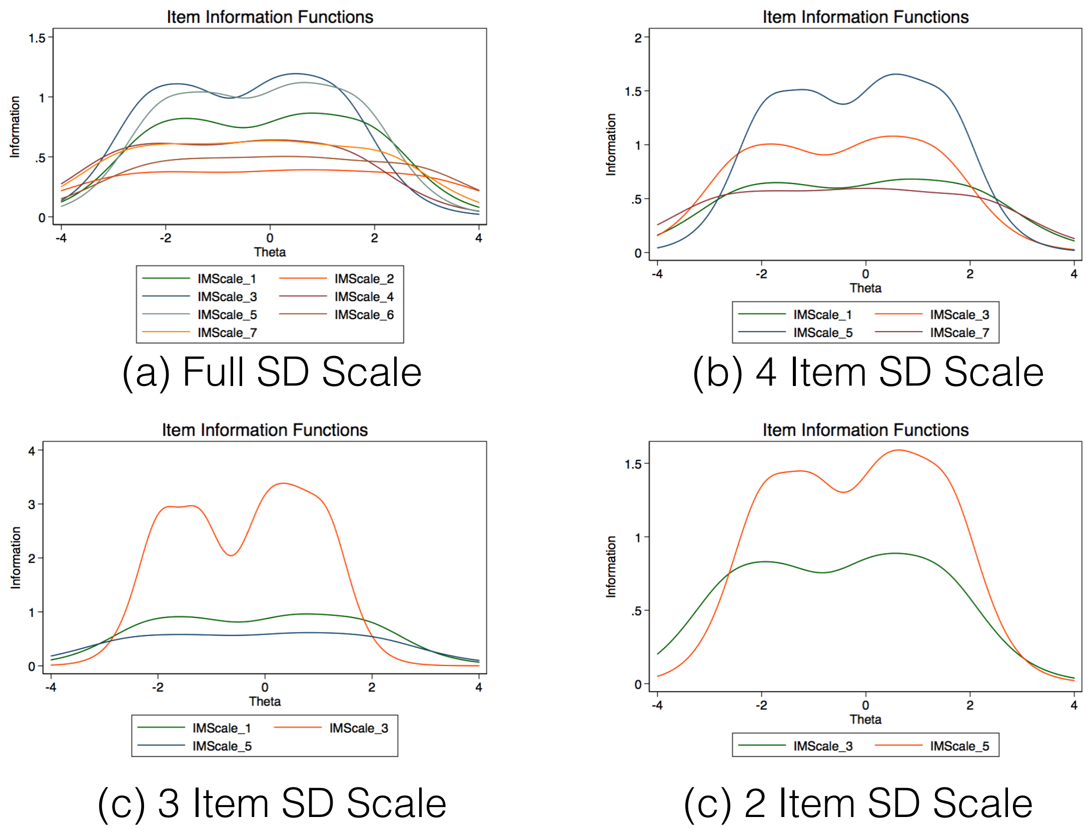
One of the goals of this dissertation is to gather evidence to either support or reject the assumption that turnout overreports in survey research are the result of socially desirable responding. Social psychologist Delroy L.Paulhus developed a battery of 40 questions meant to detect social desirability, named the Balanced Inventory of Desirable Responding (BIDR), which has been reduced to 16 items (Hart.et al., 2015) The BIDR includes a Self-Deception Scale and an Impression Management Scale in order to measure a person's tendency to either give self-deceptive or other-deceptive responses. The main difference between these two forms of socially desirable responding is intent, in the first the respondents are unconsciously deceptive and in the second they are intentionally deceptive.

This pilot study allowed for the selection of a small set of items for the 16 item BIDR, six to be exact,for inclusions in the 2016 CCES UMass Module. Including items from each scale within the BIDR in the UMass CCES Modules allowed meto carry out correlational analysis that might help determine whether respondents who falsely report participation in the 2016 General Election did so intentionally or not.

Pilot Study

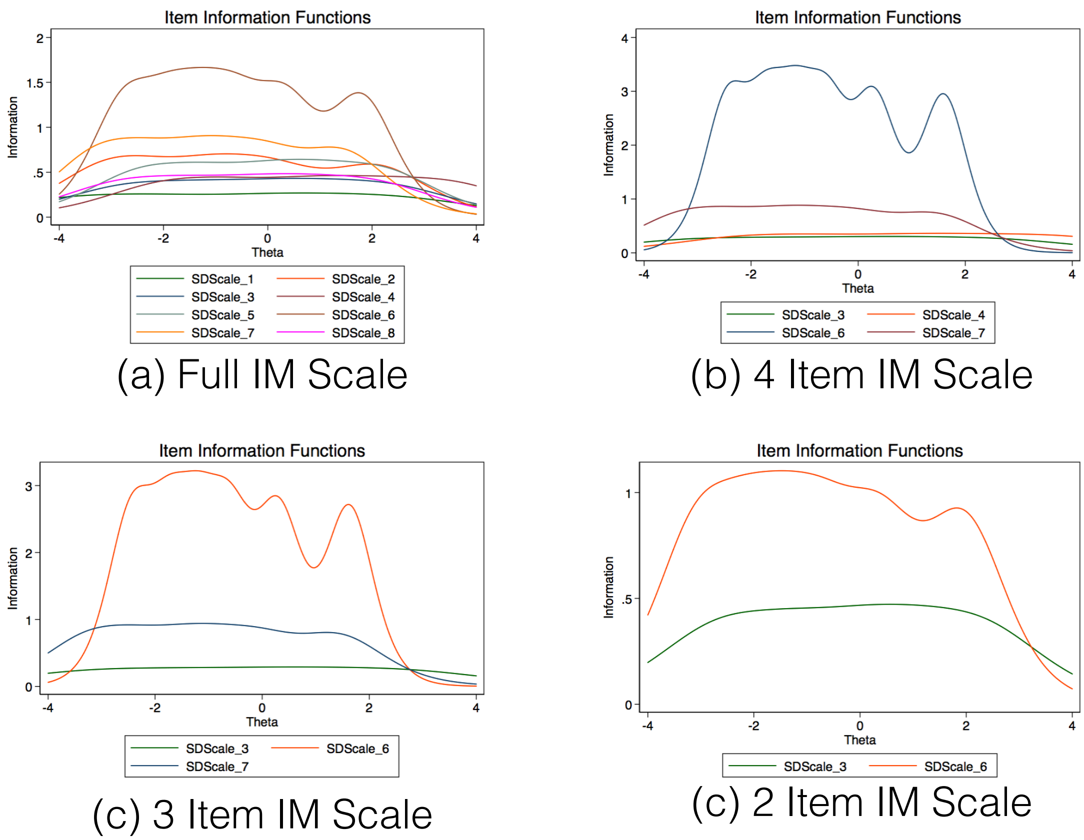
Prof. Brian F. Schaffner and I conducted a pilot study from June 8th to June 12th. The study was a post- election online survey that included 15 of the questions in the 16 item BIDR and was completed by 499 respondents. Recruitment was conducted through Amazon’s Mechanical Turk (MTurk) where MTurk workers were offered a small monetary compensation for completion of a short questionnaire regarding current primary politics. Only California residents where allowed to complete the online survey hosted on Qualtrics.

Figure 1
IRT Item Information Function Graphs for Self-Deception Scale



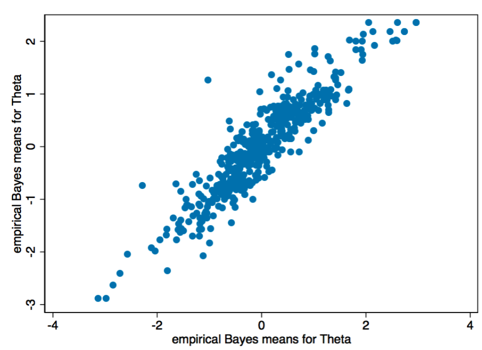
Here I present factor analysis of the Self-Deception Scale and Impression Management Scale through which I have selected six items to include in the UMass CCES Module. First, I use IRT modeling for ordinal responses to determine which of 8 items measuring respondents' tendency to give self-deceptive answers are most effective at measuring the latent variable and provide the most coverage. "Item information function" (IIF) plots were central to the process of elimination of the least effective questionnaire items along with IRT modeling outputs. Subfigure (a) of Figure 1 shows all items in the Self-Deception Scale, clearly on item is more effective than all other items at providing the most information about a person's tendency to be self-deceptive. Subfigures (b), (c) and (d) are IIF plots of the IRT models that were used to create reduced latent variables that were compared to the full Self-Deception Scale. The same process was applied to the factor analysis of the Impression Management Scale (See Figure 2 for IRT IIF plots).

Figure 2
IRT Item Information Function Graphs for Self-Deception Scale

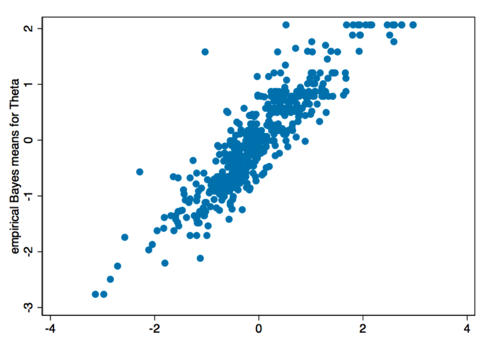


The three reduced Self-Deception Scales were compared to the full scale and so too were three reduced Impression Management Scales compared to its full corresponding scale. Scaterrplots in Figures 3 and 4 illustrate the effectiveness of each reduced scale when compared with their corresponding full scales. Correlation between the four item Self-Deception Scale and the full scale was very high (0.9198). Though correlation between the 3 item scale (0.8976) and 2 item scale (0.8651) with the full Self-Deception Scale decreased, correlation remained high enough for me to be confident that the 3 or 2 item scales wouldl be effective at measuring the latent variable. At the same time correlation between the 4 item Impression Management Scale and the full scale was exceptionally high (0.9501). A reduction is evident in the correlations between the full Impression Management Scale, 3 item scale (0.8895) and 2 item scale (0.8664), but still the 3 or 2 item scale should be sufficient to gauge a person's tendency to impression managing responses. Chapter 5 lists the questionnaires items used in the 2016 CCES UMass Module.

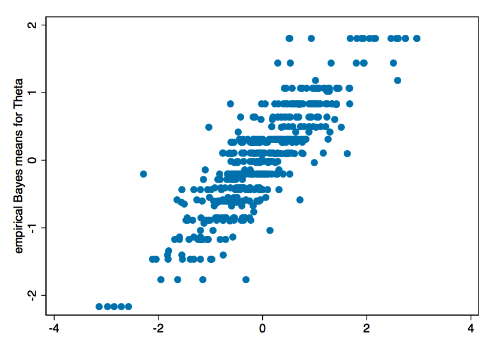
Figure 3
Scatterplots for Self-Deception Scale Latent Variables



(a) Full SD Scale by 4 Item SD Scale

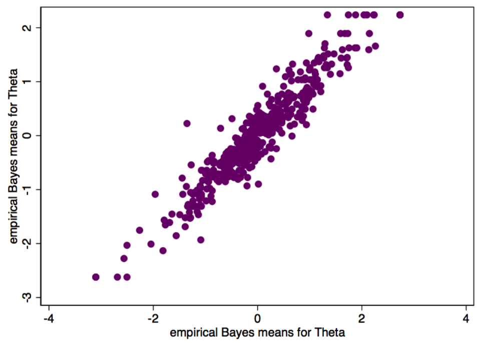


(b) Full SD Scale by 3 Item SD Scale

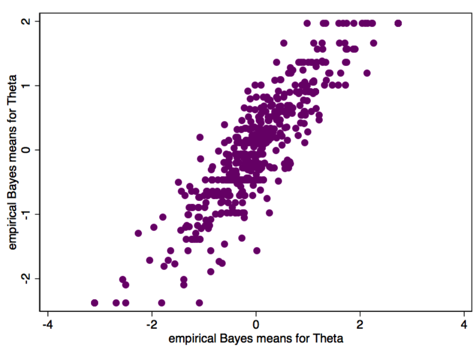


(c) Full SD Scale by 2 Item SD Scale

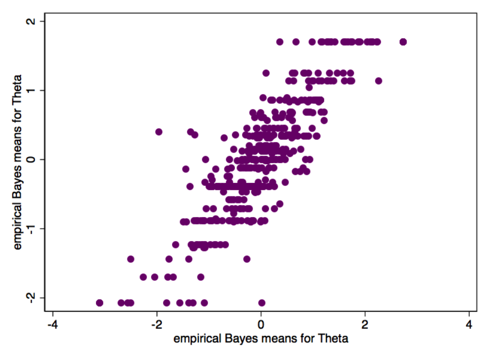
Figure 4
Scatterplots for Impression Management Scale Latent Variables



(a) Full IM Scale by 4 Item IM Scale



(b) Full IM Scale by 3 Item IM Scale



(c) Full IM Scale by 2 Item IM Scale

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