Don't Panic:
The Undercurrent of Consistency in American Voting Behavior

by

Nathan Olson

A thesis submitted in partial fulfillment of the requirements
for graduation with Honors in Politics.

Whitman College
2017

Certificate of Approval

This is to certify that the accompanying thesis by Nathan Olson has been accepted in partial fulfillment of the requirements for graduation with Honors in Politics.

_____
Susanne Beechey

Whitman College
May 10, 2017

Table of Contents

Acknowledgements

I would like to thank both Prof. Susanne Beechey and Prof. Arash Davari for their wonderful support and helpful feedback throughout the thesis writing process.

Abstract

This thesis considers the 2000, 2008, and 2016 presidential elections in an effort to determine how unique or unprecedented those elections were within the history of American presidential elections, and how consistent American voting behavior is. To accomplish this goal, I used several foundational models of voting behavior, including the Michigan Model, the retrospective voter model, and the rational voter model. I combined these foundational models into a single model and tested it using a sampling analysis and American National Election Studies data. I found that American voting behavior is consistent throughout the elections at study, and that many of the foundational models of voting behavior continue to be successful at predicting voting behavior, bringing into to question the claim that Obama, Trump, or Bush elections were truly unprecedented.

List of Figures

Introduction

At the time of writing, Donald Trump has just been elected as President. Once predicted to be an impossibility by news sources and pundits, the unthinkable has come true. Donald Trump, who is anti-immigration, anti-abortion, anti-globalization, and anti-minority has been elected president, though by the electoral college rather than a majority of votes. Many are questioning how the American nation has reached this point. American politics has reached a point where a reality TV star with no elected experience and no clear policy plans was chosen by the American people to lead.

I myself questioned how American voters came to their decisions; why they voted for such a man. So I decided to search for answers in the field of voting behavior, with the idea that there are explanations behind every citizen's vote. I was particularly drawn to several foundational models of voting behavior, models which seemed to provide the building blocks for most later models. I wanted to ask and test whether those models were still effective and still worthy of being foundational. I sought to know whether the election of President Barack Obama in 2008—seen almost as a foregone conclusion before the election—could be predicted as effectively by the foundational models as the election of President Donald Trump in 2016, which many never expected. To that end, I evaluated the effectiveness of a unified model of voting behavior, one which is built on several of the foundational models in voting behavior literature, but which combines and modifies the models in such a way as to provide a more complete picture of American voting behavior than each individual model would on its own. Put into the form of a question, how well has the predictive power of the

foundational models of voting behavior survived into the contemporary era of American politics?

What I found is that American voting behavior, at least as illustrated by the voting models I have chosen, has been consistent over the last 20 years. However, my model does not capture the entirety of American voting behavior, so it is both possible and likely that there are shifts it does not show. With that said, the fact that the foundational models of voting behavior maintain their predictive power throughout a variety of electoral settings, each unprecedented in their own way, suggests a consistency in underlying voting behavior that I find comforting in these disheartening times. Those who are optimistic will find these results hopeful for the future; while those who are pessimistic will take them to mean that the American voter is as ignorant as they have always been. I will not take sides on what the deeper meaning is in the pattern I have found, but my results do raise profound questions about both the study of voting behavior and the way in which we view the unpredictability of American politics. I asked how American voters could have elected Donald Trump, a question answered by measuring the predictive power of foundational models of voting behavior to see if they maintained consistency in the contemporary moment of American politics, and I found voter behavior this election entirely consistent with the past, though its results may define our future.

On my way to answering this research question, I formulated a number of hypotheses and narrower research questions. I began by defining the scope of my project, limiting myself to the study of non-incumbent presidential elections due to their national character and to control for the incumbency effect. Furthermore, I read

through the broad voting behavior literature, and several supplementary literatures, and chose what I considered to be the foundational models to study. A short narrative history of voting behavior and my rationales behind which models I chose to study follow in my voting models section. I combined the foundational models I chose into a single unified model, creating a modelling equation that best utilized each model's strengths and weaknesses. This equation, along with my method of data analysis, can be found in my methodology section. While creating this equation, I also formulated a number of small hypotheses to consider while testing the overall predictive power of my combined model. Due to the segmented nature of the equation I created, I was able to ask and test how each individual model's predictive power held up, with the varying answers described in my data analysis section.

During my exploration of voting behavior theory, I formulated two hypotheses that I tested with portions of my combined model. First, I hypothesized that party identification is a lagging indicator of voter behavior, which would explain the roughly one-tenth of Democrats and Republicans who vote for the opposing party's candidate each election cycle. Second, I hypothesized that independent voters would primarily be acting as rational voters, specifically considering candidates and their issue profiles when determining who to vote for, rather than any of the more amorphous concerns of party or government continuity. The reasoning behind each hypothesis, as well as how I incorporated them into my model building, is included in the discussion of the relevant models in my voting models section. While the first hypothesis turned out to be false, the second hypothesis appears to have more merit, as described in my data analysis section and conclusion. Finally, I argue that my data and analysis does show

that the foundational models of voting behavior maintain their predictive power and I will attempt in the coming pages to illustrate my thought process and methodology in reaching this conclusion.

Voting Models

The foundational models of voting are key to the history of voting behavior and the current composition of literature in the field. The first foundational model to be theorized was Anthony Downs's rational voter model, outlined in his book *An Economic Theory of Democracy*, published in 1957. Anthony Downs' model was the product of a post-war interest in the field of economics, and a determination to find other fields where economic theory could be applicable. Today, the Downsian rational voter model, as it is now known, has been modified and extended in an effort to describe voter choices. However, due to several flaws in the model itself—namely a preponderance of apparently irrational voter behavior—it is not the primary foundational model.

That distinction would go to the model created by Angus Campbell, Phillip Converse, Warren Miller, and Donald Stokes, colleagues at the University of Michigan who described their theory in *The American Voter,* published in 1960. Their theory, known now as the Michigan Model, was based on one of the first large scale studies of voter behavior, and made use of a combination of psychological and sociological theory to posit that voter choice was based off a series of factors going back to childhood, which they called the "funnel of causality." [1]

This model has driven numerous later works as well as shaped the current form of the American National Election Survey (ANES). However, it has not been without its criticism. Morris Fiorina wrote what is perhaps the most well-known critique of the

---

[1] Michael Lewis-Beck, William Jacoby, Helmut Norpoth, and Herbert Weisberg, *The American Voter Revisited*, (United States: University of Michigan Press, 2008).

Michigan model in his book *Retrospective Voting in American National Elections*, published in 1981. In it, Fiorina outlines his theory of retrospective voting, where rather than party identification being determined by the socio-psychological circumstances of birth, as in the Michigan model, it is determined by a mental scorecard of party performance. This retrospective voter model spurred the creation of a portion of voter behavior literature which considers the effects of past and future actions by parties and candidates on vote choices.

Importantly, each of these models forms the basis of large swathes of current voting behavior literature and can thus be considered the foundational models of voting behavior. As the foundational models of voting behavior, they are a strong barometer for whether the field of voter behavior modeling, as a whole, maintains its merit and if the current era of American politics is unprecedented. As they have maintained their predictive power over successive elections, as shown in my data analysis section, these models and the field as a whole should continue to play a strong role in our understanding of voter behavior. Nonetheless, each model has its flaws, and I will now examine the strengths and critiques of each model while explaining their value in my combined model of voting behavior.

The Michigan model is the primary foundational model of voting behavior, with theorists still drawing on its theoretical structure of a "funnel of causality."[2] At its simplest, the funnel metaphor is used to describe the concept that past events shape

[2] Richard Niemi and Herbert Weisberg, *Controversies in Voting Behavior*, (Washington D.C.: CQ Press, 2001), 15 Richard Lau and David Redlawsk, *How Voters Decide: Information Processing During Election Campaigns*, (New York: Cambridge UP, 2006), 10.
Larry Bartels, "The Study of Electoral Behavior" in *The Oxford Handbook of American Elections and Political Behavior*, Ed. Jan Leighley (New York: Oxford UP, 2010), 249.

future decisions, in this case, votes[3]. Taken to its fullest extent, the funnel of causality is the idea that all past events can be translated into the political sphere[4] and influence current voting behavior, though it does not mean that all events *are* translated into the political realm.[5]

Upon revisiting *The American Voter*, Lewis-Beck, et. al. broke the funnel into several slices which contained different groups of factors relevant to the future voter's decision. Furthest out are socio-demographics, the characteristics future voters are born with, which then affect their party identification, the next factor group. This then affects the final two factor groups, perceptions of candidates and issues, and then final vote.[6] As party identification is the closest variable temporally to voting, which can be easily determined, the Michigan model often gives great weight to this characteristic. It is remarkably effective at determining the votes of self-identified Democrats and Republicans, with 89% of Democrats and 88% of Republicans voting for their party's candidate in 2016, so it a strong model to use in predicting the votes of voters identifying as part of a party.[7] However, it falls short in predicting the votes of independents[8] and does not take into account changing attitudes over time.[9] Therefore, while the Michigan model is an effective predictor of votes based on party

[3] Angus Campbell, Philip Converse, Warren Miller, and Donald Stokes, *The American Voter* (New York: Wiley & Sons, 1960), 24.
[4] Campbell, et. al. *The American Voter,* 31-32.
[5] Campbell, et. al. *The American Voter,* 29.
[6] Michael Lewis-Beck, William Jacoby, Helmut Norpoth, and Herbert Weisberg, *The American Voter Revisited*, (United States: University of Michigan Press, 2008), 23.
[7] Cable News Network "2016 Exit Polls" cnn.com
[8] Campbell, et. al. *The American Voter,* 139.
[9] Andrew Healy and Neil Malhotra, "Retrospective Voting Reconsidered" *Annual Review of Political Science* 16, (2013), 286.

identification, in my model it must be combined with other models to create a comprehensive model of voting behavior.[10]

An ideal candidate for combination is a model created in opposition to the Michigan model, the retrospective voter model, explained in *Retrospective Voting in American National Elections* by Morris Fiorina. Fiorina notes that what many theorists took away from *The American Voter* was that "the typical American citizen was an irresponsible political actor caught in the coils of such arational influences as party identification and interpersonal relations,"[11] or in other words, that voters are socialized into their voting behavior by the social forces around them. Fiorina challenges this assumption, arguing that while voters do often vote for their party, which party is "their" party changes over time. Instead of simply voting for the party they were socialized into joining, voters keep "a running tally of retrospective evaluations of party promises and performance."[12] If one party underperforms with regards to an individual voter's expectations, then the retrospective model posits that the voter will then switch to the other party in an effort to find a party which performs closer to their expectations and desires. As Healy and Malhotra note in *Retrospective Voting Reconsidered*, "Voters just have to answer the kinds of questions that Ronald Reagan posed in his closing statement in his 1980 debate against Jimmy Carter: 'Are you better off than you were four years ago?'"[13] If the answer to this question is in the

---

[10] Ibid, 287.
[11] Morris Fiorina, *Retrospective Voting in American National Elections* (New Haven: Yale UP, 1981), 10.
[12] Ibid, 84.
[13] Healy and Malhotra, "Retrospective Voting Reconsidered," 286.

affirmative, then the voter should continue with the party in power, but if the answer is in the negative, then a switch in vote should occur.

However, due to a number of factors, it is likely that the effect of retrospective voting is actually quite small in the grand scheme of overall voting behavior.[14] Most importantly, most voters view one party or the other as serving their interests better and even when their party is underperforming, they will stick with it over the other party as the lesser of two evils.[15] Voters also have a wide range of issues of importance and the salience of each issue to each voter is different. Therefore, each action a government takes will only be the last straw to a small slice of people.[16]

I thought that the retrospective voter model would only have a small effect on voter behavior each election cycle, so as part of turning the theory into a workable part of my combined model, I combined it with the Michigan model. I hoped that the retrospective voter model could explain a majority of the Democratic and Republican defections and thus bring my combined model closer to explaining all of Democrats and Republicans voting behavior rather than just the 90% that the Michigan model captured. The hypothesis that led me to this was the idea that there is a delayed effect on party identification in retrospective voting. I thought that an individual who has been a member of the Democratic Party their whole life, even if fed up with the party enough to vote for a Republican presidential candidate, might not repudiate their party

---

[14] "An electorate increasingly sorted along party lines may be less likely to abandon party allegiances to vote retrospectively," Ibid, 300.

[15] This claim is based on my preliminary research, which showed a high correlation between both party identification and vote choice, as well as a high correlation between which party an individual rated higher and their party identification, even when the rating given was low.

[16] There have been a number of studies conducted showing that party vote share and turnout only marginally changes after government actions. Healy and Malhotra, "Retrospective Voting Reconsidered," 298.

identification immediately. Such a voter would likely vote for a Republican candidate based on a closer ideological position, but maintain their Democratic party affiliation while hoping for a 'revitalization' of their own party, restoring some past ideology or practice that the voter found more appealing.[17] However, should the party not be 'restored,' it is likely that the lifelong Democratic voter would eventually switch their party affiliation, though it would not be an instantaneous transition.[18] These factors gave retrospective voting a strong case for accounting for the portion of party identifying voters who defect and vote for the other party's candidate each election. However, as shown in my analysis, retrospective voting, when combined with the Michigan model, failed to explain more voting behavior than the Michigan model alone did. Therefore, it appears that my hypothesis was a mistaken one, and there will need to be work done to determine the cause of major party defections.

There is also still the matter of independent voting behavior. While I hoped that retrospective voting and the Michigan model would account for the votes of those individuals identifying as Democratic or Republican party members, independents do not fall under either of these theories well. Thus, it falls to the final foundational model, rational voting, to describe the voting behavior of independents. The rational choice model borrows from economics the concept that voters will 'rationally' choose the candidate which will bring them the most utility.[19] The form that this idea most often takes is that of proximal voting, where voters, parties, and candidates are placed

---

[17] This is based on the idea that retrospective voters are rational in their behavior, similar to the rational voter model outlined later in this section.
[18] This hypothesis came from anecdotal evidence from news articles. Former Democratic voters from the "rust-belt" were frequently quoted as citing Democrats failures to revitalize these areas as their rationale for voting for Trump, though some maintained their identity as Democrats.
[19] Suzanna Linn, Jonathan Nagler, and Marco Morales, "Economics, Elections, and Voting Behavior", 378.

on an ideological continuum and voters vote for the party or candidate whose positions

are, overall, closest to the voter on the continuum.[20] However, it is frequently noted,

including by Downs himself, that this would lead to both parties rushing towards the

center of the ideological spectrum where most voters are located.[21] Since this has not

happened, and in fact there is a substantial amount of research demonstrating the

polarization and partisanship of the American electorate,[22] either the Downsian

proximity model is incorrect or not the only factor in voting behavior. To maintain the

rational choice model of voting behavior, the directional model was created to describe

voter behavior that more closely matched up with observed reality. Directional models

posit that voters desire that the overall government match their preferred ideological

position more than they desire a party or candidate to match their ideological

position.[23] Therefore, they will vote for the candidate and party which will move the

government towards their preferred ideological position and switch parties when

necessary to continue pushing government in the direction they prefer.[24]

    I included the rational voter model in my combined model because I thought

that the independent voter would fit the profile of the rational voter well. Since

independent voters would be unlikely to make their vote decision based on party

affiliation, some other factor or set of factors would need to be considered. Borrowing

from economics, I hypothesized that people, in the absence of outside pressures, are

rational voters. If this hypothesis were true, then independents would make a rational

---

[20] Anthony Downs, *An Economic Theory of Democracy*, (New York: Harper & Row, 1957), 115-116.
[21] Downs, *An Economic Theory of Democracy*, 117.
[22] Larry Bartels, "Partisanship and Voting Behavior" *American Journal of Political Science* 44, no. 1 (2000), 35.
[23] Bernard Grofman and Samuel Merrill, *A Unified Theory of Voting: Directional and Proximity Spatial Models*, (New York: Cambridge UP, 1999), 6-7.
[24] Ibid, 6-7.

vote choice, either voting for the candidate closest ideologically to them, or for the party they thought would improve their lives. I also made the assumption that independent voters are typically directional voters, attempting to center the political equilibrium on their centrist ideological position through switching their votes between the parties relatively frequently. This would explain the frequent changes in power between the two parties, the "pendulum" of American politics. I hoped the combination of the retrospective voter model and the Michigan model would explain party member voting behavior, and that with the rational voting model to explain independent voting behavior, a comprehensive picture of overall voting behavior would be created.

As a note, there is currently a large and developing literature in the field of voting behavior which is attempting to perfect likely voter models, models which attempt to identify whether eligible citizens will actually vote or not.[25] Many pre-election polling organizations make use of likely voter screens to better predict the actual, final presidential vote. However, there are still a number of flaws in likely voter models, demonstrated by the recent spotty track record of pre-election polling, and the literature has a way to go before it will become truly effective at predicting who will stay home and who will go to the polls. However, this does emphasize the continuing need for get out the vote operations on the part of candidates and parties. Even if my model predicts a win for a candidate based on the responses of registered voters, a stronger turnout for one side or another will still be able to swing the result of an election. Nevertheless, a voter's likelihood of showing up to the polls is still considered a separate question than who they will vote for once they arrive and therefore, the

---

[25]Gregg Murray, Chris Riley, and Anthony Scime, "Pre-Election Polling: Identifying Likely Voters Using Iterative Expert Data Mining", *The Public Opinion Quarterly* 73, no. 1 (2009).

models predicting each answer are separate as well. Hopefully there will come a time where both fields are developed enough to create an effective combined model of both voter choice and likelihood of voting, but they are currently separate concerns in the field of voting behavior modeling. Therefore, this thesis will concern itself solely with predicting vote outcome with the foundational models of voting behavior discussed above.

Methodology

I have chosen to focus on these two most recent non-incumbent presidential elections in an effort to evaluate voting behavior in a similar electorate and to control for demographic shifts. While no presidential election can ever be considered truly normal or average, some have features which lend them to analysis more so than others. Since there is an academic consensus about an incumbency effect on presidential elections,[26] and a well-established body of research measuring the significance of such an effect, I have chosen to leave the incumbency effect outside the scope of my study in order to simplify my model and analysis. However, this also means that I must leave out presidential elections featuring an incumbent.

There is also a large subfield of voting behavior that is focusing on grouping behavior, which posits that members of certain socio-economic groupings will tend to vote for certain parties and candidates.[27] Importantly, this effect correlates with voters voting differently than predicted by my models.[28] For example, a voter might not vote based on party identification or 'rationally,' but based on being part of a religious group that prefers a particular party. To reduce changes in this effect over the course of time, and therefore keep the resulting error in my results consistent, I have chosen three

---

[26] Richard Born, "Congressional Incumbency and the Rise of Split-Ticket Voting" Legislative Studies Quarterly 25, no. 3 (2000).

[27] Arthur Burris and Benjamin Highton. "New Perspectives on Latin Voter Turnout in the United States" American Politics Research 30, no. 3 (2002).
Chad Kinsella, Colleen McTague, and Kevin Raleigh, "Unmasking geographic polarization and clustering: A micro-scalar analysis of partisan voting behavior" Applied Geography 62, (2015)
Melissa Goldsmith and Claudio Holzner, "Foreign-Born Voting Behavior in Local Elections" American Politics Research 43, no. 1 (2015).
Layman, Geoffrey. "Religion and Political Behavior in the United States: The Impact of Beliefs, Affiliations, and Commitment From 1980-1994". Public Opinion Quarterly 61, no. 2 (1997).

[28] Ibid.

nonincumbent presidential elections that occurred relatively close temporally and have similar electoral make-ups. As group voting behavior changes very slowly over time based on shifting issues and growing or shrinking demographics, by using elections that are relatively close in time, I can minimize the effect that changing group voting behavior has on my analysis. However, if the timeframe of study is expanded, the error caused by group voting behavior will become more inconsistent, reducing the accuracy of any test of predictive power over time. Therefore, using elections relatively close in time allows me to analyze general voting behavior without having to weight the data for specific demographic shifts, though this would be necessary for future studies seeking to expand on my work.

Presidential elections were chosen specifically because they are the only national election in the U.S. and I seek to understand the American voting public as a whole, rather than specific slices. In addition, many of the models at study were created with presidential elections in mind rather than any local types of races. To get a picture of overall American voting behavior, it is key to study an election that has a voting population representative of American voters, which only the presidential election does. Finally, to maintain the clarity of this project, I will only be testing one combined model with one type of election. Therefore, this study will concern itself solely with non-incumbent presidential elections, though it is important to note that I believe it to be extraordinarily worthwhile to extend this work to other elections. Further work has extended several of these models to be applicable to certain local elections, such as House and Senate races, but in an effort to stay as close to the original formulations as possible, I will not be studying these extensions. A key limitation to using presidential

elections to test voter behavior is that presidential elections in the U.S. use an electoral

college system. While voting models predict the popular vote rather than the electoral

college vote, it is significant to note that separate winners for the electoral and popular

votes are relatively rare. More importantly, if a model of voting behavior can be

applied both nationally and statewide, the outcomes of presidential elections could still

be predicted accurately.

  With regards to my data, in election studies there is a wealth of data from

numerous sources with a substantial variance in sample sizes, questions asked, area

covered, and representativeness of the sample. In an effort to test national voting

behavior in presidential elections, I am limiting myself solely to national survey data,

collected through both face-to-face and internet questionnaires across the 50 states. To

limit variance in results and data, I excluded national polling prior to election day.

While pre-election polling is what would be used as data for predicting elections using

models, it has a number of well documented flaws, and has missed the results of

elections a number of times. While the accuracy of the data is as important to a correct

prediction as a strong model, the two are separate concerns, and fixing pre-election

polling is outside the scope of this thesis. The American National Election Study has a

much better track record at capturing the thoughts of the electorate by asking hundreds

of detailed questions and surveying a sample constructed to be truly representative.[29]

Therefore, the primary source of the data I will be using is the ANES Time series

survey, conducted by the University of Michigan and Stanford every election cycle.

This poll has a large sample size—typically several thousand people—a standardized

---

[29] ANES, *Codebook*, 2000, 3.

set of questions, and was conducted using the same methods in 2000, 2008 and 2016, though it does have different respondents each election cycle. The data is also generally seen as representative of the American population as a whole and provides a wealth of data over time.[30] With such a broad field of datasets to choose from, I have been able to choose strong data which should provide a firm foundation for my analysis and be less susceptible to the usual critiques of the underlying datasets.

The ANES time series survey asks roughly the same questions every four years it is conducted. It consists of a survey of respondents from all 50 states and respondents are paid for their participation in the survey. It is important to note that the American National Election Studies organization is consistently testing the best way to present the survey to ensure unbiased responses, as well as making minor changes to the wording of questions to ensure an unbiased response. Furthermore, each respondent completes both a pre-election survey and a post-election survey, allowing me to test my model with their pre-election questions against their post-election vote outcome. However, this does lead to a vitally important caveat. In order to test pre-election indicators against post-election vote outcome, I had to exclude respondents who didn't vote in the election. While I could attempt to predict which candidate those respondents would have voted for had they voted, I have no recorded outcome with which to test that prediction, and thus cannot make use of their responses to test the predictive power of my model. Importantly, this might lead to an underrepresentation of swing voters, who are less likely to come to the polls out of indecision, and third-

[30]Aaron Weinschenk, "Revisiting the Political Theory of Party Identification," Political Behavior 32, no. 4 (2010), 477

party voters, who tend to turnout less than major party voters due to the low possibility of victory for their candidate.

To determine the effectiveness of the foundational voting behavior models at study, I conducted a sampling analysis where I measured the accuracy of my combined voter model by comparing the voting model predictions to the actual outcomes recorded by the respondents. To do this, I compared the number of respondents whose vote the model correctly predicted to the total number of respondents who voted using the sampling function of statistical software. Sampling is where I input an equation and the statistical software outputs the number of respondents for which that equation holds true. So, to test my model, on one side of the equation I put who the respondent voted for, recorded post-election, and on the other side of the equation I put my model, which in theory predicted the same responses based on pre-election questions, and then recorded the number of respondents for which the equation held true. In constructing the actual voting behavior model, I created a model which takes on characteristics of an if x, then y equation. The model first sorts respondents based on which party they identify as, and then sorts those groups once more based on either the retrospective voter model or the rational voter model. Therefore, the model takes a defined path, with the first check being membership in a political party, and further checks based on that initial check. This creates the final model in the figure below, with the values for each variable being described later in the data section.

Fig. 1 Vote Outcome = Voted * ((Democratic Party Identification * Democratic Retrospective Proxy) + (Republican Party Identification * Republican Retrospective Proxy) + (Independent Party Identification * Rational Voter Proxy))

18

This segmentation is both an accurate description of actual voting behavior, and is a useful tool for troubleshooting problems with the model when errors in data occur. Additionally, the form of data analysis I used, along with the segmentation in the model, allowed me to test each individual set of models separately from the combined model. This led to a clear understanding of how each individual model performed and what their contribution to the broader combined model was. As an example, I sampled the data to find the number of respondents that identified as part of a major party. Then I sampled that subset using the party identification and retrospective models and then again using just the party identification model. The equations for these models are written below as Fig. 3 and 3 respectively. This gave me the predictive percentages of each model, and in this case, showed that the retrospective voter model failed to significantly change the number of correctly predicted outcomes. A more complete analysis of the individual models and data using this method follows in the data analysis section.

Fig. 2   Vote Outcome = Voted * Major Party Identification *
((Democratic Party Identification * Democratic Retrospective
Proxy) + (Republican Party Identification * Republican
Retrospective Proxy))

Fig. 3   Vote Outcome = Voted * Major Party Identification * (Democratic
Party Identification + Republican Party Identification)

The efficacy of my work depends on the variables in my equation being accurate representations of the models I use. Therefore, I attempted to choose my variables with care, and the American National Election Survey datasets are thorough

19

enough that finding close proxy variables was not difficult.[31] A proxy variable is a variable which, while not explicitly the same as the theoretical causal variable, is close enough to be considered an acceptable stand-in. For example, the retrospective voter model relies on voters changing feelings toward the two major political parties. The ANES data has several variables which might be considered adequate proxies, including questions asking respondents to rate each party on a hundred-point scale, and questions asking respondents to rate each candidate on a hundred-point scale. After studying the predictive power of a few proxies, I went with the candidate thermometer in this case. The search for a rational voter proxy illustrates the number of possible proxy variables that I considered. While a more complete explanation for my choice in variables as well as their specific outputs into the equation follows in my data section, I will list the variables used to fill in the equation written above in Fig. 1 here for clarity.

The variable 'vote outcome' corresponds to a post-election question which asks which candidate the respondent voted for. The variable 'voted' corresponds to a post-election question which asks respondents to recall whether they voted in the most recent presidential election, necessary to ensure a vote to test my model against.[32] Both Democratic and Republican party identification variables correspond to a question which asks voters which party they identify with. The retrospective variables correspond to a pair of party 'thermometers' where respondents rated each party on a scale of 0-100. And finally, the rational voter variables correspond to a pair of candidate thermometers where respondents rated each candidate on a scale of 0-100,

---

[31] As an example, the 2000 ANES Time Series produced 1881 variables to choose from ANES, *Codebook,* 2000, 3.
[32] The voted variable will be explained more fully below, but suffice it to say that this was accomplished by setting up my sampling equation to count respondents who voted and not respondents who did not.

with ties going to the Republican candidate in the first one[33] and the Democratic

candidate in the second.[34] I hope these illustrations lend credence to my claim that the

variables I have chosen are in fact representative proxy variables for the models at

study.

It is important to note that with the exception of questions asking whether a

respondent voted and the outcome of that vote, every proxy variable is based off of a

question asked before the election. This means that I am comparing actual votes to pre-

election predictors, which leads to a possible source of error as well as a strengthening

of my conclusions. The source of error stems from the malleability of the human mind,

in that if someone comes across information which changes their mind and the

rationales underlying their voting behavior between their vote and when they answered

the pre-election survey, then it will be impossible for my model to predict their vote.

On the other hand, predictive modelling aims to predict outcomes based on prior

thoughts and survey answers. An underlying assumption is that these answers will not

change between the survey and the election, and when this assumption holds true and

the model successfully predicts outcomes based on pre-election answers, the correct

predictions can be held as proof of prior predictive power.

Modeling has been noted to be exceptionally useful in testing theoretical

hypotheses, but has the possibility of being exceptionally flawed if used improperly.[35]

For a data analysis to be successful at accurately testing the hypotheses and models in

[33] Named Rational1 in my data analysis.
[34] Named Rational2 in my data analysis.
[35] John Aldrich and Arthur Lupia, "Formal Modeling, Strategic Behavior, and the Study of American Elections" in *The Oxford Handbook of American Elections and Political Behavior*, Ed. Jan Leighley (New York: Oxford UP, 2010), 89.
Richard Berk, *Regression Analysis: A Constructive Critique*, (Thousand Oak, CA: Sage Publications, 2004), xvii.

question, then a number of factors must line up. The data must be a representative

sample of the population in question, the proxy variables used must actually be

adequate proxies, and the model in question must be workable in some form. While

there are many technical critiques of modeling—of the sort that this thesis will no

doubt encounter—there are a few areas of modeling that have received sustained

criticism, including how datasets and variables are used and how much causal

inference modeling allows.[36] The critique of data used in data analysis can be summed

up rather simply: the analysis is only as good as the data it is based on. Often, an

otherwise sound analysis will flounder upon unrepresentative data, or proxy variables

which are not actually proxies for the hypotheses at question. Above I defended the

data which this thesis is built upon and made the case for its representativeness and

soundness.

Therefore, it is necessary to address the causal inference critique. There are a

number of theorists who would defend causal inferences drawn from statistical

analyses, arguing that with the right amount of outside information—and often a

healthy understanding of psychology and sociology—that it is appropriate to assume a

chain of cause and effect between the dependent variables and the independent

variables at study.[37] However, the opposing literature argues that "Although causal

thinking seems to come naturally, causal modeling is difficult to do well. There is

nothing in the data by themselves that properly can be used to directly determine if x is

---

[36] Ibid.
[37] A. P. Dawid, "Causal Inference Without Counterfactuals" *Journal of the American Statistical Association* 95, no. 450 (2000).
Paul Holland, "Statistics and Causal Inference" *Journal of the American Statistical Association* 81, no. 396 (1986).

a cause of y (or vice versa)."[38] This is the key point in causal inference critiques, which is that models do not measure any sort of causation, they only measure association and correlation. Therefore, it is improper to assume causation where the chosen method of analysis does not support causal claims.

At first glance, this thesis looks to fall into this pitfall of making causal inferences. After all, I am attempting to evaluate predictive models using a sampling analysis, presumably with the intention of declaring that a particular model—or combined set of models in this case—do predict voter behavior. An example of a causal inference would be if I claimed that my analysis proves that party affiliation determines vote. However, this thesis is not attempting to test the causal claims of the models in question. I concede that it is entirely possible that voters choose which candidate to vote for months in advance of the actual elections, based on some set of factors which are currently entirely unclear. In fact, pre-election polling is entirely built on the assumption that a high percentage of voters will choose which candidate to vote for well in advance of actually voting for them and if exit polling is correct, this assumption is based in reality.[39] Therefore, it would be flawed to claim that a voter voted for a specific candidate out of a desire for change when it is entirely possible that the voter adopted their desire for change from a preferred candidate's platform. However, questioning the causal order does not diminish the possible predictive value of the models at study. If being a Democrat correlates strongly to voting for a Democratic candidate, then it doesn't matter if the voter in question is a lifelong

38 Berk, *Regression Analysis: A Constructive Critique*, 101.
39 Cable News Network "2016 Exit Polls" cnn.com
Cable News Network "2012 Exit Polls" cnn.com

Democrat or a Democrat because their candidate is a Democrat. What matters is that by measuring party identification, a model can predict who a voter will vote for. Therefore, though I cannot make claims about a funnel of causality or in what order factors affect a voter's final choice, I can still evaluate the predictive ability of the models in question simply by seeing how well the factors they identify predict final vote choice.

It is important to address that I have departed from common practice in my study of voting behavior, as most modelling of voter behavior is done through a form of regression analysis. Regression analysis is definitely a powerful tool for testing models, and will likely have to be performed if further work is to be done to fully explore the insights my model brings, but there are a few specific reasons that I chose to use basic sampling to test my models rather than delving into regression analysis. Any model which hopes to explain the whole of voting behavior will inevitably need to be run through a regression, since voting behavior is too complicated to be fully explained by less than a multivariate equation. However, this thesis is a study of simpler model being tested to determine if there is consistency in its predictive power, rather than an attempted proof of a comprehensive voter behavior model. While regression analysis has the benefits of providing coefficients to go along with variables and p-values to determine how accurate the author's hypothesis is, it also has the downside of introducing error through its methodology. A sampling analysis does not have coefficients or p-values, but all the error within is error I introduced through my assumptions or error introduced by my data. This has the benefit of making my

conclusions as strong as the arguments I have presented to support them, and leaves me free of a discussion of technical error in regression modelling.

In my study, I expect the vast majority of my error to come from three areas. I assumed third-party candidates didn't exist and I excluded nonvoters. Most importantly, my models won't predict everything, and this will lead to a number of votes that will differ from the predictions of my model. Furthermore, I constructed and tested my model in such a way as to exclude nonvoters and third-party voters from the resulting sample counts. Therefore, when I discuss the predictive power or predictive percentages of the constituent parts of my model, I am presenting the percentage of correctly predicted total votes if the data was perfectly representative, and nonvoters and third-party voters were excluded. This does leave the error inherent in the data present, which I cannot measure with the analysis I have used. However, since I have attempted to exclude the largest sources of error, and the ANES has been rigorously tested and designed for years to remove errors in data collection, I argue that the numbers I present are accurate enough to draw the meaningful conclusions I do from them. To confirm this, my model should be tested by a regression analysis in the future, and over a broader period of time. If my assumptions hold, it will be found accurate and consistent.

Model

Now to the model itself and the details of how I created each variable. As noted above, the key to a successful test of the predictive power of voter models is a model which accurately relates the theories at study to variables found in the data being used. I will describe the variables I created here in an effort to explain how each is a strong proxy for one of the theories considered. The first variable is a simple record of whether a respondent voted or not, with 1 being voted, and 0 being did not vote. This is the variable I used to exclude the respondents who did not vote. Next, the dummy variable for vote outcome recorded who respondents voted for with three possible outcomes. One possibility was exclusion, which resulted from a respondent not answering one of the required questions or a respondent who did not vote. I also excluded third-party votes, as they are a relatively stable number of votes that are almost impossible to predict using current models. Hopefully in the future someone will be able to predict third-party voters, but in the interest of simplicity, I stuck to studying voters who split between one of the major party candidates. The outcomes that were counted as valid were a 1 outcome and a 2 outcome, which were a vote for the Democratic candidate and the Republican candidate respectively.

For the Michigan model portion, I used party identification as the proxy variable. Since the Michigan model is based primarily on party identification, there should be no better proxy. The question itself is worded to ask which party respondents identify with, rather than whether they have membership in any particular party, to best characterize respondents' party identification independently of whether or not they maintain an actual party registration. I created three dummy variables based on party

26

identification, one for Democrats, Republicans, and independents each. For each

dummy variable, identification as the party in question would be recorded as a 1 while

identification as any other party would recorded as a zero. This allows for segmentation

based on party identification, and allows for further segmentation based on future

responses. In practice, this meant that for each respondent who identified as

Democratic, I used a Democratic retrospective dummy variable to predict their final

vote choice, and for each respondent who identified as Republican, I used a Republican

retrospective dummy variable to predict final vote choice.

The proxy variables that were used to create the retrospective dummy variable

were "feeling thermometer"[40] questions, which are questions where the respondent is

asked to rate something, in this case political parties, on a scale of 0-100. I used the

results of the feeling thermometer questions about the Democratic and Republican

Parties to create to the retrospective dummy variables. The Democratic retrospective

dummy variable recorded a vote for the Republican candidate if the respondent rated

the Republican party higher than the Democratic party, and a voter for the Democratic

candidate if the respondent rated the Democratic party as equal or higher than the

Republican party. The Republican retrospective dummy variable was exactly the

opposite, so it was a vote for the Republican candidate if the respondent rated the

Republican party higher or equal to the Democratic party, and a vote for the

Democratic candidate if the respondent rated the Democratic party as higher than the

Republican party. As the retrospective voter model relies on a hypothetical scorecard

---

[40] ANES, *Pre-Election Codebook,* 2008, 106.
The feeling thermometer questions, as noted above, ask participants to rate a candidate or organization
on a scale of 1-100 based on how "warm" they feel toward the candidate or organization under
consideration.

of each party, a variable which used a scorecard of both parties seemed to be the most effective proxy. This retrospective dummy variable was used in conjunction with the party identification screen to determine the vote outcome of voters who identified with one of the two major parties. The model up to this point looks as written below.

Fig. 4   Vote Outcome = (Democratic Party Identification*Democratic Retrospective Proxy) + (Republican Party Identification*Republican Retrospective Proxy).

The final variable was the one used to determine independent voter choice. Since I am using the directional rational voter model to describe independent voting behavior, I needed a proxy variable which adequately captured whether a voter thought they would be better off continuing with the current party or changing direction with the opposition party. I tested three proxy variables and five dummy variables in an effort to find the best proxy dummy variable for rational voter behavior. The first proxy variable I tested was a question which asked voters if they were better off now than one year ago. The respondent was given the option of answering that they were better off, worse off, or didn't know. The presence of the didn't know response made creating a dummy variable difficult, since I needed to determine if the "didn't knows" would vote to continue the incumbent party's reign, or whether they would vote to switch to the opposition party. As noted above, third-party voters were excluded, though they do make up a sizeable number of independent voters and their behavior will need to be evaluated later. Alternatively, another possible proxy variable asked respondents whether they thought the country was heading in the right direction, with the only response options being that the country was heading in the right direction or that the

country was heading in the wrong direction. This had the benefit of pushing

respondents toward a binary choice, which while skewing the data, provides for easier

sorting of responses. The final proxy I tested was similar to the retrospective voter

proxy, using candidate thermometers in the place of party thermometers. As this

variable had the most predictive power, it was the proxy variable I went with. For the

dummy variable, if the Democratic candidate was rated more highly than the

Republican candidate, they would get the vote. If the Republican candidate was rated

more highly than the Democratic candidate, they would get the vote. If the candidates

were rated equally, I assumed the Democratic candidate would win in one of the

dummy variables, and the Republican candidate would win in the other dummy

variable. With these final dummy variables, the complete model I tested can be written

out as in the figure below.

Fig. 5   Vote Outcome (0,1,2) = (Voted (yes/no)) * ((Democratic Party
Identification (yes/no) * Democratic Retrospective Proxy (0,1,2))
+ (Republican Party Identification (yes/no) * Republican
Retrospective Proxy (0,1,2)) + (Independent Party Identification
(yes/no) * Rational Voter Proxy (either variable) (0,1,2))).

This model is what was inputted into the statistical software to sample

respondents for which outcome on the left side matched the prediction on the right

side. Done each election, this sampling provided the predictive power of each model

over time. As this equation shows, 0's are those who were thrown out for an error or

nonresponse. 1 outcomes are votes for the Democratic candidate and 2 outcomes are

votes for the Republican candidates. The yes or no responses to party identification

sorted respondents into particular portions of the model, and the responses to voted

included or excluded respondents from the sample. The predictive power of the model was tested by sampling the number of respondents whose outcome the model correctly predicted. In the next section, the results of this test are described for the presidential elections of 2000, 2008 and 2016, as well as for different segments of the model such as the retrospective and rational voter portion.

Data Analysis

To recap, I wanted to test my combined model of voter behavior to see if it, and the foundational models which comprised it, maintained their predictive power in the contemporary era of American politics. The overall model, when tested with the 2016 data, predicted 2,295 observations out of 2,468 valid observations for a 93.0% prediction rate.[41] When tested with the 2008 data, it predicted 1388 observations out of 1593 valid observations, for a 87.1% prediction rate. When tested with the 2000 data, it predicted 1002 observations out of 1120 valid observations for a 89.5% prediction rate. While this separation in prediction rates is statistically significant, it is relatively minor in the overall variance experienced in voter behavior modelling. However, the individual models fared very differently upon close examination. While all experienced slight variance in predictive accuracy for both election years, their innate predictive accuracy varies substantially. The Michigan model, based on party identification, predicted 87.1% of valid observations in 2016, 91.3% in 2008 and 92.1% of valid observations in 2000. To be clear, a valid observation for the Michigan model is a respondent who identifies as a Democrat or Republican, and votes for a major party candidate. Clearly, the Michigan model is a very effective predictive model for Democrats and Republicans which has maintained its predictive power.

However, the retrospective model, meant to complement the Michigan model in my combined model, does not seem to be effective at all in predicting voter behavior. In 2016 the retrospective model predicted 1621 valid observations compared to the

---

[41] The prediction rates presented here are rounded for ease of presentation, as the actual prediction rates have significant figures out further, the number of which vary based on the number of respondents.

Michigan model's 1594 valid observations, in 2008 it predicted 998 compared to 1002, and in 2000 it predicted 695 compared to 703. This shows that it only marginally changed the number of accurately predicted observations when combined with the Michigan model in both elections. This suggests that the percentage of Democrat and Republicans that do not vote for their party's candidate must be explained by some other model or models than the retrospective voting model. This is not to say that the retrospective voter model is completely inept at describing voter behavior, and in fact, much of its theory is dedicated to describing changes in voter party identification over time rather than in a single election. So, while it may not work to predict votes in presidential elections, it will likely remain in use to describe changes in voter behavior over time, though this would need to be tested using a panel study that maintained the same pool or respondents over a long period of time.

The rational voter model fares much better than the retrospective voter model, but less well than the Michigan model in its predictive power. In 2016, the rational voter model predicted 77.5% of valid observation with the first rational voter variable[42] and 76.2% of valid observations with the second rational voter variable.[43] In 2008, the rational voter model predicted 79.9% and 82% of valid observations, respectively. In 2000, the model predicted 75.9% and 74.7% of valid observations, respectively. A valid observation in this case is an independent voter who voted for a major party candidate. While it experienced more variance than the other variables between elections, it still maintained relatively similar predictive power. However, there is still roughly 25% of the independent vote unaccounted for, which will eventually have to

[42] Rational1.
[43] Rational2.

be explained with other models and proxy variables. Overall, while the model as a whole maintains predictive power throughout elections, as do each of the individual models, the predictive power of each individual model varies significantly.

Conclusion

This not the first attempt to combine these three voter models, nor even the most sophisticated. But the very simplicity of this model and the method used to test it are its strengths. The only error is that created through my assumptions and data, with my methodology theoretically producing results as accurately as possible. These results uphold the hypothesis that voting behavior shifts slowly and that even in elections which seem unprecedented and completely unexpected, the underlying behavior of voters remains remarkably similar. Both as a combined model and as individual models, the foundational models of voting behavior maintain their predictive power over time, though several will require extensions to improve their ability to explain voting behavior. Independents should be the focus of future research since their behavior continues to be the most difficult to explain, though there also remains the one-tenth of party identifying voters whose votes also needs to be accounted for. It is my hope that future work will attempt to build on these findings and improve our understanding of voting behavior. To summarize, the foundational models of voting behavior maintain their predictive power throughout a variety of electoral settings which suggests a consistency in underlying voting behavior even as the 'pendulum' of American politics continues to swing.

This lends credence to the idea that voter behavior modeling has useful applications in determining broader patterns of behavior. Currently, the study of voting behavior is attempting to predict the outcomes of elections as simply as possible, using broad-based variables to predict the votes of large swathes of the electorate. As an example, in my study I asked whether voters were members of a political party, which

candidates they preferred, and whether they voted. I did not ask the reasons behind these choices, affiliations, and preferences. What I argued was that the foundational models of voting behavior do not vary significantly in their predictiveness from election to election, which shows that no matter the candidates and salient issues of the time, there is a consistency to voting behavior that is important for politicians, journalists, academics, and citizens to recognize.

Therefore, the next step from the work I have done would be to ask *why* the models I tested were effective at predicting voter behavior and *what* maintains the consistency within them. Roughly 90% of Democrats and Republicans vote for their own party's candidate each election. Why is party affinity such a strong driver of vote outcome, and where does it come from in the first place? Finally, why do some Democrats and Republicans defect each election? I hypothesized that voting behavior was a lagging indicator, that Republicans or Democrats might be loath to give up their party identification even if they identified and voted with a different party. Yet my results showed that a retrospective voter screen did not improve the predictive power of the Michigan model, though neither did it worsen it. Therefore, there might be a model that could better screen out Democrats and Republicans who will vote for the opposing party's candidate.

Indeed, if any model fails to explain all voter behavior, then it is likely that there is at least another strong underlying cause of their decisions in addition or in place of the models already present. My independent voter model only explains three-quarters of independent votes. So, the next question should be, why do the rest vote differently? What are the causes of segmentation in independent voting behavior?

35

While determining causality using modeling is inherently risky, with a likelihood of mistakes and bias, models can contribute evidence of correlation which can be used in arguing for one causal chain over another. As Campbell, et. al. argued in *The American Voter*, there must be a "funnel of causality" leading to a voter's final choice of candidate. Further study into voter behavior models can help elucidate the factors driving this funnel of causality and help give us a better understand of what drives American voter decisions.

Coda

      While this thesis has focused primarily on both the predictive power of the foundational models and the consistency of that predictive power over time, I think that it is important to close with a final note about the impact of a greater understanding of voting behavior on American democracy as an example of the effects that this field may have in the future. A critique of voting models is that they attempt to predict the unpredictable. Humanity is free-willed, and as such, will be inherently impulsive and ever changing in such a way as to defy easy characterization. And even if we could predict the behavior of all the voters in a nation, would that not give power to those that understood the levers driving this behavior, or immediately change it once discovered? I, for one, think not.

      An understanding of voting behavior will aid the democratic functioning of the American republic. Knowledge of voting behavior will assist incumbent politicians in catering to the desires and will of their electorate, not lend them the power to dominate it. Humanity has the free will to make their own choices, and while there will always be those who try to manipulate and control our desires, our thoughts and beliefs come from ourselves. We must choose who we follow and we must decide what issues and policies we favor based on our own morality and desires.

      There will always be challengers attempting to unseat those politicians that do not act in the wishes of their constituents. The key to a representative democracy is an understanding of the desires and wishes of the majority of the citizenry. Politicians will learn that they must respect and follow the commands of their constituents or lose elections to someone who better represents we the people. This result would have the

effect of making the United States' representative democracy more truly representative of its citizens wishes and therefore more democratic.

However, it is important to note that the predictability of voting behavior does not lead to the predictability of the future path of a nation's government. At its core, democracy is different groups and ideas battling for supremacy through discussion and debate, all in an attempt to convince a majority of the nation that one path is more in their interests than another. This idea is what free speech is based on, and comes from the theory that no one person or group has all the right answers. Rather, every individual has a portion of the best solution and it is through discussion and debate that this best solution will be elucidated. Predictive modeling will not change this core of debate, though it may allow advocacy groups to better focus on those who remain unconvinced of a certain idea's merit. A keener understanding of our own voting behavior will allow citizens to better understand where our own neighbors are coming from. Rather than being confused about other voting choices and behaviors, further study may allow us to understand the thought process and assumptions behind others voting choices. Hopefully this will promote discussion and understanding among citizens of each other's underlying beliefs and assumptions. Understanding voting behavior is key to understanding and facilitating the functioning of democracy.

Bibliography

Aldrich, John and Arthur Lupia. "Formal Modeling, Strategic Behavior, and the Study of American Elections" in *The Oxford Handbook of American Elections and Political Behavior*. Ed. Jan Leighley. New York: Oxford UP, 2010.

American National Election Studies. *Pre-election Codebook*. ANES, 2008.

American National Election Studies. *Codebook*. ANES, 2000.

Bartels, Larry. "The Study of Electoral Behavior" in *The Oxford Handbook of American Elections and Political Behavior*. Ed. Jan Leighley. New York: Oxford UP, 2010.

Bartels, Larry. "Partisanship and Voting Behavior". *American Journal of Political Science* 44, no. 1 (2000): 35-50

Berk, Richard. *Regression Analysis: A Constructive Critique*. Thousand Oak, CA: Sage Publications, 2004.

Born, Richard. "Congressional Incumbency and the Rise of Split-Ticket Voting" *Legislative Studies Quarterly* 25, no. 3 (August 2000): 365-387.

Burris, Arthur and Benjamin Highton. "New Perspectives on Latin Voter Turnout in the United States". *American Politics Research* 30, no. 3 (2002): 285-306

Campbell, Angus, Philip Converse, Warren Miller, and Donald Stokes. *The American Voter*. New York: Wiley & Sons, 1960.

Cable News Network "2016 Exit Polls" cnn.com

Dawid, A. P. "Causal Inference Without Counterfactuals" *Journal of the American Statistical Association* 95, no. 450 (2000): 407-424

Downs, Anthony. *An Economic Theory of Democracy*. New York: Harper & Row, 1957.

Fiorina, Morris. *Retrospective Voting in American National Elections*. New Haven: Yale UP, 1981.

Goldsmith, Melissa and Claudio Holzner. "Foreign-Born Voting Behavior in Local Elections". *American Politics Research* 43, no. 1 (2015): 27-58

Grofman, Bernard, and Samuel Merrill. *A Unified Theory of Voting: Directional and Proximity Spatial Models*. New York: Cambridge UP, 1999.

Healy, Andrew and Neil Malhotra. "Retrospective Voting Reconsidered". *Annual Review of Political Science* 16, (2013): 285-306

Holland, Paul. "Statistics and Causal Inference" *Journal of the American Statistical Association* 81, no. 396 (1986): 945-960

Jacobson, Gary. "Partisan Polarization in American Politics: A Background Paper". *Presidential Studies Quarterly* 43, no. 4 (2013): 688-708

Jessee, Stephen. *Ideology and Spatial Voting in American Elections*. New York: Cambridge UP, 2012.

Kinsella, Chad, Colleen McTague, and Kevin Raleigh. "Unmasking geographic polarization and clustering: A micro-scalar analysis of partisan voting behavior". *Applied Geography* 62, (2015): 404-419

Lau, Richard, and David Redlawsk. *How Voters Decide: Information Processing During Election Campaigns*. New York: Cambridge UP, 2006.

Layman, Geoffrey. "Religion and Political Behavior in the United States: The Impact of Beliefs, Affiliations, and Commitment From 1980-1994". *Public Opinion Quarterly* 61, no. 2 (1997): 288-316

Lewis-Beck, Michael, William Jacoby, Helmut Norpoth, and Herbert Weisberg. *The American Voter Revisited*. United States: University of Michigan Press, 2008.

Linn, Suzanna, Jonathan Nagler, and Marco Morales. "Economics, Elections, and Voting Behavior" in *The Oxford Handbook of American Elections and Political Behavior*. Ed. Jan Leighley. New York: Oxford UP, 2010.

Murray, Gregg, Chris Riley, and Anthony Scime. "Pre-Election Polling: Identifying Likely Voters Using Iterative Expert Data Mining". *The Public Opinion Quarterly* 73, no. 1 (2009): 159-171

Niemi, Richard, and Herbert Weisberg. *Controversies in Voting Behavior*. Washington D.C.: CQ Press, 2001.

Weinschenk, Aaron. "Revisiting the Political Theory of Party Identification". *Political Behavior* 32, no. 4 (2010): 473-494.