# Hearing the Voice of the Future: Trump vs Clinton

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**Abstract**

Many countries face growing concerns that population aging may make voting and policy-making myopic. This concern begs for an electoral reform to better reflect [illegible]ces of the youth, such as weighting votes by voters' life expectancy. This paper predicts the effect of the counterfactual electoral reform on the 2016 U.S. presidential election. Using L2 data, we find that Hillary Clinton would have won the election if votes were weighted by life expectancy.

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# 1 Introduction

Intergenerational conflicts are a long-standing regularity in politics. For example, turnout behavior, party identification, and policy preferences (e.g. liberal vs conservative) vary across generations.[1] At the same time, population aging is a pressing issue in the developed world. The two facts raise the concern that in the aging developed countries, voting and policy-making may become biased toward the elderly. This concern has generated many policy and media discussions about electoral reforms to better reflect the voices of the youth. Such electoral reforms can take many possible forms:[2]

- Giving proxy votes to parents of minor children (Demeny, 1986)[3]
- Creating generational electoral districts that accommodate only particular generations (Ihori and Doi, 1998)
- Weighting votes by voters' life expectancy[4]

This paper studies the effects of these intergenerational electoral reforms on electoral outcomes. Specifically, we focus on weighting-votes-by-life-expectancy and study its counterfactual effect on the 2016 U.S. presidential election.[5]

Our analysis proceeds as follows. Imagine the 2016 presidential election weighted votes by voters' life expectancy. For each state, we simulate the life-expectancy-weighted popular vote shares of real candidates, especially Hillary Clinton and Donald Trump, as follows:

$$\begin{aligned} &\text{counterfactual weighted \# popular votes for each candidate} \\ = &\textstyle\sum_a (\text{real \# popular votes among voters of age } a) \times (\text{life expectancy of age } a), \end{aligned}$$

where the real number of popular votes among voters of age $a$ comes from L2 data. The life expectancy of age $a$ is based on the "United States Life Tables, 2014," published by the U.S. Department of Health

[1] For such evidence, see Wolfinger and Rosenstone (1980); Leighley and Nagler (2013); Pew Research Center (2018). There is no shortage of stories about intergenerational conflicts in the media. To name a few for different continents, see "In 20 years, British politics went from being about class to being about age" *Washington Post* (June 14, 2017), "India's New Voters: We are connected" *Economist* (April 8, 2014), "Brazil's angry millennials are forming their own Tea Party and Occupy movements" *Washington Post* (March 4, 2018), and "Better off than their parents: Why Russia's youth are backing Putin" *Wall Street Journal* (March 17, 2018). The consequences of intergenerational conflicts are also a subject of many studies (Alesina and Tabellini, 1988; Tabellini, 1991; Poterba, 1998; Bassetto and Sargent, 2006; Song et al., 2012; Halac and Yared, 2014; Bisin et al., 2015).

[2] A common policy response is to try to increase young voter turnout. However, in countries where a large proportion of the electorate is the elderly, increasing young voter turnout may not sufficiently increase the youth's influence. More radical electoral reforms may be a palatable response in such a case.

[3] Phillips, Leigh, "Hungarian mothers may get extra votes for their children in election." *Guardian*, April 2011. `https://www.theguardian.com/world/2011/apr/17/hungary-mothers-get-extra-votes`

[4] Založnik, Maja, "Here's what would have happened if Brexit was weighted by age." *Independent*, July 2016. `https://www.independent.co.uk/news/uk/here-s-what-would-have-happened-if-brexit-vote-was-weighted-by-age-a7120536.html`

[5] Kamijo et al. (2015) provide a laboratory experiment on the effect of giving proxy votes to parents of minor children.

and Human Service's *National Vital Statistics Reports*. Aggregating these state-level weighted votes predicts a president under hypothetical generational vote weighting.[6]

This counterfactual simulation suggests that Hillary Clinton would have won the 2016 presidential election if votes were weighted by life expectancy. Clinton's national electoral college vote share would have been over 60% (319 votes) under generational vote weighting, as opposed to the real 40% (219 votes). It is important to caveat that our analysis assumes that voters' locations, turnout, and voting behavior do not change in response to generational vote weighting.

## 2 Data

Our analysis requires three types of data. First, we need data on each individual voter's turnout, vote choice, age, and state in which the voter is registered to vote. Second, we need data on the life expectancy of U.S. citizens at different ages, in order to construct the weights for the generational vote weighting scheme. We use these pieces of information to construct counterfactual voting outcomes. Finally, we need data on actual election outcomes for evaluating the quality of the above voter data. Below, we describe the data sets we use.

**Vote Choice and Age Data:** We use vote history and demographic data from the L2 voter file. We acquired the data set from L2, a data provider that collects, cleans, and merges state-level voter records with other private and public records on individual preferences, consumer patterns, and contact information. The file contains 185 million voter records, consisting of fields from voter registration and voting returns, consumer data, census data, as well as telephone, mail, and email records.

To model vote choice, we use data on each voter's turnout to the 2016 general election, and a party identification variable provided by L2. The latter variable is determined either by data on each voter's party registration (if the information is provided by the state), or modelled using each voter's demographic information (if voter party registration information is not available). Due to the data limitations, some voters are assigned an "Unknown" party identification. In the following sections, we omit the small proportion of voters with "Unknown" and "Non-Partisan" party identification. Although we cannot directly observe individuals' vote choices, previous studies that utilize L2 data to study U.S. elections have found L2's party identification variable to be a fairly reliable predictor of vote choice (Imai, 2013; Imai and Khanna, 2016; Hersh, 2013).

One caveat is, the L2 voter file provides data that were updated in 2019. As a result, the projected vote choices for individuals who have moved and changed their registered state and party since 2016 may not be correct. We verify the accuracy of modelled 2016 general election vote choices below,

[6]This aggregation of state-level weighted votes into a counterfactual president assumes the electoral college keeps using the same voting system. That is, in Maine and Nebraska, one electoral college vote is allocated to the plurality candidate in each congressional district, and two electoral college votes are allocated to the state-wide plurality candidate. The remaining 48 states use the winner-take-all system, where all electoral college votes go to the state-wide plurality candidate.

and find that L2 data correctly predicts the winning party in most states (42 out of 50 states and Washington D.C.).

**Life Expectancy Data:** To construct generational vote weights, we use the life expectancy data from the "United States Life Tables, 2014" published by the U.S. Department of Health and Human Service's *National Vital Statistics Reports* in August 2017. The report includes life expectancy estimates based on 2014 census and Medicare data for U.S. citizens at different ages (Aris et al., 2017).

**Actual Election Outcome Data:** For evaluating the quality of the L2 data, we use the Congressional Quarterly Voting and Elections Collection (CQ) as a benchmark for actual election outcomes. The CQ Voting and Elections Collection is a database that collects data on U.S. elections, parties, and campaigns.

# 3 Method

To construct the counterfactual 2016 presidential election under generational vote weighting, we weight votes by votes' life expectancy as follows. We first calculate each party's vote share by voter age within each state or congressional district. Let

$$y_{(a,p)j} = \begin{cases} 1 & \text{if } j\text{-th individual is of age } a \text{ and votes for party } p \\ 0 & \text{otherwise,} \end{cases}$$

where $j$ indexes individuals (survey respondents) in the data. The vote count for a given party $p$ within a given age group $a$ for state or district $s$ is

$$\hat{N}_{asp} = \sum_j I_s(j) y_{(a,p)j},$$

where $I_s(j)$ is 1 if the $j$-th individual state or district $s$, and 0 if not. As a result, the within-state or within-district vote share for each party and age group is given by $\hat{X}_{asp} = \frac{\hat{N}_{asp}}{\hat{N}_s}$, where $\hat{N}_s = \sum_p \sum_a \hat{N}_{asp}$. To find the counterfactual vote share of each party in each state or district, we multiply $\hat{X}_{asp}$ by the age-specific weights $w_a$, the expected life years for an average American citizen at age $a$. We sum the weighted vote shares across ages, and then normalize it to obtain

$$\hat{X}^{CF}_{sp} = \frac{\sum\limits_a w_a \hat{X}_{asp}}{\sum\limits_p \sum\limits_a w_a \hat{X}_{asp}}.$$

We use this formula to find the counterfactual for each party's vote share in each state or district. For major party vote shares, we only include Democrats and Republicans. For the all party vote shares, we include independent candidates and other parties under one category of "Other" since each other party gets only a small number of votes.

We determine the counterfactual president under generational vote weighting as follows. The electoral college determines the final outcome for U.S. presidential elections. There are a total of 538 electoral college votes. For each state, the number of Senate and House of Representative delegates corresponds to the number of electors. In addition, Washington D.C. has 3 electoral college votes. Electoral college votes are awarded based on the results of the general elections, in which citizens cast votes for the presidential candidate and vice presidential candidate of their choice, in the state where they are registered as voters. In 48 states and Washington D.C., the electoral votes are awarded to candidates who receive the most popular votes, i.e., plurality. In Maine and Nebraska, one electoral college vote is allocated to the plurality candidate in each district, and then two electoral college votes are allocated to the state-wide plurality candidate. The presidential and vice presidential candidates must have 270 votes out of 538 votes to win the election.

Our counterfactual simulation follows the same procedure in allocating electoral college votes, except we assume that there are no faithless electors. A *faithless elector* is a member of the electoral college who does not vote for the plurality winner in their given state. Typically, electors follow the "winner-takes-all" rule and all electoral college votes go to the candidate who wins the plurality in a state. In the 2016 election, however, 7 electors did not follow the rules.[7] Importantly, the 5 excluded votes and 7 potential faithless electoral votes fall far short of changing the final counterfactual president below.

# 4 Results: Counterfactual President

We find that Hilary Clinton would win the 2016 presidential election using generationally weighted votes. As summarized in Figure 1, Hilary Clinton would receive 60% of the electoral college votes (319 votes), while Donald Trump would receive 40% (219 votes).

**Heterogeneity across States.** We provide further details of our prediction by visualizing the electoral outcomes by state in Figures 2 and 3. Figure 3 describes the states in which the winning parties would be changed by generational vote weighting. Several of the key Rust-Belt states, such as Michigan and Pennsylvania are predicted to be flipped to Hilary Clinton by generational vote weighting. At the same time, Wisconsin and New Hampshire are predicted to be flipped to Donald Trump by generational vote weighting.

We further investigate this inter-state heterogeneity in Figure 4. Here, we plot the differences between the counterfactual and actual vote shares of Democrats and Republicans. As shown by its horizontal bars, on average across states, generational vote weighting results in an increase in the vote shares of Democrats. However, there are large variations in the magnitude of change across states, a pattern consistent with Figure 3.

[7] Schmidt, Kiersten and Wilson, Andrews, "A historic number of electors defected, and most were supposed to vote for Clinton." *New York Times*, December 2016. https://nyti.ms/2jWW5CY

**Heterogeneity across Generations.** Generational vote weighting has such big impacts because of generational differences in voter preferences. We highlight the generational differences in Table 1, which summarizes the vote shares of Democrats and Republicans for each generation. The Republican vote share increases as age-level increases. The trend identified here is similar to the results of existing studies (Pew Research Center, 2018).

# 5 Limitations

We should acknowledge a few limitations of the above analysis. First, we assume that voters' locations, turnout, and voting behavior do not change in response to generational vote weighting. Second, the L2 voter file does not allow us to directly observe vote choices. Instead, we use a party identification variable provided by L2. If a particular state makes party registration publicly available, then the party identification variable is determined by each voter's registered political party. If not, L2 models voters' preference based on other demographic information using a proprietary prediction algorithm. Moreover, the L2 data provides an up-to-date snapshot of voter information (as of 2019). As a result, we may not correctly model the vote choices of individuals who change their registered congressional district, state, and party between 2016 and 2019. Considering the aforementioned caveats, we verify the quality of the L2 vote choice data below.

### Validation of the L2 Data

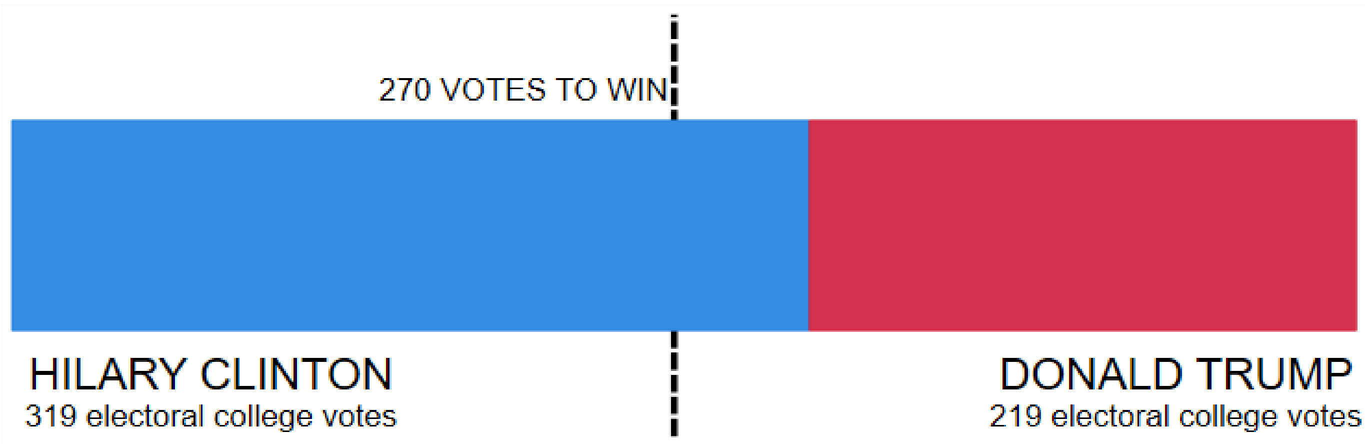
To quantify how serious these data issues are, we gauge the accuracy of the L2 data by comparing the L2 data's predicted election outcomes against the CQ election outcome data. For each state, we use the L2 data to calculate the vote shares of parties as well as their confidence intervals, without any generational vote weighting. We find that the L2 vote shares correctly capture the winning parties in 42 out of 50 states and the District of Columbia (about 82% accuracy). At the state level, L2 captures party vote shares fairly accurately, with the exception of Delaware and Washington D.C. We show this point in Figure 5, which reports the plots of the L2 and actual vote shares for Democrat and Republican candidates in the 2016 presidential election.

# 6 Path Forward

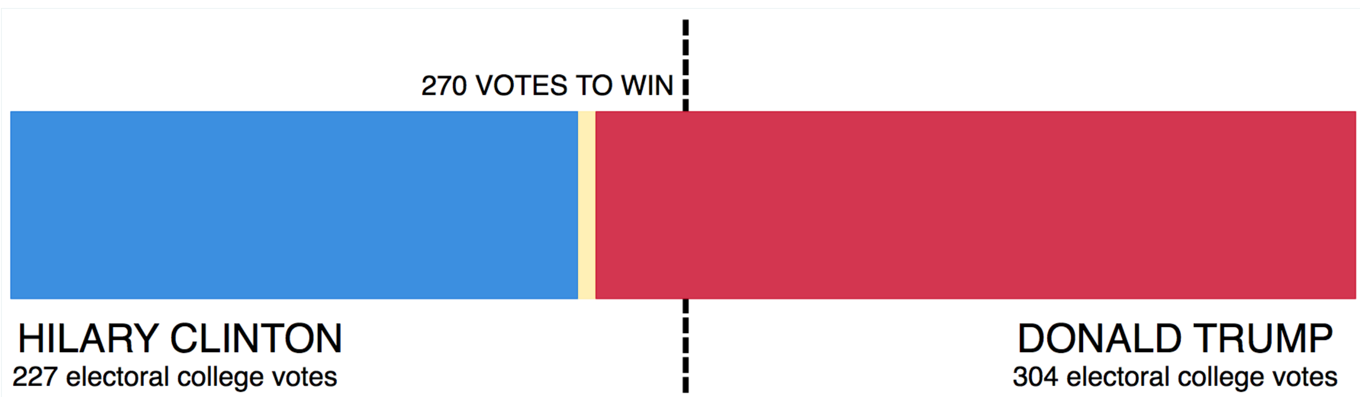
We find that generational vote weighting could change the result of a critical election like the 2016 U.S. presidential election. This analysis leads to a variety of avenues for future work. In particular, we plan to measure the effects of giving more votes to the young on a wider range of outcomes. Especially intriguing are policy outcomes and the welfare of different generations. We also plan to explore other weighting methods, such as generational electoral districts and giving proxy votes to parents of minor children. We leave these challenging directions to future work.

Figure 1: Counterfactual and Actual Electoral College Voting Outcomes

(a) Counterfactual Outcome

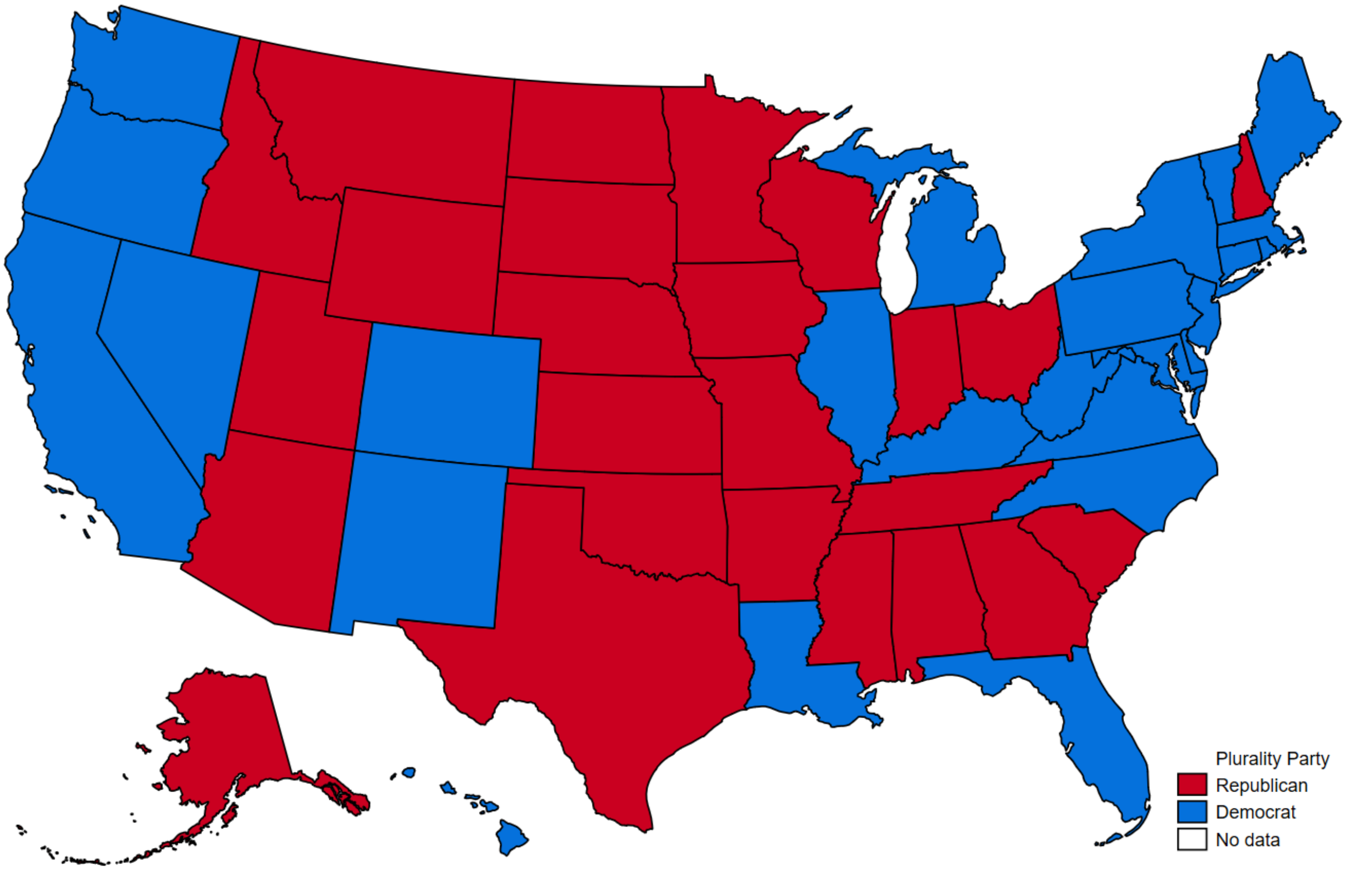



(b) Actual Outcome



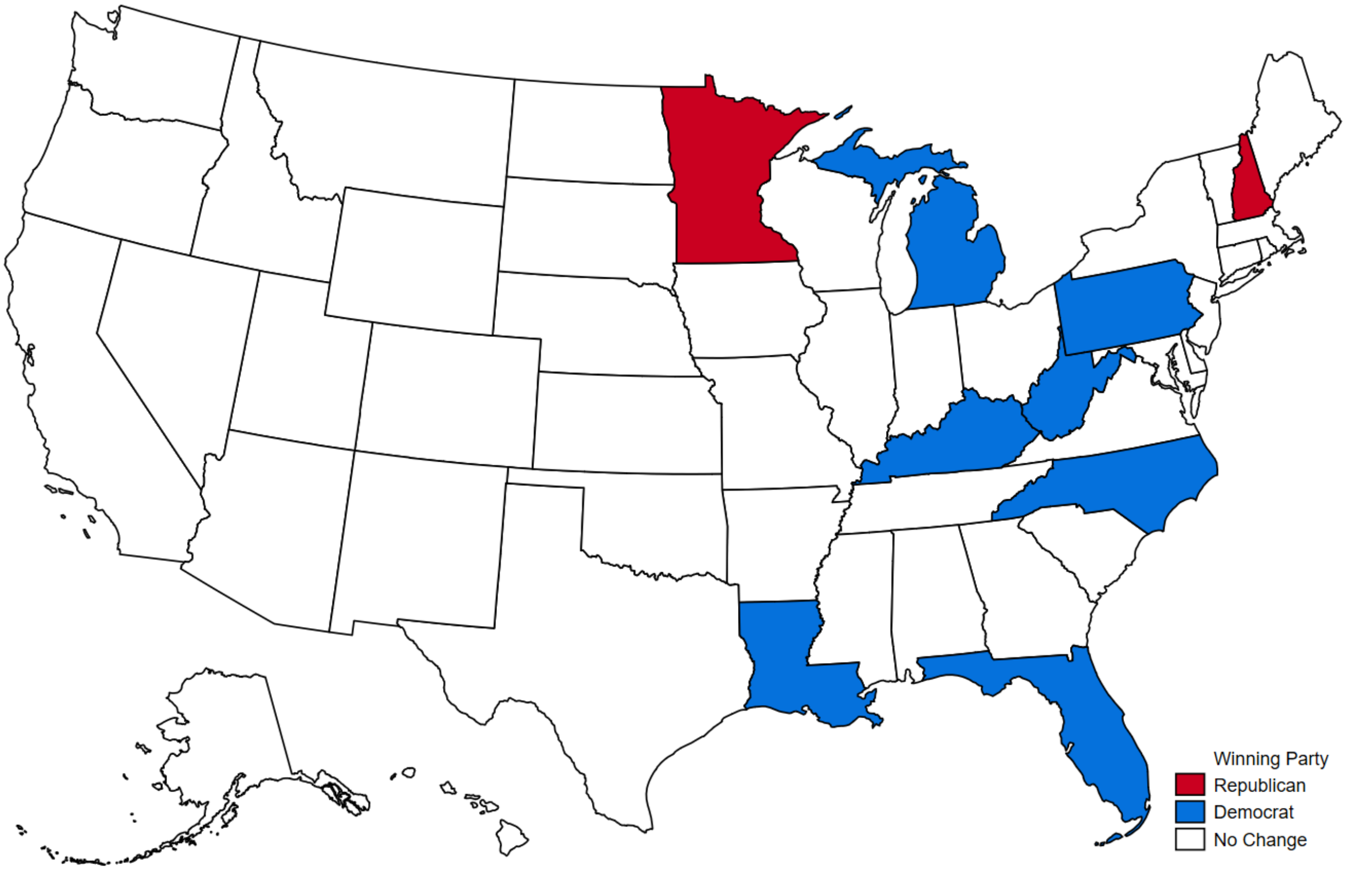

*Notes:* The figures show the counterfactual and actual distributions of electoral college votes for the 2016 presidential election, between Democrat party candidate Hilary Clinton and Republican party candidate Donald Trump. The yellow section represents the electoral votes for party candidates outside of major parties.

Figure 2: Counterfactual Plurality Party by State under Generational Vote Weighting




*Notes:* The map shows the counterfactual 2016 presidential election outcomes for each state or district with generational vote weighting.

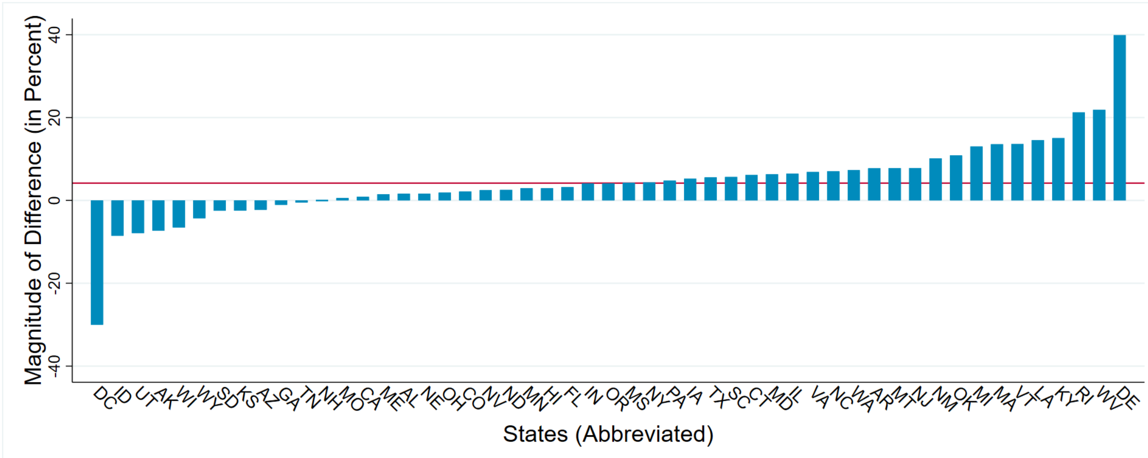
Figure 3: States where the Winner is “Flipped” by Generational Vote Weighting



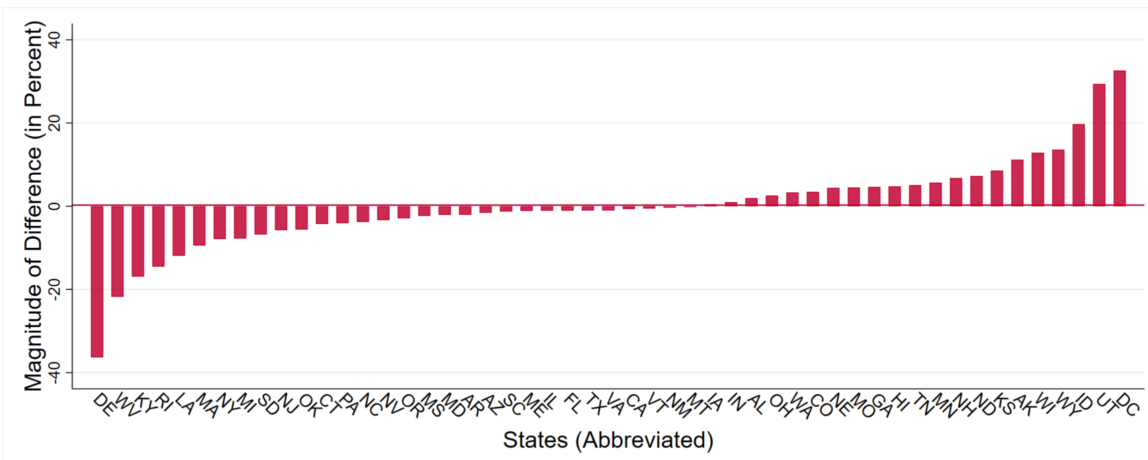

*Notes:* The map shows the counterfactual 2016 presidential election outcomes, highlighting only the states in which the plurality party is changed by generational vote weighting. There are 7 states that flipped from Republican to Democrat plurality, including: Michigan, Pennsylvania, West Virginia, Kentucky, North Carolina, Louisiana, and Florida. There are 2 states that flipped to Republican from Democrat plurality, including: Wisconsin and New Hampshire.

Figure 4: Difference between Weighted and Actual Vote Percentage by State

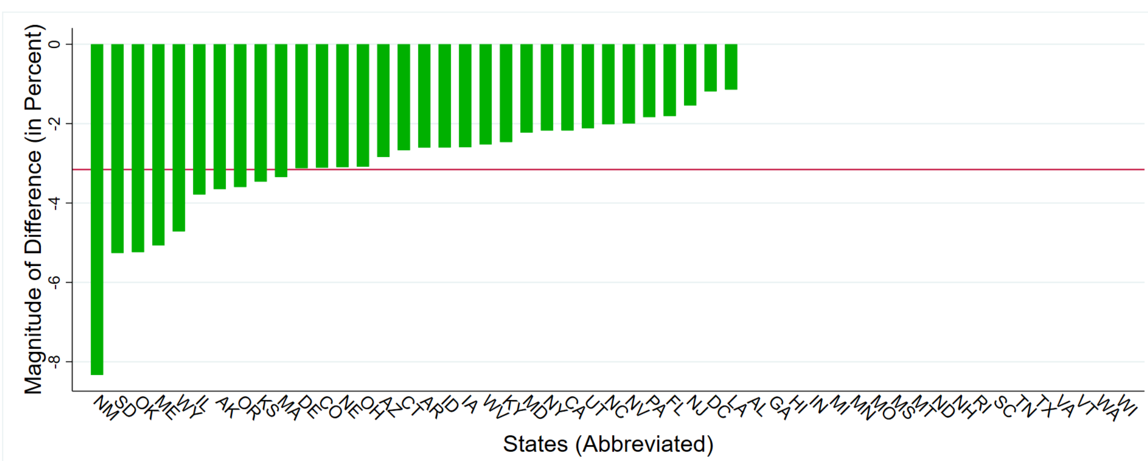
(a) Democrats




(b) Republicans




(c) Others




*Notes:* The figure shows the percentage point difference between the counterfactual (generationally weighted) and actual vote shares for Democrats, Republicans, and others. The "Others" category includes any Independent or other party candidate choice. The horizontal red line indicates the average difference across all states.

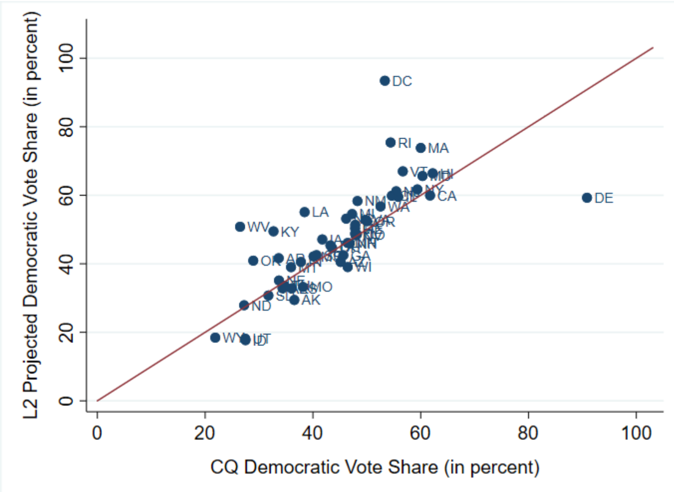
Table 1: 2016 Presidential Elections: Voting Behavior by Generations

| Generations | Democrats | Republican | Libertarian | Other |
|---|---|---|---|---|
| 18-29 | 62.88 | 33.84 | .78 | 2.49 |
| 30-39 | 55.89 | 41.24 | .65 | 2.22 |
| 40-49 | 48.62 | 49.15 | .36 | 1.88 |
| 50-59 | 46.53 | 51.64 | .2 | 1.63 |
| 60-69 | 48.85 | 49.55 | .14 | 1.47 |
| 70-79 | 45.9 | 52.67 | .08 | 1.36 |
| 80+ | 47.31 | 51.52 | .04 | 1.13 |

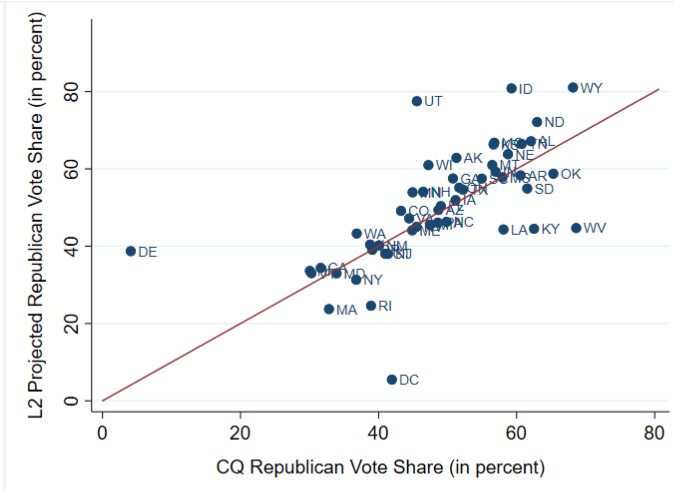
*Notes:* The table shows the vote proportion for each party by age group. The "Others" category includes any independent or other party candidate choice. We estimate the vote proportions using L2 voter file. We drop respondents who did not cast a ballot or have valid age data, as well as respondents with "Unknown" or "Non-Partisan" party affiliation.

Figure 5: L2 Vote Shares vs. Actual Vote Shares

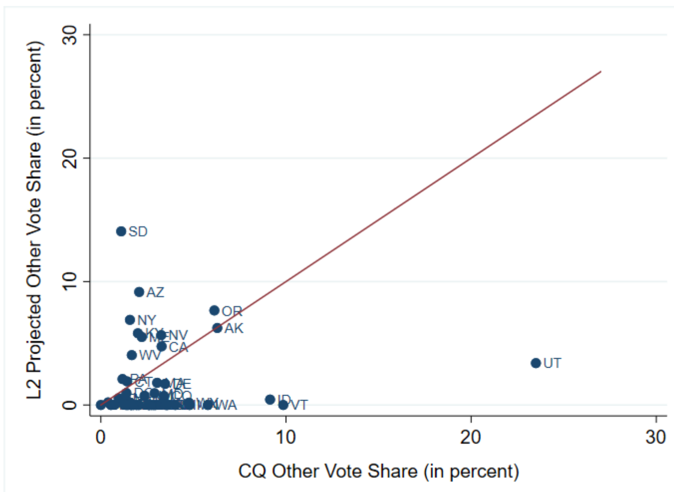
(a) Democrats




(b) Republicans




(c) Others




*Notes:* The data points represent vote shares for all parties, including Democrats, Republicans, and Others (all Independent and other parties). We exclude individuals without valid age data and those who did not vote in the 2016 general election.

Table 2: Sample Sizes for Each State

| State of Voter Registration | Size | State of Voter Registration | Size |
|---|---|---|---|
| AK | 110576 | MT | 319932 |
| AL | 1691363 | NC | 3005931 |
| AR | 731164 | ND | 199627 |
| AZ | 1880237 | NE | 639262 |
| CA | 10122004 | NH | 375826 |
| CO | 1605499 | NJ | 2525437 |
| CT | 939025 | NM | 588641 |
| DC | 164723 | NV | 793323 |
| DE | 318499 | NY | 5867542 |
| FL | 6563996 | OH | 3876079 |
| GA | 2679078 | OK | 1108786 |
| HI | 182980 | OR | 1500669 |
| IA | 1003311 | PA | 5178167 |
| ID | 398236 | RI | 233186 |
| IL | 3836402 | SC | 1751874 |
| IN | 1872633 | SD | 307368 |
| KS | 862353 | TN | 1695666 |
| KY | 1760562 | TX | 7122069 |
| LA | 1475381 | UT | 640921 |
| MA | 1329426 | VA | 3095669 |
| MD | 2190200 | VT | 234693 |
| ME | 457363 | WA | 2357432 |
| MI | 3897560 | WI | 1948938 |
| MN | 1845021 | WV | 533074 |
| MO | 2057464 | WY | 134649 |
| MS | 751589 | | |

*Notes:* The table displays the sample size, or the number of voters in each state, after we restrict the sample to individuals who voted in the 2016 general election and have valid age data in the L2 voter file. The mean sample size is 1,897,282, with a standard deviation of 2,042,685.

# References


**Alesina, Alberto and Guido Tabellini**, "Voting on the budget deficit," November 1988. National Bureau of Economic Research Working Paper 2759.

**Aris, Elizabeth, Melonie P. Heron, and Jiaquan Xu**, "United States life tables, 2014," Technical Report 4, National Center for Health Statistics (U.S.) 2017.

**Bassetto, Marco and Thomas Sargent**, "Politics and efficiency of separating capital and ordinary government budgets," *Quarterly Journal of Economics*, 2006, *121* (4), 1167–1210.

**Bernstein, Robert, Anita Chadha, and Robert Montjoy**, "Overreporting voting: Why it happens and why it matters.," *Public Opinion Quarterly*, 2001, *65* (1), 22–44.

**Bisin, Alberto, Alessandro Lizzeri, and Leeat Yariv**, "Government policy with time inconsistent voters," *American Economic Review*, 2015, *105* (6), 1711–37.

**DeBell, Matthew**, "How to analyze ANES survey data," Technical Report nes012492, ANES Technical Report Series, Palo Alto, CA, and Ann Arbor, MI: Stanford University and the University of Michigan 2010.

**Demeny, Paul**, "Pronatalist policies in low-fertility countries: Patterns, performance, and prospects," *Population and Development Review*, 1986, *12*, 335–358.

**Enamorado, Ted and Kosuke Imai**, "Validating self-reported turnout by linking public opinion surveys with administrative records," 2018.

**__ , Benjamin Fifield, and Kosuke Imai**, "Using a probabilistic model to assist merging of large-scale administrative records," *American Political Science Review*, 2018, pp. 1–19.

**Halac, Marina and Pierre Yared**, "Fiscal rules and discretion under persistent shocks," *Econometrica*, 2014, *82* (5), 1557–1614.

**Hersh, Eitan D**, "Long-term effect of September 11 on the political behavior of victims' families and neighbors," *Proceedings of the National Academy of Sciences*, 2013, *110* (52), 20959–20963.

**Ihori, Toshihiro and Takero Doi**, *Economic analysis of Japanese politics*, BokutakuSha, 1998.

**Imai, Kosuke and Kabir Khanna**, "Improving ecological inference by predicting individual ethnicity from voter registration records," *Political Analysis*, 2016, *24* (2), 263–272.

**Imai, Michael Barber Kosuke**, "Estimating Neighborhood Effects on Turnout from Geocoded Voter Registration Records," 2013. Working Paper.

**Kamijo, Yoshio, Yoichi Hizen, and Tatsuyoshi Saijo**, "Hearing the voice of future generations: A laboratory experiment of "Demeny voting"," 2015. Kochi University of Technology, School of Economics and Management Working Paper SDES-2018-2.

**Leighley, Jan E and Jonathan Nagler**, *Who votes now? Demographics, issues, inequality, and turnout in the United States*, Princeton University Press, 2013.

**Pew Research Center**, "The generation gap in American politics.," Online March 2018.

**Poterba, James M**, "Demographic change, intergenerational linkages, and public education," *American Economic Review*, 1998, *88* (2), 315–320.

**Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti**, "Rotten parents and disciplined children: A politico-economic theory of public expenditure and debt," *Econometrica*, 2012, *80* (6), 2785–2803.

**Tabellini, Guido**, "The politics of intergenerational redistribution," *Journal of Political Economy*, 1991, *99* (2), 335–357.

**Wolfinger, Raymond E and Steven J Rosenstone**, *Who votes?*, Vol. 22, Yale University Press, 1980.

# A Appendix

## A.1 ANES Analysis

Prior to using L2 data, we first used publicly available, survey data for information on voter's age, turnout, and vote choice. In particular, We use self-reported voting data from the American National Election Studies (ANES) Time Series Study.

ANES survey individuals who are U.S. citizens aged 18 or above. Their surveys have been conducted before and after presidential elections since 1948, and after most non-presidential elections since 1956. The interviews include questions on partisanship, election candidates and incumbents, government performance, political participation, media use, ideologies, values, and support for specific issues. The survey also collects personal and demographic data. ANES select a sample of 1200 to 2500 individuals for each survey. The sampling process includes oversampling racial/ethnic minorities, geographically-stratified cluster sampling, and randomly selecting a member of each household.

We use self-reported information on voter registration, turnout, and vote choice from the 2016 ANES data. We limit the data to individuals 18 years old or above, who report that they registered to vote and voted in the 2016 election. Since age is a key variable in our analysis, we also focus on individuals who correctly report their age. The resulting sample size is 4271, with 1181 individuals surveyed through face-to-face interviews and 3090 through online interviews.

### A.1.1 Method

The procedure used to construct the counterfactual 2016 presidential election under generational vote weighting using ANES data is similar to that of L2 data. The main difference is the inclusion of sampling weights in the ANES version of the analysis.

We first calculate each party's vote share by voter age within each state or district. Let

$$y_{(a,p)j} = \begin{cases} 1 & \text{if } j\text{-th individual is of age } a \text{ and votes for party } p \\ 0 & \text{otherwise,} \end{cases}$$

where $j$ indexes individuals (survey respondents) in the data.[8] The vote count for a given party $p$ within a given age group $a$ for state or district $s$ is

$$\hat{N}_{asp} = \sum_j I_s(j) w_j y_{(a,p)j},$$

where $I_s(j)$ is 1 if the $j$-th individual is in state or district $s$, and 0 if not. $w_j$ is the $j$-th individual's

[8] ANES collects self-reported information on vote choices in two phases, once prior to Election Day and once after Election Day. The pre-election vote choice captures individuals who submitted their ballot through early voting or absentee voting. If individuals indicated their vote choices in the pre-election survey, they would not be asked about their vote choices in the post-election survey. We construct a variable that indicates each respondent's vote choice, either from the pre-election or post-election survey. If an individual reported that they did not vote in both pre- and post-election surveys, we exclude the individual from the analysis.

*sampling weight*, which ANES and the STATA package "svy" provide for making the data more representative of the national population (DeBell, 2010). (Recall that the ANES study sample was not a simple, random sample from the U.S. population.) As a result, the within-state or within-district vote share for each party and age group is given by $\hat{X}_{asp} = \frac{\hat{N}_{asp}}{\hat{N}_s}$, where $\hat{N}_s = \sum_p \sum_a \hat{N}_{asp}$. To find the counterfactual vote share of each party in each state or district, we multiply $\hat{X}_{asp}$ by the age-specific weights $w_a$, the expected life years for an average American citizen at age $a$. We sum the weighted vote shares across ages, and then normalize it to obtain

$$\hat{X}_{sp}^{CF} = \frac{\sum_a w_a \hat{X}_{asp}}{\sum_p \sum_a w_a \hat{X}_{asp}}.$$

We use this formula to find the counterfactual for each party's vote share in each state or district. For major party vote shares, we only include Democrats and Republicans. For the all party vote shares, we include independent candidates and other parties under one category of "Other" since each other party gets only a small number of votes. We also calculate the standard error of each counterfactual vote share estimate, as detailed in Appendix A.2.

We determine the counterfactual president under generational vote weighting using the same method as with L2 data. In addition to assuming that there no faithless electors, we exclude the district-level electoral votes for Maine (2 votes) and Nebraska (3 votes), as the ANES does not provide information on individuals' district of voter registration.

### A.1.2 Results: Counterfactual President

Similar to the L2 analysis, we find that Hilary Clinton would have won the 2016 presidential election using generationally weighted votes. As summarized in Figure 6, Hilary Clinton would receive 63% of the electoral college votes (336 votes), while Donald Trump would receive 36% (194 votes). Given that the ANES data are collected from survey samples of the entire voter population, we also quantify statistical confidence in our result: Clinton's counterfactual victory is statistically significant at the 95% level, when we estimate the standard error of the final distribution of electoral college votes, following the method in Appendix A.3.

**Heterogeneity across States.** We provide further details of our prediction by visualizing the electoral outcomes by state and congressional district in Figures 7 and 8. With ANES data, a larger number of Rust-Belt states are flipped to Hilary Clinton by generational vote weighing, including Michigan, Ohio, Pennsylvania, and Wisconsin (shown in Figure 8). We also see a larger number of states flipped to Donald Trump using ANES data, including Maine, Minnesota, Nevada, and Virginia.

We further investigate this inter-state heterogeneity in Figure 9. Here, we plot the differences between the counterfactual and actual vote shares of Democrats and Republicans. As shown by its horizontal bars, on average across states, generational vote weighting results in an increase in the vote shares of Democrats. However, there are large variations in the magnitude of change across states, a pattern consistent with Figure 8. More detailed state-level statistics are available in Tables 5 and 6 in the appendix.

**Heterogeneity across Generations.** Generational vote weighting has such big impacts because of generational differences in voter preferences. We highlight the generational differences in Table 3, which summarizes the vote shares of Democrats and Republicans for each generation. Similar to the L2 data results, the ANES data shows the Republican vote share increasing as age-level increases. The trend identified here is similar to the results of existing studies (Pew Research Center, 2018).

### A.1.3 Limitations

The ANES analysis motivated our use of L2 data, due to the data quantity and quality limitations detailed below:

**Misreporting:** A problem with the ANES data is that individuals self-report whether they registered to vote, whether they voted, and their vote choice. Enamorado et al. (2018) and Enamorado and Imai (2018) compare the ANES voting data against national voter registration data supplied by L2, a non-partisan voter data collection firm. They found that 20 percent of ANES survey respondents who indicated that they voted in the elections did not actually vote. Many previous studies have explored why individuals would be likely to misreport when answering survey questions on voting. One prominent theory is social desirability bias. Another explanation is non-response bias, the idea that those who respond to the survey differ in a meaningful way from those who do not (Bernstein et al., 2001).

**Sample Size:** Another problem with the ANES data is sample size. While some states have hundreds of observations, other states have only a handful of observations. We report the sample size for each state of party registration in Table 4. The largest sample size is 302 (California) and the smallest sample size is 2 (Alaska). When we restrict the sample to individuals who reportedly voted in the 2016 elections, the sample size becomes even smaller for some states. As a result of the small sample size, some of the ANES vote shares are prone to bias.

### Validation of the ANES Data

To quantify how serious these data issues are, we gauge the accuracy of the ANES data by comparing the ANES data's predicted election outcomes against the CQ election outcome data. For each state, we use the ANES data to calculate the vote shares of parties as well as their confidence intervals, without any generational vote weighting. We find that the ANES vote shares correctly capture the winning parties in 40 out of 50 states and the District of Columbia (about 78% accuracy). However, ANES does not capture the exact vote shares very accurately. We show this point in Figure 10, which reports the plots of the ANES and actual vote shares for Democrat and Republican candidates in the 2016 presidential election. The correlation between the ANES proportions and actual proportions is modest. The root-mean-square error for Democrat and Republican vote shares are 14.15% and 14.25%, respectively.

## A.2 Estimating Standard Errors of State-level Vote Shares

To understand how confident I can be of the difference between the actual and counterfactual election outcomes, I estimate the standard errors for the state-level vote shares. For each counterfactual vote share for party $p$ and voter age $a$ within state or district $s$, recall that I denote the within-state or within-district vote share for each party and age group by $\hat{X}_{asp} = \frac{\hat{N}_{asp}}{\hat{N}_s}$. I estimate the variance of $\hat{X}_{asp}$ by

$$Var(\hat{X}_{asp}) = \frac{1}{\hat{N}_s^2}\left\{\hat{Var}(\hat{N}_{asp}) - 2\hat{X}_{asp}\hat{Cov}(\hat{N}_s, \hat{N}_{asp}) + \hat{X}_{asp}^2\hat{Var}(\hat{N}_s)\right\}. \tag{1}$$

Equation (1) follows the formula for the variance of sample ratio discussed in Rice (2007). I describe the steps to calculate $\hat{N}_{asp}$, $\hat{N}_s$, and $\hat{X}_{asp}$ in Section A.1.1.

Below, I describe how to calculate the remaining components of equation (1): $\hat{Var}(\hat{N}_{asp})$, $\hat{Cov}(\hat{N}_s, \hat{N}_{asp})$, and $\hat{Var}(\hat{N}_s)$. I do so by incorporating ANES's nonrandom, stratified sampling design into consideration. The ANES organizers construct strata and their sampling weights within the sample that reflect their original sampling design. Specifically, the ANES sample consists of 132 strata, or independent subsamples. Each stratum contains several primary sampling units (PSUs), which are clusters of individuals (survey respondents). Finally, ANES produces respondent-specific weights to reflect the sampling probability of each individual, based on their geographical location and demographics. For more details on how ANES constructs the strata and PSUs, see DeBell et al. (2018).

I calculate $\hat{Var}(\hat{N}_{asp})$, the variance of the vote count for party $p$ and age $a$ within state or district $s$ as follows. For each stratum $h = 1, \cdots, L$ and each PSU $i = 1, \cdots, n_h$ in stratum $h$,

$$\hat{Var}(\hat{N}_{asp}) = \sum_{h=1}^{L} \frac{n_h}{n_h - 1}\left\{\sum_{i=1}^{n_h} {y_{(a,p)shi}}^2 - \frac{(y_{(a,p)sh})^2}{n_h}\right\}, \tag{2}$$

where $y_{(a,p)shi}$ is the vote count for party $p$ and age $a$ in each PSU $i$ of stratum $h$:

$$y_{(a,p)shi} = \sum_{j=1}^{m_{hi}} w_j \times I_{s,hij} \times y_{(a,p)hij},$$

where each respondent $j$ is indexed by $j = 1, \cdots, m_{hi}$. $y_{(a,p)hij}$ is 1 if respondent $j$ is age $a$ and voted for party $p$, and 0 otherwise. The value $w_j$ is the ANES sampling probability weight for each respondent $j$. $I_{s,hij}$ is 1 if the $j$-th respondent in state or district $s$ and 0 if not. I calculate $y_{(a,p)sh}$, the total vote count for $a$ and $p$ across all PSUs of stratum $h$ by

$$y_{(a,p)sh} = \sum_{i=1}^{n_h} y_{(a,p)shi}.$$

Intuitively, equation (2) finds the variance of vote counts for each party $p$ in age $a$ across PSUs contained in the same stratum, and then sums the within-stratum variance across all strata. For a more in-depth discussion on variance estimation for survey subpopulation totals, see West et al. (2008).

My estimation of $\hat{Var}(\hat{N}_s)$ is similar to equation (2). The key difference is, I replace $y_{(a,p)shi}$ in equation (2) with $y_{shi}$, the vote count for each PSU $i$ of stratum $h$ across parties and ages:

$$y_{shi} = \sum_{j=1}^{m_{hi}} w_j \times I_{s,hij} \times y_{shij},$$

where $y_{hij}$ is the vote count for each individual $j$ in PSU $i$ and stratum $h$. All respondents who said they voted have $y_{hij} = 1$, regardless of their age or vote choice. I also replace $y_{(a,p)sh}$ in equation (2) with $y_{sh} = \sum_{i=1}^{n_h} y_{shi}$, the vote count for each stratum $h$ across parties and ages.

Finally, I estimate $\hat{Cov}(\hat{N}_s, \hat{N}_{asp})$ as follows. For each stratum $h = 1, \cdots, L$ and each PSU $i = 1, \cdots, n_h$,

$$\hat{Cov}(\hat{N}_s, \hat{N}_{asp}) = \sum_{h=1}^{L} \frac{n_h}{n_h - 1} \sum_{i=1}^{n_h} (y_{(a,p)shi} - \bar{y}_{(a,p)sh})(y_{shi} - \bar{y}_{sh}), \tag{3}$$

where $\bar{y}_{(a,p)sh}$ is the average vote count for party $p$ and age $a$ across all PSUs in stratum $h$:

$$\bar{y}_{(a,p)sh} = \frac{1}{n_h} \sum_{i=1}^{n_h} y_{(a,p)shi}.$$

$\bar{y}_{sh}$ is the average vote count across all PSUs in stratum $h$:

$$\bar{y}_{sh} = \frac{1}{n_h} \sum_{i=1}^{n_h} y_{shi}.$$

Intuitively, equation (3) finds the covariance between $y_{(a,p)shi}$ and $y_{shi}$ across all PSUs $i = 1, \cdots, n_h$ in a given stratum $h$. It then sums the stratum-specific covariances across all strata. For further details on estimating covariance for a stratified sample, see Heeringa et al. (2010).

I use $\hat{Var}(\hat{X}_{asp})$ to calculate the standard error of state-level vote shares $\hat{X}^{CF}_{sp} = \dfrac{\sum_a w_a \hat{X}_{asp}}{\sum_p \sum_a w_a \hat{X}_{asp}}$. To do that, I multiply both the vote share estimate and standard error values by age-specific weights, and sum across age-levels:

$$SE(\hat{X}^{CF}_{sp}) = \frac{1}{\sum_p \hat{X}^{CF}_{sp}} \times \sqrt{\sum_a {w_a}^2 \times \hat{Var}(\hat{X}_{asp})}.$$

I assume that if there is no vote share estimate for a given age (when the ANES sample size is 0 for a given age), the standard error value is also 0. I also assume independence between the vote shares for a given party across different ages. To relax this assumption in the aforementioned step, I can calculate $SE(\hat{X}^{CF}_{sp})$ by

$$SE(\hat{X}^{CF}_{sp}) = \frac{1}{\sum_p \hat{X}^{CF}_{sp}} \times \sqrt{\sum_a w_a^2 \times \hat{Var}(\hat{X}_{asp}) + \sum_a \sum_{a' \neq a} w_a w_{a'} \times \hat{Cov}(\hat{X}_{asp}, \hat{X}_{a'sp})},$$

which follows from this rule: $Var(aX + bY) = a^2 Var(X) + b^2 Var(Y) + 2abCov(X, Y)$. See Heeringa et al. (2010) for further details on the method.

**Testing Significant Differences between Party Vote Shares**

In Table 6, I use a one sample $t$-test to gauge at the significance of the differences between the counterfactual Democrat and Republican vote shares. For Democrats $p_1$ and Republicans $p_2$, my null hypothesis is $\hat{X}^{CF}_{sp_1} - \hat{X}^{CF}_{sp_2} = 0$ and my alternative hypothesis is $\hat{X}^{CF}_{sp_1} - \hat{X}^{CF}_{sp_2} \neq 0$. Treating each state as an individual sample, I calculate the standard error of the estimated difference between $\hat{X}^{CF}_{sp_1}$ and $\hat{X}^{CF}_{sp_2}$ by

$$SE(\hat{X}^{CF}_{sp_1} - \hat{X}^{CF}_{sp_2}) = \sqrt{SE(\hat{X}^{CF}_{sp_1})^2 + SE(\hat{X}^{CF}_{sp_2})^2 + 2 \times Cov(\hat{X}^{CF}_{sp_1}, \hat{X}^{CF}_{sp_2})}, \tag{4}$$

where I estimate $Cov(\hat{X}^{CF}_{sp_1}, \hat{X}^{CF}_{sp_2})$ as follows. Note that for $Y_1 = \sum_{j=1}^{p} c_j X_j$ and $Y_2 = \sum_{k=1}^{p} d_k X_k$, I have

$$Cov(Y_1, Y_2) = \sum_{j=1}^{p} \sum_{k=1}^{p} c_j d_k Cov(X_j, X_k).$$

I apply this formula to estimate $Cov(\hat{X}^{CF}_{sp_1}, \hat{X}^{CF}_{sp_2})$. Given $\hat{X}^{CF}_{sp_1} = \sum_a w_a \hat{X}_{asp_1}$ and $\hat{X}^{CF}_{sp_2} = \sum_{a'} w_{a'} \hat{X}_{a'sp_2}$, I calculate the covariance of the two linear combinations using

$$Cov(\hat{X}^{CF}_{sp_1}, \hat{X}^{CF}_{sp_2}) = \sum_a \sum_{a'} w_a w_{a'} Cov(\hat{X}_{asp_1}, \hat{X}_{asp_2}).$$

For more information on how $Cov(\hat{X}_{asp_1}, \hat{X}_{asp_2})$ is calculated, see StataCorp LLC (2017). I follow the same steps to calculate the covariance between counterfactual vote shares when all parties are included (with all non-major parties grouped togther as "Other"). In some election levels in the 2016 ANES Time Series data set, there were no reported votes for the "Other" category. In those states, I assume a covariance value of 0 between the counterfactual "Other" vote share and the counterfactual Democrat/Republican vote share.

I also test if the winning party vote share is significantly different from the runner up party vote share (i.e. received second most votes). For winning party $p_1$ and runner up party $p_2$, my null hypothesis is $\hat{X}^{CF}_{sp_1} - \hat{X}^{CF}_{sp_2} = 0$ and my alternative hypothesis is $\hat{X}^{CF}_{sp_1} - \hat{X}^{CF}_{sp_2} \neq 0$. I use equation (4) to calculate the standard error of $\hat{X}^{CF}_{sp_1} - \hat{X}^{CF}_{sp_2}$.

### Confidence Intervals

I calculate confidence intervals in Figure 10 as follows. Based on the "svy: tabulate twoway" documentation, I first find $f(\hat{X_{sp}})$, the logit transformation of $\hat{X_{sp}}$ by

$$f(\hat{X_{sp}}) = \ln(\frac{\hat{X_{sp}}}{1-\hat{X_{sp}}}).$$

Applying the logit transformation means the values would be contained between 0 and 1. For $\hat{s} = SE(\hat{X_{sp}})$, the standard error estimate is given by

$$\hat{SE}\{f(\hat{X_{sp}})\} = f'(\hat{X_{sp}})\hat{s} = \frac{\hat{s}}{\hat{X_{sp}}(1-\hat{X_{sp}})}.$$

I then can find the $100(1-\alpha)\%$ confidence interval using

$$\ln(\frac{\hat{X_{sp}}}{1-\hat{X_{sp}}}) \pm \frac{t_{1-\alpha/2,v}\hat{s}}{\hat{X_{sp}}(1-\hat{X_{sp}})},$$

where $t_{1-\alpha/2,v}$ is the critical value at the $(1-\alpha/2)$th quantile of the $t$ distribution with $v$ degrees of freedom. Finally, suppose that $y = \ln(\frac{\hat{X_{sp}}}{1-\hat{X_{sp}}}) \pm \frac{t_{1-\alpha/2,v}\hat{s}}{\hat{X_{sp}}(1-\hat{X_{sp}})}$, I use the formula below to find the inverse of the logit transform and the final confidence interval values

$$f^{-1}(y) = \frac{e^y}{1+e^y}.$$

## A.3 Estimating Standard Errors of Electoral College Vote Shares

In Figure 6, I assess the reliability of the final counterfactual electoral college outcome by estimating its standard error. For each state $s$, I have estimated the counterfactual vote shares for Democrats, $p_1$, Republicans, $p_2$, and Others, $p_3$, denoted as $\hat{X}^{CF}_{sp_1}$, $\hat{X}^{CF}_{sp_2}$, and $\hat{X}^{CF}_{sp_3}$, respectively. As detailed in Appendix A.2, I also estimated $\hat{SE}(\hat{X}^{CF}_{sp_1})$, $\hat{SE}(\hat{X}^{CF}_{sp_2})$, and $\hat{SE}(\hat{X}^{CF}_{sp_3})$. I use them to compute the standard error of the final counterfactual election college outcome as follows. For $t = 1, \cdots, 500$ simulations,

(1) **Draw vote shares:** For states with 10 or more observations in the ANES sample, I draw $\hat{X}^{CF}_{sp_1}(t)$ from the normal distribution with mean $\hat{X}^{CF}_{sp_1}$ and standard deviation $\hat{SE}(\hat{X}^{CF}_{sp_1})$. I also draw $\hat{X}^{CF}_{sp_3}(t)$ from the normal distribution with mean $\hat{X}^{CF}_{sp_3}$ and standard deviation $\hat{SE}(\hat{X}^{CF}_{sp_3})$. I define $\hat{X}^{CF}_{sp_2}(t) \equiv 1 - \hat{X}^{CF}_{sp_1}(t) - \hat{X}^{CF}_{sp_3}(t)$.

(2) **Allocate electoral college votes:** For states with less than 10 observations in the ANES sample, I assign electoral college votes based on the actual outcomes. For the other states, I allocate the electoral college votes based on the plurality winner. For each state $s$, I denote the electoral college votes for Democrats and for Republicans by $Dem_s(t)$ and $Rep_s(t)$, respectively.

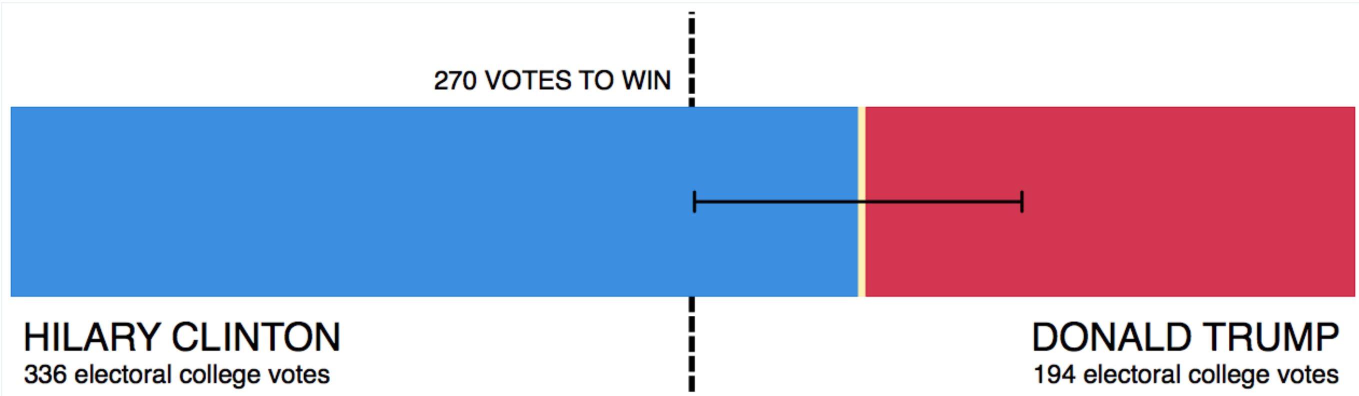
(3) **Sum electoral college votes:** I sum the electoral college votes to find $Dem(t) \equiv \sum_s Dem_s(t)$ and $Rep(t) \equiv \sum_s Rep_s(t)$.

Finally, I compute the standard deviation of electoral college votes for Democrats across 500 simulations. I use this as the standard error of my counterfactual electoral college votes for Democrats (Hilary Clinton).

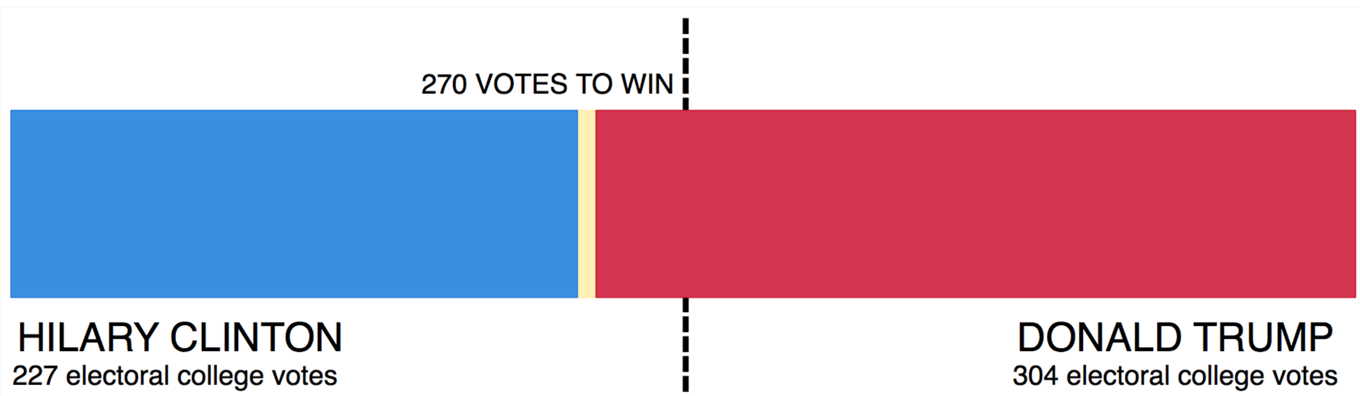
**Results.** The standard error of the electoral college votes for Hilary Clinton turns out to be 33 votes. Using this standard error, I run a $t$-test to check whether the counterfactual electoral college votes (336 votes found in Figure 6) is significantly different from the minimum threshold of electoral college votes needed for a candidate to win the election (270 votes). My null hypothesis is $h_0 : \hat{Dem} = 270$, and my alternate hypothesis is $h_a : \hat{Dem} \neq 270$. I find the counterfactual electoral college votes to be significantly different from 270 at the 95% confidence level ($p$-value = 0.046). I also test whether the estimated counterfactual electoral college votes for Democrats is significantly greater than 270, with the null hypothesis $h_0 : \hat{Dem} \geq 270$, and the alternate hypothesis, $h_a : \hat{Dem} < 270$. I find the counterfactual electoral college votes for Democrats to be significantly greater than 270 at the 95% confidence level ($p$-value = 0.023).

Figure 6: Counterfactual and Actual Electoral College Voting Outcomes

(a) Counterfactual Outcome

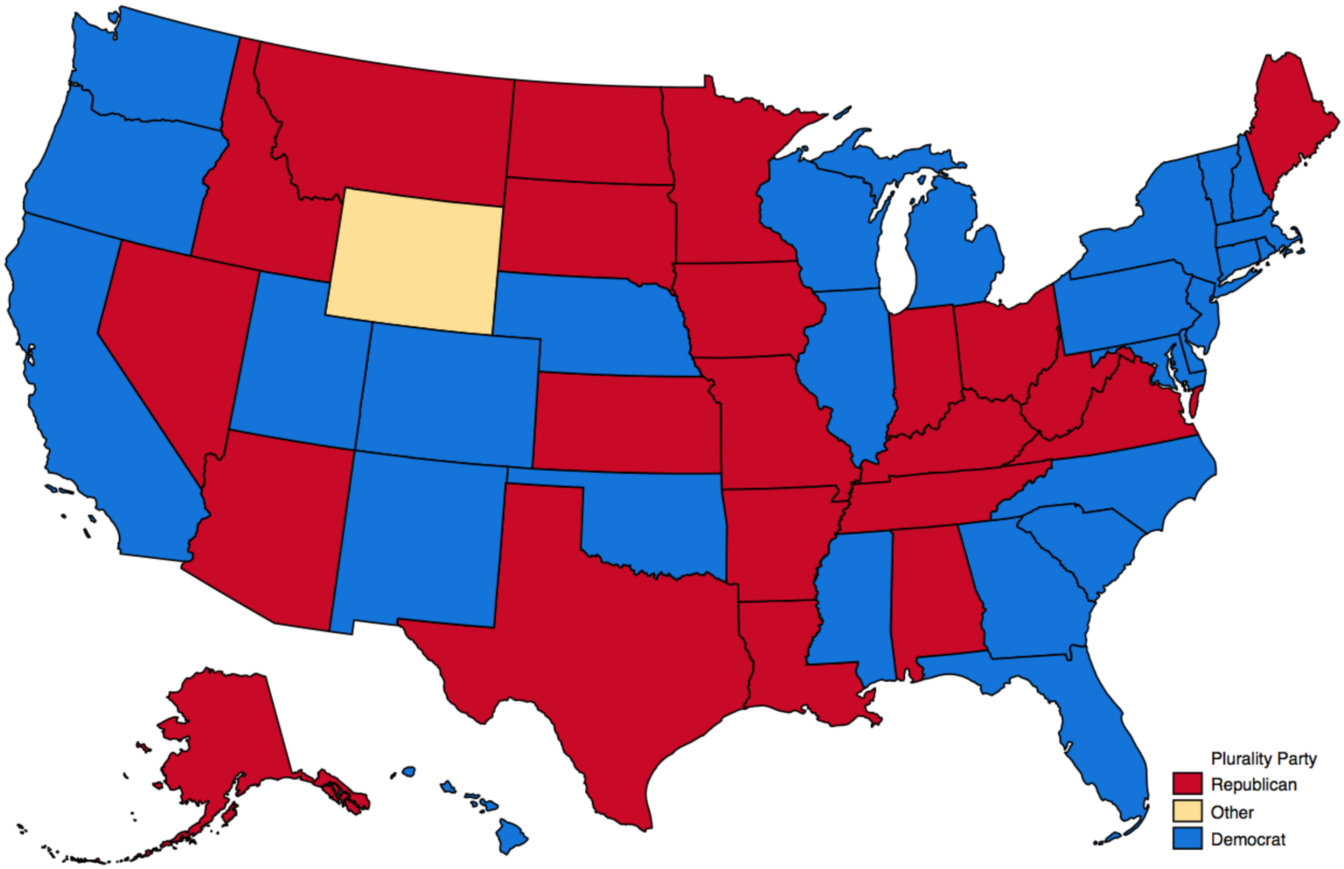



(b) Actual Outcome



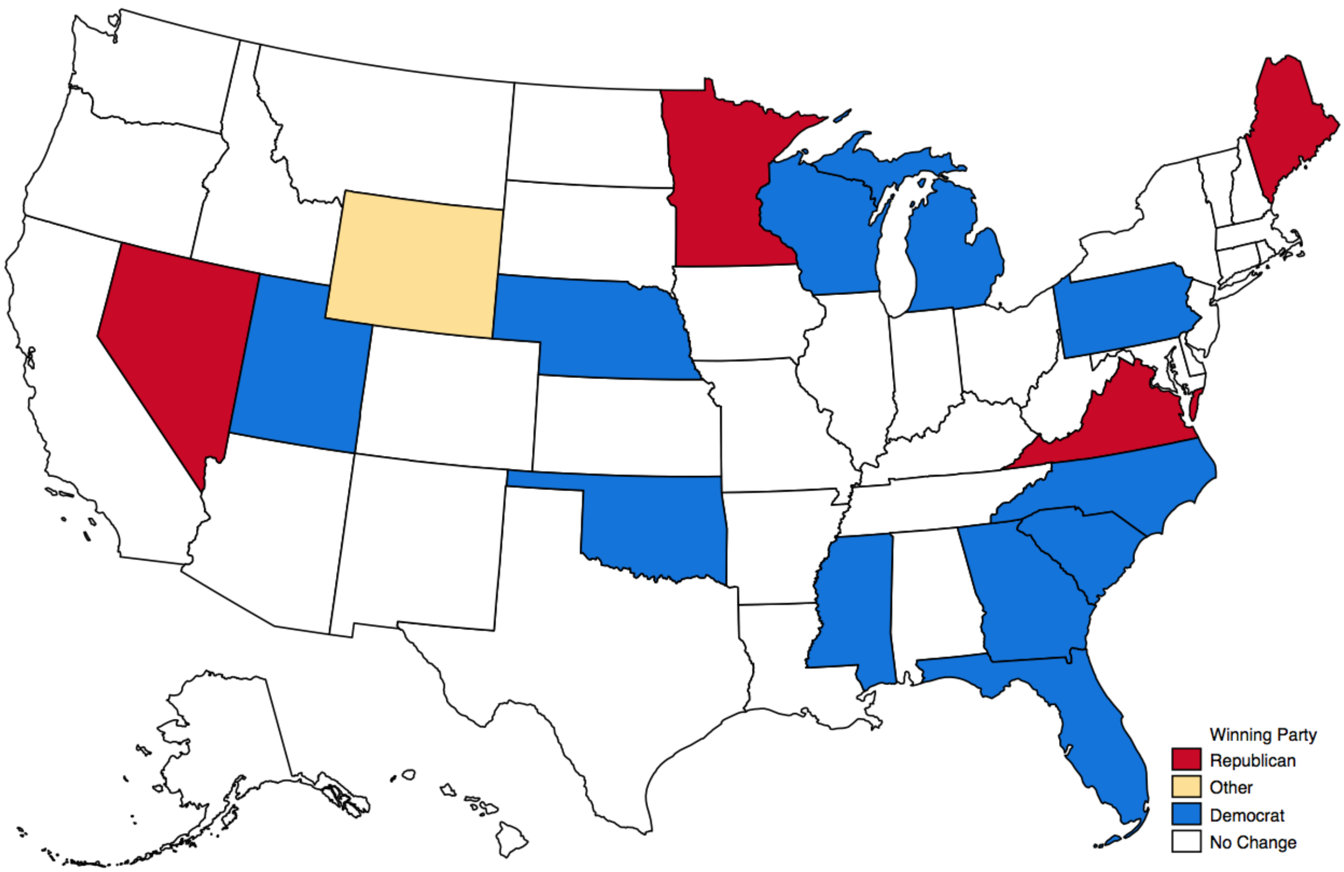

*Notes:* The figures show the counterfactual and actual distributions of electoral college votes for the 2016 presidential election, between Democrat party candidate Hilary Clinton and Republican party candidate Donald Trump. The yellow section represents the 3 votes for party candidates other than the major parties. We allocate electoral college votes to each candidate based on the "winner-takes-all" rule for 48 states and Washington D.C. We exclude the district-level electoral votes for Maine (2 votes) and Nebraska (3 votes), as we cannot estimate the plurality winner at the granularity of congressional districts using the ANES data. We also assume there are no "faithless electors," who do not vote for the candidate they pledged to vote for. We calculate the 95% confidence interval around the counterfactual votes for Clinton based on the standard error as calculated in Appendix A.3.

Figure 7: Counterfactual Plurality Party by State under Generational Vote Weighting




*Notes:* The map shows the counterfactual 2016 presidential election outcomes for each state or district with generational vote weighting. The "Others" category includes any Independent or other party candidate choice.

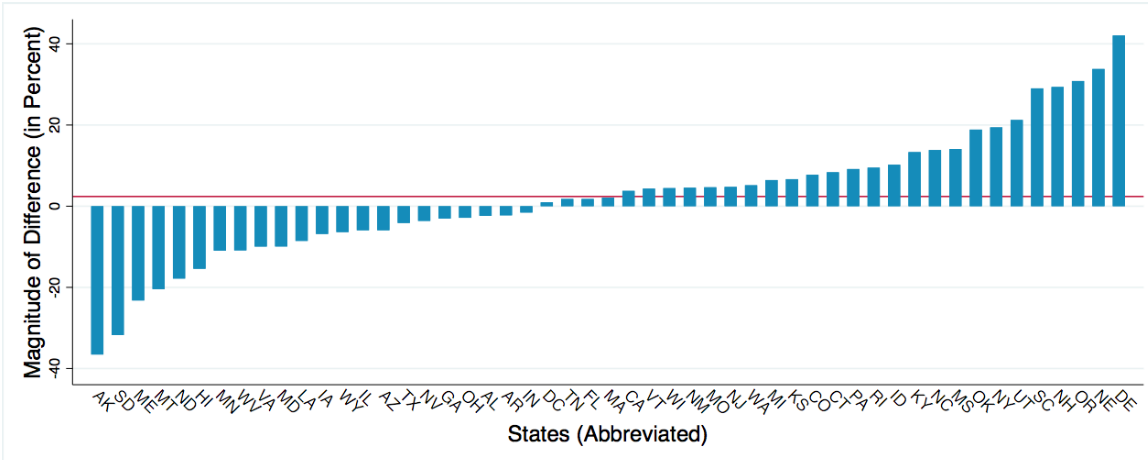
Figure 8: States where the Winner is “Flipped” by Generational Vote Weighting



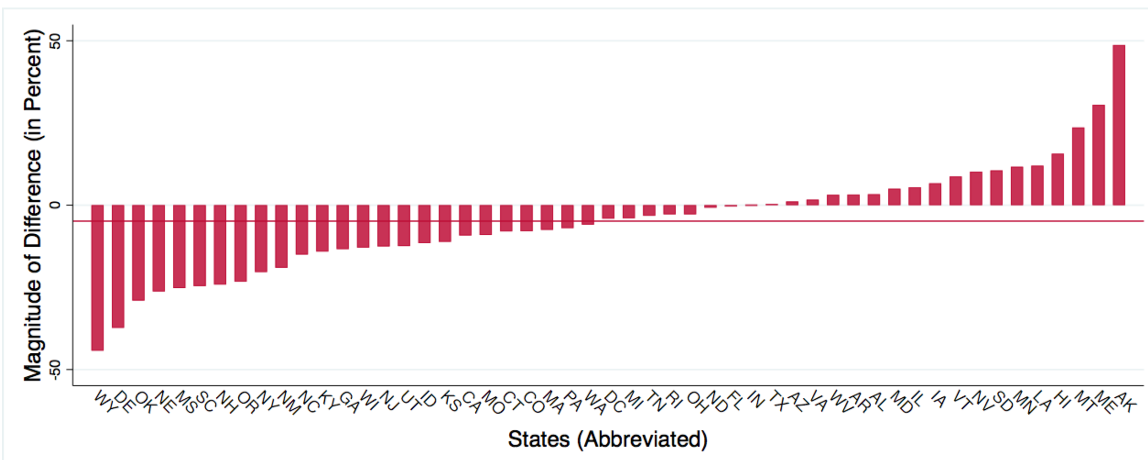

*Notes:* The map shows the counterfactual 2016 presidential election outcomes, highlighting only the states in which the plurality party is changed by generational vote weighting. There are 11 states that flipped from Republican to Democrat plurality, including: Utah, Nebraska, Oklahoma, Wisconsin, Michigan, Mississippi, Georgia, Florida, South Carolina, North Carolina, and Pennsylvania. There are 4 states that flipped to Republican from Democrat plurality, including: Nevada, Minnesota, Virginia, and Maine. The “Others” category includes any Independent or other party candidate choice.

Figure 9: Difference between Weighted and Actual Vote Percentage by State

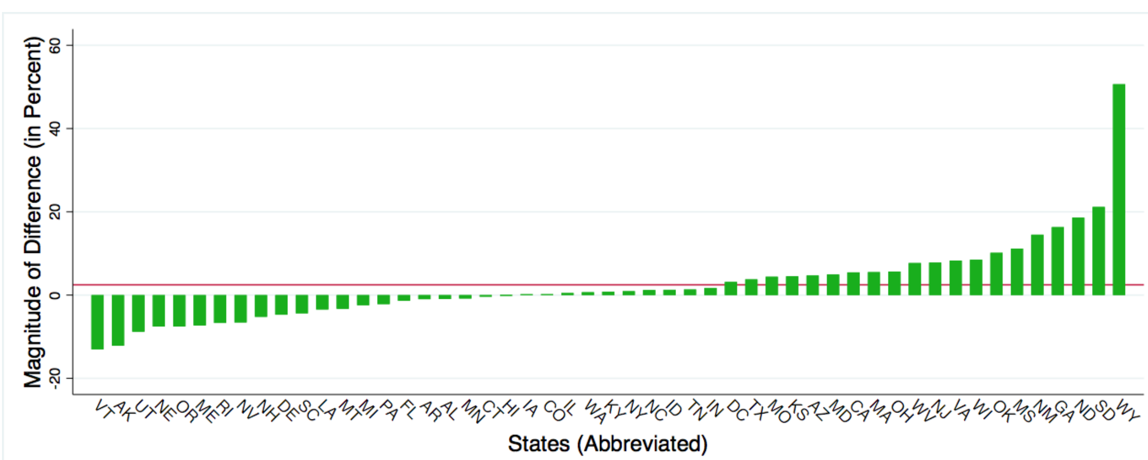
(a) Democrats




(b) Republicans




(c) Others




*Notes:* The figure shows the percentage point difference between the counterfactual (generationally weighted) and actual vote shares for Democrats, Republicans, and others. The "Others" category includes any Independent or other party candidate choice. The horizontal red line indicates the average difference across all states.

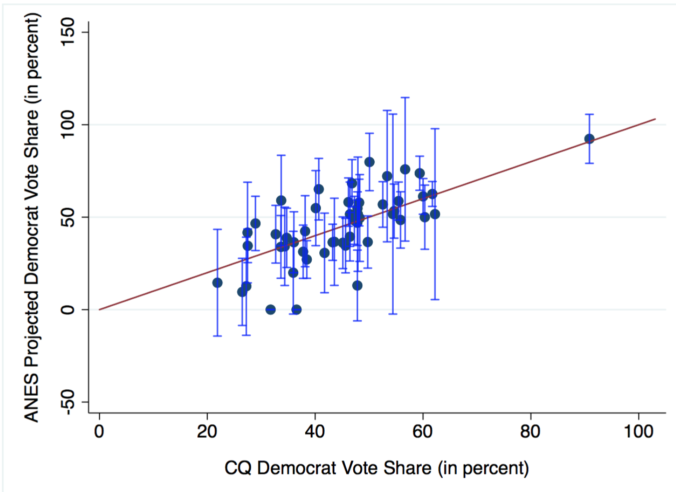
Table 3: Voting Behavior by Generations

| Generations | Democrats | Republicans | Others |
|---|---|---|---|
| 18-29 | 49.13 | 43.75 | 7.12 |
| 30-39 | 47.93 | 45.62 | 6.45 |
| 40-49 | 46.06 | 48.79 | 5.15 |
| 50-59 | 45.39 | 49.95 | 4.66 |
| 60-69 | 45.27 | 51.91 | 2.81 |
| 70-79 | 38.66 | 58.66 | 2.68 |
| 80-90 | 36.9 | 62.62 | .48 |

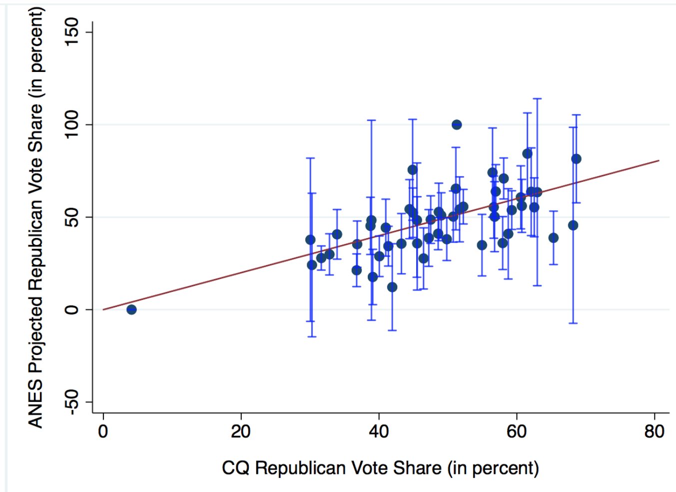
*Notes:* The table shows the vote proportion for each party by age group. The "Others" category includes any Independent or other party candidate choice. I estimate the vote proportions using vote counts from the ANES 2016 Time Series data set. I drop respondents who did not register to vote, cast a ballot, or correctly report their age. I also drop those who had inappropriate or missing answers for vote choice.

Figure 10: ANES Vote Shares vs. Actual Vote Shares

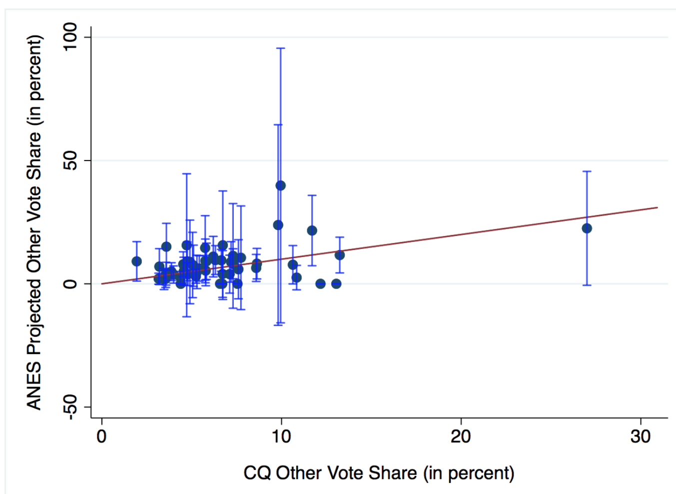
(a) Democrats




(b) Republicans




(c) Others




*Notes:* The data points represent vote shares for all parties, including Democrats, Republicans, and Others (all Independent and other parties). All 50 states and Washington D.C. are represented in the three figures above. We drop respondents who did not cast a ballot or have valid age data, as well as respondents with "Unknown" or "Non-Partisan" party affiliation.

Table 4: Sample Sizes for Each State of Party Registration

| State of Party Registration | No. | % | State of Party Registration | No. | % |
|---|---|---|---|---|---|
| Alabama | 36 | 1.1 | Nebraska | 17 | 0.5 |
| Alaska | 2 | 0.1 | Nevada | 23 | 0.7 |
| Arizona | 76 | 2.3 | New Hampshire | 28 | 0.8 |
| Arkansas | 38 | 1.1 | New Jersey | 89 | 2.7 |
| California | 327 | 9.8 | New Mexico | 32 | 1.0 |
| Colorado | 75 | 2.2 | New York | 131 | 3.9 |
| Connecticut | 46 | 1.4 | North Carolina | 135 | 4.0 |
| Delaware | 8 | 0.2 | North Dakota | 5 | 0.1 |
| Florida | 166 | 5.0 | Ohio | 135 | 4.0 |
| Georgia | 95 | 2.8 | Oklahoma | 44 | 1.3 |
| Hawaii | 8 | 0.2 | Oregon | 34 | 1.0 |
| Idaho | 46 | 1.4 | Pennsylvania | 143 | 4.3 |
| Illinois | 161 | 4.8 | Rhode Island | 6 | 0.2 |
| Indiana | 75 | 2.2 | South Carolina | 50 | 1.5 |
| Iowa | 26 | 0.8 | South Dakota | 9 | 0.3 |
| Kansas | 68 | 2.0 | Tennessee | 119 | 3.6 |
| Kentucky | 52 | 1.6 | Texas | 235 | 7.0 |
| Louisiana | 46 | 1.4 | Utah | 21 | 0.6 |
| Maine | 10 | 0.3 | Vermont | 9 | 0.3 |
| Maryland | 86 | 2.6 | Virginia | 72 | 2.2 |
| Massachusetts | 94 | 2.8 | Washington | 72 | 2.2 |
| Michigan | 111 | 3.3 | Washington DC | 22 | 0.7 |
| Minnesota | 68 | 2.0 | West Virginia | 14 | 0.4 |
| Mississippi | 37 | 1.1 | Wisconsin | 73 | 2.2 |
| Missouri | 51 | 1.5 | Wyoming | 4 | 0.1 |
| Montana | 10 | 0.3 | Total | 3340 | 100.0 |

*Notes:* The table displays the sample size, or the number of voters in each state, after we restrict the ANES 2016 Time Series sample to individuals who said they registered to vote. Here, we do not apply other sample restrictions that limit the sample to individuals who voted in specific elections (presidential, House, Senate, or governor) and individuals who correctly reported their age. The mean sample size is 62.27, with a standard deviation of 58.95.

Table 5: Original Vote Shares

| State | Dem. Vote % | Dem. SE | Dem. p-val | Rep. Vote % | Rep. SE | Rep. p-val | Other Vote % | Other SE | Other p-val |
|---|---|---|---|---|---|---|---|---|---|
| Alabama | 34.2 | 10.7 | .99 | 63.8 | 12 | .89 | 2 | 1.8 | .756 |
| Alaska | 0 | 0 | N/A | 100 | 0 | N/A | 0 | 0 | N/A |
| Arizona | 36.1 | 7.1 | .208 | 52.8 | 7.9 | .599 | 11 | 4.2 | .035 |
| Arkansas | 33.9 | 8.6 | .974 | 60.7 | 8.6 | .987 | 5.4 | 3.1 | .479 |
| California | 62.5 | 3.4 | .811 | 27.9 | 3.3 | .262 | 9.5 | 2.2 | .006 |
| Colorado | 57.9 | 6.4 | .133 | 35.7 | 8.2 | .361 | 6.4 | 2.8 | .279 |
| Connecticut | 53.3 | 7.4 | .855 | 44.3 | 7.8 | .669 | 2.4 | 1.3 | .469 |
| Delaware | 72.2 | 18 | .335 | 12.2 | 11.9 | .046 | 15.6 | 14.7 | .368 |
| District of Columbia | 92.4 | 6.7 | .825 | 0 | 0 | N/A | 7.6 | 6.7 | .541 |
| Florida | 47 | 6.2 | .893 | 50.9 | 6.2 | .757 | 2.1 | 1.1 | .325 |
| Georgia | 34.6 | 7.5 | .143 | 50.3 | 7 | .949 | 15.1 | 4.8 | .003 |
| Hawaii | 51.6 | 23.4 | .674 | 37.8 | 22.3 | .746 | 10.6 | 10.6 | .571 |
| Idaho | 34.5 | 4.6 | .136 | 53.8 | 5.3 | .31 | 11.7 | 3.7 | .494 |
| Illinois | 48.5 | 7.7 | .343 | 45.3 | 7.8 | .405 | 6.2 | 2.6 | .081 |
| Indiana | 31.3 | 7.3 | .378 | 63.9 | 7.4 | .349 | 4.8 | 3.4 | .2 |
| Iowa | 30.7 | 10.9 | .32 | 65.4 | 11.3 | .219 | 3.9 | 3.9 | .881 |
| Kansas | 36.4 | 8.3 | .963 | 55.4 | 8.5 | .885 | 8.1 | 3.1 | .077 |
| Kentucky | 40.8 | 7.9 | .31 | 55.3 | 8.1 | .376 | 3.9 | 2.3 | .419 |
| Louisiana | 27.1 | 5.1 | .033 | 70.9 | 5.6 | .027 | 2 | 2.2 | .864 |
| Maine | 13.1 | 9.7 | .006 | 75.6 | 13.8 | .053 | 11.3 | 10.7 | .418 |
| Maryland | 50 | 8.8 | .242 | 40.7 | 6.8 | .319 | 9.3 | 4.5 | .158 |
| Massachusetts | 61.2 | 4.9 | .803 | 29.9 | 5.6 | .605 | 8.9 | 4.2 | .163 |
| Michigan | 48.3 | 6.6 | .878 | 48.7 | 6.5 | .857 | 3.1 | 1.4 | .322 |
| Minnesota | 39.4 | 6.6 | .296 | 52.4 | 6.8 | .273 | 8.2 | 3.1 | .285 |
| Mississippi | 54.9 | 10.3 | .16 | 36 | 7.2 | .005 | 9.1 | 4 | .048 |
| Missouri | 42.4 | 9.7 | .663 | 50.3 | 9.6 | .501 | 7.3 | 4.2 | .185 |

| State | Dem. Vote % | Dem. SE | Dem. p-val | Rep. Vote % | Rep. SE | Rep. p-val | Other Vote % | Other SE | Other p-val |
|---|---|---|---|---|---|---|---|---|---|
| Montana | 20 | 11.3 | .196 | 74.1 | 12.2 | .185 | 5.9 | 6.1 | .53 |
| Nebraska | 59 | 12.3 | .063 | 41 | 12.3 | .175 | 0 | 0 | N/A |
| Nevada | 51.6 | 15.6 | .816 | 48.4 | 15.6 | .854 | 0 | 0 | N/A |
| New Hampshire | 68.3 | 6.5 | .003 | 27.7 | 8.4 | .035 | 4 | 4.8 | .773 |
| New Jersey | 58.7 | 5.2 | .533 | 34.3 | 5.4 | .2 | 7 | 3.7 | .129 |
| New Mexico | 49.5 | 11.9 | .915 | 28.9 | 5.5 | .054 | 21.6 | 7.2 | .013 |
| New York | 73.8 | 4.7 | .003 | 21.3 | 4.5 | .001 | 4.9 | 1.8 | .067 |
| North Carolina | 58.2 | 6.6 | .072 | 38.1 | 5.8 | .046 | 3.8 | 1.8 | .157 |
| North Dakota | 12.6 | 13.4 | .338 | 63.5 | 25.6 | .984 | 23.8 | 20.6 | .381 |
| Ohio | 36.7 | 11.9 | .564 | 54.2 | 8.9 | .776 | 9.1 | 4 | .061 |
| Oklahoma | 46.6 | 7.4 | .023 | 38.8 | 7.3 | .001 | 14.6 | 6.6 | .035 |
| Oregon | 79.8 | 7.8 | .001 | 17.6 | 7.6 | .008 | 2.5 | 2.5 | .16 |
| Pennsylvania | 54.8 | 4.5 | .125 | 41.1 | 4.4 | .091 | 4.1 | 2.3 | .211 |
| Rhode Island | 51.7 | 27.3 | .925 | 48.3 | 27.3 | .747 | 0 | 0 | N/A |
| South Carolina | 65.1 | 8.4 | .006 | 34.9 | 8.4 | .021 | 0 | 0 | N/A |
| South Dakota | 0 | 0 | N/A | 84.4 | 11.1 | .086 | 15.6 | 11.1 | .239 |
| Tennessee | 38.8 | 8.1 | .615 | 56.1 | 7.2 | .526 | 5.1 | 2.9 | .25 |
| Texas | 36.4 | 4.9 | .169 | 55.7 | 4.7 | .467 | 7.9 | 2.6 | .012 |
| Utah | 41.7 | 13.8 | .318 | 35.8 | 12.8 | .458 | 22.5 | 11.7 | .933 |
| Vermont | 75.9 | 19.6 | .357 | 24.1 | 19.6 | .762 | 0 | 0 | N/A |
| Virginia | 36.6 | 7.1 | .07 | 54.3 | 8.1 | .225 | 9.1 | 3.7 | .097 |
| Washington | 56.9 | 6.2 | .49 | 35.4 | 6.3 | .822 | 7.7 | 3.9 | .621 |
| West Virginia | 9.6 | 9.2 | .099 | 81.5 | 12 | .311 | 8.9 | 8.6 | .422 |
| Wisconsin | 51.6 | 8.8 | .56 | 38.8 | 7.8 | .279 | 9.6 | 3 | .023 |
| Wyoming | 14.5 | 14.6 | .65 | 45.6 | 26.8 | .461 | 39.9 | 28.2 | .301 |

*Notes:* The table above shows all party vote shares and standard errors estimated using 2016 ANES data. The "Others" include all Independent and other party candidates. For each party and state, I compute $p$-values using one sample $t$-tests comparing the estimated ANES vote shares to the actual CQ vote shares, as detailed in Appendix A.2. With exception of Alaska, some p-values are so small that they are displayed as 0 when I round them to 3 digits after the decimal point. Some $p$-values are missing for states in which one or two parties received no votes. I excude any ANES respondents who did not register as voters, did note vote in the presidential election, or did not correctly report their age.

Table 6: Counterfactual Party Vote Shares

| State | Dem. vote % | Dem. SE | Rep. vote % | Rep. SE | Other vote % | Other SE | p-value |
|---|---|---|---|---|---|---|---|
| Alabama | 32 | 15.9 | 65.4 | 18.3 | 2.6 | 2.3 | .406 |
| Alaska | 0 | 0 | 100 | 46.6 | 0 | 0 | .478 |
| Arizona | 39.2 | 11.5 | 49.8 | 13.3 | 10.9 | 4.7 | .991 |
| Arkansas | 31.4 | 13.1 | 63.8 | 17.1 | 4.8 | 3.1 | .426 |
| California | 65.5 | 8 | 22.4 | 3.2 | 12.1 | 3.6 | .055 |
| Colorado | 55.9 | 12.9 | 35.3 | 11.4 | 8.8 | 4.6 | .646 |
| Connecticut | 63 | 21 | 33 | 9.2 | 4 | 2.2 | .539 |
| Delaware | 95.4 | 48.6 | 4.6 | 4.5 | 0 | 0 | .386 |
| Washington DC | 91.8 | 12.5 | 0 | 0 | 8.2 | 9 | .004 |
| Florida | 49.6 | 8.6 | 48.6 | 8.7 | 1.8 | 1 | .959 |
| Georgia | 42.6 | 14 | 37.4 | 7.6 | 19.9 | 6.2 | .602 |
| Hawaii | 46.8 | 28 | 45.7 | 33.6 | 7.6 | 7.6 | .914 |
| Idaho | 37.7 | 5.2 | 47.7 | 11 | 14.5 | 4 | .839 |
| Illinois | 49.9 | 8.6 | 44.2 | 8.3 | 5.9 | 2.3 | .99 |
| Indiana | 36.2 | 8.3 | 56.9 | 11.5 | 7 | 5.6 | .552 |
| Iowa | 34.9 | 14.4 | 57.8 | 21 | 7.3 | 7.3 | .715 |
| Kansas | 42.7 | 13.2 | 45.5 | 11.2 | 11.8 | 5.5 | .689 |
| Kentucky | 46 | 13.9 | 48.4 | 11.8 | 5.6 | 3.4 | .892 |
| Louisiana | 29.9 | 8.3 | 70.1 | 13.5 | 0 | 0 | .144 |
| Maine | 24.6 | 17.9 | 75.4 | 29 | 0 | 0 | .403 |
| Maryland | 50.4 | 11.2 | 38.9 | 9.6 | 10.7 | 5.2 | .97 |
| Massachusetts | 62.1 | 13.8 | 25.3 | 7.4 | 12.7 | 6.8 | .386 |
| Michigan | 53.7 | 10.7 | 43.5 | 8.2 | 2.8 | 1.6 | .73 |
| Minnesota | 35.5 | 8.7 | 56.6 | 16.1 | 7.8 | 3.6 | .683 |
| Mississippi | 54.2 | 20.1 | 32.7 | 8.3 | 13.1 | 3.3 | .836 |
| Missouri | 42.8 | 14.2 | 47.7 | 12.1 | 9.5 | 5.7 | .848 |

| State | Dem. vote % | Dem. Std. Error | Rep. vote % | Rep. Std. Error | Other vote % | Std. Error | p-value |
|---|---|---|---|---|---|---|---|
| Montana | 15.5 | 13.4 | 80.1 | 31.9 | 4.3 | 4.5 | .373 |
| Nebraska | 67.5 | 27.6 | 32.5 | 15.8 | 0 | 0 | .537 |
| Nevada | 44.3 | 18.2 | 55.7 | 26.1 | 0 | 0 | .829 |
| New Hampshire | 76.2 | 16.4 | 22.3 | 3.6 | 1.5 | 1.8 | .125 |
| New Jersey | 60.2 | 10 | 28.8 | 5.9 | 11 | 6.6 | N/A |
| New Mexico | 52.8 | 13.9 | 21 | 4.4 | 26.2 | 3.9 | N/A |
| New York | 78.8 | 14.8 | 16.4 | 4.1 | 4.8 | 2.2 | .055 |
| North Carolina | 60 | 10.5 | 34.8 | 6.1 | 5.2 | 2.7 | .343 |
| North Dakota | 9.4 | 10 | 62.2 | 29.1 | 28.4 | 23.6 | .697 |
| Ohio | 40.7 | 8.9 | 48.9 | 9.8 | 10.4 | 4.1 | .915 |
| Oklahoma | 47.8 | 15.1 | 36.3 | 9.3 | 15.9 | 7.7 | N/A |
| Oregon | 80.9 | 19.5 | 15.8 | 10 | 3.3 | 3.3 | .123 |
| Pennsylvania | 57 | 9.5 | 41.6 | 6.8 | 1.4 | .9 | .459 |
| Rhode Island | 63.9 | 41.9 | 36.1 | 24 | 0 | 0 | .757 |
| South Carolina | 69.7 | 17.7 | 30.3 | 9.5 | 0 | 0 | .271 |
| South Dakota | 0 | 0 | 72.1 | 35.7 | 27.9 | 20.9 | .559 |
| Tennessee | 36.5 | 8.2 | 57.5 | 13.3 | 5.9 | 3.4 | .572 |
| Texas | 39.1 | 5.6 | 52.6 | 7.9 | 8.3 | 3.1 | .74 |
| Utah | 48.7 | 22.9 | 33.1 | 14.8 | 18.2 | 10.6 | .955 |
| Vermont | 61 | 23.9 | 39 | 31.7 | 0 | 0 | .657 |
| Virginia | 39.8 | 10 | 46.1 | 9.9 | 14.1 | 6.2 | .697 |
| Washington | 57.7 | 13.3 | 30.9 | 7.9 | 11.3 | 5.8 | .563 |
| West Virginia | 15.6 | 15 | 71.8 | 27.7 | 12.6 | 12.1 | .451 |
| Wisconsin | 50.9 | 10.5 | 34.3 | 7.6 | 14.8 | 5.6 | N/A |
| Wyoming | 15.5 | 15.6 | 23.9 | 15.8 | 60.6 | 42.8 | .821 |

*Notes:* The table above shows the counterfactual party vote shares and standard errors estimated using the 2016 ANES data set. Other party vote shares includes all independent and other party candidates. The $p$-values are from $t$-tests on the significance of the difference between the counterfactual plurality winner vote share and the runner-up vote share ($h_0$: Plurality winner vote share - Runner-up vote share = 0), as detailed in Appendix A.2. With the exception of California and Oregon, some p-values are so small that they are displayed as 0 when I round them to 3 digits after the decimal point. We exclude any ANES respondents who reportedly did not registered as voters, did not vote in the presidential election, or did not correctly report their age.

# References

**Bernstein, Robert, Anita Chadha, and Robert Montjoy**, "Overreporting voting: Why it happens and why it matters.," *Public Opinion Quarterly*, 2001, *65* (1), 22–44.

**DeBell, Matthew**, "How to analyze ANES survey data," Technical Report nes012492, ANES Technical Report Series, Palo Alto, CA, and Ann Arbor, MI: Stanford University and the University of Michigan 2010.

**_ , Michelle Amsbary, Vanessa Meldener, Shelley Brock, and Natalya Maisel**, "Methodology report for the ANES 2016 time series study," Technical Report, Stanford University and the University of Michigan., Palo Alto, CA, and Ann Arbor, MI February 2018.

**Enamorado, Ted and Kosuke Imai**, "Validating self-reported turnout by linking public opinion surveys with administrative records," 2018.

**_ , Benjamin Fifield, and Kosuke Imai**, "Using a probabilistic model to assist merging of large-scale administrative records," *American Political Science Review*, 2018, pp. 1–19.

**Heeringa, Steven G., Brady T. West, and Patricia A. Berglund**, *Applied survey data anlysis* Statistics in the Social and Behavioral Sciences Series, Boca Raton, FL: CRC Press, 2010.

**Pew Research Center**, "The generation gap in American politics.," Online March 2018.

**Rice, John A.**, *Mathematrical statistics and data analysis*, third ed., Duxbury, 2007.

**StataCorp LLC**, *Stata survey data reference manual* StataCorp LLC, 15 ed. 2017.

**West, Brady, Patricia A. Berglund, and Steven G. Heeringa**, "A closer examination of subpopulation analysis of complex-sample survey data," *The Stata Journal*, 2008, *8* (4), 520–531.