Partisan-linked Biases

So far, I have not paid attention to the fair treatment of political parties in the Electoral College. Indeed, the mechanical effects examined in the first three chapters are a-political and consider only how aggregate effects of elections lead to equal opportunities. It’s possible that voters are treated equally by weighting voters equitably, states are treated fairly by a proportional weighting of importance, and that inversions happen rarely, but yet voters themselves are treated unfairly. Future works should identify groups of voters who may find their power diminished due to the mechanical effects. For instance, Hispanics have been increasing their relative proportion of the electorate for at least a generation, but their political power remains relatively weak. An important question might be ‘are minority voters’ disadvantage by the Electoral College?’.

Using the same data used in chapters two and three, I can provide evidence about two relevant topics regarding partisan-linked bias. The first is about partisan bias. By partisan bias, I am referring to the differences in how votes are translated into seats in any given election. For instance, which party is expected to win the election when the vote-share is tied. If an electoral system treats political parties fairly, no party should be favored when the vote-share is tied. The second way in which the Electoral College can be biased is related to partisan bias, but instead looks at the probability that a party wins the popular vote but loses in the electoral vote. This, of course, is the same as an inversion as described in chapter three. There, I showed that there have been four inversions in the 38 elections between 1868 and 2016, and in all four the popular vote share was below 50%; meaning that they were pro-Republican inversions. But, evaluating an inversion that does not mean the same thing as the Electoral College being biased, except only in the most extreme definition of majoritarianism.

A simple descriptive example will help to illuminate why partisan-linked bias is not guaranteed simply because an inversion happened. In 2016, Donald Trump defeated Hillary Clinton in the Electoral College winning 305 out of 538 Electors despite only winning 48.9% of the two-party vote. Even though the national vote was close, the votes in several states was even closer. Had Clinton won 44,292 additional votes in Pennsylvania, 22,748 more votes in Wisconsin, and 10,704 votes in Michigan, she would have instead won the popular vote and 279 Electors – eight more than the amount needed. So, it is not obvious that indeed the EC was biased against here in a meaningful way. In fact, in order to evaluate the scientific claim of partisan bias, there needs to be a quantification of an estimate of that bias and some associated standard error.

To measure these two partisan-linked biases, I first show why the traditional measure of partisan bias is unsatisfactory. Next, I create a series of counterfactual elections using simulation methods. Instead of looking solely at the actual outcome based on one set of election results, I create a large dataset with over5million observations of elections. The counterfactuals represent election results that might have happened if turnout had been slightly different, or if voters had slightly different preferences. The hypothetical elections allow for the measurement of uncertainty. That is, what is the likelihood that the result that actually happened was due to chance instead of systematic bias. Next, I touch on several important insights that can be gleaned from the evaluation of counterfactuals.

Partisan Bias

Political scientists typically measure partisan bias in one of two ways. The first is a derivation of the Tufte (1973; 1974) model (see also Grofman 1983), which uses a seats-votes curve to estimate bias. On one axis, plot the two-party vote percentage received by a party (either one can be used as the reference, and the plot is symmetric to both parties; in my examples, the Democrats are the reference), and on the other axis, plot either the number of seats or percentage of seats (or Electors in the case of EC) won by the same party. Starting with the observed vote-share, shift ach of the states by 1 percentage point and record the new seat share. This is repeated for vote-shares over a +/- range of 10 percentage points .. The values for votes and seats is then plotted . See the left plot in Figure 4.2. .

. The best fit, typically non-linear line can be drawn through these points. From that, a researcher could find the “average” bias at 50% vote share, along with a swing ratio - the rate at which seat share increases with vote share - by finding the slope of the line at some point in the curve. Partisan bias is the difference between the average seat share at 50% vote and 50%. See the right plot of Figure 4.2.

<< Figure 4.2 about here >>

Figure 4.2 shows that in 2016, the Electoral College was biased in favor of the Republican candidate, since the average seat-share in a tied popular vote favored the Republican candidate. The actual election result is quite far from the regression line, and if you look directly above the actual result and see where the regression line is at the vote share observed in 2016, it shows that the Democratic candidate would normally win. Using the Tufte seats-votes curve provides for unsatisfactory evidence of partisan bias. I now turn to simulation-based approaches for estimating bias.

The second method for measuring bias builds on the work of Gelman and King (1994). This method creates a stochastic version of this seats-votes curve. This model includes unit-level variation and relaxes the uniform swing assumption. Bias can still be measured by looking at the seat share at 50% vote-share, but this method allows for more robust measurement of the standard errors surrounding the measurement of bias.

Simulation Method

For the rest of the analysis, I will use elections generated from a modified version of the Gelman-King simulation method. Why choose a stochastic simulation method? Elections as definitive, discrete, and only reflect one moment under very specific circumstances. And though they are objective and final, researchers often use them as if they represent the true preferences of society, or at least the electorate. But the evidence of this claim is dubious. Some votes are not counted correctly (hanging chads). Some voters are disenfranchised without due process (voter purges). Still, others are not legally able to cast a vote, sometimes because of state law (felons) or because they aren’t old enough (U.S. Const. Amend. XXVI). Other voters may rationally choose not to vote in an election in which they otherwise have discrete and expressive preferences over because they live in a place where their vote is not likely to be determinative (Downs 1957). List-wise deletion of third parties and their voters, as any two-party analysis does, eliminates some important variation. Even the institutional arrangement itself which leads to convergence on two major parties shields the true preferences of individuals (Duverger 1954).

I model elections using a baseline equal to the observed state-level distribution. Without getting too technical, let me explain how a simulated election is obtained. For any given actual election result, the national popular vote, , is the two-party vote-share (Democrats are the reference group) and is simply the total votes for the Democrats divided by the total votes for the Democrats plus the Republicans. The Electoral College seat-share an aggregation of multiple state-level elections, (),[[1]](#footnote-1) where indexes states and indexes the election year. Each state is weighted by the number of Electors assigned to them, and all of the Electors is the Electoral College. For all , Democrats get all of the Electors for state , and no Elector from a state in which . Thus, the EC seat-share is . This is observable for all elections.

To create a counterfactual election, I take the actual outcome, , and add a stochastic function to each state; the stochastic error is determined through empirical observation of the average state-level inter-election swing from the previous three elections. The error is drawn from the distribution , with mean zero. Thus, the state-level error is equally likely to go up as it is to go down. Over many simulations, the error in each state too will equal 0. Thus, each simulated election is determined by the model:

where is generalized uniform partisan swing (this can be thought of as the nation-wide political tide). The term is the errors generated from the simulation and is unobserved, and is the estimated systematic errors given the observed vote . Simulating elections at different values of allows for creating hypothetical elections at any national vote share. For evaluation of the Electoral College in year , I estimate for vote shares between over the range , in increments of 0.02. This creates 151 distinct values. For each value , I create a distribution from which 1,000 elections are simulated. I then record (,) for each simulation.

Table 4.1 shows the bias for each election (1868-2016) for both the Tufte method (regressed over the vote shares ) and the simulation method. For the Gelman-King method, bias can be measured both at the discrete vote-share of 50% and averaged across a range of vote-shares . I report only bias at 50% vote-share.

<<Table 4.1 about here>>

Several computations can be made from this data. First, find the average seat-share at each simulated vote-share (). This number returns the likely number of Electors, or percentage thereof, given some level of national support. Second, ordering all and find at the 0.025 and 0.975 percentile gives a 95% confidence interval for projected EC outcomes given a particular vote share. Third, finding the mean at gives the theoretically important value of bias. That is, what is the expected seat share for each party when the election is an exact tie. Finally, what proportion of the time the vote-share and seat-share are not in agreement. This is an inversion. When () & (), and inversion favors the Republicans. When () & (), an inversion favors the Democrats. In an unbiased system, inversions would not exist since the majority vote-gaining party would also win in the EC. This implies that . Similarly, an unbiased system would not result in one party systematically benefiting from inversions. As previously noted, unbiased systems never have inversions. But, as shown in Chapter 3, there is not an expectation to never observe inversions since the particular nature of aggregation will occasionally lead to the split result. It is therefore empirically interesting to measure if one party is more likely to benefit from these inversions, i.e., if the system is biased. Looking only at actual election outcomes, however, limits the ability to observe an inversion interval since the national vote-share and seat-share is fixed. This simulation technique relaxes both of those assumptions and allows for hypothesis testing about bias in the seats from votes conversion.

I test two separate but compatible measures of bias. The first relates to the structural bias explained above. That is, what is the probability of inversion. The second relates to partisan-linked bias, which asks, conditional on an inversion happening, is it likely to favor one party over others? I will answer this using the simulation method described above.

<< Figure 4.3 about here >>

Figure 4.3 uses the simulations described above and reports the percentage of the simulations that result in an inversion as a function of vote share. Figure 4.3 reflects the pooled data from this set of elections. The inversion probability goes down very rapidly as the vote-share moves away from a tied election. At 50% vote-share, the probability of inversion is over 40%. However, after the margin of victory exceeds +/-4%, the probability of inversion is effectively zero. Figure 4.3 reinforces the point that inversions can occur at values other than a 50% vote share. Indeed, there is an expectation of a non-trivial probability of inversion in reasonably contested elections. But it also indicates that in vote-share values beyond 48% to 52% is seldom inversion generating. Similarly, the University of Texas Electoral College Study estimates that 45% of elections with a margin of less than 1% should result in an inversion (Geruso et al 2019).

The Directionality of Bias

Looking at what happens when vote share is 50% (and thus where seat shares of the two parties should be identical) is an essential feature of analyses in which we seek to understand the magnitude and directionality of partisan gerrymandering (see esp. the elegant axiomatic approach to understanding gerrymandering in King, Katz, and Rosenblatt, 2020), but that assumption can be misleading when we are trying to understand the expected directionality of inversions when such occur. Instead, to measure the actual extent to which inversions are likely to favor a given party we need to be looking at all the popular vote shares that might lead to inversion rather than only the inversion likelihood at fifty percent.

Figure 4.4 shows seats-votes curves generated stochastically for a set of eight elections, four recent elections of which two are inversions (2000 and 2016) and two are not (2004 and 2012), and four 19th century elections in which two are inversions (1876 and 1888) and two are not (1880 and 1884). Figure 4.4 was created using the same simulation method used to create Figure 4.3. The plot shows the single-year simulations that, when aggregated with the other 37 election simulations creates the probabilities in Figure 4.3.

<< Figure 4.4 about here >>

Figure 4.4 highlights the potential inversions (in red or blue) for each election based on the simulation of hypothetical outcomes at varying vote-shares. These figures that reversals can favor either Democrats or Republicans, not just in different elections but often in the same election. Which party is being favored during an election cycle can be judged by the number of hypothetical elections falling in the red and the blue areas. Even in an election year in which a pro-Republican inversion happens, there can be a non-trivial probability of a pro-Democratic inversion having occurred in that year. For example, as shown in Table 4.2, in 2000, 62.7% of the inversions favored the Republican candidate, implying there was a 37.3% probability that had an inversion occurred it would have favored the Democrats. Moreover, there was a 35% probability of an inversion happening in 2000, regardless of whom it benefited! There can also be high probabilities of a reversal favoring the Democrat even in a year where no actual inversion occurred, such as 2004, or even in years in which the vote-share wasn’t particularly close, like 1904 (10 percentage point Republican victory). 2016, however, does look like an outlier, with 95% of inversions favored the Republican candidate. This is evidence that the Electoral College does indeed have a significant bias benefiting the Republican Party and its nominee Donald Trump.

<<Table 4.2 about here>>

It is not just in the number of elections that result in inversion, which is the characteristic of Figure 4.2 that is of interest, but rather the relative number of inversions for each of the two parties, conditional on an inversion happening. For example, in extremely close elections, the width of the 95 percentile range of seat shares might be quite large, indicating not that there is a bias or that the EC is broken, as some suggest, but rather that it is highly responsive to small permutations in vote share within states; i.e., having a large number of highly competitive states, which also happen to be the pivotal states, would result in the potential for a high proportion of the seat shares to differ from the popular vote share.

In addition to values for estimated partisan bias at a 50% vote share, Table 4.3 also reports the conditional inversion probabilities. Both the number of inversions favoring each of the two parties along with the conditional probability of an inversion favoring each of the parties are listed.

<<Table 4.3 about here>>

Table 4.3 considers the share of the vote received by each party and finds the proportion of inversions result from the set of 1,000 simulations at that vote share. For instance, in 2016, the Democratic candidate (H. Clinton) received 51.11% of the national popular vote. Looking at simulations with a vote share equal to 51.2% (rounded up to the nearest simulated vote share), there are 479 out of 1,000 inversions. To make heads of this number, symmetry is required, such that had the Republican candidate (D. Trump) also received 51.2% of the popular vote. This process is synonymous with partisan symmetry measures used in the redistricting literature. If both parties are treated equally, i.e., no bias, then inversions happen at the same rate if both parties were to receive the same percentage of the vote-share. At a Democratic vote-share of 48.8%, 13 out of 1,000 simulations were inversions. While the probability that there was an inversion favoring either party in 2016 at 51.11% of the vote was over 50% (), there was an infinitesimally small probability of an inversion had Trump won roughly the same percentage of the total national vote.

In most years, both parties are equally likely to experience an inversion with a vote margin observed. Notable, however, is 2016, and 1888; both are inversion years, both having a disproportionate probability of the Democrat winning the popular vote and losing the EC. In most years, there are no simulated inversions at the vote margin in which the election resulted (and the vote-share had the opposing candidate had won by the same margin). Still, in years when there were simulated inversions, the difference between those benefiting Democrats and those benefiting Republicans are usually low, never exceeding 20%. This analysis leads me to believe that no longer-term, substantial bias benefiting one of the two major parties exist. However, the proportion of inversions going against the party winning the popular vote by over a two-percentage-point margin (51% of the vote) in 2016 was extremely disproportionate. To wit, Donald Trump was much more likely to win the Electoral College with just 49% of the vote than Hillary Clinton would have been with a share of the vote equal to that. In the same way, traditional partisan bias measures indicate that Trump had about a 13 percentage-point advantage overall on average. Of course, had Clinton won just slightly more popular vote, the ratio of inversions between the two parties at the same vote share would have approached one quickly. Overall, the 2016 election is characterized by a large amount of partisan bias at 50% vote share, which shapes the relative number of inversions possible over the vote shares around 50% of the vote. However, her national vote share was nearly enough to overcome any bias that exists.

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| Table 4.3 Probability of Inversion at Actual Election Vote-Share |
| |  |  |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | |  | 1868 | 1872 | 1876 | 1880 |  |  | 1884 | 1888 | 1892 | 1896 | 1900 | | **Pro-Republican** | 0 | 0 | 133 | 418 |  |  | 464 | 566 | 125 | 68 | 18 | | **Pro-Democratic** | 0 | 0 | 43 | 582 |  |  | 442 | 163 | 113 | 0 | 0 | |  |  |  |  |  |  |  |  |  |  |  |  | |  | 1904 | 1908 | 1912 | 1916 | 1920 |  | 1924 | 1928 | 1932 | 1936 | 1940 | | **Pro-Republican** | 0 | 0 | 0 | 35 | 0 |  | NA | 0 | 0 | 0 | 0 | | **Pro-Democratic** | 0 | 0 | 0 | 441 | 0 |  | NA | 0 | 0 | 0 | 3 | |  |  |  |  |  |  |  |  |  |  |  |  | |  | 1944 | 1948 | 1952 | 1956 | 1960 |  | 1964 | 1968 | 1972 | 1976 | 1980 | | **Pro-Republican** | 0 | 2 | 0 | 0 | 477 |  | 0 | 532 | 0 | 256 | 0 | | **Pro-Democratic** | 0 | 77 | 0 | 0 | 523 |  | 0 | 0 | 0 | 160 | 0 | |  |  |  |  |  |  |  |  |  |  |  |  | |  |  |  |  |  |  |  |  |  |  |  |  | |  | 1984 | 1988 | 1992 | 1996 | 2000 |  | 2004 | 2008 | 2012 | 2016 |  | | **Pro-Republican** | 0 | 0 | 0 | 0 | 473 |  | 50 | 1 | 21 | 479 |  | | **Pro-Democratic** | 0 | 0 | 0 | 0 | 346 |  | 0 | 0 | 30 | 13 |  | |  |  |  |  |  |  |  |  |  |  |  |  | |
| Note: Table is organized by census period. If the Republicans won the popular vote, the pro-democratic row represents the proportion (out of 1,000) simulated elections the Democrats won. The pro-republican row would then represent the number of simulations (out of 1,000) that the Republicans would win if the Democrats had won the election with the same vote-share. For instance, H. Clinton won the popular vote with 51.2% of the vote and at that vote share Republicans win 47.9% of all elections. On the other hand, if she instead only won 48.8% of the vote, the Democrats would only have won 13 out of 1,000 simulated elections, or 0.013%. |

1. The national popular two-party vote can be found from state-level elections using a weighted average of state two-party vote , where the weights are equal to the number of total voters, . Thus, the discrete election result, . [↑](#footnote-ref-1)