It's Always Sunny in Politics

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June 28, 2022

Abstract

A desirable property of democratic elections is that they should not be influenced by forces that reveal no information about the candidate. However, the extant literature suggests that precipitation has a significant impact on electoral outcomes. This paper investigates an understudied dimension of weather—sunshine. Using novel daily weather measurements from satellites, linked to county-level U.S. Presidential electoral returns from 1948-2016, we document how sunshine affects the decision making of voters. We find that election-day exposure to sunshine increases support for the Democratic party on average. Additionally, we show that—contrary to prior findings that do not control for sunshine—precipitation has no detectable impact on partisan support, but universally depresses turnout. To rationalize our results we propose a mechanism whereby sunshine modulates voter mood which causes a change in voter choice, while precipitation only impacts turnout through increasing the cost of voting. We then build a theoretical model, which features this mechanism, and generates additional tests that find support in the data. Our main result—that election day sunshine noticeably impacts voter choice—highlights the need to reduce the effect of election day shocks (e.g. by allowing early voting). Furthermore, our results regarding precipitation suggest that reducing costs to voting does *not* confer partisan benefits—a potentially policy relevant finding for the current vote by mail discussion.

Acknowledgments: We would like to thank Laurent Bouton, Michael Bailey, and Garance Genicot for their advice and support. We would also like to thank Kevin Ankney, Gaurav Bagwe, Juan Margitic, Arturo Romero, Ben Solow, Daniel Valderrama, and Lina Yu for insightful suggestions. We have also benefited from fruitful discussions with several seminar speakers and colleagues at Georgetown University, as well as seminar participants at the Southern Economic Association 92^{nd} Annual Meeting. All errors are our own and the usual caveats apply.

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ⓡ Names are in random order following Ray ⓡ Robson (2018). Citation should be Concha-Arriagada ⓡ Naddeo (2022).

1 Introduction

Elections are crucial mechanisms in any healthy democracy. They aggregate votes and allow citizens to express their preferences for policies via selection of candidates. A desirable property of elections is that they should not be influenced by forces that reveal no information about the quality of candidate. However, there exists ample evidence, both anecdotal and empirical, that weather on election day plays an important role in voter's decisions.[2] For example, while most likely overstated, torrential rainfall in England was blamed for the Brexit outcome in 2016. Additionally, the general public in the United States devotes a substantial amount of resources into tracking election day weather. Up until now, precipitation has been the focus of all empirical inquiry into the impact of weather on election day behavior. This paper is the first, to our knowledge, to incorporate continuous measures of solar radiation (sunshine) as an important dimension by which weather interacts with voters' decisions during election day. We disentangle the independent impacts of election day precipitation and sunshine on turnout and candidate vote shares.

Our analysis utilizes novel data that includes continuous physical measures of precipitation and solar radiation linked to county level Presidential election results from 1948-2016. This long time series allows us to isolate plausibly exogenous variation by using county and election year fixed effects. Our main result is that sunshine, not precipitation, has a substantial impact on a candidate's vote share. Specifically, increasing sunshine from 1 standard deviation (std) below the mean to 1 std above the mean, results in Republicans vote share decreasing by 2.8% relative to their Democratic opponent. Conversely, moving precipitation in the same manner has no detectable impact on vote shares. Additionally, we find that increases in sunshine from 1 std below the mean to 1 std above the mean depresses turnout by approximately 1%. Coincidentally, we also find the same 1% effect on turnout when moving precipitation in the same way. Therefore, if we assume that all of the people deterred from voting by the increase in sunshine are Republicans there is still a 1.8% Democratic advantage that is unaccounted for. This 1.8% could be the result of two types of

[2] Weather has also been shown to impact decision making in numerous other settings, such as conflict (Miguel and Satyanath, 2011; Theisen, 2012), migration (Kim, 2019), and crime (Ranson, 2014) to name only a few. See Mellon (2021) for a categorization of 279 studies that utilize rainfall to study economic phenomena.

voter response to sunshine exposure: 1) changes in candidate choice and/or 2) changes in turnout decisions. In order for the latter to generate our results sunshine would need to deter Republican voters from turning out while simultaneously convincing a subset of non-voters to turn out for the Democratic candidate.[3] While the former is admittedly less intuitive, Blais (2004) documents that 4% of voters surveyed changed their vote on election day from one party to another. Without high quality individual data it is impossible to completely identify which scenario is driving the shift in vote shares that we observe. However, as we will discuss in detail later, both stories can be supported by our proposed mechanism, whereby all potential voters find the Democratic candidate more attractive as a result of being exposed to an increase in sunshine.

To convince ourselves that our results are not driven by spurious correlations in our data we use randomization inference.[4] We also ensure that no single state nor election year drive our main findings by re-running our main analysis numerous times while independently leaving out each election and state from our sample. Additionally, we probe the heterogeneity in the effect sunshine and precipitation have along important dimensions. For example, we find that counties with a higher fraction of undecided (or weakly partisan) voters tend to be more influenced by weather. Additionally, we find that as elections get more competitive the impacts of weather are diminished.[5]

After establishing our main set of results, we turn to uncovering the potential mechanisms at play. Specifically, we focus on whether voters favor riskier candidates due to an increase in risk tolerance caused by elevated mood. This mechanism was suggested by Horiuchi and Kang (2018) and confirmed experimentally by Bassi et al. (2013); Bassi (2019). To test empirically, we leverage exposure to election day sunshine as a way to isolate exogenous variation in mood. We then re-run our main regressions after re-labeling candidate's as either "safe" or "risky" based

[3]This would be a similar result documented in Chen (2013), whereby disaster aid from Republican politicians increased Republican turnout while simultaneously decreasing Democratic turnout.

[4]Recent papers have called into question results similar to ours. For example, in Fowler and Pablo Montagnes (2015) and Fowler and Hall (2018) the following well-known papers: Healy et al. (2010), documenting the electoral impacts of college football outcomes and Achen and Bartels (2004), showing shark attacks harmed incumbent support, were shown to not withstand basic robustness tests.

[5]Similar to results from Fraga and Hersh (2011), who show that rainfall only impacts turnout in noncompetitive elections.

on multiple observed dimensions.[6] In every regression we find that sunshine has a considerable negative impact on the vote shares of the safer candidate. To better understand these results we build a simple pivotal voter model which features two candidates distinguishable only by the risk profile of their platform. This model generates predictions that are coherent with our proposed mechanism, as well as some additional predictions that we also confirm with our data.[7]

We see our contributions to the extant literature as follows. To begin, we document how precipitation and sunshine impact electoral outcomes. Our results inform policies aimed at voter turnout both explicitly, and perhaps more importantly implicitly. Explicitly one has to consider weather as a multi-dimensional object that can frustrate or exacerbate policy effectiveness. For example, the impact of making election-day a holiday on turnout could be modulated by election-day weather. Kang (2019) shows that in Korea—where elections day are holidays—a good weather day decreases turnout by increasing the opportunity cost to voting.[8] Implicitly, our results signal that while increasing explicit costs to vote via precipitation lowers turnout, it has no detectable partisan benefit.[9] Until now, results from Gomez et al. (2007) and Horiuchi and Kang (2018) imply that reducing the potential cost imposed by election day weather would benefit Democrats. Our results suggest that reducing costs to voting—in the context of weather—does not confer partisan benefits. Vote by mail (VBM) is a policy that has received much attention in the United States, especially after the 2020 election.[10] With some extrapolation our results suggest that the lowering of costs by VBM may not benefit one party.

We also contribute to the literature that uses precipitation as an instrument for turnout.[11] We show that without controlling for sunshine separately, precipitation acts as an imperfect proxy for

[6]We use a candidates incumbency status, relative age, and prior experience as proxies for risk.

[7]To be specific we find empirical support for theoretical predictions about how turnout should be impacted by risk shocks conditional on which candidate is considered the *a priori* favorite.

[8]We also find weak evidence that increased sunshine depresses turnout in the US, where elections are held during normal working days.

[9]See Yoder et al. (2021) for a similar result showing that benefits offered by absentee ballots do not necessarily have a partisan bias.

[10]Most of the attention has been focused on the perceived partisan bias in electoral benefits gained by lowering the cost to vote (Bagwe et al., 2020), as well as claims of fraud (Wu et al., 2020; Eggers et al., 2021).

[11]See Hansford and Gomez (2010); Artés (2014); Lind (2019); Knack (1994); Lo Prete and Revelli (2021); Persson et al. (2014); Keele and Morgan (2013); Gong and Rogers (2014).

sunshine. Our main results document a strong impact of sunshine on vote shares, a direct violation of the exclusion restriction.[12] However, after controlling for sunshine we find that precipitations impact on vote shares disappears, thus (potentially) restoring confidence in using rainfall as an instrument for turnout only if sunshine is included as a control. We believe more empirical work in this area is warranted and leave it for future studies.

The rest of the paper is structured as follows. Section 2 briefly overviews the extant literature that was used to motivate and inspire this work. Section 3 describes the novel data that we use to test the model predictions. Section 4 outlines the strategy used to get the estimates presented in Section 5. Lastly, Section 6 discusses the results and concludes.

2 Related Literature

Previous studies focusing on the United States document a strong partisan bias in the benefits of precipitation. Gomez et al. (2007) find that *"Republicans should pray for rain"* as an extra inch of rainfall on election day would depress turnout by 1 % and increase the Republican's vote share by 2.5%. Horiuchi and Kang (2018) further investigate this result using a seemingly unrelated regression (SUR) framework and similarly conclude that Republicans are better off when it rains. Additionally, Horiuchi and Kang (2018) offer an empirical strategy that is able to decompose the increased Republican vote share into turnout and "vote-shift" channels. The former is intuitive: precipitation increases costs and deters potential voters in a partisan way.[13] The latter vote-shift channel is caused by voters being exposed to rain and changing their vote from Democrat to Republican. Using the SUR framework, and adding sunshine as a new explanatory variable, we show however that "vote-shift" results are entirely driven by sunshine, not precipitation. Essentially, without controlling for sunshine, rainfall behaves as a proxy for the sunshine effects on electoral outcomes.

[12] For an excellent review of the perils of using weather as instrument in numerous settings see Mellon (2021)

[13] For example in the United States, a voter's preferred party correlates with characteristics that may also modulate how sensitive they are to a storm. A good example of this is the fraction of a county supporting democratic candidates, which is strongly correlated with how urban the county is.

We also draw upon, and contribute to, a current literature that is divided on how a short run boost in mood should translate into the voting booth. We offer supporting evidence for the strand of literature that shows that an increase in mood lowers risk aversion and thus increases the safer candidate's vote share.[14] Conversely, there are a considerable amount of papers documenting how events that boost mood correlate with an increase in the safer candidate's vote share.[15] The mechanism implied by these studies is that voters irrationally attribute increases in election-day mood to the incumbent candidate, rewarding them at the polls. We do not completely rule this mechanism out, but we find strong evidence that increase in mood (caused by increased sunshine) lowers the vote share of safer candidates.[16]

The proposed mechanism hinges on existence of a strong relationship between weather and mood. Data from the experiment ran in Bassi (2019)[17] shows strong positive correlations between both self-reported and objective measures of good weather, and elevated self-reported mood as well as increased positive affect (as measured by responses to PANAS-X survey). There also exists a robust literature studying weather's impact on mood.[18] The mood effect is likely driven by both biological and psychological mechanisms. Medical studies on seasonal affective disorder (SAD) show that sunlight stimulates biological processes that fight against depression and regulate stress. In the SAD literature the main biological change produced by sunlight are the production of serotonin and melatonin. The former is a neurotransmitter that exerts a calming effect on both the human body and the mind, and it has been linked to clinical depression and bad moods (Williams et al., 2006). The latter regulates circadian cycles, for example it instructs the body to relax at night. Since sunlight affects both substances, it has been shown that exposure to real or artificial light for

[14] For example, recent articles have shown that in Switzerland (Meier et al., 2019) and Britain (Leslie and Arı, 2018) decreases in weather quality lead to increase in support for the status quo. As discussed earlier, Horiuchi and Kang (2018) show that incumbent support increases with poor weather.

[15] Examples of this are found in settings where mood is modulated from home sports team winnings (Healy et al. (2010); Busby et al. (2017)), shark attacks (Achen and Bartels, 2004), increased sunshine (Cohen, 2011) and winning the lottery (Bagues and Esteve-Volart, 2016). Note that Cohen (2011) looks at sunlight's impact on Presidential approval ratings, not electoral outcomes as in the current article.

[16] In fact, we find our main partisan results are stronger in elections where there is no incumbent, suggesting that while both mechanisms may be present the former is dominant.

[17] Accessed here: https://doi.org/10.7910/DVN/CVXOOS.

[18] See Øverland et al. (2019) for a review of the SAD literature.

only an hour a day can dramatically reduce SAD symptoms (Lambert et al., 2002), even among those who are not depressed (Leppämäki et al., 2002). In the psychological literature it has been proposed that mood temporarily predisposes individuals to behave according to there affections. This literature proposes that sunlight can exert a strong positive impact on mood, stimulating a positive attitude as well as optimism about the future or current events. As stated in Cohen (2011) "mood influences individuals by altering our affective, cognitive, and behavioral responses to a wide array of objects and events."

3 Data

3.1 Weather

To the best of our knowledge, this is the first paper to utilize pixel level weather measurements to study weather's impact on electoral outcomes. We extract daily measurements of net shortwave radiation (sunshine), rainfall, and snowfall from the underlying data used in the National Climate Assessment - Land Data Assimilation System (NCA-LDAS)[19] for any time from 1979-2016 and the Global Land Data Assimilation System (GLDAS)[20] for any time between 1948-1978. The data are provided as a NetCDF, where each layer is an image with pixels that represent measurements of each weather variable. The NCA-LDAS data has a spatial resolution of $0.125°$ by $0.125°$[21] and the GLDAS has a spatial resolution of $0.25°$ by $0.25°$. We first extract the layers that represent rainfall, snowfall, and net shortwave radiation and take the average pixel values that fall within each county border as defined by the 2010 Census county boundary geography.[22] To simplify the presentation of results we create a total precipitation variable as the sum of rain and snowfall, where we convert

[19] Accessed using wget to bulk download from https://hydro1.gesdisc.eosdis.nasa.gov/data/NCALDAS/NCALDAS_NOAH0125_D.2.0/.

[20] Accessed using wget to bulk download from https://hydro1.gesdisc.eosdis.nasa.gov/data/GLDAS/GLDAS_NOAH025_M.2.0/.

[21] At the equator this equates to a 13.75 km by 13.75 km, smaller than almost all counties in the US (exceptions being some independent cities).

[22] The only counties where measurement was not possible both occurred in Massachusetts. Dukes and Nantucket counties are mostly islands, and are missing weather information. Using population estimates from the 2010 Census these to counties combine for 0.4% of the total population living in Massachusetts.

snow to liquid equivalent accounting for surface temperature.

As it is a relatively novel measurement we now describe in more detail our measurement of sunshine. The shortwave radiation data in NCA-LDAS are derived from bias corrected measurements from Geostationary Operational Environmental Satellites (GOES).[23] These satellites "stare" down at the Earth and are therefore able to provide high frequency measurements. The GOES use multiple spectral channels. This is analogous to a camera having red, green, and blue (RGB) sensors to properly capture images. However, sometimes there are obstacles (e.g. clouds) that prevent the satellite from "seeing" the surface. The satellite is equipped with various spectral channels which helps account for these potential obstacles and accurately compute the downward shortwave radiation at the Earth's surface. The GLDAS utilizes shortwave radiation measurements from The Princeton Global Meteorological Forcing Dataset.[24] We choose to use the former measurements when available because they come from direct measurements whereas the latter derives values from a model and therefore are less accurate. Shortwave radiation is defined as the radiant energy from the sun with wavelengths above 0.1 μm and below 3 μm, or more naturally, shortwave radiation is the visible, ultraviolet, and infrared radiation that is incident upon the Earth from the Sun. One potential reason why sunshine has not received much attention is that most of the available historical data measures sunshine in discrete bins (e.g. clear, partly cloudy, etc.). When using these discrete measures researchers are unable to include precipitation due to near perfect collinearity. As just described, our measurements of sunshine are continuous, however there may still be some concern that collinearity between our weather variables could cast doubt on the stability of our results. Results from multiple diagnostic checks are presented in Appendix A.3 to assuage these concerns.

[23] See Berg et al. (2003); Pinker et al. (2003)

[24] See Sheffield et al. (2006)

3.2 Election

Election results were extracted from Congressional Quarterly (CQ) Press Voting and Elections Collection website.[25] Data were collected at the county level for Presidential elections from 1920-2016. These data report the names, party affiliation, and total votes cast for each democratic, republican, third party, and "other"[26] candidate running in the general election. To construct turnout we merge these county-level voting data to the voting age population (VAP) of the county.[27] Census data on the age distribution of the population living in each county was pulled from the Integrated Public Use Microdata Series National Historical Geographic Information System (IPUMS-NHGIS) for each decennial census from 1940-2010. We then created a voting age population[28] and then performed a linear interpolation of $log(VAP)$ for elections that fall in between a census. For all years post-2010 American Community Survey (ACS) data is used as it supplements the decennial census and thus is more accurate than simple extrapolation from the 2010 census. While county boundaries do not vary much over time there are some cases where counties either adopt new names, merge with a neighbor, or simply cease to exist. We chose to use 2010 geography and attempt to harmonize other years accordingly. We utilized the crosswalk provided by Eckert et al. (2020), which harmonizes historic counties using the fraction of a counties area that goes into 2010 county.[29]

4 Estimation Strategy

To empirically investigate how precipitation and sunshine affect voter's decisions, we follow previous literature and use a seemingly unrelated regression (SUR) framework developed by Tomz et

[25] Accessed here: https://library.cqpress.com/elections/index.php

[26] The other category tracks the highest vote-getter after top three candidates.

[27] Ideally, we would use voting *eligible* population (VEP), which excludes non-citizens, felons (depending on state law), and mentally incapacitated persons and includes military and persons living abroad. See http://www.electproject.org/ for discussion about the difficulties of getting VEP at the sub-state level.

[28] Note that before 1971 most states had a voting-age population of 21, with the exception of Georgia and Kentucky.

[29] Another useful tool that helped immensely with this task was Carl Klarner's County FIPS matching tool accessed here: https://doi.org/10.7910/DVN/OSLU4G

al. (2002), which produces consistent and unbiased estimators, and is more efficient than OLS.[30] This procedure accounts for two important features of our aggregated elections data: 1) vote shares for all parties are bounded between 0 and 1 and 2) the sum vote shares of each party plus the share of those that abstain from voting should sum to 1.

We start by classifying the total voting age population, VAP for each county c, state s in each presidential election t into three categories: (i) total votes for the democratic candidate, d, (ii) republican candidate, r and (iii) the rest of the voting age population within a county, which we classify as abstainers, a. For the sake of brevity we describe the following analysis assuming that all votes are cast for one of the two major parties. However, the same procedure can be extended easily to three (or more) parties. To clarify, all of the empirical results we present will add a third party that includes all other candidates that we have electoral returns for. We do this so that the impact on turnout is not driven by variation in third party voting. We then divide all of these by the voting age population within the county to create the share of voting age people who voted for each party, D and R, and abstention rate, A. All of which are related by the following equation: $D + R + A = 1$.

We can now construct two equations to jointly estimate how weather impacts the vote shares of each party and the abstention rate. Operationally, we divide each candidate vote shares by the abstention rate and take the natural log of this ratio because the SUR method requires an unbounded dependent variable.

Therefore two main equations that we estimate are:

$$ln\left(\frac{R_{cst}}{A_{cst}}\right) = \beta_p^R precip_{cst} + \beta_s^R sunshine_{cst} + \mathbf{X}_{st}\boldsymbol{\theta}^R + \nu_c^R + \tau_t^R + \epsilon_{cst}^R, \tag{1}$$

$$ln\left(\frac{D_{cst}}{A_{cst}}\right) = \beta_p^D precip_{cst} + \beta_s^D sunshine_{cst} + \mathbf{X}_{st}\boldsymbol{\theta}^D + \nu_c^D + \tau_t^D + \epsilon_{cst}^D, \tag{2}$$

where $\mathbf{X}_{st}$ is a vector of state level, time-varying, controls which include the percentage of

[30]SUR estimation procedure gains efficiency over OLS by taking into account the linear correlation between the multiple equations. In our case this is due to the fact that the votes for each candidate plus the number of abstainers should equal the voting age population.

African American voting age population that is registered to vote within each state, the motor voter laws for each state[31], and an indicator for the home state of republican candidates. The percentage of African Americans that are registered to vote is used as a proxy for the evolution of voter suppression laws over time. Meanwhile the inclusion of the National Voter Registration Act of 1993 (NVRA), also known as the Motor Voter Act, controls for increases in voter participation over time.[32] We add county, ν_c, and election-year, τ_t, fixed effects, to mitigate concerns about time-invariant unobserved differences between counties and national election-year level shocks. Therefore, our parameters of interest $(\beta_p^D, \beta_s^D, \beta_p^R, \beta_s^R)$ are estimated using deviations from the county and election-year means, while also controlling for state-level voting laws.

After estimating all model parameters in equations 1 and equation 2, we are left with a set of estimated parameters with no clear economic meaning. To recover the average effect of increasing sunshine and precipitation we proceed to run statistical simulations.[33] We first draw 1000 coefficients from a multivariate normal distribution, $N(\mu, \Sigma)$, with means, μ set at each coefficient point estimate and Σ set to the variance-covariance matrix of the coefficients. We then use the set of coefficients to predict the vote share of each candidate and the abstention rate under two scenarios: 1) the weather variable of interest set to 1 standard deviation below the mean and 2) the weather variable of interest set to 1 standard deviation above the mean. In both cases we hold all other controls at their respective means. We then subtract the predicted values of each scenario to get a distribution of first differences. At this point we display the means of these distributions as point estimates and 95% confidence intervals are calculated.[34]

[31] We utilized data from Gomez et al. (2007); Hansford and Gomez (2010) on the motor voter laws before 2000.

[32] The law advanced voting rights by requiring state governments to offer simplified voter registration processes for any eligible person who applies for or renews a driver's license or applies for public assistance, and requires the United States Postal Service to mail election materials of a state.

[33] See Tomz et al. (2002) with similar applications in Horiuchi and Kang (2018) and Leslie and Arı (2018)

[34] To account for the fact that the predicted values we produce are actually the natural logarithm of the predicted value of interest we use Duane's smearing estimator. See Duan (1983).

5 Results

This section starts with the results from our main specification where we estimate how turnout and electoral outcomes are impacted by changes in weather using the SUR framework described in section 4. We present a battery of robustness checks in Appendix A.2. We finally present the dominant mechanism that we believe drives our main results.

5.1 Seemingly Unrelated Regressions

As a first exercise using the SUR framework, we replicate Horiuchi and Kang (2018)'s results using our sample. Figure 1 shows a similar pattern to Figure 1 in their article, with slightly smaller magnitudes. Increasing precipitation depresses turnout, lowers the vote share of democrats, and increases the vote share of republicans. We find that the bounds for the potential vote-shift are 0.63-1.34%, smaller than the 2.01-3.08% identified by Horiuchi and Kang (2018).

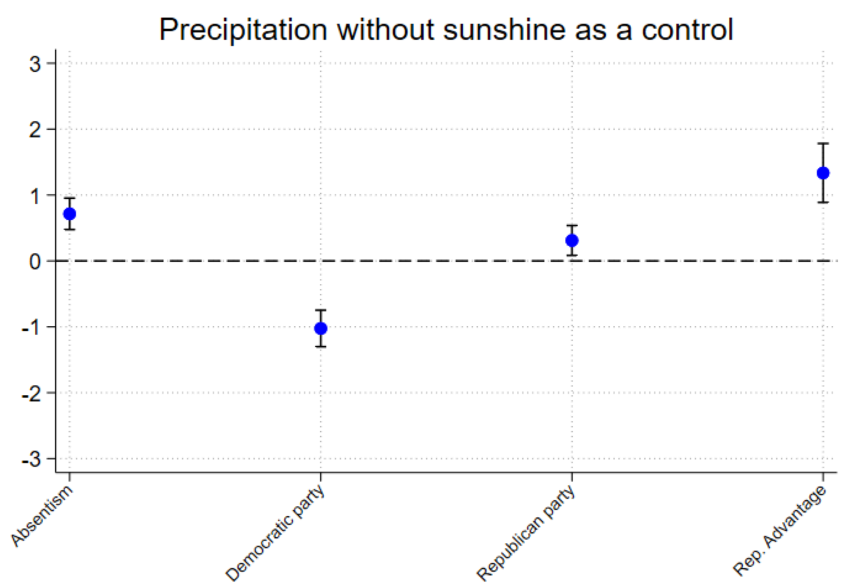
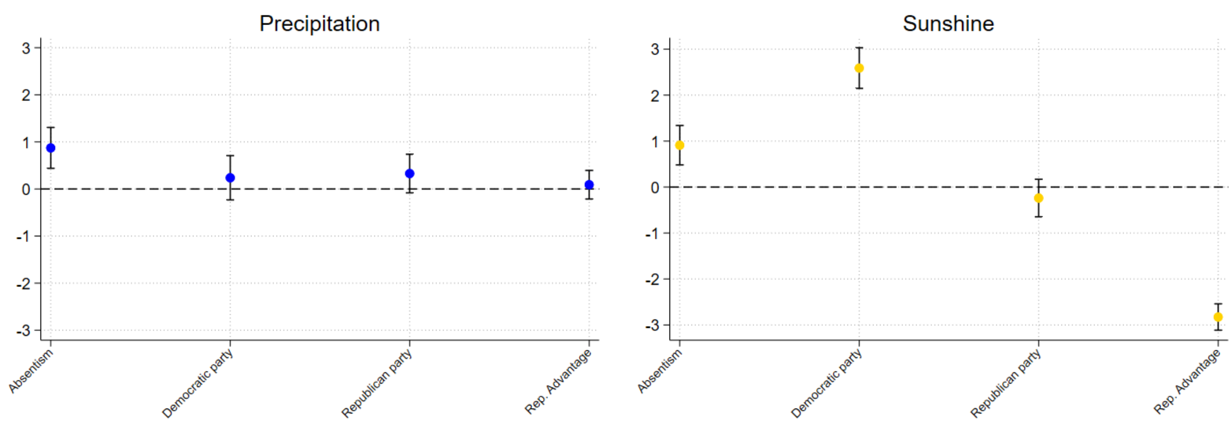


Figure 1: Effect on party vote share and abstention rate using estimates from SUR of increasing precipitation 1 inch without controlling for sunshine.

We then proceed with our main specification and include sunshine in the specification to account for weather's multi-dimensionality. As Figure 2a illustrates the vote shift bounds drop dramatically to -0.79-0.08% and the impact on vote shares becomes small in magnitude and statistically indistinguishable from zero. However, precipitation's effect on abstention remain positive and are similar to those reported by Horiuchi and Kang (2018). Our explanation for this is that sunshine, not precipitation, drove the vote shift channel and precipitation is simply an imperfect proxy for sunshine when this is not include in the analysis. Figure 2b shows the effects of increasing sunshine within the same model (i.e. while also controlling for precipitation). It is noteworthy that the vote shift bounds for sunshine are 1.93-2.84% in favor of democratic candidates.



(a) (b)

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Figure 2: Effect on party vote share and abstention rate using estimates from SUR of: (a) increasing precipitation 1 inch controlling for sunshine; (b) increasing sunshine hours by 2.8.

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

5.2 Heterogeneous Effects

To further convince ourselves of our main results we investigate how they vary along two important dimensions of heterogeneity: competitiveness and swingness.[35]

5.2.1 Competitiveness

As described in Fraga and Hersh (2011) random costs (in our case behavioral changes) do not impact voters uniformly across different electoral environments. Fraga and Hersh (2011) show that previous results in Hansford and Gomez (2010) that document a negative impact of rainfall on turnout do not hold up in competitive environments. We first create two measures of competitiveness, one at the state level to measure the competitiveness of the election and the second at the county level to measure local competition. We believe that local competition could influence voters by modulating the information they receive from daily interactions with neighbors and co-workers. For the state level competitive measures we follow Fraga and Hersh (2011) and construct the following:

$$comp_{st}^{state} = 1 - |(VSR_{st} - 0.5) \cdot 2| \tag{3}$$

where $comp_{st}^{state}$ is the *ex-post* competitiveness of state and VSR_{it} is the Republican share of votes case in in election t and state s. In the local case we first construct an *ex-post* measure of competitiveness, $comp_{it}^{local}$, for each county, c after election t, using the following formula:

$$comp_{ct}^{local} = 1 - |(VSR_{ct} - 0.5) \cdot 2| \tag{4}$$

where VSR_{it} is the Republican share of votes case in election t and county i. These measure ranges from 0, where all or none of the votes in the county or state are for the Republican to 1 where exactly half of the votes cast were for the Republican candidate. We then take the average over all the elections we have and label (non-) competitive counties or states as those above (below)

[35] For brevity we only present the main results of interest, the overall impact on Republican vote share and turnout. We are happy to share full results upon request.

the median of their respective competitiveness scores.

The top two panels of Figures 5.2.1 and 5.2.1 show the estimated impacts on electoral support and turnout using state (top right) and local (top left) competitiveness, respectively. To begin, we find the same results as Fraga and Hersh (2011), precipitation only impacts turnout in low competition environments. We also find that the electoral effects of sunshine are attenuated in high competition environments, suggesting that voters in states and counties that have closely contested elections are less affected by changes in mood.

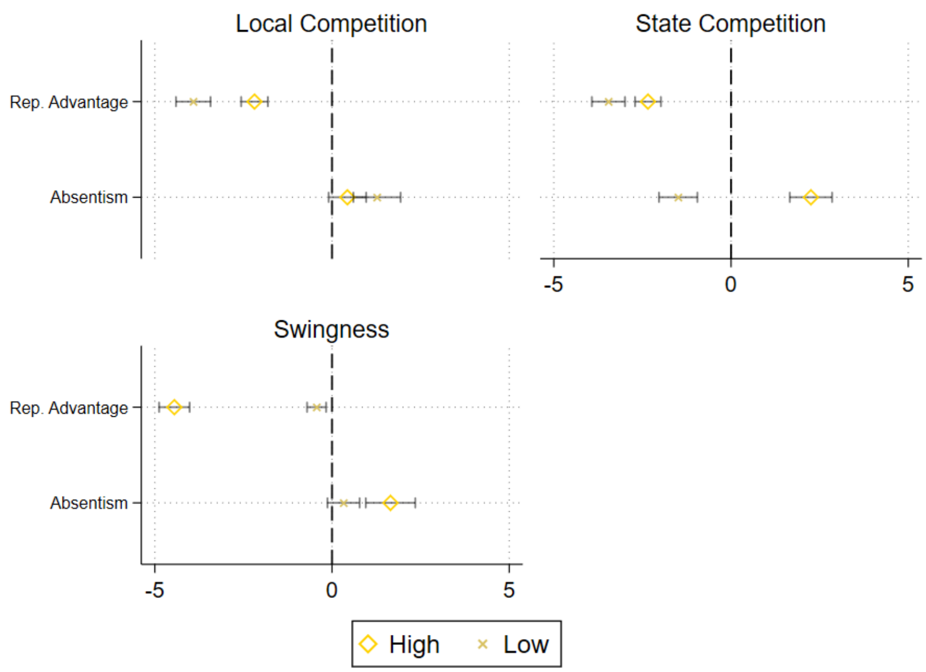
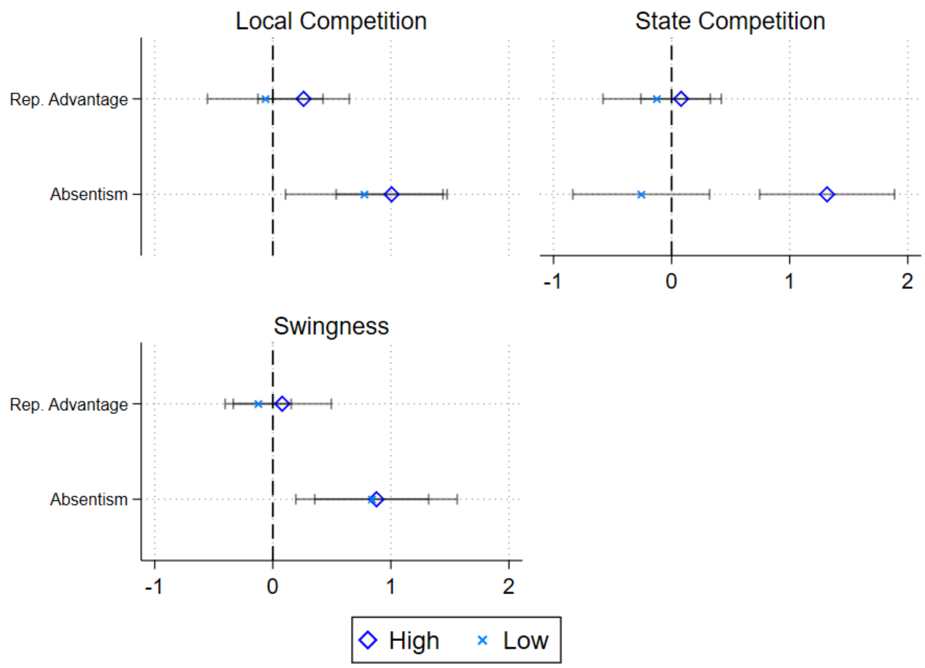


Figure 3: Heterogeneous effects of increasing sunshine hours by 2.8 by county level competition (top left), state level competition (top right), and county level swingness (bottom left).
Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

5.2.2 Swingness

The swingness of a county is a measure of how volatile the electorate is. We use it as a proxy for the fraction of voters who are eligible to change their minds. Unfortunately there is not a consensus on how to measure swingness. We define swingness as the coefficient of variation of the Republican



Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Figure 4: Heterogeneous effects of increasing precipitation by 1 inch by county level competition (top left), state level competition (top right), and county level swingness (bottom left).

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

vote share:

$$swingness_c = \frac{\sigma_c^2}{\overline{VS}_c^{rep}} \tag{5}$$

where σ_c^2 represents the standard deviation of the Republican vote share in county c over all the elections in our sample and $\overline{VS}_c^{rep}$ is the average Republican vote share in county c. We then label all counties with coefficients of variation over (under) the median as high (low) swing. Figure The bottom left panel of Figures 5.2.1 and 5.2.1 show the estimates we obtain by applying the same process that produced our main results. An interesting point becomes instantly salient: swing counties are affected much more by variation in mood than non-swing counties, while precipitation uniformly decreases turnout in both. We take this as compelling evidence that our main results are identifying the effect of voters changing their minds on the day of the election.

5.3 Mechanisms

Our main results are that Democratic candidates enjoy electoral benefits from increased sunshine. One potential explanation for this is that increased sunshine increases mood which lowers the risk aversion of voters, thus increasing support for the riskier candidate and penalizing the safer candidate. As suggested by previous literature, Republican candidates tend to represent the status quo, and run on more conservative platforms, and therefore are perceived as less risky options relative to their democratic counterparts (Horiuchi and Kang, 2018; Bassi, 2019). Kam and Simas (2010) supports this view by using survey data to show that Republican voters have a lower risk acceptance than their Democratic counterparts.[36] Additionally, we find that Republican candidates in our sample tend to be older, come from a higher previous office, and have longer tenures in public service before becoming presidential candidates. The rest of this subsection is devoted to investigating this mechanism. First, we develop a simple theoretical framework that gives clear predictions about how risk may generate our main results. Finally, we apply the same estimation strategy to other setting that *a priori* are better representations of safe versus risky candidates and show that they generate the same pattern of results as found in the previous section.

5.3.1 Model

To guide the investigation into the mechanism responsible for producing the results found in our empirical analysis, we build a probabilistic voting model of election using a game in which voters must decide whether to turn out or to abstain in an upcoming election. We extend Castanheira (2003), Myerson (1998) and Myerson (2000) adding uncertainty over how one candidate's platform translates into outcomes. In our case, we assume voters view a vote cast for candidate A as resulting in outcome A, meanwhile candidate B's platform induces outcomes distributed normally

[36] Therefore, if one assumes that candidates represent the party voters that select them then Democratic candidates should have more freedom to run with riskier platforms.

with mean -A and variance equal to $\sigma^2 > 0$.[37] Further, we assume there is a given fraction of the population, $\gamma_A \in (0, 1)$ that are predisposed to support candidate A, and a fraction, $\gamma_B = 1 - \gamma_A$ that supports candidate B. As usual in probabilistic voting models, voters derive utility from the outcome realized after the winning candidate implements their platform, their own political preferences and negatively by the cost of voting.[38] This type of setup reduces the comparison between the three options, voting for candidate A, B or abstaining, to only two, either voting for the most preferred candidate or abstaining. Additionally, since preferences between A and B are given by voters' type, we can characterize the type for the individual who are indifferent between A and B as an increasing function of candidate's B platform's volatility (i.e. σ^2). The intuition is that the riskier candidate B the more voters "defect" to the safer candidate A, due to their concave utility. Figure 5 presents the type distribution as well as the platforms for each candidate for given parameters.[39]

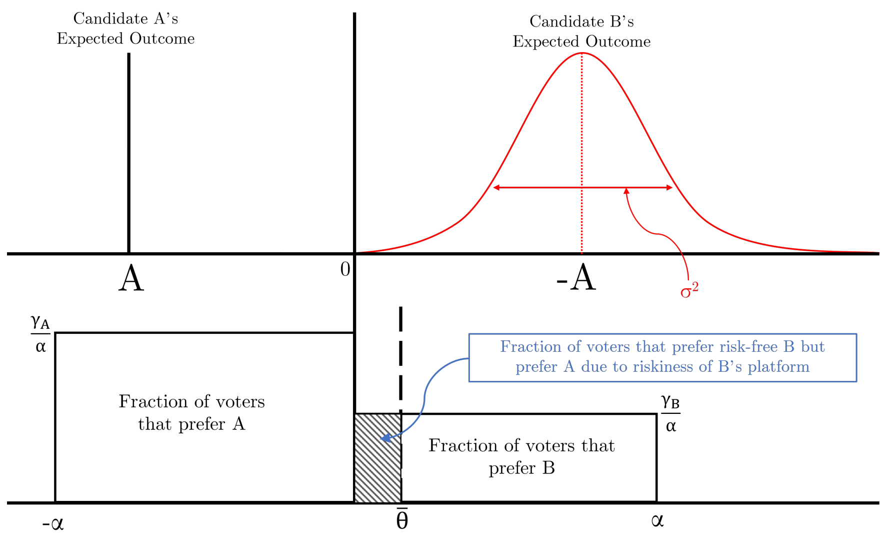


Figure 5: Visualization of types and platforms. The shaded area represents the voters that would prefer candidate B without risk, but due to their risk aversion find candidate A more preferable.

This simple model gives us clear predictions about how an increase to the perceived risk of candidate B's platform decrease candidate B's vote share while increasing candidate A vote shares, while having ambiguous effect on abstention.[40] We summarize the predictions as follows:

[37]This means both candidates are equally distant to zero in the one-dimensional policy spectrum.

[38]This cost of voting is what makes possible to have a fraction of voters who abstain.

[39]A more detail analysis of the model can be found in Appendix A.1.

[40]This ambiguity is resolved if one can identify which candidate is considered the front-runner as voters go to the

Predictions:

1. When the perceived riskiness of candidate B decreases, their vote share increases and the vote share of candidate A decreases.

2. An increase in the support in the cost of voting has no impact on the ratio of support for candidates but decreases turnout.

To test the model's main predictions, we assume that increases in sunshine raise the risk acceptance of voters, meanwhile precipitation uniformly increases the cost to voting. In our model under these conditions an increase in sunshine improves the riskier candidate's vote share (candidate B) and decreases the safer candidate's vote share. Whereas and an increase in precipitation does not impact the vote shares of either candidate but reduces overall turnout.

5.3.2 Empirical support for mechanism

Our main set of results fit the model predictions if one assumes that, on average, Republican candidates are viewed as less risky than their Democratic counterparts. While we have provided some suggestive evidence that this could be the case, we believe there are even better settings to test this mechanism. Specifically, for each election in our sample we re-label candidates as: (i) incumbent vs. challenger, (ii) older vs. younger, and (iii) higher vs. lower prior office in public service.[41]

A quick discussion about each scenario are in order. For the first setting, we expect voter's to have experience with the incumbent candidate's policies and thus view them as less risky. Additionally, the incumbent by definition represents the *status quo* and therefore *status quo* bias may also contribute to voters viewing incumbents as the overall safer option. Second,we assume voters use age as a proxy for experience and thus consider older candidates safer than younger ones. Finally for last office held prior to candidacy, we construct a categorical variables equal to: 0 if the

polls. For example, when the majority of the population supports candidate A, and the perceived riskiness of candidate B decreases, turnout will increase. While this discussion is beyond the scope of the paper, we present a more nuanced empirical investigation of this in Appendix A.1.1.

[41]Not all elections can be included in all the settings listed. This is because sometimes there is no incumbent candidate and/or candidates have the same prior offices.

candidate was not in office before, 1 if it was a state office, 2 if it was a federal office, and 3 if was president (i.e. incumbent). We assume that voters see higher prior office as a signal that the candidate is more experienced and also possibly more likely to represent the *status quo*.[42] Returning to our model, we expect to see an increase in sunshine to lower the support of the safer candidate.

Since our main specification is a SUR model, we proceed to estimate differential effects as described in section 4 for these new risk measures. Figure 5.3.2 re-estimates the models in Figure 5.1 replacing political parties with incumbent and challenger. In this case, as in figure 5.1, precipitation increases abstention but does not have a statistically significant impact on vote shares. As we suggest, sunshine shifts votes from the incumbent to the challenger. We obtain similar patters when comparing younger to older candidates in a race (see Figure 5.3.2). Finally, when we use prior office in public service, we observe vote share impacts of both weather variables. The result with respect to sunshine is consistent with our model, while the impact of precipitation is not. We take these results as being suggestive that the risk aversion mechanism as being the culprit for our main results.

An alternative mechanism proposed by previous literature is that voters irrationally attribute increases in election-day mood to the incumbent candidate, rewarding them at the polls. However, as one can see in Figure 5.3.2 we find the exact opposite: increased mood lowers support for the incumbent. To test if this mechanism is actually biasing our results towards zero, we re-run our simple test for differential effects given by equation 15 and interact the sunshine variable with a dummy that indicates if the election has no incumbent present. In these elections, the -reward the incumbent for increased mood- mechanism should not be present and therefore our results should move further from zero. Table 1 shows that in elections without an incumbent our main results move significantly away from zero. We take this as suggestive evidence that both mechanisms suggested by the literature may be present in our sample, with the risk aversion mechanism being dominant.

[42] We exclude any races where the candidates come from identical offices.

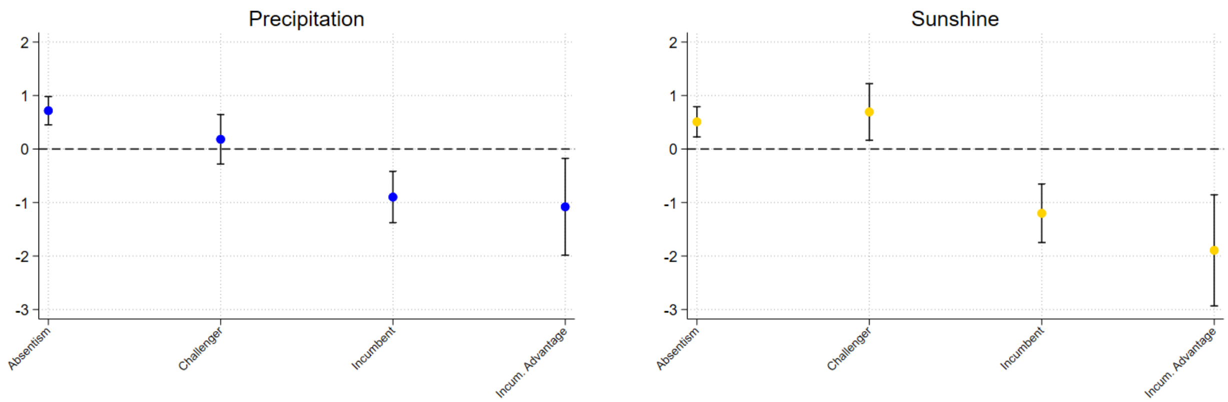
Table 1: **Main results with no incumbent**

VARIABLES	(1) ln(R/D)	(2) ln(R/D)
Average Sunshine (sunshine-hours)	-0.05**	-0.04**
	[-0.06 - -0.05]	[-0.05 - -0.03]
No Incum. #Average Sunshine		-0.02**
		[-0.03 - -0.01]
Average Precipitation (inches)	0.00	0.00
	[-0.01 - 0.01]	[-0.01 - 0.01]
Home state of Rep. Candidate	0.10**	0.10**
	[0.07 - 0.12]	[0.07 - 0.12]
Motor Voter	0.08**	0.08**
	[0.06 - 0.10]	[0.07 - 0.10]
Black Regist. Rate (State)	0.00	-0.00
	[-0.00 - 0.00]	[-0.00 - 0.00]
Observations	33,982	33,982
R^2	0.75	0.75
County FE	✓	✓
Election-Year FE	✓	✓

Robust ci in brackets
** p<0.01, * p<0.05

6 Discussion and Conclusion

This paper presents evidence that while precipitation plays a role in a voter's decision to vote (through increasing costs), sunshine plays a large role once they have ballot in hand. We use detailed weather and election data spanning nearly 70 years, to offer insight into how weather enters into a voter's election day decisions. To the best of our knowledge we are the first to combine such data. We show that the pro-Republican bump from precipitation found in Horiuchi and Kang (2018) and Gomez et al. (2007) virtually disappear after controlling for sunshine on election day. We find evidence that precipitation, when controlling for sunshine, only has a statistically significantly effect on abstention rates. On the other hand, sunshine, when controlling for precipitation, has



(a) (b)

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Figure 6: Effect on incumbent and challenger vote shares and abstention rate using estimates from SUR of: (a) increasing precipitation 1 inch controlling for sunshine; (b) increasing sunshine hours by 2.8.

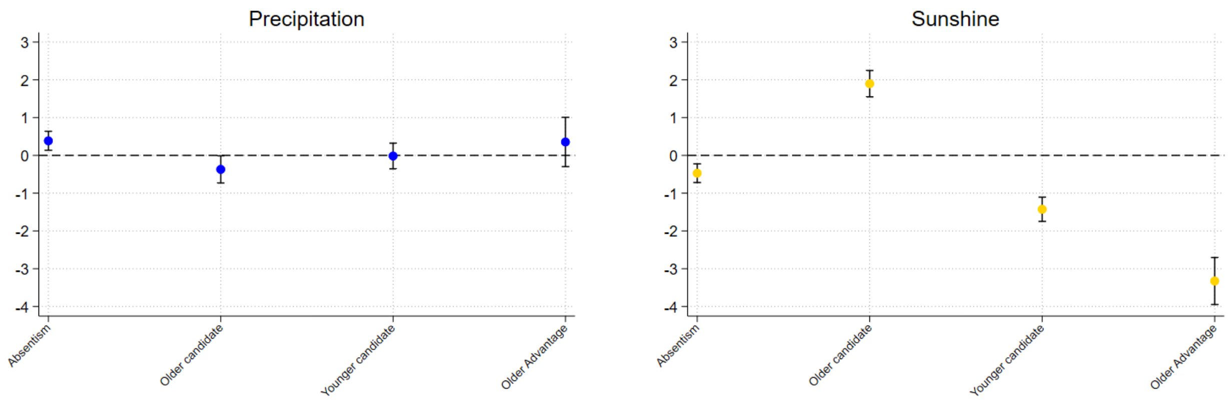
Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

almost no impact on abstention rates, but has an impact on vote shares.

To put these effects in context we create two counterfactual scenarios in which all counties experience: 1) a "bad" weather day[43] where they experience high precipitation and lower sunshine and 2) a "good" weather day[44] where they experience low precipitation and high sunshine. This is equivalent to saying what if every election had either bad or good weather. We then calculate the predicted vote shares for each party at the state level and aggregate up using the electoral college. Figure 9 summarizes the impact of changing the weather in such a dramatic way, having bad weather days in all counties would have gave the Republican an extra win in 1976, conversely having all good weather days would have denied George W. Bush the presidency in 2000 and 2004.

[43] We define bad weather by replacing the actual precipitation for each county on election day with the 90th percentile value of precipitation out of all potential election days for each county from 1976-2016. To avoid making assumptions about how this would impact sunshine we simply take the sunshine value for the same "rainy" day.

[44] We define good weather in the same as bad weather but select the 90th percentile sunshine day and the precipitation that occurred on that same day.



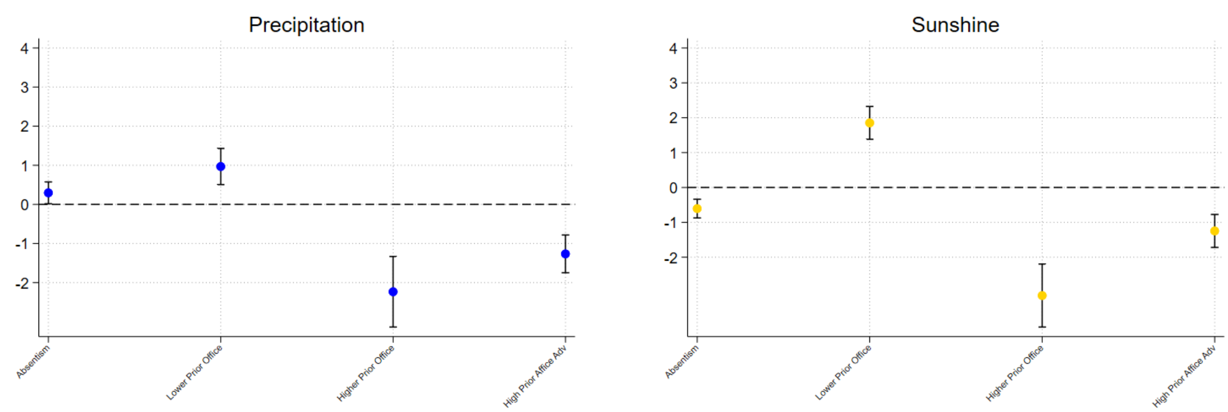
(a) (b)

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

Figure 7: Effect on oldest and youngest candidates vote shares and abstention rate using estimates from SUR of: (a) increasing precipitation 1 inch controlling for sunshine; (b) increasing sunshine hours by 2.8.

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.



(a) (b)

Figure 8: Effect on higher and lower previous public office candidates vote shares and abstention rate using estimates from SUR of: (a) increasing precipitation 1 inch controlling for sunshine; (b) increasing sunshine hours by 2.8.

Note: all results control for state level % of African American's registered to vote and the motor voter laws, as well as county and election fixed effects.

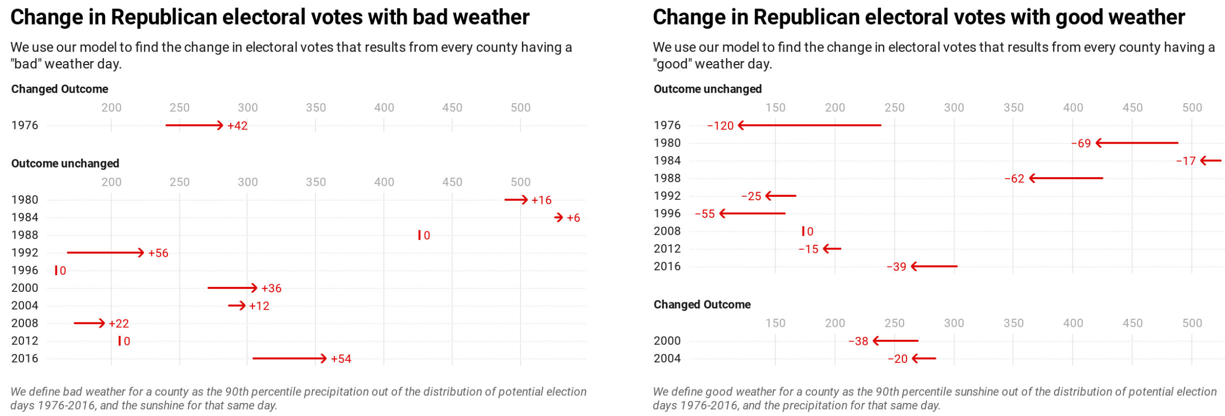


Figure 9: Impact of changing weather on the outcomes of all elections in our main sample.

There are a two caveats with these counterfactuals that deserve a mention. First, our results in top two panels of Figures 5.2.1 and 5.2.1 indicate that the real effect will be much less consequential because they are diminished when state-level elections get closer and when their local environment is competitive. We believe that it is intuitive that the impact of behavioral responses caused by weather could be diminished when voters believe themselves to be in a highly competitive environment. Therefore, the overall impact of weather on actual outcomes is likely smaller than our estimates show. Second, the counterfactual weather shock we are using is at the national level and persistent across all elections, whereas weather patterns are spatially clustered at a much finer level and are not correlated as strongly across time. A more realistic shock of poor weather would likely only affect a few states and therefore have a much smaller impact on the overall electoral outcome.

We document that an abnormally sunny day transfers support from republican candidates to democratic candidates. This result is robust to a battery of econometric tests. Perhaps most striking is that this result comes at the expense of a long standing result: precipitation drives voters from Democrats to Republicans. This is most likely because without controlling for sunshine, precipitation becomes an imperfect proxy for sunshine. Ultimately, the mechanism proposed by the existing literature to make sense of the impact of precipitation on vote shares is found to be the leading candidate for what is generating the effects produced by sunshine. This mechanism is derived from a salient fact from the psychology literature that exposure to sunshine affects individual's mood and thus impacts their willingness to take risks. Specifically, marginal voters who are exposed to a sunny election day absent precipitation are more inclined to take a chance on the riskier candidate. In our data we explicitly test this mechanism by labeling the riskier candidate using multiple dimensions: age, experience, and incumbency status. In all cases we find that sunshine increases support for the riskier candidate. These results offer suggestive evidence that our main result is driven by the fact that Republican candidates are seen as safer candidates, and thus are penalized on a sunny day. So instead of praying for rain, we find that Republicans should pray for clouds.

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A Appendix

A.1 Model

Although mood can manifest itself in many ways, this paper defines mood as an emotion that affects how voters perceive candidate risk. To formalize our hypothesis we utilize a model of turnout from Castanheira (2003) and add risk to one candidate's platform. In this model voters must decided if they find it beneficial to vote or abstain. If they vote they chose between two candidates A and B. The candidates have platforms that place them on either side of a uni-dimensional policy space. Without loss of generality we label candidate A as the risk-free candidate (the incumbent henceforth) and candidate B will be the risky candidate (the challenger henceforth). For simplicity we assume that the platforms of the candidates are distributed in the following way:

$$\begin{aligned} P_A = A \qquad & \text{s.t. } A < 0 \\ P_B \sim N(-A, \sigma^2) \end{aligned} \tag{6}$$

We assume that there is a fraction of the population, $\gamma_A \in (0, 1)$ that supports the incumbent, A, and a fraction, $\gamma_B = 1 - \gamma_A$ that supports the challenger, B. These fractions are given and do not depend on the perceived riskiness of the challenger. We denote, σ^2, as the perceived riskiness of the challenger. The utility derived by a voter is represented by the following function:

$$U(\theta_i, P, v_i) = -(\theta_i - P)^2 - c(v_i) \tag{7}$$

Where P is the platform that is realized, θ_i is voters preferred location on the policy spectrum and v_i represents the action taken by the voter. $c(v_i)$ represents the cost of going to the polls given her chosen action. If the voter abstains she incurs zero cost, if she votes her cost is drawn from a uniform distribution with some positive upper bound, $U(0, C)$.

We will assume that voter types are distributed according to the following distribution function

$$f(\theta) = \begin{cases} \frac{\gamma_A}{\alpha} & \forall\theta \in [-\alpha, 0] \\ \frac{\gamma_B}{\alpha} & \forall\theta \in [0, \alpha] \\ 0 & otherwise \end{cases}$$

As in most models of voter turnout it is assumed that voters will only go to vote is they believe their vote will have the potential to affect the result of the election. Therefore, we must only compare the expected utility of voting for the preferred candidate versus the expected utility of abstaining. Assuming the preferred candidate is A the expected utility of a pivotal voter is:

$$W_A - c_i = \mathbb{E}_P\big(U(\theta_i, A, v_i)|v_i = A\big) - \mathbb{E}_P\big(U(\theta_i, B, v_i)|v_i = \emptyset\big) = Pr(\text{pivotal for A})(4A\theta_i + \sigma^2) - c_i$$

Similarly the expected utility of being a pivotal voter for candidate B is:

$$W_B - c_i = \mathbb{E}_P\big(U(\theta_i, B, v_i)|v_i = B\big) - \mathbb{E}_P\big(U(\theta_i, A, v_i)|v_i = \emptyset\big) = Pr(\text{pivotal for B})(-4A\theta_i - \sigma^2) - c_i$$

A voter's choice is determined by her type, when $\theta < 0$ it is easy to see that the voter would prefer A over B, $W_A > W_B$. Without risk ($\sigma^2 = 0$) any $\theta > 0$ type would prefer candidate B, however because of the concavity of the utility function some voters with positive θ, above a cutoff $\overline{\theta}$, now prefer the safer incumbent, A. To find the cutoff $\overline{\theta}$ we find the θ where the expression in the parenthesis that is multiplying the pivotal probability is equal to zero:

$$\overline{\theta} = \frac{-\sigma^2}{4A} \tag{8}$$

Notice that this cutoff goes up as the coefficient of variation of candidate B's platform, $\frac{\sigma^2}{-A}$ increases. The intuition is that the riskier the challenger the more voters "defect" to the incumbent.[45] Figure 5 presents the type distribution as well as the platforms for each candidate for given

[45] A defector is defined as a voter that would have preferred B if there was zero risk, but given the riskiness of B now prefer A.

parameters $\sigma^2, \gamma^B < \gamma_A$, and α.

Another important quantity is the fraction of support for each candidate after the riskiness of B is realized. Let $\tilde{\gamma}_A$ be the fraction of the population that supports the incumbent given the perceived riskiness of the challenger, then:

$$\begin{aligned}
\tilde{\gamma}_A &= \int_{-\alpha}^{0} f(\theta_i)d\theta_i + \int_{0}^{\overline{\theta}} f(\theta_i)d\theta_i \\
&= \int_{-\alpha}^{0} \frac{\gamma_A}{\alpha}d\theta_i + \int_{0}^{\overline{\theta}} \frac{\gamma_B}{\alpha}d\theta_i \\
&= \gamma_A + \frac{\gamma_B}{\alpha}\overline{\theta}
\end{aligned}$$

Similarly, we can find the fraction of the electorate that supports the challenger:

$$\tilde{\gamma}_B = \gamma_B - \frac{\gamma_B}{\alpha}\overline{\theta} \tag{9}$$

Proposition 1 *If candidate B offers platform B with certainty, then* $\tilde{\gamma}_A = \gamma_A$ *and* $\tilde{\gamma}_B = \gamma_B$*.*

Proof. Using the stated formulas for $\tilde{\gamma}_A$ and $\overline{\theta}$ and the fact that $\sigma^2 = 0$ when there is no uncertainty:

$$\begin{aligned}
\tilde{\gamma}_A &= \gamma_A + \frac{\gamma_B}{\alpha}\overline{\theta} \\
&= \gamma_A + \frac{\gamma_B}{\alpha} \cdot \frac{-\sigma^2}{4A} \\
&= \gamma_A
\end{aligned}$$

Same for $\tilde{\gamma}_B$. ■

The total size of the population, $\tilde{n}$ is a Poisson random variable with λ representing the expected population size, $\tilde{n} \sim \text{Pois}(\lambda)$.

We then define the probability a voter that prefers each candidate shows up to the polls on election day as the probability her cost is less than the expected value of voting for her preferred candidate:

$$Pr\left[c_i \leq W_A|\theta_i \leq \overline{\theta}\right] = \frac{Pr(\text{pivotal for A})(4A\theta_i + \sigma^2)}{C} \tag{10}$$

$$Pr\left[c_i \leq W_B|\theta_i \geq \overline{\theta}\right] = \frac{Pr(\text{pivotal for B})(-4A\theta_i - \sigma^2)}{C} \tag{11}$$

Adopting the same assumption about how ties are broken as Castanheira (2003) we can use Lemma 2 from Castanheira (2003) to define the pivot probabilities given the share of electorate that votes for each candidate:

$$\begin{aligned} Pr(\text{pivotal for B } |s_A, s_B) &= \frac{e^{-(\sqrt{s_A}-\sqrt{s_B})^2}\lambda}{2\sqrt{\pi\lambda}\sqrt[4]{s_A s_B}} \\ Pr(\text{pivotal for A } |s_A, s_B) &= \sqrt{\frac{s_B}{s_A}} Pr(\text{pivotal for B}|s_A, s_B) \end{aligned} \tag{12}$$

Now we can calculate the equilibrium vote shares of each candidate and turnout. The vote share is calculated as the fraction of voters that have draws of (θ_i, c_i) that motivate them to turn up and vote for their preferred candidate.

$$\begin{aligned} s_A &= \int_{-\alpha}^{0} f(\theta_i) Pr(c_i \leq W_A) d\theta_i + \int_{0}^{\overline{\theta}} f(\theta_i) Pr(c_i \leq W_A) d\theta_i \\ &= \int_{-\alpha}^{0} \frac{\gamma_A}{\alpha} \frac{Pr(\text{pivotal for A})(4A\theta_i + \sigma^2)}{C} d\theta_i + \int_{0}^{\overline{\theta}} \frac{\gamma_B}{\alpha} \frac{Pr(\text{pivotal for A})(4A\theta_i + \sigma^2)}{C} d\theta_i \end{aligned}$$

Notice that as the coefficient of variation of the challenger's platform increases the second integral will grow, showing clearly that the riskier the challenger the larger the vote share for the incumbent. Now calculating the vote share for the challenger we can see that the converse is true, as the coefficient of variation grows $\overline{\theta}$ increases which decreases the vote share of the challenger.

$$
\begin{aligned}
s_B &= \int_{\overline{\theta}}^{\alpha} f(\theta_i) Pr(c_i \leq W_B) d\theta_i \\
&= \int_{\overline{\theta}}^{\alpha} \frac{\gamma_B}{\alpha} \frac{Pr(\text{pivotal for B})(-4A\theta_i - \sigma^2)}{C} d\theta_i
\end{aligned}
$$

As these integrals are fairly long and complex we borrow the solution strategy of Castanheira (2003) and first compute the ratio of them and then use this ratio to implicitly solve for the equilibrium turnout rate. For compactness of future formulas we call this ratio, K:

$$
K = \frac{s_A}{s_B} = \left(\frac{\frac{\gamma_A \alpha}{\gamma_B}(\sigma^2 - 2A\alpha) + \overline{\theta}(2A\overline{\theta} + \sigma^2)}{2A(\overline{\theta}^2 - \alpha^2) + \sigma^2(\overline{\theta} - \alpha)} \right)^{\frac{2}{3}} \tag{13}
$$

Using the fact that the fraction of the electorate that votes should equal the sum of the fraction that shows up for each candidate

$$
\begin{aligned}
t &= s_A + s_B \\
t &= \left(\frac{s_A}{s_B} + 1 \right) s_B \\
t(K+1)^{-1} &= s_B
\end{aligned}
$$

Substituting the expression for s_B gives us an equation that we can implicitly solve for the equilibrium turnout rate, t:

$$
t(K+1)^{-1} = \frac{\gamma_B}{\alpha C} \frac{e^{-((K^{-1}+1)^{-0.5} - (K+1)^{-0.5})^2 t\lambda}}{2\sqrt{\pi\lambda}(K^{-1}+1)^{-0.25}(K+1)^{-0.25} t^{0.5}} \left[2A(\overline{\theta}^2 - \alpha^2) + \sigma^2(\overline{\theta} - \alpha) \right] \tag{14}
$$

To check if our results against Castanheira (2003) we assume the same parameter values and first show identical results when we set $\sigma^2 = 0$. Setting $A = -10$, $\alpha = C = 1$, and $\lambda = 1500$ we are able to replicate the top curve in Figure 1 in Castanheira (2003). We then plot the turnout rate and fraction of the total population voting for each candidate as a function of the variation in the challengers platform, σ^2, in figures 10 and 11 respectively.

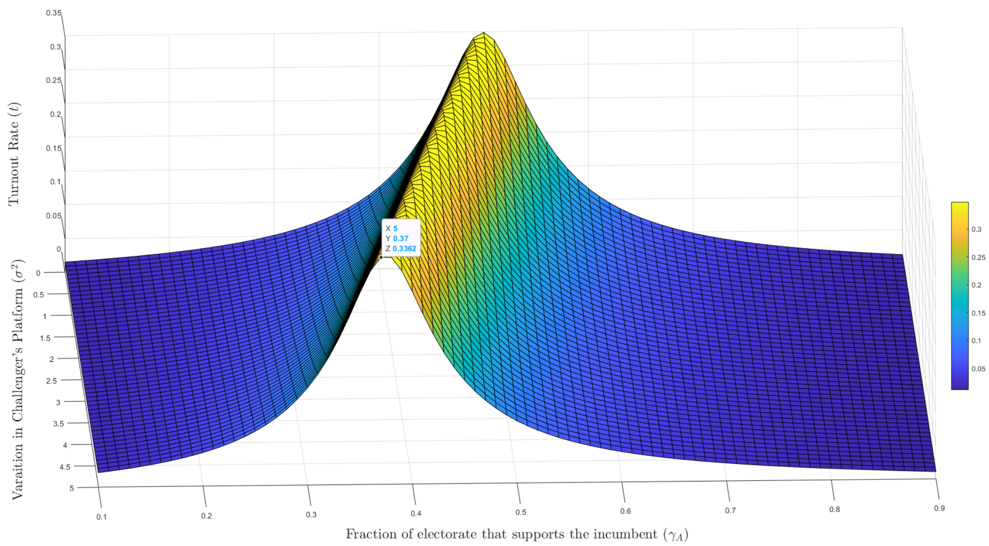


Figure 10: Turnout rate as a function of incumbent support and riskiness of challenger.

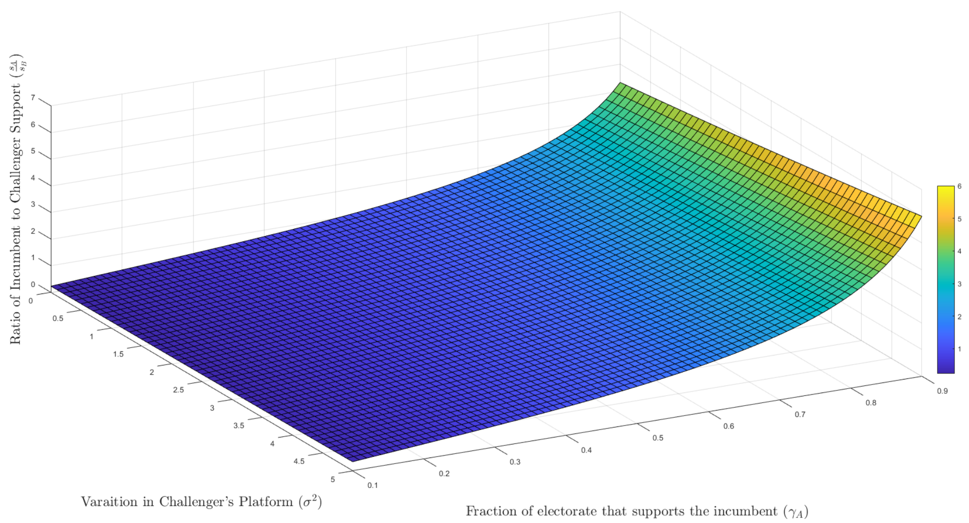


Figure 11: Ratio of share of electorate that supports incumbent vs share that supports challenger as a function of incumbent support and riskiness of challenger.

Proposition 2 *Increasing costs affect on turnout and candidate support*

An increase in the maximum cost, C, does not affect the ratio of support for the safer candidate versus the riskier candidate and reduces turnout.

Proof. Using (13) we show that the ratio of support for the safe versus risky candidate does not respond to a change in the cost distribution.

$$
\begin{aligned}
\frac{\partial K}{\partial C} &= \frac{\partial(\frac{s_A}{s_B})}{\partial C} \\
&= \frac{\partial(\left(\frac{\frac{\gamma_A \alpha}{\gamma_B}(\sigma^2 - 2A\alpha) + \bar{\theta}(2A\bar{\theta} + \sigma^2)}{2A(\bar{\theta}^2 - \alpha^2) + \sigma^2(\bar{\theta} - \alpha)}\right)^{\frac{2}{3}})}{\partial C} \\
&= 0
\end{aligned}
$$

To compute changes in equilibrium turnout with respect changes in the cost distribution, we use computational tools, since we do not have a closed form for equilibrium turnout. Figure 12 shows the change in turnout with respect to increases in C.

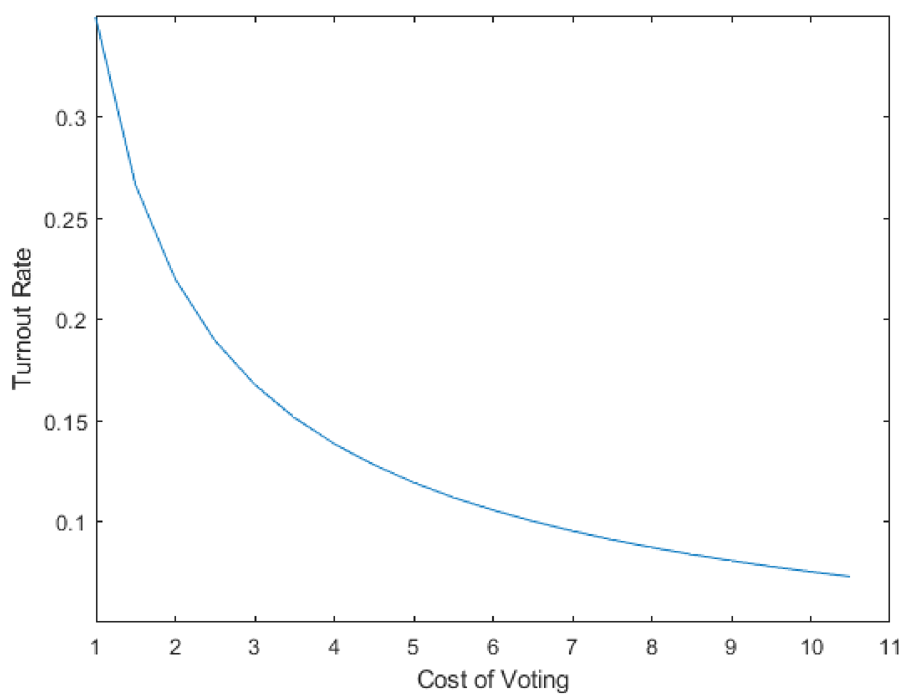


Figure 12: The effect of increasing cost on the overall turnout rate.

■

We now summarize the main model's predictions. We use them to build the intuition behind our empirical analysis.

Predictions:

1. When the majority (minority) of the population supports the incumbent, $\gamma_A > 0.5$, ($\gamma_A < 0.5$) and the perceived riskiness of the challenger decreases, turnout will increase (decrease).

2. When the perceived riskiness of the challenger decrease the ratio of share of voters for the incumbent versus the challenger also decreases.

3. An increase in the maximum draw from the cost distribution, C, has no impact on the ratio of support for candidates and decreases turnout.

Figure 10 illustrates prediction 1, for example imagine the incumbent enjoys support from the majority of the electorate ($\gamma_A > 0.5$) as we decrease risk, or move towards the back graph, we must climb towards the peak of the turnout. The converse is true when we pick a $\gamma_A < 0.5$, a movement "back" takes us away from peak turnout. This effect is driven by the fact that a decrease in risk is simply a negative shock to the incumbent's popularity. A feature of these models is that turnout is maximized in close elections, therefore when the incumbent is the front runner a negative shock (decrease in challenger risk) makes the election closer, which increases turnout. Figure 11 illustrates prediction 2 in that any decrease in risk lowers the support of the incumbent relative to the challenger.

A.1.1 Test of model predictions on turnout

While not pertinent to the set of results in the main text, we also present some more nuanced tests produced that give more credence our model in this subsection. Our model predicts that when the front-runner[46] is the riskier (safer) candidate one should observe an increase in sunshine decreasing (increasing) turnout as the probability of being pivotal decreases (increases). Meanwhile precipitation should have an unambiguously negative impact on turnout, regardless of which candidate has larger support. The empirical obstacle to testing these predictions is determining a front-runner. In the model the main channel by which this feeds into turnout is via the expected "pivotalness"

[46] A front-runner is the candidate that is perceived to have the larger support of the population before voting occurs.

of voters. To determine this we utilize ex-ante polling data and ex-post returns. And because in the US voters consider both how pivotal they are in their state election *and* how pivotal their state is we also use each measure at the state and national level. Figure 13 shows the marginal impact of sunshine on turnout split out by which party's candidate is considered the front-runner. The results largely agree with the model predictions, most the red lines slope upward (sunshine increases turnout when republicans are in the lead) while most of the blue lines slope downward (sunshine decreases turnout when democrats are in the lead). Figure 14 is the same figure but for precipitation. Again, the empirical results support the model predictions as all lines weakly slope downward (precipitation decreases turnout no matter who is in the lead).

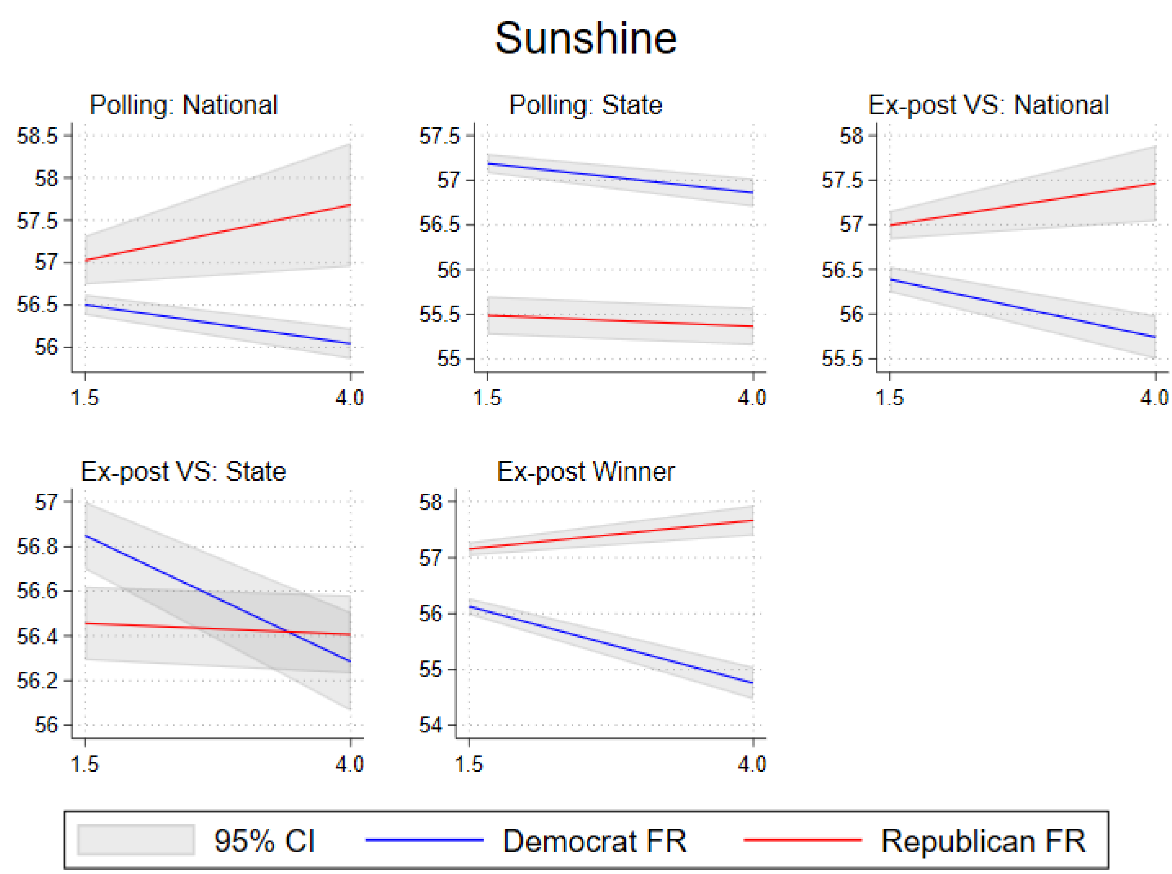


Figure 13: Impact of sunshine (x-axis in sunshine-hours across p10-p90 values of sunshine) on turnout (y-axis in turnout as %) by party who is considered the front runner using multiple different measures of which candidate is the front runner.

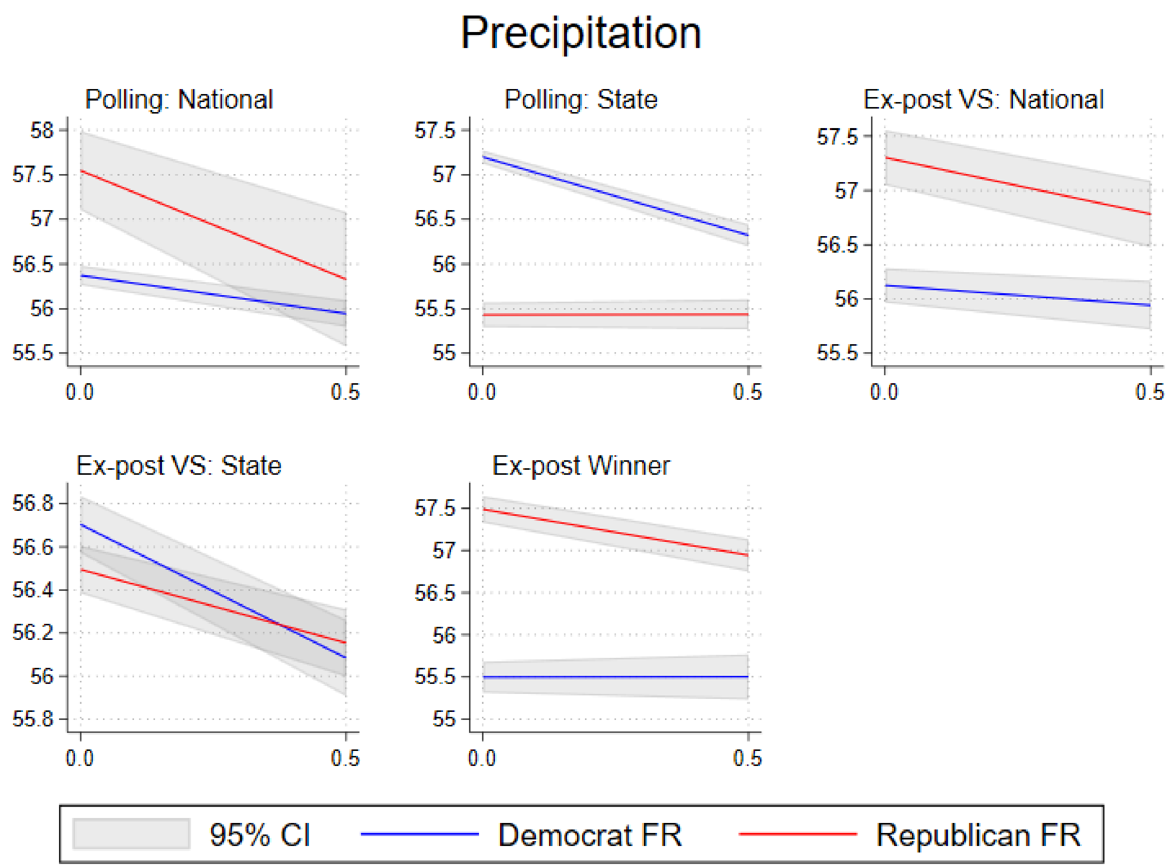


Figure 14: Impact of precipitation (x-axis in inches across p10-p90 values of precipitation) on turnout (y-axis in turnout as %) by party who is considered the front runner using multiple different measures of which candidate is the front runner.

A.2 Robustness Checks

The current literature that documents how irrational events affect candidate support is plagued with the potential that their main results are driven by spurious correlation. As pointed out in Fowler and Pablo Montagnes (2015); Fowler and Hall (2018), all papers in this literature need to present a battery of robustness check and placebos to convince the audience of their results. For example, Healy et al. (2010) analyzes whether local college football results affect incumbent vote-share, finding that a win in the 10 days before election day increases the incumbent vote by 1.61 pp. However, Fowler and Pablo Montagnes (2015) shows that these results do not pass logical placebo tests. While we can not replicate the the same placebo tests we addresses these concerns by showing that in counties that have a higher proportion of swing voters our results are stronger, and by performing randomization inference tests. We also rigorously test our mechanism by re-labeling candidates and finding support that the same pattern occurs for incumbents, older candidates, and more experienced candidates.

A.2.1 Randomization Inference

As documented by Cooperman (2017), daily weather variables offer natural potential randomization. Specifically, one can be completely agnostic about spatial clustering patterns by using all potential election days as a sampling distribution (Barrios et al. (2012)). In practice, we draw a random sample of potential election day weather[47] from the 40 years of weather data in our main sample. We estimate our effects using three different sampling procedures: (i) independent draws of county-election day weather ; (ii) independent draws of state-election day weather, and (iii) independent draws of national election day weather. Sampling procedures (i)-(iii) represent progressively stronger tests, in that they make fewer assumptions about how weather is spatially clustered. For example, using (i) we are implicitly assuming that weather experienced by each county is completely uncorrelated with neighboring counties. Conversely, (iii) uses actual national weather patterns and makes no assumptions about correlations across time.

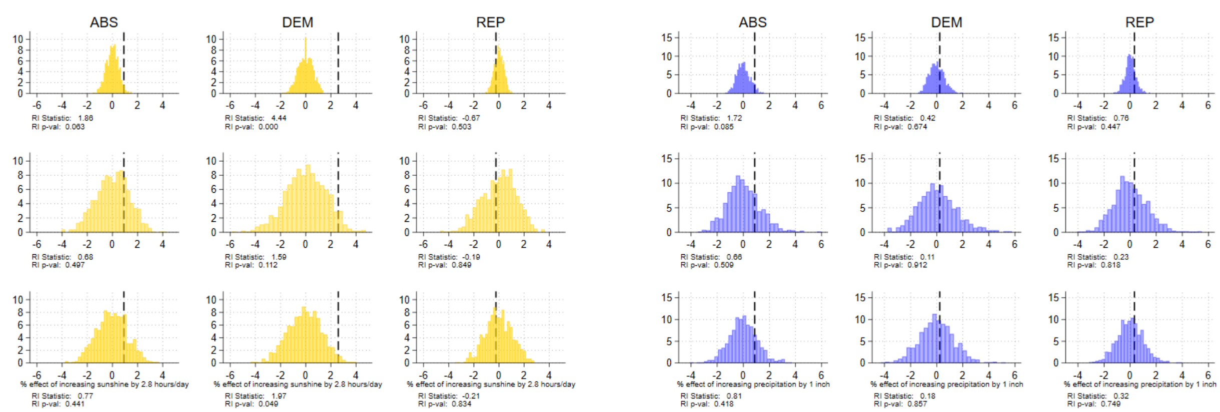
Figure 15 shows the distributions of average treatment effects (ATE) for sunshine and precipitation using republican vs. democratic candidates. Each figure presents the distribution of weather effects for absenteeism (first column), riskier candidate's vote share (second column), and the safer candidate's vote share (third column). Our main point estimates are represented as black dashed lines. The statistics and p-values presented underneath each distribution were calculated by removing the mean of each distribution from our estimates and dividing by the standard deviation of each distribution. Most of our results do not survive the strictest test where we use sampling technique (iii).[48] However, all of our results pass the weakest test, where we use sampling technique (i). This

[47] To control for correlation between our two weather variables we draw both sunshine and precipitation data from the same day.

[48] Interestingly, the only result that passes every test is the strong positive impact of increasing sunshine on democratic candidates vote share.

matches the findings in Cooperman (2017).

To compute the distribution of ATEs we replace the election day weather (a precipitation-sunshine tuple) with a random draw from a distribution of potential election days and estimate equations 2 and 1. Using this estimated model we then compute four counterfactuals for each observation high/low sunshine and high/low precipitation, and take the sample average. As before, we use 1 standard deviation below (above) the mean to be the low (high) treatment. This leaves us with four average predicted log ratios that we then convert into into predicted average vote shares and the share of non-voters. The last step is to take the difference between the high and low treatments. These two differences represent the ATE for that iteration. We repeat this procedure for 1,000 different randomizations for both main estimations: incumbent vs. challenger, and republican vs. democrat candidates.



(a) (b)

Figure 15: Distribution of ATE of (a) sunshine and (b) precipitation using republican/democratic specification. Each row represents a different sampling technique. Specifically, the re-sampling is done at the county, state, and national level respectively.

A.2.2 Leave one out

To analyze if there is a particular election or state driving our main results we analyze the robustness of our results using the leave one out procedure. Figure 16 represents our main results after removing one election year at a time from our sample. While Figure 17 represents our main results after removing one state at a time from our sample.[49] Similar to other robustness checks, the results using democrat/republican survive, while the results using challenger/incumbent loose significance. This is most likely a result of imprecision due to small sample size.

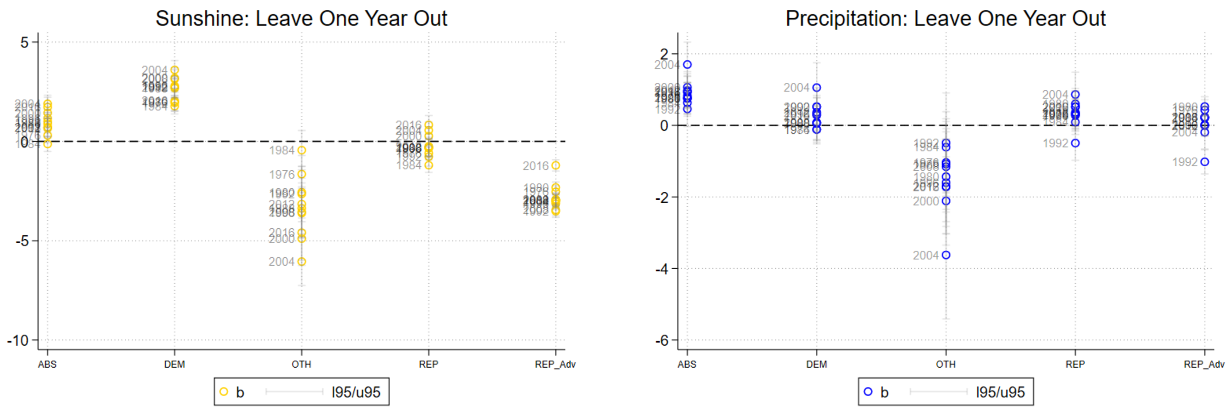


Figure 16: Coefficients of interest after leaving one election year out and re-estimating.

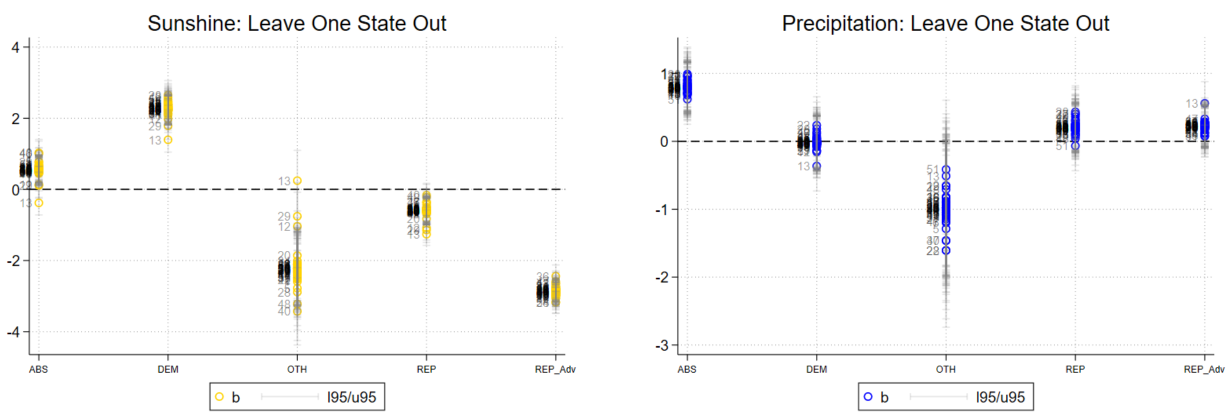


Figure 17: Coefficients of interest after leaving one state out and re-estimating.

A.2.3 Sample Selection: Solid South

For our main sample we look at all elections post 1976 The reasons for this is twofold. First, the weather data we obtained pre-1979 is heavily modeled and not as accurate as the satellite observa-

[49] The state's fips code is next to the estimate obtained after removing it from the sample.

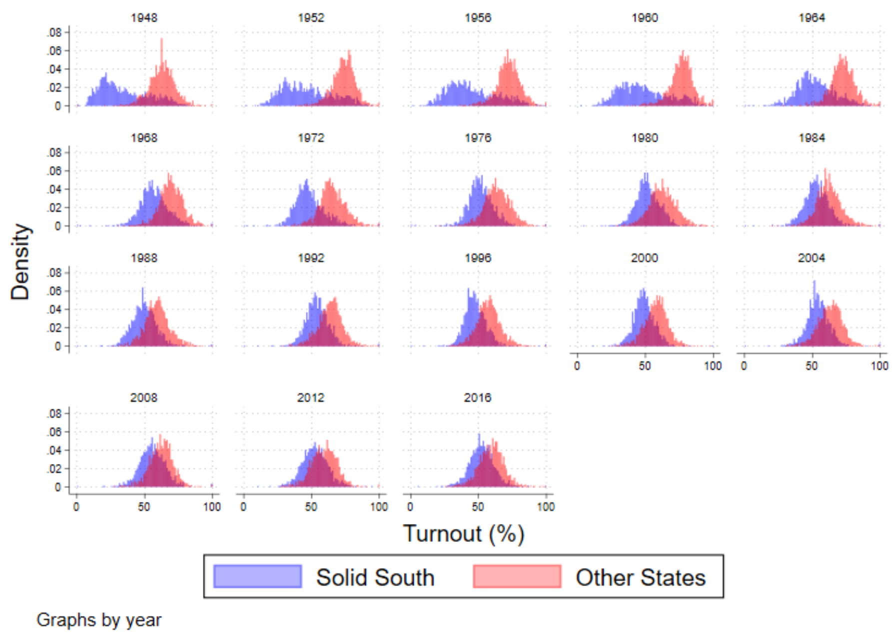


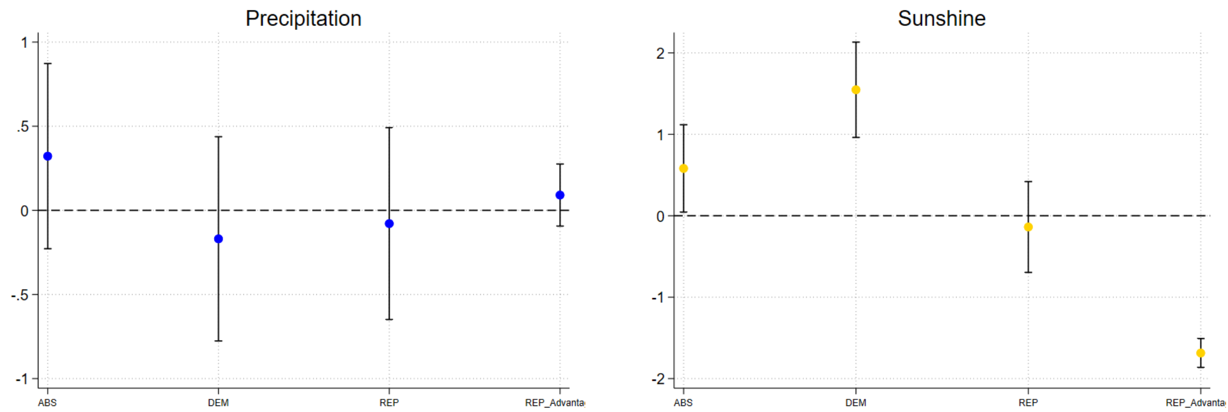
Figure 18: Histogram by year of turnout rates for the "Solid South" states (blue) and all other states (red).

tions we have post 1979. Second, and more importantly, before the mid-1970s a bloc of states in the southern region of United States were characterized by brutal voter suppression[50] and single party rule. These features of the "Solid South" are incongruent with our model of two party competition and homogeneous cost structure. Whenever a researcher chooses their sample it raises concerns that they have done so in a strategic way to engineer results. To assuage these concerns we present Figure 19 contains our main estimates using the entire sample from 1948-2016 removing counties in the solid south prior to 1976.

A.3 Collinearity of Weather Variables

One potential reason why sunshine has not received much attention is that most of the available historical data measures sunshine in discrete bins (e.g. clear, partly cloudy, etc.). When using these discrete measures researchers are unable to include precipitation due to near perfect collinearity.

[50] Evidence of this voter suppression can be seen in Figure 18 which shows turnout rates for the "Solid South" states versus all other states.



(a) (b)

Figure 19: Effect on republican and democratic candidate vote shares and abstention rate using estimates from SUR of: (a) increasing precipitation 1 inch without controlling for sunshine; (b) increasing precipitation 1 inch controlling for sunshine; (c) increasing sunshine hours by 2.8.
Note: all results control for state level % of African American's registered to vote, the motor voter laws, as well as the presence of literacy tests or poll taxes in the state, as well as county and election fixed effects.

The measures of both sunshine and precipitation used in this paper are continuous, however one may still worry that they are too correlated to both be included in our model. To assuage these concerns we present multiple checks in this section. To isolate the variation used in all of our models we first remove the election year and county means from both weather variables. The Pearson's correlation coefficient between sunshine and precipitation is -0.27.[51] We also find that the R^2 when regressing sunshine on precipitation (or vice versa) is only 0.07, implying that there is substantial variation in each weather variable not explained by the other. The last check we present is the variance inflation factors (VIF) for both weather variables from the estimation of the following equation:

$$ln\left(\frac{R_{cst}}{D_{cst}}\right) = \beta_p precip_{cst} + \beta_s sunshine_{cst} + \mathbf{X}_{st}\boldsymbol{\theta} + \nu_c + \tau_t + \epsilon_{cst}, \tag{15}$$

where all the coefficients represent the differential impact on the democratic versus republican candidates vote share of the covariate they precede. The rule of thumb is that a VIF of over 10 indicates the potential of collinearity, we find that precipitation and sunshine produce VIFs of 1.08 and 1.09, respectively. We take these three diagnostic results as ample evidence that we should not

[51] The coefficient is -0.23 without removing the election and county fixed effects.

be concerned that collinearity is preventing us from interpreting our estimated coefficients.