Article

Why Should the Republicans Pray for Rain? Electoral Consequences of Rainfall Revisited

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Abstract

Existing studies—most importantly, Gomez, Hansford, and Krause—provide empirical support for an idea often embraced by popular media: The vote share of the Republican Party (as the percentage of total votes) increases when it rains, because the magnitude of *decrease* in turnout is larger among Democratic vis-à-vis Republican supporters. Considering the compositional nature of aggregated data, we show that the alleged Republican advantage derives in part from an *increase* in the number of votes for the Republican Party. Based on the extensive literature of psychology and related fields, we provide a possible interpretation of this counter-intuitive empirical finding. Methodologically, our evidence suggests that researchers must be alert when using rainfall as an instrument to estimate the causal effects of voter turnout on electoral outcome.

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Introduction

The idea that weather conditions affect election outcomes is often embraced by popular media. For example, Ludlum (1984) shows that newspapers in New York provided detailed weather reports for polling places even as early as the 19th century. Nationally distributed newspapers, such as the *New York Times* and the *Washington Post*, commonly report weather forecasts for election days and predict how weather conditions may affect voter turnout and electoral outcomes.[1]

The notion that bad weather has electoral ramifications is not confined to nonacademic sources. Earlier studies on political participation and collective action often listed weather as an important determinant (e.g., Barry, 1970; Campbell, 1960). Other studies have sought empirical evidence to link bad weather to reduced voter turnout (e.g., Gatrell & Bierly, 2002; Knack, 1994; Merrifield, 1993; Scala, 2003; Shachar & Nalebuff, 1999). However, poor estimates of meteorological variables, as well as a lack of adequate variation, long hindered researchers from examining the relationship in an empirically rigorous way.[2] Recent developments in Geographical Information System (GIS) technology have enabled researchers to overcome these limitations and to produce intriguing findings using fine-grained geographical units of analysis (e.g., Fraga & Hersh, 2010; Gomez, Hansford, & Krause, 2007; Persson, Sundell, & Öhrvall, 2014).

These more recent studies—most importantly, Gomez et al.'s (2007) article—confirm a common belief that rainfall decreases voter turnout and increases the two-party vote share for the Republican Party. Based on three major theoretical perspectives on electoral participation (i.e., socioeconomic status, rational choice, and mobilization models), Gomez et al. (2007) write, "No matter which of the theoretical models one favors . . . , the common thread that runs through each is that the costs of participation are a major obstacle to citizen involvement" (p. 651). With this emphasis on the costs associated with voting behavior, they present the following arguments. First, bad weather may limit one's ability to travel when roads are soaked by rain or covered by snow. It also should be less pleasant to wait in line at the polls on a rainy day. Accordingly, when it rains, it is expected that voter turnout decreases. Second, when the negative effect of rainfall on turnout is heterogeneous among voters, election-day weather conditions could affect electoral outcomes, as well.[3] As a consequence, the decrease in turnout due to bad weather hurts the Democratic Party to a greater extent than the Republican Party.

In this article, we critically reexamine this conventional wisdom about the electoral consequences of rainfall; specifically, we scrutinize the validity of Gomez et al.'s (2007) study. We use the data and variables, which are exactly the

same as those used in Gomez et al. (2007). We run, however, seemingly unrelated regressions (SURs) by shedding light on an important but often ignored fact that the sum of Republican candidate votes, Democratic candidate votes, and the number of abstainers must equal the total number of eligible voters.

When this compositional nature of electoral data is taken into account, our analysis shows that Gomez, Hansford, and Krause's interpretation—the two-party vote share of the Republican Party increases because the magnitude of *decrease* in turnout is larger among Democratic supporters than among Republican supporters—is insufficient. We demonstrate that the alleged Republican advantage in bad weather derives in part from an *increase* in the number of votes for the Republican Party. This implies that at least a certain fraction of voters who vote for the Republican Party on rainy election days are those who would vote for the Democratic Party without rainfall. According to our estimate, it is at least about 1% of voters.

After showing these empirical results, we provide a possible interpretation underlying this seemingly counter-intuitive finding. Existing studies in psychology and related fields suggest that it may be due to weather conditions' purported impacts on people's attitudes toward risk. By presenting new evidence on the conventional wisdom, we intend to improve our burgeoning understanding of weather's effects on electoral outcomes. Furthermore, the results of our analysis question the use of rainfall as an instrument for studying the casual effects of voter turnout on electoral outcomes. Following Hansford and Gomez (2010), several recent studies use rainfall as an instrument, with an assumption that rainfall affects individuals' decisions on *whether* to vote (specifically, it discourages people from going to the polls) but does not affect decisions on *how* to vote (Arnold & Freier, 2015; Artés, 2014; Lind, 2017; Sforza, 2014). Our results suggest the violation of this important assumption.

Decomposition

Electoral data are compositional (Aitchison, 1986; Aitchison & Greenacre, 2002), namely, the following equation must hold in all geographical units of data aggregation[4]:

$$r + d + a = 100, \tag{1}$$

where r is the number of votes for the Republican Party candidate as the percentage of the voting age population (VAP),[5] d is the number of votes for the Democratic Party candidate as the percentage of VAP, and a is the number of abstainers as the percentage of VAP. Voter turnout rate is $100 - a = r + d$.

Although the compositional nature of electoral data is often ignored, it is an important constraint we should consider when studying aggregated electoral outcomes (Katz & King, 1999).

As we introduced earlier, the conventional wisdom is that the Republican Party's vote share vis-à-vis the Democratic Party's vote share tends to increase when it rains. To define this formally, we first define our outcome variable:

$$Y = r - d, \tag{2}$$

which is simply the difference between the two parties' vote shares. Let us also define our treatment variable of interest (X) as a binary variable: $X = 1$ when a subject (i.e., a geographical unit) is treated (i.e., when it rains) and $X = 0$ otherwise. The Republican advantage in bad weather, or the causal effect of rainfall on Y , is defined as the difference between the two potential outcomes:

$$\text{Republican Advantage: } \Delta Y = Y_1 - Y_0 \\ = (r_1 - d_1) - (r_0 - d_0), \tag{3}$$

where each subscript indicates the treatment status.

To highlight how much the number of votes for the Republican Party (r_i) and the number of votes for the Democratic Party (d_i) could change when it rains,[6] we use the following notations:

$$r_1 = r_0 - \Delta a_r + m, \tag{4}$$

$$d_1 = d_0 - \Delta a_d - m, \tag{5}$$

$$a_1 = a_0 + \Delta a_r + \Delta a_d, \tag{6}$$

where the baseline terms (when it does not rain) are r_0 , d_0 , and a_0 . Δa_r refers to the number of Republican Party supporters who abstain when it rains but would vote for the Republican Party otherwise. Δa_d is the number of Democratic Party supporters who abstain when it rains but would vote for the Democratic Party otherwise. Finally, m denotes the number of voters who vote for the Republican Party when it rains, but would vote for the Democratic Party otherwise.

By plugging r_1 and d_1 into Equation 3, the Republican advantage is now decomposed into two channels. We call the first one the "differential turnout" channel, and the second one the "vote shift" channel:

$$\Delta Y = \overbrace{\Delta a_d - \Delta a_r}^{\text{Differential Turnout}} + \underbrace{2m}_{\text{Vote Shift}} . \tag{7}$$

Let us assume that the differential turnout channel is, as widely believed, an important component of the Republican advantage, namely, $0 < \Delta a_r < \Delta a_d$. This implies that weather-induced abstainers are more likely to be Democratic Party supporters than Republican Party supporters (Fowler, 2015; Gomez et al., 2007). Under this assumption, the upper and lower bounds of the vote shift channel ($2m$) can be defined as follows:

$$\begin{cases} \text{When } \Delta a_d \sim \Delta a_r, & \overline{2m} \sim \Delta Y \\ \text{When } \Delta a_r = 0 \text{ and } \Delta a_d > 0, & \underline{2m} = \Delta Y - \Delta a \end{cases}, \tag{8}$$

where $\Delta a = \Delta a_d + \Delta a_r$, which is the overall increase in abstainers due to rainfall.

How do we interpret these bounds? Suppose that the almost same numbers of Democratic and Republican Party supporters abstain due to rainfall (i.e., $\Delta a_d \sim \Delta a_r$). Then, the Republican advantage should be ascribed almost entirely to the vote shift channel. This is, however, an extreme assumption. By contrast, when none of the Republican Party supporters would abstain due to rainfall (i.e., $\Delta a_r = 0$), which is obviously another extreme assumption, the contribution of the vote channel to the Republican advantage reaches to its lower bound. The reality should be somewhere between these two extreme cases.

Compositional Data Analysis

The previous section *logically* showed that there are two channels generating the Republican advantage. In this section, we *empirically* investigate these two channels. Our empirical analysis builds on the data used by Gomez et al. (2007). Their data include county-level returns in U.S. presidential elections from 1948 to 2000, as well as measures of county-level precipitation on the day of the elections.[7] In this section, we first introduce their data and variables, as well as our approach to reestimate their model by taking into account the compositional data structure. We then show the results of estimation and robustness test.

Data and Method

The existing studies on the effects of weather conditions on electoral outcomes do not consider the compositional nature of electoral data. Rather, they typically run separate regression models for two-party (or three-party) vote

shares as the percentages of total votes and for voter turnout (e.g., Gomez et al., 2007). As Katz and King (1999) argue, however, this approach is not appropriate when analyzing compositional data for two reasons. First, it assumes that each dependent variable is theoretically unbounded. Without imposing any constraint, there is no guarantee that the sum of predicted values for the abstention rate (i.e., 100% − Turnout) and all candidates vote shares is close to 100%.[8] Second, it treats each compositional variable as if it were independent from the others. As all dependent variables (e.g., voter turnout and vote shares) are generated from the same electoral process, it is more reasonable to assume that they are related, specifically, that their error terms are not independent of one another.

To reflect the compositional nature of electoral returns, we need to consider three (observed) outcomes at the level of each county i in each state j in each election year t. They are D_{ijt}, Democratic Party candidate's vote share; R_{ijt}, Republican Party candidate's vote share; and A_{ijt}, abstention rate. The denominator for each is the total VAP at the county level. As emphasized earlier, by definition, the sum of these proportions should be 100 for each unit of observation, namely, $D_{ijt} + R_{ijt} + A_{ijt} = 100$, $\forall_{ijt}$.[9]

The main independent variable (*Election Day Rain—Normal Rain*) used in Gomez et al. (2007) is a normalized measure of rainfall representing the number of inches of rainfall in deviation from the "normal" condition in that county on a particular day of election. The likelihood of rainfall on a specific day is different across geographical space, obviously. For example, on any specific day, rainfall in Oregon is more likely than in Nevada. Gomez et al. (2007) thus take the difference from the average rainfall over many decades. With this specification, Gomez et al. (2007) assume that the magnitude of the deviation from the average is "as-if" randomly assigned.

As long as this assumption is plausible, it is unnecessary to add control variables to obtain unbiased estimates. Following Gomez et al. (2007), however, we control for a number of socioeconomic factors and institutional factors that might affect voter turnout and vote shares. In essence, we replicate their statistical model as much as possible—the only difference being the specification of dependent variables. Specifically, Gomez et al. (2007) control for the number of farmers per capita, the percentage of African Americans in the population, the percentage of high school graduates (standardized by year), the percentage of unemployed workers, and the Consumer Price Index (CPI)-adjusted median household income in the county (1982-1984 = 100, in US$10,000). They also control for registration requirements. These institutional variables include dummy variables for a county with a poll tax, literacy tests, motor-voter programs, or a property tax. They also add the number of days between the registration deadline and the election day. Given the possibility that other statewide

elections may boost voter turnout in presidential races, they add dummy variables denoting whether there was a gubernatorial election or U.S. Senate election concurrent with the presidential election. In addition, their model uses the three-election moving average of the Republican vote share in the past three presidential elections and county-level turnout in the most recent presidential election to capture behavioral patterns in turnout and the political characteristics of a county, respectively.[10] Finally, Gomez et al. (2007) add county-fixed effects and election-year fixed effects to control for all other observable and unobservable county-specific (and time-invariant) attributes and year-specific (and space-invariant) attributes.[11]

With regard to a statistical model for compositional data analysis, we follow Tomz, Tucker, and Wittenberg (2002) and apply Zellners (1962) SUR. First, we convert the three compositional dependent variables to the two log-ratios, using the abstention rate as the base category. We then run the following set of regression models simultaneously:

$$\begin{cases} \log\left(\dfrac{D}{A}\right)_{ijt} = \beta_D X_{ijt} + \gamma_{D,ij} + u_{D,t} + \varepsilon_{D,ijt} \\[2ex] \log\left(\dfrac{R}{A}\right)_{ijt} = \beta_R X_{ijt} + \gamma_{R,ij} + u_{R,t} + \varepsilon_{R,ijt} \end{cases}, \qquad (9)$$

where β_D and β_R denote a set of coefficients for independent variable X_{ijt}. The models include $\gamma_{D,ij}$ and $\gamma_{R,ij}$, county-specific fixed effects;[12] $u_{D,t}$ and $u_{R,t}$, year-specific fixed effects; and $\varepsilon_{D,ijt}$ and $\varepsilon_{R,ijt}$, error terms.[13] The predicted values for the logged ratios are subsequently converted back to the predicted values for the three compositional dependent variables. Using one of the compositional variables as a base category, the sum of these original variables predicted values is always 100%.

Results

Table 1 shows the results of estimations.[14] Our main quantities of interest include how the amount of normalized rainfall affects the abstention rate and the vote shares of the two parties, but we cannot obtain these quantities directly from the estimates presented in Table 1. Given the form of the dependent variables in Equation 9, the coefficient estimates in Table 1 indicate how a one-unit change in rainfall changes the log-ratio of each party's vote share relative to the abstention rate, which is counter-intuitive.

Accordingly, following Tomz et al. (2002), we calculate predicted values of each compositional variable under different weather conditions using a

Table 1. Results of Seemingly Unrelated Regressions.

|	Coefficient estimates
ln(D/A)	
Election day rain—normal rain	−0.108***
	(0.008)
ln(R/A)	
Election day rain—normal rain	0.008
	(0.007)
Observations	43,301

Note. The coefficients are estimated based on seemingly unrelated regressions with two dependent variables: ln(D/A), the log-ratio of Democratic candidate's vote share vis-à-vis the abstention rate, and ln(R/A), the log-ratio of Republican candidate's vote share vis-à-vis the abstention rate. The model includes a deviation from the normal snowfall, a range of control variables, county-fixed effects, and election-year fixed effects (coefficient estimates not shown). Standard errors are in parentheses.
***$p < .01$ (two-sided).

parametric bootstrap technique. Specifically, we first produce 1,000 simulated coefficients based on the estimates in each model and calculate sets of predicted values of the two log-ratios, while varying the value of normalized rainfall from two standard deviations below the mean (a case of the *low* value in the treatment variable) to two standard deviations above the mean (a case of the *high* value in the treatment variable). Note that one standard deviation of normalized rainfall is about 0.24. Therefore, the difference in normalized rainfall between two standard deviations below the mean and two standard deviations above the mean approximates a change in normalized rainfall by about 1 inch (specifically, 0.96 inches). The values of all other covariates are fixed at their means in this process. We then apply the inverse logistic function to transform the two log-ratios into the original three compositional variables— $\widehat{D}_{ijt}$, $\widehat{R}_{ijt}$, and $\widehat{A}_{ijt}$. Finally, we produce 1,000 first-differences in predicted values (i.e., the differences between the *high* case and the *low* case) and calculate the average first-differences in prediction and their 95% confidence intervals. In addition, we calculate the Republican advantage—the average second-difference to predict the rainfall effect on the Republican vote share and the rainfall effect on the Democratic vote share. This quantity captures how much benefit (or damage) rainfall would create for the Republican relative to the Democratic Party.

Figure 1 shows the results of this simulation. Each black dot denotes the predicted average change when rainfall changes from two standard deviations below the mean to two standard deviations above the mean. Each
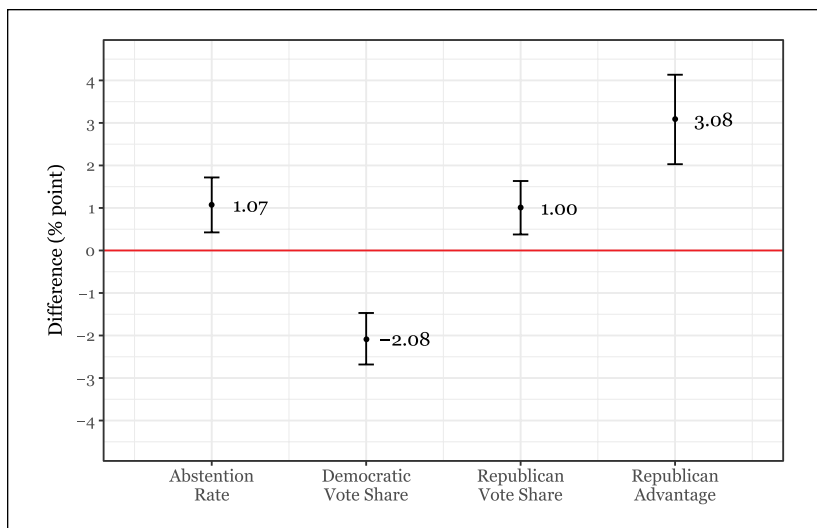
Figure 1. Predicted rainfall effects.
Note. The vertical axis indicates the predicted percentage change when rainfall increases from two standard deviations below the mean to two standard deviations above the mean.

vertical line around the dot represents its 95% confidence interval. When a vertical line does not cross the horizontal line at 0, the estimated first-difference (or second-difference for Republican Advantage) is statistically different from 0 at the .05 level.

An increase in normalized rainfall by 0.96 inches increases the abstention rate by 1.07% points. This increase is slightly larger than the estimate presented in Gomez et al. (2007), where a 1-inch increase in normalized rainfall reduces turnout in a county roughly by 0.89% points in the sample. Rainfall decreases the Democratic candidate's vote share by as much as 2.08% points, while it *increases* the Republican candidate's vote share by 1.00% point. Both effects are statistically significant. The combined (second-order) difference in predicted vote shares indicates that the Republican Party enjoys an advantage of 3.08% points with an increase in rainfall by 0.96 inches. In Gomez et al. (2007), an increase in normalized rainfall by 1 inch leads to an increase in the two-party vote share of the Republican Party by 2.43% points.

At first glance, our estimates and those of Gomez et al. (2007) are essentially similar. Both suggest that voter turnout decreases by about 1% point when it rains, and that the resultant Republican advantage is about 2% to 3% points.[15] Based on these results, one may argue that undertaking compositional

data analysis is unnecessary and does not provide any new insight into the electoral consequences of bad weather.

By considering the compositional data structure, however, we are able to demonstrate more nuanced effects of rainfall than the effects previous studies estimated. Importantly, our analysis shows that the Republican advantage is a consequence of two effects—a *decrease* in the Democratic vote share as the percentage of VAP and an *increase* in the Republican vote share as the percentage of VAP. Specifically, Equation 3 can now be filled with the estimates:

$$\text{Republican Advantage: } \Delta Y = Y_1 - Y_0$$
$$= (r_1 - d_1) - (r_0 - d_0)$$
$$= (r_1 - r_0) - (d_1 - d_0)$$
$$= 1.00 - (-2.08)$$
$$= 3.08.$$

We cannot precisely decompose this into the differential turnout channel ($\Delta a_d - \Delta a_r$) and the vote shift channel ($2m$) as in Equation 7. This is because as far as we use the aggregated observational data, we can estimate neither Δa_d nor Δa_r, which is the number of Republican or Democratic Party supporters who abstain when it rains but would vote for the Republican or Democratic Party otherwise.[16] With a widely shared assumption that at least some component of the Republican advantage is derived from the turnout differential channel ($\Delta a_d - \Delta a_r > 0$), however, we could set the upper and lower bound of the vote shift channel, as we discussed in the previous section.

Specifically, with the estimated Republican advantage ($\Delta Y = 3.08$.) and the overall increase in abstention rate due to rainfall ($\Delta a = 1.07$), Conditions in Equation 8 suggest that the lower and upper bound of the vote shift channel ($2m$) are as follows:

$$\Delta Y - \Delta a < 2m < \Delta \tag{10}$$

$$2.01 < 2m < 3.08. \tag{11}$$

On one end of the extreme, in which the same number of Democratic and Republican supporters abstain when it rains, the vote shift channel would explain all of the Republican advantage. On the other end of the extreme, in which only Democratic supporters abstain due to rainfall while none of Republican supporters do not, the vote shift channel would explain about two thirds of the Republican advantage. The remaining is through the turnout differential channel.

The 95% confidence intervals for the lower bound and the upper bounds are $[0.76, 3.26]$ and $[2.02, 4.14]$, both of which do not include zero. Thus, we conclude that even under an assumption that the turnout differential channel exists, the vote shift channel is another statistically significant channel that should also contribute to the Republican advantage in bad weather. More specifically, in opposition to the common assumption that weather conditions do not change voters party preference, at least 1% of voters among the VAP would change their support from the Democratic Party to the Republican Party when it rains.[17]

Robustness Check

As a robustness check, we estimate single-equation regressions using the Republican vote share as the percentage of VAP. As discussed earlier, this is not an optimal specification when the quantities of interests are the rainfall effects on voter turnout *and* the Republican advantage. It is, however, a straightforward approach to verify whether the vote share for the Republican Party increases or decreases due to rainfall. Specifically, following Gomez et al. (2007), we estimate three models: an ordinary least square (OLS) model, a fixed-effect model, and a random-effect model. Each model includes a deviation from the normal snowfall, the three-election moving average of the Republican vote share, and year fixed effects.[18]

The results are presented in Table A2 in the appendix. The estimated coefficients of *Election Day Rain—Normal Rain* are all positive and statistically significant. As the denominator is the VAP, which does not change by election-day weather conditions, these results imply that the *number* of votes (not just vote *share*) for the Republican Party actually *increases* when it rains. The results presented in Table A2 are consistent with the results based on compositional data analysis.

Interpretation

To recap, the results show that rainfall increases the number of votes for the Republican Party. The estimated increase in Republican votes suggests the existence of people who would either abstain or vote for the Democratic Party in good weather conditions but change their minds in bad weather. How to explain such apparently odd voting behavior? Although a full investigation of this question is beyond the scope of this article, we suggest a possibility that is worth further analysis.

Specifically, we argue, weather conditions may affect voters' *preference* as to which party they vote for. The idea that weather conditions directly affect the preference and behavior of individuals has been discussed extensively in the literature of psychology and related fields. Many existing studies

present that weather conditions affect societal phenomena and activities, such as crime, homicide, suicide, and good behaviors (e.g., Cheatwood, 1995; E.G. Cohen, 1990; Cunningham, 1979), as well as economic decisions on stock investment, local trading, consumer spending, and college enrollment (e.g., Bassi, Colacito, & Fulghieri, 2013; Glimcher & Tymula, 2017; Kamstra, Kramer, & Levi, 2003; Loughran & Schultz, 2009; Murray, Di Muro, Finn, & Popkowski Leszczyc, 2010; Simonsohn, 2010). In the literature of political science, A. Cohen (2011) and Egan and Mullin (2012) suggest that weather conditions affect people's attitudes toward the approval of an incumbent president and the perceptions about global warming.

In a similar vein, it is not unreasonable to consider a possibility that weather conditions would affect individual partisan preference. A key underlying rationale is that weather conditions, such as humidity, sunlight, and temperature, affect ones' moods (Connolly, 2008; Cunningham, 1979; Keller et al., 2005; Sanders & Brizzolara, 1982), which in turn affects risk attitudes (Isen & Patrick, 1983; Kuhnen & Knutson, 2011; Schwarz & Clore, 1983). As risk attitudes and people's preferred choices are closely related (Eckles & Schaffner, 2011; Ehrlich & Maestas, 2010; Mayda, O'Rourke, & Sinnott, 2007; Tam & McDaniels, 2013), bad weather may change not only individuals' decisions to go to the polls but also their party preference.

Given these existing studies on the links between people's moods, risk attitudes, and economic and political behavior, Bassi and Williams (2017) demonstrate, via randomized experiments, that when voters are virtually indifferent between two candidates, those who feel in an upbeat mood may lean toward the riskier candidate, while those who feel depressed and anxious lean toward the safer candidate.[19] Importantly, Kam and Simas (2010) argue that such risk attitudes are correlated with partisan and ideological orientations; specifically, conservatives and Republicans are more risk-averse than liberals and Democrats. Psychological research also suggests that people tend to embrace politically conservative ideology when they want to reduce anxiety, uncertainty, or ambiguity (Jost, Glaser, Kruglanski, & Sulloway, 2003; Thorisdottir & Jost, 2011).

For all these reasons, the "vote shift" channel on the electoral consequences of rainfall, which we pointed out earlier, is plausible. We do not, however, empirically delve into this alternative channel. Rather, we only estimate the downstream effect of rainfall on electoral outcomes. In the "Conclusion" section, we discuss a possible future study that may "unpack" the two channels discussed in this article, using individual-level data.

Conclusion

For many decades, in both popular media and academia, weather has been considered one of the most important correlates of election outcomes.

Specifically, existing studies suggest that bad weather on an election day, particularly rainfall, decreases turnout and benefits the Republican Party in American presidential elections. Most importantly, Gomez et al. (2007) claim that a 1 inch of rainfall reduces turnout by 0.89% points and generates a 2.43% point advantage for the Republican candidate in terms of the two-party vote share. They ascribe the Republican advantage to differential decreases in turnout across partisan supporters due to additional costs of voting in bad weather, assuming that weather conditions do not affect voters' political preferences and choices.

We revisited the analysis of Gomez et al. (2007). We decomposed the rainfall effect on electoral outcomes into the differential turnout channel and the vote shift channel. Then, we estimated the relative contribution of each channel in explaining the Republican advantage in bad weather in the United States. The results suggest that rainfall generates a 1.07% point increase in abstention rate and a 3.08% point change in the Republican advantage. The vote shift channel accounts for at least about two thirds of the Republican advantage even in the extreme situation when all weather-induced abstainers are Democratic Party supporters. Contrary to the widely shared belief that weather conditions do not change voters' electoral decisions, our analysis suggests that it is likely that a certain proportion of American voters would change their party preference depending on weather. As documented in the literature of psychology and related fields, weather conditions are important determinants of social and economic behaviors of human beings. Inclement weather on the election day could affect voters' moods and risk attitudes, which opens the possibility that weather conditions affect voters' electoral choices as well.

The analysis and findings presented in this article improve our understanding of the impacts of weather conditions on election outcomes. More broadly, we hope that this study contributes to the multidisciplinary literature on people's moods, risk attitudes, and human behavior. By highlighting the compositional nature of electoral data, we also hope that our analysis serves as a warning to research using aggregated electoral data. If a study's objective is to identify the determinants of both voter turnout *and* vote shares, it is often more suitable to run SURs or to apply other methods for compositional data analysis.

In addition to suggesting some under-investigated psychological and behavioral responses to weather conditions, our empirical evidence has an important methodological implication for studies using rainfall as an instrument to estimate the causal effects of voter turnout. Following Hansford and Gomez (2010), several studies use rain as an instrument (e.g., Arnold & Freier, 2015; Artés, 2014; Lind, 2017; Sforza, 2014). The estimation of causal effects using an instrumental variable is based on several assumptions, one of which is the assumption of *exclusion restriction*; that is, rainfall does not

motivate people, who otherwise vote for one party, to vote for a different party. However, the vote shift channel and its supporting evidence suggest the violation of this assumption.

There are some avenues for future research. First, it would be fruitful to examine the rainfall effects on election outcomes using data from other countries. The case of the U.S. presidential elections suggests the validity of the vote shift due to weather, but voters' moods and risk attitudes may be irrelevant in other cultural, institutional, and meteorological conditions.

It should be also with using individual-level data. Our study using the aggregated data only allows us to estimate the downstream effects of rainfall on electoral outcomes. Individual-level data analysis is expected to provide insight into the investigation of the causal mechanism, which we discussed but did not test in this study. Specifically, we would propose to merge individual-level, post-election survey data with precise geo-coded information of respondents' locations with the fine-grained precipitation data. As long as the survey includes questions measuring risk attitudes of individual respondents, we can estimate the effects of election-day weather conditions on voters' risk attitudes and, in turn, their turnout and vote choice decisions. In this analysis, it is worth applying the statistical methods of causal mediation analysis (e.g., Imai, Keele, Tingley, & Yamamoto, 2011). Under a certain set of assumptions, the causal mediation analysis would allow us to understand how exogenously determined weather conditions affect individual vote decisions via changes in their risk attitudes.

Appendix

Table A1. Summary Statistics.

Variable	M	SD	Minimum	Maximum
Republican vote share (R)	31.253	12.723	0.015	85.422
Democratic vote share (D)	26.425	9.537	0.156	81.923
Abstention ratio (A)	42.322	14.729	0.171	99.743
ln(R/A)	−0.358	0.902	−8.811	5.771
ln(D/A)	−0.479	0.707	−6.461	5.576
Election day rain—normal rain	−0.003	0.242	−0.419	4.351
Election day snow—normal snow	−0.003	0.265	−0.924	7.110
Number of farmers per capita	0.046	0.042	0	0.570
% African American population	8.653	14.450	0	85.893
% High school graduates (standardized by year)	0	0.996	−4.504	5.110

Table A1. (continued)

Variable	M	SD	Minimum	Maximum
% Unemployed workers	6.012	3.445	0	78.100
CPI-adjusted median household income in US$10,000	1.845	0.687	0.123	5.235
Dummy for poll tax	0.057	0.231	0	1
Dummy for literacy tests	0.110	0.313	0	1
Dummy for motor-voter programs	0.192	0.394	0	1
Dummy for property tax	0.007	0.083	0	1
Days between registration deadline and election day	27.022	24.213	0	180
Dummy for gubernatorial election	0.393	0.488	0	1
Dummy for senate election	0.683	0.465	0	1
Republican support (moving average)	49.526	14.188	0.239	89.855
Turnout in election t-1	58.191	15.254	1.413	100

Note. The number of observations is 43,031; the number of elections is 14; the number of counties differs by year (minimum = 3,013 in 1948; maximum = 3,099 in 1992 and in 1996). The election-related dummies are assigned 1 for elections held concurrently with the presidential election. The denominator for the Republican Vote Share, the Democratic Vote Share, and the Abstention Ratio is VAP minus the number of votes for nonmajor party candidates, not the total number of votes cast. VAP = voting age population.

Table A2. Weather Effects on the Republican Vote Share.

	OLS	Fixed effects	Random effects
Election day rain—normal rain	2.142***	0.819***	0.983***
	(0.161)	(0.104)	(0.104)
Observations	43,099	43,099	43,099

Note. The dependent variable is the Republican candidates' vote share among the VAP. Each model includes a deviation from the normal snowfall, the three-election moving average of the Republican vote share, and year fixed effects (coefficient estimates not shown). Standard errors are in parentheses. OLS = ordinary least square; VAP = voting age population.
***$p < .01$ (two-sided).

Table A3. Results of Seemingly Unrelated Regressions (Three Party).

	Coefficient estimates
ln(D/A)	
Election day rain—normal rain	−0.104***
	(0.007)
ln(R/A)	
Election day rain—normal rain	0.003
	(0.007)
ln(O/A)	
Election day rain—normal rain	−0.162***
	(0.019)
Observations	33,789

Note. The coefficients are estimated based on seemingly unrelated regressions with three dependent variables: ln(D/A), the log-ratio of Democratic candidates' vote share vis-à-vis the abstention rate; ln(R/A), the log-ratio of Republican candidates' vote share vis-à-vis the abstention rate; and ln(O/A), the log-ratio of other candidates' vote share vis-à-vis the abstention rate. The model includes deviation from normal snowfall, a range of control variables, county-fixed effects, and election-year fixed effects (coefficient estimates not shown). Standard errors are in parentheses.
***p < .01 (two-sided).
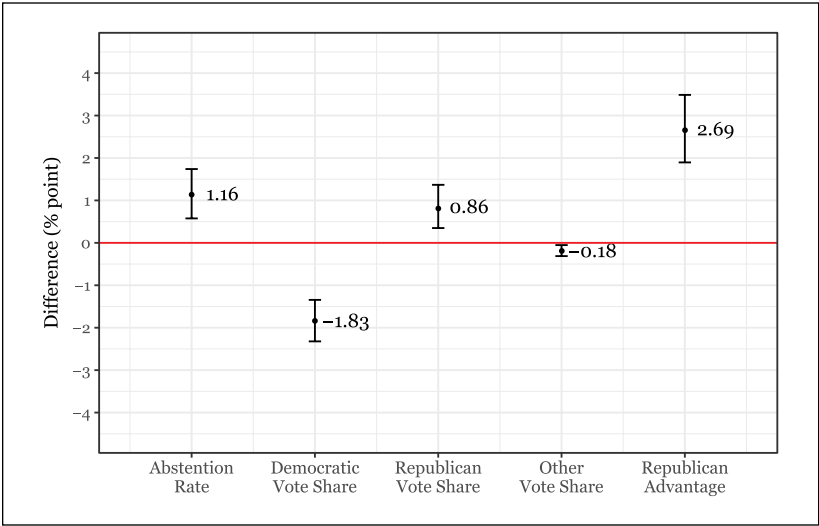
Figure A1. Predicted rainfall effects (three party).
Note. The vertical axis indicates the predicted percentage change when rainfall increases from two standard deviations below the mean to two standard deviations above the mean.

Declaration of Conflicting Interests

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Notes

1. For example, see the *New York Times* on November 6, 2006 (at http://goo.gl/u7NjkT); the *Washington Post* on October 30, 2008 (at http://goo.gl/byJI50); the *Washington Post* on November 5, 2012 (at http://goo.gl/RqzMWg).
2. For example, Merrifield (1993) and Shachar and Nalebuff (1999) used rainfall in each state's largest city to determine how weather affects nationwide elections.
3. In the United States, Fowler (2015) empirically shows that "marginal" voters—those who are likely to change their turnout decisions depending on exogenous factors that could affect the costs of voting, such as weather conditions—tend to be more supportive of the Democratic Party than "regular" voters who would vote irrespective of such exogenous factors.
4. This is apparently for districts in which two candidates compete for a seat. The generalization of our argument remains the same when the number of candidates is greater than two.
5. McDonald and Popkin (2001) argue that voting eligible population (VEP) is a more appropriate measure when studying turnout than voting age population (VAP). VAP includes noncitizens and disenfranchised felons and excludes those who are living overseas but eligible citizens. Gomez, Hansford, and Krause (2007), however, use VAP for their analysis because VEP data are not readily available at the county level. Following their approach, we also use VAP in our analysis.
6. The denominator of r_i and d_i is VAP. As VAP is constant regardless of the treatment status, any change in r_i or d_i should be attributable to the change in the numerator, which is the *number* of votes. Also, see Footnote 5.
7. Table A1 in the appendix shows the descriptive statistics of all variables used in our analysis. See Gomez et al. (2007) for details on how each variable is measured. The replication dataset is available at http://myweb.fsu.edu/bgomez/research.html
8. For example, we replicated the study of Gomez et al. (2007) and ran separate estimates of the abstention rate and the vote shares of the Republican Party

and Democratic Party candidates. We then calculated predicted values for each dependent variable. For 95% of observations, the sum of the three predicted values was within the range from 77.87% to 122.19%. Given that the magnitude of the effect on turnout is very subtle (less than 1% point), we consider that this wide variation in the prediction error could be problematic.

9. The denominator of A_{ijt} used in Gomez et al. (2007) is VAP (also see Footnote 5). We calculated D_{ijt} and R_{ijt} using the turnout variable in Gomez et al. (2007), as well as the number of Democratic candidate's votes, the number of Republican candidate's votes, and the number of other partisan votes in each county i in each state j in each election t. The county-level election return data are provided by Dave Leips Atlas of U.S. Presidential Elections at http://uselectionatlas.org/. In the main analysis, we focus on competition between the two major party candidates. Therefore, strictly speaking, to meet the condition $D_{ijt} + R_{ijt} + A_{ijt} = 100$, the denominator is set to VAP minus other partisan votes for each unit of observation. Note that the empirical results are robust to inclusion of other partisan votes. Results are reported in Table A3 and Figure A1 in the appendix.

10. Gomez et al. (2007) control for the lag of the turnout variable when analyzing the effect of weather on turnout, while they use the three-election moving average of the Republican vote share when analyzing the effect of weather on party shares. Given that each dependent variable in our compositional data analysis is a log-ratio of party vote share to abstention, we control for both variables in each equation.

11. In practice, we first demean all variables for each county (across all election years) and add year-specific dummies.

12. As a county is a geographical subunit of a state, the county-specific fixed effects also control for state-specific, time-invariant attributes. For this reason, we add a subscript ij rather than i.

13. The error terms, $\varepsilon_{D,ijt}$ and $\varepsilon_{R,ijt}$, are assumed to be correlated with each other. As the compositional variables (i.e., voter turnout and vote shares) are generated from the same electoral process, it would be unreasonable to assume that stochastic shocks affect only one of the two error terms.

14. Following Gomez et al. (2007), we include both the normalized rainfall variable and the normalized snowfall variable into all estimation models. We focus on the estimated effects of rainfall, however, because snowfall does not generate any Republican advantage in electoral outcomes. See Table 2 in their article for details.

15. Strictly speaking, we cannot compare the size of the Republican advantage based on our estimates with the size of the Republican advantage presented by Gomez et al. (2007). The denominator of our estimates is the total VAP, whereas the denominator of the estimate by Gomez et al. (2007) is the total number of votes.

16. With individual-level voter files or individual-level survey data with geo-coded information about respondents, we may be able to estimate Δa_d and Δa_r under certain assumptions. We discuss this possible extension for future research in the concluding section.

17. The estimated lower bound for the vote shift channel ($2m$) is 2.01. Thus, the estimated minimum percentage of voters who would change their partisan choice in bad weather is $m \approx 1$.

18. The right-hand side of each of our regression model is the same as the one used in Gomez et al. (2007). We also tried models with other control variables, but the results did not change substantially.
19. Also see Bassi, *Colacito, and Fulghieri (2013)*, which shows experimental evidence on the association between weather, risk attitudes, and financial decisions.

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