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Rain, Emotions and Voting for the Status Quo

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Revised Version for the *European Economic Review*

Abstract

Do emotions affect the decision between change and the status quo? We exploit exogenous variation in emotions caused by rain and analyze data on more than 870,000 municipal vote outcomes in Switzerland to address this question. The empirical tests are based on administrative ballot outcomes and individual postvote survey data. We find that rain decreases the share of votes for political change. Our robustness checks suggest that this finding is not driven by changes in the composition of the electorate and changes in information acquisition. In addition, we provide evidence that rain might have altered the outcome of several high-stake votes. We discuss the psychological mechanism and document that rain reduces the willingness to take risks, a pattern that is consistent with the observed reduction in the support for change.

JEL Classifications: D01; D02; D72; D91

Keywords: Emotions, voting, status quo, risk aversion, rain, direct democracy, turnout

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1 Introduction

Many decisions involve the choice between keeping the status quo or opting for change. The human tendency to maintain the status quo, usually the default option, has been documented in a variety of important contexts, including the decision to use default retirement plans (O'Donoghue and Rabin, 2001), organ donations (Johnson and Goldstein, 2003), and politics (Lee, 2008; Alesina and Passarelli, 2015). Previous literature has attributed the status quo effect to uncertainty (Samuelson and Zeckhauser, 1988), loss aversion (Kahneman, Knetsch and Thaler, 1991), and choice fatigue (Danziger, Levav and Avnaim-Pesso, 2011; Augenblick and Nicholson, 2016; Hessami and Resnjanskij, 2019). Little is known, however, about the effect of emotions on the tendency to keep the status quo. This is surprising in light of the recent contributions in economics which demonstrate the impact of emotions on human decision-making (Kamstra, Kramer and Levi, 2003; Ifcher and Zarghamee, 2011; Cohn et al., 2015; Callen et al., 2014; Haushofer and Fehr, 2014; Meier, 2019).[1]

In this paper, we study how emotions affect the fundamental decision between keeping or changing the status quo. We exploit rainfall as an exogenous source of variation in emotions (Lambert et al., 2002; Hirshleifer and Shumway, 2003; Baylis et al., 2018) and examine whether voters are more or less likely to support a policy change on a rainy voting weekend. We analyze a novel data set that contains more than 870,000 municipal-level direct democratic vote outcomes from 420 federal propositions in Switzerland between 1958 and 2014. We use administrative voting and individual postvote survey data to estimate the effect of rain on the propensity to vote for political change. We find that rain on a voting weekend decreases support for changing the status quo. A simple simulation indicates that this rain effect potentially swayed several vote outcomes.

We discuss two alternative explanations, other than emotional reactions, that could explain the negative relationship between rain and the share of yes votes. First, we rule out that changes in the composition of the constituency can explain the empirical regularity. Across a battery of checks we show, among others, that: (i) overall turnout is not affected

[1] An excellent general account on emotions and decision-making is provided in Lerner et al. (2015). The bridge to economic reasoning is nicely built in Loewenstein (2000).

by whether it rained on the voting weekend, (ii) there is no statistically detectable heterogeneous reaction to rain on the individual level according to the ex-ante propensity to vote yes, partisanship, or ideology, and (iii) the relationship between rain and voting for the status quo on the municipal level holds conditional on turnout and other proxies for the composition of the electorate. Second, we investigate whether the use of different information channels can explain the rain effect but find no evidence for this explanation. In addition, we show that the effect is driven by citizens who cast their ballot card on the voting weekend, rather than by those who vote beforehand by mail. Moreover, our results indicate that the effect of rain also prevails in votes that are decided by a narrow margin and high turnout votes.

Switzerland provides a unique setting to study citizens' policy choices as most major political decisions are subject to a popular vote. These political decisions are highly salient due to broad media coverage. In addition, vote outcomes from referendums and popular initiatives are binding. Examples of high-stake ballots include Switzerland's vote on its membership in the European Economic Area, a proposal to introduce a federal debt brake, and several votes on the introduction of a comprehensive minimum wage scheme. Importantly, Swiss voters have substantial experience with popular votes (Schmid, 2016; Bechtel, Hangartner and Schmid, 2016, 2018; Stutzer, Baltensperger and Meier, 2019). Thus, our findings are robust to the concern that the influence of psychological factors vanishes as individual experience increases (List, 2003; Levitt and List, 2008). Finally, the framing of the decision emphasizes the potential new future legal situation. In the official description of the ballot proposals, the new alternative statutory or constitutional law is explicitly discussed in reference to the current legal status quo. Accordingly, an approval of the policy change always requires a yes vote, while adherence to the status quo requires a no vote. This enables a straightforward interpretation of the effect of rain on vote outcomes as lowering support for political change.

What might drive this rain effect? We discuss several psychological mechanisms and conclude that a specific version of the projection bias (Loewenstein, O'Donoghue and Rabin, 2003) offers the most plausible explanation. Emotions affect risk aversion and consequently alter the evaluation of the policy options (Schwarz, 2012). The intuition is that positive emotions lead to more optimistic evaluations of change, while negative emotions lead to more cautious appraisals. Consistent with this, we document that reported willingness to take risks is lower if it rains, based on complementary data.

We think that our results are important for at least two reasons. First, the direct democratic votes that we study are collective decisions with major policy implications. If psychological factors alter such high-stake collective choices, we should take this evidence into account for institutional design. For example, one could reduce the number of concurrent votes on a voting weekend to mitigate emotional impacts. Second, our findings from field data suggest that negative emotions lead people to favor the status quo. This tendency may be relevant in other domains — for instance, in labor market decisions and health choices. Choice architects should thus be aware that decisions may be affected by external emotional cues that systematically affect peoples' trade-offs between the status quo and change.

This study relates to at least three strands of research. First, we add to a growing literature that explores the role of emotions for decision-making in field settings (DellaVigna, 2009). Studies have exploited the fact that the performance of a sports team affects mood, and consequently influences the ruling of judges, the evaluation of politicians, and family conflicts (Healy, Malhotra and Mo, 2010, 2015; Card and Dahl, 2011; Fowler and Montagnes, 2015; Eren and Mocan, 2018). Our study is, to our knowledge, the first that explicitly explores whether emotions affect outcomes through risk aversion (DellaVigna, 2009, p. 359).

Second, we add to the new field of behavioral political economy that investigates why and how citizens vote based on a broader account of human motivation (see Schnellenbach and Schubert, 2015 for a review). In this vein, DellaVigna et al. (2017) document that social image concerns are important in explaining why people vote. Augenblick and Nicholson (2016) show that choice fatigue can cause voters to take decision shortcuts, such as voting for the status quo. Previous research also examines the role of visual cues, including a candidate's physical appearance as a heuristic to assess politicians (Berggren, Jordahl and Poutvaara, 2010) and the role of general life satisfaction in retrospective voting (Liberini, Redoano and Proto, 2017). Our findings also add to the literature on emotions in politics. Scholars have argued that politics fuels emotions and, at the same time, emotions motivate political engagement, such as the decision of whether to oppose the government (Marcus, 2000; van Winden, 2015; Passarelli and Tabellini, 2017).[2]

Third, we contribute to the recent work on the effects of rain on elections. This literature argues that rainfall primarily alters the cost of voting. This in turn impacts turnout (Hansford and Gomez, 2010; Fraga and Hersh, 2011; Lind, 2017; Arnold and Freier, 2016; Fujiwara, Meng and Vogl, 2016; Becker, Fetzer and Novy, 2017) and participation rates in political rallies (Madestam et al., 2013). Our findings suggest that rainfall not only indirectly affects voting results by changing the constituency, but also directly alters the voting decisions of citizens. Our evidence from observational data complements previous experimental findings by Bassi (2019) who shows that weather conditions affect how voters evaluate the incumbent.[3]

We proceed as follows. Section 2 provides background information on the institutional environment in Switzerland, our data sources, and our empirical strategy. Section 3 explores the effect of rain on vote outcomes. We first present the main results and then conduct two placebo tests. In addition, we explore alternative explanations for the main empirical regularity including a change in composition of the electorate due to rain. Finally, we highlight the size and real-world impact of the rain effect. In Section 4, we discuss the potential mechanisms behind the relationship between rain and voting behavior and other aspects that are relevant for the assessment of the generalizability of our findings. Section 5 concludes and suggests directions for future research on emotions and the choice between change and the status quo.

[2]For reviews on emotions in economics, politics and political philosophy, see, for example, Elster (1998, 1999) and Marcus (2000).

[3]For a recent overview on the influence of weather on economic outcomes, see Dell, Jones and Olken (2013).

2 Institutions, Data and Empirical Strategy

2.1 Institutions

Switzerland is a democratic federal country with a two-chamber parliament and important elements of direct democracy. Citizens decide in several votes throughout the year on policy propositions and the corresponding vote outcomes are legally binding. Most important for our study is that a yes vote is always a vote for change. The official vote information leaflets that are sent to every eligible voter prior to a public vote reflects this as policy proposals are discussed with reference to the current status quo. This means that we can concentrate on the share of yes votes when evaluating the support for change.

Accepting a proposal may have far-reaching consequences and usually leads to changes in public policy. Notable important votes include propositions on abolishing the army, the participation in the integrated market of the European Economic Area, fundamental changes to the federal tax code, and the future of the social security system.[4] The high-stakes nature of these proposals underscores the well-known inherent risk associated with supporting change in politics (Fernandez and Rodrik, 1991; Alesina and Passarelli, 2015; Augenblick and Nicholson, 2016). Consistent with the close link between changes of the status quo and risk, we observe in our setting that a higher predicted individual willingness to take risks relates to a higher support of change as indicated by the likelihood to vote yes for a proposition (see Appendix A).

Ballot propositions can be divided into two categories: referendums and popular initiatives. A mandatory referendum takes place for every proposed amendment of the federal constitution. In addition, federal laws approved by both chambers of parliament are put to a popular vote if a committee of citizens submits 50,000 valid signatures. Popular initiatives allow citizens, parties, and interest groups to propose constitutional amendments. A vote takes place if the initiators have collected 100,000 valid signatures.

People fill in ballot cards at home and traditionally bring them to the ballot box on the voting weekend. The ballot card arrives by mail two to three weeks before the vote takes

[4] An overview of popular votes at the federal level in Switzerland is provided on the official webpage of the Swiss government at `https://www.admin.ch/gov/en/start/documentation/votes.html`.

place. The ballot boxes are open on Saturday and Sunday and they are located in the city hall or in a public building. The ballot cards state the type of popular vote and the title of the proposition.

As an alternative to voting at the polling station, all Swiss cantons have gradually introduced postal voting since 1978, most of them during the 1990s (Hodler, Luechinger and Stutzer, 2015). This has altered the way people vote. While all voters formerly had to cast their votes at the ballot box before, only a fifth of voters did so in 2005 with comprehensive postal voting (Federal Chancellery, 2005). However, roughly one third of the voters still cast their votes via mail in the week preceding the voting weekend (Federal Chancellery, 2005). More than half of the votes in our sample were cast at the ballot box or in the week before the vote.

2.2 Data

We use three comprehensive data sources for our analysis. First, we draw on administrative data on municipal vote outcomes for the years 1958 to 2014 from the Swiss Federal Statistical Office (SFSO, 2015). These data contain vote outcomes and turnout information for all Swiss municipalities and federal propositions. In total, we have data on more than 870,000 municipal-level vote outcomes from 420 propositions in 2,538 municipalities. On average, there are three voting weekends per year. We complement this data with vote recommendations for propositions from parties based on Swissvotes, a database maintained by the University of Bern and Année Politique Suisse (Swissvotes 2012). For additional analyses, we consider information on the electoral strength of parties at the municipal-level in federal parliamentary elections from 1971 to 2011. For each voting date, we assign the latest election outcome, or, in the case of the years before 1971, the electoral outcome in 1971. These data are provided by the Swiss Federal Statistical Office (SFSO, 2015).[5]

Second, we base our analysis on individual voting decisions from postvote surveys for the years 1996 to 2006 (FORS 2014).[6] Several Swiss universities and the private research

[5]We refer the reader to Appendix B for descriptive statistics.

[6]Note that for the year 1997 there is no municipality identifier available, thus we cannot use the data for this year.

institute GFS administered these surveys, called VOX surveys, after each voting weekend. A representative sample of roughly 1,000 voters is contacted by phone. The resulting data contain information on whether and how respondents voted, the method by which the ballots were submitted (via mail or via ballot box at the polling station), several socio-economic characteristics, political ideology, knowledge about the vote issues and which information channels voters used.

Third, we use data on local rainfall from the Swiss Federal Office of Meteorology (MeteoSwiss 2015). It includes information on rainfall between 7 a.m. and 7 p.m.[7] An advantage of our setting is the great variation in rainfall over time and space due to the specific topography of Switzerland shaped by the Jura Mountains and the Alps. We gathered rain data for all popular votes from 1958 to 2014 based on 116 automated meteorological stations. To construct a variable for rainfall at the municipal-level, we interpolate station-level rain data using the inverse distance weighting function for the nearest three stations. As rain conditions in the mountains can be considerably different from those in the lowlands and in the foothills of the Alps, we excluded 17 weather stations above an altitude of 2,000 meters. We further dropped all stations with a distance larger than 30 kilometers from a municipality's set of stations. We construct an indicator variable for rain that is equal to one for a municipality if it rained any time between 7 a.m. and 7 p.m. on the Saturday or the Sunday of the voting weekend. Note that measurement error in the rain variable would create attenuation and may bias the estimated coefficients towards zero.

2.3 Empirical Strategy

The extensive municipal and individual data allow us to explore the effect of rain, controlling for a substantial amount of observed and unobserved heterogeneity. We examine the effect of rain on political decisions with the following econometric model using municipal data:

$$Y_{jp} = \eta_j + \delta_p + \alpha \,\mathrm{Rain}_{jp} + X'_{jp}\beta + \varepsilon_{jp},$$

[7]This rain variable provides us with a measure of rain for a time frame that is most relevant to voters. This is in contrast to other studies that use measures which also include nightly rainfall, see, for example, Hansford and Gomez (2010).

where j indexes municipalities, p indexes propositions; Y_{jp} is our outcome of interest, namely the share of yes votes in percentage points; η_j is a municipality fixed effect; δ_p is a proposition number fixed effect for each single vote — 420 fixed effects — which allows us to exploit *within vote date variation* and therefore absorbs vote date-specific variation and seasonal variation; α is the coefficient of interest; Rain_{jp} is a dummy that is one if it rained in municipality j; X'_{jp} is a matrix of covariates that may include variables such as turnout; β is a vector of coefficients; and ε_{jp} is an idiosyncratic error term.

We cluster the standard errors at the cantonal level to take into account both spatial correlation in rain and serial correlation in voting behavior. This is analogous to state-level clustering for the United States, which is commonly regarded as most conservative option and therefore the recommended one (Cameron and Miller, 2015).[8]

We complement the analysis of municipal voting data with a detailed investigation of how rain affects voting decisions using individual-level data in a similar vein. The data allow us to control for covariates as well as to estimate the effect of rain on ballot box voters and postal voters separately.[9]

3 Rain and Votes Against the Status Quo

3.1 Main Results

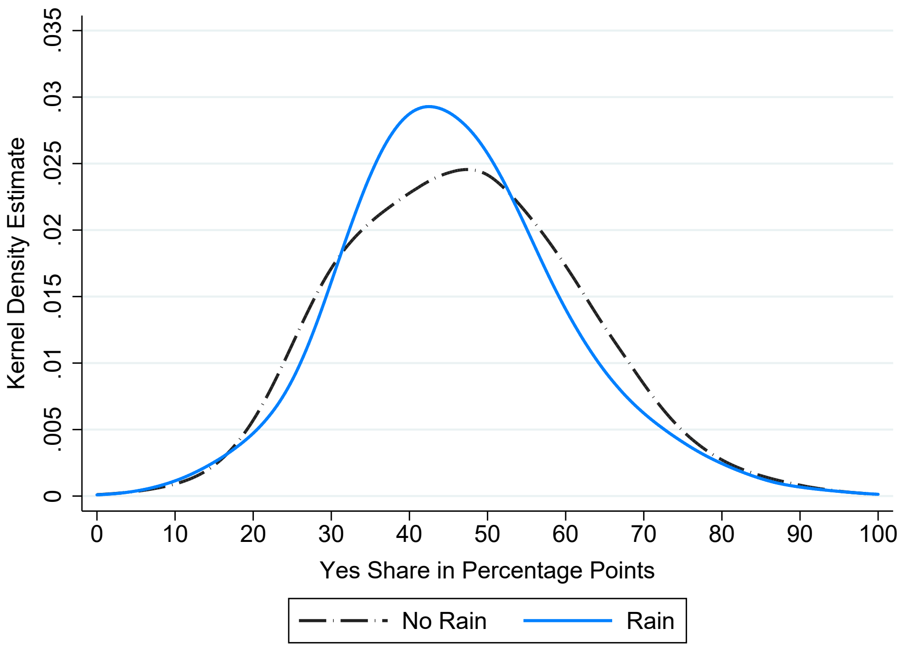
We show the bivariate relationship between the share of yes votes and rain in the raw data in Figure 1. It displays the density of the share of yes votes in percentage points on dry (dashed black line) and rainy days (solid blue line). The figure reveals that the share of yes votes is considerably lower on rainy days. While the average yes share is 46.8 percentage points on dry days, it is 45.7 percentage points on rainy days. This descriptive evidence should be interpreted with caution. It might be that municipalities with high average rainfall are more likely to oppose political reforms per se. We therefore turn to the regression analysis that

[8]Note that the null hypothesis that rain has no effect on the share of yes votes is rejected at conventional significance levels also when we use standard errors clustered at the voting weekend or two-way clustered standard errors on voting weekend×municipality level. The standard errors are similar when we apply the wild bootstrap approach.

[9]Appendix C provides a detailed exposition of the model at the individual-level.

allows us to identify the effect of rain on the share of yes votes holding constant characteristics that are specific to municipalities and propositions. We first consider the administrative, municipal-level data and second the individual-level postvote survey data.

Figure 1: Rain and the Share of Yes Votes in Percentage Points

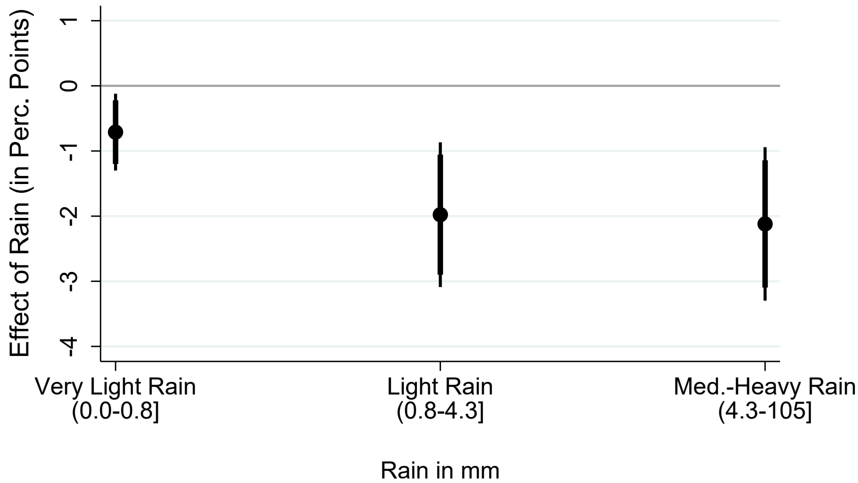


Note: The figure shows two estimated densities of the yes vote share in percentage points for rainy voting weekends (blue solid line) and dry voting weekends (black dashed line). The density estimates stem from the Epanechnikov kernel function (bandwidth = 3.0) based on 870,175 municipal-level vote outcomes. Conditional on municipal and proposition fixed effects, the yes share density for voting days with rain stochastically dominates the yes share density for voting days with no rain.

Municipal Data — Table 1 presents our main results from the municipal data set. Column (1) shows the raw difference in means. It indicates that propositions on rainy voting weekends have a yes share that is about one percentage point lower than propositions on dry voting weekends. This difference might be the consequence of temporal and spatial dependence that creates a spurious relationship between rain and the share of yes votes.

To hold constant common shocks caused by timing, we include proposition number fixed effects in column (2). Inclusion of proposition number fixed effects takes into account the idiosyncrasies of each of the 420 propositions and therefore also absorbs any date-specific effects, including season-specific effects or opinion shocks. The estimated coefficient for rain is -1.04. In column (3), we add municipality fixed effects to address the concern that municipalities with more rain may be more conservative. The effect of rain remains unchanged. Finally, we include linear municipal time trends in column (4) to demonstrate that spatio-temporal trends do not drive our results.[10] We use specification (4) as our baseline model for the municipal data set throughout the rest of the paper to capture not only time and spatial fixed effects, but also municipality-specific trends.

Figure 2: Flexible Functional Form Relationship Between Rain in Terciles and the Share of Yes Votes in Percentage Points, Municipal Data



Note: The figure shows coefficient estimates for the effect of rain on the share of yes votes in percentage points together with a 95% confidence interval (thin line) and a 90% confidence interval (thick line) using municipal data. The point estimates are based on regression model (4) in Table 1 with indicator variables for the terciles of rainfall. The reference category is zero rainfall.

In an additional analysis, we regress the share of yes votes on terciles of rainfall to investigate the functional form between the two variables. Figure 2 depicts that even very light as well as light levels of rainfall decrease the share of yes votes. These low levels of rainfall are analogous to dark skies and some rain.[11]

[10]We provide additional specification checks in Appendix E.

[11]The Swiss Metereological Service classifies rain of 2mm per hour as heavy rain. In comparison, rainfall of up to 4mm over the entire voting weekend can be considered as light rain. Therefore, we name the two

Postvote Survey Data — We also estimate the effect of rain on the propensity to vote yes using individual data from postvote surveys. The dependent variable ranges from 0 to 100 and indicates the relative share of yes votes cast by a voter on the voting weekend. The results are reported in Table 2. The point estimate of rain is consistently negative in all specifications and varies between -2.85 and -5.15. It is robust to the inclusion of voting weekend and municipality fixed effects as well as covariates that comprise age dummies, a gender dummy, dummies for income categories and a dummy for holding a university degree.[12] We also estimate the relationship between rain and voting yes using a more flexible functional form. The results indicate that the negative effect of rain is pronounced even for propositions with light rainfall, which is qualitatively equivalent to the results using municipal data. In sum, our main estimates from the two high resolution data sets suggest that there is a sizable effect of rain on vote choices. This effect prevails even when we control for a large set of fixed effects and individual covariates.

3.2 Placebo Tests

We assess the plausibility of the estimated rain effect in two tests. First, we conduct a placebo test by randomizing rainfall across voting weekends. Second, we exploit an institutional change — the introduction of postal voting — which allows voters to cast their votes before the official voting weekend.

Random Rainfall — Due to the high spatial and temporal correlation in both the rainfall and the voting data, the precision of the rain effect may be overestimated (Lind, 2019). To address this concern, we follow Lind (2019) and Fujiwara, Meng and Vogl (2016) by using flexible time trends. In a separate specification, we use municipal-year fixed effects to account for spatial correlation over time. We also check whether the estimated rain effect is spurious

lowest terciles light and very light rain. We provide additional results on the functional form relationship between rain and outcomes of interest in Appendix D.

[12]We include a dummy for 25 missing values for the variable university degree to keep those observations in the estimation sample.

Table 1: Effect of Rain on the Share of Yes Votes in Percentage Points, Municipal Data 1958–2014

Dependent Variable	Share of Yes Votes [0–100] Avg.: 47%			
	(1)	(2)	(3)	(4)
Rain Indicator	-1.06**	-1.04**	-1.28***	-1.23***
	(0.40)	(0.40)	(0.37)	(0.38)
Proposition No. FE		X	X	X
Municipality FE			X	X
Municipality Trends				X
Observations	870,175	870,175	870,175	870,175
Clusters	26	26	26	26
R–squared	0.00	0.05	0.69	0.70

Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Effect of Rain on the Share of Yes Votes in Percentage Points, Postvote Survey Data 1996–2006

Dependent Variable	Voted Yes {0,100} Avg.: 48%			
	(1)	(2)	(3)	(4)
Rain Indicator	-5.15***	-4.98***	-2.71**	-2.85**
	(0.89)	(1.07)	(1.04)	(1.06)
Vote Weekend FE		X	X	X
Municipality FE			X	X
Covariates				X
Observations	12,970	12,970	12,970	12,970
Clusters	26	26	26	26
R–squared	0.00	0.13	0.28	0.29

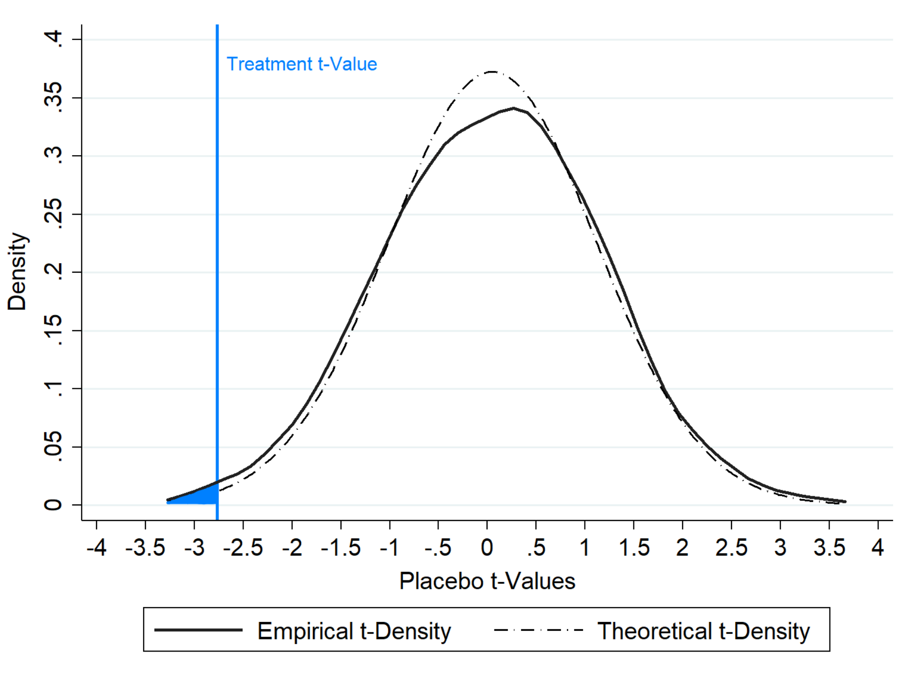
Note: The table shows the estimated effect of rain on the propensity to vote yes in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. We can at most include vote weekend FE since the dependent variable captures the share of propositions an individual voted yes for on any given voting weekend. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in a placebo study based on Lind (2019). In a first step, we randomly assign future or past voting weekend rainfall to a specific voting weekend (placebo rainfall). We then run our main specification using the share of yes votes as dependent variable and the placebo rainfall as independent variable. We repeat this procedure 500 times which should provide us with the distribution under the null hypothesis that past and future weather should have no effect on voting outcomes. If this placebo distribution of rain effects is very far from the theoretical t-distribution, the rejection rate of our main regression is likely to be wrong because our regression model fails to capture spatiotemporal trends that are present both in rainfall and voting behavior. Figure 3 indicates that our empirical t-density under the null is very close to the theoretical t-density. Accordingly, the omission of spatiotemporal trends seems to be no concern for our regression results. A comparison of our main results in Table 1 with the distribution of placebo estimates yields a p-value that is smaller than 0.01.

Figure 3 shows the resulting coefficients divided by their standard errors (black solid line) together with the theoretical t-distribution (black dotted line). As expected in a placebo study, the distribution of t-values is centered at zero. The vertical blue line depicts the t-value of our baseline specification. It indicates that the size of the coefficient estimate lies in the outer tail of the coefficient distribution. The obtained t-value of -2.77 is slightly larger in absolute value than the critical empirical t-value at the 1% level, which is -2.72. Thus, our regression coefficient for rain is statistically significant at the 1% level when compared to the empirical distribution of t-values under the null hypothesis.

Postal Voting — Swiss cantons gradually introduced the possibility of postal voting in addition to voting at the ballot box, which resulted in an increase in individuals who cast their ballot card by mail before the voting weekend (Hodler, Luechinger and Stutzer, 2015). We exploit this procedural change to shed light on the plausibility of our findings. Since rain on the voting weekend should have no effect on early postal voters, we expect larger effects in time periods with no postal-voting option. Accordingly, we compare the effect size of rain before and after the introduction of postal-voting based on the municipality data. For the individual-level data, we test whether postal voters are affected by rain on the voting

Figure 3: Randomized Rainfall



Note: The figure shows the empirical distribution of t-values under placebo rainfall, the average t-value under our baseline specification, as well as the theoretical t-distribution. Since we randomize rain at the voting weekend level, we use standard errors clustered at voting weekend in all specifications here. The theoretical t-distribution therefore has 163 degrees of freedom. Note that we have fewer observations, 671,000 on average, than in our baseline sample. This is because our panel is unbalanced and randomization of vote date rainfall therefore leads to missing values. To obtain a plausible t-value for the comparison, we computed the effect of true voting weekend rainfall in the same reduced samples and averaged the resulting t-values. The average t-value of the treatment, -2.77, is depicted by the blue line. The blue shaded area indicates the t-values which are smaller than the estimated t-value. The critical empirical t-value at the 1% level is -2.72. The t-value of the treatment in the full sample with voting weekend clustering is -3.20.

weekend. For both samples, we explore whether voters with access to postal voting might be affected by rain before the voting weekend.

Table 3 reports the results for the municipal data. The effect of rain in periods with no postal voting option is -1.4 percentage points (columns 1 and 2). Its magnitude is more than 0.41 percentage points higher than the effect on municipalities that offered supplementary postal voting (columns (3) and (4)), although the two coefficients are not statistically significantly different from each other. Note that the negative effect of rain after the introduction of postal voting is plausible as a considerable fraction of voters still voted at the ballot box.

A substantial fraction of voters, 37% on average in 2005, cast their votes in the week preceding the voting weekend (Federal Chancellery, 2005). This means a rain effect is plausible in the week before the voting weekends in periods with postal voting, while we expect to observe no effect of rain preceding the voting weekend in periods without postal voting. Columns (2) and (4) in Table 3 add an indicator for the share of rainy days in the five days prior to the voting weekend. This indicator ranges from 0, no rain, to 1, rain on all days. The entries suggest that the pre-weekend rain has no effect if there is no option to vote by mail, while pre-weekend rain has an effect if there is this possibility. For instance, if it rains one day more in the week before the vote, the yes share is reduced by a substantial 0.5 percentage points.

Table 3: Sensitivity of the Rain Effect to Postal Voting

Dependent Variable	Share of Yes Votes [0,100]			
	No Postal		Postal	
	(1)	(2)	(3)	(4)
Rain Indicator	-1.40***	-1.40***	-0.99**	-0.94**
	(0.46)	(0.47)	(0.44)	(0.44)
Rain Week Before Vote		-0.20		-2.18**
		(1.07)		(0.88)
Proposition No. FE	X	X	X	X
Municipality FE	X	X	X	X
Municipality Trends	X	X	X	X
Observations	441,731	441,502	428,444	428,264
Clusters	26	26	26	26
R–squared	0.69	0.69	0.77	0.77

Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. The variable capturing the share of rainy days in the five days before the vote date ranges from 0 to 1. On average it rained two out of five days before the voting weekend, which is equivalent to a share of rainy days in the week before the vote of 0.4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effect of Rain on Ballot Box vs. Postal Voters

Dependent Variable	Voted Yes					Ballot Box Voter	
	All	Ballot Box Voters		Postal Voters		All	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rain Indicator	-2.66**	-4.25**	-4.24**	-1.59	-1.45	-0.17	-0.17
	(1.04)	(1.79)	(1.78)	(1.83)	(1.82)	(2.06)	(2.15)
Rain Week Before Vote	-3.55		-0.20		-6.37		0.10
	(2.99)		(3.30)		(3.94)		(4.53)
Vote Weekend FE	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X
Covariates	X	X	X	X	X	X	X
Observations	12,961	4,994	4,994	7,967	7,967	12,961	12,961
Clusters	26	26	26	26	26	26	26
R–squared	0.29	0.40	0.40	0.34	0.34	0.32	0.32

Note: The table shows the estimated effect of rain on the propensity to vote yes (columns (1) through (5)) in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. The variable capturing the share of rainy days in the five days before the vote date ranges from 0 to 1. On average it rained two out of five days before the voting weekend, which is equivalent to a share of rainy days in the week before the vote of 0.4. The dependent variable in columns (6) and (7) is either 0 or 100, depending on whether the voter voted at the ballot box or not. We have 9 missing values for the share of rainy days before the voting weekend. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The individual postvote survey data allow us to distinguish traditional ballot box voters from postal voters, as respondents are asked about their methods of voting. In column (1) we show the results for all voters, irrespective of the voting method; in columns (2) through (5) of Table 4, we estimate separate regressions for the ballot box voters and postal voters. The effect of rain on the propensity of ballot box voters to vote yes is -4 percentage points and roughly three times larger than the point estimate of rain on individuals who vote by mail, which is by itself not statistically significantly different from zero.[13] Instead, postal voters might be affected by rain in the last week before the voting weekend. While our estimates are imprecise, the magnitudes of the estimates from the postvote survey data are consistent with the results from the municipal data. In a further check, we test whether rain affects the

[13]The share of voters voting at the ballot box as indicated by the postvote survey seems to be reliable. In 2005, slightly more than 20 percent voted at the ballot box according to the postvote survey, which is consistent with official estimates (Federal Chancellery, 2005). Unfortunately, this was the only year in which comprehensive administrative data on postal voting was gathered. Note that voters can cast their vote by mail in some communities on the Saturday of the voting weekend (e.g., in the city of Bern) which explains the negative point estimate of rainfall on the voting weekend on mail voters.

probability to observe ballot box voters rather than postal voters on a rainy voting weekend in columns (6) and (7). The results suggest that there is no selection to the ballot box due to rainfall. In conclusion, the results from the two data sets provide strong evidence that the effect of rain is not spurious, but is substantially driven by those voters whose decisions — because of their vote timing — are expected to be most affected by rainfall.

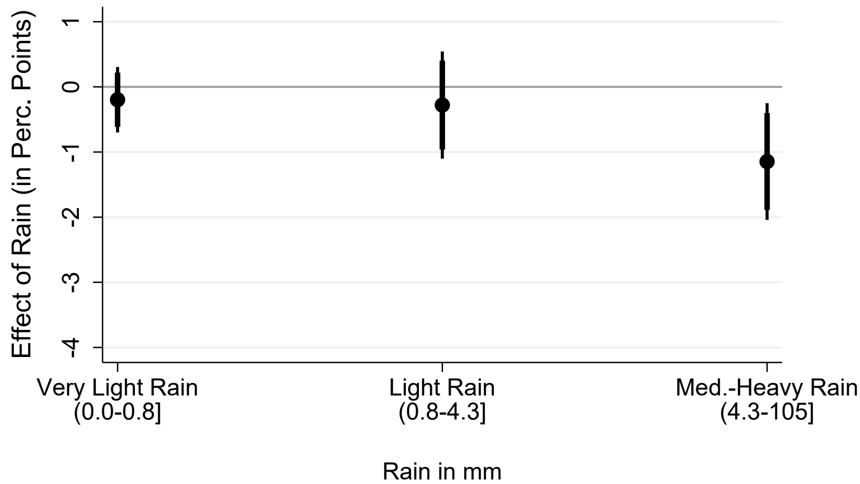
3.3 Alternative Explanations

We focus on two possible alternative explanations, other than emotions, that could drive the effect of rain on support for the status quo. First, we explore whether the effect of rain might operate through a change in the composition of the electorate. A growing literature provides evidence that rain affects turnout by altering the costs of voting (Hansford and Gomez, 2010; Fraga and Hersh, 2011; Lind, 2017; Arnold and Freier, 2016; Fujiwara, Meng and Vogl, 2016). If rain affects the electoral composition by including fewer people who vote for a status quo change, the rain effect could not be interpreted as an emotion effect, but rather as a consequence of a compositional change. We undertake four sets of tests to explore this alternative channel. Second, we study whether rain affects individual information acquisition.

3.3.1 Change in the Electoral Composition: Overall Turnout

In a first set of tests, we examine the relationship between rain and overall turnout. If we regress turnout on an indicator variable for rain on the voting weekend, municipality fixed effects, proposition fixed effects and municipal time trends, we obtain a coefficient of the rain indicator of -0.34 with a standard error of 0.28. We also find no statistically significant effect of rain on turnout in the postvote survey data, the estimate being +0.37 with a standard error of 1.53. These results are robust to using standard errors clustered at the cantonal level, the voting weekend level or at the municipality$\times$vote weekend level. The coefficients are statistically insignificant across the board and the standard errors are smallest when clustering at the cantonal level.

Figure 4: Flexible Relationship Between Rain in Terciles and Turnout in Percentage Points, Municipal Data



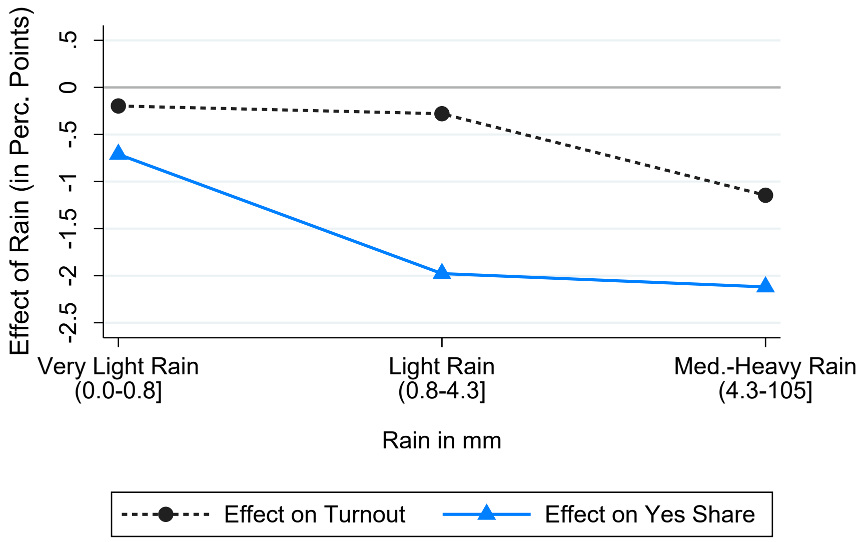
Note: The figure shows coefficient estimates for the effect of rain on turnout in percentage points together with a 95% confidence interval (thin line) and a 90% confidence interval (thick line) using municipal data. The point estimates come from a regression of turnout on indicator variables for terciles of rainfall while controlling for municipality fixed effects, proposal fixed effects and municipal time trends. The reference category is zero rainfall.

Several reasons may account for the arguably small effect of rain on turnout. With few exceptions, all municipalities have their own ballot boxes which translates into short travel distances. This is in contrast to the US context where polling stations tend to be far away. In addition, polling stations are usually well organized and queues outside the polling station are very rare.

Previous research has pointed out that the effect of rain on turnout might not be uniform with heavy rain having the most detrimental effect on voters' probability of going to the polls. To explore this, we estimate our main equation for turnout by using three dummies for the different terciles of rainfall. Figure 4 shows the results of this regression. The effect of rain on turnout is only statistically significantly different from zero for medium to heavy rainfall. This effect is driven by the highest quintile of rainfall.

In stark contrast, the effect of rain on the share of yes votes is negative and statistically significant even for very low levels of rainfall. Figure 5 compares the results for both turnout and the propensity to vote yes in percentage points. The figure indicates that low levels of rainfall do not depress turnout but still decrease the yes share. At least at low and medium levels of rain, the effect on the yes share seems not to be driven by changes in aggregate turnout due to rainfall.

Figure 5: Effect of Rain on Turnout vs. Effect of Rain on the Share of Yes Votes, Municipal Data



Note: The figure shows coefficient estimates for the effect of rain on turnout in percentage points (black dots) and on the yes share in percentage points (blue triangles) using municipal data. The dots are retrieved from regression model (4) in Table 1 using turnout or the yes share as dependent variable and with indicator variables for terciles of rainfall instead of one indicator. The reference category is zero rainfall.

3.3.2 Change in the Electoral Composition: Heterogenous Turnout Reactions

In our second set of tests, we explore the possible unequal impact of rain on turnout for different groups of voters. Even if rain has no effect on aggregate turnout, it might be that rain affects voting outcomes via turnout if turnout reactions are heterogeneous across groups in the population. Consider, for instance, a situation in which leftist voters with a high propensity to vote yes abstain on rainy days, while rightist voters with a low propensity to vote yes are motivated to go to the polls if it rains. If the positive and negative effect are similar in absolute terms and both groups are of similar size, aggregate turnout does not change, but rain affects voting outcomes purely by changing the electoral composition.

Turnout Reaction According to the Propensity to Vote Yes — The main worry is that voters with a lower likelihood to vote yes select to the ballot box on rainy days. To test this possibility, we estimate propensity scores in a linear probability model for the likelihood to vote yes. We include an extensive set of covariates: dummies for age, gender, household income, university degree, knowledge about the proposition, participation in past votes, party preference, and ideology. Then, we partition the sample into groups according to their predicted propensity to vote yes. Table 5 shows turnout reactions for individuals above and below the median of predicted individual yes share (columns (1) and (2)) and for terciles (columns (3) to (5)). The effect of rain on turnout across all groups is not statistically significant and relatively small.[14] If anything, the estimates suggest that individuals with the lowest likelihood to vote yes are more likely to *abstain* from voting on rainy days which means that any turnout effect would imply an *increase* rather than a decrease of the yes vote share on rainy voting weekends.

Turnout Reaction According to Socio-demographics and Political Preferences — Partitioning the sample with regard to covariates supports the conclusion of no systematic compositional changes in the case of rain. Appendix Tables E.4 to E.6 report the turnout reaction for different subsamples of voters conditional on party preferences, ideology, socio-demographics, past turnout, and knowledge about the propositions. None of the point estimates are statistically significantly different from zero.[15] If anything, the absolute size of the coefficient estimates indicates that voters with a high propensity to cast a no vote are more likely to abstain if it rains. This compositional change would bias the main effect against our findings because it would lead to a positive rather than a negative effect of rain on the share of yes votes. For instance, right-wing voters, with a 10 percentage points lower likelihood to vote yes than left-wing voters, show a lower propensity to vote on a rainy voting weekend.

[14] A similar picture emerges if we split the municipal level data into terciles according to the average yes share. Note that if we cluster on the municipal level, the standard errors are similarly sized (see the notes to Table 5 for the exact sizes).

[15] The estimates are all statistically insignificant also when clustering on municipal level.

Table 5: Effect of Rain on Turnout Conditional on the Propensity to Vote Yes

Dependent Variable	Turnout {0,100}				
	Median Split		Terciles Split		
	Status Quo	Reformist	Status Quo	Swing	Reformist
Median Pred. Yes Share:	33%	50%	33%	40%	50%
Avg. Turnout:	51%	70%	46%	63%	72%
	(1)	(2)	(3)	(4)	(5)
Rain Indicator	0.11	0.00	-1.70	0.96	0.55
	(1.79)	(1.77)	(1.97)	(2.46)	(1.60)
Vote Weekend FE	X	X	X	X	X
Municipality FE	X	X	X	X	X
Observations	11,223	11,222	7,482	7,482	7,481
Clusters	26	26	26	26	26
R–squared	0.17	0.18	0.21	0.24	0.23

Note: The table shows the estimated effect of rain on the propensity to vote conditional on the estimated propensity to vote yes in percentage points using OLS. The propensity to vote yes was predicted based on a linear probability model with a full set of dummies for year of age, gender, household income, university degree, knowledge, participation in past votes, party affiliation, ideology, and dummies for missing values (the R-squared is 0.07). The resulting propensities were used to partition at the median (columns (1) and (2)) or into terciles of the likelihood to vote yes (columns (3) to (5)). The average predicted propensity to vote yes is 46%. Standard errors (in parentheses) are clustered at the cantonal level. Standard errors clustered at the municipal level are 2.03 in specification (1) (1,429 clusters), 1.67 (2) (1,396 clusters), 2.50 (1,305 clusters) (3), 2.39 (4) (1,277 clusters), and 2.08 (5) (1,244 clusters) which means all coefficient estimates are statistically insignificant at conventional levels also when clustering at the municipal level. The rain indicator is 1 for all rainy voting weekends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

There are weak indications that the same kind of effect might play a role for low-income individuals, women, voters who vote less regularly, and voters with a high level of political knowledge.

Simulation of the Overall Compositional Effects of Rain — To assess the aggregate quantitative relevance of potential heterogeneous reactions to rainfall, we simulate the compositional effects of rain. Appendix E shows these and additional results we refer to below.

In a first step, we use turnout differences across groups derived from the above variables, weight them according to group size and multiply them with the average yes share of the particular group. This allows us to predict the yes share for each group under rainfall corrected for compositional changes. We do the same computation for voting weekends with no rainfall. The comparison of the predicted yes shares allows us to obtain an estimate for the change in yes votes as a consequence of compositional changes. We then correct our main estimate for the effect of rain on the propensity to vote yes for this composition effect. We find that the corrected estimates are very similar to the baseline estimates. Accordingly, compositional changes seem unlikely to drive our main effect of rain on the support for change.[16]

The reason why compositional changes have a negligible impact on vote outcomes are twofold. First, the potential turnout reactions are relatively small and thus alter the electoral composition only to a limited extent.[17] Second, preferences for change are not too different across groups based on covariates.[18]

In an additional check using individual level data, we examine whether rain is balanced across covariates in the voter sample. Strong relationships between rain and the covariates could indicate a violation of the random assignment of rainfall. However, across all estimates, we do not find statistically significant relationships between the covariates and rainfall.

Turnout Reaction According to Willingness to Take Risks — Could it be that risk averse individuals are more likely to turn out when it rains, while risk affine individuals are less likely to turn out? In a first check, we exploit information on the willingness to take risks based on the responses to a corresponding survey question on a scale from 0 ("not at all willing to take risks") to 10 ("very willing to take risks") using data from the Swiss Household

[16]One concern may be that voters react differently depending on whether their party considers a proposition important. However, when we correlate survey data on the importance of propositions as perceived by left- and right-wing voters, we see that a one point higher perceived importance for left-wing voters relates to a 0.9 point higher perceived importance for right-wing voters. Moreover, we do not see a relationship between how important left- or right wing voters perceive a proposition and their propensity to vote yes.

[17]Note that voters with a low level of political knowledge gain the most weight in the electorate from 44.7% on days with no rain to 46.2% on rainy days.

[18]The highest spread in preferences for change is between individuals who said they have a left-wing ideology (55% yes share) and those who identify with no particular ideology (40% yes share).

Panel.[19] We regress the reported willingness to take risks on dummies for each year of age, gender, and an indicator for high education, that is, characteristics which have been shown to be the most relevant predictors for willingness to take risks (Dohmen et al., 2010).[20] In the Swiss Household Panel, these covariates explain 7 percent of the variation. Using the coefficients of the relationship between willingness to take risks and socio-demographics from the Swiss Household Panel, we then predict the willingness to take risks in the VoxIt data. The result is a data set that includes the individual predicted willingness to take risks and information about voting behavior, including the propensity to vote yes and turnout.

The combined data on predicted willingness to take risks and turnout allow us to examine whether individuals with a high risk aversion are more likely to vote when it rains. If this were true, differential turnout effects for individuals with different levels of risk aversion could be an alternative explanation for our main findings. Our findings indicate that the estimates for both groups are statistically insignificant. If anything, the results point to a rather higher likelihood of voting on rainy days for individuals with a higher risk affinity.[21] This first check thus suggests that our coefficient estimates of the impact of rain on the likelihood to vote yes are a lower bound.

In a second check, we examine potential differential turnout effects using administrative turnout data combined with aggregated risk data by municipality based on the data on willingness to take risks from the Swiss Household Panel. The results show that the impact of rain on the likelihood to vote is statistically insignificant in both subsets of municipalities independent of the willingness to take risks. These two tests using individual level and aggregate data on risk aversion and turnout thus suggest close to zero effects on turnout for both risk averse and risk affine individuals.

[19]The question individuals answer is: "Are you generally a person who is fully prepared to take risk or do you try to avoid taking risks, if 0 means "avoid taking risks" and 10 means "fully prepared to take risks"?" This questionnaire item is equivalent to the one in the German Socio-Economic Panel, which was, among others, experimentally validated by Dohmen et al. (2011) and Galizzi, Machado and Miniaci (2016).

[20]Consistent with the results in Dohmen et al. (2010), we find that willingness to take risks decreases in age, increases in education and is higher for men.

[21]The estimates are also statistically insignificant if we use terciles instead of the median split.

Turnout Reaction According to Municipal Observables — Similar to the individual level data, we also conduct sample splits with the municipal level data according to party affiliation in the last parliamentary elections, population size, the share of area within the municipality for agricultural use, the share of retirees, labor force participation, and the share of individuals working in the tertiary sector. Across all the sample splits, we do not find sizeable and statistically significant effects of rain on turnout. The largest coefficient is -0.37 with a standard error of 0.29. For the same specifications, we find statistically significant effects of rain on the share of yes votes throughout.

3.3.3 Holding Turnout Fixed and Bounding the Causal Effect

Our third set of tests incorporates proxies for the electoral composition into our main analysis. We start by controlling for turnout in our preferred specification using municipal data. The entries in column (1) of Table 6 suggest that controlling for turnout does not affect the coefficient of rain. It remains statistically significant with a point estimate of -1.3 percentage points. The estimated coefficient remains at -1.3 when we control for turnout deciles, as indicated in column (2). To account for differential mobilization of parties as a consequence of rain, we interact turnout with party vote shares in the last parliamentary elections, both measured at the municipal-level. Moreover, we interact party shares and turnout with the federal party recommendations for the propositions. We do this as voters of a certain party may only be motivated to vote when their party issues a recommendation. The size of this effect may depend on the importance of the proposition, which is why we interact party recommendations with turnout. In addition, we control for the lagged yes share, to account for electoral trends. The results reported in column (3) indicate that a flexible control for electoral composition does not affect the size of the estimated coefficient of rain.

We also re-estimate the main specification using the sample of individual vote data. In column (4) of Table 6, we control for partisan preferences by including dummies indicating a voter's most preferred party. In column (5), we control for ideology captured as dummies based on a left-right scale ranging from 0 to 10. In column (6), we include partisan preferences and ideology jointly. In all three specifications, we control for average turnout in the past and voting method. The effect of rain on the probability of voting yes remains similar in magnitude and statistically significant. In supplementary tests, we document that our results are robust to leaving out specific parties or ideological positions.

Bounding the Coefficient Estimates — While the above checks do not suggest a bias in the coefficient estimates because of selection, we present lower bound estimates in case selection was present. We examine the extent of potential bias using the method proposed by Oster (2019). The estimates suggests that selection would have to be more than 60 times larger than what we capture with the observables for the causal effects to be zero. In sum, the estimated lower bounds of the rain effect are very close to the estimated effect of rain because the selection on unobservables would have to be very large for the true causal effect to be zero.

3.3.4 Information Acquisition

Instead of changing the composition of the electorate, rain might affect voting decisions by altering the type of information sources which citizens use to form an opinion. If it rains, voters may spend more time reading the information booklet that comes with the ballot card instead of watching television. Our data provides us with information about the type of information voters use to gather knowledge about the propositions. The information channels include television, radio, newspapers, and official government leaflets. In a first step, we control for the type of information voters use. The results show that the estimated effect size is very similar to the baseline model with a point estimate of -2.63 percentage points. We also check whether rain has an impact on knowledge about the title of a proposition, which in turn might affect the voting decision. We estimate the effect of rain on the probability that a voter knows the exact title of the proposition for all voters as well as for ballot box voters only. The effect of rain on knowledge is not statistically significant.

Table 6: Robustness of the Rain Effect to Compositional Changes

Dependent Variable	Share of Yes Votes (Municipal Voting Data)			Voted Yes (Individual Voting Data)		
	(1)	(2)	(3)	(4)	(5)	(6)
Rain Indicator	-1.26***	-1.26***	-1.28***	-2.91**	-2.87**	-2.91**
	(0.38)	(0.38)	(0.38)	(1.09)	(1.12)	(1.11)
Turnout	-0.09***		-0.03			
	(0.01)		(0.07)			
Turnout Deciles		X				
Dynamic Partisan Controls			X			
Lagged Yes Share			X			
Preferred Party				X		X
Ideology					X	X
Average Turnout & Method of Voting				X	X	X
Timing FE	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X
Trends or Covariates	X	X	X	X	X	X
Observations	870,175	870,175	829,848	12,970	12,970	12,970
Clusters	26	26	26	26	26	26
R–squared	0.70	0.70	0.70	0.31	0.31	0.32

Note: The table shows the estimated effect of rain on the share of yes votes (columns (1) to (3)) or the propensity to vote yes in percentage points (columns (4) to (6)) using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. In years for which no election data is available, we take those of the nearest election year. Note that we still have missing values for the election results for some municipalities. "Dynamic Partisan Controls" includes party shares in the last election, party shares interacted with turnout, party vote shares interacted with party recommendations, as well as party shares interacted with party recommendations and turnout. Party recommendations are represented by a dummy variable indicating whether a right-wing/center right party (SVP or FDP) issued a recommendation to vote yes. Party shares are represented by the combined vote shares of left-wing/center-left parties (CVP, SP) and right-wing/center-right parties (SVP, FDP). The respective vote shares are then interacted with turnout and party recommendation as indicated. "Lagged Yes Share" is the average yes share on the last voting weekend at the municipal level. "Timing FE" refers to "Proposition No. FE" in the case of municipal data and "Vote Weekend FE" in the case of postvote survey data. When data on individual level covariates is not available, we include dummy variables for missing values of the respective variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4 Relevance of the Rain Effect

The results thus far have established a stable and precisely measured effect of rain on the share of yes votes. One might, however, wonder whether the size of the rain effect is big enough to also affect aggregate vote outcomes. We therefore simulate the impact of rain for all the 420 propositions in our sample on vote majorities. Among these popular votes, 32 exhibit a yes share between 48.8% and 51.2%. We illustrate the results of the simulation showing the propositions for which rainfall could have changed the majority of votes in Figure 6.[22] The blue triangle depicts the predicted outcome if it had rained in all municipalities, the orange circle indicates the predicted outcome if rain had been completely absent across all municipalities. The gray square is the official vote outcome. Among the ten votes for which the popular majority might have changed with different rain conditions are the vote on Switzerland's membership in the European Economic Area in 1992 and one on asylum abuse in 2002.[23]

4 Discussion

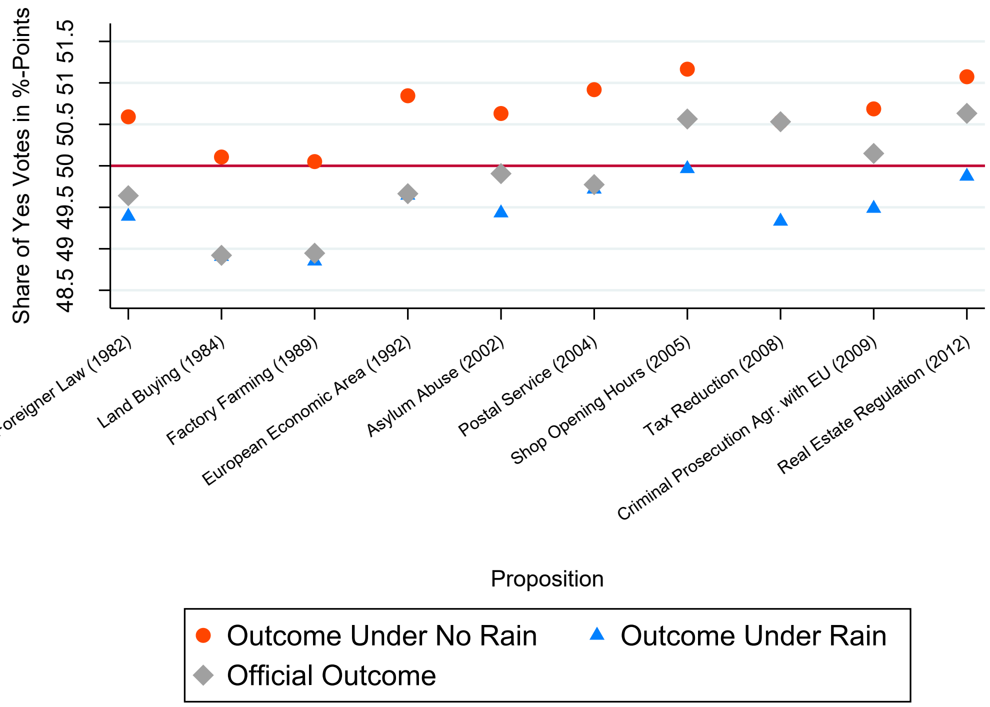
The main analysis provides evidence that the consequences of rain on voting decisions can be interpreted as the effect of emotions. In this section, we explore the psychological mechanism underlying the rain effect, test whether the effect is robust to high-stake situations, examine whether negative emotions may lead specifically to an increase in support for traditionalist conservative positions, and also whether the effect is driven by swing voters.

Psychological Mechanisms — Up to this point our results suggest that incidental emotions, defined as emotions caused by factors that should not be relevant for a particular

[22] The simulated impact on vote majorities serves as an illustration of the impact of rain. In Switzerland, however, initiatives and mandatory referendums only pass if they are approved by a majority of votes as well as by a majority of cantons. If we take this institutional feature into account, we find that seven vote outcomes might have changed.

[23] Regarding the former vote, the controversy on Switzerland's relationship with the European Union would likely be even stronger if a majority of the voters were to have approved the treaty while still failing as the majority of cantons were to be missed.

Figure 6: Simulated Vote Outcomes: Rain Effects on the Popular Majority



Note: The figure depicts all propositions that would have had a different popular majority with and without rain based on our main results. "Outcome Under No Rain" indicates the share of yes votes if there had been no rain on the voting weekend in all municipalities. "Outcome Under Rain" indicates the share of yes votes had there been rain on the voting weekend in all municipalities.

decision context (Lerner et al., 2015), may have an impact on vote choices. A large body of literature in behavioral economics, psychology and medicine has demonstrated that bad weather or long winter nights lead to negative emotions (see, e.g., Lambert et al., 2002; Kamstra, Kramer and Levi, 2003; Hirshleifer and Shumway, 2003; Baylis et al., 2018).[24] Yet, how do these negative emotions affect individual support for the status quo? In our view, the most plausible explanation is a specific version of state dependent preferences.

A prominent characterization of state dependent preferences is projection bias (Loewenstein, O'Donoghue and Rabin, 2003). The main idea is that individuals project their current preferences, which depend on their emotional state, into the future. These projected preferences distort the perception of future payoffs. In particular, the projection bias suggests

[24]In a laboratory experiment, Lerner, Small and Loewenstein (2004) show that incidental disgust affects the size of the endowement effect.

that emotional states have a large effect on decision-making. Important forward-looking decisions, even after careful deliberation, may thus be swayed by contemporaneous emotional cues (Loewenstein, 2000). An example of projection bias is the empirical regularity that a 4WD vehicle looks much more useful on rainy days, while a convertible car offers a higher projected future utility on sunny days (Busse et al., 2015).[25] In our context, voters who are in a negative emotional state caused by rainfall may project this negative state into the future when evaluating the payoffs of a new policy. Note, however, that the theoretical formulation of projection bias does not yield any prediction with respect to exactly how emotions affect the support for the status quo.

A specific psychological mechanism that describes how positive and negative emotions may alter status quo support is subsumed under feelings-as-information (Johnson and Tversky, 1983; Schwarz, 2012). It postulates that individuals become more risk averse if they experience negative emotions. As a consequence, they may evaluate the status quo relatively more favorable. Evidence from laboratory experiments and recent evidence from the field support the claim that individuals act more risk averse if they are unhappy or experience fear (Schwarz, 2012; Haushofer and Fehr, 2014; Callen et al., 2014; Cohn et al., 2015; Meier, 2019). Previous contributions point out that feelings-as-information affects stock market behavior (Hirshleifer and Shumway, 2003; Kamstra, Kramer and Levi, 2003) as well as financial decision making and voting behavior in the laboratory (Bassi, Colacito and Fulghieri, 2013; Bassi, 2019).[26]

Exploring the psychological mechanism that drives the effect of emotions requires data on risk aversion. As the postvote survey data offers no information on risk attitudes, we use the data from the Swiss Household Panel introduced before. This survey contains information on the willingness to take risks from a similar population in the same institutional environment.

[25]For further examples see Conlin, O'Donoghue and Vogelsang (2007), Simonsohn (2010), and Odermatt and Stutzer (2019).

[26]A competing hypothesis to feelings-as-information is the mood maintenance hypothesis. It postulates that individuals become more risk-averse if they experience positive emotions, because they want to preserve their current positive emotional state, and conversely, they are more-risk affine if they experience negative emotions (Isen, 2005).

If feelings-as-information is the reason why emotions affect support for the status quo, we expect that individuals are less willing to take risks on rainy days.

In Table 7, we show the estimates of the rain effect on the dichotomized measure of willingness to take risks (based on a scale ranging from 0 to 10).[27] If the willingness to take risks is larger than the median value of 5, the dependent variable is 100, and zero otherwise.[28] We regress this indicator on a rain indicator that is one if there was rain on the date of the interview in the respective municipality. We find that rain decreases the willingness to take risks by roughly 2.7 percentage points in our preferred specification in column (4) in which we control for month and municipality fixed effects as well as for several covariates including gender, age dummies, income and education dummies. Using the same rainfall terciles as with the municipal-level data, we find that light rain most heavily affects the willingness to take risks. This is consistent with our finding that already light rain substantially negatively affects the yes share. In sum, these findings offer evidence suggesting a causal mechanism whereby rainfall affects risk aversion and consequently makes people more likely to choose the status quo. The additional analyses point to feelings-as-information as being the most plausible psychological mechanism.

High-Stakes Votes — Psychological factors might play no role in high-stakes situations (List, 2003; Levitt and List, 2008). We offer two specific tests of the generality of our main effect. The first test splits the sample of propositions according to turnout and closeness. Columns (1) and (2) of Table 8 report the results for the regressions using above- and below-median turnout. Median turnout in our sample is 42 percentage points. High turnout propositions are arguably those collective decisions that are considered highly important by a large fraction of voters. The results suggest that the rain effect prevails in high-turnout propositions. Additionally, we also show the results of a sample split into close and not close votes. We classify votes as close if the difference between yes and no votes ex-post

[27] For related evidence using data from Southeast Asia, see Liebenehm, Degener and Strobl (2018).

[28] The results remain unchanged if we do not dichotomize the risk attitude measure. Rain on the day of the interview goes together with a statistically significant 0.16 point reduction on the 0 to 10 point Likert-scale conditional on month fixed effects, municipality fixed effects, and covariates (the same specification as in Table 7, column (4)).

Table 7: Effect of Rain on the Willingness to Take Risks, Swiss Household Panel Data (Cross-Section of 2009)

Dependent Variable	Willing to Take Risks {0,100} Avg.: 47.5%			
	(1)	(2)	(3)	(4)
Rain Indicator	-2.14**	-3.75***	-3.17***	-2.70**
	(0.94)	(0.93)	(1.04)	(1.17)
Month FE		X	X	X
Municipality FE			X	X
Covariates				X
Observations	7,233	7,233	7,233	7,233
Clusters	26	26	26	26
R–squared	0.00	0.00	0.01	0.06

Note: The table shows the estimated effect of rain on the propensity to be willing to take risks in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is one if there was any rain on the exact date of the interview in the respective municipality. The mean of the willingness to take risk indicator is 47 percentage points.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is less than 10 percentage points. The results in columns (3) and (4) indicate that rain decreases support for a change from the status quo in both close and not close propositions. Overall, the results sustain that the effect of emotions on support for the status quo extends to important political decisions.

Status Quo vs. Right-Wing Votes — We explore another alternative interpretation of our results, namely that negative emotions increase the support for traditional and conservative propositions. Appendix F provides the results for this and the next paragraph in tabular form. Since change is favored by the left-wing parties in some popular votes and by the right-wing parties in others, we are able to separate the effect of emotions on the support for the status quo from the effect on traditionalist conservative positions.[29] To do

[29] A prominent example for a policy change supported by the right-wing parties was the vote on asylum abuse in 2002, which demanded much stricter standards regarding asylum seekers. In about half of the votes in our sample, the right-wing parties supported a change from the status quo.

Table 8: Sensitivity of the Rain Effect to High Turnout and Close Votes

Dependent Variable	Share of Yes Votes [0,100]			
	High Turnout (1)	Low Turnout (2)	Close Votes (3)	Not Close Votes (4)
Rain Indicator	-1.24***	-1.40**	-1.20**	-1.20**
	(0.36)	(0.58)	(0.46)	(0.46)
Proposition No. FE	X	X	X	X
Municipality FE	X	X	X	X
Municipality Trends	X	X	X	X
Observations	465,484	404,691	296,589	514,047
Clusters	26	26	26	26
R–squared	0.65	0.71	0.54	0.77

Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. High turnout corresponds to above median turnout. Median turnout is 42 percentage points. Close votes correspond to an ex post difference in the share of yes votes of less than 10 percentage points. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

this, we split our sample according to the party recommendations. If emotions increase the likelihood that voters will vote for conservative propositions endorsed by a right-wing party, we expect to find that rain has a positive rather than a negative effect for this subset of propositions. The results suggest that rain decreases the share of yes votes for all the propositions independent of whether they are supported by left- or right-wing parties. Similarly, we do not see heterogeneities in voting behavior depending on whether unions supported a proposition. It seems that emotions affect the support for the status quo in general, rather than the support for specific partisan policies.

Swing Voters — We would expect that citizens with less intense policy preferences, often called swing voters, are particularly affected by emotions.[30] In order to identify swing voters in popular votes, we predict the probability of voting yes for each voter based on his or her individual characteristics with linear probability models. We then separate the electorate

[30]Note that we would expect individuals who are used to rain to react less strongly than individuals who are not usually exposed to rainfall. Indeed, we see that there is a slight differential effect of rain depending on whether municipalities are regularly exposed to heavy rainfall or not. While the effect is -1.32 ($se = 0.34$) in municipalities with below-median average rainfall, it is -1.07 ($se = 0.46$) in municipalities with above-median average rainfall.

into terciles with respect to the predicted propensity to vote yes.[31] We thus have three groups, the status quo voters ($P(\text{Yes}) < 0.44$), the swing voters ($0.44 \leq P(\text{Yes}) \leq 0.53$) and the reformists ($0.53 < P(\text{Yes})$).

For these three groups, we run the main regression without covariates. The results suggest that the swing voters are the ones who are substantially less likely to cast a yes vote if it rains, while there are no statistically significant effects on the other two groups. Consistent with this, we see the largest absolute effect of rain on vote outcomes within municipalities that are in the middle tercile with respect to their average share of yes votes.[32]

5 Conclusion

This study provides real-world evidence on the relationship between emotions and preferences for the status quo. We use exogenous variation in rainfall to show that individuals who experience negative emotions are 1.2 percentage points less likely vote for change. We explore several mechanisms. Our findings are most consistent with a theory of feelings-as-information; that is, the notion that negative emotions lead to less optimistic judgments (Schwarz, 2012).

The societal consequences of emotional choices can be substantial. Our simulation indicates that emotions not just alter individual voting behavior, but may also sway aggregate vote outcomes. A notable example is the referendum on Switzerland's membership in the European Economic Area in 1992. This proposition was rejected by a narrow margin of voters on a rainy weekend. Our results suggest that the popular majority might well have been swayed by positive emotions in case of good weather (with the proposition nonetheless being rejected due to a missed majority of cantons).

These findings suggest that citizens are well advised to take important decisions on separate days. Even if the decision maker were aware of the possibility of being influenced by rainfall, it might be difficult to alleviate the effect of emotions on behavior (Loewenstein,

[31] The split into terciles seems reasonable on substantive grounds: In the 1995 parliamentary elections, the share of swing voters was estimated to be around 33% (Lutz, 2012).

[32] We do not see statistically significant heterogeneity in turnout because of rainfall across these groups at the individual or at the municipal-level. The largest absolute effect on turnout is +0.92 ($se = 3.18$) among individuals we define as swing voters and -0.45 ($se = 0.28$) in municipalities which are most likely to vote for the status quo.

2000). The impact of weather on voting outcomes also has implications for the agenda-setting power of governments. Anecdotal evidence suggests that the Scottish independence vote was intentionally scheduled to a date with a pleasant weather forecast (Sayers, 2014).

The impact of emotions on the tendency to choose the status quo likely extends beyond the domain of voting behavior. Kahneman, Knetsch and Thaler (1991) have pointed out that the status quo effect is a well-known phenomenon in financial and insurance markets as well as in other domains. Thus far, we have a very limited understanding of how emotions affect the choice between change and the status quo in decision-making with respect to household finances, health, education and labor supply (see, e.g., Haushofer and Fehr, 2014). Exploring the impact of emotions in these domains appears to be a fruitful area for future research.

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Rain, Emotions and Voting for the Status Quo

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Online Appendix

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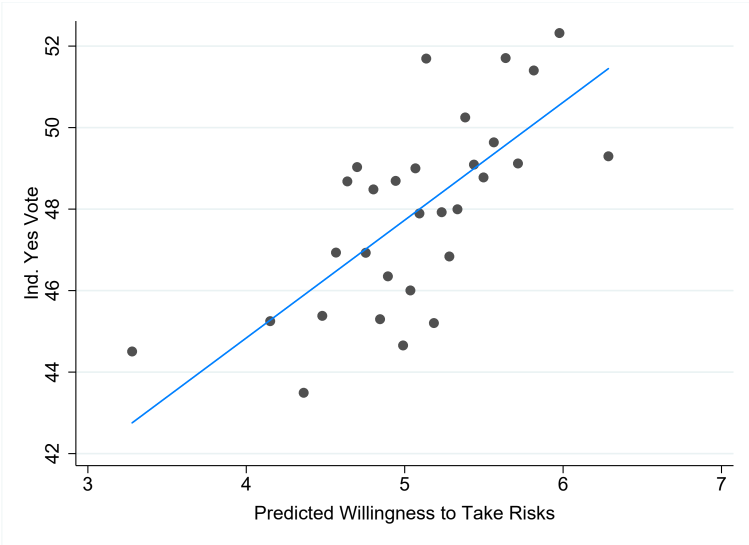
A Willingness to Take Risks and Voting

Figure A.1 shows the bivariate relationship between predicted individual willingness to take risks and the likelihood to vote yes.

Figure A.1: Predicted Willingness to Take Risks and the Propensity to Vote Yes



Note: The figure shows the relationship between predicted individual willingness to take risks and the likelihood to vote yes. We construct the figure as follows: We first regress willingness to take risks on years of age dummies, an indicator for gender, and an indicator for university degree (which we set to 0 if the information is missing in the voting data) using the data from the Swiss Household Panel. Then, we use the coefficient estimates based on the data from the Swiss Household Panel to predict the willingness to take risks in the VoxIt data where we know individual voting behavior. The figure shows the likelihood to vote yes plotted against the willingness to take risks using 40 binned averages, the grey dots, and a linear regression fit, the blue line. A regression of voting yes or no on willingness to take risks indicates that a 1-point change in willingness to take risks relates to a 2.8-points change ($se = 0.45$) in the the propensity to vote yes.

B Data and Descriptive Statistics

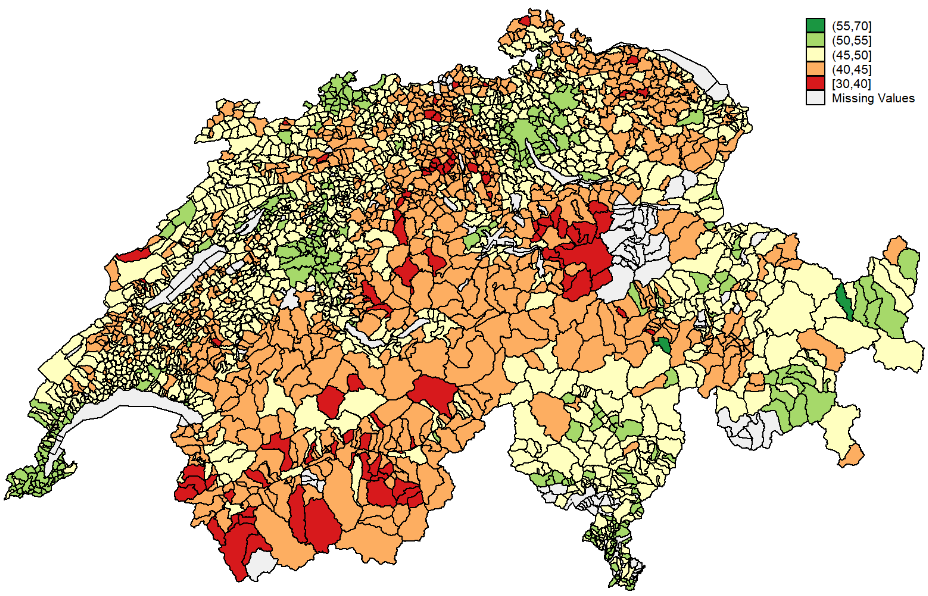
Table B.1 provides summary statistics for the main variables of both the municipal voting and the postvote survey data sets. Figure B.1 documents the average yes vote shares across municipalities in a map. Figure B.2 provides a map of the location of the 116 automated meteorological stations. Figures B.3, B.4, B.5, and B.6 provide an illustration of the temporal and spatial variation in rainfall.

Table B.1: Summary Statistics

Data	Municipal Voting Data 1958–2014				Postvote Survey Data 1996–2006†			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Yes Share in %-Points	46.20	14.49	0	100	47.93	36.91	0	100
Rain Indicator	0.55	0.49	0	1	0.68	0.47	0	1
Rain in mm	2.67	5.76	0	104.50	4.77	7.42	0	99.30
Turnout	43.59	13.21	0.16	100				
Postal Voting Dummy	0.49	0.49	0	1				
Ballot Box Voters					0.39	0.49	0	1
Mail Voters					0.61	0.49	0	1
Observations	870,175				12,970			

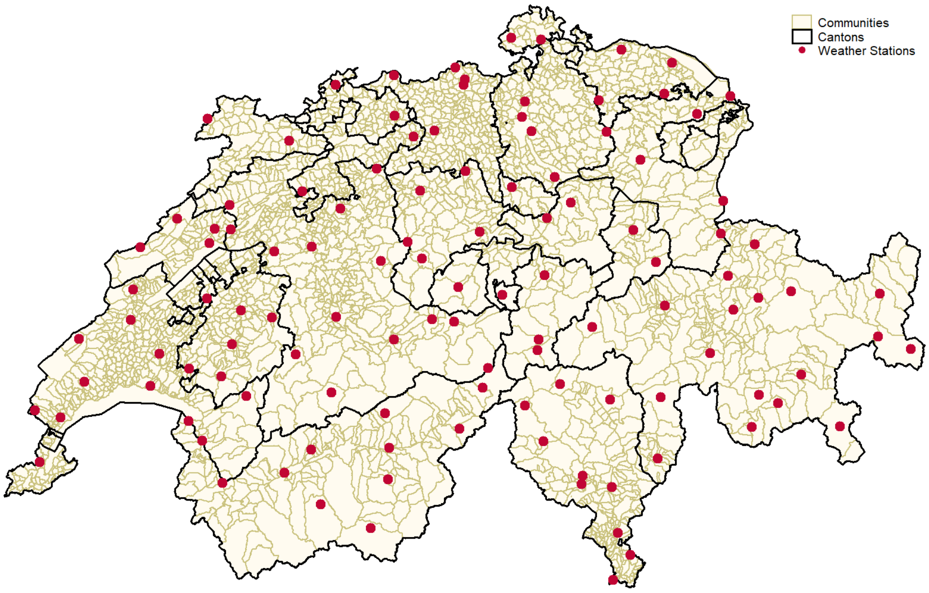
Note: †There is no municipal identifier available for the year 1997, and the data from the corresponding year is therefore not used.

Figure B.1: Map of the Share of Yes Votes



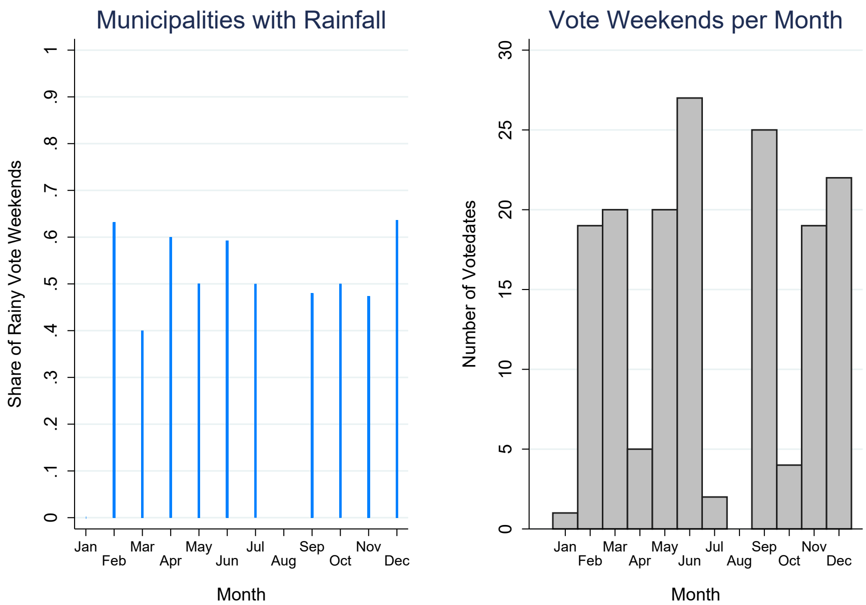
Note: The figure shows the average share of yes votes by municipality.

Figure B.2: Map of Weather Stations



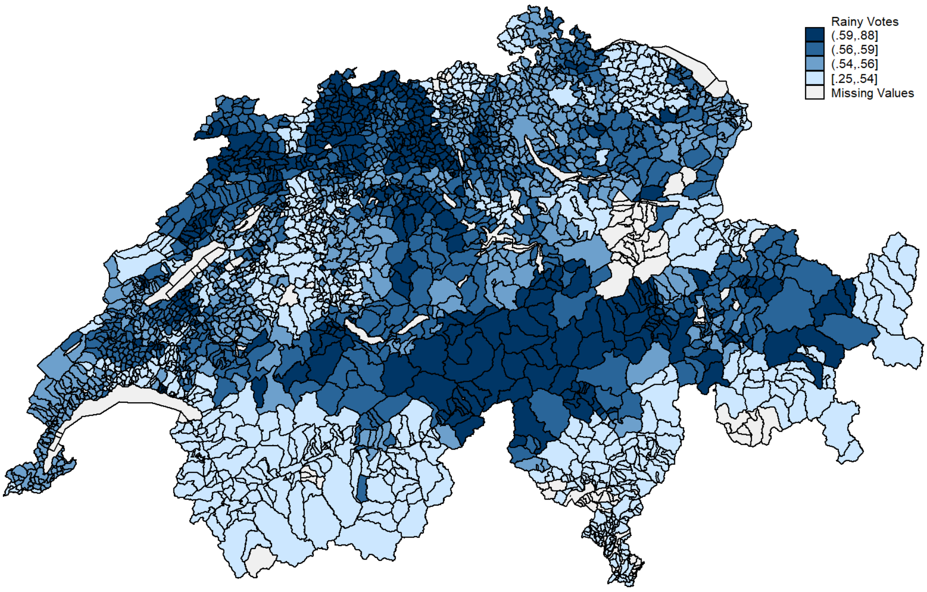
Note: The figure shows the weather stations we use for our analysis.

Figure B.3: Distribution of Votes and Rain over Months



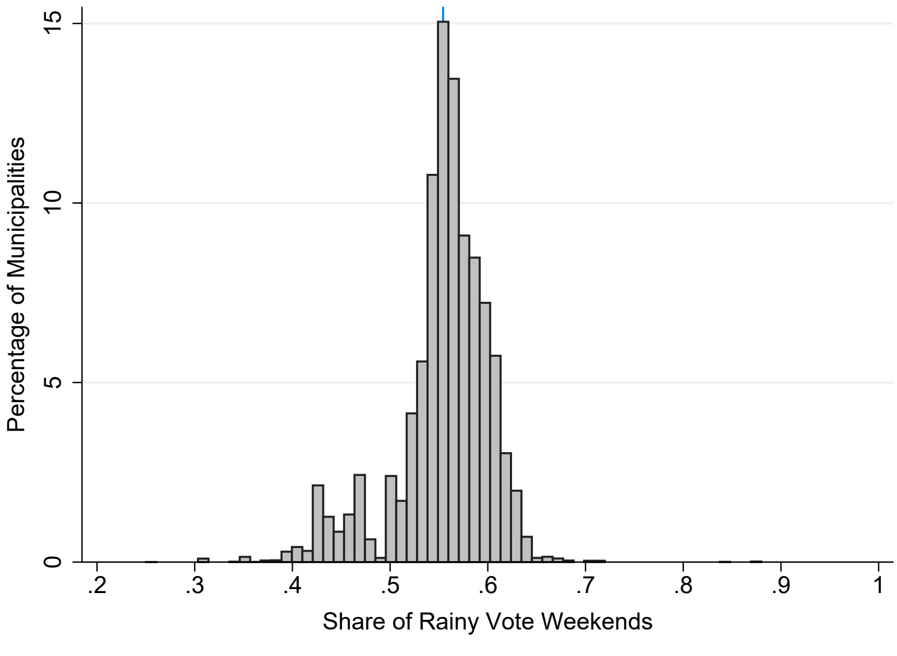
Note: The graphs show the distribution of voting weekends over months and the share of communities with rainy voting weekends by month.

Figure B.4: Map of the Share of Rainy Voting Weekends



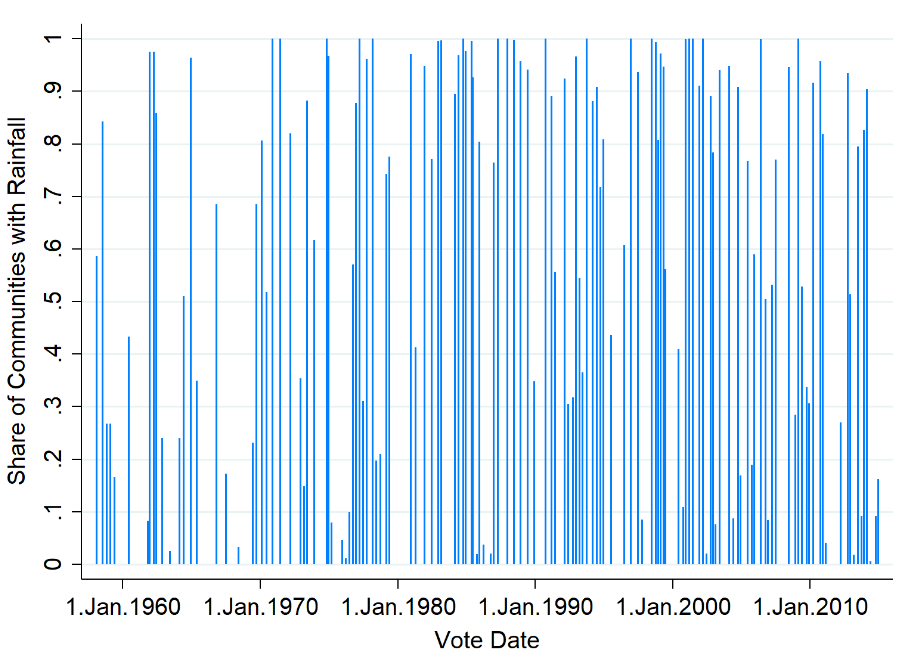
Note: The figure shows the share of rainy voting weekends. Note that the clusters with the high share of rainy weekends lie in the Alps and over the Jura mountains.

Figure B.5: Distribution of the Share of Rainy Voting Weekends over Municipalities



Note: The blue line indicates the average share of rainy voting weekends which is 55%.

Figure B.6: Share of Communities with Rainfall by Date



Note: The figure shows the share of communities with rainfall for each voting weekend.

C Econometric Model for Individual Voting Decisions

As with the municipal data, we estimate the effect of rain on the propensity of an individual to vote yes using the postvote survey data. We use the following specification:

$$Y_{ijw} = \eta_j + \delta_w + \alpha \, \mathrm{Rain}_{jw} + X'_{ijw}\beta + \varepsilon_{ijw},$$

where i indexes voters, j indexes municipalities and w indexes voting weekends; η_j is a municipal fixed effect; δ_w is a vote weekend fixed effect; Rain_{jw} is a dummy that captures rain in municipality j when voters vote on voting weekend w; X'_{ijw} is a vector of individual-level covariates; ε_{ijw} is an idiosyncratic error term. In the specifications with the survey data, we use the share of yes votes cast by an individual on the voting weekend as the main dependent variable. Accordingly, we have one observation for each voting weekend. In our baseline specification, we include dummies capturing the following covariates: gender (1 dummy), year of age (80 dummies), income categories for household income (5 dummies), and holding a university degree (2 dummies, one for 25 missing values). We replace missing income with the modal income category, which refers to the category of income between \$5,000 and \$7,000.

D Functional Form

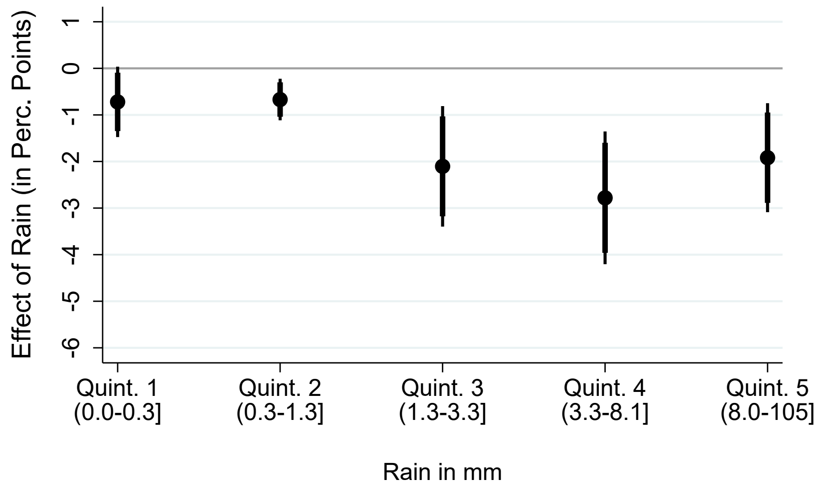
This section explores potential non-linearities in the relationship between rain and vote outcomes. Table D.1 presents the results of regressing vote outcomes on a continuous variable of rainfall (in mm) and when using a dummy variable that is one only on vote weekends with substantial rainfall. Figure D.1 complements Figure 2 in the main text by using rainfall quintiles instead of terciles. Figure D.2 shows the effect of terciles of rainfall on the share of yes votes in the postvote survey data. Figure D.3 reports the effect of rain on the willingness to take risks using terciles of rain. We also show a plot of the residual yes vote share on the municipal level against rainfall residuals in Figure D.4.

Table D.1: Effect of Rain on the Share of Yes Votes in Percentage Points, Functional Form

Dependent Variable	Share of Yes Votes [0,100] Avg.: 47%					
	(1)	(2)	(3)	(4)	(5)	(6)
Rain Indicator	-1.23***		-1.12***			
	(0.38)		(0.37)			
Rain in mm		-0.07***	-0.06***			
		(0.02)	(0.01)			
Above Median Rain				-1.83***		
				(0.45)		
Very Light Rain, (0.0-0.8]					-0.71**	
					(0.29)	
Light Rain, (0.8-4.3]					-1.98***	
					(0.54)	
Med.-Heavy Rain, (4.3-105]					-2.12***	
					(0.58)	
Quint. 1, (0.0-0.3]						-0.72*
						(0.37)
Quint. 2, (0.3-1.3]						-0.67***
						(0.22)
Quint. 3, (1.3-3.3]						-2.10***
						(0.63)
Quint. 4, (3.3-8.1]						-2.78***
						(0.70)
Quint. 5, (8.0-105]						-1.92***
						(0.57)
Proposition No. FE	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X
Municipal Trends	X	X	X	X	X	X
Observations	870,175	870,175	870,175	870,175	870,175	870,175
Clusters	26	26	26	26	26	26
R–squared	0.70	0.70	0.70	0.70	0.70	0.70

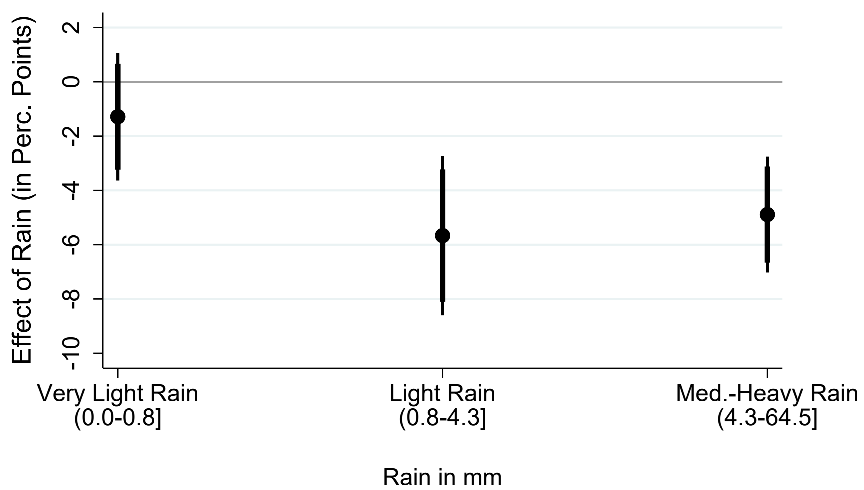
Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS. Above Median Rain is 1 if there was more than above median rainfall (conditional on any rain) on the vote weekend or 2.09 mm. Standard errors (in parentheses) are clustered at the cantonal level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure D.1: Flexible Relationship Between Rain in Quintiles and Share of Yes Votes in Percentage Points, Municipal Data



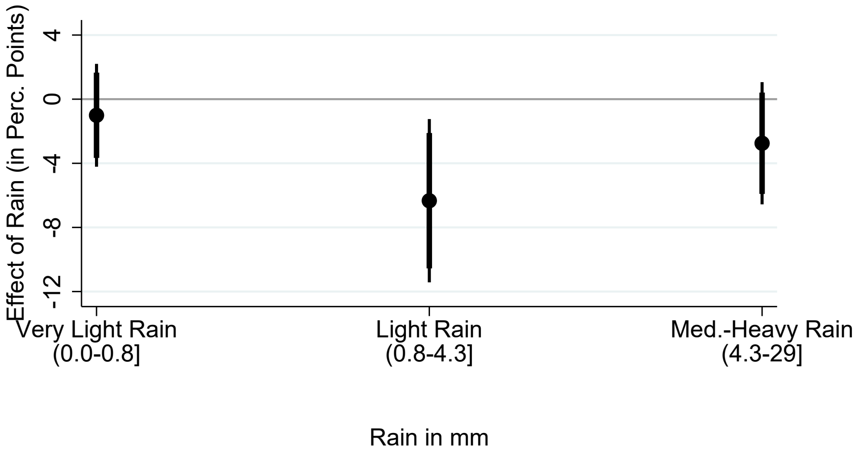
Note: The figure shows coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the share of yes votes in percentage points using municipal data. The dots are retreived from regression model (4) in Table 2 with indicator variables for the five quintiles of rainfall instead of one indicator. The reference category is zero rainfall.

Figure D.2: Flexible Relationship Between Rain in Terciles and Share of Yes Votes in Percentage Points, Postvote Survey Data



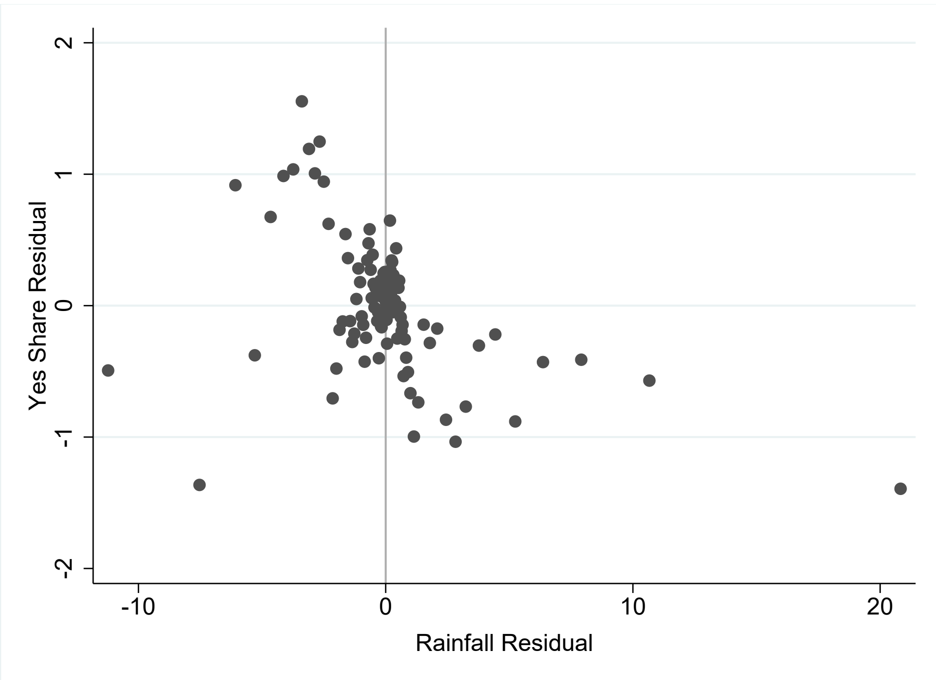
Note: The figure shows coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the share of yes votes in percentage points using postvote survey data. The reference category is zero rainfall.

Figure D.3: Flexible Relationship Between Rain in Terciles and the Willingness to Take Risks



Note: The figure shows coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the probability that an individual is willing to take risks based on data from the Swiss Household Panel. The reference category is zero rainfall.

Figure D.4: Residual in the Share of Yes Votes and Rainfall in mm



Note: The figure shows a scatterplot of the share of yes votes residuals (in bins) against the rainfall residuals (also in bins) conditional on all fixed effects and municipal trends (column 4, Table 1). The grey dots indicate 40 binned averages. The light grey line indicates residual rainfall of zero.

E Robustness Tests

In this section, we present several robustness tests that explore the sensitivity of our main results to alternative specifications, measures, and explanations. For example, we present results which indicate no differential selection to the ballot when it rains (Tables E.4 through E.6), no differential information gathering when voters are suspect to rain (Table E.14), and we bound the effect estimates in case of potential selection (Table E.13).

E.1 Fixed Effects, Standard Errors, and the Definition of the Rain Variable

Table E.1 reports the results of specifications with cubic trends, municipal-month, and municipal-year fixed effects. Table E.2 demonstrates that the coefficient of rain is also statistically significant when we use standard errors clustered on the voting weekend or the vote weekend×municipal level. Table E.3 estimates the effect of rain on the share of yes votes by focusing only on close meteorological stations.

Table E.1: Effect of Rain on the Share of Yes Votes in Percentage Points, Variants of Fixed Effects

Dependent Variable	Share of Yes Votes [0,100]			
	(1)	(2)	(3)	(4)
Rain Indicator	-1.24***	-1.26***	-1.19***	-1.30***
	(0.39)	(0.41)	(0.37)	(0.42)
Proposition No. FE	X	X	X	X
Municipality FE	X	X		
Municipality Trends	X	X	X	
Municipality Trends Quadratic	X	X		
Municipality Trends Cubic		X		
Municipality × Month FE			X	
Municipality × Year FE				X
Observations	870,175	870,175	870,175	870,175
Clusters	26	26	26	26
R–squared	0.71	0.71	0.72	0.80

Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. Mun. is a shorthand for municipality. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Effect of Rain on the Share of Yes Votes in Percentage Points, Clustering of Standard Errors

	Municipal Level						Individual Level					
Dependent Variable	Share of Yes Votes [0,100]			Turnout [0,100]			Voted Yes {0,100}			Turnout Ind. {0,100}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rain Indicator	-1.23***	-1.23***	-1.23***	-0.34	-0.34	-0.34	-2.85**	-2.85*	-2.85*	0.37	0.37	0.37
	(0.38)	(0.40)	(0.40)	(0.28)	(0.31)	(0.31)	(1.06)	(1.43)	(1.43)	(1.53)	(1.99)	(1.91)
Clustering:												
Canton	X			X			X			X		
Vote Weekend		X			X			X			X	
Mun. $\times$ Vote Weekend			X			X			X			X
Cluster No.	26	164	164×2,538	26	164	164×2,538	26	22	22×1,355	26	22	22×1,355
Proposal FE	X	X	X	X	X	X						
Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Trends	X	X	X	X	X	X						
Covariates							X	X	X	X	X	X
Observations	870,175	870,175	870,175	870,175	870,175	870,175	12,970	12,970	12,970	22,750	22,750	22,750
R–squared	0.70	0.70	0.70	0.70	0.70	0.70	0.29	0.29	0.29	0.18	0.18	0.18

Note: The table shows the estimated effect of rain on the share of yes votes (columns (1) to (3)), municipal level turnout (columns (4) to (6)), the propensity to vote yes (columns (7) to (9)), and individual level turnout (columns (10) to (12)) in percentage points using OLS. Standard errors (in parentheses) are clustered as indicated. "Community×Vote Weekend" means that clustering is allowed in both dimensions, that is, it allows for two-way clustering as specified by (Cameron, Gelbach and Miller, 2011). Note that rain is strongly spacially correlated but shows very low correlation over time, which mirrors the low sensitivity to two-way clustering on municipal×vote weekend. The rain indicator is 1 for all rainy voting weekends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.3: Effect of Rain on the Share of Yes Votes in Percentage Points, Distance to Stations

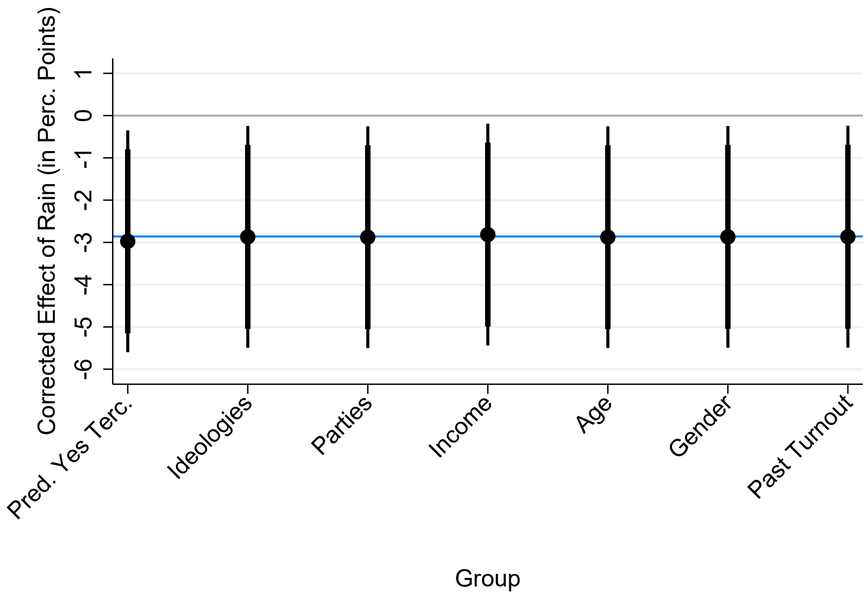
Dependent Variable	Share of Yes Votes [0,100]			
	Interpolated Rain		Closest Station Rain	
Distance to Closest Station:	$< 5,000m$	$< 10,000m$	$< 5,000m$	$< 10,000m$
	(1)	(2)	(3)	(4)
Rain Indicator	-1.04***	-1.07***		
	(0.24)	(0.25)		
Rain Indicator Closest St.			-1.41***	-1.44***
			(0.37)	(0.37)
Proposition No. FE	X	X	X	X
Municipality FE	X	X	X	X
Municipality Trends	X	X	X	X
Observations	156,404	441,768	153,818	432,677
Clusters	24	26	24	26
R–squared	0.72	0.72	0.72	0.72

Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS depending on the distance to closest weather station and on whether the interpolated rainfall or the rainfall at the closest station is used. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E.2 Turnout and the Composition of the Electorate

The tables and figures in this section show the sensitivity of the coefficient estimates when simulating the impact of turnout reactions of certain groups (e.g., Figure E.1), to dropping certain groups from the sample (such as voters according to their decile of predicted likelihood to vote yes, Figure E.2), the differential functional form relationship between rain and turnout and rain and voting for the status quo (e.g., Figure E.6), as well as the impact of rain across different types of voters and municipalities.

Figure E.1: Selection Corrected Coefficients, Postvote Survey Data



Note: The figure shows turnout corrected coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the share of yes votes in percentage points with postvote survey data. The baseline estimate is shown with the blue solid line. The depicted coefficients are corrected by heterogeneous selection within groups of voters, for instance conditional on their past turnout behavior. Distant voters are less likely to vote if it rains and are more likely to vote no — the opposite holds true for more frequent voters. Accordingly the coefficient estimate is slightly adjusted downwards, since we likely underestimate the true rain effect.

Table E.4: Effect of Rain on Turnout in Percentage Points by Party and by Ideology, Postvote Survey Data 1996–2006

Dependent Variable	Turnout {0,100}					
	Left P.	Right P.	Missing P.	Left I.	Right I.	Missing I.
Mean Yes Share	54%	45%	46%	55%	46%	40%
Avg. Turnout	71%	71%	53%	68%	64%	41%
	(1)	(2)	(3)	(4)	(5)	(6)
Rain Indicator	0.60	-1.72	0.68	-0.85	-1.89	-0.12
	(3.37)	(2.94)	(1.47)	(3.25)	(1.96)	(3.71)
Vote Weekend FE	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X
Covariates	X	X	X	X	X	X
Observations	5,343	4,646	12,761	5,350	13,392	4,008
Clusters	26	26	26	26	26	26
R–squared	0.30	0.47	0.23	0.31	0.22	0.38

Note: The table shows the estimated effect of rain on the propensity to vote in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. We categorize voters as preferring left-wing (left p.) or right-wing parties (right p.) according to their surveyed preferences over 17 parties. The major left-wing/center-left parties are SP and CVP, while the major right-wing/center-right parties are FDP and SVP. All individuals with missing values or no indication of preferences towards a specific party are characterized as "Missing P". "Left I." and "Right I." are based on a left-right scale where individuals can position themselves on a scale from 0, radical left-wing, to 10, radical right-wing. We categorize individuals with a value from 5 to 10 as having a right-wing ideology (Right I.) and those with values from 0 to 4 as having a left-wing ideology (Left I.). Missing values on the left-right scale are denoted as "Missing I." Average turnout: 60.9%, maximum number of observations containing turnout: 22,750. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.5: Effect of Rain on Turnout in Percentage Points by Sociodemographics, Postvote Survey Data 1996–2006

Dependent Variable	Turnout {0,100}								
	Inc. 1	Inc. 2	Inc. 3	Inc. 4	Inc. 5	Older	Younger	Male	Female
Mean Yes Share	45%	46%	47%	51%	54%	47%	48%	48%	48%
Avg. Turnout	53%	57%	62%	65%	71%	52%	70%	59%	63%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rain Indicator	1.79	2.36	0.88	-1.91	0.68	-0.78	1.83	-1.04	1.99
	(3.72)	(3.36)	(1.94)	(4.42)	(2.86)	(1.93)	(2.31)	(1.72)	(2.46)
Vote Weekend FE	X	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X	X
Covariates	X	X	X	X	X	X	X	X	X
Observations	2,663	5,583	8,859	3,045	2,600	11,820	10,930	11,199	11,551
Clusters	26	26	26	26	26	26	26	26	26
R–squared	0.41	0.33	0.27	0.42	0.45	0.22	0.26	0.22	0.21

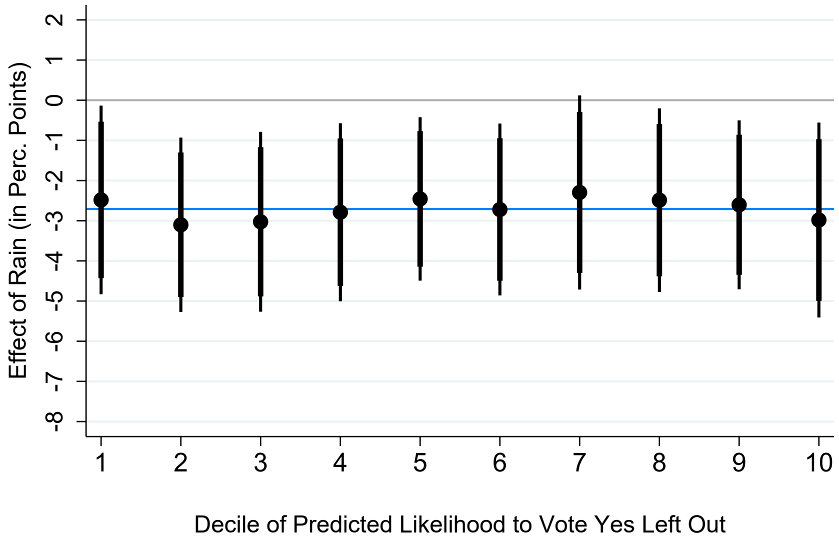
Note: The table shows the estimated effect of rain on the propensity to vote in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. Average turnout: 60.9%, maximum number of observations containing turnout: 22,750. “Inc. 1” means that the household income is lower than \$3,000, “Inc. 2” corresponds to household inc. between \$3,000 and \$5,000, “Inc. 3” to income between \$5,000 and \$7,000, “Inc. 4” between \$7,000 and \$9,000 and “Inc. 5” to income over \$ 9,000 which is the categories provided in the survey data. Missing income was replaced by modal income category “Inc. 3”. “Older” is one if an individual is older than the median age, which is 46. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.6: Effect of Rain on Turnout in Percentage Points by Past Turnout and Knowledge, Postvote Survey Data 1996–2006

Dependent Variable	Turnout {0,100}				
	Rare V.	Marginal V.	Frequent V.	Little Knowl.	Much Knowl.
Mean Yes Share	39%	46%	49%	46%	50%
Avg. Turnout	12%	53%	91%	49%	77%
	(1)	(2)	(3)	(4)	(5)
Rain Indicator	0.55	-1.71	-0.16	1.80	-1.48
	(1.64)	(3.02)	(1.77)	(2.01)	(1.88)
Vote Weekend FE	X	X	X	X	X
Municipality FE	X	X	X	X	X
Covariates	X	X	X	X	X
Observations	4,434	7,931	9,773	13,060	9,690
Clusters	26	26	26	26	26
R–squared	0.31	0.26	0.21	0.24	0.23

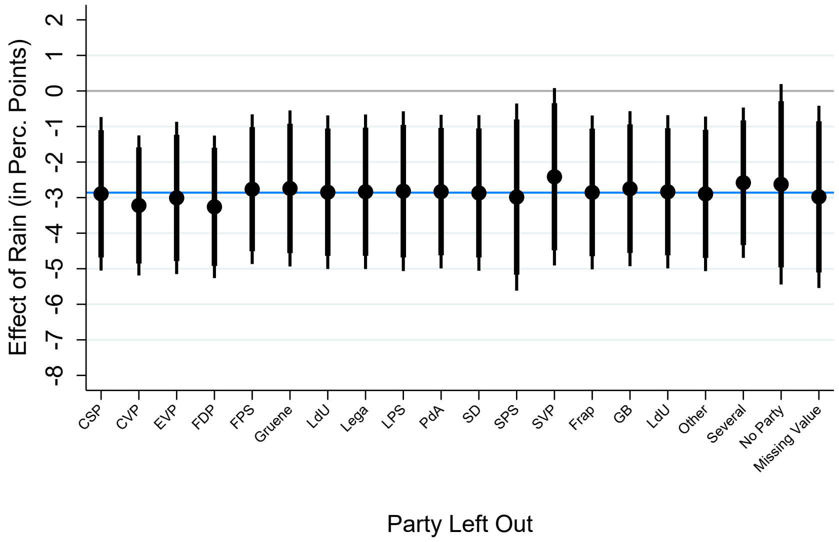
Note: The table shows the estimated effect of rain on the propensity to vote using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. Average turnout: 60.9%, maximum number of observations containing turnout: 22,750. “Rare V.” are individuals who say that they participate in less than 5 out of 10 votes; “Marginal V.” are individuals who say that they participate in more than 4, but less than 8 votes out of 10 votes; and “Frequent V.” are individuals who say that they participate in 9 or 10 out of 10 votes. We categorize individuals who know the title of less or equal to 3/4 of the votes on the ballot as voters with little knowledge and the others as voters with a high level of knowledge. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure E.2: Sensitivity to Sample Selection by Predicted Propensity to Vote Yes



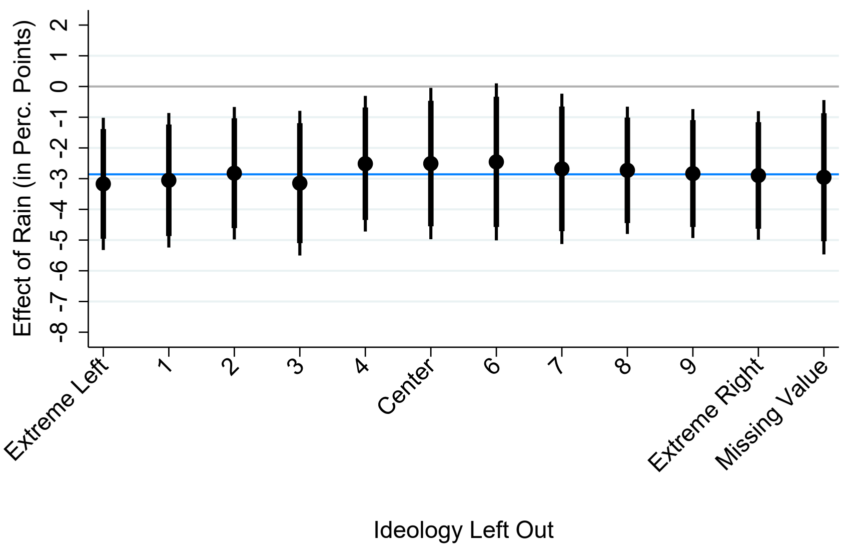
Note: The figure shows coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the share of yes votes in percentage points with postvote survey data. Each dot shows the coefficient estimate from our main specification when dropping the group of voters within a decile of predicted yes share. The propensity to vote yes is estimated in a linear probability models with dummies for age, gender, household income, university degree, knowledge, participation in past votes, party, ideology, and dummies for missing values within the group of voters. The estimate resulting from all data (see Table 2, column (3)) is shown with the blue solid line.

Figure E.3: Sensitivity to Sample Selection by Party Preferences



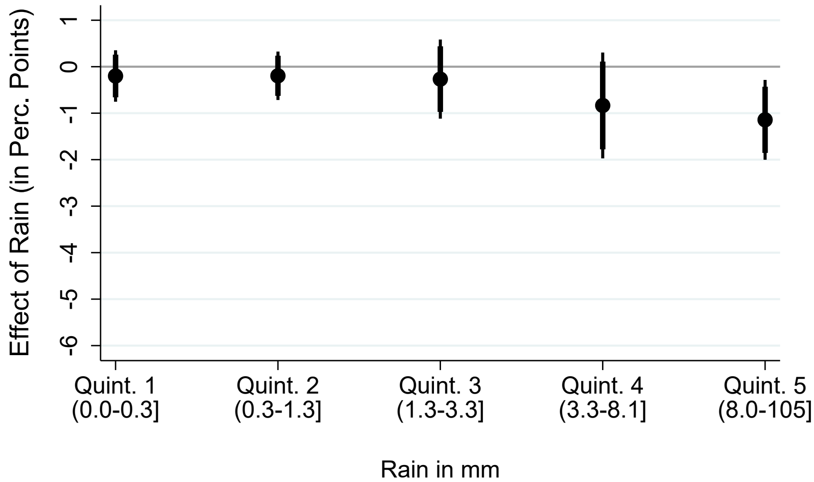
Note: The figure shows coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the share of yes votes in percentage points with postvote survey data. The estimate resulting from all data is shown with the blue solid line. We combine individuals that say they are political but do not identify with a party and individuals that do not identify with a party into one group. Similarly, we combine all missing values into one group (couldn't decide, NA, and missing).

Figure E.4: Sensitivity to Sample Selection by Ideology



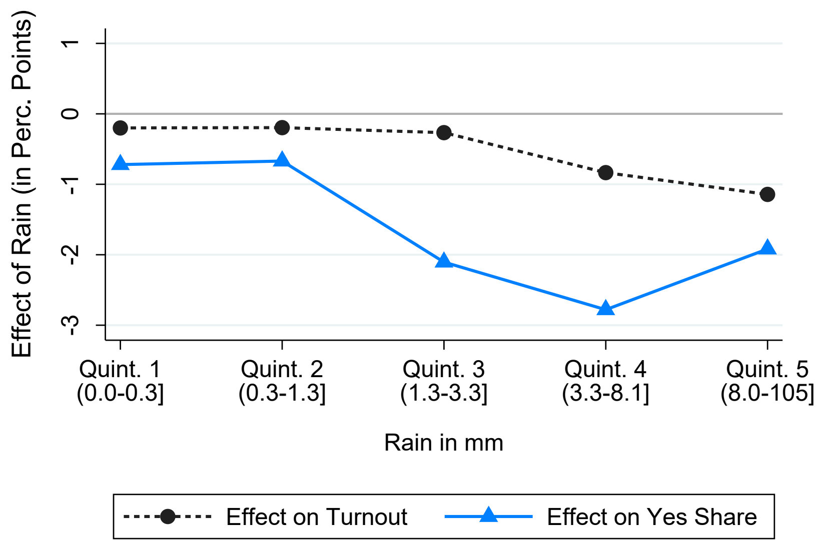
Note: The figure shows coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the share of yes votes in percentage points with postvote survey data. The estimate resulting from all data is shown with the blue line.

Figure E.5: Flexible Relationship Between Rain in Quintiles and Turnout in Percentage Points, Municipal Data



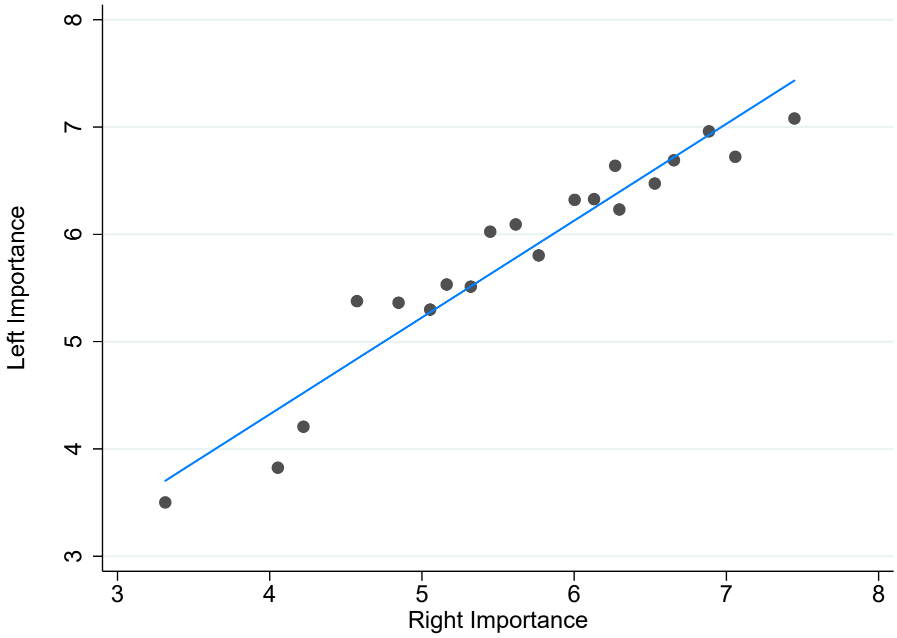
Note: The figure shows coefficient estimates, 95% confidence intervals (thin line) and 90% confidence intervals (thick line) for the effect of rain on the share of yes votes in percentage points using municipal data. The dots are retrieved from a regression of turnout on indicator variables for the five quintiles of rainfall while controlling for municipality fixed effects, proposal fixed effects and cantonal trends. The reference category is zero rainfall.

Figure E.6: Effect of Rain on Turnout vs. Effect of Rain on Share of Yes Votes, Quintiles, Municipal Data



Note: The figure shows coefficient estimates for the effect of rain on turnout in percentage points (black dots) and on the yes share in percentage points (blue triangles) using municipal data. The dots are retrieved from regression model (4) in Table 1 using turnout or the yes share as dependent variable and with indicator variables for quintiles of rainfall instead of one indicator. The reference category is zero rainfall.

Figure E.7: Importance of Propositions as Perceived by Left- and Right-Wing Parties



Note: The figure shows the relationship between the average importance of propositions as perceived by left-wing/center-left voters (CVP and SP) and right-wing/center-right voters (SVP and FDP) based on 157 propositions. The figure is constructed as follows: We first take survey responses about the perceived personal importance on a scale ranging from "not important" (0) to "very important" (10) for each individual from the standardized Vox surveys, which cover propositions from 1981 to 2010 but do not include municipal identifiers. We then collapse these scores on the proposition level based on the party affiliation of the voters. The gray dots show the binned averages of the importance by voters on the left over 20 quantiles against the perceived importance by voters on the right. The blue line indicates a simple regression of "left importance" on "right importance" based on all the 157 votes available in this data set. A one point increase in importance as perceived by voters on the right relates to a 0.9 point increase in the importance as perceived by voters on the left ($se = 0.04$).

Table E.7: Balance Tests, Postvote Survey Data 1996–2006

Dependent Variable	Pred. Prob. Yes Vote (-1.5,109)	Left Party [0,1]	Right Ideology [0,10]	Househ. Income [1,5]	Younger [0,1]	Male [0,1]	Past Turnout [0,10]	Knowledge [0,100]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rain Indicator	0.06	0.02	0.12	0.00	0.03	0.01	-0.01	-0.36
	(0.35)	(0.02)	(0.08)	(0.03)	(0.40)	(0.02)	(0.07)	(1.32)
Vote Weekend FE	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X
Observations	12,970	12,970	11,565	12,970	12,970	12,970	12,970	12,970
Clusters	26	26	26	26	26	26	26	26
R–squared	0.28	0.13	0.15	0.14	0.13	0.13	0.15	0.26

Note: The table shows the estimated relationship between rain and individual level covariates for the individuals who voted using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. The predicted probability to vote yes is from propensity score estimates from a linear probability model (hence the predictions larger than 100 and smaller than 0) with all covariates for the voter sample. "Left Party" indicates all individuals who identify with a left-wing party. "Right Ideology" is an ideology score ranging from 0, radical left-wing, to 10, radical right-wing. Household income is an ordinal variable of bracketed household income categories ranging from 1 to 5. Past turnout indicates the reported number of votes out of ten an individual would participate. Knowledge indicates the average likelihood over all propositions on a voting weekend that an individual knew the proposition title. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.8: Effect of Rain on Turnout in Percentage Points According to Willingness to Take Risks (WTR) — Individual Level

Dependent Variable	Turnout {0,100}	
	High WTR	Low WTR
Avg. Yes Share	50	46
Avg. Turnout	59	62
	(1)	(2)
Rain Indicator	0.81	0.27
	(2.10)	(1.86)
Vote Weekend FE	X	X
Municipality FE	X	X
Covariates	X	X
Observations	11,278	11,472
Clusters	26	26
R–squared	0.19	0.17

Note: The table shows the estimated effect of rain on the propensity to turnout conditional on the estimated willingness to take risks using OLS. The willingness to take risks (WTR) was predicted based on a linear probability model with dummies for age, gender, and university degree and the corresponding coefficient estimates from the Swiss Household Panel. The resulting propensities were used to partition the sample at the median predicted willingness to take risks (columns (1) and (2)). The regressions condition only on income as the other covariates are used for the prediction. The rain indicator is 1 for all rainy voting weekends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.9: Effect of Rain on Turnout and Yes Share in Percentage Points According to Willingness to Take Risks (WTR)

Dependent Variable	Turnout [0,100]		Share of Yes Votes [0,100]	
	High WTR	Low WTR	High WTR	Low WTR
	(1)	(2)	(3)	(4)
Rain Indicator	-0.41	-0.29	-0.97**	-1.23***
	(0.26)	(0.28)	(0.37)	(0.33)
Proposition No. FE	X	X	X	X
Municipality FE	X	X	X	X
Municipality Trends	X	X	X	X
Observations	285,455	146,731	285,455	146,731
Clusters	24	24	24	24
R–squared	0.73	0.70	0.75	0.74

Note: The table shows the estimated effect of rain on turnout in percentage points using OLS according to sample splits based on above or below median willingness to take risks (WTR) among municipalities in 2009. The willingness to take risks is from collapsed individual-level data from the Swiss Household Panel. The median willingness to take risks is 50%. Note that this measure may not be very informative for most years other than 2009 because of changes in the composition of municipalities over time. Standard errors (in parentheses) are clustered at the cantonal level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.10: Effect of Rain on Turnout and Yes Share in Percentage Points by Left- and Right-Wing Municipalities

Dependent Variable	Turnout [0,100]		Yes Votes [0,100]	
	Right	Left	Right	Left
Avg. Yes Share	47%	46%	47%	46%
Avg. Turnout	43%	45%	43%	45%
	(1)	(2)	(3)	(4)
Rain Indicator	-0.35	-0.35	-0.83***	-1.34**
	(0.37)	(0.22)	(0.25)	(0.61)
Proposition No. FE	X	X	X	X
Municipality FE	X	X	X	X
Municipality Trends	X	X	X	X
Observations	418,572	418,548	418,572	418,548
Clusters	26	24	26	24
R–squared	0.66	0.77	0.71	0.74

Note: The table shows the estimated effect of rain on turnout in percentage points using OLS according to sample splits based on above or below median support in a municipality of the right-wing/center right parties (FDP and SVP) in the last or closest national council elections. The median support is 52.7%. Note that we have missing values for the election results for some municipalities. Standard errors (in parentheses) are clustered at the cantonal level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.11: Effect of Rain on Turnout in Percentage Points by Municipal Characteristics

Dependent Variable	Turnout [0,100]											
	Population		Share Agriculture		Share of Retirees		Labor Force Part.		Tertiary Sector		Share Foreigners	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Avg. Turnout	45%	47%	47%	46%	46%	47%	46%	46%	45%	47%	45%	47%
Avg. Yes Share	44%	43%	43%	45%	44%	43%	43%	45%	44%	44%	44%	43%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rain Indicator	-0.37	-0.27	-0.37	-0.17	-0.37	-0.34	-0.32	-0.21	-0.31	-0.35	-0.30	-0.35
	(0.33)	(0.26)	(0.28)	(0.31)	(0.30)	(0.28)	(0.29)	(0.26)	(0.28)	(0.29)	(0.30)	(0.28)
Proposition No. FE	X	X	X	X	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Municipality Trends	X	X	X	X	X	X	X	X	X	X	X	X
Observations	426,513	425,878	428,207	424,184	428,585	423,806	430,404	421,987	426,387	426,004	427,934	421,982
Clusters	22	26	26	22	25	26	25	24	24	26	22	25
R–squared	0.69	0.71	0.67	0.73	0.71	0.68	0.66	0.75	0.70	0.70	0.70	0.71

Note: The table shows the estimated effect of rain on turnout in percentage points using OLS according to sample splits based on median municipal characteristics from the Swiss Federal Statistical Office ("Regionalporträts 2012"). Standard errors (in parentheses) are clustered at the cantonal level. Variables and corresponding years: No. of inhabitants 2010, share of agricultural area 1992, share of retirees 2010, labor force participation rate 2000, tertiary sector employment 2008, and share of foreigners 2000. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table E.12: Effect of Rain on Yes Share in Percentage Points by Municipal Characteristics

Dependent Variable	Share of Yes Votes [0,100]											
	Population		Share Agriculture		Share of Retirees		Labor Force Part.		Tertiary Sector		Share Foreigners	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Avg. Turnout	45%	47%	47%	46%	46%	47%	46%	46%	45%	47%	45%	47%
Avg. Yes Share	44%	43%	43%	45%	44%	43%	43%	45%	44%	44%	44%	43%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rain Indicator	-1.40***	-1.02***	-1.04***	-1.22**	-1.31**	-1.02***	-1.31***	-0.93*	-1.29**	-1.12***	-1.11**	-1.28***
	(0.44)	(0.29)	(0.24)	(0.59)	(0.47)	(0.29)	(0.30)	(0.48)	(0.49)	(0.30)	(0.47)	(0.33)
Proposition No. FE	X	X	X	X	X	X	X	X	X	X	X	X
Municipality FE	X	X	X	X	X	X	X	X	X	X	X	X
Municipal. Trends	X	X	X	X	X	X	X	X	X	X	X	X
Observations	426,513	425,878	428,207	424,184	428,585	423,806	430,404	421,987	426,387	426,004	427,934	421,982
Clusters	22	26	26	22	25	26	25	24	24	26	22	25
R–squared	0.66	0.77	0.70	0.73	0.72	0.69	0.69	0.75	0.67	0.74	0.68	0.74

Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS according to sample splits based on median municipal characteristics from the Swiss Federal Statistical Office ("Regionalporträts 2012"). Standard errors (in parentheses) are clustered at the cantonal level. Variables and corresponding years: No. of inhabitants 2010, share of agricultural area 1992, share of retirees 2010, labor force participation rate 2000, tertiary sector employment 2008, and share of foreigners 2000. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

E.3 Bounding the Potential Bias Because of Selection

The method proposed by Oster (2019) formalizes the following intuition: If one adds controls to a regression and both the coefficient of interest as well as the R^2 change a lot, one should be worried. The approach compares the change in R^2 to the change in the coefficient estimate to gauge the true causal effect or the amount of selection necessary such that the true causal effect is zero. The method requires a choice of the maximally attainable R^2 in our setting. We follow Oster's (2018) suggestion to assume an attainable R^2 of 1.3 times the R^2 of the specification with controls and fixed effects.

On the basis of this assumption, we estimate two parameters: δ and β^*. The parameter δ indicates how much larger the selection on unobservables would have to be, compared to the selection on observables, for the true causal effect to be zero. The parameter β^* reflects the lower bound estimate of the causal effect assuming that the selection on unobservables is weakly smaller than twice the selection on observables ($0 > \delta \geq -2$). The sign of δ is negative because the unobservables would have to be negatively correlated with the observable controls for the coefficients to be 0. The reason is that the inclusion of controls increases the absolute size of the coefficient estimates.

Table E.13 shows the results. We first estimate the regression with all fixed effects, but no controls (the baseline specifications in Table 1, column (4), for the municipal data and in Table 2, column (4), for the individual level data). In a second step, we estimate the most comprehensive specification (Table 6, column 3, for the municipal level data and Table 6, column (6), for the individual level data). The estimates suggests that selection would have to be more than 60 times larger than what we capture with the observables for the causal effects to be zero.

Table E.13: Sensitivity of the Estimates to a Potential Violation of the Exclusion Restriction

	Dependent Variable			
	Share of Yes Votes		Propensity to Vote Yes	
	(1)		(2)	
	β^*	δ	β^*	δ
Rain Indicator	-1.25	-82	-2.78	-60
Observations	829,848	829,848	12,970	12,970

Note: The table shows lower bound estimates of the effect (assuming δ = -2), β^*, and the selection parameter, δ, which indicates how much more of the selection would have to be explained by unobservables rather than observables for the true effect to be 0. The parameters are estimated based on Oster's (2018) method. Standard errors specified for the estimation are clustered on the cantonal level. The estimates are based on a comparison of the R–squared including all controls and fixed effects (Table 6, column (3), for the municipal level data and Table 6, column (6), for the indvidual level data) with the R–squared without any controls (Table 1, column (4) for the municipal level data and Table 2, column (4) for the individual level data).

E.4 Information Acquisition

Table E.14 shows results which hint at whether individuals change their media consumption and as a result know more or less about a given vote in reaction to rainfall.

Table E.14: Robustness of the Rain Effect to Change in Information Sources

Dependent Variable	Voted Yes {0,100}	Individual Knowledge [0,1]	
	All Voters	All	Ballot Box
	(1)	(2)	(3)
Rain Indicator	-2.63**	-0.00	-0.02
	(1.18)	(0.01)	(0.02)
Information Channel FE	X		
Vote Weekend FE	X	X	X
Municipality FE	X	X	X
Covariates	X	X	X
Observations	11,801	12,970	5,003
Clusters	26	26	26
R–squared	0.31	0.28	0.41

Note: The table shows the estimated effect of rain on the propensity to vote yes (column 1) or the propensity to know the title of the propositions (columns (2) and (3)) in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. "Information Channel FE" includes dummies capturing the kind of information sources a voter used. Knowledge ranges from 0 to 1 indicating the share of proposition titles the voter knew of all propositions on the ballot. We only include voters that voted at the ballot box in column (3). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

F Discussion: Heterogenous Reactions

Table F.1 splits our sample according to the vote recommendations of different parties and unions to address whether voting "no" is equivalent to voting for a specific political ideology. Table F.2 presents the results of regressing yes votes on rain for different groups of voters, namely status quo voters, swing voters, and reformist voters.

Table F.1: Effect of Rain on the Share of Yes Votes by Party and Union Recommendations

Dependent Variable	Yes Share [0,100]			
	Right R. No	Right R. Yes	Unions R. Yes	Unions R. No
	(1)	(2)	(3)	(4)
Rain Indicator	-1.03***	-1.19***	-1.05**	-1.24***
	(0.36)	(0.42)	(0.45)	(0.40)
Proposition No. FE	X	X	X	X
Municipality FE	X	X	X	X
Municipality Trends	X	X	X	X
Observations	313,998	556,177	465,081	325,551
Clusters	26	26	26	26
R–squared	0.68	0.67	0.70	0.72

Note: The table shows the estimated effect of rain on the share of yes votes in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. "Right R. Yes" corresponds to a recommendation to vote yes of the right-wing/center-right parties SVP or FDP. "Right R. No" encompasses all other votes. "Union R. Yes" corresponds to a recommendation to vote yes of the major unions. For some votes, parties and unions did not issue recommendations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table F.2: Sensitivity of the Rain Effect Conditional on the Propensity to Vote Yes

Dependent Variable	Voted Yes {0,100}			Share of Yes Votes [0–100]		
	Status Quo Voters (1)	Swing Voters (2)	Reformist Voters (3)	Status Quo Mun. (4)	Swing Mun. (5)	Reformist Mun. (6)
Rain Indicator	-1.59	-6.41***	-3.19	-0.88*	-1.27**	-0.90***
	(2.18)	(2.08)	(2.30)	(0.44)	(0.55)	(0.31)
Vote Weekend FE	X	X	X			
Proposal No. FE				X	X	X
Municipality FE	X	X	X	X	X	X
Municipality Trends				X	X	X
Observations	4,324	4,323	4,323	290,341	290,127	289,707
Clusters	26	26	26	23	23	21
R–squared	0.37	0.39	0.48	0.69	0.70	0.74

Note: The table shows the estimated effect of rain on the propensity to vote yes (columns (1) to (3)) or the share of yes votes (columns (4) to (6)) in percentage points using OLS. Standard errors (in parentheses) are clustered at the cantonal level. The rain indicator is 1 for all rainy voting weekends. The propensities to vote yes are estimated with linear probability models with dummies for age, gender, income, college degree, knowledge about the vote, past participation in votes, parties, ideologies and missing values. Propensities of yes votes at the individual level: status quo voters ($-0.14 < P(\text{Yes}) < 0.44$), swing voters ($0.44 \leq P(\text{Yes}) \leq 0.53$) and reformists ($0.53 < P(\text{Yes}) < 1.08$). Average share of yes votes at the municipal level: status quo municipalities ($0.32 < Share(Yes) < 0.45$), swing municipalities ($0.45 \leq Share(Yes) \leq 0.48$) and reformist municipalities ($0.48 < Share(Yes) < 0.57$). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$