Spurious weather effects

Jo Thori Lind*

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Abstract

Rainfall is exogenous to human actions and hence popular as an exogenous source of variation. But it is also spatially correlated. This can generate spurious relationships between rainfall and other spatially correlated outcomes. As an illustration, rainfall on almost any day of the year has seemingly high predictive power of electoral turnout in Norwegian municipalities. In Monte Carlo analyses, I find that standard tests reject true null hypotheses in as much as 99 percent of cases. Standard approaches to estimating consistent standard errors do not solve the problem. Instead, I suggest controlling for spatial and spatio-temporal trends using multi-dimensional polynomials.

Keywords: Rainfall, electoral turnout, spurious relationship, spatial correlation

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*Department of Economics, University of Oslo, PB 1095 Blindern, 0317 Oslo, Norway. Email: j.t.lind@econ.uio.no. Tel. (+47) 22 84 40 27.

1. INTRODUCTION

Both human behavior and economic outcomes, such as individual effort and agricultural productivity, depend on weather conditions. Weather phenomena, moreover, can generally be seen as exogenous to human behavior. The effect of rainfall on the demand for umbrellas, known from numerous introductions to decisions under uncertainty, is only one example. In empirical economic research, truly exogenous variables are sought after as sources of exogenous variation to provide causal inference. Going at least back to Koopmans (1949), economists have been using rainfall as an exogenous shock. In recent years, the strategy has become increasingly popular.

Few suspect that human actions affect the weather in the short run,¹ and the weather has a potential impact on a number of outcomes. But by its very nature, rainfall is spatially and temporally correlated. If it is raining in one location, the likelihood of rain in nearby areas is high. Autocorrelated explanatory variables are not usually considered problematic. I show, however, that this induces a danger of spurious correlations when omitted variables also display spatial dependency, i.e. that magnitudes in nearby locations tend to be positively correlated.

When rainfall is included in a regression with spatially dependent omitted variables, rainfall is going to appear relevant even when it is not. The problem is that omitted variables problems are exacerbated in the presence of spatial dependency. Unlike ordinary omitted variables problems, however, we face an omitted variable whose true effect is random. In both cross sectional and panel data, it is common to observe spatial patterns in most outcomes, probably including unobserved omitted variables. As there is spatial dependency in rainfall as well, I show that although rainfall is unrelated to all variables of interest, it is going to correlate with other spatially dependent variables. In panel data, where spatial trends can be controlled by fixed effects, the same problem arises if there are combined temporally and spatially trends in outcomes of interest. As shown by Granger et al. (2001) and Kim et al. (2004), a similar effect can actually arise in a pure time series setting too. This is an effect leading to biased and inconsistently estimated parameters. Hence correcting standard errors for spatial clustering at geographic entities (Moulton, 1986) or following e.g. Conley's (1999) approach, does little to solve the problem.²

To illustrate the magnitude of the problem, consider the relationship between electoral turnout

and rainfall. There may be good reasons to expect a relationship between turnout and rainfall *on election day*. But rainfall on other days, with a possible exception of a few days prior to the election, should not have any impact. Using data from Norwegian municipal elections and daily rainfall data in the window from 600 days before to 600 days after the election, I find that rainfall on almost every day has an impact on electoral turnout.³ As the regressions include both municipality and year dummies, explanations such as the probability of rain can not explain the findings.

In these analyses we should only expect to find significant results due to the expected Type I errors determined by the level of significance. That is not the case. Rather, a 5 % significance test reject the hypothesis of no effect of precipitation in 70.8 % of the cases. The estimated t-values are shown in Figure 1. Although the distribution is symmetric around zero, the variance is much higher than the expected level of unity. Moreover, the distribution is not normal, as the tails are lighter than the normal kurtosis. Clustering standard errors at the regional, rather than the local level, improves the situation somewhat. But still a 5 % test rejects in 46.4 % of cases, and this level of clustering is more conservative than what is used in most applied studies. The phenomenon can not be explained by heavy tailed distributions⁴ or geographically seasonal patterns in precipitation.⁵ If this phenomenon was unique to the effect of rainfall on electoral turnout, it would be a narrow problem. However, the problem applies potentially to all spatially correlated outcome variables⁶ as well as explanatory variables exhibiting patterns similar to rainfall.⁷

[Figure 1 about here.]

As I argue below, the reason for this odd behavior is the presence of spatio-temporal trends in the dependent variable: turnout in the eastern part of the country has decreased relative to national averages whereas it has increased in relative terms in the western part. The underlying explanation is probably differential development of macro-regional common factors. In some ways, this mimics the intricate spatial patterns detected in earnings data by Barrios et al. (2012), but here also with a temporal component. In a stylized model with an omitted spatially correlated variable, I show theoretically that OLS estimates are inconsistent with almost surely diverging point estimates and t-statistics. Using Monte Carlo simulations, I further show that the test of

the irrelevance of the irrelevant variable is vastly over-rejected. This holds both with large sample sizes, with several independent clusters of spatially dependent variables, using cross-sectional and panel data, as well as several specifications of the omitted trend including spatial AR processes. Also, the simulations indicate that neither ordinary clustered standard errors nor Conley (1999) standard errors solve the problem.

My suggested solution to the problem is to control for the trend using orthogonal polynomials.⁸ In the cross sectional spatial case, such a trend would be a polynomial in geographical coordinates. In the case of panel data, we need a time trend whose slope varies geographically, so the slope of the trend is modeled by a similar polynomial in geographical coordinates. Although any polynomial can be used in theory, sequences of orthogonal polynomials have good numerical stability. In the current study, I focus on tensor products of Legendre polynomials, which seem to perform well.

There are a few papers scrutinizing the validity of rainfall as an exogenous source of variation. Sarsons (2015) look at the relationship between rainfall and conflict in India, where rainfall typically is believed to be an instrument for income. However, she finds strong effects of rainfall both in rain-fed and dam-fed regions, possibly invalidating this identification.

Methodologically, the present paper is also closely related to the work of Bertrand et al. (2004). They show that differences in differences estimation tends to find effects of placebo “reforms” on female wages. In one way, the present paper is a converse to their study as they focus on outcomes with spatial patterns (wages) whereas I focus on explanatory variables with spatial patterns. The study by Barrios et al. (2012) also indicate that failing to accounting for spatial dependency may severely bias the results, but they also focus on standard errors.

The paper is also related to literature on spurious regressions in time series. It is well known that the presence of non-stationary variables in regressions analyses can lead to spurious regression (Granger & Newbold, 1974; Phillips, 1986). A less well known result is that this also holds for a wide range of processes, including autocorrelated stationary processes (Granger et al., 2001; Kim et al., 2004) – see Ventosa-Santaularia (2009) for a review. The problems I discuss are very similar, but in the spatial domain.

Also, my suggested solution to estimate spatial or spatio-temporal trends relates to the litera-

ture on estimating time trends (Sims et al., 1990). As this concerns units in space, it also relates to the massive literature on spatial statistics⁹ and the more modest literature on spatial econometrics.¹⁰ The literature on spatio-temporal statistics has a strong focus on space-time autoregressive moving average (STARMA) type models (Cliff et al., 1975; Pfeifer & Deutsch, 1980), characterized by linear dependence lagged in both space and time. The literature on estimating models with spatially dependent error terms is particularly relevant (Kelejian & Prucha, 1999; Chudik et al., 2011; Pesaran & Tosetti, 2011). Such models can also be extended to regression frameworks with spatial autoregressive distributed lags models (Elhorst, 2001). Although these models may be suited to handle the problem at hand, their main problem is that they are difficult to identify and estimate by themselves. When we also want to add panel data features, clustered standard errors, instrumental variables or discontinuity designs, they become intractable and not useful for practical applications. Hence, I have chosen to rely on a simpler approach.

My suggested solution is to allow for a spatially varying time trend. This relates to the literature on varying coefficients (Hastie & Tibshirani, 1993) and particularly spatially varying coefficients (Gelfand et al., 2003). Specifically, Hoover et al. (1998) and Huang et al. (2002) estimate varying coefficients models where they model the coefficients by regularized basis functions as I suggest (albeit using B-splines rather than polynomial bases).¹¹ However, they consider coefficients varying in time, not in space. To the best of my knowledge, the only spatial application of the methodology is Zhu et al. (2014) who study MRI images.

2. THE PROBLEM

2.1. Rainfall regressions

The use of meteorological data in empirical analyses has skyrocketed in recent years.¹² Some of these take worries of spurious correlations into account by running placebo studies, but this is not yet widespread. To both study the use of rainfall in applied empirical economics and see how potential issues of spurious relationships are handled, I surveyed all articles published in three top economics journals in the period 2000-2017. See Appendix Table 4 for the full list of articles.

In total, I found 45 articles. The earlier papers typically use data with coarse spatio-temporal resolution whereas it becomes more common to rely on daily or even intra-daily data with high spatial resolution over time. Clustering on spatial entities is also very common except in the earliest papers, but only a few papers go any further in their treatment of spatial dependence such as applying Conley (1999) standard errors. Moreover, only a handful of papers apply spatio-temporal time trends that would alleviate the problems of spurious relationships studied herein. Finally, I found only one paper (Madestam et al., 2013) that re-samples rainfall to check the validity of their findings.

Starting with Gomez et al. (2007) and Hansford & Gomez (2010), there is also by now a fairly large literature on the relationship between election day weather and turnout. Beyond the US, the question has been studied in Japan, Holland, Spain, Italy, Sweden, Germany, Norway, and South Korea (Horiuchi & Saito, 2009; Eisinga et al., 2012b,a; Artés, 2014; Sforza, 2013; Lo Prete & Revelli, 2014; Persson et al., 2014; Arnold & Freier, 2016; Lind, 2014; Kang, 2018). In many studies, it is found that rain on election day reduces turnout, but in Sweden there seems to be essentially no relationship between the two and in Norway the relationship is positive. It has also been argued that election day affects political outcomes either by affecting the composition of voters (Gomez et al., 2007; Lind, 2014) or by affecting the preferences of voters (Meier et al., 2016). Daily weather conditions have also been found to have an impact on participation in civil rights riots in the 1960s (Collins & Margo, 2007), Tea Party rallies (Madestam et al., 2013), and May day demonstrations (Kurrild-Klitgaard, 2013).

2.2. *Other explanations*

[Figure 2 about here.]

As already illustrated, regressions with rainfall as the independent variable seems to yield a distribution of t-values that differ markedly from the theoretical standard normal distribution. They are not normally distributed,¹³ but the main problem is that the standard deviation is much higher than unity. In the basic specification shown in Figure 1, the standard deviation of the t-statistics is 4.37 – and a test of the hypothesis if it being unity rejects vastly.

Before exploring the explanation based on spatio-temporal trends further, it is worthwhile dispensing with the alternative explanation of outliers in precipitation. It is well known that rainfall data has a heavy right tail, which could affect the regression analyses. To show that this cannot be the sole explanation, Figure 2 shows the distribution of the t-values in a number of specifications that reduces the leverage of outliers. Panel (a) is the specification shown in the introduction, where the level of turnout is regressed on the level of rain in millimeters. Panels (b) and (c) replace the measure of precipitation with dummies for substantial rain, defined as above 2.5 mm, and any rain at all. Finally, in Panel (d) both rainfall and turnout are measured using their ranks so they both have a uniform distribution on the unit interval. In all four cases, the distribution of the test statistic is far from the standard normal or t-distributions we would expect. This should indicate that mere outliers cannot explain the findings.

Another possible explanation could be spatially varying annual patterns in precipitation. Although most Norwegian municipalities have higher average precipitation during winter than summer, there is some variation to the pattern which is spatially correlated. In a dataset with several observations each year, this phenomenon can generate spurious correlations between rainfall and other spatially correlated variables – and the problem would be easily solved by controlling for seasonality. Parliamentary elections in Norway, however, are always held mid-September. Hence on election days, municipalities are always at the same stage of their climatic seasonal cycle. In the simulations, where we consider election day $\pm t$ days, we also end up with observations in the same phase of the cycle. Consequently, seasonal patterns can not be the explanation for the phenomenon.

2.3. *Omitted spatially dependent variables*

[Figure 3 about here.]

Rather, it seems that the nature of the problem is omitted variables exhibiting spatio-temporal trends and potentially spatial non-stationarity¹⁴ in the rainfall data in combination with spatio-

temporal trends in the turnout data. To explore the latter trends, I run a regression of the type

$$Turnout_{it} = \alpha_i + \tau_t + \delta_i t + \epsilon_{it}. \quad (1)$$

Here δ_i is an estimate of the municipality specific trend. I have plotted the values of δ_i in Figure 3. Panel (a) shows the geographical distribution of temporal trends. It is clear that there is a strong negative trend in the eastern part of the country and a positive trend in parts of the west and the center. Panel (b) shows a Moran plot where the municipality specific coefficient δ_i is plotted against the average δ_i in the adjacent municipalities. Again, it is clear that there is a spatial pattern. Formally, Moran's I statistic is $I = 0.456$ and the Moran test for no spatial dependency rejects with a p-value of 2.2×10^{-16} . We conclude that when controlling for two way fixed effects, turnout has been declining in the eastern part of the country and increasing in the western part. As shown in Sections 3.1 and 3.2, this can explain the t-values shown in Figure 2.

[Table 1 about here.]

Hence it seems that variables with spatial dependence may correlate spuriously with rainfall. To show this more forcefully, I run some simulations. There are many ways of running these simulations and obtaining spurious results. Here I have chosen a very simple specification which is clearly nonsensical, and still correlates strongly with rainfall.

The independent variable is the observed rainfall in Norwegian municipalities on a random day between January 1st 1968 and November 30th 2012.¹⁵ First, I consider a cross sectional setting where I simulate dependent variables

$$z_i = x_i + y_i + \epsilon_i, \quad (2)$$

where x_i and y_i is the longitude and latitude of the municipal center of municipality i and ϵ_i is a standard normally distributed residual. Regressing z_i on observed rainfall yields the results shown in Row 1 of Table 1. The full distributions are shown in Appendix Figure 9. As this is cross sectional data, season patterns are not present in the data. As in the example above, we see

massive over rejection of false null hypotheses: Here the test at the 5 % level rejects in 84 % of cases.

To account for the spatial pattern, I also attempt to cluster standard errors at the 19 regions of Norway as well as using Conley (1999) standard errors. Both approaches seems to have about the same effects of increasing the standard errors. However, as can be seen from Rows 2 and 3 of Table 1, we still have rejection of the false null in 59 % of cases using a 5 % test. Moreover, we notice that this tends to yield a heavily skewed distribution of the t-values. First, this indicates that at least a substantial part of the problems lies in the estimated regression coefficient $\hat{\beta}$, not in the computation of the standard errors. In some ways, this is unsurprising as biased regression coefficients are well known results from omitted variables problems. Second, it tells us that the problem can not be solved by correcting the standard errors alone.

I also ran simulations as above, but where municipalities were assigned rainfall data from a randomly selected municipality. This maintains the distribution of the independent variable but removes the spatial pattern. As we can see from Row 4 of Table 1, we now get almost a perfect replication of the standard normal distribution. This indicates that the cause of the problem is the spatial correlations and not the skewed distribution of the rainfall data.

A typical way to control for such spatial patterns is to include municipal fixed effects, as was done in the analysis of the turnout data above. As long as the dependent variable only exhibits spatial correlation, this solves the problem. If, however, the variable has a spatially dependent trend, fixed effects can't solve the problem. To illustrate this, I draw panels starting on a random day, with observations every four years and totally 10 observations per municipality. As all observations are on the same date, seasonal patterns are not present in the data. I then construct a dependent variable as

$$z_{it} = (x_i + y_i) t + \epsilon_{it},$$

where again x_i and y_i are the longitude and latitude of the municipality and t the year. Regressing z_{it} on observed rainfall yields the results shown in Row 5 of Table 1. Again, the false null is over rejected, this time in 81 % of cases for the 5 % test.

3. A GENERAL EXPOSITION OF THE PROBLEM

3.1. A theoretical approach

To get a better grasp of the nature of the problem at hand, I develop a simple econometric model that is able to generate the phenomenon and may approximate the problem in real world situations. The results of the model resemble those found by Granger et al. (2001) in the case of time series, but certain features are better adapted to a spatial setting. Specifically, we want to show that a spatially correlated explanatory variable that is in reality irrelevant may seem relevant – hence generating a pattern of spurious correlation.

Consider a case where space is reduced to one dimension, so observations can be represented as points $i = 1, \dots, N$ on a line. We generate an explanatory variable r_i as the sum of a number of K spatially correlated shocks. Specifically, each shock has a location¹⁶ $p_k \in [1, N]$ and a value ν_k drawn from some continuous distribution. In the case of precipitation, we may think of each shock as a weather system with intensity ν_k and center at p_k . At position i , the total effect of shocks is $r_i = \sum_k \frac{\nu_k}{1+d(i,p_k)}$ where d is a distance function which satisfies $d(i,i) = 0$ and where $d(i,j)$ is increasing in $|i-j|$. Notice that this is essentially a radial basis function network, which is commonly used to approximate functions (Buhmann, 2003). Hence this model should approximate a wide range of spatial patterns found in real life.

The outcome variable of interest y_i depends on a number of unobserved variables, some of which are spatially correlated. In the theoretical exposition, we model these are resulting in a spatial trend τi for some trend parameter τ , so the outcome variable is given by

$$y_i = \alpha + \beta r_i + \tau i + \epsilon_i. \quad (3)$$

We may suspects that r_i also enters equation (3) with a slope β . Hence we want to test the hypothesis that $\beta = 0$. Using conventional tools, we would disregard the spatial trend τi . The core of the problem, as we see below, is that a regression of y_i on r_i mixes up the trend τi and the signal r_i .

[Figure 4 about here.]

In the theoretical exposition, I focus on the metric $d(i, j) = |i - j|$ and the case with only one shock p , i.e. $K = 1$. This case is illustrated in Figure 4. As is apparent from the figure, whenever the “position” of the shock is $p \neq \frac{N}{2}$, there is scope for the shock to pick up parts of the trend. We want to show this formally and see how a test is affected by an increasing sample size N . It turns out that in this case, the problem does not diminish but rather get more acute.

When the data are generated as in equation (3), but where we fail to control for the trend τ_i in the analysis, the OLS estimator becomes

$$\hat{\beta} = \beta + \frac{\frac{1}{N} \sum (r_i - \bar{r}) \epsilon_i}{\frac{1}{N} \sum (r_i - \bar{r})^2} + \tau \frac{\frac{1}{N} \sum (r_i - \bar{r}) i}{\frac{1}{N} \sum (r_i - \bar{r})^2}. \quad (4)$$

When $\epsilon_i \sim iid(0, \sigma^2)$ the first fraction converges in distribution to a well-behaved normally distributed term by application of the central limit theorem. This is handled by ordinary estimation and hypothesis testing procedures. The second term, which stems from the omitted variable, however, is the root of the problem. In finite samples it is non-zero unless $p = \frac{N}{2}$. Moreover, the problem is exacerbated with growing sample sizes, as the following result demonstrates:

Proposition 1. *When $N \rightarrow +\infty$ and $\frac{K}{N} \rightarrow \kappa < +\infty$, we have $Pr\left(\left|\hat{\beta} - \beta\right| \rightarrow +\infty\right) = 1$.*

The full proof is provided in Appendices B.1 and B.2. Denote by $\bar{w}$ the average $\bar{w} = \frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K \frac{1}{1+|p_k-i|}$. In Appendix B.1 I show that the expression $\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K \left(\frac{1}{1+|p_k-i|} - \bar{w}\right) i$ converges to a logarithmic function and hence diverges as $N \rightarrow \infty$. The proof is based on showing that the expression can be sandwiched between two harmonic sequences which both have logarithmic growth. Moreover, in Appendix B.2 I show that if $\frac{K}{N} \rightarrow \kappa \in \mathbb{R}^+$, we have that as $N \rightarrow \infty$, the denominator $\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K \left(\frac{1}{1+|p_k-i|} - \bar{w}\right)^2 \rightarrow Q \in \mathbb{R}^+$. This is based on showing that $\sum_{i=1}^N \sum_{k=1}^K \left(\frac{1}{1+|p_k-i|} - \bar{w}\right)^2$ is closely related to the sum of reciprocals of squares of natural numbers. The sum of this sequence is known to converge to $\frac{\pi^2}{6}$. As a consequence, the sum at hand also converges to a constant. Consequently, the expression goes to 0 at rate $O\left(\frac{1}{N}\right)$. If on the other hand we allow K to grow linearly as N grows, the denominator converges to a constant.

In both cases, the estimator $\hat{\beta}$ explodes and hence is inconsistent. However, unlike conventional omitted variables biases, the sign of the bias is random.

In applied research much emphasis is on statistical significance, i.e. the t-values. As the denominator in (4) converges to a constant, the standard error of $\hat{\beta}$ also converge to a constant. As $\hat{\beta} - \beta$ diverges, this implies that the t-values also diverge. This could hence explain the unusually high t-values observed above.

One objection to this analysis could be that as N increases, the size of space, and hence the range of r_i , increases. An alternative model could be to restrict space to say $[0, 1]$ and increase the density of observations as N increases. Then the trend should be modeled as $\frac{\tau_i}{N}$, and the distance metric for the shocks replaced by $|\frac{i}{N} - \frac{p_k}{N}|$. However, it is easily seen that in computing OLS estimates, this does not change the final expression and hence the regression estimate still diverges as N increases.

The above results depends on the the specification of r_i being proportional to the inverse of the distance. If the weighting decays more quickly, a may be realistic in many applications, the proof of divergence has to be changed.¹⁷ However, it seems that the main insight would go through with other specifications of the weighting too.

3.2. Monte Carlo evidence

The results presented in Section 3.1 apply to a stylized model. To illustrate that these results are more general, I now report results from a number of Monte Carlo analyses on varieties of this model.

Table 2 shows a Monte Carlo analysis of the model from Section 3.1 for sample sizes between 10 and 10000 and number of shocks varying from 1 to 20000. The simulations are based on a model where the true $\beta = 0$ so the fraction of t-tests rejecting the null should correspond to the level of the test, here 5 %. First, we recognize the diverging t-values: The larger the sample gets, the more likely the t-test is to reject. The test at the 5 % level rejects in about half of the cases for small samples and in more than 80 % of cases in larger samples.¹⁸ Rejections rates and values of $|t|$ are slightly smaller for larger numbers of shocks, but this is not enough to take levels down

to reasonable magnitudes.

[Table 2 about here.]

In many real world applications, the assumption of a linear world is too restrictive.¹⁹ A more realistic assumption is a spatial data structure where it is meaningful to talk about the distance between two observations, and where units tend to be correlated with nearby units. Denoting observation i 's geographical position (x_i, y_i) , we can use the Euclidean distance function $d(i, p) = \sqrt{(x_i - x_p)^2 + (y_i - y_p)^2}$. A linear geographical trend can be defined as $\tau_i = \tau_x x_i + \tau_y y_i$ for constants τ_x and τ_y . Such trends, sometimes with more sophisticated specifications, are widespread in geographical data and their study goes at least back to Krumbein (1959; 1963) and Tobler (1969).

Without going into the formalism, it is easily seen that this model is essentially equivalent to the model studied in Section 3.1, and hence that the same problems arise. Monte Carlo analyses reported in Appendix Table 5 also show that the problem is indeed still present and if anything stronger than in the basic model.

In many applications including most of those mentioned in the introduction, we have access to a panel of observations. This allows for controlling for unit fixed effects, which would rule out the problem of the spatial trend τ_i . Time trends are also unproblematic as they are routinely handled by year dummies. But if time trends depend on geography, that is we have spatio-temporal trends, the problem studied above reappears. Consider the case where

$$z_{it} = \alpha_i + \beta r_{it} + \tau_i t + \epsilon_{it} \quad (5)$$

with the trend $\tau_i = \tau_x x_i + \tau_y y_i$ for constants τ_x and τ_y . If we assume a balanced panel so we can differentiate expression (5), we get

$$\Delta z_{it} = \beta \Delta r_{it} + \tau_i + \Delta \epsilon_{it},$$

which essentially is specification (3). De-meaning of course yields similar results. The only major difference is that we look at differenced shocks (or deviations from means). However, these have

the exact same properties of spatial correlation as the undifferenced shock, so the issues studied in Section 3.1 still remain. Monte Carlo simulations of this model also yield very similar conclusions – the null hypothesis of no relationship which should have been rejected in 5% of cases is rejected far too often and t-values are typically high.²⁰ Moreover, the problem is exacerbated by increasing sample sizes. There are some indications that increased panel lengths reduces the problem. As time periods are independent of each other, increasing T increases the (random) variation in Δr_i which helps uncover its independence to Δz_{it} .

The mechanism generating the spurious rejections of hypothesis tests above is that the precipitation shocks in sum are non-zero and with opposite sign in different corners of space. With a spatial trend, the two combine to form spurious correlation. The assumption of a deterministic spatial (or spatio-temporal) trend may be too strong in certain applications. However, the problem may persist in more general models of spatial dependence.

Consider a model in one-dimensional space of the form

$$\begin{aligned} y_i &= \alpha + \beta r_i + u_i \\ u_i &= \rho u_{i-1} + \epsilon_i, \end{aligned} \tag{6}$$

i.e. a simple first order auto-regressive model.²¹ Unbiased test of the hypothesis $\beta = 0$ depends on $E \sum_i r_i u_i = 0$. With the current specification, we have $u_i = \sum_{j=0}^{i-1} \rho^j \epsilon_i$. Say for simplicity that the location p is at an integer. Then

$$\sum_i r_i u_i = \sum_{j=0}^{N-p} \frac{\nu}{1+j} u_{j+p} + \sum_{j=1}^{p-1} \frac{\nu}{1+j} u_{p-j}.$$

Using the autoregressive structure of the residuals, this can be rewritten

$$\sum_i r_i u_i = \sum_{i=1}^N \epsilon_i \sum_{j=0}^{N-1} \frac{\nu}{1+|p-i+j|} \rho^j.$$

With high spatial dependence (i.e. ρ close to unity), the loading on a few of the innovations ϵ_i close to p is going to be large, and these innovations determine the whole estimated β . Even as N

gets large, this effect persists.

For $K > 1$, we compare the loading on ϵ_i around several clusters. Still, some of the clusters dominate and hence the bias remains the same if not worse.²² Moreover, when the spatial dependency is high (ρ is close to unity), we get spurious relationships in the vast majority of cases. Increasing the sample size or the number of shocks does not seem to improve the situation.

4. DETECTING AND SOLVING THE PROBLEM

In the case of the weather, the problem of spurious correlations can usually be detected by examining the weather at counterfactual dates as in Figure 1. With other independent variables, other placebos may be feasible. If rejection rates differ markedly from the expected rates, some spatial or spatio-temporal dependency may be the explanation although of course other explanations obviously also exist. The next step should be to try to get some impression of the spatial dependency. One way to do this is to simply plot maps of spatial values or estimated spatial trends. In some cases it may also be useful to use testing procedures such as Moran's I statistic.

If a spatial pattern is found, two possible solutions can be pursued. The ideal solution is to find the source of the dependency and expand the model specification to take this into account. If, for instance, geographically varying trends are due to geographical differences in demographic patterns (say young people moving toward large cities), one could potentially solve the problem by adding demographic controls. However, it may not always be easy to find a simple explanation and there may not be a single explanation for the geographical trend. In such cases, it may be a better option to attempt to control for the geo-spatial trend. In the time series literature, this is usually done by simply including the date as a variable, sometimes with a few polynomial terms. In the case of geographical data, this may be too limiting.

In the cross sectional case, we want to control for some unknown function $T(x, y)$. As the shape of T is unknown, a flexible estimator in two-dimensional space is called for. Kernel based and other standard non-parametric estimators are computationally intensive, and as their rate of convergence is typically below $\sqrt{n}$, inference of the other variables in the regression can't always be made using standard techniques. Consequently, a simpler form may be advisable.

In the case of a panel, we need to estimate a function $T(x, y, t)$. As this is a function of three variables, a fully flexible non-parametric approach gets even more demanding. At least for short panels, it seems reasonable that the trend may be kept linear, so we can rewrite $T(x, y, t) = U(x, y)t$ for some function U . One solution that seems to work well for the electoral turnout data considered below is one where U is specified as a tensor product of Legendre polynomials.²³ The choice of orthogonal polynomials is to reduce problems of multicollinearity and improve numerical stability. One justification for choosing Legendre polynomials is their orthogonality property with regard to an L^2 inner product given a uniform spatial distribution of units. Although the distribution is not exactly uniform, this approach is likely to give better behavior than most other orthogonal polynomial bases that provide orthogonality given various bell shaped distributions. Still, it seems that the choice of polynomial base has little effect on the final outcomes.

Given dimensionalities K and L , we can specify

$$T(x, y, t) = t \sum_{k=0}^K \sum_{\ell=0}^L \theta_{k\ell} P_k(x) P_\ell(y) \quad (7)$$

where $P_i(\cdot)$ is the i 'th order Legendre polynomial.²⁴ The $(K + 1)(L + 1)$ parameters $\theta_{k\ell}$ can be estimated together with the other parameters in an ordinary regression model.

The choice of the dimensions K and L has to be chosen to make the polynomial (7) provide a reasonable fit of the data. If K and L are chosen too high, there is both a danger of over fitting (Hastie et al., 2008, Ch. 7) and loosing so much variation that it becomes impossible to identify the effect of the variable of interest. Hence we would like a good fit with a low dimensional polynomial. To make a good trade off, I recommend to consider choosing K and L by maximizing a linear penalty function

$$R^2 - \xi(K + 1)(L + 1), \quad (8)$$

where R^2 is the fit of the model and ξ a penalty on the number of parameters to estimate. This is closely related to maximizing the AIC and BIC criteria, but varying the degrees of freedom penalty. Varying the parameter ξ , we can trace out the class of potentially good polynomial compositions.

It is also important to undertake counterfactual estimations as in Figure 1 to check that the polynomial at hand actually solves the problem. If the fit is good enough, most of the placebo variables should have little effect on the outcome. Another approach could also be to choose K and L high, but constrain the $\theta_{k\ell}$ by employing ridge regression, LASSO, or other versions of constrained estimation (Belloni et al., 2014; Hastie et al., 2008, Ch. 3).

5. TURNOUT IN NORWEGIAN ELECTIONS

Let us now return to the application considered in the introduction, the effect of rainfall on electoral turnout in Norwegian municipal elections. The data are described in Appendix C.

5.1. *Specifying the spatio-temporal trend*

As argued in Section 4, one way to handle the problem of spatio-temporal trends is to control them out in the estimation. I approximate the trend with the tensor product of Legendre polynomials. The first step needed is to make a choice of how many polynomial terms to include in each of the two dimensions. Figure 5 shows the the model’s fit (net of a baseline model without spatio-temporal controls) for each combination of between 0 and 10 terms in each dimensions. Combinations of polynomial orders K and L that are maxima of the penalized model (8) for some value of ξ , i.e. those which are elements of the convex hull of the points, are shown in red. There is a strong increase in fit going up to about 15 terms, then the effect of additional terms seems to flatten out. To avoid over fitting the data and preserve some degrees of freedom, my preferred model specifies spatio-temporal trends using a first order polynomial in the longitude and a sixth order polynomial in the latitude, using 13 terms and increasing the fit as measured by R^2 by 0.083.

[Figure 5 about here.]

Adding more terms not only have a minor impact on the model’s fit, it turns out that the exact specification of the spatio-temporal has little importance once we reach a minimum level of complexity. Figure 6 shows the distribution of t-values for eight specification with increasing complexity of the tensor product of Legendre polynomials and regional dummies and with linear

and quadratic time trends.²⁵ The distributions are almost perfectly overlapping for each of the eight models. Indeed, the correlation between the most and the least complex models are between .85 and .9.

Moreover, we notice that the distribution of t-values is much more well behaved than the t-values obtained without controlling for spatio-temporal trends. Although the distribution is somewhat fatter than the theoretical Student's t distribution, the distribution is much more sensible to work with.

Finally, it seems that using region specific trends has a comparable effect in improving estimation results to spatio-temporal trends. As argued above there are many cases where it is implausible that the trend has a spatial discontinuity at regional borders. Still, it seems that this potential mis-specification has little impact in practice.

[Figure 6 about here.]

5.2. *The effect of rainfall on turnout*

Table 3 shows the actual estimation results regressing turnout on election day weather. First, specifications (1) and (2) show the estimation results using a two-way fixed effects specification without controlling for spatio-temporal trends. The simplest specification indicate that rainfall does not affect turnout. When we interact rainfall with a time trend, it seems that rainfall suddenly has a time-varying effect. In Panel A of Appendix Table 8 I show some additional specifications, where signs and significance levels are even more erratic. As argued above, this specification is probably not trustworthy.

In specifications (3) and (4) of Table 3, I show the estimation results from the preferred specifications. The general pattern is that rain seems to increase turnout in Norway – see Lind (2014) for a discussion of the rationale behind this. Column (1) shows the plain regression of turnout on precipitation in cm. The effect of 1 cm increase in precipitation is about .3 percentage point increase in turnout. Columns (2) includes a time interaction. We see that with this specification, the results seem to be stable over time as the interaction is insignificant. In Panel B of Appendix Table 8 I include the same specifications as above. Now, the picture arising is homogenous across

specifications indicating a much more stable specification.

[Table 3 about here.]

6. CONCLUSION

In this paper, I have shown that when outcomes of interest are regressed on weather data, there is a danger of spuriously detecting relationships. To illustrate the occurrence of the problem, I have shown nonsensical relationships such as a relationship between electoral turnout and rainfall 100 days before the election. In such cases, the relationship can be rejected by common sense. But for more relevant questions, such as whether rain on the day of the election affect turnout, the problems of spatial correlation remain the same. To give a satisfactory answer in the potentially interesting cases, we need a proper understanding of the phenomena generating the spurious relationships.

The reason for these relationships, I argue, is that spatial patterns in weather conditions are likely to align up with spatial or spatio-temporal patterns in the outcomes of interest. I have shown that this does indeed occur in a simple model of spatially dependent data as well as in an extensive range of Monte Carlo analyses. Moreover, the analyses reveal that standard techniques, such as clustering on spatial entities (Moulton, 1986) or using Conley's (1999) approach to computing standard errors does solve the problem.

Rather, I suggest introducing controls for spatial or spatio-temporal trends in regressions to solve the problem. This is a simple remedy that can easily be combined with other techniques, such as instrumental variables or regression discontinuity designs. In a sample of Norwegian municipal elections, I show that this reduces the problem of spurious relationships in statistical tests to close to the theoretical properties.

The question of more sophisticated approaches to controlling for spatial and spatio-temporal trends, possibly borrowing from the literature on spatial statistics and econometrics is left for future research. There are probably possibilities to do better, but it is unclear that such approaches are sufficiently simple to implement that they actually matter for the applied researcher.

In studies of the effect of short term weather changes, as studied in this paper, weather data are typically available for a large number of periods, of which only a few matter. Then there is

ample supply of placebo data. Such data should regularly be used to test the validity of empirical approaches used. In studies of the effect of long term weather effects, such as the effect on agricultural production, surplus data are harder to find. Still it may be possible to run placebo studies by temporally moving the whole or parts of the rainfall pattern.

When placebo data can be constructed, one may also ask whether these they could be used to construct a more correct null distribution of the parameter of interest, somewhat along the lines of bootstrapping techniques. Saunders (1993) implements a version of this estimator, but does not go into its statistical properties and potential advantages compared to ordinary inference.

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Notes

¹As pointed out by Miller (2015), however, although weather phenomena are exogenous, they may in many cases be predicted in advance.

²An econometric model that properly models the spatially correlated pattern of rainfall as well as other variables of interest might be able to yield correct results. However, no such model is readily available to practitioners and in the fairly extensive literature reviewed below, no such attempts are made.

³The estimation uses data from ten elections between 1971 and 2007 using a two way fixed effects specification $\text{Turnout}_{it} = \alpha_i + \tau_t + \beta_s \text{Rainfall}_{i,t+s} + \epsilon_{it}$ for $s \in [-600, 600]$. To account for possible correlations between rainfall on election day t and day $t+s$, I also consider the specification $\text{Turnout}_{it} = \alpha_i + \tau_t + \beta_s^0 \text{Rainfall}_{i,t} + \beta_s \text{Rainfall}_{i,t+s} + \epsilon_{it}$. See Section 5 for further details and Appendix C for a description of the data.

⁴Results remain the same if one looks at dummies for precipitation above different thresholds, normalize by municipality means or variances, normalize the turnout variable and so on, which all should be robust to heavy tailed distributions.

⁵Parliamentary elections are always held in mid-September in Norway. This means that in the simulations behind Figure 1, we compare precipitation at almost the same date in all 1200 replications.

⁶As an example, I also regressed median gross income by municipality and year on rainfall on every day of the year, one day at a time. The distribution of the t-values are shown in Appendix Figure 8. A 5 % test of the (probably) true null hypothesis of no relationship rejects on 62.5 % of days. One could expect to find a relationship between income and rainfall in countries with a large agricultural sector (Paxson, 1992), but in that case only between rainfall over longer periods of time. Moreover, Norway does not have an important agricultural sector any more.

⁷The problem is not unique to rainfall. First, various terrain characteristics such as ruggedness and gradients, the use of which was popularized by e.g. Duflo & Pande (2007), clearly exhibit spatial correlation. In the empirical analysis of violent conflict, for instance, researchers have found strong spatial and spatio-temporal patterns (see e.g. Buhaug & Gleditsch, 2008; Weidmann & Ward, 2010). There is also a vast literature on the spatial and spatio-temporal nature of housing and property prices (see e.g. Holly et al., 2011; Brady, 2014). More examples could easily be listed. In all these cases, there is a danger of spurious relationships stemming from joint spatial patterns.

⁸A number of papers using rainfall as an exogenous source of variation, e.g. Brückner & Ciccone (2011) and Fujiwara et al. (2016), also include spatially varying trends. However, it is not yet well understood why this is necessary and hence the practice is not as widespread as it probably should be.

⁹Cressie (1993) and Ripley (2004) provide introductions to parts of the literature.

¹⁰See e.g. LeSage & Pace (2009) for an introduction.

¹¹See also Matsui et al. (2011, 2014) for some recent development.

¹²See Dell et al. (2014) for a survey of parts of this literature.

¹³We can reject normality for all the t-values for all the four specification shown in Figure 2 using most conventional tests and significance levels. The reason is mostly the low kurtosis.

¹⁴Spatial non-stationarity is commonly found in meteorological data even after demeaning, see e.g. Fuglstad et al. (2015) and Ingebrigtsen et al. (2015). However, to the best of my knowledge no general procedure for formally testing for stationarity exists.

¹⁵See Appendix C for details on the meteorological data.

¹⁶For simplicity I condition on given values of p_k , but little would change if these were drawn from some continuous distribution on $[0, N]$.

¹⁷Typically one can show that although the numerator in (4) converges to zero, the denominator converges at a higher rate so the fraction diverges.

¹⁸These numbers could of course be reduced by increasing the noise, i.e. increasing the variance of ϵ_i , but this does not reduce the importance of the problem.

¹⁹An exception is time series data, but the current modeling of shocks does not seem particularly relevant to that case.

²⁰See Appendix Table 6 for details.

²¹To simplify, correlation is only to the left. The model would be essentially unchanged if u_i was correlated with both u_{i-1} and u_{i+1} .

²²Results are reported in Appendix Table 7

²³See e.g. Judd (1998, Ch. 6) for an overview of Legendre polynomials and other polynomial basis with applications in economics and Totik (2005) for the mathematical background.

²⁴These polynomials are usually defined recursively with $P_0(x) = 1$, $P_1(x) = x$, and for $i \geq 2$, $P_i(x) = [(2i - 1)xP_{i-1}(x) - (i - 1)P_{i-2}(x)]/i$ where the variable x is normalized to be in the interval $[-1, 1]$.

²⁵The distribution of the estimated coefficients can be found in Appendix Figure 10

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A. EMPIRICAL LITERATURE USING RAINFALL

[Table 4 about here.]

B. PROOFS

B.1. Proof of divergence of the numerator in (4)

Proof. Let $\lceil \cdot \rceil$ and $\lfloor \cdot \rfloor$ denote the ceil and floor operators, that is, for any $x \in \mathbb{R}_+$, $\lceil x \rceil = \min \{y \in \mathbb{N} : x \leq y\}$ and $\lfloor x \rfloor = \max \{y \in \mathbb{N} : x \geq y\}$. Define the relative position of the location of a shock as $\zeta = \frac{p_k}{N}$. Finally define $\lambda = \lceil \zeta N \rceil - \zeta N$ (so $1 - \lambda = \zeta N - \lfloor \zeta N \rfloor$). To study the behavior of $\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K \left(\frac{1}{1+|p_k-i|} - \bar{w} \right) i$, we need the behavior of $\sum_{i=1}^N \sum_{k=1}^K \frac{1}{1+|p_k-i|}$ and $\sum_{i=1}^N \sum_{k=1}^K \frac{i}{1+|p_k-i|}$.

1) The behavior of $\sum_{i=1}^N \sum_{k=1}^K \frac{1}{1+|p_k-i|}$:

For simplicity of notation, we disregard the subscript k . We split the absolute value in the denominator into the terms with i below and above $p = \zeta N$. This yields

$$\begin{aligned} \sum \frac{1}{|\zeta N - i| + 1} &= \frac{1}{\lceil \zeta N \rceil - \zeta N + 1} + \frac{1}{\lceil \zeta N \rceil - \zeta N + 2} + \dots + \frac{1}{\lceil \zeta N \rceil - \zeta N + (N - \lceil \zeta N \rceil)} \\ &\quad + \frac{1}{\zeta N - \lfloor \zeta N \rfloor + 1} + \frac{1}{\zeta N - \lfloor \zeta N \rfloor + 2} + \dots + \frac{1}{\zeta N - \lfloor \zeta N \rfloor + \lfloor \zeta N \rfloor} \\ &= \frac{1}{1 + \lambda} + \frac{1}{2 + \lambda} + \dots + \frac{1}{(N - \lceil \zeta N \rceil) + \lambda} \\ &\quad + \frac{1}{1 + (1 - \lambda)} + \frac{1}{2 + (1 - \lambda)} + \dots + \frac{1}{\lfloor \zeta N \rfloor + (1 - \lambda)}. \end{aligned}$$

Define

$$S_{N-\lceil \zeta N \rceil}^1 = \frac{1}{1 + \lambda} + \frac{1}{2 + \lambda} + \dots + \frac{1}{(N - \lceil \zeta N \rceil) + \lambda}$$

and

$$S_{\lfloor \zeta N \rfloor}^2 = \frac{1}{1 + (1 - \lambda)} + \frac{1}{2 + (1 - \lambda)} + \dots + \frac{1}{\lfloor \zeta N \rfloor + (1 - \lambda)}.$$

The series S_n^1 is a generalized harmonic series of length n . If we define $S_n^0 = 1 + \frac{1}{2} + \dots + \frac{1}{n}$ as the standard harmonic series of length n , we see that $S_{N-\lceil \zeta N \rceil+1}^0 - 1 < S_{N-\lceil \zeta N \rceil}^1 < S_{N-\lceil \zeta N \rceil}^0$. For large n we know that $S_n^0 \rightarrow \gamma + \ln n$ where γ is the Euler–Mascheroni constant ($\gamma \approx .577$). Hence

$\gamma + \ln \frac{N - \lceil \zeta N \rceil + 1}{e} < S_{N - \lceil \zeta N \rceil}^1 < \gamma + \ln (N - \lceil \zeta N \rceil)$. From a similar reasoning, $\gamma + \ln \frac{\lfloor \zeta N \rfloor + 1}{e} < S_{\lfloor \zeta N \rfloor}^2 < \gamma + \ln (\lfloor \zeta N \rfloor)$. It follows that

$$2\gamma + \ln \frac{N - \lceil \zeta N \rceil + 1}{e} + \ln \frac{\lfloor \zeta N \rfloor + 1}{e} < \sum \frac{1}{|\zeta N - i| + 1} < 2\gamma + \ln (N - \lceil \zeta N \rceil) + \ln (\lfloor \zeta N \rfloor).$$

Hence $\frac{1}{N} \sum \frac{1}{|\zeta N - i| + 1} \rightarrow 0$ as $N \rightarrow +\infty$. As this hold for any p_k , it also holds for the sum so $\bar{w} \rightarrow 0$ as $N \rightarrow +\infty$. Moreover, it also holds for the sum weighted by ν_k so $\bar{r} \rightarrow 0$ as $N \rightarrow +\infty$.

2) *The behavior of $\sum_{i=1}^N \sum_{k=1}^K \frac{i}{1 + |p_k - i|}$:*

We proceed by splitting in the same manner, yielding

$$\begin{aligned} \sum \frac{i}{|p - i| + 1} &= \frac{\lceil \zeta N \rceil}{\lceil \zeta N \rceil - \zeta N + 1} + \frac{\lceil \zeta N \rceil + 1}{\lceil \zeta N \rceil - \zeta N + 2} + \cdots + \frac{N}{\lceil \zeta N \rceil - \zeta N + (N - \lceil \zeta N \rceil)} \\ &\quad + \frac{\lfloor \zeta N \rfloor}{\zeta N - \lfloor \zeta N \rfloor + 1} + \frac{\lfloor \zeta N \rfloor - 1}{\zeta N - \lfloor \zeta N \rfloor + 2} + \cdots + \frac{1}{\zeta N - \lfloor \zeta N \rfloor + \lfloor \zeta N \rfloor}. \end{aligned}$$

We have

$$\begin{aligned} &\frac{\lceil \zeta N \rceil + 1}{\lceil \zeta N \rceil - \zeta N + 1} + \frac{\lceil \zeta N \rceil + 2}{\lceil \zeta N \rceil - \zeta N + 2} + \cdots + \frac{N}{\lceil \zeta N \rceil - \zeta N + (N - \lceil \zeta N \rceil)} \\ &= (\lceil \zeta N \rceil - 1) \left(\frac{1}{\lceil \zeta N \rceil - \zeta N + 1} + \frac{1}{\lceil \zeta N \rceil - \zeta N + 2} + \cdots + \frac{1}{\lceil \zeta N \rceil - \zeta N + (N - \lceil \zeta N \rceil)} \right) \\ &\quad + \frac{1}{\lceil \zeta N \rceil - \zeta N + 1} + \frac{2}{\lceil \zeta N \rceil - \zeta N + 2} + \cdots + \frac{N - \lceil \zeta N \rceil}{\lceil \zeta N \rceil - \zeta N + (N - \lceil \zeta N \rceil)} \\ &= (\lceil \zeta N \rceil - 1) S_N^1 + T_{N - \lceil \zeta N \rceil}^1, \end{aligned}$$

where the series

$$T_n^1 = \frac{1}{1 + \lambda} + \frac{2}{2 + \lambda} + \cdots + \frac{n}{n + \lambda}.$$

We know that

$$\frac{n}{1 + \lambda} < T_n^1 < n.$$

Similarly,

$$\begin{aligned}
& \frac{\lfloor \zeta N \rfloor}{\zeta N - \lfloor \zeta N \rfloor + 1} + \frac{\lfloor \zeta N \rfloor - 1}{\zeta N - \lfloor \zeta N \rfloor + 2} + \dots + \frac{1}{\zeta N - \lfloor \zeta N \rfloor + \lfloor \zeta N \rfloor} \\
&= (\lfloor \zeta N \rfloor + 1) \left(\frac{1}{\zeta N - \lfloor \zeta N \rfloor + 1} + \frac{1}{\zeta N - \lfloor \zeta N \rfloor + 2} + \dots + \frac{1}{\zeta N - \lfloor \zeta N \rfloor + \lfloor \zeta N \rfloor} \right) \\
&- \left(\frac{1}{\zeta N - \lfloor \zeta N \rfloor + 1} + \frac{2}{\zeta N - \lfloor \zeta N \rfloor + 2} + \dots + \frac{\lfloor \zeta N \rfloor}{\zeta N - \lfloor \zeta N \rfloor + \lfloor \zeta N \rfloor} \right) \\
&= (\lfloor \zeta N \rfloor + 1) S_N^2 - T_{\lfloor \zeta N \rfloor}^2
\end{aligned}$$

where the series

$$T_n^2 = \frac{1}{1 + (1 - \lambda)} + \frac{2}{2 + (1 - \lambda)} + \dots + \frac{n}{n + (1 - \lambda)}.$$

We know that

$$\frac{n}{2 - \lambda} < T_n^2 < n.$$

It follows that

$$\frac{1}{N} \sum \frac{i}{|p - i| + 1} = \frac{(\lceil \zeta N \rceil - 1) S_{N - \lceil \zeta N \rceil}^1 + (\lfloor \zeta N \rfloor + 1) S_{\lfloor \zeta N \rfloor}^2 + T_{N - \lceil \zeta N \rceil}^1 - T_{\lfloor \zeta N \rfloor}^2}{N}.$$

Hence

$$\begin{aligned}
\frac{1}{N} \sum \left(\frac{1}{|p - i| + 1} - \bar{w} \right) i &= \left(\frac{\lceil \zeta N \rceil - 1}{N} - \frac{N + 1}{2N} \right) S_{N - \lceil \zeta N \rceil}^1 \\
&+ \left(\frac{\lfloor \zeta N \rfloor + 1}{N} - \frac{N + 1}{2N} \right) S_{\lfloor \zeta N \rfloor}^2 + \frac{T_{N - \lceil \zeta N \rceil}^1 - T_{\lfloor \zeta N \rfloor}^2}{N}.
\end{aligned}$$

When $N \rightarrow +\infty$, we see that the two first parentheses converge to $\zeta - \frac{1}{2}$ and the last fraction to a constant $\Xi \in (-\frac{\lambda}{1+\lambda}, \frac{1-\lambda}{2-\lambda})$. Hence the expression converges to a log function, so $w_k = \frac{1}{N} \sum \left(\frac{1}{|p-i|+1} - \bar{w} \right) i \rightarrow +\infty$ as $N \rightarrow +\infty$.

3) *Behavior of the numerator:*

Then the full numerator can be written as $\sum_{k=1}^K w_k \nu_k$. Define the set $K_+ = \{k : \nu_k > 0\}$ and

$K_- = \{k : \nu_k < 0\}$. Now as $N \rightarrow +\infty$, the numerator converges to

$$\frac{1}{N} \sum_{k \in K_+} \nu_k w_k + \frac{1}{N} \sum_{k \in K_-} \nu_k w_k.$$

At least one of the sums diverge. If only one diverge, the numerator converges to either $+\infty$ (only the first diverge) or $-\infty$ (only the second diverge). Furthermore, if both diverge we have

$Pr \left(\left| \sum_{k=1}^K w_k \nu_k \right| \rightarrow +\infty \right) = 1$. To see this, notice that for a given realization of $\{\nu_2, \dots, \nu_K\}$ (and the p_k s if they are taken as random), there is only one value of ν_1 that assures convergence.

The probability of this realization is zero as the ν_k s have continuous distributions. Hence with probability 1 the numerator of (4) diverges.

□

B.2. Proof of convergence of the denominator in (4)

Proof. We want to study the behavior of $\sqrt{\frac{1}{N^2} \sum_{i=1}^N \left(\sum_{k=1}^K \frac{1}{|p_k-i|+1} - \bar{w} \right)^2} =: \sqrt{\frac{1}{N^2} A_N}$. We have $A_N = \sum_{i=1}^N \left(\sum_{k=1}^K \frac{1}{|p_k-i|+1} \right)^2 - N\bar{w}^2$. We know from the proof in Appendix B.1 that $\bar{w}$ converges to a log function so $\frac{\bar{w}^2}{N} \rightarrow 0$ as $N \rightarrow \infty$.

We first study the behavior of $\sum_{i=1}^N \left(\frac{1}{|p_k-i|+1} \right)^2$ for any choice of k . We want to show that as $N \rightarrow \infty$, it converges to a finite positive value $Q_{k\infty}$. As for the proof in B.1, define $\lambda = \lceil \zeta N \rceil - \zeta N$ (so $1 - \lambda = \zeta N - \lfloor \zeta N \rfloor$). Then we have

$$\begin{aligned} \sum \left(\frac{1}{|\zeta N - i| + 1} \right)^2 &= \left(\frac{1}{\lceil \zeta N \rceil - \zeta N + 1} \right)^2 + \left(\frac{1}{\lceil \zeta N \rceil - \zeta N + 2} \right)^2 + \dots \\ &\quad + \left(\frac{1}{\lceil \zeta N \rceil - \zeta N + (N - \lceil \zeta N \rceil)} \right)^2 \\ &\quad + \left(\frac{1}{\zeta N - \lfloor \zeta N \rfloor + 1} \right)^2 + \left(\frac{1}{\zeta N - \lfloor \zeta N \rfloor + 2} \right)^2 + \dots \\ &\quad + \left(\frac{1}{\zeta N - \lfloor \zeta N \rfloor + \lfloor \zeta N \rfloor} \right)^2 \\ &= \left(\frac{1}{1 + \lambda} \right)^2 + \left(\frac{1}{2 + \lambda} \right)^2 + \dots + \left(\frac{1}{(N - \lceil \zeta N \rceil) + \lambda} \right)^2 \\ &\quad + \left(\frac{1}{1 + (1 - \lambda)} \right)^2 + \left(\frac{1}{2 + (1 - \lambda)} \right)^2 + \dots + \left(\frac{1}{\lfloor \zeta N \rfloor + (1 - \lambda)} \right)^2. \end{aligned}$$

Define the series

$$Q_{N-\lceil \zeta N \rceil}^1 = \left(\frac{1}{1 + \lambda} \right)^2 + \left(\frac{1}{2 + \lambda} \right)^2 + \dots + \left(\frac{1}{(N - \lceil \zeta N \rceil) + \lambda} \right)^2$$

and

$$Q_{\lfloor \zeta N \rfloor}^2 = \left(\frac{1}{1 + (1 - \lambda)} \right)^2 + \left(\frac{1}{2 + (1 - \lambda)} \right)^2 + \dots + \left(\frac{1}{\lfloor \zeta N \rfloor + (1 - \lambda)} \right)^2,$$

and define the sum of the the reciprocals of the squares of natural numbers $Q_n^0 = \sum_{i=1}^n \left(\frac{1}{i} \right)^2$. Then we see that $Q_{1+N-\lceil \zeta N \rceil}^0 - 1 \leq Q_{N-\lceil \zeta N \rceil}^1 \leq Q_{N-\lceil \zeta N \rceil}^0$ and $Q_{1+\lfloor \zeta N \rfloor}^0 - 1 \leq Q_{\lfloor \zeta N \rfloor}^2 \leq Q_{\lfloor \zeta N \rfloor}^0$. Hence for given ζ we get $\lim_{N \rightarrow \infty} \sum \left(\frac{1}{|\zeta N - i| + 1} \right)^2 = Q_{k\infty}$. Moreover, as $\lim_{n \rightarrow \infty} Q_n^0 = \frac{\pi^2}{6}$, we have

$$\frac{\pi^2}{3} - 2 \leq Q_{k\infty} \leq \frac{\pi^2}{3}.$$

Consider next the cross terms $\sum_{i=1}^N \frac{1}{|p_k-i|+1} \frac{1}{|p'_k-i|+1} =: B_{kk'N}$ for any choices of $k \neq k'$. As $\frac{1}{|p_k-i|+1} > 0$ for any $p_k \in [1, N]$, we have $B_{kk'N} > 0$. Moreover, it follows from the Cauchy-Schwarz inequality that $B_{kk'N} \leq \sqrt{Q_{k\infty} Q_{k'\infty}} \leq \frac{\pi^2}{3}$.

Hence as $N \rightarrow \infty$, we have $A_N \rightarrow \sum_{k=1}^K \sum_{k'=1}^K \sqrt{Q_{k\infty} Q_{k'\infty}}$, so $0 < A_n \leq K^2 \frac{\pi^2}{6}$. Hence if $\frac{K}{N} \rightarrow \kappa \in \mathbb{R}^+$, the denominator in (4) converges to a non-zero constant whereas if $\frac{K}{N} \rightarrow 0$, the denominator in (4) converges to 0. $\square$

C. THE DATA

The meteorological data used in the paper are created by the Norwegian Meteorological Institute (met.no). The data are based on daily observations of precipitation at all 421 measurement stations in Norway, and based on spatial interpolation using a residual kriging approach (Tveito & Førland, 1999; Mohr, 2008). First, each observation is regressed on a number of geographic properties to separate between a deterministic and a stochastic part. The residuals are then interpolated using kriging and combined with deterministic parts to obtain a grid of 1×1 km cells for Norway. As one would expect, average rainfall is larger along the west coast and in parts of the north.

To get municipal averages, I combine the data with GIS data on municipal boundaries to construct data on average precipitation by municipality for each election year. Municipal boundaries have changed over time, and GIS data on past municipal borders are essentially non-existent. To solve this I map municipalities that no longer exist into their current municipality and use weather data from the present day municipality.

Average precipitation values on election days are shown in Panel (a) of Appendix Figure 7. Panel (b) of Appendix Figure 7 show the average election day precipitation and turnout for the period 1971-2007. There are no clear geographical trends in average turnout.

My preferred measure is a dummy variable for substantial rain on election day, specified as above 1/10 of an inch or 2.5 mm. However, other cut off as well as a linear specification yield comparable results.

Data on electoral turnout taken from the recent collection of Norwegian municipal data made available by Fiva et al. (2012), originating from Statistics Norway and the Norwegian Social Science Data Services. Data from the ten municipal elections between 1971 and 2007 were used. The data on median gross household incomes was taken from Statistics Norway's StatBank. The sample covers all municipal medians for the years 1993-2012.

[Figure 7 about here.]

D. ADDITIONAL MONTE CARLO RESULTS

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

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Figure 1: Spurious t-values

Notes: The graph shows the coefficient from two way fixed effects regression of electoral turnout on a dummy for substantial daily precipitation. The dotted orange line shows the distribution when controlling for real election day rainfall whereas the solid green line excludes this variable. Standard errors are clustered at the municipal level. Precipitation for 600 days before to 600 days after election day employed, but data from +/- 10 days are excluded.

Figure 2: Distribution of the t-values

Notes: The graph shows the distribution of the t-values when regressing municipal turnout on daily precipitation for 600 days before and after election day. The dotted orange line shows the distribution when controlling for real election day rainfall whereas the solid green line excludes this variable. The 10 days before and after the actual election day are omitted. Panel (a) shows results from regressing levels on levels. Panel (b) shows the regression of turnout on a dummy for more than 25 mm rain while Panel (c) employs a dummy for any rain. Panel (d) shows results from a regression where the rank of turnout is measured on the rank of rain, i.e. both variables are uniform on the unit interval.

Figure 3: Spatio-temporal patterns in turnout

(a) Trends by municipality

(b) Trends in neighboring municipalities

Notes: The figure shows municipality specific coefficients δ_i from the regression (1). Red areas are strong negative, blue areas strong positive.

Figure 4: The stylized econometric model

Notes: Panel (a) shows the simulated y_i and r_i against the observation number i . Panel (b) shows a scatter plot of y_i versus r_i as well as a linear fit of the data. Data are simulated for $\beta = 0$.

Figure 5: The number of terms in the nonparametric trend model

(a) Model fit and number of longitude and latitude terms

(b) Model fit and total number of terms

Notes: Panel (a) shows model fit as a function of the number of terms in the longitudinal and latitudinal polynomials, whereas Panel (b) shows fit as a function of the total number of terms included in the tensor product. Approximation is with tensor products of Legendre polynomials of varying degrees. In Panel (b), combinations that belong to the convex hull are shown with solid orange dots and other combinations with hollow green dots.

Figure 6: Distribution of t-values controlling for spatio-temporal trends

Notes: The graph shows the distribution of the t-values when regressing municipal turnout on daily precipitation for 600 days before and after election day. The 10 days before and after the actual election day are omitted. Panel (a) shows results from regressing levels on levels. Panel (b) shows the regression of turnout on a dummy for more than 2.5 mm rain while Panel (c) employs a dummy for any rain. Panel (d) shows results from a regression where the rank of turnout is measured on the rank of rain, i.e. both variables are uniform on the unit interval.

Spatio-temporal trends are controlled for using tensor products of Legendre polynomials with 1×6 , 3×10 , and 7×8 terms as well as regional trends. The graph also includes the t-values obtained without spatio-temporal trends. Linear temporal trends are shown in solid lines and quadratic linear trends in dashed lines.

Figure 7: Average rainfall

Notes: The graph shows average precipitation on election day, averaged over the elections 1971-2007. Dark colors indicate high levels of precipitation.

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Table 1: Monte Carlo simulations based on actual rainfall

	Mean	Std. dev.	Skewness	Share rejected
1) No clustering	0.38	9.13	0.43	0.84
2) Clustered on region	0.25	3.41	1.20	0.59
3) Conley standard errors	0.18	3.15	0.62	0.59
4) Random municipality	-0.04	1.00	0.17	0.05
5) Panel	-0.62	7.96	0.12	0.81

Notes: The Table shows the results of Monte Carlo analyses simulating data as in (2) with $\epsilon_i \sim N(0, 1)$ and 1000 replications. All regressions are cross sectional analyses except the last row which is based on a two way fixed effects panel data estimator. The cut offs for the Conley standard errors were chosen as the standard deviation of the coordinates (longitude ± 3.5 , longitude ± 5 degrees).

Table 2: A Monte Carlo analysis of the simple model

N	K					N	2N
	1	2	5	10	100		
10	0.59	0.57	0.51	0.49	0.49	0.49	0.51
	2.6	2.6	2.4	2.4	2.4	2.3	2.3
50	0.77	0.67	0.64	0.66	0.62	0.62	0.63
	3.9	3.5	3.4	3.4	3.3	3.3	3.5
100	0.79	0.74	0.69	0.68	0.67	0.67	0.66
	4.3	4	3.8	3.8	3.8	3.8	3.7
1000	0.86	0.82	0.82	0.80	0.78	0.75	0.82
	6.2	6.1	6	5.7	5.6	5.4	5.9
10000	0.90	0.88	0.86	0.87	0.83	0.86	0.83
	8.8	8.5	8.2	8.3	7.9	7.7	7.9

Notes: The table shows the fraction of cases where a t -test of $\beta = 0$ is rejected at the 5 % level (first line) and the average of the absolute value of the associated t -value (second line). The true model is $\beta = 0$, $\tau = 1$, $\epsilon_i \sim N(0, 1)$, and for each k , $\nu_k \sim N(0, 1)$ and the position $p_k \sim U(0, N)$. Each model is replicated 1000 times.

Table 3: The effect of precipitation on turnout

	Without trend		With trend	
	(1)	(2)	(3)	(4)
Rain (in cm)	-0.000339 (-0.50)	0.00134** (2.46)	0.00299*** (5.34)	0.00283*** (5.29)
Rain $\times$ Year		0.00185*** (6.96)		-0.000356 (-1.56)
Mean dep. var	0.681	0.681	0.681	0.681
Obs	4417	4417	4417	4417
R ²	0.612	0.624	0.698	0.698

Notes: Outcome variable is municipal electoral turnout. All specifications include municipal and year fixed effects. Specifications (3) and (4) also include the tensor product of Legendre polynomials with 1×6 terms to control for spatio-temporal trends. Standard errors are clustered at the municipality level (using the 2010 municipal structure).

*t-values in parentheses, and *, **, and *** denotes significant at the 10%, 5%, and 1% levels.*

Table 4: Empirical work including rainfall in some top journals

Author	Title	Year	Reference	Weather variables	Spatial resolution	Fixed effects and controls	Clustering
Robert Jensen	Agricultural Volatility and Investments in Children	2000	AER P&P 90(2): 399-404	Monthly rainfall	Region		
Alwyn Young	The Razor's Edge: Distortions and Incremental Reform in the People's Republic of China	2000	QJE 115(4): 1091-1135	Monthly rainfall	Province	Province	
Andrea Ichino and Giovanni Maggi	Work Environment and Individual Background: Explaining Regional Shirkng Differentials in a Large Italian Firm	2000	QJE 115(3): 1057-1090	Yearly rainfall and temperature	Province		Province
Stefan Dercon and Pramila Krishn	In Sickness and in Health: Risk Sharing within Households in Rural Ethiopia	2000	JPE 108(4): 688-727	Annual rainfall	Village		
Carol H. Shiue	Transport Costs and the Geography of Arbitrage in Eighteenth-Century China	2002	AER 92(5): 1406-1419	Annual aridity index	Prefecture		
Timothy Besley and Robin Burgess	The Political Economy of Government Responsiveness: Theory and Evidence from India	2002	QJE 117(4): 1415-1451	Annual rainfall	States	States	
Abhijit V. Banerjee, Paul J. Gertler and Maitreesh Ghatak	Empowerment and Efficiency: Tenancy Reform in West Bengal	2002	JPE 110(2): 239-280	Annual rainfall	District	District	
Dora L. Costa and Matthew E. Kahn	Average annual rainfall, average January and July temperature	2003	AER P&P 93(2): 227-232		Metropolitan area		Metropolitan area
The Rising Price of Nonmarket Goods							
Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market							
Kaivan Munshi		2003	QJE 118(2): 549-599	Annual rainfall	Community	Individual	Community-year
Andrew D. Foster and Mark R. Rosenzweig	Economic Growth and the Rise of Forests	2003	QJE 118(2): 601-637	Annual rainfall	Village	Village	Village
Stephen Coate and Michael Conlin	A Group Rule: Utilitarian Approach to Voter Turnout: Theory and Evidence	2004	AER 94(5): 1476-1504	Daily rainfall and snowfall	County		
Edward Miguel, Shanker Satyanath and Ernest Sergenti	Economic Shocks and Civil Conflict: An Instrumental Variables Approach	2004	JPE 112(4): 725-753	Monthly rainfall	Country	Country FE and time trend	Country
Zeynep K. Hansen and Gary D. Libecap	Small Farms, Externalities, and the Dust Bowl of the 1930s	2004	JPE 112(3): 665-694	Annual rainfall	County	State	State
History, Institutions, and Economic Performance: The Legacy of Colonial Land Tenure Systems in India							
Abhijit Banerjee and Lakshmi Iyer		2005	AER 95(4): 1190-1213	Mean annual rainfall	Spatial cross-section	Region FE	Region
Henry S. Farber	Hourly rainfall, daily snowfall, min/max temperature	2005	JPE 113(1): 46-82		New York City	Individual	Driver shift
Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers							
Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach							
Wolfram Schlenker, W. Michael Hanemann and Anthony C. Fisher		2005	AER 95(1): 395-406	Monthly rainfall	County		
Edward L. Glaeser and Joseph Gyourko	Urban Decline and Durable Housing	2005	JPE 113(2): 345-375	Annual rainfall and temperature	City		
Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries							
Seema Jayachandran		2006	JPE 114(3): 538-575	Annual rainfall	District	District	Region-year
Aaron S. Edlin and Pinar Karaca-Mandic	The Accident Externality from Driving	2006	JPE 114(5): 931-955	Annual rainfall and snowfall	State	State	Month-region, year-region
Michael Conlin, Ted O'Donoghue and Timothy J. Vogelsang	Projection Bias in Catalog Orders	2007	AER 97(4): 1217-1249	Daily temperature and snowfall	Zip code		Household
Esther Duflo and Rohini Pande	Dams	2007	QJE 122(2): 601-646	Annual rainfall	District	District	None, autocorrelation robust method
Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers							
Henry S. Farber	Hourly rainfall, daily snowfall, min/max temperature	2008	AER 98(3): 1069-1082		New York City		
Nathan Nunn	The Long-Term Effects of Africa's Slave Trades	2008	QJE 123(1): 139-176	Average monthly temperature and rainfall	Country	Colonizer	
Gustavo J. Bobonis	Is the Allocation of Resources within the Household Efficient? New Evidence from a Randomized Experiment	2009	JPE 117(3): 453-503	6 month average	Village-period	Household FE	Village
Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall							
Sharon Maccini and Dean Yang	Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden	2009	AER 99(3): 1006-1026	Monthly rainfall	District	District-season FE and trend	Province
Douglas Almond, Lena Edlund and Mårten Palme		2009	QJE 124(4): 1729-1772	Daily rainfall	County	Sibling	County
Gordon Dahl and Stefano DellaVigna	Does Movie Violence Increase Violent Crime?	2009	QJE 124(2): 677-734	Daily weather conditions	National		
Joseph H. Davis, Christopher Hanes and Paul W. Rhode	Harvests and Business Cycles in Nineteenth-Century America	2009	QJE 124(4): 1675-1727	Monthly rainfall and temperature	Cotton belt		
Can Openness Mitigate the Effects of Weather Shocks? Evidence from India's Famine Era							
Robin Burgess and Dave Donaldson	Climate, Grapevine Phenology, Wine Production, and Prices: Pauillac (1800-2009)	2010	AER P&P 100(2): 449-453	Annual rainfall	District-year	2-way FE	District
Jean-Michel Chevet, Sébastien Lecocq and Michael Visser		2011	AER P&P 101(3): 142-146	Daily rainfall and temperatures (aggregated)	Time series		
John S. Felkner and Robert M. Townsend	The Geographic Concentration of Enterprise in Developing Countries	2011	QJE 126(4): 2005-2061	Annual rainfall variation	Village		Various spatial techniques
Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars							
Jennifer Brown		2011	JPE 119(5): 982-1013	Daily temperature, wind, rainfall	Golf course	Course*player	Player*year
Lori Beaman and Jeremy Magruder	Who Gets the Job Referral? Evidence from a Social Networks Experiment	2012	AER 102(7): 3574-3593	Daily rainfall	Time series for study site	None	None
Andreas Madares, Daniel Shoag, Stan Veuger, David Yanagizawa-Drott	Do Political Protests Matter? Evidence from the Tea Party Movement	2013	QJE 128(4): 1633-1685	Daily rainfall	Country/congressional district	Region	State, Conley
Risk Sharing and Transactions Costs: Evidence from Kenya's Mobile Money Revolution							
William Jack and Taveet Suri	Rainfall Forecasts, Weather, and Wages over the Agricultural Production Cycle	2014	AER 104(1): 183-223	Season rainfall	Location	Location	
Mark R. Rosenzweig and Christopher Udry	Satellites, Self-reports, and Submersion: Exposure to Floods in Bangladesh	2014	AER P&P 104(5): 278-283	Monthly rainfall	Village	Village	
Raymond Guiteras, Amir Jina, and A. Mushfiq Mobarak		2015	AER P&P 105(5): 232-236	Monthly rainfall	District		
Solomon M. Hsiang and Kyle C. Meng	Tropical Economics	2015	AER P&P 105(5): 257-261	Average temperature and rainfall	Country	Country	Conley
Meghan R. Busse, Devin G. Pope, Jaren C. Pope, Jorge Silva-Risso	The Psychological Effect of Weather on Car Purchases	2015	QJE 130(1): 371-414	Daily weather conditions	Designated market area	DMA*week of year	DMA*day
Why you Can't Find a Taxi in the Rain and Other Labor Supply Lessons from Cab Drivers							
Henry S. Farber		2015	QJE 130(4): 1975-2026	Hourly rainfall	Central Park		Driver
Peter Koudijs	Those Who Know Most: Insider Trading in Eighteenth-Century Amsterdam	2015	JPE 123(6): 1356-1409	Daily wind, rainfall, temperature	Amsterdam, London		
Jérôme Adda	Economic Activity and the Spread of Viral Diseases: Evidence from High Frequency Data	2016	QJE 131(2): 891-941	Weekly rainfall and temperatures	Region	Region	Region
Alan Barreca, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro	Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century	2016	JPE 124(1): 105-159	Daily rainfall and temperature	Stat	State*month	State
Joyce J. Chen, Valerie Mueller, Yuanyuan Jia, and Steven Kuo-Hsin Tseng	Validating Migration Responses to Flooding Using Satellite and Vital Registration Data	2017	AER P&P 107(5): 441-445	Monthly rainfall	Subdistrict-month	Year FE, historical climate	Primary sampling unit
Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital							
Manisha Shah and Bryce Millett		2017	JPE 125(2): 527-561	Monthly rainfall	District	District	District
Steinberg							

Notes: The table shows the articles found in the survey of the American Economic Review, the Quarterly Journal of Economics, and the Journal of Political Economy 2000-2017. The search was a search for the presence of the work “rainfall” somewhere in the article text. A few articles discussing rainfall theoretically, as well as work on rainfall index insurance are not included on the list.

Table 5: A Monte Carlo analysis of the spatial model

N	K						N	2N
	1	2	5	10	100			
9	0.37	0.36	0.31	0.32	0.30	0.29	0.25	
	1.76	1.71	1.59	1.59	1.56	1.53	1.42	
25	0.57	0.58	0.55	0.54	0.54	0.54	0.51	
	2.84	2.78	2.57	2.52	2.44	2.49	2.43	
49	0.65	0.66	0.66	0.65	0.63	0.66	0.64	
	3.8	3.84	3.59	3.47	3.28	3.41	3.35	
100	0.73	0.76	0.73	0.74	0.72	0.71	0.75	
	5.21	5.12	4.79	4.87	4.61	4.6	4.64	
400	0.85	0.85	0.84	0.85	0.85	0.85	0.83	
	9.15	8.98	8.5	8.6	8.12	8.56	7.79	
1024	0.88	0.90	0.90	0.91	0.89	0.89	0.90	
	13.1	12.9	12.7	12.7	12.3	11.7	12.2	
10000	0.95	0.96	0.96	0.94	0.96	0.95	0.96	
	31.5	31.6	31.5	30.3	29.8	31	31.4	

Notes: The table shows the fraction of cases where a t -test of $\beta = 0$ is rejected at the 5 % level (first line) and the average of the absolute value of the associated t -value (second line). The true model is $z_i = \alpha + \beta \sum r_i + \tau (x_i + y_i) + \epsilon_i$ with $\beta = 0$, $\tau = 1$, $\epsilon_i \sim N(0, 1)$, and for each k , $\nu_k \sim N(0, 1)$ and the position $p_k \sim U([0, N] \times [0, N])$. Each model is replicated 1000 times.

Table 6: A Monte Carlo analysis of the panel data model

T		2							5						
		1	2	5	10	100	N	2N	1	2	5	10	100	N	2N
K	9	0.90	0.83	0.82	0.81	0.82	0.81	0.84	0.58	0.57	0.55	0.51	0.54	0.54	0.56
		4.51	4.18	4.23	4.16	4.22	4.11	4.18	2.84	2.87	2.73	2.61	2.67	2.73	2.74
	25	0.93	0.92	0.88	0.89	0.89	0.88	0.87	0.71	0.73	0.72	0.71	0.71	0.71	0.71
		7.23	6.90	6.71	6.54	6.44	6.57	6.52	4.32	4.39	4.52	4.36	4.25	4.23	4.28
	49	0.94	0.91	0.89	0.90	0.91	0.90	0.89	0.79	0.77	0.75	0.78	0.78	0.76	0.75
		9.75	9.16	8.78	8.80	8.94	8.87	8.66	5.98	5.66	5.68	5.73	5.88	5.65	5.57
	100	0.94	0.94	0.92	0.93	0.91	0.92	0.91	0.84	0.85	0.84	0.85	0.85	0.86	0.84
		13.29	11.87	11.84	11.50	11.28	11.45	11.86	8.15	8.32	7.92	8.06	7.90	7.90	7.72
	400	0.96	0.96	0.94	0.95	0.95	0.94	0.95	0.92	0.91	0.90	0.91	0.91	0.90	0.91
		22.06	20.94	19.66	19.16	19.73	19.39	19.69	14.43	14.25	14.21	14.17	14.30	13.55	14.02
1024	0.97	0.96	0.96	0.97	0.97	0.95	0.96	0.93	0.94	0.94	0.94	0.94	0.94	0.94	
	31.18	28.84	28.25	28.79	28.70	27.38	27.07	22.64	20.83	21.14	21.14	21.49	20.80	21.08	
10000	0.99	0.99	0.98	0.98	0.98	0.99	0.98	0.97	0.98	0.98	0.97	0.98	0.98	0.98	
	76.86	70.88	65.82	68.79	68.76	67.55	66.95	59.49	57.21	58.50	55.25	56.76	54.96	57.06	
T		10							20						
		1	2	5	10	100	N	2N	1	2	5	10	100	N	2N
K	9	0.49	0.48	0.51	0.52	0.51	0.49	0.50	0.49	0.48	0.49	0.50	0.48	0.47	0.50
		2.40	2.28	2.42	2.43	2.44	2.37	2.42	2.21	2.30	2.30	2.23	2.24	2.21	2.31
	25	0.69	0.67	0.67	0.66	0.69	0.67	0.66	0.66	0.66	0.68	0.66	0.65	0.69	0.64
		3.87	3.89	3.91	3.66	3.77	3.75	3.67	3.55	3.63	3.68	3.66	3.61	3.72	3.57
	49	0.76	0.73	0.76	0.74	0.73	0.78	0.75	0.73	0.73	0.74	0.75	0.73	0.76	0.74
		5.09	5.01	5.13	5.09	5.04	5.41	5.02	4.74	4.72	5.03	4.92	4.75	4.96	5.05
	100	0.82	0.82	0.85	0.82	0.82	0.82	0.81	0.82	0.83	0.81	0.83	0.81	0.83	0.82
		7.09	6.78	7.70	7.30	7.16	7.43	7.01	7.07	6.76	6.72	6.97	6.61	6.77	7.03
	400	0.92	0.90	0.90	0.92	0.91	0.91	0.92	0.92	0.91	0.90	0.90	0.89	0.90	0.89
		14.32	12.66	13.23	13.55	13.30	13.23	12.84	13.27	12.24	12.47	12.80	12.16	13.02	12.07
1024	0.94	0.94	0.94	0.93	0.93	0.94	0.95	0.95	0.94	0.93	0.92	0.94	0.94	0.92	
	20.93	20.36	20.47	19.70	19.85	18.82	20.23	19.54	19.17	19.44	19.41	18.31	18.95	18.06	
10000	0.97	0.98	0.97	0.98	0.97	0.97	0.98	0.97	0.99	0.98	0.98	0.98	0.98	0.98	
	53.43	54.44	55.01	52.13	53.25	52.16	53.80	53.64	53.30	52.11	51.07	51.52	51.83	51.21	

Notes: The Table shows Monte Carlo simulations of model (5) for different panel lengths T , sample sizes N , and number of shocks K . The table shows the fraction of cases where a t -test of $\beta = 0$ is rejected at the 5 % level (first line) and the average of the absolute value of the associated t -value (second line). The true model is $\beta = 0$, $\tau = 1$, $\epsilon_i \sim N(0, 1)$, and for each k , $\nu_k \sim N(0, 1)$ and the position $p_k \sim U([0, N]^2)$. Each model is replicated 1000 times.

Table 7: A Monte Carlo analysis of a model with autoregressive spatial correlation

ρ	.5							.75							
K	1	2	5	10	100	N	2N	1	2	5	10	100	N	2N	
$\mathbb{Z}$	10	0.19	0.19	0.17	0.18	0.17	0.19	0.18	0.25	0.26	0.24	0.22	0.25	0.24	0.22
		1.2	1.2	1.1	1.2	1.2	1.2	1.2	1.5	1.4	1.4	1.3	1.4	1.4	1.3
	50	0.24	0.22	0.21	0.22	0.22	0.22	0.22	0.36	0.35	0.35	0.36	0.36	0.35	0.31
		1.3	1.3	1.2	1.3	1.2	1.3	1.3	1.8	1.7	1.7	1.7	1.7	1.7	1.6
	100	0.24	0.22	0.23	0.19	0.24	0.22	0.21	0.38	0.42	0.39	0.38	0.40	0.34	0.38
		1.3	1.3	1.3	1.2	1.3	1.3	1.3	1.8	1.8	1.8	1.8	1.8	1.7	1.8
	1000	0.25	0.20	0.23	0.23	0.26	0.19	0.26	0.44	0.39	0.39	0.39	0.39	0.39	0.42
		1.3	1.3	1.3	1.3	1.4	1.2	1.4	1.9	1.8	1.8	1.8	1.9	1.8	1.9
	10000	0.24	0.22	0.25	0.22	0.22	0.24	0.22	0.41	0.41	0.41	0.40	0.40	0.40	0.39
		1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.9	1.9	1.9	1.9	1.9	1.9	1.8
ρ	.95							1							
K	1	2	5	10	100	N	2N	1	2	5	10	100	N	2N	
$\mathbb{Z}$	10	0.40	0.33	0.33	0.29	0.31	0.34	0.29	0.39	0.39	0.34	0.34	0.31	0.34	0.34
		1.8	1.7	1.6	1.6	1.6	1.7	1.6	1.9	1.8	1.8	1.7	1.6	1.7	1.7
	50	0.57	0.50	0.49	0.51	0.47	0.49	0.49	0.59	0.55	0.52	0.55	0.54	0.52	0.53
		2.6	2.4	2.3	2.4	2.3	2.3	2.3	2.8	2.7	2.5	2.6	2.7	2.6	2.6
	100	0.56	0.58	0.56	0.56	0.53	0.53	0.52	0.68	0.64	0.60	0.59	0.59	0.61	0.58
		2.7	2.8	2.7	2.8	2.6	2.5	2.6	3.4	3.2	3.1	3.1	3	3.1	3
	1000	0.60	0.61	0.63	0.61	0.64	0.63	0.59	0.81	0.79	0.77	0.75	0.75	0.74	0.75
		3.1	3.3	3.2	3.1	3.3	3.2	3	5.5	5.1	5.1	5	4.9	5	5
	10000	0.65	0.64	0.64	0.65	0.64	0.61	0.63	0.86	0.86	0.80	0.85	0.82	0.83	0.83
		3.2	3.3	3.3	3.4	3.4	3.2	3.3	7.8	7.5	7.3	7.1	7.3	7.2	7.4

Notes: The Table shows Monte Carlo simulations of model (6) for different autoregressive coefficients ρ , sample sizes N , and number of shocks K . The table shows the fraction of cases where a t -test of $\beta = 0$ is rejected at the 5 % level (first line) and the average of the absolute value of the associated t -value (second line). The true model is $\beta = 0$, $\tau = 1$, $\epsilon_i \sim N(0, 1)$, and for each k , $\nu_k \sim N(0, 1)$ and the position $p_k \sim U([0, N]^2)$. Each model is replicated 1000 times.

E. ADDITIONAL GRAPHS AND TABLES

Figure 8: Spurious t-values in regressions of income on rainfall

Notes: The graph shows the coefficient from two way fixed effects regression of municipal median gross income on a dummy for substantial daily precipitation. Standard errors are clustered at the municipal level. Data for the 365 days of the year are used.

Figure 9: Distribution of simulated t-values

Notes: The graphs show the distribution of t-values obtained from the Monte Carlo analyses of spatial trends on actual rainfall. Panel A shows the distribution of the t-values without clustering in the cross sectional setting (solid green lines) and with a panel (dashed orange). Panel B shows the values in the cross section clustering at the regional level (solid green) and using Conley standard errors (dashed orange). The cut offs for the Conley standard errors were chosen as the standard deviation of the coordinates (longitude ± 3.5 , longitude ± 5 degrees). Panel C shows the distribution of the placebo with randomly chosen municipalities (solid green) and the standard normal distribution (dotted orange).

Figure 10: Distribution of estimated coefficients controlling for spatio-temporal trends

Notes: The graph shows the distribution of the estimated coefficients when regressing municipal turnout on daily precipitation for 600 days before and after election day. The 10 days before and after the actual election day are omitted. Panel (a) shows results from regressing levels on levels. Panel (b) shows the regression of turnout on a dummy for more than 25 mm rain while Panel (c) employs a dummy for any rain. Panel (d) shows results from a regression where the rank of turnout is measured on the rank of rain, i.e. both variables are uniform on the unit interval. Spatio-temporal trends are controlled for using tensor products of Legendre polynomials with 1×6 , 3×10 , and 7×8 terms as well as regional trends. Linear temporal trends are shown in solid lines and quadratic linear trends in dashed lines.

Table 8: The effect of precipitation on turnout – additional specifications

Panel A: Estimation without spatio-temporal trends

	(1)	(2)	(3)	(4)	(5)	(6)
Rain (in cm)	-0.000339 (-0.50)			-0.000579 (-0.84)	-0.000436 (-0.51)	0.00134** (2.46)
Rain positive		0.00546*** (3.55)		0.00572*** (3.57)		
Rain above 2.5 mm			-0.000143 (-0.12)		0.000396 (0.26)	
Rain $\times$ Year						0.00185*** (6.96)
Mean dep. var	0.681	0.681	0.681	0.681	0.681	0.681
Obs	4417	4417	4417	4417	4417	4417
R ²	0.612	0.613	0.612	0.613	0.612	0.624

Panel B: Estimation with spatio-temporal trends

	(1)	(2)	(3)	(4)	(5)	(6)
Rain (in cm)	0.00299*** (5.34)			0.00270*** (4.81)	0.00244*** (3.58)	0.00283*** (5.29)
Rain positive		0.00742*** (5.31)		0.00618*** (4.41)		
Rain above 2.5 mm			0.00511*** (4.94)		0.00215* (1.69)	
Rain $\times$ Year						-0.000356 (-1.56)
Mean dep. var	0.681	0.681	0.681	0.681	0.681	0.681
Obs	4417	4417	4417	4417	4417	4417
R ²	0.698	0.697	0.697	0.699	0.698	0.698

Notes: Outcome variable is municipal electoral turnout. All specifications include municipal and year fixed effects. All specifications in Panel B also include the tensor product of Legendre polynomials with 1×6 terms to control for spatio-temporal trends. Standard errors are clustered at the municipality level (using the 2010 municipal structure).

*t-values in parentheses, and *, **, and *** denotes significant at the 10%, 5%, and 1% levels.*