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On Climate Fat Tails and Politics

Abstract

Transitioning the economy from one that relies on fossil fuels to one that emphasizes renewable energy sources will have important implications for the pattern of natural resource use. Such a transition depends on government policies. As elected politicians have an incentive to weigh the spatially heterogeneous costs and benefits on their constituents from taking political action, one might hope that particularly unusual climate events might provide an impetus to increased action. We undertake an analysis using a variety of data sources. We first investigate the stochastic process governing temperature anomalies allowing for "fat tails", which can arise either from a "jump" diffusion process or a time-varying volatility process. Using the parameter estimates from this first stage, combined with demographic and socio-economic variables, we analyze features promoting support for policies addressing climate change. Several of the parameter estimates that capture fat tails in temperature anomalies play a statistically important relation.

JEL-Codes: Q200, D800, L150.

Keywords: climate policy, temperature anomalies, fat tails, politics.

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1 Introduction

Perhaps the most pressing issue currently facing environmental economists is the potential for large-scale damages arising from climate change. Reducing greenhouse gas emissions and other pollutants is crucial if society is to successfully address this challenge; this will almost surely necessitate substituting away from traditional fossil-fuel based energy. Such adaptations will have significant implications for the pattern of natural resource use, including reductions in the demand for fossil fuels (petroleum for motor vehicle transport, coal and natural gas for power generation) and increases in the demand for resources associated with renewable energy generation ("rare earth" minerals that are required for the production of wind turbines, solar panels and batteries for electric vehicles). As a result, virtually any climate policy society might consider going forward will be associated with important effects on natural resources.

An emerging literature has examined the factors influencing public opinion as to the existence of anthropogenic climate change.[1] We discuss elements of this literature below; one main line of inquiry is the examination of the relation between climate-related events, such as periods of hotter than normal weather, and individuals' beliefs. One conjecture implied by this line of inquiry is that elected government officials may be more likely to take action when they perceive the electorate is more concerned about climate change. Somewhat surprisingly, though, relatively little attention has been directed to the relation between climate-related events and politicians' behavior. A key goal of our analysis is to address this lacuna. To this end, we examine how information related to climate events influences behavior of United States (US) representatives.

The connection between our line of inquiry and the existing literature on citizens' climate-

[1] See Howe et al. (2019) for a detailed discussion of this literature.

related beliefs is inspired by Peltzman (1984), wherein politicians weigh the costs and benefits of taking action. There is good reason to believe these benefits and costs are heterogeneous across the United States (US). One important benefit of policy intervention is the potential mitigation of the adverse effects from climate change, which differ across space (Hsiang et al., 2017). For example, to the extent that damages are linked to adverse impacts on agriculture they will depend on the spatial distribution of crops, as well as the vulnerability of different crops; in this regard, rural areas are more exposed. On the other hand, urban areas have a larger population base that might suffer from climate change. The costs of adopting a climate policy such as a carbon tax or a cap-and-trade program seem likely to fall most heavily on those jurisdictions that rely more on fossil fuels to generate electricity, or who have industrial activity that generates emissions, and there is considerable variation across the country with respect to such reliance (Cragg et al., 2013).

To address these spatial considerations, we analyze climate data from a large, longitudinal data set which we then process to obtain monthly observations for each US state over the period from 1958 to 2020.[2] We also gather data on precipitation and droughts, two other measures of climate events that have been considered in the literature mentioned above. For both of these variables we construct the difference between the particular observation and a historical comparator (thereby mimicking the climate anomaly variable for temperatures).[3] These data are then combined with

[2]The source data provides measures of the "temperature anomaly" – the difference between temperature and an historical comparator – for each of several hundred geographic locations (called "stations") along with information allowing us to identify the state in which the station is located, for each month during this 62 year period. Accordingly, there are over one million data points on temperature anomalies. Using "temperature anomalies" can be interpreted as taking into account patterns that would be likely to occur irrespective of a changing climate.

[3]Monthly observations on precipitation are also available at hundreds of stations for the period from 1926 to 2020, along with information allowing us to identify the state in which the station is located. These data are available for all US states except Hawaii, yielding over an additional million data points. For Hawaii we use information from the US National Weather Service (NWS) for four stations; here there are monthly observations for the 31 year period from 1990 to 2020, also adding thousands of additional data points. We measure drought levels using the "Drought Severity and Coverage Index (DSCI)," which consists of monthly observations for the 21 year period from 2000 - 2020, yielding a total of just over 12,000 data points. The U.S. Drought Monitor is jointly produced by the National Drought Mitigation Center at the University of Nebraska-Lincoln, the United States Department of Agriculture, and

information on political behavior, taken from multiple annual reports by the League of Conservation Voters (LCV); this source produces an annual scoresheet for all US representatives, which allows us to construct a variable reflecting average annual environmentally-facing performance in each state. We also include demographic and socio-economic information relevant to each state, across time. Combining these two sources, along with information on relevant demographic factors, allows us to preform an analysis of the dynamic aspects of political economy factors as they influence behavior related to climate policy.

The database we obtain in this manner contains several characteristics that align with a conceptualization of "big data" as a socio-culturally evolving concept (Favaretto et al., 2020) that includes "large amounts of different types of data produced from various types of sources, such as people, machines, or sensors" (European Commission, Directorate-General for Justice and Consumers, 2018). Such a definition would extend beyond the traditional "3V"s – volume, velocity, and variety – to include such attributes as variability, value, portentous and predictive. Our goal in this paper is to use our "big data" to investigate patterns in political behavior related to climate policy, which – as we noted above – has particular implications for natural resource use. In this way, our investigation applies big data to a particularly pressing use of natural resources in the future related to policies designed to address climate change.

2 Literature review

Our investigation touches on multiple strands of the literature: climate patterns and their influence on peoples' expectations; modeling stochastic processes involving abrupt changes or time-varying

the National Oceanic and Atmospheric Administration.

volatility; inferring the damages induced by increased temperatures; and the political economy implications of climate policy related to heterogeneous costs from climate change or policy interventions.

We adopt an interpretation of "climate" taken from the literature: that it is a spatially-specific distribution of weather outcomes for a given location; "weather" then refers to a particular draw from that probability distribution over an interval of time (Hsiang, 2016; Deryugina and Hsiang, 2017; Acevedo et al., 2020; Kolstad and Moore, 2020). Climate change can then be thought of as a shift in the distribution of outcomes, potentially increasing the likelihood of extreme outcomes (Hansen et al., 2012). This interpretation highlights the expository value of focusing on the potential for dramatic changes, which we refer to as "jumps," and for time-varying volatility.

Such a focus echoes a robust literature regarding the evolution of energy prices, many of which are relevant to climate policy. Some of the work in this strand of the literature focuses on volatility concerns. For example, Pindyck (2004) studies volatility in natural gas and crude oil price returns, using a "Generalized Autoregressive Conditional Heteroscedasticity" (GARCH) process. Other analysts have allowed for jumps in a variety of energy prices (Chevallier and Ielpo, 2014). Examples include oil (Askari and Krichene, 2008; Gronwald, 2012; Wilmot and Mason, 2013), natural gas (Benth et al., 2008; Mason and Wilmot, 2014), and coal (Wilmot, 2016). The potential presence of jumps in various energy prices can induce jumps in electricity prices (Benth et al., 2008) and carbon prices (Alberola et al., 2008; Chevallier and Sévi, 2014; Hammoudeh et al., 2014).

Information from changing weather patterns might influence a typical citizen's thought process, which Hsiang (2016) refers to as the "belief effect." Several papers use a survey methodology to evaluate individuals' beliefs, with an eye towards linking stated beliefs about climate change with weather effects. One group of papers focus on smaller geographic areas such as specific states

(Borick and Rabe, 2010; Hamilton and Stampone, 2013; Villar and Krosnick, 2010) while a second group uses national-level surveys (Borick and Rabe, 2010; Brody et al., 2008; Brooks et al., 2014; Brulle et al., 2012; Donner and McDaniels, 2013; Egan and Mullin, 2012; Howe et al., 2015; Myers et al., 2013). Some analyses use data drawn from phone surveys (Brody et al., 2008; Brooks et al., 2014; Hamilton and Stampone, 2013; Howe et al., 2015; Krosnick et al., 2006) while others use surveys executed by large, well-know national organizations (Brulle et al., 2012; Deryugina, 2013; Donner and McDaniels, 2013; Egan and Mullin, 2012; Howe et al., 2015; Konisky et al., 2016) or internet-based surveys (Howe et al., 2015; Konisky et al., 2016; Myers et al., 2013; Zaval et al., 2014). Other papers use surveys based on countries outside of North America (*e.g.*, Gärtner and Schoen (2021), who use a survey of Germans, and Lee et al. (2015), who use survey data from multiple countries), or meta-analysis (Hornsey et al., 2016). Some studies use different samples obtained at multiple points in time (Brooks et al., 2014; Brulle et al., 2012; Egan and Mullin, 2012; Konisky et al., 2016). A handful of analyses use data where respondents were surveyed at multiple points in time (Myers et al., 2013; Palm et al., 2017), yielding a panel dataset. The list of papers further falls into two sets: those that focus on local- or state-effects from climate events (Brody et al., 2008; Brooks et al., 2014; Egan and Mullin, 2012; Gärtner and Schoen, 2021; Kaufmann et al., 2017; Konisky et al., 2016; Krosnick et al., 2006; Myers et al., 2013; Palm et al., 2017; Zaval et al., 2014) and those that use information at a geographically larger, such as national, scale (Borick and Rabe, 2010; Brulle et al., 2012; Deryugina, 2013; Donner and McDaniels, 2013; Krosnick et al., 2006). Most papers in this strand of the literature focus on the effect of warmer temperatures, though Brooks et al. (2014), Deryugina (2013) and Hamilton and Stampone (2013) ask whether either cooler or warmer anomalies matter. Most of these papers allow for socio-economic / demographic effects such as age, education, race, and gender, often finding that such effects matter, though political ideology or affiliation seems to play at least as important a role (*e.g.*, Hornsey et al. (2016)). In general, opinions exhibit substantial geographic heterogeneity.[4]

On balance, mixed messages emerge from this set of papers. On the one hand, several papers find the potential for either: greater climate change concern, belief that human-caused climate change is happening, or support for climate policies to result from changes in local temperatures (Brooks et al., 2014; Deryugina, 2013; Donner and McDaniels, 2013; Egan and Mullin, 2012; Hamilton and Stampone, 2013; Kaufmann et al., 2017; Krosnick et al., 2006; Lee et al., 2015; Zaval et al., 2014) or extreme weather events (Konisky et al., 2016). But Brulle et al. (2012) offer a competing view, arguing against such relationships; Gärtner and Schoen (2021) also find evidence that local events are unimportant – though they admit that the personal experience with local weather events may have played a larger role "in a period or region with more extreme weather events of longer duration with more tangible personal consequences" (p. 16). There are mixed results as well regarding the connection between longer-term temperatures or temperature trends and public opinion: Deryugina (2013) and Donner and McDaniels (2013) find such a relationship but Kaufmann et al. (2017) and Palm et al. (2017) do not.

Deryugina's paper provides evidence directly relevant to our inquiry; in particular, she finds that observed temperatures that are sufficiently far from historical averages have a statistically significant impact on beliefs – what one might call "tail events."[5] Hansen et al. (2012) provides evidence that highlights the potential importance of tail events. These authors show that the distribution

[4]For example, (Howe et al., 2015, p. 599) state "public opinion about global warming exhibits substantial variation between and within regions, states and cities."

[5]In particular, she finds that abnormally cold days erode beliefs in global warming more than abnormally hot days enhance beliefs. Moreover, there is reason to expect that longer periods of abnormal temperatures will have a greater effect than shorter periods. The potential importance of tail events underscores the role of "fat tails" – which refers to a probabilistic distribution with a greater amount of weight placed on outliers, or events relatively far from the mean Weitzman (2009a,b). The idea is closely related to the notion of excess kurtosis – probability distributions with values of kurtosis (the fourth moment of the distribution) that exceed 3, the value associated with a Normal distribution.

of temperature anomalies is not Gaussian: in a warming climate the distribution of temperature anomalies will shift upward, with positive anomalies and heat events becoming more frequent. This latter result points to the important potential for non-stationarity in temperature anomalies; Kaufmann et al. (2017) also argue for non-stationarity. These results point to the need for a model that corrects for non-stationarity, for example focusing on the percentage change in anomalies (as we do). Furthermore, there is evidence that temperature anomalies[6] are subject to considerable spatial variation in kurtosis (the fourth moment of the distribution of anomalies), as indicated by Figure 1. In that figure, we show the average value of kurtosis for changes in temperature anomalies from one month to the next, by US states; for all but four US states, the kurtosis exceeds 3 – which as we noted in footnote 5 is closely related to the concept of fat tails.

While much of this strand of the literature focuses on the role played by temperatures, some studies use data related to precipitation. These studies commonly find little to no relation to climate opinions (Hamilton and Stampone, 2013) – though (Konisky et al., 2016, p. 3) argue that "extreme weather events predict climate opinion." Offering an alternative to precipitation, Brulle et al. (2012) evaluates the potential role played by weather extremes (for example, as measured by the "Climate Extremes Index"), but fails to find a relation to climate opinions.

Changes in climate can also affect economic production through its influence on weather realizations, which can then impact economic outcomes. One immediate way this "indirect effect" – to use the terminology in Hsiang (2016) – can manifest is via impacts on agriculture (Schlenker, 2010); it can also occur in a range of other areas including mortality, crime and labor productivity (Hsiang et al., 2017). Climate impacts can vary substantially between regions, even in extremely

[6] "Temperature anomaly" refers to the difference between current temperatures and an historical comparator. The figure is based on data available at `https://www.ncei.noaa.gov/data/us-historical-climatology-network/2.5/access/`, in the "tavg-raw" subdirectory; the historical baseline is taken as the January 1951 - December 1980 average. Using these data, one may calculate the kurtosis for month-on-month changes in temperature anomalies.

urbanized contexts (Deryugina and Hsiang, 2017).[7] Effects from temperature variability can also affect the profitability of the US corporate sector; these effects can vary substantially across time and space (Bortolan et al., 2022).

The literature discussed above suggests that the potential for abnormal changes in temperatures or prolonged periods of unusual temperatures – either of which can induce “fat tails” in patterns of temperature anomalies – might thereby exert an influence towards increased political activism. But while much of the work summarized above examines the effect of single events, there is good reason to expect persistent climate changes to occur over the course of many years. This observation raises two points: first, that there is value in using data on unusual climate events over the course of several years. The approach we take – analyzing the potential for fat tails over the course of several hundreds of months fits this characterization. Second, the potential for elected officials' political behavior to also adjust over time, perhaps due to changes in key socio-economic / demographic variables, also suggests the need for a lengthy time series of observations. The data we use to analyze political behavior, which uses data on voting patterns over twenty years, fits this characterization as well.

The strand of the literature discussed above suggests a potential for elections to increase the tendency for political intervention to address climate change. To the extent that citizens become more inclined to believe in anthropogenic climate change, or that business interests perceive that they are at increasing risk of adverse consequences from climate change, pressure on elected officials is likely to mount. However, the ‘political’ effects measured by papers in the literature we discussed above generally arise via survey responses, not elections; the difference can matter

[7]One can think of adverse effects arising through uncertainty over future climatic developments: “Extreme temperature oscillations, if wide or frequent enough, can influence decision making by raising attention towards the future repercussions of climate change” (Natoli, 2022, p. 6).

(Vossler et al., 2003). One way to resolve this concern is to focus on political behavior, as opposed to citizen beliefs. A main goal in our paper is to bring together the themes in the literature discussed above, with a focus on the potential for abnormally large changes in temperature (either larger or smaller) to exert an influence on political behavior.

In his seminal paper, Peltzman (1984) suggests that politician's actions will reflect a weighing of costs and benefits to their constituency. To the extent that unusual events change citizens' perspectives (belief effect) or yield adverse productivity impacts (indirect effect), one can easily imagine such events ultimately influencing elected representatives' interest in considering climate policies. Indeed, these elements are likely to influence citizens' perceptions of the cost of inactivity, *i.e.* the benefits of regulatory intervention. Weighing against these factors is the notion that there will be costs from regulatory intervention, and that these costs will be heterogeneous across states. Indeed, heterogeneous fossil-fuel carbon emissions could potentially explain variation in politicians' voting patterns (Cragg et al., 2013). This suggests by extension that reliance on fossil-fuel based energy usage, for example by their dependence on coal for electricity generation, can play a meaningful role.[8]

3 Background

Our interest lies in examining the relation between the stochastic process governing temperature anomalies, particularly as those processes include the potential for fat tails, and political behavior of elected representatives. In this section we sketch out the empirical models we employ for these inquiries; some of the more technical aspects of the modeling are relegated to the Appendix.

[8] That said, jurisdictions with a greater reliance on coal-fired electricity generation are also likely to have greater amounts of local air pollutants, which could motivate a greater degree of regulatory intervention.

3.1 Econometric framework: fat tails

We start by describing the model we use to analyze the stochastic processes characterizing temperature anomalies in each of the 50 US states. The foundation for this model is a Brownian motion process with drift:

$$\mathrm{d}x_t = \mu dt + \sigma \mathrm{d}z_t, \tag{1}$$

where $\mathrm{d}z_t$ represents an increment of a Wiener process, μ is the deterministic trend, and σ is the square root of the variance of the stochastic process, and x_t is the variable of interest (here, temperature anomalies in a particular state). We refer to this model as "pure diffusion" (PD) in the pursuant discussion. This model has been analyzed in a wide range of applications, largely owing to its relative ease of application. However, there are reasons to think that a more complicated model – one allowing for fat tails – is appropriate for describing the evolution of temperatures.[9] Periods of abnormally high temperatures (sometimes referred to as heat waves), or abnormally cold temperatures (*e.g.*, polar vortex events), would be examples here, as would more extended periods of "larger than usual" temperatures. The first class of epochs might reflect transitory events, while the second class could reflect periods where the variance associated with temperature anomalies becomes larger than historic norms. Addressing these types of events requires adjusting the PD model by including elements that are consistent with fat tails.

To allow for spikes or jumps and time-varying volatility, we utilize the following framework. Jumps enter into the model in the style of Merton (1976), by assuming month-on-month changes

[9] As we noted above, the concept of fat tails is closely related to kurtosis values exceeding 3 (the value of kurtosis for a Normal distribution). As illustrated in Figure 1, all but four US states exhibit kurtosis levels above 3. Weitzman (2009b) emphasizes the potential importance of fat tails in variables measuring the climate, such as temperatures. As we discuss later in this section, fat tails can be explained by both a jump process and a process that captures time-varying volatility such as the GARCH process.

in temperature anomalies fall into one of two types: The first type are 'normal' fluctuations, represented through the PD process, while the second type are 'abnormal' transitory shocks, modeled by a Poisson process. The key parameter is such a process is the jump intensity, λ, which describes the mean number of shocks occurring per unit of time; during an interval of time of length dt, the probability of observing a jump is then λdt. We model the size of these jumps as independently and normally distributed, with mean θ and variance δ^2. Combining these two aspects of the jump process into a term J_t, we can describe the mixed jump-diffusion (JD) process as

$$\mathrm{d}x_t = \mu + \sigma z_t + J_t. \tag{2}$$

An alternative explanation for the fat tails described above is that temperature anomalies follow a time-varying error process. We capture this effect via the generalized autoregressive conditional heteroskedastic (GARCH) framework. Under this approach, the variance component σ^2 above is replaced by a time-varying conditional variance term, h_t:

$$h_t \equiv E_{t-1}(\sigma^2) = \kappa + \alpha_1 (x_{t-1} - \mu)^2 + \beta_1 h_{t-1}. \tag{3}$$

Allowing for both jumps and time-varying volatility results in the combined GARCH jump-diffusion (GJD) process:

$$\mathrm{d}x_t = \mu + \sqrt{h_t}\sqrt{z_t} + J_t. \tag{4}$$

Combining the aspects discussed above, one can express the log-likelihood function for the GJD model as

$$L(\boldsymbol{\phi},\mathbf{x}) = -T\lambda - \frac{T}{2}ln(2\pi) + \sum_{t=1}^{T}\left[\sum_{n=0}^{\infty}\frac{\lambda^n}{n!}\frac{1}{\sqrt{h_t+n\delta^2}}exp(\frac{-(x_t-\mu-n\theta}{2(h_t+n\theta^2})\right], \tag{5}$$

where $\mathbf{x}$ is the vector of observations on the variable of interest. The econometric problem is then to maximize this likelihood function by choice of the parameter vector $\boldsymbol{\phi} = (\mu,\kappa,\alpha,\beta,\lambda,\theta,\delta)$. Such estimates are known to be consistent and invariant with asymptotically normal distributions of the parameters. The GJD and PD models defined can be compared within this framework using the log-likelihood statistic

$$LR = 2ln\left(\frac{L(\hat{\boldsymbol{\phi}};\mathbf{x})}{L(\boldsymbol{\phi}^*;\mathbf{x})}\right), \tag{6}$$

where $\hat{\boldsymbol{\phi}}$ represents the estimated parameter vector under a particular list of m restrictions and $\boldsymbol{\phi}^*$ represents the unrestricted parameter vector estimate. If the parameter restriction is valid LR will be distributed as a Chi-square random variable with m degrees of freedom. In our application, the test that the GJD model does not render a statistically important improvement over the PD model corresponds to restricting the parameter vector by setting $\alpha=\beta=\lambda=\theta=\delta=0$, whence $m=5$.[10]

3.2 Econometric framework: politician's behavior

The next step in our analysis is to assess the implications of the GJD model for political behavior. To this end we describe a regression model where the left-side variable, Y_{it}, is a measure of the voting behavior of politicians from state i in year t. The key explanatory variables of interest are the state-specific parameters produced in the first part of the analysis: $\phi = (\mu,\kappa,\alpha,\beta,\lambda,\theta,\delta)$. Additional explanatory variables in this regression include a variety of demographic variables proposed

[10]Under this hypothesis, the variance would be constant; referring to eq. (3), that (constant) variance would coincide with κ – which would therefore not be restricted to zero.

in the extant literature, including: a state's population, the fraction of the population that is white, the fraction of the population that is over 65, and the population of the state that lives in an urban area. We also include the state's annual coal purchases for the purpose of generating electricity, which we interpret as capturing the cost to that state associated with adopting some form of climate policy. This variable captures an effect that is similar to per-capita carbon dioxide emissions, which has been used to capture heterogeneous costs of addressing climate change (Brody et al., 2008; Lee et al., 2015). Finally, to address the pervasive finding in the literature that political predisposition plays an important role in driving climate change beliefs (as discussed in Section 2), we include the "Partisan Voting Index" produced by the Cook Political Report (as discussed below in subsection 4.2). This collection of variables, which we denote by $\mathbf{X_{it}}$, appears in each of the regressions we report below. In some of the regressions we also include one or more variables intended to reflect recent climate-related events; these variables are recent temperature anomalies, recent precipitation anomalies, and recent drought anomalies (each using a historic baseline as the comparator), as well as the square of each.[11] The logic behind including variables from this last set is that changing temperatures might only influence political behavior if they are "sufficiently large," which we interpret in terms of the underlying variation in the evolution of temperatures.[12]

We treat the data as a panel, with the cross-section elements corresponding to US states and the time series element corresponding to calendar years from 2001 to 2020. The regression equation for this part of the analysis is:

[11]The squared values allow for the potential that effects only become important for anomalies that differ substantially from zero (Brooks et al., 2014; Deryugina, 2013).

[12]The idea here is that politicians disinclined to take action fall back on arguments such as "it's always been hot here" or 'it's always been rainy (or dry) here", thereby explaining away temporary changes in any of these variables. Such an argument seems less likely to be convince when the changes in question are large enough to be "noticeable" to a typical citizen (Deryugina, 2013).

$$Y_{it} = \Pi_i \mathbf{X_{it}} + \Gamma_i \phi_{\mathbf{i}} + \nu_t + e_{it}, \tag{7}$$

where i indexes states, t indexes years, Π_i, Γ_i are parameters to be estimated, ν_t captures year-specific effects and e_{it} is an error term assumed to be mean zero and independent of the various regressors.[13] The hypothesis of interest in our analysis is that the set of coefficients $(\alpha, \beta, \lambda, \theta, \delta) = 0$, *i.e.* none of the parameters capturing potential fat tails in temperature anomalies exerts an influence on observed political behavior; the alternative is that at least some of these parameters matter.

4 Data

In this section, we explore the publicly available data that we will bring to bear in our analysis. The climate data we draw from is a large, longitudinal data set. As outlined below, this state-level heterogeneous sample has undergone processing to obtain geographically-specific climate anomaly variables. The political variable we employ is taken from the annual League of Conservation Voters' (LCV) publications for years 2001 to 2020. We rely on scores for US representatives as elections for these officials are the most frequently held – suggesting that these elected officials will be particularly mindful of their constituents' opinions about the desirability of various environmental regulations.

[13] An alternative here is to employ the two-stage process articulated in Phillips et al. (2005). Under that approach one collects the residuals from a regression that omits the time-invariant regressors, such as $\phi_{\mathbf{i}}$, and then regresses the residuals on $\phi_{\mathbf{i}}$. But one could equally well combine the two stages, folding the time-invariant regressors into the first step in the analysis – which is our approach. Noting that the political index (PVI) and the demographic variables all change slowly over time, we prefer to use random effects to capture idiosyncratic state effects.

4.1 Climate data

We obtain data on the mean surface temperature anomalies from the U.S. National Oceanic and Atmospheric Administration (NOAA), who provide information for hundreds of individual "stations". The records allow us to identify the state in which each station is located; we use this information to calculate average monthly state values for the period from 1958 to 2020.[14] In addition, we collected data on average monthly precipitation levels at each station, along with state-level data on a drought index.[15] For both precipitation and drought, we compared the monthly value to a baseline, thereby deriving what we refer to as "anomalies" below.[16]

Summary statistics for the temperature anomaly data are presented in Table 1. These summary statistics are listed for the full set of state-month combinations in column two; we also show the smallest value in the sample for each of the summary statistics in column three, with the state associated with that minimum value given in parentheses. In column four we list the largest value in the sample for each statistic from column two, with the state associated with that maximum value given in parentheses. These statistics reveal substantial variation across the sample, and reinforce the image from Figure 1 showing the broad presence of fat tails (*i.e.*, kurtosis in excess of 3).

[14] These data on temperature are available at `https://www.ncei.noaa.gov/data/us-historical-climatology-network/2.5/access/`, in the "tavg-raw" subdirectory. We use the full sample for the analysis based on subsection 3.1 and the subsample from 2001 - 2020 for the analysis based on subsection 3.2.

[15] Precipitation levels, measured in inches per month, are available at `https://www.ncei.noaa.gov/data/nclimdiv-monthly/access/`. We measure drought using the "Drought Severity and Coverage Index," available at `https://droughtmonitor.unl.edu/DmData/DataDownload/DSCI.aspx`.

[16] This terminology is intentionally parallel to the labeling of temperature anomalies. The baseline precipitation values are given by the average precipitation levels over the 75 years prior to the start of our sample (*i.e.*, the period from 1926 to 2000), by calendar month. Because data on the drought index was only available for months in the 21^{st} century we use the average value of the index for each calendar month over the period form 2000 to 2020 as the baseline. In each case, the "anomaly" is given by the observed value in a particular month and year for a particular state less the baseline value for that same month for that state.

4.2 Political data

To obtain a variable that captures the average environmentally-based attitudes for each state in each of the twenty years from 2001 to 2020 we rely on LCV scores for each year from 2001 to 2020; this annually reported measure reflects each US representative's votes on key environmental legislation (Cragg et al., 2013). To the extent that these scores reflect politicians' attitudes towards protecting the environment they provide information about willingness to consider important policies, including steps that might be taken to address climate change. We then calculate the average annual LCV score across all representatives for every state. In the political regressions we discuss below, we match these data to the temperature anomaly data (averaged across the twelve months in each calendar year).

A number of the papers we discussed in Section 2 argue that political disposition is an important variable for explaining individuals' beliefs about climate change. To the extent that such beliefs among the electorate of a state might impact their voting patterns, one might imagine that these beliefs could play an important role in driving politicians' voting behavior. While one might entertain the view that these patterns are relatively constant over time, and as such are built into any idiosyncratic effects governing a state's elected officials' voting behavior, a compelling alternative would be to collect data that could capture each states' pre-existing political philosophies. To this end, we obtained the "Partisan Voting Index" (PVI), produced by the Cook Political Report. This index compares the tendencies of each U.S. congressional district to the nation as a whole, based on how that district voted in the previous two presidential elections.[17] The index provides values of the form "D+x" or "R+y," with the former implying the district voted x% more for the Democratic

[17] Data can be accessed at `https://www.cookpolitical.com/cook-pvi`. This is proprietary data, obtained via a subscription.

candidate in the two previous presidential elections, with the latter indicating the district voted y% less for the Democratic candidate in the two previous presidential election. We transform these alphanumeric values into numeric scores of the form x in the former case and $-y$ in the latter; as such, smaller values of the index correspond to districts that are more inclined to vote Republican. We then average these indices across the state to obtain an implied index for the state as a whole; we refer to this index as "PVI" in the discussion below.

4.3 Demographic data

The last group of variables used in our analysis relates to demographic characteristics. As discussed above, a number of existing analyses highlight the importance of controlling for such variables as population within a jurisdiction (*i.e.*, US state), the percentage of that population that is older than 65 years of age, the percentage of that population that is white, the percentage of that population that is male, and the percentage of that population residing in urban areas has been highlighted in the extant literature (Peltzman, 1984; Cragg et al., 2013). This demographic information is available from the US Census Bureau, on an annual basis.[18] In addition, we employ data related to fossil fuel usage to generate electricity, by state. This information is tabulated by the Energy Information Administration (EIA). Optimally, we would have this information for every year for each state; unfortunately, while the EIA tabulates information on carbon dioxide emissions – arguably the measure most directly relevant to climate policy – these data are only available after 2011. Instead, we use information on coal consumption for electricity generation, which seems likely to

[18]These data are available through the American Community Survey (ACS), which can be accessed from `https://data.census.gov/all?q=ACS`.

be closely related to emissions.[19]

5 Econometric Results

We now turn to a discussion of our various empirical results.

5.1 Temperature Fat Tails

As noted above, our model of the stochastic process governing temperature anomaly changes includes a Poisson process with arrival rate λ, where the size of a jump, if it occurs, is distributed with mean θ and variance δ^2. We also allow for GARCH effects, captured by the parameters κ, α and β. Estimation results based on the resultant GJD model are given in Tables 3 – 4. These tables list parameter estimates for mean (μ), the three components of from the GARCH process (κ, α, β), and the three parameters from the jump process $(\lambda, \theta, \delta)$. Standard errors for these estimates are shown in parentheses below the estimates.[20] Also listed is the likelihood-ratio test statistic for the null hypothesis that none of the GJD model parameters are important (*i.e.*, that the restriction $\alpha = \beta = \lambda = \theta = \delta = 0$ is supported), presented in the column labeled "LR test." All results are organized by two letter acronym for the US states, with outcomes for states from Alaska (AK) to Montana (MT) contained in Table 3 and outcomes for states from North Carolina (NC) to Wyoming (WY) contained in Table 4.

The estimated coefficients from both the GARCH model and the jump diffusion model demon-

[19]These data, which are available for each state for all the years where we have observations on the LCV scores, can be accessed at `https://www.eia.gov/coal/data/browser/\#/topic/20`.

[20]The missing standard errors are a result of the Gauss algorithm reaching a constraint on a parameter estimate – namely, that λ should be non-negative; the algorithm achieves this by selecting a value that approaches 0, yet remains positive, as the lower bound – thereby preventing issues associated with a 0 value in the likelihood function.

strate statistical significance across numerous states. Importantly, restricting the GJD model to the PD model induces a relatively poor fit of the data; indeed, the likelihood-ratio test statistic comparing the unrestricted GJD model to the PD model is very large, and is significant at better than the .01% level for every state. In addition, we note that the likelihood ratio test statistics indicate that the null hypothesis ($\alpha = \beta = \lambda = \theta = \delta = 0$) is rejected for every state, supporting the use of the GJD model. We conclude there is powerful empirical support for including GARCH and jump effects into the model of stochastic changes in temperature anomalies.

We present a visual representation of the variation in certain GJD parameters in Figures 2 – 4. Figure 2 displays estimated values for λ across the US states; here we see that there is significant spatial variation, with estimates ranging from very small values for some states to substantial values for other states. In general, larger estimates of λ are associated with states in the middle latitudes of the continental US and the southeast. Figure 3 displays lt, the multiple of estimated values of λ and θ across the US states; one can think of this construct as showing the induced impact of jumps upon temperature anomaly changes. Here again we see that there is significant spatial variation with estimates ranging from values that are very small in magnitude (generally, for more northerly states) to values that are larger in magnitude and are negative – suggesting a prevalence of *downward* jumps. These latter states tend to fall in the middle and southern latitudes of the continental US. The prevalence of negative impacts is interesting in light of Deryugina's (2013) result that abrupt changes in temperature towards colder levels seem to have a more pronounced effect of individuals' perspective towards climate change. We supplement these visuals with a display of the spatial variation in average values of the variance induced by the GARCH model, $\overline{h}$; this is contained in Figure 4. Here we see an interesting spatial pattern – with larger values of the induced variance often occurring in the coldest states (the upper midwest, Alaska and Maine).

To expand on our discussion of the geographic variation in the estimated parameters we focus on two constructs that capture the essence of our stochastic models: lt (the imputed impact from jumps) and $\overline{h}$ (the average of the imputed value of time-varying variance, taken over the 240 months in the twenty years 2001-2020). For each of these two constructs, using the sample of all 50 states we identify correlation with the state's LCV score; these correlations are presented in panel A of Table 5. There is a seemingly positive relation between LCV and lt, whose correlation is .1148; this is consistent with the prior notion that a greater tendency towards jumps coincides with more political activism aimed at addressing climate change. However, the correlation between LCV and higher $\overline{h}$ is negative, suggesting that states with fat tails due to greater variation have lower LCV scores. While at first blush this might appear somewhat surprising, we believe it is consistent with the results from Deryugina (2013) discussed above. To provide additional insights, we next sort the states into six geographical regions in the US.[21] Using this classification scheme, we calculate the correlation between average LCV score, lt, and $\overline{h}$ for each of the six regions; these correlations are presented in panel B of Table 5. The key takeaway message from this information is that the correlations discussed above using the sample of 50 states are amplified when we focus on regions, suggesting that there may be more going on than is apparent at first blush.

We next list the average values of LCV, lt, and $\overline{h}$ for the six regions, along with the US as a whole, in Table 6. We see that the imputed effect of jumps is largest on the West Coast (and in fact is the only region where this effect is positive) and smallest numerically in the Mountain

[21]The six regions are "West", containing the five states that border the Pacific Ocean; "SouthWest", consisting of the five the states in the southern tier lying to the west of the Mississippi River, all of whom have hot, arid climates; the "Mountain", consisting of five states, each of which contain part of the Rocky Mountain range; "SouthEast", consisting of all states n the southern tier lying to the east of the Mississippi River, all with hot and humid climates; "NorthEast", containing all states north of the Southeast cohort that are on or near the Atlantic Ocean (all of which tend to have cold and we winters); and "MidWest", consisting of all states east of the Rocky Mountains, north of Southwest and Southeast, and west of the Northeast.

and Northeast regions, while the imputed variance is largest in the Mountain and Midwest regions and smallest in the and Southeast and West Coast regions. These broad characterizations suggest smaller values of lt and larger values of $\overline{h}$ in regions that have colder winters. In two of these regions (West, Northeast – regions that are associated with "coastal elites" these days) politicians have LCV scores among the largest in the US.

5.2 Political Impacts

The culmination of our analysis is to analyze political behavior, as measured by the LCV variable. Results from regressions based on eq. (7) are collected in Table 7. The first column in this table lists the potential regressors; these include the parameter estimates drawn from the analysis of temperature anomalies, discussed in the preceding subsection, along with various demographic variables proposed by the extant literature (including a state's population, the fraction of the population that is white, the fraction of the population that is over 65, and the population of the state that lives in an urban area); the state's annual coal purchases for the purpose of generating electricity (which we interpret as capturing the state-specific heterogeneous costs of addressing climate change; the Partisan Voting Index (PVI), which captures each state's political predisposition); three variables intended to reflect recent climate-related events (recent temperature anomalies, recent precipitation anomalies, and recent drought anomalies); and the square of each of these last three variables (which allows for these effects to become important for anomalies differ substantially from zero).

We report results from five regressions. Column 2 reports results from a regression that excludes the recent effects, while columns 3, 4, and 5 include one of the recent events along with its square. Column 6 includes all three measures of recent events and their squares. Statistical significance is indicated by the number of asterisks, with significance at the five (respectively, one) percent level corresponding to two (respectively, three) asterisks. We draw three conclusions from the results in Table 7.

First, there is meager support for the hypothesis that recent climate events influence political behavior. In none of regressions 2, 3 or 4 does the corresponding recent event – nor the square of that event – exert a statistically important influence. Likewise, including all three types of events along with their squares – as reported in regression 5 – adds little to explain political behavior. Five of the six parameter estimates are statistically insignificant, with only the square of temperature anomalies showing some significance (and there only at the 10% level). Moreover, there is virtually no increase in explanatory power (as measured by the R^2 goodness-of-fit statistic) when comparing regressions 1 and 5; we also note that the other parameter estimates are largely similar across all regressions. This finding conflicts with a number of the papers in the extant literature discussed in Section 2.

Second, we find evidence that a number of the socio-economic / demographic variables do influence political behavior. While neither population nor percent of population residing in urban areas is statistically important, all three of percent male, percent white and percent below age 65 are statistically significant, with all three exerting a negative effect. The implication of the first two effects is that political behavior consistent with efforts to address climate change is less likely the larger is the white or male population in the state, corroborating the "white male effect" hypothesis (Hornsey et al., 2016). A possible explanation of the third effect is that older people care about the world they leave their offspring. We also find that the amount of coal used to generate electricity is not a statistically important determinant of environmental activism. While at odds with arguments in Peltzman (1984), this could be reflective of competing effects related to coal-fired power (with that variable measuring the opportunity cost of climate policy on the one hand, but the potential benefits from mitigating local air pollution associated with burning coal on the other). Finally, we find compelling evidence that political predisposition matters, with larger values of PVI overwhelmingly corresponding to greater climate activism by a state's elected representatives.

Third, there is clear evidence that the parameters emerging from our analysis of potential fat tails in temperature anomalies are important determinants of political behavior, with four of these parameters (κ, α, β and θ) exerting a statistically important effect in each of the regressions. In addition, the null hypothesis that the parameter restriction imposed by setting the parameter vector $(\alpha, \beta, \lambda, \theta, \delta) = 0$ (*i.e.*, that none of the five coefficients from the fat tail analysis matters here) is soundly rejected.[22] The parameters κ, α, β each relate to time-varying volatility, while θ relates to the potential influence of abnormal changes (*i.e.*, jumps). But while each of these variables matters the effect is not in the anticipated direction, as each of the four has a negative influence on the state's LCV score. While somewhat surprising at first blush, this result is consistent with Deryugina (2013), who finds that abnormally cold periods (*i.e.*, those with negative jumps) erode beliefs in global warming more than abnormally hot period (*i.e.*, associated with positive jumps) enhance them. She also finds that longer periods of abnormal temperatures will have a greater effect than shorter periods (consistent with a statistically significant role arising from time-varying volatility).

To give some context to the effects associated with the elements describing fat tails, we note that the coefficient on the expected magnitude of the jump, θ, is comparable in magnitude to the

[22]Under this null hypothesis, the test statistic would follow an F distribution with 5 and 966 degrees of freedom. The value taken by the test statistic here is 31.76, which is significant at better than the .1% level.

political index. And while it is about one-ninth the size of the coefficient on the percentage of males in a state, it is significantly larger than all the other demographic variables. While of questionable statistical significance, the coefficient on the probability of a jump occurring in a given month, λ, is about four times the size of the expected value. Combined, these observations indicate that the potential for abrupt changes in temperature anomalies from one month to the next exert a meaningful impact on political behavior. The coefficients describing the evolution of time-varying variance (α and β) are even more important, underscoring the potential for protracted periods of unusual temperature changes to exert an important impact on political behavior. Altogether, these results point to the plausible impact of fat tails upon political behavior over the course of our 20-year sample period.

6 Discussion

In this paper, we analyzed data from multiple sources to investigate the spatial aspects of the stochastic process describing variations in temperature anomalies, and to infer the relation between these processes and political behavior. Persistent changes in climate are likely to occur on relatively long time scales (*e.g.*, decades), over which time it is conceivable that other variables likely to influence the political behavior of elected representatives may also adjust – suggesting the need for a lengthy time series of observations. The data we use to analyze political behavior is comprised of twenty years' worth of observations on voting patterns. The data we employ in the analysis of climate anomalies is comprised of a long time series, with over 750 monthly observations; as such, our approach differs from the related work we summarized in Section 2, much of which examines the effect of single events.

Our results provide compelling evidence that temperature anomalies are characterized by two features that each contribute to “fat tails”; the potential for abrupt changes – or jumps – and the potential for time-varying volatility in that stochastic process. The estimates we report show substantial variation across US states. Interpreting these elements as ingredients that could contribute to political pressure for political action by elected representatives, as has been proposed by scholars following in the path laid out by Peltzman (1984), we ask if and how the spatially diverse parameter estimates are related to differences in the annual scores, published by the League of Conservation Voters, that reflect a tendency towards environmental regulatory intervention. These scores can be viewed as a marker of a politician’s willingness to consider climate policies – regulatory intervention that addresses climate change.

We find a statistically important connection to demographic variables whose inclusion was suggested by various papers in the existing literature, including the percentage of a state’s electorate that is white, the percentage that is male, and the percentage that is over the age of 65. In the first two instances, increase in the explanatory variable are linked to political behavior that is less embracing of environmental intervention, corroborating the so-called “white male effect”: that white males are less interested in climate policy, and hence politicians who represent states with larger fractions of white males are less supportive of climate policies. But we also find that states with relatively older populations have politicians who are more inclined to climate policies. Finally, we find compelling evidence that politicians representing states that are more conservative than the country as a whole are less inclined to support climate policies. While a number of these results are consistent with earlier studies, our analysis extends the existing literature by considering dynamic patterns, and emphasizing the role played by fat tails in influencing behavior.

In addition, we find a statistically important relation between parameters characterizing time-varying volatility, as well as the estimated mean value of any jumps, and politicians' LCV scores. These results point to a statistically important relation between characteristics of "fat tails" in temperature anomalies and political behavior. While one might conjecture that fat tails would encourage citizens to demand more climate activism, and hence induce a greater tendency towards policies directed at combatting climate change, our results find the reverse: both time-varying volatility and jumps seem to encourage less, as opposed to more, support for environmental intervention. While surprising at one level, this result does corroborate arguments made by Deryugina (2013): that abnormally cold periods – those with negative jumps in temperature anomalies – erode beliefs in global warming more than abnormally hot periods enhance such beliefs; and that these effects are more pronounced for longer periods of abnormal temperatures – consistent with a statistically significant role arising from time-varying volatility.

The policy implications or these results are immediate: to the extent that there is an increased tendency for dramatic weather events – consistent with fat tails in temperature anomalies – we see these results as highlighting the potential that citizens will exert a *decreasing* amount of pressure upon politicians to seriously consider policies directed towards potential climate change. By their nature, any such climate policies will have to consider the role played by fossil fuels in the US economy – and by extension, the nature of development for such resources as coal, natural gas and oil. Accordingly, our analysis, which capitalizes on a unique "big data" set, suggests that pressures to move away from fossil fuels, and towards renewable energy (thereby increasing the demand for rare earth minerals necessary to promote such technologies) are less likely to mount than one might hope. That said, impacts from interventions directed at these fossil fuel resources will fall in sharply heterogeneous ways across space, which suggests there may be value in further careful consideration of the nature of these heterogenous impacts, and actions that might blunt any adverse impacts upon states that are particularly reliant upon fossil fuel extraction.

7 Appendix: Details of the GARCH-Jump model

In this Appendix, we provide a more detailed derivation of the log-likelihood function presented in the text. We model the stochastic process governing temperature anomalies as composed of two parts (Merton, 1976). The first represents "normal" fluctuations, modeled through a Brownian motion process, while the second – "abnormal" shocks due to unexpected events – are modeled by a Poisson process. The Poisson distribution allows us to describe the probability that the number of discrete-valued events, $N_t \in \{0,1,2,...\}$, occur during the interval $(t-1,t)$, equals some j:

$$P(N_t = j) = \frac{\exp(-\lambda)\lambda^j}{j!}, \tag{8}$$

where λ is the jump intensity. The mean number of jumps N_t observed over a particular unit of time is then described by

$$\mathrm{d}N_t = \begin{cases} 0 & \text{with probability } 1-\lambda \mathrm{d}t \\ 1 & \text{with probability } \lambda \mathrm{d}t \end{cases} \tag{9}$$

As in Askari and Krichene (2008), when abnormal events occur during time t, the change in temperature anomaly jumps from x_{t-} (the limit from left) to $x_t = \exp(J_t)x_{t-}$. The resultant stochastic process for x_t may then be written as

$$\mathrm{d}x_t = \mu dt + \sigma dz_t + (exp(J_t)-1)\mathrm{d}N_t. \tag{10}$$

where dz_t has the same properties assumed in eq. (1) and dN_t is the independent Poisson process described in eq. (9). Together the terms dz_t and dN_t make up the instantaneous component of the unanticipated yields. It is natural to assume these terms are independent, since the first component reflects ordinary movements in the convenience yield, while the second component reflects unusual changes in yields. The jump size, $Y_{t,k}$, is assumed to be independent and normally distributed with mean θ and variance δ^2. The jump component affecting yields between time t and time $t+1$ is

$$J_t = \sum_{k=1}^{N_t} Y_{t,k}. \tag{11}$$

Thus, the *JD* process for monthly changes in temperature anomalies is given as

$$x_t = \mu + \sigma z_t + J_t. \tag{12}$$

The probability density function governing x can be derived by applying Bayes' law (Chan and Maheu, 2002; Maheu and McCurdy, 2004). To this end let $f(x_t|N_t = j, \kappa_{t-1})$ denote the conditional density of returns if j jumps have occurred and given the available information κ_{t-1}. Based on Bayes' law, when x_t is observed, the posterior probability that j jumps will occur at time t is

$$P(N_t = j|\kappa_{t-1}) = \frac{f(x_t|N_t = j, \kappa_{t-1})P(N_t = j|\kappa_{t-1})}{P(x_t|\kappa_{t-1})}. \tag{13}$$

Then, assuming that the conditional density of x_t is normally distributed, and using eq. 9 to describe the probability that j jumps occur, we obtain:

$$f(x_t|N_t = j, \kappa_{t-1}) = \frac{1}{\sqrt{2\pi(\sigma^2 + j\delta^2)}} \exp\left(-\frac{(x_t - \mu - \theta j + \theta\lambda)^2}{2(\sigma^2 + j\delta^2)}\right). \tag{14}$$

Finally, integrating out the discrete valued number of jumps yields an expression for the conditional density in terms of observable variables:

$$P(x_t|\kappa_{t-1}) = \sum_{j=0}^{\infty} f(x_t|N_t = j, \kappa_{t-1}) P(n_t = j|\kappa_{t-1}). \tag{15}$$

Combining this description with the formulation of the GARCH model then leads directly to the log-likelihood function

$$L(\phi, x_t) = -T\lambda - \frac{T}{2} ln(2\pi) + \sum_{t=1}^{T}\left[\sum_{n=0}^{\infty} \frac{\lambda^n}{n!} \frac{1}{\sqrt{h_t + n\delta^2}} exp(\frac{-(x_t - \mu - n\theta}{2(h_t + n\theta^2})\right], \tag{16}$$

which is eq. (5) in the text.

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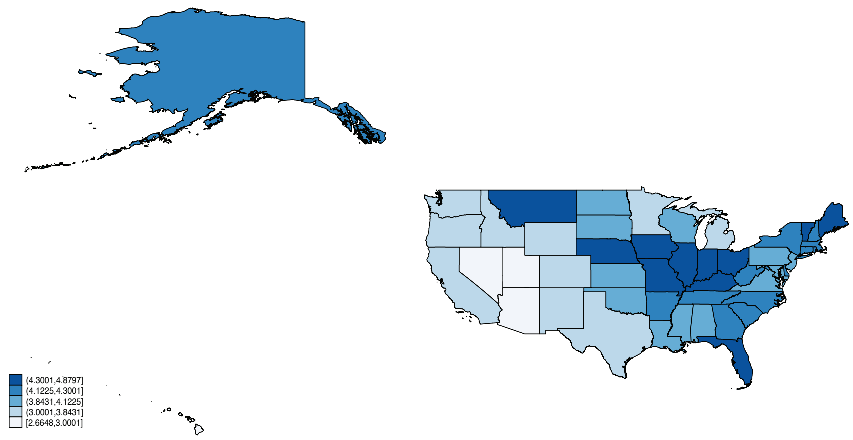
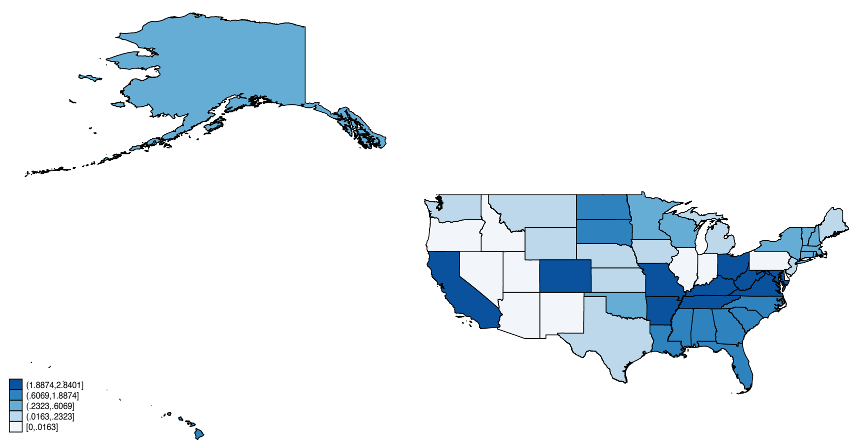
Figure 1: Spatial variation of temperature anomalies fat tails (Kurtosis), by US state



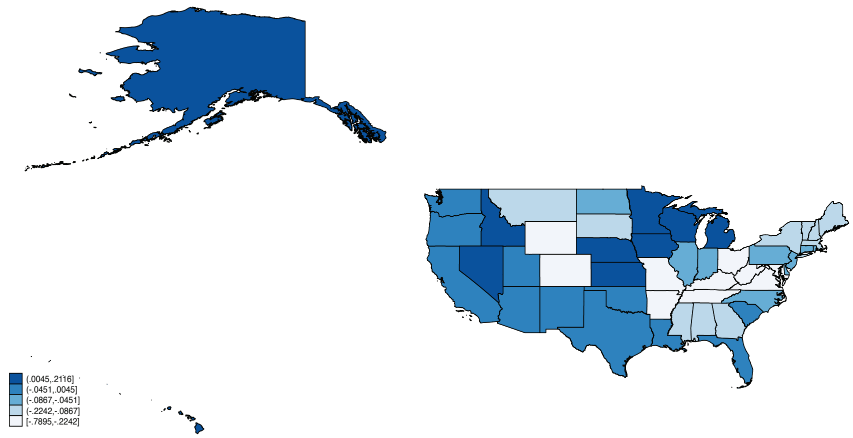
Note: Monthly observations from 1958 - 2020; Minimum value 2.6650 (HI); Maximum value 4.8797 (FL)

Figure 2: Spatial variation of the estimated jump intensity from the GJD model ($\hat{\lambda}$), by US state.



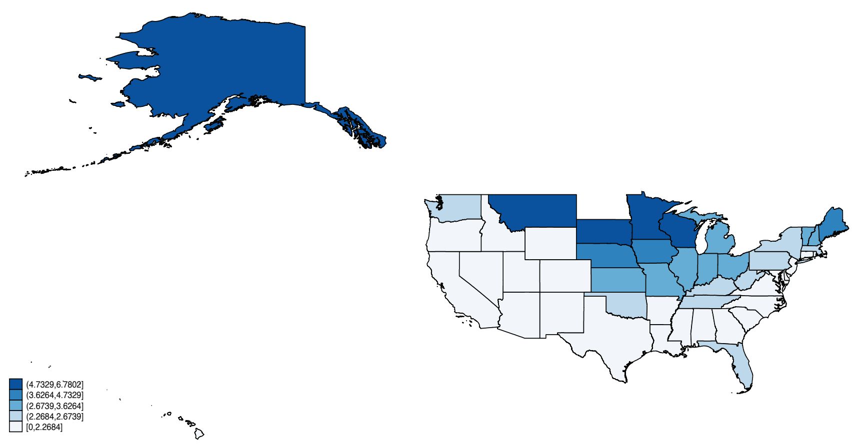
Note: $\hat{\lambda}$ value for each state based on estimates in Tables 3, 4. Minimum (nonzero) value 0.0015 (ID); Maximum value 2.8400 (TN)

Figure 3: Spatial variation of the estimated jump impact from the GJD model ($\hat{\lambda}\hat{\theta}$), by US state.



Note: $\hat{\lambda}, \hat{\theta}$ values for each state based on estimates in Tables 3, 4; Minimum value -0.7895 (MO); Maximum value 0.2116 (MN)

Figure 4: Spatial variation of the average estimated variance ($\bar{h}$), by US state.



Note: $\bar{h}_t$ values calculated for each state using eq. (3) and estimates in Tables 3, 4. Average taken for each state using 20 observations from 2001-2020. Minimum value 0.0956 (HI); Maximum value 6.7802 (MT).

Table 1: Summary Statistics, monthly temperature anomaly changes across states

statistic	full sample	min (state)	max (state)
mean	0.0009	-0.0034 (MT)	0.0049 (AK)
median	-0.0070	-0.1760 (MN)	0.1100 (OR)
min	-14.7860	-14.7860 (MT)	-1.8470 (HI)
max	15.9230	1.4360 (HI)	15.9230 (AK)
std. dev.	2.2866	0.4210 (HI)	3.3700 (ND)
skewness	0.1521	-0.1851 (WA)	0.3323 (AK)
kurtosis	2.1801	0.0037 (ID)	2.6688 (AK)

Sample: 756 observations for each state. Sample range: Jan. 1958 – Dec. 2020.

Table 2: Summary Statistics, LCV scores across US states

statistic	full sample	min (state)	max (state)
mean	45.2740	3.0000 (WY)	95.6000 (MA)
median	40.0000	1.5000 (WY)	96.0000 (MA)
min	0.0000	0.0000 (7 states)	90.0000 (MA)
max	100.0000	11.0000 (WY)	100.0000 (NH)
std. dev.	29.3801	2.6036 (MA)	35.0823 (ND)
skewness	0.2848	-2.1767 (RI)	2.6689 (ID)
kurtosis	1.9749	1.2268 (ND)	9.6325 (ID)

Sample: 20 observations for each state. Sample range: 2001 – 2020.

Table 3: GARCH-Jump Diffusion estimates: AK – MT

State	code	μ	κ	α	β	λ	θ	δ	LR test
Alaska	AK	-0.0943	1.2055	0.0645	0.4375	0.5983	0.1202	2.6384	236.98
std.err.		0.1116	0.4094	0.0553	0.0687	0.2138	0.2368	0.3992	
Alabama	AL	0.1653	0.3208	0.3477	0.1254	1.8293	-0.0966	1.1116	84.95
std.err.		0.1627	0.3258	0.0681	0.0670	0.9483	0.1063	0.2335	
Arkansas	AR	0.2184	0.6043	0.3312	0.1119	2.2860	-0.1091	1.0009	73.30
std.err.		0.2569	0.7926	0.0636	0.0705	1.5081	0.1459	0.2387	
Arizona	AZ	0.0206	2.2427	0.0113	0.2179	0.0000	23.5910	0.5700	24.48
std.err.		0.0529	0.4469	0.1425	0.0584	.	.	.	
California	CA	0.0266	0.9231	0.2839	0.0315	1.9080	-0.0236	0.7336	46.10
std.err.		0.2214	0.8325	0.0614	0.1312	3.0324	0.1338	0.3669	
Colorado	CO	0.4493	1.6914	0.2500	0.0607	2.2149	-0.2375	0.6616	35.33
std.err.		0.2972	1.0340	0.0622	0.1080	1.9617	0.2396	0.2864	
Connecticut	CT	0.0485	1.6595	0.0001	0.2687	0.3019	-0.2587	1.8455	81.20
std.err.		0.0937	0.3962	.	0.0545	0.2840	0.3089	0.5973	
Delaware	DE	0.0525	2.3540	0.0188	0.3350	0.0145	-4.7923	0.0001	78.81
std.err.		0.0609	0.3039	0.0581	0.0613	0.0093	0.9626	.	
Florida	FL	0.0227	0.1615	0.1530	0.3522	0.6834	-0.0384	1.4460	170.39
std.err.		0.0461	0.0646	0.0501	0.0699	0.1553	0.1005	0.1605	
Georgia	GA	0.0931	0.2798	0.3254	0.1380	1.6078	-0.0586	1.1641	83.17
std.err.		0.1397	0.2767	0.0697	0.0705	0.7809	0.1014	0.2358	
Hawaii	HI	-0.0317	0.0557	0.1065	0.2090	0.6155	0.0623	0.3399	51.65
std.err.		0.0240	0.0244	0.1749	0.0558	0.4685	0.0569	0.0855	
Iowa	IA	-0.0818	3.6786	0.1415	0.2443	0.0865	1.4786	3.8490	84.77
std.err.		0.1069	0.7158	0.1073	0.0648	0.0728	1.1552	1.1111	
Idaho	ID	-0.0479	3.4286	0.0001	0.2683	0.0015	6.1802	0.0001	32.31
std.err.		0.0645	0.2788	.	0.0618	0.0025	2.9672	.	
Illinois	IL	0.0775	3.6335	0.1000	0.3308	0.0116	-5.4170	0.0070	81.65
std.err.		0.1119	0.6570	0.0895	0.0613	0.0303	4.5310	0.6781	
Indiana	IN	0.0809	3.3011	0.1258	0.3177	0.0162	-5.3055	0.0096	79.10
std.err.		0.0951	0.5892	0.0906	0.0584	0.0224	2.4427	0.5336	
Kansas	KS	-0.0422	3.7394	0.0001	0.2098	0.1158	0.5814	3.1675	59.83
std.err.		0.0988	0.5040	.	0.0560	0.1082	0.7316	0.9870	
Kentucky	KY	0.4018	0.0091	0.3177	0.1489	2.5817	-0.1867	1.1875	82.43
std.err.		0.0921	0.0322	0.0583	0.0802	0.5903	0.0619	0.1420	
Louisiana	LA	0.0379	0.5564	0.1456	0.3929	0.7081	-0.0467	1.4269	93.68
std.err.		0.0864	0.2082	0.0579	0.0764	0.3439	0.1501	0.2731	
Massachusetts	MA	0.0695	1.7064	0.0001	0.2601	0.3967	-0.2701	1.8288	80.40
std.err.		0.1171	0.5787	.	0.0531	0.4297	0.2807	0.6572	
Maryland	MD	0.5298	1.2184	0.3246	0.0659	2.5158	-0.2534	0.7275	73.80
std.err.		0.3937	0.9442	0.0604	0.0822	1.3065	0.2334	0.3085	
Maine	ME	0.0603	1.8058	0.0001	0.2927	0.2247	-0.4397	2.4685	111.71
std.err.		0.0740	0.3312	.	0.0564	0.1352	0.4143	0.5325	
Michigan	MI	-0.0904	3.8281	0.0001	0.2018	0.0270	4.5037	0.0001	40.99
std.err.		0.1223	0.4079	.	0.0579	0.0318	1.5629	0.5750	
Minnesota	MN	-0.1857	2.4169	0.1693	0.2401	0.3783	0.5593	2.9358	88.12
std.err.		0.1352	0.9415	0.1044	0.0603	0.2869	0.4572	0.7376	
Missouri	MO	0.6761	1.3882	0.3139	0.1404	2.3646	-0.3339	0.9426	86.90
std.err.		0.3678	1.2668	0.0597	0.0769	1.5516	0.2734	0.2696	
Mississippi	MS	0.1236	0.7561	0.3678	0.1344	1.0967	-0.1252	1.2355	83.01
std.err.		0.2522	0.8830	0.0698	0.0629	1.8435	0.1514	0.6969	
Montana	MT	0.0547	4.3148	0.0001	0.3635	0.0934	-1.4734	3.7521	132.33
std.err.		0.1091	0.7138	.	0.0606	0.1019	1.2767	1.3146	

Table 4: GARCH-Jump Diffusion estimates: NC – WY

State	code	μ	κ	α	β	λ	θ	δ	LR test
North Carolina	NC	0.0672	1.0423	0.1181	0.3134	0.9828	-0.0736	1.2498	75.18
std.err.		0.2405	1.4210	0.0730	0.0640	2.7228	0.1893	1.1245	
North Dakota	ND	0.0412	2.0352	0.1256	0.2760	0.7690	-0.0944	2.6507	90.38
std.err.		0.1652	0.9653	0.0941	0.0613	0.4117	0.2521	0.5335	
Nebraska	NE	-0.0089	3.8217	0.0001	0.2735	0.1663	0.1501	3.1616	77.38
std.err.		0.1094	0.8014	.	0.0668	0.1831	0.6841	1.1537	
New Hampshire	NH	0.0608	1.9561	0.0001	0.2683	0.3445	-0.2962	2.1671	88.07
std.err.		0.0958	0.5142	.	0.0525	0.2684	0.3186	0.5719	
New Jersey	NJ	0.0587	2.5309	0.0001	0.3198	0.0164	-4.6289	0.0001	70.49
std.err.		0.0634	0.2182	.	0.0605	0.0109	1.0084	.	
New Mexico	NM	0.0166	1.7103	0.1165	0.1698	0.0000	-0.4972	6.5013	23.18
std.err.		0.0499	0.3495	0.1433	0.0479	.	32.9977	696.5189	
Nevada	NV	-0.0642	2.9092	0.0398	0.2308	0.0150	3.6596	0.0001	29.11
std.err.		0.0945	0.6399	0.1447	0.0562	0.0312	2.4059	.	
New York	NY	0.0602	2.1677	0.0001	0.2938	0.3594	-0.2435	2.1402	81.67
std.err.		0.1134	0.5949	.	0.0592	0.3238	0.3253	0.6661	
Ohio	OH	0.5883	1.0720	0.3195	0.1246	2.5827	-0.2754	0.9534	79.07
std.err.		0.3348	1.1466	0.0595	0.0885	1.1845	0.1811	0.2672	
Oklahoma	OK	0.0491	2.1900	0.1324	0.2396	0.2400	-0.1757	2.1031	59.05
std.err.		0.1145	0.9408	0.1330	0.0593	0.5770	0.6720	1.3829	
Oregon	OR	-0.0477	2.521	0.0483	0.2599	0.000	-0.4949	6.4871	35.43
std.err.		0.0567	0.5725	0.1598	0.0599	.	42.1162	993.8855	
Pennsylvania	PA	0.0613	2.9893	0.3269	0.0412	0.0154	-4.5971	0.0016	70.63
std.err.		0.0854	0.5178	0.0617	0.0910	0.0211	2.0418	0.4362	
Rhode Island	RI	0.0487	1.6251	0.0001	0.2672	0.3067	-0.2581	1.8267	81.89
std.err.		0.0934	0.3933	.	0.0542	0.2879	0.3034	0.5890	
South Carolina	SC	0.0423	0.4790	0.3148	0.1440	1.8668	-0.0217	1.0340	72.40
std.err.		0.2006	0.7496	0.0676	0.0702	2.0578	0.1222	0.3761	
South Dakota	SD	0.1568	1.6267	0.2750	0.1001	1.1004	-0.1808	2.0949	83.24
std.err.		0.1954	1.3020	0.0625	0.0943	0.8474	0.2186	0.5557	
Tennessee	TN	0.3842	0.0864	0.3473	0.1166	2.8400	-0.1597	1.0346	81.06
std.err.		0.1714	0.2985	0.0626	0.0691	0.7397	0.0749	0.1319	
Texas	TX	0.0314	1.2361	0.1841	0.3030	0.1212	-0.3717	1.9954	59.83
std.err.		0.0669	0.3016	0.0797	0.0673	0.1674	0.7452	0.7537	
Utah	UT	0.0070	3.1391	0.0615	0.1594	0.0000	-0.4859	6.4884	16.39
std.err.		0.0645	0.7468	0.1795	0.052	.	18.3544	323.9952	
Virginia	VA	0.5990	1.4215	0.3324	0.0947	2.4594	-0.2874	0.6506	73.27
std.err.		0.4777	1.3912	0.0614	0.0661	1.7215	0.3688	0.4955	
Vermont	VT	0.0511	2.1368	0.0001	0.2798	0.3157	-0.2922	2.3383	93.54
std.err.		0.0958	0.5321	.	0.0539	0.2423	0.3381	0.6150	
Washington	WA	-0.0394	2.2164	0.0001	0.3321	0.0245	-0.7001	3.0941	72.59
std.err.		0.0582	0.1983	.	0.0658	0.0300	1.4192	1.4289	
Wisconsin	WI	-0.1237	2.6634	0.0828	0.2231	0.4154	0.3436	2.4520	66.97
std.err.		0.1358	1.0187	0.1549	0.0620	0.3444	0.3863	0.6587	
West Virginia	WV	0.6185	0.8956	0.3339	0.1357	2.6699	-0.2793	0.8861	78.30
std.err.		0.5037	1.4660	0.0612	0.0735	1.1423	0.2695	0.3952	
Wyoming	WY	0.3204	2.7522	0.0001	0.3544	0.1982	-2.2315	0.5277	71.17
std.err.		0.2482	0.6262	.	0.0645	0.4013	3.7935	5.1901	

Sample: 755 observations for each state. Sample range: Feb. 1958 – Dec. 2020. 1% critical value for likelihood ratio test is 15.09. LR test statistic exceeds 1% critical value for all states.

Table 5: Correlation Matrix: LCV, $\hat{\lambda}\hat{\theta}$ and $\overline{h}_t$

Panel A: US states

	LCV	$\hat{\lambda}\hat{\theta}$	$\overline{h}_t$
LCV	1.0000		
$\hat{\lambda}\hat{\theta}$	0.1148	1.0000	
$\overline{h}_t$	-0.2661	0.1703	1.0000

Panel B: Geographic US Regions

	LCV	$\hat{\lambda}\hat{\theta}$	$\overline{h}_t$
LCV	1.0000		
$\hat{\lambda}\hat{\theta}$	0.2842	1.0000	
$\overline{h}_t$	-0.3649	-0.0909	1.0000

$\hat{\lambda}, \hat{\theta}$ based on estimates in Tables 3, 4. State $\overline{h}_t$ values calculated using eq. (3) and estimates in Tables 3, 4. Correlations using all 50 US states in panel A; 6 regions in panel B described in footnote 20.

Table 6: Regional Averages: LCV, $\hat{\lambda}\hat{\theta}$ and $\overline{h}_t$

Region	LCV	$\hat{\lambda}\hat{\theta}$	$\overline{h}_t$
Mountain	16.1300	-0.2194	4.1598
MidWest	37.0125	-0.1021	5.1836
NorthEast	76.9083	-0.1871	2.9929
SouthEast	29.7545	-0.2247	2.2539
SouthWest	37.2700	-0.0064	3.1119
West	60.4700	0.0096	2.4435
US	45.2740	-0.1405	3.4298

$\hat{\lambda}, \hat{\theta}$ based on estimates in Tables 3, 4. $\overline{h_t}$ values calculated for each state using eq. (3) and estimates in Tables 3, 4. Average taken for each state using 20 observations 2001 – 2020.

Table 7: Analysis of LCV data

variable	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
population	0.0688	0.0942	0.0802	0.0673	0.0919
(millions)	(0.2014)	(0.2042)	(0.2042)	(0.1994)	(0.2015)
percent white	-0.2798**	-0.2997***	-0.2927**	-0.2708**	-0.2900**
	(0.1130)	(0.1140)	(0.1140)	(0.1123)	(0.1130)
percent male	-9.8918***	-9.5417***	-9.9266***	-9.7492***	-9.2484***
	(1.5156)	(1.5513)	(1.5329)	(1.5057)	(1.5384)
percent below age 65	0.1199	-0.0440	0.1314	0.1382	-0.0156
	(0.2842)	(0.2887)	(0.2851)	(0.2844)	(0.2887)
percent population urban	-0.1780*	-0.1824*	-0.1793*	-0.1709*	-0.1697
	(0.1045)	(0.1058)	(0.1059)	(0.1035)	(0.1045)
coal for electricity	0.0383	0.0286	0.0447	0.0343	0.0258
(million tons)	(0.0743)	(0.0747)	(0.0748)	(0.0739)	(0.0743)
PVI	1.0999***	1.0604***	1.0826***	1.1085***	1.0788***
	(0.1230)	(0.1237)	(0.1238)	(0.1227)	(0.1232)
μ	15.0860	14.0771	15.1910	15.0368	13.9242
	(10.7158)	(10.8943)	(10.8769)	(10.5979)	(10.7317)
κ	-8.6226***	-8.4167***	-8.5256***	-8.6351***	-8.3300***
	(1.7149)	(1.7410)	(1.7448)	(1.6968)	(1.7202)
α	-183.3736***	-184.8393***	-185.1314***	-182.2579***	-182.6718***
	(21.9251)	(22.2439)	(22.2279)	(21.7115)	(21.9402)
β	-141.6037***	-139.9853***	-142.4806***	-141.6787***	-139.2644***
	(21.4927)	(21.8422)	(21.8125)	(21.2885)	(21.5481)
δ	0.6527	0.6687	0.7164	0.6811	0.7661
	(0.8082)	(0.8201)	(0.8211)	(0.8003)	(0.8098)
θ	-1.1753***	-1.1964***	-1.1617***	-1.1608***	-1.1507***
	(0.3235)	(0.3284)	(0.3287)	(0.3201)	(0.3240)
λ	-4.6818	-4.1186	-4.6379	-4.7387	-4.1592
	(3.4716)	(3.5296)	(3.5248)	(3.4327)	(3.4750)
Temperature anomaly		0.3047			0.2897
		(1.5203)			(1.5268)
(Temperature anomaly)^2		-1.2606*			-1.2643*
		(0.7364)			(0.7395)
Precipitation anomaly			0.5014		0.8564
			(1.1080)		(1.2793)
(Precipitation anomaly)^2			1.0689		1.0522
			(1.0965)		(1.1217)
DSCI anomaly				0.0031	0.0066
				(0.0083)	(0.0093)
(DSCI anomaly)^2				-0.0001	-0.0001
				(0.0001)	(0.0001)
Constant	636.7263***	635.4967***	638.3341***	627.1874***	616.5070***
	(77.3496)	(78.9021)	(78.2930)	(76.8619)	(78.2848)
R^2	.6541	.6581	.6556	.6608	.6622

Number of observations = 1,000. Standard errors in parentheses. Stars indicate significance; *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.