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# U.S ELECTRIC UTILITY ADAPTATION TO NATURAL DISASTERS SHOCKS AND GREEN POWER MANDATES

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**ABSTRACT**

Access to electricity is a crucial determinant of quality of life and productivity. The United States has a highly reliable electricity grid but it faces new resilience challenges posed by more intense natural disasters and rising state level green power requirements. Using a U.S electric utility panel dataset from 2013 to 2020, we document that natural disaster exposure disrupts service, but utilities have made some progress in adapting to such shocks. Over the last decade, there has been a tradeoff between achieving local carbon mitigation goals and offering reliable power access.

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## Introduction

In February 2021, the freeze in Texas left more than ten million people without access to electricity for days. The freeze had devastating effects on services that rely on electricity such as water treatment and home heating. The power outage may have caused up to 700 deaths and $130 billion economic losses in Texas alone (Busby et al. 2021). In summer 2022, extreme heat waves strained the American electric grid and caused large-scale blackouts. Hurricane Ian knocked out power for millions of people in Florida in September 2022.

Going forward, the United States electricity grid faces increases risks posed by extreme weather and by the ramping up of state level renewable power generation requirements (Bushnell and Noval 2018; Delmas and Montes-Sancho 2013; Stock 2020). The reliability of the grid will be tested. The power grid is a crucial piece of U.S infrastructure. Benchmarking infrastructure quality dynamics poses a fundamental measurement challenge (Glaeser and Poterba 2020).

In this paper, we compare the quality of a utility's performance based on its ability to "keep the lights on". We use utility level data from 2013 to 2020 to benchmark the resilience progress of American utilities. Numerous recent natural disasters provide us with a set of natural experiments to test the resilience of our electric infrastructure.

In 2013, the average American did not have access to electricity for 240 minutes. In 2020, this number has risen to 390 minutes. Given that there are 525,600 minutes in a year, the percentage of time when the power is down is tiny. Power reliability depends on disruptions to the generating, transmission, or distribution facilities. Investments can reduce disruption risk for each link in this supply chain.

Our paper builds on past research that has used different measures to benchmark adaptation progress. Barreca et al. (2016) document that the mortality risk as a function of heat waves has flattened over time due to increased access to air conditioning. Using global panel dataset, Kahn (2005) documents that the death toll from natural disasters has shrunk over time, especially in richer nations. Gandi et. al. (2022) document a similar finding in exploring local lights at night dynamics as a function of flood events.

We document that over the last decade there has been a tradeoff between achieving resilience goals (adaptation) and carbon mitigation. In recent years, many states have enacted more ambitious green power goals. The average state Renewable Portfolio Standard (RPS) has increased from 4.9% in 2013 to 11.9% in 2020. Liberal states generally have higher RPS. In California, RPS was 20% in 2013 and 33% in 2020. The "green grid" features a lower carbon emissions factor, but an unintended consequence is that the short-term electricity generation becomes more volatile and less reliable when more power is generated using renewables (Mabel, Raj, and Fernandez 2011; Shaner et al. 2018). Planners face a challenge determining the long-term resource adequacy for service delivery when the electricity wholesale market features a substantial amount of intermittent renewable capacity (Wolak 2022). Based on our reduced form regressions, we document a positive correlation between a utility's service disruption and its state's RPS standard. This finding informs policy debates concerning the benefits of demand side management tools such as dynamic pricing and technological progress regarding battery storage technology.

We start by discussing a utility's incentives to provide reliable power. We then discuss recent research studying how electricity consumers adapt when they face an intermittency problem. We then present our data sources. Next, we use utility-level panel data to study utility reliability patterns over time and across space. After quantifying reliability, we estimate the effects of natural disasters on utility maintenance expenditure and how much of these additional costs are passed on to consumers. Finally, we discuss the adaption versus mitigation tradeoff and point to areas for future research.

## Incentives to Supply Reliable Power

In the US, most urban areas are served by investor-owned or government-owned utilities (i.e. municipal utilities), whereas cooperative utilities are primarily located in rural areas.[1] Among these three types of utilities, only investor-owned utilities are profit-driven. Large shareholders have prominent influence on these corporations' policy. These shareholders are not customers of the utilities, and these investor-owned utilities face little competition in output markets.

Municipal utilities are run by city governments, and each local resident (also a customer of the local electric utility) is a de-facto shareholder. Due to this fragmented ownership,

[1] The population density of areas served by cooperative utilities is approximately one-fifth of those served by investor-owned or government-owned utilities. Cooperative utility customers average distance to CBD is 50% and 120% higher than that of investor-owned utility customers and government-owned utility customers respectively.

government-owned utilities have greater discretion in decision-making when compared to private enterprises. Their decisions should benefit consumers because residents keep local public utilities accountable through voting. The city government attempts to establish a coalition that maximizes the difference between the number of net gainers and that of net losers from its policy (Peltzman 1971). In a municipality with many environmentalists who have high willingness to pay for clean power, municipal utilities are more likely to increase generation from renewable energy and raise electricity prices to compensate the investments in green electricity infrastructure (Kotchen and Moore 2008; Costa and Kahn 2013). Cooperative utilities have a similar structure to municipal utilities. They are run by an executive board elected by local customers, and each customer is a shareholder of the utility.

Local utilities such as the municipal and cooperative ones face greater pressure from consumers as they could show up to the utilities and protest. Investor-owned utilities are usually non-local and anonymous. They face pressure from the local regulators such as the state PUC. Instead, local regulators bear the anger from customers.[2] We expect that local public or cooperative utilities to supply greater baseline reliability than investor-owned ones, although in reality the reliability of cooperative utilities may be limited by the overall underinvestment in rural infrastructure.

**The Simple Analytics of the Reliability Tradeoff**

We consider investor-owned electric utilities subject to the rate-of-return regulations. We sketch the equilibrium conditions for these regulated monopolies (Spann 1974). We assume that each utility chooses its capital (K), labor (L), and reliability (R) to maximize its profits. The quantity of electricity produced (Q) is a function of capital and labor. Electricity restructuring has enabled some retail consumers to switch electricity provider when reliability is low (Borenstein and Bushnell 2015). Thus, in the retail market, electricity price (p) is a decreasing function of quantity and an increasing function of reliability. The rate-of-return (s) is set by the local PUC, and the wage (w) is exogenously determined by the labor market. The marginal cost of capital (r) is an increasing convex function of reliability because of

[2] In California, instead of protesting against PG&E, consumers protested in front of California PUC for the rising energy bills and the frequent disruptions in services. In Puerto Rico, people marched along a main highway to pressure the state regulators to end the contract with the private electricity provider LUMA Energy.
https://www.nbcnews.com/news/us-news/raucous-protests-against-california-utility-pg-e-facing-wildfire-claims-n957351
https://www.nytimes.com/2021/10/19/us/puerto-rico-electricity-protest.html

diminishing returns ($r'$>0 and $r''$>0). More reliable capital is more expensive. The profit of an electric utility can be written as:

$$\pi = p(Q,R)Q(K,L) - wL - r(R)K, \tag{1}$$

with the regulatory constraint given by $pQ - wL \leq sK$. In this inequality, $pQ - wL$ is the utility's total returns from capital, which should be lower than the amount of capital (K) multiplied by the maximum rate of returns (s) set by the regulators. The utility's decision problem can be expressed as:

$$Max_{K,L,R}\ \ p(Q,R)Q(K,L) - wL - r(R)K - \lambda(p(Q,R)Q(K,L) - wL - sK). \tag{2}$$

The first-order conditions are obtained by differentiating the Lagrange function with respect to K, L, and R and setting them to zero:

$$(1-\lambda)\frac{\partial p}{\partial Q}\frac{\partial Q}{\partial K}Q(K,L) + (1-\lambda)p(Q,R)\frac{\partial Q}{\partial K} + \lambda s = r(R) \tag{3a}$$

$$\frac{\partial p}{\partial Q}\frac{\partial Q}{\partial L}Q(K,L) + p(Q,R)\frac{\partial Q}{\partial L} = w \tag{3b}$$

$$(1-\lambda)\frac{\partial p}{\partial R}Q(K,L) = r'(R)K \tag{3c}$$

Equation (3a) embodies the Averch-Johnson effect. $p(Q,R)\frac{\partial Q}{\partial K}$ is the marginal return of capital investments. It is always smaller than s because the profit-maximizing would not produce otherwise. If consumers do not have electricity choice, $\frac{\partial p}{\partial Q}$ is negative but close to 0, so does $(1-\lambda)\frac{\partial p}{\partial Q}\frac{\partial Q}{\partial K}Q(K,L)$. A simplification of equation (3a) shows $p(Q,R)\frac{\partial Q}{\partial K}$ < r(R) when utilities constitute local monopolies, suggesting overinvestment in capitals that depreciates the equilibrium marginal return to below the marginal cost.

In equation (3c), $\frac{\partial P}{\partial R}$ is low when consumers cannot switch to other utilities in response to low reliability. For a given level of capital and labor input, this implies a low $r'(R)$. Because $r'' > 0$ by our assumption of diminishing marginal return, our model predicts utilities facing limited threats of consumer switching would choose to produce at a lower reliability.[3]

[3] Prior to the 1990s, electricity was mainly provided by vertically integrated utilities that generate electricity and distribute it to end-users. In the 1990s, electricity restructuring allowed non-utility generators to sell electricity to utilities and non-utility power retailers to sell electricity to final customers. Following the restructuring, the electricity market consists of the wholesale and the retail market. In the wholesale market, power providers purchase electricity from power generators. In the retail market, end-use consumers purchase power from power

## The Demand for Reliable Electricity Service

Previous work has quantified the cost of power outages on electricity consumers in the United States (Gilmer and Mack 1983; LaCommare and Eto 2006). This cost is likely to rise in the medium term. Labor productivity and student learning rate both decline under extreme weather (Zander et al. 2015; Park et al. 2020; Zivin and Neidell 2012; Kahn and Li 2020). Firms, schools, and households purchase and operate air conditioners and heaters to mitigate the negative impacts of environmental shocks (Davis, Fuchs, and Gertler 2014). Power outages reduce the returns on such investments because people cannot operate these electric appliances when disasters hit.

Recent work has documented the consequences of unreliable power in the developing world, especially in the commercial and the industrial sector. In China, in response to disruptions to electricity provision, firms outsource the production of energy-intensive intermediate goods (Fisher-Vanden, Mansur, and Wang 2015). If intermediate goods are outsourced to regions with dirty electric grids, this would exacerbate the climate change externality. Allcott, Collard-Wexler, and O'Connell (2016) find that electricity scarcity reduces producer surplus in India. In Africa, one fifth of firms own self-generators as backup power sources during outages, even though self-generation raises the production cost by three times (Steinbuks and Foster 2010). Power outages significantly reduce African firms' profits and total factor productivity, but those with self-generators are only moderately affected (Cole et al. 2018). Firms and households with higher willingness to pay for reliable electricity are more likely to engage in self-generation, but their marginal increase in willingness to pay is usually less than the marginal cost increase of self-generation (Oseni 2017). Relying on dirty power generators increases local air pollution and this raises the social cost of grid disruption. Improving utility reliability could bring net welfare gains as the demand for self-generation drops.

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providers. Borenstein and Bushnell (2015) document that the restructuring improved the overall electricity reliability. The restructuring lowers the reliability risks by unbundling the generation, transmission, and distribution process. For example, if a utility's generating capacity is hit by disasters, the utility can now purchase electricity in the wholesale market and resell it to its customers so that customers do not have to experience power outages.

## Data

To analyze the reliability of American electric utilities over time, we create a comprehensive dataset at the utility/year level. Our core data on electric utilities is provided by the U.S. Energy Information Administration (EIA).[4] The EIA data is at utility/state/year level. It includes information on the reliability, sales, revenues, and other utility characteristics for each utility every year. We use the data from 2013 to 2020. We create our own utility identifier based on the utility IDs in the EIA dataset.[5]

The EIA keeps track of three main reliability metrics: the System Average Interruption Frequency Index (SAIFI), the System Average Interruption Duration Index (SAIDI), and the Customer Average Interruption Duration Index (CAIDI).[6] For a given utility, SAIFI is the percentage of customers affected by a power outage. SAIDI is the average interruption time per customer.[7] CAIDI is the average interruption time per customer who is affected by an outage (aka. the average time to restore service). CAIDI measures whether a utility efficiently responds to an interruption. SAIDI measures both the response to and the prevention of interruptions. SAIDI declines if a utility restores service more quickly or reduces the total number of interruptions. In this paper, we use SAIDI as our primary metric of reliability. We include major event days in our analysis because we are interested in how utilities perform under disasters. To calculate the average residential electricity price, we divide the total revenue from residential electricity sales by the total sales for each utility and each year.

We obtain the natural disaster data from the Federal Emergency Management Agency

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4 https://www.eia.gov/electricity/data/eia861/

5 In the EIA data, each utility number identifies a unique utility company. A utility company may serve multiple counties in a single state or even multiple states. For example, PacifiCorp provides services in six states: California, Idaho, Oregon, Utah, Washington, and Wyoming. Different states have different regulations on electricity provision, so facilities of the same utility company could have different reliability across its operating states. To address this within-company heterogeneity, we create a utility ID based on utility company/state in the EIA data. In the case of PacifiCorp, we create six different utility IDs for our dataset.
Our sample includes all utilities whose reliability data is available. There are 465 public utilities, 182 investor-owned utilities, and 594 cooperative utilities.

6 These indices only refer to sustained interruptions. As defined by the Institute of Electrical and Electronics Engineers (IEEE), sustained interruptions last at least five minutes.

7 Utilities' customers include residential, commercial, and industrial ones. SAIDI gives each customer an equal weight, regardless of their electricity consumption. Because most customers are residential, SAIDI is a valid measure of residential electricity reliability. Previous electrical engineering has casted doubt on the accuracy of SAIDI when used to evaluate grid reliability for non-residential sectors (Schuerger, Arno, and Dowling 2016). Updated measures are also needed as more distributed generators and energy storage owners enter the market. We acknowledge that our results in this paper apply mostly to the residential sector.
https://www.sandc.com/globalassets/sac-electric/documents/sharepoint/documents---all-documents/technical-paper-100-t128.pdf?dt=637989340505021535

(FEMA).[8] The FEMA data lists every natural disaster from 2013 to 2020. The dataset provides the date, type, and location of each disaster. We collapse this dataset by county/year and create a dummy variable for each of the 13 types of disasters. We aggregate these 13 categories into a smaller set of categories: hurricane, storm, fire, and other.

The FEMA disaster dataset does not include extreme heat or drought. When people use air conditioners on very hot days, the aggregate demand strains the power grids. Severe droughts reduce the reliability of hydroelectric plants (Eyer and Wichman 2018). We use summer cooling degree days (CDDs) as a measure of electricity demand under heat waves. To calculate county-level CDDs, we use the monthly average temperature data provided by the PRISM Climate Group.[9] We overlay the GIS files with county shape files to obtain the average summer temperature (June to August) for each county/year. Using this summer temperature, we calculate the summer cooling degree days (CDDs), a commonly used proxy for summer energy demand. A higher CDD indicates higher cooling demand, and electricity demand rises when people turn on air conditioners. In addition, we create a drought dummy based on the Drought Severity and Coverage Index (DSCI)[10]. We calculate the average DSCI for each state each year and define the drought dummy to 1 if DSCI is greater than 250, which indicates that the state is under moderate to severe drought. We also include the precipitation data from PRISM as an alternative measure of drought. For each year, we overlay the precipitation GIS file with state shape files to calculate the total precipitation in each state. We merge the county/year summer CDD, the state/year drought dummy, and the state/year precipitation into our environmental panel.

The final piece of our environmental data panel includes each state's renewable portfolio standard (RPS) over time and each county's fire risk score in 2021 provided by the First Street Foundation.[11] RPS is the state mandate of the minimum percentage of electricity generated from renewable energy. The fire risk score provides an indicator of a geographic

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[8] https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2

[9] https://prism.oregonstate.edu/

[10] https://droughtmonitor.unl.edu/DmData/DataDownload/DSCI.aspx
https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx
Drought severity is rated on a scale from 0 to 5, where 2 means moderate drought, and 3 means severe drought. DSCI is calculated using the following formula: DSCI=$\sum_0^5 Drought\ level * Area\ coverage$. A DSCI of 300 means that the area is on average under severe drought.

[11] https://firststreet.org/data-access/public-access/
The First Street Foundation is a non-profit research group that provides data on flood and wildfire risks in the US. The fire risk is rated on a scale of 1 to 10, with 1 being least risky and 10 most risky. In 2021, the average score was 2.255, and the standard deviation was 1.395.

location's expected exposure to fire events. To merge our county/year environmental panel data into our core utility/year dataset, we set disaster dummies to 1 if any of the counties served by a utility is hit by the corresponding disaster in a given year. For the county/year continuous variables including summer CDD and fire risk, we take the average among all counties served by a utility. According to our definition of a utility (see footnote 9), each utility only covers one state, so the state-level variables including drought, RPS, and precipitation can be merged in by state/year.

To create our economic and demographic dataset, we obtain home prices data from Zillow as a measure of each county's income level.[12] Zillow provides the median home prices in each county every year from 2013 to 2020. We obtain cross-sectional data on educational attainment from the American Community Survey.[13] We use the percentage of the adult population with a bachelor's or higher in 2019. We also include the percentage votes for the Republican candidate in the 2020 presidential election as a measure of political affiliation[14]. Both education and voting variables are available at county level. The county-level climate belief variables are from Yale Program on Climate Change Communication.[15] Specifically, our measure of climate belief is the percentage of residents believing climate change is real in each county in 2021. We merge these cross-sectional variables into the demographic panel by county. We merge these county-level demographic variables into the core utility/year dataset in the same manner as how we merge in the environmental panel.

We augment our core dataset with private utilities' costs data and cities' night lights data. Each investor-owned utility publishes its electric utility annual report on the website of the Federal Energy Regulatory Commission (FERC).[16] We pick a random sample of 22 investor-owned utilities and compile their reported annual operation and maintenance costs data from 2013 to 2020.[17] The night lights data is from the Earth Observation Group and is available at the year/month level as GIS files.[18] We overlay them with US county shape files and calculate the average monthly night lights by county. This is an alternative measure of a

[12] https://www.zillow.com/research/data/
[13] https://data.census.gov/cedsci/
[14] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ
[15] https://climatecommunication.yale.edu/visualizations-data/ycom-us/
[16] https://elibrary.ferc.gov/eLibrary/search
[17] There are 442 cooperative, 154 investor-owned, and 286 government-owned utilities in our dataset. In terms of total residential electricity sales in 2020, 68% are provided by investor-owned utilities, 18% by cooperative, and 14% by government-owned.
[18] https://eogdata.mines.edu/products/vnl/
The unit of night lights is $W/cm^2/sr$ (watts per squared centimeter per steradian).

utility's resilience. Utilities are resilient if night lights do not significantly dim during natural disasters.

**Lights at Night Correlate with Electric Utility Reliability Indices**

We use the SAIDI and SAIFI as our key reliability metrics. Past works have extensively used these two metrics or the revised versions of them to study utilities' resilience dynamics (Ankit et al. 2022). In this section, we examine whether SAIDI and SAIFI correlate with an independent measure of local economic activity, namely lights at night. To study this, we create a nightlights panel dataset at the county/year/quarter level from 2013 to 2020. We test whether lights are dimmer in counties with higher SAIDI or SAIFI (i.e. less reliable utilities). We also test whether night lights dim when natural disasters take place. We estimate the following econometric models for county k in quarter q of year t:

$$\log(\mathrm{Nightlights}_{kt}) = \beta_0 + \beta_1 \log(\mathrm{Utility\ Reliability}_{kt}) + \gamma_t + \omega_k + \varepsilon_{kt} \tag{4}$$

$$\log\left(\mathrm{Nightlights}_{ktq}\right) = \beta_0 + \beta_1 X_{ktq} + \beta_2 \mathrm{Trend}_{tq} \times \mathrm{Disaster}_{ktq} + \delta_{kt} + \varepsilon_{kt} \tag{5}$$

In the above specifications, nightlights refer to the average nightlights level in a county in the given period (year or quarter). In equation (4), the reliability metric could be SAIDI or SAIFI. If there are multiple electric utilities in a county, we take the customer count-weighted average of all utilities' reliability. We include year-fixed effects ($\gamma_t$) and county-fixed effects ($\omega_k$). Standard errors are clustered at county level.

In equation (5), X is a vector of natural disaster dummies or counts.[19] There are three natural disaster categories: hurricane, storm, and other. The disaster variable is measured either by the total disaster count at a given place and time or as a dummy indicating that at least one disaster occurred. The trend is a chronological variable at year/quarter level, with 2013Q1 equal to 1 and 2020Q4 equal to 32. The interaction between trend and disaster measures the adaptation progress over time. Evidence of adaptation progress is indicated by whether this

[19] If a disaster starts in the last 5 days of a quarter, we count it into the next quarter. For example, if a hurricane starts on March 29, we count it into Q2.

interaction has a positive coefficient. We include county/year fixed effects ($\delta_{kt}$). Standard errors are clustered at county/year level.

Table 1 reports the results from the estimation of equations (4) and (5). In columns (1) and (2), both SAIDI and SAIFI are statistically significant at the 1% level and have a negative coefficient. On average, a 10% increase in SAIDI and SAIFI causes the annual average night lights to dim by 0.066% and 0.2% respectively. The significant coefficients indicate that the reliability metrics we choose are valid measures of utilities' ability to "keep the lights on". In columns (3) to (6), most of disaster dummies and counts have negative and statistically significant coefficients. Night lights dim when there are more disasters, implying that natural disasters significantly disrupt electricity generation.

**Are Utilities Adapting to Natural Disaster Shocks?**

In 2020, the FEMA data reports that there were 22 hurricanes, 23 storms, and 88 wildfires. 19% of U.S electric utility's counties were struck by at least one hurricane in 2020. In 2013, this percentage equaled 10%. Figure 1 shows that the median SAIDI was 146 minutes in 2013 and 176 in 2020. However, the 75$^{th}$ percentile SAIDI rose by 38% from 265 minutes to 363 over the same time. This implies that extreme weather significantly disrupts utility services and increases the likelihood of tail events such as the 2021 Texas power outage.

In this section, we test whether utilities are becoming more resilient over time. Such utilities have private information about their marginal cost of providing high quality, consistent service. Facing data limitations, we present a reduced form approach. Our first test is based on the lights at night. In Table 1's columns (4) and (6), we report estimates of equation (2) and document a positive coefficient on the interaction term between the time trend and natural disasters. We find the same result when we measure disasters using the count or a dummy variable for at least one occurrence of such an event. As predicted by the adaptation hypothesis, over time, the negative effects of natural disasters on night lights shrink.

As a second adaptation test, we test whether utilities are adapting to environmental shocks using the reliability metrics SAIDI and SAIFI. We estimate the following specifications for utility i in year t:

$$\log(\text{Utility Reliability}_{it}) = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} \times \text{Trend}_t + \gamma_t + \mu_i + \varepsilon_{it} \quad (6)$$

In equation (6), the measure of utility reliability is either SAIDI or SAIFI. X is a vector of environmental attributes at utility/year level. It includes a list of dummies for hurricane, storm, and other disasters, summer daily CDDs, and state RPS and its square. To test whether hydropower becomes unreliable due to water scarcity, we include drought or precipitation and their interaction with states' percentage of generation capacity relying on hydropower. We also include the interaction between precipitation and state fire risk to test whether the increased precipitation in fire-prone regions raises the reliability of local power plants. Z is a vector of environmental and utility attributes relevant to our adaptation hypothesis, including most variables in X and ownership dummies. In the vector Z, the aggregate disaster dummy equals 1 if the utility's service area is hit by any natural disaster. Ownership dummies include investor-owned and government-owned dummies. The omitted category is a cooperative utility. Z is interacted with the annual time trend or a dummy indicating whether it is 2017 onward (in the second half of our sample). There is evidence of adaptation if the coefficients vector $\beta_2$ contains significantly negative values. We include year-fixed effects ($\gamma_t$) and utility-fixed effects ($\mu_i$). Standard errors are clustered at the utility level.

Table 2 shows the results from the estimation of equation (6). The results are similar when we use SAIDI and SAIFI as the reliability measure.[20] The three disaster dummies are significantly positive in all columns, showing that natural disasters raise both the duration and the frequency of power outages.[21] Among all disasters, hurricanes are associated with the largest service disruption. Hurricane causes average SAIDI to increase by 34.2% to 44.1% (see columns 1 to 3). It causes SAIFI to increase by 7.5% to 10.8% (see columns 4 to 6).[22] Heat

[20] In our dataset, SAIDI and SAIFI have a positive correlation of 0.49.

[21] Extreme weather reduces power plants' generating capacity. Also, blackouts can be caused by trees falling on distribution lines. Severe blackouts are usually caused by damages to transmission facilities. Data shows that the trend of outages from extreme weather is increasing. The annual cost of storm-related outages in the US is between $20 billion to $55 billion.
https://www.ourenergypolicy.org/wp-content/uploads/2016/02/R42696.pdf

[22] Our disaster dummies equal 1 if at least one county where the utility's end-users are in is hit by the disaster. Our disaster thus captures the environmental shock's impacts on local distribution facilities. The EGRID data shows that the counties where a utility's generators (the ones it owns or purchases power from) are in is usually a subset of the counties where the utility's end-users are in. This means that our disaster dummies also capture the disruptions to the generating facilities. However, we do not have data on the areas that the power goes through when transmitted from the generators to end-users. The power may pass through counties where none of the utility's end-users are in. Our dummies thus may fail to capture the disruptions to the transmission lines. Nevertheless, since most natural disasters are often regional, counties close to each other would be affected at the same time. If generators and customers are located in counties near each other, it is unlikely that a natural disaster

waves also reduce the reliability of power plants, as indicated by the significantly positive coefficient of summer CDDs in most columns. When the daily CDD increases by 1 degree Fahrenheit, SAIDI and SAIFI rise by 2.5% to 5% on average. This shows that grid reliability is severely affected by surging electricity demand. Aside from extreme weather events, column (1) shows that an 1% increase in RPS causes SAIDI to rise by 1.53%.

In columns (1) and (2), we find statistically significant evidence that SAIDI is a convex quadratic function of a state's RPS. The squared RPS term is significantly positive, and the level RPS term is not significantly different from 0. As the mandated RPS increases, the marginal reliability damage increases. This estimated correlation is consistent with the previous environmental science literature documenting that renewable energy is unreliable when used for a large proportion of electricity generation (Mabel, Raj, and Fernandez 2011; Shaner et al. 2018).

We recognize that our reduced form regressions only sketch out what has been the past tradeoff that has existed under the "old rules of the game". Going forward, these estimates are useful for establishing the business as usual case as utilities consider introducing greater participation in dynamic pricing programs and expanding battery storage.

**A Test of Adaptation Progress**

We test the adaptation hypothesis by reporting interaction effects in Table 2's columns (2), (3), (5), and (6). We find statistically significant evidence of adaptation in columns (2) and (3) based on the SAIDI measure. The positive coefficient on disasters shrinks by 3% per year. Given the baseline coefficients, this represents a large reduction. In columns (5) and (6), the interaction term between the time trend and natural disasters is negative but statistically insignificant in the case of the SAIFI resilience measure. Although the discrete derivative of the frequency of power outages as a function of natural disasters does not change over time, the discrete derivative of the change in average outage durations associated with disasters shrinks.

We test whether the relationship between utility power reliability and CDDs, RPS, drought, or precipitation changes over time. Based on the statistically insignificant interaction

hits the transmission counties without hitting the generation or distribution areas. Therefore, we believe that our dummies capture the disruptions to the transmission facilities in most cases.

terms, we find no evidence that the utilities are adapting to high heat or heavy rainfall. In columns (2) and (5), we find that utilities are adapting to droughts. In columns (5), the interaction term between the late dummy and RPS is statistically significant and has a positive coefficient, and the interaction with $RPS^2$ is statistically significant and negative. Our calculations show that the discrete derivative of SAIFI with respect to RPS has shrunk for states whose RPS is greater than 13.2%.

The interaction terms between time trend and utility ownership type show that cooperative utilities have adapted more than investor-owned and government-owned utilities. Based on the SAIDI metric, the cooperative utility adaptation progress is more than 3% faster than for the two other types of utilities. Based on the SAIFI metric, the cooperative utility's pace of adaptation is 2.04% faster than government-owned utilities. Public utilities have made the least reliability progress. One possible explanation that merits further research is that these utilities have greater access to federal and state transfers to repair their facilities after each disaster. From the logic of the moral hazard, such utilities may not be incentivized to make lump-sum investments on costly resilient infrastructure to reduce the damage from the next shock. Cooperative and investor-owned utilities receive less funding and thus have a greater incentive to minimize their long-run maintenance costs by upgrading to more resilient facilities.

Cooperative plants also have a adaptation advantage because they do not own generating facilities and purchase most of their power in the wholesale market. They can switch power supplier when one supplier becomes unreliable. In 2020, only 1.3% of the sold electricity from cooperative utilities came from self-generation, while the percentage was 61.5% for investor-owned utilities and 40.4% for government-owned ones. The high cost of maintaining and upgrading the generating facilities poses adaptation challenge to investor-owned and government-owned utilities.

**Cross-Sectional Correlates of Electric Power Service Reliability**

In this section, we explore the spatial correlates of utility service resilience. Figure 2 shows log(SAIDI) across all US counties in 2020. The SAIDI metric is higher in coastal regions, where disasters like storms are more frequent. The geographical variations in SAIDI are evident on the map. In the South, the average SAIDI (weighted by population) is 657 minutes, while the average is only 283 minutes in the Midwest. This is consistent with the distribution of natural disasters. In 2020, each southern county is hit by 0.7 natural disaster on average. Each midwestern county is only hit by 0.12 disaster.  Across the four regions, utilities in the West are the most reliable, and those in the Northeast are the least reliable. The weighted average SAIDI is 242 minutes in the West and 732 minutes in the Northeast. However, there is 0.41 natural disaster in each western county but only 0.16 in each northeastern county.

The analysis on natural disasters suggests that they are not the only factor that explains the spatial variations in reliability. We hypothesize that utilities in more educated and richer cities are more resilient. We also study whether utilities perform better in cities with more liberals and climate believers. These more progressive and richer cities tend to have cleaner power plants, but electricity generation from intermittent renewable energy such as wind could reduce reliability (Wolak 2022). The mechanism in Section II implies that utilities' reliability differs by ownership types, which we will also examine in this section. To test these hypotheses, we estimate the following regression specifications for utility i (in state s) in year t:

$$\log(\text{Utility Reliability}_{\text{it}}) = \beta_0 + \beta_1 X_{\text{it}} + \beta_2 Z_{\text{it}} + \beta_3 F_{it} + \beta_4 R_{\text{st}} + \text{fixed effects} + \varepsilon_{\text{it}} \qquad (7)$$

In equation (7), X is a vector of disaster dummies and environmental attributes as in equation (6). Z is a vector of utility features and demographic features associated with each utility. Utility features include logged customer count and ownership dummies. Demographic variables include college graduates, votes for Republicans, climate belief, and logged home prices (see the data section).

We use the fire risk data to test whether utilities take precautionary measures against expected risks. F is a vector of variables relate to wildfire, including the interaction between the fire dummy and fire risk. A significantly negative value of the interaction term would indicate adaptation. We also test whether dynamic pricing increases power reliability under high-renewable generation scenarios. Because dynamic pricing causes consumers to cut their electricity use during peak hours (Wolak 2011), it could reduce the likelihood of power shortages when renewables fail to deliver. R is a vector of adaptation techniques, including dynamic pricing and energy storage, and their interaction with RPS. A negative coefficient of the interaction terms would indicate the medium-term adaptation benefit of scaling up dynamic pricing and energy storage during the transition to zero-carbon generation. To estimate equation (7), we include different fixed effects such as year-fixed effects, NERC-fixed effects, and NERC/year fixed effects. Standard errors are clustered at the utility level.

Table 3 presents the estimation results of equation (7). Most of the disaster dummies have positive and statistically significant coefficients. Environmental shocks significantly disrupt electricity provision. Summer CDD is significant in columns (2) to (4), which is probably because its correlation with the fire and drought dummies. Compared with Table 2, in Table 3, we find more significant evidence of the convex quadratic relationship between reliability and RPS. RPS is significantly negative in all columns, and $RPS^2$ is significantly positive. The estimated turning point is 12% to 15% for both SAIDI and SAIFI. States diversify their power sources through renewable generations. This increases utilities' resiliency to unexpected shocks that hamper electricity generation from fossil fuels. However, if power generation overly relies on renewables, this would eventually lead to reliability issues as the supply of renewables is more volatile than that of fossil fuels. Utilities often have backup generators powered by conventional fuels, but these generators are insufficient to meet the electricity demand during a large-scale power outage on a low-wind or low-sun day.

The log of the customer count coefficient is positive and statistically significant in all specifications, suggesting that there are no economies of scale in providing reliable services. This provides empirical support for theoretical models that posit a tradeoff between scale economies in generation and reliability improvements (Gilmer and Mack 1983). One explanation of this fact is that larger utilities face less competition. Borenstein and Bushnell (2015) find that electricity generation efficiency improves significantly as more retail service providers enter the retail market. Large utilities are often located in regions where customers do not have electricity choice. The inelastic demand enables these utilities to provide lower-quality services without losing customers (see Section III).

Another explanation is based on the cost of upgrading infrastructure. Investor-owned and government-owned utilities often have transmission and distribution lines spanning across multiple counties. Due to diminishing marginal returns, the cost of improving these facilities rises as the scale of operation increases.

Using our cross-sectional regressions reported in equation (7), we test the relationship between reliability and local demographics. We find significant evidence that more educated areas have more reliable service provision. When educational attainment increases by 1%, SAIDI falls by approximately 1.17% to 1.37%. We find no evidence that an area's political attitudes, climate belief, or home prices affect grid reliability.[23]

We compare the reliability differences between different types of utilities. In all columns, the investor-owned and government-owned dummies are significantly negative. They both have lower baseline SAIDI and SAIFI than cooperative plants do. Based on the SAIDI and SAIFI reliability metrics respectively, we find that investor-owned utilities are nearly 30% more reliable than cooperative ones, and the government-owned utilities are about 120% (SAIDI) or 84% (SAIFI) more reliable. These results are broadly consistent with the mechanisms we proposed in Section II. Cooperative utilities underperform other utilities due to the less well-maintained rural infrastructure. Government-owned utilities (mostly municipal) face more intense customer pressure and are thus more incentivized to keep reliability high.

**Service Reliability in the American West**

The American West faces rising drought risk and fire risk. Without investment in infrastructure maintenance and upgrading, climate change is likely to increase the frequency and the severity of power disruptions. The nation's aging power grid infrastructure may increase the natural disaster risk in fire prone areas.[24] In California, the Pacific Gas and Electricity (PG&E) Company now pre-emptively shuts off power to reduce the fire risk brought by active transmission lines. In fire zones, there has been an active debate about the cost-effectiveness of burying power lines (Larsen et al. 2018).

We explore how these threats are associated with service reliability. Currently, roughly 8% of electricity in the US is generated by hydroelectric plants, and hydropower contributes to over 30% of renewable generation. Although hydropower is low carbon, Eyer and Wichman (2018) document that utilities substitute hydropower with fossil fuels under water scarcity. In

[23] We acknowledge the spatial correlation between utilities' reliability. Cascading outages could occur when environmental shocks in one county disrupt regional electricity provision (Vaiman et al. 2012). For example, when a utility company's transmission lines are damaged by a storm, this would affect transmission lines in nearby areas operated by other utilities. To address this issue, in column (2), we run the specification in column (1) but with NERC region/year fixed effects. All coefficients have the same sign and significance as in column (1). This implies that the occurrence of cascading failures would not alter our main results.
We also drop the customer count from column (1)'s specification, weight the regression by customer count, and rerun it. The results are qualitatively similar to the unweighted results with the exception of the coefficient on college graduates and home prices. Education becomes insignificant, but home prices become significantly negative.

[24] In the US, roughly 70% of the transmission lines are in the second half of their expected lifespan. Grid modernization (e.g. the smart grid) can improve grid reliability and lower the natural disaster risk caused by the grid.
https://infrastructurereportcard.org/wp-content/uploads/2020/12/National_IRC_2021-report-2.pdf

Table 2, the interaction between states' hydropower percentage and drought is significantly positive, and its interaction with precipitation is significantly negative. States featuring a large share of hydroelectric plants improve their service reliability when precipitation increases, but their grid reliability is affected more by droughts. Utilities are incentivized to generate more electricity with fossil fuels if they expect droughts to be more frequent. In columns (3) and (6), the interaction between fire risk and precipitation has a significantly negative coefficient. In fire-prone areas, increased precipitation could reduce the risk of fire and raise the reliability of the power plants. These interaction terms show the heterogenous effects of precipitation on grid reliability. The positive coefficient of precipitation shows that heavy rainfall or snowfall reduces reliability in general, but it could increase grid reliability in areas with high hydropower generation and high fire risk.[25]

The big data revolution has given rise to the climate risk analytics industry. Utilities can now access environmental risk data provided by such analytics companies such as First Street Foundation, Jupiter, and several others. If utilities are increasingly aware of the risks they face, they have an incentive to invest in resilient infrastructure. In column (3) of Table 3, the interaction term between the fire dummy and the fire risk is significantly negative. In counties with higher fire risks (as predicted by First Street Foundation), actual wildfires cause less power blackouts. For an electric utility, if the average fire risk of its service areas is rated one standard deviation higher, an actual fire's disruptions to its reliability (as measured by SAIDI) decline by 11.6%. We interpret this finding as consistent with adaptive investments (e.g. hardening the power lines) being made because of expected risks. Although the fire dummy is significantly positive in column (3), a t-test on the coefficients of fire and the interaction term between fire and fire risk shows that wildfire does not increase utility reliability in an area with average fire risks. In column (6), we run the same specification using SAIFI as the reliability measure. We find no evidence that fire significantly raises SAIFI or utilities are adapting to fire based on the expected risks.

**Does Demand Side Management Increase Resilience?**

We have documented that the intermittent renewable generation increases reliability

[25] A t-test on the coefficients of drought and its interaction with hydropower percentage shows that droughts do not reduce reliability on average. A test on the coefficients of precipitation and its interaction with hydropower percentage and fire risk shows that precipitation significantly raises SAIDI and SAIFI on average.

challenges after RPS rises above 15%. Utilities can apply demand-side management tools such as dynamic pricing to reduce such risks.[26] In the water market, Baisa et al. (2010) have found that dynamic water prices reduce the distributional inefficiencies. Similarly, if electricity prices rise on low-wind and low-sun days to signal resource scarcity, the probability of blackouts declines as the aggregate demand decreases. Wolak (2007, 2011) has found that respond to the real-time pricing mechanisms by reducing their electricity consumption during peak hours. In column (6) of Table 3, the interaction term between RPS and the proportion of customers enrolled in dynamic pricing is significantly negative. As states mandate higher RPS, critical-peak pricing could reduce the proportion of customers affected by blackouts, as measured by SAIFI.[27] Nevertheless, there is no evidence that average blackout time per customer, as measured by SAIDI, decreases as more customers sign up for dynamic pricing.

As a complement of dynamic pricing, energy storage is a supply-side solution to the reliability challenges of intermittent renewables. Utilities can generate excess electricity on windy and sunny days and store this electricity for use on days with less favorable weather. In 2020, there were 1438 MW storage capacity, and this number has risen to 4631 MW in 2021.[28] We calculate each state's energy storage capacity as a percentage of total capacity. We test whether clean power is more reliable in states featuring more storage capacity in Table 3's columns (5) and (8). When SAIFI is used as the metric, we find the interaction term between RPS and storage capacity to be significantly negative. Because energy storage was not adopted on a large scale in 2020, our result is suggestive of the benefit of investing in energy storage as a complement to renewable generation.

[26] We test whether utilities enroll more customers in dynamic pricing after severe power disruptions. For each utility, we calculate the percentage of residential, commercial, and industrial customers enrolling in dynamic pricing each year. We regress this percentage on lagged log(SAIDI), utility fixed effects, and year fixed effects. Significantly more commercial customers opt in to dynamic pricing after experiencing severe power disruptions in the previous year, but there is no significant evidence of adaptation in the two other sectors.

In 2020, 12.21% of investor-owned utilities' customers have signed up for dynamic pricing. The percentage was 1.84% for cooperative utilities and 6.69% for government-owned utilities. Meter workers in cooperative and public utilities are often union workers, which makes it more difficult to deploy smart meters. Therefore, investor-owned utilities have a much larger proportion of customers opting in to dynamic pricing.

[27] Jacobson and Stewart (2022) note that event-based critical-peak pricing is less effective in incentivizing energy conservation when daily time-of-use pricing is already in place. This suggests that not all types of dynamic pricing could increase reliability of clean power on low-wind or low-sun days.

[28] The Vehicle-to-Grid (V2G) technology is an emerging form of energy storage not included in the data. V2G stores excessive electricity in EVs that are charged during off-peak hours, and this electricity would be fed back to the grid during a supply shortage. States have initiated pilot programs to incentivize EV drivers to opt in to V2G.

**The Role of Supply Chains in Determining Power Plant Resilience**

In this section, we use the power plant level data to examine the drop in reliability exclusively resulted from shocks to the electricity generation supply chain.[29] Investor-owned and government-owned utilities generate a large proportion of power using their own generators. They are more vulnerable to local environmental shocks because they tend to locate their generating facilities in close proximity to take advantage of the scale economies in power generation. Cooperative utilities do not generate by themselves and instead purchase power from diverse generators in the wholesale market. The diverse supply shields them from local climate shocks.

As indicated by the coefficient of RPS in Table 3, the reliability of the electricity supply chain also hinges upon the power sources. Intermittent renewables increase the reliability risk from the generation phase but have limited impact on the transmission and distribution phases. Figure 3 shows the power plants' percentage of green generating capacity (either owned by themselves or by the power generators they purchase power from) for each type of electric utilities. All three types have increasing green capacity share over time. In 2020, 57.1% of an average cooperative utility's generating capacity uses renewable energy. This number is 31.9% for investor-owned utilities and 38.6% for government-owned ones. From 2013 to 2020, cooperative utilities added in the most green capacity, while investor-owned and government-owned utilities show a much smaller rise in green capacity.

Both investor-owned and government-owned utilities face soft budget constraints. To invest in green infrastructure, investor-owned utilities could request a price increase so that their rate of return stays the same. Government-owned utilities often receive government subsidies to upgrade their facilities. With flexible budgets, these two types of utilities are likely to invest in renewable energy and energy efficient facilities despite the higher costs. Most cooperative utilities do not own generators. They can reduce emission rates by purchasing from green generators without investing in green generating capacity. This explains their highest percentage of green generation in Figure 3.

Cooperative plants have the greenest generating capacity yet the lowest reliability (see

[29] The power plant data is part of the eGRID dataset. For each plant, this dataset provides its capacity and the energy source. It also includes a list of utilities each plant sells electricity to in the wholesale market. We don't know how much electricity that a utility purchases from each plant. We assume the purchased quantity is proportional to the plant's capacity. The vintage of each power plant is from the EIA861 dataset. To convert the plant/year dataset into utility/year, we group the plants by utility/year and take the capacity-weighted averages of their attributes.

Table 3). This correlation implies that intermittent renewables may reduce electricity reliability. When there is a demand surge, renewable energy supply cannot always be ramped up to fulfill the demand. Without effective energy storage facilities or transmissions from other states, utility customers would have to bear lower reliability when renewable generation is limited.

We run the following specifications for utility i in year t to quantify how environmental shocks in generation areas affect grid reliability and whether green grids are less resilient to disasters.

$$\log(\text{SAIDI}_{it}) = \beta_0 + \beta_1\text{Disaster}_{it} + \beta_2\text{Capacity hit by disasters}_{it} + \beta_3\text{Green capacity hit by disasters}_{it} + \beta_4\text{Green capacity}_{it} + \beta_5 X_{it} + \text{fixed effects} + \varepsilon_{it} \quad (8)$$

In equation (8), disaster is a dummy that equals 1 if any of the county served by utility i is hit by any natural disaster in year t. Total capacity and green capacity hit by disasters are the percentages of the (green) generating capacity hit by at least one natural disaster. Green capacity is the percentage of total generating capacity fueled by clean energy (nuclear, hydropower, or other renewable energy). X is a vector of control variables including the plant age and all utility and demographic features in equation (7). Plant age is the average age of the generating capacity for utility i in year t. We include NERC fixed effects and year fixed effects, NERC/year fixed effects, or state/year fixed effects. Standard errors are clustered at utility level.

Table 4 displays the results from the estimation of equation (8). In all columns, generating capacity hit by disaster is significantly positive. When 1% more capacity is hit by disaster, SAIDI increases by 0.22% to 0.5% based on different fixed effects. When the total capacity hit by disaster is controlled, the percentage of green capacity hit by disaster is insignificant. This implies that there is no significant difference between fossil fuel plants' and green plants' resiliency to natural disaster shocks. Nevertheless, the percentage of green capacity is significantly positive in all columns, showing that green power plants tend to be less reliable than dirty plants on average. T-tests on coefficients show that both $\beta_1+\beta_2+\beta_3$ and $\beta_3+\beta_4$ (see equation 5) are both significantly greater than 0 at the 1% significance level. Based on this joint significance, we conclude that disruptions to electricity generation reduce service quality, and greener power plants face more reliability challenges.[30]

The coefficients of log plant age are significantly positive, showing that the power grid becomes less reliable as facilities age.[31] A few demographic variables are significant in Table 4. Reliability is higher in areas with higher home prices and more Republican voters. After we control for the green generating capacity in Table 4, climate belief is associated with utility reliability. With power plant level data, the reliability difference by ownership type remains robust. Both ownership dummies have the same sign and similar significance level as in Table 3.

In columns (4) and (5), we use these power generation data to carry out another test of adaptation. We split our sample into the earlier period (2013 to 2016) and the later period (2017 to 2020). We run the specification of column (1) on these two periods separately. If the coefficient of percentage capacity hit by disasters or that of green capacity percentage shrinks over time, this would indicate utilities' adaptation progress. However, when 1% more capacity is hit, SAIDI increases by 0.39% in the earlier period and by 0.6% in the later period. When there is 1% more green capacity, SAIDI rises by 0.4% and 0.49% in these two periods respectively. The increasing magnitude of the coefficients suggests that generating facilities are not adapting to environmental shocks. The adaptation evidence we documented in Table 2 and Table 3 is more likely a result of utilities' investments in resilient transmission and distribution facilities.

### The Role of Maintenance Costs in Determining Service Quality

Severe natural disasters disrupt electricity provision and damage physical capital. In response to the decline in service quality, utility operators repair and upgrade their facilities. The maintenance costs are likely to increase as the severity of disasters increases. Larsen et al.

[30] In this paper, we have addressed the reliability challenges that arise from the power generation and distribution process. However, we do not have a comprehensive dataset on transmission lines. We do not know where the power goes through when transmitted from generators to end-users and thus cannot pinpoint which utilities are adversely affected by transmission line disruptions. In our econometric specifications, we include NERC region/year and state/year fixed effects attempt to control for these shocks.

[31] In 2020, the average capacity age of American power plants was 28.4 years. In 2015, the average age was 28.6 years. The US utilities have been phasing out old grids. In 2020, the average vintage of green plants was 28.5 years, and that of dirty plants was 28.4 years. In 2015, the average vintage of green plants was 31 years, and that of dirty plants was 27.7 years. The average vintage of green plants dropped, while the vintage of dirty plants increased. Utilities phased out older green plants (especially nuclear and hydroelectric plants) faster than older dirty plants such as coal-fired plants.

(2020) document that utilities' increasing spending in the current year is correlated with lower reliability, but higher cumulative spendings in previous years improve future reliability.

In the aftermath of environmental disasters, facing rate-of-return regulations, utilities often ask state PUCs to raise electricity prices to cover their costs in capital maintenance and upgrades. For example, after the 2012 Hurricane Sandy, utilities in New York demanded state subsidies to upgrade their facilities.[32] In California, PG&E asked for rate hikes to submerge 10,000 miles of power lines to lower fire risks.[33]

In this section, we test whether maintenance costs surge following natural disasters and whether higher maintenance costs lead to lower SAIDI in the face of future disasters. We estimate the following specifications for utility i (located in region k) in year t. We restrict our sample to investor-owned utilities because the maintenance costs data are not available for cooperative and government-owned utilities.

$$\log(\text{Maintenance costs})_{\text{it}} = \beta_0 + \beta_1 X_{\text{it}} + \beta_2 X_{\text{i,t}-1} + \gamma_t + \varepsilon_{it} \quad (9)$$

$$\log(\text{SAIDI})_{\text{it}} = \beta_0 + \beta_1 \text{Maintenance costs}_{\text{i,t}-1} + \beta_2 X_{\text{it}} + \beta_3 X_{\text{i,t}-1} + \beta_8 Z_{\text{it}} + \gamma_t + \varphi_k + \varepsilon_{it} \quad (10)$$

In the above equations, X is a vector of disaster dummies. We also include the one-year lag of all these dummies. Maintenance costs are compiled from the FERC Form 1 submitted by each investor-owned utility each year. We compile these data for a random sample of 22 utilities and estimate equation (6).[34] The results are shown in column (1) of Table 5. We use our estimates of equation (6) to predict the maintenance costs for the other 84 private utilities. Columns (2) and (3) are estimated on the random sample, and columns (4) and (5) are estimated for the whole sample using the predicted maintenance costs. Costs are adjusted for inflation (in 2013 US dollars). Z is a vector of control variables. We include year-fixed effects ($\gamma_t$) and region-fixed effects ($\varphi_k$). Standard errors are clustered at the utility level.

[32] https://www.nytimes.com/2012/12/29/business/hurricane-sandy-alters-utilities-calculus-on-upgrades.html
[33] https://www.npr.org/2021/07/21/1019058925/utility-bury-power-lines-wildfires-california?t=1653594318581
[34] We use a random number generator to choose 20 utility IDs from all investor-owned utilities. We conduct a balancing test for these 22 utilities. None of their SAIDI, disaster counts, educational attainment, political affiliation, or home prices is significantly different from the rest of investor-owned utilities.

Column (1) shows that both hurricane and the one-year lag of hurricane significantly raise maintenance costs. Hurricanes in the previous year increase the maintenance costs by 65% and those in the current year increase the costs by 110%. This is consistent with our expectation that severe weather conditions disrupt services and damage physical capital.

Columns (2) and (4) report similar results. In both columns, lagged maintenance costs significantly reduce SAIDI. When the maintenance costs in the past year increase by 10%, SAIDI in the current year declines by 3.08% in column (2) and by 4.09% in column (4), after controlling for disasters and lagged disasters. The results are still significant when we control for educational attainments, Republican votes, and home prices. In columns (3) and (5), SAIDI decreases by 2.7% and 3.9% respectively as lagged maintenance costs increase by 10%. This shows that investor-owned utilities respond to natural disasters by investing in more resilient infrastructure, consistent with the adaptation evidence we have found previously.[35]

In states where consumers can choose their electricity providers, investor-owned utilities face competitions from other electricity resellers in the retail market. If they have less reliable transmission and distribution pipelines, consumers could substitute to sellers with more reliable facilities. Meanwhile, the damaged generating facilities feature lower capacity factor and higher marginal cost of generation. Because utilities in the US are required to fulfill all electricity demand, they must bear the high generation cost or purchase from alternative power plants at higher prices.[36] Under this circumstance, unreliable generating facilities raise utilities' operating expenditure, and customer switching lowers their revenues. If this profit loss outweighs the maintenance cost, profit-maximizing utilities are incentivized to upgrade their facilities. This explains the significantly positive effect of lagged maintenance costs on SAIDI.

### The Association Between Electricity Prices and Green Power Mandates

When utilities invest in new infrastructure, they will seek to pass the costs on to consumers. Such electricity price increases could have disproportional impacts on poor families. In this section, we test for the determinants of electricity prices. We hypothesize that

[35] We admit that out result is only suggestive because we predict the maintenance costs based on a small sample. More accurate tests could be conducted if a full panel of maintenance costs data is available.
[36] Jha, Preonas, and Burlig (2021) document the opposite fact for utilities in the developing world. Not required to fulfill all consumer demand, Indian utilities purchase less electricity in the wholesale market when wholesale electricity prices rise due to the higher generation costs. The wholesale electricity demand is downward sloping in many developing countries but vertical in the US.

service reliability, regional attributes, and ownership type all affect electricity prices. We estimate the following cross-sectional regressions for each utility i (in state k) in each year from 2014 to 2020:

$$\log\,(\text{Electricity price})_{\mathrm{i}} = \beta_0 + \beta_1 \log\,(\text{Lagged SAIDI})_{\mathrm{i}} + \beta_2 \text{Lagged RPS}_{\mathrm{k}} + \beta_3 \mathrm{X}_{\mathrm{i}} + \varepsilon_k \qquad (11)$$

In equation (11), electricity price refers to the average residential electricity price in a given year for utility i. Lagged SAIDI is the one-year lag of SAIDI of utility i. Lagged RPS is the one-year lag of the state RPS. X is a vector of disaster dummies, demographic attributes, and ownership dummies. Standard errors are clustered at the state level.

Table 6 reports the estimates of equation (11). From 2014 to 2018, we find no evidence that utilities' lagged reliability significantly affects prices. However, in 2019 and 2020, when lagged SAIDI increases by 1%, electricity prices increase by roughly 2% on average. This estimate is statistically significant at the 5% level. When utilities have low reliability in the previous year, they spend more on infrastructure maintenance and pass these costs to customers by raising electricity prices. As natural disasters become more frequent, utilities feel a growing pressure to invest in resilient infrastructure, so the coefficient of lagged SAIDI becomes significantly positive since 2019. As we have discussed, this confirms the Averch-Johnson effects on utilities under rate-of-return regulations.

Lagged state RPS has a statistically significant and positive coefficient in all years. In 2020, if lagged RPS is 1% higher, electricity prices in the subsequent year increase by 0.7% on average. Greener power comes at the expense of higher electricity bills. Nevertheless, the coefficient of RPS trends down overall, with the price elasticity dropping from 0.87 in 2013 to 0.7 in 2020. This is consistent with previous works that document renewables benefit from learning-by-doing (Newbery 2018). The result is robust when we use the full panel and control for utility fixed effects and year fixed effects in column (8). However, a 1% increase in RPS is associated with only a 0.15% increase in electricity price under this specification. This implies that the unobservable utility-level pricing mechanisms can explain a large part of the price change under higher RPS.

While other demographic variables are insignificant, a region's political affiliation affects its electricity prices. Electricity prices are lower in conservative regions, and the disparity is increasing over time. In 2013, 1% more votes for Republican lead to a 0.47% decrease in electricity price in 2014 and a 0.94% decrease in 2020. We also find that government-owned utilities are 7% to 12% cheaper than cooperative ones. We do not find significant evidence that investor-owned plants are cheaper than cooperative ones, although the investor-owned dummy has negative coefficients in all years.

Past literature has studied consumer willingness to pay (WTP) for more reliable power (Ozbafli and Jenkins 2016; Oseni 2017; Deutschmann, Postepska, Sarr 2020) and cleaner power (Roe et al. 2001; Guo et al. 2014). In this paper, we do not observe consumers' WTP and cannot analyze the welfare impacts of the documented price hikes. We have found a tradeoff between reliability investment and clean power investment.

**Improving the Reliability of Clean Power through Market Integration**

We have presented evidence from generation and service areas that both shows cleaner power features lower reliability (see Table 2 and 3). We have presented some evidence that individual utilities use dynamic pricing and energy storage to improve the reliability of renewable generation (see Table 3).

Recent research suggests that this tradeoff could be attenuated by a more regionally integrated energy market and better demand management practices (Peter and Wagner 2021; Klass et al. 2022; Wolak 2022). Given the reliability challenges posed by ramping up the reliance on renewables, utilities face decisions over building in excess capacity to avoid scenarios where renewables do not deliver. Such investments impose greater fixed costs on utilities and may lead to electricity price hikes. These backup generating facilities may also face political backlash in liberal regions if they feature higher emission rates.[37] In a competitive electricity wholesale market, utilities could diversify their power suppliers as an insurance against regional environmental shocks. An integrated wholesale market features elastic electricity supply. In the case that local renewable generating facilities are knocked down by natural disasters or limited by the local weather, utilities can avoid blackouts by drawing electricity from power plants farther away, where there exists excess supply. Using data from

[37] In the face of the potential heat waves that could knock out power, Californian governors have proposed to extend the life of gas-powered plants as electricity reliability reserves during high-demand times. This proposal has drawn skepticisms from state lawmakers.
https://www.latimes.com/opinion/story/2022-06-24/california-electricity-reliability-reserve

the integrated European electricity market, Hagspiel, Knaut, and Peter (2018) have documented such cross-border balancing effects and their positive impacts on utility reliability. Unlike Europe, the US does not have an integrated electricity market. Klass et al. (2022) have noted that policy differences across states and the lack of inter-state transmission facilities limit US utilities' ability to purchase electricity from generators in other states.

A typical example is the electric grid in Texas. It is separate from grids in other states and subject to limited federal regulations. Utilities in Texas cannot import power from out-of-state sources. In 2020, the average SAIDI in Texas was 548 minutes (the 11th highest among all states), 40% higher than the national SAIDI. We recover the residuals from column (2) in Table 3. Across all percentiles, Texas's residuals are higher than the national average.[38] This implies that the Texas electricity system underperforms relative to the rest of the nation. Texas's isolated electricity system has become more vulnerable to power outages as a larger share of electricity in the state is generated from intermittent wind power. Past work using data from Africa and Europe suggests that regional cooperation in the electricity market is a cost-efficient approach to reduce the risk of supply shortages in the scenario of high renewable generation (Gnansounou et al. 2007; Patt et al. 2011; Peter and Wagner 2021).[39]

A few East Coast states are using capacity markets as supplements to the conventional wholesale market to address the resource adequacy challenge. Capacity markets compensate generators for promising to supply power in the future rather than their actual generation. Regulators determine the level of necessary future reserve and auction it to generators through competitive processes. Generators are paid for maintaining their excess capacity in the long run. To decarbonize the power plants without sacrificing reliability, Klass et al. (2022) propose the use of region-wide uniform RPS in combination with two separate capacity auctions, one exclusively for reliable clean capacity and another traditional auction. If the market-clearing price in the clean capacity market is higher than that in the traditional market, more green electricity providers would enter the market. This raises supply elasticity, and the competition in the wholesale market would incentivize generators to improve reliability. When there are

[38] At the 25th, 50th, 75th, and 90th percentile, Texas's residual is –0.58, 0.11, 0.91, and 1.5 respectively, and the rest of the nation's is -0.62, 0.01, 0.63, and 1.28.

[39] Although an integrated electricity market features higher reliability overall, an unintended consequence is that it increases the risk of regional cascading failures, especially when the system has a high renewable energy penetration (Beyza and Yusta 2021).

diverse suppliers, a regional climate shock has less effect on the supply chain also because green power can be purchased from areas not affected by the shock (Peter and Wagner 2021).

## Conclusion

Electricity is a key input in home production, in our emerging Work from Home economy. Residential electricity consumption is increasing (Reiss and White 2005; Cicala 2022). The growth of electric vehicles will only further increase electricity demand. As electricity demand rises, the social cost of unreliable electricity increases.

Power blackouts can be measured across utilities at a point in time and for a given utility over time. This reliability benchmark offers a measure of the quality of infrastructure service provision. We have used an eight-year panel dataset to explore the time series and cross-sectional correlates of reliable service provision. Natural disasters severely disrupt services, but we have documented reduced form evidence that the utilities have grown more resilient as measured by the increase in blackouts as a function of natural disasters has shrunk over time. Government-owned utilities are more reliable than investor-owned and cooperative ones, but their pace of adaptation is the slowest.

Given current technologies, there is an empirical tradeoff between electricity reliability and generating green power. Evidence from Europe shows that green power significantly increase electricity supply security when within and inter-region electricity transmission is available (Hagspiel, Knaut, and Peter 2018; Peter and Wagner 2021). The Inflation Reduction Act has provided $2.8 trillion funding for electricity transmission development, with an emphasis on interstate transmission.[40]

To overcome the reliability challenges induced by intermittent renewables, utilities can apply supply or demand management tools such as energy storage and dynamic pricing. The emerging energy storage capacity creates a more elastic supply. Wolak (2007, 2011) finds that consumers are more price sensitive than was previously believed. His research suggests that an expansion of opt-in participation in critical peak pricing programs could help to create a more elastic aggregate demand curve. Improvements in battery storage technology represent another supply side approach to achieving the dual goals of grid reliability and environmental

[40] https://crsreports.congress.gov/product/pdf/IN/IN11981

performance.  Future research should study their complementarities with infrastructure investment in increasing the resilience of our nation's electricity grid.

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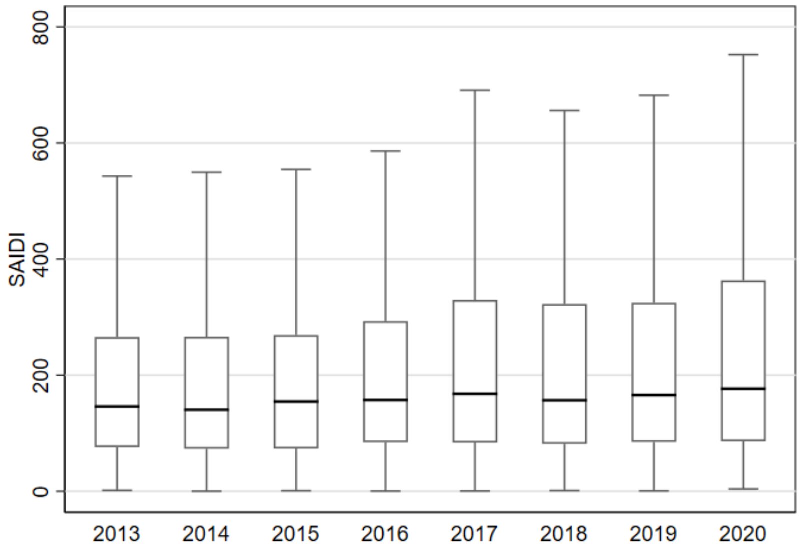
**Figure 1**

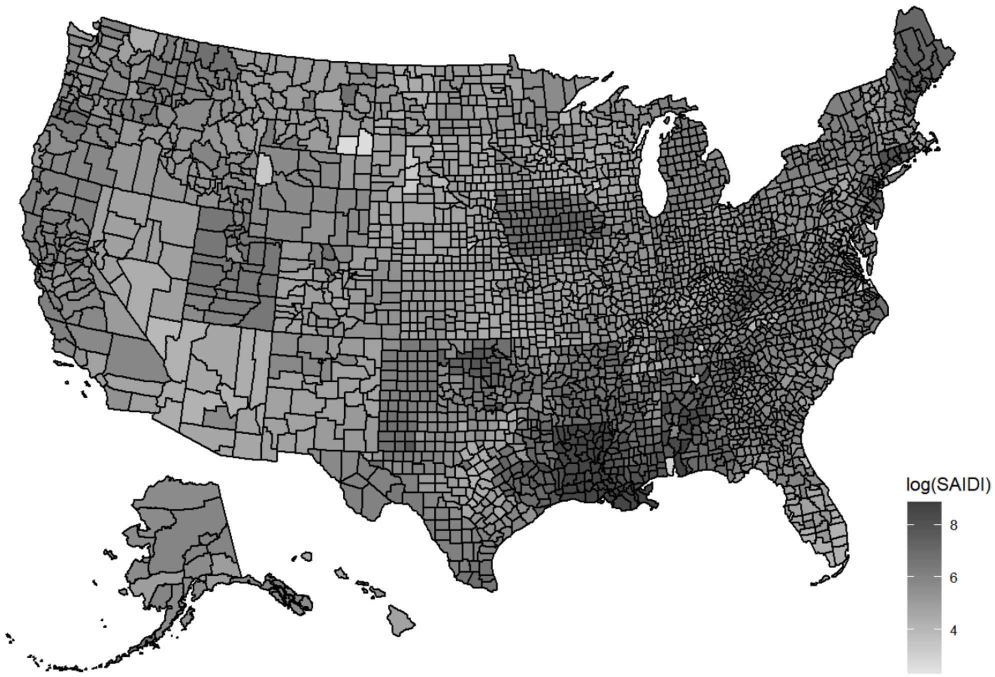
**The SAIDI Empirical Distribution**




Notes: The bar graph shows the minimum, maximum, median, 25th percentile, and 75th percentile of SAIDI across all utilities in our sample each year.

**Figure 2**

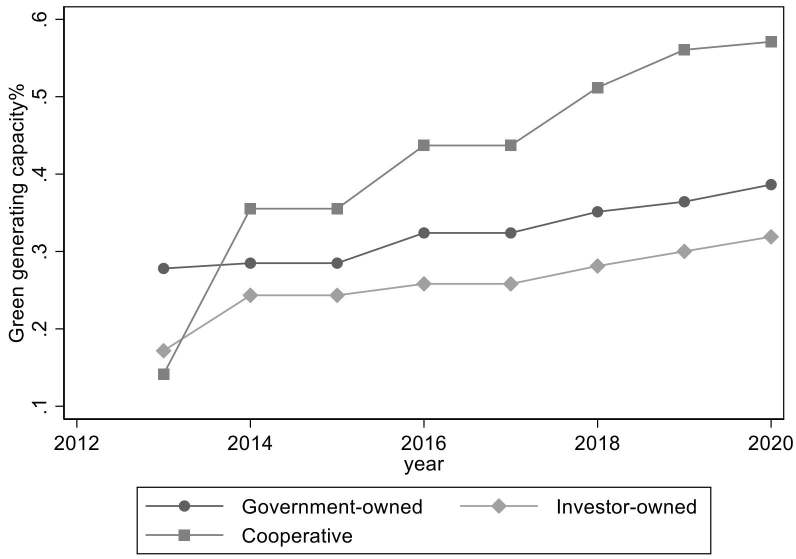
**Electric Utility Reliability in 2020**




Notes: If a county has multiple utilities, we use the average SAIDI of all utilities as that county’s resilience measure. If SAIDI data is not available for a county, we use the state’s average SAIDI as that county’s SAIDI.

**Figure 3**

**Utility Renewable Power Generating Capacity Dynamics**




Notes: For each utility, the capacity includes both that owned by the utility and that owned by the power generators from whom the utility purchases power from. The sample includes all utilities whose power plant data is available in the EGRID dataset. There are 569 public utilities, 174 investor-owned utilities, and 236 cooperative utilities. We weight each utility's green capacity percentage by its total capacity.

**Table 1**

**Nightlights and Grid Reliability**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | log(Nightlights) | | | |
| log(SAIDI) | -0.00669*** | | | | | |
| | (0.00215) | | | | | |
| log(SAIFI) | | -0.0206*** | | | | |
| | | (0.00644) | | | | |
| Count of hurricanes | | | -0.0192*** | -0.198*** | | |
| | | | (0.00257) | (0.0210) | | |
| Count of storms | | | -0.179*** | -0.294*** | | |
| | | | (0.0164) | (0.0250) | | |
| Count of other | | | 0.00760 | -0.115*** | | |
| | | | (0.0126) | (0.0194) | | |
| Hurricane | | | | | -0.0380*** | -0.276*** |
| | | | | | (0.00421) | (0.0265) |
| Storm | | | | | -0.191*** | -0.335*** |
| | | | | | (0.0174) | (0.0273) |
| Other | | | | | 0.0110 | -0.148*** |
| | | | | | (0.0145) | (0.0229) |
| Trend x disaster count | | | | 0.00746*** | | |
| | | | | (0.000861) | | |
| Trend x disaster | | | | | | 0.0102*** |
| | | | | | | (0.00110) |
| Constant | -0.294*** | -0.315*** | -0.353*** | -0.353*** | -0.353*** | -0.353*** |
| | (0.0118) | (0.00353) | (0.000631) | (0.000619) | (0.000636) | (0.000625) |
| Year-fixed effects | Yes | Yes | No | No | No | No |
| County-fixed effects | Yes | Yes | No | No | No | No |
| County/year-fixed effects | No | No | Yes | Yes | Yes | Yes |
| Observations | 21,953 | 21,659 | 99,695 | 99,695 | 99,695 | 99,695 |
| R-squared | 0.984 | 0.984 | 0.843 | 0.843 | 0.843 | 0.843 |

Robust standard errors are clustered by county.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is county/year in columns (1) and (2) and the county/year/quarter in the four other columns. Nightlight is the average night light level in a county each year or quarter. Count of disasters is the total number of each type of disaster within the given time period, and disaster dummies equal 1 if the corresponding disaster takes place at least once. Trend refers to the year/quarter trend. 2013Q1 equals 1 and 2020Q4 equals 32.

## Table 2

## Electric Utility Service Reliability Time Trends

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | log(SAIDI) | | | log(SAIFI) | |
| Hurricane | 0.343*** | 0.417*** | 0.451*** | 0.0759** | 0.0919** | 0.110*** |
| | (0.0530) | (0.0643) | (0.0653) | (0.0308) | (0.0400) | (0.0401) |
| Storm | 0.223*** | 0.290*** | 0.248*** | 0.0552** | 0.0759*** | 0.0539* |
| | (0.0355) | (0.0458) | (0.0460) | (0.0241) | (0.0280) | (0.0282) |
| Other | 0.170*** | 0.247*** | 0.247*** | 0.0542*** | 0.0731*** | 0.0698** |
| | (0.0336) | (0.0488) | (0.0490) | (0.0197) | (0.0277) | (0.0276) |
| Summer CDD | 0.320* | 0.225 | 0.622*** | 0.351*** | 0.324** | 0.541*** |
| | (0.166) | (0.187) | (0.186) | (0.112) | (0.131) | (0.135) |
| RPS | -0.131 | -0.255 | -0.244 | 0.0356 | -0.126 | -0.133 |
| | (0.153) | (0.215) | (0.214) | (0.106) | (0.129) | (0.124) |
| $RPS^2$ | 0.0762* | 0.131* | 0.113 | 0.00451 | 0.0595 | 0.0494 |
| | (0.0443) | (0.0761) | (0.0739) | (0.0251) | (0.0369) | (0.0349) |
| Drought | -0.137* | -0.00120 | | -0.148** | -0.0560 | |
| | (0.0816) | (0.111) | | (0.0688) | (0.0938) | |
| Hydro% x Drought | 1.705** | 1.468** | | 1.143*** | 1.107*** | |
| | (0.682) | (0.697) | | (0.395) | (0.407) | |
| log(Precipitation) | | | 1.434*** | | | 0.771*** |
| | | | (0.270) | | | (0.176) |
| Hydro% x log(Precipitation) | | | -1.792*** | | | -0.666 |
| | | | (0.675) | | | (0.424) |
| Fire risk x log(precipitation) | | | -0.210*** | | | -0.102** |
| | | | (0.0782) | | | (0.0496) |
| Trend x Disaster | | -0.0268** | -0.0323*** | | -0.00679 | -0.0100 |
| | | (0.0106) | (0.0108) | | (0.00680) | (0.00686) |
| Trend x Summer CDD | | 0.0127 | 0.00822 | | 0.000602 | -0.000322 |
| | | (0.0106) | (0.0107) | | (0.00916) | (0.00922) |
| Late x RPS | | 0.0915 | 0.0436 | | 0.122* | 0.0966 |
| | | (0.0973) | (0.0975) | | (0.0673) | (0.0678) |
| Late x $RPS^2$ | | -0.0430 | -0.0229 | | -0.0468** | -0.0339 |
| | | (0.0448) | (0.0435) | | (0.0230) | (0.0232) |
| Trend x Drought | | -0.0400 | | | -0.0369 | |
| | | (0.0250) | | | (0.0224) | |
| Trend x log(Precipitation) | | | -0.00128 | | | -0.00175 |
| | | | (0.0145) | | | (0.0103) |
| Trend x Investor-owned | | 0.0343** | 0.0423 | | -0.00609 | 0.00130 |
| | | (0.0156) | (0.0507) | | (0.0120) | (0.0376) |
| Trend x Government-owned | | 0.0369*** | 0.0453 | | 0.0204* | 0.0275 |
| | | (0.0140) | (0.0515) | | (0.0120) | (0.0385) |
| Constant | 4.574*** | 4.607*** | 1.414*** | -0.206** | -0.174* | -2.050*** |
| | (0.127) | (0.141) | (0.539) | (0.0869) | (0.0995) | (0.357) |
| Utility-fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |

| | | | | | | |
|---|---|---|---|---|---|---|
| Observations | 5,411 | 5,411 | 5,411 | 5,041 | 5,041 | 5,041 |
| R-squared | 0.669 | 0.670 | 0.675 | 0.723 | 0.724 | 0.727 |

Robust standard errors are clustered by utility.
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is utility/year. SAIDI and SAIFI are both calculated with major events days. Hurricane, storm, and other disasters are three dummies that equal 1 if a utility's service area is hit by the corresponding disaster in the given year. Summer CDD is a utility/year variable that refers to the average daily cooling degree days within each utility's service area. We scale the unit to 10 degrees. RPS is each state's renewable portfolio standard each year, and the unit is 10%. Drought is a state/year dummy that equals 1 if the annual drought severity and coverage index of the state is greater than 250. Precipitation is also a state/year variable. Hydro% and fire risk are two state-level cross-sectional variables. They refer to the state's hydroelectric generating capacity as a percentage of total capacity in 2014 and the state's fire risk in 2021 respectively. Trend is the annual time trend. Late is a dummy that equals 1 if it is 2017 or later. Disaster dummy equals 1 if the utility's service area is hit by at least one disaster in the given year. Investor-owned and government-owned are two dummies representing the ownership of the utility. The omitted ownership category is cooperative.

## Table 3

## The Cross-Sectional Determinants of Service Quality

| | (1)<br>log(SAIDI) | (2)<br>log(SAIDI) | (3)<br>log(SAIDI) | (4)<br>log(SAIDI) | (5)<br>log(SAIDI) | (6)<br>log(SAIFI) | (7)<br>log(SAIFI) | (8)<br>log(SAIFI) |
|---|---|---|---|---|---|---|---|---|
| Hurricane | 0.464*** | 0.397*** | 0.406*** | 0.408*** | 0.413*** | 0.0679* | 0.0666* | 0.0701* |
| | (0.0574) | (0.0711) | (0.0565) | (0.0567) | (0.0567) | (0.0397) | (0.0399) | (0.0399) |
| Storm | 0.254*** | 0.226*** | 0.244*** | 0.247*** | 0.253*** | 0.0928*** | 0.0933*** | 0.0967*** |
| | (0.0392) | (0.0445) | (0.0394) | (0.0392) | (0.0396) | (0.0300) | (0.0301) | (0.0303) |
| Fire | 0.0204 | -0.0136 | 0.363 | -0.0265 | -0.0201 | 0.134 | -0.0535 | -0.0485 |
| | (0.0769) | (0.0802) | (0.228) | (0.0789) | (0.0794) | (0.194) | (0.0552) | (0.0554) |
| Other | 0.207*** | 0.262*** | 0.259*** | 0.259*** | 0.260*** | 0.127*** | 0.127*** | 0.129*** |
| | (0.0388) | (0.0414) | (0.0383) | (0.0380) | (0.0380) | (0.0271) | (0.0272) | (0.0271) |
| Summer CDD | -0.0596 | -0.231*** | -0.218*** | -0.217*** | -0.233*** | -0.0681 | -0.0831 | -0.0891 |
| | (0.0542) | (0.0750) | (0.0764) | (0.0722) | (0.0723) | (0.0626) | (0.0590) | (0.0592) |
| RPS | -0.411*** | -0.296*** | -0.294*** | -0.291*** | -0.349*** | -0.219*** | -0.213*** | -0.250*** |
| | (0.0848) | (0.0886) | (0.0865) | (0.0874) | (0.0791) | (0.0690) | (0.0693) | (0.0672) |
| $RPS^2$ | 0.135*** | 0.111*** | 0.114*** | 0.115*** | 0.151*** | 0.0803*** | 0.0802*** | 0.100*** |
| | (0.0306) | (0.0334) | (0.0318) | (0.0321) | (0.0299) | (0.0246) | (0.0248) | (0.0259) |
| Drought | 0.0912 | 0.0543 | 0.0734 | 0.0694 | 0.0538 | -0.0109 | -0.0107 | -0.0212 |
| | (0.0849) | (0.0955) | (0.0812) | (0.0813) | (0.0827) | (0.0617) | (0.0620) | (0.0618) |
| log(Customers) | 0.124*** | 0.102*** | 0.102*** | 0.102*** | 0.102*** | 0.0613*** | 0.0611*** | 0.0616*** |
| | (0.0259) | (0.0271) | (0.0269) | (0.0269) | (0.0267) | (0.0223) | (0.0222) | (0.0222) |
| College graduates | -1.373** | -1.224** | -1.162* | -1.188* | -1.173* | -0.492 | -0.542 | -0.536 |
| | (0.573) | (0.610) | (0.601) | (0.605) | (0.603) | (0.512) | (0.511) | (0.509) |
| Votes for Republican | -0.222 | -0.215 | -0.237 | -0.248 | -0.243 | 0.382 | 0.329 | 0.307 |
| | (0.539) | (0.580) | (0.582) | (0.580) | (0.575) | (0.500) | (0.497) | (0.494) |
| Climate belief | -0.413 | -0.266 | -0.350 | -0.381 | -0.338 | -0.288 | -0.292 | -0.329 |
| | (1.411) | (1.531) | (1.523) | (1.527) | (1.516) | (1.342) | (1.342) | (1.336) |
| log(Home prices) | -0.0464 | -0.135 | -0.144 | -0.133 | -0.140 | -0.0680 | -0.0574 | -0.0619 |
| | (0.112) | (0.132) | (0.130) | (0.131) | (0.130) | (0.113) | (0.113) | (0.113) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Investor-owned | -0.297*** | -0.284*** | -0.285*** | -0.274*** | -0.288*** | -0.287*** | -0.293*** | -0.292*** |
| | (0.0915) | (0.0979) | (0.0972) | (0.0978) | (0.0969) | (0.0789) | (0.0793) | (0.0792) |
| Government-owned | -1.160*** | -1.177*** | -1.172*** | -1.179*** | -1.173*** | -0.817*** | -0.814*** | -0.812*** |
| | (0.0714) | (0.0711) | (0.0709) | (0.0711) | (0.0712) | (0.0628) | (0.0624) | (0.0626) |
| Fire risk | | | 0.0249 | | | -0.00957 | | |
| | | | (0.0333) | | | (0.0273) | | |
| Fire x Fire risk | | | -0.116* | | | -0.0556 | | |
| | | | (0.0623) | | | (0.0542) | | |
| Dynamic pricing | | | | -0.0104 | | | 0.181* | |
| | | | | (0.138) | | | (0.108) | |
| Dynamic pricing x RPS | | | | -1.400 | | | -1.646* | |
| | | | | (1.147) | | | (0.950) | |
| Storage capacity | | | | | 7.883 | | | 4.224 |
| | | | | | (5.831) | | | (4.039) |
| Storage capacity x RPS | | | | | -3.964* | | | -2.131 |
| | | | | | (2.173) | | | (1.428) |
| Constant | 5.283*** | 6.581*** | 6.839*** | 6.807*** | 6.881*** | 1.069 | 0.985 | 1.077 |
| | (1.465) | (1.837) | (1.834) | (1.842) | (1.830) | (1.396) | (1.398) | (1.387) |
| | | | | | | | | |
| NERC-fixed effects | No | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-fixed effects | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes |
| NERC/year-fixed effects | No | Yes | No | No | No | No | No | No |
| Observations | 5,404 | 5,212 | 5,212 | 5,212 | 5,212 | 4,860 | 4,860 | 4,860 |
| R-squared | 0.302 | 0.351 | 0.335 | 0.334 | 0.335 | 0.303 | 0.303 | 0.303 |

Robust standard errors are clustered by utility.
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is utility/year. The omitted category of ownership is cooperative. Dynamic pricing is a utility/year variable that equals the percentage of customers who sign up for critical peak pricing. Storage capacity is a state/year variable that equals the percentage of capacity used for energy storage. Education, voting, climate belief, home prices, and fire risk are available at county level. We convert them into utility level variables by taking the averages of all counties served by the utility. Other variables are the same as in Table 2.

## Table 4

## Reliability Challenges Arising from Disruptions to Generating Facilities

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | log(SAIDI) | | |
| Disaster | 0.0371 | 0.111* | 0.113 | 0.0986 | -0.0160 |
| | (0.0591) | (0.0640) | (0.0703) | (0.0805) | (0.0763) |
| Generating capacity hit by disaster | 0.504*** | 0.398*** | 0.221* | 0.387*** | 0.595*** |
| | (0.112) | (0.109) | (0.122) | (0.147) | (0.136) |
| Green capacity hit by disaster | -0.0331 | -0.0411 | 0.0435 | 0.0510 | -0.0943 |
| | (0.115) | (0.114) | (0.124) | (0.151) | (0.141) |
| Green capacity | 0.445*** | 0.410*** | 0.243** | 0.402*** | 0.488*** |
| | (0.107) | (0.111) | (0.111) | (0.131) | (0.117) |
| log(Plant age) | 0.104*** | 0.129*** | 0.0699* | 0.0722 | 0.123*** |
| | (0.0396) | (0.0387) | (0.0390) | (0.0524) | (0.0458) |
| log(Customers) | 0.149*** | 0.151*** | 0.101*** | 0.146*** | 0.151*** |
| | (0.0316) | (0.0342) | (0.0309) | (0.0355) | (0.0350) |
| College graduates | -0.428 | -0.306 | 0.190 | -0.0899 | -0.613 |
| | (0.661) | (0.722) | (1.032) | (0.819) | (0.704) |
| Votes for Republican | -1.616** | -1.253 | -1.214 | -2.039** | -1.393* |
| | (0.670) | (0.812) | (0.966) | (0.807) | (0.721) |
| Climate belief | -0.0424** | -0.0395* | -0.0320 | -0.0590*** | -0.0325 |
| | (0.0186) | (0.0209) | (0.0238) | (0.0220) | (0.0200) |
| log(Home prices) | -0.252** | -0.265* | -0.319 | -0.345** | -0.204 |
| | (0.116) | (0.156) | (0.231) | (0.141) | (0.124) |
| Investor-owned | -0.270** | -0.305** | -0.284** | -0.300* | -0.252* |
| | (0.129) | (0.133) | (0.133) | (0.155) | (0.138) |
| Government-owned | -1.153*** | -1.150*** | -1.295*** | -1.198*** | -1.124*** |
| | (0.113) | (0.114) | (0.123) | (0.148) | (0.123) |
| Constant | 10.00*** | 9.707*** | 10.46*** | 12.55*** | 8.768*** |
| | (1.720) | (2.106) | (3.112) | (2.054) | (1.924) |
| Year-fixed effects | Yes | No | No | Yes | Yes |
| NERC-fixed effects | Yes | No | No | Yes | Yes |
| NERC/year-fixed effects | No | Yes | No | No | No |
| State/year-fixed effects | No | No | Yes | No | No |
| Sample | Full | Full | Full | 2013-16 | 2017-20 |
| Observations | 2,393 | 2,303 | 2,393 | 947 | 1,446 |
| R-squared | 0.357 | 0.419 | 0.540 | 0.372 | 0.348 |

Robust standard errors are clustered by utility.
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is utility/year. Disaster is a dummy that equals 1 if the utility's service area is hit by at least one disaster. Generating capacity hit by disaster, green capacity hit by disaster, and green capacity are all in percentage term. Plant age is the average age of the generating capacity of the utility (including plants it owns or purchases electricity from).

**Table 5**

**Maintenance Costs and Service Improvements**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | log(maintenance cost) | | log(SAIDI) | | |
| log(Lagged maintenance cost) | | -0.308*** | -0.270** | | |
| | | (0.0906) | (0.106) | | |
| log(Predicted lagged maintenance cost) | | | | -0.409** | -0.390** |
| | | | | (0.164) | (0.162) |
| Hurricane | 1.096*** | 0.871** | 0.867*** | 0.540*** | 0.527*** |
| | (0.253) | (0.326) | (0.296) | (0.132) | (0.127) |
| Storm | -0.232 | 0.366** | 0.310* | 0.271*** | 0.265*** |
| | (0.223) | (0.168) | (0.160) | (0.0713) | (0.0697) |
| Other disaster | -0.221 | 0.284* | 0.314** | 0.277*** | 0.304*** |
| | (0.316) | (0.140) | (0.127) | (0.0741) | (0.0735) |
| Lagged hurricane | 0.650** | -0.0395 | -0.0113 | 0.591** | 0.569** |
| | (0.260) | (0.225) | (0.219) | (0.255) | (0.250) |
| Lagged storm | -0.235 | -0.239 | -0.280* | -0.114 | -0.114 |
| | (0.211) | (0.169) | (0.150) | (0.0813) | (0.0802) |
| Lagged other disaster | -0.0451 | 0.00958 | 0.0445 | 0.0447 | 0.0777 |
| | (0.272) | (0.123) | (0.116) | (0.0840) | (0.0805) |
| College graduate | | | 2.300 | | -1.576 |
| | | | (4.747) | | (1.269) |
| Votes for Republican | | | 1.486 | | -0.432 |
| | | | (1.921) | | (0.697) |
| log(Home prices) | | | -0.308 | | -0.139 |
| | | | (0.578) | | (0.230) |
| Constant | 18.58*** | 11.24*** | 12.87* | 12.96*** | 15.06*** |
| | (0.247) | (1.697) | (6.849) | (3.066) | (3.984) |
| Year-fixed effects | Yes | Yes | Yes | Yes | Yes |
| Region-fixed effects | No | Yes | Yes | Yes | Yes |
| Observations | 154 | 154 | 154 | 832 | 818 |
| R-squared | 0.163 | 0.317 | 0.335 | 0.165 | 0.196 |

Robust standard errors are clustered by utility.
*** p<0.01, ** p<0.05, * p<0.1

Notes: The unit of analysis is utility/year. Maintenance costs are in 2013 dollars. In columns (1) to (3), the regressions are run on the random sample of 22 investor-owned utilities. The lagged disaster dummies equal 1 if a utility's service area is hit by the corresponding disaster in the previous year. We use the model from column (1) to predict the annual maintenance costs of each of the other investor-owned utilities. We lag this predicted value by one year to create the predicted lagged maintenance costs variable in columns (4) and (5). Region-fixed effects include four regions: the Northeast, the Midwest, the South, and the West.

## Table 6

## The Determinants of Electricity Prices

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Year | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2013-2020 |
| | log(Electricity price) | | | | | | | |
| log(Lagged SAIDI) | -0.0119 | 0.00644 | -0.00417 | 0.00981 | 0.0117 | 0.0203** | 0.0222*** | -0.00138 |
| | (0.0130) | (0.0101) | (0.0126) | (0.0101) | (0.00742) | (0.00791) | (0.00784) | (0.00114) |
| Hurricane or Storm | 0.0537* | 0.000959 | -0.0525 | -0.00247 | 0.0963*** | -0.000749 | -0.00300 | -0.00167 |
| | (0.0271) | (0.0374) | (0.0332) | (0.0295) | (0.0323) | (0.0277) | (0.0298) | (0.00227) |
| Other disaster | -0.0466 | -0.0369 | -0.0486* | -0.0328 | 0.0112 | -0.0428* | -0.0984** | -0.00119 |
| | (0.0308) | (0.0277) | (0.0285) | (0.0278) | (0.0205) | (0.0235) | (0.0424) | (0.00197) |
| Lagged state RPS | 0.869** | 0.827** | 0.767*** | 0.709** | 0.817*** | 0.733*** | 0.700*** | 0.150** |
| | (0.431) | (0.367) | (0.271) | (0.302) | (0.233) | (0.234) | (0.212) | (0.0656) |
| College graduates | -0.266 | -0.0453 | 0.00974 | 0.0235 | -0.114 | -0.176 | -0.376 | |
| | (0.241) | (0.267) | (0.271) | (0.352) | (0.344) | (0.340) | (0.324) | |
| log(Home prices) | 0.00122 | 0.00970 | -0.0105 | -0.00160 | 0.0332 | 0.0428 | 0.0943 | |
| | (0.0581) | (0.0589) | (0.0578) | (0.0698) | (0.0707) | (0.0721) | (0.0717) | |
| Climate belief | -0.000202 | -0.00297 | -0.00517 | -0.00613 | -0.0102* | -0.0132** | -0.0153** | |
| | (0.00567) | (0.00517) | (0.00423) | (0.00492) | (0.00597) | (0.00568) | (0.00592) | |
| Votes for Republican | -0.466** | -0.425** | -0.470*** | -0.498** | -0.610** | -0.779*** | -0.941*** | |
| | (0.211) | (0.192) | (0.175) | (0.209) | (0.255) | (0.248) | (0.271) | |
| Investor-owned | -0.0373 | -0.0121 | -0.0217 | -0.0168 | -0.0161 | -0.0367 | -0.00447 | |
| | (0.0224) | (0.0240) | (0.0220) | (0.0226) | (0.0240) | (0.0245) | (0.0254) | |
| Government-owned | -0.113*** | -0.0890** | -0.119*** | -0.0765** | -0.0668** | -0.0730** | -0.0740*** | |
| | (0.0383) | (0.0342) | (0.0359) | (0.0328) | (0.0289) | (0.0292) | (0.0261) | |
| Constant | -1.742** | -1.824** | -1.346* | -1.445* | -1.543* | -1.333 | -1.689** | -2.148*** |
| | (0.848) | (0.783) | (0.702) | (0.802) | (0.782) | (0.828) | (0.730) | (0.00745) |
| Utility-fixed effects | No | No | No | No | No | No | No | Yes |
| Year-fixed effects | No | No | No | No | No | No | No | Yes |
| Observations | 528 | 591 | 634 | 674 | 719 | 633 | 664 | 4,469 |
| R-squared | 0.173 | 0.179 | 0.214 | 0.181 | 0.257 | 0.244 | 0.293 | 0.961 |

Robust standard errors are clustered by state.

*** p<0.01, ** p<0.05, *p<0.1

Notes: These are cross-sectional regressions, and the unit of analysis is a utility. Electricity price is the residential electricity price. RPS is the state-level renewable portfolio standard. They are both lagged by one year. In this table, the unit of RPS is 1%.