NBER WORKING PAPER SERIES

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

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Working Paper 30583
http://www.nber.org/papers/w30583

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2022, Revised June 2023

We thank Dora Costa and Bhaskar Krishnamachari for useful discussions. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 30583
October 2022, Revised June 2023
JEL No. H40,L0,Q40

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 ambitious green power requirements. Using a US electric utility panel dataset from 2013 to 2020, we document that natural disasters disrupt service, but utilities have made progress in adapting to such shocks. Over the last decade, utilities have faced a tradeoff between achieving local carbon mitigation goals and offering reliable power access. We discuss alternative approaches to attenuate this tradeoff.

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1. 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 September 2022, Hurricane Ian knocked out power for millions of people in Florida.

In 2013, the average American did not have access to electricity for 240 minutes. In 2020, this number has risen to 390 minutes. Going forward, the United States electricity grid will face increasing risks from natural disasters (Ward 2013; Stock 2020). In this paper, we benchmark the climate change adaptation progress of American utilities, using two independent metrics: night lights and reliability indices (SAIDI and SAIFI) from the EIA. Numerous recent natural disasters provide us with a set of natural experiments to test the resilience of our electric infrastructure. We find that hurricanes significantly reduce grid reliability, but their effects diminish over time.

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. The "green grid" features a lower carbon emissions factor, but an unintended consequence is that the short-term electricity generation becomes more volatile (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). Our empirical results document that green generating capacity is more vulnerable to environmental shocks. The generation from renewables declines when natural disasters hit, so utilities have to turn on emission-intensive generators to meet the reliability criteria. We discuss several potential approaches to attenuate this tradeoff between climate change adaptation and greenhouse gas mitigation.

This paper is organized as follows. In Section 2, we introduce our datasets. In Section 3, we discuss a utility's incentives to supply reliable power. In Section 4, we quantify the effects of natural disasters on grid resilience. In Section 5, we test whether utilities have made progress in adapting to these shocks. In Section 6 and 7, we provide evidence on and discuss potential solutions to the tradeoff between grid resilience and decarbonization.

2. Data

We compile a comprehensive dataset at the electric utility/year level from 2013 to 2020. We restrict our sample of utilities to investors-owned utilities (IOUs), publicly owned utilities (POUs), and distribution cooperatives (i.e. no individual power retailers or G&T cooperatives). Our core data are provided by the US Energy Information Administration (EIA).[1] The EIA data are reported at the utility/state/year level and includes information on each utility's reliability. The EIA keeps track of the System Average Interruption Frequency Index (SAIFI) and the System Average Interruption Duration Index (SAIDI.[2] SAIFI is the percentage of customers affected by a power outage. SAIDI is the average interruption time per customer.[3] We use these two metrics to benchmark each utility's reliability.

We supplement the EIA data with night lights data from the Earth Observation Group (EOG).[4] We overlay the original geospatial files with US county shapes and calculate the average monthly night lights by county. We use this as an alternative metric to benchmark utilities' ability to keep the lights on.

We obtain the natural disaster data from the Federal Emergency Management Agency (FEMA).[5] The FEMA data lists every natural disaster from 2013 to 2020. The dataset provides the date, type, and location of each disaster. We aggregate this dataset by county/year and create a dummy variable for each of the thirteen types of disasters. We aggregate these thirteen categories into three categories: hurricane, storm, and other. We assign the value of these disaster dummies to utilities based on their service territory. A utility is defined as exposed to a disaster if any county within its territory is hit.

3. Supplying Reliable Power

[1] https://www.eia.gov/electricity/data/eia861/

[2] 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.

[3] A utility's 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). 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

[4] https://eogdata.mines.edu/products/vnl/
The unit of night lights is W/cm2/sr (watts per squared centimeter per steradian).

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

There are three major types of electric utilities in the United States: investor-owned, publicly owned (a.k.a. municipal), and cooperative. IOUs are private companies that operate with the goal of maximizing shareholder value. They are typically regulated by state public utility commissions (PUCs), which oversee their rates and service quality. Municipal utilities are established by cities, counties, or other governmental entities to provide electric services to the local community. They are non-profits and focus on meeting the needs of the community they serve. Electric cooperatives are owned and governed by their consumers. They predominantly operate in rural areas, and unlike other utilities, most of them purchase electricity in the wholesale market instead of generating power by themselves.[6] In 2020, 78% of the American electricity customers were served by investor-owned utilities, and municipal and cooperative utilities each served half of the rest of the customers.

The NERC (North American Electric Reliability Council) has established and has been improving the set of reliability standards that electric utilities are mandated to follow. Such standards range from the planning of the bulk power system to the standards of power lines.[7] These regulations target the electricity wholesale market and interstate transmissions, ensuring that a few isolated faults in the system could not bring down the whole network (Albert and Nakarado 2004; Ward 2013; Veloza and Santamaria 2016). They do not extend to local distribution and the retail market, which are regulated by state authorities. Disruptions to transmission capacity are costly as they can cause regional blackouts, whereas local distribution failures usually affect only the local electricity customers. Utilities have an incentive to comply with these federal and state rules to avoid potentially enormous penalties (Watson 2017).[8]

Utilities' adaptation progress can differ by their ownership structure even when they face the same technological and performance mandates. IOUs are profit-maximizing agencies subject to rate-of-return regulations. The Averch-Johnson (1962) model implies that they have an incentive to invest in capitals to improve grid resilience . However, because shareholders of IOUs are not their customers and IOUs face little threat of customer switching especially in traditionally regulated retail markets, they may have weak incentives to improve reliability beyond meeting the reliability standards (Joscow and Tirole 2007).

Municipal utilities are kept accountable by their customers (de-factor shareholders)

[6] https://www.cooperative.com/remagazine/articles/Pages/Go-Co-op-electric-cooperative-generation-transmission-relationship.aspx
[7] https://www.nerc.com/pa/Stand/Pages/USRelStand.aspx
[8] https://www.nytimes.com/2022/04/11/business/energy-environment/pge-wildfire-settlement.html

through political elections. 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). Cooperative utilities have a similar structure, except that they are run by an elected executive board instead of the local government. 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 non-local and anonymous. Instead, local regulators bear the anger from customers.[9]

Figure 1 shows the empirical distribution of SAIDI over time by ownership. Publicly owned utilities provide the most reliable services. Notably, the average SAIDI does not vary a lot from year to year, but the empirical distribution becomes more right-skewed. This suggests that extreme weather has caused more intense power outages (Hines, Apy, and Talukdar 2009; Waseem and Manshadi 2020). Cooperative utilities seem to be affected the most, as benchmarked by their 75th percentile and maximum SAIDI.

4. Natural Disasters and Power Supply Reliability

4.1 Effects of disasters on generation, transmission, and distribution

Weather events have caused more than half of the large-scale blackouts in the US (Hines, Apt, and Talukdar 2009). Based on the FEMA data, from 2013 to 2020, 35% of the natural disasters in the US were hurricanes and 28% were storms. An average county was hit by 0.04 hurricane, 0.036 storm, and 0.02 other disasters such as flood and wildfire. Figure 2 shows each county's count of natural disasters within the time period we study. All graphs show that natural disasters tend to be regional (i.e. hit a contiguous set of counties). While storms and floods are more evenly distributed across space, hurricanes concentrate in the Southeast, and wildfires take place exclusively in the West. In Figure 3, we plot log(SAIDI) in 2020 by county. These graphs indicate a positive correlation between SAIDI and disaster counts, especially hurricanes (see the Southwestern states). Hurricane counts have a correlation of 0.47 with SAIDI. Previous studies have discussed different natural disasters' impacts on grid

[9] In California, instead of protesting against PG&E, consumers protested in front of the California PUC to express their concerns about 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

reliability (Ward 2013; Waseem and Manshadi 2020).

The electricity supply chain consists of three stages: generation, transmission, and distribution. Blackouts can occur when electricity generation falls short of real-time demand or when transmission and distribution networks are disrupted by extreme weather. Because of the NERC reliability standards, there is redundancy in generation and transmission, yet typically not in distribution. Most blackouts are results of local distribution line failures (Veloza and Santamaria 2016). When strong winds knock down trees, they damage overhead distribution lines, and it could take weeks to restore these facilities. In our paper, we interpret SAIDI and SAIFI as the reliability of the distribution system.

In the generation phase, conventional fossil fuel power plants are controllable and can be ramped up to meet the peak demand. Adverse environmental conditions can reduce the productivity of renewable power plants. Wind speed of hurricanes is too high for wind turbines to safely operate. There is no solar power when hurricanes or storms hit, and solar panels' efficiency declines during wildfires or heat waves (Dubey, Sarvaiya, and Seshadri 2013). The increasing penetration of these intermittent renewables pose new challenges to resource adequacy (Shaner et al. 2018; Wolak 2022). RTOs require electric utilities to maintain excess capacity to meet the reliability targets, except in Texas where there is not a target. Such generation plannings minimize the risk that power outages occur due to an imbalance in electricity supply and demand. However, the "missing money" problem suggests that utilities tend to underinvest in the necessary capacity required to meet peak demand when renewable energy sources cannot deliver (Cramton, Ockenfels, and Stoft 2013). In our empirical work , we study how utilities' generation mix changes when disasters take place.

Although extreme weather can reduce the reliability of transmission lines, the transmission network is overall resilient to climate shocks due to the NERC reliability mandates (Albert and Nakarado 2004; Ward 2013; Rezaei et al. 2016). In California, utilities are placing power lines under ground to reduce the risk from wildfires. These costly investments can further elevate the resilience of transmission facilities.

4.2 Quantifying the effects of natural disasters

To study the effects of natural disasters on grid reliability, we use three different metrics: night lights, SAIDI, and SAIFI. Our unit of analysis is county/quarter and utility/year when the dependent variable is night lights and SAIDI/SAIFI respectively. We estimate the following equation using ordinary least squares (OLS) for county/utility i at time t:

$$\log(\mathrm{Y_{it}}) = \beta_0 + \beta_1{'}\mathrm{X_{it}} + \beta_2{'}\mathrm{Z}_{it} + fixed\ effects + \varepsilon_{\mathrm{it}} \tag{1}$$

In equation (1), X is a vector of disaster dummies or disaster counts. When the unit of analysis is an electric utility, we include utilities' time-varying attributes (Z) such as customer counts and state RPS. We interpret RPS as a proxy for local environmental regulations. With strict regulations, it may be more difficult for utilities to manage trees that disrupt distribution lines. We include different fixed effects and cluster standard errors by county or utility. The results are reported in Table 1.

In columns (1) and (2), we find that each hurricane reduces average quarterly night lights by 4%, which is statistically significant at the 1% level. Since hurricanes do not last the whole quarter, the numerical value of the coefficient would be larger if we run the same regressions on daily or monthly average night lights. We find no statistically significant evidence that storms or other disasters are negatively correlated with night lights.

In columns (3) and (4), all disaster dummies have significantly positive correlation with SAIDI and SAIFI. The coefficients on hurricanes have the largest numerical values, indicating that hurricanes are the most damaging to the grid. When hurricanes hit in the year, SAIDI drops by 34%, and SAIFI drops by 8%. In column (3), the RPS has a significantly positive correlation with SAIDI at 10% level. Grid reliability tends to be lower for utilities in states with stricter environmental regulations. We interpret this as a result of the damages to distribution lines by falling trees (Ward 2013).

5. Are Electric Utilities Adapting to Natural Disaster Shocks?

In this section, we test whether electric utilities are becoming more resilient to climate shocks. Such utilities have private information about their marginal cost of providing high quality, consistent service. Our tests are based on the same metrics in Table 1, and we expand equation (1) by including an interaction term between the time trend and the disaster dummy, which equals 1 if the county or the utility is exposed to any disaster in the time period. We allow this coefficient to vary by utility ownership when the unit of analysis is a utility. Specifically, we estimate the following equation for county/utility i at time t:

$$\log(\mathrm{Y_{it}}) = \beta_0 + \beta_1{'}\mathrm{X_{it}} + \beta_2{'}\mathrm{trend} \times \mathrm{disaster}_{it} \times Onwership_i + fixed\ effects + \varepsilon_{\mathrm{it}} \tag{2}$$

where X denotes all variables in equation (1). The omitted category of ownership is investor-owned. We include the same fixed effects and cluster standard errors in the same way as in Table 1. The results are reported in Table 2.

In columns (1) and (2), the coefficient on the interaction term between the time trend and natural disasters is significantly positive. We find the same result when measuring disasters using a dummy variable or counts. As predicted by the adaptation hypothesis, over time, the negative effects of natural disasters on night lights shrink.

In the second adaptation test, where we use SAIDI and SAIFI as reliability metrics, we find that natural disasters' effects on SAIDI, but not SAIFI, are declining over time. This suggests that natural disasters in recent years did not hit fewer electricity customers, but the duration of blackouts has shrunk.

The triple interaction term for cooperative utilities is positive and statistically significant. This implies that the adaptation progress of electric co-ops lagged that of the IOUs. A t-test on the coefficients show no evidence that cooperative utilities' SAIDI and SAIFI are becoming more resilient to climate shocks. The marginal cost of upgrading distribution lines could be higher for cooperative utilities due to poor infrastructure in the rural areas. Meanwhile, rural residents may have lower willingness to pay for reliable electricity, so adaptation investments are not cost efficient (Joskow and Tirole 2007). Also, cooperative utilities sign long-term power purchase agreements with Gas and Transmission co-ops. Since cooperative utilities do not generate power, their electricity supply hinges heavily upon their contracted generators in the wholesale market. This power purchase "lock-in" can limit cooperative utilities' ability to diversify their power supply and adapt to regional weather shocks in the short term.

6. A Tradeoff Between Climate Change Mitigation and Adaptation

Although wind and solar generators produce lower emissions, these intermittent renewables pose long-term resource adequacy problems as their productivity drop significantly under extreme weather events (Shaner et al. 2018; Wolak 2022). Electricity planners determine the generation mix to meet the reliability targets. Given that intermittent renewables are less productive during environmental shocks, a larger proportion of electricity needs to be generated from controllable but dirtier energy sources such as coal and natural gas.[10] To test this claim, we estimate the following regression for county i, energy type k (green or brown), in quarter t:

$$\log(\mathrm{Generation_{ikt}}) = \beta_0 + \beta_1{}'\mathrm{Disaster_{it}} \times green_k + \beta_2{}'Z_{ikt} + \text{fixed effects} + \varepsilon_{\mathrm{ikt}} \quad (3)$$

where generation refers to the actual electricity generation in county i from energy type k at time t, disaster is a vector of disaster dummy variables, and Z is a vector of covariates including each county's generation capacity by energy type. Green is a dummy indicating electricity generation from wind, solar, or hydropower. These variable energy sources are the most susceptible to natural disasters. We include county/year fixed effects and quarter fixed effects. Results are reported in Table 3.

In both columns, our estimates show that electricity generation from brown energy increases by 7% when hurricanes hit. The interaction term between hurricanes and green power is significantly negative in both columns. The coefficients indicate that generation from green power sources drops by over 10% amid hurricanes. We find no evidence that the resource mix of generation changes when other disasters take place.

7. Adapting to Climate Shocks in the Face of Green Mandates

In the previous section, we have presented evidence that utilities ramp up generation from brown energy when intermittent renewables cannot generate under extreme weather. In this section, we discuss some approaches to attenuate this tradeoff between climate change adaptation and mitigation.

7.1 Interstate transmission and market integration

In the continental US, the electricity network is made up of three interconnection regions with limited power transmissions between them: the Western, the Eastern, and Texas interconnection.[11] Within each interconnection, the siting of generators and transmission capacity are regulated by different RTOs. With regional transmission facilities, when local generators are knocked down by natural disasters, utilities can avoid blackouts by drawing

[10] Due to 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.
https://www.latimes.com/opinion/story/2022-06-24/california-electricity-reliability-reserve
[11] https://www.epa.gov/green-power-markets/us-electricity-grid-markets

electricity from non-affected regions. Hagspiel, Knaut, and Peter (2018) have documented such cross-border balancing effects in the European electricity markets. Market integration is especially important for regions that rely more on generation from renewables, which are more susceptible to weather events. Without interstate transmissions, they have to site controllable, dirty backup capacity to prevent blackouts caused by natural disasters.

Since the Texas electricity market is isolated, we compare Texas to the rest of the nation to provide suggestive evidence that market integration can hedge against regional climate shocks. In 2020, the average SAIDI in Texas was 548 minutes (the 11th highest among all states), 40% higher than the national SAIDI. 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. We calculate the residuals in 2020 from column (3) of Table 2 (where the dependent variable is log(SAIDI)). Across all percentiles, Texas's residuals are higher than the national average.[12] This implies that Texas systematically underperforms other states in supplying reliable power.

However, interstate transmission developments have been slow in the US due to local NIMBYism (Gross 2020). This hinders climate adaptation given the regional nature of many disasters (i.e. the whole state is impacted at the same time). Transmission plannings have traditionally been decided between state regulators, which means every state that the line goes through has veto power on the construction.[13] Klass et al. (2022) have argued that the federal government should be empowered to involve more in approving transmission projects. To reduce local backlash, the Inflation Reduction Act (IRA) has allocated $760 million to state governments to compensate communities that may be affected by the new transmission lines in exchange for faster permitting.[14]

7.2 Forward capacity markets

In Section 6, we have documented that building in excess brown capacity can ensure sufficient power supply when green capacity cannot deliver. Yet, the "missing money" problem

[12] At the 25th, 50th, 75th, and 90th percentile, Texas's residual is –0.53, 0.31, 1.43, and 2.47 respectively, and the rest of the nation's is -0.92, 0.09, 1.06, and 2.24.

[13] For example, the 780-mile Great Belt Express Clean Line was intended to pass through Kansas, Indiana, Illinois, and Missouri. It could not be built due to the opposition from Missouri governors despite the approval from all other states.

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

has emerged as a growing concern in deregulated electricity markets (Cramton, Ockenfels, and Stoft 2013). The "missing money" problem refers to the situation when revenues from electricity sales and ancillary service provisions cannot cover the cost of investments in generating capacity.

In energy-only markets, wholesale electricity prices rise during scarcity hours, and generators recover their investment expenditure by selling at these peak hours. Given the inelastic electricity demand, regulators cap the electricity price to prevent it from rising unlimitedly (Joskow and Tirole 2007). In response to this, generators add in new capacity up until the point when the marginal cost of an additional unit of capacity equals the capped electricity price. The market can achieve efficiency if the electricity price is capped at the value of lost load (VoLL), customers' marginal willingness to pay for uninterrupted services.

However, implementing a price-based approach can be challenging due to the difficulty in accurately estimating the VoLL and the potential for electricity suppliers to exert market power (Stoft 2002; Borenstein, Bushnell, and Wolak 2002). A forward capacity market has been used as a more efficient alternative (Cramton and Stoft 2008). Capacity markets compensate generators for maintaining excess capacity and promising to supply power when real-time price exceeds a strike price. Regulators determine the level of necessary capacity reserve and auction it to generators. This approach hedges against high spot prices and reduces the market power of suppliers that would emerge in energy-only markets (Cramton and Stoft 2008; Cramton, Ockenfels, and Stoft 2013).

To decarbonize the power sector while building in sufficient capacity, Klass et al. (2022) propose the use of region-wide uniform RPS in combination with two separate capacity auctions, one exclusively for green capacity and another traditional auction. If the market-clearing price in the green market is higher, more renewable electricity providers would enter. Such new green capacity can improve power supply security if its capacity value (defined as the ratio between functioning capacity during peak hours and the rated capacity).is accurately credited (Peter and Wagner 2021).

7.3 Microgrids and energy storage

A microgrid is a localized power system typically paired with distributed generators such as solar PVs and energy storage facilities. They key feature of microgrids is that they can operate independently of the main power grid when needed. This localized nature is an insurance against natural disasters because microgrids are less likely to be affected by disruptions in long-distance transmission or cascading failures (Kwasinski 2011). Also, because microgrid systems are compact, they are unlikely to be damaged by disasters if placed at optimal sites (Kwasinski et al. 2012).

Energy storage converts electricity into other forms of energy such as thermal and mechanical (e.g. pumped hydro). Such stored power can be released to feed microgrids when the bulk electricity system is down. In competitive wholesale electricity markets, storage developers can make profits by engaging in energy arbitrage (Walawalkara, Apt, and Mancini 2007). They store electricity when the cost of generation or the wholesale price is low and sell it during peak hours. Their private incentives are aligned with the public interests of grid resiliency and cheaper power generation. Additionally, energy storage systems can provide ancillary services such as frequency control. Frequency instability can damage components of the grid and reduce its resilience. Energy storage can inject power into the grid instantly to stabilize the frequency.

Renewables have zero marginal cost in generation, and electricity demand tends to be low when wind and solar supply is plenty (e.g. early morning). Distributed generators powered by intermittent renewables are thus complements to energy storage. From 2014 to 2020, total energy storage capacity has increased from 200MW to over 1500MW, and new installations have taken place predominantly in states with more wind and solar capacity (e.g. California and Texas). Figure 4 shows a strong positive correlation (r=0.57) between the increase in storage capacity and the increase in green generating capacity. Storage systems can thus accelerate the green transition while enhancing grid reliability.

7.4 Demand side Management Adaptation Strategies

While capacity markets and energy storage are supply-side solutions to the reliability challenges from natural disasters and intermittent renewables, dynamic pricing is a demand-side solution. In the past decade, an increasing fraction of retail customers substituted mechanical metering (that had to be read manually) to smart metering, and this enabled them to opt into dynamic pricing of electricity (Wolak and Hardman 2021). In Figure 5, we plot the proportion of customers enrolled in dynamic pricing by the ownership of utilities. From 2013 to 2020, this proportion has doubled for IOUs and tripled for POUs. Cooperative utilities had the least progress in signing customers up for dynamic pricing. This correlates with their slow adaptation progress (reported in Table 2).

Wolak (2011) has documented that dynamic pricing can reduce electricity demand at peak hours. This induces two environmental impacts. First, it can reduce the likelihood of power outages in a more cost-efficient way. Electricity generation declines under extreme weather events, and such declines are even larger in areas with higher renewable penetration (see Table 3). In the absence of dynamic pricing, electricity demand does not respond to the scarcity of resources, so electricity supply has to catch up to avoid power outages. In capacity auctions, generators bid to produce power and the optimal choice for them is to bid their marginal cost of generation. If peak demand does not shrink when supply drops, more backup capacity will be needed, which may increase the market clearing price in the capacity (Cramton, Ockenfels, and Stoft 2013). This implies a higher cost of keeping the lights on.

The second effect is that dynamic pricing can facilitate climate mitigation by reducing the marginal emissions from the grid. The average emissions intensity of the grid has dropped as more renewable generation is used to meet the base load. Yet, the marginal emissions from electricity generation have risen because controllable, fossil fuel power plants are now used to fulfil the marginal increase in demand (Holland et al. 2022). As dynamic pricing reduces this marginal increase, fewer brown power plants would be needed during peak hours, leading to overall lower emission rates.

8. Conclusion

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. Using an eight-year panel dataset, we have documented reduced form evidence that the utilities have grown more resilient to natural disasters.

We have presented a tension between electricity reliability and grid decarbonization. A regionally integrated capacity market may attenuate this tradeoff by incentivizing utilities to build in sufficient green capacity to meet the reliability criteria. Yet, one caveat is that the capacity auctions are not always competitive (McCullough et al. 2020). The strong market power of the pivotal suppliers reduces efficiency. Another challenge lies in accurately crediting the capacity value of renewable capacity (Peter and Wagner 2021). An overvaluation could lead to insufficient dispatchable backup capacity, while an undervaluation could inflate the cost of generation as more electricity is generated from brown energy sources with higher marginal costs.

To increase resilience while decarbonizing, utilities can apply supply or demand management tools. A growing literature explores the potential of mobile energy storage such as vehicle-to-grid (V2G) (Dugan, Mohagheghi, and Kroposki 2021). EVs can store electricity when supply exceeds demand and discharge the stored energy during peak hours. V2G systems are more flexible and less costly than conventional stationary storage systems. Future research can study whether mobile and stationary storage systems are complements or substitutes in enhancing grid resilience.

References

Albert, Réka, István Albert, and Gary L. Nakarado. "Structural vulnerability of the North American power grid." *Physical review E* 69, no. 2 (2004): 025103.

Averch, Harvey, and Leland Johnson. “Behavior of the Firm Subject to External Regulatory Constraint,” 1962.

Borenstein, Severin, James B. Bushnell, and Frank A. Wolak. "Measuring market inefficiencies in California's restructured wholesale electricity market." *American Economic Review* 92, no. 5 (2002): 1376-1405.

Busby, Joshua W., Kyri Baker, Morgan D. Bazilian, Alex Q. Gilbert, Emily Grubert, Varun Rai, Joshua D. Rhodes, Sarang Shidore, Caitlin A. Smith, and Michael E. Webber. “Cascading Risks: Understanding the 2021 Winter Blackout in Texas.” *Energy Research & Social Science* 77 (2021): 102106.

Cramton, Peter, Axel Ockenfels, and Steven Stoft. "Capacity market fundamentals." *Economics of Energy & Environmental Policy* 2, no. 2 (2013): 27-46.

Cramton, Peter, and Steven Stoft. "Forward reliability markets: Less risk, less market power, more efficiency." *Utilities Policy* 16, no. 3 (2008): 194-201.

Dubey, Swapnil, Jatin Narotam Sarvaiya, and Bharath Seshadri. "Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world–a review." *Energy Procedia* 33 (2013): 311-321.

Dugan, Jesse, Salman Mohagheghi, and Benjamin Kroposki. "Application of mobile energy storage for enhancing power grid resilience: A review." *Energies* 14, no. 20 (2021): 6476.

Gross, Samantha. "Renewables, land use, and local opposition in the United States." *Brookings Institution, January* (2020).

Hines, Paul, Jay Apt, and Sarosh Talukdar. "Large blackouts in North America: Historical trends and policy implications." *Energy Policy* 37, no. 12 (2009): 5249-5259.

Holland, Stephen P., Matthew J. Kotchen, Erin T. Mansur, and Andrew J. Yates. "Why marginal CO2 emissions are not decreasing for US electricity: Estimates and implications for climate policy." *Proceedings of the National Academy of Sciences* 119, no. 8 (2022): e2116632119.

Hagspiel, Simeon, Andreas Knaut, and Jakob Peter. “Reliability in Multi-Regional Power Systems: Capacity Adequacy and the Role of Interconnectors.” *The Energy Journal* 39, no. 01 (2018).

Joskow, Paul, and Jean Tirole. "Reliability and competitive electricity markets." *The RAND Journal of Economics* 38, no. 1 (2007): 60-84.

Klass, Alexandra, Joshua Macey, Shelley Welton, and Hannah Wiseman. "Grid reliability through clean energy." *Stan. L. Rev.* 74 (2022): 969.

Kwasinski, Alexis. "Local energy storage as a decoupling mechanism for interdependent infrastructures." In *2011 IEEE International Systems Conference*, pp. 435-441. IEEE, 2011.

Kwasinski, Alexis, Vaidyanathan Krishnamurthy, Junseok Song, and Ratnesh Sharma. "Availability evaluation of micro-grids for resistant power supply during natural disasters." *IEEE Transactions on Smart grid* 3, no. 4 (2012): 2007-2018.

McCullough, Robert, Michael Weisdorf, Jean-Carl Ende, and Aiman Absar. "Exactly how inefficient is the PJM capacity Market?." *The Electricity Journal* 33, no. 8 (2020): 106819.

Peltzman, Sam. “Pricing in Public and Private Enterprises: Electric Utilities in the United States.” *The Journal of Law and Economics* 14, no. 1 (1971): 109–47.

Peter, Jakob, and Johannes Wagner. “Optimal Allocation of Variable Renewable Energy Considering Contributions to Security of Supply.” *The Energy Journal* 42, no. 1 (2021).

Schuerger, Robert, Robert Arno, and Neal Dowling. "Why existing utility metrics do not work for industrial reliability analysis." *IEEE Transactions on Industry Applications* 52, no. 4 (2016): 2801-2806.

Shaner, Matthew R., Steven J. Davis, Nathan S. Lewis, and Ken Caldeira. "Geophysical constraints on the reliability of solar and wind power in the United States." *Energy & Environmental Science* 11, no. 4 (2018): 914-925.

Stock, James H. "Climate change, climate policy, and economic growth." *NBER Macroeconomics Annual* 34, no. 1 (2020): 399-419.

Stoft, Steven. *Power system economics: designing markets for electricity*. Vol. 468. Piscataway: IEEE press, 2002.

Veloza, Olga P., and Francisco Santamaria. "Analysis of major blackouts from 2003 to 2015: Classification of incidents and review of main causes." *The Electricity Journal* 29, no. 7 (2016): 42-49.

Ward, David M. "The effect of weather on grid systems and the reliability of electricity supply." *Climatic Change* 121, no. 1 (2013): 103-113.

Waseem, Muhammad, and Saeed D. Manshadi. "Electricity grid resilience amid various natural disasters: Challenges and solutions." *The Electricity Journal* 33, no. 10 (2020): 106864.

Watson, William F. "NERC mandatory reliability standards: A 10-year assessment." *The Electricity Journal* 30, no. 2 (2017): 9-14.

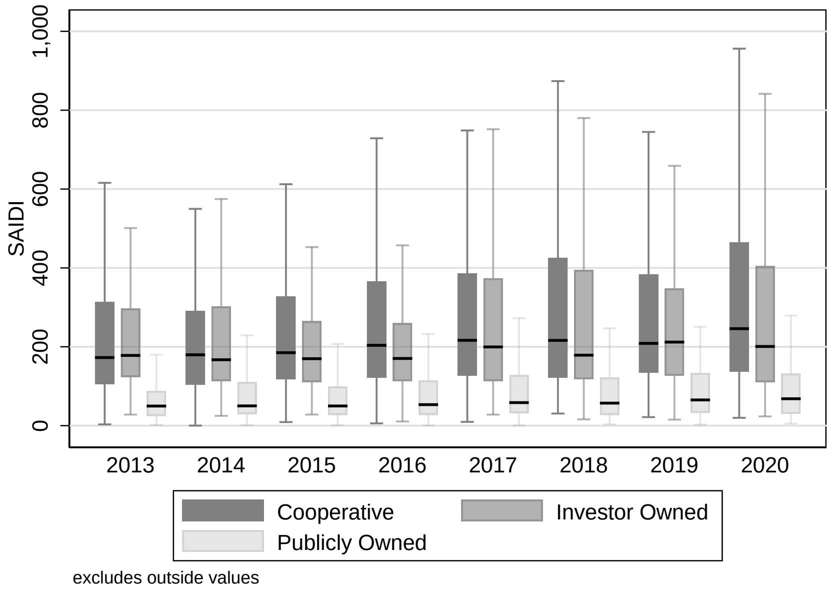
Wolak, Frank A. "Do residential customers respond to hourly prices? Evidence from a dynamic pricing experiment." *American Economic Review* 101, no. 3 (2011): 83-87.

Wolak, Frank A. "Long-term resource adequacy in wholesale electricity markets with significant intermittent renewables." *Environmental and Energy Policy and the Economy* 3, no. 1 (2022): 155-220.

Wolak, Frank A., and Ian H. Hardman. *The Future of Electricity Retailing and How We Get There*. Vol. 41. Springer Nature, 2021.

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

Geographical Distribution of Natural Disasters

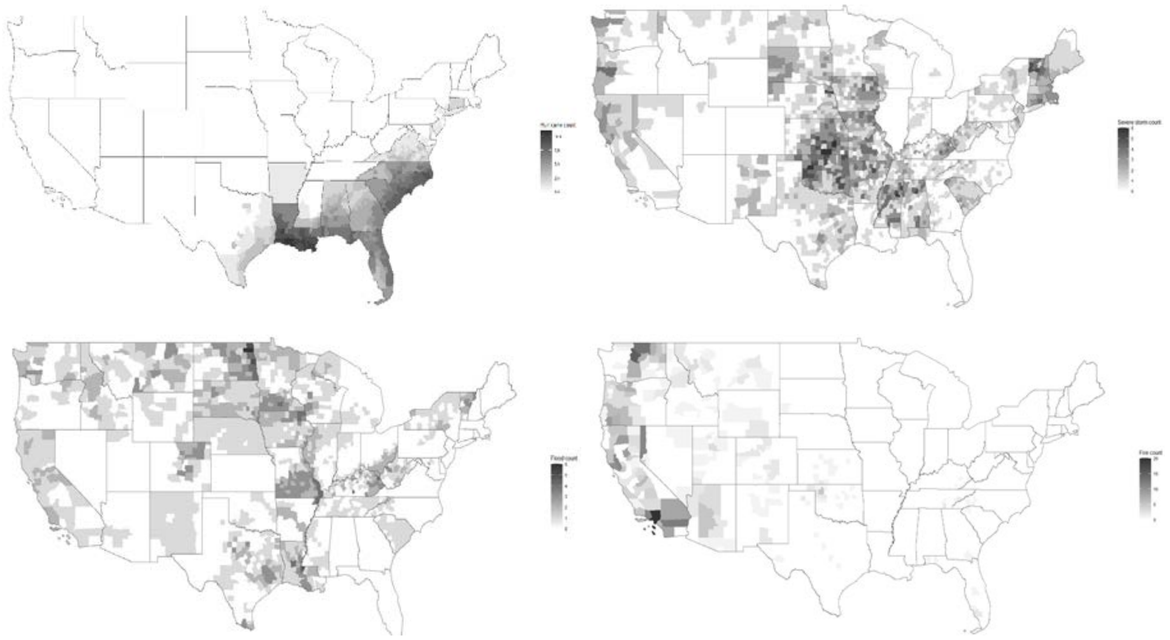


Figure 3

Electric Utility Reliability in 2020

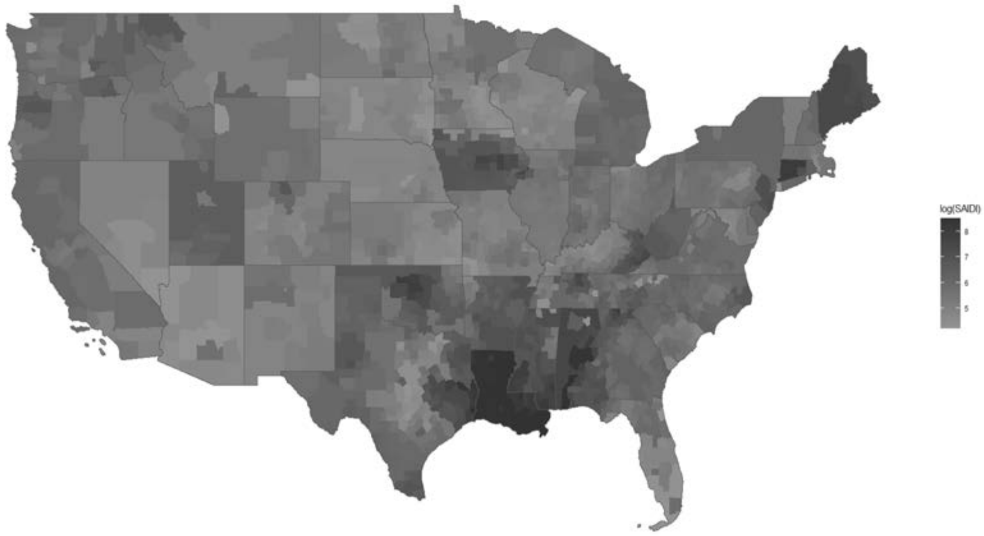


Figure 4

Energy Storage as Complement to Green Generators

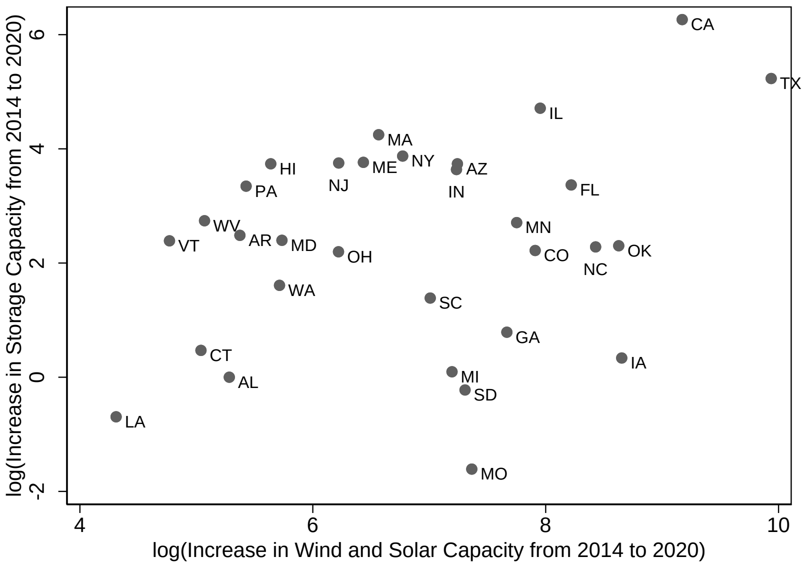


Figure 5

Proportion of Residential Customers Enrolled in Dynamic Pricing

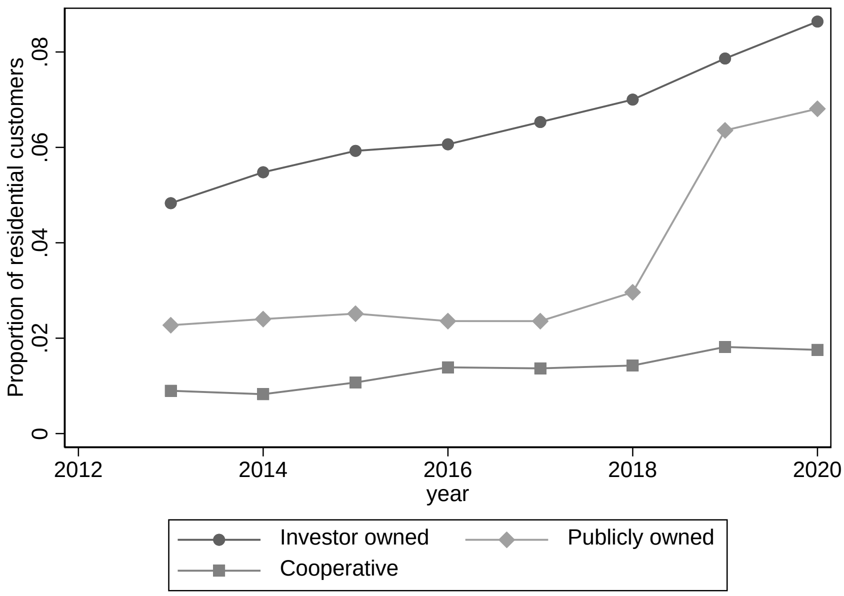


Table 1

The Correlates of Natural Disasters and Grid Reliability

	(1)	(2)	(3)	(4)
	log(Night lights)		log(SAIDI)	log(SAIFI)
Hurricane	-0.0474***		0.337***	0.0764**
	(0.00669)		(0.0531)	(0.0303)
Storm	0.00530		0.218***	0.0571**
	(0.0109)		(0.0353)	(0.0239)
Other	-0.000658		0.168***	0.0523***
	(0.0103)		(0.0335)	(0.0195)
Hurricane count		-0.0381***		
		(0.00408)		
Storm count		0.00778		
		(0.0103)		
Other count		-0.00699		
		(0.00897)		
RPS			1.253*	0.392
			(0.712)	(0.395)
County/year FE	Yes	Yes	No	No
Quarter FE	Yes	Yes	No	No
Utility FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Observations	99,695	99,695	5,469	5,099
R-squared	0.929	0.929	0.667	0.722

In columns (1) and (2), the unit of analysis is county/quarter. Standard errors are clustered by county. In columns (3) and (4), it is utility/year. Standard errors are clustered by utility.

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

Table 2

A Test of Adaptation Progress

	(1)	(2)	(3)	(4)
	log(Night lights)		log(SAIDI)	log(SAIFI)
trend x disaster	0.00923***		-0.0408***	-0.0126
	(0.000792)		(0.0148)	(0.00844)
trend x disaster count		0.00706***		
		(0.000621)		
trend x disaster x public			-0.000591	-0.00834
			(0.0173)	(0.0129)
trend x disaster x cooperative			0.0292**	0.0169**
			(0.0140)	(0.00788)
County/year FE	Yes	Yes	No	No
Quarter FE	Yes	Yes	No	No
Utility FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Observations	99,695	99,695	5,469	5,099
R-squared	0.929	0.929	0.669	0.723

The unit of analysis is the same as in Table 1, and we cluster the standard errors in the same ways. All regressors in Table 1 are also included in Table 2 (but not shown). The omitted category is investor-owned.
*** p<0.01, ** p<0.05, * p<0.1

Table 3

Generation Mix during Natural Disasters

	(1)	(2)
	disaster dummies	disaster counts
	log(Generation)	
Hurricane	0.0748**	0.0697***
	(0.0345)	(0.0207)
Storm	-0.0358	-0.0376
	(0.0302)	(0.0290)
Other	-0.00799	0.0151
	(0.0281)	(0.0224)
Hurricane x green	-0.117*	-0.109***
	(0.0641)	(0.0364)
Storm x green	0.0486	0.0486
	(0.0541)	(0.0517)
Other x green	0.0391	-0.00847
	(0.0530)	(0.0418)
County/year FE	Yes	Yes
Quarter FE	Yes	Yes
Observations	198,417	198,417
R-squared	0.929	0.929

The unit of analysis is county/quarter. Standard errors are clustered by county.
*** p<0.01, ** p<0.05, * p<0.1