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Unequal resilience: The duration of electricity outages

Raoul S. Liévanos[a,*], Christine Horne[b]

[a] Department of Sociology, 1291 University of Oregon, Eugene, OR 97403-1291, USA
[b] Department of Sociology, Washington State University, Pullman, WA 99164-4020, USA

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ABSTRACT

The resilience of social, biophysical, and technological systems is of increasing scholarly and practical import. Guided by scholarship on disaster resilience, environmental inequality, and urban service inequality, we advance the study of “unequal resilience” in a critical infrastructure – the electric grid. We analyze inequality in electricity outage duration at the census block group level using data from the U.S. Census, the U.S. Geological Survey, and a U.S. electrical utility's database of power outages from 2002 to 2004. Our intersectional approach identifies a factor variable of American Indian disadvantage as a correlate of average outage duration – suggesting possible support for an institutional bias hypothesis. However, spatial error regression models demonstrate that unequal resilience within our study area is most consistently explained by proximity to priority assets (i.e., hospitals), average downstream customers affected by outages, and environmental conditions (i.e., the seasonality of outages). These results are consistent with existing research on utilities' response to power outages, and more broadly with the bureaucratic decision rules perspective on service inequalities. We discuss the implications of our findings for future research and energy policy.

1. Introduction

Scholars, policymakers, and planners are paying increasing attention to the resilience of social, biophysical, and technological systems. The resilience of critical infrastructures is viewed as particularly important. Such infrastructures are “so vital that their incapacitation or destruction would have a debilitating impact on defense or economic security” (U.S. President’s Commission on Critical Infrastructure Protection, 1997:B-1). Resilience as it pertains to critical infrastructures refers to “the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions” (U.S. Department of Homeland Security, 2015). Thus, a key part of the resilience of critical infrastructures is the speed with which function is restored (Davoudi, 2012; Francis and Bekera, 2014; Holling, 1973, 1986, 1996; Maliszewski and Perrings, 2012; Tierney, 2014).

Our critical infrastructure of study is a portion of the electric power grid in the United States. The U.S. electricity delivery system is the largest machine ever created, representing more than $1 trillion (U.S.) in asset value. It includes more than 3,000,000 km of transmission lines, 950,000 MW of generating capability, and nearly 3500 utility organizations serving well over 100 million customers and 283 million people (Liscouski and Elliot, 2004). The electrical grid is a vast, complex infrastructure that is essential to human life in the United States. Substantial research investigates the causes of power outages and effective strategies for rapid restoration.

However, while policy makers, utilities, and researchers are concerned about the resilience of the electric grid, little attention has been paid to exactly *who* is affected by failures in resilience (e.g., Francis and Bekera, 2014; Maliszewski and Perrings, 2012). Because electricity is essential for life in contemporary society, lack of knowledge about disparities in provision is a problem. Given the monopoly status that utilities enjoy and the “just and reasonable” U.S. utility regulatory compact (McDermott, 2012; Oppenheim, 2016), utilities have an obligation to provide reliable electricity. If disadvantaged communities consistently experience longer electricity outages than their more advantaged neighbors, then utilities are arguably not meeting their mandate to serve the public interest (RAP, 2011). Further, such dynamics mean that utilities may be producing or exacerbating distributional energy injustices with potentially life-threatening consequences for disadvantaged communities (Bickerstaff et al., 2013; Browning et al., 2006; Ghanem et al., 2016; Halff et al., 2014; Heffron et al., 2015; Hernández, 2015; Jenkins et al., 2016; Klinenberg, 2002; Lin et al., 2011; Procupez, 2016; Reames, 2016; Sovacool and Dworkin, 2014; Sze, 2007; Walker and Day, 2012).

Existing research on the provision of a variety of services highlights the importance of two dynamics. On the one hand, socially marginalized people and places experience longer service disruptions and other adverse negative environmental consequences of institutional actions, suggesting potential institutional bias. This theme points to the

* Corresponding author.
E-mail addresses: raoull@uoregon.edu (R.S. Liévanos), chorne@wsu.edu (C. Horne).

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existence of what we call "unequal resilience;" that is, the extent to which the return to system equilibrium is unevenly experienced throughout the system. On the other hand, bureaucratic rules of organizations shape the environmental and service experiences of communities, suggesting that factors other than institutional bias play a role in producing unequal outcomes. Given these insights, the present study seeks to answer two research questions. First, do socially disadvantaged neighborhoods experience greater disruption to their electricity supply than more advantaged neighborhoods? Second, to what extent are inequalities in electrical service disruption due to institutional bias or to other factors?

To answer our research questions, we analyze the relationship between block group-level population composition and average outage duration in our U.S. investor-owned utility service area from 2002 to 2004. Data are drawn from the U.S. Census, the U.S. Geological Survey, and the utility's database of electrical power outages. Guided by the literature on intersectional environmental inequality (e.g., Ard, 2015; Collins et al., 2011; Downey and Hawkins, 2008; Liévanos, 2015, 2017; Pulido, 1996), we identify a factor variable of American Indian disadvantage as a positive demographic correlate of average outage duration. This initial finding suggests possible support for an institutional bias hypothesis of unequal resilience. However, spatial error regression models demonstrate that unequal resilience within our study area is most consistently explained by proximity to priority assets (i.e., hospitals), the average number of downstream customers affected by outages, and environmental conditions (i.e., the seasonality of outages). Results support the bureaucratic decision rules perspective (Meier et al., 1991; Oakley and Logan, 2007) – showing that utilities prioritize essential community assets and engage in customer triage (Maliszewski and Perrings, 2012).

That is, we find that disadvantaged neighborhoods experience longer outage duration. This difference in duration is not due to bias, but rather to rational bureaucratic decision-making, which is reflected in faster service restoration for neighborhoods near qualitatively important priority assets and with the greatest number of downstream customers affected. Nonetheless, we argue that such utilitarian bureaucratic decision rules limit the recognition of systematically-patterned and unequal service disruptions and the development of corrective actions. We conclude by discussing some of the policy implications of this inequality, especially for expanding the U.S. utility regulatory compact and the Low Income Home Energy Assistance Program, and we outline directions for future research on unequal resilience and energy justice.

2. Background and hypotheses

We begin by exploring insights from existing literature on dynamics that contribute to inequality, and the implications of this work in the context of the electric grid. We then examine work that seeks to disentangle inequalities due to institutional bias from those that are unintended. Our study does not provide a comprehensive analysis of all the factors that cause electrical outages and their duration. Rather, we focus on key factors relevant for testing our theoretical argument and apply our theory to a specific empirical case – a U.S. investor-owned utility district with particular forms of socioeconomic and racial disadvantage.

2.1. Neighborhood disadvantage and institutional bias

Research shows that socially marginalized people and places generally do not experience their material and social environment the same way as other segments of the population. Some environmental inequality researchers attribute these differences to biased institutions. For example, Ard (2015) uses an institutional bias perspective to explore enduring racial inequalities across the U.S. She highlights the contributions of policy-salient geographic areas to unequal environmental exposures. Such areas include, for example, U.S. Environmental Protection Agency regional divisions that oversee environmental enforcement activities, counties that carry out planning activities, and central city districts that have a legacy of segregated spaces and concentrated industrial activity (see also Sze, 2007).

Similarly, urban service inequality researchers have tested an "underclass hypothesis" (Lineberry, 1977). This perspective suggests that the concentration of socioeconomically disadvantaged, nonwhite, and/or politically marginalized residents in a neighborhood is associated with inferior services. This outcome is attributed to institutions favoring elite neighborhoods or overtly discriminating against disadvantaged neighborhoods (Lineberry, 1977; Wells and Thill, 2012). Researchers have found varying levels of support for this hypothesis in the distribution of police and fire (Boyle and Jacobs, 1982; Cingranelli, 1981), education (Feiock, 1986), parks (Talen, 1997), and transportation (Wells and Thill, 2012) services in some U.S. urban areas.

Thus, a theme across the literature is that particular segments of the population may experience biased treatment by institutions in a manner that varies depending on geography, history, and institutional context. It is therefore usually up to the researcher to empirically specify the disadvantaged population that is relevant to their study area. For example, Wells and Thill's (2012) study of bus service access in four southern U.S. cities expanded Lineberry's (1977) notion of the underclass to transportation-dependent riders like students and the elderly in addition to nonwhites and low-income individuals. Liévanos (2017) deployed an intersectional approach that specified the multiple domains of disadvantage – race, ethnicity, poverty, limited educational attainment, and English-speaking ability – that were correlated with vulnerability of exposure to toxic surface waters in California's Bay-Delta region (see also, Collins et al., 2011; Downey and Hawkins, 2008; Liévanos, 2015; Pulido, 1996).

We focus on neighborhood concentrations of socioeconomically disadvantaged American Indians.[1] American Indians were the most numerous minority group in our study area and time period, constituting 2.11% of the population in 2000. They have a history of subjugation reflected in centuries of forced assimilation, relocation, and isolation (Steinman, 2012). They have also experienced exclusionary environmental policy and disproportionate exposure to environmental hazards, often for the purposes of U.S. national security and energy resource development (Hooks and Smith, 2004; Vickery and Hunter, 2016). Research indicates that the disadvantaged social and historical position of American Indians may compromise their contemporary access to secure and stable energy resources (Brookshire and Kaza, 2013). Despite the recent growth in Native gaming establishments in the U.S., marginalized segments of the American Indian population (e.g., those with low to moderate income and tenuous employment) experience particularly enduring disadvantages (Davis et al., 2016). Such marginalized households are prominent in the urbanized, non-tribal land settings in our study area. Accordingly, we use American Indian disadvantage to test an institutional bias hypothesis of electrical outage duration:

Hypothesis 1. The *institutional bias hypothesis* states that neighborhood levels of American Indian disadvantage will be positively associated with neighborhood levels of average outage duration.

Because communities differ in population settlement patterns and racial histories (Pulido, 2006), hypotheses regarding a particular racial-ethnic group in one region of the world do not necessarily apply to that same group in other areas. We limit our focus to the disadvantaged

[1] We follow convention and use "American Indians" to refer to Native and indigenous populations in our study area because of the prevalent use of the term within previous related scholarship (e.g., Brookshire and Kaza, 2013; Davis et al., 2016), American Indian communities, and our U.S. Census data which technically refers to American Indian and Alaska Natives.

group that is most salient in our utility's service territory – disadvantaged American Indians. Appropriate tests of institutional bias outside our study area would focus on regionally-salient disadvantaged populations – for example, African Americans or Latinos in other urbanized settings of the U.S. (Reames, 2016); disabled, ill, and very young or elderly in the U.K. (Walker and Day, 2012); or the urban poor of West Africa (Silver, 2015).

2.2. Bureaucratic decision rules: priority assets and customer triage

Organizational factors other than biased actions can also shape the resilience, environmental, and service experiences of communities (Gotham and Greenberg, 2014; Grant et al., 2010; Koehler and Wrightson, 1987; Lineberry, 1977; Meier et al., 1991; Tierney, 2014). In particular, the urban service inequality literature shows that “bureaucratic decision rules” can produce differential outcomes. That is, “the quality and/or quantity of urban services are primarily functions of bureaucratic decision-rules made to simplify complex allocations of administrative time and resources” (Lineberry, 1977:67). On this view, the unequal distribution of services does not reflect an underclass bias nor is it related to the broader social and political context. Rather, it is an “unpatterned” inequality, resulting from organizational codes of conduct and routines “coupled with idiosyncratic historical events” (Oakley and Logan, 2007:218; Koehler and Wrightson, 1987).

This bureaucratic perspective is captured in triage approaches highlighted in existing research.[2] This research shows that electrical power utilities often prioritize restoration efforts based on the quality or significance of community assets and the number of customers affected (Maliszewski and Perrings, 2012), following a utilitarian notion of energy justice that seeks to maximize “the greatest good of the greatest number” (Sovacool and Dworkin, 2014:2). In the utility context, the bureaucratic decision approach suggests two hypotheses regarding the effects of neighborhood proximity to significant assets (i.e., hospitals) and the number of affected customers downstream from the neighborhood on outage duration:

Hypothesis 2. The *priority assets hypothesis* states that neighborhood distance to priority assets will be positively associated with neighborhood levels of average outage duration.

Hypothesis 3. The *customer triage hypothesis* states that numbers of affected customers downstream from a neighborhood will be negatively associated with neighborhood levels of average outage duration.

Research shows that organizations sharing institutional contexts (e.g., shared regulatory environments and professional standards) tend to behave in similar ways due to isomorphic pressures (DiMaggio and Powell, 1983). We therefore expect our hypotheses to apply to U.S. utilities broadly. We test our hypotheses in the service area of one particular investor-owned utility. Future research should test the bureaucratic decision rules hypotheses in a range of utility companies.

3. Data and methods

3.1. Investor-owned electric utility case and study area

Our study area falls within the service territory of a U.S. investor-owned electric utility. We refer to the utility with the pseudonym, “U.S. Electric,” to keep the identity of the utility confidential. We selected the utility with a convenience, non-probability sampling technique (Lofland et al., 2006) in which we took advantage of our second author's access to the utility. U.S. Electric is a member of the Edison Electric Institute (EEI), an association of investor-owned utilities whose members “serve more than 220 million Americans and make up 70% of the U.S. electric power industry” (EEI, 2016). Table 1 “cases” (Ragin, 1992) U.S. Electric in relation to the population quartiles of EEI-member U.S. investor-owned electric holding/consolidated companies ranked by the EEI (2015) for their market value, assets, employees, megawatt generating capacity, megawatt hour sales, total retail customers, revenues from megawatt hour sales to total retail customers, and service territory as of 2014. As shown in the final column in the table, U.S. Electric ranks below average on almost all characteristics – having medium levels of generating capacity, sales, customer base, and revenues. However, it has one of the larger service territories. The particularities of our case study present an organizational and geographic limitation, but there is reason to expect that the findings in this case have implications for other utilities. Because of institutional isomorphism, organizations within a field tend to behave in similar ways (DiMaggio and Powell, 1983). Thus, our analysis of U.S. Electric can inform future research and policy on how U.S. investor-owned power utilities respond to power outages and the consequences of those responses for patterns of resilience throughout the electric grid.

3.2. Units of analysis

We use census block groups with year 2000 boundaries (Minnesota Population Center, 2004) as our units of analysis. Similar to Liévanos (2017) and Reames (2016), we use these units because they are the smallest available for all data used in this study, and they facilitate more precise measurement of neighborhood exposure to electrical outage segments than other, larger spatial units like census tracts (c.f., Oakley and Logan, 2007). We found 133 census block groups whose boundaries intersected U.S. Electric's outage segment network from 2002 to 2004. After excluding one census block group with missing data, our analysis includes 132 census block groups with a respective average, standard deviation, minimum, and maximum area of 82.80; 197.86; .21; and 1233.21 km^2.

3.3. Dependent variable

We obtained complete data from U.S. Electric on modeled electricity outages throughout the utility's network from January 2002 to December 2014 as part of a larger project that seeks to understand risk and resilience in the evolving electric grid. The data set included a total of 76,735 confirmed and restored outage segments that occurred during the 2002–2014 time span. Outage segments are portions of the network that experience service disruption. We focus on outage duration patterns from 2002 to 2004 (rather than the entire 13 years) because this shorter time period is best matched with the 2000 U.S. Census.[3] There were 18 outage segments in 2002, 68 in 2003, and 53 in 2004. Outage duration per outage segment in minutes averaged 137.17 in 2002, 139.29 in 2003, and 151 in 2004.

Map A in Fig. 1 displays the 133 census block groups that intersected the electrical outage network from 2002 to 2004. Maps B and C in Fig. 1, respectively, represent the average minutes per outage segment and natural log of that average outage duration from 2002 to 2004 at the census block group level. We used the natural logged version of average outage duration as our dependent variable because it was a better approximation of a normal distribution than the raw average duration measure (c.f., Maliszewski and Perrings, 2012). The

[2] Previous research identifies additional factors, such as access to outages – outage locations that are easier to access are likely to be repaired more quickly (Maliszewski and Perrings, 2012). Here we do not develop hypotheses regarding all of the factors that might affect utility decision-making. Instead, we focus on the few that provide good indicators of the bureaucratic approach. Future research should more fully explore the range of factors that drive utility decision-making.

[3] In future work, we intend to match the utility outage data between 2005 and 2014 with corresponding U.S. Census American Community Survey population and housing estimates. Doing so will yield understanding of *the temporal* dimensions of unequal resilience that we do not address here.

Table 1
Comparison of U.S. Electric to other EEI-member investor-owned electric holding/consolidated companies by select characteristics for 2014.

Characteristic	EEI-member population							U.S. Electric value in relation to population percentile ranges
	N	Mean	Minimum	Maximum	25 percentile	50 percentile	75 percentile	
Market value ($1,000 s)	51	11.980	.471	53.324	2.977	6.629	17.042	0–25
Assets ($1,000 s)	62	23.626	1.000	120.709	4.909	11.684	37.460	0–25
Employees (1000 s)	62	7.789	.300	28.993	1.890	5.040	12.948	0–25
Generating capacity (1000 mw)	57	10.381	.008	62.653	1.542	3.957	13.185	25–50
Sales (1000,000 mwhs)	62	43.691	.976	211.832	7.615	21.472	69.900	25–50
Customers (1000,000 s)	62	1.725	.051	7.269	.308	.838	2.579	25–50
Revenues: mwh sales to customers ($1000 s)	62	3.736	.100	18.890	.729	2.036	4.896	25–50
Service territory (1000 km^2)	62	38.268	.402	311.382	5.078	16.917	47.644	50–75

Note: mw = megawatt; mw h = megawatthour, km^2 = square kilometers

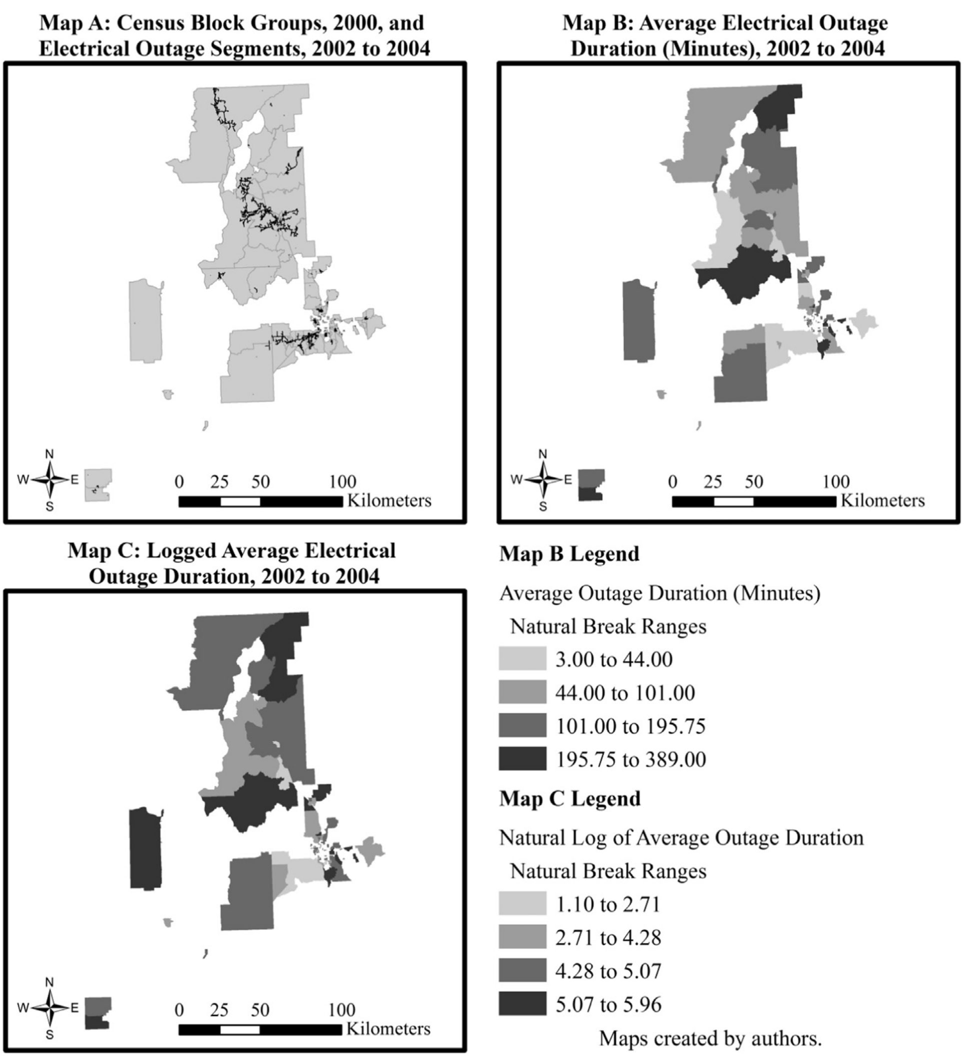

Fig. 1. U.S. study area census block groups and raw and transformed average electrical outage duration, 2002–2004.

descriptive statistics of our dependent variable and independent variables for our final 132-block group analytical sample are shown in Table 2.

3.4. Explanatory variables

To test the institutional bias hypothesis, we measure American Indian disadvantage. We did so with a factor variable comprised of four highly-correlated block group-level measures of socioeconomically-disadvantaged American Indians from the 2000 census. This composite measure helps us to avoid problems of multicollinearity while capturing the interlocking socioeconomic statuses of American Indians that are relevant for our study. To the best of our knowledge, this measure has yet to be used in prior research.[4] The variable was constructed

[4] We considered using a tribal lands variable to maintain comparability with research on energy-related challenges experienced by American Indians (Brookshire and Kaza, 2013). We did not do so because, in our study area, 98.5% of our units of analysis are not on tribal lands. Thus, our factor variable was a more valid indicator of American Indian disadvantage than a tribal lands variable.

Table 2
Descriptive statistics for variables used in the spatial regression analysis.

Variable	Mean	*SD*	Min.	Max.	Moran's *I*
Natural log of average total duration of outages per outage segment, 2002–2004	4.172	1.168	1.099	5.964	.545***
American Indian disadvantage, 2000	.000	1.000	−.264	8.218	.305**
Kilometers to nearest hospital, 2002–2004	5.231	6.086	.000	27.602	.720***
Average downstream customers affected per outage segment, 2002–2004	310.409	509.377	.000	2046.000	.571***
Number of outage segments, 2002–2004	2.205	2.146	1.000	11.000	.230**
Percent population inside urbanized clusters * median year housing units built interaction, 2000	8675.869	37,711.792	.000	198,400.000	.375**
Kilometers to nearest major road, 1999	.511	.839	.000	3.443	.747***
Percent block group covered with forest tree cover, 2001	20.615	26.648	.000	86.667	.694***
Percent of outage segments begun in summer, 2002–2004	34.697	42.043	.000	100.000	.339***

Note: N = 132 block groups. Moran's I analysis Based on 9999 permutations and a first-order queen adjacency spatial weights matrix.
** Pseudo p < .01 (two-tailed test).
*** Pseudo p < .001 (two-tailed test).

using similar principal component factor analysis techniques as in previous related research (e.g., Feiock, 1986; Liévanos, 2015, 2017). That is, American Indian disadvantage "represents a z score that is the uncorrelated linear combination of factor loadings that weigh each component variable" (Liévanos, 2015:55).

American Indian disadvantage is a reliable analytical construct with an eigenvalue of 3.864, a Cronbach alpha score of .896, and a 96.60% variance explained in the component variables. The factor loadings for each of the components were high. They ranged from .992 for percent households with 1999 income equal to or less than $59,999 and American Indian, .985 for percent persons 25 years and over with a high school diploma (or equivalent) or some college education and American Indian; and .981 for percent civilian population 16 years and over unemployed and American Indian to .973 for percent housing units renter occupied and American Indian.[5] Block groups with higher levels of this factor variable – reaching a maximum of 8.218 as shown in Table 2 and Fig. 2, Map A – do not represent the typical marginalized urban populations in literature on service inequality (Lineberry, 1977), environmental inequality (Ard, 2015; Liévanos, 2015), or energy vulnerability (Bouzarovski et al., 2013). Rather, those block groups reflect higher concentrations of disadvantaged American Indians in our study area – the unemployed, renters, and those with low-to-moderate income and education levels.

To test the priority assets hypothesis pertaining to the quality of customers affected by outages, we follow Maliszewski and Perrings (2012) and measure the distance from each block group to its nearest hospital. This variable was derived by assembling a dataset from regulatory sources of all hospitals within the utility's service area. We then extracted from the dataset all hospitals we verified were in operation from 2002 to 2004 and calculated the kilometers from each block group centroid to the centroid of the nearest hospital. The resulting block group-level distance calculations are mapped in Fig. 2, Map B.

To test our customer triage hypothesis regarding the quantity of customers affected by outages, we used a measure similar to that used in Maliszewski and Perrings (2012). We averaged the number of downstream customers affected per outage segment in the utility dataset and assigned those average estimates to the block groups that intersect each respective outage segment. This measure, mapped in Fig. 3, captures the number of affected customers downstream from each block group.

3.5. Control variables

Our analysis includes a number of control variables that approximate the broad set of physical factors featured in Maliszewski and Perrings (2012) that are posited to affect outage duration patterns. Our control variables also attempt to address broader claims of the bureaucratic decision rules perspective that researchers should take into account external pressures on the service provider (Koehler and Wrightson, 1987; Oakley and Logan, 2007). In addition, including the control variables reflects the point that understanding resilience dynamics requires a simultaneous examination of localized risk exposures (Francis and Bekera, 2014; Tierney, 2014).

We derive two control variables from the utility's dataset. The first is the number of outage segments that intersected each block group boundary from 2002 to 2004. This variable represents the extent of block group exposure to the network of electricity outages in our study area. A similar variable used by Maliszewski and Perrings (2012) was found to be positively correlated with outage duration patterns, suggesting that frequent exposure to outages is associated with longer average outage duration. The second control variable pertains to the seasonality of outages. Weather events generally increase outage duration (Davidson et al., 2003; Reed et al., 2010). The hotter summer months, in particular, can be peak times for residential electricity use and present situations in which outage restoration times are prolonged due to resulting stress on the grid (Maliszewski and Perrings, 2012). We control for the seasonality of outages by calculating the percent of outage segments intersecting each block group from 2002 to 2004 that began in the summer months of June, July, and August.

In addition to the seasonality of outages, research shows that areas with extensive tree cover are more likely to experience prolonged outages. This may be due to a number of factors, including the damage of fallen trees or tree limbs on power lines and the challenging environments that such land cover presents for crews attempting to restore power (Guikema et al., 2006; Maliszewski and Perrings, 2012; Simpson and Van Bossuyt, 1996). We calculated the percent of each block group that was covered by forest tree cover using version 2.0 of the U.S. Geological Survey, 2001 National Land Cover Database (Homer et al., 2004; U.S. Geological Survey, 2011). The variable was produced by first vectorizing raster spatial data representing "areas dominated by trees generally greater than 5 m tall, and greater than 20% of total vegetation cover," and deciduous forest (code 41), evergreen forest (code 42), and other predominantly non-deciduous and non-evergreen mixed forest (code 43) (Homer et al., 2004: 836). We then combined those percentages into a single measure of percent forest tree cover.

As suggested by the urban service inequalities literature (Lineberry, 1977), the ecological context of localized electrical power outages may be related to outage duration. For example, Maliszewski and Perrings (2012):677-8) found that "outage locations farther from arterial roads tend to have longer durations than outage locations closer to arterial roads." Following Liévanos (2015), we use the U.S. Geological Survey (1999) to measure the number of kilometers from the block group centroid to the nearest major road. In our regional study area, proximity to major roads within and beyond cities (not just arterial

[5] We did not use percent of persons 25 years and over without a high school education and American Indian (c.f., Liévanos, 2015, 2017) because it had a lower correlation with the other American Indian disadvantage variables (eigenvalue of 3.845, Cronbach alpha score of .833, and a 96.13% variance explained in the component variables).

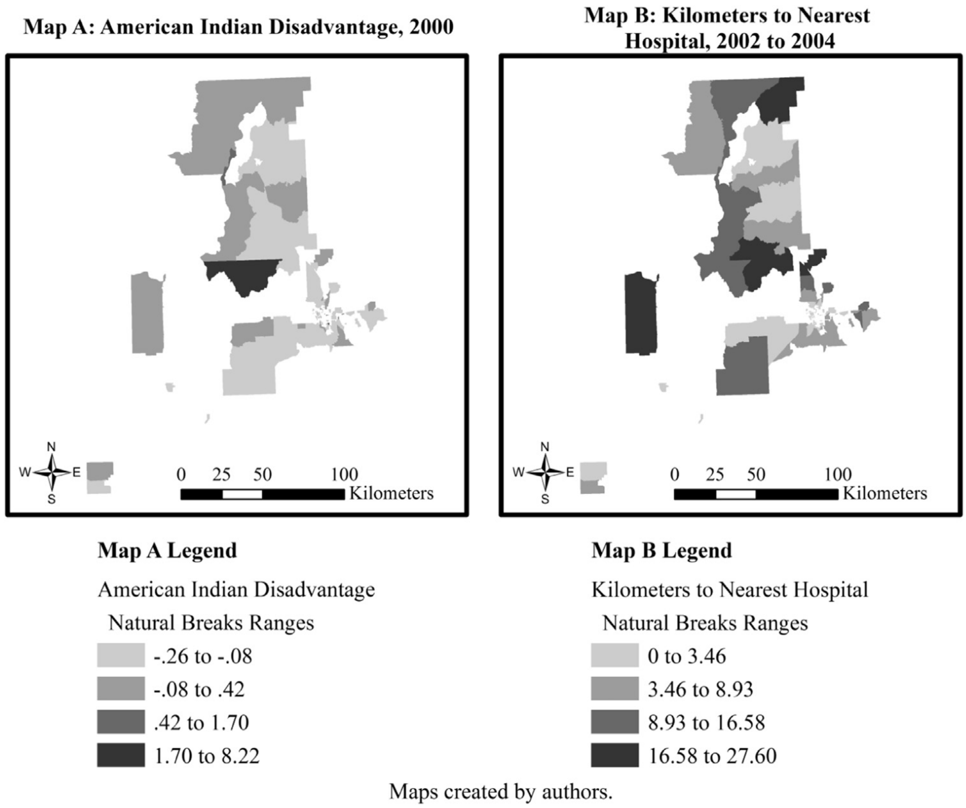

Fig. 2. American Indian disadvantage, 2000, and kilometers to nearest hospital, 2002–2004.

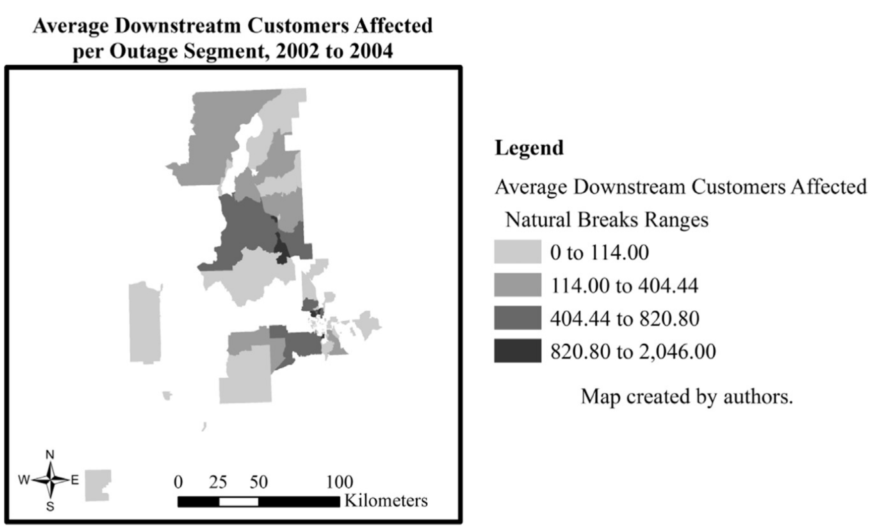

Fig. 3. Average downstream customers affected per outage segment, 2002–2004.

roads within a city) may facilitate faster response to electrical outages (c.f., Maliszewski and Perrings, 2012). Accordingly, this indicator includes both arterial roads and highways.

Lastly, Maliszewski and Perrings (2012) found that the distance from households to the central business district and the age of the housing unit (a proxy for infrastructure age where older houses represent older and more vulnerable infrastructure) had an interaction effect on average outage duration. This suggests that newer housing and infrastructure closer to the center city will experience shorter outage duration. We experimented with comparable measures for our regional analysis from available 2000 U.S. Census, summary file 3 data. We ultimately found that an interaction of the percent of population inside urbanized clusters (i.e., urban areas from 2500 to 50,000 people) and the median year built of housing units was the closest approximation we could achieve to Maliszewski and Perrings's (2012) urban-infrastructure interaction variable. Accordingly, we anticipate this control to be negatively associated with average outage duration, suggesting that block groups in a moderately-urbanized context with newer housing stock will have shorter average outage duration times.

3.6. Analytic strategy

We used linear regression techniques to test our hypotheses and assess the multivariate association between logged average outage duration and our explanatory and control variables. The Moran's *I* values shown in Table 2 reveal that all variables included in the regression analyses exhibit significant positive spatial autocorrelation. The spatial patterning for the dependent variable and the three explanatory variables is shown in Figs. 1–3. These patterns suggest a high likelihood that spatial relationships between block groups mediate the relationship between the within-block group values of our dependent and independent variables.

Accordingly, we used spatial econometric techniques (Anselin, 2005), as applied in environmental inequality (Chakraborty, 2009; Grineski et al., 2010; Liévanos, 2017) and power outage duration studies (Maliszewski and Perrings, 2012) to account for spatial effects. Moran's I tests on initial ordinary least squares (OLS) regression model residuals indicated that the OLS residuals exhibited significantly positive spatial autocorrelation. The Lagrange Multiplier (LM) diagnostic revealed a higher LM value for the spatial error model over the spatial lag model. This result suggested that the spatial error specification appropriately accounts for spatial effects in our regression analyses because it mitigates against biased standard error estimates produced in spatially-dependent OLS models (Anselin, 2005, 2009). Our approach thus accords with the notion that spatial error models are appropriate for studying the spatial dimensions of outage duration because outage duration is more dependent on the outage network and other spatial externalities than on spatially clustered residential settlements (Maliszewski and Perrings, 2012).

The spatial error model is generally defined as:

$$y = \alpha + \sum_k \beta_k X_k + \lambda We + u,$$

where y represents logged average outage duration, α is the constant, β is the coefficient for the k number of X explanatory and control variables, λ is the spatial autoregressive coefficient, W is the spatial weights matrix, e is the OLS model random error term, and u is the spatially independent error term (Anselin, 2005, 2009).

The spatial weights matrix captures the spatial relationships between block groups. Related research (e.g., Chakraborty, 2009; Grineski et al., 2010; Maliszewski and Perrings, 2012; Liévanos, 2017) used inverse, distance-based, row standardized spatial weights matrices. In contrast, we found that a row-standardized, queen first-order adjacency weights matrix successfully accounted for spatial dependence in our spatial error models. This spatial weights matrix resulted in 13 (9.85%) "neighborless" block groups because they did not share boundaries with other block groups – an acceptable neighborless percentage in this sort of spatial regression analysis (Chakraborty, 2009). The spatial weights matrix also produced a maximum of 9 and mean of 3.68 neighbors for the remaining 119 (90.15%) of block groups with an adjacent neighbor. For consistency, we use this spatial weight matrix for all spatial autocorrelation analyses.

4. Results

We begin by reviewing the bivariate correlations between our independent variables and logged average outage duration (Table 3). These bivariate correlations show that our independent variables do not exhibit alarming levels of intercorrelation. They also show that, as predicted, our explanatory variables have significant associations with logged average outage duration.

In particular, American Indian disadvantage has a low yet positive and statistically significant correlation with logged average outage duration. The correlation for American Indian disadvantage allows us to answer our first research question in the affirmative – socially disadvantaged neighborhoods in our study experienced greater disruption to their electricity supply. This finding provides evidence of a possible institutional bias in how the utility responds to outages.

The correlations are also consistent with the bureaucratic decision rules perspective – including attention to both the quality (Hypothesis 2) and quantity (Hypothesis 3) of customers. Average outage duration is longer in block groups that are farther from hospitals. The number of average downstream customers affected per outage segment has a moderate, negative, and statistically significant correlation with logged average outage duration. These correlations are consistent, respectively, with Hypothesis 2 and Hypothesis 3.

Only two of the control variables have significant and expected bivariate correlations with logged average outage duration. The urbanized cluster-housing stock interaction variable is negatively associated with outage duration. The summer outage variable is positively associated with outage duration. These associations show that average outage duration is shorter in medium-sized urban contexts with newer residential developments but more prolonged during the summer months.

Table 4 reports the results of the spatial error regression analysis. Model 1 assesses the extent to which our explanatory variables representing institutional bias or bureaucratic decision rules explain variation in logged average outage duration. Model 2 tests those explanatory variables and associated hypotheses net of our control variables. The unstandardized regression coefficients (b) aid in the interpretation of percent changes in the dependent variable with a unit change in a given independent variable. The standardized coefficients (B) are unit-less coefficients that allow us to identify the strongest performing independent variable in each model. The multicollinearity condition indices further verify the lack of collinearity between the independent variables. The indices are well below the suggested threshold of 30 (Anselin, 2005). The highly statistically significant spatial error coefficient (Lamda, λ) in both models and the insignificant Moran's I statistics for the regression residuals indicate that the models successfully addressed the spatial dependence in the relationship between the independent variables and logged average outage duration.

There are several important takeaways from the regression analysis. Model 1 features our three explanatory variables. It reveals that net of the two bureaucratic decision rules variables pertaining to priority assets and customer triage, the coefficient for American Indian disadvantage is positive as expected but not significant. This finding is inconsistent with the first hypothesis regarding institutional bias.

Instead, the results support the second hypothesis pertaining to priority assets (quality of customers) and the third hypothesis pertaining to customer triage (quantity of customers) – both of which reflect the bureaucratic decision rules perspective. The coefficient for kilometers to nearest hospital is statistically significant and positively associated with logged average outage duration. A one-kilometer increase in distance away from the block group's nearest hospital is associated with a 3.9% increase in logged average outage duration. Further, the standardized coefficient for the hospital distance variable indicates it is the second-strongest determinant of logged average outage duration in Model 1.

In addition, a one-person increase in the average number of downstream customers affected is significantly associated with a .1% decrease in logged average outage duration. The standardized coefficient for the average downstream customers affected variable demonstrates that it is the strongest determinant of logged average outage duration in Model 1. This highly significant relationship lends the strongest support for the customer triage hypothesis and bureaucratic decision rules perspective.

Model 2 adds our five control variables and produces no substantive change to the multivariate relationships between our explanatory variables and logged average outage duration as seen in Model 1. The only statistically significant control variable in Model 2 is the percent of outage segments begun in summer months. As expected, this variable is a positive determinant of logged average outage duration. It provides evidence that seasons significantly affect average outage duration in our study area. The unstandardized coefficients for this variable suggests that net of other factors, a one-point increase in the percent of outage segments occurring in the summer months is associated with a .3% increase in logged average outage duration. The standardized coefficient for the summer outage segment variable

Table 3
Pearson correlation coefficients for variables used in the regression analyses.

	1	2	3	4	5	6	7	8
1. Natural log of average total duration of outages per outage segment, 2002–2004								
2. American Indian disadvantage, 2000	.194*							
3. Kilometers to nearest hospital, 2002–2004	.222*	.328***						
4. Average downstream customers affected per outage segment, 2002–2004	−.523***	−.103	−.145					
5. Number of outage segments, 2002–2004	.092	.105	.174*	.029				
6. Percent population inside urbanized clusters* median year housing units built interaction, 2000	−.232**	−.035	.112	.018	−.113			
7. Kilometers to nearest major road, 1999	.018	−.079	−.209*	−.106	−.095	−.118		
8. Percent block group covered with forest tree cover, 2001	.100	.228**	.417**	−.022	.384***	−.064	−.316**	
9. Percent of outage segments begun in summer, 2002–2004	.380***	−.039	−.002	−.317***	.043	−.191*	.272**	−.111

Note: N = 132 census block groups.
* $p < .05$ (two-tailed test).
** $p < .01$ (two-tailed test).
*** $p < .001$ (two-tailed test).

Table 4
Spatial error regression results for logged average outage duration, 2002–2004.

Variable	Model 1			Model 2		
	b		B	b		B
Explanatory variables						
American Indian disadvantage, 2000	.025	(.071)	.021	.037	(.069)	.031
Kilometers to nearest hospital, 2002–2004	.039*	(.016)	.203	.035*	(.016)	.180
Average downstream customers affected per outage segment, 2002–2004	−.001***	(.000)	−.584	−.001***	(.000)	−.539
Control variables						
Number of outage segments, 2002–2004				.007	(.031)	.013
Percent population inside urbanized clusters * median year housing units built interaction, 2000				−3. E−06	(2. E−06)	−.086
Kilometers to nearest major road, 1999				−.012	(.122)	−.009
Percent block group covered with forest tree cover, 2001				.003	(.004)	.079
Percent of outage segments begun in summer, 2002–2004				.003*	(.002)	.122
Lambda	.696***	(.058)		.694***	(.058)	
Constant	4.517***	(.158)		4.330***	(.189)	
Pseudo R2	.671			.693		
Multicollinearity condition index	2.783			5.135		
Log likelihood	−145.475			−140.786		
Degrees of Freedom	128			123		
Akaike Information Criterion	298.950			299.571		
Moran's I	−.037			−.001		

Note. Standard errors are in parentheses. N = 132 census block groups. A first-order queen adjacency spatial weights matrix was used in the regression analyses and Moran's I analysis of regression residuals. Insignificance of Moran's I is based on 9999 permutations.
* $p < .05$ (two-tailed test).
*** $p < .001$ (two-tailed test).

indicates it is the strongest determinant of logged average outage duration among the control variables and the third-strongest determinant behind the bureaucratic decision rules variables in Model 2.

The pseudo R^2, Akaike information criterion (AIC), and log likelihood values are provided for reference in interpreting the fit of both models in Table 4. The pseudo R^2 for Models 1 and 2 suggest that, respectively, they account for about 67% and 69% of the variance explained in logged average outage duration. While informative, we follow convention and use the AIC and the log likelihood statistics to compare models, as larger log likelihood values and smaller AIC values suggest improved model fit across competing models (Anselin, 2005; Chakraborty, 2009). In this case, Model 2 is a marginal improvement upon Model 1 with an increase in the log likelihood of 4.69 points (3.22%) and barely detectible increase in the AIC of .62 points (.21%). Overall, the multivariate results demonstrate that unequal resilience and logged average outage duration patterns within our study area are most consistently explained by proximity to priority assets (i.e., hospitals), average downstream customers affected per outages, and environmental conditions (i.e., the seasonality of outages). Results support the bureaucratic decision rules perspective of service inequalities and the priority assets and customer triage hypotheses of utility response to electrical outages.

5. Conclusions and policy implications

Previous work on electricity outages has focused primarily on the biophysical and infrastructural causes of power disruption and restoration (e.g., Maliszewski and Perrings, 2012). Such research is essential for understanding how to reduce the number and duration of outages. But, it provides little insight into *who* is experiencing extended electricity disruptions. Our study shows that neighborhoods with a higher proportion of disadvantaged residents (in our case, disadvantaged American Indians) experienced longer outage duration. However, this association does not persist when other factors are included in the analysis. Instead, inequalities appear to be due to bureaucratic decision rules.

Our research has several limitations. First, it is restricted to one utility in one part of the country with a particular socioeconomic and racial-ethnic make-up. Thus, we do not make claims about the generalizability of our findings regarding American Indian disadvantage and outage duration. But, we expect the general theoretical argument to hold for utilities in other contexts. That is, because utilities across the U.S. are subject to related institutional pressures, they too are likely to follow similar bureaucratic decision-making rules. Future research should explore the implications of such decision-making for utilities in areas with different sociodemographic characteristics. It is likely, for example, that in areas with other historical settlement patterns, different groups may be disadvantaged. Such work could inform the understanding of how and under what conditions unequal resilience within the electrical grid is a local, regional, or national issue.

In addition, our study is limited in that is not a comprehensive analysis of all the factors that cause outages and their duration. There is substantial research on environmental, physical, and technological factors that affect outage duration (see Maliszewski and Perrings, 2012). But, researchers have very little understanding of the intersection of these factors with neighborhood sociodemographic characteristics. Our study represents a first step towards assessing the sociodemographic and spatial distribution of outage duration. Future research should expand on these efforts to incorporate other factors known to affect outage duration, alternative approaches to assess the effects of bureaucratic decision rules, as well as broader assessments of sociodemographic and spatial factors. It should also explore the extent to which factors that contribute to unequal electrical grid outage patterns (such as institutional biases or bureaucratic decision rules) vary across utilities that differ in size, governance (e.g., public or investor- owned), and other characteristics that differentiate utilities (see, e.g., Table 1). Such work could aid in integrating hitherto missing social science perspectives into energy and resilience research (Sovacool, 2014; Tierney, 2014).

Despite our study's limitations, our finding that unequal resilience exists but is not due to institutional bias is important. Given continued popular expression of distrust in institutional actors (Freudenburg, 1993) as well as recent surges in populist and anti-elite sentiment, it is useful to know that inequalities are due to objective factors. At the same time, given our results, one might be tempted to conclude that energy utilities and policy analysts need not consider the relationship between neighborhood disadvantage and power outage duration. As long as utilities follow utilitarian decision rules (Sovacool and Dworkin, 2014) – prioritizing important community assets and the greatest number of affected customers – inequalities may appear benign. After all, such an approach is not inherently discriminatory; it merely reflects the organizational rules of the game (Meier et al., 1991; Oakley and Logan, 2007). We believe that such a conclusion would be misguided. There are important reasons to care about inequality in resilience, even if that inequality is not due to bias.

A key problem is that blind adherence to bureaucratic rules can limit the ability of organizational actors and policy-makers to recognize how organizational behaviors contribute to the production or reproduction of subtle yet systematically-patterned inequalities (Lutzenhiser and Shove, 1999; Perrow, [1972] 1986). On its face, the rational bureaucratic approach to power outage restoration appears fair – consistent with the century-old “regulatory compact” that mandates that utilities offer universal service at just and reasonable rates (Oppenheim, 2016; McDermott, 2012). But, there are no rules or guidelines requiring electrical utilities to monitor the extent to which outage duration is correlated with neighborhood socioeconomic disadvantage. Utility companies are therefore unlikely to recognize inequalities in service provision. Indeed, our personal communications with U.S. Electric's staff indicated that they had no knowledge of the relationship between outage duration and neighborhood sociodemographic composition.

In turn, when institutions fail to recognize the diversity of people's needs and experiences, they tend to produce or reproduce distributional inequalities (Fraser, 1995). Accordingly, energy justice researchers argue that energy policy should explicitly recognize the challenges faced by the energy poor because “[w]ithout recognition of difference, specific needs and vulnerabilities can remain hidden and neglected in the formulation of policy interventions” (Walker and Day, 2012:72; see also Jenkins et al., 2016). In the context of our study, established bureaucratic decision rules for U.S. Electric results in not recognizing unequal electrical grid resilience for neighborhoods with elevated levels of disadvantaged American Indians. Such outcomes reflect another form of inequality experienced by American Indian communities (Brookshire and Kaza, 2013; Davis et al., 2016; Hooks and Smith, 2004; Steinman, 2012; Vickery and Hunter, 2016).

Our data do not speak to residents' perceptions. Accordingly, it is unclear whether residents of disadvantaged neighborhoods in U.S. Electric's service area are aware that they had longer outages than other more advantaged neighborhoods. Nonetheless, we recommend that utilities be particularly clear in their information-sharing efforts with disadvantaged communities. Such efforts may help to avoid perceptions of institutional bias and improve customers' communications with utilities in the context of power outages (Ghanem et al., 2016). They are also consistent with a form of procedural energy justice that extends access to information for marginalized and impacted social groups (Walker and Day, 2012). Utilities are beginning to move in this direction. Like other power utilities, U.S. Electric has taken steps to become increasingly transparent in its customer service by conveying to the public through internet, social media, and other digital communication channels the procedures the utility follows to restore power outages under normal and weather-related conditions. Also, current with practices in its field, U.S. Electric has implemented a digital system to alert customers of outage situations. It has a web-based interactive power outage mapping system that allows interested parties to view outages on a Google map and click links on the map to obtain additional information about the outage (e.g., time of outage, estimated restoration time, customers affected, and rationale for the outage).

As seen in other energy policy contexts (e.g., Reames, 2016), knowledge regarding the sociodemographic and spatial distribution of outages could be used to advance distributional energy justice goals by locating unequally impacted groups and neighborhoods for the targeted distribution of resources to manage outages through established government programs. In particular, notwithstanding important criticisms of the U.S. Low Income Home Energy Assistance Program (LIHEAP) (Higgins and Lutzenhiser, 1995), LIHEAP has become the largest energy assistance program in the U.S. for low-income customers. It helps customers who need help paying energy bills during hot or cold months, fighting the termination of energy service, or improving household energy efficiency (Murray and Mills, 2014). LIHEAP could be expanded further to provide to disadvantaged neighborhoods experiencing outages with back-up power such as generators or household battery storage. Such back-up sources can sustain technologies important for health and safety (e.g., medical devices) (Ghanem et al., 2016). LIHEAP could also help low-income customers gain access to otherwise inaccessible renewable sources of electricity generation such as solar power (Perez et al., 2011; Stram, 2016). At a smaller scale, LIHEAP could offer small solar panels to power specific devices – smart phones, battery powered lamps, and other technologies – during outage events. Given our findings, disadvantaged American Indian neighborhoods may be important starting points for this new way of distributing LIHEAP funding for U.S. Electric.

Our unequal resilience framework provides an example of how energy utilities and policy analysts might approach monitoring disparities in electricity provision. It shows that analysts can use outage records in conjunction with publicly available data (such as the U.S. Census) to track the sociodemographic and spatial distribution of outages. In turn, the knowledge gained could be used to implement programs tailored to particular contexts of disadvantage. Such efforts could improve energy justice, electrical grid resilience, and the ability of utilities to fulfill their mandate of universal service provision.

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