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Energy inequality and clientelism in the wake of disasters: From colorblind to affirmative power restoration

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ABSTRACT

Do social vulnerabilities and ruling party support shape government responsiveness in times of disasters? The 2017 hurricane María territory-wide power outage, the second longest in world history, is a tragic natural experiment that provides a unique opportunity to examine the determinants of government responsiveness during disaster recovery processes. We use data on power restoration crew deployments (N = 18,614 deployments), a novel measure of government responsiveness, and a new social vulnerability index to assess the determinants of government responsiveness in the wake of disasters. We find that communities with ties to the ruling party elicit greater government responsiveness while socially vulnerable communities are less likely to be prioritized during the disaster relief efforts, controlling for disaster damage as well as logistical, economic, and essential service recovery priorities. Existing power restoration policies place larger burdens on marginalized communities, motivating the need for including power restoration to vulnerable communities among restoration priorities.

1. Introduction

Energy is unequally distributed in ways that reflect longstanding socioeconomic inequalities (Bednar and Reames, 2020; Wu et al., 2017). In times of disaster, this unequal distribution becomes a matter of life and death (Carleton and Hsiang, 2016). Left in the dark, powerless areas experience excess mortalities, economic hardships, and weakened health systems (Anderson and Bell, 2012; Shuai et al., 2018). Thus, disaster recovery efforts and existing power restoration policies can exacerbate existing inequalities and generate new vulnerabilities (Sovacool et al., 2018; Thomas et al., 2019).

In 2017, the combined impact of hurricanes Irma and María on Puerto Rico's power grid led to a complete power outage, leaving 1.4 million consumers without power for months. With sustained winds of 250 km per hour (Pasch et al., 2019) and an aging power grid, hurricane María's devastating impact on the Puerto Rico Electric Power Authority's (PREPA) energy generation, transmission, and distribution infrastructure made this the longest outage in US history, and the second longest in world history. It took more than 425 days to completely restore power in the wake of hurricane María.

This outage had fatal consequences, contributing to the more than 1200 estimated excess fatalities (Cruz-Cano and Mead, 2019). Excess death affected those in the most socioeconomically marginalized sectors of Puerto Rican society (Milken Institute School of Public Health, 2018). Further, the hurricane María power disruption delivered a shock to the local and global economy and medical supply chain due to the increasingly global impacts of local cyclone damage and Puerto Rico's critical role in the global pharmaceutical supply chain (Aton, 2017; Shughrue et al., 2020). While parts of the San Juan metro area were brought back online within days of hurricane María's landfall, other areas waited more than 300 days to get power restoration crews assigned to their communities.

Existing electric utility approaches to post-disaster power restoration do not take indicators of socioeconomic status and political affiliation into account in the process of allocating disaster recovery resources. Instead, the electrical utility industry power restoration policies call for prioritizing restoration to essential services first, and second, the largest number of consumers per crew deployment, also known as the density-based approach (Edison Electric Institute, 2019). We term existing power restoration policies the *colorblind restoration approach*. Existing

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power restoration standards neglect preexisting inequalities that make some people more vulnerable than others to disasters, including ethnoracial, health, and economic disparities. In doing so, the colorblind restoration approach places a larger burden of powerlessness on race-class subjugated communities. Thus, colorblind recovery approaches exacerbate existing dimensions of disaster vulnerability.

2. Background

Previous research points to the inadequacy of the existing energy restoration approach and calls for considering multiple factors for the design of power recovery strategies and priorities (Román et al., 2019; Ji et al., 2016). However, existing research does not offer sufficient insight into the social and political drivers of energy restoration. Further, previous research on disaster recovery resource allocation has not considered how politics can impact differential power restoration rates, despite evidence of the electorally beneficial and socioeconomically unequal ways in which government officials allocate resources (Bertelli and Grose, 2009). This study holds the potential to inform the policies that govern how disaster energy resource allocations can be reprioritized and new restoration policies adopted so as to mitigate the fatal consequences of disaster response inequalities.

2.1. *The political economy of disaster resource allocations*

Critical disasters studies emphasize how disasters are “unnatural” – socially-produced by the existing socioeconomic and political conditions of the society, as well as the actions or inactions of states, corporations, and civil society groups (Wisner et al., 2004). Government inaction or partisan biases can reproduce and exacerbate existing inequalities through various practices, including clientelism and neglect of vulnerable communities (Bullard, 2008; Collins, 2010; Kammerbauer and Wamsler, 2017; Muñoz and Tate, 2016; Pastor, 2006). Governments can engage in a practice known as clientelism during disaster recoveries, which refers to the practice of allocating resources and services in exchange for political support. Previous studies have documented how party politics shape disaster responses and recoveries. For instance, communities with ties to powerful politicians recovered at faster rates in the wake of Japan’s 3/11 disasters (Aldrich, 2015).

Governments can neglect the needs of marginalized groups throughout disaster recoveries while prioritizing resources and services for those with ties to ruling parties (Thomas et al., 2019; Aldrich, 2015; Hicken et al., 2018; Sainz-Santamaria and Anderson, 2013; Reeves, 2011; Garrett and Sobel, 2003; Cohen and Werker, 2008). Political officials can allocate resources in ways that yield political gains or reward electorally supportive regions (Gallego, 2018; Hilhorst, 2013; Pelling and Dill, 2010). In turn, voters reward incumbents for their disaster response and favorable resource allocations (Reeves, 2011; Gallego, 2018; Cole et al., 2012; Healy and Malhotra, 2009).

Vulnerable populations are particularly at risk of government neglect in times of disaster. Disaster studies recurrently identify socioeconomic marginalization as a central aspect of vulnerability to disasters (Wisner et al., 2004; Fothergill and Peek, 2004; Karim, 2016; Sawada and Takasaki, 2017; Thomas et al., 2019). Vulnerability refers to a population’s exposure to risk, loss, and harm, and the attributes of that population shape the negative impacts from a disaster as well as its resilience (Cutter, 1996; Eakin et al., 2018). The case of Hurricane Katrina in New Orleans in 2005 demonstrated how race-class subjugated communities are more vulnerable to disasters and less likely to elicit government responsiveness (Bullard, 2008; Bullard and Wright, 2009; Elliot and Pais, 2006; Lubiano, 2008; Rodríguez and Russell, 2006; Flanagan et al., 2011).

Analyses on Puerto Rico after hurricane María show how pre-existing inequalities shaped inequalities experienced post-hurricane María in exposure to toxic pollution, water scarcity and sanitation, energy distribution, and food supplies (Brown et al., 2018; García-López, 2018; Lloréns et al., 2017; López-Marrero and Wisner, 2012; Cruz-Martínez et al., 2018; Padilla-Elías et al., 2016; Segarra, 2018). The vast majority of people residing in Puerto Rico inhabit urban and sub-urban areas (93.8%).[1] Further empirical assessments are needed to examine the extent to which non-urban localities were subject to neglect during the hurricane María recovery.

3. Objectives

Disasters have been labelled as an opportunity to transform socioeconomic institutions and infrastructures in ways that reduce vulnerability (Eakin et al., 2018). Yet, research has observed a tendency for disasters to become opportunities of profit-making and approval of unpopular measures by state and corporate actors taking advantage of the ‘shock’, furthering the inequalities of disaster reconstruction processes, what scholars have called “disaster capitalism” (Klein, 2007, 2018; Gunewardena and Schuller, 2008; Letelier and Irazábal, 2018). Scholarship on the hurricane María recovery identify instances of the enactment of recovery practices and policies that privilege powerful private actors (Klein, 2018; García-López, 2020). This study examines the extent to which government officials prioritized certain politically and economically privileged actors in the process of allocating energy resources in the wake of hurricane María. We expect that areas with lower support for the ruling party and areas with high social vulnerability took longer to elicit government responsiveness. We measure government responsiveness as the days that it takes to get a crew deployed to a locality.

Government responsiveness during times of disasters is particularly consequential, thereby motivating research on the socioeconomic and political drivers of responsiveness in the wake of disasters. Yet, to date, research has not applied these insights to the case of energy restoration following disasters. Thus, little is known about the impact of party politics and socioeconomic inequalities on power restoration rates after disasters. Further, post-disaster energy restoration can offer a useful measure of government responsiveness with the potential to reveal socioeconomic and politically driven inequalities. This study examines how community socioeconomic and political traits are associated to vulnerability, influence government responsiveness.

The case of the territory-wide blackout in Puerto Rico after hurricane María presents a unique opportunity to examine the social and political determinants of government responsiveness, and specifically, of power restoration rates. The harmful implications of differential power restoration rates across communities point to the need to adopt measures to ameliorate these disparities and develop more equitable restoration approaches. Yet, the lack of comprehensive and granular power restoration data hinders this kind of analysis. Electric utilities rarely share detailed power outage and restoration data. To fill this data void, previous assessments of outages and recoveries relied on satellite imaging, customer calls, and web scraping of investor-owned utility self-reports of aggregated outage reports (Ji et al., 2016; Román et al., 2019).

A previous study relying on satellite images over a six-month period revealed socioeconomic disparities in power outages and energy distribution (Román et al., 2019). However, the hurricane María power restoration exceeded a year in duration. Further, satellite data may overestimate energy access in areas in which residents have the means to purchase generators. Satellite data can also underestimate restoration due to sources of noise, including cloud cover, and their use of streetlight as a proxy for restoration. In order to address this extraneous noise, light data must be aggregated into multiple day periods. A comprehensive

[1] Puerto Rico is a small island archipelago with three inhabited islands, the mainland (Puerto Rico) and the eastern islands of Vieques and Culebra. Further data on Puerto Rico’s urban-rural classification is available at: https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/2010-urban-rural.html.

accounting of all crew deployments provides a more accurate measure of government responsiveness to energy outages.

To address these gaps and limitations, we use data on the date and location of all power restoration crew assignments during the hurricane María recovery in Puerto Rico to examine the social and political determinants of differential power restoration rates. We take advantage of the Puerto Rico courts' jurisprudential mandate of government data transparency on all matters of public interest to gather detailed and comprehensive restoration crew deployment data. This dataset contains detailed information of restoration crew deployments, including location and date, as well as important covariates expected to shape power restoration crew deployments. This study accounts for the effect of hurricane damage, social vulnerabilities, local political party support, social capital, the presence of pharmaceutical factories, hospitals, government buildings, and hotels.

PREPA, which managed restoration crew deployments, is a public corporation. PREPA crew assignments are a useful measure of government responsiveness. PREPA –as with other public institutions in Puerto Rico– has a documented history of being used for political gain. Indeed, the post-María reconstruction process has been marred by scandals (Safstrom, 2019), including claims of government favoritism towards municipalities of its own party in the use of reconstruction (Ortiz Menchaca, 2018). These processes mirror a longstanding dynamic of party patronage linked to Puerto Rico's public sector governance before María (Ortiz Menchaca, 2018; Pantojas-García, 2016).

Using the case of Puerto Rico, we examine the effect of community socioeconomic status and ruling political party support on energy restoration and test the claim that governments are less responsive to socioeconomically disadvantaged communities and opposition party strongholds in the wake of disasters. To this end, we develop a novel measure of social vulnerability designed to provide a more accurate accounting of vulnerability in majority-minority communities than prominent measures of vulnerability. Majority-minority communities are among the most vulnerable to disasters (Frank, 2020). We demonstrate that it takes less days to deploy restoration crews to less socioeconomically vulnerable areas and municipalities that support the ruling party executive, controlling for logistical, economic, and essential services restoration priorities. The results suggest that governments are more responsive to communities that lend electoral support for the ruling party and less responsive to highly vulnerable communities.

4. Method

4.1. Study design and measurement of government responsiveness

This study uses a sequential mixed method design where a qualitative phase precedes and informs a quantitative phase. The first stage of this sequence entailed qualitative interviews and archival research. The authors conducted 15 interviews with various key informants, including federal, state, and local emergency operations officials, officials from the Puerto Rico Electric Power Authority, and officials from US-based power utilities who were involved in the Puerto Rico energy restoration efforts after hurricane María as part of mutual aid agreements.[2] The authors also analyzed two archival documents that, along with the analysis of interviews, informed the selection of variables for statistical analysis. These archival documents were the transcriptions of a Puerto Rico House of Representatives hearing on the question of favoritism during the energy restoration efforts after hurricane María[3] and a document from the Edison Electric Institute (2019) outlining the electric utility industry's standard approach to restoring power after a storm. The authors analyzed interview and archival data through a grounded theory approach, which builds on the strengths of deductive and inductive reasoning by coding themes that emerge from existing theories on the outcome of interest as well as new themes that emerge from the data collected (Glaser and Strauss, 2017).

Using negative binomial regression model, we investigate the determinants of differential power restoration rates across census tracts in Puerto Rico during the hurricane María power outage of 2017–2018. We use PREPA's assignment of electric utility line worker crews by date and location during the hurricane María energy restoration as our measure of government responsiveness. PREPA managed and kept detailed records of all deployments during the hurricane María power restoration efforts and used this data to report deployment progress on a weekly basis to the USACE and FEMA officials, among other stakeholders. Thus, the data chosen for this is the most comprehensive and accurate record of restoration crew deployments. PREPA recorded a total of 18,736 deployments to 78 municipalities in 8 service regions.[4]

We use crew deployment data to calculate the numbers of days it took to deploy each crew. The data contains detailed information regarding the date of the crew deployment and the geo-location of the deployment (latitude and longitude in geo-locations). For each data point, we calculate the numbers of days it took PREPA to deploy the crew through the difference between the date hurricane María made landfall (September 20th, 2017) and the date PREPA deployed the service restoration crew.

We find that a negative binomial regression model to be the best fit given the structure of the PREPA deployment data. The days until deployment data is structured as count data, and thus a generalized Poisson model best fits the independent variable. Yet, the distribution of this data is over-dispersed. Thus, the negative binomial structure adds an extra parameter to the model to control for this over-dispersion.

4.2. Data on determinants of government responsiveness

4.2.1. Hurricane damage

We use the geographic coordinates of the PREPA crew deployment data to acquire Census tract level geographic identification for each deployment location. We then used the Census tract level of analysis for covariates and municipal level data where census tract data was not available or not applicable to the covariate. We use Census tract level data for our measures of social vulnerability and urban density, while our election data, building density (hotels, shopping malls, government buildings, and pharmaceutical factories), and social capital covariates are at the municipal level. Hospitals and María water intake zones are binary variables on whether an address comes within 2-miles of either a hospital or a María intake zone. María water intake zones refers to flooding, which we use as a proxy for hurricane damage. We also use wind damage as a proxy for hurricane damage.

4.2.2. Social vulnerability

The Center for Disease Control (CDC) calculates a widely used social vulnerability index (SVI) (Flanagan et al., 2011), which we used as the basis for the construction of a new social vulnerability index that we termed the Puerto Rico Social Vulnerability Index (PRSVI). We generated a new index because the existing CDC SVI is an inadequate tool for accounting for variations of vulnerability in majority-minority regions

[2] Utility companies frequently develop partnerships with other utility companies in cases in which the magnitude of power outages is too complex for one utility to address by itself. These partnerships are known as mutual assistance networks. More information about mutual assistance among utilities is available at: https://www.eei.org/issuesandpolicy/electricreliability/mutualassistance/Pages/default.aspx.

[3] Public hearing, Puerto Rico House of Representatives, Comisión de Desarrollo Integrado de la Región Oeste. 6/11/18.

[4] We removed 96 deployment addresses from the dataset due to issues with geographical identification computation.

(Rodriguez-Díaz and Lewellen-Williams, 2020). This is because the CDC SVI does not capture vulnerability across minority ethnic and racial subgroups in majority-minority regions like Puerto Rico, where 98.8% identify as Hispanic or Latino. This poses a challenge for disaster research, as previous research identifies an association between minoritized communities and disaster outcomes.

We generated the PRSVI to consider the unique dynamics of vulnerability in majority-minority regions like Puerto Rico. Our PRSVI, like the CDC SVI, uses Census data and includes measures for three distinct forms of social vulnerability: socioeconomic, household composition and disabilities, and housing and transportation variables. We also generate an overall social vulnerability measure. Our PRSVI, however, accounts for the distinct definition of "minority" in the Puerto Rican archipelago in two ways. First, given that the inability to speak English well does not necessarily preclude Puerto Ricans for engaging in everyday life or increase their disaster vulnerability, we drop this measure from our index. While the CDC SVI uses English language proficiency with the purpose of accounting for immigrant status, there is no reason to assume that the inability to speak English would be a vector of vulnerability in a region like Puerto Rico, in which the Spanish language is dominant. Second, minority status as a measure of vulnerability in Puerto Rico also differs from notions of minority status in the mainland US. We calculated a new minority variable to account for the racial groups that are considered minorities in Puerto Rico, including Black/African American, Asian/Asian American, Native American/Native Puerto Rican. In contrast to the CDC SVI, we exclude measures of Hispanic/Latinx, which is not a minority in Puerto Rico.

We follow the CDC SVI's method of index construction for all of our new PRSVI categories and an overall PRSVI. Both the CDC SVI and our new PRSVI are calculated as *percentile rank* for each individual index and one overall index of social vulnerability using the formula

$$Percent\ Rank = \frac{Rank_1 \pm Rank_2 \pm \cdots \pm Rank_n}{N}$$

where *Rank* is the percentage or total number of that variable and *N* is the total number of data points. For each social vulnerability variable, 1 equals to the Census tracts with lowest SVI, while 0 refers to Census tracts with the highest SVI.

In aims of providing assessing the validity of our new social vulnerability index, we compared the association between each SVI (CDC SVI and PRSVI) and another outcome of hurricane María that could have been associated with vulnerability. In this case, we chose to examine the association between the PRSVIs and excess deaths. We calculated the mortality rate ratio at the municipal level by dividing the number of deaths in September to December of 2017 by the number of deaths in September to December of 2016 and multiplying by 100. We ran an OLS with the PRSVI as the key independent variable and the log mortality rate ratio as the outcome variable, accounting for other potential determinants of excess deaths (Appendix A, Table A.8). We find a statistically significant relationship between the PRSVI and the log mortality rate ratio, controlling for the median days to power restoration crew deployment, social capital, urban area, density of government buildings, ruling party support, hurricane damage, and hospital proximity. This is the first statistical analysis of the determinants of hurricane María excess deaths that accounts for vulnerability and government responsiveness.

4.2.3. Ruling political party support

The Puerto Rico Electoral Commission provides data on the 2016 Puerto Rico gubernatorial election at the municipal level. We use data on electoral victories during the 2016 elections of the incumbent governor at the municipal level to examine the effect of partisan politics on restoration crew deployments. We choose to operationalize ruling political party support as a binary variable because it allows us to examine whether the electoral victories of the ruling party's gubernatorial candidate at the municipal level influenced the allocation of power restoration crews. We chose a binary variable over a continuous variable (percentage of municipal-level votes for the gubernatorial candidate) because we expect that those tasked with allocating power restoration crews incur in greater costs to identify the relative strength of the ruling party's hold on a locality than they do to identify whether the ruling party's gubernatorial candidate won the elections in a given locality. Prior research suggests that executives use disaster resource allocations to reward voters for their electoral support (Gallego, 2018).

Government officials can influence power restoration through various mechanisms. Given that PREPA is a highly politicized public utility under the local Puerto Rico government's control, we consider PREPA's power restoration crew assignments to be a useful and one of the most important proxies of government responsiveness in the wake of the hurricane María.[5] PREPA has been described in US House Committee on Natural Resources hearings as a "a vertically-integrated self-regulated monopoly" (San Miguel, 2016). Further, PREPA was the subject of multiple allegations of corruption during the hurricane María power restoration effort (Bases, 2018). Opposition party mayors held a demonstration more than 100 days into the hurricane Maria power outage denouncing without power and alleging favoritism for ruling party-supportive municipalities (CB en Español, 2018). Existing analyses of PREPA show a history of the ruling party's use of PREPA for political purposes and subject to political interference (see for example Sanzillo and Kunkel, 2018). The ruling party appoints PREPA executives and has the authority to remove them, an authority that the governor exercised three times during the hurricane María recovery. Interviews with state and local government officials in Texas and Florida involved in the 2017 recoveries in the wake of hurricane Irma and Harvey detail the reciprocal relationships developed between local and state executives.[6,7] State executives hold influence over energy government resource allocations and policies, which affect electric utility companies and the extent to which they benefit from these allocations and policies.

4.2.4. Social capital

Social capital, which consists of social ties and networks that communities can mobilize in ways that counter these negative effects of environmental hazards and disasters, can improve their disaster recovery outcomes, such as reduced mortality, and elicit government responsiveness (Kammerbauer and Wamsler, 2017; Pelling and Dill, 2010; Aldrich, 2012). Civic groups and community organizations are important conduits of information and resources during critical junctures and distributors risk mitigation resources (Aldrich and Sawada, 2015; Beggs et al., 1996; Granovetter, 1973). We draw from a database of non-profit organizations in Puerto Rico from the Puerto Rico Department of State in 2019 to account for social capital, which we measure as the presence of non-profit organizations per capita at the municipal level that were active during the hurricane María power outage (2017–2018).

4.2.5. Restoration priorities

Interviews with PREPA officials served to identify PREPA's stated priorities for power restoration, which echoed energy industry power restoration standards that stipulate that power should be restored to essential services (e.g. hospitals) first, then to large and densely populated service areas, and eventually to smaller service areas and homes (Edison Electric Institute, 2019). During interviews, PREPA officials also identified pharmaceutical factories and large commercial properties as

[5] Since June 1st, 2021, transmission and distribution operations in Puerto Rico are under the purview of the firm LUMA energy.

[6] Interview with Florida state government emergency management official. (3/26/2019).

[7] Interview with Harris County, Texas emergency management official. (3/7/2019).

priorities, citing the government's interest in reducing the economic impact of the outage and addressing the shortage of medical supplies manufactured in pharmaceutical factories based in Puerto Rico.[8] The severity of damages is also known to affect disaster recovery (Kates and Pijawka, 1977), including power restoration (Duffey, 2019).

We include measures of proximity to hospitals as a covariate in our analysis to account for PREPA's priority to restore energy to essential services. With data from the Puerto Rico Government GIS website, we created a 2-mile buffer around hospitals and government buildings and generated a dummy variable for each address based on its location within or outside of this 2-mile buffer. To account for the electric industry standard of customer density-based restoration (Edison Electric Institute, 2019), we use U.S. Census data to control for urban density. Our measure of urban density consists of the percentage of the total geographical area considered "urban" as of 2010.

Given PREPA's assessment of the damaging impact of flooding on its grid (New York Power Authority et al., 2017), we account for flooding damage with data from the Environmental Response Management Application (ERMA) of the National Oceanic and Atmospheric Administration (NOAA). To this end, we generate a dummy for each deployment address based on its location within or outside a 2-mile buffer zone around hurricane María water intake zones. We account for economic priorities for restoration (hotels and shopping malls) with data from the Puerto Rico Industrial Development Company. The Pharmaceutical Industry Association of Puerto Rico provided data on the location of pharmaceuticals.

5. Results

Hurricane María power restoration crew deployments took a median 78 days and an average 91 days. Of the 18,736 crew deployments, 92.4% of PREPA crew deployments occurred within 150 days (approximately 5 months) of the hurricane's landfall, with deployments plateauing afterwards (Appendix Fig. C.1). It would take an additional 275 days to complete the power restoration deployments, generating broad restoration rate disparities across communities. The map of days-to-restoration at the Census tract level for the municipality of San Juan, shown in Fig. 1, demonstrates that affluent areas like Condado waited less than 40 days on average for crew deployments while nearby areas like the Luis Llorens Torres public housing project waited more than 100 days on average. Similar disparities are observed in Carolina, shown in Fig. 2.C, where Isla Verde, an affluent locality, waited significantly less days on average for crew deployments than more socially vulnerable communities South of Isla Verde. Fig. 2 displays the disparities of the days it took to deploy energy restoration crews across census tracts in Puerto Rico after hurricane María. We display the municipalities of Caguas, Río Grande, Ponce, and Carolina due to their ability to illustrate the spatial disparities of crew deployments across census tracts following hurricane María. The maps included in Fig. 2 demonstrate disparities in restoration crew deployment within differentially vulnerable and contiguous communities in urban areas.

This study seeks to reconcile whether socioeconomically and politically marginalized groups are less likely to benefit from government responsiveness in times of disasters. We use negative binomial regression to assess the effect of a socioeconomic vulnerability index and ruling party support on the days-to-deployment of power restoration crews, controlling for geographic, atmospheric, logistical, and economic variables.

5.1. The politics of energy restoration

We are interested in assessing the effect of support for the ruling party incumbent on the deployment of energy restoration crews. Only 38% of crew deployments that took over 150 days during the outage went to ruling party-supportive municipalities, whereas more than half of the crews deployed after 150 days of the hurricane María power outage went to municipalities that did not support the ruling party (62%). The median days to restoration crew deployment to municipalities that voted for the ruling PNP gubernatorial candidate in 2016, the incumbent during the hurricane María recovery, was 74 days, compared to 83 days to municipalities in which the majority voted for the opposition Popular Democratic Party (PPD) gubernatorial candidate. The differential rates of power restoration crew deployments across ruling party supportive and opposition municipalities suggests the plausibility of a relationship between party politics and energy restoration rates, accounting for logistical, economic, and essential services restoration priorities.

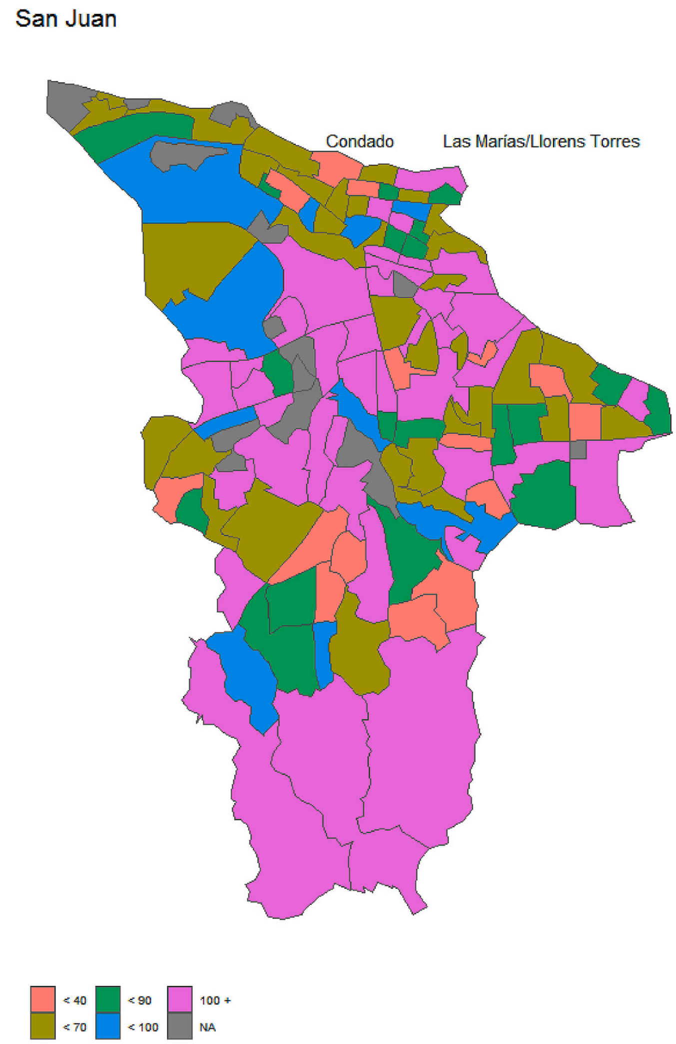

Fig. 1. Disparities in days to energy restoration crew deployment across census tracts in San Juan during the hurricane María power outage. Difference of colors demonstrates the disparities across census tracts in the municipality of San Juan. Labels represent the location of coastal residential neighborhoods of Condado (in red) and Las Marías/Llorens Torres (in purple). While the more affluent Condado census tract received crews within less than 40 days on average, the nearby less affluent Las Marías/Llorens Torres census tract waited more than 100 days on average for crew deployments. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

We use negative binomial regression to examine the relationship between political support for the ruling party incumbent and energy restoration rates. For this analysis, we are interested in covariates with a

[8] Interview with PREPA official. (3/25/2019).

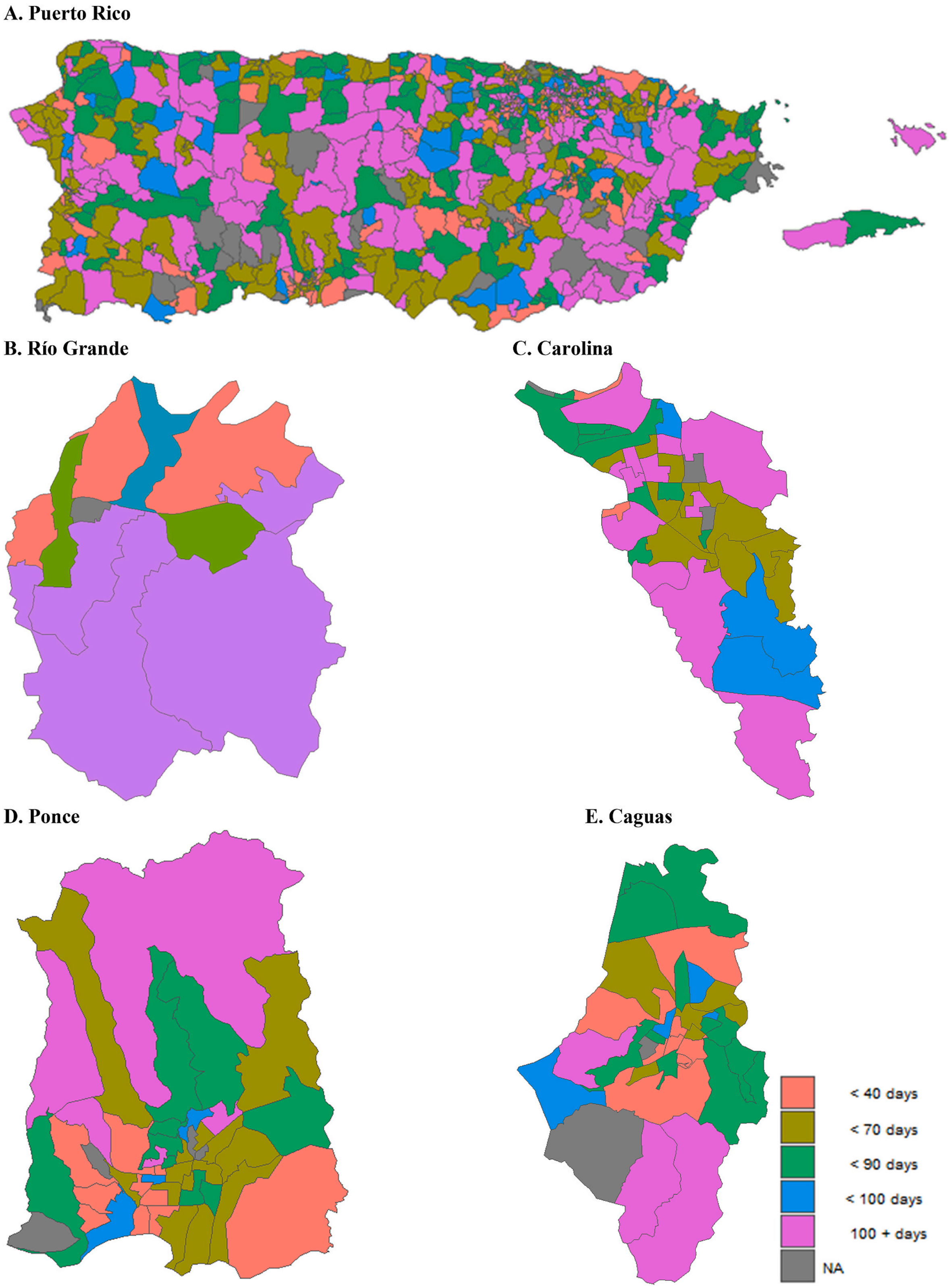

Fig. 2. Disparities in days to energy restoration crew deployment across Census tracts in Puerto Rico during the hurricane María power outage. Difference of colors demonstrates the disparities across census tracts. While some census tracts received energy restoration crew deployments within less than 40 days on average, other census tracts waited more than 100 days on average for their first restoration crew deployment after hurricane María. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

statistical significance at 95% or above, which include support for the ruling party governor, socioeconomic vulnerability, household composition and disability vulnerability, housing and transportation vulnerability, urban density, and residing within two miles of a hospital. We find that ruling party support has a significant impact on the length of time it takes to get a service restoration crew assigned. Addresses in municipalities in which the ruling PNP incumbent won the 2016 gubernatorial election were assigned power restoration crews in less days than in municipalities in which the opposition PPD candidate won (marginal effect coefficient: 2.52; p-value: < 0.05). The marginal effects of party demonstrate that service crews arrived in municipalities in which the ruling PNP won the 2016 gubernatorial election approximately 3 days sooner than municipalities in which the opposition party candidate won. Communities experiencing longer power outages faced numerous hardships, including mortalities (Milken Institute School of Public Health, 2018). Further, in a context of extreme heat like Puerto Rico after hurricane María, where there was fuel scarcity that hampered the use of generators and where there are disparities with respect to access to generators, and where there is relatively high number inhabitants needing electricity-dependent devices (e.g. dialysis patients and patients on ventilators and respirators), a day without power can determine whether a person survives an extreme weather event.

There is a notion that proposes that hurricane María most severely impacted opposition party strongholds (PPD party), and that these PPD supportive municipalities are also higher in vulnerability than PNP ruling party municipalities, therefore explaining why PPD strongholds took longer to get a power restoration crew deployed to their municipalities. To further examine the claim that restoration crew deployment may have taken longer for opposition party strongholds (PPD) and areas with higher vulnerabilities due to increased hurricane damage in these areas, we ran a Welch Two Sample t-test and found that PPD support is significantly different from hurricane María damage. We ran this analysis for both measures of hurricane damage (wind and flooding) and we find that PPD support is significantly different from damage for each of these measures. Further, PPD support and damage from hurricane María are not correlated with each other. Finally, we ran a linear regression to assess the relationship between ruling party electoral support (PNP) and percentage of people below poverty (Appendix A) during the 2016 gubernatorial election in Puerto Rico, and find that PNP electoral support and poverty are positively correlated. Ruling party votes increase as poverty increases. Thus, the notion that PPD municipalities took longer to receive power restoration crew deployments due to higher vulnerability and hurricane damage is not supported by our analyses.

5.2. Social vulnerability and power restoration

Fig. 3 displays the predicted number of days to restoration crew deployment by type of social vulnerability: socioeconomic, household composition, housing and transportation, and overall social vulnerability. Linear correlation analysis between days until deployment and our social vulnerability indices show higher vulnerability correlating with longer waits for power restoration crew assignments. There is an

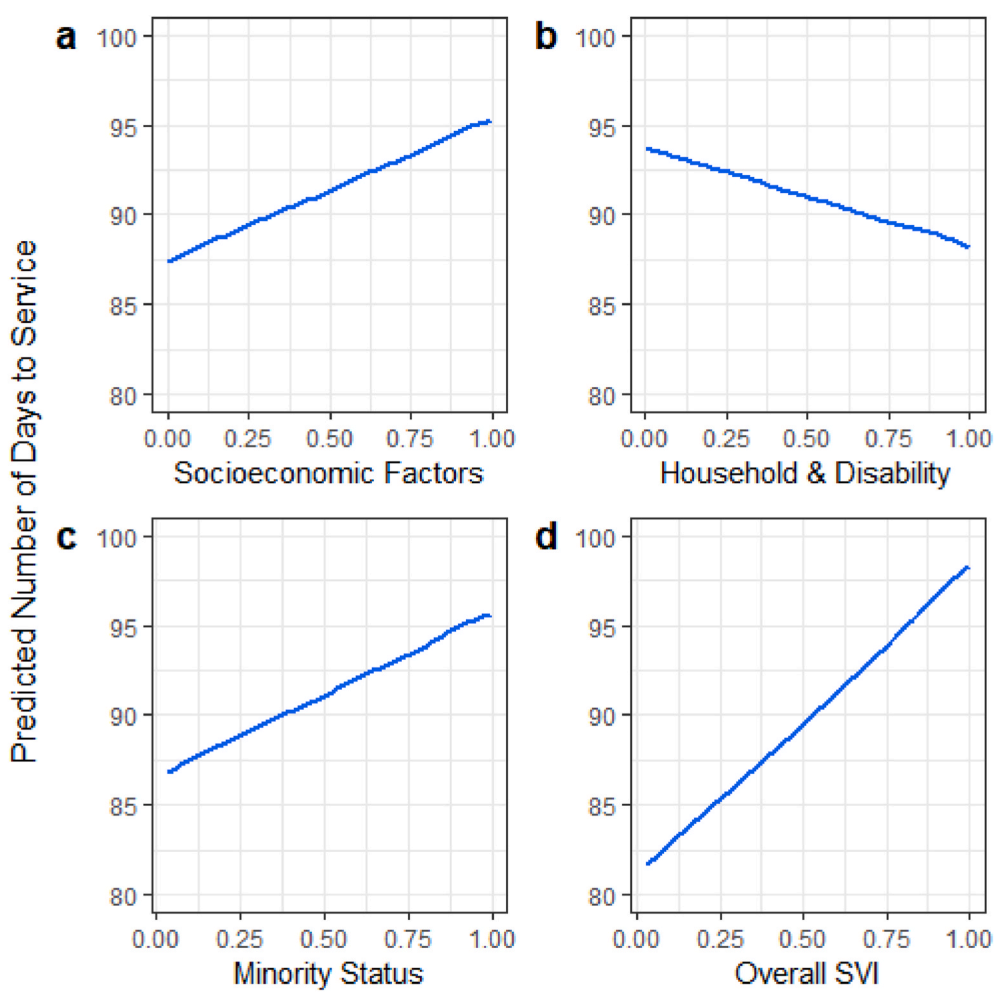

Fig. 3. Predicted number of days to crew deployment by social vulnerability. The charts represent the predicted number of days to crew deployment by the percentage of social vulnerability for a given census tract. The predictive probability accounts for all covariates held at their means. These models include all 18,614 deployments. **A.** Socioeconomic Vulnerability. **B.** Household Composition & Disability. **C.** Minority Status. **D.** PR SVI Overall.

increase in approximately 8 days to crew deployment for every one-unit increase in socioeconomic vulnerability (marginal effect coefficient: 7.94; p-value < 0.01). The same relationship does not exist for the young, elderly, disabled, and household density; as the percentage of these groups increases by one-unit, there is a decrease until crew assignment of 5 days (marginal effect coefficient: 5.41; p-value < 0.01). Traditionally, in the study of disasters, household density is assumed to be an aspect of vulnerability. High-density can pose challenges for evacuation (Cutter et al., 2003). Yet, in the case of energy restoration, areas with high household density can have an advantage over less densely populated areas, as the energy industry prioritizes crew deployments to areas with high volumes of customers, where each deployment will yield a higher number of customers with power restored (Edison Electric Institute, 2019). There was no statistically significant relationship between housing and transportation and days to crew deployment.

We find a substantive relationship between minority status and days-to-crew deployment. As a community's percentage of minority residents increases by one unit, there is an approximately 9-day increase in the days it took the community to receive a power restoration crew (marginal effects coefficient: 9.24; p-value < 0.001). This finding provides further empirical support for the notion that ethnoracially marginalized communities are less likely to elicit government responsiveness during disaster recoveries. Further, it demonstrate the inadequacy of restoration approaches that fail to consider how their priorities place larger burdens of powerlessness on racially marginalized communities.

The overall PRSVI is a substantive predictor in long wait times for crew deployment: when taking into account all four areas of vulnerability, places where overall vulnerability increases by one-unit, wait until crew deployment increase over 17 days (marginal effect coefficient: 17.51; p-value < 0.001). This finding suggests that intersectional dynamics can shape social vulnerability to disasters and its consequences, including government neglect. Intersectionality posits that multiple intersecting systems of oppression interact to shape lived experiences (Collins and Chepp, 2013). In this view, vulnerability, marginality, and oppression cannot be understood in isolation through examinations of single axes, such as class. Accordingly, assessments of marginalization should examine how social group dynamics such as race and class interact to shape lived experiences, including how communities experience disasters. When we account for the interaction between socioeconomic and racial marginalization, and their impact on energy restoration, we observe the greatest government neglect.

We do not claim, however, that our PRSVI is an adequate tool for examining the intersectional dynamics of social vulnerability to disasters. The PRSVI, modeled after the CDC SVI, relies on an additive measure that assumes that vulnerability is the sum of multiple disadvantages, such as socioeconomic status, race, immigrant status, among other categories (See Flanagan et al., 2011 for greater details on the construction of the CDC Index). Yet, intersectionality breaks with essentialist views of social groups by avoiding biological, static, and additive notions of identity (Hancock, 2007; Weldon, 2006). Thus, our analysis provides limited evidence about the impact of vulnerability on government responsiveness and further research is needed to understand the intersectional dynamics of social vulnerability and their impact on disaster outcomes. Recent research considers potential pathways for quantitative analysis of intersectional dynamics (Bauer et al., 2021).

5.3. Electric industry standards and power restoration

We examine the extent to which PREPA followed electric utility industry restoration standards, which dictate that restoration must first focus on restoring power to essential services and then adopt a density-based approach that restores power to the highest number of customers per mission (Shughrue et al., 2020). We use interviews with PREPA utility officials to identify additional priorities for restoration. PREPA officials shared that, in addition to essential services, they prioritized local pharmaceutical manufacturing factories so as to restart the economy.[9,10]

In a simple univariate linear regression, every one-unit increase in urban density, it took approximately 30 less days until restoration crew deployment. Our negative binomial regression results show that areas with higher urban density were assigned restoration crews sooner than those with lower urban density (marginal effect coefficient: 30.03; *p*-value < 0.001). The marginal effects for urban density are also quite high, with increased density leading to substantial decrease in the number of days to restoration crew deployment. We find similarly high effects of the proximity to a hospital on days to power restoration crew deployment. Our negative binomial regression model finds that addresses within two miles of a hospital, which provide essential services, were assigned power restoration crews sooner than areas without hospitals (marginal effect coefficient: 7.82; p-value < 0.001). Controlling for other variables, areas with a hospital within two miles were serviced approximately seven days sooner than those without a hospital. We also find that municipalities with higher densities of government buildings were also serviced sooner than those with less density of these building types (marginal effects coefficient: 199.34; *p*-value < 0.01). The associations between hospitals and crew deployments as well as government buildings and crew deployments provide an indicator of the extent to which government officials followed energy industry restoration standards, whereby electric utilities first restore power to essential service providers (Shughrue et al., 2020).

5.4. Economic priorities, social capital, and hurricane damage

We account for the effect of economic motivations for power restoration, including restoration to hotels, shopping malls, and pharmaceutical factories. We do not find an effect of economic restoration priorities on days to power restoration crew deployments. This study also tests the claim that damage is the strongest predictor of rates of disaster recovery (Kates and Pijawka, 1977). We use hurricane María flooding data, also known as water intake zones (2-mile radius), as a proxy for hurricane damage and do not find that areas with increase flooding damage waited less for power restoration crew deployments than those outside of the intake zones, accounting for logistical, economic, and essential services restoration priorities as well as social and political determinants. Further, we find no association between varying wind speeds and days to restoration crew deployments.

Lastly, we examine the effect of social capital on days to restoration crew deployments. Contrary to previous research that points to the positive impact of social capital on disaster recovery outcomes (Aldrich, 2012), we find that increases in social capital extend the number of days until crew deployment by almost one month using this measure (marginal effect coefficient: 911.59; *p*-value < 0.001). While prior research has conceptualized social capital as ties to government officials and powerful elites, through the term linking social capital (Szreter and Woolcock, 2004), our study adopts a notion of social capital as social ties among community members. We consider the partisan political dynamics that impact government responsiveness during disasters to be conceptually distinct from the ties among community groups that can be mobilized to elicit government responsiveness and share information and resources.

6. Conclusion and policy implications: from colorblind to affirmative restoration

In recent decades, Latin America and the Caribbean became the

[9] Interview with PREPA official. 4/15/19.

[10] Public hearing, Puerto Rico House of Representatives, Comisión de Desarrollo Integrado de la Región Oeste. 6/11/18.

region with the second highest annual average of disasters, after Asia (Padilla-Elías et al., 2016). The historic 2017 Atlantic hurricane season was only the second time that multiple Category 5 hurricanes made landfall and was the costliest tropical hurricane season on record (Drye, 2017). Climate change is expected to increase the frequency of cyclones and their damage (Mendelsohn et al., 2012), and disaster-related outages will ensue.

Previous research investigates the relationship between differential electric restoration rates and socioeconomic vulnerability, but a study on the effects of politics on differential restoration rates does not yet exist. We build an original dataset that derives crew deployment data directly from the government agency tasked with making crew deployment assignments, PREPA. We used negative binomial regression to assess the effect of social vulnerability and political marginalization on government responsiveness, measured as the days it takes to get a power restoration crew deployed. This study offered two main innovations. The first is the use of the allocation of energy as a resource as a novel measure of government responsiveness during periods of disasters. This is an aspect of government responsiveness with life and death implications. The second innovation is the development of a novel index of social vulnerability that enables an accounting of vulnerability in majority-minority regions.

The results provide further evidence for the claim that socially vulnerable and political marginal communities are less likely to elicit government responsiveness in the wake of disasters. During the hurricane María power restoration effort, communities with higher social vulnerability indices waited longer for power restoration deployments than less vulnerable communities. This provides further evidence of government neglect of vulnerable communities during the hurricane María recovery (Segarra, 2018; Román et al., 2019), while specifically showing the racial and economic dynamics of government responsiveness – a historically neglected issue in Puerto Rico. Similarly, communities that did not provide electoral support for the ruling party governor waited longer for service restoration crew assignments than those that voted for the governor. This finding confirms previous research that highlights the electorally favorable ways in which governments allocate disaster recovery resources (Sainz-Santamaria, 2013; Reeves, 2011; Garrett and Sobel, 2003; Cohen and Werker, 2008), while applying it to the context of energy restoration. As such, it illuminates the political determinants of disaster recovery resource allocation and its potential use as a form of pork barrel spending and clientelism. In the case of Puerto Rico, these localized inequities in government responsiveness were compounded with the ineffective and unequal Federal government disaster response vis a vis US states during the 2017 hurricane season (Willison et al., 2019).

We find that areas with higher urban density waited less for power restoration crew assignments. This finding points to a way in which vulnerability during energy outages is different from vulnerability to other kinds of disasters. Traditionally, housing density is considered a social vulnerability because it can pose challenges for evacuation (Cutter et al., 2003). Yet, in the case of energy outages, densely populated areas hold an advantage over areas with lower housing density because the electric utility industry prioritizes restoration in areas with high housing density (Edison Electric Institute, 2019). Future research on social vulnerability must provide further empirical assessments of how vulnerability varies across types of disasters and adjust their conceptualizations and measurements of vulnerability accordingly.

Our findings also point to the inadequacy of density-based energy restoration approaches and have various policy implications. We refer to existing restoration standards as the colorblind restoration approach because they exclude any consideration of racial and socioeconomic vulnerability when allocating restoration crews during outages. By virtue of ignoring pre-existing inequalities, density-based restoration approaches can exacerbate and reproduce inequalities. Thus, existing restoration approaches are unequal by design, placing a disproportionate burden of powerlessness on already marginalized communities, including ethnoracially minoritized and class-subjugated communities. Our findings on the delayed restoration on the basis of social and political marginality motivates the need for an alternative power restoration approach –which we term affirmative power restoration– that continues to prioritize essential services while also using social vulnerability indices to identify marginalized communities as restoration priorities. The means of approaching more equitable and just disaster resource allocations in the energy sector is an critical area for future research.

Energy inequality in the context of disasters begins prior to the event, during disaster preparedness, as governments and utility corporations choose where to invest resources in hardening and modernizing the electric grid, thereby making some communities more resilient and prepared for disaster events than others. Proactive disaster preparedness measures, such as grid hardening and modernization as well as measures to curtail the impact of politically partisan dynamics, can serve to ameliorate these energy inequities prior to disasters. In doing so, governments and utilities may prevent loss of life associated with disaster outages.

Despite its contributions, this study has some limitations. Our energy restoration data reflects the time and location of PREPA restoration crew deployments. Therefore, the study does not account for the extent to which restoration crew deployment translates into actual energy restoration. Additionally, given the fragility of the Puerto Rican energy grid and generation capabilities in the aftermath of hurricane María, households lost or had intermittent service after their energy was first restored. This study, however, does not aim to explain total outage hours, but rather, government responsiveness in the wake of hurricane María, which we capture with data on the date and location of PREPA's crew deployments.

Future research can examine the impact of social capital on disaster resource allocations through other measures of social capital, such as customer calls reporting outages to utilities. These calls can provide information that can help utilities assess the magnitude and location of damages, and thereby, facilitate energy restoration. Future work can use other measures to assess the impact of politically partisan dynamics on disaster resource allocations, such as the number of legislators or parliamentarians in nation or state-wide office from a given locality (e.g. Aldrich, 2015), a continuous measure of electoral support (percentage of votes) to assess the relative strength of a ruling party at the local level, the partisan alignment between municipal or county executives and the governor, or the partisan alignment between bureaucrats and localities receiving disaster resources (e.g. Bertelli and Grose, 2009). Lastly, in the process of validating our new index, we find an association between social vulnerability and excess deaths. Future research can investigate the extent to which power restoration crew allocations had an impact on hurricane Maria mortality.

Data availability

The dataset generated for the current study is available at: https://figshare.com/articles/dataset/Data_and_Script_for_Puerto_Rico_Social_Power_Projects/12551261.

Human subjects

The University of Missouri – St. Louis IRB approved the protocol for this research involving human subjects and determined that the project qualifies for exemption from full committee review under Title 45 Code of Federal Regulations Part 46.101b. Informed consent was obtained from all participants.

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CRediT authorship contribution statement

Fernando Tormos-Aponte: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Gustavo García-López:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Mary Angelica Painter:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Tables

Table 1
Full Coefficient Estimates - No Wind Data

	Estimate	Std. Error	z value	Pr(>z/)
(Intercept)	4.5577	0.0578	78.82	0.0000
PNPWin1	−0.0278	0.0128	−2.17	0.0297
SOCECO	0.0872	0.0275	3.18	0.0015
HCD	−0.0594	0.0234	−2.54	0.0110
HT	−0.0202	0.0229	−0.88	0.3770
MIN	0.1015	0.0249	4.07	0.0000
overall	0.1923	0.0239	8.05	0.0000
urban	−0.3265	0.0566	−5.77	0.0000
gov.perc	−1.3106	0.4745	−2.76	0.0057
pharma.perc	0.0224	0.2473	0.09	0.9279
hospital1	−0.0865	0.0146	−5.93	0.0000
mariain1	0.0251	0.0137	1.84	0.0665
SocCap	10.0109	1.7547	5.71	0.0000

Table 2
Full Coefficient Estimates - Wind Data

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	4.6262	0.0706	65.56	0.0000
PNPWin1	−0.0291	0.0128	−2.27	0.0231
SOCECO	0.0860	0.0275	3.13	0.0017
HCD	−0.0649	0.0236	−2.75	0.0059
HT	−0.0165	0.0230	−0.72	0.4733
MIN	0.1066	0.0251	4.25	0.0000
overall	0.1900	0.0239	7.95	0.0000
urban	−0.3298	0.0566	−5.83	0.0000
gov.perc	−1.3094	0.4745	−2.76	0.0058
pharma.perc	0.0906	0.2496	0.36	0.7166
hospital1	−0.0850	0.0146	−5.80	0.0000
mariain1	0.0265	0.0137	1.93	0.0532
SocCap	9.7868	1.7600	5.56	0.0000
meanwind	−0.0016	0.0009	−1.68	0.0933

Table 3
Marginal Effects - No Wind Data

	Model 1
PNPWin1	−2.52*(1.16)
SOCECO	7.94** (2.50)
HCD	−5.41*(2.13)
HT	−1.84 (2.08)
MIN	9.24*(2.27)

(*continued on next page*)

Table 3 (*continued*)

	Model 1
overall	17.51*(2.18)
urban	−29.73*(5.15)
gov.perc	−119.34** (43.22)
pharma.perc	2.04 (22.52)
hospital1	−7.82*** (1.31)
mariain1	2.29 (1.26)
SocCap	911.59*(159.87)
Num. obs.	18614
Log Likelihood	−101722.11
Deviance	20433.44
AIC	203472.22
BIC	203581.87

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 4
Marginal Effects - Wind Data

	Model 1
PNPWin1	−2.64*(1.16)
SOCECO	7.83** (2.50)
HCD	−5.91**(2.15)
HT	−1.50 (2.09)
MIN	9.71*(2.28)
overall	17.30*** (2.18)
urban	−30.03*(5.16)
gov.perc	−119.23** (43.21)
pharma.perc	8.25 (22.73)
hospital1	−7.68*** (1.32)
mariain1	2.42 (1.26)
SocCap	891.14*** (160.34)
meanwind	−0.14 (0.08)
Num. obs.	18614
Log Likelihood	−101720.69
Deviance	20433.23
AIC	203471.38
BIC	203588.85

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 5
Marginal Effects - Social Capital Data

	Model 1
PNPWin1	−2.52* (1.16)
SOCECO	7.94** (2.50)
HCD	−5.41*(2.13)
HT	−1.84 (2.08)
MIN	9.24***(2.27)
overall	17.51*** (2.18)
urban	−29.73***(5.15)
gov.perc	−119.34** (43.22)
pharma.perc	2.04 (22.52)
hospital1	−7.82*** (1.31)
mariain1	2.29 (1.26)
SocCap	911.59***(159.87)
Num. obs.	18614
Log Likelihood	−101722.11
Deviance	20433.44
AIC	203472.22
BIC	203581.87

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 6
Marginal Effects - No Social Capital Data

	Model 1
PNPWin1	−3.65**(1.14)
SOCECO	5.81* (2.47)
HCD	−6.82**(2.13)
HT	0.39 (2.06)
MIN	8.44***(2.26)
overall	15.73*** (2.16)
urban	−27.15***(5.13)
gov.perc	33.76 (33.60)
pharma.perc	15.07 (22.44)
hospital1	−7.08*** (1.31)
mariain1	2.12 (1.26)
Num. obs.	18614
Log Likelihood	−101738.72
Deviance	20435.86
AIC	203503.44
BIC	203605.25

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table 7
Excess Death Measured as Mortality Ratio

PR SVI Estimate		Std. Error	t value	Pr (>|t|)
(Intercept)	−7.6931	0.4846	−15.88	0.0000
meddays	0.0009	0.0022	0.39	0.6948
prsvi	0.0865	0.0385	2.25	0.0279
SocCap	−13.5539	12.0507	−1.12	0.2646
urban	0.8088	0.2772	2.92	0.0048
gov.perc	8.1169	4.7017	1.73	0.0888
PNPWin	0.1167	0.0912	1.28	0.2049
hosprate	1.2735	0.1781	7.15	0.0000
mirate	−0.3347	0.1497	−2.24	0.0286

Table 8
Excess Death Measured as Mortality Ratio - CDC SVI

Estimate		Std. Error	t value	Pr (>|t|)
(Intercept)	−7.3851	0.4121	−17.92	0.0000
meddays	0.0008	0.0022	0.36	0.7185
cdcsvi	0.4281	0.1864	2.30	0.0247
SocCap	−6.1432	12.8534	−0.48	0.6342
urban	0.8258	0.2775	2.98	0.0040
gov.perc	8.5306	4.6976	1.82	0.0737
PNPWin	0.1005	0.0907	1.11	0.2718
hosprate	1.2469	0.1792	6.96	0.0000
mirate	−0.3693	0.1544	−2.39	0.0195

Table 9
Demographic Information – Puerto Rico 2017 (US Census)

Sex	Male: 47.7%	Female: 52.3%
Age	Under 16: 19.7%	Over 65: 19.7%
Race	White: 66.2%	Black/African Am.: 12.1%
	Asian 0.2%	Two or More: 5.3%
	Hispanic/Latino: 95.9%	
Education	Less than High School: 23.9%	
	High School: 27.9%	Some College: 22.5%
Employ.	Unemployment Rate: 7.1%	
Poverty	Poverty Rate: 44.4%	
Disability	People with Disability: 21.6%	

Appendix B. Correlations

B.1 Welch Two Sample t-test

data: pr*overallandpr*meanwind t = −836.22, df = 18705, p-value < 2.2e-16 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: 40.33810 -40.14944 sample estimates: mean of x mean of y 0.5886821 40.8324494.

B.2. Welch Two Sample t-test

data: pr*overallandpr*mariain t = 63.071, df = 30079, p-value < 2.2e-16 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: 0.2449876 0.2607028 sample estimates: mean of x mean of y 0.5886821 0.3358369.

B.3. Welch Two Sample t-test

data: pr*meanwindandpr*PPDWin t = 834.51, df = 18847, p-value < 2.2e-16 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: 40.14304 40.33206 sample estimates: mean of x mean of y 40.8324494 0.5949034.

B.4. Welch Two Sample t-test

data: pr*PPDWinandpr*mariain t = 51.921, df = 37222, p-value < 2.2e-16 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: 0.2492867 0.2688463 sample estimates: mean of x mean of y 0.5949034 0.33583.

Appendix C. Figures

C.1. Cumulative crew deployment over time after hurricane María

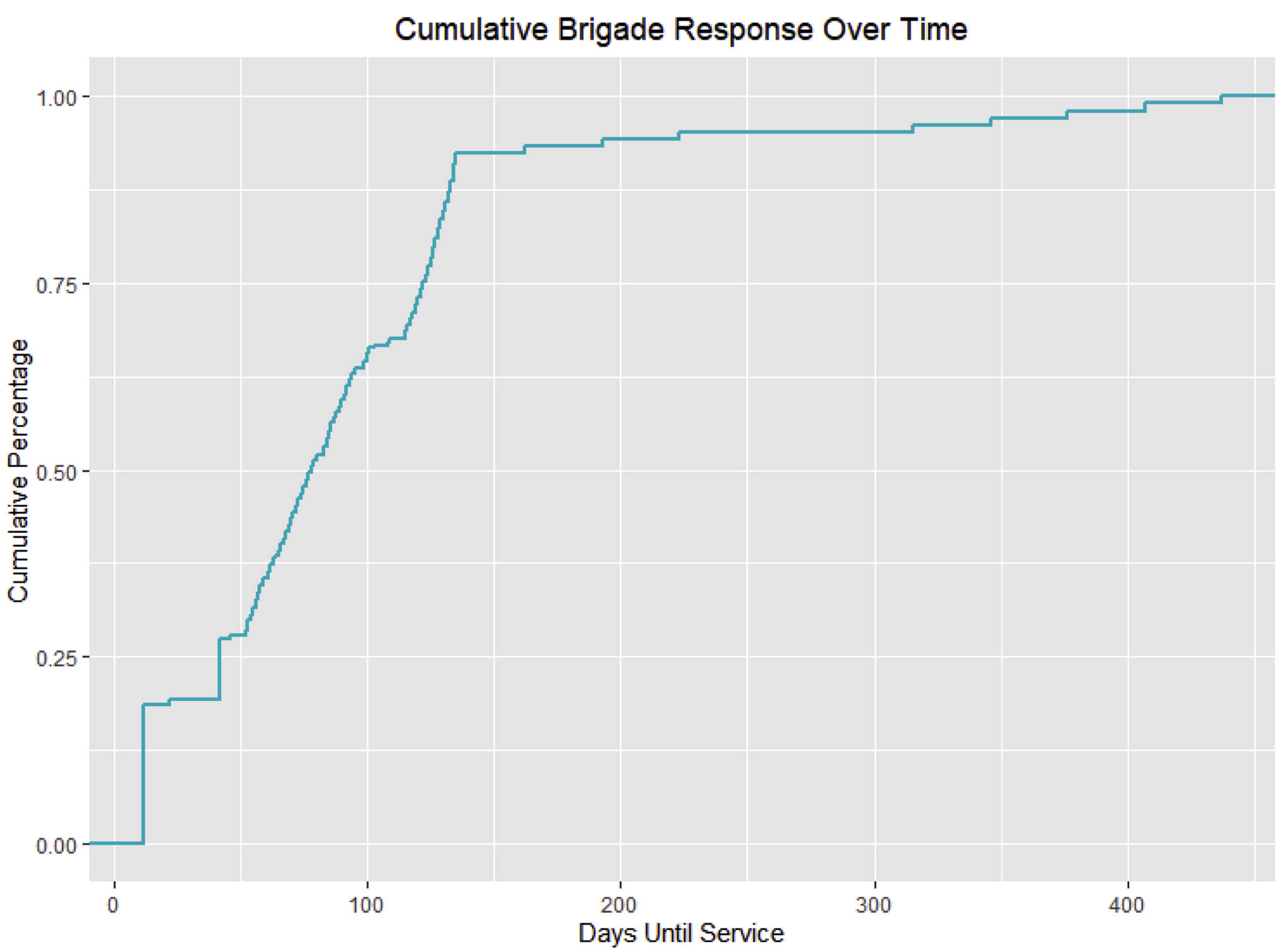

Fig. C.1. The line represents the 18,614 crew deployments that made after hurricane María made landfall. Cumulative percent refers to the percentage of total crews deployed across Puerto Rico over time. By the 150th day of the energy restoration efforts after hurricane María made landfall, nearly all PREPA crews had been deployed to restore power.

Appendix D. Codebook

Id2 - US Federal FIPS Code for state (Puerto Rico) and municipality.

Source: US Census Data

Day/Days – Number of days until power service since hurricane María made landfall (9-20-2017).

Source: Dates serviced from Puerto Rico Electric Power Authority (PREPA)

PNPWin – Whether the gubernatorial candidate for the ruling PNP party won in the municipality during the 2016 election. 1 equals a PNP win; 0 equals a PNP loss.

Source: Comisión Estatal de Elecciones 2016 election results.

SOCECO – Socioeconomic status – social vulnerability index (SVI).

Calculated using the following: poverty level, percent unemployment, education and per capital income. Poverty level is the percent of total population that falls below the poverty level for a municipal area. Percent unemployment is the percent of individuals between the ages of 16–65 who are unemployed for a municipal area. Education is the percent of adult individuals with a high school or less education for a municipal area. The per capita income is the mean for the municipal area.

The socioeconomic status is calculated by summing the poverty level, percent unemployment, and education, subtracting mean per capita income (to control that negativity/positivity is flipped for income compared to the rest of the variables), and divided that by the *N*. This number is used to create a percentile rank for socioeconomic status: 1 equals the county with the worst SVI status, while 0 equals the county with the best socioeconomic status.

Source: US Census Data

HCD – Household composition and disability status – social vulnerability index (SVI).

Calculated using the following: percent elderly, percent young, percent disabled, and percent single-parent households. Elderly population is the percent of total population for a municipal area 65 years of age and older. The youth population is the percent of total population for the municipal area 17 years and younger. Disability population is the percent of the total population for the municipal area five years and older with a disability. Single-parent households is the percentage of the total households with a single-parent.

The household composition and disability status is calculated by adding percent elderly, young, disabled, and single-parent households and dividing that number by *N*. This number is used to create a percentile rank for socioeconomic status: 1 equals the county with the worst SVI status, while 0 equals the county with the best household composition and disability status.

Source: US Census Data

HT – Housing/Transportation status – social vulnerability index (SVI).

Calculated using the following: multi-unit housing, crowding, and vehicle accessibility. Multi-unit housing is the percent of housing with more than one unit for a municipal area. Crowding is the percentage of houses with more than one occupant per room for a municipal area. Vehicle accessibility is the percentage of households with no vehicle ownership for a municipal area.

The housing/transportation status is calculated by summing multi-unit housing, crowding, and vehicle accessibility and dividing that number by *N*. This number is used to create a percentile rank for socioeconomic status: 1 equals the county with the worst SVI status, while 0 equals the county with the best housing/transportation status.

Source: US Census Data

Overall – Overall Social Vulnerability Index (SVI).

Percent white, socioeconomic status, household composition and disability status, and housing/transportation status were used to calculate an overall SVI. Income and percent white were subtracted, and all other variables were summed. For the percentile rank of the overall SVI, 1 equals most vulnerable, while 0 is the least.

Source: US Census Data

Urban – Percentage of the total geographical area considered “urban.”

Source: US Census Data (as of 2010)

MunicipalArea – The name of the municipal area (municipality) in Puerto Rico.

Source: US Census Data

Hotel.perc – Percentage density of hotels for a municipal area. Calculated by taking the frequency of hotels and dividing it by the number of *N*.

Source: Gobierno de Puerto Rico website, Sistemas de Información Geográfica (GIS) (gis.pr.gov)

Gov.perc - Percentage density of government buildings for a municipal area. Calculated by taking the frequency of government buildings and dividing it by the number of *N*.

Source: Gobierno de Puerto Rico website, Sistemas de Información Geográfica (GIS) (gis.pr.gov)

Malls.perc - Percentage density of malls for a municipal area. Calculated by taking the frequency of malls and dividing it by the number of *N*.

Source: Gobierno de Puerto Rico website, Sistemas de Información Geográfica (GIS) (gis.pr.gov)

Pharma.perc - Percentage density of pharmaceutical factories for a municipal area. Calculated by taking the frequency of pharmaceutical factories and dividing it by the number of *N*.

Source: Compañía de Fomento Industrial and the Pharmaceutical Industry Association of Puerto Rico

Hospital – Addresses that fall within a 2-mile radius from a hospital. Calculated using buffers of GIS data.

Source: Gobierno de Puerto Rico website, Sistemas de Información Geográfica (GIS) (gis.pr.gov)

Mariain – Addresses that fall within a 2-mile radius from a Hurricane María water intake area. Calculated using buffers of GIS data.

Source: Environmental Response Management Application (ERMA) from National Oceanic and Atmospheric Administration (NOAA)

np.perc – Percentage density of active non-profit organizations in a municipal area. Calculated by taking the frequency of non-profit organizations and dividing it by the number of municipal residents.

Source: Puerto Rico Department of State

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