Effects of Infrastructure Service Disruptions Following Hurricane Irma: Multilevel Analysis of Postdisaster Recovery Outcomes

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Abstract: Widespread power outages and related critical infrastructure disruptions after major storms can thwart household and community recovery by limiting access to critical facilities and services. In this analysis, we examine the impact of infrastructure disruptions on the individual, household, and community recovery using logistic regressions and multilevel mixed-effects models with a four-level hierarchical structure: household, urban/rural, county, and region. Household-level recovery is assessed using responses from a cross sectional survey (n = 988) collected through telephone landlines and an online platform in 29 Florida counties eight months after Hurricane Irma. We find that the severity of the damage, number of days without electricity, insurance, and access to health services are significant predictors of household recovery. At the county level, the percent of accounts served by rural and municipal cooperatives, as well as the percent of individuals with disabilities, are statistically significant. The random intercepts for the region and the urban/rural divide are also statistically significant, suggesting that the regional effects of disruptions play an important role in household recovery. The findings from this study provide insights on the impact of infrastructure disruptions on household recovery and the importance of multilevel modeling, supporting the case for further, more comprehensive interdisciplinary studies to reduce the power outage-related exposure of vulnerable populations. **DOI: 10.1061/(ASCE)NH.1527-6996.0000421.**

Introduction

Postdisaster recovery is complex, dynamic, multidimensional, and occurs at multiple scales (i.e., individuals and households, businesses, institutions, communities, and regions). In recent years, emerging topics in postdisaster recovery increasingly focus on the nexus between extreme events, dependency on critical infrastructures, and human and societal vulnerabilities to disruptions of infrastructure services (Birkmann et al. 2016; Karakoc et al. 2020). While there is a recognition that individual and household recovery outcomes are indelibly linked to macroscale processes that encompass social, economic, and infrastructure resilience factors, as well as institutional arrangements and policies (Kapucu et al. 2010; Chandrasekhar et al. 2018; Gori et al. 2020; Koliou and van de Lindt 2020), relatively few studies have focused on assessing the patterns of recovery across multiple scales with a focus on infrastructure interdependencies.

Individual and household recovery are shaped by microlevel and contextual or macrolevel factors but oftentimes these are considered independently. Empirical research tends to focus on explaining individual- or household-level outcomes in terms of individual- or household-level risk factors (Malmström et al. 1999; Diez-Roux 2000; Chakalian et al. 2019). Similarly, community-level and regional analyses tend to rely on aggregate data with limited consideration of individual or household-level recovery outcomes (Diez-Roux 2000; Arcaya et al. 2018). Recent studies have highlighted the need for a multiscale-type of analyses noting that past studies generally focused on unique dimensions of recovery (such as housing, healthcare delivery, or psychosocial factors) at a particular scale (individual, household, or region) while ignoring the interdependencies between impacts, vulnerabilities, assets, capacities, and recovery outcomes across multiple levels (NRC 2006; Chandrasekhar et al. 2018). As noted in a report by the National Research Council (NRC 2006, p. 151), "studies generally focus on particular units of analysis and outcomes, such as household, business, economic, or community recovery, rather than how these different aspects of recovery are interrelated."

In this paper, we report on the effects of electric power disruptions after Hurricane Irma (August 30–September 14, 2017) on short-term household recovery using multilevel analysis that allows for the simultaneous examination of the associations between household and macrolevel variables to elicit their independent and interdependent effects on the individual and household recovery outcomes. More specifically, we pool survey data with additional secondary source datasets, including demographic characteristics, the average duration of power outages at the county level, and type of electric service providers to make inferences about the probability of household recovery given household-level characteristics as well as local and regional factors affecting recovery. Household-level data were

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collected using a survey population drawn from both random (via telephone landlines) and nonrandom (via the Internet) sampling. Contextual and macrolevel factors related to physical exposure to hurricanes, demographic characteristics, type of electric service providers, and aggregated counts of accounts without service were added to the modeling framework with the notion that contextual factors are relevant to and affect household recovery in ways that are pertinent to understanding the underlying factors of the reported recovery outcomes.

The paper begins with a brief literature overview followed by a description of the rationale, methods, and results of the multilevel analysis of recovery outcomes. The statistical analysis involves two types of models: (1) bivariate logistic regression models based on individual/household-level covariates only; and (2) multilevel mixed-effects models with both individual/household-level and macrolevel covariates. Appendix provides details on the statistical methods used to combine probability (randomized) and nonprobability (nonrandomized) survey samples used in the analysis.

Infrastructure Disruptions and Recovery

Prior research has shown that power outages can have cascading impacts on numerous other critical infrastructures such as water, communication, transportation, healthcare, and emergency management (Han et al. 2009; Hasan and Foliente 2015; FEMA 2017; Zimmerman et al. 2017; Mitsova et al. 2018, 2019, 2020), which can affect access to these critical infrastructures and related perceptions of recovery. Recent studies examining infrastructure disruptions and risk disparities reveal that households with low socioeconomic status, particularly among racial minority groups, had a low zone of tolerance for power service disruptions (Mitsova et al. 2018; Coleman et al. 2020). Coleman et al. (2020) highlighted the link between the duration of the service disruptions caused by Hurricane Harvey (August 17–September 2, 2017) in Harris County, Texas (i.e., extent of exposure), and the residents' ability to withstand service disruptions (i.e., tolerance). Their findings suggested that infrastructure service disruptions caused a significant disparity in terms of hardship and coping capacity, particularly among the most vulnerable segments of the population (Coleman et al. 2020). Miles et al. (2016) quantified the multiplicative effects of power outages on transportation, business continuity, communications, fuel availability, water and wastewater systems, backup power generation, school closures, healthcare facilities, and evacuation in the aftermath of Hurricane Isaac. In such circumstances, homebound medically fragile and chronically ill high-risk individuals are particularly vulnerable because of their reliance on power-dependent durable medical equipment and inability to self-relocate during a mass power outage (FEMA 2017).

The widespread devastation caused by the catastrophic hurricanes of 2017 and 2018 provided further evidence of the linkages between infrastructure disruptions, short-term household recovery, and the need to address impacts across multiple scales. Hurricane Irma left millions of people from the Florida Keys to the Florida Panhandle without electricity for several days. Hurricane Michael (October 7–16, 2018) severely damaged over 700 structures in the Mexico Beach area (Davis et al. 2019) while leaving thousands without electricity for nearly a month. In Puerto Rico, Hurricane Maria (September 16–October 2, 2017) severely damaged the already fragile infrastructure systems, causing widespread loss of infrastructure services. Almost a month after the hurricane, 90% of Puerto Rico's 1.23 million households remained without power, and half of them had no water or cell phone service (Roman 2018; Zorrilla 2018). The lack of electrical service, communications, water and fuel, remoteness of towns and villages, inaccessible roads, and delays in federal response and aid coordination resulted in a humanitarian crisis that lasted for months (Roman 2018; Zorrilla 2018).

In the critical days following the landfall of Hurricane Maria, only 10% of the island's major hospitals were operational as doctors, patients, caregivers, and families were struggling to reconnect (Zorrilla 2018). Kishore et al. (2018, p.162) quantified the death toll in Puerto Rico after Hurricane Maria, noting that roughly one-third of the excess deaths were due to "delayed or interrupted health care" resulting from the disruptions of infrastructure services. Similarly, in an analysis of Hurricane Irma-related mortality in Florida, Georgia, and North Carolina, the Centers for Disease Control and Prevention found that the most common circumstances-of-death were related to power outages that contributed to the exacerbation of existing medical conditions, heat stress, and failure of oxygen-dependent therapies for homebound patients (Issa et al. 2018).

Multilevel Analysis of Recovery

Within disaster recovery studies, significant attention has been given to disparities based on income, race, gender, ethnicity, and age as determinants of poor recovery outcomes at individual, household, and community levels (Dash et al. 1997; Fothergill et al. 1999; Cutter et al. 2001, 2003; Esnard et al. 2011). Research on individual and household recovery from natural disasters have also centered on stabilizing individual housing needs (Comerio 1998, 2017; Cutter et al. 2001; Wu and Lindell 2004), hazard adjustments (Lindell and Prater 2000, 2002; Peek et al. 2011), health-related effects, and access to health and social services (Rhodes et al. 2010; Sutley et al. 2016; Shin et al. 2017; CDC 2017). The Hazards and Vulnerability Research Institute based at the University of South Carolina is a good source for a broader list of population characteristics, socioeconomic variables, and resilience indicators that influence the social burdens of risk factors in urban and rural areas (HVRI 2020 website; Cutter et al. 2016).

At the household level, traditional social and demographic vulnerability risk factors include female gender, housing tenancy, minority racial status, educational attainment, poverty, and age (Peacock and Girard 1997; Cutter et al. 2003; Laska and Morrow 2006; Cutter et al. 2010, 2016; Esnard et al. 2011; Peacock et al. 2012; Chakalian et al. 2019). Chakalian et al. (2019) examined the social implications of power failures and household experiences with infrastructure service provisions in the aftermath of Hurricane Irma. The authors conducted semistructured interviews in two counties in Florida and calculated the relative risk of poor recovery outcomes as a function of the household socioeconomic and demographic characteristics and prolonged power failure. The authors found that the household size, gender, race, and ethnicity were significant predictors of relative risk associated with various types of exposure resulting from electrical service interruptions (Chakalian et al. 2019).

At the macro/regional level, recovery outcomes are shaped by a number of interdependent processes. An example is the regional-level restoration of infrastructure services, including electrical power, transportation, water, wastewater, and communications. Repair and restoration of critical infrastructure in a region can also serve as indicators of community recovery (Rubin et al. 1985; Chandrasekhar et al. 2018) and can affect the perceptions of individual and household recovery. In their study of household recovery after Hurricane Sandy (October 22–November 2, 2012), Chandrasekhar et al. (2018) highlighted the linkages between household and neighborhood recovery. The authors noted that recovery is a complex and interconnected phenomenon and that neighborhood and infrastructure restoration can be critical to household recovery by helping households return to normalcy and reestablish a sense of communality (p. 17). When the restoration of infrastructure services occurs, it builds positive perceptions of neighborhood vitality, as was found in a study of evacuees after Hurricane Katrina (Henry 2013). Regional restoration and recovery of infrastructure can encourage businesses to reopen, and this can affect the return of households to the hardest hit areas (Xiao and Van Zandt 2012).

Location in urban or rural areas is another important regional consideration. Preliminary data from the Florida Public Service Commission (2017) indicated that the rural Calhoun and Jackson counties that did not experience a direct hit from Hurricane Michael had longer power outages than the coastal counties located directly on the path of the hurricane. Some of these findings could be explained by the differences between electricity providers by region. In Florida, for example, three types of utility service providers serve residential, commercial, and industrial sectors: investor-owned electric utilities, municipal electric utilities, and rural-electrical cooperatives (Florida Public Service Commission 2017). Mitsova et al. (2018) found a strong relationship between the duration of extended power outages and electricity provision by cooperatives and municipally-owned utilities.

In multilevel analysis, the variation in the dependent variable is explained as a cross level interaction between individual-level covariates (microfactors) and contextual macrolevel factors (Diez-Roux 2000; Congdon 2009; Owen et al. 2016). Congdon (2009) used data from the 2005 Behavioral Risk Factor Surveillance System to estimate a prevalence model that considers person-level risk factors and the effect of geographic disparities across states, regions, and the rural/urban divide. Arcaya et al. (2018) examined residential segregation in the United States using a random intercept multilevel logistic regression model. The model effectively predicted the proportion of nonwhite population accounting for the variation in demographic composition across a nested hierarchical model structure including random intercepts for metropolitan statistical areas, census tracts, and census block groups (Arcaya et al. 2018, p. 1094). When data are systematically organized as nested structures, multilevel models provide the necessary tools to account for statistical dependency across each level of the covariates (O'Dwyer and Parker 2014). Clusters or dependencies based on both individual and contextual factors are included in the analytical framework to model outcomes and test hypotheses about cross level effects and interactions (Gelman 2006; O'Dwyer and Parker 2014).

Respondent and Household Characteristics

In this study, we consider both respondent and household-level data (see also Chakalian et al. 2019). Respondent characteristics include age, gender, race/ethnicity, and language while household characteristics encompass housing tenure (rent or own), income, damage to the place of residence, loss of infrastructure services, and homeowner's insurance. Respondent and household-level data were collected using a survey, consisting of 30 questions divided into five sections: (1) damage to structures and duration of infrastructure disruptions, (2) access to food, water, healthcare, prescriptions, and transportation, (3) insurance coverage and disaster assistance, (4) evacuation decisions, and (5) demographic and socioeconomic characteristics. The survey was administered in 29 counties in central and south Florida (Fig. 1).

The survey, conducted in both English and Spanish, was administered in May 2018 using random probabilistic sampling (landline telephone users) and nonprobability sampling (online volunteers) to obtain respondents. The combined sample included 988 respondents over the age of 18. The Zip Code Tabulation Areas (ZCTAs) of residence were available for the reference (telephone) sample and self-reported for the online sample, helping align individual and household experiences with contextual and macrolevel factors. The telephone survey was administered using automated telephone interviewing (ATI) technology, which integrates automatic phone systems and software that call individuals and conduct telephone surveys. Telephone numbers were drawn randomly from a sample of 100,000 Florida residents. The phone lists for ATI were supplied by Aristotle International (2020). The ATI sample consisted of n = 334 with a response rate of 8.9%. This response rate is not uncommon as Pew Research Center reports that their response rates for telephone (landline) surveys have declined dramatically over time, from 37% in 1997 to 6% in 2018 (as cited in Valliant et al. 2013). Valliant et al. (2013) highlight several methodological approaches to using nonprobability sampling to supplement the conventional probability sampling using phone surveys. In order to have a representative sample and to reduce the problem of nonresponse bias, we supplemented the telephone (landline) survey with an online survey. The online sample was administered through Survey Sampling International (SSI) (2020) using a variety of digital sources such as online communities, social networks, emails, in-app alerts, and websites. The online sample consisted of n = 654, with a response rate of 27.5%. The approach to address the methodological challenges of merging the two samples is discussed in the Appendix.

For the purposes of this study, we focus on *recovery outcomes* that are defined as "the extent to which the recovery activities are judged, either objectively or subjectively, as 'complete' or 'successful'" (NRC 2006, p. 148). The survey respondents were asked to rate their overall recovery from Hurricane Irma eight months after the storm's landfall using the following categories: (1) completely recovered; (2) mostly recovered; (3) somewhat recovered; (4) not recovered at all; and (5) not affected by Hurricane Irma. The ordinal categories were established under the assumption that there was a natural ordering of recovery (low to high), but the distances between adjacent levels were unknown. Therefore, we collapsed the outcome measure into a binary response variable to better understand the effects of the predictors on the overall recovery process. The cases in which the respondents said "they were not affected by Hurricane Irma" were removed from further analysis.

The remaining responses were examined for completeness resulting in an adjusted count of $n = 936$ for the purposes of the statistical modeling. The cases in which the survey respondents said they "completely recovered" or "mostly recovered" were grouped in a new category "recovered" and coded as 1. The cases in which the respondents rated their overall recovery as "somewhat recovered" or "not recovered at all" were grouped into a new category "not fully recovered" and coded as 0. Further considerations in opting to use a binary dependent variable included: (1) some dependent variables levels by subpopulations had zero frequencies; and (2) in a proportional odds model for ordered responses, the event being modeled does not have an outcome in a single category (as in binomial or multinomial model) but in any of the adjacent levels of the response variable which, in this case, would confound the effects of the predictors on the outcome measure. See Table 1 for a list of the respondent and household-level variables derived from survey questions.

Contextual Macrolevel Factors

In order to account for broader macrolevel factors, we used four county-level variables: average duration of power outages, percent

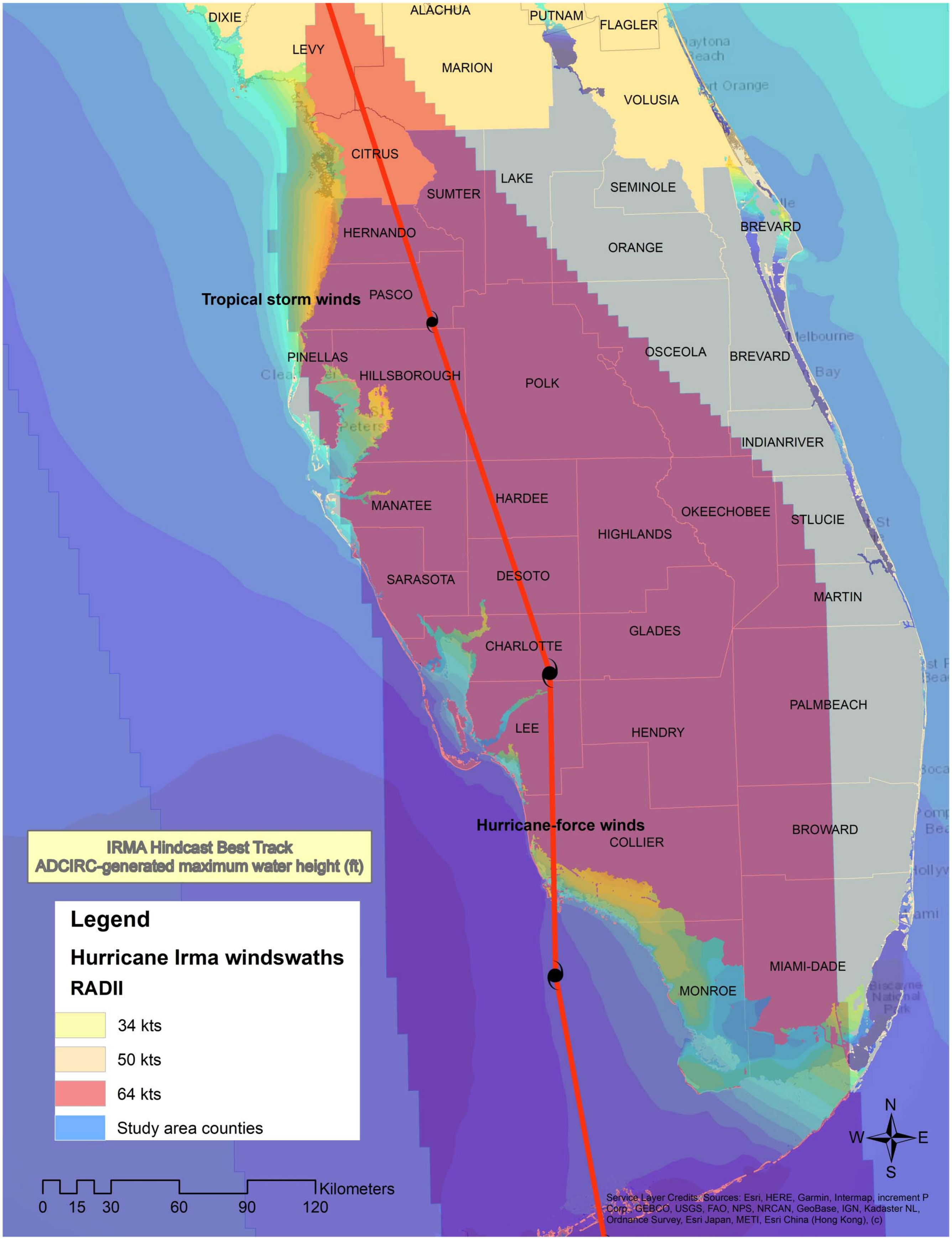

Fig. 1. Florida counties included in the study area together with hindcast of Hurricane Irma's best track, wind swaths, and ADCIRC-generated maximum storm surge height. [Map Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), ©.]

Table 1. Selected survey questions, response frequencies, and percent by response category

Variable	Question	Response category	Frequency	Percent
Damage ($n = 988$)	Did Hurricane Irma cause any damage to your place of residence?	Not at all	333	33.7
		Minor damage (broken tree branches and debris)	357	36.1
		Some damage (fallen trees, broken fences)	217	22.0
		Severe damage (structural damage to the roof or loss of business)	81	8.2
Power outage ($n = 982$)	For how long did you lose electricity?	Did not lose electricity	230	23.4
		Less than a few hours	128	13.0
		1 day or less	138	14.1
		2–3 days	174	17.7
		4–7 days	190	19.3
		More than 7 days	122	12.4
Cell/Internet loss of service ($n = 964$)	For how long did you lose cell phone and Internet service?	Did not lose cell phone or Internet service	343	35.6
		Less than a few hours	130	13.5
		1 day or less	141	14.6
		2–3 days	146	15.1
		4–7 days	114	11.8
		More than 7 days	90	9.3
Access to health care ($n = 967$)	How much of a problem for you was getting access to health care services	Not at all a problem	495	51.2
		A little problem	135	14.0
		Somewhat of a problem	80	8.3
		A big problem most of the time	84	8.7
		I did not seek this type of service	173	17.9
Access to medications ($n = 972$)	How much of a problem for you was getting medications	Not at all a problem	544	56.0
		A little problem	110	11.3
		Somewhat of a problem	77	7.9
		A big problem most of the time	68	7.0
		I did not seek this type of service	173	17.8
Recovery ($n = 988$)	How would you rate your overall recovery from Hurricane Irma?	Completely recovered	609	61.6
		Mostly recovered	215	21.8
		Somewhat recovered	89	9.0
		Not recovered at all	53	5.4
		I was not affected by Hurricane Irma	22	2.2

of accounts served by rural cooperatives and municipal providers, hurricane return period, and percent of people with disabilities. Table 2 describes the variables derived from secondary data sources. Florida's residential, commercial, and industrial sectors are served by three types of utility service providers: investor-owned electric utilities, municipal electric utilities, and rural-electrical cooperatives (Florida Public Service Commission 2017). The study area also includes counties with high probabilities of hurricane strikes. For the purposes of this analysis, we collected and processed hurricane strike data for the period 1851–2018 and calculated the hurricane return period following the methodology reported in Esnard et al. (2011).

Previous studies have shown that demographic, socioeconomic, health, and disability status are important determinants of hurricane vulnerability (Esnard et al. 2011; Chandrasekhar et al. 2018). Additional data were collected at the county level from the US Census Bureau: population, percent of individuals below the federal poverty level, percent of county households on the Supplemental Nutrition Assistance Program (SNAP), percent of people with disabilities, percent of people 65 and over, and unemployment rate. In a previous study, we found that the percent of the population with a sensory, physical, and mental disability was a highly statistically significant predictor of the effect of power outages (Mitsova et al. 2018), and consequently, this variable was considered for inclusion in the model. Additionally, Florida zip code-level data for gender, age, race, ethnic group, and educational attainment were obtained from the US Census Bureau. These data were used to calculate the survey weights.

Multilevel Modeling of Recovery Outcomes

Multilevel models are generalized regression models to predict an outcome when the covariates are structured hierarchically (Witte et al. 2000; Congdon 2009; O'Dwyer and Parker 2014; Weinmayr et al. 2017; Evans et al. 2018). To predict the odds of household recovery, we fitted two types of models: (1) bivariate logistic regression models based on household-level covariates only; and (2) multilevel mixed-effects models with both household-level covariates and macrolevel covariates. All models were estimated using STATA version 15 statistical software. We used bivariate logistic regression models to predict the odds of recovery using the independent variables derived from the survey responses to the questions included in Table 1. The independent variables include the level of hurricane damage with four response categories (from none to severe); duration of power outages (with five response categories from less than an hour to more than seven days); disruptions of Internet and cell phone service (with five response categories similar to the previous category), and access to healthcare services and medications (each with four response categories, respectively). We considered a set of control variables, including age, gender, educational attainment, race, ethnicity, housing tenure, insurance coverage, and language spoken by the respondent. Several of the control variables initially included in the regression analysis (e.g., gender, educational attainment, and age) were omitted from the final models since they were not found to be statistically significant predictors of recovery when considering disruptions of infrastructure services.

When asked what helped the respondents the most to resume their normal daily routines after Irma, the overwhelming majority

Table 2. County and regional-level (geographic) variables

Variable/level	Description	Data source
Return period (county)	Measure of exposure of county to hurricanes (Categories 1–5 and tropical storms) and tropical storms for 1851–2018.	Hurricane strike data (1851–2017) was downloaded from the Atlantic hurricane database (HURDAT2). The best track data for Hurricane Michael which made landfall near Mexico Beach, Florida, in October 2018 was obtained from the Tropical Cyclone Report (Beven et al. 2019)
Average power outage duration (in days) (county)	Number of days of power outages recorded for each county for period September 9–29, 2017.	Florida Division of Emergency Management (originally downloaded December 2017)
Percent of accounts served by municipal/rural providers (county)	Percent of customers served by rural and municipally owned utility cooperatives for each county. See FEMA (2017) for detailed descriptions of municipal electric utilities and rural electric cooperatives.	Florida Division of Emergency Management (originally downloaded December 2017)
Wind swath (county)	Counties with centroids within areas affected by hurricane-force wind swath coded as 1. Counties with centroid within areas affected by tropical storm wind swath coded as 0 (variable wind swath).	National Hurricane Center GIS Archive
Region	Regions were based on the Regional Planning Councils' jurisdictional boundaries and coded from 1 to 6. The area of interest included South Florida, Southwest Florida, Treasure Coast, and parts of Central Florida, East Central Florida, and Tampa Bay.	Florida Regional Planning Councils
Urban/rural classification	Urban/rural classification using CDC's 2013 NCHS six-level urban–rural classification scheme. Classifications 1–4 coded as 1 (urban). Classifications 5–6 coded as 0 (rural).	CDC National Center for Health Statistics (NCHS)

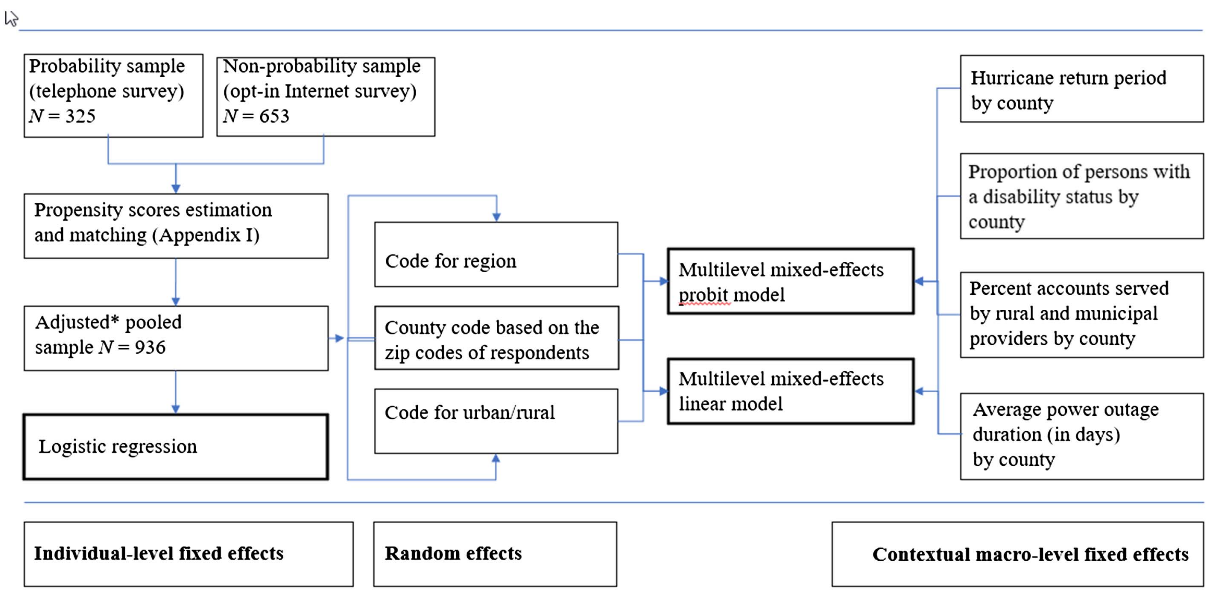

Fig. 2. Analytical framework (*The sample size was adjusted by removing the cases in which the respondents said they "were not affected by Hurricane Irma" and those that did not meet the criteria for completeness).

(66.7%, $n = 936$) identified power restoration as the most important factor. Since restoring grid function after a major disruption was identified by the respondents as a significant recovery factor, we consider a linear mixed-effects model with a fixed predictor for power restoration (based on survey responses) and randomly varying intercepts and slopes for county-level variables (Table 2), regions, and the effect of the urban/rural divide. We held power restoration as a fixed predictor while allowing the slopes for power outage duration to vary across counties, regions, and the urban/rural continuum. Additionally, we estimated a multilevel probit regression with fixed household-level and contextual predictors and a Bayesian multilevel mixed-effects probit model with Metropolis–Hastings random-walk sampling. The models included county-level covariates for hurricane return period, average power outage duration, percent accounts served by rural electrical cooperatives and municipal providers, and percent persons with a disability status as contextual variables. Fig. 2 provides an overview of the analytical framework.

Household-Level Effects

During Hurricane Irma, nearly half of the survey respondents did lose electrical service. Among those who were affected by power outages, 12.4% remained without electrical service for more than seven days. Overall, 36.3% of the survey respondents did not have a cell phone or Internet service for more than two days. Among them, 9.3% were without cell phone service or the Internet for more than seven days. Approximately 17.0% of the survey participants reported difficulties with getting access to health care services. Additionally, 14.9% said that they experienced difficulties obtaining prescription medications. Among those affected by Hurricane Irma, 36.1% reported minor damages to their place of residence, 22.0% had some damage, while 8.2% suffered severe damage. The respondents were also asked to rate their overall recovery from Hurricane Irma. Overall, 61.6% responded that they completely recovered, and 21.8% said that they mostly recovered. Nearly 9% responded that they somewhat recovered, while 5.4% said that they did not recover at all.

Our survey sample consisted of both probability and nonprobability samples. The literature suggests care should be exercised when pooling two datasets derived from random and nonrandom sampling (Valliant et al. 2013; Valliant and Dever 2018; Valliant 2019). To reduce the selection bias inherent to nonrandom samples, we used propensity score estimation to match the respondents in the nonprobability sample to those in the probability sample and adjusted survey weights. See Appendix for a related scholarship, the methodological approach used, and the results of the propensity scores estimation and matching.

Once the probability and nonprobability samples were merged, we estimated three logistic regression models to predict the probability of full recovery considering the severity of damage as well as the effects and duration of disrupted infrastructure services. Table 3 shows the logistic regression coefficients, standard errors, and odds ratios for each of the predictors. Levels of damage, number of days without electricity, insurance, and access to health services were found to be significant predictors of household recovery. All three models indicated that "severe damage" significantly decreased the odds of recovery ("some damage" was found to be statistically significant at $\alpha = 0.05$ in Model 3 only). In contrast, there is no statistically significant association between "minor damage" and postdisaster recovery. The odds ratios for power duration indicated that when holding all other variables constant, households that experienced more prolonged power outages were less likely to recover in the short-run (e.g., within a few months after a major hurricane strike). Power outage duration of more than two days was found to be statistically significant in both Model 1 and Model 2. The results indicated that the magnitude of the negative effect increased as the duration of the power interruption increased. There was a highly statistically significant association (p-value $= 0.001$) between postdisaster recovery and power outages of more than three days (specifically, as it refers to categories *four to seven days* and *more than seven days*). A similar association was observed for loss of cell phone and Internet service (p-value < 0.1). The dummy variable for power restoration was found to be a significant predictor of recovery in all three models with the greatest observed effect in Model 2, which included access to prescriptions as one of the predictor variables.

The results also showed evidence that there was a statistically significant association between postdisaster recovery and the ability to access healthcare services. We found a strong statistically significant association between full recovery and concerns for access to medications (Model 2). Additionally, our findings indicated that there was a statistically significant association between recovery and low to medium income range. The association was not found to be statistically significant for the higher-level income brackets. According to the survey results, renting decreased the odds of full recovery while having homeowners' insurance increased the likelihood of recovery.

Among the control variables, race was found to be a strong predictor of a decreased likelihood of recovery. In particular, being Black/African American decreased the odds of a full recovery in the months following Hurricane Irma almost by half compared to the reference group of White/Caucasian. There was no evidence of a statistically significant association between recovery and being Hispanic or Latino. However, for those who opted to take the survey in Spanish, the odds of a full recovery were significantly lower. These seemingly contradictory findings could be explained by the fact that in South and Central Florida, ethnic differentials may not necessarily convey socioeconomic disadvantage. Conversely, linguistic competence is often correlated with issues of educational attainment as a proxy for earnings as well as "health literacy" (Congdon 2009, p. 7). We found a strong negative statistically significant association (Kendall's $tau\text{-}c = -4.012$; p-value < 0.001) between preferred language and educational attainment.

Fixed and Random Effects across Scales

The effects of the geographic context were modeled at the county and regional levels as well as along the urban/rural divide. We estimated three mixed-effects linear models (Models 4–6) with a fixed predictor for power restoration and randomly varying intercepts and slopes for power outage duration using recovery as the dependent variable (whereas 1 denotes r*ecovered* and 0 denotes *not fully recovered*). We found a highly statistically significant fixed effect for power restoration in all three models. The variance estimates for the residuals for the dependent variable (*recovery*) indicated that they were significantly different from zero across the three models. The level variables for the random effects equation included the urban/rural divide (Model 4), region (Model 5), and county (Model 6). Model 4 and Model 5 included a power outage of more than three days (as reported by the survey respondents) as a fixed predictor for the random effects' equation, whereas in Model 6, the predictor variable was average power outage by county. By setting power outage duration as the predictor variable for the random effects' equation, we allowed the slope for that variable to vary across the specified levels. The varying slopes for the power outage durations (as reported by the respondents) were highly statistically significant (p-value < 0.001). The slope for the average power outage by county was statistically significant at the 90% significance level. These results suggested that the power outage differentials at a finer scale (e.g., household) might not follow the patterns revealed at an aggregate (county) level. The variance estimates for the intercept and slope provided evidence that the random effects across the level variables (urban/rural divide, region, and county), although small in magnitude, were statistically significant (Table 4). The largest observed effect was found along the urban/rural divide, followed by region.

Furthermore, we estimate a mixed-effect probit model and a Bayesian multilevel probit regression model with Metropolis–Hastings (MH) random-walk sampling, both of which include both survey responses and contextual variables (Table 5). County-level contextual variables consist of the hurricane return period, percent of people with disabilities, percent accounts served by rural electrical cooperatives and municipal providers, and average duration of power outages. The results, shown in Table 5, indicate that at the household level, the estimated parameters for the multilevel probit regression (Model 7) are similar to those found in the logistic

Table 3. Results from the logistic regression models

Predictor variables	Model 1 Coefficient (standard error)	Model 1 Odds ratio	Model 2 Coefficient (standard error)	Model 2 Odds ratio	Model 3 Coefficient (standard error)	Model 3 Odds ratio
Damage (no damage[a])						
Minor damage	−0.146	0.864	−0.212	0.809	−0.422	0.656
	(0.446)		(0.454)		(0.419)	
Some damage	−0.712	0.491	−0.761	0.467	−1.117**	0.327
	(0.497)		(0.511)		(0.469)	
Severe damage	−2.817***	0.060	−2.747***	0.064	−2.976***	0.051
	(0.519)		(0.526)		(0.511)	
Power outage duration (did not lose electricity[a])						
Less than few hours	−0.574	0.563	−0.616	0.540	—	—
	(0.656)		(0.685)			
1 day or less	−1.272**	0.280	−1.279**	0.278	—	—
	(0.596)		(0.582)			
2–3 days	−1.750**	0.174	−1.761***	0.172	—	—
	(0.579)		(0.569)			
4–7 days	−2.260***	0.104	−0.254***	0.105	—	—
	(0.619)		(0.608)			
More than 7 days	−2.255***	0.105	−2.300***	0.100	—	—
	(0.621)		(0.600)			
Loss of cell/Internet service (did not lose service[a])						
Less than a few hours	—	—	—	—	−0.321	0.725
					(0.464)	
1 day or less	—	—	—	—	0.038	1.039
					(0.565)	
2–3 days	—	—	—	—	−0.393	0.675
					(0.476)	
4–7 days	—	—	—	—	−0.736*	0.479
					(0.420)	
More than 7 days	—	—	—	—	−0.812*	0.444
					(0.482)	
Problem getting healthcare (not a problem at all[a])						
Minor problem	−0.108	0.898	—	—	−0.315	0.730
	(0.465)				(0.420)	
Somewhat of a problem	−1.013**	0.363	—	—	−1.083**	0.338
	(0.459)				(0.517)	
Serious problem	−1.672***	0.188	—	—	−1.624***	0.197
	(0.482)				(0.468)	
Did not seek assistance	−0.267	0.766	—	—	−0.443	0.642
	(0.410)				(0.395)	
Problem getting medications (not a problem at all[a])						
Minor problem	—	—	−0.597	0.550	—	—
			(0.403)			
Somewhat of a problem	—	—	−0.767	0.465	—	—
			(0.562)			
Serious problem	—	—	−2.102***	0.122	—	—
			(0.533)			
Did not seek assistance	—	—	0.146	1.157	—	—
			(0.388)			
Power restoration	1.079**	2.943	1.112***	3.039	0.725**	2.065
	(0.340)		(0.347)		(0.300)	
Race/ethnicity (White[a])						
Black/African American	−0.657**	0.518	−0.771**	0.462	−0.572*	0.565
	(0.338)		(0.326)		(0.325)	
Hispanic/Latino	−0.450	0.638	−0.471	0.624	−0.403	0.668
	(0.344)		(0.354)		(0.334)	
Other	0.657	1.929	0.566	1.762	0.728	2.072
	(0.775)		(0.828)		(0.706)	
Income ($0–$25,999[a])						
$26,000–$49,999	0.752*	2.122	0.645	1.905	0.836**	2.307
	(0.394)		(0.428)		(0.417)	
$50,000–$99,999	1.036**	2.819	0.904**	2.468	1.051***	2.861
	(0.408)		(0.411)		(0.386)	

Nat. Hazards Rev., 2021, 22(1): 04020055

Table 3. (*Continued.*)

Predictor variables	Model 1 Coefficient (standard error)	Model 1 Odds ratio	Model 2 Coefficient (standard error)	Model 2 Odds ratio	Model 3 Coefficient (standard error)	Model 3 Odds ratio
$100,000–$149,999	0.738 (0.626)	2.091	0.660 (0.615)	1.935	0.912 (0.590)	2.488
More than $150,000	0.117 (0.502)	1.125	0.120 (0.485)	1.128	0.132 (0.488)	1.141
Housing tenure (own[a])						
Rent	−0.683** (0.349)	0.505	−0.809** (0.369)	0.445	−0.611* (0.344)	0.543
Homeowners' insurance	0.565* (0.354)	1.759	0.572* (0.367)	1.772	0.631* (0.337)	1.879
Language (English[a])						
Spanish	−0.995** (0.331)	0.370	−1.010*** (0.341)	0.364	−0.898** (0.366)	0.407
Constant	3.950*** (0.650)	51.927	4.115*** (0.646)	61.226	2.991*** (0.643)	19.911
Number of observations	—	936	—	936	—	936
Wald chi-square	—	141.520	—	143.550	—	127.020
p-value	—	0.000	—	0.000	—	0.000
Log-likelihood	—	−245.872	—	−244.988	—	−260.306
Pseudo R2	—	0.311	—	0.313	—	0.270

Note: $^*p < 0.1$; $^{**}p < 0.05$; and $^{***}p < 0.01$.
[a]Reference category.

Table 4. Fixed and random effects linear models[a]

Fixed effects	Model 4 coefficient (standard error)	Model 5 coefficient (standard error)	Model 6 coefficient (standard error)
Power restoration	0.125*** (0.023)	0.116*** (0.023)	0.075*** (0.023)
Constant (intercept)	0.956*** (0.024)	0.944*** (0.024)	0.826** (0.019)
Random-effect[b] parameters			
var (more than 3 days without electricity)	0.161*** (0.017)	0.019* (0.013)	0.030* (0.023)
var (intercept)	0.131*** (0.041)	0.098*** (0.013)	0.023*** (0.002)
var (residuals)	0.133*** (0.045)	0.102** (0.005)	0.108** (0.005)
Model parameters			
Wald chi-square	29.710	25.250	10.840
Log-likelihood	−260.302	−269.093	−286.952
Prob > chi-square	0.000	0.000	0.000

Note: $^*p < 0.1$; $^{**}p < 0.05$; and $^{***}p < 0.01$.
[a]In all models the dependent variable is a binary variable for recovery.
[b]Assuming independent variance-covariance structure of the random effects.

regression analysis (Table 5) except for the Hispanic/Latino ethnic group for which we found a statistically significant negative association with the odds of recovery. Among the county-level variables, there was a statistically significant association between recovery and two of the contextual predictors: percent accounts served by rural electrical cooperatives and municipal providers ($p < 0.05$) and percent of people with disabilities ($p < 0.10$). The association between self-reported recovery status and the hurricane return period (which is used as a proxy for previous experience with major natural disasters) was not found to be statistically significant. Similarly, the association between the duration of the average power outage at the county level and recovery was not statistically significant. The results suggested that aggregate measures (such as the average number of days without power at a county level) did reflect experiences with power outages at a household or individual level, which were found to be highly statistically significant, especially for longer durations.

Table 5 shows the posterior means, standard deviations (STDs), Monte Carlo standard errors (MCSE), medians, and posterior means of the odds ratios [Exp(β)] for the fixed effect parameters of the Bayesian multilevel probit regression (Model 8). The acceptance rate of 0.427 for the Bayesian model falls within the 0.2–0.5 interval, which is typical for the random-walk MH algorithm. The maximum efficiency of 19.3% indicates that autocorrelation is relatively low. Fig. 3 displays the trace, autocorrelation, and density plots for the random intercepts for the region [*UU0: Region*] and the urban–rural divide [*UU0: Urban_Rural*]. The trace plots for both parameters demonstrate proper mixing. The autocorrelation becomes negligible fairly quickly, and the density plots indicate a close match between the analytical and sampling posterior distributions, indicating that there are no immediate convergence problems.

The estimated posterior means for severe damage, power outage durations, power restoration, and access to health care in Model 8 were found to be closer to the probit regression estimates (Model 7) but lower than the logistic regression estimates (Models 1 and 2). However, the standard errors (MCSE) in the Bayesian model were much smaller than those in the logistic regression and probit regression models. The results from the bootstrapping using an MCMC sample size of 10,000 indicated that the magnitude of the negative effect of power outages increased with duration. Those who experienced difficulties with access to health care services were, on average, 2.5 times ($1/0.401$) less likely to recover within the study period. The most significant variable among the county-level variables was the percent of people with disabilities. The county-level fixed effect showed that the posterior odds $\exp(\beta)$ for a full recovery are about six times ($1/0.164$) lower for areas with a higher percentage of people with disabilities.

Summary and Conclusions

In disaster studies, both individual and contextual factors are likely to be relevant in explaining variations in recovery outcomes. It is important to understand household-to-household variation as well as group-to-group or community-to-community variation simultaneously to fine-tune decision-making and recommend appropriate policies. A multilevel analysis provides a tool to overcome the limitations inherent to approaches focusing on a particular level of analysis and can play a key role in decision-making for a number of reasons: (1) pooling relevant information from multiple levels of data at various scales; (2) providing an analytical framework to evaluate and draw inferences about multiple experiences, exposures, stressors, and outcomes; and (3) developing a method to characterize the extent to which microlevel versus mesolevel and macrolevel processes drive the overall variability in recovery outcomes. A multilevel analysis offers an analytical framework that allows researchers to account for the multiplicity of outcomes considering both scale and perspective. As noted in NRC (2006, p. 149), "[a] community may be considered 'recovered' on the basis of objective social or economic indicators, while constituent social units may not be faring as well, in either objective or subjective terms." In such cases, conventional approaches would draw either household-level or broad macroscale inferences but overlook the interaction that exists between these levels.

This study contributes to scholarship on the multilevel modeling of household vulnerability to disaster impacts by examining the relationship between disruptions of infrastructure services and household recovery outcomes. Specifically, we used mixed-effect multilevel models to estimate variation in recovery outcomes considering contextual influences modeled as county, region, and urban/rural effects. Household-level recovery outcomes were assessed using responses from a cross sectional survey that included both probability and nonprobability samples. The samples were combined based on propensity score estimation and adjustment of sampling weights (Appendix). The methodology contributes to the scholarship on the application of methodological solutions used to pool probability and nonprobability samples. We fitted a logistic regression using the survey responses as independent variables and the overall rating of recovery as the dependent variable. The severity of the damage, number of days without electricity, insurance, and access to health services were found to be significant predictors of household recovery. At the county level, percent accounts served by rural and municipal cooperatives, as well as the percent of people with disabilities, were found to be statistically significant. The random intercepts for regions and urban/rural areas were also statistically significant, suggesting that the regional effects of disruptions play an important role in household recovery.

In this study, we refer to multilevel analysis as a statistical approach that requires data structure groupings to unveil patterns at multiple levels of analysis simultaneously (Malmström et al. 1999; Congdon 2009; Weinmayr et al. 2017; Evans et al. 2018). The approach certainly has limitations. As with any statistical method, it does not provide an explanation of causal relationships, which can only come from broad-based theories and further empirical testing (Diez-Roux 2000). We also acknowledge limitations related to inferences from cross sectional survey data. Future research could consider longitudinal analyses to develop measures of the rate of change in individual and household recovery outcomes over time as they relate to the effects of the evolving contextual factors. Another limitation stems from the relatively low response rate (8.9%) of our reference sample based on telephone landlines. As noted by Blumberg and Luke (2016), the number of households with telephone landlines has decreased dramatically over the past 10 years, especially among younger adults. Among those 65 and over, only about 25% live with wireless-only service (Blumberg and Luke 2016). In order to reduce the problem of nonresponse bias and

Table 5. Estimated parameters for the multilevel probit regression (Model 7) and the Bayesian multilevel probit regression with random-walk Metropolis–Hastings sampling (Model 8)

	Model 7			Model 8				
Predictor variables (person-level)	Coefficient (standard error)	Z	P > $\lvert z \rvert$	Posterior mean	Posterior STD	MCSE	Posterior median	$\mathrm{Exp}(\beta)$
Damage (no damage[a])								
Minor damage	−0.073	−0.45	0.656	−0.059	0.202	0.010	−0.060	0.943
	(0.163)	—	—	—	—	—	—	—
Some damage	−0.700***	−3.25	0.001	−0.748	0.195	0.011	−0.743	0.473
	(0.216)	—	—	—	—	—	—	—
Severe damage	−1.595***	−6.28	0.000	−1.670	0.229	0.011	−1.664	0.188
	(0.254)	—	—	—	—	—	—	—
Power outage duration (did not lose electricity[a])								
Less than few hours	−0.210	−0.79	0.430	−0.262	0.324	0.017	−0.271	0.770
	(0.266)	—	—	—	—	—	—	—

Table 5. (*Continued*.)

Predictor variables (person-level)	Model 7 Coefficient (standard error)	Z	P > $\|z\|$	Model 8 Posterior mean	Posterior STD	MCSE	Posterior median	Exp(β)
1 day or less	−0.723**	−2.26	0.024	−0.768	0.284	0.020	−0.765	0.464
	(0.319)	—	—	—	—	—	—	—
2–3 days	−0.814**	−2.48	0.013	−0.856	0.265	0.017	−0.854	0.425
	(0.328)	—	—	—	—	—	—	—
4–7 days	−1.073***	−5.88	0.000	−1.141	0.265	0.019	−1.136	0.319
	(0.183)	—	—	—	—	—	—	—
More than 7 days	−1.289***	−4.73	0.000	−1.339	0.276	0.019	−1.337	0.262
	(0.273)	—	—	—	—	—	—	—
Problem getting healthcare (not a problem at all[a])								
Minor problem	−0.189	−1.120	0.261	−0.159	0.208	0.007	−0.159	0.853
	(0.168)	—	—	—	—	—	—	—
Somewhat of a problem	−0.666***	−3.260	0.001	−0.684	0.218	0.007	−0.681	0.505
	(0.204)	—	—	—	—	—	—	—
Serious problem	−0.889***	−3.960	0.000	−0.914	0.229	0.008	−0.907	0.401
	(0.224)	—	—	—	—	—	—	—
Did not seek assistance	−0.067	−0.330	0.741	−0.042	0.190	0.007	−0.041	0.959
	(0.203)	—	—	—	—	—	—	—
Power restoration	0.432***	3.810	0.000	0.485	0.143	0.006	0.486	1.624
	(0.113)	—	—	—	—	—	—	—
Race/ethnicity (White[a])								
Black/African American	−0.345**	−2.300	0.021	−0.285	0.181	0.006	−0.284	0.752
	(0.150)	—	—	—	—	—	—	—
Hispanic/Latino	−0.299**	−2.710	0.007	−0.248	0.158	0.005	−0.251	0.780
	(0.110)	—	—	—	—	—	—	—
Other	0.378	1.460	0.144	0.410	0.368	0.009	0.400	1.507
	(0.259)	—	—	—	—	—	—	—
Income ($0–$25,999[a])								
$26,000–$49,999	0.509**	2.550	0.011	0.528	0.187	0.007	0.527	1.696
	(0.200)	—	—	—	—	—	—	—
$50,000–$99,999	0.537***	3.220	0.001	0.490	0.190	0.008	0.485	1.632
	(0.167)**	—	—	—	—	—	—	—
$100,000–$149,999	0.577	2.620	0.009	0.559	0.267	0.009	0.556	1.749
	(0.220)	—	—	—	—	—	—	—
More than $150,000	0.067	0.380	0.704	0.027	0.256	0.008	0.032	1.027
	(0.177)	—	—	—	—	—	—	—
Housing tenure (own[a]) Rent	−0.302**	−2.290	0.022	0.123	0.147	0.007	0.124	1.131
	(0.132)	—	—	—	—	—	—	—
Language (English[a])								
Spanish	−0.632***	−4.930	0.000	−0.629	0.151	0.006	−0.629	0.533
	(0.128)	—	—	—	—	—	—	—
Predictor variables (county level)								
Return period	0.001	0.360	0.717	0.052	0.008	0.000	0.045	1.053
	(0.003)	—	—	—	—	—	—	—
Percent persons with disability	−0.077*	−1.780	0.075	−3.576	1.530	0.447	−3.488	0.164
	(0.026)	—	—	—	—	—	—	—
Percent accounts served by municipal/rural providers	−0.079**	−2.260	0.024	−0.011	0.004	0.001	−0.011	0.689
	(0.003)	—	—	—	—	—	—	—
Average power outage duration by county (days)	0.048	1.520	0.128	−1.213	0.733	0.185	−1.340	0.297
	(0.031)	—	—	—	—	—	—	—
Constant	1.589***	3.340	0.001	1.312	0.680	0.162	1.267	3.714
	(0.475)	—	—	—	—	—	—	—
Model parameters								
Number of observations	—	—	—	936	—	—	—	936
MCMC iterations	—	—	—	—	—	—	—	12,500
Log-likelihood	—	—	—	−237.112	—	—	—	−432.571
DIC	—	—	—	—	—	—	—	535.129
Acceptance rate	—	—	—	—	—	—	—	0.427
Efficiency (max)	—	—	—	—	—	—	—	0.193
Wald chi-square	—	—	—	4,950.10	—	—	—	—
Prob > chi-square	—	—	—	0.000	—	—	—	—

Note: Marginal likelihood (ML) is computed using Laplace-Metropolis approximation. MCMC = Markov chain Monte carlo; and DIC = deviance information criterion. *p < 0.1; **p < 0.05; and ***p < 0.01.
[a]Reference category.

Nat. Hazards Rev., 2021, 22(1): 04020055

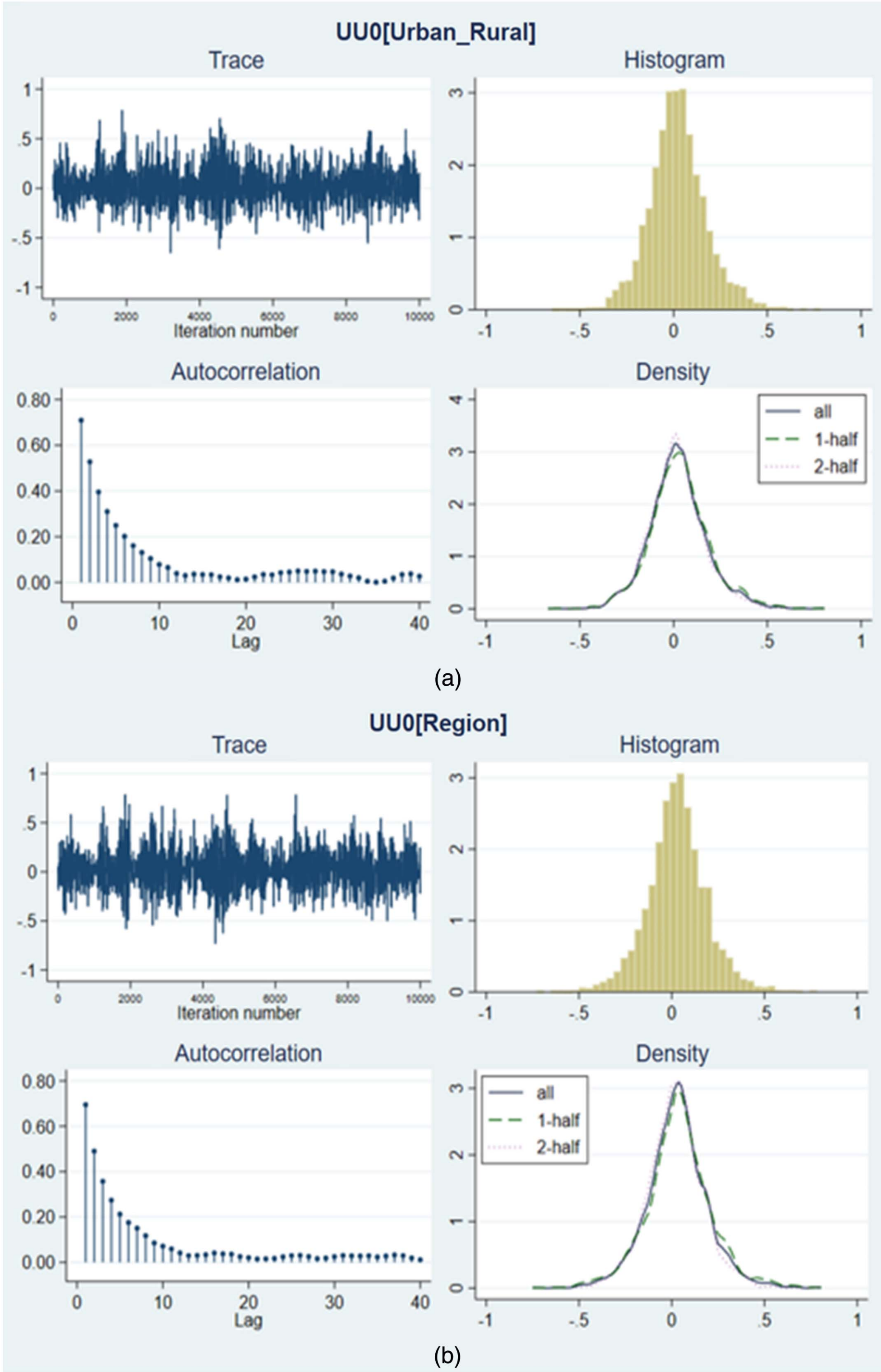

Fig. 3. Trace plots, histograms, and autocorrelation and density plots for the random intercepts for (a) the urban/rural divide; and (b) region.

obtain a representative sample given these discrepancies, we supplemented the telephone (landline) survey with an online survey. A discussion of the methodological considerations related to merging the two samples can be found in Appendix.

Overall, adopting a multiscale approach addresses the need for a broader perspective that will engage novel ways of thinking that lead "to more holistic understanding of the multifaceted dynamics of household recovery" (Chandrasekhar et al. 2018, p. 2). The findings from this study provide insights on the impact of infrastructure disruptions on household recovery, making a case for more comprehensive interdisciplinary studies to reduce power outage-related exposure of vulnerable populations. The results indicate that certain subpopulations, including Black/African Americans, those who have limited English-speaking ability, or those who need timely uninterrupted medical care are more at risk of a protracted partial recovery. The findings draw attention to issues of equity in restoring infrastructure services and the need for reassessment of infrastructure asset lifecycle and investment in vulnerable communities to increase their resilience to future disasters. As Coleman et al. (2020, p. 12) point out, there needs to be "a paradigm shift" from a policy perspective that will allow us to see the physical vulnerabilities of infrastructure systems through the lenses of their

Table 6. Parameters of the propensity score model and matching methods

Variables		Coefficient			(95% confidence interval)	
Gender		0.329***			0.149	0.508
—		(0.091)			—	—
Age		−0.834***			−0.950	−0.718
—		(0.059)			—	—
Race/ethnicity		−0.194***			−0.293	−0.095
—		(0.051)			—	—
Constant		2.730***			2.200	3.260
—		(0.271)			—	—
Number of respondents	—	—	—	—	—	936
Number of respondents in the nonprobabilistic sample					—	611
Number of respondents in the reference sample			—	—	—	325
LR chi-square	—	—	—	—	—	256.750
Prob > chi-square	—	—	—	—	—	0.000
Log-likelihood	—	—	—	—	—	−476.007
Pseudo R2	—	—	—	—	—	0.212
Region of common support (min/max)	—	—	—	—	0.195	0.991
Estimated propensity scores						
Mean	0.652				Median 50%	0.690
STD	0.234	Percentiles	1%	0.195	75%	0.872
Variance	0.055		5%	0.298	90%	0.936
Skewness	−0.256		10%	0.319	95%	0.976
Kurtosis	1.777		25%	0.443	99%	0.991
Matching methods	Treated cases in the non-prob sample	Matched cases in the reference sample	—	ATT	t	Standard error
Nearest nighbor	611	321	—	0.015	0.338	0.044
Radius matching	611	323	—	0.018	0.663	0.027
Kernel matching	611	323	—	−0.001	−0.037	0.029
Stratification matching	611	323	—	−0.009	−0.275	0.031

Note: *p < 0.1; **p < 0.05; and ***p < 0.01. ATT = average treatment effect for the treated.

socioeconomic implications. This new paradigm calls for a systems design approach that is multidisciplinary and problem-solving in nature and takes into account technical and organizational as well as economic, social, and public health needs across multiple scales.

Appendix. Propensity Scores Estimation to Pool Probability and Nonprobability Samples

We used propensity score estimation to combine the random sample of respondents with the sample of volunteers by estimating pseudoinclusion probabilities for the participants in the nonprobability sample (DiSogra et al. 2011; Valliant et al. 2013; Valliant and Dever 2018; Robbins et al. 2019). The probability sample was weighted by gender, age, educational attainment, race, and ethnic group to reflect the distribution of the population in the study area. The weights for the nonprobabilistic sample were estimated using the approach proposed by Valliant et al. (2013), Valliant and Dever (2018), and Valliant (2019). When controlling for propensities, matched samples of volunteers and nonvolunteers will have almost identical covariate distributions that fundamentally reconfigure an observational study into a quasi-randomized block experiment (DiSogra et al. 2011; Valliant et al. 2013; Kim and Steiner 2016; Valliant and Dever 2018; Robbins et al. 2019). In order to estimate the propensity scores, we coded the respondents in the reference sample as 0 and the respondents in the online sample as 1 (Valliant and Dever 2018, p. 117). Two assumptions need to be considered when applying the proposed methodology. First, both the reference and volunteer surveys must include the same covariates (Valliant and Dever 2018, p. 116). Second, we must have nonzero selection probabilities, also known as "common support" (Valliant and Dever 2018, p. 118). Given that both requirements were satisfied, we fitted a binary logistic regression using the mode of data collection as the response variable while controlling for a set of covariates on which the two samples would be matched. In this study, gender, age, race, and ethnicity were used as covariates for the propensity score matching. Four matching methods were considered, including nearest-neighbor, radius, kernel, and stratification matching. For all the matched cases, the sampling weights assigned to the cases of the reference sample were assigned to the matching cases in the nonprobability sample.

We conducted a series of diagnostic tests to understand whether there were statistically significant differences in the mean response of the two groups (i.e., the random telephone sample and the opt-in Internet sample) using recovery as the dependent variable. In these models, the mode of conducting the survey served as a dummy independent variable (where the nonprobability sample using an opt-in Internet survey is coded as 1, and the reference sample using a telephone survey is coded as 0). These models are practically equivalent to a two-sample t-test for unpaired data to determine if the null hypothesis H0: $\mu_1 = \mu_2$ holds. The p-value of 0.186 suggested that the two groups were similar in terms of their reported recovery outcomes (no evidence was found to reject the null hypothesis). In the next step, we estimated a propensity score matching model (Table 6) with common support. In this model, the dependent variable was a binary variable for a mode of data collection where the nonprobability sample is coded as 1 and the reference sample is coded as 0. The propensity scores were estimated using a probit regression model with an LR chi-square of 256.75 (p-value < 0.001) and a log-likelihood of −476.007. The small p-value associated with the LR test led us to reject the null hypothesis that at least one of the regression coefficients included in the model was equal to zero. The model results indicated a region of common support between 0.195 and 0.991. Table 6 provides a summary of the estimated propensity scores by percentile. The estimated propensity scores facilitated the process of matching the records in the probability sample with the records in the nonprobability sample. Overall, 611 records in the nonprobability sample were matched to 321 records in the probability sample using the nearest-neighbor method. The same number of nonprobability records were matched to 323 cases in the reference sample using the radius, kernel, and stratification matching methods. After the two samples were matched, the survey weights computed from the census data for the reference sample were assigned to the cases in the nonprobability sample using the estimated propensity scores. The weights were calibrated to the survey population counts.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request. Aggregated data from secondary sources, as described in Table 2, can be shared without restrictions. In accordance with the approved IRB protocol, only summaries and aggregated data from the household survey can be made available from the corresponding author upon request.

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