A Framework for Quantifying Disaster Level Social Hardship: The case of Hurricane Maria in Puerto Rico

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A Framework for Quantifying Disaster Level Social Hardship: The case of Hurricane Maria in Puerto Rico

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Summary. We propose a supervised learning approach to statistically quantify the impact of an extreme event on vulnerable communities using publicly available panel data directly reflective of the different dimensions and manifestations of social hardship. These manifestations include suicides, substance abuse, excess mortality, unemployment, and others. Our modified treatment-effect model allows counterfactual baseline conditions to be posited for each manifestation from which an aggregated quantitative multi-faceted measure of social hardship can be determined. The developed statistical methodology should be greatly beneficial to policymakers who must allocate scarce resources to mitigate social hardship. Our work represents a distinct alternative to the established approach of assessing social vulnerabilities of communities subject to extraordinary events that rely on composite indices (such as Social Vulnerability Index SoVI) based on published census data. We illustrate applicability of our approach using annual and monthly panel data from 2012-2018 encompassing the 2017 Hurricane Maria event across various municipalities in Puerto Rico. Our statistical modeling methodology stands apart since (i) it explicitly and more realistically captures the effect of different manifestations of the actual event, (ii) it is flexible enough to accommodate individual preferences of various stakeholders in how they assign importance to multiple manifestations of social hardship.

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1. Introduction/Motivation

Extreme weather hazards represent geophysical events that induce extensive physical damage and great social hardships that affect populations worldwide. A common example of such hazards are hurricanes and the associated flooding, extreme winds, and landslides that damage neighborhoods, halt livelihoods, and disrupt critical infrastructure like energy and water distribution systems. When vulnerable communities are

exposed to extreme weather hazards, the outcome is often termed a climate-related *disaster*, heretofore referred to simply as disaster, due to the tremendous economic and social costs. Just in 2020, over 389 recorded disasters have resulted in 15,080 deaths and left injured, homeless, or affected 98.4 million people (see Guha-Sapir (2020)). *Social hardship* – here taken as the sustained human suffering endured physically and mentally that manifest long after exposure to an extreme weather hazard – is also associated with disasters. When it comes to stakeholders and decision-makers in humanitarian (e.g., USAID; United Nations), emergency response (e.g., FEMA), and infrastructure management (e.g., local utilities) organizations, it is important to strategize limited resources efficiently, consider the relative importance of undesirable outcomes, and effectively reduce social hardship. That is why in this work we address the needs of such organizations in effectively guiding remedial strategies. Specifically, we develop tools that can identify, quantify and create index-based measures of social hardship due to disaster events while distinguishing them from other causes.

Disasters and socioeconomic conditions. The relationship between disasters and socioeconomic conditions, along with the respective outcomes, have been of interest to international stakeholders focused on human safety, wellbeing, and sustainable development. For example, the United Nations (UN) has identified disasters as an integral part of social and economic planning, urging the need for disaster risk reduction to achieve Sustainable Development Goals (see noa (2019), Maskrey et al. (2020)). The U.S. Agency for International Development (USAID) Office of Foreign Disaster Assistance (OFDA) stresses the role of national and local entities in supporting life-safety and livelihoods during disasters, along with the importance of decisionmakers to efficiently identify where to direct aid (see OFDA (2019)). When proper planning and mitigation is overlooked by public and humanitarian entities, disasters can degrade the sustainability of livelihoods and offset economic development trajectories for neighborhoods, cities, states, and even entire regions (see Adger (2003), Griffith (2020), Hillier and Nightingale (2013), Mochizuki et al. (2014), Shahzad et al. (2021)). Furthermore, already existing socioeconomic challenges may be aggravated, which over time, may lead to intergenerational disparities in income, life chances, gender and ethnic equality, and social status (see GAR (2019)); in extreme cases, widespread displacement and poverty (see Griffith (2020)).

Adverse outcomes. Disasters also have significant and adverse outcomes at the individual, household, and community-levels. Historically, past disaster events have been associated with an increased prevalence of severe psychiatric symptoms, somatic complaints, and nightmares (see Peek and Mileti (2002)). Ongoing mental health issues including anxiety, depression, post-traumatic stress (PTSD), and grief can affect quality of life for several years (see Asugeni et al. (2015), Bland et al. (1996), Sattler et al. (2018)). Some losses cannot be recovered or valued in monetary terms, such as the disruption of cultural rituals and communal lifestyles that support social cohesion, a sense of place and belonging, and spiritual bonds (see McNamara et al. (2021)). Targeting recovery and mitigation with human-oriented and well-informed strategies is essential to reduce short and long-term social hardships for households and communities at risk.

Case of Puerto Rico. In the case of Puerto Rico, Hurricane Maria in 2017 was an unprecedented disaster that caused catastrophic infrastructure damages, population

diaspora, and over 3,000 estimated deaths (see Kishore et al. (2018a), Lugo (2019)). Electrical infrastructure recovery was driven mainly by storm exposure, remoteness from urban areas, and proximity to power stations, while some of the most vulnerable communities were left waiting over nine months for electricity (see Kwasinski et al. (2019), Román et al. (2019)). Anxiety, depression, crime, civic unrest, and public health crises were widespread, and the extended lack of essential lifeline services induced a massive migration (see Lugo (2019)). As an unincorporated U.S. Island Territory, Puerto Rico is "islanded" in both geographic and sociopolitical terms and is thus representative of isolated communities worldwide where the added challenges for data acquisition and disaster management make the providence of decision tools and analysis difficult yet imperative (see Beccari (2016), Carvalhaes et al. (2020), Chi et al. (2018)). The characteristics of Puerto Rico in terms of its islanded conditions and the devastating outcomes after Hurricane Maria make it a unique event that can be informative to other isolated communities with the similar limiting conditions and scarce resources. We thus focus on Puerto Rico and the importance of targeting populations who disproportionately endure social hardships as an imperative context and application for our study.

Treatment-effect methodology. We propose a treatment-effect methodology for identifying and quantifying determinants of social hardship when a population is exposed to specific extreme weather hazards. Our goal is to develop a scale-dependent social hardship index at the disaster-level and demonstrate its applicability using Puerto Rico as a case study. This methodology can be adapted in context of other isolated or vulnerable regions. Our model can also be integrated with technical simulations of engineered infrastructure systems in the framework of planning studies aimed at optimizing the allocation of limited resources toward maximum mitigation of human suffering (i.e., social hardships) (e.g., Boyle et al. (2021)). Thus, in this work, we provide a novel methodology for disaster indices based on measurable social outcomes (i.e., data-driven and non-self-reported). Additionally, we provide a numerical benchmark in the form of an index that is explicitly focused on the revealed vulnerability (i.e., social hardship) due to a specific extreme weather hazard.

Consistent with literature where qualifying social hardship and validation is of fundamental importance, our objectives are to use Hurricane Maria in Puerto Rico as a case study to:

(a) Develop a broadly applicable methodology for quantifying and validating a disaster-level social hardship index that reflects psychological, demographic, and economic determinants that is,

  (i) Based on publicly available data per administrative unit.
  (ii) Flexible to be aggregated at higher-levels via input by stakeholders who may have varying disaster management preferences for a combined view of social hardships that is subjective, yet with individual elements that are still validated.

(b) Illustrate the methodology using the impact of Hurricane Maria on Puerto Rico as a case study.

The remainder of this paper is organized as follows: Section 2 discusses selected

articles that illustrate approaches for providing social metrics for hardship and identifies gaps in the literature; Section 3 explains the Treatment-Effect methodology and model procedure; Section 4 includes the case study application for Puerto Rico and discusses results; and lastly, Section 5 provides a summary and conclusions.

2. Key Concepts and Common Approaches for Quantifying and Validating Social Hardship

Households and communities have spatially varied environmental and socioeconomic conditions (e.g., a country or region) that affect their ability to cope with damages and loss of infrastructure services (e.g., power outages). Stated differently, several communities across a region may be equally exposed to the stressors of a hurricane (e.g., extreme wind), yet unequally vulnerable in terms of suffering social hardships. That is, a hurricane as an extreme weather hazard is otherwise agnostic to human suffering, and it is the subsequent interaction with social vulnerability that makes the disaster. Social vulnerability is an established concept in disaster risk and community resilience research, but it does not have a single canonic definition. However, social vulnerability can generally be considered as the spatially heterogeneous predisposition of a community to suffer adverse personal, household, or neighborhood outcomes when exposed to extreme weather hazards (see Cutter et al. (2003), Engle (2011)). Within the established literature, we frame social hardship here as the realization of social vulnerability, such as physical ailments, aggravated mental conditions, and extensive disruptions to livelihoods such that families are left without a home and basic sustenance like food and water † (see Fekete (2019)). Given that most of the established literature focuses on social vulnerability and the respective construction and validation of indices, the remainder of this section will review common methodologies from this respective perspective.

To evaluate relative risk in a spatial context, Cutter et al. (2003) introduced a seminal composite index method based on Census data that rank orders U.S. counties using indicators of structural qualities of social vulnerability (e.g., household composition and language as proxies for sensitivity to disruptions, ability to evacuate, and access to resources). Indices have been a popular form of measurement tools for social vulnerability due to their ability to directly reveal priority areas for optimal resource allocation and their amenability to visualization for stakeholders and planners (see Carvalhaes et al. (2021), OECD/European Union/EC-JRC (2008), Vincent (2004)). Indices are usually composed of various indicators (e.g., income, age, educational level) that are combined into a single aggregated metric via several methods including simple summation of normalized values, averaging, or factor analysis, and can be weighted or non-weighted ‡ (see Beccari (2016)). Despite advances toward quantitative indicators for social vulnerability, there are two on-going challenges. First, social vulnerability indices must be validated with a response variable (see Beccari (2016), Fekete (2019), Yoon et al. (2016)). Sec-

†See Yarris (2011) for a detailed example of social hardships in hurricane afflicted Nicaragua including mental strain and headaches. See Pacheco and Plutzer (2008) for an economic perspective.

‡See the Centers for Disease Control (CDC) Social Vulnerability Index (SoVI), which is a publicly available map-based online tool as an example (Flanagan et al. (2011)).

ondly, models need to account for the manifested hardships that are a direct result of an extreme weather hazard (i.e., revealed vulnerability) (see Béné et al. (2014), Eakin et al. (2016), Fekete (2019)).

In the field of disaster risk reduction, the primary challenge involving social metrics for disasters is validation (see Fekete (2019)). Bakkensen et al. (2017) and Carvalhaes et al. (2021) have identified the sustained insufficiencies in grounding social metrics with clear disaster outcomes (external validity) and improved quantitative methods toward selecting and weighting key variables. Fekete (2019) has outlined external validity challenges in terms of capturing "revealed vulnerability" to define validation criterion, including varying interpretations of vulnerability § and uncertainty in attributing validation criteria to a recent disaster. Furthermore, there is still a need for disaster-level benchmarks that capture revealed vulnerability toward a global database of disaster cases.

To address the challenge validation, methods have been proposed that leverage both qualitative and quantitative techniques (see FEMA (2021), Tate (2013)). Qualitative methods may involve interviewing field experts such as emergency responders and infrastructure managers or involve more collaborative methods where experts heuristically qualify visual maps and help filter, rank, or place weights on a set of indicators in an iterative cycle such as the Delphi method (Nguyen et al. (2017)). Quantitative approaches have applied statistical techniques to social vulnerability index frameworks for index validation. Tate (2012) has used global sensitivity analysis to internally validate model specifications (e.g., variable selection). Yoon et al. (2016) used total human loss and property damage as response variables for a linear model by leveraging well-established theoretical indicators alongside factor analysis, Ordinary Least Squares Regression, and Geographically Weighted Regression to develop a Community Disaster Resilience Index. Leveraging Kaplan-Meier Curves and subjective field data (i.e., polling), Esmalian et al. (2020) developed an empirical approach for identifying logistic functions for household tolerance to sustained lack of critical infrastructure services like power after a disaster.

Despite the range aforementioned approaches for index validation, shortcomings and limitations remain in terms of relating indicators to the occurrence of extreme weather hazards and the ensuing human-centric responses. Kontokosta and Malik (2018) point out that while several validation attempts have been made, such as correlation of indices with derived loss functions and discriminant analysis, a more robust validation, *"requires measurement of post-disaster recovery after the occurrence of an actual disaster event using independent proxies for normal and atypical activity"*. Furthermore, research has been overly focused on capital-oriented responses (e.g., property damage, GDP, foreign aid), while overlooking the suffering that people experience during and after disasters (see Mochizuki et al. (2014)). A gap remains because non-monetary social outcomes (i.e., outside of economic valuation) are still underacknowledged, and research on slow-onset effects (e.g., excess mortality, post-traumatic stress) is nascent (see McNamara et al. (2021)). Clearly capturing the marginal effect of disasters on social outcomes remains an under-researched area for index development. It is thus becoming increasingly recognized that it is important to develop a measure of the incremental effect on social hardship due to specific disasters as distinct from other background causes. We address these gaps and the need to design and validate a non-economic social metric using publicly

§Vulnerability as either exposure, sensitivity, or lack of critical capacities.

Table 1. Human dimensions of disaster impacts with examples of common impacts as working response variables (see NAS (2006)).

Dimensions of Human Impacts	Common Post-disaster Outcomes
Psychological	Increases in suicide and substance abuse rates
Demographic	Excess mortality, migration
Economic	Public aid requests, higher unemployment
Political	School closures, civil unrest

available data in order guide mitigation efforts and infrastructure robustness in the face of future disasters.

3. Methodology

To set up an estimation model and construct a validated index for social hardship, it is first necessary to identify a conceptual framework to guide the selection of potential indicators and orient their respective relationships (i.e., explanatory and response variables). There are several such frameworks in the social vulnerability and disaster risk research stream, but here we aim for a framing that is more focused on the specific manifestations of disaster-related human suffering and losses to hone in on variables for social hardship. In terms of the *Human Dimensions of Disaster Impacts*, The National Academies of Sciences NAS (2006) offers a synthesis of social science contributions to disaster research. In this work, specific social hardships and losses are outlined along four key social dimensions: psychological, demographic, economic, and political. Table 1 presents common post-disaster social hardship outcomes along each of the four human dimensions as an example. To contextualize a set statistical models for non-monetary impacts and focus on outcomes of social hardships, we leverage this NAS framing to guide our model specification. Additionally, our use of this framing serves as a demonstrative example for identifying and relating human-oriented variables for future disaster studies that go beyond economic impacts.

The proposed set of models is based on leveraging panel data to measure the effect of a specific treatment on a set of exposed units. Here, the treatment is Hurricane Maria as a type of environmental intervention that changes the living conditions of affected communities. In this sense, the effect of the environmental intervention is understood as the treatment effect. Observational data can proxy the socioeconomic and living conditions before and after such an environmental intervention to validate the measure of social hardship due Hurricane Maria. However, the manifestation of the intervention precludes the ability to simultaneously observe the outcomes had the intervention occurred or not occurred. That is, we cannot observe the *counterfactual*¶, which is a well-known limitation when using non-experimental data and treatment-effect models (see Dehejia and Wahba (1999)).

¶The "counterfactual" measures what would have happened to beneficiaries (units) in the absence of the intervention, and impact is estimated by comparing counterfactual outcomes to those observed under the intervention. https://www.worldbank.org/en/programs/sief-trust-fund/publication/impact-evaluation-in-practice

Let y_{it}^1 and y_{it}^0 be the outcome under an intervention and with no intervention, respectively, for i subjects (units) and t time points, which are not simultaneously observed. A primary challenge in the treatment-effect literature is to construct counterfactual values for the unobserved y_{it}^1 or y_{it}^0 (see Heckman and Vytlacil (2007a,b)). Hsiao et al. (2012) proposed a panel data method to exploit the correlation between cross-sectional units to estimate y_{it}^1 and y_{it}^0‖.

Based on observations before and after the intervention (response and predictor variables), we fit a panel data model and forecast y_{it}^0 with $t \leq T_0$ where T_0 denotes the point in time the intervention occurs. These forecasts, denoted as $\hat{y}_{it}^0$, constitute the counterfactual condition. By comparing y_{it}^1 (observed) with $\hat{y}_{it}^0$ for $t \leq T_0$, it is possible to model the effect of the intervention. To determine the number of units that show a statistically significant impact from the intervention, we study the interaction term between the unit indicator and the intervention indicator, as outlined in section 3.3. Lastly, based on the subset of significant units, we follow Hsiao et al. (2012) and Hsiao and Zhou (2019) as an alternative to construct the counterfactual.

3.1. Panel data model

Panel data are repeated measurements taken from a cross section of units (households, countries, etc.) (see Frees (2004)). Panel data involve observations on N subjects (units) at $T \leq 2$ time periods denoted as,

$$(X_{it}, y_{it}),\ i = 1, \ldots, N \text{ and } t = 1, \ldots, T$$

where the index i refers to the unit (cross-sectional index) while t refers to the time period. Thus, a simple panel data model with one predictor (X_{it}) can be framed as,

$$y_{it} = \beta_0 + \beta_1 X_{it} + u_{it}. \tag{1}$$

Most panel data applications use one-way error component by splitting the error term u_{it} as,

$$u_{it} = \alpha_i + \nu_{it} \tag{2}$$

where α_i is the unobservable unit-specific effect and ν_{it} the remainder error, which can vary with units and time and be assumed as the usual error in regression models. Note that α_i is time invariant, and ν_{it} varies with units and time. By combining (1) and (2) we obtain the well-known Fixed Effects (FE) regression model. Considering more than one predictor the FE results in the following model form:

$$y_{it} = \alpha_i + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \nu_{it}. \tag{3}$$

‖In the context of (see Hsiao et al. (2012)), the counterfactual are the unobserved outcomes not under intervention (social policy).

The α_i's are unit-specific intercepts that capture heterogeneities across units where $\alpha_1 = \beta_0$ (see Hanck et al. (2020)). An equivalent representation of this model is given by,

$$y_{it} = \beta_0 + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \gamma_2 I_{2i} + \gamma_3 I_{3i} + \cdots + \gamma_N I_{Ni} + u_{it} \tag{4}$$

where $I_{2i}, I_{3i}, \ldots, I_{Ni}$ are indicator variables (dummy variables) such that $I_{ji} = 1$ if $j = i$ and zero where $j = 2, ..., N$. Thus, we interpret $\alpha_1 = \beta_0$ as the intercept of the fitted model in the omitted unit (first unit); $\gamma_2 = \beta_0 + \alpha_2$ is the unit 2 intercept relative to the first unit intercept, and so forth for the rest of γ parameters.

Next we consider the intervention effect. Let D_{it} be the dummy variable equal to 1 if the ith unit is under intervention at time t, i.e.,

$$D_{it} = \begin{cases} 1, & t \geq T_0 \text{ (under treatment or after intervention)} \\ 0, & t < T_0 \end{cases}$$

Note that T_0 is fixed for all i, the time when the intervention happens. Thus, the observed data takes the form,

$$y_{it} = D_{it} y_{it}^1 + (1 - D_{it}) y_{it}^0. \tag{5}$$

Therefore, the treatment effect (intervention effect), denoted as Δ_{it}, for the ith unit at time t, is the difference between the outcome under intervention y_{it}^1, and the outcome under no intervention y_{it}^0, as outlined in the previous section,

$$\Delta_{it} = y_{it}^1 - y_{it}^0. \tag{6}$$

To construct counterfactual values, and ultimately, Δ_{it}, we follow Hsiao and Zhou (2019) to estimate the counterfactual y_{it}^0 after the intervention and thus approximate Δ_{it} as,

$$\hat{\Delta}_{it} = y_{it}^1 - \hat{y}_{it}^0, \text{ for } t \leq T_0 \tag{7}$$

where y_{it}^1 are the observed outcomes, and $\hat{y}_{it}^0$ are the forecasts based on the fitted model (3) or (4) with $t < T_0$. Therefore, $\hat{\Delta}_{it}$ constitutes the estimation of the intervention effect on the unit i at time t. The next section describes the step by step procedure to forecast counterfactual conditions.

3.2. Methodology

Step 0: Given the full set of observations (for all t) we fit the reduced model simultaneously for all i

$$y_{it} = \alpha_i + \delta D_{it} + u_{it}. \tag{8}$$

where α_i is the unit-specific effect, and δ is the common effect among the units that measure the average change pre and post intervention.

Step 1: To find the subset of potential predictors from the full set of observations, we follow a stepwise regression and the parameters of the following model:

$$y_{it} = \alpha_i + \delta D_{it} + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + u_{it}, \tag{9}$$

given the usual assumption of independence between the error term u_{it} and each of the predictors $\{D_{it}, X_{1,it}, ..., X_{k,it}\}$. Following the stepwise (SW)** procedure to select the most appropriate model, we get $\{X^*_{j,it}\}$ $j \subset \{1, 2, ..., k\}$.

Step 2: Based on the predictors selected in Step 1 $\{X^*_{j,it}\}$ for some $j \subset \{1, 2, ..., k\}$ we fit the model:

$$y^0_{it} = \alpha^*_i + \beta^*_j X^*_{j,it} + u^*_{it}, \text{ for } t < T_0, \tag{10}$$

where y^0_{it} represents the outcomes before the event at (T_0), and $X^*_{j,it}$ is the selected predictor (for all $t < T_0$). Thus, $\hat{\alpha}^*_i$ and $\hat{\beta}^*_j$ are the estimators that represent the unit-specific effects and the predictors effects before the intervention.

Step 3: Forecast or estimate the counterfactual based on $\hat{\alpha}_i{}^*$ and $\hat{\beta}^*_j$ as:

$$\hat{y}^0_{it} = \hat{\alpha}^*_i + \hat{\beta}^*_j X_{j,it}, \ (T_0 \leq t \leq T), \tag{11}$$

where $X_{j,it}$ are the observations for the selected predictors post-intervention, and T is the total number of time points in the sample.

Step 4: From y_{it} and $\hat{y}^0_{it}$ with $(t \leq T_0)$, estimate the difference $\hat{\Delta}_t = y_{it} - \hat{y}^0_{it}$ constructing the usual paired $t-$statistic, also called the dependent sample t-test. This is a statistical procedure used to determine whether the mean difference between two sets of observations is zero. Thus, by testing the null hypothesis,

$$H_0 : \ \Delta_t = 0, \tag{12}$$

we can evaluate whether the intervention is statistically significant.

3.3. Procedure to estimate units (municipalities) with significant changes

To identify the number of units that show a statistically significant impact from the intervention, we fit the model in (4) by including the intervention variable D_{it}, and the interaction between D_{it} and the indicator variables per unit $I_{1i}, I_{2i}, \ldots, I_{Ni}$. Such a model assumes the form:

$$\begin{aligned} y_{it} =& \alpha_i + \delta D_{it} + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} \\ &+ \theta_1 D_{it} * I_{1i} + \theta_2 D_{it} * I_{2i} + \cdots + \theta_N D_{it} * I_{Ni} + u_{it}. \end{aligned} \tag{13}$$

Notice that the model in (13) includes the indicator for the first unit. The interaction terms allow us to measure the average change pre-post intervention at unit level. To get the estimation of all the parameters we follow the so-called "unit-demeaned" OLS

**Based on the AIC criteria and in the both directions (forward and backward).

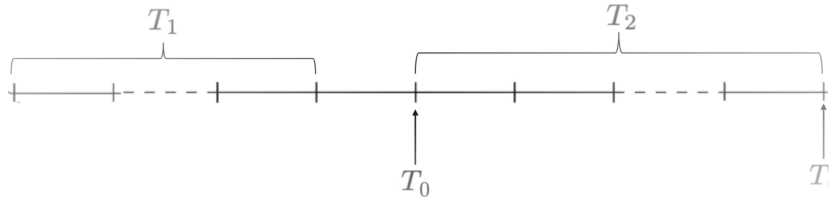


Fig. 1. Timeline of the time series, intervention at T_0, T_1 is the number of observations before intervention, and T_2 is the number of observations after intervention including it. $T = T_1 + T_2$ is the total amount of time points

algorithm (see Hanck et al. (2020), Baltagi (2005), or Frees (2004)). By using this estimation method and the usual construction of the dummy variables, the effect of the first unit is not estimated directly, and the estimation of the parameters θ_2,..., θ_N are relative to the change of the first unit in the sample (relative to the estimation of θ_1). To avoid this inconvenience, and to estimate the average change for all the units we add to the data set a new constructed unit, here named *reference unit* (RU), as further outlined below.

Following this approach for the inference over each parameter, from the interaction in (13), we can settle significant changes in slope at the municipality level. That is, θ_i is the average change in slope between pre and post intervention of the unit ith relative the average change in slope of the RU. The RU change in slope is the total average change as the parameter δ established in (1). Therefore, the subset of units that for the null hypothesis $H_0 : \theta_i = 0$ is not rejected, in equation (13), is called the *control group* ††. Consequently, the complement group is named the *treatment group*. This control group represents the subset of units that are not affected by the intervention. The new unit or RU has two values pre and post the intervention. Both values are the average of the outcome for all i and for all t before and after the intervention, respectively. That is,

$$y_t^{RU} = \begin{cases} \frac{1}{N}\frac{1}{T_1}\sum_i \sum_t y_{it}, & t < T_0 \\ \frac{1}{N}\frac{1}{T_2}\sum_i \sum_t y_{it}, & t \geq T_0 \end{cases} \tag{14}$$

with $i = 1, .., N$ being N the total number of units, and T_1, T_2 the number of time points before and after the event, respectively (see Figure 1). The subset of predictor values, for this unit, is defined as the average of each predictor, i.e., $X_j^{RU} = \frac{1}{N(T_1+T_2)}\sum_i \sum_t X^*_{j,it}$. In the cases where the outcome for the municipalities has extreme observations or outliers, as the example of Death rate application (in section 4.3), we use the median instead of the average to define the outcome of the reference unit.

††The usual definition in the treatment effect literature for a control group is a group in the absence of treatment. In our context, according to the estimated model in (13) , control group is the set of municipalities that were not affected by the intervention effect or the Hurricane Maria.

3.4. Approaches for the fitted models

In addition to the methods in section 3.2, we consider two simple modifications to the methodology. First, to select the subset of predictors $\{X^*_{j,it}\}$ for $j \subset \{1, 2, ..., k\}$, in Step 1, we estimate the model (9) including only the pre-intervention sample ($t < T_0$). With this change, we hypothetically isolate the intervention effect in the selection of predictors, as suggested by (see Xu (2017)).

Second, using the control group outlined in the previous section, we estimate the model in Step 2 and forecast the counterfactual via (11), in Step 3. Since we do not have estimations for the unit-specific effects in this group, we define these as random effects to forecast the counterfactual for the treatment group from Step 3.

Specifically, we define a random term ξ_i with a normal distribution $N(\mu_\alpha, \sigma^2_\alpha)$ where μ_α and σ^2_α are the mean and variance of $\hat{\alpha}$'s, respectively, from the units in the control group, i.e.,

$$\hat{y}^0_{it} = \hat{\beta}^*_j X_{j,it} + \xi_i, \text{ for } T_0 \leq t \leq T \tag{15}$$

where $\hat{y}^0_{it}$ is the counterfactual for units in the treatment group, and $\hat{\beta}^*_j$ are the estimations from Step 2 using only the control group. This random term is defined based on the unit-specific effects $\hat{\alpha}$'s from the control group. These effects are also called the loading factors by Xu (2017).

This procedure mimics the parametric method described in Hsiao and Zhou (2019), where the error term in equation (2) is defined as $u_{it} = \boldsymbol{\alpha}'_i \mathbf{f}_t + \nu_{it}$, where $\boldsymbol{\alpha}'_i$ are the unit-specific effects, and $\mathbf{f}_t$ is the common time-specific effects or a set of common factors. Following Hsiao et al. (2012), we consider the units of the control group as a set of common factors to avoid the estimation of a set of common factors, which is primarily difficult when either T_1 or N are small.

To fit the proposed models we use the plm function from the R package plm (see Croissant and Giovanni (2008)). For the Step 1 we adapted the lme function from the R package nlme (see Pinheiro et al. (2021)) to use the SW procedure.

4. Case Study Analysis Results

In order to measure and validate the social impact of Hurricane Maria on the population of Puerto Rico, we consider variables that align with the different human-oriented dimensions previously introduced in Section 2. Table 2 summarizes the specific response and predictor variables chosen for this study and their respective human dimensions. Response variables in the Psychological dimension include the rate of suicides‡‡ per 10000 inhabitants at municipality level (78 municipalities), and the rate of admissions from substance abuse per 10000 inhabitants at region level. Data is available yearly from 2013-2019 for suicide cases and from 2003 to 2018 for substance abuse reports. For

‡‡Due to issues of data availability we consider 3 regions which cover 70% of the total number of municipalities, approximately. (Source: Substance Abuse and Mental Health Data Archive (SAMHDA). See https://www.datafiles.samhsa.gov/study-series/treatment-episode-data-set-admissions-teds-nid13518

Table 2. Response and predictor variables within respective human dimensions. Numerals **I-VIII** pertain to the set of predictors for each response, which are further described in Table 3 (see below)

	Variables	
Dimensions	Response	Predictors
Psychological	Suicides (S)	I - VI
	Substance Abuse (SA)	I - VI
Demographic	Excess of Mortality (EM)	I, IV - VIII
Economic	Median Home price (MHP)	I, III - VII
	Employment rate (ER)	I, III - VII

outcome variables in Demographic dimension, we leverage death rate§§ per 10000 inhabitants (Excess of Mortality). Lastly, outcomes for the Economic dimension are captured by annual median house Prices for 2012-2018, and by annual employment rates for the same period.

We analyze each outcome individually by considering a subset of predictors (see Table 3 and Figures 11 in the Appendix), respective to each of the dimensions shown in Table 2. Based on the proposed method, we set $T_0 = 2017$ as the year of intervention (Hurricane Maria). The unit of analysis is based on administrative geographical boundaries, which in this case, are the 78 municipalities of Puerto Rico.

Within the objectives in section 2, the aim of the case study analysis is to gain insights into a specific set of research questions:

a What are the statistically significant predictors for each outcome, and which are common among all four outcomes?
b What proportion of municipalities exhibit significant changes for each case?
c How can the results from *a* and *b* be leveraged toward a validated social hardship index?

To answer to the two first inquiries stated above, we follow the proposed methodology in section 3.2, which enables the identification of the subset of significant predictors, the proportion of significant changes at level of municipality, and the intervention effect for each case. Throughout our analysis, a different subset of predictors were identified for each response. Two predictors¶¶ are common for all the responses: *age-group* and *income per capita*. Summarizing in Table 4, we show the percentage of municipalities that exhibit a significant changes and the estimates of the Hurricane Maria effect through the responses S, EM, MHP and ER, respectively. The details of these results are discussed in the following sections. Further, in section 4.5 we outline the construction of our proposed social hardship index (SHI).

§§Leveraging data from the (George Washington project) by aggregating available data by year for 2012-2018.
¶¶except for substances abuse data analysis

Table 3. Set of predictors for case study analysis.

Predictors (Code	abbreviation)	Description	Available data (yearly)
I	Ages	*Ages groups*	2012 - 2018
	y5_17	5 to 17 years	
	y18_34	18 to 34 years	
	y35_64	35 to 64 years	
	y65_74	65 to 74 years	
II	cogni	Cognitive disability (percentage of population per municipality with any cognitive disability)	2012 - 2018
III	HI	Health and insurance (percentage of population per municipality with Health and insurance coverage)	2012 - 2018
IV	Unemp	Unemployment rate	2010 - 2018
V	Male (%)	Gender	2010 - 2018
VI	IncomePC	Income Per Capita (USD)	2010 - 2018
VII	BLSratio	Ratio of large v.s. small business	2012 - 2018
VIII	seitert	Stratus*	

* According to Santos-Burgoa et al. (2018) percentage of population per municipality in lowest, mid and highest socioeconomic development level

Table 4. Summary from M1: *Sig. CP* denotes significant common predictor (at 95% confidence level), *Sig. Munic* is the percentage of municipalities with significant changes after the Hurricane Maria

			2017 - 2018		
Response	Sig. CP	Sig. Munic (%)	Estimation	LB(95%)	UB(95%)
S	y5_17	39.7	0.292	0.200	0.383
	y65_74				
	Income				
EM	y35_64	66.7	1825	917	2733
	Income*				
MHP	y5_17	26.9	-3344.528	-4515.763	-2173.292
	Income				
ER	y5_17	19.2**	-1.965	-2.415	-1.515
	Income				

* Income for EM is not significant for in *M1* but *M2*
** Negative significant changes

4.1. Psychological Impacts: Suicide Rate (S)

Based on the approaches in Section 3.4, the three fitted models for suicide cases identify almost the same set of predictors (Table 5). $Time$ is a time trend that increases in equal steps having the length of one year. The estimation for $Time$ shows a negative tendency, which suggests that suicide rates are decreasing in Puerto Rico. However, when we identify or filter by municipalities that exhibit significant change (Figure 2), it is clear that the suicide rates began to increase from 2016 (top right panel of Figure 2), with a more pronounced increase after Hurricane Maria. This increase in suicide rates can be detected in approximately 40% of the municipalities. Conversely, the top left panel of Figure (2) identifies the municipalities that jointly follow a decreasing tendency for total suicide rate. The two bottom box plots show the variability based on quantiles of the forecasts from each approach and for each group ("not significant" and "significant changes") for both years 2017 and 2018. The gray boxes represent the observations and the colored boxes represent the forecasts from each model ($M1$, $M2$, and $M3$). $M4$ is the average forecast of $M1$, $M2$, and $M3$.

The forecast from $M3$ shows high variability, which is mainly due to the fact that the third model only considers a subset of the total municipalities (municipalities that do not exhibit a significant change; see Figure (2) bottom left panel). In addition, age groups 5-17 and 65-74 years old, and income per capita show a negative significant effect suggesting that populations between 17 and 65 years old and having lower income are more susceptible to suicides as an outcome of Hurricane Maria. Conversely, Cognitive disability, and especially, Health and Insurance (HI), show positive estimations suggesting an increasing tendency for suicides (see Figure 11 in the Appendix).

Regarding the Hurricane Maria effect predicted from models $M1$ and $M2$, an average increase of between 0.27 and 0.29, which is significant within a 95% confidence interval (0.178, 0.38) for the years 2017-2018, as shown in Table 6. For these years, this means that suicide rates in Puerto Rico increase by an average of 92 people annually with a 95% confidence interval between (58, 124 people). Similar results are obtained for the individual effects for both years 2017 and 2018.

4.2. Psychological Impacts: Substance Abuse (SA)

Based on data availability and conceptual alignment, Substance Abuse (SA) reports were chosen as the outcome variable for the psychological dimension of social hardship. Because SA data was available only at the Region level in PR, this outcome variable faces greater limitations in the analysis. Since SA rate is calculated based on the reports of admissions rate to specialized centers that support people with alcohol and drug problems, this information is usually limited to locations that cover these centers. Several additional challenges emerged due to insufficient data in respect to the format of the proposed model. The first limitation is the number of subjects, according to the available data (three SA regions). Despite more data points for SA, data for predictor variables are only available from 2010 on. Fitting a panel data model with missing points from 2003 to 2009 for the covariates causes difficulties in fitting a significant model, given the few degrees of freedom.

To overcome these challenges, an ARIMA backcasting method was leveraged to impute predictor data between 2003 and 2009. The ARIMA backasting method was de-

Table 5. Linear Panel Regression Models for Suicides Rate.

	Fitted models:			
	$M0$	$M1$	$M2$	$M3$
D	0.018			
	(0.051)			
Time		-0.103^{***}	-0.106^{***}	-0.078^{**}
		(0.028)	(0.028)	(0.033)
HI		3.594^{**}	3.465^{**}	3.438^{*}
		(1.669)	(1.726)	(2.044)
Cognitive		2.490^{**}	2.141^{*}	2.148^{*}
		(1.178)	(1.166)	(1.194)
y5_17		-10.606^{**}	-10.415^{**}	-6.816
		(4.630)	(4.640)	(5.581)
y18_34		-3.144		-7.274^{*}
		(2.156)		(3.895)
y65_74		-9.730^{**}	-7.429^{*}	-12.867^{**}
		(4.249)	(3.800)	(5.369)
Unemp		-0.009		0.004
		(0.012)		(0.012)
IncomePC		-0.00004^{***}	-0.00004^{***}	-0.00003^{*}
		(0.00001)	(0.00001)	(0.00001)
Observations	462	308	308	184
R^2	0.0002	0.101	0.097	0.094
Adjusted R^2	-0.002	0.077	0.079	0.052
F Statistic	0.109	33.555^{***}	32.474^{***}	18.081^{**}
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6. Hurricane Maria effect for Suicides Rate jointly for the years 2017-2018 and marginally for 2017 and 2018. $Suicides$ is the average change (estimation of the intervention effect) of the suicides rate post Hurricane Maria and LB and UB are the 95% confident interval limits. $M1$, $M2$, and $M3$ are the results from the three proposal approaches. $M4$ is the average result among the three models.

	2017 - 2018			2017			2018		
	Suicides	LB(95%)	UB(95%)	Suicides	LB(95%)	UB(95%)	Suicides	LB(95%)	UB(95%)
M1	0.292	0.200	0.383	0.229	0.181	0.277	0.355	0.297	0.413
M2	0.274	0.178	0.370	0.204	0.154	0.253	0.344	0.282	0.406
M3	0.261	-0.099	0.621	-0.118	-0.349	0.113	0.640	0.446	0.835
M4	0.276	0.135	0.416	0.105	0.021	0.188	0.446	0.362	0.531

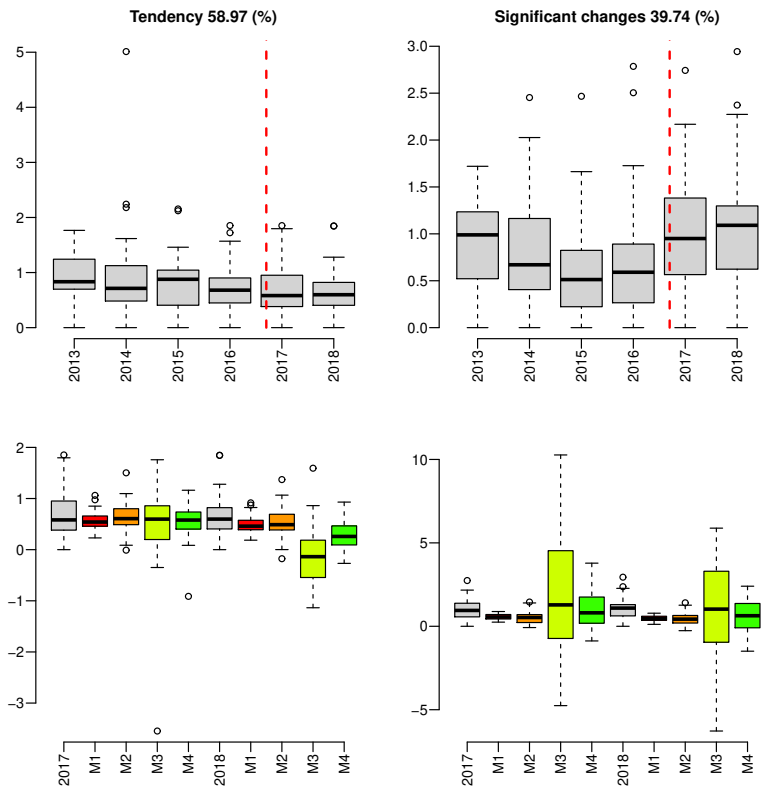
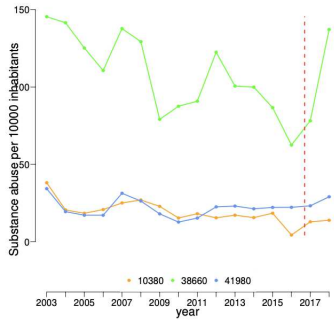


Fig. 2. Suicides: Significant cases at the 95% confidence level. The top two panels describe the quantile variability of the municipalities over time for 2013-2018.The top right panel shows the subset of municipalities that display an apparent intervention effect (Hurricane Maria) according to the model. Conversely, the top left panel shows the subset of municipalities that do not display an apparent intervention effect (Hurricane Maria) according to the model. The two bottom panels show the variability of the $M1$, $M2$ and $M3$ forecasts (colored boxes) relative to the observed variability (grey boxes) for the post-intervention years 2017 and 2018. The bottom left panel shows forecasts for the subset of municipalities that follow historical tendencies (no significant intervention effect). The bottom right panel shows forecasts for the subset of municipalities that show a significant intervention effect.

(a) Substance Abuse Rates 2003-2018



(b) SAMHDA Substance Abuse Regions

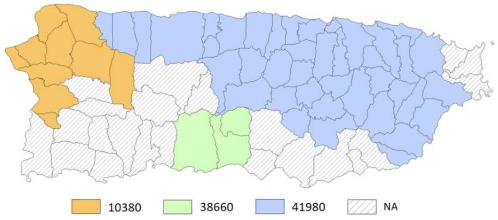


Fig. 3. (a) Time series of substance rates 2003-2018 per (b) Puerto Rico municipality as grouped by SAMHDA administrative regions.

veloped by following Hyndman and Athanasopoulos (2018) Chapter 5, see Figure 9 in the Appendix, as previously used by Breidt and Davis (1992) and Chan et al. (2006). Figure 3 shows the time series of SA rate per Region, and the municipality coverage of each Region. The backcasting procedure enables an improved model fit in terms of having greater degrees of freedom and greater confidence in the parameter estimations. Based on the results shown in Table 7, we conclude that the model fit is significant and that the unemployment rate variable has a significant effect. Given data limitations regarding the Hurricane effect, only predictions from $M1$ without confidence intervals are reported. Comparing observed versus predicted values per region (see Table 8), the positive differences for regions 38660 and 41980 (see Figure 3) suggest that SA rates in these two regions increased, respectively, by 13% and 5% in 2017; and more remarkably, by 80% and 15% in 2018.

Finally, model $M1$ is fit by considering different values for the predictor variables (Gender, Income, and Unemployment) from the Backcasting Fan Chart (BFC) Figure 9 in the Appendix. These models were fit to inspect the stability of the estimations (see Table 18 in Appendix for examples of these models). Results suggest that unemployment is a statistically significant predictor in all models whose point estimation is between 9 and 13.4. Furthermore, the confidence intervals for the point estimations intersect with each other, indicating that parameters and standard errors have been accurately calculated. Thus, the model fitting approach addresses two common challenges for imputing missing panel data: (1) Underestimation of standard errors, and (2) large bias. The former challenge results in underestimated confidence intervals, whereas the latter causes confidence intervals to exclude the true parameter (see Kleinke et al. (2011)).

4.3. Demographic Impacts: Excess mortality (EM)

Excess mortality (EM), meaning the estimated deaths that occurred beyond normal trends in each municipality and are thus attributed to Hurricane Maria impacts, was

Table 7. Linear Panel Regression Models for Substance Abuse Rate.

	Fitted models:	
	$M0$	$M1$
D	−0.932	
	(3.693)	
Time		−1.526
		(1.164)
Gender		−9.293
		(40.729)
Income		0.0001
		(0.0003)
Unemp		10.947**
		(4.455)
Observations	48	42
R^2	0.0004	0.640
Adjusted R^2	−0.021	0.578
F Statistic	0.017	15.543*** (df = 4; 35)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8. Substance Abuse rate forecast after Hurricane Maria for the years 2017 and 2018.

	2017		2018	
Region	Observed	Predicted	Observed	Predicted
10380	12.845	15.094	13.849	6.218
38660	78.185	64.696	137.170	58.445
41980	23.183	17.189	29.017	15.670

leveraged as the outcome variable representative of human impacts in the demographic dimension. The original number of deaths officially reported, 64, caused much skepticism and criticism over death reporting process, how the cause of death is determined, and ultimately, the validity of the reported number Kishore et al. (2018a).

Fortunately, several studies have addressed this controversy, which provides sample frameworks and results that enable comparison and interpretation. Santos-Burgoa et al. (2018) considered migration, age (three groups), sex (male or female) and stratum effects (three strata) in a time-series analysis to estimate 2098 excess deaths with a 95% interval (1872, 2315) between September-December 2017, and 2975 excess deaths with a 95% interval (2658, 3290) between September 2017 to February 2018. Cruz-Cano and Mead (2019) used an ARIMA modeling approach to forecast EM including exogenous variables such as sex, age group, and the top 5 causes of excess deaths (heart disease, other causes, diabetes, Alzheimer's disease, and septicemia). Others, such as Kishore et al. (2018b), leveraged surveys to estimate an EM of 4645 deaths with a 95% interval (793, 8498) from September through December, 2017. More recently, Spagat and van Weezel (2020) leveraged monthly data similar to that used by Santos-Burgoa et al. (2018) and Cruz-Cano and Mead (2019) in an Bayesian linear regression approach. Spagat and van Weezel (2020) report an estimated total of 910 excess of deaths with a 95% interval (440, 1400) for the period September-October, 2017, and remarks there was no substantial excess of deaths for the months November and December, 2017.

Our analysis based on annual data estimates EM between 2017 and 2018 to be an average of 1825 deaths within a 95% CI (917, 2733). The proportion of municipalities that were impacted was estimated directly as manifested by a death rate increase due to Hurricane Maria controlled by *Age, Sex (Male), Income, etc.* (as summarized in Tables

Table 9. Linear Panel Regression Models for excess mortality.

	Fitted models:			
	$M0$	$M1$	$M2$	$M3$
D	4.366***			
	(0.851)			
Time		1.792***	1.504***	1.641***
		(0.389)	(0.467)	(0.479)
y35_64		−354.669**	−343.696**	−441.048***
		(156.255)	(155.654)	(147.088)
Male		2.430	2.503	2.150
		(1.519)	(1.558)	(1.653)
IncomePC			0.001*	
			(0.001)	
Observations	546	390	390	130
R^2	0.052	0.175	0.181	0.348
Adjusted R^2	0.050	−0.038	−0.034	0.168
F Statistic	29.546***	21.907***	17.061***	18.002***
		(df = 3; 309)	(df = 4; 308)	(df = 3; 101)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 10. Hurricane Maria effect for Excess of mortality jointly for the years 2017-2018 and marginally for 2017 and 2018. EM is the average change (estimation of the intervention effect) of the Excess of mortality post Hurricane Maria and LB and UB are the 95% confident interval limits. $M1$, $M2$, and $M3$ are the results from the three proposed approaches. $M4$ is the average result among the three models.

	2017 - 2018			2017			2018		
	EM	LB(95%)	UB(95%)	EM	LB(95%)	UB(95%)	EM	LB(95%)	UB(95%)
M1	1825	917	2733	2534	1969	3100	1116	625	1607
M2	1640	771	2510	2401	1857	2945	879	407	1351
M3	15821	7825	23818	16685	11636	21734	14958	10870	19045
M4	6429	3318	9539	7207	5111	9303	5651	4174	7128

2 and 3. Furthermore, a set of predictors was identified as having a significant effect over the excess of deaths allowed to estimate a closer estimations to the true effect from Hurricane Maria through the excess of mortality, Table 9. However, we recognize the data limitations exist, primarily in terms of the small sample size for the time points. Despite this limitation, we estimate an EM in average of 1825 deaths with a 95% interval (917, 2733) for the years 2017-2018, and 2534 deaths with a 95% interval (1969, 3100) and 1116 (625, 1607) for the years 2017 and 2018, respectively).

Results for the $M1$ model (Table 10) estimate that approximately 67% percent of municipalities exhibit a significant increase of in death rates (Figure 4). This result differs from Santos-Burgoa et al. (2018), whose estimation was 40%. Table 11 reports the forecasts for number of deaths for the years 2017 and 2018, following our three proposed modeling approaches.

Table 11. Observations and forecast for the number of deaths for the years 2017 and 2018. $M1$, $M2$, and $M3$ are the results from the three proposed approaches. $M4$ is the average result among the three models.

year	Obs Death	Pred. M1	Pred. M2	Pred. M3	Pred. Av
2017	30981	28447	28580	14296	23774
2018	27911	26795	27032	12953	22260

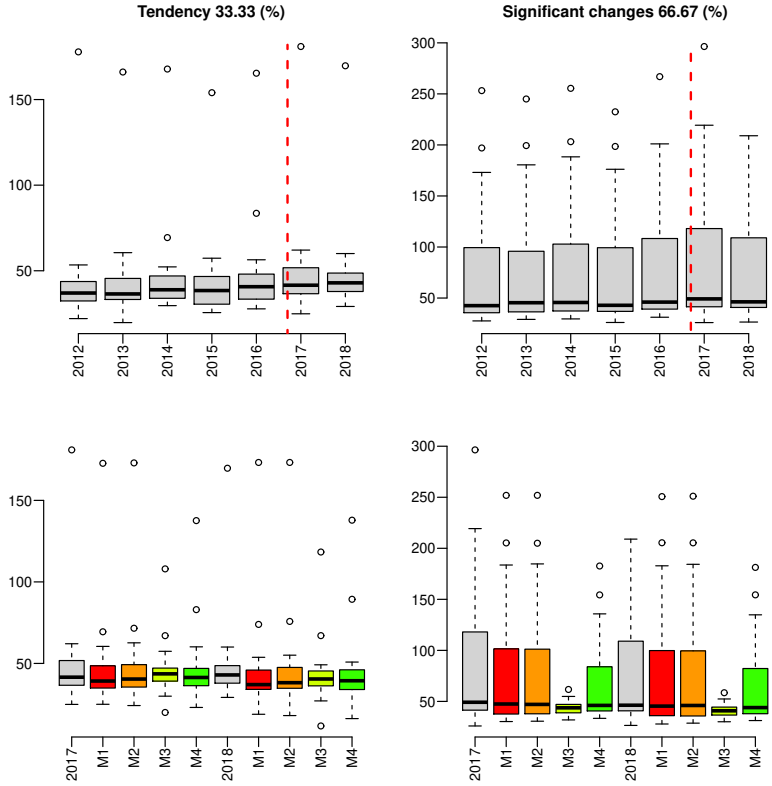


Fig. 4. Excess mortality: Significant cases at the 95% confidence level. The top two panels show the quantile variability of the municipalities over time for 2012-2018. The top left panel describes municipalities that follow historical trends (tendency persists without apparent effect from Hurricane Maria), and the top right panel describes the municipalities that exhibit a significant change after Hurricane Maria. The lower panels compare the variability of observed cases for the years 2017-2018 (grey boxes) with the forecasts after Hurricane Maria (counterfactual effect) according to models $M1$, $M2$ and $M3$ (colored boxes). The lower left panel describes municipalities that follow historical trends, and the lower right panel describes the municipalities that exhibit a significant change after Hurricane Maria.

Table 12. Linear Panel Regression Models for median house price.

	Fitted models:			
	$M0$	$M1$	$M2$	$M3$
D	$-6{,}210.385^{***}$ (777.938)			
Time		$-2{,}370.250^{***}$ (657.417)	$-2{,}264.125^{***}$ (566.941)	$-1{,}074.567^{**}$ (521.554)
HI		$-37{,}948.510$ (55,296.660)	$-43{,}987.400$ (49,038.200)	$-114{,}447.900^{***}$ (41,563.860)
y5_17		$-190{,}916.800^{**}$ (83,084.550)	$-159{,}046.800^{**}$ (62,969.950)	$-204{,}655.500^{**}$ (103,113.500)
y18_34			108,168.600 (114,123.100)	
y35_64		62,487.420 (46,975.060)	135,205.500 (83,358.220)	$-53{,}665.600$ (73,234.080)
Male			1,573.743 (977.161)	
IncomePC		5.321^{***} (0.394)	5.556^{***} (0.457)	4.134^{***} (0.646)
Observations	546	390	390	285
R^2	0.232	0.400	0.409	0.323
Adjusted R^2	0.231	0.392	0.398	0.311
F Statistic	164.787^{***}	255.554^{***}	264.712^{***}	133.194^{***}
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 13. Hurricane Maria effect for Median House Prices jointly for the years 2017-2018 and marginally for 2017 and 2018. MHP is the average change (estimation of the intervention effect) of the Median House Prices post Hurricane Maria and LB and UB are the 95% confident interval limits. $M1$, $M2$, and $M3$ are the results from the three proposed approaches. $M4$ is the average result among the three models.

	2017 - 2018			2017			2018		
	MHP	LB(95%)	UB(95%)	MHP	LB(95%)	UB(95%)	MHP	LB(95%)	UB(95%)
M1	-3344.528	-4515.763	-2173.292	-3520.447	-4183.297	-2857.598	-3168.608	-3841.478	-2495.738
M2	-4280.391	-5478.471	-3082.310	-3701.286	-4330.164	-3072.407	-4859.496	-5608.157	-4110.834
M3	-464.172	-3630.934	2702.590	-1968.739	-4637.067	699.590	889.033	-989.829	2767.895
M4	-2696.363	-4053.439	-1339.288	-3063.491	-4062.018	-2064.963	-2379.690	-2938.367	-1821.013

4.4. Economic Impacts: Median House Prices (MHP) and Employment Rate (ER)

Two response variables were identified in the economic dimension with available data sources: Median House Price (MHP) and Employment Rate (ER). First, we observed a decreasing tendency for MHP, which aligns with findings by Hinojosa and Meléndez (2018), which suggests that MHP have declined across the island by at least 10% since 2005, and suffered an overall drop in home prices estimated to be around $8,000 after Hurricane Maria. The subset of variables that have a significant effect includes $Time$, $y5\_17$ (ages 5-17), and $IncomePC$ (income per capita)(see Table 12). $Time$ and $y5\_17$ have a decreasing tendency in respect to the response, while $Income$ has a positive tendency. In terms of the $M1$ results for the Hurricane effect on MHP, a decrease of -$3344.5 in MHP for 2018-2019 was estimated with an 95% interval (-4515.8, -2173.3) (Table 13). Table 13 shows results for models $M2$ and $M3$, and the marginal effect over the years 2017 and 2018. Figure 5 shows the behavior of municipalities that exhibit both significant and insignificant changes, and the performance of each model in forecasting the counterfactual effect. These results suggest that 27% of the municipalities show a significant decrease in MHP due to Hurricane Maria.

For ER, our results show that 70% of the municipalities displayed significant changes

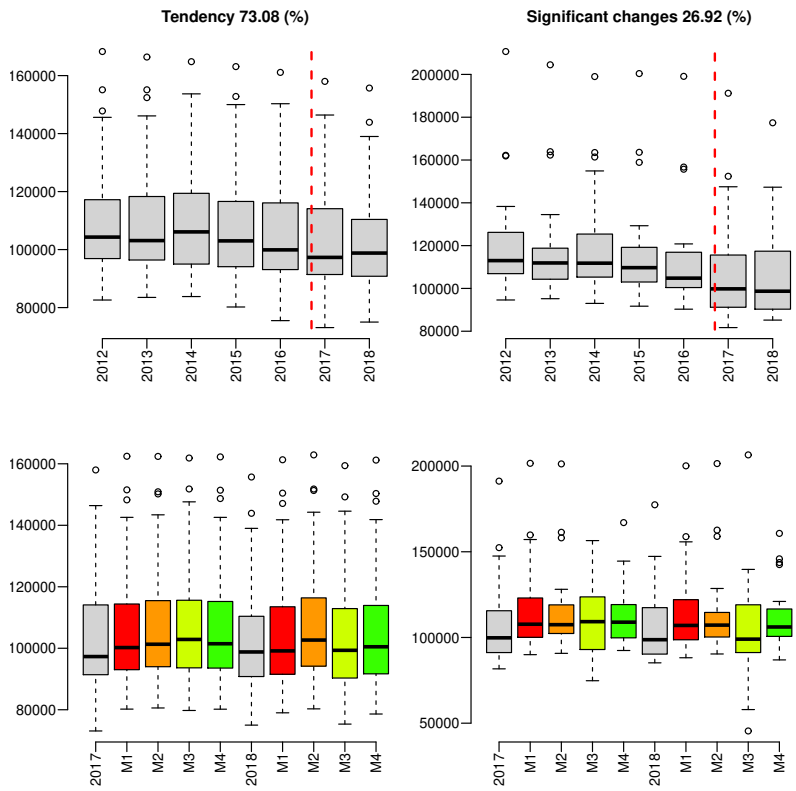


Fig. 5. Median House Prices: Significant cases at the 95% confidence level. The top two panels describe the quantile variability of the municipalities over time for 2012-2018. The top left panel shows the subset of municipalities that tend to follow historical trends, and the top right panel the subset of municipalities exhibiting significant change after Hurricane Maria. The lower panels compare the variability of the observed cases for the years 2017-2018 (grey boxes) with the forecasts after Hurricane Maria (counterfactual effect) according to models $M1$, $M2$ and $M3$ (colored boxes). The lower left panel shows forecasts for the subset of municipalities that follow historical tendencies, and the lower right the subset of municipalities that show a significant intervention effect.

Table 14. Linear Panel Regression Models for employment rate.

	Fitted models:			
	$M0$	$M1$	$M2$	$M3$
D	-0.487^{**}			
	(0.224)			
Time		-0.592^{**}	-0.382^{**}	-0.669^{**}
		(0.264)	(0.151)	(0.302)
HI		-8.169	-6.453	11.201
		(13.784)	(12.844)	(19.857)
y5_17		74.504^{***}	71.879^{***}	76.513^{***}
		(18.159)	(17.824)	(11.713)
y65_74		42.894		-25.224
		(50.497)		(60.879)
y18_34			41.694	
			(38.426)	
Male		0.881^{***}	0.666^{*}	1.372^{***}
		(0.330)	(0.388)	(0.180)
IncomePC		0.002^{***}	0.002^{***}	0.003^{***}
		(0.0003)	(0.0003)	(0.001)
BLSratio			-0.231	
			(0.149)	
Observations	546	390	390	115
R^2	0.019	0.514	0.520	0.743
Adjusted R^2	0.018	0.383	0.388	0.660
F Statistic	10.761^{***}	53.997^{***}	47.218^{***}	41.487^{***}
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15. Hurricane Maria effect for Employment rate jointly for the years 2017-2018 and marginally for 2017 and 2018. $Employ$ is the average change (estimation of the intervention effect) of the Employment rate post Hurricane Maria and LB and UB are the 95% confident interval limits. $M1$, $M2$, and $M3$ are the results from the three proposal strategies. $M4$ is the average result among the three models.

	2017 - 2018			2017			2018		
	Employ	LB(95%)	UB(95%)	Employ	LB(95%)	UB(95%)	Employ	LB(95%)	UB(95%)
M1	0.356	0.068	0.643	0.263	0.153	0.372	0.448	0.221	0.676
M2	0.107	-0.185	0.400	0.056	-0.050	0.163	0.159	-0.078	0.395
M3	0.771	-0.002	1.543	0.620	0.193	1.047	0.921	0.466	1.376
M4	0.411	0.023	0.799	0.313	0.128	0.498	0.509	0.249	0.770

after the Hurricane Maria, with an overall reduction of 19% (Figure 6). Results for Model $M1$ show that Hurricane Maria had a significant effect during the years 2018-2019 (Table 15). These results suggest that employment rate in Puerto Rico increased by 0.26% and 0.44% for the years 2017 and 2018, respectively. However, focusing on the 19% of municipalities that exhibit a significant decrease for 2018-2019 shows a reduction in ER of 2% with a 95% confident interval (1.5, 2.41), and for 2017-2018, a decrease of 1.5% and 2.5%, respectively (Table 16). Models $M1 - M3$, however, suggest that $Time$, $y5_7$ (ages 5-17), Male, and $IncomePC$ are jointly significant (Table 14). Particularly, the $Time$ variable indicates the decreasing tendency of the ER in Puerto Rico from the years 2012-2018.

4.5. Social hardship index

The results of the set of approaches above can be used to extend the proposed methodology toward a validated Social Hardship Index (SHI). As discussed in Section 3, vul-

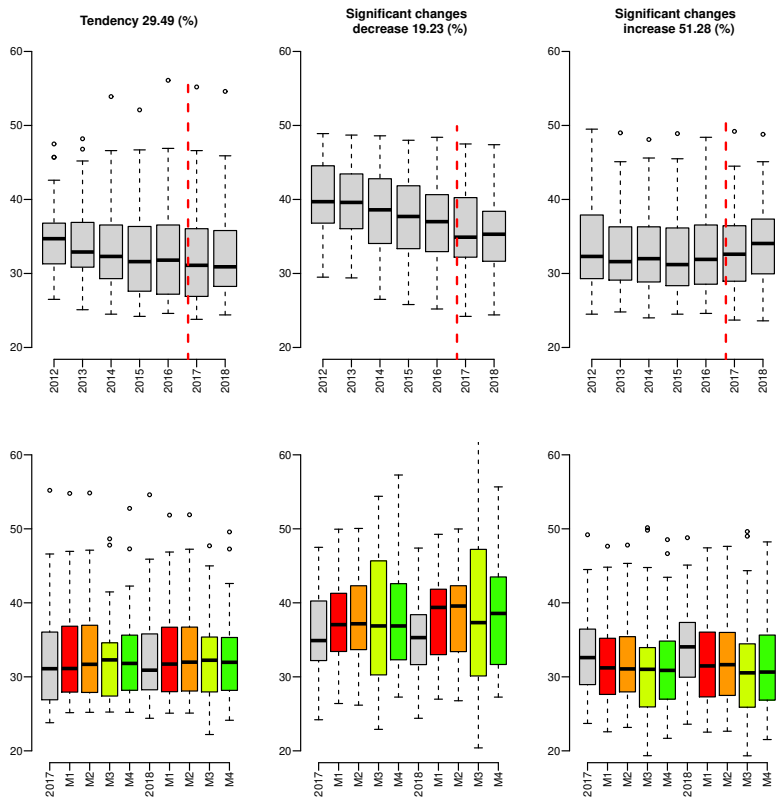


Fig. 6. Employment: Significant cases at the 95% confidence level. The top three panels describe the quantile variability of the municipalities over time for 2012-2018. The top left panel pertains to the subset of municipalities showing no intervention effect, the top center panel the subset showing a negative significant effect, and the top right panel the subset showing a positive significant effect. The bottom panels compare the variability of the observed cases for the years 2017-2018 (grey boxes) with the forecasts after Hurricane Maria (counterfactual effect) according to models $M1$, $M2$ and $M3$ (colored boxes). The lower left, middle, and right panels pertain to the subsets of municipalities showing no intervention effect, a negative significant effect, and a positive significant effect, respectively.

Table 16. Hurricane Maria effect for Employment rate jointly for the years 2017-2018 and marginally for 2017 and 2018 considering only the 20% of municipalities that exhibit a negative tendency. $Employ$ is the average change (estimation of the intervention effect) of the Employment rate post Hurricane Maria and LB and UB are the 95% confident interval limits. $M1$, $M2$, and $M3$ are the results from the three proposal strategies. $M4$ is the average result among the three models.

	2017 - 2018			2017			2018		
	Employ	LB(95%)	UB(95%)	Employ	LB(95%)	UB(95%)	Employ	LB(95%)	UB(95%)
M1	-1.965	-2.415	-1.515	-1.481	-1.573	-1.390	-2.449	-3.009	-1.889
M2	-2.286	-2.764	-1.808	-1.792	-1.840	-1.743	-2.780	-3.498	-2.063
M3	-3.152	-6.317	0.014	-2.734	-4.417	-1.051	-3.570	-5.009	-2.130
M4	-2.468	-3.571	-1.365	-2.002	-2.632	-1.373	-2.933	-3.431	-2.435

nerability indices are a common approach to determine the relative risks and potential social outcomes in the face of future environmental hazards, and can be integrated into planning tools or infrastructure models. The preliminary method introduced below follows a supervised learning approach to develop a disaster-level index based on specific outcomes of social hardship.

In other words, the advantage of this index is that it maps social hardships relative to the effects of Hurricane Maria, thereby tying sociodemographic drivers (i.e., indicators or model parameters) to objective disaster outcomes. Additionally, our approach offers a method to weigh individual indicators and is readily computable in annual time-steps. Given a series of panel data, several vintages of the SHI, such as versions corresponding to each Census year, can be produced for a given range of years. These vintages make the SHI dynamic through time, and can be used to identify vulnerability trends by municipality, such as which are becoming more or less vulnerable, and to keep up with demographic changes as annual data is released.

The SHI is developed using a linear combination of the set of significant predictors (we consider both including and ignoring the Hurricane Maria effect D) over each response: Suicides rate (S), Excess of Mortality (EM), Median House Prices (MHP), and Employment rate (ER). The index is based on the estimation of treatment effect model outlined in Step 1 of the proposed methodology. This model, equation (9), is fit using the full dataset (these estimations are different from the ones shown in the previous results since here we consider the full data set while for $M1$, $M2$, and $M3$ models we only used the pre-intervention data set) and the corresponding estimations per response are available in Table 17.

There are three major steps to construct the SHI. Predictors are first aggregated for each time point, such that $X_{j,t} = \sum_{i=1}^{N} X_{j,it}$, and then multiplied by the corresponding parameter estimation in equation (9), $\hat{\beta}_j X_{j,t}$. Lastly, all statistically significant j where $j \subset \{1, 2, ..., k\}$ are summed.

The final formula of the SHI index can be expressed as:

$$SHI_t^r = \begin{cases} \hat{\delta} D_t + \sum_j \hat{\beta}_j X_{j,t}, & \text{if } \delta \text{ is statistically significant} \\ \sum_j \hat{\beta}_j X_{j,t}, & \text{otherwise} \end{cases} \tag{16}$$

where $t = 1, ..., T$ is the sample of time points, and r denotes the response $r = \{S, EM, MHP, ER\}$. The proposed SHI is a set of sensors for each one of the responses considered in this analysis for Puerto Rico (see Figure 7): Suicides, Excess Mortality, Median House Prices, and Employment Rate. In other words, the SHI is a set of sub-indices respectively labeled $SHI^S, SHI^{EM}, SHI^{MHP}$, and SHI^{ER}. Figure 7 shows a decreasing tendency for SHI^S and SHI^{MHP}, and increasing tendency for SHI^{EM} and SHI^{ER} over time. However, the results for SHI^S are misleading given the low R^2 (see Table 17). To demonstrate the magnitude of the effect of Hurricane Maria as the intervention, we develop and illustrate the SHI with and without the intervention (see the red and black lines, respectively, in Figure 7). Exemplary results for the SHI at the municipality level are shown in Figure 12 in the Appendix.

To facilitate interpretation, the SHI is re-scaled by dividing all the values by the first, then multiplied by 100. Thus, index values over 100 indicate an increase in the response.

For example, for SHP^{MHP} in Figure 7, all index values are below 100, which implies that Median House Prices have been decreasing from 2012 to 2017 with a little increment in 2018.

Finally, a class of index is proposed based on these results:

$$SHI_t(\omega_1, \omega_2, \omega_3, \omega_4) = \omega_1 SHI_t^S + \omega_2 SHI_t^{EM} + \omega_3 SHI_t^{MHP} + \omega_4 SHI_t^{ER} \tag{17}$$

where $\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$. This class index is an overall index where the weights ω_m with $m = 1, .., 4$ is determined ad-hoc according to the relevance of each response.

To illustrate an initial pass for SHI outcomes at the municipal level for 2018, a sub-index was calculated according to each response per equation (16), then as a composite of the sub-indices (SHI_{2018}^{PR}). Because each response has a different range of values, a min-max scaling method was first applied to each sub-index so that values range from $0 - 1$:

$$\frac{x_i - min(x)}{max(x) - min(x)} \tag{18}$$

Equal weights were assumed between responses and including all municipalities according to equation (17). Since response variables can have either a positive or negative relationship with vulnerability, the sub-indices SHI^{MHP} and SHI^{ER} were multiplied by -1 since an increase in these sub-indices are considered an indication of lesser hardship (per Cutter et al. (2010); Flanagan et al. (2011)). To highlight the hardship landscape due to Hurricane Maria in Puerto Rico, the composite SHI_{2018}^{PR} and its respective sub-indices were geographically mapped as the difference between the calculated indices as with and without the intervention effect (i.e., the points between the red and black lines in 7).

Figure 8 shows the composite SHI assuming a series of differing assumptions for weighting schemes to show how the index varies based on stakeholder preferences, rather than equal weighting. Visual inspection of the maps shows that the spatial distributions and clustering of social hardship can differ depending on how responses are weighted. Additionally, decomposing the index by response shows that index values may cluster differently in space between responses. These dynamics that emerge between the composite and sub-indices can be useful for interpretation and future development of SHI-based planning tools.

5. Conclusions

A novel and adaptable method was proposed to identify and validate geographic units potentially affected by an intervention based on a treatment-effect model. In this case, the geographic units are municipalities that proxy the people in Puerto Rico who are exposed to the intervention, Hurricane Maria in 2017. Several limitations were incurred due to data availability and quality. For instance, it was necessary to use backcasting techniques to fit a significant model because of the scarcity of time point observations for some variables (i.e., datasets with sparse vintages).

Table 17. SHI model results according to equation (9).

	Dependent variable:			
	S	EM	MHP	ER
D	0.261^{***}	3.433^{***}	$-4{,}883.000^{***}$	0.491^{***}
	(0.093)	(0.725)	(688.000)	(0.138)
Time	-0.087^{***}	1.462^{***}	$-2{,}122.000^{***}$	-0.178
	(0.027)	(0.200)	(557.200)	(0.182)
HI	2.877^{**}		$-44{,}579.000$	-16.320
	(1.379)		(33,908.000)	(11.360)
Cognitive	2.737^{***}			
	(0.987)			
y5_17	-8.381^{*}		$-130{,}072.000$	56.250^{***}
	(4.751)		(80,543.000)	(19.450)
y18_34	-5.684^{***}			
	(1.640)			
y65_74	-8.648^{**}			-36.530
	(4.040)			(23.640)
Unemp	-0.022^{*}			
	(0.011)			
IncomePC	-0.00004^{***}		4.329^{***}	0.002^{***}
	(0.00001)		(0.489)	(0.0002)
y35_64		-273.200^{***}	$131{,}392.000^{***}$	
		(35.670)	(45,551.000)	
seitert		13.960^{**}		2.170^{***}
		(5.441)		(0.518)
Male		2.865^{***}		0.843^{**}
		(0.538)		(0.346)
Constant	2.184	-6.568	$91{,}675.000^{***}$	-17.440
	(1.428)	(27.600)	(24,397.000)	(14.920)
Observations	462	546	546	546
R^2	0.079	0.113	0.408	0.515
Adjusted R^2	0.061	0.104	0.401	0.508
F Statistic	38.690^{***}	68.540^{***}	371.100^{***}	569.800^{***}
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

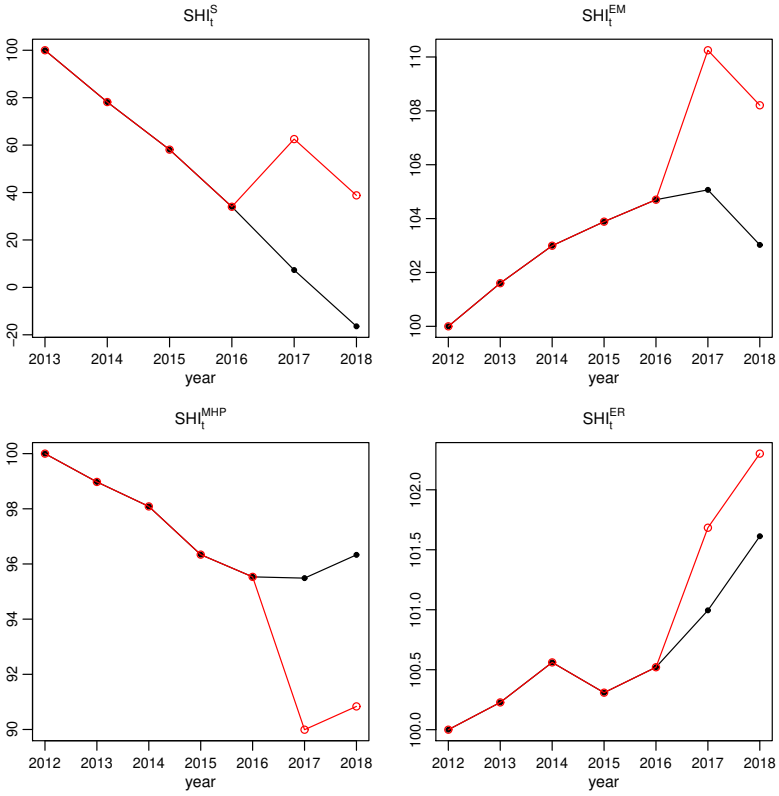


Fig. 7. The Social Hardship Index (SHI) for Puerto Rico according to four responses: suicides, excess mortality, median home prices, and employment rate. The red lines show the SHI with the Hurricane Maria effect, and the black lines show the SHI calculated without considering the Hurricane Maria effect.

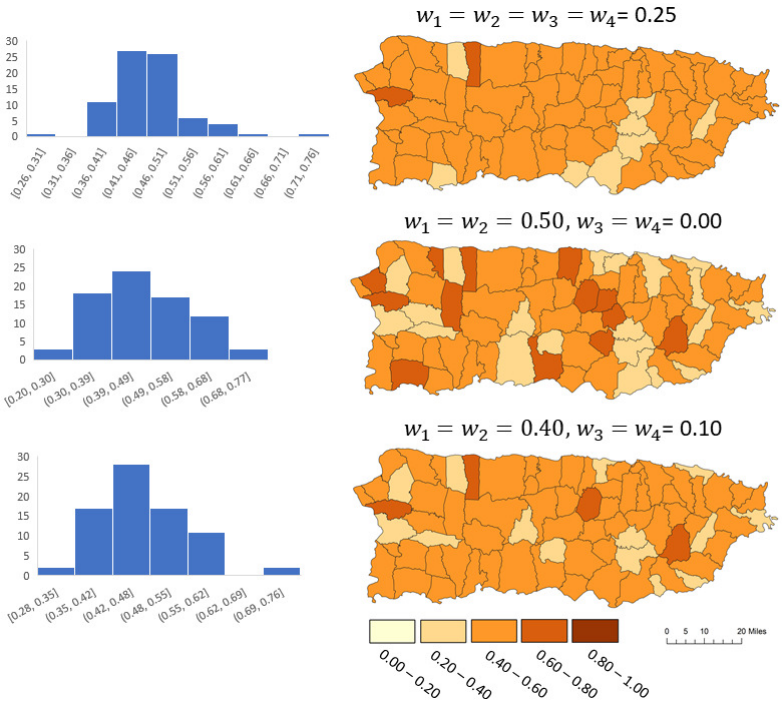


Fig. 8. Composite Social Hardship Index for Hurricane Maria in Puerto Rico, 2018 (SHI^{PR}_{2018}). The darker the orange, the greater social hardship is implied. The SHI^{PR}_{2018} below is a composite of the four sub-indices assuming equally weighted responses ($w_1 = w_2 = w_3 = w_4 = 0.25$, or Suicides, Excess Mortality, Median House Prices, and Employment, respectively), death-related responses as equally weighted ($w_1 = w_2 = 0.5, w_3 = w_4 = 0$), and $w_1 = w_2 = 0.4, w_3 = w_4 = 0.1$ to illustrate the implications of value-based weighting schemes, and how the distributions of the SHI can subsequently vary.

Despite data limitations, conclusions can be drawn in terms of the methodology. A subset of common predictors was identified for all the considered outcomes at the municipality level (Suicides, Excess of mortality, Median House Prices, and Employment rate). These common predictors are Age Group and Income (Table 4). The percentage of municipalities that exhibit a significant change was established, and the effect of Hurricane Maria was estimated to be increasingly significant for suicide rates and excess mortality, while decreasingly significant for median home prices and employment rate.

We briefly demonstrated a potential extension of our methodology to develop a composite Social Hardship Index (SHI) with validated elements. The SHI was built according to each of the response variables for each of the 78 municipalities in Puerto Rico. These four subsequent sub-indices illuminate the landscape of vulnerability in Puerto Rico in terms of three human dimensions of disaster hardships (psychological, demographic, and economic), the social drivers behind these hardships, and how the vulnerability landscape may change over time. Moreover, the SHI explicitly ties the role of extreme weather hazards like Hurricane Maria to the emergence of vulnerability and human suffering. These results reinforce the importance of human-centered impacts that go beyond economic outcomes, such as the psychological and demographic outcomes shown here.

In the future, the performance of the model can be improved, and subsequently, the accuracy of the SHI. For example, the number of observations can be expanded to include a more comprehensive set of predictors, or instrumental variables can be identified. Augmenting the predictors would increase the degrees of freedom for more accurate and precise parameter estimations.

In terms of the proposed framework for social hardship, future work can leverage the SHI approach for novel cases or refine the choice of scale and unit of analysis. The SHI methodology is adaptable to alternative spatial or administrative units for analysis at scales that fit the needs of researchers and stakeholders. For example, the index may be calculated per county or neighborhood district. Given data availability, the SHI can include a more comprehensive set of response variables among the four dimensions used to frame human impacts due to disasters (psychological, demographic, economic, political). Impacts manifesting in the psychological and political dimensions, for example, are particularly difficult to include due to limitations in data collection and availability.

Future work can address the challenge of developing an SHI as a composite of response variables for a broad view of vulnerability and the subsequent question of how to weigh the response variables. Weighting schemes at the level of outcomes are difficult because the components to be weighted are now value-based outcomes, such as mortality, mental health, and employment. For these reasons, weighting is often addressed by way of expert opinion and policymaker choices. One potential pathway would be to group outcomes by overall impact (e.g., deaths), such as suicides and excess mortality, in a dynamic framework that allows decision makers to observe SHI outputs based on different sets of outcomes. Furthermore, social hardship can have many manifestations along human dimensions that go beyond the set introduced here, and those outcomes of value can be identified by stakeholders and policymakers aiming to reduce disaster impacts.

It is important to note that our framework aims to isolate the outcomes of vulnerability, what we are calling *social hardship*, due to a specific disaster. This framing differs

conceptually from other quantitative frameworks for disaster indices that focus more on the precedent sociological structures of vulnerability or seek a hazard-agnostic index (see Johansen et al. (2017)). On the one hand, the advantage of the SHI is that we directly account for the burdens that people have faced as an outcome of a past disaster using objective responses. On the other, the SHI is less applicable in terms of general hazards vulnerability. Social vulnerability, especially in a general respect to environmental hazards, is a complex and continuously evolving property of communities that is difficult to capture in a single metric (see Carvalhaes et al. (2021)). However, despite data and robust results being more difficult to obtain due to the nature of intertwined social and ecological contexts, it is heavily imperative to continue drive toward better analytical methods as we did here. In this sense, the SHI is a proper metric when interpreted specifically to adverse human outcomes of Hurricane Maria, and can be further generalized in interpretation by combining observations of several hurricane events in a locality.

The disaster-level specificity and adaptability of the proposed methodology are central to the broader research implications of this work. The Treatment-Effect models and the SHI can be applied to other contexts using human-oriented response variables identified by local researchers and stakeholders, thus enabling isolated communities to better address and mitigate the human hardships that come with disasters. The SHI produced should be interpreted in terms of vulnerability to Hurricane Maria, but also in terms of future hurricanes of similar magnitude. Maria was a category 4 hurricane with winds up to 155mph (see Pasch et al. (2019)), which represents an extreme event with a certain, and relatively high, level of impact. Considering the historical hurricane risks of the Caribbean region along with climate change, we can expect that Puerto Rico will likely cope with hazards of similar intensity as Maria in the future. The SHI can also be applied to infrastructure models that couple social and technical considerations to include social outcomes as objectives for optimal infrastructure recovery and robustness when resources are scarce (see Boyle et al. (2021); Karakoc et al. (2019)). Integrating social considerations in the form of objective metrics can support the development of planning tools and infrastructure simulations that help identify effective strategies to reduce human hardships in the face of oncoming future climate hazards.

In terms of the broader societal meaning of this study, the proposed Treatment-Effect methodology and SHI can enable science-driven tools that support disaster risk reduction and sustainable development. Toward achieving sustainable development goals (SDG) including eradicating poverty, supporting good health and well-being, reducing inequality, and taking climate action to combat climate-related impacts, it is important to have methods available to directly tackle social hardships. Our framework can be used to address climate-related hazards to the sustainability of livelihoods, or go beyond monetary and economic considerations to capture aspects of human suffering, such as depression and anxiety. Focusing on human outcomes of social hardships can enable decision makers to prioritize and allocate critical resources that mitigate the factors that cause distress and degrade the sustainability of livelihoods for the most vulnerable. For isolated places like Puerto Rico, infrastructure recovery and emergency response can be driven by social vulnerability and the reduction of human hardships.

Declaration of competing interests

The authors declare no conflicts of interest relevant to this work.

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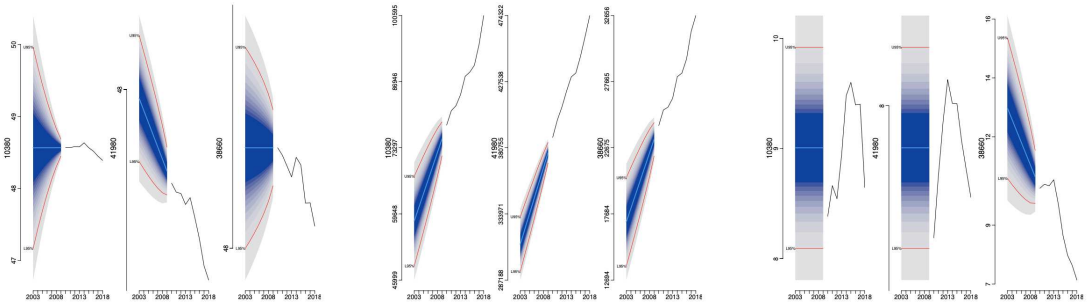

(a) Gender (b) Income (c) Unemployment

Fig. 9. Substances Abuse Backcasting predictors. Observed values for the three predictors per region (three regions - black line) considered in the Substances Abuse model. The Backcasting Fan-chart is the range of values estimated for the predictors for the years 2003 to 2010. Red lines are the 95% interval limits of the Fan-chart

6. Appendix

Table 18. Estimations by considering several values from the Backcasting Fan Chart (BFC) Figure 9. Source data (SD) means the values use for the variables Gender, Income and Unemployment from the BFC; for example, SD1 correspond to the model fitted using the point forecast, this model is the same fitted in (7) (second column). SD2 is the model fitted using inferior limit of the forecast interval 50% from the BFC; SD3 is the corresponding to the superior limit from the same 50% interval. SD4 and SD5 are the inferior and superior limits 80%, respectively. SD6 and SD7 are the inferior and superior limits 95%, respectively.

Source data	Variable	Estimate	std_error	t value	$Pr(>\|t\|)$	LB(95%)	UB(95%)
SD1	Time	-1.5263	0.8788	-1.7368	0.0912	-3.3105	0.2578
	Gender	-9.2926	39.9593	-0.2326	0.8175	-90.4144	71.8291
	Income	0.0001	0.0002	0.2944	0.7702	-0.0004	0.0005
	Unemp	10.9468	3.1835	3.4386	0.0015	4.4840	17.4096
SD2	Time	-1.4343	0.4216	-3.4020	0.0016	-2.2886	-0.5800
	Unemp	13.0199	1.8999	6.8530	0.0000	9.1704	16.8695
SD3	Time	-0.6523	0.4305	-1.5151	0.1382	-1.5246	0.2200
	Unemp	10.7207	1.4056	7.6269	0.0000	7.8726	13.5688
SD4	Time	-1.9223	0.4364	-4.4047	0.0001	-2.8065	-1.0380
	Unemp	13.3914	2.0085	6.6674	0.0000	9.3218	17.4610
SD5	Time	-0.4352	0.4194	-1.0378	0.3061	-1.2850	0.4145
	Unemp	9.6373	1.2131	7.9441	0.0000	7.1792	12.0953
SD6	Time	-2.4659	0.5597	-4.4057	0.0001	-3.6000	-1.3319
	Unemp	12.5451	1.7798	7.0487	0.0000	8.9390	16.1513
SD7	Unemp	9.0760	0.2181	41.6179	0.0000	8.6345	9.5175

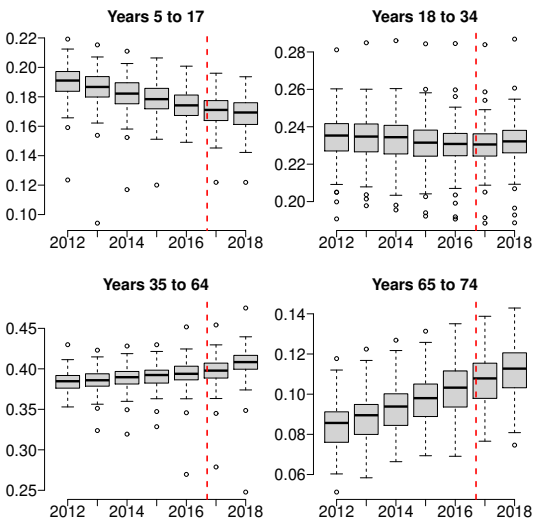

Fig. 10. Distribution of the predictor Ages

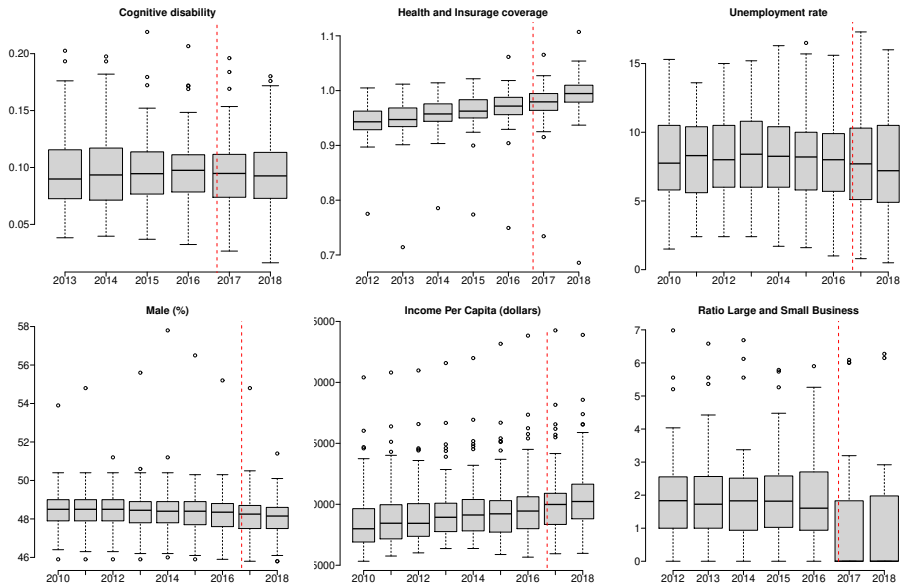

Fig. 11. Distribution of the predictors Cognitive disability, Health and insurance coverage, and Unemployment rate (top panel). Male in percentage, Income per capita (left), and Ratio large and small business (bottom panel)

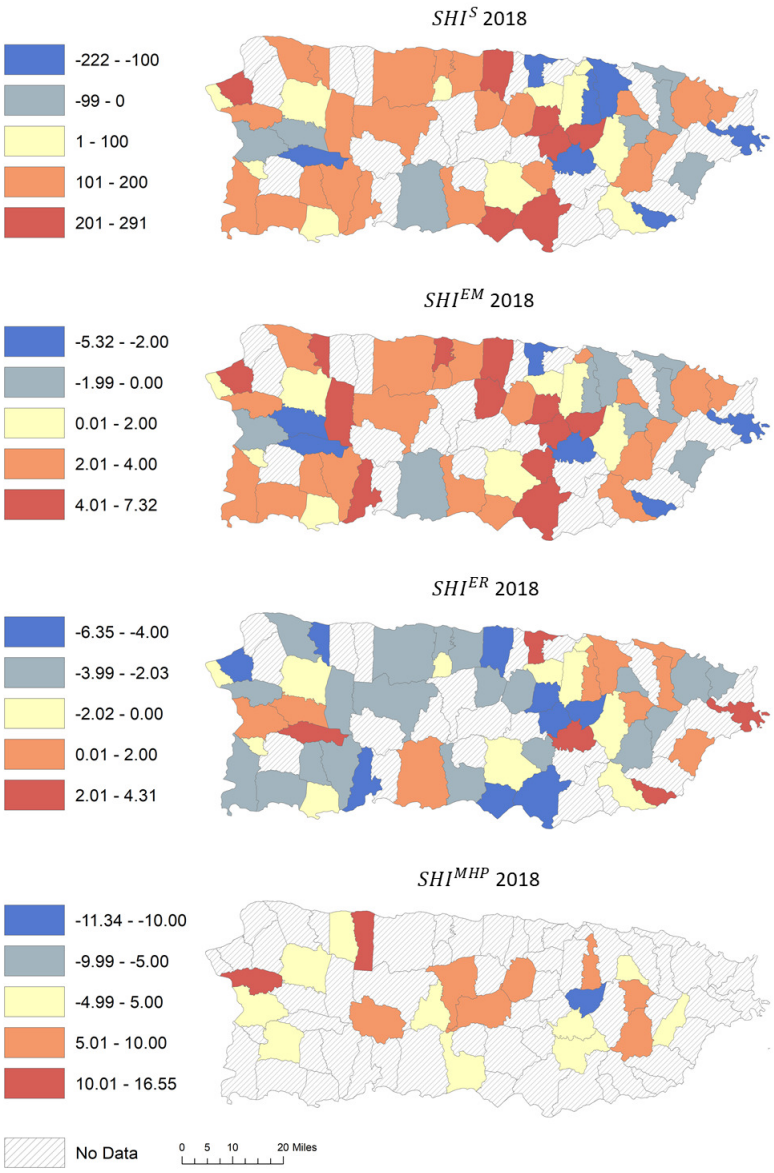

Fig. 12. *SHI* sub-indices based on the four response variables: Suicides, Excess Mortality, Employment Rate, and Median House Prices. Values represent the effect of Hurricane Maria compared to the projected counterfactual of no hurricane effect. Blue suggests municipalities with decreasing hardships due to Hurricane Maria as proxied by each response, whereas red represent those with increasing hardships. Yellow municipalities show relatively lesser effects due to Hurricane Maria.