The Cost of Being Under the Weather: Droughts, Floods, and Health-Care Costs in Sri Lanka

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We measure the impact of extreme weather events—droughts and floods—on health-care utilization and expenditures in Sri Lanka. We find that frequently occurring local floods and droughts impose a significant health risk when individuals are directly exposed to these hazards. Individuals are also at risk when their communities are exposed even if they themselves are unaffected. These impacts, especially the indirect spillover effects to households not directly affected, are associated with land use in affected regions and access to sanitation and hygiene. Finally, both direct and indirect health risks associated with floods and droughts have an economic cost: our estimates suggest that Sri Lanka spends $19 million per year directly on health-care costs associated with floods and droughts. This cost is divided almost equally between the public purse and households, with 83% of it spent on flood-related health care and the rest on drought-related health care. In Sri Lanka, both the frequency and intensity of droughts and floods are likely to increase because of climatic change. Consequently, the health burden associated with these events will likely increase.

I. Introduction

Extreme weather events or disasters can potentially lead to significant and adverse health outcomes. There are myriad ways in which disasters can lead to a deterioration of health and to the economic challenges associated with this deterioration. In many places, climate change is predicted to increase both the frequency and intensity of extreme events, such as heat waves, drought, storms, and floods (Elsner, Kossin, and Jagger 2008; Emanuel 2005; Intergovernmental Panel on Climate Change 2014). The financial costs of the health burden associated with such

events could increase as well (Yonson 2018). This health risk will grow significantly if global warming continues unabated, the economic burden of climate-induced health risks goes unchecked, and the investment to avoid these costs is not made. Maybe surprisingly, there is a paucity of quantitative evidence on the extent of the current cost burden of health risks associated with extreme weather events (Smith et al. 2014, United Nations International Strategy for Disaster Reduction 2011). This paper therefore examines the impact of such risks on health-care utilization and costs (public and private), by focusing on floods and droughts and their effects on the health sector in Sri Lanka.

Extreme weather events cause physical injuries, but they may also increase health risks, including stress-related ailments, communicable diseases, and indirect mortality (Cook et al. 2008; Heutel, Miller, and Molitor 2017; Philipsborn et al. 2016). For example, increasing intensity of rainfall and subsequent floods likely elevate the risk of waterborne and vector-borne diseases, while extreme heat can cause deaths due to heat stress and increase the incidence of cardiovascular and respiratory diseases. Droughts decrease food production and, in poor regions, may result in malnutrition and its associated health risks. Floods and droughts can also cause health spillovers into unaffected populations in disaster-affected regions since health consequences occur through complex interactions. These interactions include the impaired ability of the health system to reduce these risks and the adverse economic consequences borne by indirectly affected households through reduced potential income and the strain on public services provision (Smith et al. 2014, Nomura et al. 2016, Noy and Patel 2014).

Health consequences can vary with individual characteristics (age, education, income, and occupation) and the community-wide socioeconomic and political context (the health-care system, national and international involvement, public security concerns, and public health policy). Changes in land use, urbanization, trade, and travel are other drivers that can affect the spread of diseases in the aftermath of extreme events (Sutherst 2004). For example, changes in land use can increase the risk of infectious diseases (McFarlane, Sleigh, and McMichael 2013; Eisenberg et al. 2007). Higher population densities with inadequate urban infrastructure, changes in vegetation and ground cover, deforestation, and artificial water storage facilities can all determine the link between adverse events and the spread of diseases (Sutherst 2004; Cheong, Leitão, and Lakes 2016; Kweka, Kimaro, and Munga 2016; Berazneva and Byker 2017; Deryugina et al. 2017).

Our analysis uses a cross section of households from the national Sri Lankan household income and expenditure survey of almost 80,000 individuals conducted during 2012–2013. We match this survey data with disaster, meteorological, and land use data across the 25 administrative districts in the country to assist us in identifying the links in question. We ultimately aim to quantify the cost burden of providing more health-care services associated with extreme weather events.

The findings of this paper can also inform us about the additional future cost burden we should expect should climate change predictions materialize and lead to a significant change in the likelihood and intensity of extreme weather events. Without accounting for these health-care costs, we are potentially underestimating the benefits of disaster risk reduction and climate mitigation policies.

The next section discusses the relevant literature, section III describes the Sri Lankan context, and section IV focuses on the methodology and data used in this study. Sections V and VI describe the results and their robustness, respectively, and section VII concludes with some relevant caveats and policy implications.

II. Related Literature: The Health Impact of Disasters

Nomura et al. (2016) analyzed 28 peer-reviewed observational studies on mid- and long-term health impacts of major disasters in the postemergency period (3 months or more after the event). The studies address seven health outcomes: mortality (discussed in 4 studies), suicide (1), mental and behavioral disorders (17), diseases of the circulatory system (4), infectious and parasitic diseases (2), nutritional diseases (1), and biometric measures such as blood pressure (4). In the authors' metastudy, these health impacts are influenced by 35 factors related to the socioeconomic and political context, personal characteristics, and intermediating factors (e.g., behavioral responses, health system functioning, sanitation, food supply, and psychosocial circumstances). In online Appendix 1, we describe in detail the main diseases relating to both inpatient and outpatient treatments in Sri Lanka and some of the related epidemiological literature that examined the determinants of disease outbreaks.

Ultimately, we are interested in the economic burden that disasters impose via the increasing incidence of diseases and the increasing need to provide both inpatient and outpatient health services. In Sri Lanka, much of health care is provided by the government (and paid for by tax revenue). Some services are provided by both the private and public sectors, with the private sector usually serving the high-end market. As such, market prices of various services frequently do not exist or are rather inaccurate in proxying for well-being (welfare) costs associated with these services. Studies in health economics attempt to understand the total welfare cost of health care in terms of three components: resource costs (costs of health and nonhealth goods and services used in medical treatments), lost productivity due to an illness, and the disutility that accompanies many inflictions (experienced pain and inconvenience). We focus on the first component.

When deriving the health costs of infectious diseases, a number of studies focusing on malaria have found a substantial increase in household and public sector expenditures for preventing and treating the disease. For example, two studies identified a decrease in labor inputs and low school attendance due to malaria (Chima, Goodman, and Mills 2003; Malaney, Spielman, and Sachs 2004).

Bleakley (2010) observed higher earnings among people who were born just after the eradication of malaria in the United States, enabling a calculation of the previous cost associated with malaria there. Using the estimated costs of the disease, and assuming that these costs are equivalent to a benefit should the disease be prevented, other studies have calculated the benefit–cost ratios for malarial prevention interventions (e.g., Mills and Shillcutt 2004).

Another strand of this literature examined pandemics. For example, Smith et al. (2009) modeled the economic impact of influenza in the United Kingdom, while another study examined the impact on income associated with an outbreak of severe acute respiratory syndrome (SARS) (Keogh-Brown and Smith 2008). Research in poorer countries identified, for example, the direct cost of illnesses due to waterborne diseases in Pakistan (Malik et al. 2012) or the overall economic burden of waterborne diseases in the South Pacific (Asian Development Bank 2014).

There is, however, only a limited amount of work evaluating the health cost burden associated specifically with extreme natural hazard events such as floods and droughts (Merson, Black, and Mills 2006; Intergovernmental Panel on Climate Change 2014; Dell, Jones, and Olken 2014). The available literature on this topic can be grouped into three types of studies: health impacts, adaptation costs, and health economics evaluation. This last strand uses different monetary valuation methods such as the value of statistical life, disability-adjusted life years, treatment cost estimations, household health expenditure measures, and preventive health provision cost estimates (e.g., Noy 2016).

For example, when isolating the health impact of a 1°C increase in global annual temperature, Bosello, Roson, and Tol (2006) estimate the costs for attributed cases using a multicountry general equilibrium model. Mortality due to vector-borne diseases (such as malaria, dengue, and schistosomiasis) is calculated first using temperature, diseases, and associated mortality risks as parametrized in previous studies, and then the associated health costs in terms of death avoidance are calculated using treatment costs as reported by the World Health Organization. These provide inputs into the authors' general equilibrium model. Kovats, Lloyd, and Watkiss (2011) also use a modeling approach to estimate the marginal effect of climate change in 27 European Union countries by quantifying the value of lives lost due to heat mortality, deaths from additional cases of salmonella, and fatalities due to coastal floods.

The estimates produced from these models inevitably depend on the many assumptions associated with their construction. Statistical quantification of observed data provides a different approach that is less structural and assumption dependent. Knowlton et al. (2011), for example, attempt to calculate the cost of health impacts associated with events that can be related to climate change—ozone air pollution, heat waves, hurricanes, outbreaks of infectious diseases, river flooding, and wildfires—for over a decade in the United States. Mortality and

morbidity from such events are measured using epidemiological studies, aggregate public health data, and extrapolations when required. These are then matched with statistical estimates of the value of life, medical care costs, and lost productivity.

In low- and middle-income countries, micro-observational approaches are more common and probably more accurate. Lohmann and Lechtenfeld (2015), for example, empirically estimate the household-level impact of a drought on health expenditure in Viet Nam by first estimating an illness and drought shock model, aggregating drought-associated illnesses at the household level, and then regressing household health expenditure on the instrumented illness measure. This study identified a 9% to 17% health expenditure burden on households due to drought-related health shocks. Our study uses a similar microeconometric approach to reveal more insights into the health economic impact of floods and droughts at the individual household level.

Another segment of the literature estimates the costs of adapting to climate change-related differences in health risks. These studies focus on preventing treatment costs of diarrheal cases for Europe and Central Asia (World Health Organization 2013); the total net cost savings in disease treatment (Agrawala et al. 2009); preventing the risk of malaria and diarrheal diseases using preventive service costs in Europe (Ebi 2008); evaluation of cardiovascular and respiratory disease treatment due to air pollution (Hutton 2008); and waterborne disease vaccination programs (Goossens et al. 2008, Melliez et al. 2008).

III. Background on Natural Hazards and Health in Sri Lanka

Sri Lanka has a land area of 65,610 square kilometers. Rainfall is largely associated with tropical monsoons, but rain also occurs in other seasons. The mean annual rainfall varies from under 900 millimeters in the driest parts (southeastern and northwestern regions) to over 5,000 millimeters in the wettest parts (western slopes of the Central Highlands). The mean annual temperature of the lowlands varies between 26.5°C and 28.5°C. In the highlands, the temperature can fall to 15.9°C.[1] The country has an irregular topography comprising a broad coastal plain and a central mountainous area rising to elevations of 2,500 meters. This topography and differences in regional climates are underlying causes of the variation in agroecological zones that are identified based on variation in rainfall and its seasonal distribution, soil, and altitude. About 33% of the land is covered

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[1]The island is divided into three climatic zones based on the annual rainfall: dry, wet, and intermediate. The location of the southern part of the central highlands causes interception of monsoonal rains from the southwest and creates a "rain shadow" on the other side. This has given rise to an ever-wet region which receives abundant rainfall from two monsoons and a dry zone that receives rainfall from only the northeast monsoon. The northeast dry zone is characterized by long spells of drought during other months. See Department of Meteorology. http://www.meteo.gov.lk/ (accessed 6 November 2015).

with forest, 43% is used for agriculture (permanent and temporary crops), and 4% is surface water bodies.[2]

Sri Lanka is affected by numerous disasters. The most frequent weather-related disasters are floods, cyclones, and droughts. For the period 1974–2008, the Sri Lankan government reported 1,397 flood events; 1,263 instances of cyclones, strong winds, surges, and gales; and 285 drought events (Disaster Management Centre 2010).[3] The seasonal distribution of floods shows two peaks: one from April to June and the other from October to December, representing the two monsoon seasons.

Sri Lanka is a lower-middle-income country, with a per capita income of $11,500 (purchasing power parity) and a population of 20.9 million in 2015, according to World Bank data. Sri Lanka has made considerable progress on immunization against infectious diseases. Still, the most prevalent infectious diseases in recent years include vector-borne ones, such as dengue and leptospirosis, and diseases transmitted orally through contamination of food or water, such as diarrhea (dysentery), hepatitis, and typhoid fever (Ministry of Health 2012a, 2012b). About 18% of the population suffer from chronic diseases and 15% from acute diseases (United Nations 2015, Department of Census and Statistics 2014).

During 2012–2013, the government reported more than 64,000 cases of dengue, a vector-borne (mosquito) viral disease, with 270 reported deaths. Leptospirosis is the second-highest prevalent disease. Caused by bacteria and transmitted mainly by rodents, there were almost 7,000 cases of leptospirosis and almost 100 deaths in the same time period (Ministry of Health 2012a, 2013). There are more reported outbreaks of both diseases during high-rainfall months. Mumps, measles, and chicken pox are other common infectious diseases. The national communicable disease surveillance undertaken in 2012 also reported 80,660 outpatient visits for influenza-like illnesses and 2,580 inpatients for severe respiratory tract infections (Ministry of Health 2012b). In the last few years, influenza in Sri Lanka has been generally observed from April to June and again from November to January.[4]

Health care in Sri Lanka is mainly provided by the public sector. Total health expenditure accounts for 3.3% of total gross domestic product. According to World Bank data, health expenditure in Sri Lanka in 2015 is comparable to those of Bangladesh and the Philippines, which are in the same income category, and to upper-middle-income countries such as Thailand.

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[2]Sri Lanka has many major river basins as well as a large number of artificial reservoirs. See World Data Atlas. https://knoema.com/atlas/Sri-Lanka/topics/Land-Use/Area/Inland-water (accessed 19 March 2016).
[3]By far the worst disaster experienced in Sri Lanka since its independence was the Boxing Day tsunami in 2004 (following an earthquake in Indonesia). Details about this event are available from numerous sources. De Alwis and Noy (2019) document the tsunami's long-term impact on Sri Lankan households.
[4]Sri Lanka faced an outbreak of influenza (mainly due to the H1N1 virus) in 2015, causing 74 deaths (World Health Organization 2015).

The government health sector is predominantly financed from general revenue taxation, while private sector financing is from out-of-pocket spending, private insurance, enterprise direct payments, insurance paid for by enterprises, and contributions from nonprofit organizations. Public sector health care is universally accessible to the entire population and is almost wholly free of charge. Annual per capita total expenditure (from all sources) is $105, for which the government contribution is $62 (Institute for Health Policy 2015). According to the 2013 national health accounts, the largest health expenditure is attributed to the treatment of noncommunicable diseases (35%) followed by infectious and parasitic diseases (22%). Reproductive health services accounted for nearly 10% of health expenditures, while injuries required 7.7%. Classified by the way health care is delivered and based on government health sector data, inpatient care accounted for 37.1% of total health expenditure by the public sector, and outpatient treatment with medical products (e.g., medicines) was 46.5%. Inpatient care is mainly provided by the public sector (Institute for Health Policy 2015).

In this context, this study attempts to

   (i) quantify the individual health risk attributable to floods and droughts,

  (ii) quantify health spillovers from flood- and drought-affected populations to those not directly affected and identify the associated trigger factors, and

 (iii) identify the costs associated with the health-related disaster impacts identified in (i) and (ii) for both the private and public health sectors.

IV. Data and Methodology

Our data come from the National Household Income and Expenditure Survey (NHIES) conducted between June 2012 and July 2013. The data include information on whether each household member received inpatient hospital treatment in the past year and visited a hospital (private or public) for outpatient treatment in the previous month.[5] The survey questionnaire also posed a question on whether the households were affected in the past year by a flood or drought. We combine this data with flood and drought information compiled in a separate national database to identify our treatment variables for each district, that is,

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[5]In a study about health expenditure surveys, Xu et al. (2009) specify the standard recall period as 1 month for frequent health expenditures and 1 year for infrequent ones, including hospitalizations. As such, the Sri Lanka survey follows the global practice. O'Donnell et al. (2008) investigate health expenditures in Asia and argue that recall mistakes most likely do not bias their estimations (i.e., they are not systematically biased). We note that because the outpatient data request a recall of the past month, and because utilization of outpatient services might not be evenly distributed throughout the year, it is impossible to directly compare the extrapolated data from the survey with the aggregate numbers available at the end of each year from the Ministry of Health.

Table 1. **Data Summary**

Variables	Mean	Std. Dev.	Min	Max
Sex (dummy for male = 1)	0.48	0.50	0	1
Age (years)	32.60	21.50	0	99
Education (years)	8	4.70	0	19
Ethnicity Singhalese (dummy)	0.65	0.48	0	1
Ethnicity Tamil (dummy)	0.34	0.47	0	1
Employed (dummy)	0.23	0.42	0	1
Employer (dummy)	0.01	0.80	0	1
Own family worker (dummy)	0.12	0.33	0	1
Reside in rural sector (dummy)	0.65	0.48	0	1
Reside in estate sector (dummy)	0.10	0.29	0	1
Outpatient visit at least once last month	0.28	0.45	0	1
Inpatient visit at least once last year	0.09	0.28	0	1
Flood affected last year (dummy for self-reported)	0.04	0.20	0	1
Flood affected last year (dummy for district-wide flood)	0.72	0.45	0	1
Drought affected (dummy for self-reported)	0.03	0.17	0	1
Drought affected last year (in affected district)	0.32	0.47	0	1
Flood affected last month (in affected district)	0.11	0.31	0	1
Drought affected last month (in affected district)	0.14	0.35	0	1
Flood spillover	30	46	0	1
Drought spillover	68	46	0	1
Households toilet shared (dummy)	0.06	0.24	0	1
Households toilet public (dummy)	0.04	0.19	0	1
Households drinking water well (dummy)	0.48	0.49	0	1
Households drinking water open sources (dummy)	0.18	0.38	0	1
Agricultural water retention area (% of land in district)	11.09	5.73	0	23.7
Natural water retention area (% of land in district)	4.98	3.24	0	18.6
Household income (Sri Lanka rupees)	29,790	31,656	−3,750	324,275
Household health expenditure (Sri Lanka rupees)	1,544	13,645	0	1,103,400

Note: There are 79,381 observations.
Source: Authors' estimates of National Household Income and Expenditure Survey 2012/2013 data.

whether districts were affected by flood and drought in the past year or in the month before the NHIES survey was undertaken in the 25 administrative districts across the country. District-level land use data come from the district profiles maintained by the Sri Lanka Census and Statistics Department. We also use district land use data to identify how land use affects the health-care costs associated with floods and droughts.

The summary statistics for our sample (Table 1) show that 28% of household members sought outpatient treatment in the previous month and 9% sought inpatient treatment in the previous year.[6] About 4% reported they were affected by a flood

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[6]Inpatient care generally refers to any medical service that requires admission into a hospital and is typical for more serious ailments and trauma. Outpatient care, on the other hand, is any medical service that does not require a prolonged stay at a facility. This can include routine services such as checkups or visits to clinics (even more involved emergency care procedures are included, so long as the hospital or facility allows the patient to leave on the same day). In Sri Lanka, there are accident and emergency care units (A&E units) in secondary and tertiary care hospitals (around 120 hospitals) that allow patients to stay a maximum of 4 hours; after which the patient is

and 3% by a drought in the past year. In the month before the survey was conducted, 11% (14%) were residing in districts affected by floods (droughts).[7]

We estimate individual (inpatient and outpatient) health impacts using a probit model specification. Our outcome variable is a binomial response for inpatient or outpatient treatment. The empirical model specification is

$$Y_{id} = \beta_1 Z_{id} + \beta_2 D_{id} + \beta_3 DSpill_{id} + \beta_5 [Z_{id} * D_{id}] + \beta_6 [Z_{id} * DSpill_{id}]$$
$$+ \delta_m + \gamma_d + U_{id} \tag{1}$$

In the benchmark model, Y_{id} is the dependent variable—a dummy variable for hospital inpatient or outpatient treatment, and the unit observed is for household i in district d. D_{id} is the flood or drought variable (a "treatment" binary indicator) and the demographic and household covariates. Z_{id} are incorporated to control for heterogeneity of health outcomes due to structural factors. Month fixed effects (δ_m) and district fixed effects (γ_d) are incorporated to control for seasonality and district heterogeneity, respectively, in some of the reported specifications (when the district-level land-use measures X_d are not included). The coefficient of interest is β_2, which denotes the marginal effect of floods and droughts on the probability of needing inpatient or outpatient treatment. U_{id} controls for unobserved variation and is assumed to be independent and identically distributed with mean 0. To isolate health vulnerability to floods and droughts based on structural factors (age groups, rural and urban sectors, household sanitation), model specifications incorporating the interaction of treatment with structural factors $\beta_5[Z_{id} * D_{id}] + \beta_6[Z_{id} * DSpill_{id}]$ are estimated.

The previous literature finds that both floods and droughts affect human health directly (e.g., deaths; injuries; mental health; and cardiovascular, respiratory, and kidney diseases) and through indirect pathways (e.g., vector-borne and waterborne diseases). Both can lead the affected population to seek inpatient or outpatient health-care services (see more details in online Appendix 1). As the health impacts associated with disasters are hypothesized to be mediated through other characteristics (vulnerabilities such as limited household sanitation), these can also affect households that are not directly impacted. These spillovers may lead

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admitted to a continuum care unit, short stay unit, or intensive care unit, depending on care needs and the expected length of the patient's stay. These are then classified as inpatient care. Admission to an A&E unit is decided locally (at the local facility) or by a senior medical officer at the A&E. All other hospitals (965 hospitals) have emergency care rooms (inpatient). Therefore, we can expect that only sometimes will an intravenous fluids (IV) treatment be given to a patient and not be classified as inpatient. In particular, while larger (urban) hospitals have good emergency care services, the smaller hospitals in rural areas that are more vulnerable to droughts and floods do not have such facilities for outpatient IV delivery (Wimalaratne et al. 2017).

[7]Thus, the majority of residents in affected districts do not report being affected by either floods or droughts. For floods, these nonaffected households may live farther away from waterways and reservoirs that were flooded. For droughts, these households might live in areas of the district that were less affected by the drought, or their agricultural land might be irrigated, or they might not work in agriculture, and therefore the drought had no direct observable impact on their lives.

to impaired health outcomes for people who are not directly affected by a flood or drought but live in the vicinity of directly affected households. To identify these spillovers, we estimate the model including a variable ($DSpill_{id}$) that defines a separate treatment group for those people who live in flood- or drought-affected districts but did not self-report as being affected by a flood or drought in the survey questionnaire. β_3 is the coefficient of interest to quantify the indirect health spillovers associated with these natural hazards. To identify how land use factors may induce disaster-triggered health risks, we incorporated these into the estimation as well; in these specifications, the district fixed effects are replaced with these district-level measures (X_d), as shown in equation (2):

$$Y_{id} = \beta_1 Z_{id} + \beta_2 D_{id} + \beta_3 DSpill_{id} + \beta_4 X_d + \beta_5 [Z_{id}X_d * D_{id}]$$
$$+ \beta_6 [Z_{id}X_d * DSpill_{id}] + U_{id} \qquad (2)$$

To identify how the external household-specific and district-level factors may induce disaster-triggered health risks, we incorporated these into the estimation in several interaction terms. In these specifications in equation (2), interaction terms of the disaster measure and the district-level factors are also introduced to the model ($Z_{id}X_d * D_{id}$) to examine the causal connection between these factors and disaster exposure and between the same factors and the disaster spillover indicator ($Z_{id}X_d * DSpill_{id}$). β_5 and β_6 are therefore the coefficients of interest in equation (2) that identify the answer to our second question.[8]

Unfortunately, interpreting interaction terms in nonlinear regressions is not straightforward, as the marginal impact of a variable depends on the values that other variables take. In fact, even the sign of the coefficient of the interaction term may depend on the level of other independent variables and may even change along their distribution (Hoetker 2007). We present our results on the interaction effects in a series of graphs that describe the marginal effect at various points. To construct these figures, we employ the Stata command routine developed and described in Norton, Wang, and Ai (2004).

In order to estimate the private cost of health impacts due to natural hazards, we use the household health expenditure data collected in the survey. Most health care in Sri Lanka is provided by the public sector (which is free). However, many households choose to use the private sector instead (because of queues for specialists or because of a perceived difference in the quality of service) and much of the expenditure on medicines is paid privately. The monthly household health expenditure for a member experiencing inpatient treatment (at least once in the

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[8]We also estimated a more restricted model: $Y_{id} = \beta_1 + \beta_2 Z_{id} + \beta_3 D_{id} + \gamma_d + U_{id}$. This model does not include the hypothesized spillover effects (directly unaffected households that reside in affected districts). Results for these regressions are available from the online Appendix: https://sites.google.com/site/noyeconomics/research /natural-disasters.

last year) and receiving outpatient treatment (in the past month) is derived from estimating the household health expenditure model shown in equation (3):

$$Y_{hd} = \beta_1 + \beta_2 X_{ihd} + \beta_3 I_{ihd} + \gamma_d + U_{id} \qquad (3)$$

Y_{hd} is the household health expenditure and I_{ihd} is the inpatient or outpatient i in family h and district d. γ_d is the district dummy variable to control for district heterogeneity in health costs. Using equation (3), we can then estimate the average private health-care costs associated with both inpatient and outpatient treatment.

Finally, the total public costs of health care due to floods and droughts are calculated using the average per capita public health expenditure for inpatient and outpatient treatment in each district. These numbers are reported in the national health accounts of Sri Lanka (Institute for Health Policy 2015).

In the last step, the marginal effects estimated in our models are used to predict the number of inpatients and outpatients associated with extreme weather events at the district level. The estimated figures are used in conjunction with the per capita public and private health expenditure costs, estimated as described in equation (3), to calculate the overall health-care costs of floods and droughts for each Sri Lankan district.

We note that our main identifying assumption, if we were to argue that causality is identified, would be to assume that the shocks are randomly distributed. Since, obviously, some areas are more prone to disasters than others, that assumption is too restrictive, and it is possible that people "sort out" according to their willingness to take on disaster risk. Since mobility is not that high, especially in between rural areas, we do not believe that this is a major source of bias in our estimates.[9] Still, a strict interpretation of our model would argue that we are identifying only correlations between disaster occurrence and health-care utilization. We retain this interpretation in the rest of the paper.

V. Results

We estimate our models (1) and (2) separately for inpatient and outpatient care. Table 2 provides the results for the inpatient model based on equation (1), Table 3 for the inpatient model based on equation (2), and Table 4 and Table 12 in the online Appendix for outpatient services (using equations [1] and [2], respectively). All of these are discussed separately in each of the sections below.

A.   Health Impacts of Extreme Weather: Inpatient Care

Estimates of the parameters for equation (1) are provided in Table 2. In all columns, controls for demographic factors are included, and the results for their

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[9]There is significant movement of people from rural areas to urban centers.

Table 2. **Health Impacts of Floods and Droughts: Inpatient Health Treatments**

Variables	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Self-reported flood (dummy)	0.02* (0.010)	0.02* (0.010)	0.02* (0.010)	0.02* (0.010)	0.02* (0.010)	0.01 (0.009)
Flood spillover (dummy)	0.02** (0.005)	0.02** (0.005)	0.02** (0.005)	0.01*** (0.004)	0.01*** (0.004)	0.02*** (0.004)
Self-reported drought (dummy)	0.04*** (0.014)	0.04** (0.014)	0.04** (0.014)	0.07 (0.050)	0.07 (0.050)	0.03** (0.010)
Drought spillover (dummy)	0.01 (0.008)	0.01 (0.006)	0.01 (0.010)	0.05 (0.050)	0.05 (0.050)	0.00 (0.010)
Shared toilet (dummy)			0.02*** (0.005)	0.02** (0.005)	0.02** (0.005)	0.02** (0.010)
Public toilet (dummy)			0.04*** (0.005)	0.04*** (0.004)	0.04*** (0.004)	0.04*** (0.010)
Drinking water well (dummy)			0.02** (0.005)	0.01** (0.005)	0.01** (0.005)	0.01** (0.006)
Drinking water unsafe source (dummy)			0.00 (0.006)	0.00 (0.006)	0.00 (0.040)	−0.01 (0.010)
Water reservoirs (%)						0.003*** (0.001)
Natural water bodies (%)						0.00 (0.001)
Month fixed effects	No	Yes	Yes	Yes	No	Yes
District fixed effects	No	No	No	Yes	Yes	Yes
District land use (%)	No	No	No	No	No	Yes
Pseudo R-squared	0.03	0.03	0.03	0.04	0.04	0.03

Notes: Robust standard errors in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. There are 79,381 observations. Structural demographic covariates included in all specifications are sex, age, years of education, ethnicity, employment status, living in rural sector, living in estate sector, income, and time to hospital. Model (v) is used for cost calculations.
Source: Authors' estimates.

Table 3. **Health Impacts of Floods and Droughts: Inpatient Health Treatments for Different Groups**

Variables	Rural		Urban		Estate		Young		Old	
Self-reported flood (dummy)	0.02*	(0.010)	0.00	(0.003)	0.00	(0.00)	0.01	(0.010)	0.03***	(0.010)
Flood spillover (dummy)	0.01**	(0.005)	0.00	(0.002)	−0.05*	(0.03)	0.02***	(0.005)	0.02***	(0.006)
Self-reported drought (dummy)	0.07	(0.060)	0.02**	(0.006)	−0.96***	(0.07)	0.05	(0.050)	0.10*	(0.060)
Drought spillover (dummy)	0.05	(0.060)	0.10***	(0.030)	−0.94***	(0.08)	0.04	(0.050)	0.08	(0.060)
Shared toilet (dummy)	0.02***	(0.005)	0.00	(0.002)	0.05***	(0.02)	0.02**	(0.006)	0.02**	(0.007)
Public toilet (dummy)	0.04***	(0.006)	0.01***	(0.003)	0.05**	(0.02)	0.03***	(0.005)	0.05***	(0.007)
Drinking water well (dummy)	0.01**	(0.005)	0.00	(0.001)	0.10***	(0.02)	0.01	(0.005)	0.02**	(0.006)
Drinking water unsafe source (dummy)	0.00	(0.007)	0.00	(0.001)	0.09***	(0.01)	0.00	(0.004)	0.00	(0.009)
Pseudo R-squared	0.05		0.06		0.05		0.04		0.04	
No. of observations	51,364		20,451		7,514		40,300		39,081	

Notes: All models estimated in this table include month and district fixed effects but not land use variables. Robust standard errors in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.
Source: Authors' estimates.

Table 4. **Short-Run Health Effects (district-wide exposure): Outpatient Health Treatments**

Variables	(i)		(ii)		(iii)		(iv)		(v)		(vi)	
Flood last month	0.01	(0.010)	0.01	(0.010)	0.01	(0.010)	0.00	(0.010)	0.00	(0.010)	0.00	(0.010)
Drought last month	0.04***	(0.010)	0.04***	(0.010)	0.04***	(0.010)	0.02	(0.020)	0.03**	(0.010)	0.01	(0.020)
Shared toilet (dummy)					0.02**	(0.010)	0.02**	(0.010)	0.03***	(0.010)	0.02**	(0.010)
Public toilet (dummy)					0.01	(0.010)	0.02	(0.020)	0.02	(0.020)	0.01	(0.010)
Drinking water well (dummy)					−0.01	(0.010)	0.00	(0.010)	0.00	(0.010)	−0.01	(0.010)
Drinking water unsafe source (dummy)					−0.01	(0.010)	0.00	(0.010)	0.00	(0.010)	0.00	(0.010)
Water reservoirs (%)											0.01***	(0.001)
Natural water bodies (%)											−0.01***	(0.002)
Month fixed effects	No		Yes		Yes		Yes		No		Yes	
District fixed effects	No		No		No		Yes		Yes		No	
District land use (%)	No		No		No		No		No		Yes	
Pseudo R-squared	0.03		0.04		0.05		0.05		0.05		0.05	

Notes: Robust standard errors in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. There are 79,381 observations. Structural demographic covariates include sex, age, years of education, ethnicity, employment status, living in rural sector, living in estate sector, income, and time to hospital. Model (v) is used for cost calculations.
Source: Authors' estimates.

coefficients are presented in the online Appendix. The basic specifications are presented in columns (i) and (ii), which include self-reported and spillover flood and drought binary indicators and month fixed effects in column (ii). In these results, we find that having been directly affected by floods or living in a community affected by floods increases the probability of needing inpatient care by about 2 percentage points, while the impact for those directly affected by a drought is about 4 percentage points.

Columns (iii)–(vi) in Table 2 include hygienic factors (shared or public toilet indicators and access to drinking water) and combinations of month and district fixed effects. Throughout the estimations in columns (iii)–(v), we consistently observe that the likelihood of receiving inpatient treatments associated with direct exposure to flooding increases by about 2 percentage points. The spillover risk, once we control for other factors, is lower by about 1 percentage point and less consistently estimated. Relying on either shared or public toilets (the default being private ones) is associated with increased inpatient treatment, as is drinking water that comes only from wells. Surprisingly, unsafe drinking water (as reported in the survey) is not associated with increased use of inpatient services. The presence of water bodies is investigated in column (vi)—we find that reservoirs are associated with increased use of inpatient care, but the magnitude of this coefficient is quite small. We find no association between the presence of natural water bodies and inpatient services.

In Table 3, we divide the population sample we have into several subsamples and estimate these separately. In particular, we estimate rural households, urban households, and those residing in estates (the first three columns in Table 3).[10] In the last two subsamples (columns 4 and 5), we separate the sample according to age (at the median age). Maybe not surprisingly, the impact of floods is higher for rural households than it is for urban households in terms of inpatient health treatments. This is also true for droughts, though the coefficient estimates for rural households are not statistically significant. Surprisingly, the coefficient for the drought spillover indicator, which is statistically significant, is twice as large for the urban sample as it is for the rural sample.

More important than these distinctions between rural and urban are the estimated coefficients in the estate sector. These are much larger for droughts, suggesting that this population, already the poorest and most disadvantaged, also suffers from a much higher need for inpatient care as a consequence of droughts (and spillover from floods). Also notable is that the impacts of hygiene and water on the estate sector are also both larger and more statistically significant, which is surprising given that the size of the estate sample is much smaller. This is a further

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[10]Estate sector consists of all plantations that are 20 acres or more in extent and have 10 or more resident laborers. Estate laborers reside in the plantation areas.

indication of the intensity of the impact of natural hazards on health utilization in the estate sector.

The differences between the estimated coefficients for the young and old populations are less pronounced. However, we do note that the impact of both hazards on inpatient health services appears to be higher for the older subsample and also more statistically significant.

In an additional set of regressions, we investigate the interaction effects of the occurrence of floods and droughts using hygiene and water as interaction terms. The interpretation of interaction effects in limited dependent variable models is more involved and, as Norton, Wang, and Ai (2004) show, frequently misestimated and misunderstood. We follow their recommendation and present these results in a series of graphs discussed below in section V.C.

B.   Health Impacts of Extreme Weather: Outpatient Care

Table 4 presents the impact of floods and droughts on the likelihood of outpatient treatment, similar to the presentation of results for inpatient hospitalizations in Table 2. The dependent variable in Table 4 is whether a household member used outpatient services in the previous month, and the main variable of interest is whether a district-wide flood occurred during that same month. We no longer have the data available to allow us to separate those that were directly and indirectly (spillovers) affected.

Unlike earlier results (for inpatient care), we no longer observe that households that live in a district that was flooded are significantly more likely to require outpatient services. The results in all the regressions for the district-wide flood measure are always statistically not significantly different from zero. One explanation for this lack of statistical significance is that our flood indictor is no longer identified precisely, so that it erroneously identifies many households that were not actually affected by floods.

Droughts are a more spatially widespread hazard, and therefore our identifying independent variable (district-wide exposure) is more relevant in this context. We indeed find more consistent results for the drought-treatment variable—the coefficient in most of the estimates is both statistically and economically significant, with droughts increasing the likelihood of outpatient treatment in the following month by 1–4 percentage points. It is, however, important to note that once we estimate the full model with all controls, neither the flood nor the drought indicators retain their statistical significance.

The estimated model consistently shows that households that share toilet facilities with other families are at a significantly higher risk of requiring outpatient health treatment (irrespective of their weather-hazard exposure). When households do not possess an in-house source for drinking water, evidence of their need for outpatient health services is less consistent (columns [iii]–[vi]). Where the presence

of water bodies is included in the estimation, the presence of artificial reservoirs is associated with an increased probability of requiring outpatient health-care services, while the presence of natural water bodies is associated with the opposite (in both cases the results are statistically significant and not very large; column [vi]).

C.   Interactions of the Hazard Variables with Hygiene Controls

As stated earlier, the magnitude and even the sign of the interaction effects are difficult to present because in nonlinear models these depend on the level of all the variables. As suggested by Norton, Wang, and Ai (2004), the easiest way to present these interactions is through a series of graphs where the coefficient size is presented on the vertical axis while the estimated probability of the event (in this case, seeking inpatient or outpatient care) is presented on the horizontal axis. We note that there might be multiple combinations of independent variables that lead to a similar estimated probability, and the size of the interaction coefficient associated with each one of these combinations might be different.

These interaction effects for inpatient care are presented in the figure. In each case, the companion figure to each of the estimated interaction effect (per estimated probability) describes the statistical significance of these results, with the 5% significance threshold noted in the graph. Examining the inpatient model, for example, the interaction between having shared toilets and being affected by floods (self-reported) appear to be negative, but it is not statistically significant for any estimated probability. More nuanced and more difficult to interpret is the interaction effect between the same flood-affected measure and having access to a public toilet. In this case, the results appear to be statistically significant for estimated probabilities >0.2, but the sign of the coefficient associated with this interaction can be either negative or positive for different combinations of the independent variables yielding these larger estimated probabilities.

Overall, the estimated interaction effects in most cases are not consistently statistically significant and of the same sign all across the range of associated probabilities. Exceptions are few but worth noting. A household that is indirectly affected by flooding and has access only to a well or unsafe drinking water faces a higher likelihood of needing inpatient care for the whole distribution of estimated probabilities. Rural households that are exposed to flood risk also appear to experience much larger impacts (this is a result we only reported using different subsamples in this section). All interaction effects of floods and droughts on seeking inpatient health are available in online Appendix 14.

The figure available in online Appendix 15 presents the interaction effects for outpatient care. In this case, none of the interaction effects are statistically significant. This might be because there are no interactions, or because our identification of hazard exposure at the district level is not precise enough, as we discussed in section V.B.
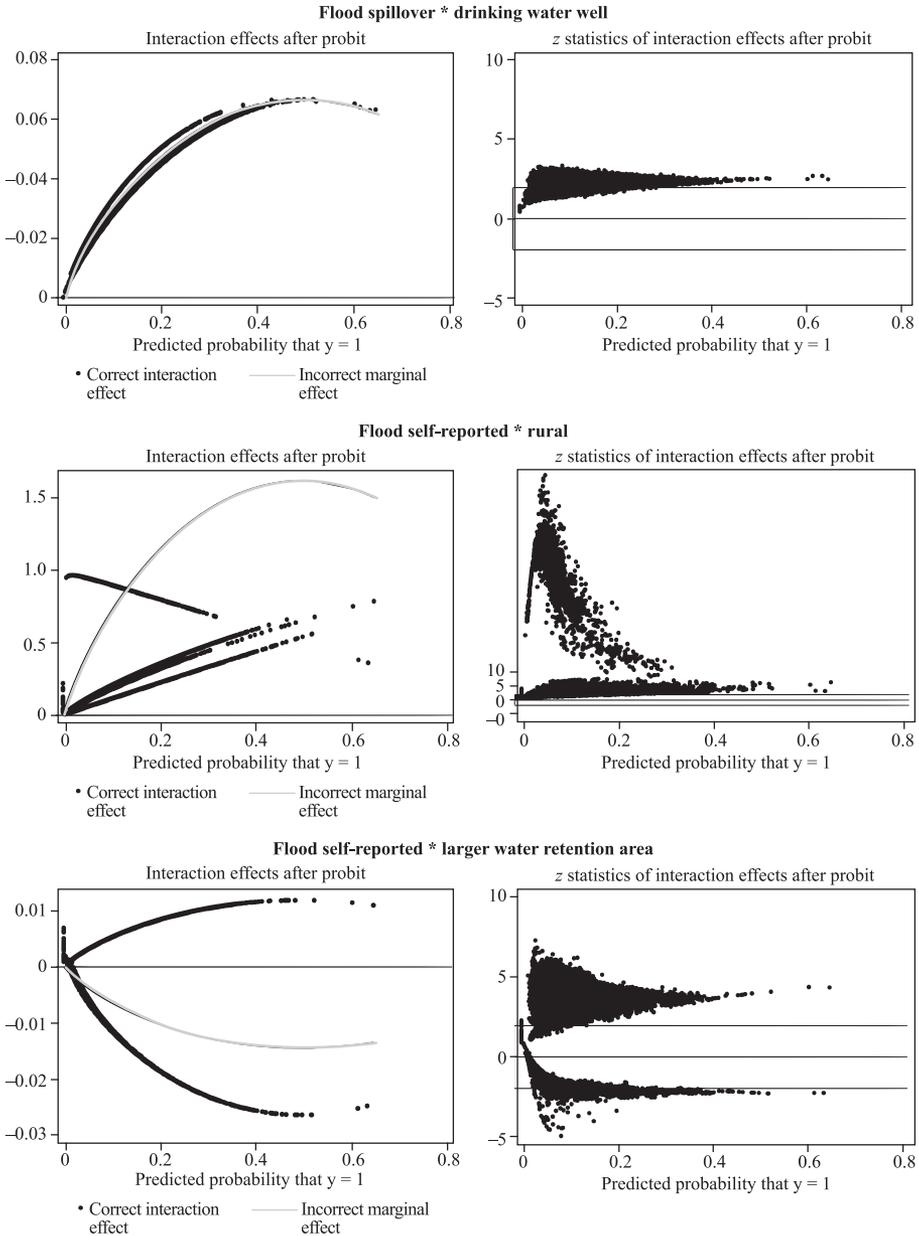
Figure 1.   **Interaction Effects of Floods and Droughts on Seeking Inpatient Health Care**
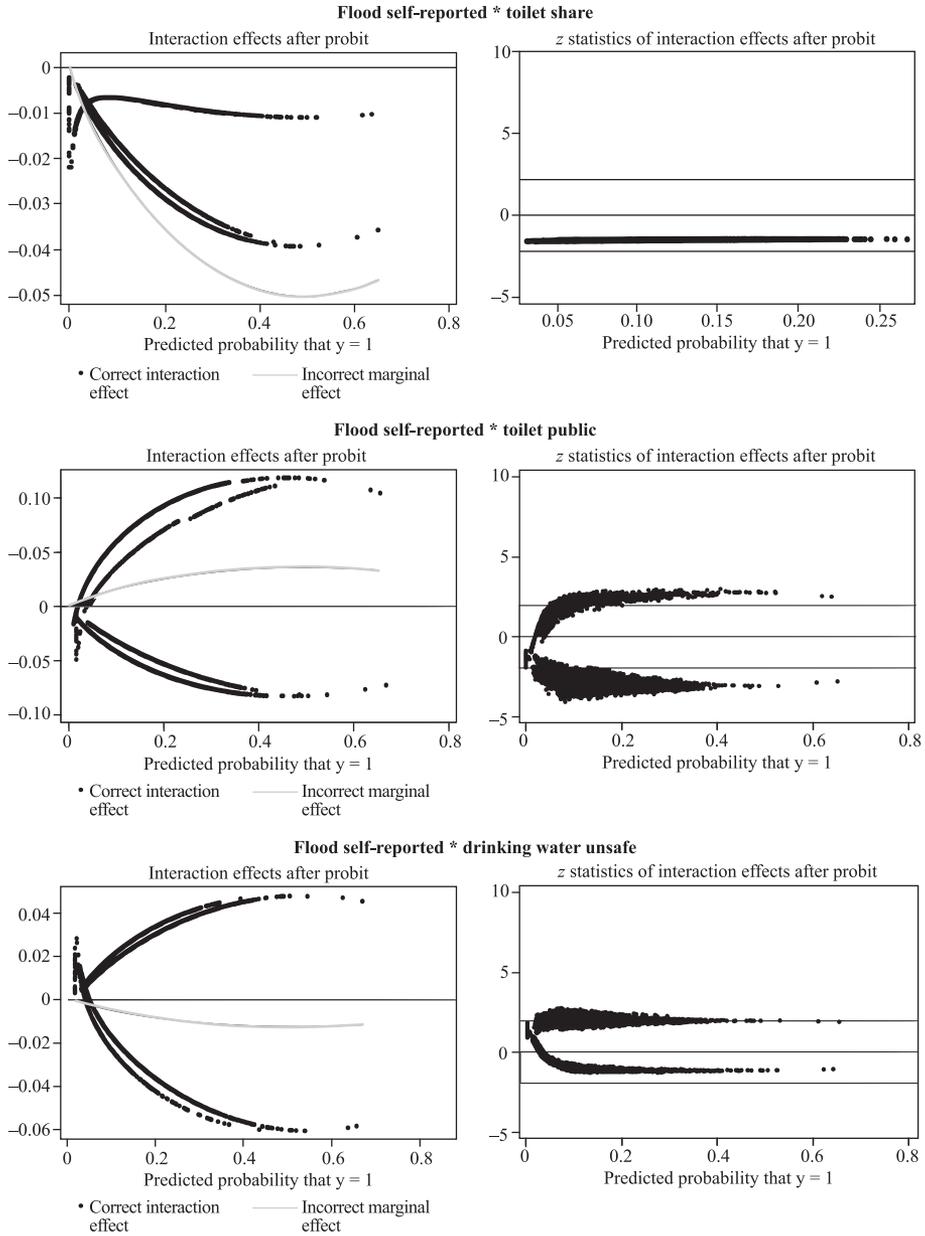
D.   District-Level Health Costs of Floods and Droughts

        Table 5 provides information about the estimation specification described in equation (3). In these specifications, we estimate the average increase in health

Figure 1. *Continued.*

Flood spillover * drinking water well

Interaction effects after probit — *z* statistics of interaction effects after probit

• Correct interaction effect   Incorrect marginal effect

Flood self-reported * rural

Interaction effects after probit — *z* statistics of interaction effects after probit

• Correct interaction effect   Incorrect marginal effect

Flood self-reported * larger water retention area

Interaction effects after probit — *z* statistics of interaction effects after probit

• Correct interaction effect   Incorrect marginal effect

expenditures at the household level associated with an episode of inpatient or outpatient health service utilization. Not very surprisingly, we note that inpatient care is on average about 3 times as costly for a household as it is for outpatient care (column [iii]). Other interesting observations that arise out of these estimates

Figure 1. *Continued.*

Flood spillover * larger water retention area

Interaction effects after probit

z statistics of interaction effects after probit

Predicted probability that y = 1

Predicted probability that y = 1

• Correct interaction effect   —— Incorrect marginal effect

Drought self-reported * larger water retention area

Interaction effects after probit

z statistics of interaction effects after probit

Predicted probability that y = 1

Predicted probability that y = 1

• Correct interaction effect   —— Incorrect marginal effect

Drought spillover * larger water retention area

Interaction effects after probit

z statistics of interaction effects after probit

Predicted probability that y = 1

Predicted probability that y = 1

• Correct interaction effect   —— Incorrect marginal effect

Source: Authors' estimates.

is that the expenditure associated with males and older patients are on average higher. Households with higher socioeconomic status (better educated, belong to the Sinhalese majority, have higher income, and live in an urban area) are all associated

Table 5. **Private Health-Care Costs (per month, for inpatient and outpatient services)**

Variables	(i)		(ii)		(iii)	
Inpatient (at least once last year)			1,720.18***	(166.900)	1,602.20***	(176.430)
Outpatient (at least once last month)	709.30***	(111.000)			502.40***	(113.030)
Male or female (dummy)	180.70*	(104.100)	171.33*	(104.030)	169.90*	(103.980)
Age (years)	10.92***	(2.550)	10.82***	(2.530)	8.47***	(2.560)
Education (years)	64.71***	(11.420)	58.54***	(11.340)	63.16***	(11.420)
Sinhalese (dummy)	449.64	(753.520)	469.45	(750.890)	467.38	(753.470)
Tamil (dummy)	227.57	(753.580)	170.25	(753.200)	543.61	(760.990)
Employed (dummy)	−486.24***	(131.590)	−509.70***	(131.130)	−458.47***	(131.570)
Employer (dummy)	−564.42	(607.370)	−553.99	(607.110)	−5,484.53	(606.810)
Own family worker (dummy)	−710.62***	(163.470)	−716.05***	(163.220)	−546.22***	(164.440)
Rural sector (dummy)	−290.97**	(121.340)	−305.15***	(121.310)	−179.87***	(127.300)
Estate sector (dummy)	−778.76***	(197.290)	−755.90***	(197.150)	−672.13***	(224.020)
Total income (Sri Lanka rupees)	0.02***	(0.002)	0.02***	(0.001)	0.02***	(0.001)
Time to hospital	−29.90***	(7.770)	−30.72***	(7.760)	−26.81	(8.030)
Constant	31.31	(760.310)	49.19	(758.890)	−1,149.43	(890.560)
Observations	79,381		79,381		79,381	
R-squared	0.005		0.006		0.01	
F-statistic	32.85		37.32		36.26	
Degrees of freedom	13		13		14	

Notes: Robust standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.
Source: Authors' estimates.

with more health expenditures. Low expenditures are especially associated with the estate (plantation) sector and, maybe obviously, those that live in communities that are more distant from hospitals. We note that while all of these results are statistically significant, the overall explanatory power of the model is quite minimal.

In order to assess the overall costs associated with health services provided to a hazard-impacted population, we need to measure the population's vulnerability to flood- and drought-related utilization of health services across districts. The estimates provided in Table 6 are calculated by multiplying the district population and the point estimates of the disaster shock variable (marginal effect of floods and droughts on health services utilization) as estimated in the regressions detailed above.

Table 7 shows the total cost estimates due to droughts and floods, separated for the costs associated with the private and public sectors. The estimates are based

Table 6. District-Level Population Vulnerability to Flood- and Drought-Related Health Risks

Province	District	Flood-Associated Inpatient Care Cost per Year						Drought-Associated Outpatient Care Cost per Month		
		Inpatients if total population is directly affected	Public sector inpatient care cost ($)	Private sector inpatient care cost ($)	Inpatients if each district experiences a flood	Public sector inpatient care cost ($)	Private sector inpatient care cost ($)	Outpatients if total population is affected by drought	Public sector outpatient care cost ($)	Private sector outpatient care cost ($)
Western	Colombo	46,196	956,918	569,277	23,098	478,459	284,638	69,294	148,716	267,581
	Gampaha	45,892	353,577	565,531	22,946	176,788	282,765	68,838	54,949	265,821
	Kalutara	24,346	471,327	300,018	12,173	235,664	150,009	36,519	73,246	141,020
Central	Kandy	27,398	530,413	337,628	13,699	265,206	168,814	41,097	82,428	158,698
	Matale	9,644	99,528	118,844	4,822	49,764	59,422	14,466	15,467	55,861
	Nuwaraeliya	14,132	113,305	174,150	7,066	56,652	87,075	21,198	17,609	81,857
Southern	Galle	21,176	326,363	260,953	10,588	163,181	130,477	31,764	50,720	122,658
	Matara	16,186	165,384	199,461	8,093	82,692	99,731	24,279	25,702	93,754
	Hambantota	11,932	130,408	147,039	5,966	65,204	73,519	17,898	20,266	69,114
Northern	Jaffna	11,660	188,497	143,687	5,830	94,249	71,844	17,490	29,293	67,538
	Mannar	1,982	33,728	24,424	991	16,864	12,212	2,973	5,242	11,480
	Vavuniya	3,430	47,298	42,268	1,715	23,649	21,134	5,145	7,351	19,868
	Mulativu	1,838	33,815	22,650	919	16,907	11,325	2,757	5,255	10,646
	Kilinochchi	2,258	20,366	27,826	1,129	10,183	13,913	3,387	3,165	13,079
Eastern	Batticaloa	10,502	148,435	129,417	5,251	74,218	64,708	15,753	23,067	60,831
	Ampara	12,962	182,688	159,732	6,481	91,344	79,866	19,443	28,391	75,080
	Trincomalee	7,564	80,236	93,212	3,782	40,118	46,606	11,346	12,469	43,813
North Western	Kurunegala	32,206	391,127	396,877	16,103	195,564	198,439	48,309	60,784	186,547
	Puttlam	15,196	131,870	187,261	7,598	65,935	93,631	22,794	20,494	88,020
North Central	Anuradhapura	17,124	255,677	211,020	8,562	127,839	105,510	25,686	39,734	99,187
	Polonnaruwa	8,066	114,533	99,398	4,033	57,266	49,699	12,099	17,799	46,721
Uva	Badulla	16,236	268,250	200,077	8,118	134,125	100,039	24,354	41,688	94,044
	Moneragala	8,962	112,079	110,439	4,481	56,039	55,220	13,443	17,418	51,911
Sabaragamuwa	Ratnapura	21,646	251,114	266,745	10,823	125,557	133,373	32,469	39,025	125,380
	Kegalle	16,732	171,248	206,190	8,366	85,624	103,095	25,098	26,614	96,917

Source: Authors' estimates.

Table 7. Public Health Cost of Floods and Droughts ($)

| | Flood-Associated Inpatient Care Cost per Year | | | | | | | | Drought-Associated Outpatient Care Cost per Month | | | | |
| | If the total population in each district is directly affected by a flood | | | | Health spillovers if all districts experience a flood | | | | If all districts experience a drought | | | | Total Cost per Capita |
Province	Public sector inpatient care cost	Private sector inpatient care cost	Private and public sector cost	Per capita cost	Public sector inpatient care cost	Private sector inpatient care cost	Private and public sector cost	Per capita cost	Public sector outpatient care cost	Private sector outpatient care cost	Private and public sector cost	Per capita cost	Total Cost per Capita
Western	1,781,822	1,434,825	3,216,647	0.60	890,911	717,413	1,608,324	0.30	276,910	674,422	951,332	0.20	1.0
Central	743,245	630,621	1,373,866	0.50	371,623	315,311	686,933	0.30	115,504	296,416	411,920	0.20	1.0
Southern	622,154	607,454	1,229,608	0.50	311,077	303,727	614,804	0.20	96,688	285,526	382,214	0.20	0.9
Northern	323,704	260,855	584,559	0.60	161,852	130,427	292,280	0.30	50,305	122,612	172,917	0.20	1.0
Eastern	411,360	382,360	793,720	0.50	205,680	191,180	396,860	0.30	63,928	179,724	243,651	0.20	0.9
North Western	522,997	584,138	1,107,135	0.50	261,498	292,069	553,568	0.20	81,277	274,567	355,844	0.20	0.9
North Central	370,210	310,418	680,628	0.50	185,105	155,209	340,314	0.30	57,533	145,908	203,441	0.20	1.0
Uva	380,329	310,517	690,846	0.50	190,164	155,258	345,423	0.30	59,106	145,955	205,061	0.20	1.0
Sabaragamuwa	422,362	472,935	895,297	0.50	211,181	236,468	447,648	0.20	65,639	222,297	287,936	0.20	0.8
Total	5,578,183	4,994,124	10,572,307	0.50	2,789,091	2,497,062	5,286,153	0.30	866,891	234,7425	3,214,317	0.20	0.9

Notes: Currency conversion is $1 = SLRs130, which was the average exchange rate in 2013.
Source: Authors' estimates.

on Sri Lanka's population census of 2012. Public health costs are based on the reported district-level per capita health expenditure, while the private costs were estimated in Table 5. The estimated realization of the district-level health burden is derived from the population in each district in each year and from whether districts were actually exposed to a flood or drought in the same year. Finally, the online Appendix also presents the same results on a map of Sri Lanka, identifying the costs associated with both inpatient and outpatient care at the district level and in per capita terms.

VI. Robustness

The self-reported binary treatment variable we use does not provide detailed information on the severity of the treatment. It is also possible that self-reported treatment is motivated by factors other than the damage intensity, such as the hope of becoming eligible for disaster relief, and therefore might be inaccurate.[11] When examined against district-level administrative data on disasters, the self-reported treatment indicator matches well—all affected districts reported were also locations where people self-reported as affected.[12] Certain self-reported households, however, were in districts that were not reported as affected by a disaster in the administrative data. This is not necessarily an indication of any misreporting as the aggregate datasets are frequently criticized for not reporting on local events that were destructive in a very limited geographic area and therefore did not cause that much damage in the aggregate (even if the loss for affected households was very high).

The district-level flood and drought impact reported in the administrative data is reasonably matched with the district-level rainfall data and, accordingly, provides further evidence that the treatment variable we use is not overtly biased. We also include specifications in the online Appendix that use measured rainfall data; the results of these specifications (when treatment is identified by district-measured rainfall) are very similar.

Similarly, there may be problems with the self-reported health outcome variable used in the analysis. This variable provides only limited information, because it reports only on whether there was an inpatient or outpatient visit at least once in the past year (or month), even though more than one visit could have occurred within that year (or month). This can cause an underestimation of the health risk due to disasters in our analysis—estimates reveal only the association of exposure to extreme weather and the likelihood of seeking inpatient and outpatient health care at least once in the past year (or month). The estimated costs of health

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[11] In reality, of course, the survey and the disaster relief program are completely independent from each other. The two programs are implemented by different administrative authorities reporting to different ministries.

[12] This conclusion is in contrast with a finding from Bangladesh, where the congruence between self-reports and objective observations is less reassuring (Guiteras, Jina, and Mobarak 2015).

care after a disaster may still be biased if frequently affected households take (costly) adaptation measures or if frequent disasters cause people to relocate to other areas. If adaptation is similar at the district level, the district fixed effects in our model control for any district-level adaptations.

VII. Conclusions, Caveats, and Climate Change

This study's objective was to determine the economic costs associated with extreme weather impacts on health care. The most obvious finding emerging from our analysis is that frequently occurring local floods and droughts appear to impose a significant health risk when individuals are directly exposed to these hazards, and that this exposure sometimes requires even higher hospitalization rates. Our observations are not surprising given that Sri Lanka experiences a high incidence of several infectious diseases (e.g., large numbers of leptospirosis and dengue cases) that are related to floods and droughts and that require affected people to seek health-care services (see online Appendix 1). Those impacts, and especially the indirect spillover effects to households that are not directly affected by the hazard, are at least partly associated with land use in the affected environs of the hazard and with the household's access to sanitation and hygiene. Why sanitation and hygiene are important in mediating the impact of floods and droughts probably does not need explaining. The most likely causal story behind our observations about land use interacting with both floods and droughts is that both disasters lead to a higher likelihood of contaminants and infections being transmitted (most likely orally or through contact) when artificial reservoirs are prevalent in the affected area as they interact with the water available for human consumption.[13]

The health spillovers we identified almost always appear to be associated with household sanitation and hygienic conditions. Health spillovers due to floods are associated with households using unsafe drinking water sources (wells and other unsafe sources). It seems that flooding increases the likelihood of contamination of public water sources. Other possible epidemiological explanations for our spillover finding is the increased presence of disease- transmitting vectors (e.g., mosquitos) in the aftermath of floods, an increase that also affects households that were not directly damaged by the event.

Finally, both direct and indirect risks of floods and droughts on individual health have an economic cost and, consequently, a welfare loss associated with it. Overall, our estimates suggest that Sri Lanka spends at least $19 million per year on health-care costs associated with floods and droughts. This cost is divided almost equally between the public and household sectors, with 83% of it spent on flood-related health care and the rest on drought-related health care. Worryingly, our calculations show that the health burden is distributed spatially so that the highest

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[13] It is important to note that Sri Lanka has many artificial reservoirs, some dating back many centuries.

health burden due to floods and droughts is borne by the Western and Central provinces followed by the Southern and North Western provinces. The total per capita burden is almost equal across all regions. The Western province is the richest region in the country—it has nearly double the monthly per capita income when compared to the poorest one, and it also bears the highest health burden associated with floods and droughts (online Appendix 16).

It is worth noting that the estimated health expenditure burden quantified in this paper is only a part of the full economic cost of this health burden. The cost in this paper is estimated in terms of direct public and household expenditure on disease treatment, not the full accounting of costs. Underestimation of actual costs is likely since household members presumably experience reduced productivity and reduced ability to generate income during their treatment. Equally, the opportunity cost of government spending resources on these health costs is probably substantial, as the opportunities for more productive fiscal expenditures are more numerous in countries with a low capital base and one that is rapidly developing (as is the case in Sri Lanka). Our estimated drought effect may also be underestimated since droughts cause longer-term effects beyond 1 year, while our estimates focus only on same-year health expenditures.

Finally, regional climate model projections for future temperatures predict increases for Sri Lanka: 1°C–1.1°C by 2030, and 2.3°C–3.6°C by 2080. Accordingly, precipitation is likely to increase by 3.6%–11% by 2030, and 31.3%–39.6% by 2080 (Ahmed and Suphachalasai 2014). Studies also predict higher frequencies of high intensity rainfall events causing floods and dry periods generating drought conditions (Ministry of Environment 2010). In short, both the frequency and the intensity of droughts and floods are projected to increase because of climatic change, though the magnitude of these increases is as yet unknown. Consequently, the health burden of these events is only likely to increase, further demanding precious resources that are required elsewhere in a rapidly growing but still relatively poor country.

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List of Additional Tables Available in Online Appendix

The online Appendix is posted at: https://sites.google.com/site/noyecono mics/research/natural-disasters.

Appendix 1: Epidemiological Literature on the Links between Disasters and Diseases

Appendix 2: Agricultural-Ecological Regions in Sri Lanka

Appendix 3: Selected Cases of Notifiable Diseases in Sri Lanka

Appendix 4: Chronic Illnesses in Sri Lanka

Appendix 5: Seasonality of Diseases, 2012

Appendix 6: Seasonality of Diseases, 2013

Appendix 7: Monthly Reported Dengue Cases in Sri Lanka

Appendix 8: District-Level per Capita Public Health Expenditure (Sri Lanka rupees)

Appendix 9: Diseases in Sri Lanka

Appendix 10: Inpatient and Outpatient Private and Public Health Costs (percentage of total costs)

Appendix 11: Restricted Models

Appendix 12: Immediate Health Effects of Floods: Outpatient Treatments for Different Groups

Appendix 13: Rainfall Specification Model

Appendix 14: Interaction Effects for Floods and Droughts on Seeking Outpatient Health Care

Appendix 15: Health Care Cost Maps Due to Floods and Droughts