Health and Hurricanes

Studying Disparate Health Impact of Extreme Climate Events, 2017-2020

Diversity, Equity and Inclusion

Catastrophe and Climate

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CONTENTS

Introduction

In certain regions, natural catastrophes pose a continual threat to property, business, and the wellbeing of people. Because the effects of these events are varied and broad, studying the totality of their consequences is difficult. Some metrics such as property damage, economic loss, or direct and indirect deaths resulting from an event are regularly estimated by insurance companies and federal agencies, such as the Federal Emergency Management Agency (FEMA) and the National Oceanic and Atmospheric Administration (NOAA). Other potential consequences, while likely present, are not studied as consistently, because the effects are thought to be small, necessary data is not available, and the complexity of indirect consequences is difficult to quantify, among many other possible reasons.

In the United States, hurricanes (also known as tropical cyclones) account for a higher cost, and nearly as many deaths, as the combined totals for other weather-related natural catastrophes, including drought, flooding, freeze, severe storm, wildfire, and winter storm from 1980-2021.[1] In addition to extreme wind, rain, and flooding, hurricanes indirectly affect populations by displacing them from their homes for short-term evacuations, or permanently, for those whose homes are destroyed. Hurricanes can cause healthcare access issues during or after the storm and can result in chronic unsafe living or working conditions that persist well beyond the timeframe of the original event. Further consequences could be even more indirect; for example, the local economy could be affected by a storm, creating hardships for those in an affected region.

Within the population affected by these storms, there may be a varying degree to which certain groups are prepared for, or affected by, this array of potential consequences. Some may not have means to protect health and property through insurance, mobility to safely follow evacuation orders, or access to safe lodging or regular employment as the community rebuilds.

In this Society of Actuaries (SOA) report, authored by consultants from Milliman, Inc. (Milliman) we aim to study the effects of hurricanes on human health: whether there is a relationship between hurricanes and the observed prevalence of healthcare utilization or certain health conditions among the affected population, whether this relationship can be observed through a healthcare utilization dataset, and whether there is an interaction between this observation and metrics of socioeconomic vulnerability.

[1] https://www.ncdc.noaa.gov/billions/summary-stats

Summary

Questions

In this research study, we considered whether there was a change in observed healthcare utilization for certain health categories to a population that was affected by four major hurricanes that made landfall in the United States during 2017 and 2018, and whether any observed change was more or less intense across geographic categorizations of socioeconomic status.

We first reviewed findings from other studies considering the relationship between hurricanes and health to identify possible interactions, and identified four main categories for investigation: mental health, emergency injuries, environmental exposure, and preventive care, with some of these categories divided into a number of subcategories.

Methods

Our methods relied on a combination of four main data sources: geographic data that provided maximum hurricane windspeeds by location, census data that characterized the populations and prevalence of insurance of those affected by hurricanes, an existing demographic model that relates geography with socioeconomic status, and a healthcare dataset representing utilization across a broad population with the potential for fine categorization.

We used the windspeed data to define the populations affected by the hurricanes, and then made observations of weekly utilization across the health categories we defined. To measure whether changes to the utilization patterns were significant, we used a data science technique known as isolation forest anomaly detection to assess the likelihood that various observations were a function of chance, and another technique known as a seasonal decomposition in an effort to separate time-dependent trends or seasonal factors. We examined the results of these techniques across multiple time horizons, and considered the consistency of those results across storms to further discern the likelihood that hurricanes were causal drivers in utilization patterns, or whether the patterns were a function of chance, or of other factors.

Findings

We found compelling evidence of an escalation in utilization due to carbon monoxide poisoning, consistently across a number of storms, and generally persisting for a few weeks post-event before returning to baseline levels. This result as been observed in other studies, and is generally attributable to a combination of the use of gas generators and with poor ventilation during power outages. This finding underscores the notion that the risk of hurricanes goes beyond the direct consequences of the storms themselves, but that indirect hazards also exist in connection with the aftermath of the storms.

For the other health categories we considered, there did not appear to be a significant change in observed healthcare utilization in the aftermath of these storms. We certainly wouldn't discount the possibility that some individuals in the storms did experience injury or illness associated with some of the selected health categories, but it appears unlikely that there is a significant change in utilization for these categories across a broad population in combination with storms of the intensity and duration of the ones we considered.

The Possible Effects of Hurricanes on Health

When a hurricane strikes, high winds, fast moving debris, and floodwater create an immediate threat to anyone in the area impacted by the storm. Deaths resulting from these physical threats are classified as 'direct' deaths and are tracked by the National Hurricane Center (NHC). Since hurricanes affect large areas, substantial populations are subject to these threats, and almost all major landfalls result in dozens of direct deaths. These threats can be mitigated via accurate forecasting and appropriately targeted evacuation orders, which seek to identify the geographic areas at risk and move the affected populations to safe areas until the storm subsides. While these efforts are undoubtedly successful in greatly reducing the direct casualties for most storms, two US storms in the past 20 years – Katrina (2005) and Maria (2017) – each resulted in over a thousand deaths. [2]

"Indirect" deaths may be just as numerous as those caused by a storm's physical threats. Indirect deaths result from events like auto accidents that occur during unsafe driving conditions, electrocutions from downed power lines, carbon monoxide poisoning (often resulting from the use of gas generators in areas where electrical service has been interrupted), and medical complications of individuals with severe preexisting medical conditions who do not have regular or immediate access to the services they need.

Data on direct and indirect hurricane-related fatalities is available and readily tracked, but what nonfatal effects do hurricanes have on human health? Some of these effects can likely be inferred from the fatality data. For example, if individuals died because of direct physical interaction with the storm, then it is likely that some other individuals in similar circumstances were merely injured. If some individuals with preexisting conditions died because they did not have access to their needed medical care, it is likely that there also were other individuals who were similarly situated and suffered greatly but survived. Therefore, it is likely that common causes of direct and indirect deaths are also among the major threats to human health, where the hazardous environment and lack of access to medical services during and after the storm create or escalate an array of health conditions, ranging from mild to fatal.

There may be other health conditions that manifest because of a hurricane event that do not correspond with recorded fatalities. These conditions would not be represented in storm fatality data either because they are generally nonfatal or because they manifest over a longer time period and therefore are not clearly associated with the event in the data. For example, many residences damaged by flooding in Hurricane Katrina were further damaged by the growth of mold in the ensuing months, which threatened the respiratory health of returning residents long after the event.[3] Additionally, people who evacuate an affected area to avoid direct physical threats of the event may be burdened by additional health consequences, such as the development or exacerbation of mental health conditions or substance use disorders or missed regular appointments for preventive care. The possible effects could manifest over various time horizons, ranging from short-term to long-term. In the research presented in this report, we considered a variety of time horizons, ranging between 4 and 24 months. While we would not necessarily apply strict definitions to "short-term" vs. "long-term" for purposes of analysis, it is important to consider the range of possible health consequences, including whether they would result from the direct physical effects of a hurricane and/or manifest shortly after the event or, alternatively, follow from a series of indirect consequences and/or manifest over a longer time period. For further examples, the range of possible health effects of hurricanes is summarized below, broadly classified into short-, medium-, and long-term effects:

[2] The causes of direct and indirect deaths for hurricanes can be reviewed through the NHC Tropical Cyclone Reports, which are published for every hurricane. For example, the report for Hurricane Harvey can be found here: https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf
[3] Mold exposure and health effects following hurricanes Katrina and Rita. https://pubmed.ncbi.nlm.nih.gov/20070193/

POTENTIAL SHORT-, MEDIUM-, AND LONG-TERM HEALTH IMPACTS OF HURRICANES

Short-term	Medium-term	Long-term
• Drowning from floodwater • Injury from debris during storm, evacuation, or mitigation (for example preparing home for storm), electrocution from downed power lines • Threats to high-risk individuals (for example dialysis patients, cardiac patients, or persons in nursing homes) in connection with evacuation, medical centers without power • Auto accidents during evacuation or resulting from unsafe roads • New or exacerbated mental health conditions, including anxiety, post-traumatic stress disorder, substance use disorder, or depression at the time of the incident, evacuation or displacement	• Infections – skin, gastrointestinal, eye, ear resulting from unsafe conditions • Unsafe premises, lack of food or water, contamination to food or water, carbon monoxide poisoning from poor ventilation • Impaired access to usual healthcare for displaced people • New or exacerbated mental health conditions, including post-traumatic stress disorder, substance use disorder, depression, or anxiety following incident, evacuation, or displacement • New or escalated physical abuse / maltreatment	• Consequences from disruption to preventive care • New or exacerbated mental health conditions, including post-traumatic stress disorder, substance use disorder, depression, or anxiety following incident, evacuation, or displacement • Respiratory ailments due to mold growth in damaged homes or dust from repair activities – asthma, chronic obstructive pulmonary disease

Ultimately, the negative consequences that hurricanes could have on human health can be quite varied, ranging between direct and indirect and varying in timeline from short-term, medium-term, and long-term. Similarly, the population affected could include those directly in the path of the storm when it occurred, storm evacuees, or people whose residences or cities were otherwise affected.

Prior Research

We first conducted a literature review to help define which specific health conditions were most likely to be affected by hurricanes. There are hundreds of studies on the subject, but the following ones appeared most relevant based on our review and were used in formulating our initial areas of research:

"Health Effects of Tropical Storms and Hurricanes in Florida." By the Florida Department of Health. [4] This study was based on data from the Florida public health system and details the rates of relevant health conditions for affected versus unaffected counties. The strongest observed effect was on carbon monoxide (CO) poisoning. Injury-related emergency department visits and infectious diseases (salmonellosis and vibriosis) were also conditions with observed effects. Drowning was considered but did not appear to be affected.

"Health Effects of Coastal Storms and Flooding in Urban Areas: A Review and Vulnerability Assessment." By Lane et al.[5] This consisted of a literature review of 70 studies which summarized results into broad categories from other published research that made connections between hurricanes and health:

- Hazards of storm exposure: drowning, electrocution, physical trauma
- Evacuation: prevalence and facility implications
- Secondary effects stemming from utility outages
- Secondary effects stemming from contamination or mold
- Population displacement or healthcare disruption
- Mental health effects
- Clean-up and reconstruction work hazards

"Disparities in Health Effects and Access to Health Care Among Houston Area Residents After Hurricane Harvey." By Flores, et al.[6] This survey-based study polled 403 participants from the greater Houston area in the aftermath of Hurricane Harvey (2017) and investigated the physical and mental health of those who did not evacuate versus those who did, those who lost jobs, and persons with disabilities. Researchers used multivariate methods to assess a range of predictors for the dependent variables of physical health problems, post-traumatic stress, and lack of access to healthcare. Evacuation was shown to predict lower adverse health outcomes, bad experience during the event was linked with post-traumatic stress, and job loss was linked with adverse mental health outcomes.

"Lessons from Hurricane Katrina for Predicting the Indirect Health Consequences of the COVID-19 Pandemic." By Raker, Zacher, and Lowe.[7] This survey-based study focused on 1,019 young, low-income mothers who survived Hurricane Katrina (2005) and found variables such as bereavement or fearing for loved ones' well-being to be predictors of adverse health one-year post-disaster, with some effects persisting 12 years later.

"Preliminary Assessment of Hurricane Harvey Exposures and Mental Health Impact." By Schwartz et al.[8] This survey-based study of 41 participants from the greater Houston area found that a higher number of storm-related exposures to person or property associated with greater mental health symptoms three weeks post-hurricane.

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[4] Division of Disease Control and Health Protection, Bureau of Epidemiology, March 2015. *National Center for Environmental Health Project Number 5UE1EH001047-03.*
[5] *Journal of Environmental and Public Health.* Volume 213, Article ID 913064. http://dx.doi.org/10.1155/2013/913064
[6] *National Center for Environmental Health Project Number 5UE1EH001047-03.*
[7] *Proceedings of the National Academy of Sciences 117 (23): 12595.* https://doi.org/10.1073/pnas.2006706117.
[8] *International Journal of Environmental Research and Public Health* 15 (5). https://doi.org/10.3390/ijerph15050974.

"Houston Hurricane Harvey Health Study: Assessment of Allergic Symptoms and Stress After Hurricane Harvey Flooding." By Oluyomi et al.[9] In this survey-based study, 347 participants reported details on demographics, flood-related exposures, and health outcomes, including allergic symptoms and stress. Researchers found that those exposed to flooding that occurred because of Hurricane Harvey experienced negative impacts on their respiratory health and stress.

"Disparate Health Implications Stemming from the Propensity of Elderly and Medically Fragile Populations to Shelter in Place During Severe Storm Events." By Behr and Diaz[10]. Victims of Hurricane Irene (2011), including 2,367 households in the 18 to 64 age group and 1,437 households in the above 65 age group, were surveyed. Researchers assessed whether households chose evacuation versus shelter-in-place by variables such as dependency for activities of daily life, ongoing pain management appointments, presence of medical equipment in home, and mobility, sensory, or cognitive limitations. Ultimately, the study found that decisions about whether to evacuate or shelter-in-place were similar between vulnerable and non-vulnerable populations; however, researchers noted the potential heightened importance of evacuation for vulnerable individuals.

"Disparities in Health Care Among Vietnamese New Orleanians and the Impacts of Hurricane Katrina." By Hutchinson, May, and VanLandingham[11]. This study focused on the long-term health care utilization patterns, taking into consideration socioeconomic status, of 127 Vietnamese immigrants to New Orleans over a two-year period following Hurricane Katrina and found that routine healthcare declined significantly during this period.

"Examining the Long-Term Racial Disparities in Health and Economic Conditions Among Hurricane Katrina Survivors: Policy Implications for Gulf Coast Recovery." By Ivory, Ray, Hatcher, and Straughn.[12] This study analyzed the responses of 216 Black/African American and 508 white Hurricane Katrina survivors from an anniversary poll in 2006 and found that Black/African American hurricane survivors were more likely than white survivors to report adverse outcomes in terms of health and well-being.

"The Short- and Long-Term Impacts of Hurricane Irma on Florida Agricultural Leaders as Early Emergency Responders: The Importance of Workplace Stability." By Grattan et al.[13] This survey-based study considered the short- and long-term medical and behavioral outcome of 36 Agricultural Extension Agents within two months and one year after Hurricane Irma and found greater anxiety, depression, and medical symptoms among those who were impacted at both work and home.

[9] *Environmental Health* 20 (1): 9. https://doi.org/10.1186/s12940-021-00694-2.
[10] *Virginia Modeling, Analysis, and Simulation Center*. https://digitalcommons.odu.edu/cgi/viewcontent.cgi?article=1019&context=vmasc_pubs.
[11] *Res Social Health Care. 2009; 27:301-319. Doi:10.1108/S0275-4959(2009)0000027016*
[12] Journal of Black Studies 2011;42(3):360-78. doi: 10.1177/0021934710372893. PMID: 21905324. https://pubmed.ncbi.nlm.nih.gov/21905324/
[13] International Journal of Environmental Research and Public Health 17 (3): 1050. https://doi.org/10.3390/ijerph17031050.

Initial Questions, Data Sources, and Methodology

Our review of the above studies and their conclusions noted several main themes, including distinguishing short-term versus long-term effects, the effects on mental health, the interaction with socioeconomic factors, and the role of storm evacuations. Based on this review and the nature of our study data, we formulated questions in four main categories:

1. Do populations living in hurricane-affected areas experience an increase in mental health conditions, such as depression, anxiety, post-traumatic stress disorder, or substance use disorder?

2. Is there an observed increase in injuries and emergency department visits in the affected area shortly after a hurricane?

3. Are routine and preventive healthcare disrupted in the affected area during and after an event?

4. Do populations living in hurricane-affected areas exhibit adverse health effects stemming from environmental, occupational, or habitational hazards, such as CO poisoning, food poisoning, or mold exposure?

Within the categories above, we sought to understand whether healthcare utilization patterns appeared to be affected, and whether any of the effects demonstrated different patterns across different population dimensions or geodemographic proxies of those dimensions across different timeframes.

We utilized Milliman's Emerging Experience (MEE) research database of health insurance claims for this retrospective study. At the time of our analysis, this dataset contained de-identified healthcare claims data from 2017 to 2020 for approximately 30 million lives, covered by Commercial, Medicare, Medicaid, and Affordable Care act (ACA) insurance plans, spanning 50 states. We utilized pre-defined sets of diagnostic and procedural codes to define target conditions, and hurricane windspeed data to identify cohorts. We categorized anonymized data at the ZIP code level, the finest available granularity, and reported aggregate outputs.

To manage the large size of the claims dataset, our research involved a process in which we first 'cast a wide net' with respect to storm events, timeframes, health outcomes, and analytical methods and subsequently narrowed our focus to more refined geographic areas, dates, specific health conditions, and quantitative tests. In this way, we progressively eliminated avenues of inquiry for which we could not detect any meaningful signals, while expanding our analysis of the more promising leads.

Selecting Hurricane Events and Defining Affected Areas

The geographic scope of the MEE data allowed us to study multiple events in different US regions, but the temporal scope was limited to the period from 2017 to 2020. We began our research by defining the areas impacted by the top 12 most severe and costly Atlantic hurricane events to make landfall on the United States during this period. Hurricanes that hit the US during this period were exceptionally destructive – four of the top 10 costliest hurricanes in US history occurred in 2017 (Harvey, Maria, Irma) and 2018 (Michael) alone.[14] The initial set of selected events to investigate included:

- 2017: Hurricanes Harvey, Irma, Jose, Maria
- 2018: Hurricanes Florence, Michael
- 2019: Hurricane Dorian
- 2020: Hurricanes Hanna, Isais, Laura, Sally, Delta

To define the areas impacted by these events, we utilized the National Oceanic and Atmospheric (NOAA) National Hurricane Center (NHC) Tropical Cyclone "Final Best Track" wind swath geographic information systems (GIS) layer for each selected storm. This layer delineates the geographic area affected by sustained wind speeds of 34-49 knots 50-63 knots, and 64 knots or greater. Since we planned to aggregate claims data at the ZIP code level, we also defined the affected areas at the ZIP code level. We considered a ZIP code area to be "affected" by the storm if the ZIP code's latitude/longitude centroid was within 10 kilometers of the wind swath. After defining the affected areas, we utilized the 2015-2019 US Census American Community Survey 5-year estimates at the ZIP code Tabulation Area (ZCTA) level (US Census Bureau, 2020) to summarize the demographic makeup of the affected areas.

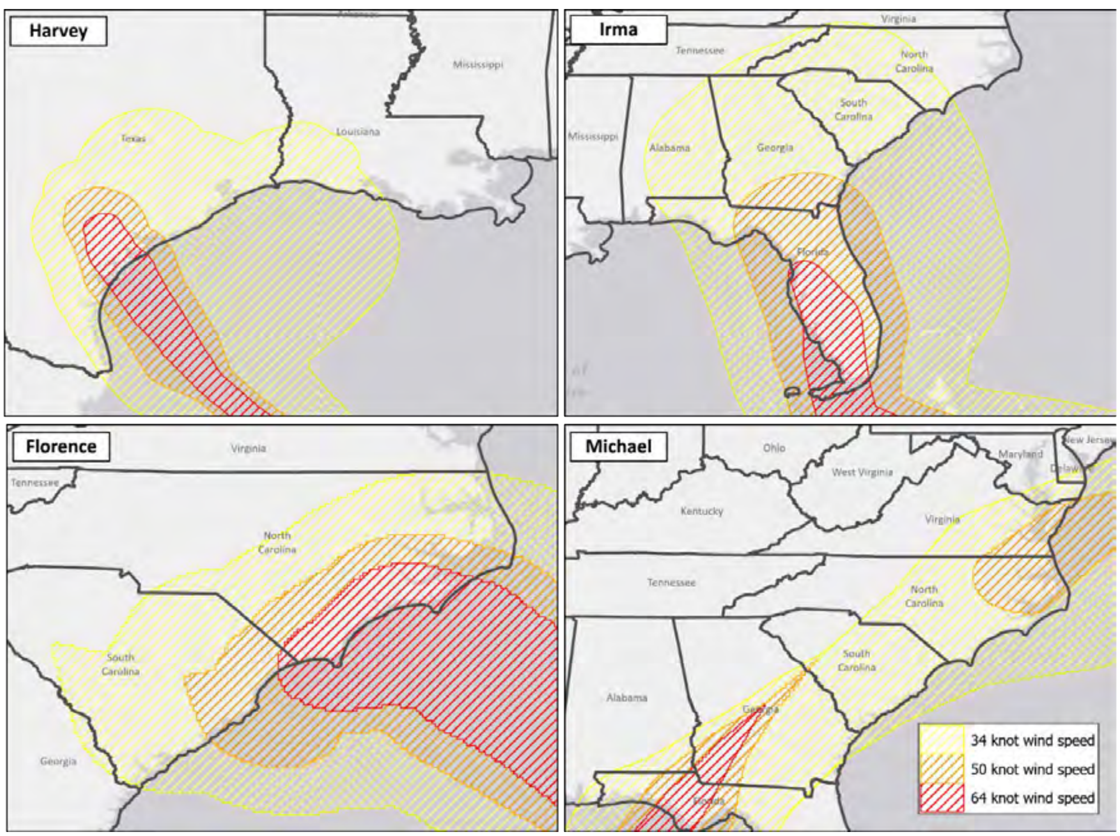
POPULATION SIZE AND CHARACTERISTICS OF AFFECTED REGIONS BASED ON 34-KNOT WINDSPEED DEFNITION[15]

Storm	Affected States	Approximate Start Date	Population Affected	Median Income ($)	% White	% Black/African American	% Asian	% Other	Damage (Billions$)
Harvey	LA, TX	08/25/2017	12,272,331	68,065	71	14	6	9	136.3
Irma	AL, FL, GA, NC, PR, SC, TN, VA	09/06/2017	51,306,639	56,294	70	21	3	7	54.5
Jose	CT, MA, NJ, NY, RI	09/20/2017	2,942,570	78,884	83	6	3	8	0.03
Maria	NC, PR	09/19/2017	3,348,428	22,058	66	12	0	22	98.1
Florence	GA, NC, SC, VA	09/13/2018	7,276,715	55,782	64	28	2	7	25.7
Michael	AL, DE, FL, GA, MD, NC, SC, VA	10/09/2018	17,475,780	58,080	64	28	2	6	26.5
Dorian	FL, GA, MA, ME, NC, PR, SC, VA	08/28/2019	12,854,433	59,097	69	22	3	7	1.7
Hanna	TX	07/25/2020	1,876,813	44,010	90	1	1	8	1.1
Isaias	CT, DC, DE, FL, MA, MD, ME, NC, NH, NJ, NY, PA, PR, RI, SC, VA, VT	07/30/2020	65,735,505	76,487	66	17	6	10	4.8
Laura	AR, LA, MS, PR, TX	08/22/2020	9,506,706	40,517	65	24	1	10	19.7
Sally	AL, FL, GA, LA, MS	09/12/2020	3,511,151	53,628	71	23	2	4	7.6
Delta	AR, LA, MS, TX	10/09/2020	6,759,128	56,281	65	28	2	5	3.0

[14] https://www.nhc.noaa.gov/news/UpdatedCostliest.pdf
[15] Damage and landfall timing estimates from NHC Hurricane Reports for each storm. All other estimates use a combination of NOAA wind swath data and estimates form the 2015-2019 American community survey, using the methodology described later in this report.

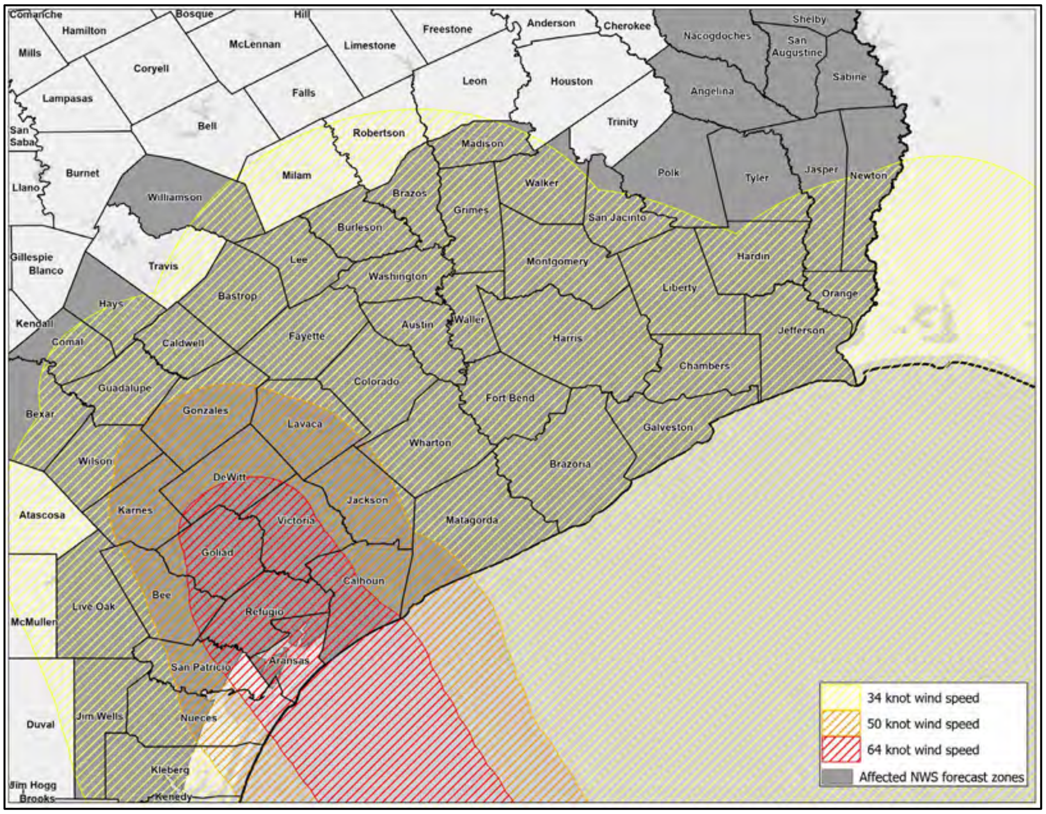
Based on the information above, we decided to focus our analysis on a smaller subset of these selected storms: Hurricanes Harvey, Irma, Florence, and Michael. Several considerations influenced this decision. First, these storms caused significant damage and affected large populations, whereas many of the other storms affected much smaller populations, and thus it was likely that there would be more credible data for examining the health-related impact of these four storms. Other storms, for example Hurricane Dorian (2019), affected a large population and many states, but caused very little property damage ($1.7 Billion, compared to a minimum of $25.7 Billion for the four storms we selected), indicating a relatively benign event compared to others. Hurricane Maria (2017) was an exceptionally destructive and devastating storm, likely rivaled in US history by only Hurricane Katrina (2005) in terms of its total human toll, but it primarily affected Puerto Rico where the MEE medical claims data was sparsely reported; as such it was not available for study. Finally, while several severe and destructive storms occurred during the 2020 COVID-19 pandemic, an initial review of the MEE data revealed that shifts in healthcare utilization beginning in February 2020 were likely much larger than any post-hurricane shifts that could have been observed. Consequently, we believed that if any storms occurring after February 2020 had any impact on utilization, it would be extremely difficult to differentiate any storm-related effects from those caused by the pandemic. Thus, after eliminating small storms, those with limited health insurance claims data for the population in the affected region, and those that occurred in 2020, we were left with four major storms for study. The "affected regions" as defined by various wind swaths, are depicted below:

NOAA NHC "FINAL BEST TRACK" WIND SWATH GIS LAYERS AND ASSOCIATED AFFECTED AREAS (FIGURE 1)

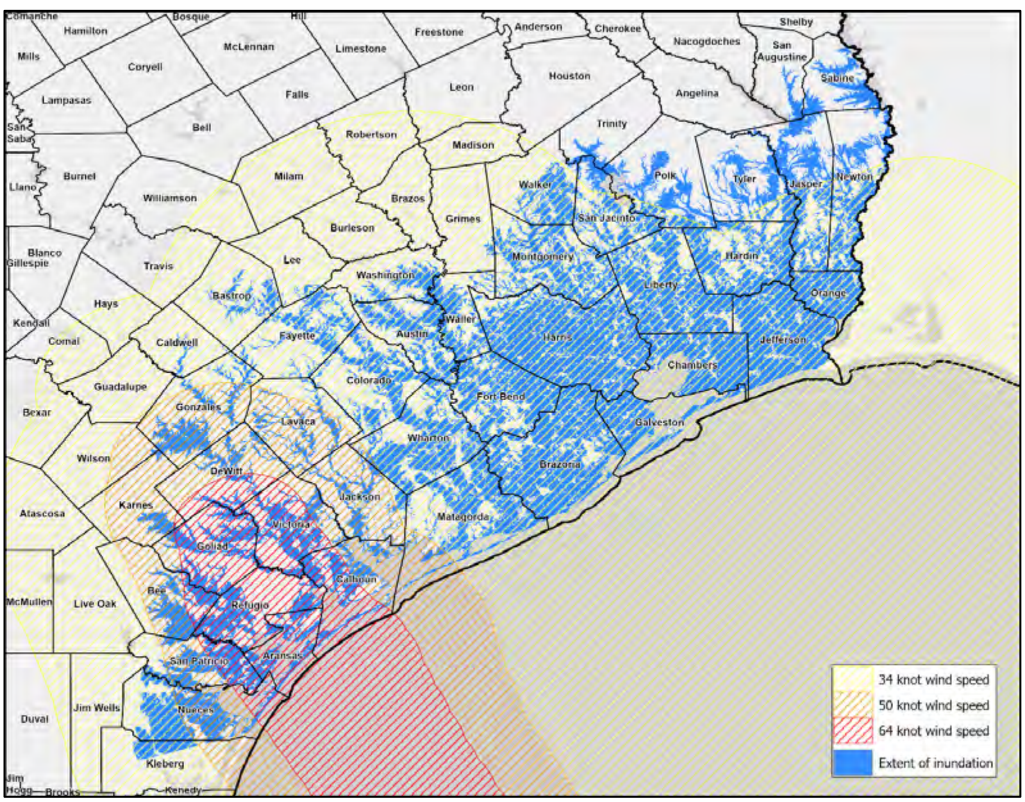


We recognize that hurricanes impact areas beyond those exposed to high winds, so we also explored other methods to define the affected area, including evaluating flooding extent by utilizing modeled observed inundation GIS layers produced by FEMA, as well as county-level data from the National Weather Service's (NWS) storm events database. For Hurricane Harvey, comparisons of the potential alternative definitions appear in the figures below:

COMPARISON BETWEEN WIND SWATH LAYERS AND NWS COUNTY-LEVEL DISASTER DATA (FIGURE 2)



COMPARISON BETWEEN WIND SWATH LAYERS AND FEMA INUNDATION LAYERS (FIGURE 3)



Based on these comparisons, we observed that defining the affected areas as those delineated by the NOAA wind swath layers broadly yielded a region which was similar to the county-defined NWS disaster areas. While the inundation layer itself is more granular than ZIP code areas, because we were only able to summarize the MEE data to the ZIP code level, any categorization in which ZIP codes were in or out of the region affected by flooding would ultimately be similar to the one based on the wind swath layer. Thus, in the case of Hurricane Harvey, all three definitions would have yielded a similar affected region for study. Additionally, despite our interest in investigating the relationship between hurricane-induced flooding and respiratory ailments, we were unable to find observed flooding data for most of the events.

We also considered defining the affected regions as those areas affected by 50 knot and greater wind speeds (as opposed to 34 knot and greater wind speeds) as delineated in the NOAA wind swath layers. Assuming wind speed represents a good measure of the severity of a storm at any given location, there seems to be a tradeoff between the specificity of a definition and the credibility of available data available. Determining the affected area based on a less severe windspeed could mask any potential effects that occurred in only the severe region, but using only the severe region would substantially limit the population available for study. Further, a disadvantage of using the severe wind speed approach can be observed in the comparison of wind swath layers and inundation layers for Harvey pictured above. Although there is a high correlation between the 34-knot zone and the areas that experienced inundation, the 50-knot and 64-knot zones delineate much smaller areas and do not capture much of the region that experienced flooding, especially Houston's Harris County where the human toll was most significant.[16]

Despite their limitations, the wind swath layers were consistent and available for each event, and we were able to define affected areas across all the events utilizing a consistent approach. We selected all areas within the 34-knot or greater wind speed bands to define the population affected by each storm. Having selected the main storms for analysis, we reviewed some of the details of the "severity" of each. As illustrated by the table below, the perceived severity of a given storm can vary by how it is measured–deaths, dollar damage, displacement, or another metric:

DIFFERENT MEASURES OF HURRICANE SEVERITY

Storm	Date Range	Landfall Date	Category at Landfall[17]	Damage[2]	US Deaths Direct / Indirect[2]	Displaced Population[18]	Affected Population[19]	Evacuations[20]
Harvey	8/17/2017 to 9/1/2017	8/25/2017	4	$136.3B	68/35	848,000	12,272,331	Evacuations began 8/24. Half of deaths in Harris County which was evacuated late.
Irma	8/30/2017 to 9/12/2017	9/6/2017	4	$54.5B	10/82	202,000	51,306,639	Evacuations 9/6-9/17. Largest evacuation in history.
Florence	8/31/2018 to 9/17/2018	9/13/2018	4	$25.7B	22/30	464,000	7,276,715	Coastal evacuations began 9/11/2018.
Michael	10/7/2018 to 10/11/2018	10/9/2018	5	$26.5B	16/43	375,000	17,475,780	Evacuations in Florida coastal zones began 10/8.

[16] Source: NHC Hurricane Report for Hurricane Harvey
[17] Source: NHC Hurricane Reports for each storm
[18] Internal displacement monitoring center: https://www.internal-displacement.org/database/displacement-data
[19] Estimated by Milliman using NOAA wind swaths, see later description of methodology
[20] There is no single source for evacuation information, but it was obtained from researching news reports from the time of each storm.

Defining Conditions for Study, Data Classification and Aggregation

Based on our four main areas of inquiry, we selected a broad spectrum of potential outcomes and structured our analysis to search for trends or discontinuities in healthcare utilization over various timeframes post-event. To apply precise definitions to various conditions under study, the MEE data was classified based on a combination of three standards:

- International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM)[21] – Universal diagnosis coding system designed for classifying and reporting diseases in all U.S. healthcare settings. Approximately 70,000 diagnosis codes exist.

- AHRQ Clinical Classification Software (CCS)[22] – Classifies ICD-10-CM diagnosis codes into several hundred meaningful health condition categories. CCS groupings exist in single-level and multi-level varieties for diagnoses.

- Milliman Health Cost Guidelines (HCG) groupings – Generally irrespective of diagnosis, groups claims primarily by setting/service type - facility inpatient (inpatient), facility outpatient (outpatient; emergency department and PPACA-mandated preventive services can be broken out), prescription drugs, medical professional (professional; physicals and PPACA-mandated preventive services can be broken out), and ancillary services (including dental).

Based on these standards, we applied the definitions in the table below to define four main categories for investigation, with sub-categories specified for some:

SELECTED HEALTH CONDITIONS AND ASSOCIATED CLASSIFICATIONS EVALUATED IN THIS RESEARCH

Health Category	Health Sub-Category	HCG Setting(s)/ Service Types	CCS Classification	ICD-10-CM Classification
Mental Health	Adjustment Disorders	Inpatient, Outpatient, Professional	5.1 Adjustment disorders	
Mental Health	Anxiety Disorders	Inpatient, Outpatient, Professional	5.2 Anxiety disorders	
Mental Health	Mood Disorders	Inpatient, Outpatient, Professional	5.8 Mood disorders	
Mental Health	Alcohol-Related Disorders	Inpatient, Outpatient, Professional	5.11 Alcohol related disorders	
Mental Health	Substance-Related Disorders	Inpatient, Outpatient, Professional	5.12 Substance related disorders	
Mental Health	Suicide and Intentional Self-Inflicted Injury	Inpatient, Outpatient, Professional	5.13 Suicide and intentionally self-inflicted injury	
Injuries	Emergency Visits	Inpatient, Outpatient,	16-Injury and poisoning (excluding 16.11 Poisoning)	

[21] https://www.cdc.gov/nchs/icd/icd10cm.htm
[22] https://www.hcup-us.ahrq.gov/toolssoftware/ccsr/ccs_refined.jsp

Health Category	Health Sub-Category	HCG Setting(s)/ Service Types	CCS Classification	ICD-10-CM Classification
		Professional, Ancillary		
Preventive Care	Physicals	Physicals		
Preventive Care	Dental	Ancillary		
Preventive Care	Preventive services as defined under Patient Protection and Affordable Care Act (PPACA)	PPACA-mandated preventive services		
Environmental Exposure	Acute Respiratory	Inpatient, Outpatient, Professional	8.1- Acute Respiratory infections 8.4 Aspiration pneumonitis; food/vomitus 8.6 Respiratory failure; insufficiency; arrest 8.7 Lung disease due to external agents 8.8 Other lower respiratory disease	
Environmental Exposure	Chronic Respiratory	Inpatient, Outpatient, Professional	8.2 Chronic obstructive pulmonary disease and bronchiectasis 8.3 Asthma	
Environmental Exposure	Carbon Monoxide (CO) Poisoning	Inpatient, Outpatient, Professional		T58 - Toxic effect of carbon monoxide

Health Category	Health Sub-Category	HCG Setting(s)/ Service Types	CCS Classification	ICD-10-CM Classification
Environmental Exposure	Food and Water Borne Illnesses	Inpatient, Outpatient, Professional		A04.5 Campylobacter enteritis A05.2 Foodborne Clostridium perfringens intoxication A35 Tetanus/B96.7 Clostridium A03 Shigellosis A02 Other salmonella infections A01 Typhoid and paratyphoid fevers A01.4 Paratyphi A07.1 Giardiasis A07.2 Cryptosporidiosis A08.11 Acute gastroenteropathy due to Norwalk agent B15 Acute Hepatitis A

For our initial exploratory analysis, we aggregated the data based on these classifications by week of experience. Our rationale for using weekly data was that examining daily data would be intractable due to dataset sizes and would demonstrate too high day-over-day volatility, making any patterns impossible to discern. Monthly data on the other hand seemed too coarse, as our goal was to look at the immediate aftermath of the storm, and any effects could be washed out by other seasonal factors or trends.

As described in the previous section, we defined the "affected" group as consisting of the experience of those included in the MEE database whose home ZIP code's geographic centroid was within 10 kilometers of the 34-knot or greater wind speed band for each storm. We also defined a "Non-Affected" or "Control" region, which consisted of all the experience in the affected states that was not in the affected region. For example, the "affected" region for Hurricane Harvey included parts of Texas and Louisiana, so the "Control" group for Harvey would have consisted of the remainder of ZIP codes for those two states. We recognize several shortcomings to this approach, with the most significant being that the affected and non-affected regions would often contain distinctly different populations. A more optimal control group might control for other population characteristics in an effort to eliminate differences beyond whether each group experienced a hurricane. Additionally, because hurricanes repeatedly happen in similar regions, there is a tangled relationship between the groups/regions in many cases. For example, Hurricanes Michael and Irma both struck different regions of Florida, so there is a degree of separation and intersection in the affected regions for those storms.

Nevertheless, since the goal was to examine the temporal experience patterns, which are subject to volatility, seasonality, and trends, we thought it crucial to have a reasonably constructed control group for purposes of comparison. This way, an observation in the affected region might be more strongly inferred to be associated with a hurricane if a similar pattern could not be detected in the control region. Alternatively, a similar pattern between control and affected regions would call into question the hypothesis that the hurricane was a causal variable, implying other drivers.

Preliminary Observational Analysis

Once the data was classified by health category for the affected and control groups, we made preliminary observations of the utilization rate[23] over time to assess whether an apparent change in utilization had occurred, or whether any temporal pattern could be identified in the utilization in the weeks following each event. We aggregated the data by weekly and monthly exposures, and visually examined the utilization rates using charts.

The initial set of charts was quite extensive, consisting of 16 health categories, 4 hurricanes, and weekly and monthly data, for a total of 128 charts. To balance completeness and brevity for this report, we have included a smaller subset of the initial observations in the pages that follow. We provided several examples to give the reader a sense of what the analysis looked like but omitted several of the conditions originally considered, either because we observed them to be unchanged or because they yielded a similar observation to the ones we do show.

In general, but with a few exceptions, there did not appear to be a discernable relationship between the timing of the storm and subsequent patterns in the utilization. Although we were working with a very extensive dataset in terms of covered experience, we were also attempting to zero in on very specific timing and geography. Week over week (or even month over month) observations included considerable volatility in most cases, meaning that any observed signal would need to be strong enough to stand out in a noisy series.

Beyond statistical noise, many of the conditions exhibited trend and seasonality, creating an additional challenge in interpreting the data. For example, rising post-event utilization could have nothing to do with the event and simply be part of an underlying trend that was already rising, or the event could have occurred during a certain part of the year where utilization for a given health category always rises (e.g., increases in respiratory ailments in the winter months). The North Atlantic hurricane season generally occurs between June and October of each year. The four storms we are observing all occurred between late August and early October in their respective calendar years, a span of approximately 6 weeks. As a result, any post-storm effect would always be coincident with any seasonal utilization changes in the late summer or early fall. Finally, as mentioned in the section about selecting storms, the COVID-19 pandemic rendered experience data from 2020 almost entirely unusable and incomparable to every other year, with a large decrease in utilization for almost every observation beginning in March of 2020 and extending, to a variable extent, throughout that year. Thus, in addition to the pandemic preventing study of the 2020 storms, it also impairs 2020 as a baseline observation for comparison to other years like 2017 and 2018, when the storms of interest occurred.

Examples of our preliminary observations appear in the next several charts, and a description of our interpretation of each follows. Please note the scale of the graphs, the Y-axis minimum is always 0, but the maximum varies from observation to observation.

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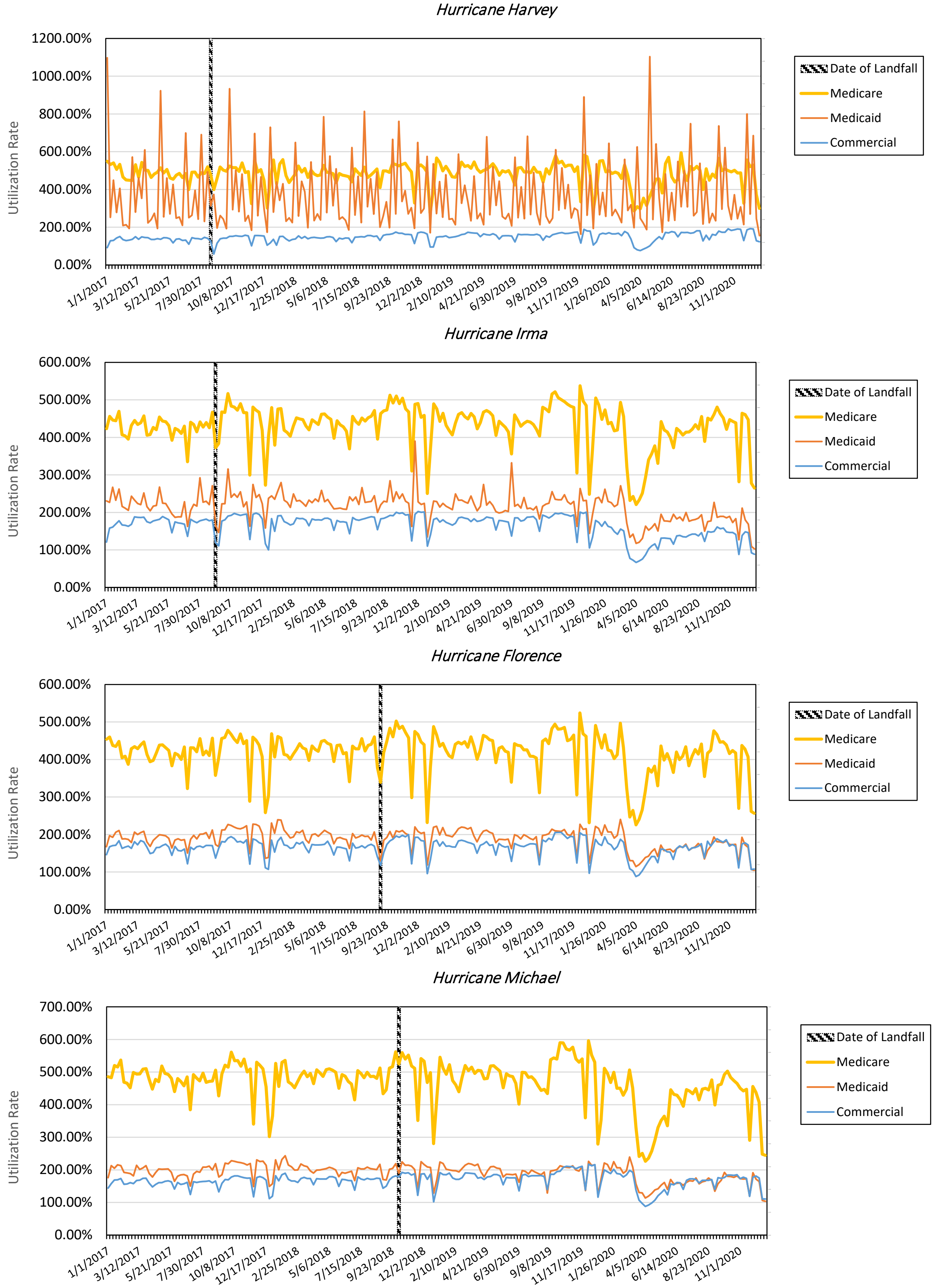
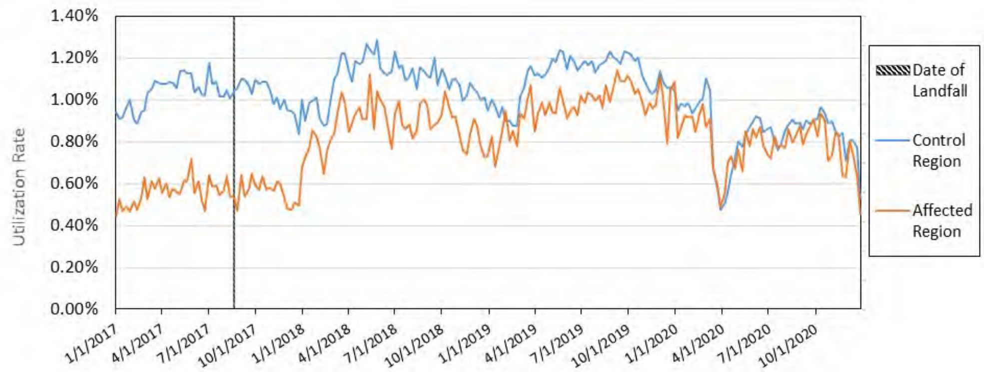
[23] Throughout this report, we use “utilization” as the target metric for analysis. Utilization generally measures the volume of health care services per insured person or exposure in a given timeframe. Due to the complexity and variability of healthcare services, settings and procedures associated with any given health condition, the utilization can vary significantly by context. For example, utilization can refer to hospital admissions in the facility inpatient setting, outpatient or emergency department or office visits or service units in the ambulatory setting, and pharmacy scripts for prescription medications. Utilization, in context, is expected to be comparable across time for specific health conditions and in the aggregate, unless other factors influenced the health condition prevalence. This study did not measure healthcare resource use or healthcare costs.

OVERALL UTILIZATION BY PAYER BY STORM (FIGURE 4)



EMERGENCY UTILIZATION BY STORM (FIGURE 5)

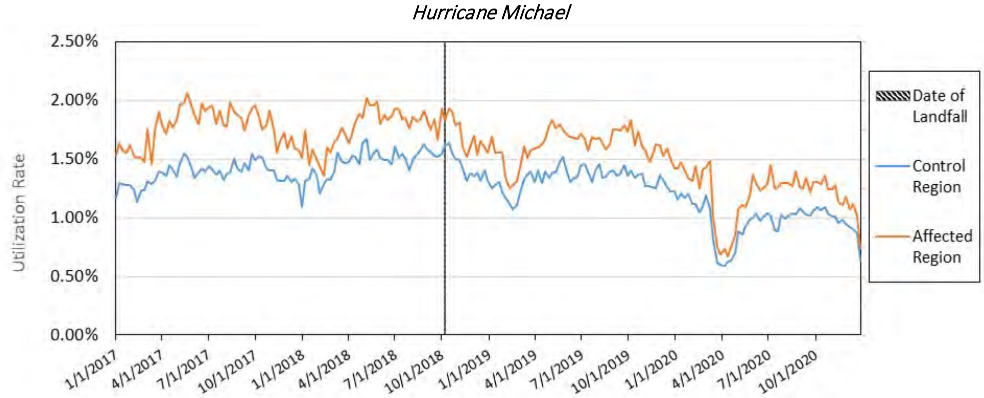
Hurricane Harvey



Hurricane Irma

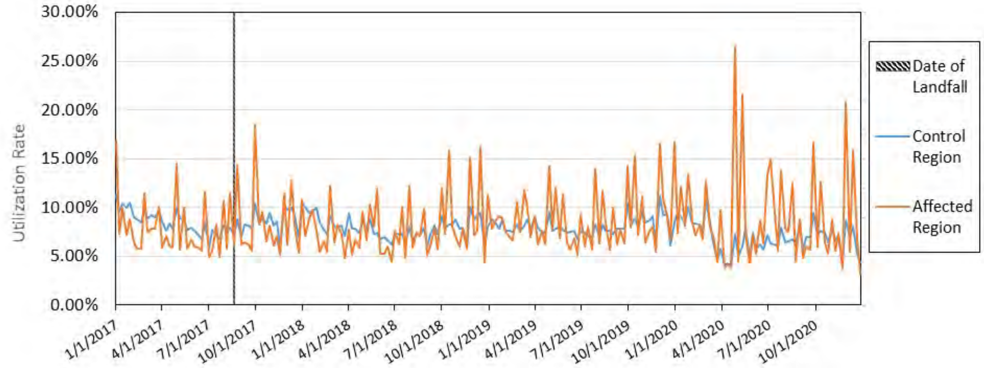
Hurricane Florence

Hurricane Michael



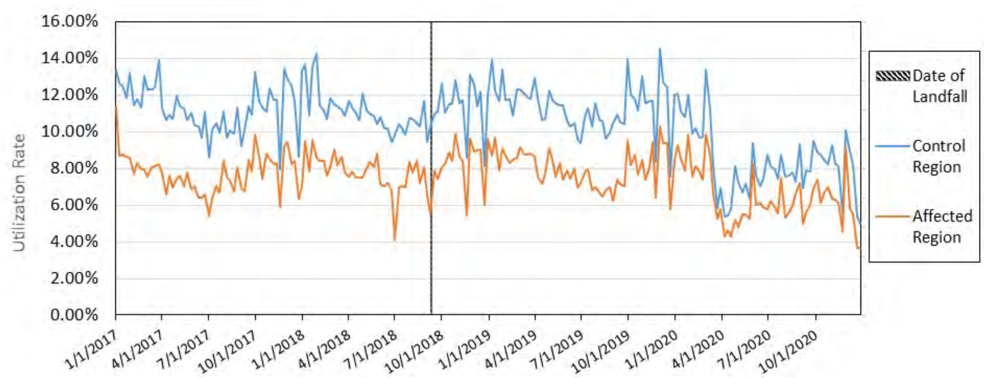
CHRONIC RESPRIATORY UTILIZATION BY STORM (FIGURE 6)

Hurricane Harvey

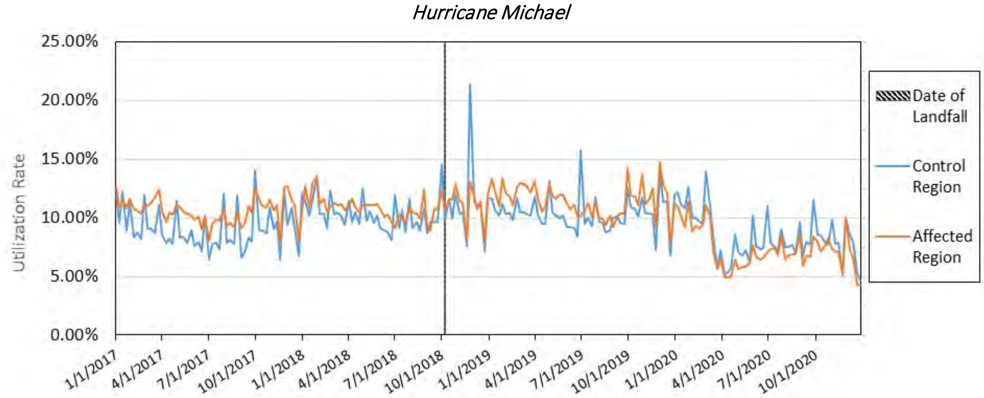


Hurricane Irma

Hurricane Florence

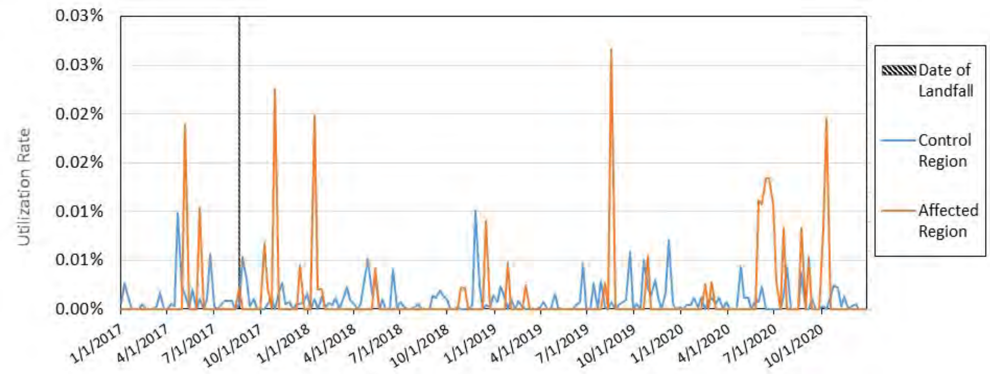


Hurricane Michael

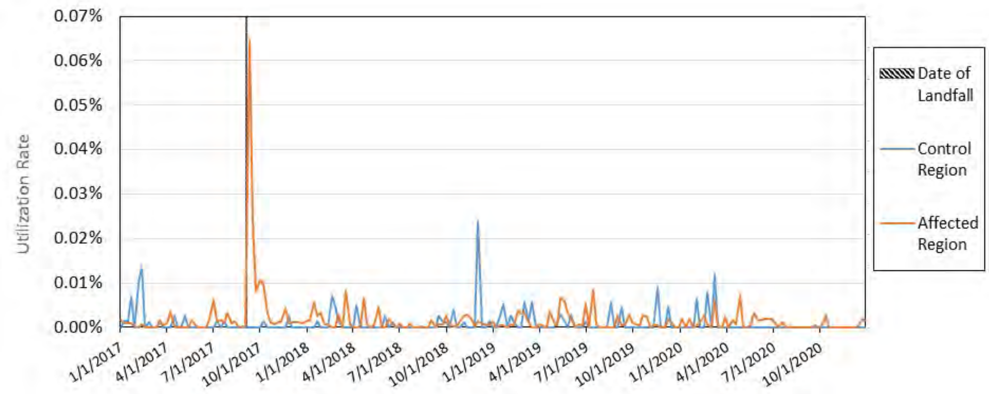


CARBON MONOXIDE POISONING UTILIZATION BY STORM (FIGURE 7)

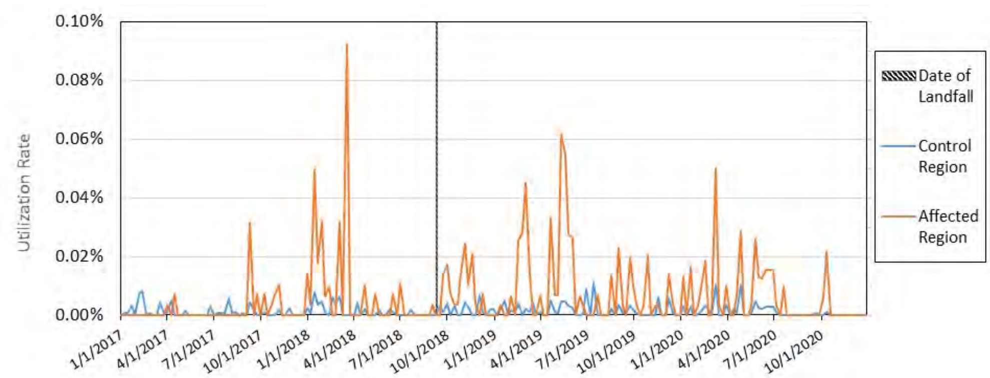
Hurricane Harvey



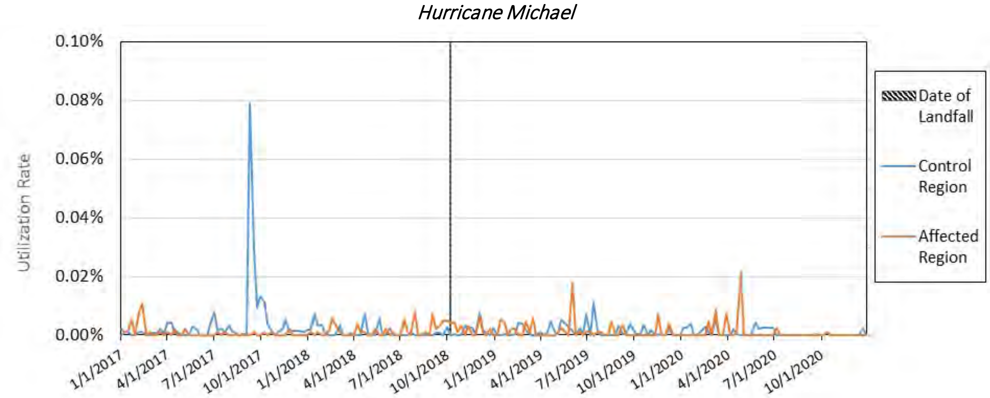
Hurricane Irma



Hurricane Florence

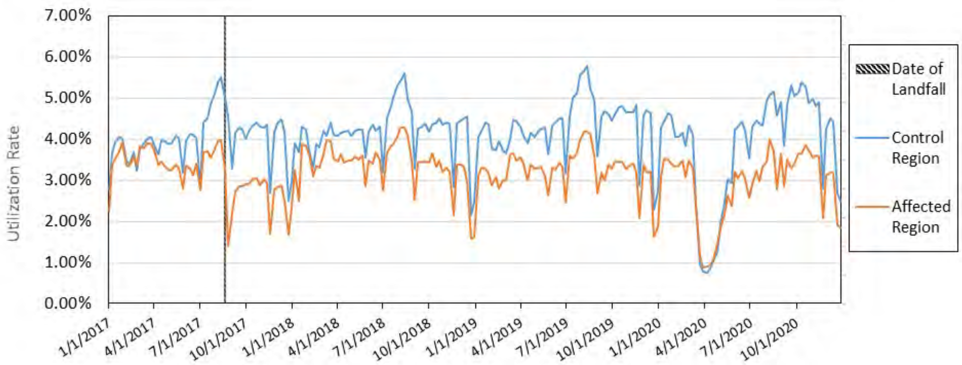


Hurricane Michael



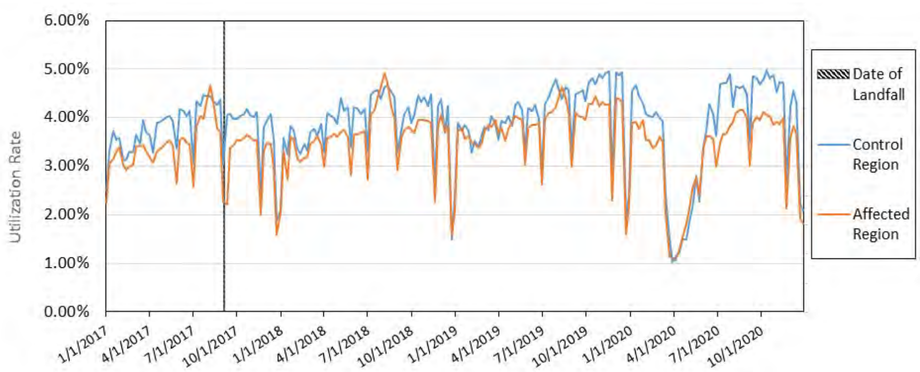
PHYSICALS UTILIZATION BY STORM (FIGURE 8)

Hurricane Harvey

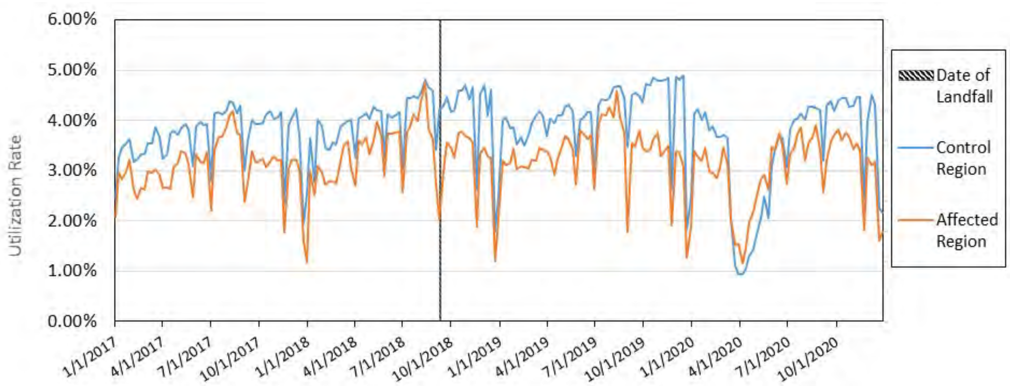


v

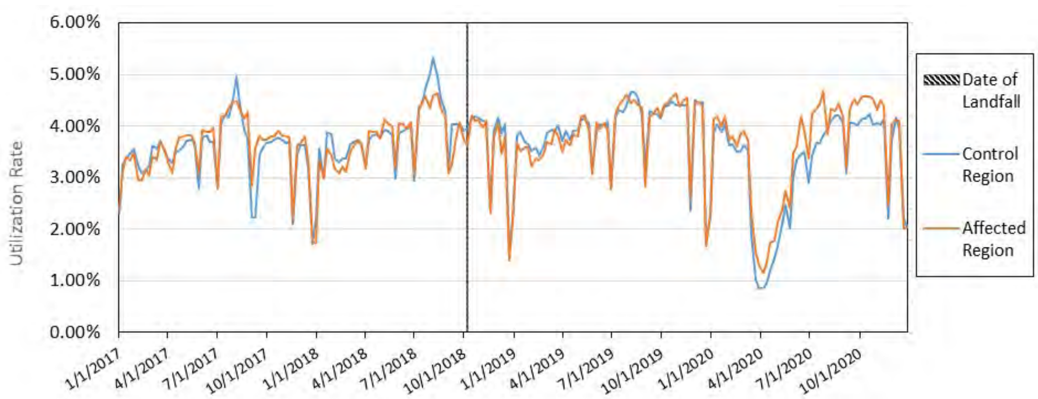
Hurricane Irma



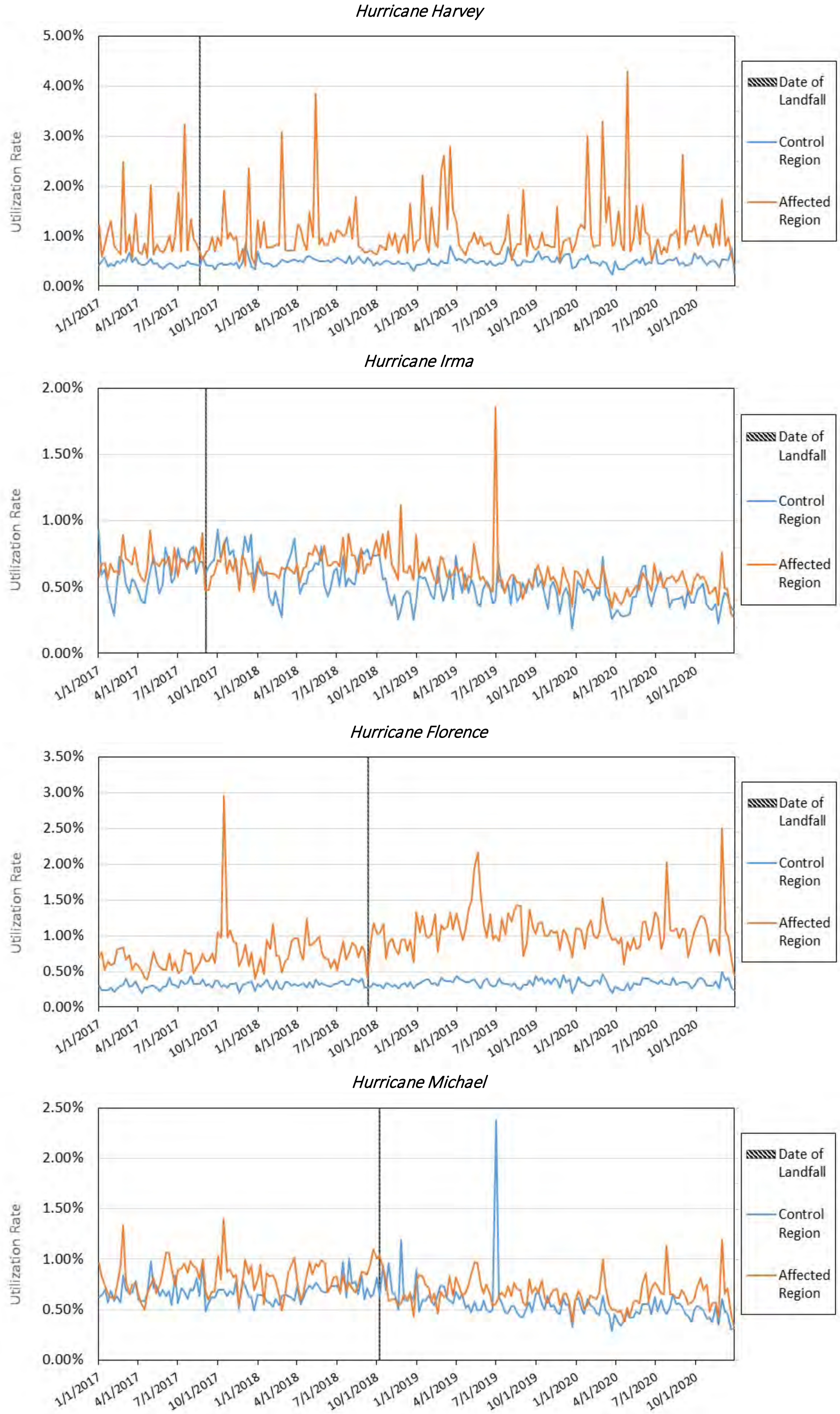
Hurricane Florence



Hurricane Michael



ALCOHOL-RELATED DISORDERS UTILIZATION BY STORM (FIGURE 9)



Overall Utilization by Payer by Storm (Figure 4)
We observed overall healthcare utilization by Medicaid vs. Medicare vs. commercial (payer groups) insurance for each storm. Stratifying the data by these major types of healthcare insurance is one way to observe healthcare impacts for potentially vulnerable or disadvantaged populations, since Medicare generally covers an older population (52 million of Medicare's 59.9 million insured are age 65 or older)[24] as well as certain people with disabilities who are under age 65, and Medicaid covers a low-income population, with a high concentration of women and children (and with a definition of low-income that varies by state). Each payer group generally demonstrates a different baseline utilization. While it appears that for a couple of storms (Hurricanes Irma and Florence) there was a mild reduction in utilization the week of the storm, this does not appear very significant and is comparable to other fluctuations that occurred throughout the remainder of the observation period. Thus, it does not appear these storms had a meaningful effect on overall utilization. Note that these graphs apply only to the affected area for each storm. The first set of graphs pertains to overall utilization rather than individual health categories and represents the sum of utilization across all health categories (including the ones we studied). As a result, the total utilization is much higher in these observations than for any of the individual health categories.

Emergency Utilization by Storm (Figure 5)
Emergency department utilization appears unaffected by the storms. Although hurricanes do cause emergency injuries, because most of the population at risk of those injuries would likely have been evacuated, they would not truly be at risk of these injuries. For most of the populations we considered affected, the evacuation period was short and even if the risk of injury was elevated immediately post-storm, it likely would have returned to a baseline level quickly. Thus, although hurricanes result in a heightened risk of emergency injuries for those directly in their path, we see no evidence that the populations affected by these storms had a meaningfully heightened rate of emergency injury-related healthcare utilization immediately following the storms.

Chronic Respiratory Utilization by Storm (Figure 6)
This is an example of a condition for which seasonal drivers are very clear, and no meaningful discontinuity can be discerned around the time each storm occurred. The questions surrounding respiratory conditions generally contemplate longer-term exposures, such as mold that grows consequent to unaddressed flooding damage in the home. Given the strong seasonal pattern and general prevalence of chronic respiratory conditions for reasons unrelated to storms, we believe that these mold exposures, if they exist and result in healthcare utilization, would be very difficult to observe in population-level utilization data. Thus, while we do not discount the notion that this risk exists consequent to hurricanes or flooding, we do not believe this data and analytic methodology are effective in measuring it. Nevertheless, given other research on this subject, we did not discard the condition at this point but instead chose to include it in our next phase of analysis.

Carbon Monoxide Poisoning Utilization by Storm (Figure 7)
Carbon monoxide (CO) poisoning in general is rare, and thus the data is especially volatile. However, CO poisoning can also be very severe or deadly, so the low prevalence does not mean it is unimportant. There is a large spike in the Hurricane Irma-affected area immediately following the storm. For the other storms, it is much more difficult to discern whether CO poisoning-related utilization was subsequently elevated. There are spikes in utilization following some of the storms; however, it is unclear whether this is a random pattern given the small numbers. Because of the strong signal for Hurricane Irma and potential signal for other storms, we considered CO poisoning to be worth studying further.

Physicals Utilization by Storm (Figure 8)
Like overall utilization, it appears there may have been a reduction in physicals during the week of occurrence of some storms (Hurricanes Harvey, Irma, and Florence, but not Michael), with very little difference thereafter.

[24] 2019 Annual Report of the Medicare Trustees (for the year 2018), April 22, 2019. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/ReportsTrustFunds/Downloads/TR2019.pdf

Although not shown, this pattern seemed consistent with some of the other preventive care sub-categories. We considered preventive care services worth studying further.

Alcohol-Related Disorders Utilization by Storm (Figure 9)
Whether there is any observable pattern in the alcohol-related disorders utilization is debatable at best. It appears utilization in the Hurricane Florence area increased after the storm; however, this may also have been part of an ongoing unrelated trend. Hurricane Harvey shows many weeks with unusually high utilization shortly after the event, but these could certainly be aberrations due to statistical noise or driven by unrelated factors.

However, between this and some of the other mental health sub-categories there seemed to be sufficient observations of post-storm utilization that differed from pre-storm to support maintaining the alcohol-related and substance-related disorders sub-categories active for the next round of analysis.

Upon considering the health categories and sub-categories presented above, as well as those not described in detail, we decided which to study further, which to discard, and which to group into broader health categories in an effort to improve the credibility of the data and make the analysis more tractable. The table below summarizes our decisions on the treatment of the initial health categories for the next phase of the analysis.

REASONS TO INCLUDE OR EXCLUDE SELECTED HEALTH CONDITIONS IN NEXT STEP OF ANALYSIS

Health Category	Health Sub-Category	Action	Reason
Mental Health	Adjustment Disorders	Merge into Combined Mental Health	Possible observed changes in utilization
Mental Health	Anxiety Disorders	Merge into Combined Mental Health	Possible observed changes in utilization
Mental Health	Mood Disorders	Merge into Combined Mental Health	Possible observed changes in utilization
Mental Health	Alcohol-Related Disorders	Merge into Alcohol- and Substance- Related Disorders	Possible observed changes in utilization
Mental Health	Substance-Related Disorders	Merge into Alcohol and Substance Related Disorders	Possible observed changes in utilization
Mental Health	Suicide and Intentional Self-Inflicted Injury	Discard	Low frequency/credibility, no observed pattern
Injuries	Emergency Visits	Discard	Low frequency/credibility, no observed pattern
Preventive Care	Physicals	Combine into Preventive Care	Observed dips in utilization
Preventive Care	Dental	Combine into Preventive Care	Observed dips in utilization
Preventive Care	PPACA - mandated preventive services	Combine into Preventive Care	Observed dips in utilization
Environmental Exposure	Acute Respiratory	Discard	Driven by seasonal factors, no apparent relationship to storms
Environmental Exposure	Chronic Respiratory	Keep	Despite low frequency/credibility, this was considered in the next round of analysis due to belief that mold/asthma claims could be implicated
Environmental Exposure	CO Poisoning	Keep	Observed spike in data
Environmental Exposure	Food and Water Borne Illnesses	Discard	Low frequency/credibility, no observed pattern

Testing Observed Patterns: Anomaly Analysis

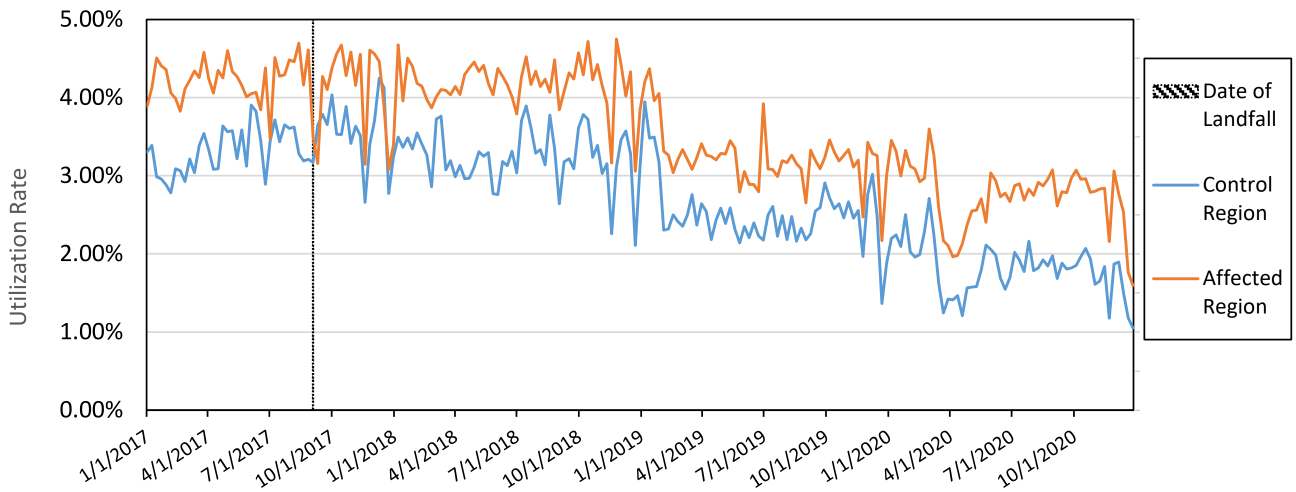
After the process described above, we were left with a shorter list of health categories and a question as to whether any observed patterns or changes in post-event utilization could be deemed significant.

Due to data volatility and uncertainty, the challenge was to determine any if observation was meaningful, as opposed to random. We also had a desire for a test that could look across multiple post-event time horizons and give us an indication of whether the observed utilization was unexpected, and if so, how anomalous it might be.

To perform this assessment, we devised a testing procedure to identify weekly observations of unusually high or low utilization over various post-event time horizons and then to assess whether these unusual observations happened at a rate beyond what could be explained by chance.

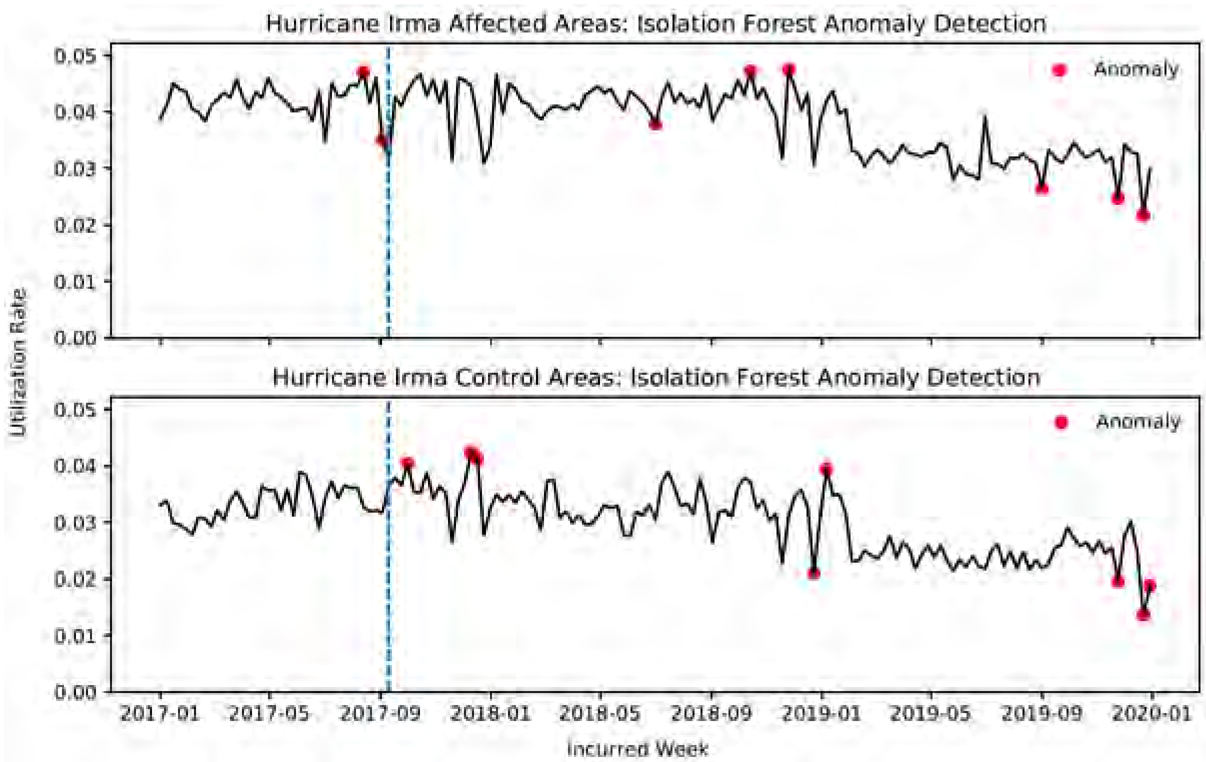
The first step of this procedure was to begin with the weekly raw utilization rates for affected and non-affected areas for each storm, for example:

ALCOHOL- AND SUBSTANCE-RELATED DISORDERS - UTILIZATION RATE FOR HURRICANE IRMA (FIGURE 10)



As previously mentioned, due to the changes in 2020 associated with the COVID-19 pandemic, we did not include experience from 2020 in this analysis. The first step was to define temporal thresholds to count the number of "anomalies" in the observed data, using a procedure known as an isolation forest. This is a sequential algorithm that identifies outliers by partitioning the data and finding the number of partitions to isolate an observation. The first outlier identified is the one that can be separated from the rest of the data with the fewest partitions. This is iterated until a specified number of outliers are identified. This procedure is similar in intent to using a distribution (e.g., a normal distribution), calculating the variance, and then setting a threshold such that those observations beyond a specified number of standard deviations are identified as outliers. Instead of calculating a variance, this procedure automatically identifies the outliers based on a bisection algorithm. The result is the identification of a preset number of datapoints that are farthest from the rest of the data. For example, the red dots below depict those identified as anomalous, based on a preset threshold that 5% of datapoints should be recognized:

ANOMALY DETECTION APPLIED TO UTILIZATION RATE – HURRICANE IRMA –
ALCOHOL- AND SUBSTANCE-RELATED DISORDERS (FIGURE 11)

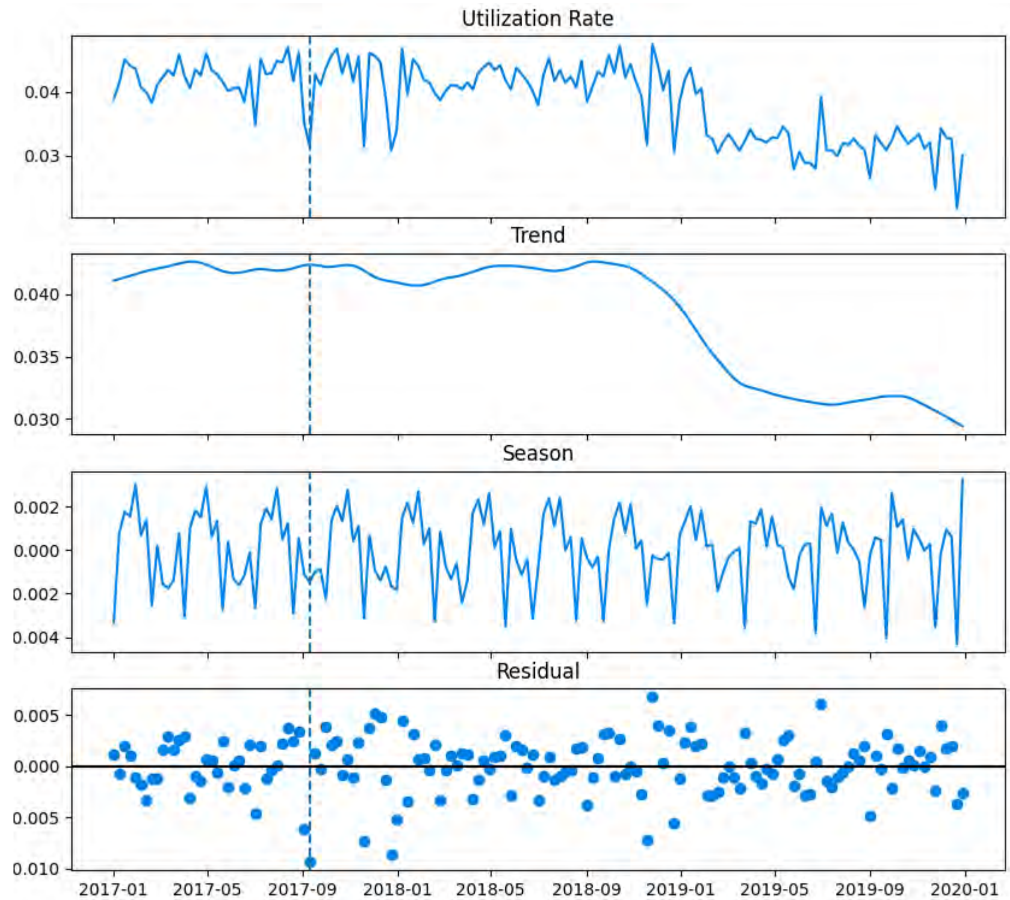


As mentioned, we felt the data was subject to seasonality and or/trend, so we applied the algorithm two ways: first on the raw data as depicted above and second on a set of residuals, intended to remove the effects of seasonality or trend. The residuals were obtained using a "seasonal decomposition", as depicted below, where the residuals are the raw observation after the net effect of a fitted trend factor, intended to account for the datapoint's position in the series, and a seasonal factor, intended to account for the datapoint's position in the year.

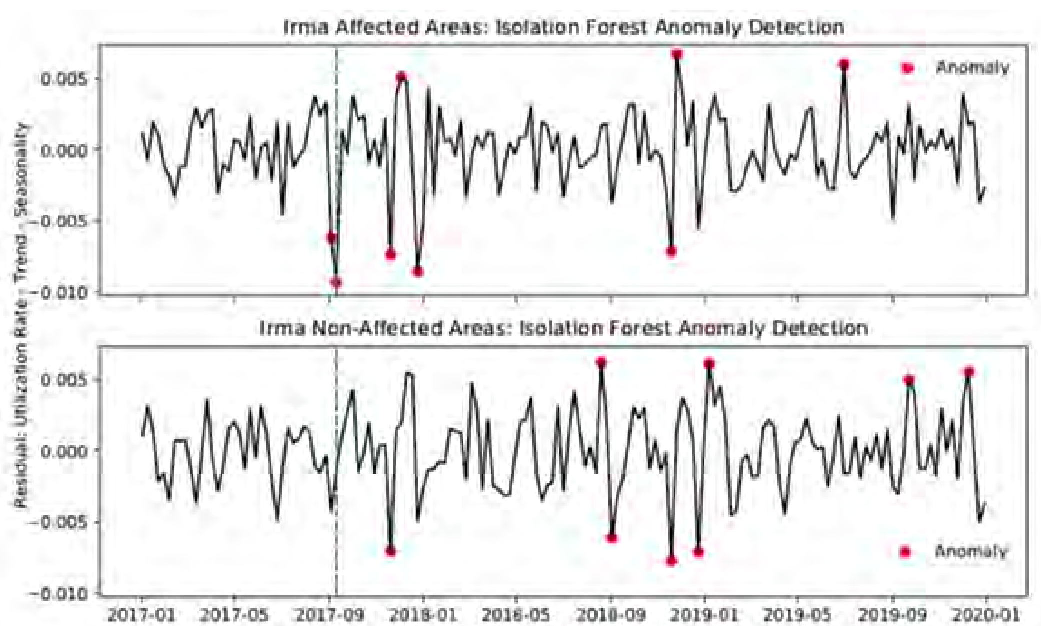
Using this procedure, we applied the anomaly detection algorithm to the raw observations and residuals for the affected and non-affected areas for each combination of storm and health category. The final output for any number of weeks post event is a count of anomalous observations, given a threshold. For example, we would be able to make a statement like "For 3 of 5 weeks after Hurricane Harvey, we observed utilization rates to a degree of unusualness that we would only expect to observe 5% of the time."

Since there was no clear choice what time horizon or number of anomalies would be significant, we looked at a range for each, ultimately choosing to consider anomaly thresholds of 5% and 20%, and time horizons of 4-, 8-, 12-, and 24-weeks post-event.

SEASONAL DECOMPOSITION – HURRICANE IRMA – ALCOHOL- AND SUBSTANCE-RELATED DISORDERS (FIGURE 12)



ANOMALY DETECTION APPLIED TO RESIDUALS – HURRICANE IRMA – ALCOHOL- AND SUBSTANCE-RELATED DISORDERS (FIGURE 13)



To get an idea how unlikely an observed number of anomalies in each timeframe could be, we devised a test based on the binomial distribution. For example, if we have identified the most anomalous 5% of datapoints, then for any given week, there would be a 5% chance of observing an anomaly, and a 95% chance of not observing one. Over the course of 4 weeks, there would be an 18.5% chance of observing at least one 5% anomaly, or a 33.7% chance of observing one in 8 weeks, as depicted in upper left-hand corner of the table below and the cell immediately below it, respectively. The table below depicts these binomial probabilities for each time horizon and threshold.

BINOMIAL PROBABILITIES FOR EACH TIME HORIZON AND THRESHOLD (FIGURE 14)

Probability of Chance Observation of at Least Number of Observed Outliers When 5.0% of Data are Outliers

Weeks	Number of Outlier Weeks Observed											
After	1	2	3	4	5	6	7	8	9	10	11	12
4	18.5%	1.4%	0.0%	0.0%								
8	33.7%	5.7%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%				
12	46.0%	11.8%	2.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
24	70.8%	33.9%	11.6%	3.0%	0.6%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Probability of Chance Observation of at Least Number of Observed Outliers When 20.0% of Data are Outliers

Weeks	Number of Outlier Weeks Observed											
After	1	2	3	4	5	6	7	8	9	10	11	12
4	59.0%	18.1%	2.7%	0.2%								
8	83.2%	49.7%	20.3%	5.6%	1.0%	0.1%	0.0%	0.0%				
12	93.1%	72.5%	44.2%	20.5%	7.3%	1.9%	0.4%	0.1%	0.0%	0.0%	0.0%	0.0%
24	99.5%	96.7%	88.5%	73.6%	54.0%	34.4%	18.9%	8.9%	3.6%	1.3%	0.4%	0.1%

Probability Less Than 5%
Probability 5% to 20%

While there was no clear choice of how unlikely an observation should be to be considered significant, the general direction of interpretation would be that the more unusual an observation, the more worthy of further consideration. On the other hand, if a series of unusual utilization following the storm could be explained by chance, this would more strongly reinforce the notion that our data was too sparse or volatile to identify meaningful patterns. As a visual guide, we again used thresholds of 5% and 20%, this time applied to the binomial probabilities, depicted in dark green and light green above. A result would be considered a strong result if it demonstrated unlikely behavior in affected areas, as well as a lack of unlikely behavior in non-affected areas. We compared these results for consistency across all storms and each threshold, as depicted on the next page.

RESULT OF BINOMAL TEST FOR CHRONIC RESPIRATORY CONDITIONS (FIGURE 15)

Application of Binomial Test to Outliers - Chronic Respiratory Conditions

Number of Outlier Weeks Observed
When 5.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	1	0	0	0	0	0	0	0
8	1	0	1	1	0	0	2	1
12	1	1	2	1	0	0	3	1
24	2	1	2	2	1	2	3	3

Chance Probability of at Least Observed
Number of Outliers When 5.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	18.5%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
8	33.7%	100.0%	33.7%	33.7%	100.0%	100.0%	5.7%	33.7%
12	46.0%	46.0%	11.8%	46.0%	100.0%	100.0%	2.0%	46.0%
24	33.9%	70.8%	33.9%	33.9%	70.8%	33.9%	11.6%	11.6%

Number of Outlier Weeks
Observed When 20.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	2	0	0	0	1	1	0	1
8	2	1	2	2	1	1	2	2
12	3	3	3	2	2	3	4	2
24	7	6	5	3	6	5	6	7

Chance Probability of at Least Observed
Number of Outliers When 20.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	18.1%	100.0%	100.0%	100.0%	59.0%	59.0%	100.0%	59.0%
8	49.7%	83.2%	49.7%	49.7%	83.2%	83.2%	49.7%	49.7%
12	44.2%	44.2%	44.2%	72.5%	72.5%	44.2%	20.5%	72.5%
24	18.9%	34.4%	54.0%	88.5%	34.4%	54.0%	34.4%	18.9%

Probability Less Than 5%
Probability 5% to 20%

RESULT OF BINOMAL TEST FOR CARBON MONOXIDE POISONING (FIGURE 16)

Application of Binomial Test to Outliers - Carbon Monoxide Poisoning

Number of Outlier Weeks Observed
When 5.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	4	1	0	0	0	0	0	0
8	5	1	1	1	0	0	1	0
12	5	1	1	2	0	0	1	0
24	5	1	1	3	1	0	1	0

Chance Probability of at Least Observed
Number of Outliers When 5.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	0.0%	18.5%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
8	0.0%	33.7%	33.7%	33.7%	100.0%	100.0%	33.7%	100.0%
12	0.0%	46.0%	46.0%	11.8%	100.0%	100.0%	46.0%	100.0%
24	0.6%	70.8%	70.8%	11.6%	70.8%	100.0%	70.8%	100.0%

Number of Outlier Weeks
Observed When 20.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	4	1	2	0	0	0	1	3
8	6	1	4	2	0	0	2	3
12	7	1	4	3	1	2	3	5
24	9	1	9	7	2	6	4	6

Chance Probability of at Least Observed
Number of Outliers When 20.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	0.2%	59.0%	18.1%	100.0%	100.0%	100.0%	59.0%	2.7%
8	0.1%	83.2%	5.6%	49.7%	100.0%	100.0%	49.7%	20.3%
12	0.4%	93.1%	20.5%	44.2%	93.1%	72.5%	44.2%	7.3%
24	3.6%	99.5%	3.6%	18.9%	96.7%	34.4%	73.6%	34.4%

Probability Less Than 5%
Probability 5% to 20%

RESULT OF BINOMAL TEST FOR ALCOHOL- AND SUBSTANCE- RELATED DISORDERS (FIGURE 17)

Application of Binomial Test to Outliers - Alcohol and Substance Related Disorders

Number of Outlier Weeks Observed
When 5.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	1	1	1	1	0	0	0	0
8	1	1	3	1	0	0	2	0
12	2	2	4	1	1	1	2	0
24	4	3	5	1	1	2	2	3

Chance Probability of at Least Observed
Number of Outliers When 5.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	18.5%	18.5%	18.5%	18.5%	100.0%	100.0%	100.0%	100.0%
8	33.7%	33.7%	0.6%	33.7%	100.0%	100.0%	5.7%	100.0%
12	11.8%	11.8%	0.2%	46.0%	46.0%	46.0%	11.8%	100.0%
24	3.0%	11.6%	0.6%	70.8%	70.8%	33.9%	33.9%	11.6%

Number of Outlier Weeks
Observed When 20.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	2	2	2	2	2	1	0	1
8	2	3	5	2	2	1	3	2
12	4	6	6	2	3	4	4	2
24	10	9	11	3	6	5	5	8

Chance Probability of at Least Observed
Number of Outliers When 20.0% of Data are Outliers

Weeks	Affected Area				Non-Affected Area			
After	Irma	Florence	Michael	Harvey	Irma	Florence	Michael	Harvey
4	18.1%	18.1%	18.1%	18.1%	18.1%	59.0%	100.0%	59.0%
8	49.7%	20.3%	1.0%	49.7%	49.7%	83.2%	20.3%	49.7%
12	20.5%	1.9%	1.9%	72.5%	44.2%	20.5%	20.5%	72.5%
24	1.3%	3.6%	0.4%	88.5%	34.4%	54.0%	54.0%	8.9%

Probability Less Than 5%
Probability 5% to 20%

As with the raw observations, we assessed many exhibits like those presented above, and for the sake of brevity we only included a handful of examples based on the test on residuals for three health categories. A description of each appears below:

Chronic Respiratory Conditions (Figure 15)
Very few anomalous observations in affected areas, and more in non-affected areas, implying that post-storm utilization was not unusual.

Carbon Monoxide (CO) Poisoning (Figure 16)
Some anomalous observations at 5% threshold in affected area for Hurricanes Irma, Florence, and Harvey, and no anomalous observations in non-affected areas. At 20% threshold, anomalous observations in affected are for Hurricanes Irma, Michael, and Harvey, with some in non-affected area for Harvey.

Alcohol- and Substance-Related Disorders (Figure 17)
At 5% and 20% thresholds, anomalous observations in affected areas for all storms, with fewer anomalous observations in non-affected areas.

The remainder of observations that were not described did not appear significant. For each item that was considered in this round of analysis, the table below provides our interpretation of the results, and supporting reasoning.

INTERPRETATION OF BINOMIAL TEST RESULT

Health Category	Apparent Significant Result?	Reason
Overall Utilization	No	Low rate of observed anomalies in affected group/Similar in non-affected group
Chronic Respiratory Conditions	No	Low rate of observed anomalies in affected group/Similar in non-affected group
Carbon Monoxide (CO) Poisoning	Yes	High rate of observed anomalies in affected group/Lower in non-affected group. Since CO poisoning is rare and based on visual examination of the data, it appears that the post-event instance of CO poisoning was elevated after these events.
Preventive Care	No	Low rate of observed anomalies in affected group/Similar in non-affected group
Combined Mental Health Disorders	No	Low rate of observed anomalies in affected group/Higher rate in non-affected group
Alcohol- and Substance-Related Disorders	Maybe	High rate of observed anomalies in affected group/Low in non-affected group. Since our test only identifies unusual weeks, not necessarily higher or lower ones, we need to compare utilization across storms to assess this result.

Measuring Across Demographic Dimensions

As described, our original goal was to identify post-event changes in utilization for various health categories, and then to assess those changes across demographic or geodemographic dimensions to determine whether any segments of the population were particularly affected. Ultimately, except for a few meaningful observations, we were unable to show that post-event changes in utilization existed for most of the health categories. Additionally, the utilization rates for the entire population exhibited high volatility, which led us conclude that finely grained analysis across many demographic dimensions was not feasible.

Due to these limitations, instead of testing across specific dimensions, we used the “Area Deprivation Index” (ADI),[25] which is a one-dimensional measure of socioeconomic disadvantage, scored and maintained by the University of Wisconsin School of Public Health.

The ADI is a census-based measure composed from several socioeconomic indicators that “allows for rankings of neighborhoods by socioeconomic disadvantage.” The index was based on a principal component analysis, originally created as part of a mortality study.[26] It collates indicators into a single score from least deprived (lowest score) to most deprived (highest score). Variables include average educational attainment, racial composition, median income, percent of families in poverty, and others. It is available at the Census Block Group level.

The advantage of using an index like the ADI is that it can be used as a holistic measure of social or economic advantage given that it encapsulates several socioeconomic branches from main domains such as income, education, employment, and housing quality. Thus, it can be useful in assessing how things may vary across a generalized measure of advantage versus disadvantage, without analyzing the individual component variables. Additionally, indices like the ADI allow for comparisons across time, allowing a gauge for changes in the degree of deprivation for areas relative to others.

The limitations of the ADI arise from the same properties its advantages. Since it is a catch-all index, there may be disparities across some dimensions of the population, but not others, that could be masked by the ADI. Additionally, given that socioeconomic data is everchanging, the factor loadings for certain variables (e.g., homes without telephone) may change dramatically, which brings into question the timeliness of the ADI methodology and whether certain socioeconomic indicators may need to be removed or altered in the future.

As described, we were faced with specific challenges that led us away from a fine-grained analysis, so despite some limitations, the ADI seemed to be optimal for assessing our healthcare response data against socioeconomic disadvantage. We obtained the ADI data and applied it to the affected regions for each storm, first conducting a basic exploratory analysis. A visual depiction of the ADI compared with NOAA wind swaths for each of the hurricanes we examined appears below.

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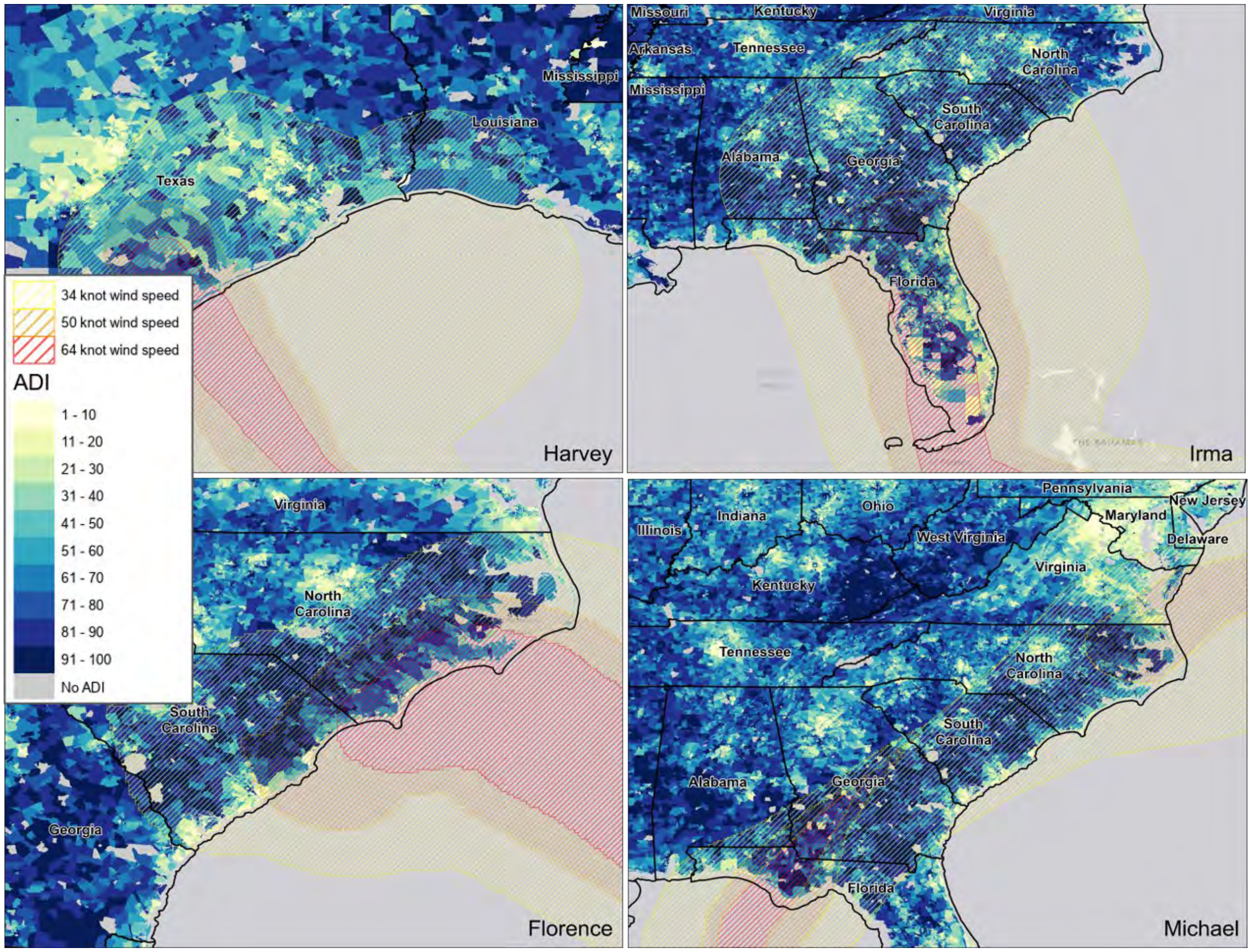
[25] Kind AJH, Buckingham W. Making Neighborhood Disadvantage Metrics Accessible: The Neighborhood Atlas. *New England Journal of Medicine*, 2018. 378: 2456-2458. DOI: 10.1056/NEJMp1802313. PMCID: PMC6051533. AND University of Wisconsin School of Medicine Public Health. 2021 Area Deprivation Index v2.0. Downloaded from https://www.neighborhoodatlas.medicine.wisc.edu/ September 1, 2021.

[26] Gopal K. Singh, “Area Deprivation and Widening Inequalities in US Mortality, 1969–1998”, *American Journal of Public Health* 93, no. 7 (July 1, 2003): pp. 1137-1143.

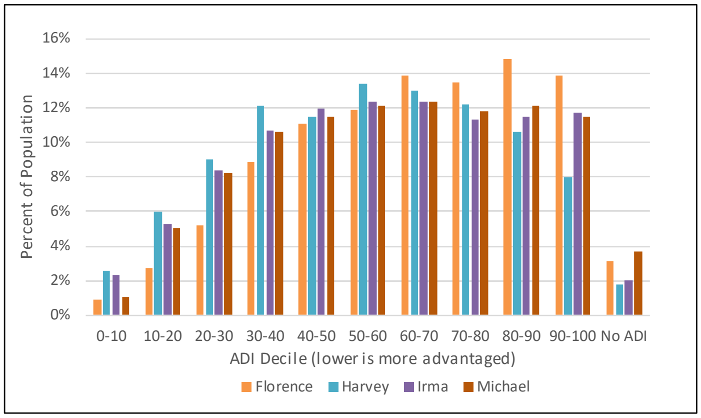
EXAMPLE: ADI OVERLAYED BY NOAA STORM WIND SWATHS (FIGURE 18)[27]



These maps provide a visual depiction of the relationship between storm intensity and socioeconomic characteristics, with light colors (low ADI) representing advantaged populations, and dark colors (high ADI) representing disadvantaged populations. While there is certainly no distinct relationship between hurricane risk or impact and ADI, we can see for the locations of various cities such as Houston how the ADI varies widely within a small area and how that area was situated during Hurricane Harvey compared to other coastal areas where the windspeeds were more extreme. Using census data, we also used to look at the distribution of ADI for each storm:

[27] Sources: Neighborhood rank (ADI), NOAA Wind swaths.

ADI DISTRIBUTION – PERCENT OF POPULATION BY STORM (FIGURE 19)



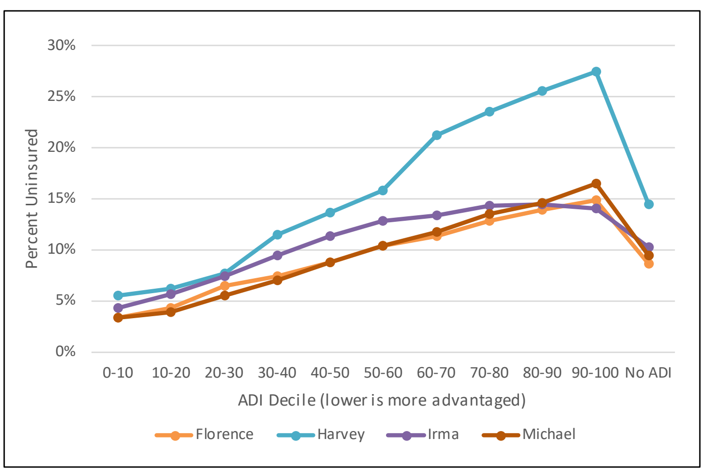
ADI	Florence	Harvey	Irma	Michael
0-10	1%	3%	2%	1%
10-20	3%	6%	5%	5%
20-30	5%	9%	8%	8%
30-40	9%	12%	11%	11%
40-50	11%	11%	12%	11%
50-60	12%	13%	12%	12%
60-70	14%	13%	12%	12%
70-80	14%	12%	11%	12%
80-90	15%	11%	12%	12%
90-100	14%	8%	12%	11%
No ADI	3%	2%	2%	4%
Average ADI	**63.35**	**55.19**	**57.54**	**58.68**

These distributions can be used to get a rough idea of the degree of socioeconomic advantage of the population in each storm's affected area. For reference, ADI scores are based on national percentiles, so territories with an ADI of 90-100 would be the 10% most disadvantaged, and we would expect 10% of the population to fall into each group.

As the table shows, the regions affected by these hurricanes (and hurricanes in general) are significantly more disadvantaged than the national average, each with a very small population in the most advantaged 0-10 group and all but Harvey with greater than 10% in the 90-100 least advantaged group. In general, hurricanes affect the southeastern United States, an area with distinct pockets of disadvantage. This should underscore the notion that while it is difficult to distinguish effects on one population versus another, hurricanes affect a region of high socioeconomic vulnerability and thus may create different or additional complications than other catastrophic perils that affect different populations.

Within this measure of socioeconomic vulnerability, we can also consider a particular attribute that pertains specifically to health vulnerability – the prevalence of health insurance with any given population. The US Census Bureau reports prevalence and type of health insurance by various census geographies. We obtained this data at the Census Block Group level and appended it to our storm affected regions and ADI dataset to examine the rate that coverage exists across storm affected populations. Please note this information reflects 2020 estimates, not estimates at the time each storm occurred.

ADI – PERCENT OF POPULATION UNINSURED BY ADI BY STORM (FIGURE 20)



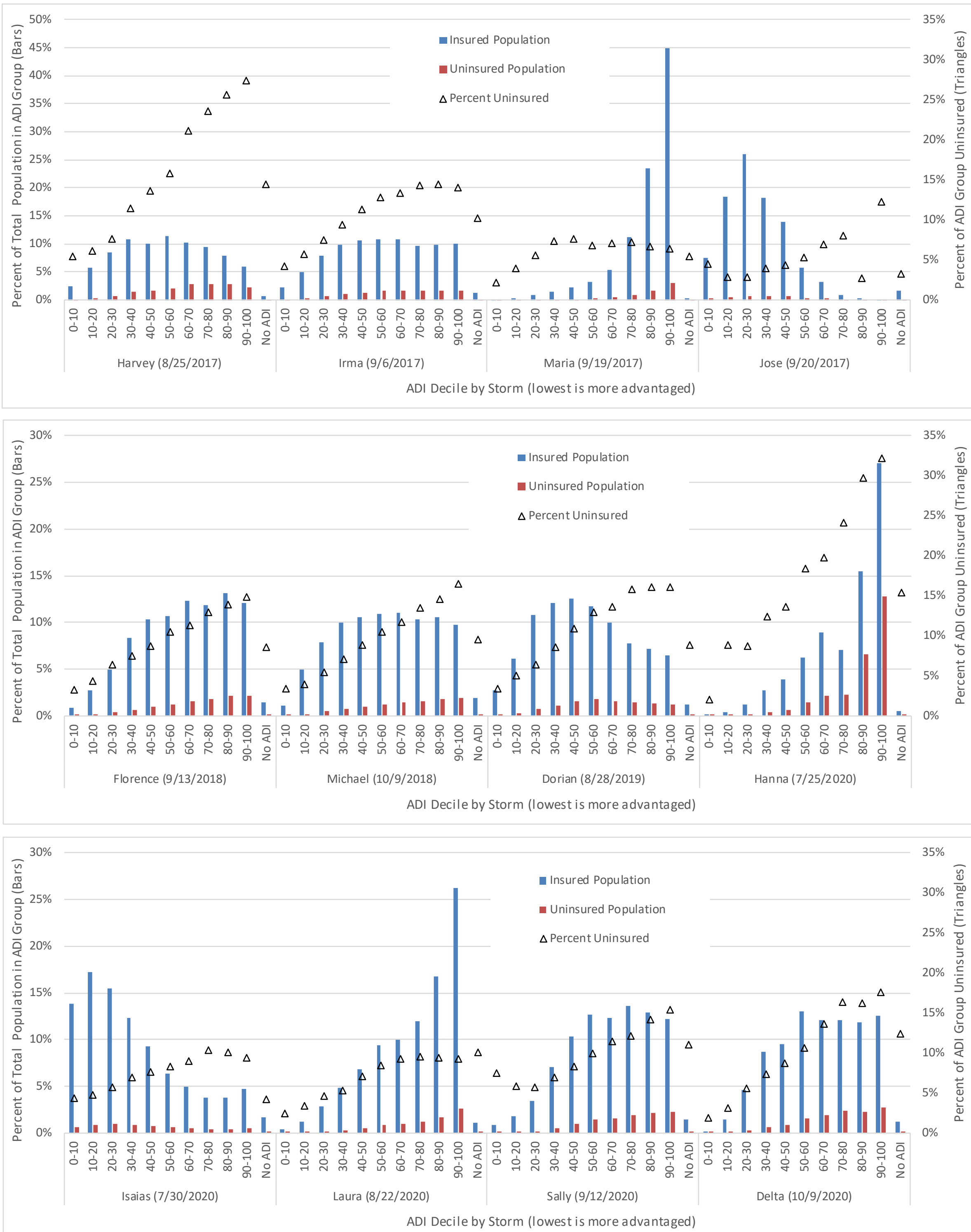
Percent of ADI Group Uninsured				
ADI	Florence	Harvey	Irma	Michael
0-10	3%	5%	4%	3%
10-20	4%	6%	6%	4%
20-30	6%	8%	7%	5%
30-40	7%	12%	9%	7%
40-50	9%	14%	11%	9%
50-60	10%	16%	13%	10%
60-70	11%	21%	13%	12%
70-80	13%	24%	14%	14%
80-90	14%	26%	14%	15%
90-100	15%	27%	14%	16%
No ADI	9%	14%	10%	9%
% Uninsured	**11%**	**17%**	**12%**	**11%**

In all cases, ADI correlates strongly with insured rates, with populations identified by ADI as disadvantaged lacking insurance at a considerably higher rate. Affected populations for Florence, Irma, and Michael have similar rates of coverage by ADI group. The high ADI population for Hurricane Harvey, while a smaller fraction of the total population than for other storms, exhibits a very high percentage uninsured. The low rate of insurance for Hurricane Harvey's most disadvantaged people reinforces an important point that has been discussed throughout this report – that vulnerability comes in many forms, and that various attributes can compound to pose a serious threat to certain populations, like those who are at high risk of natural hazard, do not have the means to evacuate (such as transportation or alternative accommodation during displacement), do not have healthcare insurance or property insurance, have a higher risk of chronic conditions, or any of a number of other risk factors that can co-exist.

To further get a sense the relationship between ADI, health insurance, and individual hurricanes, we examined similar information for all 12 US hurricanes in the period from 2017-2020. The charts on the following page display information for all storms. The differences among storms provide a striking contrast between these metrics and how they vary among various US regions. For example, rates of health insurance in Puerto Rico are higher than many other affected regions and are not particularly low in the high ADI groups. Hurricanes Hanna (Texas) and Laura (Louisiana and Texas) also struck populations that skew heavily toward the disadvantaged. However, the population impacted by Hurricane Laura was largely insured, while the population impacted by Hurricane Hanna was significantly uninsured, with an uninsured rate above 30% for the most disadvantaged group and above 25% for the entire population (see appendix for complete estimates of ADI and uninsured data by storm).

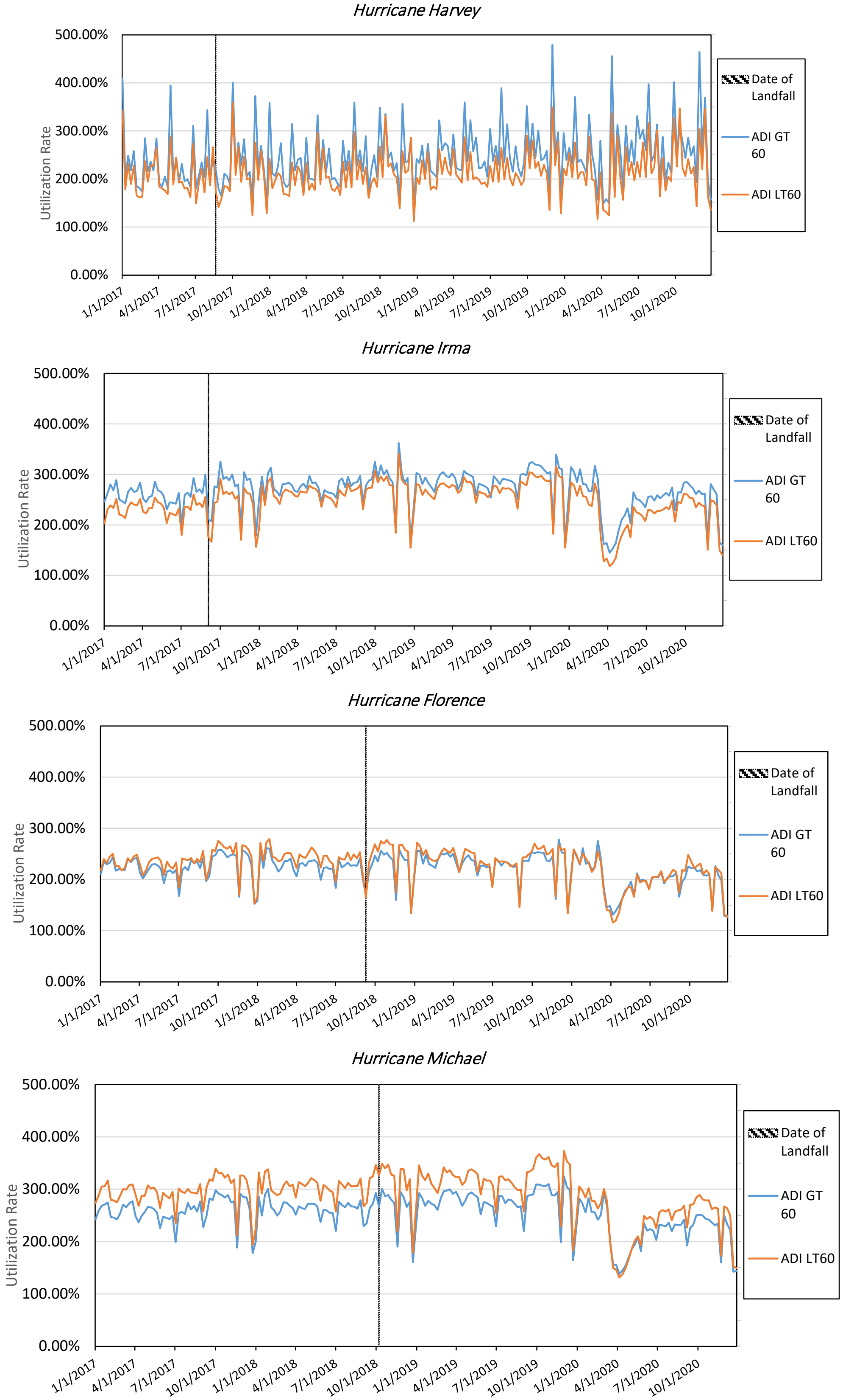
The relatively lower rates of health insurance generally observed among socioeconomically disadvantaged populations present a crucial caveat to our analysis. Our goal was to identify whether adverse health impacts occur among the vulnerable using insurance data. Unfortunately, our data does not represent the conditions of those who did not have insurance, and thus the experience of the group that may be of most interest is disproportionately absent from claims data. However, with the exception of Hurricane Harvey, the uninsured rates were only marginally higher for the high ADI groups compared to median groups for the storms we studied, suggesting that the bias in most cases is not extreme. Despite these caveats, we examined our health utilization data by ADI group. We classified the ZIP code level MEE data by ADI based on each ZIP code centroid's containing Census Block Group. We then examined the overall healthcare utilization in the affected regions for the high ADI and low ADI groups. Since the population is skewed toward high ADI, we separated these groups at an ADI of 60 which is roughly the median for the affected regions. Hurricane Maria for example struck the most disadvantaged population with nearly half in the 90-100 range, the lowest US decile.

ADI DISTRIBUTION AND PERCENT UNINSURED FOR ALL STORMS (FIGURE 21)[28]



[28] Sources: Milliman estimates based on neighborhood rank (ADI), NOAA Wind swaths, US Census Bureau American Community Survey table B27010.

OVERALL UTILIZATION BY STORM BY ADI REGION (FIGURE 22) *



ADI Region where ADI Greater than 60 represents the disadvantaged region and ADI less than 60 represents the advantaged region.

Overall Utilization by ADI Region (Figure 22)
Based on the utilization data, there does not appear to be any hurricane-related difference or discontinuity between the high ADI and low ADI regions within the affected areas. In fact, the utilization patterns in the high and low ADI regions tend to move with one another, suggesting common drivers.

Finally, as described in the previous section, we had identified CO poisoning and alcohol- and substance-related disorders as health categories exhibiting unusual post-storm utilization patterns in the affected regions. While the CO poisoning finding seemed strong, the evidence for alcohol- and substance- related disorders was less clear. We wanted to further assess these items, determine the directionality of any result, and measure any effect against our chosen measure of socioeconomic disadvantage, the ADI.

In the pages that follow, we compare each storm's high ADI population, low ADI population, and total population. First, we calculated a baseline utilization rate for each health category/population. We then compared that to the cumulative average post-event utilization rate for that health category/population to give us a sense of whether the observed rate was above or below a baseline for the period, and if so, how long it took for the average to return closer to baseline levels. As before, we recognize certain shortcomings to this approach, namely its susceptibility to noise or trend. However, we believe observing this depiction for consistency across storms will help us assess how systematic any observed effect may be.

Carbon Monoxide (CO) Poisoning (Figure 23)
All storms demonstrate some pattern of elevated post-storm CO poisoning for some period, then later approaching baseline levels. For Hurricanes Irma and Florence, the CO poisoning appears to have occurred distinctly in the high ADI (disadvantaged) areas, and for Harvey in the low ADI areas. For Hurricane Michael, there appears to have been post-event CO poisoning in both areas.

Since the level of CO poisoning is anomalously high and consistent across storms in affected areas, we believe this data does demonstrate this post-event risk. The risk of CO poisoning associated with gas-powered generators and storms is already known, so this result is not necessarily surprising, but it corroborates the notion that this an important risk that could be offset by increased public awareness. Although two storms demonstrate a stronger pattern for the disadvantaged population, this result was mixed, so we do not believe there is strong evidence that this effect is stronger for one population or the other.

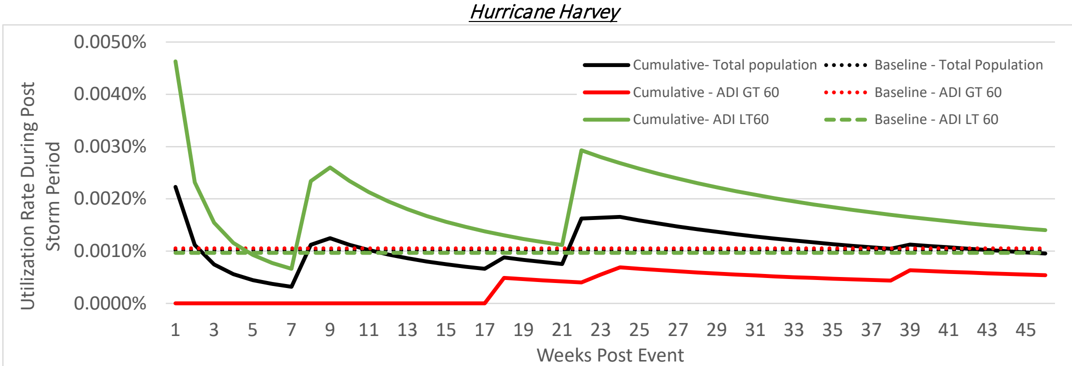
Alcohol- and Substance-Related Disorders (Figure 24)
The result is much more mixed than for CO poisoning. Here, the results for Hurricane Harvey and Florence both display lower than baseline utilization shortly after the storm, eventually returning to baseline levels. The results for Hurricane Michael are the opposite, with high post-storm utilization, eventually dropping to a baseline level. The results for Hurricane Irma show a dip shortly after the storm, then a rise, eventually stabilizing but at a level higher than the baseline for the total period. As described, the fact that the results from Hurricane Irma do not return to a baseline is not necessarily significant, due to an increasing trend throughout the total period in the areas impacted, causing the average rate later to be higher than the earlier one.

Demographically, in all affected areas, the high ADI regions display higher rates of alcohol- and substance-related disorders than the low ADI regions.

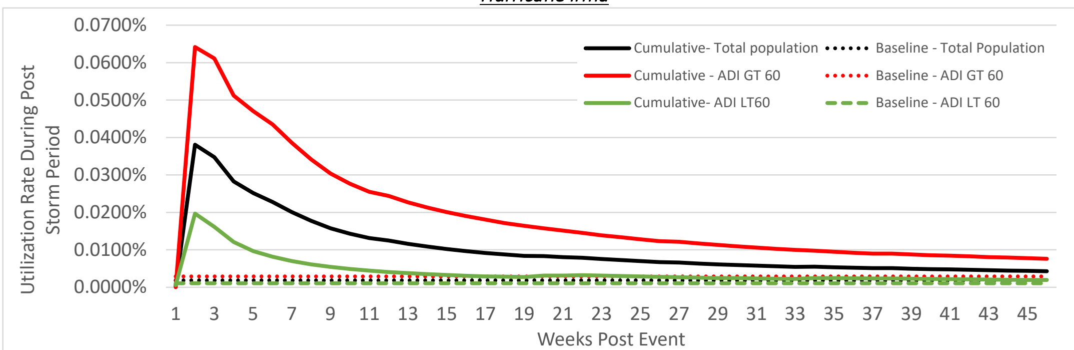
Ultimately, while the testing procedure we devised did demonstrate some post-storm effects, the direction of those effects is not consistent between storms. If anything, it appears as though the utilization may have been immediately affected after Hurricanes Harvey, Florence, and Irma, ultimately returning to normal levels within weeks after. Thus, it seems there is no consistent effect of storms on alcohol- and substance-related disorders, in general or by ADI.

CO POISONING – CUMULATIVE UTILIZATION COMPARED TO BASELINE BY ADI* BY WEEKS POST EVENT (FIGURE 23)

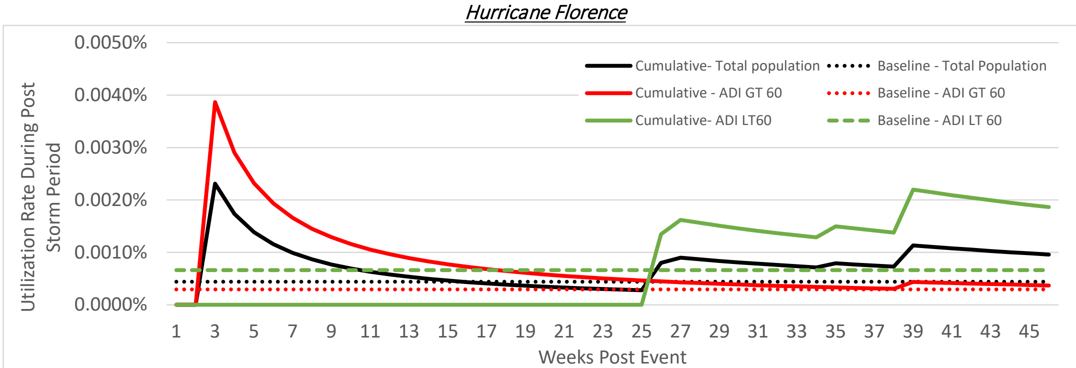
Hurricane Harvey



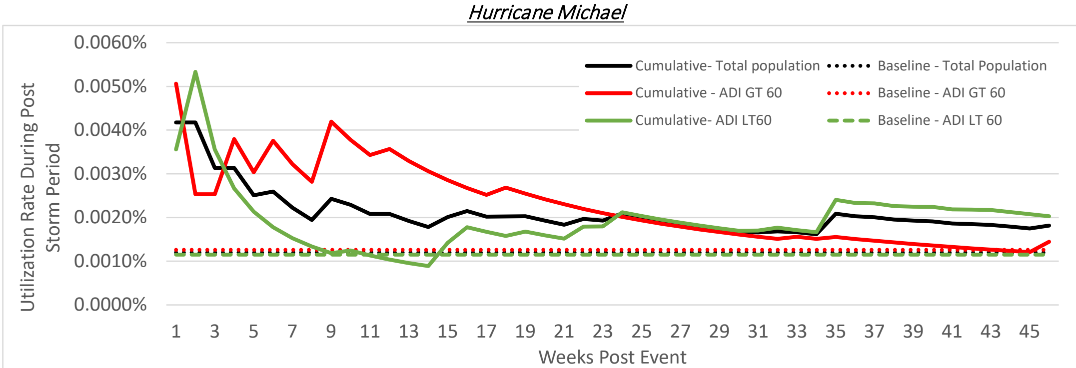
Hurricane Irma



Hurricane Florence



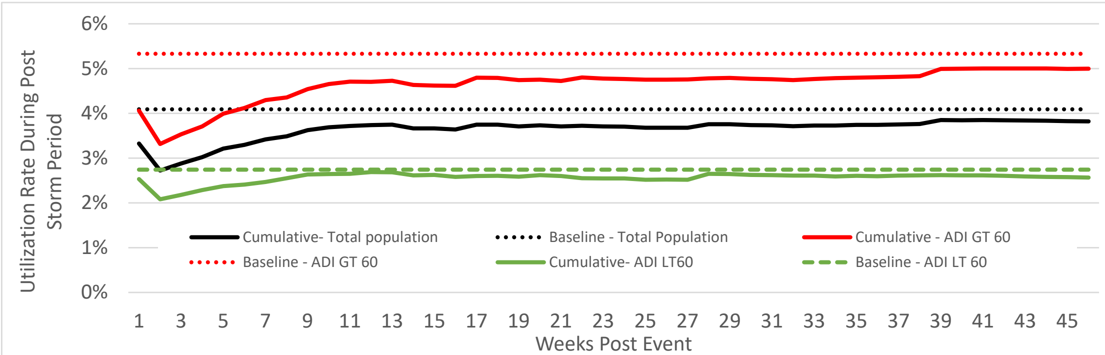
Hurricane Michael



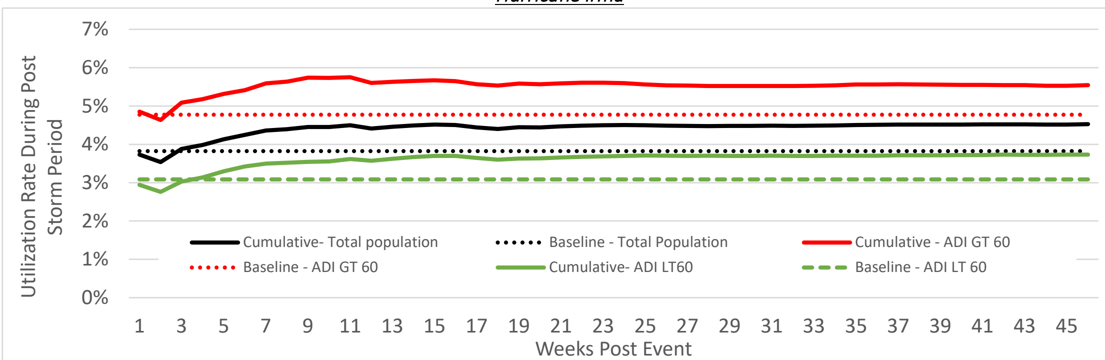
**ADI Region where ADI Greater than 60 represents the relatively disadvantaged region and ADI less than 60 represents the relatively advantaged region.*

ALCOHOL- AND SUBSTANCE-RELATED DISORDERS – CUMULATIVE UTILIZATION COMPARED TO ADI* BASELINE BY ADI BY WEEKS POST EVENT (FIGURE 24)

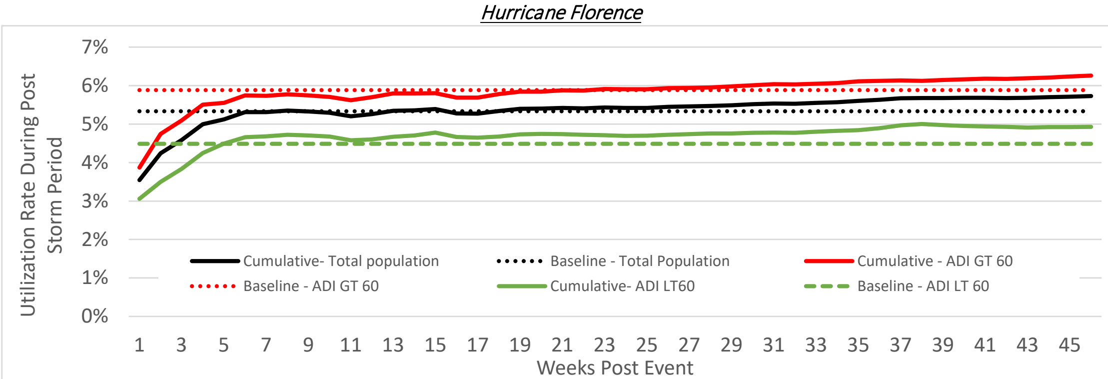
Hurricane Harvey



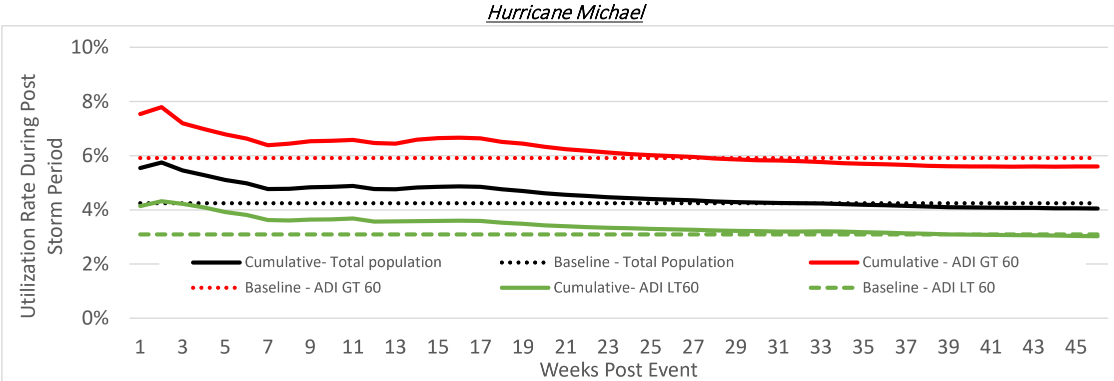
Hurricane Irma



Hurricane Florence



Hurricane Michael



**ADI Region where ADI Greater than 60 represents the relatively disadvantaged region and ADI less than 60 represents the relatively advantaged region.*

Discussion

Conclusion

Ultimately, our sole conclusive finding was an observed increase in CO poisoning across the storms we considered. As our results show, an escalation in healthcare utilization due to CO poisoning appears to be a recurring observation, consistent across a number of storms, lasting for a number of weeks post-event. Additionally, this observed escalation in healthcare utilization represents only a partial account of the intensification of risk. As noted in the beginning of this report, CO poisoning represents one of the main causes of death reported in connection with many storms, meaning that the most severe cases do not necessarily contribute to healthcare utilization because fatalities may occur before healthcare can be sought or received. Furthermore, beyond the most severe cases that result in death, and the moderate cases that appear in healthcare utilization data, there are likely additional milder cases arising from the increased exposure, that are never reported, and thus never recorded through either healthcare utilization or fatality data. Therefore, our observation of heighted healthcare utilization should be taken as a partial account of the heightened risk, representing cases in the middle of the spectrum of possible severities, but that the totality of increased hazard would also include both more severe and less severe cases.

While the risk of CO poisoning in connection with hurricanes is well known, we hope our research will serve to corroborate this knowledge and underscore the importance of safety in connection with gas-powered generators and ventilation for those who lose power during a storm. Ultimately, the operation of these generators generally happens in an emergency context, and their operators may rarely use them, and may not be focused on the hazard they can present.

For the numerous other health categories we studied, we were unable to demonstrate that these hurricanes had a measurable effect on healthcare utilization at the population level. We would not discount the notion that these events could have affected the health of many individuals in the affected area, and numerous accounts exist of individuals who were afflicted with some of these illnesses during or after hurricanes. Nevertheless, based on our observations, it appears unlikely that there is a significant change in utilization for these health categories across a population as broad as the ones we studied in combination with storms of the intensity and duration as Hurricanes Harvey, Irma, Florence, and Michael.

Comparing results with prior research

Many prior studies have focused on smaller sample sizes and employed survey-based data collection methodologies. While questionnaire-type studies are extremely valuable, they are generally limited to small populations. We produced a larger-scale analysis across several states and events by utilizing a large health insurance claims dataset across various payer types, aiming to examine similar health categories as the survey-based studies in an effort to further illuminate or buttress their conclusions. For many categories, those studies found significant results where ours were inconclusive. The seemingly conflicting findings between our study and others obliges us to provide a further discussion to explain the inherent differences in data, methodology, and target of measurement to reconcile the appearance of inconsistent results.

First, each data source has distinct strengths and limitations. The advantage of a healthcare utilization dataset is that the researcher can study many parameters using a consistent methodology, has access to a large sample size, can look for consistency of patterns across different periods of time, geographies, or events, can stratify results by relevant factors such as insurance and demographic factors, can apply the same methodology in the future to later events, time periods, or other variations of potential relevance. By comparison, the survey-based studies are more limited in sample size, subjective due to self-reporting rather than formal clinical diagnosis, and limited in their ability to compare hurricane-related effects to concurrent and historical effects or the many other factors that influence utilization patterns. On the other hand, in some respects, they enable a more precise focus than is available through a utilization dataset. For example, whether a respondent was evacuated from an affected area or remained during the storm can be ascertained via a survey question, but would be difficult to discern through a healthcare utilization dataset.

Second, there is a significant difference in what is being measured by each data source or methodology. Because they rely on self-reporting, survey-based techniques generally measure the experience of the respondent, while utilization data measures the healthcare that was actually administered. Using mental health as an example, many of the survey-based studies elicit respondents to report whether depression or anxiety was experienced in the post-event period. In practice, many of those who experience this type of distress may not seek treatment, so these effects would be captured in a survey, but not a utilization dataset, and only more severe cases would present through increased healthcare cost or utilization. The same can be said about alcohol- and substance-related disorders, where an increase in substance use or abuse could be present following a traumatic event like a hurricane, perhaps ultimately resulting in addiction, but this process would develop over a long timeframe and not immediately manifest through healthcare costs.

Finally, the storms we studied, while among the most severe in United States history in terms of landfall windspeed, dollars of property damage, or size of affected population, also were not as severe in terms of human toll as some of the storms considered by other studies. Many of the prior studies focused on Hurricane Katrina, which had a devastating effect on New Orleans, causing the city's population to decline by nearly 30% between 2005 and 2006, not to recover to pre-storm levels for 15 years.[29] Hurricane Harvey on the other hand, while displacing by far more residents than the other storms we studied[30], did not cause any year-over-year or permanent decline in the population of Houston, which continued to grow after the storm.[31] Thus, although Hurricane Harvey's toll was quite severe, it simply was not close to Hurricane Katrina in terms of its impact on a city or long-term displacement. Other storms like Hurricanes Irma, Florence, and Michael, did not displace populations as large, and those whose residences were not severely impacted would have been able to return to their communities shortly following the event.

Ultimately based on the discussion above, the fact that we were unable to conclusively corroborate the findings of many of these studies should not be taken to cast doubt on the findings of the studies themselves or interpreted to be inconsistent with their conclusions. As described, our finding was that there was no observable effect in healthcare utilization for certain categories, and certain storms. Other studies focused on similar conditions but in manifestations that were less severe (self-reported as opposed to those who sought healthcare), and often on storms that were more severe (Katrina instead of the ones we studied). As a result, we caution that our results should not be taken to detract from the results of other studies, but rather to add to the discussion by illustrating the array of possible methodologies and target variables available for different contexts or purposes.

Complexities, challenges, and notes for future research

We conclude our discussion with a description of challenges and limitations of our study, which we hope will be helpful in considerations for future research.

First, we could not precisely target the population most affected by the storms, and instead cast a wide net across a population that was likely more mildly affected by the storms, whose health conditions we studied were likely also significantly impacted by non-hurricane-related drivers. As a result, most of the effects we sought to observe may have been diluted by other factors that had a bigger effect on the health of these populations during the observed period. Thus, we could not discount the notion that many of the conditions for which we were unable to make significant findings are real potential risks to populations affected by hurricanes, and our lack of positive conclusions should not be taken as evidence that these effects do not exist.

[29] https://www.macrotrends.net/cities/23082/new-orleans/population
New Orleans' estimated 2005 population was 996,000, and 2006 population was 703,000, for a decline of 29.4%. New Orleans' estimated 2021 population was 998,000, the first year it exceeded its 2005 level
[30] See the table on page 13 for displacement data and citation. Similar displacement data not available for Hurricane Katrina.
[31] https://www.macrotrends.net/cities/23014/houston/population

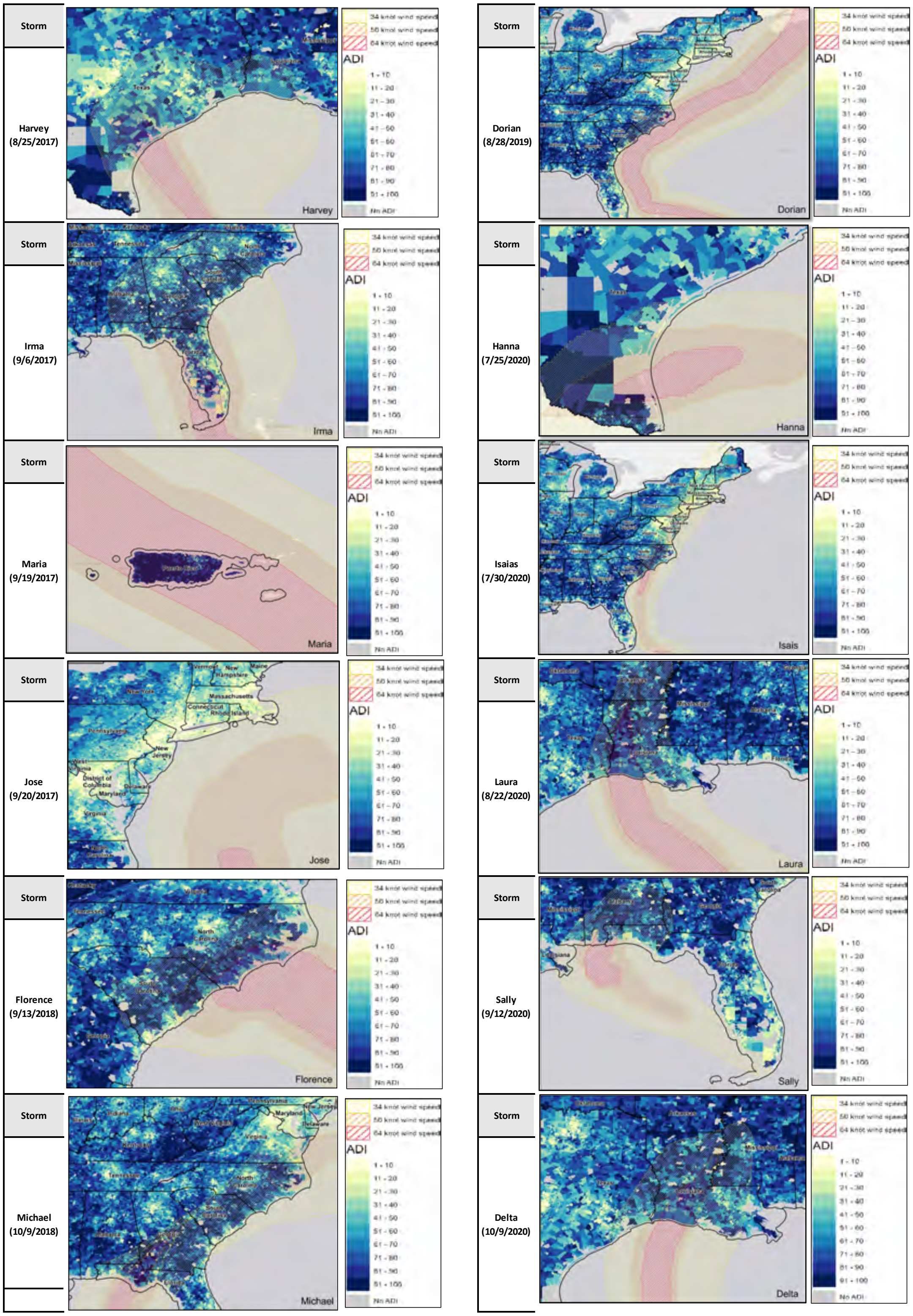
Additionally, people often leave town or are evacuated prior to a storm and may stay away from the affected area for months to years following an event. The health claims data, however, reflects the claimant's home ZIP code. Therefore, there could be a significant disconnect between instances of health effects as evidenced in the claims data and where the claimants were living when the claims were made.

Furthermore, not everyone who suffers a health condition seeks medical care, especially those without insurance. This analysis used insured data to search for post-event patterns in an effort to identify socioeconomic disparities. However, the most disadvantaged population is also more likely to be uninsured, and thus if that population suffered disproportionate negative consequences, there is an inherent bias associated with using an insured claims dataset.

Moreover, certain health conditions have an inherent seasonality, which may confound our ability to attribute health impact to storms if storm events have a similar seasonality. It may be possible to adjust for known seasonality of clinical conditions through some of the techniques we explored, but these methods certainly do not eliminate the confounding nature of seasonality.

Finally, there are many ways to define affected areas based on the duration and intensity of the storm event, evacuation orders, flooding, and wind severity, among others. Our results could vary based on the definition used to define these areas. It seems a different approach could include a precise identification of people affected by a particular hurricane-related threat, for example flooding, to the condition such a threat would affect, for example chronic respiratory conditions due to moldy living conditions.

APPENDIX – ADI MAPS FOR ALL STORMS (FIGURE 25)[32]



[32] Sources: Neighborhood rank (ADI), NOAA Wind swaths.

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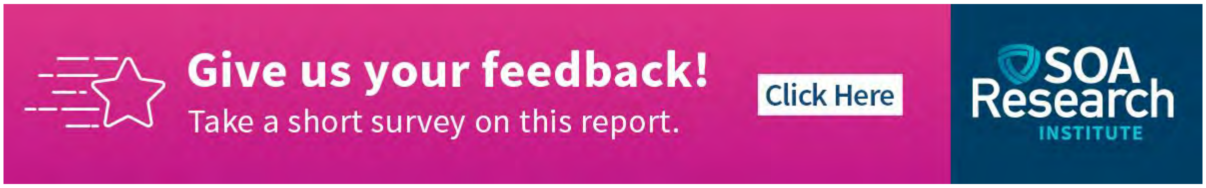
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