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Here Today, Gone Tomorrow? Essay on the Economics of Hurricanes

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ABSTRACT

HERE TODAY, GONE TOMORROW?

ESSAYS ON THE ECONOMICS OF HURRICANES

By

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This dissertation examines the health and economic consequences of recurring natural disasters by estimating the effect of hurricane exposure on various health outcomes, as well as associated changes in labor supply and housing cost. Considering that a substantial portion of the US population lives in hurricane-prone areas, and hurricanes are likely to grow in magnitude in future as a result of global warming, understanding the full short and long-term impacts of hurricanes are essential to craft optimal policy responses.

The first chapter on this topic, "Behavioral Health Burden of Hurricane Katrina", evaluates the long-lasting effects of Hurricane Katrina on the mental health and risky health behaviors of individuals residing in affected counties in the seven years after the disaster. The majority of earlier studies on Katrina focus only on immediate and short-term mental health effects, and sometimes lack pre-disaster data and / or an appropriate control group, as well as using data that only include a small subsample of survivors. I address these shortcomings in the literature by using the Behavioral Risk Factor Surveillance System, a large individual-level dataset that provides information on my outcomes of interest before and after Katrina for

randomly selected individuals residing in Katrina affected counties. I use both difference-in-differences and synthetic control methods to estimate the causal impact of Katrina. I find that Katrina impaired individual mental health and increased the likelihood of smoking, and these effects persisted over the years.

In the second chapter, I consider a more comprehensive set of health outcomes for a large set of hurricanes over a long-time period. While a growing body of research shows the long-term adverse effects of extreme weather events on growth, employment, and income, we know little about the short and long-term impacts of these events on the health of adults, which can adversely affect labor productivity and reduce economic activity. By using spatial data on hurricane strikes linked to individual-level panel data from the restricted version of the Panel Survey of Income Dynamics between 1990 and 2017, I estimate both the short and long-term effects of hurricanes on the health of adults. I compare hurricane survivors (i.e. those residing in counties struck by a hurricane) to those who were not exposed to a hurricane but resided in the same state in a difference-in-differences framework. The results show that exposure to a hurricane has a negative and substantial impact on the mental health of survivors in the decade after the disaster, while I find no statistical impact on the probability of reporting poor physical health, smoking, or heavy drinking. To see why psychological distress may be increasing, I consider two potential channels: economic losses and traumatic experiences following hurricane exposure. The results show no change in the household income, the earnings, and other labor market outcomes after hurricane exposure. Thus, my findings suggest that the long-lasting worse mental health impact is likely driven by traumatic experiences rather than the economic reasons. In addition, I find that low-educated individuals differentially suffer from worse physical health that may be resulting from the increase in the likelihood of reporting disability in the ten years after hurricane exposure. These findings provide one of the first comprehensive estimates of the impact of hurricanes on the health of adults in the United States. Moreover, since poor health can reduce labor productivity, my results may partially explain recent findings from the macroeconomics literature, which suggests these recurring disasters reduce economic productivity and increase non-disaster government expenditures such as unemployment and public medical insurance payments.

The third chapter examines the long-lasting impacts of hurricanes based on renter status. Recent studies show that hurricanes only have small economic effects on survivors. In this essay, I show that this may not be the case for renters. I estimate the long-lasting effects of hurricane exposure on monthly rental payments, as well as the health and labor supply of renters. I merge spatial data on hurricane strikes with individual-level longitudinal data from the restricted version of the Panel Survey of Income Dynamics for the period 1990 - 2017. Using difference-in-differences and triple difference models, I compare hurricane survivors to those who were not exposed to a hurricane but lived in the same state. The results show that hurricane exposure increased monthly rental payments for renters, while I find no statistically significant impact on monthly mortgage payments and self-reported house value for homeowners. Moreover, renters experienced worse physical health and increased their labor supply at the intensive margin (i.e., worked longer hours) in the following years after hurricane exposure. Given the fact that twenty percent of the US population lives in the path of hurricane strikes, understanding the heterogeneous impact on renters allows for a more complete estimate of the costs of hurricanes. This information is an essential input to create an optimal policy response.

HERE TODAY, GONE TOMORROW?

ESSAYS ON THE ECONOMICS OF HURRICANES

BY

YASIN CIVELEK

A Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree

of

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in the

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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DEDICATION

To my paternal grandmother Emine & my mother Şerife

for making education a priority.

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INTRODUCTION

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CHAPTER 1. BEHAVIORAL HEALTH BURDEN OF HURRICANE KATRINA

1. Introduction

In 2005, the United States was struck by Hurricane Katrina (henceforth, referred to as "Katrina"), resulting in massive damage, economic costs and substantial mortality particularly for individuals residing in three states, Alabama, Louisiana, and Mississippi. Several studies examine the impact of Katrina on labor market outcomes and other economic conditions (Vigdor, 2007; Groen and Polivka, 2008b; McIntosh, 2008; Gallagher and Hartley, 2017; Deryugina et al.; 2018). However, little is known about the long-term causal impacts of Katrina on health and health-related outcomes. In this study, I address this shortcoming in the literature by exploring the long-term effects of Katrina on the mental health and risky health behaviors of adults, which are outcomes that have not previously been examined causally using a difference-in-differences approach.

Due to the use of small and non-random sample sizes, the lack of pre-disaster data, and the lack of a credible control group, the prior literature on natural disasters and health is primarily descriptive in nature.[1] Exceptions include a few studies on birth outcomes (Torche, 2011; Currie and Rossin-Slater, 2013) and one looking at short run behavioral health impacts of those not directly impacted by Katrina (Pesko, 2018). To the best of my knowledge, Deryugina and Molitor (2018) is the first causal study of the long-run mortality effects of a natural disaster. They track Medicare beneficiaries and find that mortality declines among the elderly and disabled individuals residing in New Orleans before Katrina.

[1] Some of the studies are Sastry and VanLanddingham, 2009; Rhodes et al. 2010; Olteanu et a. 2011; and Paxson et al. 2012.

Why might we expect there to be long run impacts of Katrina on behavioral health outcomes? For years after Katrina made landfall, survivors remained at risk for impaired mental health due to potential negative social and financial circumstances. Goldmann and Galea (2014) point out that a large proportion of individuals living in disaster-affected counties are likely to suffer from various mental disorders, including post-traumatic stress disorder (PTSD), due to the loss of a loved one or economic resources in the months following the disaster. Extraordinarily stressful events are thought to have a higher impact on the development of PTSD in later years. According to recent media reports, "some mental health conditions become more prevalent over time for Katrina survivors."[2] Many survivors are faced with impaired mental health conditions such as cognitive impairment, insomnia, and short-term memory loss, which is known as "Katrina Brain" among researchers.[3] Consequently, long after Katrina struck, its effects continued to impact the mental health of survivors. Furthermore, natural disasters are thought to lead to higher cigarette smoking and alcohol consumption as individuals look for ways to deal with the associated stress and anxiety (Grieger et al. 2003; Nandi et al. 2005). Therefore, I examine the impact of Katrina on smoking and alcohol consumption in addition to mental health outcomes.

The present study draws on individual-level data from the Behavioral Risk Factor Surveillance System (BRFSS) from 2003 to 2012. The BRFSS is well suited for this analysis due to its inclusion of state and county identifiers, its large sample size, and its availability before and after 2005, as well as the information it provides on my outcomes of interest. I use a difference-in-differences methodology to causally assess the long-term effect of Katrina on mental health

[2] https://www.cnn.com/2017/09/19/health/psychological-aftermath-hurricanes-harvey-irma/index.html
[3] https://www.nytimes.com/2017/11/13/us/puerto-rico-hurricane-maria-mental-health.html

and risky health behaviors (smoking and alcohol consumption) of individuals residing in the 168 counties directly affected by Katrina as compared to similar individuals residing in other counties along the East Coast states. I consider both a seven year post-period (2006-2012) as well as a stratification of the post-period into a three year short run (2006-2008) and a four year long run (2009-2012) time period.

My results suggest that those living in the hurricane-affected regions suffered from 0.40 days per 30 days (11.6 percent) increase in reporting poor mental health in the combined seven year post-period of 2006-2012. This result is stronger (14 percent) in the four year long run time period of 2009-2012. I also find 1.2 percentage points (5.3 percent) and 1.4 percentage points (3.1 percent) increase in the likelihood of being a current and lifetime smoker, respectively among those living in the hurricane-affected regions between 2006-2012. Like the impact on mental health, the impact of Katrina on smoking is stronger in the long run (5.7 and 4.6 percent, respectively). Finally, I find no statistically significant impact of Katrina on the likelihood of being a binge drinker. These results are robust to different sample and functional form specifications. From a policy perspective, these findings suggest that long run effects need to be included in any analysis of the impact of natural disasters in order to capture their full effect.

2. Background

Katrina is widely considered to be one of the worst natural disasters in U.S. history. An estimated 1,800 people died as a result of the hurricane, which resulted in an estimated $125 billion (2005 USD) insured and uninsured physical damage. Thus making Katrina the costliest hurricane to ever happen in the U.S.[4] Louisiana, Mississippi, and Alabama were directly affected

[4] https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

by hurricane winds and storm surge. Approximately 90,000 square miles were declared a federal disaster area, which is almost equivalent to the size of the United Kingdom. Eighty percent of New Orleans flooded after the failure of the levee system of the city. Multiple populated areas along the Mississippi Gulf Coast and in rural Louisiana were completely destroyed.

In the days preceding Katrina's landfall, approximately 1.5 million residents of Alabama, Louisiana and Mississippi left their homes and as many as 500,000 people were displaced for several months, of 60 percent returned to their homes within 14 months (Groen and Polivka, 2008a). In New Orleans, around 100,000 remained in the city, which unfortunately increased the death toll. Deaths rates were disproportionally high for the elderly, with two-thirds of deaths in New Orleans coming from those at least 65 years old. Along the Gulf Coast, more than a million housing units and thousands of businesses were wiped off the map. Hence, this brief consideration of the scope of pecuniary and non-pecuniary losses helps explain why Katrina is likely to have long lasting behavioral health impacts on the survivors.

3. Data

The main dataset for this analysis is the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a telephone survey of health conditions and risky health behaviors of randomly chosen individuals aged 18 or older conducted by state health departments and the Centers for Disease Control and Prevention (CDC). It is a repeated cross-section rather than a panel survey. Besides health conditions and risky health behaviors, the BRFSS also provides the respondent's state and county of residence, along with various socio-demographic variables such as age, gender, race, education, marital status, employment, and income.

The BRFSS contains a standard question on poor mental health days: "Now thinking about your mental health which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" I use responses to this question to construct two measures of mental health status. First, I examine directly how many days during the last 30 the responded reported their mental health as not being good. Second, I create an indicator of persistently bad mental health, which equals 1 if the respondent experiences 30 days of poor mental health over the last 30 days. This second indicator should pick up extreme cases of poor mental health.

For smoking, I utilize the following question to construct an indicator for being a lifetime smoker: "Have you smoked at least 100 cigarettes in your entire life? [Note: 5 packs=100 cigarettes]." I also directly utilize the current smoker indicator available in the BRFSS.[5] These two variables allow me to examine whether Katrina had any impact on smoking behavior among survivors. For excessive alcohol consumption, I utilize the binge drinking question in the BRFSS. Individuals are asked whether they have consumed 5 or more drinks on any occasion in the last 30 days. However, the number of drinks in the binge drinking question was reduced to 4 or more drinks for females starting in 2006. For this reason, I only use males in my binge drinking models to prevent potential noisiness in my estimates.[6,7]

My analysis controls gender, race/ethnicity, marital status, age in years, employment status, education, household income category, and whether the individual was part of the cell

[5] It is already calculated in the data based on whether the respondent smokes every day or some days.
[6] Basically, the change in the binge drinking question was in the following year after Katrina. Pesko (2018) follows the same approach of restricting attention to men for this outcome.
[7] Two-thirds of alcohol consumption, by binge drinkers, is beer consumption (Naimi et al. 2007). Thus, I use beer taxes as a proxy to control differences across states for binge drinkers. Ruhm et al. 2012 suggest utilizing UPC scanner data for alcohol prices. However, the scanner data is available since 2006. Therefore, I cannot utilize the scanner data due to the time interval of this study.

phone sample as opposed to the land line sample. Also, as discussed in more detail below, controls for time-varying state and county level socio-economic factors taken from other sources are included in the analysis. To control for spillover effects of county-level unemployment beyond individual-level unemployment, annual county-level unemployment rates are included in the analysis.[8] Moreover, I control differences in the generosity of public health insurance coverage (i.e. Medicaid expansions), which could lead to different treatment options for mental disorder and substance use. This is done using data from several Kaiser Family Foundation reports on the Medicaid income eligibility limits as a percent of the federal poverty line for low-income families. Moreover, cigarette prices and smoke-free laws are controlled for in the smoking analysis. [9,10] Lastly, all monetary values were adjusted to 2010 dollars using the Consumer Price Index.

FEMA designated a number of counties in Alabama, Louisiana, and Mississippi impacted by Katrina to receive public assistance for purposes such as repair or replacement of disaster-damaged facilities, debris removal, and emergency protective measures. Moreover, those counties were also chosen for individual assistance to persons and households for housing, health, and transportation-related expenses due to the disaster. I defined my treatment group to include all counties which received both public and individual assistance from FEMA due to Katrina in these three states.[11] I obtained the affected county names from FEMA Disaster

[8] Unemployment rates are provided by the Bureau of Labor Statistics. https://www.bls.gov/lau/#cntyaa (accessed in May 2017).

[9] The data on cigarette prices comes from Orzechowski and Walker (2016).

[10] Information on smoke-free laws comes from CDC, STATE System Tobacco Legislation (2017).

[11] The same approach was adopted by the Bureau of Labor Statistics (BLS), https://www.bls.gov/katrina/data.htm#5. The BLS lists the counties affected by both Hurricane Katrina and Hurricane Rita by referring to the FEMA disaster declarations. Since I focus on the impacts of Hurricane Katrina on my analysis, I excluded all counties that were affected by other hurricanes rather than Katrina in 2005 from my analysis. However, I also estimated the same set of regressions using the BLS classification for Hurricane Katrina and Rita together. My point estimates and statistical significance levels largely remain the same. These results are available on request.

Declarations and matched the individual level BRFSS data to these counties using the county identifiers, which are publicly available until 2013 in the BRFSS data.

In table 1, I compare the sample means of my outcomes of interest and control variables for the treatment and control groups, both before and after Katrina. T-tests suggest that treatment and control counties are similar in the pre-disaster period in terms of mean poor mental health days and binge drinking while they are statistically significantly different in terms of mean persistently bad mental health and current and lifetime smoking rates. However, the differences tend to be small. In the treatment (control) group, the average individual experienced 3.44 days (3.39 days) of poor mental health, 6 percent (5 percent) of individuals experienced persistently bad mental health, 24 percent (21 percent) and 45 percent (46 percent) of individuals were a current and lifetime smoker, respectively and 21 percent (23 percent) of men binge drank.

Individual characteristics of those in the treated counties are quite similar to those living in control counties in both the pre-disaster and post-disaster periods. If there is a positive relationship between mobility and health, one may be concerned that selective migration may lead to reductions in the share of healthy individuals in disaster-affected counties after Katrina. However, table 1 indicates that there are not substantial differences in social-economic characteristics on average between the pre-disaster and post-disaster periods in the treatment group. In terms of state and county characteristics, the treatment region had a slightly higher county-level unemployment rate, weaker smoking bans, and lower cigarette prices. I control both individual, as well as county and state level economic and demographic characteristics in all regressions.

Figure 1 shows how the difference in the average number of poor mental health days between the treatment counties and the control counties changed from 2003 to 2012. Prior to Katrina, the trends in the average number of poor mental health days appear to be extremely similar in treatment and control counties, both of which are similar to the U.S. average. In fact, these three trend lines almost sit on top of each other. After Katrina, we see an immediate relatively large increase in the average number of poor mental health days in the treated counties, whereas we see a continuation of a slight downward trend in control counties. Over the next two years, the average number of poor mental health days then falls in treatment counties, while trending upward in control counties. This surge followed by a decline in treatment counties may be due to the time limited nature of FEMA relief efforts such as free post-disaster housing support which was ended by the spring of 2008 (Fothergill and Peek, 2015). Subsequently, and of particular interest in this paper, we see further increases in the average number of poor mental health days in treated counties between 2008 and 2011 that exceeds the growth in this outcome in the control counties. This is suggestive of potential long run impacts of Katrina on mental health outcomes.

4. Methodology

My econometric objective is to estimate the causal effects of Katrina on each behavioral health outcome of interest. A major challenge in evaluating the causal effects of a natural disaster is in finding a valid control group to measure counter-factual outcomes. A natural, though perhaps naïve, starting point would be to define the control group as consisting of all unaffected counties in the continental US. However, significant differences between the disaster-affected counties and the rest of the US are expected. For this reason, my primary control group consists of all counties that were not affected by Katrina but are in the 19 states that have experienced hurricanes and are prone to future hurricanes in the Atlantic region (henceforth, referred to as the "hurricane region").[12,13] The composition of the treatment and control groups used in this study appears in Figure 2. Moreover, I define the pre-Katrina time period to run from January 1, 2003 up to August 28, 2005, whereas the post-disaster period covers all of calendar years 2006 to 2012. Thus, to eliminate the short-term noisiness as in Datar et al. (2013), I drop any observations whose interview date is between August 29, 2005 and December 31, 2005 (i.e. Katrina made landfall on August 29, 2005).[14]

I use the following difference-in-differences model to explore the long-run impact of Katrina on the outcomes of interest.

$$\boldsymbol{O_{ict}} = \alpha + \boldsymbol{\beta_1}(\textbf{Post Katrina}_{\boldsymbol{t}} * \textbf{ Affected County}_{\boldsymbol{c}}) + \delta\mathbf{X}_{\boldsymbol{ict}} + \boldsymbol{\omega_{ct}} + \gamma_{\boldsymbol{c}} + \eta_{\boldsymbol{t}} + \varepsilon_{\boldsymbol{ict}} \qquad \textbf{(1)}$$

where O_{ict} stands for my outcomes of interest such as mental health conditions and risky health behaviors of individual *i* in county *c* and at time *t* separately; $\textit{Post Katrina}_t$ equals to 1 if the time is after the hurricane (i.e. calendar years 2006 to 2012) and is not included separately in the regression because it is collinear with the vector of year fixed effects; $\textit{Affected County}_c$ equals one if the individual lived in the treatment county, which is defined to be any county affected by Katrina. The interaction term between $\textit{Post Katrina}_t$ and $\textit{Affected County}_c$ is the key variable of interest in all regressions. Moreover, X_{ict} includes the individual characteristics such as age, gender, marital status, education, income, and employment and an indicator of being in the cell

[12] For more information: National Hurricane Center, U.S. Mainland Hurricane Strikes by State: https://www.nhc.noaa.gov/paststate.shtml
[13] Deryugina (2017) studies the impacts of hurricanes on government transfers and follows the same approach of constructing a control group using counties that do not experience hurricanes in hurricane states.
[14] Moreover, Pesko (2018) finds that Katrina increased poor mental health days in the non-damaged storm surge region for the first month after Katrina. Thus, dropping the immediate term may eliminate the short-term noisiness. However, the results remain the same when I include those observations into the post period rather than dropping them.

phone sample. Additionally, γ_c and η_t is county and year fixed effects, respectively, while ε_{ict} is the error term. By including county (year) fixed effects, I control the average time-invariant differences across counties (years) in any observable or unobservable predictors. However, fixed effects do not capture time-varying changes across both counties and years. For this reason, I include a variety of state and county characteristics, ω_{ct}, that may potentially be correlated with disaster-affected counties and the outcomes of interest. Thus, I control county-level unemployment rates, Medicaid income eligibility limits as a percent of the federal poverty level, smoke-free air laws, and cigarette prices (smoking models), beer taxes (binge drinking). The results are estimated using OLS for poor mental health days and a linear probability model (LPM) for other outcomes, but they are also robust to nonlinear specifications. I used the BRFSS sample weights, and clustered all robust-standard errors at county level.[15]

Unlike acute physical health problems, poor mental health conditions associated with disasters can be persistent over time (Norris et al. 2002). In the months immediately after Katrina, survivors received nationwide social and financial relief support commensurate with Katrina's devastating impacts. Tens of thousands of volunteers responded and thousands of troops were deployed to the disaster areas. However, the inevitable decline in support coming from disaster relief programs over the subsequent years may lead to recurrences of PTSD and related mental health issues in the long run. Understanding how the behavioral health outcomes examined in this paper evolved in the aftermath of Katrina provides valuable insights into the long-term economic and health impacts of disasters. Therefore, I perform a heterogeneity check by separating the post period into two time periods. The treatment and control groups remain the

[15] Since BRFSS weighting methodology has changed in 2011, I re-calculated each individuals' sample weights by following Simon et al. (2017). Basically, I assigned sample weights by using the fraction of each respondents' assigned BRFSS sample weights over the sum of all respondents' sample weights in each survey wave.

same, but I use the years 2006-2008 and 2009-2012 as the short-term and the long-term time periods after Katrina, respectively.[16] Based on this approach, I estimate the following econometric model:

$$\begin{aligned} \boldsymbol{O_{ict}} = \alpha &+ \boldsymbol{\vartheta_1}(\textbf{Short Post Katrina}_{\boldsymbol{t}} * \textbf{ Affected County}_{\boldsymbol{c}}) \\ &+ \boldsymbol{\vartheta_2}(\textbf{Long Post Katrina}_{\boldsymbol{t}} * \textbf{ Affected County}_{\boldsymbol{c}}) + \boldsymbol{\delta}\mathbf{X}_{\boldsymbol{ict}} + \boldsymbol{\omega_{ct}} + \boldsymbol{\gamma_c} + \boldsymbol{\eta_t} \\ &+ \boldsymbol{\varepsilon_{ict}} \end{aligned} \qquad \textbf{(2)}$$

The validity of a difference-in-differences strategy is based on the parallel trends identifying assumption. It suggests that average change in the outcome of interest would have been the same for the treated and the control group in the post-period in the absence of the treatment. I formally test this assumption using the following event study model:

$$\begin{aligned} \boldsymbol{O_{ict}} = \alpha &+ \boldsymbol{\beta_1}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2003}_{\boldsymbol{t}}) + \boldsymbol{\beta_2}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2004}_{\boldsymbol{t}}) \\ &+ \boldsymbol{\beta_3}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2006}_{\boldsymbol{t}}) + \boldsymbol{\beta_4}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2007}_{\boldsymbol{t}}) \\ &+ \boldsymbol{\beta_5}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2008}_{\boldsymbol{t}}) + \boldsymbol{\beta_6}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2009}_{\boldsymbol{t}}) \\ &+ \boldsymbol{\beta_7}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2010}_{\boldsymbol{t}}) + \boldsymbol{\beta_8}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2011}_{\boldsymbol{t}}) \\ &+ \boldsymbol{\beta_9}(\textbf{Affected County}_{\boldsymbol{c}} * \boldsymbol{Y}\mathbf{2012}_{\boldsymbol{t}}) + \boldsymbol{\delta}\mathbf{X}_{\boldsymbol{ict}} + \boldsymbol{\omega_{ct}} + \boldsymbol{\gamma_c} + \boldsymbol{\varepsilon_{ict}} \end{aligned} \qquad \textbf{(3)}$$

where *Y2003, Y2004, Y2006, Y2007, Y2008, Y2009, Y2010, Y2011,* and *Y2012* are indicators for whether year t is 2003, 2004, and from 2006 to 2012, respectively (omitting 2005 as the reference year). In order to indirectly test the parallel trends assumption, I test the null hypothesis

[16] The periods of the short-run (2006-2008) and the long-run (2009-2012) are arbitrarily chosen. However, I checked the sensitivity of long-run and short-run time intervals. Results remain the same with different short-run and long-run time specifications like the short-run is 2006-2007 and the long-run is 2008-2012. The results are available on request.

that the coefficients on the "Affected County" variables in pre-Katrina years ($\beta_1$and β_2) are equal to zero.[17]

I also perform a series of robustness checks to assess the validity of my baseline results, presented in table 5. First, I estimate a probit model for binary outcomes for my pooled sample, rather than LPM used in my baseline estimates. This addresses the potential concerns that the LPM does not give consistent and unbiased estimates of marginal effects. Second, I run the same set of regressions without using the BRFSS sample weights.[18] The debate on using sample weights in regression analysis has a long history (Winship and Radbill, 1994; Gelman, 2007; Solon, Haider, and Wooldridge, 2015). Using weights for calculating sample means is informative while it can be tricky when estimating causal effects in a regression analysis. Therefore, I also estimate unweighted models to check robustness of the main results. Third, I apply the synthetic control method, as suggested by Abadie et al. (2010). This allows me to construct a data-driven control group to compare the outcomes of interest before and after Katrina hit. Finally, I define an alternate control group which includes all counties that were affected by other hurricanes in 2005 (280 counties in Alabama, Florida, and Texas). These counties are in geographically close to Katrina affected counties and these hurricanes caused much less damage than Katrina did. So, I check the sensitivity of sample specification by including those counties in the control group.

[17] Both equations 2 and 3 are informative about variation in the effects in the post period. However, due to the flexibility of the event study, the results are not efficient if some coefficients are not very distinct from each other. Therefore, I also use equation 2 that combines the years 2006-2008 and 2009-2012 as the short-run and long-run time periods after Katrina, respectively.

[18] Simon et al. (2017) and Carpenter et al. (2018) also employ similar sensitivity analysis with BRFSS data.

5. Results

5.1. Baseline Results

Table 2 presents the results from the main difference-in-differences regression for each outcome. Columns indicate the results for poor mental health days, persistently bad mental health, current and lifetime smokers, and binge drinking. Positive and significant point estimates in the first row of Table 2 show the negative effect of Katrina on poor mental health days, persistently bad mental health, and smoking behavior throughout the 2006 - 2012 period. However, I find no statistically significant effect on binge drinking. The point estimates suggest that Katrina increased poor mental health days by 0.40 days per 30 days (11.6 percent), persistently bad mental health status by 0.4 percentage points (6.8 percent), the likelihood of being a current or lifetime smokers by 1.3 percentage points (5.3 percent) and 1.4 percentage points (3.1 percent), respectively, on average.[19] These results suggest that Katrina led to worse behavioral health outcomes in the combined seven-year post period of 2006-2012.

Table 3 presents the short vs. long run effect of Katrina on my outcomes of interest. The results suggest that Katrina had a much higher and statistically significant impact on individuals' mental health and smoking behavior in the long-run compared to the short-run time period. Katrina, on average, increased the poor mental health days by 0.48 days per 30 days (14 percent) in the long-run as compared to 0.28 days per 30 days (8.1 percent) in the short-run. Likewise, current and lifetime smokers increased 1.4 and 2.1 percentage points (5.7 percent and 4.6 percent) in the long-run whereas the effect was 0.8 and 0.5 percentage points (3.2 percent and 1.1

[19] The point estimates on poor mental health days and lifetime smoker are statistically significant at the 1 percent level whereas current smoker and persistently bad mental health are significant at the 5 and 10 percent level, respectively.

percent) in the short-run, respectively.[20] In the long-run, Katrina appears to have exerted a greater impact on the mental health and smoking behavior of individuals living in the affected counties as compared to the short-term. On the other hand, the effect of Katrina on binge drinking remains statistically insignificant in both the short and long run, though the point estimate is larger in the long run as well.[21]

One concern associated with using the BRFSS for this sort of analysis is the cross-sectional nature of the data. This means I am not able to track the same individuals over time, which may raise some concerns about migration and self-selection biasing my results. Brodie et al. (2006) suggest that a relatively less healthy group of individuals were forced to evacuate due to Katrina. Almost 60 percent of evacuees from Louisiana returned to their pre-Katrina addresses within 14 months (Groen and Polivka, 2008a). Which evacuees returned does not appear to be random. Previous work suggests that those that did not return were more likely to have lower household income and lower levels of education (Groen and Polivka, 2010). In addition, those that did not return were more likely to be in poor health (Deryugina and Molitor, 2018). This selection based on who returns actually works to my advantage in this context given that it implies that my estimates can be interpreted as lower bounds of the detrimental impact of Katrina on behavioral health outcomes.

In summary, these baseline results suggest that Katrina impaired individual mental health and increased the likelihood of being a current or lifetime smoker. I find a larger impact of Katrina on mental health and smoking behavior in the long run, which statistically significant

[20] The short-run and the long-run estimates are statistically different from each other for poor mental health days, current and lifetime smokers, but not for persistently bad mental health and binge drinking.
[21] I also test whether there are differential effects based on gender, race, income, and education. However, I do not find any significant differences.

and different from the short run effect. This suggests that mental health further deteriorated and the likelihood of smoking increased over time, and this effect was caused by Katrina.

5.2. Event Study Results

In my difference-in-differences model, I assume common counterfactual trends in behavioral health outcomes between Katrina affected counties and the control counties in the post period in the absence of Katrina. A common way to indirectly test this assumption is to look for differences in trends for the outcomes of interest in the pre-period (i.e. testing the parallel trends assumption). A causal interpretation of my estimates depends on the validity of this assumption. Therefore, I check this identifying assumption of my econometric model by conducting an event study analysis (i.e. estimating equation 3).

The results of the event study are presented in table 4. The coefficient estimates on the interactions between the $Affected\ County_c$ indicator and the pre-Katrina year indicators (2003 and 2004) indicate pretreatment trends for each behavioral health outcomes in columns 1 - 5. The estimates suggest that the pretreatment trends are not significantly different between Katrina affected and control counties for any of the outcomes of interest. Therefore, these results validate the key assumption of my econometric model, which provides causal effects of the impact of Katrina.

5.3. Sensitivity Analysis

I examine the sensitivity of my main results to various modifications of the model or the sample. These results are presented in table 5. First, I estimate a probit model for binary outcomes such as persistently bad mental health, current and lifetime smoker, and binge drinker in my pooled sample, rather than the linear probability model used in my baseline model. Probit marginal effects are presented in column 1 of table 5. The point estimates and the statistical significance of the results are very similar to my main results, with slightly higher (lower) point estimates for smokers (persistently bad mental health). Second, I estimate the same set models on the same pooled sample, but without using the BRFSS sample weights. The results, in column 2 of Table 5, are also quite similar to the main results. Likewise, the findings suggest that poor mental health days, persistently bad mental health, and smokers significantly increased in the long run after Katrina.

Third, I test my findings using the synthetic control method proposed by Abadie et al. (2010) for a single treated unit. Here I collapse Katrina affected counties into a single treated unit with annual observations and aggregate all other individual-level data to the state-by-year level for all unaffected states in the continental U.S. to form a donor pool. I then allow the data to select the combination of other states that best matches Katrina affected counties on mental health, smoking, binge drinking, and the control variables during the pre-Katrina period from 2003 to 2005. Following by Fitzpatrick (2008), Courtemanche and Zapata (2014), and Courtemanche et al. (2017), I apply this method to individual data multiplying the BRFSS weights by the synthetic weights for all unaffected states and leaving the BRFSS weights of individuals living in Katrina affected counties unchanged. The results of the synthetic control, presented in column 3 of table 5, suggest that Katrina increased poor mental health days by 0.32 day per 30 days (9.3 percent) and current smokers by 1.2 percentage points (4.9 percent) and lifetime smokers by 1.4 percentage points (3.1 percent). These point estimates are similar to those presented in table 2, thus my conclusion remains the same.

Finally, I excluded some counties in Alabama, Florida, and Texas, hit by Hurricane Rita, Wilma, and Dennis in 2005, in my main analysis to eliminate any confounding effects, which may appear since all four hurricanes occurred in the 2005 hurricane season.[22] I check the sensitivity of my findings by including those counties in Alabama, Florida, and Texas into my control group. As the results in column 4 of table 5 indicate, the inclusion of those counties in my control group does not change my results.

6. Discussion

This study explores the long-term causal impacts of Katrina on behavioral health outcomes of individuals residing in Katrina affected counties. Following a traumatic event, only a small number of people with PTSD seek medical treatment, and years pass between experiencing the symptoms and seeking treatment in most cases (Goldmann and Galea, 2014). Without appropriate treatment, an individual's mental health is likely to get worse. The results suggest that Katrina led to worse individual mental health and an increase in the likelihood of smoking, but did not have a significant impact on the likelihood of binge drinking. Also, the long-run effects of Katrina on these outcomes were much larger than the short-run effects. These findings indicate that Katrina had significant impacts on the behavioral health outcomes of adults living in the affected counties even long after the disaster occurred.

The existing literature on natural disasters and behavioral health is mainly descriptive in nature. Moreover, only few studies examine the long-run associations between exposure to a

[22] The intensity and the overall impact of Hurricane Rita, Wilma, and Dennis are much smaller compared to Hurricane Katrina. Therefore, I included the affected counties from these three hurricanes in Alabama, Florida, and Texas in my control group, rather than including into the treatment group.

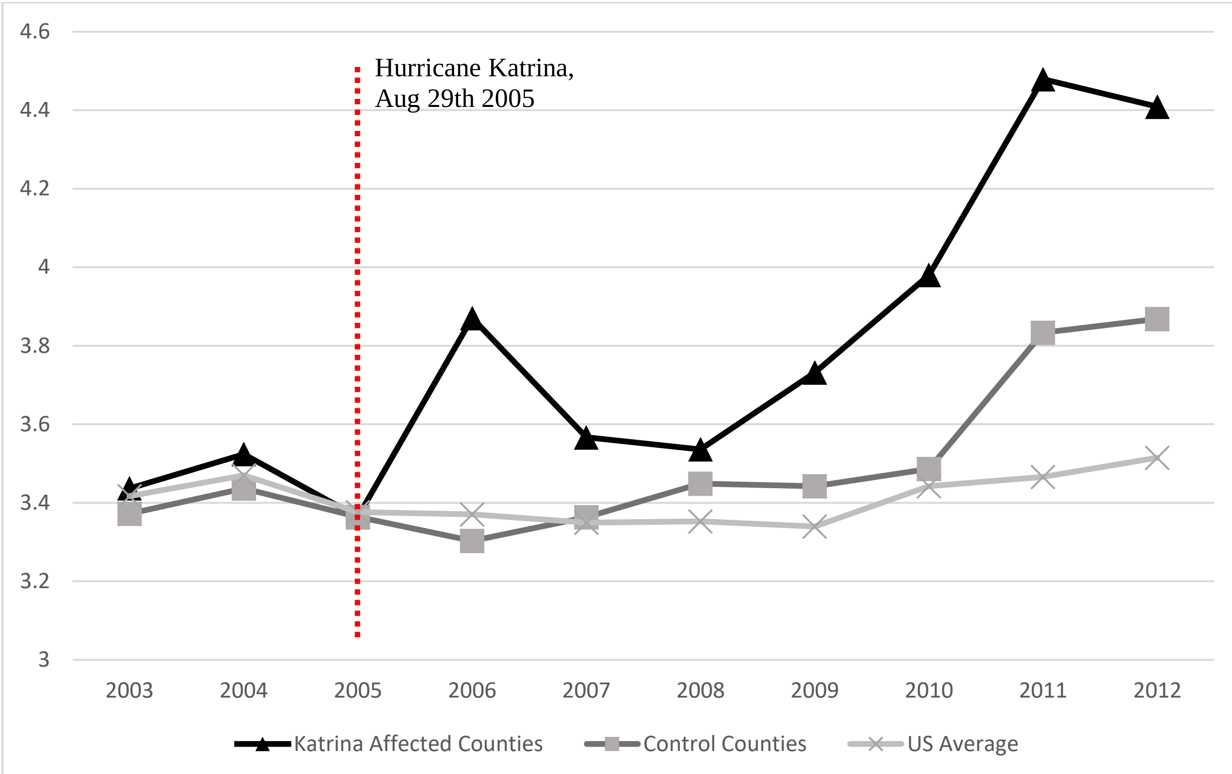
disaster and behavioral health outcomes in later years.[23] Thus my study advances this literature by exploring the long-run effects of Katrina on behavioral health outcomes and providing the first causal estimates on these outcomes up to seven years after this disaster. My findings on the short-run impacts of Katrina are similar to the descriptive literature that provide evidence of an association between mental health disorders and hurricane survival (Kessler et al., 2006; Galea et al., 2007; Rhodes et al., 2010). Based on my results, we can now say with some confidence that this relationship is a causal one. In addition, we can now also say that the impact of Katrina on both mental health and smoking increases in the long run rather than declining.

This work is subject to some limitations. I employ a quasi-experimental research design due to inability to observe the counter-factual situation in which Katrina did not happen. This research design may threat the internal validity. I address this limitation by conducting an event study analysis and robustness checks. Another limitation is that the BRFSS is a repeated cross-section. So, I cannot observe changes in specific individuals' behavioral health outcomes after Katrina that I could do with a panel data. Also, all outcomes are self-reported. The subjective self-reported measure of health outcomes may be subject to some measurement errors. Despite these limitations, the dataset's large sample size, its comprehensiveness before and after Katrina, and its inclusion of state and county identifiers, as well as the information it provides on behavioral health outcomes of randomly chosen individuals offer an important opportunity to explore the long-run impacts of Katrina on behavioral health outcomes.

[23] To the best of my knowledge, Paxson et al. (2012) is the first study that looked at the relatively long-run impact of Katrina on mental health outcomes of a subset of survivors (i.e. 532 low-income mothers living in New Orleans), employing data from a survey conducted one year before Katrina, and 7-19 and 43-54 months after Katrina, respectively. They report that the prevalence of mental health disorder was 36 percent and 30 percent of their sample in the 7-19 months and 43-54 months after Katrina, respectively, whereas pre-Katrina prevalence rate was 24 percent.

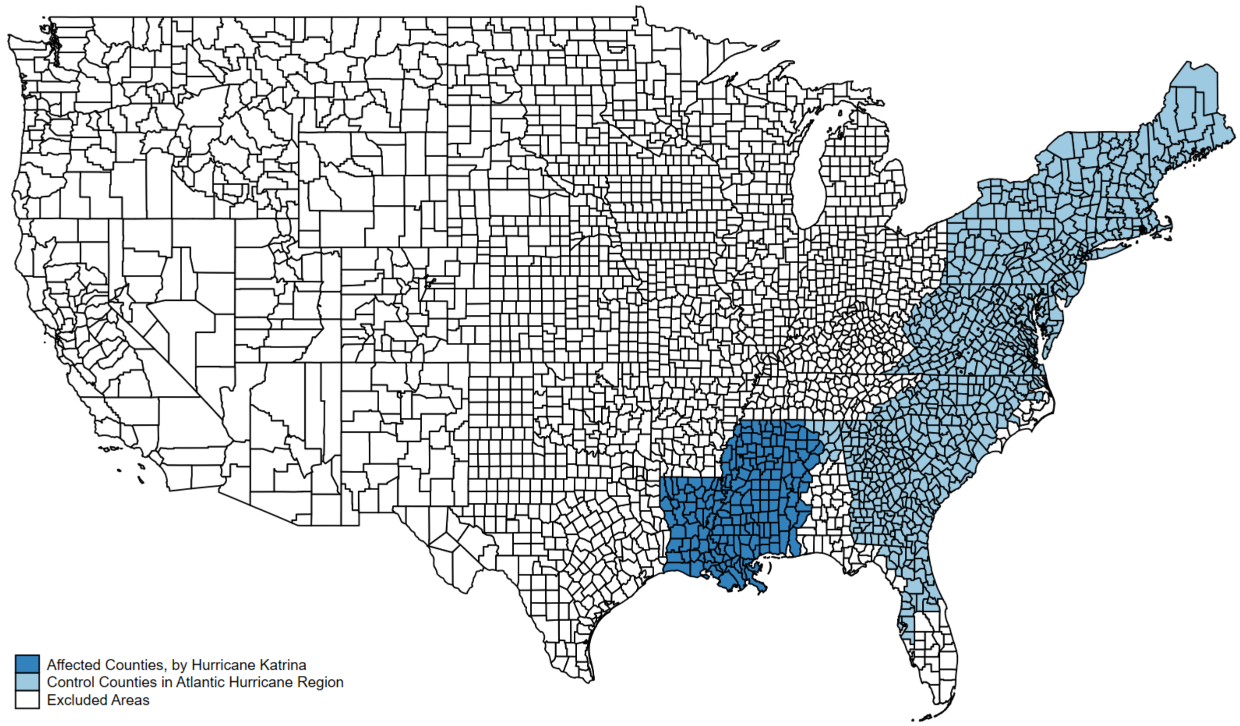
In terms of policy implications, poor mental health reduces the quality of social and occupational life by causing serious health and economic costs for individuals, families, and society. Moreover, the social and economic burden of PTSD extends far beyond the individuals who experience the disorder and affect families, colleagues, and a broader population (McCrone et al., 2003). Similarly, smoking creates a substantial health burden on individuals, families, and society as a whole. According to the report of the U.S. Surgeon General (2014), use of tobacco is the leading preventable cause of mortality in the U.S. It is the cause of almost one in five deaths in the nation. Additionally, smoking increases other health risks. Smokers are more likely to develop lung cancer, stroke, and heart disease than nonsmokers. Furthermore, Max et al. (2012) estimate the number of deaths and the costs attributable to secondhand smoke (SHS) exposure for the U.S. in 2006. Their findings indicate more than 42,000 deaths and $6.6 billion of lost productivity resulting from SHS, which suggest large economic and social costs of smoking on not only smokers, but also non-smokers. A range of policy interventions needs to be considered to address these costs related to impaired mental health and smoking caused by a large-scale disaster, with the understanding that these impacts might be felt for many years after the disaster.

Figure 1. Average poor mental health days



Notes: The BRFSS poor mental health question is “Now thinking about your mental health which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?”

Figure 2. Impacted counties and control group



Notes: The counties affected by Katrina are identified using FEMA Disaster Declarations. Katrina affected counties are the ones receiving both public and individual assistance in three southern states; Alabama, Louisiana, and Mississippi. The counties affected by other hurricanes in 2005 (Rita, Wilma, and Dennis) in Alabama, Florida, and Texas are excluded from the analysis to eliminate the confounding effects. The counties outside of the treatment and the control groups are not included.

Table 1. Descriptive statistics for sample used in analysis, 2003-2012

		Pre-Katrina (2003-2005)		Post-Katrina (2006-2012)	
BRFSS		Treatment Mean	Control Mean	Treatmen t Mean	Control Mean
Outcomes of Interest	Days Mental Health Not Good over Past 30 Days (n=1,367,986)	3.436	3.389	3.942	3.532
	Persistent Bad Mental Health (n=1,367,986)	0.059	0.049	0.066	0.053
	Current Smoker % (n=1,385,687)	0.244	0.210	0.232	0.188
	Life-time Smoker % (n=1,385,687)	0.454	0.461	0.451	0.445
	Binge Drinker % (n=507,679)	0.213	0.228	0.195	0.207
Gender	Male %	0.477	0.480	0.476	0.480
	Female %	0.523	0.520	0.524	0.520
Race	White %	0.660	0.760	0.660	0.762
	Black %	0.302	0.147	0.303	0.151
	Other race %	0.038	0.093	0.037	0.087
	Age	44.942	45.949	46.380	47.168
Education	Never Attended School or Only Kindergarten %	0.001	0.001	0.001	0.002
	Elementary %	0.035	0.031	0.034	0.028
	Some High School %	0.100	0.071	0.110	0.075
	High School Graduate %	0.332	0.293	0.320	0.291
	Some College or Technical School %	0.264	0.247	0.277	0.258
	College %	0.267	0.356	0.257	0.347
Labor	Employee %	0.515	0.539	0.471	0.513
	Self-Employed %	0.074	0.083	0.078	0.080
	Out of Work > 1 Year %	0.026	0.022	0.033	0.033
	Out of Work < 1 Year %	0.032	0.035	0.039	0.039
	Homemaker	0.070	0.070	0.071	0.070
	Student %	0.052	0.045	0.050	0.046
	Retired %	0.157	0.161	0.168	0.167
	Unable to work %	0.075	0.046	0.090	0.056
Marital Status	Married %	0.565	0.573	0.548	0.573
	Divorced %	0.106	0.089	0.103	0.089
	Widowed %	0.075	0.071	0.076	0.069
	Separated %	0.028	0.026	0.028	0.024
	Never Married %	0.206	0.201	0.227	0.207
	Other Marital Status %	0.020	0.040	0.017	0.039

Income	Income < $10,000 %	0.072	0.047	0.071	0.045
	Income < $15,000 %	0.065	0.049	0.067	0.046
	Income < $20,000 %	0.101	0.074	0.095	0.071
	Income < $25,000 %	0.113	0.089	0.101	0.085
	Income < $35,000 %	0.151	0.124	0.120	0.107
	Income < $50,000 %	0.168	0.159	0.150	0.141
	Income < $75,000 %	0.155	0.177	0.152	0.162
	Income > 75,000 %	0.176	0.281	0.244	0.343
Merged State/County Level Data					
County-Level Unemployment Rate %		6.064	5.107	7.827	7.181
State Medicaid Income Eligibility (% of FPL)		25.094	101.825	30.571	117.204
State Smoke-Free Air Law (index 1-3)		0.000	0.589	0.728	1.585
Avg. Price of Pack of Cigarettes (inf. adj.)		3.869	4.865	4.284	5.605
Beer Taxes (dollars per gallon)		0.380	0.275	0.468	0.259

Notes: The estimates are based on BRFSS 2003-2012. Sample is restricted to include only individuals living in the treatment and the control counties. The number of valid observations varies for each outcome because of missing data (respondents either refused to answer, or respondent was “unsure”, or was not asked the question). BRFSS sample weights are used to adjust data. See Figure 2 for the treatment and the control regions.

Table 2. The impact of Katrina in the affected counties

	Poor Mental Health Days (1)	Persistently Bad Mental Health (2)	Current Smoker (3)	Lifetime Smoker (4)	Binge Drinker (5)
Post-Katrina, 2006-2012	0.403***	0.004*	0.013**	0.014***	0.005
	(0.091)	(0.002)	(0.005)	(0.005)	(0.008)
Pre-Katrina Mean	3.43	0.059	0.244	0.454	0.213
Individual Characteristics	Yes	Yes	Yes	Yes	Yes
State / County Controls	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,136,954	1,136,954	1,164,203	1,164,544	438,873

Notes: Results are conditional on individual characteristics (gender, age, race/ethnicity, education, employment, marital status, and income), year fixed effects, county fixed effects, county level unemployment rate, Medicaid insurance eligibility, smoke-free air laws (smoking model), cigarette prices (smoking model), and whether the respondent was a part of cell phone sample. BRFSS sample weights are used. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 3. The impact of Katrina – short vs. long-run

Short-run vs. Long-run Impacts	Poor Mental Health Days (1)	Persistently Bad Mental Health (2)	Current Smoker (3)	Lifetime Smoker (4)	Binge Drinker (5)
Post-Katrina, Short-term Impact 2006-2008	0.279***	0.003	0.008	0.005	0.003
	(0.100)	(0.003)	(0.006)	(0.006)	(0.009)
Post-Katrina, Long-term Impact 2009-2012	0.478***	0.005**	0.014**	0.021***	0.008
	(0.105)	(0.003)	(0.006)	(0.006)	(0.008)
Individual Characteristics	Yes	Yes	Yes	Yes	Yes
State / County Controls	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,438,033	1,438,033	1,452,710	1,453,102	561,395

Notes: Short-run vs. long-run estimates are statistically different from each other for poor mental health days (at 5% significance level) and smokers (at 1% significance level); but not statistically different for persistently poor mental health and binge drinking. The periods of the short-run (2006-2008) and the long-run (2009-2012) are arbitrarily chosen. However, I checked the sensitivity of long-run and short-run time interval. Results remain the same with different short-run and long-run time specifications like the short-run is 2006-2007 and the long-run is 2008-2012. Results are conditional on individual characteristics (gender, age, race/ethnicity, education, employment, marital status, and income), year fixed effects, county fixed effects, county level unemployment rate, Medicaid insurance eligibility, smoke-free air laws (smoking model), cigarette prices (smoking model), and whether the respondent was a part of cell phone sample. BRFSS sample weights are used. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 4. Event study of the impact of Katrina in affected counties

	Poor Mental Health Days	Persistently Bad Mental Health	Current Smoke	Lifetime Smoker	Binge Drinker
	(1)	(2)	(3)	(4)	(5)
Pre-Katrina					
2003 * Affected Counties	0.213	0.004	0.001	-0.001	0.000
	(0.196)	(0.006)	(0.014)	(0.016)	(0.025)
2004 * Affected Counties	0.257	0.003	-0.002	-0.004	0.000
	(0.220)	(0.007)	(0.016)	(0.014)	(0.020)
Post-Katrina					
2006 * Affected Counties	0.658***	0.012**	0.012	0.007	-0.005
	(0.204)	(0.006)	(0.017)	(0.016)	(0.017)
2007 * Affected Counties	0.453**	0.005	0.010	0.002	-0.007
	(0.202)	(0.005)	(0.016)	(0.013)	(0.020)
2008 * Affected Counties	0.321	-0.002	0.005	0.001	0.021
	(0.202)	(0.006)	(0.015)	(0.014)	(0.019)
2009 * Affected Counties	0.575***	0.005	0.015	0.023	0.001
	(0.190)	(0.005)	(0.015)	(0.014)	(0.018)
2010 * Affected Counties	0.650***	0.008	0.017	0.019	0.025
	(0.192)	(0.006)	(0.016)	(0.013)	(0.021)
2011 * Affected Counties	0.853***	0.014**	0.015	0.021	-0.006
	(0.198)	(0.006)	(0.017)	(0.014)	(0.017)
2012 * Affected Counties	0.695***	0.004	0.012	0.013	0.008
	(0.227)	(0.007)	(0.016)	(0.015)	(0.020)
Individual Characteristics	Yes	Yes	Yes	Yes	Yes
State / County Controls	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,136,954	1,136,954	1,164,203	1,164,544	438,873

Notes: Following the literature, the last period before the treatment (2005Q1-Q3) is chosen as base year. Results are conditional on individual characteristics (gender, age, race/ethnicity, education, employment, marital status, and income), year fixed effects, county fixed effects, county level unemployment rate, Medicaid insurance eligibility, smoke-free air laws (smoking model), cigarette prices (smoking model), and whether the respondent was a part of cell phone sample. BRFSS sample weights are used. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at the 5 percent level. * Significant at 10 percent level.

Table 5. Sensitivity analyses

	Probit Model	Without BRFSS weights	Synthetic Control	Including other hurricanes in 2005 in the control group
	(1)	(2)	(3)	(4)
Poor Mental Health Days	N/A	0.402***	0.320***	0.372***
		(0.086)	(0.118)	(0.091)
		N=1,152,739	N=350,298	N=1,308,850
Persistently Bad Mental Health	0.003	0.005**	0.002	0.003
	(0.002)	(0.002)	(0.003)	(0.002)
	N=1,152,435	N=1,152,739	N=307,090	N=1,308,850
Current Smoker	0.015***	0.009**	0.012*	0.013**
	(0.005)	(0.004)	(0.006)	(0.006)
	N=1,164,188	N=1,164,203	N=574,621	N=1,322,308
Lifetime Smoker	0.015***	0.016***	0.014**	0.016***
	(0.004)	(0.004)	(0.006)	(0.005)
	N=1,164,328	N=1,164,544	N=505,522)	N=1,322,739
Binge Drinker	0.007	0.002	0.003	0.004
	(0.007)	(0.005)	(0.009)	(0.007)
	N=444,978	N=445,006	N=122,910	N=503,681
Individual Characteristics	Yes	Yes	Yes	Yes
State / County Controls	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: Results are conditional on individual characteristics (gender, age, race/ethnicity, education, employment, marital status, and income), year fixed effects, county fixed effects, county level unemployment rate, Medicaid insurance eligibility, smoke-free air laws (smoking model), cigarette prices (smoking model), and whether the respondent was a part of cell phone sample. Column 1 shows marginal effects for the Probit model. Except column 2, BRFSS sample weights are used. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

CHAPTER 2. THE HEALTH IMPACTS OF HURRICANES IN THE UNITED STATES

1. Introduction

Extreme weather events cause substantial destruction in local communities, and these effects are expected to be more significant in the future due to global warming and climate change (Nordhaus 2010; Emanuel 2005). A growing literature focuses on long-run impacts of these recurring disasters, such as tropical storms and hurricanes, on economic outcomes (Hsiang and Jina 2014; Deryugina 2017; Deryugina, Kawano, Levitt 2018; Karbownik and Wray 2019; Groen, Kutzbach, and Polivka 2019). While considerable attention has been paid to the effects of hurricanes on growth, employment, and income, little is known about the short and long-run impacts of these recurring disasters on the health of adults, which can adversely affect labor productivity and reduce economic activity (Bloom et al. 2019). Existing studies of natural disasters typically focus on the elderly, children, or babies (including the in-utero period). In this study, I address this shortcoming in the literature by estimating the effects of hurricanes on the physical and mental health of adult survivors in the ten years after hurricane exposure in the United States.

Why would we expect there to be an impact of hurricanes on survivors' health? For years after a hurricane strike, survivors remain at risk for poor health due to adverse social and financial circumstances. Mental disorders, including post-traumatic stress disorder (PTSD), are one of the most common health issues due to loss of a loved one or economic resources following a disaster (Goldmann and Galea, 2014; Civelek 2019). Also, survivors may use self-medication methods such as smoking and drinking to deal with stress and other mental health disorders (Reed et al. 2013; Pesko and Baum 2016). An adverse social or financial shock caused by a disaster may limit survivors' ability to deal with post-disaster recovery, and these constraining conditions can affect survivors' mental and physical health conditions in the following years after hurricane exposure. Low-educated individuals, in particular, may have less human capital and social capital to evaluate and manage post-hurricane circumstances (Muttarak and Lutz 2014; Pesko 2018). Also, while much attention is given to homeowners in disaster recovery policies, survivors who are renters may disproportionately be affected by hurricanes due in part to differential access to financial assistance between renters and homeowners (Fussell and Harris, 2014; Mukherji 2017).

One of the major difficulties in evaluating the impacts of hurricane exposure on survivors is data limitations. In order to provide causal estimates, it is essential to identify individuals who were affected by hurricanes and link them to post-disaster outcomes. I overcome this challenge by linking spatial data on hurricane strikes to individual-level panel data from the restricted version of the Panel Survey of Income Dynamics between 1990 and 2017.[24] I estimate the causal effects of exposure to a hurricane on the physical health, mental health, and risky health behaviors of survivors up to ten years following a hurricane that made landfall in the United States. Using a difference-in-differences framework, I compare the health outcomes of survivors from ten years before to ten years after hurricane exposure to other individuals who were not exposed to hurricanes during my sample period, but residing in the same state. I focus on the first hurricane exposure of an adult during the time period of this study while controlling any individual hurricane experience occurring before the time period of my study.

[24] Studies provide evidence that hurricane-strength storms have significant and substantial effects whereas tropical storms cause relatively much less damage and have statically insignificant impacts (Deryugina 2017; Karbowski and Wray 2019). Thus, in this study, our focus is on hurricane-strength storms, which is defined as at least 74 mph wind speed. I discuss this further in the data section.

My study provides one of the first comprehensive estimates of the health consequences of hurricanes on survivors, considering both the short-run and long-run effects. The results show that exposure to a hurricane has a negative and substantial impact on the mental health of survivors in ten years after hurricane exposure, while I find no statistical impact on the probability of reporting poor physical health, smoking or heavy drinking. The effect on the mental health was stronger in the short-run (in the first five years) compared to the long-run (in six to ten years after hurricane exposure) while the event study analysis suggests that the impact persisted in the long-run even though it was not statistically significant. Moreover, I find some evidence on worse physical health for low-educated individuals and renters. Low-educated individuals reported worse physical health, and were more likely to experience disability in the long-run. Furthermore, renters suffered an increase in poor physical health, and this effect is stronger within the first five years after hurricane exposure. During the same time period, I find an increase in rental expenses, but no significant changes in housing prices. Therefore, the reported worse health status of renters could potentially be driven by the increase in rental expenses.

These results make many contributions to the literature. First, this study contributes to a growing body of research on the economic consequences of global warming resulting in natural disasters. In particular, two recent macroeconomic studies (Hsiand and Jina 2014; Deryugina 2017) suggest adverse long-term effects of these recurring disasters on economic growth and non-disaster fiscal expenditures. Since poor health can reduce individual labor productivity (Bloom et al. 2019), my results may partially explain these findings and shed light on them at the micro level. Second, a set of studies has provided empirical evidence on the health impacts of hurricanes for the elderly population, children, or babies (including the in-utero period) (Smith

2008; Simenova 2011; Curie and Rossin-Slater 2013; Deuchert and Felfe 2015; Deryugina and Molitor 2018; Karbownik and Wray 2019). I contribute to this literature by providing the impacts of hurricane exposure on the health of adult survivors. Third, majority of studies in the literature either focus on the short-run or long-run impacts of these recurring disasters. I contribute by considering both the short and long-run impacts. Lastly, I consider a more comprehensive set of health outcomes for a large set of disasters whereas most research focuses on a single outcome (e.g. mental health or mortality) for one disaster (e.g. Hurricane Katrina).

From a policy perspective, an effective mitigation strategy requires knowledge of the local risks in order to strategically invest more in the short and long-term wellbeing of local communities in hurricane-prone areas. In the United States, a significant portion of the population lives in the path of hurricanes. Moreover, the frequency and intensity of these disasters are likely to increase. Therefore, exploring the link between exposure to a hurricane and the timing of the impact on later health outcomes not only highlights the hidden costs of hurricanes but also provides information necessary to create an optimal policy response.

2. Background and Conceptual Framework

2.1. Hurricanes in the United States

A hurricane is a type of tropical cyclone whose sustained winds exceeds 74 mph.[25] The Saffir-Simpson Hurricane Wind Scale categorizes hurricanes from 1 to 5 based on their wind speeds. While the maximum sustained surface wind speeds of 74 - 95 and 96-111 mph are classified as category 1 and category 2 hurricanes, respectively, and considered “minor” hurricanes, category 3-5 hurricanes are the ones with maximum sustained wind speed higher than

[25] When a cyclone reaches the maximum sustained wind speed of 39 mph, it is named as a tropical storm.

111 mph and are considered “major” hurricanes. Hurricanes cause relatively much larger and non-trivial destruction than tropical storms cause (Deryugina 2017; Karbowski and Wray 2019). Therefore, in this study, I focus on all types of hurricanes that made landfall in the United States.[26]

Webster et al. (2005) report that the world experienced 85 tropical cyclones each year, on average, from 1970 to 2004. Although the existence of a global upward trend in tropical storm occurrence is still by debated, there is an upward trend in the frequency and intensity of hurricanes that hit the United States.[27] Nordhaus (2010) reported that the frequency of storms formed in the North Atlantic Ocean increased over the years of 1851 to 2005 and is predicted to grow in magnitude in the future. Likewise, Emanuel (2005) suggests a similar trend in the intensity of hurricanes since the mid-1970s using a function of the cube of maximum wind speed. While studies suggest that the immediate physical damage is likely to increase with this trend, we still know little about the hidden impacts of hurricanes, which may appear over a relatively longer time period, on individual outcomes.

Nineteen states along the East coast and Gulf of Mexico from Texas to Maine are prone to hurricanes, which forms in the North Atlantic Ocean. When a hurricane makes landfall, it brings several hazards, including high winds, a storm surge, heavy rains, and causes extensive and long-lasting damage to local communities. While we cannot stop a hurricane before it hits

[26] I ignore tropical cyclones and storms which did not reach hurricane-strength wind.
[27] Global satellite data is only available since 1960, so we don’t have enough data to reach a conclusion on global storm frequency. See Landsea et al. (2006) for further discussion on the topic. However, Emanuel (2005) claims that there is a globally increasing trend in the intensity of tropical storms using a different intensity measurement.

these states, the degree of vulnerability is endogenous and can be reduced by understanding the risks and needs in these communities.

Hurricanes cause large scale of physical destructions in local communities. Federal agencies such as the Federal Emergency Management Agency (FEMA), the Small Business Administration (SBA), and the Department of Housing and Urban Development (HUD) provide disaster reliefs to the survivors in the form of grants and loans. These government organizations and non-government organizations, as well as private insurance companies play a significant role in responding to the immediate needs following a hurricane strike. However, recovery and reconstruction periods take several years (Fothergill 1996). During these years, social and financial circumstances impacted by the hurricane may continue to affect the survivors and their physical and mental health.

2.2. Adverse shocks and expected effects on the health of adult survivors

According to 2016 Census population estimates, 144.4 million people live in the states along the Atlantic Ocean and the Gulf of Mexico, where most are threatened by Atlantic hurricanes.[28] Hurricanes Sandy, Harvey, and Irma are the most recent ones that struck heavily populated counties along the Atlantic coast. For example, the Census reported that Hurricane Sandy caused over $70 billion (2012 USD) in damages and affected more than 65.2 million people along its path in 2012. However, most of the attention on hurricanes focuses on their immediate impacts, such as the physical damage they inflict. On the other hand, survivors of hurricanes continue to struggle and suffer well after news agencies stop covering hurricane-related news as a top story. Post-traumatic stress disorder (PTSD) and depression are the most

[28] Population estimates is calculated using data from https://www.census.gov/topics/population.html. (Last access on July 25th, 2019).

common health issues associated with a hurricane (Rhodes et al. 2010; Brown et al. 2011; Paxson et al. 2012).

How does hurricane exposure affect mental health? Theoretically, hurricane exposure can affect survivors' mental health as a life-threatening traumatic experience and through economic losses. While an extraordinary stressful experience is expected to trigger PTSD and other stressors following hurricane exposure, economic losses are likely to affect the mental health of survivors as well. For instance, losing employment or income following a hurricane may worsen mental health. To design an optimal policy response, it is essential to identify which mechanisms have a negative impact on mental health. Therefore, I will examine the changes in economic outcomes following hurricane exposure to explore the underlying mechanisms.

Why do we expect persistent mental health problems caused by disasters? Goldmann and Galea (2014) discuss that survivors mostly do not seek treatment for their mental disorders following a natural disaster. Thus, their mental health disorders are likely to persist in the absence of appropriate treatment. Civelek (2019) provides one of the first long-run causal estimates of the impact of Hurricane Katrina on mental health. His findings suggest that Hurricane Katrina not only caused worse mental health, but this effect also persisted and increased over the years. Furthermore, survivors may also choose self-medication techniques such as higher cigarette and alcohol consumption to deal with stress, anxiety and other mental health issues (Reed et al. 2013; Pesko and Baum, 2016). Therefore, hurricane exposure is likely to have an impact on mental health and risky health behaviors.

Hurricanes cause large-scale destruction on general infrastructure and healthcare capacity, as well as on housing units which likely creates harsh environments for survivors lasting several years during the reconstruction. For instance, destructions of healthcare facilities can lead to worse physical health of survivors by reducing access to healthcare and thus by exacerbating their pre-existing medical conditions. Also, financial constraints due to a decline in income or an increase in household expenditure following hurricane exposure may cause financial distress, resulting in poor physical health for survivors as well. Thus, besides the expected effects on mental health and risky health behaviors, survivors may also suffer from worse physical health after hurricane exposure due to social and financial disruptions in hurricane-affected counties.

Education has a direct influence on risk perception, skills, knowledge, and health. It also advances access to information and resources (Muttarak and Lutz 2014). Thus, low-educated individuals have fewer resources and capacity to evaluate and manage post-disaster conditions compared to those who have a higher level of education. For this reason, I estimate the differential impact of hurricanes on my outcomes of interest by education level.[29]

3. Data

3.1. Spatial Data on Hurricane Strikes

To track the path of hurricanes and where they hit, I use the Extended Best Track Dataset (EBTD) maintained by Colorado State University.[30] It contains the geographic coordinates of the storm center location, maximum wind speed, and central pressure in six-hourly intervals, as well as the radius of maximum sustained winds for each North Atlantic storm since 1988. As another dataset, HURDAT2 is provided by the National Hurricane Center and tracks all tropical storms

[29] I discuss the differential impacts on the sub-group of survivors in detail in the Appendix.
[30] Available at http://rammb.cira.colostate.edu/research/tropical_cyclones/tc_extended_best_track_dataset/.

formed in the Atlantic Ocean since 1851.[31] Despite its information on each hurricane's center location, HURDAT2 does not provide information on storm structure like the radius of storm wind speed for the hurricanes before 2004. However, the EBTD allows me to take the structure of storms into consideration while defining the hurricane impacted counties and hurricane survivors residing in these counties at the time of a hurricane strike.

Deryugina (2017) shows that counties fall into the radius of maximum wind speed of a hurricane experienced substantial, nontrivial damage compared to their neighboring counties. Thus, I define hurricane affected counties as any county whose centroid fall within a hurricane's radius of strongest wind speed. The PSID collects the information on the county of residence for each household across survey years. Moreover, if a respondent moves to another county, the information on their moving dates, reasons, and their new location are also collected. Using information both from the hurricane and the PSID datasets, I define a hurricane survivor as any individual who resides in a hurricane affected county at the time of a hurricane strike.

Table 6 provides the list of the 28 hurricanes that hit the United States between 1999 and 2016. The states along the Atlantic and Gulf of Mexico coasts have experienced these hurricanes and their catastrophic damage. Deryugina (2017) notes that the physical damage caused by hurricanes in the United States is, on average, \$4.8 billion per hurricane and \$8.1 billion per year, using data covering the years from 1970 to 2005. Between 1999 and 2016, a total of 337 counties experienced hurricanes (185 counties experienced only once). Figure 3 demonstrates the

[31] The National Hurricane Center made some revisions on "best track" for the hurricanes before 1960. After the changes, it was reported as HURDAT2, the second generation of HURDAT, which is available at https://www.nhc.noaa.gov/data/#hurdat

hurricane-affected states and counties. Lastly, hurricanes that made landfall in 2017 were not included in this study since the post-hurricane data is not available.[32]

3.2. Individual Health Data

In order to explore the health and health related behaviors of hurricane survivors, I link the spatial hurricane data described above to the restricted version of Panel Survey of Income Dynamics (PSID).[33] The PSID is a household panel survey that started in 1968 with a sample of the US population over 18,000 individuals in around 4,800 families. It collects extensive information on a wide range of topics including employment, wealth, and education from the individuals in the PSID families and their descendants. The restricted version of the PSID allows me to use household county of residence to merge with the geo-spatial hurricane dataset.

The PSID has continuously asked a rich set of health-related questions to household heads and their spouses since 1999.[34] Thus, I employ the PSID data covering the years 1999-2017 and restrict my sample to those individuals who were a head or a spouse in the PSID sample in these years. I use the self-reported health status (SRHS) to observe the changes in survivors' health after hurricane exposure. A large set of studies provide evidence in favor of the validity of self-reported health measurement. For instance, Idler and Benyamini (1997) show that self-reported poor health independently predicts mortality even after controlling physician health assessments and specific health conditions. The SRHS is a categorical variable on a scale 1 (excellent) to 5 (poor). Following Wang et al. (2018), I transformed it into a dichotomous

[32] My hurricane sample period includes the years 2000, 2001, 2006, 2009, 2010, 2013, and 2015 in which no storm reached hurricane strength on land.
[33] The restricted version of the data provides the county of residence for each respondent.
[34] Even though the PSID provides data on some health outcomes earlier than 1999, except general health and disability questions, those health variables were not continuously asked through the PSID surveys. Therefore, I plan to use a panel data of PSID health variables since 1999.

variable that I call “poor health” when the SRHS is reported as four or five. Henceforth, I refer this self-reported poor health as poor physical health. To observe the changes in their mental health, I use the K6 non-specific psychological distress as an indicator for poor mental health outcomes.[35] It is designed to measure psychological distress based on six questions as follows: During the past 30 days, how often did you feel… “so sad that nothing could cheer you up?”, “hopeless?”, “worthless?”, “restless or fidgety?”, “nervous?”, “that everything was an effort?”. The answers are scaled from “all of the time” (4) to “never” (0). The K6 index is a weighted sum of the answers to these six questions. While 13 points and above considered as serious mental health indicator, K6 < 5 and 5≤ K6 <13 are measured as indicators for low and moderate mental distress (Kessler et al. 2003; Prochaska et al. 2012). I use this index to estimate the impact of hurricane exposure on the poor mental health of survivors.

In addition to the general health status and mental health questions, the PSID collects information on smoking and drinking as well. For smoking, I use the current smoker question: “Do you smoke” to observe changes in smoking behavior. For drinking, I construct a heavy drinking variable by utilizing the question that asks the number of alcoholic drinks per day.[36] If a male (female) consumes more than two (one) drinks per day, I create an indicator variable to detect heavy drinking.[37]

[35] This question is asked in the following years: 2001, 2003, 2007 – 2017. It was also used by Charles and DeCicca (2008) and Wang et al. (2018) to measure mental health.
[36] Binge drinking is widely used in the literature. However, since the PSID started to ask questions on binge drinking in 2005, I use heavy drinking to detect changes in drinking behavior, which is available in all years between 1999 and 2017.
[37] I construct heavy drinking by following the definition from U.S. Department of Health and Human Services and U.S. Department of Agriculture. *2015 – 2020 Dietary Guidelines for Americans*. 8th Edition, Washington, DC; 2015.

In table 7, I show the sample statistics of my sample, which includes the outcomes of interest and individual characteristics collected from individuals resided in nineteen hurricane-prone states between 1999 and 2017. During my sample period, the mean psychological distress index is 3.43, which is a low level of mental health distress. 16.3 percent of my sample reported poor physical health. In terms of health behaviors, 19 percent of individuals are current smoker, and 22.5 percent are heavy drinker. Fifty-six percent of individuals are female, whereas forty-eight of those are nonwhite. Also, 66 percent of individual are married and almost 70 percent are working. Lastly, forty-six percent of individual have high-school or lower level of education. While I control all time varying individual characteristics, I use individual fixed effects to control time invariant individual characteristics like race in all regressions.

4. Methodology

My econometric objective is to estimate the causal effects of hurricanes on the health outcomes of survivors. One challenge in estimating the causal impacts of natural disasters is utilizing a credible control group to evaluate counter-factual outcomes. A starting point would be to define a control group consisting of all unaffected individuals residing in the rest of the US from the whole PSID sample. But, significant differences are expected between the individuals living in hurricane-prone counties and those living in the rest of the country. For this reason, my control group consists of all individuals who were not exposed to hurricanes but lived in 19 states that experienced at least one hurricane and are prone to future hurricanes in Gulf and Atlantic regions (henceforth, referred to as “hurricane states”). This means that individuals living in a non-affected county in a hurricane state included into the control group.

I estimate the effects of hurricanes on survivors' health outcomes up to ten years after its strike using three different specifications of difference-in-differences models: 1) one combined 10-year post period; 2) a 5-year short-run and a 5-year long-run post period; 3) an event study model with separate indicators for each year. In my preferred specification, I compare hurricane survivors to those who have not been exposed to hurricanes but living in the same state.[38]

The set of tropical storms that hit the US with hurricane-strength winds between 1999 and 2016 is included in this study. Some of the individuals in my sample experience more than one hurricane during this time period; other individuals experience a hurricane before 1999. While controlling any hurricane experience prior to 1999 in the econometric model, I use only the first instance of individual hurricane experience between 1999 and 2016 in my estimation. In other words, I ignore other hurricane exposure in later years after a survivor already experienced one between 1999 and 2016. Conditional on individual fixed effect, this technique should not bias my estimates because hurricane hits are random (Deryugina 2017).[39] Alternatively, I could exclude all individuals who were exposed to a hurricane before 1999 from the sample. However, this strategy would reduce my sample size by eliminating many individuals that are good controls and reducing the number of treated individuals in my treatment group as well.

4.1. Econometric Framework

First, my basic specification is a difference-in-differences model, where I compare adult health outcomes for those with exposure to a hurricane to those without a hurricane exposure but living in the same state. I estimate the average impact of a hurricane up to ten years on the

[38] I also use different fixed effect specifications such as only state fixed effect or state specific time trends. Results remain the same. I provide the point estimates and statistical significance levels in the sensitivity analysis part.
[39] Deryugina (2017) applies the same procedure to address previous or multiple hurricane exposures.

outcomes of interest, conditional on individual, interview year, and state-year fixed effects, as well as individual characteristics such as age, education, employment, marital status, and income. I use the following equation:

$$\boldsymbol{y_{icst} = \alpha + \gamma_1 H_{ics,1\ to\ 10} + X_{icst}\beta + \theta_i + \mu_s \otimes t + \delta_{-99} H_{ics,-99} + \varepsilon_{icst}} \quad (1)$$

where $\mathbf{y_{icst}}$ is the health outcomes of interest for individual *i*, resided in county *c* and state *s*, at time *t*. $\boldsymbol{H_{ics,1\ to\ 10}}$ equals to one for [τ +10] years if individual *i* exposed to a hurricane at time τ. In other words, it indicates an exposure to a hurricane within the next ten years after hurricane exposure. Thus, the coefficient $\boldsymbol{\gamma_1}$ will provide the average effect on outcome $\boldsymbol{y_{icst}}$ in years 1-10 after the hurricane. $\boldsymbol{\theta_i}$ and is individual fixed effects, whereas $\boldsymbol{\mu_s \otimes t}$ represents state-by-year fixed effects. I control for individual fixed effects in order to remove time-invariant individual heterogeneity. State by year fixed effects capture state specific shocks and trends in health outcomes or unobserved characteristics of state population in a given year that allows me to compare hurricane survivors to those who were not exposed but living in the same state. In order to capture time-varying individual characteristics that can affect the outcomes of interest, I also control a set of individual characteristics $\boldsymbol{X_{icst}}$ such as age, education, employment status, marital status, and total family income.[40] Lastly, $\boldsymbol{H_{ics,-99}}$ indicates a hurricane exposure that affected any individual in my sample before 1999, and equals to one up to ten years after each hurricane that occurred before 1999. The standard errors are clustered at the county level (Bertrand, Duflo, and Mullainathan 2004; Hoynes and Schanzenbach 2009).

[40] Family income includes all transfer payments that a household received in a given year.

To briefly show how the impact differs between the short and long-run, I combine post-hurricane years 1-5 and 6-10 into two indicators and re-estimate equation (1). Specifically, I estimate the following equation:

$$\boldsymbol{y_{icst} = \alpha + \delta_1 H_{ics,1\ to\ 5} + \delta_2 H_{ics,6\ to\ 10} + X_{icst}\beta + \theta_i + \mu_s \otimes t + \delta_{-99} H_{ics,-99} + \varepsilon_{icst}} \quad (2)$$

where $\boldsymbol{H_{ics,1\ to\ 5}}$ and $\boldsymbol{H_{ics,6\ to\ 10}}$ equal to one for hurricane survivors for years 1-5 and 6-10 following a hurricane exposure, respectively. So, $\boldsymbol{\delta_1}$and $\boldsymbol{\delta_2}$ will show us the mean effect 1-5 and 6-10 years after the hurricane. Other parameters are defined as the same in equation (1).

The validity of my estimates from equations (1) and (2) is based on the parallel trends identifying assumption. It suggests that average change in the health outcomes of individuals would have been the same for the treated and the control groups in the post period in the absence of the hurricane. I utilize an event study analysis to formally test this assumption and also to assess the year by year pattern of the effect of hurricane exposure in the 10 years after the event. To conduct the event study, I estimate a set of hurricane dummy variables from ten years before to ten years after hurricane exposure on the outcomes of interest, conditional on individual, interview year, and state by year fixed effects, as well as on individual characteristics using the following equation:

$$\boldsymbol{y_{icst} = \alpha + \sum_{\tau=-10,\tau\neq-1}^{10} \delta_\tau H_{ics\tau} + X_{icst}\beta + \theta_i + \mu_s \otimes t + \delta_{-99} H_{c,-99} + \varepsilon_{icst}} \quad (3)$$

where $\boldsymbol{H_{ics\tau}}$ indicates any hurricane exposure to individual *i* and equals to one from ten years before up to ten years after the hurricane. In other words, $\boldsymbol{H_{ics\tau}}$ =1 in the following time interval [τ -10, τ +10] if and only if an individual was exposed to a hurricane at time τ. The PSID data is collected as biannual between 1999 and 2017. Thus, in order to reduce noisiness across individuals and years, I combined hurricane dummies into two-year bins before and after the event when estimating the event study equation such as 1 and 2, 3 and 4, 5 and 6, 7 and 8, 9 and 10+. I normalize the interview year before a hurricane exposure to zero.[41]

As discussed in section 2, post-hurricane conditions may differentially affect two sub-groups of survivors due to differences in individual risk perceptions and capacity, as well as changes in rental markets for housing following a hurricane. Thus, heterogeneity may exist in the impact of a hurricane on the outcomes of interest depending on education level and homeownership status of the survivors. For this reason, I perform two heterogeneity checks by interacting the treatment variable with an indicator for low-educated individuals and homeownership in all equations (1)-(3).

I also perform a series of sensitivity checks to assess the validity of my baseline results. I estimate equation (1) without state fixed effects, with state fixed effects, and with state-specific time trends. To recall, my main specification is with state-by-year fixed effects. I show that the results are not sensitive to different fixed effect specifications. I also drop each state from 19 states once, and re-run the model 19 times to show that impacts are not driven by a particular state. Recall that 28 hurricanes hit the US between 1999 and 2016. I run equation (1) 28 times in such a way that I drop the survivors who were exposed to a specific hurricane each time. The results from this analysis confirms whether my baseline estimates are driven by a specific hurricane. Lastly, I estimate a probit model for binary outcomes for my pooled sample, rather

[41] Both equations (2) and (3) provide information about variation in the impacts in the post period. However, the event study results are not efficient if some coefficients are not very distinct from each other due its flexibility. Therefore, I also use equation (2) to summarize the effect of a hurricane more concisely.

than a linear probability model (LPM) used in my baseline estimates. This addresses the potential concerns that the LPM may not provide consistent and unbiased estimates of marginal effects.

5. Results

I begin with my baseline sample of all household heads and spouses in hurricane states and analyze the causal effect of exposure to hurricanes on four health and health-related outcomes: physical health, mental health, smoking, and heavy drinking. I then extend the analysis to explore heterogeneity by education level and homeownership status among survivors. Lastly, I present the results from a set of robustness checks.

5.1. Baseline Results

Table 8 presents the results from the main difference-in-differences regression specified by equation (1) for each outcome of interest. Columns indicate the results for poor physical health, psychological distress index, smoking, and heavy drinking. For the next 10 years following a hurricane, positive and significant point estimates in the first row of table 8 show the negative impact on mental health while there are no significant impacts on probability of reporting poor physical health, smoking, or heavy drinking. The point estimates for psychological distress index indicate that hurricane exposure increased poor mental health of its survivors by 0.276 scale points (9 percent of the mean) per year in the next 10 years following a hurricane. This finding suggests that the adverse impact of hurricanes on the mental health of survivors persisted for several years after hurricane exposure.

Next, I present the short vs. long-run effects of hurricane exposure on my outcomes of interest in table 9. The results suggest that hurricane exposure had a larger and statistically significant impact on survivors' poor mental health in the short-run compared to the long-run time period. Exposure to a hurricane, on average, increases psychological distress by 0.389 scale points (12.7 percent) per year in the short-run as compared to 0.215 scale points (7.1 percent) per year in the long-run.[42] Differently, the probability of smoking increased by 1.4 percentage points (9.2 percent) per year in the long-run whereas the effect was 0.4 percentage points (2.6 percent) per year in the short-run.[43] Thus, hurricane exposure appears to have exerted a greater impact on poor mental health in the short-run compared to the long-run while the effect on smoking behavior of survivors is greater in the long-run. The effect of hurricane exposure on poor physical health and heavy drinking remains statistically insignificant in both the short and long-runs, though the point estimate is larger for poor physical health (heavy drinking) in the long-run (short-run).

In summary, these results suggest that hurricane exposure impaired survivors' mental health and increased the likelihood of smoking. I find a larger impact of hurricane exposure on psychological distress in the short-run whereas the impact on smoking behavior was larger in the long-run.

5.2. Event Study Results

My difference-in differences model depends on the assumption of common counterfactual trends in health outcomes between hurricane survivors and other individuals in the control group in the post period in the absence of a hurricane. Thus, a causal interpretation of my findings builds on the validity of this assumption. A popular way to indirectly test this

[42] The short-run point estimates on mental health are statistically significant at 5% level whereas the long-run estimates are not statistically significant but positive.
[43] The long-run point estimates on current smoking are statistically significant at 10% level whereas the short-run estimates are not statistically significant but positive.

identifying assumption is to look for differences in trends in the pre-period for the outcomes of interest. Therefore, I conduct an event study to check the key assumption of my econometric model and also explore how the impact of hurricanes evolves over time following a hurricane strike.

The results from the event study analysis are presented in figure 4. The point estimates and 95 percent confidence intervals are shown for each health outcome. The estimates suggest that the pre-hurricane trends are not significantly different between hurricane survivors and the control group for any of my outcomes of interest. Thus, these results validate the identifying assumption of my econometric model, which provides causal effects of the impact of a hurricane. Figure 4 also shows how the impact varies across years after hurricane exposure. To be more specific, psychological distress index increases by 0.36 to 0.58 scale points (11.7 to 18.9 percent) per year in the first four 4 years after hurricane exposure while staying larger than pre-hurricane estimates but not statistically significant in the rest of the post period. On the other hand, the point estimates on the probability of reporting poor health, being a smoker or a heavy drinker are generally statistically insignificant in each individual year during the post-period, while we see a slight statistically significant increase in point estimates on reporting poor health and on drinking behavior around 7-8 years and 5-6 years after hurricane exposure, respectively.

5.3. How does Hurricane Exposure Affect Mental Health?

In this section, I explore changes in economic outcomes that may, indeed, cause worse mental health among survivors. Besides the traumatic experience, losing employment, earnings, or income may trigger or exacerbate mental health problems among survivors. Thus, I estimate the models in equation (1) and (3) using a set of economic outcomes. I use employment status and average weekly work hours to explore changes in the employment of survivors along the extensive and intensive margins following a hurricane. Similarly, I utilize individual earning and household income as dependent variables. While individual earning captures any economic loss related to a survivor's labor market conditions after a hurricane, household income provides a more comprehensive income measure covering a diverse set of sources such as income from assets, earnings, and businesses.

Event study results for these outcomes are given in figure 5 and table 10. Consistent with studies on the economic impacts of hurricanes (Deryugina 2017; Deryugina et al. 2018; Groen et al. 2019), my findings show that hurricane exposure does not have a statistically significant impact on my economic outcomes of interest. These results provide some evidence that the worse mental health is not likely to be because of changes in survivors' economic outcomes.

Eliminating economic reasons suggests that the traumatic experience of going through a hurricane is likely to be an underlying cause of worse mental health. However, even following the most catastrophic disaster in the US, few Katrina survivors sought mental health treatment (Wang et al. 2007). My event study estimates show that the worse mental health lasted for the next four years after a hurricane. As Norris et al. (2002) suggest, early mental health treatment interventions following disasters may lead to better mental health outcomes. Therefore, early interventions may reduce the long-lasting prevalence of worse mental health among survivors.

5.4. Low-educated Individuals

Next, I examine the results shown in table 8 and 9, as well as in figure 4 for the subsample of individuals with a high school education or less compared. Education can be a key factor that is associated with the degree of vulnerability following a disaster (Muttrak and Lutz, 2014). Thus, I hypothesize that less educated individuals may be affected more by hurricanes due to having fewer resources to learn how to manage post-hurricane circumstances. As table 11 shows, survivors with a high school or less education were 3.8 percentage points (15.3 percent of the mean) per year, on average, more likely to report poor physical health in the decade following hurricane exposure, while the estimates of the psychological distress index are positive but insignificant. Also, I show the short vs. long-run impacts of hurricane exposure on the outcomes of interest for the low-educated subsample in table 12. The results show that the estimated impact on poor physical health is much higher and statistically significant in the long-run compared to the short-run.

Event study results for the low-educated subsample in figure 6 shows that the increase in poor physical health becomes significant five to ten years after hurricane exposure even though points estimates start to increase three years after hurricane exposure. This result is in line with the canonical health capital model (Grossman, 1972). It suggests that health capital changes gradually, as may be the case with low-educated individuals. Also, the results in figure 6 show a significant pre-trend in the probability of being a heavy drinker indicating that the point estimates on heavy drinking in table 10 and 6 may not be causally interpretable.

Next, I show that low-educated individuals experienced an increase in the likelihood of disability by 3.3 percentage points (16.7 percent of the mean) per year in the decade following hurricane exposure in the appendix table 1 and appendix figure 1.[44] This finding suggests that the reported increase in poor physical health may represent a real reduction in health status and also provides a potential mechanism for the increase in disability insurance payments estimated in

[44] The PSID survey respondents were asked whether they had any physical or nervous condition that limits the type of work or the amount of work they can do.

Deryugina (2017). Although there is a significant negative impact of hurricane exposure on the health of low-educated individuals, I do not have a clear explanation whether the increase in disability due to their education level or due to a physical or mental health condition that originates from a harsh working environment in post hurricane exposure period. The latter could be related to the occupational status of the low-educated since low educated individuals tend to work in jobs that are more physically demanding than their higher educated counterparts. Thus, this result leads to the question of whether the education level or the occupational status of the low-educated causes the estimated effect on disability. I articulate this point in detail in the appendix.

5.5. Sensitivity Analysis

I checked the sensitivity of my results to different model specifications. Individual and year fixed effects are included in all regressions, which take care of any time-invariant individual heterogeneity and differences across years, respectively. However, time-invariant differences between two states (e.g.: poorer vs. wealthier) may be problematic since they may affect individual outcomes differently. The inclusion of state fixed effects solves this issue. I check the sensitivity of my findings by adding a state specific linear time trend to account time varying characteristics of states that may be correlated with my outcomes of interest. That is, I assume that each state has a unique linear time trend across years, respectively. The results are presented in table 13. The resulting point estimates and their significance levels are very similar across different set of controls. The biggest change is the point estimates on smoking. Inclusion of state by year and state specific linear time trends makes the estimates lower. This suggests that smoking-related state policies have an effect on individual smoking behavior as a large set of studies on smoking documents.

As another sensitivity check, I show whether the estimated impacts are not driven by a particular state. I drop each hurricane state from my sample one by one each time. Recall that 19 states are prone to hurricanes in the US. I re-estimate equation (1) 19 times by dropping one hurricane state each time. The results are presented at figure 7. The estimated impact does not change substantially each time for my outcomes of interest for all states. Therefore, I can conclude that the effects are not driven by a particular state.

6. Discussion

This study estimates the short and long-term causal health effects of US hurricane exposures. Hurricanes are considered the costliest natural disasters, and they impact a significant portion of the population and economic activity in the US. Understanding the short and long-term health impacts are essential for effective mitigating policies, whereas most research focuses on their immediate impacts. This need is becoming even more salient, considering that the size and number of hurricanes are expected to increase in the future and a large portion of the US population lives in hurricane-prone areas. My results suggest that exposure to a hurricane has a negative and substantial impact on the mental health of survivors in the decade after the disaster, which is stronger in the first five years. This effect is likely to cause by the traumatic experience of experiencing a hurricane rather than economic losses. Thus, early mental health treatment interventions for hurricane survivors may help to prevent long-lasting mental disorders after a disaster. In addition, I find that the low-educated individuals differentially suffer from worse physical health in the decade following hurricane exposure. Those with low education experienced an increase in the likelihood of disability in five to ten years after hurricane exposure, which might lead to the report of poor physical health. However, we need to interpret this finding cautiously since education status might be an indicator of various socio-economic characteristics, which, indeed, may drive the results.

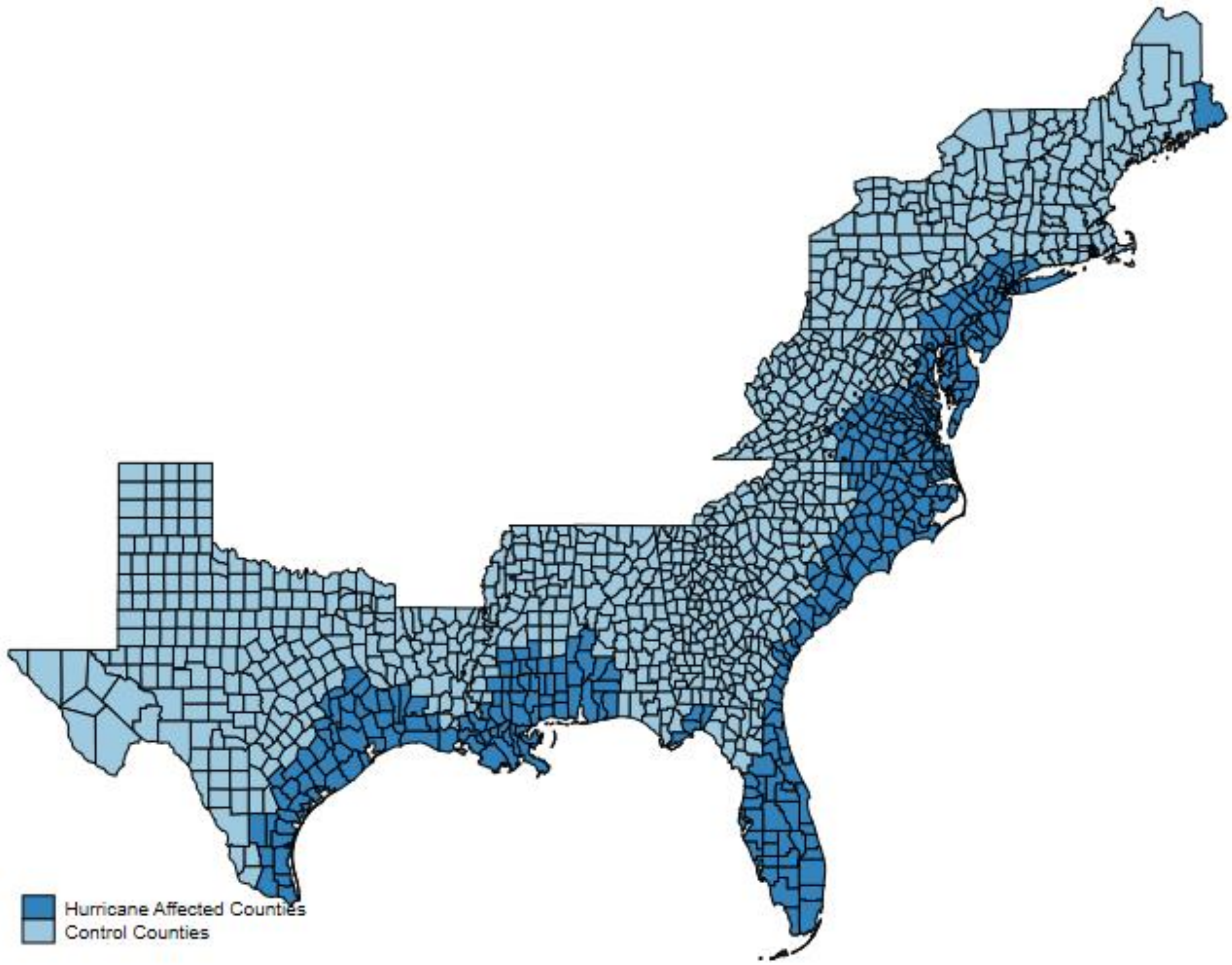
This paper contributes to a set of recent studies on the long-term economic consequences of global warming and the results of natural disasters, which has not explored the adult health outcomes. Such outcomes are a channel for labor productivity and a pathway that can lead to long-lasting macroeconomic effects (Bloom et al. 2019). My findings may partially explain and shed light on the earlier findings of lower labor productivity and economic growth, and higher non-disaster fiscal expenditures following hurricanes (Hsiang and Jina 2014; Deryugina 2017). I also contribute to the literature on the effects of tropical storms on health outcomes, which mainly focused on babies, including the in-utero period, (Currie and Rossin-Slater, 2013; Karbownik and Wray 2019); on children (Deuchert and Felfe 2015); or on the elderly (Smith 2008; Deryugina and Molitor, 2018). I contribute to this literature by looking at the health outcomes of adult survivors. Also, I consider a more comprehensive set of outcomes for a large set of disasters for both short-run and long-run time period.

This work is subject to some limitations. I use a quasi-experimental research design due to the inability to randomize hurricane strikes. This limitation may raise concerns regarding internal validity. I address this potential concern by presenting pre-hurricane trends for each outcome of interest in an event study analysis. Also, all my outcomes are self-reported. Self-reported measure of health may be subject to measurement error. Another potential limitation is sample attrition in the PSID. Fitzgerald (2011) provides no strong evidence of attrition bias in the PSID. Although attrition is a concern, the PSID health estimates are comparable to other national health surveys. Also, Insolera and Freedman (2017) compare the health-related measures in the

PSID to the National Health Interview Survey (NHIS) over the years of 2001-2015. Although the PSID has a lower response rate to health-related questions compared to the NHIS, they conclude that the measures in PSID and the NHIS followed a similar trend over the years, which suggest that attrition does not have a substantial effect on health-related estimates.

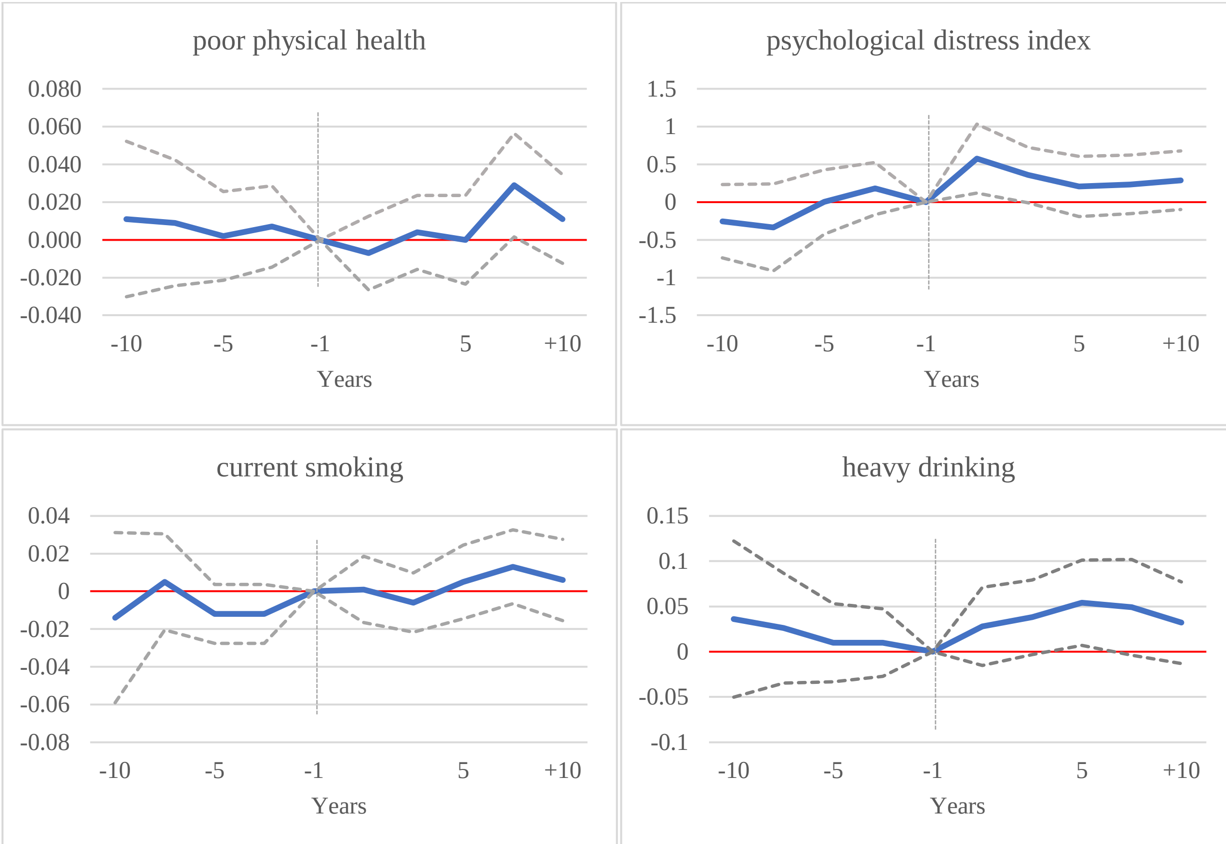
In terms of policy implications, my findings on the short and long-term effects of hurricanes provide insights into the hidden costs of these recurring events. Considering that a substantial portion of the US population lives in the path of hurricanes and the magnitude of hurricanes are expected to grow, measuring the impacts of environmental shocks on health and economic performance is essential for an optimal policy response. Therefore, understanding the link between exposure to a hurricane and the timing of the impact on later health outcomes not only illustrates the true costs of hurricanes in the US but also provide an incentive to create a timely policy response.

Figure 3. Hurricane strikes in the United States, by 1999 – 2016



Notes: It shows 19 hurricane-prone states along the Atlantic Ocean and Gulf of Mexico. Dark blue areas indicate the hurricane impacted counties whereas lighter blue areas show the counties that are not directly impacted by hurricanes but are in the same states with hurricane affected counties between 1999 and 2016.

Figure 4. The impact of hurricanes – event study

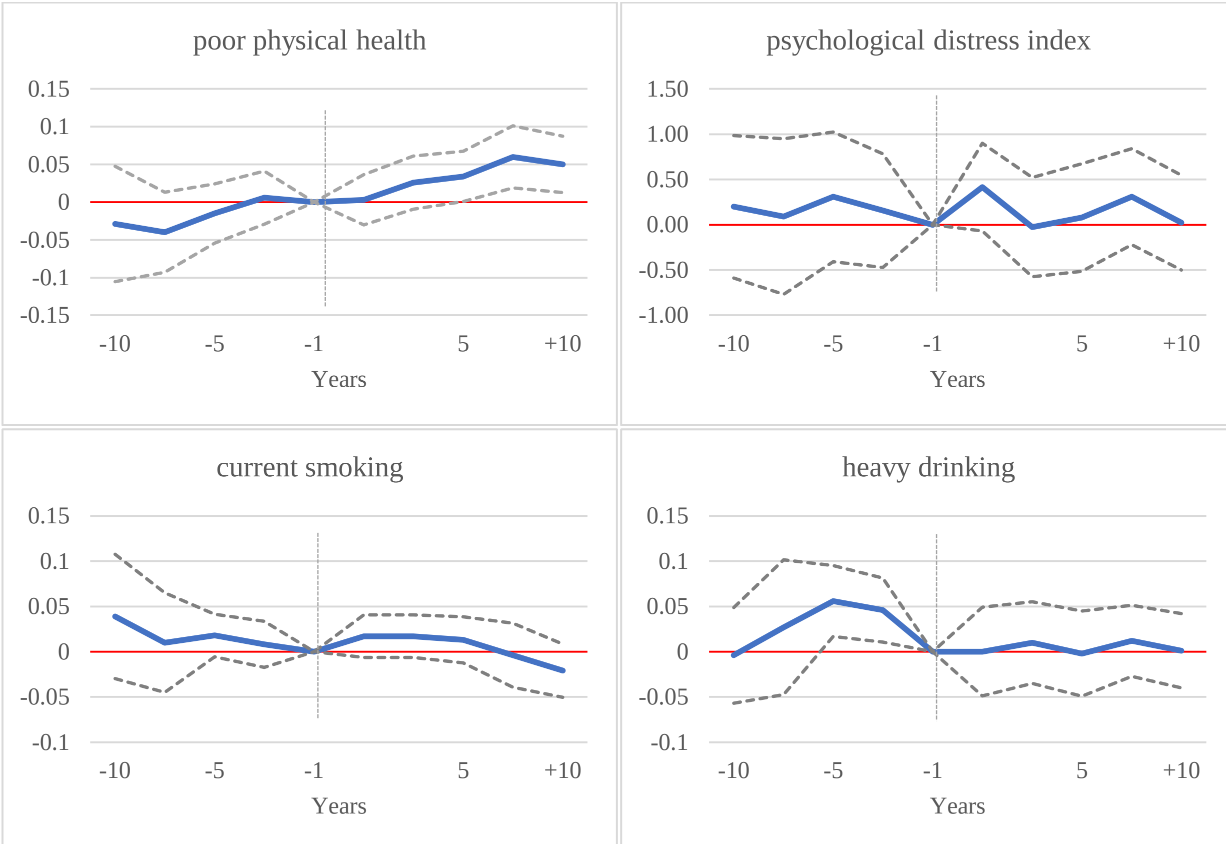


Notes: Point estimates and 95% confidence intervals are shown. The last survey year before the hurricane is chosen as base year following the literature. Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level.

Figure 5. The impact of hurricanes on economic outcomes

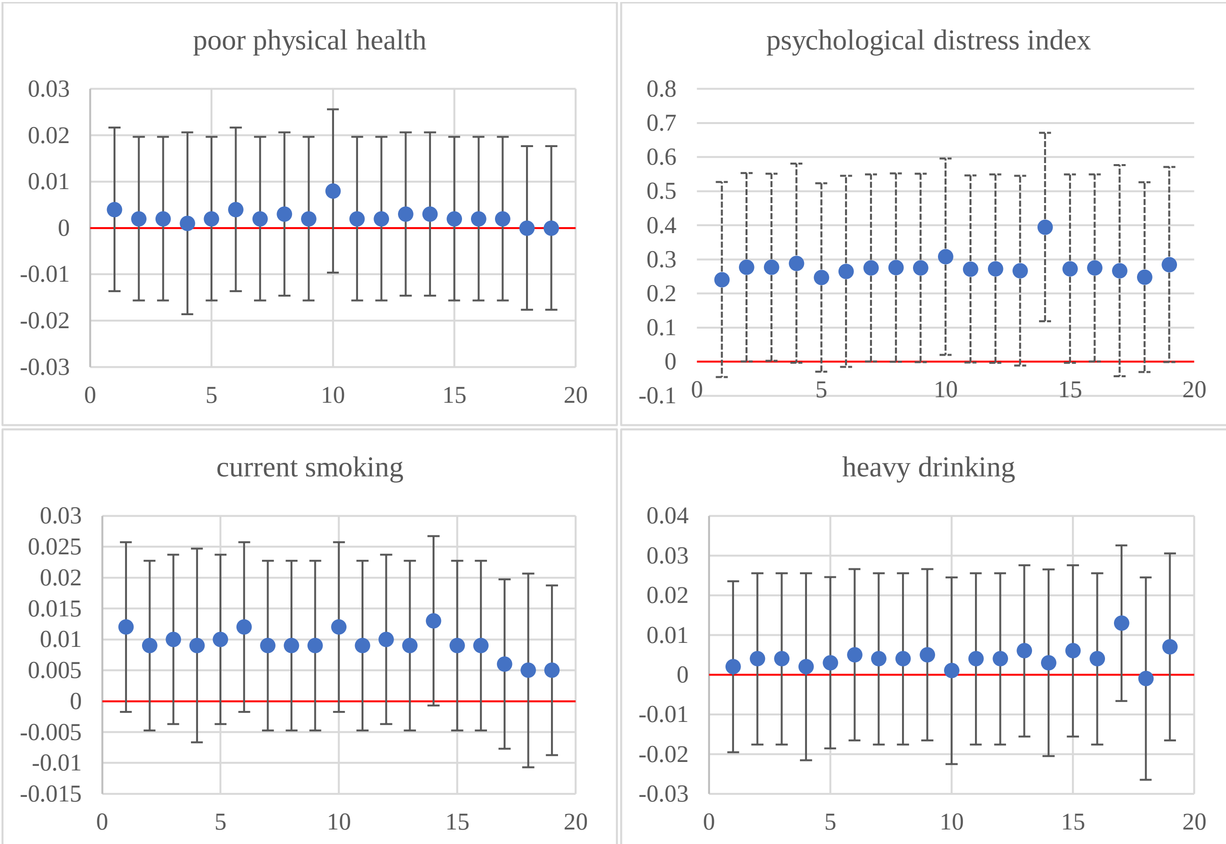
Notes: Point estimates and 95% confidence intervals are shown. The last survey year before the hurricane is chosen as base year following the literature. Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level.

Figure 6. The impact of hurricanes on the low-educated



Notes: Point estimates and 95% confidence intervals are shown. The last survey year before the hurricane is chosen as base year following the literature. Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level.

Figure 7. The impact of hurricanes: dropping one state at a time



Notes: Point estimates and 95% confidence intervals are shown. Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. I dropped a hurricane state at a time in the following order: Alabama, Connecticut, DC, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, and Virginia.

Table 6. List of US hurricanes, 1999 and 2016

Name	Month	Year
Hurricane Bret	August	1999
Hurricane Floyd (*)	September	1999
Hurricane Irene	October	1999
Hurricane Lili (*)	October	2002
Hurricane Claudette	July	2003
Hurricane Isabel (*)	September	2003
Hurricane Alex	August	2004
Hurricane Charley (*)	August	2004
Hurricane Gaston	August	2004
Hurricane Frances (*)	September	2004
Hurricane Ivan (*)	September	2004
Hurricane Jeanne (*)	September	2004
Hurricane Cindy	July	2005
Hurricane Dennis (*)	July	2005
Hurricane Katrina (*)	August	2005
Hurricane Ophelia	September	2005
Hurricane Rita (*)	September	2005
Hurricane Wilma (*)	October	2005
Hurricane Humberto	September	2007
Hurricane Dolly (*)	July	2008
Hurricane Gustav (*)	September	2008
Hurricane Ike (*)	September	2008
Hurricane Irene (*)	August	2011
Hurricane Isaac (*)	August	2012
Hurricane Sandy (*)	October	2012
Hurricane Arthur	July	2014
Hurricane Hermine	September	2016
Hurricane Matthew (*)	October	2016

Notes: 28 hurricanes made landfall in the continental United States between 1999 and 2016. (*) indicates the hurricanes that costed at least a billion-dollar damage. Source: NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2019). https://www.ncdc.noaa.gov/billions/

Table 7. Summary statistics

	Observations	Mean	St. Dev.	Min	Max
Psychological distress index	33,015	3.432	3.978	0	24
Poor physical health	61,638	0.163	0.369	0	1
Measures of Health Behaviors					
Smoking	61,663	0.19	0.392	0	1
Heavy drinking	61,551	0.225	0.417	0	1
Characteristics					
Female	61,638	0.561	0.496	0	1
Nonwhite	61,644	0.482	0.499	0	1
Education in years	61,637	13.324	2.639	0	17
Age	61,624	44.829	15.458	15	102
Married	61,638	0.669	0.471	0	1
Working	61,605	0.696	0.459	0	1
log(total family inc.)	61,275	10.900	1.044	0.033	15.758
High school or less education	61,637	0.466	0.498	0	1

Notes: The table shows the tabulations of 1999-2017 PSID. Sample consists of heads and spouses living in 19 hurricane-prone states. Poor physical health equals to 1 if health is reported as poor or fair. K-6 index (1-24) is used to measure poor mental health. Earning and income variables are adjusted to 2015 dollars.

Table 8. The impact of hurricanes - main results

	Poor Physical Health (1)	Psychological Distress Index (2)	Current Smoking (3)	Heavy Drinking (4)
Post-hurricane 1 to 10 years	0.002	0.276**	0.009	0.004
	(0.009)	(0.140)	(0.007)	(0.011)
Pre-hurricane Mean	0.183	3.060	0.153	0.200
Individual Characteristics	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes
Number of Observations	60,055	31,964	60,076	59,871

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 9. The impact of hurricanes – short vs. long-run

Short-run vs. Long-run Impacts	Poor Physical Health (1)	Psychological Distress Index (2)	Current Smoking (3)	Heavy Drinking (4)
Post-hurricane SR Impact 1 to 5 years	-0.004	0.389**	0.004	0.006
	(0.010)	(0.152)	(0.007)	(0.012)
Post-hurricane LR Impact 6 to 10 years	0.007	0.215	0.014*	0.003
	(0.011)	(0.154)	(0.009)	(0.012)
Pre-hurricane Mean	0.183	3.060	0.153	0.200
Individual Characteristics	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes
Number of Observations	60,055	31,964	60,076	59,871

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 10. The impact on economic outcomes

	working	log(work hours)	log(labor income)	log(family income)
	(1)	(2)	(3)	(4)
Post-hurricane 1 to 10 years	-0.005 (0.015)	0.006 (0.016)	-0.012 (0.034)	0.028 (0.034)
Pre-hurricane Mean	0.687	-	-	-
Individual Characteristics	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes
Number of Observations	31,964	24,656	24,122	31,674

Table 11. The impact of hurricanes on the low-educated

	Poor Physical Health	Psychological Distress Index	Current Smoking	Heavy Drinking
	(1)	(2)	(3)	(4)
Post-hurricane 1 to 10 years	0.038*** (0.010)	0.033 (0.205)	-0.004 (0.008)	-0.018 (0.017)
Pre-hurricane Mean	0.251	4.035	0.243	0.250
Individual Characteristics	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes
Number of Observations	60,055	31,964	60,096	59,891

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 12. The impact of hurricanes on the low-educated – short vs. long-run

Short-run vs. Long-run Impacts	Poor Physical Health (1)	Psychological Distress Index (2)	Current Smoking (3)	Heavy Drinking (4)
Post-hurricane SR Impact 1 to 5 years	0.019 (0.012)	0.011 (0.224)	0.01 (0.009)	-0.017 (0.021)
Post-hurricane LR Impact 6 to 10 years	0.052*** (0.014)	0.031 (0.226)	-0.014 (0.011)	-0.018 (0.017)
Pre-hurricane Mean	0.251	4.035	0.243	0.250
Individual Characteristics	Yes	Yes	Yes	Yes
Individual Fixed Effect	Yes	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes	Yes
Number of Observations	60,055	31,964	60,096	59,891

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 13. The impact of hurricanes - model specifications

	(1)	(2)	(3)	(4)
Poor Physical Health	0.011	0.011	0.002	0.004
	(0.007)	(0.007)	(0.009)	(0.008)
	n=60,075	n=60,074	n=60,055	n=60,074
Psychological Distress Index	0.238**	0.251**	0.276**	0.245**
	(0.129)	(0.128)	(0.140)	(0.120)
	n=32,013	n=32,011	n=31,964	n=32,011
Current Smoking	0.018***	0.017***	0.009	0.008
	(0.006)	(0.006)	(0.007)	(0.006)
	n=60,096	n=60,095	n=60,076	n=60,095
Heavy Drinking	-0.010	0.011	0.004	-0.006
	(0.012)	(0.012)	(0.011)	(0.011)
	n=59,892	n=59,891	n=59,871	n=59,891
Individual Characteristics	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE		Yes		Yes
State by year FE			Yes	
State specific time trend				Yes

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, year fixed effects. State fixed effects are included in model 2, state by year fixed effects are included in model 3, and state specific time trends are included in model 4. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

CHAPTER 3. HETEROGENEOUS IMPACTS OF HURRICANES ON RENTERS

1. Introduction

Natural disasters such as tropical storms and hurricanes cause large scale destruction to property. In particular, residential units are vulnerable to these extreme weather events. While a growing literature focuses on the effects of natural disasters on various outcomes such as economic growth, fiscal expenditures, and employment, the differential impact of hurricanes based on homeownership is still unclear (Strobl 2011; Hsiang and Jina 2014; Deryugina 2017; Karbownik and Wray 2019). Considering that the magnitude of hurricanes and their catastrophic destruction are expected to grow in the future, understanding the impact of these recurring disasters on rental payments for renters and the heterogeneous health and labor impacts based on renter status provides information necessary for an optimal policy response.

Recent studies show that hurricanes have only small economic effects on survivors (Deryugina, Kawano, and Levitt 2018; Groen, Kutzbach, and Polivka 2019). In this essay, I show that this may not be the case for renters. I postulate that hurricane damage to residential units may create a negative supply shock in rental housing markets while increasing the demand for housing from both renters and homeowners in the affected locations. Thus, a decrease in supply and an increase in demand may lead to a higher rate of renting (i.e., monthly rental payments) following a hurricane. Moreover, a higher cost of renting can create financial distress for renters that may drive a differential impact on the health and labor outcomes of renters. For this reason, heterogeneity in the impact of hurricane exposure may also exist in health and labor outcomes depending on homeownership status.

Precise estimation of the impact of natural disasters on the outcomes of survivors is challenging due to data limitations. For a causal interpretation of the estimates, one needs to identify the individuals who were exposed to a hurricane and link their pre-disaster health and labor outcomes to the post-disaster period along with the information on their homeownership status. To overcome this challenge, I merge spatial data on hurricane strikes with individual-level longitudinal data using the county of residence from the restricted version of the Panel Survey of Income Dynamics between 1990 and 2017. I estimate the causal effects of hurricane exposure on monthly rental payments, monthly mortgage payments, and house values as well as the health and labor outcomes of renters within the next ten years after a hurricane that hit the continental Unites States. First, utilizing a difference-in-differences model**,** I compare the monthly rental payments of renters that were exposed to a hurricane to the monthly rental payments of other renters who were not exposed to a hurricane but living in the same state from ten years before to ten years after hurricane exposure. Likewise, I also estimate the impact on both monthly mortgage payments and house values for homeowners using the same empirical framework. Then, in the second part of my analysis, I compare the health and labor outcomes of renters who were exposed to a hurricane to all homeowners and renters by employing a difference-in-difference-in-differences model with differences coming from before and after a hurricane, exposed vs. non-exposed group, and homeowner vs. renter status.

To the best of my knowledge, this study provides the first comprehensive estimates of the health and labor effects of hurricanes on renters, considering both the short and long-term consequences. My findings suggest that exposure to a hurricane is likely to increase the monthly rental payments of renters. The impact on the monthly rental payments was stronger in the short-term (in the first five years) compared to the long-term (in six to ten years) following hurricane exposure, whereas event study estimates suggest that the effect persisted in the long-term even though it was not statistically significant. On the other hand, I show that there is no impact of hurricane exposure on either monthly mortgage payments or house values. This set of findings may suggest that renters are differentially affected by these recurring disasters. Then, in the next part of my analysis, I find evidence on the health and labor outcomes of renters, such as worse physical health and an increase at the intensive margin of labor supply (i.e., the weekly average work hours) following hurricane exposure.

These findings make several contributions to the literature. First, I contribute to a set of studies on the economic impacts of natural disasters. While the literature focuses on economic growth, employment, and earnings, the heterogeneous impact of disasters on renters has not been studied. I show that rental payments significantly increase after a hurricane while there is no such an impact on mortgage payments or house values, suggesting that a differential vulnerability may exist for renters. These findings also make a significant contribution to the housing markets literature in urban economics, where studies only focus on property values following a disaster and ignore the impact on rental price. Moreover, several studies provide evidence on the detrimental effects of economic conditions on health. I contribute to this literature by showing the impact of a disaster on the physical health of renters that may result from the higher monthly rental payments following the disaster. A vast majority of studies either focus on very short-term impact (i.e., 1-3 years after the disaster) or very long-run effects of disasters (i.e., 10-20 years after the disaster). However, I provide how the estimated impacts evolve within the ten-year framework following hurricane exposure. Lastly, I consider a set of disasters, while several studies focus on a particular disaster.

Following a hurricane strike, much attention is given to homeowners in disaster policies, but renters may become more vulnerable following hurricanes (Fussell and Harris, 2014). Differential vulnerability to hurricanes may exist among renters, whereas homeowners are compensated through various disaster relief payments by the Federal Emergency Management Agency (FEMA) (Fothergill and Peek 2004). This study provides evidence that renters suffer from hurricane exposure during the recovery stage. Therefore, exploring the vulnerability to hurricanes based on homeownership status provides a piece of information needed to design an optimal policy response to the impact of hurricanes.

2. Background and Conceptual Framework

2.1. Hurricanes in the US

The United States is prone to extreme weather disasters such as tropical storms and hurricanes that form over the North Atlantic Ocean.[45] These extreme storms are unpredictable events, which can escalate and shift direction without prior notice. Hurricane is a stronger type of a tropical storm, whose one-minute sustained wind speed exceeds 74 mph. According to the Saffir-Simpson Hurricane Wind Scale, hurricanes are categorized as minor and major hurricanes using data on wind speed and other parameters such as air pressure and temperatures. While minor hurricanes cause roof and siding damage, major hurricanes are likely to destroy the unit more significantly, like blowing the roof off.

Hurricanes directly target the buildings. The strong force of hurricane-strength winds can destroy housing units. Once we consider flying debris like road signs or similar items, the potential damage to residential units is likely to be greater. Thus, hurricane winds have a

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[45] Every year, from the beginning of June to the end of November is accepted as hurricane season.

destructive effect on houses and other buildings through two different channels, in general: the direct wind pressure on the building envelope (i.e., roof, wall, and other associated parts), and the debris carried out by winds may hit the building that may cause damage on windows and doors. Also, falling trees may impact the buildings as well. Furthermore, flooding damage is likely to occur when building envelope gets damage.

Although hurricanes cause catastrophic damage to residential units, this effect may differ between homeowners and renters. While various private and public insurance programs generally protect the housing units (indirectly homeowners), renters are likely to be more vulnerable in the recovery following the disasters. However, it is still unclear how the recovery following a natural disaster differs between homeowners and renters.

2.2. Heterogeneous Impacts on Renters

The recovery and reconstruction stages in the following years after a disaster may include considerable differences, particularly in regard to housing. Public and private insurance programs frequently compensate for the damage to residential units that may cover the financial burden of disaster for homeowners. After housing damage occurs, landlords may use disaster payments to reconstruct their properties for a higher rate of rent (Pais and Elliott 2008; Zhang and Peacock 2010). Therefore, I expect a differential vulnerability based on renter status through a change in monthly rental payments. Notably, an increase in rental payments following hurricane exposure can cause a financial burden for renters that may differentially affect the health and economic status of renters during the recovery and reconstruction stage. Given the fact that one-third of households in the United States rent their houses, differential vulnerability to hurricanes based on renter status is of importance for policymakers.

Following hurricane exposure, a decline in the supply of and an increase in the demand for rental units are expected to raise rents. Housing damage is likely to cause a decline in the available rental housing units in a given hurricane-affected location. On the other hand, we may expect to observe an increase in the demand for temporary housing options such as renting an apartment since housing damage caused by hurricanes is likely to lead both homeowners and renters to seek a new housing unit (at least, until their original home gets repaired). Therefore, we expect that a decline in the supply of rental housing units and an increase in the demand is likely to increase rental payments. I illustrate this hypothetical case in figure 8, which shows that a contraction in supply and an increase in demand for rental units leads to a higher rental payment following hurricane exposure.

Due to household budget constraints, this increase in rental payments may create financial distress for renters and may force households to change their spending patterns. For example, in order to cover a higher rate of renting, they may choose to reduce the expenditure on health-related items, or they may choose to increase their household income by working more than usual (at the intensive margin). Therefore, following a hurricane, we expect to see some potential changes in the health and labor market outcomes of individuals who rent their homes. In figure 9, I illustrate the expected effects of hurricane exposure on the rental payments, as well as on the health and labor outcomes of renters.

Homeowners with a mortgage must have homeowners' insurance, which protects their investment against hurricane damage.[46] Following the disaster, insurance companies quickly assess the damage and provide checks to homeowners that cover most of the cost and facilitate

[46] Those residing in flood zones must buy flood insurance as well.

the reconstruction (Fussell and Harris 2014). Therefore, I expect that homeowners would be protected from housing damage by private insurance policies as well as public disaster programs. On the other hand, differences between homeowners and renters in access to financial policies and disaster assistance programs may create disadvantageous post-disaster circumstances for renters (Comerio 1998). In the United States, a significant portion of the population are renters and vulnerable to these recurring disasters. Therefore, studying the long-lasting impacts of hurricane exposure on monthly rental payments as well as the health and labor effects on renters gives insight into the economic impact of these events and also provides a piece of information that is essential to create optimal policy responses.

3. Data

3.1. Hurricane Data

I utilize the Extended Best Track Dataset (EBTD) to track the path of hurricanes between 1990 and 2016.[47] For each storm that occurred in the North Atlantic Ocean, the EBTD provides the latitudes and longitudes of storm center location at six-hourly intervals, as well as their maximum sustained wind speed (MWS) and the radius of MWS. I assume that storm center location and wind speed changes linearly at any given sequential point. Then, I define hurricane affected-counties using the information on each storm's center coordinates, MWS, and the radius of MWS, which allows me to take the structure of the storm into account.

The destruction caused by hurricanes is substantial and nontrivial compared to neighboring counties that may be impacted by storm-strengthened winds (Derygina 2017, Karbownik and Wray 2019). For this reason, I define the affected counties as any county whose

[47] The EBTD is available at http://rammb.cira.colostate.edu/research/tropical_cyclones/tc_extended_best_track_dataset/.

centroid falls within the radius of hurricane-strengthened winds in a given year. The restricted version of the PSID provides the county of residence information for each respondent as well as other information on their migration to other counties such as the date, the reason, and the new county of residence of respondents if they move to another county any given time during my sample period. Utilizing both information on the date of hurricane exposure at a given county from the EBTD and the county of residence at the time of hurricane from the PSID, I define hurricane survivors as any PSID respondent who lives in a hurricane-affected county at the time of hurricane exposure.

I provide the list of the 28 hurricanes by year-month that made landfall in the US between 1999 and 2016 in table 6. The states along the east coast of the Atlantic Ocean and the Gulf of Mexico have been exposed to these hurricanes and their catastrophic damage. During my sample period, 337 counties were exposed to hurricanes in total (185 counties were exposed only once). Additionally, the sample period of my study includes the following years in which no storm reached hurricane-strengthened winds on the continental US: 2000, 2001, 2006, 2009, 2010, 2013, and 2015. I demonstrate the hurricane-affected states and counties in figure 3.

3.2. Individual-level Data

I use the Panel Survey of Income Dynamics (PSID) to estimate the impacts of hurricane exposure on the health and labor market outcomes of renters. The PSID is a longitudinal household survey that provides information on a wide range of topics, including health, labor, and housing-related outcomes. Importantly, the longitudinal nature of the restricted PSID allows me to track each survey respondent’s county of residence before, during, and after each hurricane exposure during the time period of this study, which is the most superior feature of the data as compared to other publicly available datasets on health and labor market outcomes. For this reason, I employ the PSID and link it with the spatial hurricane data to define hurricane survivors.

The PSID asks the following homeownership question to the respondents: “Do you (or anyone else in your family living there) own the (home /apartment), pay rent, or what?”. I utilize this question to indicate homeowners and renters using dummy variables. The PSID also asks for monthly mortgage payments and house values for homeowners and monthly rental payments for renters. For homeowners, “How much are your monthly mortgage payments?” and “Could you tell me what the present value of your house/apartment is – I mean about how much would it bring if you sold it today?”; and for renters, “About how much rent do you pay a month?” I use these amounts to measure changes in house values and rents after hurricane exposure.

For health and labor outcomes, I observe the changes in the general health status and labor supply of survivors. I use the self-reported health status (SRHS) question to estimate the health impact of hurricane exposure on renters. I utilize the question on the average number of work hours to detect any changes in the intensive margin of labor supply of renters. The PSID provides information on household rent expenditure (for renters) and a set of health-related outcomes, which has been continuously collected from household heads and spouses, since 1999. Therefore, I utilize the PSID survey waves from 1999 to 2017, which is the latest available data, and restrict my sample to the respondent who was a household head or spouse in any of the survey years between 1999 and 2017.

In table 13, I provide the summary statistics of the sample. About one-third of my sample is a renter. On average, while renters are paying around $700 per month, homeowners reported their home value nearly $200,000. More than half of my sample are female; and, forty-seven percent are nonwhite population. Around seventy percent are working, and sixty-eight percent are married, on average, during the sample period.

4. Methodology

The objective of this paper is to provide the causal estimates of hurricane exposure on the health and labor outcomes of renters. In a difference-in-differences setup, a credible control group is essential to estimate counter-factual outcomes. One could consider a control group, including all unaffected individuals living in the rest of the United States from the PSID sample. However, substantial differences between individuals living in the rest of the US and those living in hurricane-prone counties are expected. Therefore, I define my control group to consist of all individuals who were not exposed to a hurricane but living in a neighboring county in a hurricane-prone state. Moreover, while I define hurricane-exposed households and individuals based on their county of residence and the date of a hurricane strike, being a renter (homeowner) may clearly change over years. In this case, my estimates capture those survivors who rent (own) their place of residence and as long as they rent (own) it in the post period.

For my first set of regressions, I compare the monthly rental payments of renters that were exposed to a hurricane to other renters that were not exposed to a hurricane but residing in a neighboring county in a hurricane-prone state. Likewise, for house values, I compare the house values reported by homeowners who were exposed to a hurricane to other homeowners who were not exposed but living in a neighboring county in a hurricane-prone state. Formally, I estimate the effects of hurricane exposure on monthly rental payments and house values up to ten years following hurricane exposure using difference-in-differences models with three different specifications: i) a combined 10-year post-period; ii) one 5-year short-term and one 5-year long-term post periods; iii) an event study model with separate dummy variables for each year covering pre and post periods. In my preferred specification, I compare monthly rental payments (house value) of renters (homeowners) exposed to a hurricane to those who were not but residing in the same state, although I check the sensitivity of results with different model specifications.

For my second set of regressions, I use a difference-in-difference-in-differences specification in my econometric model, such as before hurricane vs. after hurricane (first difference), hurricane exposed vs. not exposed individuals (second difference), and hurricane exposed renter vs. hurricane exposed homeowner (third difference). This allows me to compare the health and labor outcomes of renters to all homeowners and renters living in hurricane-prone states in my sample. Specifically, I estimate the effects of hurricane exposure on renters' health and labor outcomes up to ten years following hurricane exposure using three different specifications of triple difference strategy: 1) a combined 10-year post period; 2) one 5-year short-term and one 5-year long-term post periods; 3) an event study model with distinct indicators for each year covering pre and post periods. In my preferred specification, I compare renters who were exposed to a hurricane to all other individuals residing in the same hurricane-prone state. However, I check the sensitivity of results with different model specifications.

The set of the North Atlantic storms that made landfall and reached to a hurricane's sustained wind speed between 1999 and 2016 is included in this study. Some of the survivors in my hurricane-exposed group experienced more than one hurricane during the sample period; other individuals experience a hurricane before my sample period starts. I control any hurricane exposure prior to 1999 in my analysis while I use the first instance of individual hurricane exposure in the econometric models during my sample period. Namely, after a survivor is already exposed to a hurricane for the first time between 1999 and 2016, I ignore other subsequent hurricane exposures that the survivor is exposed. Considering that hurricane exposure is random conditional on year and individual fixed effects, this approach should not bias my estimates.[48] Alternatively, restricting the whole PSID sample to individuals who were only exposed to one hurricane and eliminating all individuals who were exposed to multiple hurricanes. But, this approach would significantly reduce the sample size by reducing the number of individuals that are good controls and excluding many survivors in hurricane-exposed group.

4.1. Econometric Framework

4.1.1. Difference-in-Differences: Rental Payments, Mortgage Payments, and House Value

For the first set of regressions, I use a traditional difference-in-differences model to estimate the average change in monthly rental payments, monthly mortgage payments, and house values in the next ten years after a hurricane. I compare the monthly rental payments (monthly mortgage payments and house values) of renters (homeowners) that were exposed to a hurricane to those renters (homeowners) who were not exposed to a hurricane but residing in the same state. I estimate the average impact of hurricane exposure on my outcomes of interest up to ten years conditional on household level time-varying characteristics such as the number of household residents, household income, the age, gender, race, education, marital and employment status of household head, as well as on household and state-by-year fixed effects. I

[48] Deryugina (2017) also use the same approach to address multiple hurricane hits.

employ the following estimation model by combining ten post-hurricane years into a single dummy variable:

$$\boldsymbol{V_{hcst}} = \boldsymbol{\alpha} + \boldsymbol{\gamma_1 H_{hcs[\tau+1,\tau+10]}} + \boldsymbol{X_{hcst}\beta} + \boldsymbol{\theta_h} + \boldsymbol{\mu_s} * \boldsymbol{t} + \boldsymbol{\delta_{-99} H_{-99,hcst}} + \boldsymbol{\varepsilon_{hcst}} \qquad (1)$$

where $\boldsymbol{V_{hcst}}$ is the outcomes of interest such as monthly rental payment, monthly mortgage payment, and house value for household *h* living in county *c* and state *s* in year *t*. $\boldsymbol{H_{hcs[\tau+1,\tau+10]}}$ is the hurricane exposure dummy and equals to one within the next ten years following the disaster that occurred at time τ. For this reason, the coefficient $\boldsymbol{\gamma_1}$ shows the estimated mean impact of hurricane exposure on the monthly rental payment for renters, and monthly mortgage payments and house values for homeowners in the next ten years following hurricane exposure. Time-varying household characteristics are likely to affect rental payments and house value. Thus, I control a set of household characteristics, denoted by $\boldsymbol{X_{hcst}}$, including the number of people in the household, the age, gender, race, marital status, education, and employment of household head, as well as household income.[49] Also, I use fixed effect specifications to control time invariant observable and unobservable characteristics at household, state, year levels. $\boldsymbol{\theta_h}$ and $\boldsymbol{\mu_s} * \boldsymbol{t}$ represents household and state-by-year fixed effects, respectively. While household fixed effects allow me to control observable and unobservable time-invariant heterogeneity across households, state-by-year fixed effects capture state specific shocks and trends in the outcomes of interest as well as unobservable state level characteristics in a given year. In particular, I prefer state-by-year fixed effects to be able to compare the individuals in the hurricane-exposed group to those who were not exposed to a hurricane but residing in the same

[49] Some individual level time invariant characteristics can change in my household level analysis as household head changes. Therefore, I include the gender and race of household head in the model although I use household fixed effect specification.

state. Additionally, $\boldsymbol{H_{-99,icst}}$ indicates any individual who were exposed to a hurricane prior to 1999 in my sample and equals to one within the next ten years following the hurricane. Lastly, I cluster the standard errors at the county level since the exposure is assigned based on the county of residence (Bertrand, Duflo, and Mullainathan 2004).

I use a second estimation model to briefly show how the effect differs between the first five years (short-run) and second five years (long-run) in the ten-year post period following the event. Specifically, I combine the post period the first five years and the second-five years into two dummy variables and estimate the following equation:

$$\begin{aligned} \boldsymbol{V_{hcst}} &= \boldsymbol{\alpha} + \boldsymbol{\delta_1 H_{hcs[\tau+1,\tau+5]}} + \boldsymbol{\delta_2 H_{hcs[\tau+6,\tau+10]}} + \boldsymbol{X_{hcst}\beta} + \boldsymbol{\theta_h} + \boldsymbol{\mu_s} * \boldsymbol{t} \\ &\quad + \boldsymbol{\delta_{-99} H_{-99,hcst}} + \boldsymbol{\varepsilon_{hcst}} \end{aligned} \tag{2}$$

where $*\,\boldsymbol{H_{hcs[\tau+1,\tau+5]}}$ and $*\,\boldsymbol{H_{hcs[\tau+6,\tau+10]}}$ indicates hurricane exposure for the years 1-5 and 6-10 following the disaster and equals to one within the 1-5 and 6-10 years after the hurricane that occurred at time τ. Thus, the coefficients $\boldsymbol{\delta_1}$ and $\boldsymbol{\delta_2}$ show the average effect 1-5 and 6-10 years after the hurricane. Other parameters in equation (2) are defined as in equation (1).

The internal validity of difference-in-differences models relies on the parallel trends assumption. It suggests that in the absence of hurricane, the average change in my outcomes of interest would have been the same for the hurricane-exposed and the control group in the post-period; in other words, the difference between the hurricane-exposed group and the control group would be constant over time. The violation of this identifying assumption may lead to biased causal estimates. Therefore, I conduct an event study analysis to informally test this assumption but also present the year-by-year changes in the impact of hurricane exposure in the following ten years after a hurricane.

As a third estimation model, I run an event study analysis by estimating a set of indicator variables from ten years before up to ten years after hurricane exposure on my outcomes of interest, controlling household characteristics as well as household and state-by-year fixed effects. I use the following equation:

$$\boldsymbol{V_{hcst}} = \boldsymbol{\alpha} + \left(\sum_{\boldsymbol{\tau}=\,\boldsymbol{-10},\boldsymbol{\tau}\neq\boldsymbol{-1}}^{\boldsymbol{10}} \boldsymbol{\delta_{\tau}} \boldsymbol{H_{hcs\tau}}\right) + \boldsymbol{X_{hcst}}\boldsymbol{\beta} + \boldsymbol{\theta_{h}} + \boldsymbol{\mu_{s}} * \boldsymbol{t} + \boldsymbol{\delta_{-99}}\boldsymbol{H_{-99,hcst}} + \boldsymbol{\varepsilon_{hcst}} \qquad (3)$$

where $\boldsymbol{H_{hcs\tau}}$ indicates hurricane exposure and equals to one from ten years before the hurricane exposure up to ten years after hurricane hit. Thus, $\boldsymbol{H_{hcs\tau}}$=1 in the following time interval [τ -10, τ +10] if and only if household *h* is exposed to a hurricane at time τ. The PSID surveys are conducted as biannual during my sample period. So, in order to reduce noisiness across households and years, I combined hurricane exposure indicators into two-year bins. Lastly, I normalize the year before hurricane exposure to zero. Thus, the event study coefficients show the estimated impacts compared to one year before hurricane hits.

4.1.2. Triple Differences: Health and Labor Outcomes of Renters

In the second part of my main analysis, I focus on estimating the health and labor impacts of hurricanes on renters. I utilize a triple difference model and compare the health and labor outcomes of renters who were exposed to a hurricane to all other individuals in my sample using renter status, which may change across survey years, as a third difference. Specifically, I compare my outcomes of interest for renters who were exposed to a hurricane to those homeowners who were exposed to a hurricane and to those who were not exposed to a hurricane but residing in a neighboring county in a hurricane-prone state. I estimate the average impact of hurricane exposure on the outcomes of interest up to ten years conditional on individual time-varying characteristics such as age, marital status, education, employment, and income, as well as on individual and state-by-year fixed effects. I employ the following estimation model:

$$\boldsymbol{O_{icst}} = \boldsymbol{\alpha} + \boldsymbol{\gamma_1}(\boldsymbol{H_{ics[\tau+1,\tau+10]}} * \boldsymbol{Renter_{icst}}) + \boldsymbol{X_{icst}\beta} + \boldsymbol{\theta_i} + \boldsymbol{\mu_s} * \boldsymbol{t} + \boldsymbol{\delta_{-99}H_{-99,icst}} + \boldsymbol{\varepsilon_{icst}} \tag{4}$$

where $\boldsymbol{O_{icst}}$ is the outcomes of interest such as poor physical health and average work hours per week for individual *i* living in county *c* and state *s* in year *t*. $\boldsymbol{Renter_{icst}}$ is a dummy variable that indicates the individuals who rent their home in county *c*, state *s*, and in year *t*. $\boldsymbol{H_{ics[\tau+1,\tau+10]}}$ denotes hurricane exposure and equals to one within the next ten years after the disaster occurred at time τ. So, the coefficient $\boldsymbol{\gamma_1}$ shows the average impact of hurricane exposure on the outcomes of interest in years 1-10 following hurricane exposure. Time-varying individual characteristics are likely to affect my outcomes of interest. Thus, I control a set of characteristics, denoted by $\boldsymbol{X_{icst}}$, including age, marital status, education, employment, and income. Similar to equation (1), I also use fixed effect specifications to capture time invariant observable and unobservable characteristics at individual, state, year levels. While $\boldsymbol{\theta_i}$ represents individual fixed effects that allow me to control observable and unobservable time-invariant individual heterogeneity, other parameters in equation (4) are defined as the same in equation (1) above.

Similar to equation (2), I use another estimation model to concisely demonstrate how the impact differs between the short (first five years) and long-run (second five years) during the ten-year post period following the exposure. In particular, I divide the post period into two dummy variables as years 1-5 and 6-10 and estimate the following equation:

$$\boldsymbol{O_{icst}} = \boldsymbol{\alpha} + * \boldsymbol{\delta_1}(\boldsymbol{H_{ics[\tau+1,\tau+5]}} * \boldsymbol{Renter_{icst}}) + \boldsymbol{\delta_2}(\boldsymbol{H_{ics[\tau+6,\tau+10]}} * \boldsymbol{Renter_{icst}}) + \boldsymbol{X_{icst}\beta} + \boldsymbol{\theta_i} + \boldsymbol{\mu_s} * \boldsymbol{t} + \boldsymbol{\delta_{-99}H_{-99,icst}} + \boldsymbol{\varepsilon_{icst}} \tag{5}$$

where $* \boldsymbol{H_{ics[\tau+1,\tau+5]}}$ and $* \boldsymbol{H_{ics[\tau+6,\tau+10]}}$ indicates hurricane exposure for the short and long-run following a hurricane and equals to one within the 1-5 and 6-10 years, respectively, after the event occurred at time τ. Similar to equation (4) above, $\boldsymbol{Renter_{icst}}$ is an indicator variable for renters. Thus, the coefficients $\boldsymbol{\delta_1}$ and $\boldsymbol{\delta_2}$ will give us the mean impact 1-5 and 6-10 years after the hurricane. Other parameters in equation (5) are defined as the same in equation (1).

The causal interpretation of my estimates from equation (4) and (5) relies on the parallel trends assumption, which suggests counterfactual trends between the exposed and control groups. Thus, I conduct an event study analysis to explore this assumption as well as show how the estimated impact changes year-by-year during the ten-year post period. So, similar to equation (3), I run an event study analysis by estimating a set of dummy variables that indicates each year from ten years before up to ten years after hurricane exposure on my outcomes of interest, controlling individual characteristics as well as individual and state-by-year fixed effects. Specifically, I run the following equation:

$$\boldsymbol{O_{icst}} = \boldsymbol{\alpha} + \Big(\sum_{\boldsymbol{\tau=-10,\tau\neq-1}}^{\boldsymbol{10}} \boldsymbol{\delta_\tau H_{ics\tau}} * \boldsymbol{Renter_{ics\tau}}\Big) + \boldsymbol{X_{icst}\beta} + \boldsymbol{\theta_i} + \boldsymbol{\mu_s} * \boldsymbol{t} + \boldsymbol{\delta_{-99}H_{-99,icst}} + \boldsymbol{\varepsilon_{icst}} \tag{6}$$

where $\boldsymbol{H_{ics\tau}}$ * $\boldsymbol{Renter_{ics\tau}}$ indicates hurricane exposure for renters and equals to one from ten years before the hurricane exposure up to ten years after hurricane hits. Thus, $\boldsymbol{H_{ics\tau}}$ * $\boldsymbol{Renter_{ics\tau}}$ =1 in the following time interval [τ -10, τ +10] if and only if individual *i* is exposed to a hurricane and is a renter at time τ. Since the PSID interviews are conducted as biannual between 1999 and 2017, I combined year dummies into two-year bins to reduce noisiness across individuals and years. Lastly, I normalize the year before hurricane to zero. Therefore, the event study coefficients present the estimated effects compared to one year before the disaster.

To assess the robustness of my baseline results, I run a set of sensitivity checks. First, I estimate my set of regressions on the health and labor effects of hurricane exposure on renters using a difference-in-difference model, in which I will compare renters who were exposed to a hurricane to other renters living in a neighboring county in the same state.[50] Second, I re-run equation (1) and (4) 19 times, dropping a state each time to show that estimated effects are not driven by a particular state. Additionally, since my preferred specification is a state-by-year fixed effect model, I also estimate the equations (1) and (4) with only year and household/individual fixed effect, including only state fixed effect (i.e. not interacting with year fixed effect), and also with state-specific time trends.

5. Results

First, I begin my analysis estimating the effect of hurricane exposure on monthly rental payments, monthly mortgage payments, and house values. The sample in this part of my analysis consists of households residing in hurricane states. Then, in the second part of my analysis, I estimate the impact of hurricane exposure on the health and labor outcomes of renters using the

[50] I am still working on this section. I will update this part in a later version of my dissertation.

poor physical health and weekly average work hours outcomes, respectively. In this part, my sample includes all individuals living in hurricane states.

5.1. Baseline Results

In table 14, I provide the results from the main difference-in-differences model from equation (1) for each outcome of interest. Columns indicate the results for house value and monthly rental payment. For the following ten years after a hurricane, positive and significant point estimates in the first row of table 14 present the causal effect of hurricane exposure on my outcomes. The point estimates for monthly rental payments suggest that hurricane exposure increased the household monthly rental payments by 10 percent per year in the next ten years after the hurricane while I do not find a statistically significant impact of hurricane exposure on house value. My finding on monthly rental payments is in line with my previous assumption that rents may go up because of the contraction in the rental housing market following a hurricane.

Table 15 briefly presents the short vs. long-run impacts of the exposure on the outcomes of interest. The results show that the exposure had a larger and statistically significant effect on monthly rental payments in the first five years compared to six-to-ten years in the post-period. Hurricane exposure, on average, increased monthly rental payments by 11.2 percent (significant at 5% level) per year in the first five years as compared to 10.5 percent (significant at 10% level) per year in six-to-ten years in the post period. Therefore, these results suggest that the impact on the monthly rental payment was greater in the short-run as compared to the long-run.

An increase in monthly rental payment is likely to create financial distress on renters.[51] Thus, I show the heterogeneous effect of hurricane exposure on the health and labor market outcomes of renters. Table 16 presents the estimates from the difference-in-difference-in-differences models that show renters experienced a 2.8 percentage point (14.6 percent) increase in the likelihood of reporting poor physical health and increased their labor supply at the intensive margin by 4.5 percent per week. In table 17, I present the triple difference estimates as short vs. long-run impacts of the exposure on both my outcomes of interest. The impact on poor physical health is greater in the first five years, which is in line with the statistically significant effect on monthly rental payment, as compared to six-to-ten years after the disaster. On the other hand, the effect of the exposure on work hours is greater in the long-run as compared the first five years. Thus, in addition to the higher rental payments, these findings suggest that the health and labor outcomes of renters were differentially affected.

These results, in summary, present evidence that renters are likely to face financial difficulties such as higher rental payments in the following years after the hurricane. Considering the household budget constraint of renters, an increase in rents, one of the major household expenditure items, is likely to affect health status (i.e., reducing health-related spending) and labor supply (i.e., work longer hours to earn more). My findings show that following a hurricane exposure, renters reported worse physical health and also worked longer hours. However, a causal interpretation of these findings is based on the parallel trend assumption that I present the results from event study models in the next sub-section.

[51] Renters, on average, spend one-third of their monthly household income on rent. More details are available in a PEW report, available at https://www.pewtrusts.org/-/media/assets/2018/04/rent-burden_report_v2.pdf (accessed on June 2019)

5.2. Event Study Results

The internal validity of my difference-in-differences estimates reported in tables 2 - 4 is based on the assumption of post-disaster counterfactual trends in my outcomes of interest between individuals in the hurricane exposure group and those in the control group in the absence of the event. A standard approach to indirectly test this assumption is to look for differences in pre-period trends for the outcomes of interest. Thus, I run an event study analysis to check the identifying assumption of my econometric model and also analyze how the effect of the exposure changes over time after hurricane hits.

Figure 10 presents the event study results from equation (3). For each outcome of interest, the point estimates and 95 percent confidence intervals are plotted. The estimates show that the pre-exposure trends are not statistically significantly different between individuals in the exposure group and those in the control group for my outcome of interest. Therefore, these estimates provide supporting evidence in favor of the parallel trends assumption and validate the estimates derived from the econometric model. Also, figure 10 illustrates that rental payment significantly increased following the exposure and remained statistically significant in the first five years. Likewise, figure 11 shows the event study estimates from equation (6) and suggests evidence in favor of the identifying assumption of my main model. Furthermore, figure 11 demonstrates that renters reported worse health immediately after hurricane exposure, and the effect remains positive and statistically significant in the first five years then gradually fades away.

5.3. Sensitivity Analysis

I conducted a series of robustness checks of my baseline results using different sample and model specifications. First, for the health and labor outcomes of renters, I utilized a difference-in-differences model rather than a triple difference model. I compare the health and labor market outcomes of renters who were exposed to a hurricane to other renters who were living in the same state but were not exposed to a hurricane. In other words, I did not include homeowners in this robustness check. One would argue that homeowners and renters could be very different in terms of several observable and unobservable socio-economic characteristics, which may indeed drive the results. This analysis addresses this potential concern and checks the sensitivity of my findings within the renter sample. Table 18 shows the results, which are very consistent with the baseline results presented in table 16. Thus, my conclusions are robust across different samples and models.

Additionally, I re-estimate my baseline results by dropping one state from my sample each time. This robustness check addresses a potential concern that a particular state drives my findings. Since I have 19 states in the hurricane region, I re-run my baseline model 19 times by dropping one state each time. The point estimates with 95% confidence intervals are presented in figure 12. I do not observe any substantial change each time across my estimates. Therefore, this robustness check shows that the estimates are not driven by any particular state.

I also checked the robustness of my findings to different model specifications. I included individual and year fixed effects in my models. While individual fixed effect controls any time invariant observable and unobservable characteristics, year fixed effect captures the differences across years. I estimate my baseline model with four different specifications such as: (i) individual and year fixed effects; (ii) individual, year, and state fixed effects; (iii) individual, year, and state by year fixed effects; (iv) individual, year fixed effects and state specific time trend. While state fixed effect takes care of time invariant heterogeneity across states, state specific time trend accounts for time varying characteristic of states, assuming a linear trend. As we can see the results in Table 19, the point estimates and statistical significance levels are very similar for all my outcomes of interest across different specifications.

6. Discussion

This chapter estimates the heterogeneous impact of hurricane exposure on renters in the next ten years following hurricane exposure. Hurricanes cause catastrophic level destructions in buildings and infrastructure in the affected communities. In the US, nineteen states are prone to hurricanes, which is around 44 percent of the whole US population, whereas 20 percent of the US population lives on the path of hurricane strikes. Housing damage may lead to changes in house values and rental payments, which may also lead to heterogeneous health and labor impacts among survivors. Thus, I also explore the impact of hurricanes on renters' health and labor outcomes. My findings suggest that exposure to a hurricane is likely to increase the monthly rental payments for renters, which may increase financial distress given the household budget constraint. In addition, I find that renters reported worse physical health and longer work hours in the following years after the disaster. Furthermore, monthly rental payments significantly increased around the same time period as renters reported worse physical health, which may be suggestive evidence that financial distress leads to worse health. Considering that the magnitude of hurricanes is likely to grow in the future and one-fifth of the US population lives on the path of hurricane strikes, these results provide essential input to create effective mitigation policies.

This study contributes to the literature on the economic consequences of natural disasters. While the majority of studies estimate the impact of disasters on economic growth, employment, and earnings, the differential impacts on renters after a disaster have not been studied. My findings show the heterogeneous impacts of disasters on renters. Moreover, my findings contribute to the set of studies in urban economics. Most studies focus on property prices following a disaster and ignore the impact on rental prices. I also contribute to the literature on the effect of financial distress on health and labor market outcomes. Considering hurricane exposure as a natural experiment, these results may provide suggestive evidence that financial distress resulted from higher rental payments may lead worse physical health and an increase in the intensive margin of labor supply for renters. Additionally, I also consider a set of disasters whereas the majority of studies in the literature focus on a particular disaster. Lastly, most of the studies either focus on immediate impacts or very long-run effects. I provide estimated impacts from one to ten years after a disaster.

This analysis has some limitations. Quasi-experimental research design may raise concerns about the internal validity of the study. I address this potential issue by informally testing the parallel trend assumption and conducting an event study analysis. Additionally, my outcomes of interest are self-reported, which may be subject to measurement error. In particular, homeowners may be biased on the value of their property. Since the information on home values is not based on actual sales data, the observed home values may not change due to homeowner's bias on their property. However, the reported rental payment is likely to represent the real values since renters are more likely to make these payments monthly.

In terms of policy implications, my findings provide insight into the hidden consequences of recurring disasters. Considering that one-third of the US households are a renter and a considerable portion of the US population lives on the path of hurricane strikes, estimating the heterogeneous health and labor impacts of hurricane exposure on renters is an important input to craft an optimal policy response. Thus, measuring the heterogeneous impacts of hurricanes on renters not only uncover the true costs of these recurring events but also incentivize to design a timely policy response.

Figure 8. Rental market following hurricane exposure

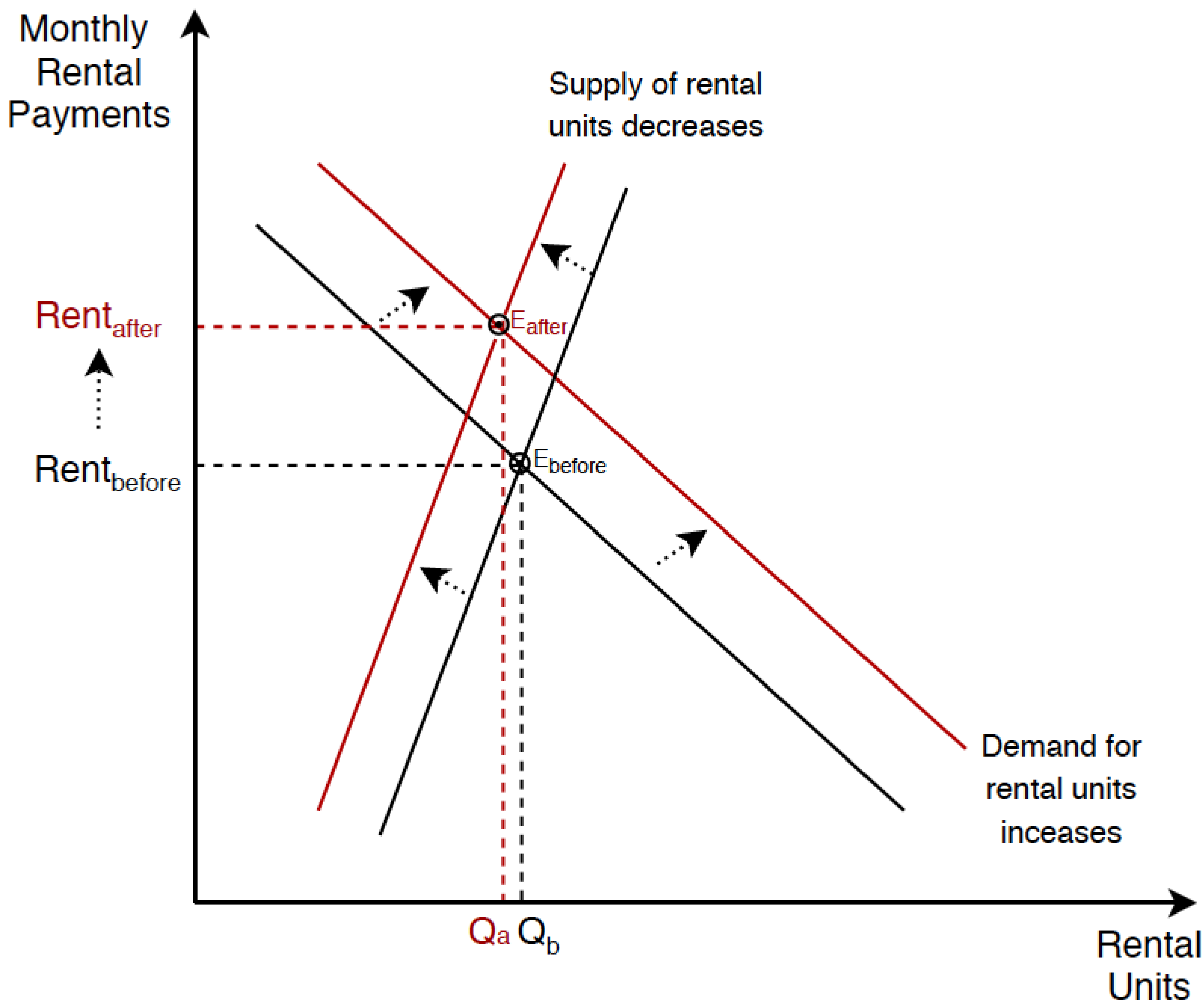


Figure 9. Expected impact of hurricane exposure on renter's health and labor outcomes

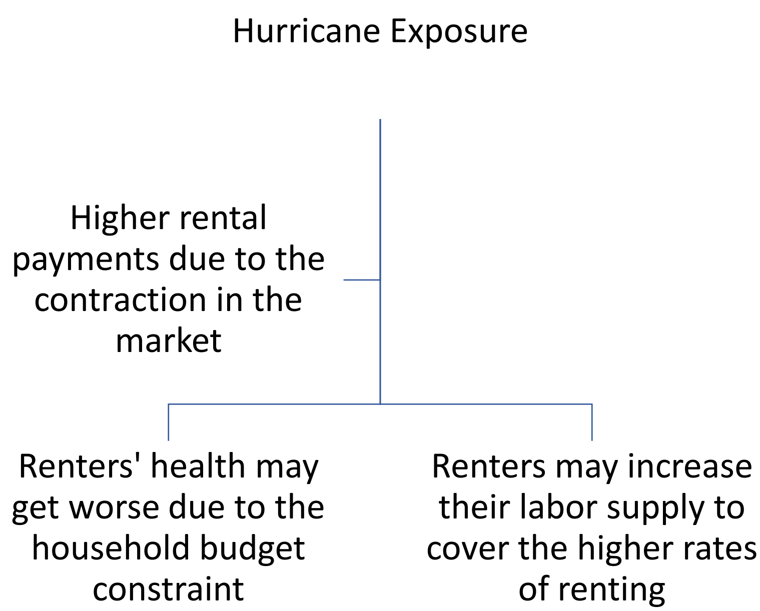
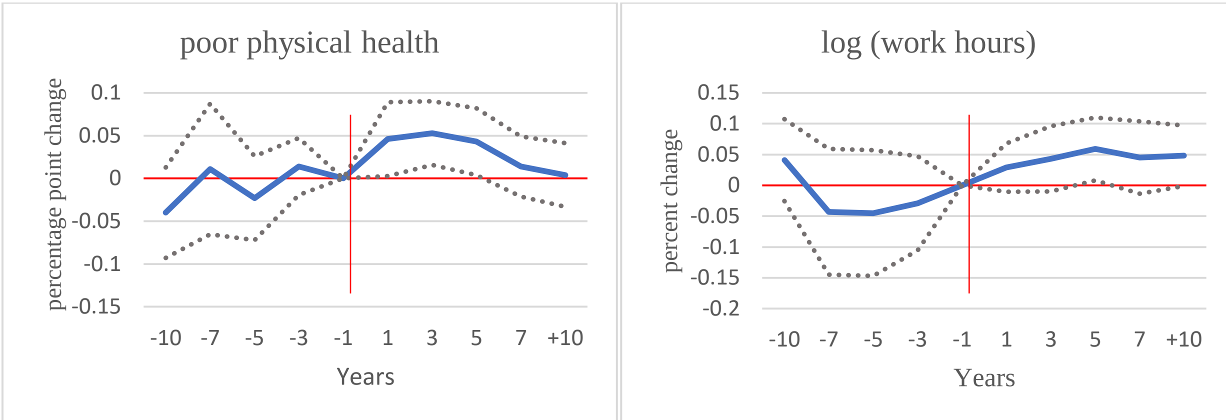


Figure 10. The impact of hurricanes on house value and rental payment

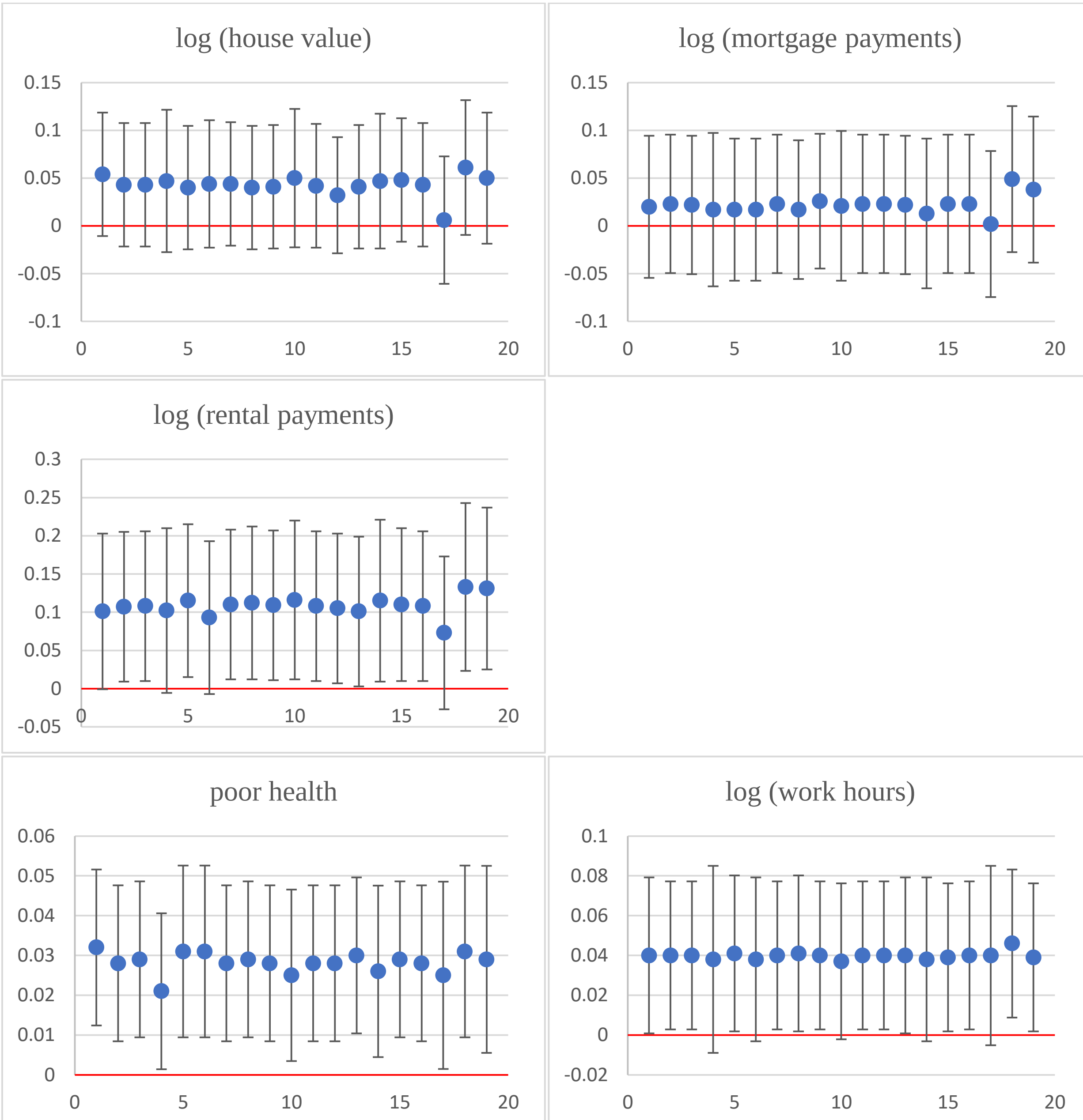
Notes: Point estimates and 95% confidence intervals are shown. The last survey year before the hurricane is chosen as base year following the literature. Results are conditional on household characteristics (head's age, education, employment, marital status, as well as household income and the number of residents), household fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level.

Figure 11. The impact of hurricane on renters' outcomes



Notes: Point estimates and 95% confidence intervals are shown. The last survey year before the hurricane is chosen as base year following the literature. Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level.

Figure 12. Sensitivity analysis: results are not driven by a particular state



Notes: Point estimates and 95% confidence intervals are shown. Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. I dropped a hurricane state at a time in the following order: Alabama, Connecticut, DC, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, and Virginia.

Table 14. Summary statistics

	Observations	Mean	St. Dev.	Min	Max
Outcomes of interest					
Poor physical health	58,908	0.159	0.365	0	1
log (weekly work hours)	46,427	3.647	0.428	0	4.718
log (house value)	21,398	11.922	1.005	4.791	15.285
log (monthly mortgage payment)	15,377	6.904	0.665	3.929	11.514
log (monthly rental payment)	13,482	6.339	0.736	2.199	10.473
Characteristics					
Renter	59,186	0.363	0.481	0	1
Female	59,186	0.559	0.496	0	1
Nonwhite	58,940	0.477	0.499	0	1
Education in years	59,185	13.335	2.658	0	17
Age	59,161	45.037	15.326	15	102
Married	59,181	0.689	0.462	0	1
Working	59,127	0.706	0.455	0	1
Earnings (including 0s)	59,186	37,597	76,916	0	493,840
log(total family inc.)	58,933	10.949	1.001	2.268	15.758

Notes: Tables shows the summary statistics of 1999 – 2017 PSID. Sample consists of household head and spouses residing in 19 hurricane-prone states and reported their household either homeowner or renter. Poor physical health equals to 1 if health is reported as poor or fair. K-6 index (1-24) is used to measure psychological distress. Log of house value and monthly rental payment variables are calculated per household for homeowners and renters, respectively. All monetary variables are adjusted to 2015 dollars.

Table 15. The impact of hurricanes on house value, mortgage and rental payments

	log (house value)	log (monthly mortgage payment)	log (monthly rental payment)
	(1)	(2)	(3)
Post-hurricane (1-10 years)	0.043	0.023	0.108**
	0.032	(0.036)	(0.050)
Household Characteristics	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes
Number of Observations	20,464	14,496	12,791

Notes: Results are conditional on household and household head characteristics (number of household members, the gender, age, race/ethnicity, education, employment, marital status of head, as well as household income), household fixed effects, and state by year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 16. The impact of hurricanes on house value and monthly rental payment

Short-run vs. Long-run Impacts	log (house value) (1)	log (monthly mortgage payment) (2)	log (monthly rental payment) (3)
Post-hurricane (1 to 5 years)	0.017	0.006	0.112**
	(0.032)	(0.036)	(0.045)
Post-hurricane (6 to 10 years)	0.055	0.041	0.105*
	(0.040)	(0.043)	(0.060)
Household Characteristics	Yes	Yes	Yes
Household Fixed Effect	Yes	Yes	Yes
State by Year FE	Yes	Yes	Yes
Number of Observations	20,464	14,496	12,791

Notes: Results are conditional on household and household head characteristics (number of household members, the gender, age, race/ethnicity, education, employment, marital status of head, as well as household income), household fixed effects, and state by year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 17. The impact of hurricanes on renters

	poor physical health	log (work hours)
	(1)	(2)
Post-hurricane (1 – 10 years)	0.028***	0.045**
	(0.010)	(0.018)
Pre-hurricane Mean	0.192	-
Household Characteristics	Yes	Yes
Household Fixed Effect	Yes	Yes
State by Year FE	Yes	Yes
Number of Observations	57,282	44,655

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 18. The impact of hurricanes on renters – short vs. long-run

Short-run vs. Long-run Impacts	poor physical health (1)	log (work hours) (2)
Post-hurricane (1 - 5 years)	0.050*** (0.015)	0.036* (0.0190)
Post-hurricane (6 - 10 years)	0.017 (0.014)	0.051** (0.022)
Pre-hurricane Mean	0.192	-
Individual Characteristics	Yes	Yes
Individual Fixed Effect	Yes	Yes
State by Year FE	Yes	Yes
Number of Observations	57,282	44,655

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 19. Sensitivity analysis – using only the sample of renters

	poor Health	log (work hours)
	(1)	(2)
Post-hurricane 1 to 10 years	0.031**	0.040**
	(0.013)	(0.019)
Pre-hurricane Mean		
	0.192	
Household Characteristics	Yes	Yes
Household Fixed Effect	Yes	Yes
State by Year FE	Yes	Yes
Number of Observations	19,425	15,198

Notes: Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

Table 20. Sensitivity analysis – different model specifications

	(1)	(2)	(3)	(4)
	0.041	0.04	0.043	0.057
log (house value)	(0.031)	(0.031)	(0.033)	(0.042)
	n=20,529	n=20,526	n=20,464	n=20,526
	0.02	0.02	0.023	0.047
log(mortgage payment)	(0.030)	(0.031)	(0.037)	(0.036)
	n=14,583	n=14,583	n=14,496	n=14,583
	0.136***	0.121***	0.108**	0.120***
log (rental payments)	(0.043)	(0.042)	(0.050)	(0.042)
	n=12,863	n=12,860	n=12,791	n=12,860
	0.028***	0.028***	0.028***	0.028***
Poor Health	(0.010)	(0.010)	(0.010)	(0.010)
	n=57,303	n=57,302	n=57,282	n=57,302
	0.036*	0.036*	0.040**	0.032*
log (work hours)	(0.019)	(0.020)	(0.019)	(0.019)
	n=44,686	n=44,685	n=44,655	n=44,685
Individual Characteristics	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes		Yes
State FE		Yes		Yes
State by year FE			Yes	
State specific time trend				Yes

Notes: Results are conditional on household and household head characteristics (number of household members, gender of head, age, race/ethnicity, education, employment, marital status, and income), household/individual fixed effects, year fixed effects. State fixed effects are included in model 2, state by year fixed effects are included in model 3, and state specific time trends are included in model 4. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

APPENDIX FOR CHAPTER 2

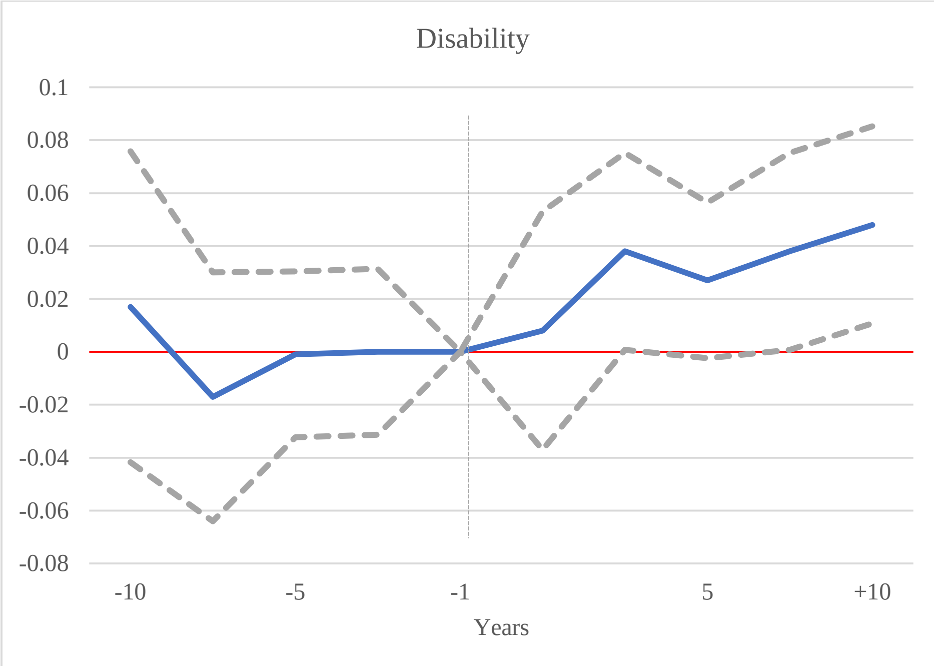
A2. Low-educated hurricane survivors

Muttarak and Lutz (2014) discuss that education can be the most effective factor in post-disaster period. They argue that less educated individuals are likely to be more vulnerable due to their lower social capital compared to those with higher level of education. The heterogeneity analysis in this paper supports their argument that survivors with high school education or less were disproportionately affected by hurricanes. As reported in table 5, they suffered from an increase in the likelihood of reporting poor physical health (15.1 percent of the mean) in the decade following hurricane exposure.

In addition to the general health status and mental health questions, the PSID collects information on disability. The survey respondents are asked if they have any physical or nervous condition that limits the type of work or the amount of work. Using this information, I estimated the impact of hurricane exposure on disability. The results are reported in appendix table 1, which shows that the low-educated subsample experienced a 3.3 percentage points increase in the likelihood of disability (16.7 percent of the mean) in the ten years after hurricane exposure. This finding suggests that survivors with high school education or less were more likely to suffer from disability.

However, it is not clear if this effect stems from their education level or their occupations since low educated individuals tend to work in jobs that are more physically demanding than their higher educated counterparts. In other words, people who are low-educated are more likely to be involved in more hazardous professions. Following a disaster, working conditions might get tougher for low-educated individuals. Therefore, more work needs to be done to examine the impact of hurricane exposure on low-educated individuals since the estimated health impacts may arise due to low social capital and capacity to manage post-hurricane circumstances, as well as due to the occupational status of those individuals.

Appendix figure 1: The impact of hurricanes on disability, high school graduate



Notes: Point estimates and 95% confidence intervals are shown. The last survey year before the hurricane is chosen as base year following the literature. Results are conditional on individual characteristics (age, education, employment, marital status, and income), individual fixed effects, state-year fixed effects. Standard errors are robust, clustered at county level.

Appendix table 1. The impact of hurricane on disability, high school graduates

	(1)	(2)	(3)	(4)
Post-hurricane 1 to 10 years	0.032***	0.032***	0.033***	0.033***
	(0.012)	(0.012)	(0.012)	(0.012)
	n=60,057	n=60,056	n=60,037	60,056
Pre-hurricane Mean	0.198	0.198	0.198	0.198
Individual Characteristics	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE		Yes		Yes
State by year FE			Yes	
State specific time trend				Yes

Notes: Results are conditional on individual characteristics (age, employment, marital status, and income), individual fixed effects, year fixed effects. State fixed effects are included in model 2, state by year fixed effects are included in model 3, and state specific time trends are included in model 4. Standard errors are robust, clustered at county level. *** Significant at 1 percent level. ** Significant at 5 percent level. * Significant at 10 percent level.

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