Hurricane Katrina: Behavioral Health and Health Insurance in Non-Impacted Vulnerable Counties

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May 2014

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May 16, 2014

Abstract

I find causal evidence that Hurricane Katrina increased stress, smoking, binge drinking, and health insurance coverage in the non-impacted storm surge region. In this region, Hurricane Katrina increased health insurance coverage by 440,000 young adults, the number of smokers by 930,000, and the number of binge drinkers by 510,000. Results are robust to varying the location and time of Hurricane Katrina, varying the pre-Hurricane Katrina time window, and excluding counties within 400 miles of New Orleans. Findings suggest that disasters are integral to the formation of risk perceptions and affect the demand for behavioral health and health insurance.

JEL Classification Numbers: D81, I13, I19, Q54

*Address: 402 East 67th Street; LA-216, New York, NY 10065, USA, telephone: 1-646-962-8048, e-mail: *mip2037@med.cornell.edu*. Please do not repost this draft online. I thank Frank Chaloupka, Lawrence Casalino, Andrew Ryan, Donald Kenkel, Catherine Maclean, Amitabh Chandra, Anthony LoSasso, Lillian Madrigal, Katherine Klem, and numerous seminar participants for helpful comments. I am especially grateful to Elaine Hallisey of the Geospatial Research, Analysis and Services Program at the Centers for Disease Control and Prevention for the hurricane risk data and GIS assistance. Jayme Mendelsohn provided excellent research coordination.

I Introduction

Hurricane Katrina (hereafter referred to as "HK") was a unique event in terms of severity and media coverage. It was the deadliest natural disaster in the United States in nearly a century, causing 1,836 deaths in total. The city of New Orleans in Louisiana took the brunt of its impact on August 29, 2005, and the damage extended to states of Mississippi, Alabama, and Florida. 24/7 news coverage transferred images of HK-induced death and destruction to households across the United States. A few examples of this ubiquitous news coverage are that the *Los Angeles Times* had a HK front-page headline and lead image for 15 days straight, and the *New York Times* had a HK front-page headline for 13 out of 15 days (Kimball et al. 2006). In polling conducted a week following HK, 93% of Americans believed HK to be the worst natural disaster in their lifetime (Gallup News Service 2005a). The public was mostly unhappy with the government's response, with various aspects of government receiving approval ratings of between 36-42% for their response (Gallup News Service 2005b). The director of the Federal Emergency Management Agency (FEMA) resigned two weeks following the disaster.

This paper examines secondary effects of HK in areas that were not directly impacted by the damage of the storm but are susceptible to future hurricanes. The objective of this paper is to examine how large-scale disasters influence the demand for behavioral health, which I define as mental health and lifestyle behaviors, and health insurance. Changes in demand following HK may be mediated by changes in risk perceptions, as Americans living in non-impacted areas vulnerable to future hurricanes may have become aware or reminded of hurricane risks by 24/7 media coverage.

I explore the impact HK had on self-reported stress, smoking, binge drinking, exercising, and having health insurance (hereafter referred to as "behavioral health responses") that may be impacted by a sudden change in risk perceptions. Stress may increase following a sudden change in risk perceptions, as individuals feel threatened in new ways. Individuals may attempt to use lifestyle behaviors of smoking, drinking, or exercising in an attempt to

self-medicate this stress. Individuals may also obtain health insurance to either lower the costs of potential future hurricane-related injuries that they feel newly threatened by, or as another self-medication option by potentially obtaining improved access to mental health professionals and stress-reducing prescription drugs. Health insurance increases self-reported happiness (Finkelstein et al. 2012), so demand for it may increase during times of stress or associated negative feelings.

My key hypothesis is that smoking, binge drinking, exercising, and holding health insurance increased following HK in non-impacted areas that are vulnerable to future hurricanes in comparison to non-impacted areas not subject to the same vulnerability, and I exploit the fact that individuals reside in counties with different hurricane risks (proxy for risk perceptions) using county-level meteorological and geographical data. Additionally, I also hypothesize increases in stress following HK in the treatment group of non-impacted vulnerable areas if self-medication devices did not fully sterilize the increase in stress.

To obtain measures of behavioral health responses, I use individual-level data from the Behavioral Risk Factor Surveillance System from 2004-2006 for 974,100 adults ($\geq$ 18 years of age) residing in the continental United States, and from 2002-2006 for 1,456,794 adults. After excluding counties directly impacted by HK, I use a difference-in-difference (DD) analysis to compare post-HK outcome measures for individuals residing in counties differentially at-risk to future hurricanes with individuals residing in counties largely impervious to future hurricanes. While objective risks are unlikely to have changed for non-impacted, vulnerable counties after HK, perceptions of these risks may have changed, in particular for individuals residing in areas of greater vulnerability to hurricanes. I estimate the increase in outcomes, controlling for socio-demographic characteristics, month indicators, state indicators, and time-varying environmental and policy characteristics that could affect the outcomes (e.g. cigarette prices). A key identifying assumption is that HK provided variation in behavioral health responses across regions of differential hurricane risks exogenous to migration and economic climate, and I provide evidence to support this.

Ceteris paribus, in non-impacted, vulnerable counties, HK was associated with an increase in stress of six hours per 30 days (6.8% of the mean), an increase in smoking of 2.1 percentage points (10.2% of the mean), and an increase in health insurance coverage of 1.0 percentage points (1.2% of the mean). In counties with the largest exposure to storm surge, binge drinking increased by 2.1 percentage points (14.1% of the mean). I argue that these results exhibit evidence of causality after ruling out the possibility of non-parallel time trends in the pre-HK period and observable population shifts across the different non-impacted hurricane risk regions after HK. While stress, smoking, binge drinking, and health insurance coverage appear to have increased, I do not find evidence that exercise increased after controlling for seasonal considerations. I demonstrate that effect sizes are higher in areas with higher risk, are insensitive to excluding counties within 400 miles of New Orleans, are insensitive to using a synthetic control group analysis, and are insensitive to using a longer pre-HK time trend.

A key challenge for my identification strategy is potential confounding from migration to and from the disaster area. Outcomes may be different for HK evacuees than native residents. If this is true, then the DD estimators will be biased to the extent that evacuees disproportionately moved into the treatment and control groups. Additionally, a large presence of evacuees could endogenously produce changes in employment and crime associated with the outcomes. For example, the population of the Houston, Texas metropolitan area is estimated to have increased by 7 percent from HK evacuees (Hussey, Nikolsko-Rzhevskyy, and Pacurar 2011)—a demographic shift associated with a decline in wages and employment among native Houstonians (McIntosh 2008), as well as an increase in violent crime (Hussey, Nikolsko-Rzhevskyy, and Pacurar 2011).

I address the issue of migration in several ways. First, I exclude counties that were directly impacted by HK, as measured by counties receiving HK federal assistance through a FEMA disaster declaration, because there was large migration throughout this region. I instead focus on areas that are vulnerable to hurricanes but were not impacted directly by HK. For remaining counties, I test for observed differences in socio-demographic characteristics of

gender, race/ethnicity, age, education, employment, marital status, and income before and after the adverse event in the control and treatment groups. I find no evidence of a change in population between these two groups based on observable characteristics. As an additional sensitivity analysis, I use information from approximately 1.3 million FEMA disaster aid applications to identify HK evacuees and the ZIP code of their post-HK dwelling. I use this information to create a county-level variable for evacuees per capita that I include in the analysis as a sensitivity check. Results are unaffected by the inclusion of this control variable. Finally, in another sensitivity analysis, I remove all counties within 400 miles of New Orleans, which includes Houston, home to a large number of refugees and mega-shelters, and find that results are not affected by this removal. In sum, I am able to substantially mitigate confounding from migration.

This paper is related to two strands of literature. The first strand uses home sales data and DD methodologies to estimate the impact of hurricanes as sources of new risk information on property prices. New risk information, such as from an information campaign on radon exposure, has been found to raise risk perceptions (Smith and Johnson 1988). Following Hurricane Andrew that struck Florida in 1992 and controlling for damage and changes in insurance, property values were found to decline in Dade County, which was directly impacted. Property values also decreased in Lee County, a near-miss county, by less than in Dade County (Carbone, Hallstrom, and Smith 2006; Hallstrom and Smith 2005). These results suggest that households notice disasters, even "near miss" disasters, and update risk perceptions in response to this new information. Market responses follow. These responses appear to be temporary rather than permanent: property value differentials disappeared after five years (Bin and Landry 2013).

The second strand of literature relevant to my research relates to the mental health of individuals directly impacted by large-scale disasters. Using longitudinal data, Smith found that a proxy for risk perception, longevity expectations, declined for older adults in Dade County due to a direct hit from Hurricane Andrew (Smith 2008). A recent contribution

by Currie and Rossin-Slater used vital records data to explore the impact of exposure to hurricanes during pregnancy on the probability of stress-related abnormal birth conditions. Stress was found to be a residual explanation on some abnormal birth outcomes after accounting for migration, changes in medical care, and changes in maternal behavior (Currie and Rossin-Slater 2013).

This paper attempts to bridge the literature on market responses in near-miss areas due to risk information provided by hurricanes with literature on behavioral health responses to hurricanes. The paper exploits HK as a unique natural disaster with destructive force not seen in generations. The remainder of the paper is organized as follows: Section II provides information on hurricanes and the damage they can cause, Section III describes the data, Section IV articulates the empirical strategy, Section V presents the results, shows evidence of causality, and shows evidence of risk perceptions as the causal mechanism, and Section VI concludes.

II Background on Hurricane Risks

Hurricanes/typhoons are rapidly-rotating storm systems formed over water with sustained winds of at least 74 miles per hour. Storm surge poses the greatest risk from hurricanes and occurs when a column of water pushed inside and in front of the storm is released over land, causing hydraulic impacts and debris collisions far inland. Storm surge from HK was as high as 25-28 feet and pushed up to 20 miles inland. The United States is particularly vulnerable to storm surge, as much of the country's densely populated Atlantic and Gulf Coast coastlines are less than 10 feet above sea level (NOAA 2013). Further, residents may be unaware and uninsured against the dangers of coastal storm surge flooding because FEMA special flood hazard areas (SFHAs) are defined only for areas at-risk of fresh water flooding.[1] The percentage of homes in storm surge zones, but not in SFHAs, is greater

[1]SFHAs are defined by FEMA as areas with a 1% or greater chance of fresh water flooding in a given year. Since 1973, flood insurance has been required to purchase homes in the SFHA using a mortgage from a federally regulated or insured lender.

than 50% for 11 of 14 major coastal metro areas (Botts et al. 2012). A secondary danger of hurricanes is wind damage, which can extend as far inland as Oklahoma, Arkansas, and Tennessee (Kaplan and Demaria 1995) and can spawn tornadoes. Hurricane-induced tornadoes are heavily concentrated in the immediate coastal areas and typically occur within 12 hours before to 48 hours after the hurricane makes landfall (Schultz and Cecil 2009).

Due to warmer climates and geographical considerations, southern coastal states are more prone to being hit by hurricanes than others. In the 10 years prior to HK, the states with more than two hurricane landfalls are Florida (9), North Carolina (6), and Louisiana (3). The states of Mississippi, South Carolina, Texas, and Virginia were each hit by one or two hurricanes during this time period. Prior to HK, the northeast states of New York, Connecticut, Massachusetts, and Rhode Island had not seen a hurricane since Hurricane Bob in 1991 (NOAA 2008).

III Data

A Primary Data

The primary data are provided by the Behavioral Risk Factor Surveillance System (BRFSS). State health departments and the Centers for Disease Control and Prevention (CDC) collect these cross-sectional data on risky personal health behaviors via landline telephone surveys of individuals aged 18 years and older. The data are nation- and state-representative of the non-institutionalized population. The data identify 100% of respondents' states and counties of residence and date of interviews, as well as a variety of socio-demographic characteristics including gender, race/ethnicity, age, education, employment/labor force participation, marital status, and income. For the primary analysis, I use data from 2004, 2005, and 2006, with HK roughly in the middle, on August 25, 2005. I also perform a sensitivity analysis by adding data from 2002 and 2003 to the pre-HK period, and find that baseline results and time trend parallelism changed little when using a longer

pre-HK time trend. I use the shorter window of time for my primary analysis to reduce the computation burden.

As a proxy for stress, survey respondents are asked a standard question of recent emotional and mental distress: "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?" These data are heavily rightward skewed, with 65.6% of individuals reporting having 0 days of stress and 4.8% reporting having 30 days of stress. The remaining 29.6% report integer values between 1 and 29.

For smoking, survey respondents are asked if they have smoked 100 or more cigarettes in their lifetime and, if so, if they have smoked over the past 30 days. If the individual answers yes to both questions, then I classify them as a smoker. For binge drinking, individuals are asked if they have consumed 5 or more drinks on any one occasion over the past 30 days, but starting in 2006 this number was reduced to 4 or more drinks for women. For exercise, individuals were asked: "During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?" For health insurance, individuals are asked: "Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare?"

Summary statistics for the raw data and population weighted data are reported in Appendix Table A1. Men, racial/ethnic minorities, and younger individuals are underrepresented in the raw data, so I use the population weighted data in all regression analyses. In the sample, from 2004 to 2006, 76% of individuals exercised, 20.2% smoked, and 14.9% binge drank (all three defined over the course of 30 days). Health insurance was held by 83.9%. On average, individuals experienced 3.4 days of stress over the past 30 days.

B Secondary Data

Data from the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) system are used to determine counties at-risk of storm surge depending on hurricane category strength.[2] I use these data to proxy increases in risk perception following HK. In addition to strength, this system takes into account land elevation, unique bay and river configurations, water depths, rainfall, and physical features such as bridges, roads, and levees. The SLOSH data were overlaid with county borders to determine for each category of hurricane if any part of the county was in the SLOSH plane. Coastal counties are always in the SLOSH plane, and in some areas the SLOSH plane extends deeper inland.

I use the inland wind decay model developed by Kaplan and DeMaria to identify counties outside of the storm surge region but potentially still vulnerable to wind damage, including tornado damage, from hurricanes (Kaplan and DeMaria 1995). This model takes into account increased penetration of dangerous wind speeds for stronger hurricanes, but it does not take into account the changing topography or other possible local factors that may affect wind speed. Similar to the SLOSH data, the wind data were overlaid with county borders to determine for each category of hurricane if any part of the county could be affected by strong gale strength wind damage of 47 miles per hour. This wind strength category was chosen because this is the point at which winds begin to cause structural damage. The wind data extend much further inland than in the SLOSH model and vary more greatly by hurricane category strength.

To avoid confounding from the actual disruption in the HK-impacted counties, two additional sources of data are used. The first identifies counties that received any federal assistance because of HK. These counties include all of Louisiana and Mississippi, west Alabama, and west and south Florida.[3] These counties are excluded from the analysis to avoid

[2]Hurricane categories operate on a scale of 1-5, with five being the worst. Upon landfall, HK was a strong category 3 hurricane. From 1851-2004, only three category five hurricanes have struck the United States, (NOAA 2008) although many, including HK, have been category 5 hurricanes at some point at sea.

[3]In route to striking New Orleans on August 29, 2005, HK struck the southern coast of Florida on August 25, 2005.

capturing disruption from the actual hurricane rather than changes in risk perception.

The second source is ZIP code-level FEMA application information for aid as of September 23, 2005, approximately one month after HK, providing evacuee information for 1.3 million applicants with valid ZIP codes in the continental United States. I was able to match 97% of these ZIP codes to a county.[4] In my preliminary analysis, confounding from migration is addressed using two mechanisms: 1) removing counties directly impacted by HK as measured by counties receiving federal disaster assistance, and 2) controlling in some specifications for FEMA applicants per capita in the post-HK period to address the possibility that influxes of evacuees caused changes in outcomes. I also confirm that the population composition did not change between hurricane risk regions in the post-HK period.

A map showing counties at risk of storm surge and wind damage from a category 3 hurricane, as well as excluded directly impacted counties (that received federal disaster aid), is presented in Figure 1.

[Insert Figure 1]

Also shown in Figure 1 is six regions that I create from counties not impacted by HK and not vulnerable to storm surge or wind damage from hurricanes. I use these regions in later synthetic control group analysis.[5]

Other merged data are used to control for environmental differences. Cigarette price data from the Tax Burden on Tobacco (Orzechowski and Walker 2009) and smoke-free air law data from the ImpacTeen project were included in the smoking prevalence model. The American Chamber of Commerce Researchers Association (ACCRA) Cost of Living Index quarterly beer data were aggregated to the state level and was used as a proxy for alcohol prices[6] in

[4]For cases in which an applicant's ZIP codes overlapped two or more county borders, I partially assigned the application to each county depending on number of residential ZIP codes in each county.

[5]Placebo regions include all or most of four census divisions, Pacific coastal counties (which may be unobservably correlated with Atlantic coastal counties that are at-risk of storm surge), and remaining counties not impacted by storm surge or wind damage from a category 3 hurricane.

[6]No price data are provided for New Hampshire and until 2006 for Maine, so these states are subset from the analysis in models of binge drinking. Additionally, Pennsylvania liquor control board restrictions result in the ACCRA prices being much higher than typical prices of beer purchased there (Ruhm et al. 2012), so I discard Pennsylvania as well in models of binge drinking.

the binge drinking model, along with pub smoking restrictions. All monetary values were deflated to 2004 dollars using the consumer price index, city average. Monthly state-level unemployment data are used to construct a state-level unemployment rate to control for spillover effects of unemployment beyond individual-level employment status.

IV Empirical Framework

In this paper, I test the conjecture that HK led to behavioral health responses in non-impacted, but vulnerable areas. In the most basic specification, I separately estimate the amount of stress or the probability that an individual smokes, binge drinks, exercises, or is insured as a function of individual controls and DD estimators for post-HK counties at risk to hurricanes. Using the BRFSS data and excluding counties directly impacted by HK, I estimate this preliminary model:

$$\begin{aligned} y_{irt} &= \alpha + \beta_1 hurricane\_risk_r + \beta_2 post_t + \beta_3 hurricane\_risk_r * post_t + \\ &\quad \beta_4 X_{irt} + \epsilon_{irt} \end{aligned} \tag{1}$$

where y_{irt} is one of five outcomes. It is either equal to 1 if individual i living in region r at time t has smoked, binge drank, or exercised in the past 30 days or has health insurance, or is equal to the number of days of stress over the past 30 days (outcomes analyzed separately). X_{irt} is a set of controls at the individual level: gender, race/ethnicity, household income, household income squared, top income category, age, age squared, education attainment, marital status, and employment status. Post_t is equal to 0 before the initial impact of HK in Florida in August 25, 2005, and is equal to one 15 days after this initial impact. I use a delay to minimize confounding from supply disruptions in the immediate aftermath of HK, which shut the Port of New Orleans for two weeks (Alexander and Irwin 2005). Hurricane_risk_r includes three regions: non-impacted counties at-risk of storm surge from a category 3 hurricane, non-impacted counties at-risk of wind damage only from a category

3 hurricane, and control counties in the interior and west.[7] I hypothesize that individuals living in non-impacted counties vulnerable to storm surge experienced increases in behavioral health outcomes following HK. Increases in the non-impacted storm surge counties are expected to be greater than increases in the non-impacted wind damage only counties because the relative risk is greater and risk perception increases should be larger. Utilizing two treatment groups with varying levels of hurricane risks, each of which is compared to the control group, presents an opportunity to test for internal model validity. In all regressions, survey weights are used and standard errors are clustered within states.[8]

I re-estimate (1) by adding environmental characteristics of state-level unemployment rates to all models, smoke-free air laws and after-tax cigarette prices to smoking models, and pub smoking restrictions and after-tax alcohol prices to binge drinking models. Following, I iteratively add state indicators and then month indicators. My baseline model is specified as:

$$\begin{aligned} y_{irstm} &= \alpha + \beta_1 hurricane\_risk_r + \beta_2 post_t + \beta_3 hurricane\_risk_r * post_t + \\ &\quad \beta_4 X_{irstm} + \beta_5 environment_{st} + \zeta_s + \lambda_m + \epsilon_{irstm} \end{aligned} \tag{2}$$

This specification allows me to exploit variation in outcomes within each state, as well as remove seasonal considerations in outcome variables.

I find evidence from a joint test of significance of the presence of heterogeneity in exercise within months across the hurricane risk regions. It appears that exercise declined by more in the control counties than the storm surge counties in winter months, potentially due to harsher winters that limit opportunities for exercise. Therefore, in models of exercise with month indicators, I allow month to vary by hurricane risk region. I found no evidence of

[7] In later analyses I recalibrate results for category 1 and category 5 hurricanes.

[8] In all regressions I cluster standard errors using 794 unique clusters provided in the data. These clusters are perfectly nested within states. I also recalculated base model results by creating and using 1,150 unique clusters that are perfectly nested within states and hurricane risk regions. Standard errors remained virtually identical.

heterogeneity within regions by month for the other outcomes.

Finally, I estimate each model controlling for HK evacuees per capita at the county level in the post-HK period. This serves as a check for how sensitive my results are to migration from the impacted counties to the non-impacted counties.

I estimate the probability of smoking, binge drinking, exercising, and having health insurance with a logit model. For stress, I use a generalized linear model with a logarithmic link and a Gaussian variance function as chosen by the modified Park test for use with non-negative skewed dependent variables as recommended by Manning and Mullahy (2001). This modeling technique has been used in at least one behavioral health context to model conditional cigarette demand (Tauras 2006). I apply this modelling technique anew to the number of days that mental health is not good over 30 days. I convert all estimates to marginal effects to assist with interpretation.

V Econometric Results

A Associations

In all analyses, I exclude counties directly impacted by HK. The DD estimators for both the storm surge region and wind damage only region are provided for each of the five dependent variables (days of stress, smoking, binge drinking, health insurance, and exercise) across five different specifications that iteratively adds controls for socio-demographic characteristics, environmental characteristics, state indicators, month indicators, and a DD estimator for evacuees per capita. My variable of primary interest is the DD estimator for the storm surge region.

These preliminary results for stress and substance use outcomes are provided in Table 1. I initially regress socio-demographic controls and the DD estimators for the storm surge region and wind damage only region on stress in the first column. I show that HK was associated with 0.25 days of extra stress (7.4% of the mean) per 30 days in the storm surge

region for the period from September 10, 2005 to the end of 2005. I next rule out the possibility that this increase in stress is associated with changing state-level unemployment rates after HK (column 2), time-invariant unobservables across states (column 3), and time-invariant unobservables for a given month (column 4). Finally, I find no effect of the number of evacuees per capita being associated with the increase in stress in the storm surge region (column 5). The coefficient on the DD estimator for the storm surge region remained stable across these five specifications. The finding that stress in the wind damage only region had insignificant coefficients roughly 20% of that in the storm surge region provides evidence of internal model validity, as I would not expect the coefficient in this region to be larger than that for the storm surge region due to the higher risks in the storm surge region.

[Insert Table 1]

For the two substance use dependent variables, I repeat the same sequence of estimations. For smoking and binge drinking, price data and smoking restriction data are included as environmental controls in addition to unemployment rates. Smoking prevalence was associated with HK in the non-impacted storm surge counties, increasing by 2.1 percentage points (10.2% of the mean) in the column 4 baseline specification. This effect was roughly three times greater than the insignificant coefficient in the wind damage only region, and remained consistent across the different specifications. Unlike smoking, I do not find evidence of an increase in binge drinking associated with HK when using all storm surge counties.[9]

I next turn to analyzing when and for how long increases in stress and smoking occurred. I first re-estimate Table 1 adding data from 2006 to observe if HK is associated with increases in stress and smoking through 2006. Due to the revision in how females are asked about binge drinking in 2006, I am unable to calculate a DD estimate for this outcome using the longer time horizon. I show in online Appendix Table A2 that there is no evidence of an association with stress or smoking in the 16 months following HK, suggesting that the

[9]In upcoming analyses, I demonstrate that binge drinking did substantively increase in storm surge counties with above the median surface area exposure to storm surge from hurricanes.

association is temporary and stress and smoking return to baseline relatively quickly.

But how quickly? In online Appendix Table A3, I remove wind damage only counties and present a breakdown of the results for the first three quarters after the disaster. In my baseline specification HK was only associated with increases in stress and smoking in the storm surge region in the quarter immediately following the disaster. In Table 2, I further decompose the associations for the first 90 days after HK. I find that HK was associated with stress in only the first 30 day interval after HK (Sept. 9-Oct. 9, 2005). During this period of time, individuals in the storm surge region experienced nearly a half of an extra day of stress per 30 days (13.2% increase from the mean). Coefficients remain positive in periods 2 and 3, but decline to $\frac{1}{5}$th and then to $\frac{1}{7}$th of an extra day of stress, and these differences are no longer statistically significant. Smoking declined to baseline more slowly, potentially due to addiction, as statistically significant differences were observed in the first two 30-day intervals post-HK. Binge drinking did not increase in any of the first three months, consistent with earlier findings of no increase in the 4 months post-HK when using the full sample of storm surge counties. To answer how quickly stress and smoking returned to baseline, it appears that stress remained elevated for roughly one month and smoking for two.

[Insert Table 2]

Results for health insurance and exercise are presented in Table 3. DD estimators for four months after HK are presented in panel A (i.e. 2004-2005 sample) and sixteen months after HK are presented in panel B (i.e. 2004-2006 sample). For health insurance, the baseline specification (column 4) suggests that coverage increases by 1.0 percentage points (1.2% from the mean) in the storm surge region relative to the control region in both the 4 month and 16 month period after HK, although this difference is only significant across all specifications in the longer term.[10] The coefficient is also positive, but smaller, for the wind damage only region. HK may have encouraged individuals residing in non-impacted vulnerable counties

[10]The association is significant in the 4 month post-HK period when state and month indicators are not used.

to obtain health insurance.

[Insert Table 3]

In specifications 1-3 I initially find evidence of an increase in exercise in the non-impacted storm surge region following HK compared to the control region in the first four months after HK, but this association disappears after controlling for month-region indicators in specifications 4-5.[11] In the sixteen month post-HK period I find no association between exercise and HK in any specification. In sum, exercise appears to be the only behavioral health response that did not increase after HK.

I stratify health insurance results by age. Most United States citizens 65 and older have access to government-provided health insurance through Medicare, so I do not expect changes to occur within this population in response to HK. Young adults, however, are the population least likely to be insured and so changes in their demand for health insurance could lead to more purchases made on the open market, or migration to employment with health insurance benefits. In online Appendix Table A4, I present a breakdown of the health insurance results for age categories of 18-30, 31-64, and $\geq$65. I find that in the four months after HK, HK was associated with a self-reported health insurance coverage increase of 3.2 percentage points (4.5% of the mean) in the storm surge region relative to the control region for the 18-30 year old population. This is in comparison to an insignificant increase of 0.2 percentage points for the other two age groups. The increase for young adults in the storm surge region is attenuated over the 16 month post-HK period to a 2.4 percentage point increase (3.4% of the mean). In sum, it appears from this analysis that HK was associated with an immediate increase in health insurance coverage among young adults $\leq$30 years of age residing in the storm surge region compared to the control region.

In these results, level of risk perception has been explored by comparing effects in regions

[11] Month-region indicators are jointly significant in the model for exercise, but not in models for the other outcomes. Nevertheless, when I allow month to vary by region for the other outcomes, the estimated magnitudes of the association between the outcomes and HK in the non-impacted storm surge counties increases (results available upon request).

of different hurricane risks: storm surge counties, wind damage only counties, and control counties. I further explore the influence of risk perceptions on these results by excluding the wind damage only counties and dividing storm surge counties into a high-exposure group with above the median surface area exposure to storm surge from hurricanes (7.2% of the mean), and another with at or below the median surface area exposure to storm surge from hurricanes. Surface area exposure is an imperfect measure of risk because it does not capture where individuals actually live, work, and visit, which may be disproportionately clustered in or out of the storm surge plane. Nevertheless, to the extent that residents are equally dispersed throughout a county, a high amount of the county being vulnerable to storm surge is predicted to increase risk perceptions for more people. I expect behavioral health responses to be larger in counties with larger storm surge exposure.

Results in Table 4 provide further evidence in support of level of risk affecting outcomes. In the baseline specification (column 4), stress increased by $\frac{1}{3}$rd of an extra day per 30 days (9.8% of the mean) in counties with high surface area exposure to hurricanes. Smoking increased by roughly similar percentage points in both regions. Binge drinking is also found to increase in high risk counties by 2.1 percentage points (14.1%). While the coefficients on health insurance and exercise are not statistically different from zero, both are larger in the high exposure storm surge counties than in the lower exposure counties. Taken together, these results provide evidence that larger risk (proxy for risk perceptions) is associated with larger behavioral health responses.

[Insert Table 4]

HK was associated with substantive behavioral health responses. Approximately 44.4 million adults lived in the storm surge counties in 2005, so estimates suggest that these individuals experienced a total of 19.8 million days of extra stress in the first 30 days, and 930,000 of these individuals smoked in the first quarter than would have if HK had not occurred. Binge drinking increased in high exposure storm surge counties by 510,000 individuals. Self-medication devices did not fully sterilize the increase in stress. While these

effects were short-lived, in the conclusion I discuss how even short-term smoking may have life-threatening consequences for both smokers and others. Potentially in response to this deterioration in behavioral health, approximately 440,000 young adults were insured for at least a year that would not otherwise have been.

B Causal Evidence

A key assumption in a DD model for claims of causality is that the event must be uncorrelated with pre-existing differences in outcome trends. If this assumption is violated, then the DD estimators will be biased. I test for this by estimating (3) using a flexible functional form for time, 13 quarters from 2004 to 2006,[12] and controlling for socio-demographic characteristics, time varying controls, and time invariant state and month characteristics. In particular, I estimate:

$$\begin{aligned} y_{irstm} &= \alpha + \beta_1 hurricane\_risk_r(D_{t-7} + \cdots + D_0 + \cdots + D_{t+6}) + \\ &\quad \beta_2 X_{irstm} + \beta_3 environment_{ist} + \zeta_s + \lambda_m + \epsilon_{irstm} \end{aligned} \tag{3}$$

Following, I examine the joint significance of the interactions between the regions and the quarters in the pre-HK period to determine if the parallel time trends assumption is violated.

The parallel time trends assumption is met for all outcomes except exercise. Results available in online Appendix Table A5 show that smoking and health insurance coverage were not different between the storm surge region and control region in the pre-HK period in any quarter (compared to the first quarter) or jointly (i.e. across all quarters). Stress was different in one quarter (compared to the first quarter), exercise in two quarters, and binge drinking in four quarters, but joint tests of significance found that the time trends were jointly different for only exercise across these two regions in the pre-HK period. A linear regression of these coefficients suggests that exercise is increasing in the storm surge region

[12] I divide the 3rd quarter of 2005, when HK made landfall, into two separate quarters.

relative to the control region over time, which overestimates any causal effect. I do not find evidence of an effect regardless, since HK is not associated with exercise in the storm surge region relative to the control region. In results available upon request, I also redid the time trend analysis excluding wind damage only counties and dividing storm surge counties into groups with above and below the median of storm surge surface area exposure and again found that the time trend only differed in the pre-HK period for exercise. Results were identical for both analyses when using a period of 2002-2006, with the exception that health insurance also had a divergent time trend. A linear regression of the coefficients suggests that health insurance declined over the longer pre-HK period in the storm surge region relative to the control region, which underestimates the causal effect.

Graphical evidence from (3), replacing quarter time intervals with month time intervals, is provided in Figure 2 for the four outcomes besides exercise. To produce this graph, I first subtracted the predicted value for the storm surge region from the predicted value for the control region for each month for each outcome. Following, to standardize these predicted value differences, I subtracted the predicted value means and divided by the predicted value standard deviations. Spikes in the outcomes can be interpreted as that outcome being relatively large in the storm surge region relative to the control region.

[Insert Figure 2]

The graphical evidence shows discontinuous increases for behavioral health responses in the storm surge region relative to the control region following HK. The differences appear to decay relatively quickly for stress and less quickly for smoking and health insurance coverage. Binge drinking is not displayed on this graph for 2006 because of the question wording change affecting women, but in online Figure 1, I provide graphical evidence for women in 2004-2005 and for men in 2004-2006. This graph suggests that the response following HK was similar for both women and men in 2005, and for men the temporary increase in binge drinking subsided four months after HK. This graphical evidence suggests that stress declined to baseline first,

followed by substance use a few months later. Health insurance coverage remained elevated throughout the study period.

Another key assumption for valid inference is that observable population characteristics for each region should not diverge between the pre-HK period and the post-HK period. Table 5 provides results testing for possible divergence in the post-HK period in observable characteristics (e.g. gender, race/ethnicity) between the different hurricane risk regions. In 14 tests that I performed across post-HK periods of 4 months and 16 months, only one socio-demographic group exhibits statistically significant changes between the regions after HK at a 10 percent level.[13] This is within the range that can be expected from random chance. It appears that excluding counties directly impacted by HK has provided a stable population across remaining regions after HK,[14] therefore meeting a key assumption for DD modeling and suggesting that evacuees did not disproportionately move into any region.

[Insert Table 5]

In a later section, I investigate the possibility of HK evacuees affecting the composition of the hurricane risk regions in ways that lead to spurious results. I remove all counties within 400 miles of New Orleans, including Houston, which sheltered an unusually high number of evacuees. I find that my results are unaffected by using this more restrictive sample.

I perform two sets of falsification exercises. The first uses a date of HK of one year prior. If there are any differential time trends between the storm surge and wind damage only counties and control counties, then I may observe significant, spurious effects in the year prior to HK. The results are presented in online Appendix Table A6 and suggest that the model passes the test for the storm surge region, with none of the coefficients statistically significant.

[13] In the 16 months after HK, results suggest that an increase in Asian Americans and individuals with missing race/ethnicity in the storm surge region relative to other regions contributed to the significant change of race/ethnicity at a 10 percent level. I am unaware of any reason for this population to have increased its presence in the storm surge region following HK, so assume that this is a Type 1 error.

[14] When non-impacted counties are not excluded and included as their own region, this test fails for race/ethnicity in the 4 months after HK, and for race/ethnicity, education and employment in the 16 months after HK. Excluding directly impacted counties, which I do in all analyses, is important for addressing confounding from migration.

However, there is evidence that the time trend for stress may be different between the wind damage only region and the control region. This finding is not particularly troublesome given that I use the wind damage only counties solely as a validity check on my main results of interest for the storm surge counties.

For a second falsification exercise, I perform a synthetic control group analysis (Abadie, Diamond, and Hainmueller 2010). I adopt this methodology for use with survey data. The idea behind the synthetic control method is that a combination of units often provides a better comparison for the unit exposed to the intervention than any single unit alone. I used survey data and control variables of socio-demographic characteristics, environmental characteristics, and state indicators to produce predicted values for each dependent variable in each month in each of seven regions.[15] I used all 20 pre-HK lagged levels of the predicted values for the outcome as matching variables and constructed a synthetic control group to calculate a DD estimate for the storm surge region. Following this, I perform a series of placebo studies by iteratively applying this same process to estimate the effect of HK in each of the other six regions previously used in the donor pool.[16] That is, I proceed as if individuals living in other regions, rather than the storm surge region, had reason to suddenly increase behavioral health responses following HK. This iterative procedure produces estimated effects of HK in each region. I hypothesize that the estimated effect should be largest in the storm surge counties compared to the placebo regions.

Results from the synthetic control group analysis for all storm surge counties (Table 6, panel A) are in line with baseline results.[17] Stress was found to increase to 0.19 days per 30 days in storm surge counties using the synthetic control group analysis compared to 0.23

[15]These regions are presented in the bottom of Figure 1 and include non-impacted storm surge counties, four census divisions, Pacific coastal counties, and remaining counties that were not impacted by HK and are not vulnerable to storm surge or wind damage from a category 3 hurricane. I use regions rather than state because of a heavy computation burden in producing risk adjusted monthly predicted values for all states.

[16]The storm surge region is added to the donor pool for these placebo analyses.

[17]Baseline results refer to column 4 in Table 1 for stress, smoking, and binge drinking, column 4 in Table 3, panel A for health insurance, and all results in Table 4 for high exposure storm surge counties (minus exercise).

days per 30 days in baseline results. Smoking increased to 2.6 percentage points (compared to 2.1), binge drinking to 1.0 percentage points (compared to 1.0), and health insurance coverage to 1.3 percentage points (compared to 1.0). The effect sizes in the storm surge counties were the largest for all outcomes except stress, where the effect size was the second largest. This means that only 1 falsification exercise out of 24 failed (4.2%). Also of comfort is that except for the storm surge counties, there is no discernable pattern of effect sizes being larger or smaller in any one region in particular.

[Insert Table 6]

In line with earlier estimates, effect sizes are larger in counties with greater storm surge surface area exposure (Table 6, panel B). I redo the synthetic control group analysis excluding counties with less than or equal to the median surface area exposure. In high exposure counties, stress now increases 0.35 days per 30 days, smoking 3.4 percentage points, binge drinking 2.4 percentage points, and health insurance coverage to 1.4 percentage points. For all four outcomes effect sizes in the high exposure storm surge region are the largest, meaning that 0 out of 24 falsification exercises fail.

Finally, in online Appendix Table A7, I check the sensitivity of my baseline results to using a longer pre-HK time trend starting in 2002. Stress was found to increase to 0.30 days per 30 days in storm surge counties using the longer pre-HK time trend compared to 0.23 days per 30 days in baseline results.[18] Smoking increased to 2.6 percentage points (compared to 2.1), binge drinking to 0.7 percentage points (compared to 1.0), and health insurance coverage to 1.0 percent points (unchanged from before). In sum, using a longer pre-HK time trend results in a strengthening of the effect size for stress and smoking, and an attenuation of the effect size for binge drinking, but coefficients do not change dramatically.

Taken together, these results suggest that associations reported earlier for stress, smoking, binge drinking, and health insurance exhibit evidence of causality. Parallel time trends

[18]This coefficient is now significant at the 5% level compared to a 10% level found using the 2004-2005 time period.

appear to be met by finding that a flexible functional form for time did not vary across regions in the pre-HK period, and falsification exercises provide additional assurances. I find no evidence of a changed population composition after HK.

C Mechanism

I now turn to providing evidence that risk perceptions mediate the impact of HK on the demand for behavioral health and health insurance. I go beyond efforts I made when constructing the model to avoid confounding economic disruption and individual risk (a proxy for risk perceptions). Media attention may have contributed to individuals that live in counties vulnerable to hurricanes to focus on being harmed by a future hurricane rather than on the small probability of this occurring (Sunstein 2003). Economists have also found evidence for the substantial overweighting of small probabilities in deductible choices for home and auto insurance (Barseghyan et al. 2013).

I first remove counties within 400 miles from New Orleans. These counties arguably have stronger economic ties with New Orleans than counties further away, and so post-HK responses in these areas may be associated with changes in economic climate rather than changes in risk perception. Since directly impacted counties are already excluded, this additional restriction removes some counties in Texas and Florida that are nearer to New Orleans, as well as some wind damage only and control counties. Included in this removal is Houston, which as of May 2006 still had 153,000 HK evacuees, 15 times more than any other Texas city (Pullin 2006). The primary purpose of this test is to observe if results are strongly influenced by counties with stronger economic ties to New Orleans, a major shipping city, which would suggest that economic disruption is a mechanism underlying the relationship

between HK and outcomes.[19]

Results in Table 7 are largely unchanged from baseline results. To the extent that economic disruption is correlated with proximity to New Orleans after HK, this finding provides evidence that economic disruption is not driving the observed behavioral health responses.

[Insert Table 7]

I perform another test that compares responses in areas of differential risk by removing the wind damage only counties and testing for heterogeneity in responses to HK by hurricane probability regions. This adds to the tests I performed earlier comparing responses in storm surge areas to wind damage only areas, and comparing responses in counties with greater surface area exposure to those with less exposure. To perform this test, I divide the storm surge counties into a region south of, and including, North Carolina and a region north of, and including, Virginia.[20] If risk perceptions are a mechanism through which HK affects outcomes, then I expect to find larger responses in the southern region with a higher probability of any hurricane.[21]

Table 8 supports this theory. The DD estimators in models of stress, smoking, and binge drinking are larger in southern storm surge counties, the region with a greater chance of any hurricane in a given year, than in the north. The coefficients on stress, smoking, and binge drinking are respectively 1.5, 2.2, and 2.5 times larger in the southern regions. These differences became larger when I removed counties with below the median surface area

[19] Many of the counties with large numbers of evacuees and arguably stronger economic ties are already excluded from the analysis because they were directly impacted by HK. Further, most of the economic disruption occurred in the immediate days after HK, and I already exclude the first 15 days from the analysis. DD estimators are independent of state-level unemployment rates and individual employment status. Finally, results hinging on economic disruption or migration would require either to be disproportionately larger in the storm surge region compared to the control region. In particular, it seems unlikely that economic disruption in the storm surge region was greater considering that the storm surge region has greater availability of other ports and less reliance on the Mississippi River than the control region.

[20] After excluding Louisiana and Mississippi, these southern states have experienced 81% of all hurricane landfalls of any category strength, and 83% of all hurricane landfalls of category 3 and higher strength (Tropical Meteorology Project).

[21] This test assumes that HK was unique and individuals living in the southern region, which is more frequently struck by hurricanes, still learned new information from HK. If hurricane experience in the southern region reduces behavioral health responses, this will bias coefficients toward the null in this region. Despite this possibility, I find larger effects in the southern region.

exposure. However, in both regions the increase in health insurance does not display this same variation depending on hurricane probability region, remaining near the one percentage point increase range observed in the baseline results. Taken together, these results provide evidence that risk perceptions are a possible mechanism through which HK affects stress, smoking, and binge drinking.

[Insert Table 8]

Additionally, I test if risk perceptions mediate the relationship between HK and outcomes by recalibrating the model and comparing results for category 1 and 5 hurricanes instead of a category 3 hurricane. While the percentage of individuals residing in the storm surge region for a category 1 or 5 hurricane changes little (from 19.9% to 20.2%), the percentage of individuals residing in the wind damage only counties varies greatly (14.1% to 29.6%) due to wider reach of wind damage from hurricanes. The number of control counties are reduced when the wind damage only counties increase, so DD estimators in this sensitivity analysis are calculated using different control counties. If risk perceptions are a mechanism through which HK affects outcomes, then I would expect the DD estimators to be larger for a category 5 hurricane than for a category 1 hurricane, as well as larger in the storm surge region than in the wind damage only region.

Results from this sensitivity analysis are presented in Table 9. Regardless of hurricane category strength, results are broadly consistent with baseline findings. For all four outcomes, the DD estimate becomes larger for the category 5 storm surge region compared to the category 1 storm surge region. This provides additional evidence that risk perceptions are a mechanism underlying the causal relationship between HK and outcomes.

[Insert Table 9]

I provide evidence that risk perceptions are a possible mechanism through which HK affects stress, substance use, and health insurance. I exploit disproportionate risks from

hurricanes by considering: 1) storm surge versus wind damage only, 2) storm surge counties with high versus low surface area exposure to hurricanes, 3) hurricane category strengths with larger as opposed to smaller impacts, and 4) regions with higher versus lower probabilities of any hurricane. With few exceptions, these results suggest that when"risk" is increased, so are the effect sizes on outcomes of stress, smoking, binge drinking, and health insurance. This points to risk perceptions as a possible mechanism since subjective risk perceptions may have increased post-HK in areas with actual objective risk, and differentially based on the level of the objective risk. Further, other possible mechanisms such as uncontrolled migration and economic considerations do not appear to drive the results to the extent that these are correlated with distance from New Orleans (within 400 miles). In sum, there is evidence that risk perception changes for individuals residing in non-impacted areas with hurricane risks mediate the causal relationship between HK and outcomes.

VI Conclusion

This study uses an unprecedented large-scale disaster, HK, as a natural experiment to study how increases in risk perceptions affect behavioral health and health insurance. A DD analysis is used to exploit differences in risks from hurricanes across counties of residence. I find causal evidence that HK increased stress in storm surge counties compared to the control counties by 6.8%, smoking by 10.2%, and binge drinking in the highly vulnerable storm surge counties by 14.1%. Health insurance increased by 1.2% in the 16 months following HK in the storm surge region, contributing to an estimated 440,000 young adults holding health insurance for at least a year that would not otherwise have been insured.

The effects of HK on stress, smoking, and binge drinking appear to have been short-lived; nevertheless, even short-term use of these substances has health consequences and negative externalities according to a report issued by Doe and colleagues (2009). Smoking immediately increases blood pressure, heart rate, and constricts blood vessels, leading to

increased risk for sudden strokes and myocardial infarction. Additionally, smoking immediately increases susceptibility to pneumonia. Smoking and second-hand smoke interferes with drug breakdown processes for certain blood-thinners, antidepressants, and anti-seizure medications, causing prescription drugs to not work as effectively and for drugs to potentially stay in the body at dangerous concentrations for longer. Finally, infants and children are especially susceptible to secondhand smoke exposure, so temporary smoking may have affected outcomes of birth weight, sudden infant death syndrome, and infant middle ear and respiratory infections (Doe et al. 2009). Impaired driving is a possible consequence of short-term increases in binge drinking.

It appears that risk perceptions are informative in increasing demand for health insurance among young adults. With the Affordable Care Acts' emphasis on enrolling individuals, in particular young adults, into health insurance plans on a voluntary basis, results from this study suggest that an effective strategy for motivating young adults to enroll may be to alter risk perceptions by focusing on risks, such as risks of not being insured and from natural disasters.

Research suggests that the most effective government response to the public's miscalculating of small probabilities may be information and education (Becker and Rubinstein 2011; Sunstein 2003). An example of a benefit of information and education is that following a Mississippi River flood, home prices fell only in flooded areas outside the SFHA, but prices did not fall in the SFHA. This may have been because individuals in the SFHA were more likely to know of flooding risks *ex-ante* because of notification and insurance requirements, and so home prices already reflected accurate risk perceptions (Carolyn 2010). Similarly, behavioral health responses to HK may not have been as dramatic if individuals were better informed of accurate risks in advance. Mandating notification for home owners and renters living in the storm surge plane similar to the notification individuals receive when living in SFHAs may help prevent sudden behavioral health responses to unusually destructive hurricanes.

Studying the simultaneous relationships among explored and omitted behavioral health responses in response to large-scale disasters may be a ripe area for future research. In this study, I did not attempt to disentangle how behavioral health responses may have impacted each other. For example, while I calculate the causal impact that HK had on stress in the treatment region, this effect may have been greater if individuals did not self-medicate. Similarly, increased smoking following HK may precipitate increased binge drinking, and decreases in behavioral health in general may stimulate the demand for health insurance. I also cannot rule out the possibility that other outcomes affected by post-HK risk perception changes influence the results for the outcomes that I do document; for example, property values may have declined in the storm surge region in response to HK, driven by changes in risk perception, and that contributed to behavioral health changes. It is worth noting that due to possible simultaneous relationships, a policy option affecting any one behavioral health response could have spillover effects on others. It is also worth noting that possible simultaneous relationships do not affect my primary conclusion that HK increased behavioral health responses of stress, smoking, binge drinking, and having health insurance in substantive ways in non-impacted areas vulnerable to future hurricanes.

The results of this study provide evidence of the impact that risk perceptions have on behavioral health responses. Natural disasters are only one example of something that can alter risk perceptions. Crime and terrorism affect risk perceptions on a macro-level, and on a micro-level so do employment and relationships. Risk perceptions stemming from these risks may also have large-scale secondary effects.

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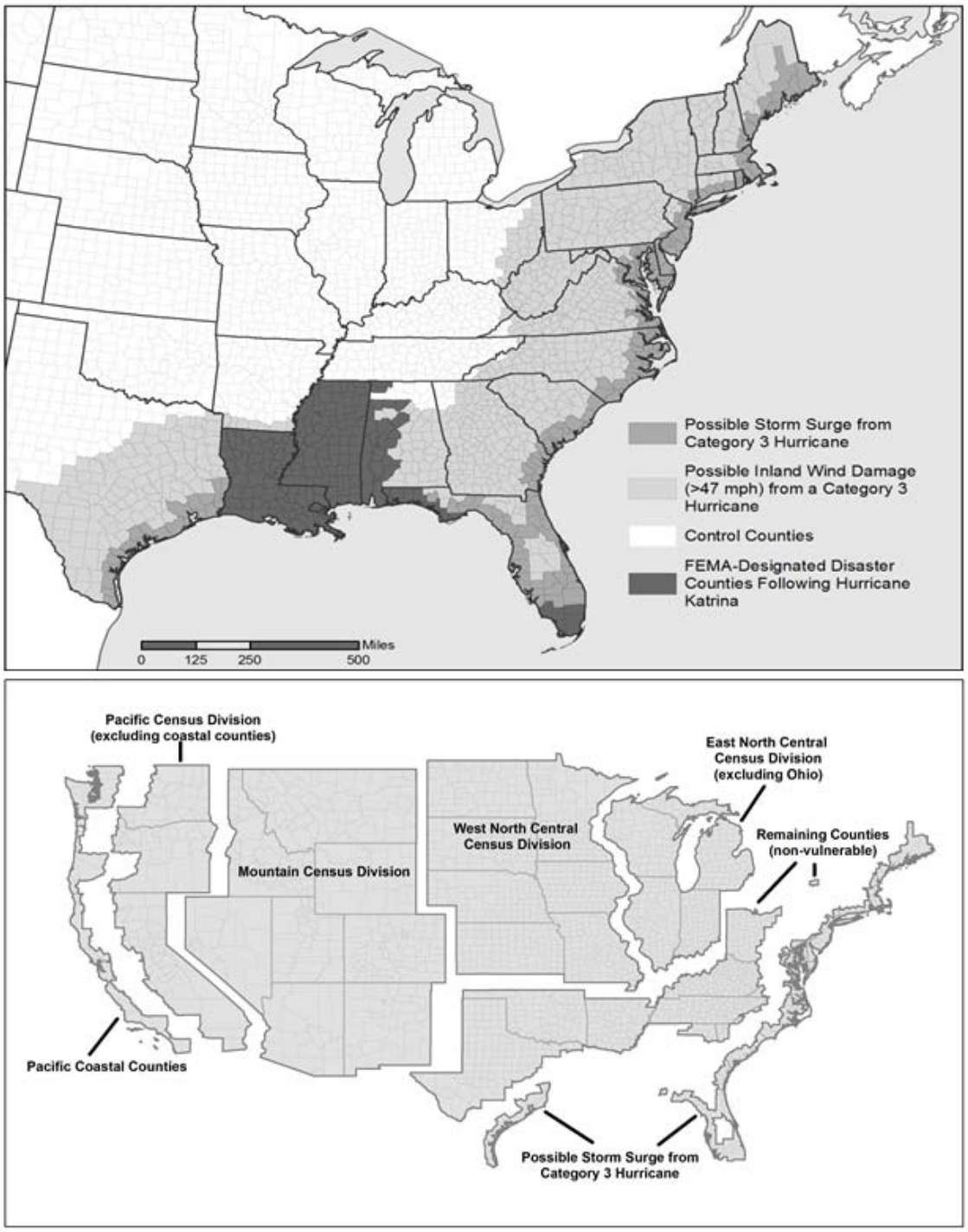


FIGURE 1. HURRICANE RISK REGIONS, DIRECTLY IMPACTED COUNTIES, AND SYNTHETIC CONTROL REGIONS

Notes: The storm surge counties are identified using the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) system maintained by the National Oceanic and Atmospheric Administration. The wind damage only counties are identified as counties outside of the storm surge region that are vulnerable to strong gale strength wind speeds of 47 MPH from hurricanes (Kaplan and DeMaria 1995).

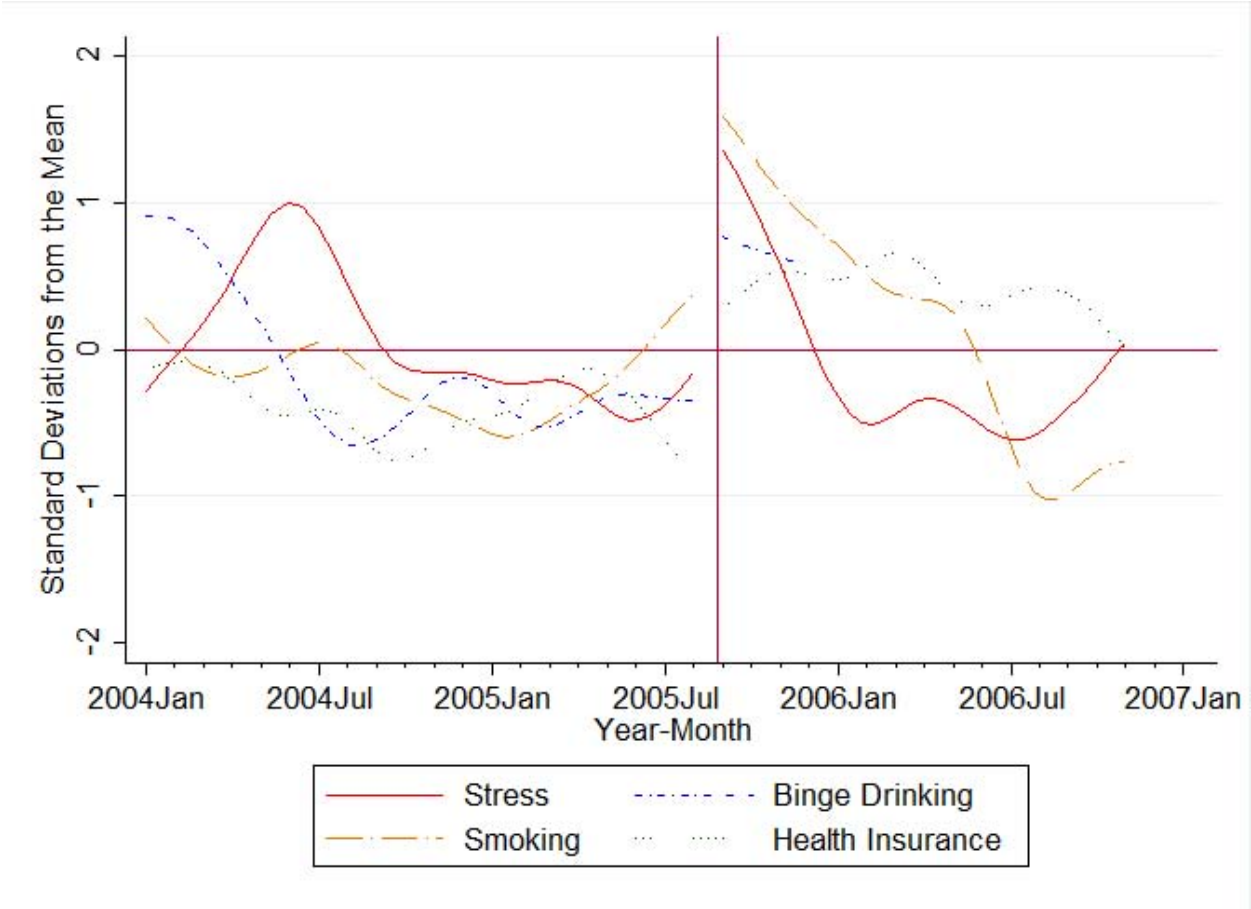


FIGURE 2. ADJUSTED DIFFERENCE BETWEEN STORM SURGE REGION AND CONTROL REGION

Notes: This graph shows local polynomial smoothed plots (bandwidth of 1.5) of the differences in predicted values between the storm surge region and the control region. A spike represents an increase in the storm surge region relative to the control region. The data are risk-adjusted with socio-demographic characteristics, environmental characteristics, and state indicators. The outcomes are standardized by subtracting the predicted value means and dividing by the predicted value standard deviations. The vertical line is the date of Hurricane Katrina.

TABLE 1—STRESS AND SUBSTANCE USE, 2004-2005

	Stress (mean=3.395)				
	(1)	(2)	(3)	(4)	(5)
(1) Storm Surge Region x Post	0.249*	0.245*	0.251*	0.232*	0.252*
	(0.144)	(0.145)	(0.141)	(0.141)	(0.141)
(2) Wind Only Region x Post	0.050	0.046	0.054	0.038	0.060
	(0.118)	(0.119)	(0.117)	(0.117)	(0.118)
(3) Evacuees Per 1,000 x Post					-0.028
					(0.03)
Difference between (1) and (2)	0.199	0.199	0.197	0.195	0.192
N			584,986		
Socio-demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Environmental Characteristics	No	Yes	Yes	Yes	Yes
State Indicators	No	No	Yes	Yes	Yes
Month Indicators	No	No	No	Yes	Yes
Evacuees per Capita	No	No	No	No	Yes

	Smoking (mean=0.206)					Binge Drinking (mean=0.146)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
(1) Storm Surge Region x Post	0.021***	0.022***	0.022***	0.021***	0.021***	0.010	0.011	0.010	0.010	0.011
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
(2) Wind Only Region x Post	0.007	0.009	0.008	0.007	0.007	0.010	0.012*	0.010	0.011	0.012
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
(3) Evacuees Per 1,000 x Post					0.000					-0.001
					(0.002)					(0.001)
Difference between (1) and (2)	0.014*	0.013	0.014*	0.014*	0.014*	0.000	-0.001	-0.001	-0.001	-0.001
N			592,839					550,573		
Socio-demographic Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Environmental Characteristics	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
State Indicators	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Month Indicators	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Evacuees per Capita	No	No	No	No	Yes	No	No	No	No	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. Survey data are used for all results and standard errors are clustered at the sub-state level. Additional parameter estimates are provided for the baseline specification, column 4, in online Appendix Table A1. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 2—STRESS AND SUBSTANCE USE IN 30 DAY INTERVALS

	Stress	Smoking	Binge Drinking
	(1)	(2)	(3)
(1) Storm Surge Region x Period 1	0.446*	0.026**	0.007
	(0.254)	(0.012)	(0.014)
(2) Storm Surge Region x Period 2	0.185	0.023*	0.008
	(0.264)	(0.013)	(0.014)
(3) Storm Surge Region x Period 3	0.145	0.008	0.017
	(0.251)	(0.013)	(0.014)
Difference between (1) and (2)	0.261	0.003	-0.001
Difference between (1) and (3)	0.301	0.018	-0.010
N	449,540	455,305	439,862
Mean	3.379	0.202	0.149
Socio-demographic Characteristics	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of period x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. Survey data are used for all results and standard errors are clustered at the sub-state level. Results are similar when controlling for evacuees per 1,000, and are available upon request. Period 1 = Sept. 9, 2005 - Oct. 8, 2005. Period 2 = Oct. 9, 2005 - Nov. 7, 2005. Period 3 = Nov. 8, 2005 - Dec. 7, 2005. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 3—HEALTH INSURANCE AND EXERCISE

	Health Insurance (mean=0.838)					Exercise (mean=0.758)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Panel A. 2004-2005 sample										
(1) Storm Surge Region x Post	0.013*	0.013*	0.010	0.010	0.011	0.016**	0.017**	0.022***	0.007	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
(2) Wind Only Region x Post	0.008	0.008	0.005	0.005	0.006	0.005	0.006	0.009	-0.008	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)
(3) Evacuees Per 1,000 x Post					-0.001					-0.001
					(0.001)					(0.002)
Difference between (1) and (2)	0.005	0.005	0.005	0.005	0.005	0.011	0.012	0.012	0.015	0.015
N			595,084					594,453		
Socio-demographic Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Environmental Characteristics	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
State Indicators	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Month Indicators	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Evacuees per Capita	No	No	No	No	Yes	No	No	No	No	Yes

	Health Insurance (mean = 0.839)					Exercise (mean = 0.760)				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Panel B. 2004-2006 sample										
(1) Storm Surge Region x Post	0.010**	0.010**	0.009**	0.010**	0.011**	-0.006	-0.004	-0.001	-0.008	-0.005
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
(2) Wind Only Region x Post	0.008**	0.008*	0.006	0.007*	0.008**	0.000	0.001	0.003	-0.003	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
(3) Evacuees Per 1,000 x Post					-0.001					-0.003**
					(0.001)					(0.001)
Difference between (1) and (2)	0.004	0.005	0.004	0.004	0.004	-0.006	-0.005	-0.005	-0.005	-0.004
N			916,932					915,932		
Socio-demographic Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Environmental Characteristics	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
State Indicators	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Month Indicators	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Evacuees per Capita	No	No	No	No	Yes	No	No	No	No	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. The outcomes are estimated with logit. Survey data are used for all results and standard errors are clustered at the sub-state level. Additional parameter estimates are provided for the baseline specification, panel A column 4, in online Appendix Table A1. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 4—HIGH EXPOSURE COUNTIES, 2004-2005

	Stress	Smoking	Binge Drinking	Health Insurance	Exercise
	(1)	(2)	(3)	(4)	(5)
(1) >Median Exposed Storm Surge	0.331*	0.018**	0.021**	0.013	0.012
Land Area x Post	(0.189)	(0.009)	(0.010)	(0.009)	(0.011)
(2) $\leq$ Median Exposed Storm	0.125	0.022**	-0.002	0.007	0.002
Surge Land Area x Post	(0.170)	(0.009)	(0.010)	(0.008)	(0.011)
Difference between (1) and (2)	0.206	-0.004	0.023*	0.006	0.011
N	449,540	455,305	439,862	456,999	456,538
Mean	3.379	0.202	0.149	0.840	0.761
Socio-demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. The median storm surge surface area in storm surge counties is 7.2%. Survey data are used for all results and standard errors are clustered at the sub-state level. Results are similar when controlling for evacuees per 1,000, and are available upon request. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 5—RANDOMIZATION CHECK

	Post-Hurricane Katrina
Panel A: Years 2004-2005	
(1) Sex x Region	0.42
(2) Race/Ethnicity x Region	0.44
(3) Age x Region	0.19
(4) Education x Region	0.19
(5) Employment/Labor Force x Region	0.18
(6) Marital Status x Region	0.22
(7) Income x Region	0.74
Observations	595,084
Panel B: Years 2004-2006	
(1) Sex x Region	0.86
(2) Race/Ethnicity x Region	0.09
(3) Age x Region	0.18
(4) Education x Region	0.33
(5) Employment/Labor Force x Region	0.14
(6) Marital Status x Region	0.29
(7) Income x Region	0.94
Observations	916,932

Notes: Each column presents the p-value from the joint significance test of each category when interacted with the regions of control, wind damage only, and storm surge. An indicator for post-Hurricane Katrina is used as the dependent variable and the models are estimated with logit. Survey data are used for all results and standard errors are clustered at the sub-state level.

TABLE 6—SYNTHETIC CONTROL GROUP ANALYSIS

	Stress	Smoking	Binge Drinking	Health Insurance
	(1)	(2)	(3)	(4)
Panel A: Storm surge and control samples				
(1) East North Central Census Division (excluding Ohio)	-0.049	-0.013	0.001	0.007*
(2) West North Central Census Division	0.207**	0.009	-0.005	-0.014
(3) Mountain Census Division	-0.063	0.021*	0.008*	-0.004
(4) Pacific Census Division (excluding coastal counties)	-0.298	-0.006	-0.006	0.001
(5) Pacific Coastal Counties	-0.190	-0.047	0.001	-0.001
(6) Remaining Non-Vulnerable Counties	-0.075	-0.012	-0.004	-0.005
(7) Storm Surge Counties	0.190*	0.026**	0.010**	0.013**
Panel B: >Median exposed storm surge land area and control samples				
(1) East North Central Census Division (excluding Ohio)	-0.011	-0.011	-0.003	0.008*
(2) West North Central Census Division	0.171*	0.008	-0.006	-0.012
(3) Mountain Census Division	-0.019	0.012*	0.005*	-0.001
(4) Pacific Census Division (excluding coastal counties)	-0.289	-0.001	-0.004	-0.006
(5) Pacific Coastal Counties	-0.294	-0.047	0.004	-0.004
(6) Remaining Non-Vulnerable Counties	0.030	-0.011	-0.011	-0.005
(7) >Median Exposed Storm Surge Land Area	0.348**	0.034**	0.024**	0.014**

Notes: Results are for the first 90 days after Hurricane Katrina. The median storm surge surface area in storm surge counties is 7.2%. ** Largest effect. * 2nd largest effect.

TABLE 7—BEHAVIORAL HEALTH RESPONSES ≥400 MILES FROM NEW ORLEANS, 2004-2005

	Stress	Smoking	Binge Drinking	Health Insurance
	(1)	(2)	(3)	(4)
Panel A: Storm surge, wind damage only, and control samples				
(1) Storm Surge Region x Post	0.255*	0.021***	0.010	0.010
	(0.142)	(0.008)	(0.007)	(0.007)
(2) Wind Only Region x Post	0.042	0.009	0.008	0.003
	(0.121)	(0.007)	(0.008)	(0.006)
Difference between (1) and (2)	0.213	0.012	0.002	0.007
N	567,188	574,693	532,595	576,862
Mean	3.386	0.205	0.147	0.841
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes
Panel B: Storm surge and control samples				
(1) > Median Exposed Storm Surge	0.339*	0.019**	0.018*	0.012
Land Area x Post	(0.191)	(0.009)	(0.010)	(0.008)
(2) ≤ Median Exposed Storm	0.159	0.018**	0.000	0.006
Surge Land Area x Post	(0.173)	(0.009)	(0.010)	(0.008)
Difference between (1) and (2)	0.180	0.001	0.018	0.006
N	438,981	444,561	429,205	446,201
Mean	3.382	0.201	0.149	0.843
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. The median storm surge surface area in storm surge counties is 7.2%. Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 8—HIGH PROBABILITY STATES, 2004-2005

	Stress	Smoking	Binge Drinking	Health Insurance
	(1)	(2)	(3)	(4)
Panel B: Storm surge and control samples				
(1) Storm Surge Region (North Carolina and South) x Post	0.321	0.033**	0.020	0.010
	(0.311)	(0.015)	(0.016)	(0.012)
(2) Storm Surge Region (Virginia and North) x Post	0.210	0.015**	0.008	0.010
	(0.129)	(0.007)	(0.008)	(0.007)
Difference between (1) and (2)	0.111	0.019	0.012	0.000
N	449,540	455,305	439,862	456,999
Mean	3.379	0.202	0.149	0.840
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes
Panel B: >Median exposed storm surge land area and control samples				
(1) >Median Exposed Storm Surge Land Area (North Carolina and South) x Post	0.601	0.044**	0.050**	0.009
	(0.446)	(0.020)	(0.021)	(0.017)
(2) >Median Exposed Storm Surge Land Area (Virginia and North) x Post	0.250	0.008	0.012	0.012
	(0.174)	(0.009)	(0.012)	(0.008)
Difference between (1) and (2)	0.351	0.036*	0.038*	-0.003
N	392,243	397,349	393,730	398,766
Mean	3.397	0.203	0.149	0.839
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. The median storm surge surface area in storm surge counties is 7.2%. Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 9—CATEGORY 1 AND 5 HURRICANES, 2004-2005

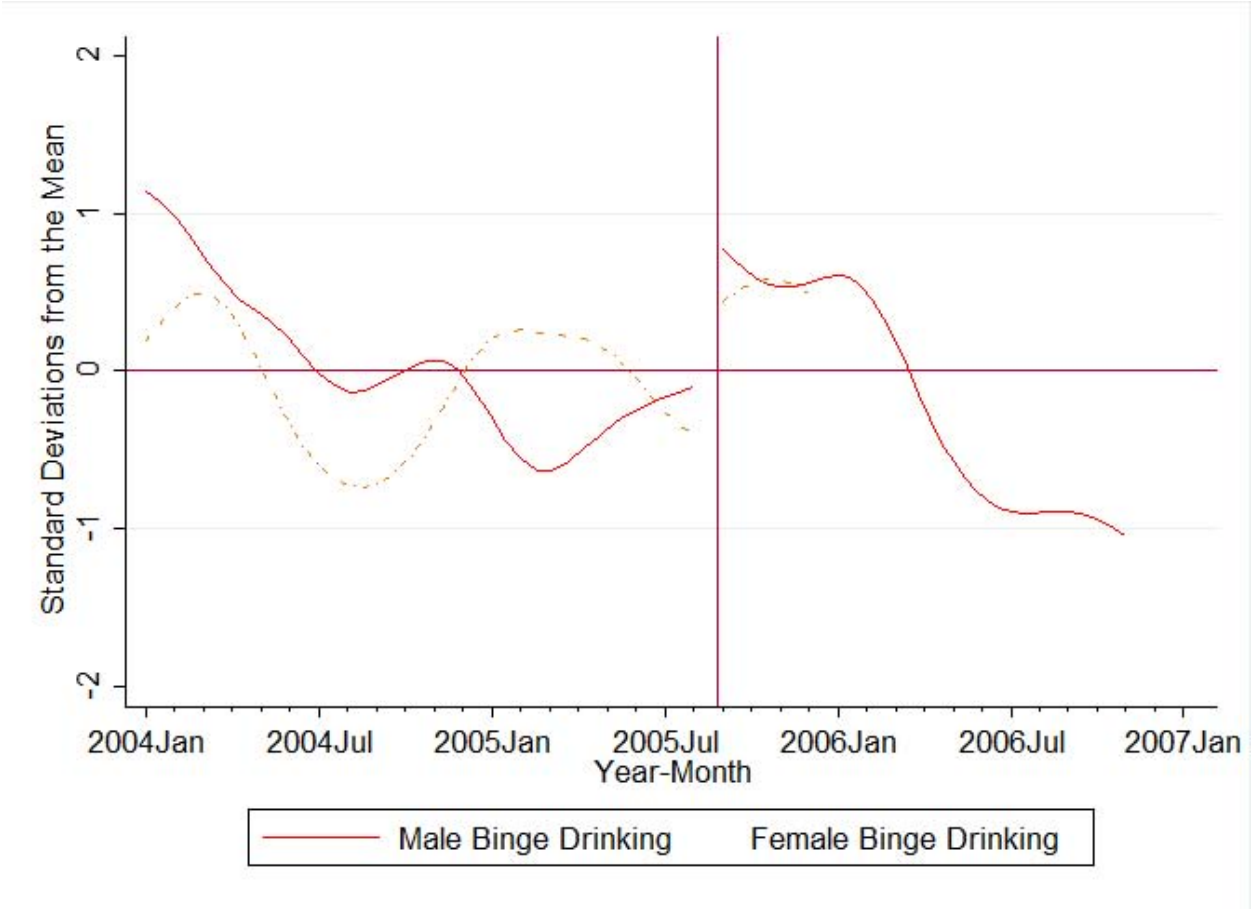
	Stress	Smoking	Binge Drinking	Health Insurance
	(1)	(2)	(3)	(4)
Panel A: Category 1 Hurricane				
(1) Storm Surge Region x Post	0.234*	0.020***	0.009	0.009
	(0.137)	(0.007)	(0.007)	(0.007)
(2) Wind Only Region x Post	-0.060	0.007	0.012	0.000
	(0.130)	(0.007)	(0.009)	(0.007)
Difference between (1) and (2)	0.294*	0.012	-0.003	0.009
N	584,986	592,839	550,573	595,084
Mean	3.395	0.206	0.146	0.838
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Panel B: Category 5 Hurricane				
(1) Storm Surge Region x Post	0.317*	0.023**	0.014	0.010
	(0.185)	(0.009)	(0.009)	(0.008)
(2) Wind Only Region x Post	0.158	0.018*	0.001	0.010
	(0.177)	(0.009)	(0.010)	(0.008)
Difference between (1) and (2)	0.159	0.006	0.014	0.000
N	433,944	439,434	424,114	441,052
Mean	3.377	0.199	0.151	0.841
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region, with the control region dependent on the hurricane category strength. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE A1—SAMPLE DESCRIPTIVE STATISTICS FOR CONTINENTAL UNITED STATES, NON-HURRICANE KATRINA DISASTER AREAS, 2004-2006

	Unweighted		Weighted	
	Mean	Standard Deviation	Mean	Standard Deviation
BRFSS				
Male (%)	0.385	0.486	0.485	0.500
Female (%)	0.615	0.486	0.515	0.500
White non-Hispanic (%)	0.810	0.392	0.705	0.456
Black non-Hispanic (%)	0.071	0.257	0.089	0.284
Asian non-Hispanic (%)	0.012	0.111	0.028	0.166
Native American non-Hispanic (%)	0.014	0.118	0.010	0.101
Hispanic (%)	0.062	0.241	0.137	0.344
Missing Race/Ethnicity (%)	0.030	0.171	0.031	0.174
Age	51.669	17.092	45.668	17.645
Junior High (%)	0.035	0.184	0.045	0.207
Some High School (%)	0.067	0.250	0.076	0.265
High School (%)	0.305	0.461	0.295	0.456
Some College (%)	0.264	0.441	0.261	0.440
College (%)	0.325	0.468	0.319	0.466
Missing Education (%)	0.003	0.051	0.004	0.061
Employed (%)	0.567	0.496	0.612	0.487
Unemployed (%)	0.041	0.197	0.052	0.222
Student (%)	0.022	0.146	0.045	0.208
Not Student, Not in Labor Force (%)	0.368	0.482	0.286	0.452
Missing Employed Status (%)	0.003	0.055	0.005	0.068
Married (%)	0.553	0.497	0.594	0.491
Divorced (%)	0.163	0.369	0.111	0.315
Widowed (%)	0.122	0.328	0.065	0.247
Unmarried and Other Marital Status (%)	0.158	0.365	0.226	0.418
Missing Marital Status (%)	0.004	0.062	0.004	0.062
Real Household Income (without imputation)	44,179	26,156	46,634	26,803
Real Household Income (with imputation)	43,374	25,251	45,588	25,904
Top Household Income Category (%)	0.194	0.395	0.228	0.420
Stress (Days Mental Health Not Good over Past 30 Days) (%)	3.396	7.662	3.391	7.473
Current Smoker (%) (Past 30 Days)	0.196	0.397	0.203	0.402
Binge Drinker (%) (Past 30 Days)	0.113	0.317	0.149	0.356
Health Insurance (%)	0.877	0.328	0.839	0.368
Exercise (%)	0.750	0.433	0.760	0.427
Merged Outside Data				
State-Level Unemployment Rate (%)	4.851	1.050	5.095	0.960
Real Price of Pack of Cigarettes (in dollars)	3.852	0.711	3.841	0.708
Real Price of 6-Pack of Heineken Beer (in dollars)	7.228	0.363	7.224	0.318
State-Level Smoke-Free Air Law Index (scale of 1-9)	2.829	3.053	3.312	3.410
State-Level No Pub Smoking Restrictions (%)	0.772	0.419	0.697	0.460
Reside in Counties At-Risk for Storm Surge from Category 3 Hurricane (%)	0.200	0.400	0.201	0.401
Reside in Counties At-Risk for Wind Damage from Category 3 Hurricane Only (%)	0.238	0.426	0.255	0.436
County-Level Hurricane Katrina Evacuees Per 1,000	0.610	1.286	1.033	2.300

Notes: All prices are in 2004 dollars.



ONLINE FIGURE 1. ADJUSTED DIFFERENCE BETWEEN STORM SURGE REGION AND CONTROL REGION FOR BINGE DRINKING

Notes: This graph shows local polynomial smoothed plots (bandwidth of 1.5) of the differences in binge drinking predicted values between the storm surge region and the control region. A spike represents an increase in the storm surge region relative to the control region. The data are risk-adjusted with socio-demographic characteristics, environmental characteristics, and state indicators. The outcomes are standardized by subtracting the predicted value means and dividing by the predicted value standard deviations. The definition of binge drinking changed for women in 2006, so I provide graphs for females in 2004-2005 and men in 2004-2006.The vertical line is the date of Hurricane Katrina.

ONLINE APPENDIX TABLE A1—ADDITIONAL PARAMETER ESTIMATES, 2004-2005

	Dependent Variable				
	Stress	Smoking	Binge Drinking	Health Insurance	Exercise
Male	-	-	-	-	-
Female	0.1860*** (0.0148)	-0.3000*** (0.0144)	-1.2447*** (0.0187)	0.2807*** (0.0187)	-0.1585*** (0.0139)
White non-Hispanic	-	-	-	-	-
Black non-Hispanic	-0.2333*** (0.0220)	-0.4859*** (0.0266)	-0.6014*** (0.0380)	0.0842*** (0.0308)	-0.2601*** (0.0231)
Asian non-Hispanic	-0.3501*** (0.0604)	-0.5514*** (0.0777)	-0.9800*** (0.0830)	-0.3325*** (0.0737)	-0.5356*** (0.0569)
Native American non-Hispanic	0.1096** (0.0452)	0.3269*** (0.0596)	-0.0188 (0.0783)	-0.2803*** (0.0701)	-0.1449** (0.0617)
Hispanic	-0.4841*** (0.0332)	-0.8362*** (0.0352)	-0.1457*** (0.0370)	-0.6229*** (0.0303)	-0.4263*** (0.0270)
Missing Race/Ethnicity	0.1277*** (0.0297)	0.0733* (0.0392)	-0.2034*** (0.0579)	-0.3241*** (0.0488)	-0.0953*** (0.0367)
Age	0.0689*** (0.0029)	0.0956*** (0.0031)	0.0101** (0.0042)	-0.0538*** (0.0039)	-0.0328*** (0.0025)
Age Squared	-0.0009*** (0.0000)	-0.0013*** (0.0000)	-0.0005*** (0.0000)	0.0010*** (0.0000)	0.0002*** (0.0000)
Junior High	-	-	-	-	-
Some High School	0.1057*** (0.0387)	0.5920*** (0.0513)	0.0880 (0.0817)	0.3545*** (0.0510)	0.1544*** (0.0427)
High School	-0.0588 (0.0374)	0.1282*** (0.0487)	0.0896 (0.0750)	0.6049*** (0.0470)	0.4203*** (0.0390)
Some College	-0.0050 (0.0381)	-0.1201** (0.0496)	0.1013 (0.0752)	0.8550*** (0.0488)	0.7613*** (0.0401)
College	-0.2645*** (0.0398)	-0.8945*** (0.0509)	-0.1048 (0.0759)	1.2034*** (0.0517)	1.1507*** (0.0410)
Missing Education	-0.3530** (0.1536)	-0.2824 (0.1864)	-0.1424 (0.2516)	0.4196** (0.1658)	0.4048*** (0.1318)
Employed	-	-	-	-	-
Unemployed	0.4200*** (0.0222)	0.2834*** (0.0310)	-0.0461 (0.0443)	-0.7880*** (0.0359)	-0.0485 (0.0327)
Student	0.1399*** (0.0334)	-0.5848*** (0.0508)	-0.1856*** (0.0511)	0.3587*** (0.0511)	0.4582*** (0.0535)
Not Student, Not in Labor Force	0.4988*** (0.0153)	0.0252 (0.0189)	-0.3241*** (0.0298)	0.2300*** (0.0266)	-0.1261*** (0.0178)
Missing Employed Status	-0.0311 (0.1266)	-0.1202 (0.1650)	-0.1296 (0.2526)	-0.0597 (0.1677)	-0.1386 (0.1308)
Married	-	-	-	-	-
Divorced	0.3610*** (0.0179)	0.7228*** (0.0197)	0.5282*** (0.0272)	-0.3040*** (0.0260)	-0.0224 (0.0199)
Widowed	0.2287*** (0.0282)	0.6428*** (0.0294)	0.4034*** (0.0614)	-0.0038 (0.0445)	0.0250 (0.0234)
Unmarried and Other Marital Status	0.2229*** (0.0193)	0.4870*** (0.0223)	0.5204*** (0.0262)	-0.4637*** (0.0261)	0.0501** (0.0228)
Missing Marital Status	0.1511 (0.1103)	0.0983 (0.1336)	-0.0180 (0.1891)	-0.0190 (0.1508)	0.2684** (0.1215)
Real Household Income (in 1,000s of dollars)	-0.0216*** (0.0014)	-0.0053*** (0.0020)	0.0080*** (0.0030)	0.0192*** (0.0024)	0.0210*** (0.0019)
Real Household Income Squared in 1,000s of dollars)	0.0001*** (0.0000)	-0.0000* (0.0000)	-0.0001 (0.0000)	0.0002*** (0.0000)	-0.0001*** (0.0000)
Top Income Category	-0.0538 (0.0489)	0.0766 (0.0584)	0.1766** (0.0730)	-0.7807*** (0.0937)	0.1023* (0.0557)
Pre	-	-	-	-	
Post	-0.0376 (0.0264)	-0.0511* (0.0309)	-0.0185 (0.0409)	-0.0590 (0.0424)	-0.0719** (0.0335)
Control	-	-	-	-	-
Wind Only Region	-0.0307 (0.0398)	-0.0351 (0.0481)	0.0745 (0.0614)	0.0212 (0.0560)	1.077 (0.0691)
Storm Surge Region	-0.0250 (0.0439)	-0.0168 (0.0528)	0.1198* (0.0679)	-0.0747 (0.0622)	1.1494* (0.0854)
Post x Control Region	-	-	-	-	-
Post x Wind Only Region	0.0109 (0.0356)	0.0512 (0.0435)	0.0921 (0.0642)	0.0477 (0.0568)	-0.0465 (0.0515)
Post x Storm Surge Region	0.0692* (0.0414)	0.1434*** (0.0498)	0.0832 (0.0628)	0.0944 (0.0659)	0.0443 (0.0577)
State-Level Unemployment Rate	0.0150 (0.0165)	0.0135 (0.0208)	0.0356 (0.0271)	-0.0013 (0.0262)	0.0129 (0.0197)
Real Price of Pack of Cigarettes	-	-0.0509 (0.0477)	-	-	-
State-Level Smoke-Free Air Law Index	-	-0.0021 (0.0072)	-	-	-
Real Price of 6-Pack of Heineken Beer (in dollars)	-	-	-0.0076 (0.0472)	-	-
State-Level No Pub Smoking Restrictions	-	-	0.0447 (0.0607)	-	-
Constant	0.5321*** (0.1268)	-1.9310*** (0.2327)	-1.3958*** (0.4125)	0.3510* (0.1904)	0.5077*** (0.1408)
Observations	584,986	592,839	550,573	595,084	594,453
Model Type	GLM, Log-Link, Gaussian Distribution	Logit	Logit	Logit	Logit

Notes: This table presents additional regression coefficients for the baseline specification (column 4, Table 1 and panel A, column 4, Table 3). Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

ONLINE APPENDIX TABLE A2—STRESS AND SMOKING, 2004-2006

	Stress (mean = 3.392)				
	(1)	(2)	(3)	(4)	(5)
(1) Storm Surge Region x Post	-0.023	-0.029	-0.017	-0.025	-0.020
	(0.094)	(0.095)	(0.089)	(0.089)	(0.086)
(2) Wind Only Region x Post	-0.041	-0.045	-0.044	-0.052	-0.049
	(0.078)	(0.078)	(0.077)	(0.077)	(0.077)
(3) Evacuees Per 1,000 x Post					-0.005
					(0.023)
Difference between (1) and (2)	0.018	0.016	0.028	0.027	0.028
N					
Socio-demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Environmental Characteristics	No	Yes	Yes	Yes	Yes
State Indicators	No	No	Yes	Yes	Yes
Month Indicators	No	No	No	Yes	Yes
Evacuees per Capita	No	No	No	No	Yes
	Smoking (mean = 0.203)				
	(1)	(2)	(3)	(4)	(5)
(1) Storm Surge Region x Post	0.005	0.007	0.006	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
(2) Wind Only Region x Post	0.001	0.002	0.002	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
(3) Evacuees Per 1,000 x Post					-0.001
					(0.001)
Difference between (1) and (2)	0.004	0.005	0.004	0.004	0.004
N					
Socio-demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Environmental Characteristics	No	Yes	Yes	Yes	Yes
State Indicators	No	No	Yes	Yes	Yes
Month Indicators	No	No	No	Yes	Yes
Evacuees per Capita	No	No	No	No	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

ONLINE APPENDIX TABLE A3—STRESS AND SMOKING IN QUARTER INTERVALS

	Stress	Smoking
	(1)	(2)
(1) Storm Surge Region x Period 1	0.247*	0.021***
	(0.135)	(0.007)
(2) Storm Surge Region x Period 2	-0.237	0.006
	(0.169)	(0.010)
(3) Storm Surge Region x Period 3	-0.027	0.011
	(0.155)	(0.008)
Difference between (1) and (2)	0.484**	0.016
Difference between (1) and (3)	0.274	0.011
N	687,714	696,327
Mean	3.384	0.198
Socio-demographic Characteristics	Yes	Yes
Environmental Characteristics	Yes	Yes
State Indicators	Yes	Yes
Month Indicators	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of period x control region. Stress was estimated using GLM with a log-link and Gaussian distribution, and smoking using logit. Survey data are used for all results and standard errors are clustered at the sub-state level. Results for binge drinking are not shown because the definition of binge drinking changed for women in 2006. Results are similar when controlling for evacuees per 1,000, and are available upon request. Period 1 = Sept. 9 - end of 2005. Period 2 = 1Q of 2006. Period 3 = 2Q of 2006. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

ONLINE APPENDIX TABLE A4—HEALTH INSURANCE AND AGE

	Ages 18-30	Ages 31-64	Ages ≥65
	(1)	(2)	(3)
Panel A: Years 2004-2005			
(1) Storm Surge Region x Post	0.032	0.002	0.002
	(0.022)	(0.008)	(0.006)
(2) Wind Only Region x Post	0.012	0.001	0.006
	(0.033)	(0.007)	(0.005)
Difference between (1) and (2)	0.019	0.000	-0.004
N	78,311	371,206	141,330
Mean	0.709	0.850	0.974
Socio-demographic Characteristics	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes
Panel A: Years 2004-2006			
(1) Storm Surge Region x Post	0.024*	0.005	0.001
	(0.014)	(0.005)	(0.004)
(2) Wind Only Region x Post	0.024**	0.001	0.005
	(0.012)	(0.004)	(0.003)
Difference between (1) and (2)	0.000	0.004	-0.004
N	112,534	570,894	226,195
Mean	0.706	0.853	0.976
Socio-demographic Characteristics	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. The health insurance outcome is stratified by age and is estimated with logit. Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

ONLINE APPENDIX TABLE A5—PRE-HURRICANE KATRINA TIME TRENDS CHECK

		Stress	Smoking	Binge Drinking	Health Insurance	Exercise
		(1)	(2)	(3)	(4)	(5)
(1)	1Q 2004*Storm Surge Region	-	-	-	-	-
(2)	2Q 2004*Storm Surge Region	1.123* (0.071)	0.982 (0.075)	0.876 (0.083)	0.957 (0.096)	0.959 (0.070)
(3)	3Q 2004*Storm Surge Region	1.059 (0.067)	1.031 (0.079)	0.812** (0.076)	1.019 (0.104)	1.161 (0.110)
(4)	4Q 2004*Storm Surge Region	1.016 (0.062)	0.977 (0.072)	0.839* (0.076)	0.985 (0.098)	1.129* (0.079)
(5)	1Q 2005*Storm Surge Region	1.005 (0.062)	0.945 (0.071)	0.816** (0.075)	0.965 (0.094)	0.850** (0.055)
(6)	2Q 2005*Storm Surge Region	0.995 (0.061)	0.965 (0.071)	0.873 (0.081)	1.029 (0.100)	1.010 (0.070)
(7)	partial 3Q 2005 *Storm Surge Region	1.019 (0.075)	1.077 (0.095)	0.822* (0.086)	0.925 (0.102)	1.190 (0.129)
(8)	Control	-	-	-	-	-
(9)	Storm Surge Region	0.929 (0.053)	0.978 (0.068)	1.337*** (0.117)	0.919 (0.081)	1.217*** (0.092)
(10)	p-value of the joint significance of the storm surge region quarter time trend in pre-HK period (1-7)	0.433	0.781	0.307	0.951	0.043
(11)	p-value of the joint significance of the wind only region quarter time trend in pre-HK period	0.516	0.730	0.698	0.889	0.620
(12)	Observations	901,544	913,359	841,157	916,932	915,932

Notes: This table presents odds ratios of individual quarters in the pre-Hurricane Katrina period, as well as tests of joint significance. The difference between the storm surge region and the control region in the first quarter is used as the reference (row 1), and the deviations from this difference in future quarters are reported by the odds ratios in rows 2-7. Survey data are used for all results and standard errors are clustered at the sub-state level. Unreported results include non-interacted quarters, socio-demographic characteristics, environmental characteristics, and state indicators. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

ONLINE APPENDIX TABLE A6—YEAR PRIOR FALSIFICATION EXERCISE, 2004-2005

	Stress	Smoking	Binge Drinking	Health Insurance
	(1)	(2)	(3)	(4)
Panel A: Storm surge, wind damage only, and control samples				
(1) Storm Surge Region x Post	-0.126	0.000	-0.004	-0.002
	(0.111)	(0.006)	(0.006)	(0.005)
(2) Wind Only Region x Post	-0.223**	0.000	-0.004	0.003
	(0.096)	(0.005)	(0.006)	(0.005)
Difference between (1) and (2)	0.097	0.000	0.000	-0.005
N	585,874	593,766	551,186	596,014
Mean	3.386	0.206	0.146	0.838
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes
Panel B: Storm surge and control samples				
(1) > Median Exposed Storm Surge Land Area x Post	-0.034	0.002	-0.001	0.000
	(0.146)	(0.007)	(0.008)	(0.007)
(2) ≤ Median Exposed Storm Surge Land Area x Post	-0.233*	-0.004	-0.007	-0.003
	(0.133)	(0.007)	(0.008)	(0.007)
Difference between (1) and (2)	0.199	0.006	0.007	0.004
N	449,832	455,605	440,100	457,302
Mean	3.372	0.202	0.149	0.840
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. The median storm surge surface area in storm surge counties is 7.2%. Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

ONLINE APPENDIX TABLE A7—BEHAVIORAL HEALTH RESPONSES, 2002-2005

	Stress	Smoking	Binge Drinking	Health Insurance
	(1)	(2)	(3)	(4)
Panel A: Storm surge, wind damage only, and control samples				
(1) Storm Surge Region x Post	0.304**	0.026***	0.007	0.010
	(0.135)	(0.007)	(0.007)	(0.007)
(2) Wind Only Region x Post	0.138	0.007	0.008	0.003
	(0.114)	(0.006)	(0.007)	(0.006)
Difference between (1) and (2)	0.166	0.020**	-0.001	0.007
N	907,391	1,046,627	970,576	1,050,113
Mean	3.383	0.215	0.152	0.841
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes
Panel B: Storm surge and control samples				
(1) > Median Exposed Storm Surge Land Area x Post	0.458**	0.027***	0.018*	0.011
	(0.186)	(0.009)	(0.009)	(0.008)
(2) ≤ Median Exposed Storm Surge Land Area x Post	0.108	0.023**	-0.006	0.008
	(0.170)	(0.009)	(0.010)	(0.008)
Difference between (1) and (2)	0.351	0.005	0.024*	0.003
N	703,382	804,994	779,119	807,633
Mean	3.390	0.210	0.155	0.843
Socio-demographic Characteristics	Yes	Yes	Yes	Yes
Environmental Characteristics	Yes	Yes	Yes	Yes
State Indicators	Yes	Yes	Yes	Yes
Month Indicators	Yes	Yes	Yes	Yes

Notes: This table presents marginal effects of DD estimators compared to the reference category of post x control region. Stress is estimated using GLM with a log-link and Gaussian distribution, and the other outcomes are estimated using logit. Stress was part of an optional module in 2002 completed in only 20 states. The median storm surge surface area in storm surge counties is 7.2%. Survey data are used for all results and standard errors are clustered at the sub-state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.