# The Effects of National Disasters on Stress and Substance Use in the United States

BY

Michael F. Pesko
B.A., Hamline University, 2007
M.A., University of Illinois at Chicago, 2010

THESIS

Submitted as partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Economics
in the Graduate College of the
University of Illinois at Chicago, 2012

Chicago, Illinois

Defense Committee:

Frank Chaloupka, Chair and Advisor
Houston Stokes
John Tauras
Jidong Huang, Institute for Health Research and Policy
Roy Wada, Institute for Health Research and Policy

**ACKNOWLEDGEMENTS**

I appreciate assistance provided by dissertation committee members Frank Chaloupka (chair), John Tauras, Houston Stokes, Jidong Huang, and Roy Wada. Frank Chaloupka's guidance, contributions, and support were invaluable for this dissertation and my graduate school experience. Additionally, others who have helped at different stages in the dissertation process include Xin Xu, Haytham Abu Zayd, Richard Nugent, Christopher Baum, Nathan Anderson, Christina Gebel, Lisa Powell, Michael Hunstad, Erik Byro, Stacy Miller, Lillian Madrigal, and an anonymous referee. The author also appreciates assistance provided by Elaine Hallisey of the Geospatial, Research, Analysis and Services Program at the Centers for Disease Control and Prevention, for providing the storm surge and wind damage data.

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| 2SLS | Two Stage Least Squares |
| ACCRA | American Chamber of Commerce Researchers Association |
| BRFSS | Behavioral Risk Factor Surveillance System |
| CDC | Centers for Disease Control and Prevention |
| DHHS | Department of Health and Human Services |
| DID | Difference-in-Difference |
| DIDID | Difference-in-Difference-in-Difference |
| FEMA | Federal Emergency Management Agency |
| HRAC | High Risk Alcohol Consumption |
| NIAAA | National Institute on Alcohol Abuse and Alcoholism |
| NOAA | National Oceanic Atmospheric Administration |
| SFHA | Special Flood Hazard Area |
| SLOSH | Sea, Lake, and Overland Surges from Hurricanes |
| USDA | United States Department of Agriculture |

# SUMMARY

The relationship between national disasters, risk perceptions, stress, and substance abuse has never been comprehensively studied. The recent national disasters of the Oklahoma City bombing, the 9/11 terrorist attacks, and Hurricane Katrina provides several natural experiments to study these relationships. Behavioral Risk Factor Surveillance System (BRFSS) data collected before and after the national disasters is used for measures of stress and substance abuse. This dissertation helps to advance the literature on the self-medication of stress with substance abuse in line with the Becker-Murphy rational addiction utility framework.

The first essay of this dissertation, “Terrorism, Stress, and Smoking Using Behavioral Risk Factor Surveillance System Data,” analyzes the effects of the Oklahoma City bombing and 9/11 terrorist attacks on stress, smoking, and smoking quit attempts using 1,657,985 observations from the BRFSS. In the fourth quarter of 2001, regression discontinuity results suggest that stress increased by an extra half day per 30 days (13.5%) amongst ever smoking adults. In the two years after 9/11, smoking prevalence increased by 1.1 percentage points (2.3%) amongst ever smoking adults, resulting in between 930,000 to 1,300,000 adult former smokers becoming smokers again due to terrorism. This resulted in a net cost to the government of between $550 million to $820 million through the end of 2003. Adults reported disproportionate stress increases based on proximity to the terrorist attack epicenters, community military participation, and education. Simultaneity between smoking and stress is addressed by an instrumental variables model, providing validity to the hypothesized causal pathway between terrorism, stress, and smoking and providing an unbiased estimate of the effect of stress on smoking.

Individuals may also attempt to maximize utility by using alcohol to self-medicate higher stress. This is explored in the second essay of this dissertation, “The Effects of 9/11 on High

Risk Alcohol Consumption." High risk alcohol consumption (HRAC) is defined as any binge drinking, excessive drinks per month, excessive average drinks per drinking days, and drinking during pregnancy. Results suggest that in the fourth quarter of 2001, stress increased 13.3% nationally and the prevalence of HRAC increased 11.2%, resulting in 3.6 million terrorism-induced HRAC drinkers per month at a cost of $5.5 billion. Proximity to the terrorist attack epicenters and community military participation were associated with disproportionate increases in HRAC. In an instrumental variables approach, 9/11 is used as an instrument for self-reported stress to remove simultaneity and provide an unbiased estimate of the effect of stress on HRAC. Results from these first two essays help to quantify a hidden cost of terrorism, as well as provide a better understanding of utility maximization during stressful events.

Hurricane Katrina, with its 24/7 news coverage and 1,836 deaths, increased awareness of hurricane dangers nationally. Increased risk perceptions may generate stress, which individuals may attempt to self-medicate with smoking or drinking to maximize utility. People with less formal education may disproportionately increase risk perceptions if they have less skill in matching subjective and objective risk, or if Hurricane Katrina provided risk information that was disproportionately new information to them. These hypotheses are explored in the third essay of this dissertation, "The National Effects of Hurricane Katrina on Risk Perception and Substance Abuse." BRFSS data from one year before and after Hurricane Katrina on August 29, 2005 is analyzed at a county level using difference-in-difference modeling to compare stress, smoking, and HRAC increases for individuals living in areas of hurricane risk (e.g. coastline borders, storm surge areas, and wind damage areas) compared to interior residents isolated from hurricane dangers. Results suggest that Hurricane Katrina increased the odds of former smokers relapsing in counties at risk of storm surge from a category 3 hurricane by 11.3%, and by 21.1% for those with less than a high school education. Hurricane Katrina also increased the odds of a low-educated individual in this same treatment group engaging in HRAC by 22.0%. Results suggest that Hurricane Katrina increased awareness of hurricane risks. Substance abuse, especially for low-educated individuals, was a secondary harmful consequence.

**ESSAY ONE:** TERRORISM, STRESS, AND SMOKING USING BEHAVIORAL RISK FACTOR SURVEILLANCE SYSTEM DATA

## 1. INTRODUCTION

The costs of tobacco use in the United States are large. Tobacco use remains the highest preventable cause of disease and death in the United States, causing approximately 443,000 deaths each year and 5.1 million lost years of potential life (CDC, 2008). Additionally, tobacco use costs approximately $157 billion in annual health-related economic losses, and the direct costs attributable to smoking comprise 6 to 9 percent of the total national health care budget (U.S. DHHS, 2004). Considering the large national costs of smoking, stressful life events that trigger smoking could ideally be identified and the stress treated before smoking begins or addiction forms. A form of stress that has received much attention recently in the United States is terrorism, which threatens individuals' sense of security in carrying out ordinary activities. Recent terrorist attacks include the April 19, 1995 Oklahoma City bombing, which killed 168 people, and 9/11, which killed 2,937 people in New York City and Washington DC.

When disaster strikes, information from the media and people with knowledge of the disaster triggers perceived risk reactions across the population at large, which in turn generates secondary social and economic consequences (Burns and Slovic, 2007). These perceived risk reactions can be deadlier and costlier than the initial disaster. One example from a study using commercial vehicles as a control group found that 2,300 noncommercial car passengers died in traffic accidents in the two years after 9/11 due to people substituting long car trips for plane travel (Blalock et al., 2009). People did this despite the risk of death in a plane accident being the same as driving 11.2 miles on a rural highway, even taking into account the recent airplane hijackings (Mueller, 2004). Unless people assumed that there would be a 9/11-like attack each month and drove instead of flew as a result, or were greatly disturbed by more lengthy and invasive airport security procedures, they grossly overestimated the threat against them (Sivak and Flannagan, 2003).

Former ABC news anchor Peter Jennings provides an example of a secondary consequence of terrorism. Jennings had quit smoking for more than a decade before relapsing on 9/11/2001. Dr. Michael Rabinoff provides a disturbing description of the scene unfolding around Peter Jennings when he resumed smoking.

> Picture that day, when people in New York City were burning ... falling to their deaths ... or breathing ash and dodging fragments from buildings as they came tumbling down, when the whole nation was stressed, when the possible future adverse effects of smoking seemed insignificant, it was then that Peter Jennings, who personally felt connected and identified with America, lit up again. (Rabinoff, 2009, pg. 20)

Underscoring the dangers of terrorism-induced smoking, Peter Jennings died of lung cancer four years later.

This study investigates the possibility that 9/11 caused a large increase in national stress, far above what can be accounted for by an increase in the objective risk of terrorism-related injury or death. This high national stress, in part due to miscalculated fears of remote dangers, in turn is hypothesized to cause concerning smoking increases as people attempt to maximize utility by reducing stress with a perceived stress-relieving commodity.

This study makes several important contributions. First, this study improves upon the methodologies of other research investigating the relationship between terrorism and substance use by using data that is not subject to memory error or response biases. Second, this is the first study on this topic using national data, allowing a national estimation of the costs of terrorism-induced smoking. Third, to the best of the author's knowledge, this study provides the first estimate of the unbiased effect of stress on smoking, using the natural experiment of 9/11 as an instrument for stress to solve the problem of simultaneity between smoking and stress. Finally, this research provides an opportunity to apply to a defining national event two important economics models, Becker and Murphy's rational addiction model (1998) and Becker and Rubinstein's rational fear model (2010).

## 2. LITERATURE REVIEW AND THEORETICAL MODELS

In a review of the literature on the effects of terrorism on stress, medical studies that use 9/11 pre-post analysis of stress-induced bad health outcomes were found to use the strongest methodologies, as these studies use data that is not subject to memory error or response biases. In a national study, increased stress from 9/11 was associated with a 53% increase in cardiovascular ailments over three subsequent years after controlling for prior stress and history of cardiovascular disease. Proximity to the terrorist attack epicenters was not found to be a predictor of stress or stress-induced bad health outcomes (i.e. cardiovascular ailments) (Holman et al., 2008), which contrasts with findings from sociological studies using retrospectively-collected data (Schlenger et al., 2002; Stein et al., 2004; Smith et al., 1999). A small cohort of implantable cardioverter-defibrillator patients in Florida had a 2.8-fold increase in experiencing ventricular arrhythmias that required therapy in the 30-days following 9/11. This finding was consistent with other heart disease studies done in New York City (Shedd et al., 2004). In Columbia, longitudinal data was used to link terrorism stress to lower birth weights for babies carried by women who lived near a terrorist attack during their first trimester of pregnancy (Camacho, 2008). One study of births in New York City around 9/11 also found birth weights to be lower depending on the trimester that the fetus was in at the time of the terrorist attack, although this seems likely due to seasonal variation rather than 9/11 (Lipkind et al., 2010). A second birth-related study used time series data to find a rise in male fetal death in September

2001, consistent with theory explaining those pregnant for longer than 20 weeks are at increased risk of losing male fetuses due to stress (Bruckner et al., 2010). Collectively, these studies highlight the magnitude of stress felt from 9/11 and the national, not strictly local, nature of this stress.

There is evidence that stress is a determinant in causing people to smoke (U.S. DHHS, 2001; Naquin and Gilbert, 1996; Todd, 2004; Pfefferbaum et al., 2002). Economics theory of maximizing utility subject to constraints can help explain why. The Becker-Murphy rational addiction model explains that former and current smokers have higher marginal utility of smoking than never smokers following an unexpected stressful event because former smokers know of the stress-relieving potential of smoking (i.e. reinforcement) whereas never smokers do not (Becker and Murphy, 1988). Additionally, current smokers have less incentive to make a quit attempt during these periods of greater stress because of the added benefit that smoking now has. When reinforcement causes or prolongs smoking following a stressful event, the utility of smokers temporarily increases relative to the utility of never smokers by reducing stress. Unfortunately, a temporarily helpful decision from the perceptive of the smoker can have utility diminishing and unhealthy long term consequences because of addiction. Addiction may cause smoking beyond the time it takes for the extra stress to return to baseline.

Becker and Rubinstein (2010) present a rational fear model that explains that terrorism generates large behavioral responses (for example, following 9/11, use of air transportation fell by 15%) because people have a hard time matching their subjective fears of terrorism with the objective reality. However, people can make investments in education that allow them to better match the subjective risk with the objective reality. The authors found that after terrorist attacks in Israel, the less-educated reduced purchases of bus tickets for a longer period of time than the more-educated, implying that the less-educated overestimated for a longer period of time the likelihood of future terrorist attacks (Becker and Rubinstein, 2010). This research attempts to apply this theoretical model to a commodity that people will substitute towards (cigarettes) because of its stress-reducing potential rather than a commodity that people substitute away from (buses, airplanes) because of perceived danger.

A potential violation of a critical assumption of the Becker and Rubinstein theory is that terrorist attacks investigated in the United States may be different than terrorism in Israel if there is a perception that terrorism in the United States does not homogenously impact people based on education. Air travel, skyscrapers, and the Pentagon were targeted in the United States terrorist attacks and are arguably more frequently utilized by more-educated populations. The rational fear model in its current form may be less applicable to this study if 9/11 was not perceived to homogenously impact people based on education.

This research employs a regression discontinuity design to observe how the effect of terrorism changes over time. Imbens and Lemieux provide an excellent overview of this method (Imbens and Lemieux, 2008) and this method was used in one other study on the effect of 9/11 on stress and substance use (Ford et al., 2003). The effect of terrorism on stress and smoking is not expected to be homogenous across the post-terrorist attack dates. Interview-based studies of 9/11 suggest that rates of post-traumatic stress disorder and more general distress return to baseline in a matter of months as opposed to years (Perrine et al., 2004; Galea et al., 2003); however, other research suggests longer periods of time (Holman et al., 2008; Norris et al., 2001). Gallup polling provides evidence that terrorism-induced stress slowly decays with time. For example, 24% of people said they were somewhat or very worried about terrorism in April of 2000 (the last time it was polled before 9/11), but 58% said they were on 9/11. As of January

2010, 42% still said they were somewhat or very worried about terrorism, suggesting that terrorism-induced stress has still not returned to baseline.[1]

Additionally, people who begin to smoke during periods of high stress form addiction. Even when smoking is no longer justified based on the decreased level of terrorism stress, addictive stock has been accumulated and quitting will be hard. This is especially true for former smokers because they resumed smoking with existing addictive stock.

The result of these two forces is that people who start smoking following terrorism (or current smokers who are now unmotivated to quit) may take longer to quit than non-terrorism-induced smokers because the terrorism-induced smokers will first have to wait until stress returns to baseline. Only then will they begin the normal cessation process that may take just as long as it would for non-terrorism-induced smokers, depending on the amount of addictive stock that has been accumulated.

Several studies have attempted to quantify the prolonging effect of addiction on smoking. The Surgeon General reports that each year only 2-3% of smokers—or about 7-10% of those who try to quit—manage to stop smoking for 1 year (U.S. DHHS, 1994). A study of California smokers found that smokers classified as relatively heavily addicted had, depending on their quitting history, between a 5.4-5.8% chance of currently being a former smoker for at least 1 year, 2 years later. Relatively lightly addicted smokers had between a 3.2-10.8% chance (Pierce et al., 1998). Another study found that the proportion of recent dependent smokers who had quit for at least 6 months in the past year was 5-8.5%, depending on age, with younger smokers more successful in quitting (Messer et al., 2008). These studies suggest that addiction may account for a large amount of time it takes for terrorism-induced smoking to return to baseline. A regression

[1] Data was obtained from the article 'Terrorism in the United States,' found on the Gallup website. Data was accessed on July 8, 2011 at http://www.gallup.com/poll/4909/Terrorism-United-States.aspx.

discontinuity design can help observe how terrorism differentially influences stress and smoking over time.

## 3. DATA DESCRIPTION

### 3.1 Behavioral Risk Factor Surveillance System Data

This research uses Behavioral Risk Factor Surveillance System (BRFSS) data from the years 1994 to 2003. State health departments and the Centers for Disease Control and Prevention (CDC) collect the BRFSS data on risky personal health behaviors via landline telephone surveys of individuals aged 18 years and older. The data is weighted for the probability of selection of a telephone number, the number of adults in a household, and the number of telephones in a household. The data is nation and state representative of the non-institutionalized adult population. A final poststratification adjustment is made for non-response and non-coverage of households without telephones. The individual-level repeated cross-sections database has interview date and state identifying information. Additionally, county information is provided by 80.9% of respondents.

The number of individuals interviewed annually in the BRFSS survey increased from 105,793 in 1994 to 265,090 in 2003. Observations were dropped due to invalid dates (6), respondents residing in U.S. territories besides Washington D.C. (35,309), and respondents not providing smoking status (4,526). The cleaned dataset contains 1,657,985 observations. Within these years, all states completed the survey except for Rhode Island in 1994 and the District of Columbia in 1995.

Population-weighted and unweighted descriptive statistics for the years 1994-2003 are provided in Table I.

# TABLE I: POPULATION DESCRIPTIVE STATISTICS – 1994-2003

| | Unweighted | | Weighted | |
|---|---|---|---|---|
| | Mean | Standard Deviation | Mean | Standard Deviation |
| **BRFSS** | | | | |
| Male (%) | 40.65 | 49.12 | 48.07 | 49.96 |
| Female (%) | 59.35 | 49.12 | 51.93 | 49.96 |
| White non-Hispanic (%) | 80.44 | 39.67 | 74.19 | 43.76 |
| Black non-Hispanic (%) | 7.98 | 27.10 | 9.58 | 29.43 |
| Asian non-Hispanic (%) | 2.01 | 14.05 | 2.61 | 15.94 |
| Native American non-Hispanic (%) | 1.41 | 11.77 | 0.96 | 9.74 |
| Hispanic (%) | 5.96 | 23.68 | 10.74 | 30.96 |
| Missing Race/Ethnicity (%) | 2.20 | 14.66 | 1.93 | 13.76 |
| Age | 47.64 | 17.64 | 45.23 | 17.72 |
| Junior High (%) | 4.39 | 20.48 | 5.19 | 22.18 |
| Some High School (%) | 7.62 | 26.53 | 8.34 | 27.64 |
| High School (%) | 31.95 | 46.63 | 31.74 | 46.55 |
| Some College (%) | 27.24 | 44.52 | 27.01 | 44.40 |
| College (%) | 28.56 | 45.17 | 27.46 | 44.63 |
| Missing Education (%) | 0.24 | 4.94 | 0.27 | 5.18 |
| Employed (%) | 61.86 | 48.57 | 62.71 | 48.36 |
| Unemployed (%) | 3.80 | 19.11 | 4.39 | 20.48 |
| Student (%) | 3.00 | 17.07 | 4.26 | 20.19 |
| Not Student, Not in Labor Force (%) | 30.94 | 46.22 | 28.22 | 45.00 |
| Missing Employed Status (%) | 0.40 | 6.30 | 0.43 | 6.58 |
| Married (%) | 54.15 | 49.83 | 59.22 | 49.14 |
| Divorced (%) | 15.98 | 36.64 | 11.72 | 32.17 |
| Widowed (%) | 10.73 | 30.95 | 7.16 | 25.78 |
| Unmarried and Other Marital Status (%) | 18.86 | 39.12 | 21.66 | 41.19 |
| Missing Marital Status (%) | 0.29 | 5.34 | 0.24 | 4.85 |
| Real Household Income (without imputation, in 1,000s of dollars) | 31.02 | 19.04 | 32.27 | 19.62 |
| Real Household Income (with imputation, in 1,000s of dollars) | 30.39 | 18.29 | 31.51 | 18.84 |
| Top Household Income Category (%) | 12.91 | 33.54 | 13.81 | 34.50 |
| Stress (Days Mental Health Not Good over Past 30 Days) | 3.23 | 7.42 | 3.11 | 7.17 |
| Every Day Smoker (%) | 18.17 | 38.56 | 17.88 | 38.32 |
| Some Day Smoker (%) | 4.50 | 20.72 | 4.83 | 21.43 |
| Former Smoker (%) | 25.34 | 43.50 | 24.44 | 42.97 |
| Never Smoker (%) | 52.00 | 49.96 | 52.85 | 49.92 |
| Smoking Quit Attempt (as % of Current Smokers) | 49.67 | 50.00 | 50.69 | 50.00 |
| **Merged Outside Data** | | | | |
| Smoke-Free Air Law Index (scale of 1-9) | 1.37 | 1.61 | 1.77 | 2.24 |
| Real After-Tax Price per Pack of Cigarettes (in dollars) | 2.1087 | 0.5539 | 2.0296 | 0.5602 |
| State-Level Unemployment Rate (%) | 4.84 | 1.31 | 5.14 | 1.29 |
| County Population Density per Respondent (in 1,000s of people) | 1.35 | 4.06 | 2.54 | 6.59 |
| Reverse Distance from Terrorist Attack (in 1,000s of miles) | -0.90 | 0.74 | -0.82 | 0.59 |
| County Per Capita Military Pay (in dollars) | 0.276819 | 0.726757 | 0.223625 | 0.629596 |
| Violent and Property Crime (in trillions of people) | 0.0433 | 0.0122 | 0.0457 | 0.0113 |
| Military Casualties in Past 30 Days (in 100s of deaths) | 0.072516 | 0.197094 | 0.051138 | 0.169084 |
| DOW Past 30 Days (in 1,000s of dollars) | 6.2884 | 1.4672 | 6.0554 | 1.6010 |

Men, racial/ethnic minorities (except Native Americans), and younger people are underrepresented in the unweighted data. The weighted data will be used in all analyses.

## 3.2 Dependent Variables

Survey respondents are asked if they have smoked 100 or more cigarettes in their lifetime and, if so, the frequency of smoking days. Responses are categorized as every day smoker, some day smoker, former smoker, and never smoker.[2] These four categories of smoking make between-group testing possible, such as if former smokers respond to terrorism more than never smokers. While smoking prevalence slightly decreased over the years investigated, from 22.7% in 1994 to 22.3% in 2003, this research hypothesizes that the decline in smoking prevalence would have been even greater had it not been for the Oklahoma City bombing or 9/11 terrorist attacks.

A second smoking question asks current smokers if a quit attempt has been made in the past year. It is expected that terrorism would cause current smokers to be less motivated to quit smoking, and smokers should reduce quit attempts as a result. The wording of the question changed slightly in 2001. The question was originally, "During the past 12 months, have you quit smoking for 1 day or longer?" and this was changed to "During the past 12 months, have you stopped smoking for one day or longer because you were trying to quit smoking?"

Survey respondents are also 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?" The question is phrased to minimize non-reporting of the sensitive area of mental health.

[2] The year 1994 was chosen as the cutoff for this study because the smoking prevalence questions have been consistently asked since this time.

In the survey period investigated, 98.5% of people asked the question answered it. However, the stress question was part of an optional module in year 2002 and was only asked in 21 states.[3] In 1999 and 2001, stress was 4.9% higher in these 21 states compared to the 30 other states. Analysis will be conducted using years 1999-2001, when the sample of stress respondent was consistent, as well as samples from longer periods of time. Results suggest little impact of the reduced stress sample in the year 2002.

Table II provides national and state-level estimates of select dependent variable means one year before and after 9/11.

[3] The 21 states that asked this question pertaining to stress in 2002 were Alaska, California, Hawaii, Idaho, Iowa, Kansas, Kentucky, Minnesota, Missouri, New Jersey, New Mexico, New York, North Carolina, Oregon, Rhode Island, South Carolina, Texas, Utah, Virginia, Washington, Wyoming.

TABLE II: COMPARISON OF DEPENDENT VARIABLE MEANS PRE- AND POST-9/11

| | Smoking Prevalence | | | Smoking Intensity | | | Quit Attempt in Past Year | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean 9/10/2000-9/10/2001 | Mean 9/12/2001-9/12/2002 | Percent Change | Mean 9/10/2000-9/10/2001 | Mean 9/12/2001-9/12/2002 | Percent Change | Mean 9/10/2000-9/10/2001 | Mean 9/12/2001-9/12/2002 | Percent Change |
| **USA** | 22.67% | 22.86% | 0.85% | 0.84 | 0.86 | 1.81% | 54.00% | 56.12% | 3.91% |
| | | | | | | | | | |
| **AL** | 24.15% | 24.53% | 1.57% | 0.87 | 0.92 | 5.91% | 53.01% | 56.91% | 7.37% |
| **AK** | 26.50% | 28.71% | 8.35% | 0.84 | 0.95 | 13.31% | 61.44% | 54.79% | -10.82% |
| **AZ** | 21.62% | 21.54% | -0.36% | 0.80 | 0.78 | -2.25% | 52.91% | 57.46% | 8.61% |
| **AR** | 25.89% | 25.66% | -0.90% | 0.95 | 0.91 | -4.17% | 54.15% | 53.80% | -0.65% |
| **CA** | 16.71% | 17.13% | 2.49% | 0.67 | 0.69 | 3.20% | 55.28% | 61.32% | 10.93% |
| **CO** | 22.36% | 20.64% | -7.71% | 0.79 | 0.78 | -0.55% | 48.72% | 54.16% | 11.17% |
| **CT** | 20.04% | 19.72% | -1.60% | 0.71 | 0.69 | -3.27% | 54.29% | 61.64% | 13.55% |
| **DE** | 24.66% | 24.92% | 1.06% | 0.88 | 0.87 | -1.63% | 50.69% | 57.57% | 13.58% |
| **DC** | 20.75% | 20.44% | -1.51% | 0.78 | 0.79 | 1.71% | 63.35% | 60.83% | -3.99% |
| **FL** | 22.49% | 22.42% | -0.28% | 0.79 | 0.85 | 7.87% | 54.15% | 52.73% | -2.62% |
| **GA** | 23.35% | 23.42% | 0.31% | 0.90 | 0.92 | 3.27% | 58.58% | 59.59% | 1.73% |
| **HI** | 20.12% | 20.91% | 3.94% | 0.81 | 0.82 | 1.26% | 61.69% | 53.62% | -13.08% |
| **ID** | 20.16% | 19.76% | -1.97% | 0.81 | 0.79 | -2.18% | 50.20% | 58.90% | 17.32% |
| **IL** | 22.15% | 23.33% | 5.33% | 0.83 | 0.88 | 5.45% | 56.07% | 56.28% | 0.38% |
| **IN** | 27.54% | 27.67% | 0.49% | 1.01 | 0.98 | -3.60% | 51.99% | 54.43% | 4.69% |
| **IA** | 23.10% | 22.25% | -3.64% | 0.87 | 0.88 | 1.37% | 51.89% | 51.14% | -1.45% |
| **KS** | 21.61% | 22.87% | 5.83% | 0.86 | 0.85 | -1.47% | 50.05% | 51.03% | 1.96% |
| **KY** | 31.03% | 32.24% | 3.91% | 1.05 | 1.12 | 6.04% | 46.78% | 48.68% | 4.06% |
| **LA** | 23.21% | 24.69% | 6.40% | 0.96 | 1.02 | 7.15% | 56.43% | 58.37% | 3.43% |
| **ME** | 22.76% | 23.91% | 5.06% | 0.75 | 0.77 | 2.84% | 59.28% | 60.76% | 2.50% |
| **MD** | 20.95% | 21.83% | 4.20% | 0.82 | 0.82 | 0.77% | 54.71% | 56.25% | 2.82% |
| **MA** | 20.08% | 18.42% | -8.25% | 0.71 | 0.69 | -3.57% | 57.36% | 59.61% | 3.92% |
| **MI** | 25.53% | 25.05% | -1.89% | 0.88 | 0.89 | 0.85% | 55.67% | 57.91% | 4.03% |
| **MN** | 22.23% | 21.85% | -1.68% | 0.79 | 0.78 | -1.38% | 57.36% | 58.28% | 1.60% |
| **MS** | 25.16% | 26.26% | 4.36% | 0.96 | 1.00 | 4.13% | 55.72% | 56.82% | 1.97% |
| **MO** | 25.96% | 27.16% | 4.63% | 0.92 | 0.95 | 3.73% | 53.49% | 48.98% | -8.42% |
| **MT** | 20.34% | 21.17% | 4.10% | 0.75 | 0.79 | 5.43% | 46.95% | 54.16% | 15.36% |
| **NE** | 20.37% | 21.80% | 7.01% | 0.85 | 0.87 | 2.39% | 48.20% | 55.94% | 16.05% |
| **NV** | 27.96% | 26.29% | -5.95% | 0.93 | 0.91 | -2.78% | 50.65% | 53.74% | 6.10% |
| **NH** | 25.29% | 23.39% | -7.51% | 0.82 | 0.80 | -2.45% | 57.72% | 58.97% | 2.16% |

**(continued on next page)**

**(continued from previous page)**

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **NJ** | 20.88% | 19.35% | -7.33% | 0.77 | 0.76 | -0.23% | 54.58% | 60.16% | 10.21% |
| **NM** | 23.63% | 21.81% | -7.69% | 0.83 | 0.78 | -5.59% | 52.60% | 56.53% | 7.47% |
| **NY** | 23.58% | 22.37% | -5.13% | 0.84 | 0.83 | -0.98% | 54.15% | 59.70% | 10.25% |
| **NC** | 27.12% | 25.23% | -6.95% | 0.96 | 0.95 | -1.71% | 55.90% | 56.29% | 0.68% |
| **ND** | 22.52% | 21.47% | -4.66% | 0.84 | 0.78 | -6.67% | 53.64% | 56.23% | 4.83% |
| **OH** | 26.58% | 26.80% | 0.83% | 0.96 | 0.93 | -3.38% | 45.79% | 52.21% | 14.03% |
| **OK** | 27.47% | 26.72% | -2.74% | 1.05 | 1.01 | -4.22% | 51.22% | 51.98% | 1.48% |
| **OR** | 20.33% | 21.99% | 8.16% | 0.72 | 0.76 | 5.89% | 59.58% | 54.67% | -8.23% |
| **PA** | 23.85% | 24.94% | 4.54% | 0.88 | 0.88 | -0.42% | 51.02% | 53.21% | 4.29% |
| **RI** | 23.09% | 22.59% | -2.15% | 0.79 | 0.77 | -2.50% | 56.66% | 65.46% | 15.54% |
| **SC** | 25.37% | 26.28% | 3.58% | 0.94 | 0.95 | 0.87% | 54.29% | 57.09% | 5.15% |
| **SD** | 21.95% | 23.24% | 5.88% | 0.82 | 0.90 | 9.81% | 53.58% | 56.67% | 5.75% |
| **TN** | 25.02% | 26.74% | 6.87% | 1.00 | 1.10 | 10.05% | 53.99% | 53.62% | -0.69% |
| **TX** | 22.92% | 22.89% | -0.12% | 0.89 | 0.89 | -0.62% | 56.17% | 54.37% | -3.21% |
| **UT** | 13.08% | 12.76% | -2.40% | 0.70 | 0.75 | 7.02% | 64.02% | 64.69% | 1.05% |
| **VT** | 21.88% | 21.63% | -1.15% | 0.73 | 0.73 | 0.35% | 54.50% | 54.46% | -0.07% |
| **VA** | 21.75% | 25.10% | 15.39% | 0.84 | 0.91 | 8.91% | 53.02% | 52.92% | -0.17% |
| **WA** | 21.63% | 22.16% | 2.46% | 0.75 | 0.76 | 1.03% | 60.29% | 60.22% | -0.12% |
| **WV** | 27.75% | 28.42% | 2.41% | 0.96 | 1.00 | 4.05% | 50.85% | 51.92% | 2.09% |
| **WI** | 23.38% | 23.86% | 2.06% | 0.80 | 0.84 | 5.04% | 56.13% | 56.57% | 0.79% |
| **WY** | 22.81% | 22.95% | 0.63% | 0.84 | 0.83 | -0.81% | 46.68% | 56.67% | 21.38% |

[a] Stress is used as a dependent variable, but is not included in this chart because stress was part of an optional module completed by only 21 states in 2002.
[b] Survey features of the data and subpopulations are used in computing these estimates.
[c] Smoking intensity is defined as a 2 for every day smokers, a 1 for some day smokers, and a 0 for former smokers, with never smokers dropped.
[d] Quit attempt information was only collected from current smokers.

Smoking prevalence increased .9%, smoking intensity increased 1.8%, and, opposite expectations, smoking quit attempts increased 3.9%. The three states experiencing the largest increases in smoking prevalence were Virginia (15.4%), Alaska (8.4%), and Oregon (8.2%). Tennessee and South Dakota replace Virginia and Oregon in the top three smoking intensity increases. Hawaii (-13.1%), Alaska (-10.8%), and Missouri (-8.4%) had the greatest declines in quit attempts. From the national mean comparisons, increases in smoking from 9/11 appear plausible, but there is no evidence in support of this hypothesis for quit attempts. Smoking increases do not appear to be concentrated near the terrorist attack epicenters.

Figures 1-2 presents a mapping over time of the data on stress and smoking from 1999 to 2003, shown in terms of standard deviations from the mean. A strength of the BRFSS data is that it is free of memory error or response biases by collecting information on stress and smoking before and after the terrorist attacks. In Figure 1, a clear spike in stress is seen around 9/11/2001. This relationship is less clear in Figure 2, but an increase in both smoking prevalence and intensity does push smoking above the mean from a point below it prior to 9/11/2001. The persistence of a potential terrorism effect is unclear, as stress declines below baseline before January, 2002 and smoking shortly thereafter. Following, both oscillate across the mean, with stress staying above the mean for much of year 2003. Multivariate analysis is needed to determine if terrorism or other factors contributed to the stress and smoking increase around 9/11 and if there is a persistence effect.

Limitations of the data are that it does not survey youth, the never smoker age group most pliable on whether to smoke or not (U.S. DHHS, 2012). Additionally, there is no psychiatric verification of days of stress or biochemical verification of smoking status. However, both measures have been found to have high validity and estimates are comparable with other datasets (CDC, 2005; CDC, 1998).

### 3.3. Control Variables

Socio-demographic information is provided for all respondents and is used to control for other factors that could explain stress and smoking. These controls include indicator variables for gender, race/ethnicity, education attainment, marital status, and employment status. Household income information was provided as a categorical variable, and this was converted into a continuous variable using the median for each of the categories. Age is used as a continuous variable.

Missing indicator variables were set equal to one for respondents with missing race/ethnicity, education, employment, and marital status information. Household income information was not provided by 13.7% of survey respondents. Dropping these observations could bias the estimates; therefore, missing household income values were linearly imputed by regressing household income on variables likely to explain household income and then predicting missing values.[4] Additionally, a small number of observations were missing information on age and values were similarly imputed.[5]

### 3.4 Merged Data

Data that controls for determinants of smoking were merged, including after-tax cigarette prices and smoke-free air law strengths. The Tax Burden on Tobacco contains weighted price averages for a pack of 20 cigarettes, including pack, carton, and machine sales of both brand and

[4] Inflation-adjusted household income category values were used as a lower bound for any predictions.
[5] Age was imputed first and household income second. The age bounds of 18 and 99 were used for any predictions that fell outside the range.

generic cigarettes (Orzechowski and Walker, 2009). These prices are inclusive of federal and state excise taxes. These prices are disaggregated to a quarterly level by ImpacTeen and were further adjusted by the author for changes in state excise taxes occurring mid-quarter.[6] All monetary data, including the cigarette price data, was adjusted for inflation using the Bureau of Labor Statistic's city average for all consumers consumer price index.

Smoke-free air law data was collected by the ImpacTeen project through the MayaTech consulting firm. This data measures the strength of each state's restaurant, workplace, and bar smoke-free air laws respectively (on a scale of 0-3, 3 being the strongest restrictions). This information is summed to create an index value of between 0-9 and matched to the BRFSS data based on each respondent's state of residence and survey date.

The Bureau of Labor Statistics' monthly state-level unemployment data is used in constructing a state-level unemployment rate variable, which is included in all regressions to control for spillover effects of unemployment beyond individual-level employment status. The variable captures a wide-range of activity, including less stress from greater leisure time (some of it involuntary) and other labor market considerations (e.g. increased susceptibility of being fired for taking smoke breaks when unemployment rates are high).

People living closer to the epicenters of the terrorist attacks may experience disproportionate stress (Smith et al., 1999; Stein et al., 2004; Schlenger et al., 2002). These people are more likely to have been directly impacted by the attacks, and this can cause negative emotions, such as stress, that can lead to smoking. To test this hypothesis, distance data was calculated using ArcGIS software. Distances were measured from the centers of New York City, Washington DC, and Oklahoma City to the centers of each of the respective counties in the

[6] In these instances, the weighted proportion of the increased cigarette excise tax (Orzechowski and Walker, 2009) was first removed from the average state price for that quarter. If the interview date was after the state excise tax increase came into effect, then the full state excise tax increase was added back to the adjusted price.

United States.[7] If county data was missing, as it was in 19.1% of cases, the average quarterly distance data for residents of the state was used instead.

Unfortunately, the BRFSS data does not provide employer information, which would be useful for identifying military personnel and analyzing any differential effect of terrorism on this population. Instead, county-level military pay data, provided by the Consolidated Federal Funds Report, a government expenditures report, is used.[8] The federal military pay for active duty and national guard/reservist soldiers in each county is divided by interpolated annual July Census population estimates by county to obtain county per capita military pay information, which is merged with the BRFSS data. State per capita military pay information was used for observations with missing county data. A benefit of this county-level data is that it captures family and community effects of terrorism.

People living in high population density areas may have greater stress following terrorism because terrorists are likely to target high population density centers. If this is true, then people living in counties with higher population densities may show larger increases in stress and smoking following terrorism than people living in low population density counties. Interpolated July Census population estimates and county land area data were used to determine population densities by county. If county data was missing in the BRFSS data, then the average quarterly population density for respondents in the state was used.

Data on military casualties, stock market valuation, and crime is used in sensitivity analysis to determine if these factors have the effect of weakening measured impacts of terrorism. The attacks of 9/11 were associated with substantial falls in stock market valuation

[7] Following 9/11, the distance measure used was the distance from New York City to the center of each county unless the distance to Washington DC was less than 100 miles, in which case only the distance to Washington DC was used.

[8] Data was obtained from the National Priorities Project website. Data was accessed on July 8, 2011 at http://nationalpriorities.org/en/tools/database/.

(personal wealth) and two wars. The first causalities of Operation Enduring Freedom occurred in October of 2001 and the first casualties of Operation Iraqi Freedom occurred in March of 2003. Casualty data for these two operations[9] were used to generate a measure of military casualties over the past 30 days. A past 30-day moving average of the closing values for the Dow Jones Industrial Average was matched to the daily BRFSS data to control for financial stress and changes in wealth that could affect cigarette consumption. Finally, annual state-level violent and property crime data is summed and used for comparing terrorism with another form of violence related stress.[10]

## 4. SINGLE EQUATION MODELING WITH A REGRESSION DISCONTINUITY DESIGN

### 4.1 Model

The effect that terrorism has on stress and smoking will first be explored using single equation modeling, with a regression discontinuity design, to observe the effect of terrorism on stress and smoking over time. An algebraic representation of the single equation models is identified in equations 1-4.

$$\mathrm{stress}_{ist} = \alpha + \beta_1 \emptyset_{st} + \beta_2 X_{ist} + \beta_3 \mathrm{post}_t + \beta_4 \mathrm{time}_t + \gamma_s + \gamma_{day} + \gamma_{season} + \varepsilon_{ist} \quad (1)$$

$$\mathrm{smoke\_prevalence}_{ist} = \alpha + \beta_1 \emptyset_{st} + \beta_2 X_{ist} + \beta_3 \mathrm{post}_t + \beta_4 \mathrm{time}_t + \gamma_s + \gamma_{season} + \varepsilon_{ist} \quad (2)$$

$$\mathrm{smoke\_intensity}_{ist} = \beta_1 \emptyset_{st} + \beta_2 X_{ist} + \beta_3 \mathrm{post}_t + \beta_4 \mathrm{time}_t + \gamma_s + \gamma_{season} + \varepsilon_{ist} \quad (3)$$

---

[9] Data was obtained from the Department of Defense Personnel & Procurement Statistics website. Data was accessed on July 8, 2011 at http://siadapp.dmdc.osd.mil/personnel/CASUALTY/castop.htm. Over the time period investigated, military casualties included in this measure are 105 casualties in Operation Enduring Freedom and 486 casualties in Operation Iraqi Freedom. Smaller involvements that resulted in casualties, including 17 casualties in the USS Cole bombing in 2000 and 2 casualties in the Kosovo conflict in 1999, are not included in this measure.

[10] Data was obtained from the Federal Bureau of Investigation's "Crime in the U.S." website. Data was accessed on July 8, 2011 at http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s.

$$\text{quit\_attempt}_{\text{ist}} = \alpha + \beta_1\Psi_{\text{st}} + \beta_2\text{X}_{\text{ist}} + \beta_3\text{post}_{\text{t}} + \beta_4\text{time}_{\text{t}} + \beta_5\text{99-00}_{\text{t}} + \gamma_{\text{s}} + \gamma_{\text{season}} + \varepsilon_{\text{ist}} \quad (4)$$

The subscript *i* refers to the individual, *s* to the state, and *t* to the date. To investigate the effect of the Oklahoma City bombing, the estimation sample always contains observations from 1994 to the Oklahoma City bombing on 4/19/1995. For the effect of 9/11, the estimation sample always contains observation from 1999 to 9/11/2001. Months or quarters though 1995 or 2003 for the respective terrorist attacks are iteratively added to the base sample with replacement. This extra month or quarter is individually captured by the $\text{post}_t$ variable, making $\beta_3$ the coefficient of interest. This regression discontinuity design allows an observation of how the effect of terrorism changes over time.

The dependent variables include $\text{stress}_{ist}$, which is an integer variable with values between 0-30 for days in the past 30 days that mental health was not good. The dependent variable $\text{smoke\_prevalence}_{ist}$ is a 1 for a smoker and a 0 for the category of non-smoker investigated, depending on which population is being investigated. In an alternative specification of this information, the variable $\text{smoke\_intensity}_{ist}$ is an ordinal ranking of smoking prevalence intensity, taking on the value of 2 for individuals that are every day smokers, 1 for individuals that are some day smokers, and 0 for individuals that are either former smokers or never smokers, depending on which population is being investigated. The variable $\text{quit\_attempt}_{ist}$ is a 1 for smokers that attempted to quit smoking in the past year and 0 for smokers that did not.

In all equations, $\text{X}_{ist}$ is a matrix of individual-level control variables (gender, race/ethnicity, household income, age, education attainment, marital status, and employment status).[11] This rich set of individual characteristics controls for demographic and socio-demographic shifts correlated with stress and smoking. Included in $\text{X}_{ist}$ is an indicator variable

[11] Reference categories are male, White non-Hispanic, some high school, married, and employed.

for the highest category of household income to account for a downward bias when household income categories were converted into a continuous variable. Squared household income and age terms are also included in non-average marginal effect specifications to account for any non-linearity. $\emptyset_{st}$ is a matrix of state-level control variables (real after-tax cigarette prices, smoke-free air law strengths, and unemployment rates) that vary across state and time.[12] In equation 4, $\Psi_{st}$ is past year moving averages of the same variables in $\emptyset_{st}$ ($\Psi_{\mathrm{st}} = \frac{\sum_t^{t+365} \emptyset_{\mathrm{st}}}{365}$), matching the annual nature of the quit attempt dependent variable. Additionally, the slight change in quit attempt question wording after 2000 may have contributed to a 10.1% increase in reported quit attempts in 2001, so an indicator variable to capture the original wording of the question is included when using the 9/11 sample.

Several controls are used in the models to limit potential omitted variable biases. A linear month time variable, $\mathrm{time}_t$, is used to account for the downward drift in smoking prevalence due to factors not already mentioned. Season indicator variables[13] are used to control for seasonal effects of smoking, which includes seasonal travel and seasonality of prices. State indicators are included to capture unobservable time-invariant differences across geographical regions (including differences in anti-smoking sentiment). In the stress model, day fixed effects are included to control for any variation in stress reported depending on the day of the week the interview was conducted (e.g. Mondays are stressful days).

The dependent variable data type was considered when deciding on the estimation techniques for the single equation models. For the stress model, the mean of the dependent stress variable is 3.1 days and variance of the variable is 51.4 days, over 16 times greater. Parameters

---

[12] In the single equation model for stress (1), smoke-free air law strengths and real after-tax cigarette prices are not included in $\emptyset_{st}$.

[13] December, January, and February are winter months and all seasons have three months.

would be biased if using an OLS model because of the strong rightward skew of the data; therefore, this variable will be analyzed as a continuous count variable using a negative binomial distribution to account for the large over-dispersion. For the smoking intensity model, an ordered logit model will be used to test the transition between never smokers or former smokers, some day smokers, and every day smokers. An ordered logit model is not estimated with a constant term and instead uses cut points. Logit estimation will be used for the smoking prevalence and quit attempt equations.

## 4.2 Determining the Effect of Terrorism Over Time

Stock charts of the average marginal effects on the quarterly post coefficients for equations 1-4, using the 9/11 sample, are presented in Figures 3-10. Figures 11-26 show the monthly effects for the Oklahoma City bombing and 9/11. Using equation 1, individuals experienced a sharp increase in stress in the fourth quarter of 2001, shown in Figure 3. The increase in stress returned to baseline immediately in subsequent quarters.

Previously discussed hypotheses regarding former smokers being more at-risk of terrorism-induced smoking due to reinforcement and addiction are tested by discarding from the sample either former smokers or never smokers, estimating equations 2 and 3, and comparing estimated average marginal effects and trend lines (Figures 4-9). There is evidence to support the hypothesis that only former smokers become smokers again following terrorism. For both smoking dependent variables, no increases in smoking following terrorism were found in the sample using never smokers, but increases in smoking were found in the sample using former smokers. Using smoking intensity as the dependent variable, probabilities of being a some day smoker or an every day smoker increased in the first,[14] third, fifth, and seventh quarters following 9/11 compared to baseline. Using smoking prevalence as the dependent variable, the probability of being a smoker increased in the fourth quarter of 2001 at a 10% significance level.

Using equation 4, there is no evidence that quit attempts declined following 9/11 (Figure 10). None of the average marginal effects are statistically different from zero. Additionally, the trend following 9/11 does not have the hypothesized slope, declining towards baseline rather than increasing. Earlier, it was also reported that mean estimates for smoking quit attempts actually increased in the year following 9/11. These unexpected results may be due to difficulty in modeling the annual nature of the quit attempt dependent variable and/or insufficiently controlling for the question wording change in 2001.

Based on earlier results, future analysis will use one of three time horizons. A conservative specification will investigate just the impact in the fourth quarter of 2001, as statistically significant increases in stress and smoking were observed there. Alternatively, the trend lines produced by regressing the average marginal effects against time may yield information about how long it takes before the terrorism-induced reactions return to baseline. Using a linear time variable suggests that it takes 2 years for smoking prevalence to decline to baseline, between 8.6 to 9.6 years for smoking intensity to decline to baseline, and 6.3 years for stress to decline to baseline. A middle estimate of the effect of terrorism will be estimated by using the trend line observed in the smoking prevalence model with September, 2003 as the cutoff point, approximately two years after 9/11. Alternatively, stress and smoking intensity trend line estimates suggest that the terrorism impact lingers past the end of 2003. Discounting will be ignored for the third time specification, which contains all post-9/11 dates through the end of 2003 and is a more liberal estimate of the effect of terrorism. This specification captures

[14] Result is significant at a 10% level for the probability of being an every day smoker.

the statistically-significant increases in smoking intensity observed as late as seven quarters after 9/11.

This same analysis was conducted using a three-year window around the Oklahoma City bombing, but no changes compared to baseline were detected in either the quarterly data or in the monthly data in the months immediately preceding the terrorist attack; therefore, the rest of this analysis will focus on only the 9/11 attacks.[15] Additionally, given the finding that changes in smoking were not detected in never smokers, never smokers are dropped in all future models to provide more precise estimates. Finally, smoking quit attempt models will not be investigated further given the unexpected earlier findings.

### 4.3 Results from Different Time Estimates

Table III shows the terrorism average marginal effect estimates from equations 1-3. Full results are provided in Tables IV-VI.[16]

---

[15] There are some key differences between 9/11 and the Oklahoma City bombing that may contribute to no stress or smoking increases. The Oklahoma City bombing had one-twentieth the number of casualties, the perpetrator of the attack was a US citizen and apprehended almost immediately after the attack, and popular air travel was not involved.

[16] Full results show that smoke-free air law strength parameters have negative coefficients that are significant in one of the three samples. Cigarette prices are never statistically significant, but do have the desired negative coefficients using the larger samples (year 2002 and 2003). The unemployment rate parameter is found to be statistically significant negative in the smoking prevalence model using the larger samples, which corroborates other findings of a procyclical relationship between employment and smoking (Ruhm, 2000, 2005).

TABLE III: SINGLE EQUATION MODELS

| | Independent Variable: 4Q of 2001 | 9/11 Decay Variable | Full Post 9/11 |
|---|---|---|---|
| Equation (1) - Stress | | | |
| Negative Binomial | **0.4929*** ** | **0.1963*** | **0.1931*** |
| | (0.1561) | (0.1103) | (0.1166) |
| Equation (2) - Smoking Prevalence | | | |
| Logit | **0.0124*** | **0.011** ** | **0.0092*** |
| | (.007) | (0.0048) | (0.005) |
| Equation (3) - Smoking Intensity, predicted some day smoker | | | |
| Ordered Logit | **0.0006** ** | **0.0005** ** | **0.0007*** ** |
| | (.0003) | (0.0002) | (0.0003) |
| Equation (3) - Smoking Intensity, predicted every day smoker | | | |
| Ordered Logit | **.0123*** | **.0094** ** | **.0122*** ** |
| | (.0064) | (.0043) | (.0045) |

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with linearized standard errors.
[b] Each cell presents the result of interest from different regressions.
[c] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[d] Never smokers are subset from the models because they are not found to change smoking statuses.
[e] Two-tailed t-statistics are reported.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

TABLE IV: STRESS SINGLE EQUATION MODEL FULL RESULTS

| | Dependent Variable: | | |
|---|---|---|---|
| | **Stress** | | |
| State-Level Unemployment Rate | -22.1946*** | -17.6392*** | -17.5659*** |
| | (6.0475) | (4.2773) | (4.3206) |
| Female | 1.5128*** | 1.5054*** | 1.5173*** |
| | (0.0609) | (0.0508) | (0.0491) |
| Black non-Hispanic | -0.3129** | -0.2686*** | -0.2709*** |
| | (0.1238) | (0.1034) | (0.0989) |
| Asian non-Hispanic | -0.9527*** | -0.6517*** | -0.6661*** |
| | (0.275) | (0.2361) | (0.2222) |
| Native American non-Hispanic | 0.8546*** | 0.8035*** | 0.7717*** |
| | (0.2705) | (0.2287) | (0.2176) |
| Hispanic | -0.5188*** | -0.4933*** | -0.5036*** |
| | (0.1221) | (0.1052) | (0.1036) |
| Missing Race/Ethnicity | 1.3926*** | 1.3176*** | 1.3186*** |
| | (0.2677) | (0.1969) | (0.1873) |
| Age | -0.0725*** | -0.0739*** | -0.0741*** |
| | (0.0028) | (0.0024) | (0.0023) |
| Some High School | -0.0699 | -0.0901 | -0.0804 |
| | (0.2205) | (0.1901) | (0.1823) |
| High School | -0.6119*** | -0.6456*** | -0.6454*** |
| | (0.1946) | (0.1709) | (0.1659) |
| Some College | -0.5418*** | -0.5853*** | -0.5981*** |
| | (0.199) | (0.1752) | (0.1691) |
| College | -1.2159*** | -1.1879*** | -1.2035*** |
| | (0.2014) | (0.1771) | (0.1709) |
| Missing Education | 0.4458 | -0.1164 | 0.063 |
| | (1.1124) | (0.8534) | (0.8639) |
| Unemployed | 1.9373*** | 2.0363*** | 2.2116*** |
| | (0.1586) | (0.1326) | (0.1446) |
| Student | -0.0249 | -0.1463 | -0.0824 |
| | (0.1564) | (0.1261) | (0.1233) |
| Not Student, Not in Labor Force | 1.3687*** | 1.4894*** | 1.512*** |
| | (0.105) | (0.0874) | (0.0846) |
| Missing Employed Status | 0.1478 | 0.9946 | 0.8702 |
| | (0.5852) | (0.6327) | (0.5949) |
| Divorced | 1.5339*** | 1.4946*** | 1.5338*** |
| | (0.0899) | (0.0749) | (0.0725) |
| Widowed | 0.7948*** | 0.8211*** | 0.8477*** |
| | (0.1547) | (0.128) | (0.1295) |
| Unmarried and Other Marital Status | 0.7418*** | 0.6986*** | 0.7069*** |
| | (0.0903) | (0.0744) | (0.0715) |
| Missing Marital Status | 3.4888*** | 2.6711*** | 2.5273*** |
| | (1.2113) | (0.9306) | (0.8801) |

**(continued on next page)**

**(continued from previous page)**

| | | | |
|---|---|---|---|
| Real Household Income | -0.0563*** | -0.0589*** | -0.0595*** |
| | (0.0035) | (0.0029) | (0.0028) |
| Top Household Income Category | -0.826*** | -0.75*** | -0.7671*** |
| | (0.2398) | (0.1963) | (0.1861) |
| Time (Month) | 0.0153*** | 0.0167*** | 0.0127*** |
| | (0.0038) | (0.0026) | (0.0029) |
| 9/11 Terrorism Variable, 4Q of 2001 | 0.4929*** | | |
| | (0.1561) | | |
| 9/11 Terrorism Variable, 9/11 Decay Variable | | 0.1963* | |
| | | (0.1103) | |
| 9/11 Terrorism Variable, Full Post 9/11 | | | 0.1931* |
| | | | (0.1166) |
| State Fixed Effects | X | X | X |
| Season Fixed Effects | X | X | X |
| Day Fixed Effects | X | X | X |
| Observations | 249,680 | 378,427 | 423,407 |

[a] The average marginal effect (averaged for each weighted observation) for all variables are reported with linearized standard errors.
[b] Average marginal effects for factor variables of sex, race/ethnicity, education, employment, marital status, top household income category, and terrorism measure discrete changes from the base level.
[c] Each column presents full results from different regressions.
[d] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[e] Never smokers are subset from the models to maintain uniformity with smoking samples.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

# TABLE V: SMOKING PREVALENCE SINGLE EQUATION MODEL FULL RESULTS

| | Dependent Variable: | | |
|---|---|---|---|
| | **Smoking Prevalence** | | |
| Real After-Tax Price per Pack of Cigarettes | 0.0108 | -0.0117 | -0.012 |
| | (0.0208) | (0.0083) | (0.0076) |
| Smoke-Free Air Law Index | -0.019*** | -0.0033 | -0.0018 |
| | (0.0067) | (0.0032) | (0.0019) |
| State-Level Unemployment Rate | 0.1473 | -0.3588* | -0.3842** |
| | (0.306) | (0.1933) | (0.1942) |
| Female | 0.0158*** | 0.0106*** | 0.0102*** |
| | (0.0031) | (0.0024) | (0.0023) |
| Black non-Hispanic | 0.0163*** | 0.0187*** | 0.0198*** |
| | (0.0062) | (0.0048) | (0.0046) |
| Asian non-Hispanic | 0.0371** | 0.0366*** | 0.0396*** |
| | (0.0173) | (0.0132) | (0.0126) |
| Native American non-Hispanic | 0.0542*** | 0.0673*** | 0.0708*** |
| | (0.015) | (0.0113) | (0.011) |
| Hispanic | -0.0383*** | -0.0487*** | -0.0493*** |
| | (0.0074) | (0.0058) | (0.0056) |
| Missing Race/Ethnicity | 0.0454*** | 0.0523*** | 0.0521*** |
| | (0.0108) | (0.0073) | (0.0071) |
| Age | -0.0088*** | -0.0086*** | -0.0086*** |
| | (0.0001) | (0.0001) | (0.0001) |
| Some High School | 0.0444*** | 0.0591*** | 0.0582*** |
| | (0.0104) | (0.0082) | (0.0079) |
| High School | -0.0052 | 0.0058 | 0.0058 |
| | (0.0096) | (0.0075) | (0.0073) |
| Some College | -0.0479*** | -0.0362*** | -0.0367*** |
| | (0.0098) | (0.0077) | (0.0074) |
| College | -0.1397*** | -0.129*** | -0.1291*** |
| | (0.0101) | (0.0079) | (0.0076) |
| Missing Education | -0.0167 | -0.0139 | -0.0079 |
| | (0.0369) | (0.0289) | (0.0277) |
| Unemployed | 0.0321*** | 0.0361*** | 0.0403*** |
| | (0.0085) | (0.0059) | (0.0058) |
| Student | -0.0714*** | -0.0681*** | -0.0644*** |
| | (0.0118) | (0.009) | (0.0087) |
| Not Student, Not in Labor Force | -0.0383*** | -0.0351*** | -0.0346*** |
| | (0.0047) | (0.0035) | (0.0034) |
| Missing Employed Status | -0.0343 | -0.002 | 0.0038 |
| | (0.0344) | (0.026) | (0.025) |
| Divorced | 0.1164*** | 0.1209*** | 0.1212*** |
| | (0.0043) | (0.0033) | (0.0032) |
| Widowed | 0.1038*** | 0.1014*** | 0.1035*** |
| | (0.0067) | (0.0052) | (0.005) |
| Unmarried and Other Marital Status | 0.1113*** | 0.1126*** | 0.1125*** |
| | (0.0051) | (0.0039) | (0.0038) |
| Missing Marital Status | 0.0698** | 0.0785*** | 0.0812*** |
| | (0.0353) | (0.0279) | (0.027) |

**(continued on next page)**

**(continued from previous page)**

| | | | |
|---|---|---|---|
| Real Household Income | -0.0028*** | -0.0027*** | -0.0027*** |
| | (0.0002) | (0.0001) | (0.0001) |
| Top Household Income Category | 0.0101 | 0.0024 | 0.0032 |
| | (0.0131) | (0.0098) | (0.0094) |
| Time (Month) | -0.0002 | 0.0002 | 0 |
| | (0.0003) | (0.0002) | (0.0002) |
| 9/11 Terrorism Variable, 4Q of 2001 | 0.0124* | | |
| | (0.007) | | |
| 9/11 Terrorism Variable, 9/11 Decay Variable | | 0.011** | |
| | | (0.0048) | |
| 9/11 Terrorism Variable, Full Post 9/11 | | | 0.0092* |
| | | | (0.005) |
| State Fixed Effects | X | X | X |
| Season Fixed Effects | X | X | X |
| Observations | 253,925 | 454,281 | 500,055 |

[a] The average marginal effect (averaged for each weighted observation) for all variables are reported with linearized standard errors.
[b] Average marginal effects for factor variables of sex, race/ethnicity, education, employment, marital status, top household income category, and terrorism measure discrete changes from the base level.
[c] Each column presents full results from different regressions.
[d] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[e] Never smokers are subset from the models because they are not found to change smoking statuses.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

# TABLE VI: SMOKING INTENSITY SINGLE EQUATION MODEL FULL RESULTS

| | Dependent Variable: Smoking Intensity, Predicted Some Day Smokers | | | Smoking Intensity, Predicted Every Day Smokers | | |
|---|---|---|---|---|---|---|
| Real After-Tax Price per Pack of Cigarettes | 0.0002 | -0.0006 | -0.0006 | 0.0031 | -0.0109 | -0.0108 |
| | (0.0011) | (0.0004) | (0.0004) | (0.0188) | (0.0075) | (0.0069) |
| Smoke-Free Air Law Index | -0.0009** | -0.0002 | -0.0001 | -0.0151** | -0.0031 | -0.0021 |
| | (0.0004) | (0.0002) | (0.0001) | (0.0061) | (0.0029) | (0.0017) |
| State-Level Unemployment Rate | 0.0045 | -0.0077 | -0.0152 | 0.0787 | -0.1361 | -0.2654 |
| | (0.0158) | (0.0099) | (0.0101) | (0.2766) | (0.1751) | (0.176) |
| Female | 0.001*** | 0.0007*** | 0.0007*** | 0.0175*** | 0.0123*** | 0.012*** |
| | (0.0002) | (0.0001) | (0.0001) | (0.0028) | (0.0021) | (0.0021) |
| Black non-Hispanic | -0.0008** | -0.0006*** | -0.0005** | -0.0138*** | -0.0117*** | -0.0099** |
| | (0.0003) | (0.0002) | (0.0002) | (0.0053) | (0.0041) | (0.0039) |
| Asian non-Hispanic | 0.0008 | 0.0008** | 0.0008** | 0.0187 | 0.0207* | 0.0207* |
| | (0.0005) | (0.0004) | (0.0003) | (0.0154) | (0.0116) | (0.0109) |
| Native American non-Hispanic | 0.0012*** | 0.0013*** | 0.0013*** | 0.0337** | 0.0439*** | 0.0466*** |
| | (0.0003) | (0.0001) | (0.0001) | (0.0134) | (0.0101) | (0.0098) |
| Hispanic | -0.0063*** | -0.0073*** | -0.0074*** | -0.0741*** | -0.0825*** | -0.0827*** |
| | (0.0007) | (0.0005) | (0.0005) | (0.0057) | (0.0044) | (0.0042) |
| Missing Race/Ethnicity | 0.0011*** | 0.0012*** | 0.0012*** | 0.0294*** | 0.0373*** | 0.0371*** |
| | (0.0002) | (0.0001) | (0.0001) | (0.0097) | (0.0067) | (0.0065) |
| Age | -0.001*** | -0.001*** | -0.001*** | -0.0067*** | -0.0066*** | -0.0065*** |
| | (0) | (0) | (0) | (0.0001) | (0.0001) | (0.0001) |
| Some High School | -0.0002 | -0.0002 | -0.0002 | 0.0473*** | 0.0588*** | 0.0583*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0099) | (0.0077) | (0.0074) |
| High School | -0.0001 | 0 | 0 | -0.0067 | 0.0014 | 0.0015 |
| | (0.0001) | (0.0002) | (0.0002) | (0.0091) | (0.007) | (0.0068) |
| Some College | -0.0024*** | -0.0022*** | -0.0022*** | -0.0565*** | -0.0483*** | -0.0485*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0093) | (0.0072) | (0.0069) |
| College | -0.0131*** | -0.0129*** | -0.013*** | -0.1468*** | -0.1398*** | -0.14*** |
| | (0.0005) | (0.0004) | (0.0004) | (0.0095) | (0.0073) | (0.007) |
| Missing Education | -0.0028 | -0.0022 | -0.0019 | -0.0627** | -0.049* | -0.0442* |
| | (0.0023) | (0.0017) | (0.0015) | (0.0317) | (0.0256) | (0.0247) |

**(continued on next page)**

**(continued from previous page)**

| | | | | | | |
|---|---|---|---|---|---|---|
| Unemployed | 0.001*** | 0.0011*** | 0.0012*** | 0.0246*** | 0.0284*** | 0.0317*** |
| | (0.0002) | (0.0001) | (0.0001) | (0.0071) | (0.005) | (0.0049) |
| Student | -0.0059*** | -0.0055*** | -0.0053*** | -0.07*** | -0.0668*** | -0.0644*** |
| | (0.001) | (0.0007) | (0.0007) | (0.0083) | (0.0063) | (0.0061) |
| Not Student, Not in Labor Force | -0.0023*** | -0.0021*** | -0.0021*** | -0.0347*** | -0.0317*** | -0.0316*** |
| | (0.0003) | (0.0002) | (0.0002) | (0.0043) | (0.0032) | (0.0031) |
| Missing Employed Status | -0.0022 | -0.0005 | -0.0004 | -0.0335 | -0.0098 | -0.0076 |
| | (0.0025) | (0.0014) | (0.0013) | (0.0299) | (0.0229) | (0.0218) |
| Divorced | 0.0049*** | 0.005*** | 0.0051*** | 0.1085*** | 0.1125*** | 0.1126*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0041) | (0.0031) | (0.003) |
| Widowed | 0.0049*** | 0.005*** | 0.0051*** | 0.1011*** | 0.0986*** | 0.1004*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0067) | (0.0053) | (0.0051) |
| Unmarried and Other Marital Status | 0.0047*** | 0.0049*** | 0.0049*** | 0.0834*** | 0.0868*** | 0.0872*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0044) | (0.0033) | (0.0032) |
| Missing Marital Status | 0.0043*** | 0.0048*** | 0.0049*** | 0.0671** | 0.082*** | 0.0865*** |
| | (0.001) | (0.0005) | (0.0004) | (0.0311) | (0.0263) | (0.0256) |
| Real Household Income | -0.0001*** | -0.0001*** | -0.0001*** | -0.0025*** | -0.0025*** | -0.0024*** |
| | (0) | (0) | (0) | (0.0001) | (0.0001) | (0.0001) |
| Top Household Income Category | 0.0007 | 0.0002 | 0.0002 | 0.0137 | 0.0028 | 0.0039 |
| | (0.0006) | (0.0005) | (0.0005) | (0.0122) | (0.009) | (0.0086) |
| Time (Month) | 0 | 0 | 0 | -0.0003 | 0.0001 | -0.0001 |
| | (0) | (0) | (0) | (0.0003) | (0.0001) | (0.0001) |
| 9/11 Terrorism Variable, 4Q of 2001 | 0.0006** | | | 0.0123* | | |
| | (0.0003) | | | (0.0064) | | |
| 9/11 Terrorism Variable, 9/11 Decay Variable | | 0.0005** | | | 0.0094** | |
| | | (0.0002) | | | (0.0043) | |
| 9/11 Terrorism Variable, Full Post 9/11 | | | 0.0007*** | | | 0.0122*** |
| | | | (0.0003) | | | (0.0045) |
| State Fixed Effects | X | X | X | X | X | X |
| Season Fixed Effects | X | X | X | X | X | X |
| Observations | 253,925 | 454,281 | 500,055 | 253,925 | 454,281 | 500,055 |

[a] The average marginal effect (averaged for each weighted observation) for all variables are reported with linearized standard errors.

[b] Average marginal effects for factor variables of sex, race/ethnicity, education, employment, marital status, top household income category, and terrorism measure discrete changes from the base level.
[c] Each column presents full results from different regressions.
[d] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[e] Never smokers are subset from the models because they are not found to change smoking statuses.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Estimates suggest a 1.1 percentage point (2.3%) increase in smoking prevalence in the fourth quarter of 2001 for the ever smoking adult population, and this estimate is slightly reduced to a .9 percentage point increase (1.9%) in the full time period. The estimates of terrorism on smoking intensity show that both some day and every day smoking was positively associated with 9/11, with estimates of the impact virtually the same in both the short term and the long term. Stress increased by approximately an extra half day per 30 days (13.5%) in the fourth quarter of 2001. Estimates of terrorism-induced stress are smaller over longer periods of time. These collective results provide evidence that smoking declines to baseline slower than stress due to addiction.

### 4.4 Sensitivity Analysis

The threat of omitted variable biases caused by uncontrolled factors that vary over time and are correlated with terrorism merits careful attention and can be dealt with using three approaches: a clear treatment group for performing difference-in-difference analysis, a short time window around 9/11, or placebo testing to confirm the absence of omitted variable biases. The first approach of using a control group does not appear applicable to this research considering the national as opposed to local nature of 9/11, as suggested by the state-level comparison of dependent variable means one year before and after the attacks in Table II. All population segments on some level may have been affected by 9/11. The second approach of using a narrow window of time around 9/11 is achieved by showing increases in stress and smoking in the fourth quarter of 2001, but the longer specifications using the 9/11 decay variable or the full post-9/11 variable creates the possibility of omitted variable biases influencing results.

A third approach, using placebo testing, was used in another terrorism-related study (Abadie and Gardeazabal, 2003). If omitted variables are not driving the results, then moving the terrorism variable to a time when it is known there was not terrorism should result in the terrorism variable becoming statistically insignificant 90% of the time. Placebo variables were created on the dates of 9/11/1999, 9/11/2000, and 9/11/2002. Results are presented in Table VII and none of the placebo parameters were found to be statistically significant, suggesting that previously estimated confidence levels are not underestimated and restricting possible omitted, time-varying variables that could be influencing the results.

TABLE VII: PLACEBO TESTING MODELS

| 9/11 Terrorist Attack On This Date: | Dependent Variable: Stress | Smoking Prevalence | Smoking Intensity, predicted some day smoker | Smoking Intensity, predicted every day smoker |
|---|---|---|---|---|
| 9/11/1999 | **-0.0091** | **-0.0106** | **-0.0004** | **-0.0064** |
| | (0.105) | (0.0053) | (0.0003) | (0.0048) |
| 9/11/2000 | **-0.1247** | **0.0025** | **-0.0003** | **-0.0046** |
| | (0.0885) | (0.004) | (0.0002) | (0.0036) |
| 9/11/2001 | **0.1963**** | **0.011**** | **0.0005**** | **.0094**** |
| | (0.1103) | (0.0048) | (0.0002) | (.0043) |
| 9/11/2002 | **0.1609** | **-0.0092** | **-0.0002** | **-0.0038** |
| | (0.1376) | (0.005) | (0.0003) | (0.0045) |

[a] The average marginal effect (averaged for each weighted observation) for the placebo and actual terrorism variables are reported with linearized standard errors.
[b] Each cell presents the result of interest from different regressions. Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[c] Never smokers are subset from the models because they are not found to change smoking statuses.
[d] Actual 9/11 terrorism measure is replaced with the placebo measure in all regressions.
[e] One-tailed t-statistics are reported to provide greater sensitivity in the search for smoking- and stress-increasing omitted variables.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Additional sensitivity analysis was conducted by separately investigating the impact of the following three stressors on post-9/11 estimates: military casualties over the past 30 days, 30-day moving average of the DOW Jones Industrial Average, and state-level crime per capita. With the exception of some estimates made in the fourth quarter of 2001, results were not substantially affected by the inclusion of any of these variables, nor were these variables themselves found to be particularly useful determinants of stress or smoking.[17]

## 4.5 Net Costs to the Government of Terrorism-Induced Smoking

The effect of 9/11 on stress and smoking prevalence is found to be economically significant. To help contextualize some of the results, back-of-the-envelope calculations are made on the increase in the number of adult smokers due to 9/11[18] and net costs to the government of these additional smokers.[19]

---

[17] In the sample containing observations from years 1999-2001, the terrorism parameters in the smoking and stress models fall from statistically significant to insignificant when the military casualties over the past 30 days variable is added. However, the military casualties parameter itself is not statistically significant. In the short time period of the first quarter after 9/11, it may be difficult to isolate the effect of 9/11 from the war in Afghanistan without introducing potential collinearity that could impact estimates. This is supported by the finding that the inclusion of the military casualties variable actually increases the statistical significance of the terrorism parameter when the model is recalculated with additional observations from the years 2002 and 2003.

State-level crime per capita is statistically significant positive in the stress model using the full timeframe.

[18] The average marginal effect point estimates were multiplied by the share of the population accounted for by former smokers and current smokers to obtain population percentage point differences. The population percentage point differences were multiplied by the average adult population during the respective periods to determine the raw number of new adult smokers.

[19] Total costs and revenues from terrorism-induced smoking are needed to determine net costs. Costs are estimated using a 1998-estimated net cost of $9 billion per year in smoking-related Medicare and Medicaid expenses, which takes into consideration future medical cost savings as smokers die younger (U.S. Department of Treasury, 1998). The calculation will also use an estimated 1997-2001 annual smoking-related productivity loss of $92 billion (CDC, 2005). Assuming that the government would have captured a third of the lost productivity through taxes and ignoring other smoking-related costs, smoking cost the government $661 annually for each adult smoker there was during this period. Multiplying this annual cost by terrorism-induced smokers provides a total cost to the government. Terrorism-induced some day smoker costs from the smoking intensity model are ignored.

The 9/11 decay variable provides middle estimates of the effect of terrorism on smoking over the period two years after 9/11. Using smoking prevalence as the dependent variable, results suggest that 1,100,000 adult former smokers became smokers, representing an adult population .5% smoking prevalence increase, and at an estimated net cost to the government of $640 million. Using smoking intensity as the dependent variable, results suggest a terrorism-induced net increase of 950,000 adult every day smokers and 50,000 adult some day smokers. These additional adult every day smokers had an estimated net cost to the government of $550 million through September of 2003.

Upper estimates are provided by using the full post 9/11 variable. Using smoking prevalence as the dependent variable and the average marginal effect point estimates, results suggest that 930,000 adult former smokers became smokers, representing a population .4% smoking prevalence increase. Estimated net costs to the government were $620 million. Results are larger using smoking intensity as the dependent variable, suggesting a terrorism-induced net increase of 1,240,000 adult every day smokers and 70,000 adult some day smokers. These additional adult every day smokers had a net cost to the government of $820 million through the end of 2003.

In sum, this interpretation of the results suggests that between 930,000-1,300,000 adult former smokers became smokers due to terrorism and net costs to the government were between

---

Extra revenue from terrorism-induced smoking can be calculated using sales weighted federal and state cigarette excise taxes per pack for 2001 ($.77), 2002 ($1.00), and 2003 ($1.12) (Orzechowski and Walker, 2009) and making assumptions about how many packs of cigarettes these terrorism-induced smokers smoke. For purposes of this back-of-the-envelope calculation, terrorism-induced every day smokers are estimated to smoke 10 cigarettes daily. This calculation does not consider the possibility that existing cigarette smokers increased their cigarette consumption (paying more in taxes), nor the possibility that increases in cigarette consumption increase the use and total costs of government paid medicine. Terrorism-induced some day smoker revenues from the smoking intensity model are ignored.

$550-820 million, or $290 per terrorism-induced smoker per year. Net costs would be higher if smoking increases persisted beyond the end of 2003.

## 5. INTERACTION VARIABLE MODELS

Interaction variables are created by interacting a terrorism variable with other measures to test if people who live closer to the epicenters of the terrorist attacks, are from a county with a higher military participation rate, or are from a county with a higher population density have disproportionate stress or smoking increases following terrorism. Additionally, interaction variables will be created to test if people were differentially impacted by terrorism based on age or education.[20] The middle terrorism measure is used, which decays towards zero two years after 9/11. All constitutive terms of the interaction variables are included as stand-alone variables in the models (Brambor et al., 2005; Braumoeller, 2004). Results are presented in Table VIII.

[20] An ordinal ranking of education is used. The education information was merged into a continuous education variable by assigning the following values for the highest level of education completed: 0 for junior high, 1 for some high school, 2 for high school, 3 for some college, and 4 for college. The average value, 2.6, was used for those with missing education information.

TABLE VIII: INTERACTION MODELS

| | Dependent Variable: | | |
|---|---|---|---|
| | Stress | Smoking Prevalence | Smoking Intensity |
| Interaction Variable: | | | |
| Reverse County Distance * 911 Decay Variable | **0.0766*** | **-0.0115** | **-0.0177** |
| | (0.0424) | (0.0467) | (0.0424) |
| Reverse County Distance Squared * 9/11 Decay Variable | **-0.0593** | **-0.0379** | **-0.0578** |
| | (0.0616) | (0.0624) | (0.0566) |
| County Population Density * 9/11 Decay Variable | **-0.0032** | **-0.0025** | **-0.0029** |
| | (0.0035) | (0.0035) | (0.0032) |
| County Population Density Squared * 9/11 Decay Variable | **0.0002** | **0.0002** | **0.0002** |
| | (0.0002) | (0.0002) | (0.0001) |
| County Per Capita Military Pay * 9/11 Decay Variable | **-0.0237** | **0.0016** | **0.0126** |
| | (0.0288) | (0.0236) | (0.0218) |
| County Per Capita Military Pay Squared * 9/11 Decay Variable | **0.0190*** ** | **-0.0079** | **-0.0063** |
| | (0.0060) | (0.0053) | (0.0051) |
| Age * 9/11 Decay Variable | **0.0019** | **0.0013** | **0.0014** |
| | (0.0014) | (0.0012) | (0.0011) |
| Education * 9/11 Decay Variable | **.0398*** | **0.0047** | **-0.0024** |
| | (0.0217) | (0.0184) | (0.0168) |

[a] Each cell presents the result of interest from different regressions.
[b] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[c] Never smokers are subset from the models because they are not found to change smoking statuses.
[d] Added to the respective models (full controls) are any necessary constitutive terms.
[e] Two-tailed t-statistics are reported.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

It is hypothesized that people living closer to the 9/11 epicenters may have disproportionate stress and smoking increases following terrorism than people living further away. This relationship is searched for in the continental United States, with Alaska and Hawaii observations subset to remove potential outliers. Two different specifications are used, a standard interaction specification and a second specification in which distance is squared and interacted with the terrorism variable to allow for nominal distances to be weighted more heavily closer to the terrorist attack epicenters than further away from it. When interacting ArcGIS county distance data with the terrorism measure, people living closer to the terrorist attack epicenters were found to have greater stress increases in the regular specification relative to those living further away, a finding consistent with three other studies (Schlenger et al., 2002; Stein et al., 2004; Smith et al., 1999). However, there is no evidence that proximity caused relative increases in smoking, nor does this stress relationship hold in the distance squared specification.

County military pay data and county population density data were also interacted with the terrorism measure and no significant findings were detected in the standard specifications, which is consistent with findings from other studies that failed to detect differential responses to terrorism by either military participation or population density (Endara et al., 2009; Schlenger et al., 2002; Stein et al., 2004). However, statistically significant findings were found for stress when the county military pay data was squared, providing some evidence that military communities experienced disproportionate increases in stress compared to non-military communities after 9/11. This increase in stress was not sensitive to inclusion of the military casualties over the past 30 days variable, suggesting that 9/11 had an independent effect from the subsequent wars in these communities.

Results indicate that people of different ages did not have differential changes in stress or smoking as a result of terrorism. However, more-educated individuals had greater stress increases following 9/11. This suggests that there was a perception that more-educated people were more at-risk of future terrorism, likely through terrorists targeting infrastructure more frequently utilized by higher educated individuals (e.g. skyscrapers, airplanes). This perception appears to have had a greater effect on stress and smoking than the neutralizing effect of more-educated individuals being better able to match subjective expectations of terrorism with the objective reality.[21]

Sensitivity analysis was conducted by interacting the terrorism measure with the fourth quarter of 2001 to ensure that the stress sample change in year 2002 was not influencing results presented earlier. Results remained the same at conventional levels of statistical significance, with the additional finding that older individuals experienced disproportionate stress increases in the fourth quarter of 2001.

## 6. UNBIASED EFFECT OF STRESS ON SMOKING

An instrumental variable approach, two-stage least squares (2SLS), is used to explore the unbiased effect that stress has on smoking. Regressing smoking on stress may result in biased estimates due to simultaneity between stress and smoking, as individuals may want to smoke during times of high stress to decrease their stress (Parrott, 1998). 2SLS purges the correlation between stress and the error term, using the instrument of 9/11 to isolate the variation in stress

[21] Analysis was also done to determine if, post-9/11, higher educated people returned to baseline stress and smoking quicker than less-educated people, which would suggest that time-preference may play a role in coping with terrorism. This was done by multiplying the aforementioned education interaction terms by a dichotomous indicator variable for the first year after 9/11, splitting the post-9/11 dates roughly in half. The new triple variable interaction shows if education had any differential effects at different points in time following 9/11. No evidence was found supporting this hypothesis.

that is uncorrelated with the error term in the smoking models. The 2SLS models are identified in equations 5-7.

$$\text{stress}_{\text{ist}} = \alpha + \beta_1 \emptyset_{\text{st}} + \beta_2 X_{\text{ist}} + \beta_3 4Q\_2001_t + +\beta_4 \text{time}_t + \gamma_s + \gamma_{\text{season}} + v_{\text{ist}} \quad (5)$$

$$\text{smoke\_prevalence}_{\text{ist}} = \alpha + \beta_1 \emptyset_{\text{st}} + \beta_2 X_{\text{ist}} + \beta_3 \widehat{\text{stress}}_{\text{ist}} + \beta_4 \text{time}_t + \gamma_s + \gamma_{\text{season}} + \varepsilon_{\text{ist}} \quad (6)$$

$$\text{smoke\_intensity}_{\text{ist}} = \alpha + \beta_1 \emptyset_{\text{st}} + \beta_2 X_{\text{ist}} + \beta_3 \widehat{\text{stress}}_{\text{ist}} + +\beta_4 \text{time}_t + \gamma_s + \gamma_{\text{season}} + \varepsilon_{\text{ist}} \quad (7)$$

The 1999-2001 sample is used because previous results have shown that this generates a high *t*-statistic in the first-stage and because the sample of stress respondents changed in the year 2002. The predicted value for stress is generated from equation 5 and is then entered directly into the two separate second-stage smoking models, 6-7, with error correction in the second-stage.

2SLS estimation uses linear modeling. Consistency of 2SLS estimates does not depend upon linearity of the reduced form equations (Kelejian, 1971). Further, even though the second-stage uses dichotomous or ordered dependent variables, 2SLS results typically capture the local average treatment effect of interest (Angrist and Krueger, 2001). Therefore, little harm is done by using limited dependent variables in the respective stages of 2SLS.

Results are presented in Table IX.

TABLE IX: 2SLS ESTIMATES FOR UNBIASED EFFECT OF STRESS ON SMOKING

| | | |
|---|---|---|
| First Stage - Equation 5 | | |
| Dependent Variable: Stress | | |
| Independent Variable: 4Q of 2001 | **.353*** | |
| | (.120) | |
| F-test | 8.70 (p-value=0.003) | |
| | | |
| Second Stage - Equations 6-7 | | |
| Dependent Variable: Smoking | Smoking Prevalence | Smoking Intensity |
| Independent Variable: Stress_hat | **0.034*** | **0.066*** |
| | (0.023) | (0.043) |
| | | |
| Number of Observations | 249,680 | |

[a] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[b] Never smokers are subset from the models because they are not found to change smoking statuses.
[c] One-tailed *t*-statistics are reported for the second-stage because the unbiased effect of stress on smoking is hypothesized to either have zero influence or a positive influence.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

In the first-stage, the *t*-statistic shows that terrorism is strongly associated with stress. Additionally, an *F*-statistic of 8.70 is generated, which rejects the null hypothesis at a 10% significance level that the instrument is weak (Stock, Wright, and Yogo, 2002). In the second-stage, a one-tailed *t*-statistic is used to test the null hypothesis that the unbiased effect of stress has no positive impact on smoking, which is rejected at the 10% significance level. Evaluated at the means, results suggest that in the population of former smokers and current smokers, a 1 day increase in stress over 30 days has a 3.4 percentage point increase in smoking prevalence and a .07 increase in the level of smoking intensity.[22] The first-stage suggests an increase in stress from 9/11 of roughly a third of a day, so assuming that stress is the only causal pathway through which terrorism influences smoking, 2SLS estimates suggest that terrorism increased smoking within this ever smoker population by 1.2 percentage points or by .02 smoking intensity levels. These effect sizes closely match estimates obtained from single equation modeling and presented in Table III, suggesting that the entire increase in smoking generated from terrorism is through stress rather than alternative causal pathways.

## 7. DISCUSSION AND CONCLUSION

Results support findings from localized studies that terrorism is associated with an increase in smoking (Wu et al., 2006; Vlahov et al., 2004a; Vlahov et al., 2004b), but this study expands these findings by detecting the increase nationally. Adult smoking increases following 9/11 appear to be entirely accounted for within the former smoker population, who become both some day smokers and every day smokers. Terrorism was also associated with national stress

[22] While outside the main focus of this paper, a related question is if the unbiased effect of smoking reduces stress. Cigarette prices and smoke-free air law strengths are theoretically valid instruments for smoking; however, these variables generate a low *F*-statistic in the first-stage that fails to reject the null hypothesis of weak instrumentation, thus preventing exploration of this question.

increases that were relatively larger for higher educated individuals and for individuals living closer to the terrorist attack epicenters and/or in heavy military participation communities. Results suggest that stress from terrorism returns to baseline faster than smoking due to addiction. Finally, to the best of the author's knowledge, this study provides the first unbiased estimate of the effect of stress on smoking, with smoking prevalence increasing amongst ever smoking adults by 3.4 percentage points from an extra day of stress each month.

In the unfortunate event that our nation faces a similar terrorist attack in the future, it may be cost-effective for the government to intervene against terrorism-induced smoking. Stress-reduction and smoking cessation treatments (such as free nicotine replacement therapy) may be a cost-effective way to treat smoking resulting from terrorism, especially considering many terrorism-induced smokers may be better than average at quitting since many were previously former smokers. A natural experiment in New York City conducted around the time of a large cigarette tax increase found that 33% of participants in a free nicotine replacement therapy distribution program were found to have managed a successful quit of at least a week at the time of a follow-up interview. This was higher than 8% of control group participants who did not receive the free nicotine replacement therapy and counseling. The study authors provided the conservative cost of $464 per successful minimum one-week quit (Miller et al., 2005). Another study suggests that costs per quit attempt are lower for lower-duration free nicotine replacement therapy and for vouchers (Cummings et al., 2006). This study suggests an annual government cost per terrorism-induced smoker of $290. A more thorough analysis is needed to determine if treating terrorism-induced smoking is cost effective.

Secondary recommendations stemming from this research are for health professionals to be extra vigilant in asking smoking status and encouraging cessation following terrorism. Also, policymakers and the media should be more contextually-accurate about the threat of terrorism to discourage overshooting of perceived risk.

The study's primary limitation is that it is cross-sectional, which precludes causal inferences. Longitudinal analyses on associations between terrorism and smoking may provide more robust findings. Future research could be useful to determine how minors are impacted by terrorism through smoking. One local study using retrospectively collected data found evidence of youth substance use increases following 9/11 (Wu et al., 2006), but two other studies did not (Ford et. al, 2003; Wu et al., 2006). A more rigorous research methodology should be employed to further explore this issue. Research is also needed to address if current smokers increase their consumption of cigarettes following terrorism. Research would be useful to explore if tobacco companies attempt to profit from terrorism through business practices such as changing pricing strategies or their mix of advertisements in response to terrorism. Finally, research should be conducted on the extent to which the findings of this study can be applied to other types of national disasters, such as Hurricane Katrina, and to other stress-reducing goods, such as alcohol and other forms of tobacco.

## 8. FIGURES

The following pages contain the figures referenced in this essay.

Figure 1: Stress and 9/11 Over Time, standard deviations from the mean

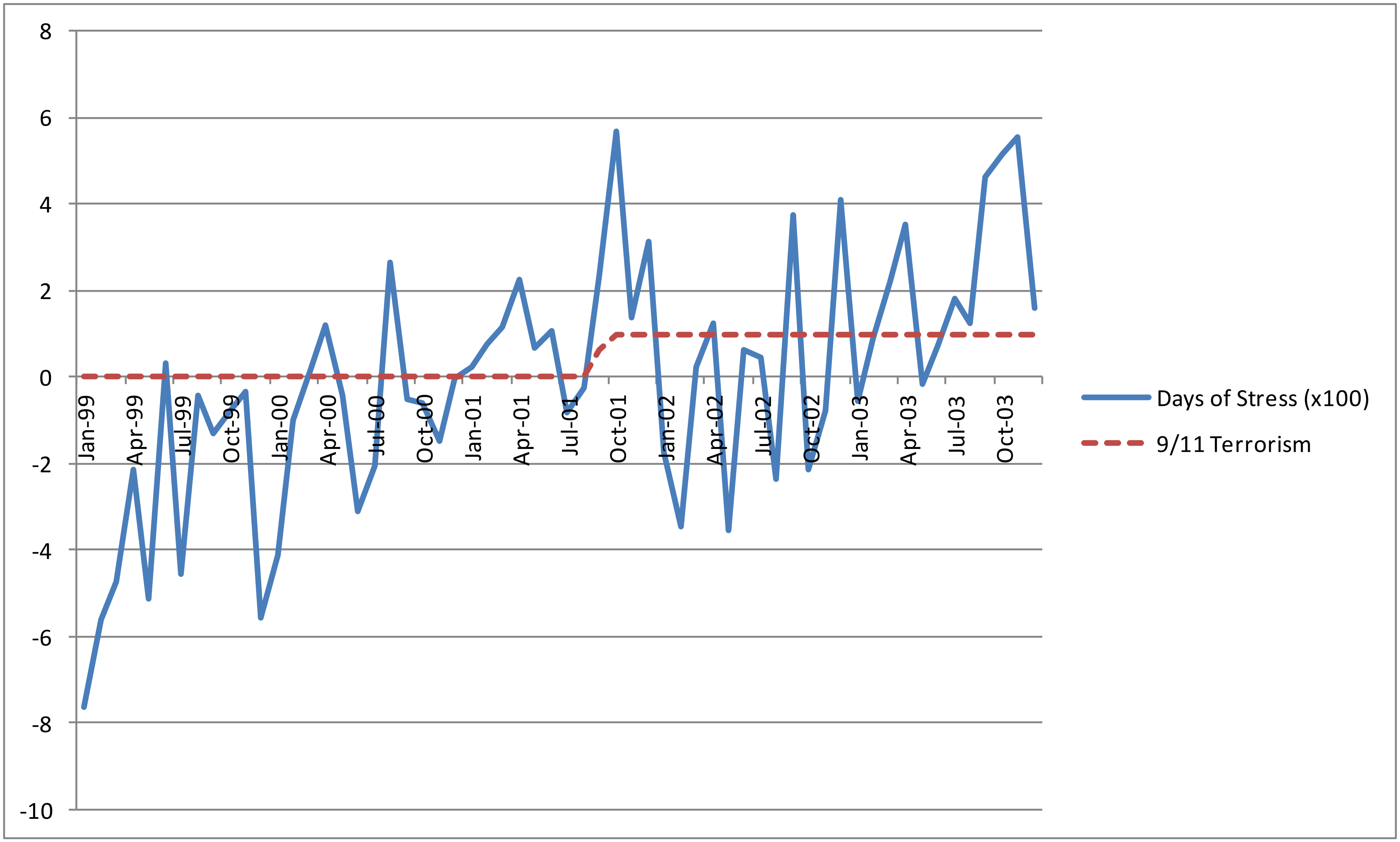
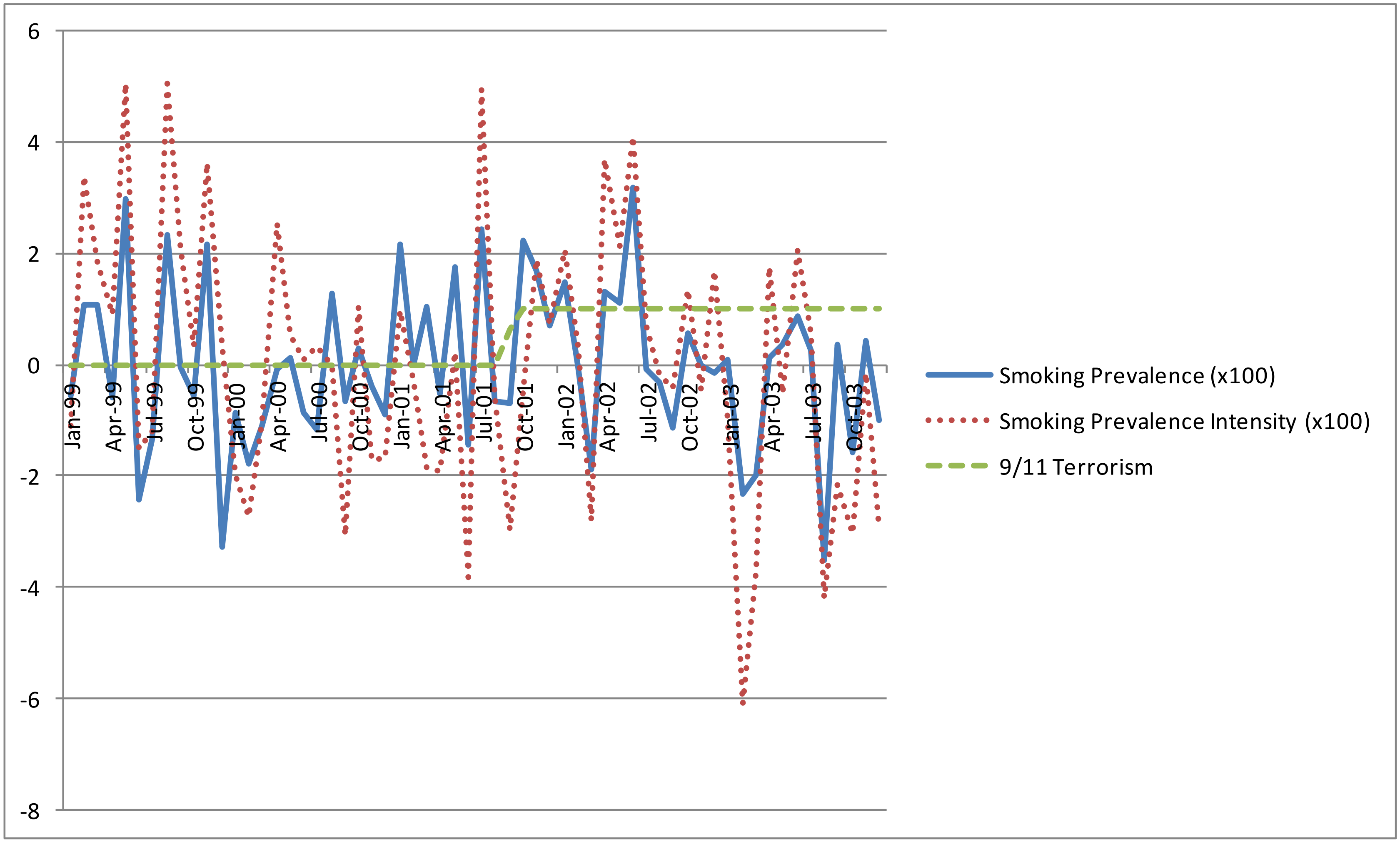
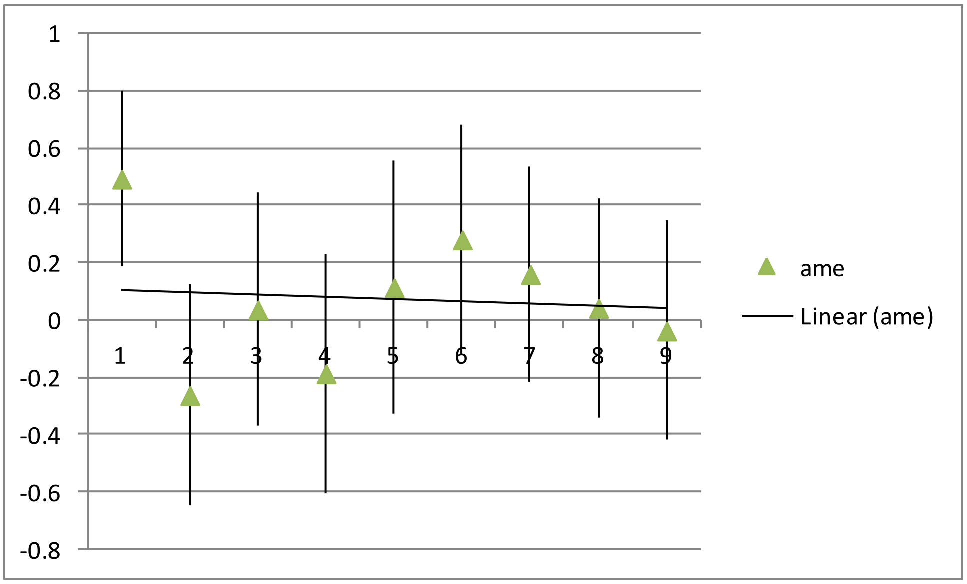


Figure 2: Smoking and 9/11 Over Time, standard deviations from the mean



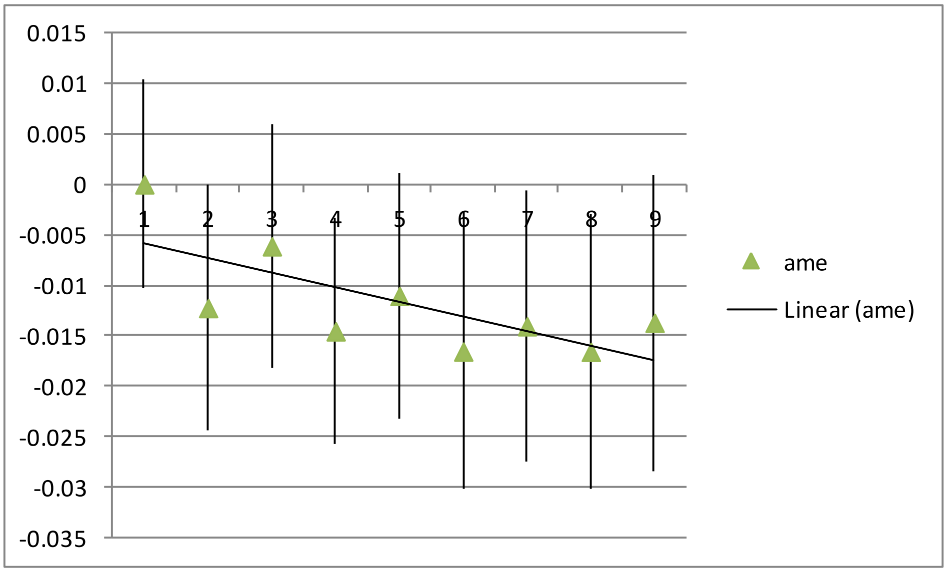

[a] Smoking intensity is defined as a 2 for every day smokers, a 1 for some day smokers, and a 0 for former smokers, with never smokers dropped.

Figure 3: Influence of Time on Stress after 9/11, ever smokers, marginal effects, quarterly (equation 1)



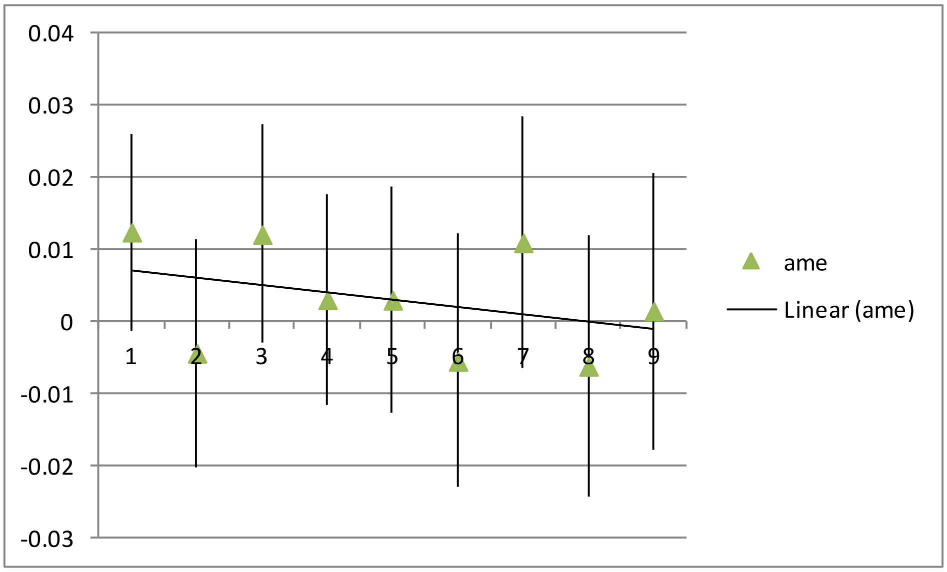

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Never smokers are subset from the models to maintain uniformity with smoking samples.

Figure 4: Influence of Time on Smoking Prevalence after 9/11, never smokers to smokers, marginal effects of terrorism, quarterly (equation 2)



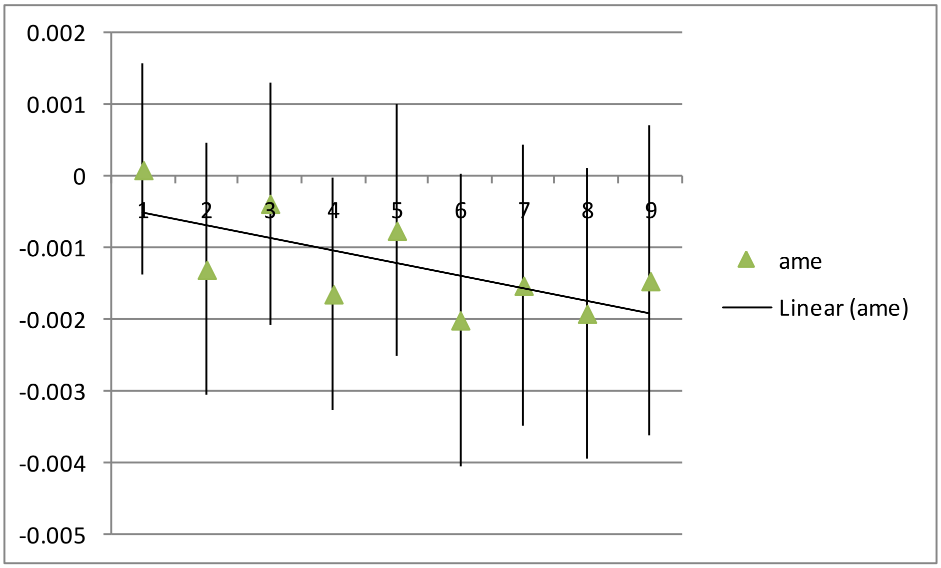

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 5: Influence of Time on Smoking Prevalence after 9/11, former smokers to smokers, marginal effects of terrorism, quarterly (equation 2)



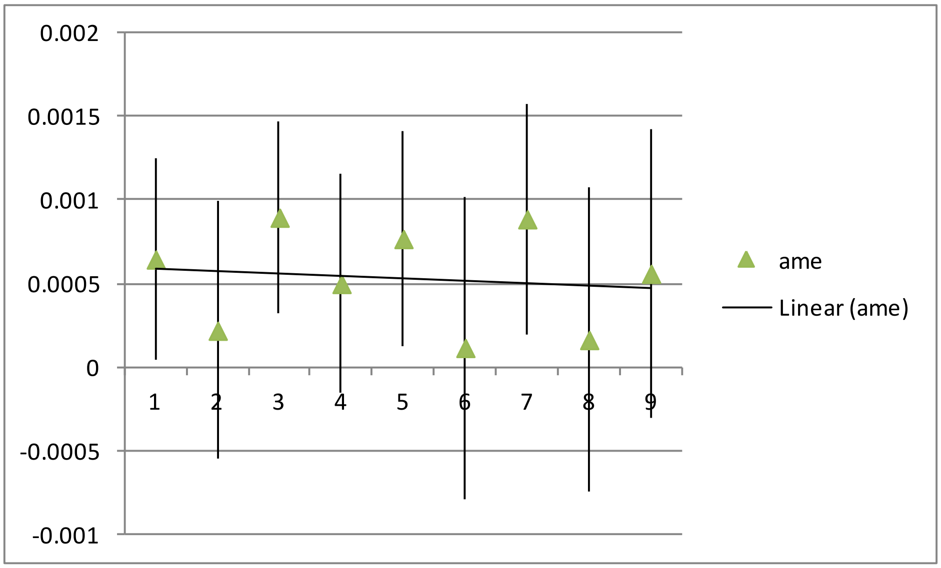

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 6: Influence of Time on Smoking Intensity after 9/11, never smokers to smokers, marginal effects of terrorism for predicted some day smokers, quarterly (equation 3)



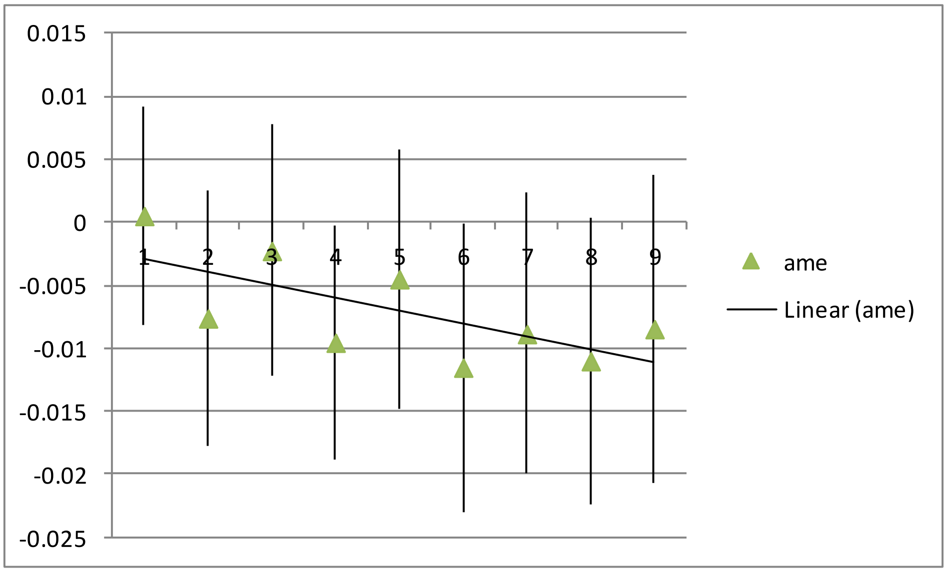

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 7: Influence of Time on Smoking Intensity after 9/11, former smokers to smokers, marginal effects of terrorism for predicted some day smokers, quarterly (equation 3)



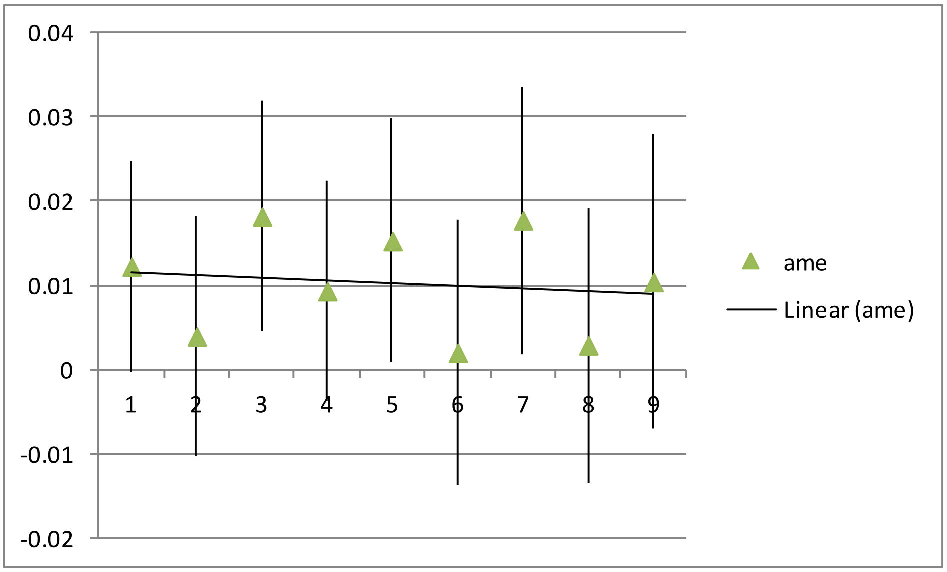

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 8: Influence of Time on Smoking Intensity after 9/11, never smokers to smokers, marginal effects of terrorism for predicted every day smokers, quarterly (equation 3)



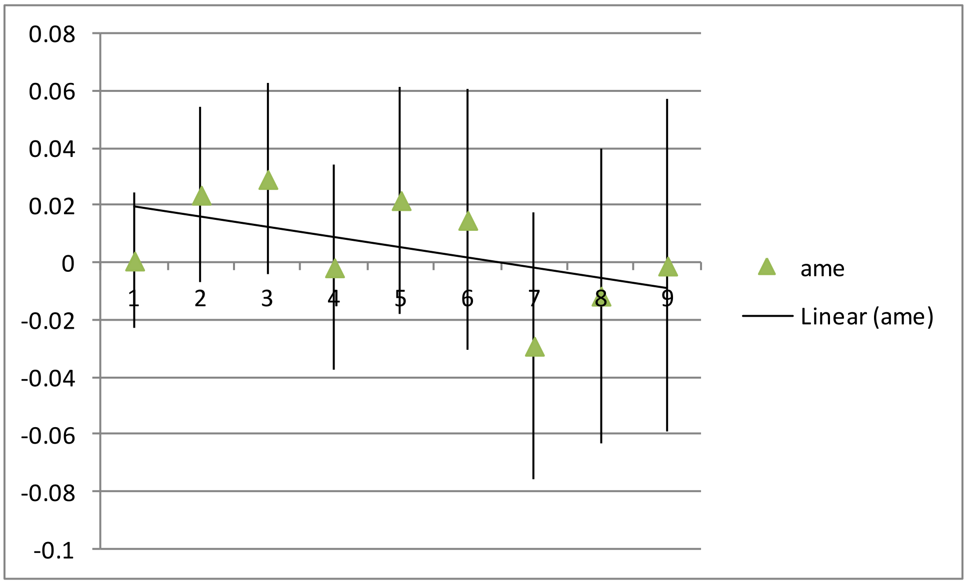

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 9: Influence of Time on Smoking Intensity after 9/11, former smokers to smokers, marginal effects of terrorism for predicted every day smokers, quarterly (equation 3)



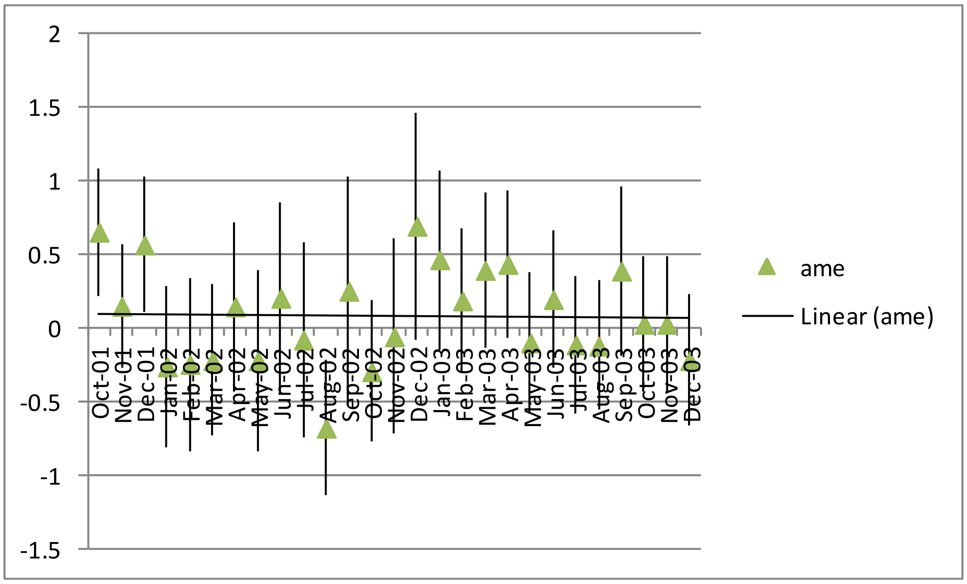

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 10: Influence of Time on Smoking Quit Attempts after 9/11, marginal effects of terrorism, quarterly (equation 4)



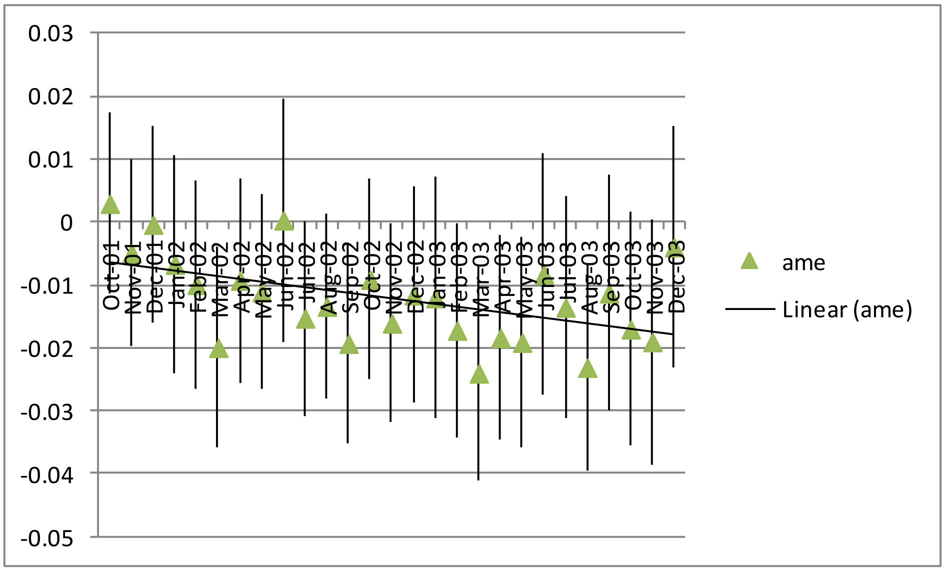

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 11: Influence of Time on Stress after 9/11, ever smokers, marginal effects of terrorism, monthly (equation 1)



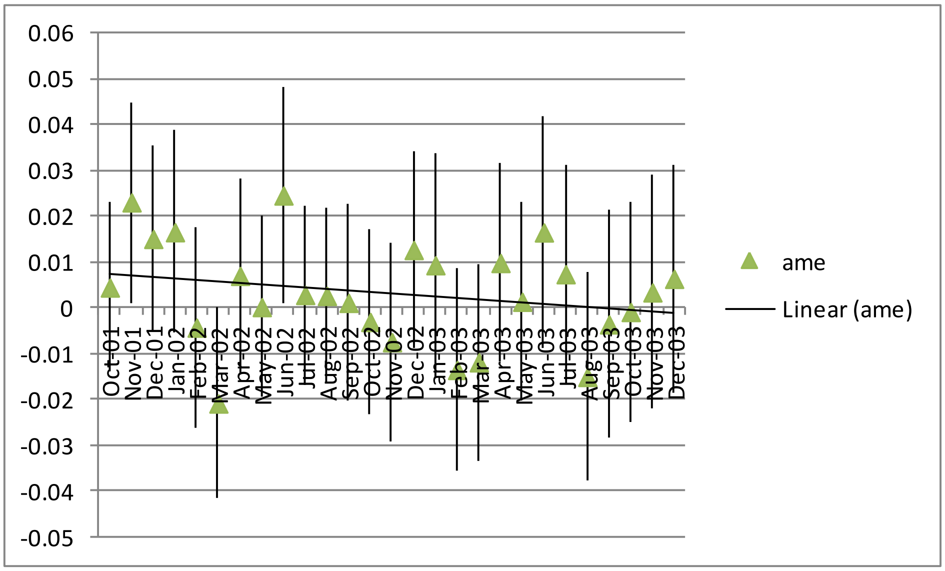

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Never smokers are subset from the models to maintain uniformity with smoking samples.

Figure 12: Influence of Time on Smoking Prevalence after 9/11, never smokers to smokers, marginal effects of terrorism, monthly (equation 2)



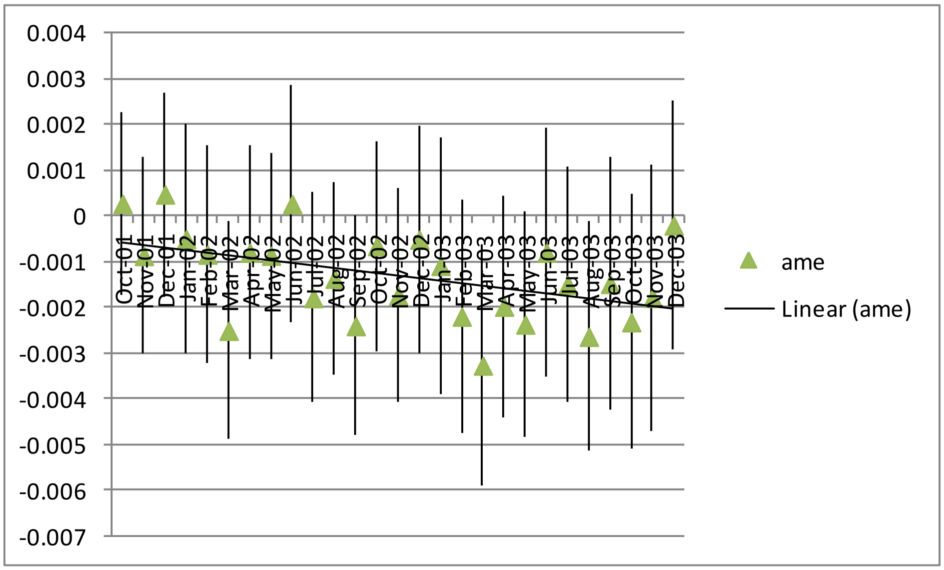

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Never smokers are subset from the models to maintain uniformity with smoking samples.

Figure 13: Influence of Time on Smoking Prevalence after 9/11, former smokers to smokers, marginal effects of terrorism, monthly (equation 2)



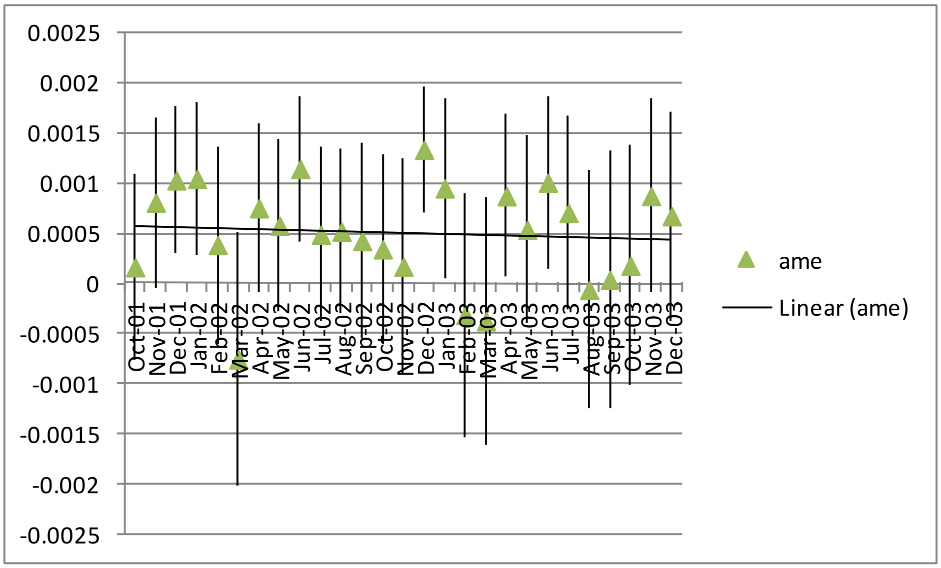

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 14: Influence of Time on Smoking Intensity after 9/11, never smokers to smokers, marginal effects of terrorism for predicted some day smokers, monthly (equation 3)



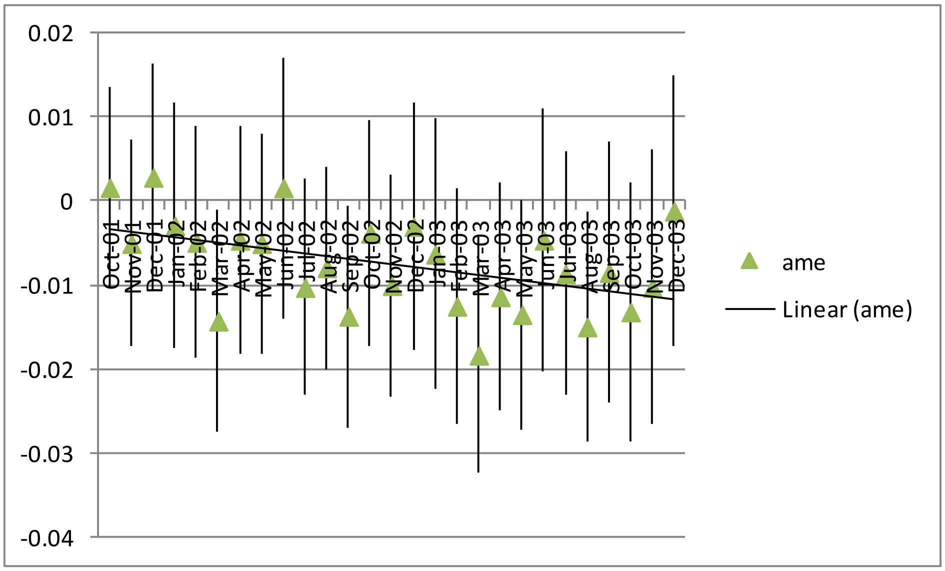

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 15: Influence of Time on Smoking Intensity after 9/11, former smokers to smokers, marginal effects of terrorism for predicted some day smokers, monthly (equation 3)



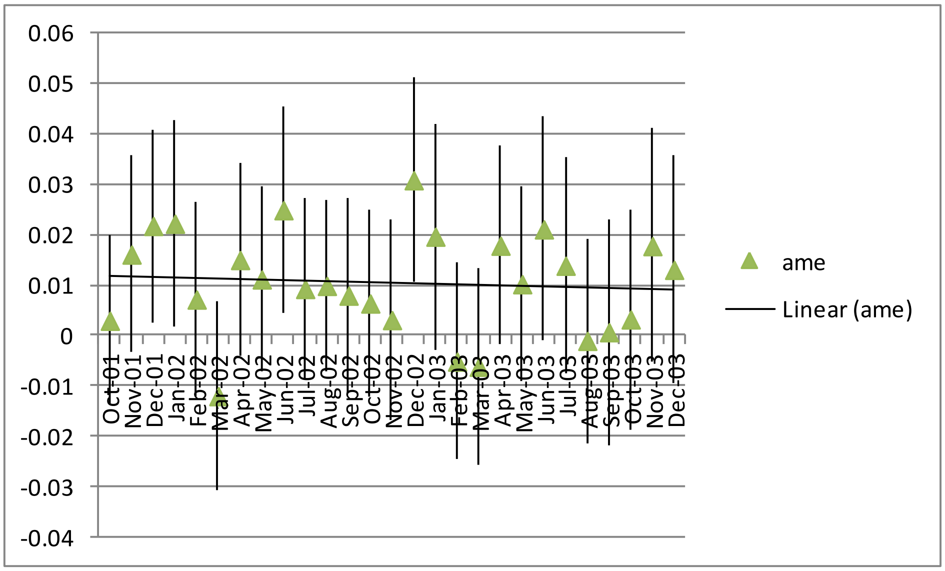

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 16: Influence of Time on Smoking Intensity after 9/11, never smokers to smokers, marginal effects of terrorism for predicted every day smokers, monthly (equation 3)



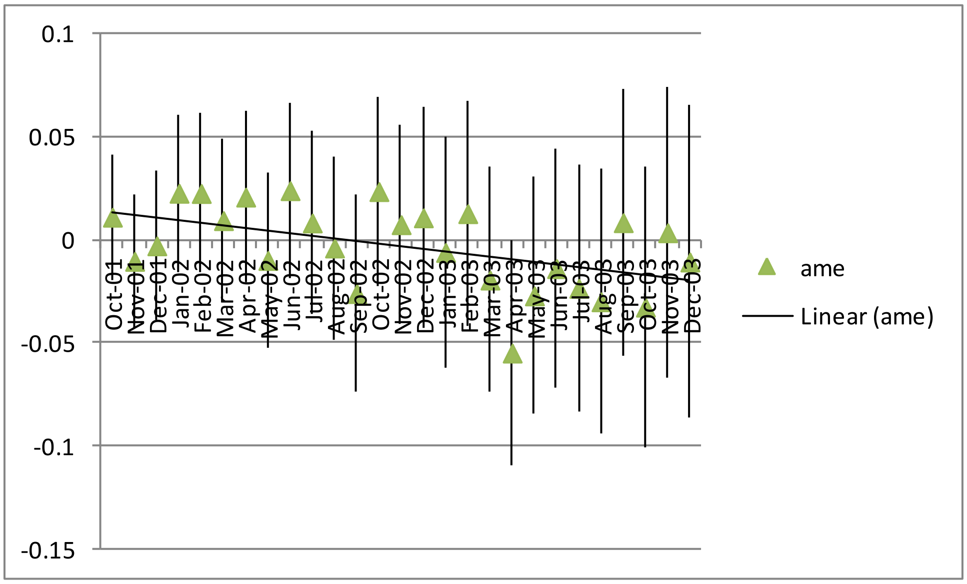

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 17: Influence of Time on Smoking Intensity after 9/11, former smokers to smokers, marginal effects of terrorism for predicted every day smokers, monthly (equation 3)



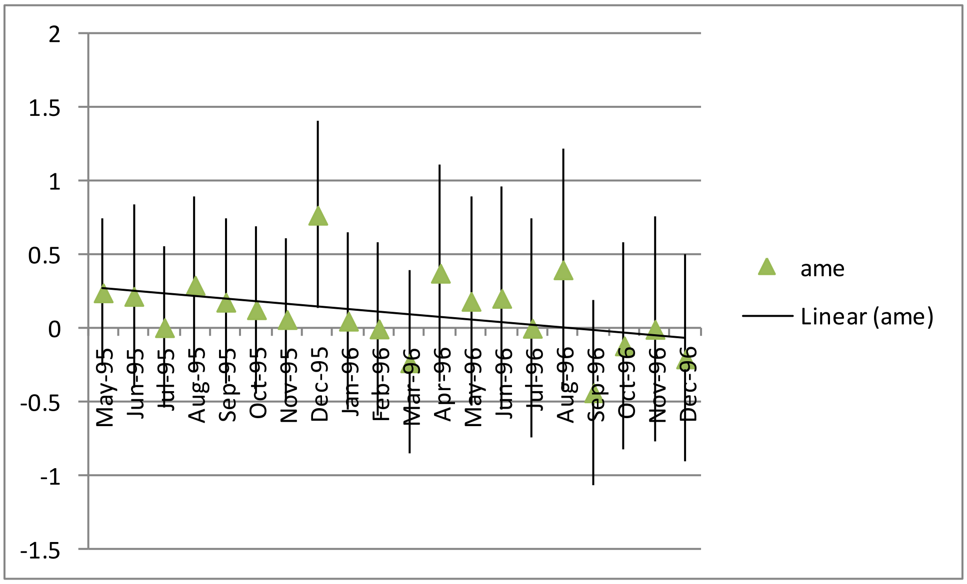

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 18: Influence of Time on Smoking Quit Attempts after 9/11, marginal effects of terrorism, monthly (equation 4)



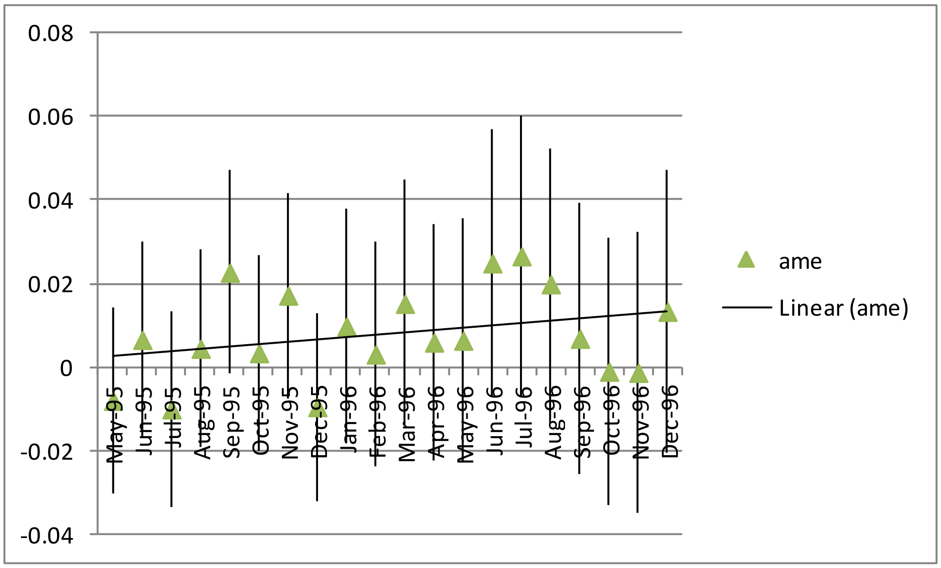

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 19: Influence of Time on Stress after the Oklahoma City Bombing, ever smokers, marginal effects of terrorism, monthly (equation 1)



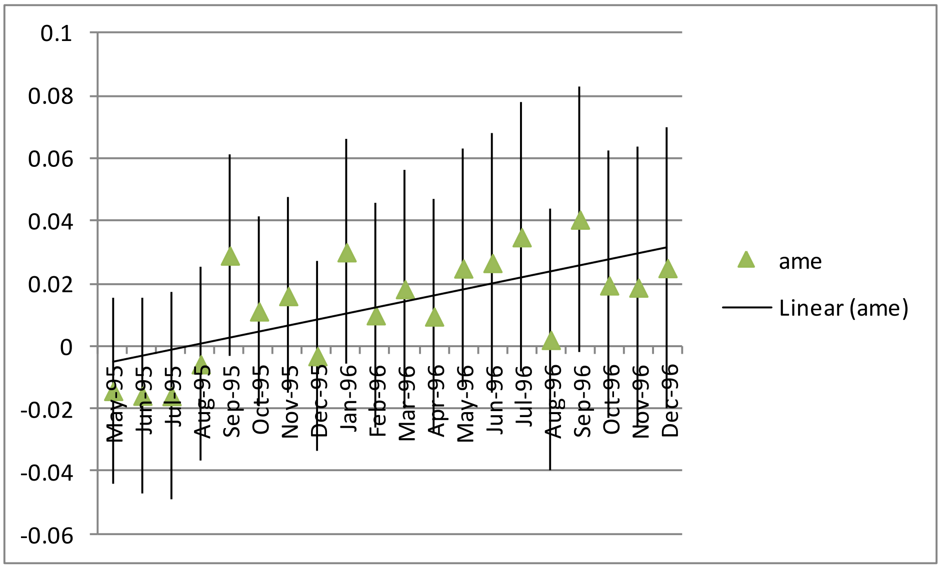

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Never smokers are subset from the models to maintain uniformity with smoking samples.

Figure 20: Influence of Time on Smoking Prevalence after the Oklahoma City Bombing, never smokers to smokers, marginal effects of terrorism, monthly (equation 2)



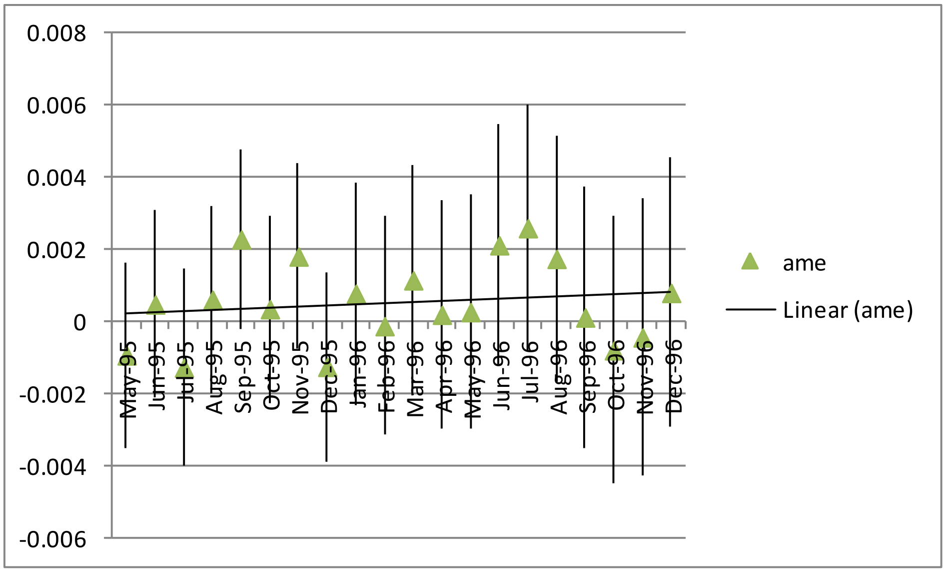

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 21: Influence of Time on Smoking Prevalence after the Oklahoma City Bombing, former smokers to smokers, marginal effects of terrorism, monthly (equation 2)



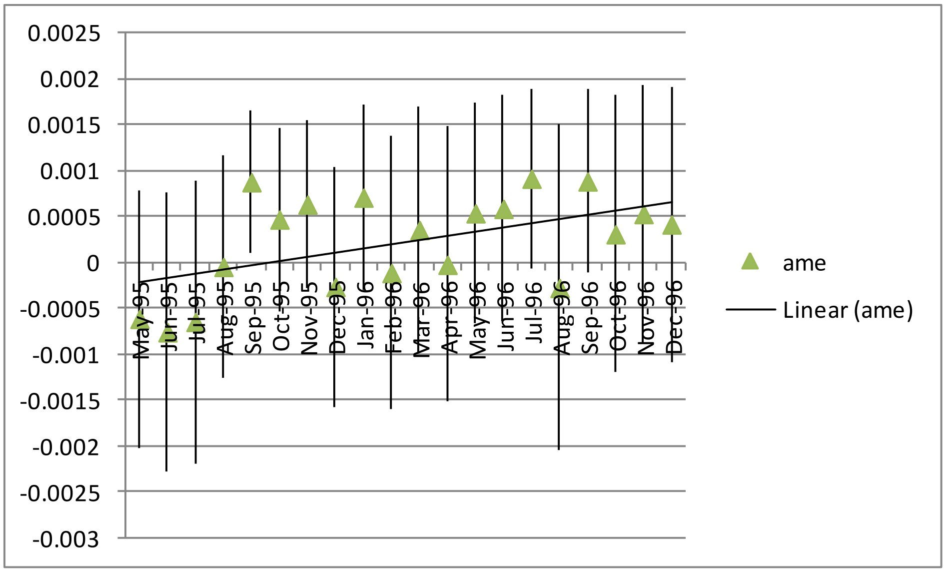

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 22: Influence of Time on Smoking Intensity after the Oklahoma City Bombing, never smokers to smokers, marginal effects of terrorism for predicted some day smokers, monthly (equation 3)



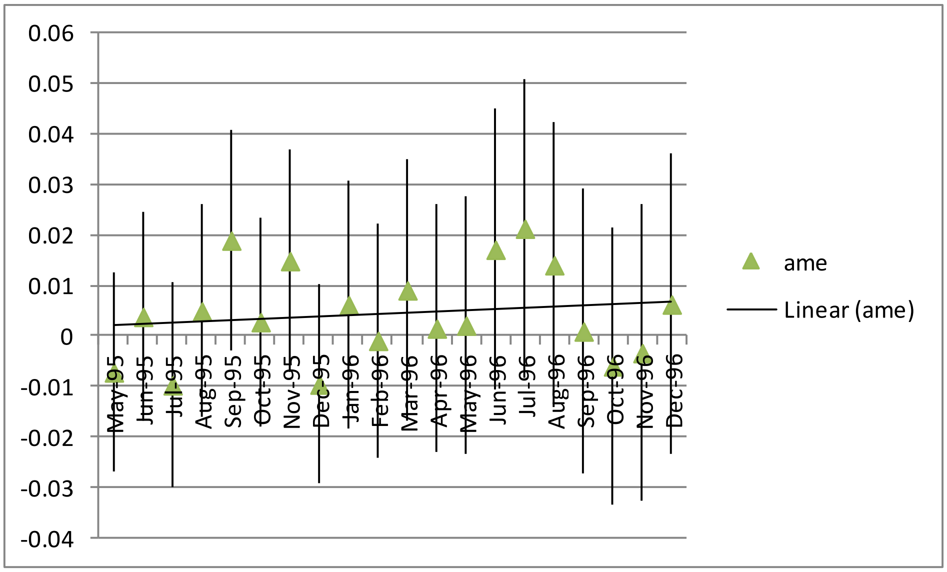

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 23: Influence of Time on Smoking Intensity after the Oklahoma City Bombing, former smokers to smokers, marginal effects of terrorism for predicted some day smokers, monthly (equation 3)



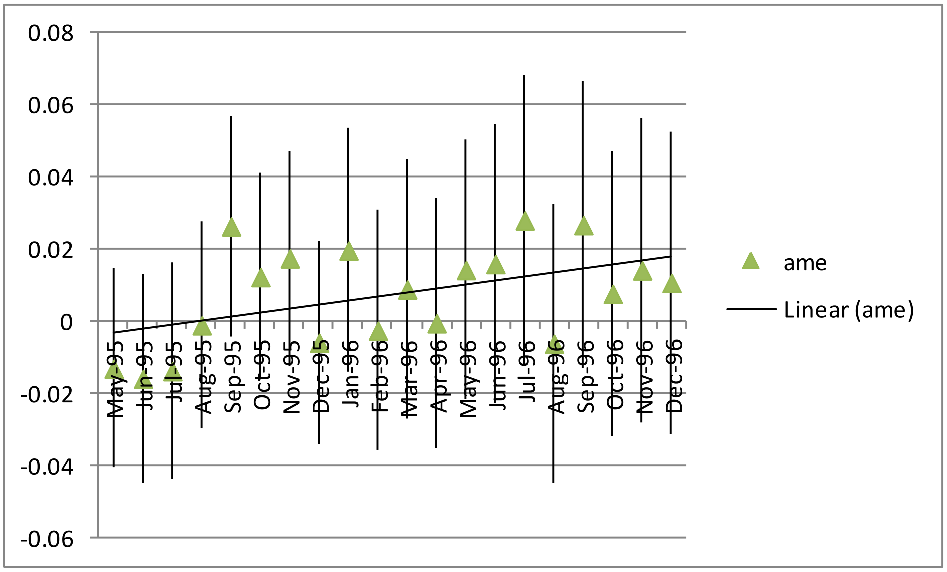

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 24: Influence of Time on Smoking Intensity after the Oklahoma City Bombing, never smokers to smokers, marginal effects of terrorism for predicted every day smokers, monthly (equation 3)



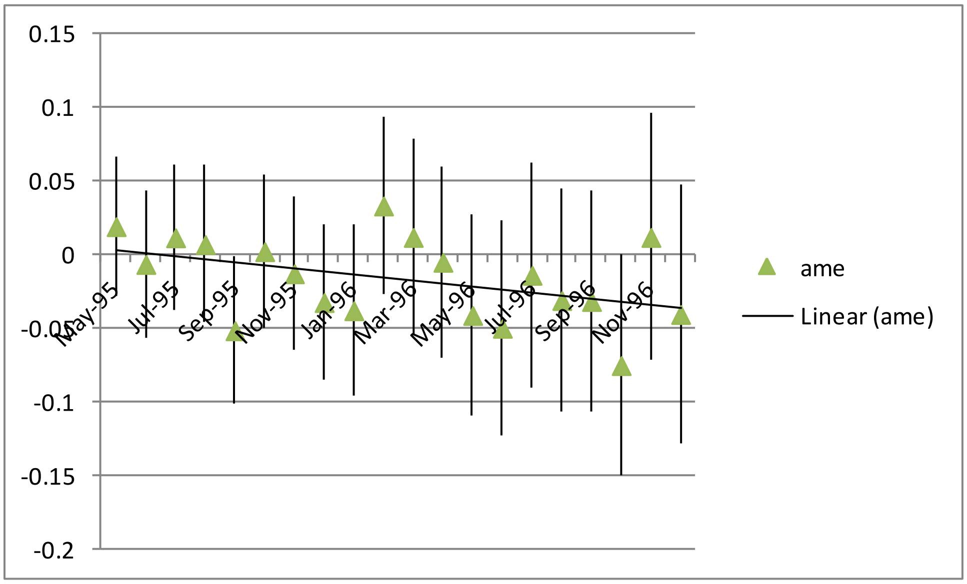

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 25: Influence of Time on Smoking Intensity after the Oklahoma City Bombing, former smokers to smokers, marginal effects of terrorism for predicted every day smokers, monthly (equation 3)




[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 26: Influence of Time on Smoking Quit Attempts after the Oklahoma City Bombing, marginal effects of terrorism, monthly (equation 4)




[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] A linear trend line is fit to the average marginal effect point estimates.
[d] Unused data was subset from the analysis to maintain the correct survey weighting.

## 9. CITED LITERATURE

Abadie, A., & Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, *93*(1), 113-132.

Angrist, J. D., & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives*, *15*(4), 69-85.

Becker, G. S., & Murphy, K. M. (1988). A Theory of Rational Addiction. *Journal of Political Economy*, *96*(4), 675.

Becker, G. S., & Rubinstein, Y. (2010). Fear and the Response to Terrorism : An Economic Analysis. *Working Paper*.

Blalock, G., Kadiyali, V., & Simon, D. (2009). Driving fatalities after 9/11: a hidden cost of terrorism. *Applied Economics*, *41*(14), 1717-1729.

Brambor, T., Clark, W. R., & Golder, M. (2005). Understanding Interaction Models: Improving Empirical Analyses. *Political Analysis*, *14*(1), 63-82.

Braumoeller, B. F. (2004). Hypothesis Testing and Multiplicative Interaction Terms. *International Organization*, *58*(04), 807-820.

Bruckner, T. A., Catalano, R., & Ahern, J. (2010). Male Fetal Loss in the U.S. Following the Terrorist Attacks of September 11, 2001. *BMC Public Health*, *10*, 273.

Burns, W. J., & Slovic, P. (2007). The Diffusion of Fear: Modeling Community Response to a Terrorist Strike. *The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology*, *4*(4), 298-317.

CDC. (1998). Self-Reported Frequent Mental Distress Among Adults -- United States, 1993-1996. *MMWR. Morbidity and Mortality Weekly Report*, *47*(16), 325-331.

CDC. (2005). Annual Smoking-Attributable Mortality, Years of Potential Life Lost, and Productivity Losses--United States, 1997-2001. *MMWR. Morbidity and Mortality Weekly Report*, *54*(25), 625-8.

CDC. (2008). Smoking-attributable mortality, years of potential life lost, and productivity losses--United States, 2000-2004. *MMWR. Morbidity and Mortality Weekly Report*, *57*(45), 1226-8.

Camacho, B. A. (2008). Stress and Birth Weight : Evidence from Terrorist Attacks. *American Economic Review: Papers & Proceedings*, 511-515.

Cummings, K. M., Fix, B., Celestino, P., Carlin-Menter, S., O'Connor, R., & Hyland, A. (2006). Reach, efficacy, and cost-effectiveness of free nicotine medication giveaway programs. *Journal of Public Health Management and Practice*, *12*(1), 37-43.

Endara, S. M., Ryan, M. A. K., Sevick, C. J., Conlin, A. M. S., Macera, C. A., & Smith, T. C. (2009). Does acute maternal stress in pregnancy affect infant health outcomes? Examination of a large cohort of infants born after the terrorist attacks of September 11, 2001. *BMC Public Health*, *9*, 252.

Ford, C. A., Udry, J. R., Gleiter, K., & Chantala, K. (2003). Reactions of young adults to September 11, 2001. *Archives of Pediatrics & Adolescent Medicine*, *157*(6), 572-8.

Galea, S., Vlahov, D., Resnick, H., Ahern, J., Susser, E., Gold, J., Bucuvalas, M., et al. (2003). Trends of Probable Post-Traumatic Stress Disorder in New York City after the September 11 Terrorist Attacks. *American Journal of Epidemiology*, *158*(6), 514-524.

Holman, E. A., Silver, R. C., Poulin, M., Andersen, J., Gil-Rivas, V., & McIntosh, D. N. (2008). Terrorism, acute stress, and cardiovascular health: a 3-year national study following the September 11th attacks. *Archives of General Psychiatry*, *65*(1), 73-80.

Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, *142*(2), 615-635.

Kelejian, H. H. (1971). Two-Stage Least Squares and Econometric Systems Linear in Parameters but Nonlinear in the Endogenous Variables. *Journal of the American Statistical Association*, *66*, 373-374.

Lipkind, H. S., Curry, A. E., Huynh, M., Thorpe, L. E., & Matte, T. (2010). Birth Outcomes Among Offspring of Women Exposed to the September 11, 2001, Terrorist Attacks. *Obstetrics and Gynecology*, *116*(4), 917-25.

Messer, K., Trinidad, D. R., Al-Delaimy, W. K., & Pierce, J. P. (2008). Smoking cessation rates in the United States: a comparison of young adult and older smokers. *American Journal of Public Health*, *98*(2), 317-22.

Miller, N., Frieden, T. R., Liu, S. Y., Matte, T. D., Mostashari, F., Deitcher, D. R., Cummings, K. M., et al. (2005). Effectiveness of a large-scale distribution programme of free nicotine patches: a prospective evaluation. *Lancet*, *365*(9474), 1849-54.

Mueller, J. (2004). A False Sense of Insecurity? *Regulation*, *27*(3), 42-46.

Naquin, M. R., & Gilbert, G. G. (1996). College Students' Behavior, Perceived Stress and Coping Styles. *Journal of Drug Education*, 367-376.

Norris, F. H., Byrne, C. M., Diaz, E., & Kaniasty, K. (2001). The Range, Magnitude, and Duration of Effects of Natural and Human-Caused Disasters: A Review of the Empirical Literature. *National Center for PTSD*.

Orzechowski and Walker. (2009). The Tax Burden on Tobacco: The Historical Compilation, Vol. 44. *Arlington, VA: Orzechowski and Walker*, *44*.

Parrott, A. C. (1998). Does Cigarette Smoking Cause Stress? *American Psychologist*, *54*(10), 817-820.

Perrine, M. W. B., Schroder, K. E. E., Forester, R., McGonagle-Moulton, P., & Huessy, F. (2004). The Impact of the September 11, 2001, Terrorist Attacks on Alcohol Consumption and Distress: Reactions to a National Trauma 300 Miles from Ground Zero. *Journal of Studies on Alcohol*, *65*(1), 5-15.

Pfefferbaum, B., Vinekar, S. S., Trautman, R. P., Lensgraf, S. J., Reddy, C., Patel, N., & Ford, A. L. (2002). The Effect of Loss and Trauma on Substance Use Behavior in Individuals Seeking Support Services after the 1995 Oklahoma City Bombing. *Annals of Clinical Psychiatry*, *14*(2), 89-95.

Pierce, J. P., Farkas, A. J., & Gilpin, E. A. (1998). Beyond stages of change: the quitting continuum measures progress towards successful smoking cessation. *Addiction*, *93*(2), 277-86.

Rabinoff, M. (2009). *Toward A Tobacco Free World*. Santa Rosa, CA: Elite Books.

Ruhm, C. J. (2000). Are recessions good for your health? *Quarterly Journal of Economics*, *115*(2), 617-650.

Ruhm, C. J. (2005). Healthy living in hard times. *Journal of Health Economics*, *24*, 341-363.

Schlenger, W. E., Caddell, J. M., Ebert, L., Jordan, B. K., Rourke, K. M., Wilson, D., Thalji, L., et al. (2002). Psychological reactions to terrorist attacks: findings from the National Study of Americans' Reactions to September 11. *JAMA : the Journal of the American Medical Association*, *288*(5), 581-8.

Shedd, O. L., Sears, S. F., Harvill, J. L., Arshad, A., Conti, J. B., Steinberg, J. S., & Curtis, A. B. (2004). The World Trade Center attack: increased frequency of defibrillator shocks for ventricular arrhythmias in patients living remotely from New York City. *Journal of the American College of Cardiology*, *44*(6), 1265-7.

Sivak, M., & Flannagan, M. J. (2003). Flying and driving after the September 11 attacks. *American Scientist*, *91*(1), 6–8.

Smith, D., Christiansen, E. H., Vincent, R., & Hann, N. E. (1999). Population Effects of the Bombing of Oklahoma City. *The Journal of the Oklahoma State Medical Association*, *92*(4), 193-198.

Stein, B. D., Elliott, M. N., Jaycox, L. H., Collins, R. L., Berry, S. H., Klein, D. J., & Schuster, M. A. (2004). A National Longitudinal Study of the Psychological Consequences of the September 11, 2001 Terrorist Attacks: Reactions, Impairment, and Help-Seeking. *Psychiatry: Interpersonal and Biological Processes*, *67*(2), 105–117.

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business and Economic Statistics*, *20*(4), 518-529.

Todd, M. (2004). Daily processes in stress and smoking: effects of negative events, nicotine dependence, and gender. *Psychology of Addictive Behaviors : Journal of the Society of Psychologists in Addictive Behaviors*, *18*(1), 31-9.

U.S. DHHS. (1994). Youth & Tobacco - Preventing Tobacco Use Among Young People: A Report of the Surgeon General.

U.S. DHHS. (2001). Women and Smoking: A Report of the Surgeon General.

U.S. DHHS. (2004). The Health Consequences of Smoking: A Report of the Surgeon General.

U.S. DHHS. (2012). Preventing Tobacco Use Among Youth and Young Adults: A Report of the Surgeon General.

U.S. Department of Treasury. (1998). The Economic Costs of Smoking in the United States and the Benefits of Comprehensive Tobacco Legislation.

Vlahov, D., Galea, S., Ahern, J., Resnick, H., Boscarino, J. A., Gold, J., Bucuvalas, M., & Kilpatrick, D. (2004a). Sustained Increased Consumption of Cigarettes, Alcohol, and Marijuana Among New York City Residents Six Months After the September 11 Terrorist Attacks. *American Journal of Public Health*, *94*(2), 253-254.

Vlahov, D., Galea, S., Ahern, J., Resnick, H., Boscarino, J. A., Gold, J., Bucuvalas, M., & Kilpatrick, D. (2004b). Consumption of Cigarettes, Alcohol, and Marijuana Among New York City Residents Six Months After the September 11 Terrorist Attacks. *The American Journal of Drug and Alcohol Abuse*, *30*(2), 385-407.

Wu, P., Duarte, C. S., Mandell, D. J., Fan, B., Liu, X., Fuller, C. J., Musa, G., et al. (2006). Exposure to the World Trade Center attack and the use of cigarettes and alcohol among New York City public high-school students. *American Journal of Public Health*, *96*(5), 804-7.

**ESSAY TWO:** THE EFFECTS OF 9/11 ON HIGH RISK ALCOHOL CONSUMPTION

# 10. INTRODUCTION

This study investigates the impact of 9/11 on high-risk alcohol consumption (HRAC). It expands upon another study by the same author finding large increases in smoking amongst ever smokers using national data. In this previous study, the author used a utility-maximization framework to hypothesize that former smokers rationally chose to become smokers because of higher terrorism-induced stress, believed stress-reduction benefits of smoking, and known costs of smoking. Similarly, this study hypothesizes that individuals may attempt to self-medicate terrorism-induced stress with HRAC for utility maximization reasons.

When disaster strikes, information from the media and people with knowledge of the disaster triggers perceived risk reactions across the population at large, which in turn generates secondary social and economic consequences (Burns and Slovic, 2007). These perceived risk reactions can be deadlier and costlier than the initial terrorist attack. One example from a study using commercial vehicles as a control group found that an excess 2,300 noncommercial car passengers died in traffic accidents in the two years after 9/11 due to people substituting long car trips for plane travel (Blalock et al., 2009), suggesting that individuals overestimated the threat against them.

The costs of HRAC in the United States are large and HRAC increases stemming from terrorism could represent a large hidden cost of terrorism. Alcohol attributed deaths accounted for approximately 79,000 deaths per year and 2.3 million years of potential life lost during 2001-2005 (CDC, 2010), with youth and young adults being much more prone to these types of deaths than smoking attributed deaths (CDC, 2004). The economic costs of alcohol abuse in the United States totaled $223.5 billion in 2006, which includes costs associated with healthcare, productivity losses, property damage, crime, motor vehicle crashes, fire damage, underage drinking, and drinking during pregnancy. These costs resulted in a cost per standard drink of about \$1.90, with the government portion of these costs being \$.80 (Bouchery et al., 2011).

Alcohol consumption is different from tobacco consumption in two key ways. Unlike tobacco usage in which any level has harmful health effects, moderate alcohol consumption has been found to have some beneficial health effects. These beneficial health effects include reduced mortality from gall bladder disease (CDC, 2004), lower risk of cardiovascular disease, and greater cognitive function with age (USDA, 2010). Further, unlike tobacco, people that consume moderate amounts of alcohol are less likely to become addicted (Chaloupka, Grossman, and Saffer, 2002).

## 11. LITERATURE REVIEW OF THE IMPACT OF TERRORISM ON DRINKING

A literature review by Knudsen and colleagues provides evidence of stress and alcohol usage increases following 9/11. The literature review finds that researchers primarily used respectively-collected data of residents in close proximity to New York City or of employees at the Pentagon. Negative mental health effects and alcohol prevalence increases were generally found. However, caution should be used in applying the conclusions of these studies to the national population because of the unique effect that the terrorist attacks had on people in close proximity (Knudsen et al., 2005).

Unlike localized studies, studies using national data did not find increases in alcohol use following 9/11. One study found no increase in alcohol use for young adults (Ford et al., 2003), and other studies found decreases in alcohol use among adults (U.S. DHHS, 2002; Pfefferbaum et al., 2008; Knudsen et al., 2005). These studies used data from Wave III of the National Longitudinal Study of Adolescent Health, the National Household Survey on Drug Abuse, a nationally representative sample of telephone-interviewed substance users, and a worker longitudinal survey. These studies did not attempt to construct a measure of HRAC, instead surveying alcohol use which may or may not be dangerous. Another study found no effect of 9/11 on the alcohol use patterns of clients entering substance abuse treatment in a number of large U.S. cities (Johnson et al., 2002).

One national study did survey a dangerous form of alcohol use. The authors found a statistically significant increase in both alcohol- or drug-related traffic citations and traffic fatalities in the Northeast, the region struck by the terrorist attacks, in 2001 compared to other regions and years. The authors hypothesized that driving impairment due to the use of alcohol or drugs in response to 9/11 may have been a factor in the observed regional increase in traffic fatalities after 9/11 (Su et al., 2009).

Longitudinal data suggests that women but not men increased drinking following 9/11. In a longitudinal workplace cohort study of a Midwestern university, women were found to have both greater anxiety and alcohol use negative outcomes in the months following 9/11 than did women completing the survey before 9/11, controlling for demographic characteristics (Richman et al., 2004). However, differences in dangerous drinking by gender had returned to baseline two years later (Richman et al., 2009). Another longitudinal study in Vermont, 300 miles from New York City, found that women increased alcohol consumption on the day of 9/11/2001 compared to the previous fifty-two Tuesdays, but no evidence of an increase in alcohol consumption was found for men (Perrine et al., 2004).

In sum, the literature shows an inconclusive relationship between the effect of 9/11 on alcohol use, with some evidence for increases found using localized data and weak evidence found using national data. Findings suggest that women may have been more likely than men to use alcohol in response to 9/11. Only one study specifically investigated the impact of 9/11 on HRAC.

## 12. DATA DESCRIPTION

### 12.1 Behavioral Risk Factor Surveillance System Data

This research uses the Behavioral Risk Factor Surveillance System (BRFSS) data. State health departments and the Centers for Disease Control and Prevention (CDC) collect the BRFSS data on risky personal health behaviors via landline telephone surveys of individuals aged 18 years and older. The data is nation and state representative of the non-institutionalized population. The data has date, state, and county identifying information. Further information on the BRFSS can be obtained from http://www.cdc.gov/brfss/.

The years of 1999, 2001, and 2002 are used in this analysis, providing 600,831 observations. The alcohol module was optional in year 2000, [23] so this year is not used. Unweighted and weighted descriptive statistics for this data are provided in Table X.

[23] In 2000, the optional module was completed by 12 states reporting higher average alcohol usage. These states are Alaska, Idaho, Illinois, Iowa, Minnesota, Nevada, New Mexico, Ohio, Tennessee, Texas, Vermont, and Wisconsin. The alcohol prevalence sample mean for these states was 3.8 percentage points higher than for the other states, suggesting that larger alcohol consuming states participated in the optional alcohol module. Conditional number of drinks consumed and conditional binge drinking averages were also higher for the twelve states.

TABLE X: POPUALTION DESCRIPTIVE STATISTICS - 1999, 2001-2002

| | Unweighted | | Weighted | |
|---|---|---|---|---|
| | **Mean** | **Standard Deviation** | **Mean** | **Standard Deviation** |
| **BRFSS** | | | | |
| Male (%) | 40.54 | 49.10 | 48.12 | 49.96 |
| Female (%) | 59.46 | 49.10 | 51.88 | 49.96 |
| White non-Hispanic (%) | 79.68 | 40.24 | 71.92 | 44.94 |
| Black non-Hispanic (%) | 7.67 | 26.61 | 9.65 | 29.53 |
| Asian non-Hispanic (%) | 2.17 | 14.59 | 2.84 | 16.61 |
| Native American non-Hispanic (%) | 1.47 | 12.04 | 1.04 | 10.16 |
| Hispanic (%) | 6.13 | 23.99 | 11.88 | 32.36 |
| Missing Race/Ethnicity (%) | 2.87 | 16.71 | 2.67 | 16.11 |
| Age | 47.93 | 17.62 | 45.52 | 17.71 |
| Junior High (%) | 4.03 | 19.66 | 4.87 | 21.52 |
| Some High School (%) | 7.36 | 26.11 | 8.14 | 27.34 |
| High School (%) | 31.82 | 46.58 | 31.28 | 46.36 |
| Some College (%) | 27.01 | 44.40 | 26.93 | 44.36 |
| College (%) | 29.54 | 45.62 | 28.48 | 45.13 |
| Missing Education (%) | 0.25 | 5.00 | 0.30 | 5.43 |
| Employed (%) | 62.01 | 48.54 | 62.78 | 48.34 |
| Unemployed (%) | 3.89 | 19.34 | 4.57 | 20.88 |
| Student (%) | 2.89 | 16.76 | 4.12 | 19.87 |
| Not Student, Not in Labor Force (%) | 30.95 | 46.23 | 28.21 | 45.00 |
| Missing Employed Status (%) | 0.26 | 5.07 | 0.33 | 5.73 |
| Married (%) | 53.70 | 49.86 | 58.38 | 49.29 |
| Divorced (%) | 16.35 | 36.98 | 12.19 | 32.72 |
| Widowed (%) | 10.55 | 30.71 | 7.02 | 25.55 |
| Unmarried and Other Marital Status (%) | 19.09 | 39.30 | 22.12 | 41.51 |
| Missing Marital Status (%) | 0.31 | 5.60 | 0.28 | 5.31 |
| Real Household Income (without imputation, in 1000s of dollars) | 31.52 | 18.85 | 32.73 | 19.27 |
| Real Household Income (with imputation, in 1000s of dollars) | 30.82 | 18.10 | 31.90 | 18.54 |
| Top Household Income Category (%) | 14.77 | 35.48 | 16.51 | 37.13 |
| Stress (Days Mental Health Not Good over Past 30 Days) | 3.34 | 7.55 | 3.21 | 7.28 |
| Alcohol High Risk Measure #1 - Excessive Drinks Per Drinking Day (%) | 5.67 | 23.13 | 7.18 | 25.82 |
| Alcohol High Risk Measure #2 - Any Binge Drinking (%) | 13.10 | 33.74 | 15.08 | 35.79 |
| Alcohol High Risk Measure #3 - Excessive Drinks per Month (%) | 5.01 | 21.81 | 5.65 | 23.08 |
| Alcohol High Risk Measure #4 - Drinking During Pregnancy (%) | 0.13 | 3.66 | 0.14 | 3.71 |
| Alcohol High Risk Measure (Any) (%) | 14.98 | 35.68 | 17.11 | 37.66 |
| Alcohol High Risk Measure (Cumulative) | 0.23 | 0.62 | 0.27 | 0.68 |
| **Merged Outside Data** | | | | |
| Real After-Tax Price of Ounce of Ethanol (in dollars) | 1.3668 | 0.1640 | 1.3458 | 0.1698 |
| No Pub Smoking Restrictions (%) | 93.83 | 24.07 | 85.50 | 35.21 |
| State-Level Unemployment Rate (%) | 4.70 | 1.17 | 4.93 | 1.11 |
| County Population Density per Respondent (in 1,000s of people) | 1.26 | 3.79 | 2.45 | 6.49 |
| Reverse Distance from Terrorist Attack (in 1,000s of miles) | -0.97 | 0.77 | -0.94 | 0.61 |
| County Per Capita Military Pay (in dollars) | 0.268363 | 0.738657 | 0.218129 | 0.642795 |
| Violent and Property Crime (in trillions of people) | 0.0403 | 0.0104 | 0.0418 | 0.0092 |
| Military Casualties in Past 30 Days (in 100s of deaths) | 0.019429 | 0.038191 | 0.016555 | 0.035317 |
| DOW Past 30 Days (in thousands of dollars) | 7.2037 | 0.7570 | 7.2766 | 0.7542229 |

Men, racial/ethnic minorities, younger, unemployed, and non-married individuals are underrepresented in the unweighted data. The weighted data is used in all regression analysis.

## 12.2 Alcohol Questions in BRFSS Data and HRAC Construction

Five alcohol measures are provided in the BRFSS data: 1) alcohol prevalence over the past 30 days, 2) number of drinking days over the past 30 days, 3) conditional number of drinks consumed on drinking days, 4) conditional number of times that one has driven after having "had perhaps too much to drink" over the past 30 days, and 5) conditional number of times having had five or more beverages on any one occasion over the past 30 days. The conditional questions were asked only to those answering in the affirmative to having used alcohol or reporting a positive number of drinking days. The conditional drinking and driving question was not asked in the year 2001, so will not be used in this analysis. Besides the exclusion of the drinking and driving question in 2001, the survey designs for 2001-2002 were identical. There were slight differences in the survey design in year 1999 compared to years 2001-2002.[24] Sensitivity analysis will later show that results remain robust for a portion of the analysis conducted using only years 2001-2002.

Responding to alcohol-related questions was high in the years used in this study. 99.7% of respondents provided alcohol prevalence information, and conditional measures of alcohol use had response rates of between 98.7-98.9%.

[24] While the questions from 1999 to 2001-2002 are substantially similar, there are three main differences in the phrasing of the alcohol questions. First, in 1999, the timeframe referred to is "past month" rather than "past 30 days." Second, in 1999, to measure alcohol prevalence, respondents were directly asked if alcohol was consumed over the past month. Starting in 2001, this information was imputed based on answers to a subsequent question asking how many days over the past 30 days alcohol was consumed. Finally, in 1999, drinking prevalence and drinking days are asked without a clear definition of what a "drink" is, which is defined in 2000-2001 to be "1 can or bottle of beer, 1 glass of wine, 1 can or bottle of wine cooler, 1 cocktail, or 1 shot of liquor." In 1999, it is not until the third question of the alcohol module (i.e. number of drinks consumed on drinking days) that this preface is provided. These three differences may have contributed to a 4.2% lower drinking prevalence rate in 1999 compared to 2001-2002.

Moderate amounts of alcohol consumption have health benefits (CDC, 2004; USDA, 2010), so this research will focus on the effect of 9/11 on HRAC. There are at least four scientifically-established components of HRAC: 1) the consumption of four or more drinks on any day for men or three drinks on any day for women, 2) the consumption within 2 hours of 4 or more drinks for women and 5 or more drinks for men (i.e. binge drinking), 3) the consumption over the past week of more than two drinks per day for men or more than one drink per day for women, and 4) drinking during pregnancy (Bouchery et al., 2011; USDA, 2010). BRFSS data is used to construct HRAC components similar to these definitions, denoting HRAC if individuals report 1) an average number of drinks on drinking days exceeding three for women and four for men, 2) any binge drinking (i.e. 5 or more drinks on any occasion for both women and men), 3) consuming more than 60 alcoholic beverages over the past month for men or more than 30 for women, and 4) any alcohol usage during pregnancy for women.

There was overlap between the different components of HRAC,[25] but Pearson test statistics indicate differences between groups except for two tests involving drinking during pregnancy, likely due to the low sample size for this component of HRAC. Alcohol prevalence increased from 53.0% to 55.0% of the population in the post-9/11 period; therefore, any increase in prevalence of HRAC in the national population (i.e. alcohol users and non-users) can be attributed to either new drinkers or existing drinkers becoming HRAC drinkers.

---

[25] If people drank excessively on drinking days (HRAC component #1), 84.86% also binge drank, 41.55% also consumed excessive drinks per month, and .69% of women drank during pregnancy. If people binge drank (HRAC component #2), 40.30% also drank excessively on drinking days, 27.57% also consumed excessive drinks per month, and .64% of women also drank during pregnancy. If people consumed excessive drinks per month (HRAC component #3), 52.77% also drank excessively on drinking days, 73.88% binge drank, and .35% of women drank during pregnancy. If women drank during pregnancy (HRAC component #4), 11.80% drank excessively on drinking days, 17.92% binge drank, and 6.03% consumed excessive drinks per month.

## 12.3 Dependent Variables

The components of HRAC, except for pregnancy, are used as dependent variables in regression analysis. Drinking during pregnancy is not used as a stand-alone dependent variable because of low sample size. Additionally, the four components are used to construct a dichotomous measure of *any* HRAC and an ordered measure of HRAC intensity that is a 0 for no HRAC and increases by 1 for each individual component of HRAC. This variable can have a maximum value of 4 for a pregnant woman or a 3 for everybody else. Both any HRAC and HRAC intensity are used as dependent variables in regression analysis.

In creating any HRAC and the HRAC intensity measure, observations with missing conditional alcohol drinks on drinking days, conditional alcohol days, conditional alcohol binge drinking, and/or missing pregnancy status were subset, even if information was present to determine at least one of the components of HRAC. Sensitivity analysis will later show that treating these observations (1.6% of the alcohol prevalence sample) in different ways changes the magnitude of estimates, but not the general conclusions.

A final dependent variable used in this analysis is stress, which is derived from responses to the question of how many days over the past 30 days was mental health not good. The question is phrased to minimize non-reporting of the sensitive area of mental health. In the survey period investigated, 98.2% of people asked the question answered it. However, the stress question was part of an optional module in year 2002 and was only asked in 21 states.[26] In 1999 and 2001, stress was 4.9% higher in these 21 states. To obviate the issue of a changed sample in 2002, analysis in this paper will typically either use alcohol data, which is a required module for the three years investigated, or will use the stress data for only the years 1999 and 2001.

[26] The 21 states that asked this question pertaining to stress in 2002 were Alaska, California, Hawaii, Idaho, Iowa, Kansas, Kentucky, Minnesota, Missouri, New Jersey, New Mexico, New York, North Carolina, Oregon, Rhode Island, South Carolina, Texas, Utah, Virginia, Washington, Wyoming.

Descriptive statistics in Table X shows that HRAC users were underrepresented in the unweighted data. 7.2% of the weighted population consumed excessive drinks on drinking days, 15.1% binge drank, 5.7% consumed an excessive number of drinks during the past month, and .14% consumed alcohol during pregnancy (18.7% of pregnant women). 17.1% of the population reported any HRAC, with the average person reporting .27 components of HRAC. The average person reported experiencing 3.2 days when mental health was not good.

Figures 27-28 presents a mapping over time of the data on stress and HRAC, shown in terms of standard deviations from the mean. In Figure 28, a clear spike in stress is seen around 9/11/2001. The relationship between 9/11 and HRAC is not as clear in Figure 29, but a small increase around 9/11/2001 does temporarily push HRAC above the mean from a point far below. The persistence of a potential terrorism effect is not clear; however, as HRAC declines below the mean almost immediately and stress declines below the mean several months after. Following, both begin an oscillation pattern across the mean. Multivariate analysis is needed to determine if terrorism or other factors contributed to the stress and HRAC increase around 9/11.

Table XI provides national and state-level estimates of select dependent variable means in pre-9/11 (1/1/2001-9/10/2001) and post-9/11 (9/12/2001-9/12/2002) periods.

TABLE XI: COMPARISON OF DEPENDENT VARIABLE MEANS PRE- AND POST-9/11

| | Any Binge Drinking | | | HRAC | | | HRAC Intensity | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean 1/1/2001-9/10/2001 | Mean 9/12/2001-9/12/2002 | Percent Change | Mean 1/1/2001-9/10/2001 | Mean 9/12/2001-9/12/2002 | Percent Change | Mean 1/1/2001-9/10/2001 | Mean 9/12/2001-9/12/2002 | Percent Change |
| **USA** | 14.41% | 15.62% | 8.39% | 16.06% | 17.38% | 8.22% | 0.25 | 0.28 | 8.28% |
| | | | | | | | | | |
| **AL** | 12.26% | 12.91% | 5.26% | 13.44% | 14.06% | 4.62% | 0.21 | 0.23 | 6.19% |
| **AK** | 17.94% | 19.11% | 6.49% | 18.73% | 21.46% | 14.59% | 0.29 | 0.32 | 10.09% |
| **AZ** | 16.25% | 16.60% | 2.15% | 18.47% | 18.44% | -0.19% | 0.31 | 0.31 | 0.18% |
| **AR** | 10.53% | 13.17% | 25.08% | 10.83% | 14.28% | 31.80% | 0.18 | 0.25 | 33.38% |
| **CA** | 15.04% | 15.42% | 2.55% | 17.48% | 17.30% | -1.02% | 0.28 | 0.28 | -0.22% |
| **CO** | 16.44% | 18.44% | 12.16% | 18.22% | 20.29% | 11.41% | 0.28 | 0.31 | 11.78% |
| **CT** | 13.91% | 15.49% | 11.31% | 16.10% | 17.54% | 8.96% | 0.24 | 0.26 | 8.39% |
| **DE** | 15.96% | 16.41% | 2.82% | 17.65% | 18.77% | 6.31% | 0.30 | 0.31 | 4.40% |
| **DC** | 12.90% | 16.10% | 24.77% | 15.96% | 18.65% | 16.84% | 0.25 | 0.28 | 10.27% |
| **FL** | 11.79% | 13.54% | 14.83% | 13.82% | 15.78% | 14.13% | 0.22 | 0.24 | 11.85% |
| **GA** | 11.95% | 12.99% | 8.73% | 12.81% | 14.07% | 9.85% | 0.19 | 0.20 | 6.72% |
| **HI** | 10.88% | 10.94% | 0.48% | 13.65% | 13.58% | -0.50% | 0.23 | 0.23 | -0.66% |
| **ID** | 12.53% | 14.96% | 19.35% | 13.73% | 16.35% | 19.12% | 0.21 | 0.26 | 23.28% |
| **IL** | 16.57% | 18.43% | 11.23% | 17.43% | 19.83% | 13.75% | 0.27 | 0.33 | 21.05% |
| **IN** | 13.63% | 15.69% | 15.08% | 14.93% | 17.53% | 17.39% | 0.23 | 0.28 | 19.62% |
| **IA** | 16.43% | 18.93% | 15.20% | 17.15% | 19.84% | 15.64% | 0.28 | 0.33 | 20.66% |
| **KS** | 15.11% | 15.71% | 4.01% | 16.21% | 16.94% | 4.50% | 0.26 | 0.27 | 2.03% |
| **KY** | 8.95% | 8.85% | -1.15% | 10.29% | 9.89% | -3.85% | 0.17 | 0.17 | -3.25% |
| **LA** | 13.69% | 13.89% | 1.48% | 14.63% | 14.23% | -2.74% | 0.23 | 0.21 | -7.28% |
| **ME** | 15.57% | 14.98% | -3.78% | 17.24% | 17.68% | 2.58% | 0.27 | 0.26 | -4.03% |
| **MD** | 11.97% | 14.35% | 19.90% | 14.37% | 16.17% | 12.48% | 0.22 | 0.25 | 12.56% |
| **MA** | 17.82% | 18.58% | 4.29% | 20.08% | 21.07% | 4.92% | 0.33 | 0.32 | -0.13% |
| **MI** | 16.29% | 18.61% | 14.23% | 18.34% | 21.06% | 14.84% | 0.29 | 0.33 | 14.12% |
| **MN** | 19.07% | 20.66% | 8.36% | 20.22% | 21.85% | 8.09% | 0.32 | 0.34 | 5.28% |
| **MS** | 10.75% | 12.65% | 17.67% | 11.75% | 13.26% | 12.84% | 0.19 | 0.21 | 11.05% |
| **MO** | 14.12% | 16.41% | 16.17% | 15.05% | 17.86% | 18.66% | 0.25 | 0.29 | 15.82% |

**(continued on next page)**

**(continued from previous page)**

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **MT** | 16.15% | 19.64% | 21.60% | 17.63% | 21.15% | 19.97% | 0.28 | 0.33 | 17.95% |
| **NE** | 14.66% | 16.39% | 11.81% | 16.16% | 17.77% | 9.99% | 0.26 | 0.28 | 5.65% |
| **NV** | 17.85% | 17.84% | -0.06% | 20.52% | 20.09% | -2.10% | 0.34 | 0.33 | -1.16% |
| **NH** | 15.43% | 16.12% | 4.46% | 17.56% | 18.99% | 8.16% | 0.27 | 0.29 | 4.90% |
| **NJ** | 13.42% | 13.43% | 0.05% | 15.25% | 15.09% | -1.01% | 0.22 | 0.23 | 0.79% |
| **NM** | 15.22% | 14.65% | -3.76% | 17.10% | 16.22% | -5.13% | 0.26 | 0.25 | -3.79% |
| **NY** | 14.17% | 16.91% | 19.35% | 15.64% | 18.79% | 20.19% | 0.24 | 0.28 | 17.76% |
| **NC** | 10.02% | 10.38% | 3.52% | 11.41% | 11.39% | -0.18% | 0.19 | 0.18 | -5.35% |
| **ND** | 23.11% | 21.51% | -6.90% | 24.47% | 23.42% | -4.31% | 0.39 | 0.36 | -6.97% |
| **OH** | 16.47% | 16.29% | -1.10% | 17.87% | 18.45% | 3.22% | 0.30 | 0.30 | -0.51% |
| **OK** | 11.11% | 12.10% | 8.88% | 11.71% | 13.18% | 12.54% | 0.19 | 0.22 | 12.67% |
| **OR** | 15.36% | 15.18% | -1.15% | 16.97% | 16.88% | -0.50% | 0.26 | 0.27 | 3.94% |
| **PA** | 15.44% | 16.61% | 7.60% | 17.56% | 18.70% | 6.50% | 0.28 | 0.31 | 11.01% |
| **RI** | 15.24% | 16.75% | 9.88% | 18.19% | 19.56% | 7.56% | 0.29 | 0.31 | 7.66% |
| **SC** | 12.85% | 11.68% | -9.07% | 14.49% | 13.74% | -5.16% | 0.23 | 0.22 | -4.40% |
| **SD** | 18.63% | 18.33% | -1.59% | 19.56% | 19.75% | 0.97% | 0.30 | 0.30 | 1.12% |
| **TN** | 7.22% | 7.45% | 3.21% | 8.06% | 8.57% | 6.32% | 0.12 | 0.13 | 5.91% |
| **TX** | 15.68% | 16.68% | 6.31% | 17.40% | 18.66% | 7.25% | 0.28 | 0.32 | 11.30% |
| **UT** | 9.49% | 10.04% | 5.74% | 10.28% | 10.61% | 3.28% | 0.16 | 0.17 | 5.93% |
| **VT** | 15.38% | 16.43% | 6.83% | 18.03% | 18.95% | 5.13% | 0.27 | 0.28 | 5.37% |
| **VA** | 12.72% | 15.89% | 24.98% | 14.17% | 17.56% | 23.86% | 0.22 | 0.27 | 26.08% |
| **WA** | 14.65% | 15.17% | 3.55% | 16.44% | 17.09% | 3.92% | 0.25 | 0.25 | 2.09% |
| **WV** | 9.38% | 10.80% | 15.11% | 9.49% | 11.30% | 19.12% | 0.17 | 0.20 | 17.16% |
| **WI** | 25.33% | 26.09% | 3.01% | 27.06% | 28.35% | 4.76% | 0.45 | 0.47 | 4.24% |
| **WY** | 16.33% | 17.63% | 7.97% | 17.86% | 19.23% | 7.68% | 0.28 | 0.30 | 7.30% |

[a] Stress is used as a dependent variable, but is not included in this chart because stress was part of an optional module completed by only 21 states in 2002.
[b] Survey features of the data and subpopulations are used in computing these estimates.

Nationally, any binge drinking increased 8.4%, HRAC increased 8.2%, and HRAC intensity increased 8.3%. The three states experiencing the largest increases in any binge drinking were Arkansas (25.1%), Virginia (25.0%), and the District of Columbia (24.8%). The three states experiencing the largest increases in HRAC were Arkansas (31.8%), Virginia (23.9%), and New York (20.2%). Idaho replaces New York in the top three HRAC intensity increases.

### 12.4 Independent Variables

Indicator variables were created for socio-demographic information of gender, race/ethnicity, education attainment, marital status, and employment status. Missing indicator variables for all categories were constructed. Household income information was provided as a categorical variable, and this was converted into a continuous variable using the median for each of the categories. Missing household income values and age values were linearly imputed.[27]

### 12.5 Merged Data

Alcohol price data for the years 1999-2002 was merged onto the BRFSS data. The American Chamber of Commerce Researchers Association (ACCRA) Cost of Living Index provides quarterly prices on beer, liquor, and wine for 300 cities. The prices are for households in the top income quintile, so discount alcohol stores are likely to be underrepresented in the computation of these prices. Prices are exclusive of sales taxes but inclusive of state and federal excise taxes. Over the years of this study, the liquor bottle tracked was a 750-ml bottle of J&B Scotch. The beer tracked was a six-pack of Budweiser or Miller Lite in 1999, and a six-pack of Heineken in 2001-2002.

---

[27] Age was imputed first and household income second. The age bounds of 18 and 99 were used for any predictions that fell outside the range. Inflation-adjusted household income category values were used as a lower bound for any predictions.

Composite prices for an ounce of pure ethanol were computed using the liquor and beer prices from the ACCRA data. The composite price was formed by dividing the ACCRA prices for beer and alcohol by the ounces of ethanol in each package.[28] Following, these prices per ounce of ethanol were multiplied by the fraction of total U.S. ethanol consumption accounted for by liquor and beer, which is provided annually by the National Institute on Alcohol Abuse and Alcoholism (NIAAA).[29] This provides an average price per ounce of ethanol. The standard drink contains roughly a half an ounce of ethanol (NIAAA, 2008). All monetary data, including the ethanol price data, was adjusted for inflation using the Bureau of Labor Statistic's city average for all consumers consumer price index.

All price observations were averaged by state and quarter and matched to BRFSS state residency data. Past state alcohol prices were used for any missing prices, or future prices were used if there were no prices provided at an earlier point in time. No price data is provided for the states of Maine and Rhode Island, and price data for Hawaii was not provided until 2002, so these states are subset from the analysis.

Other state-level control variables merged onto the BRFSS data is unemployment rates and the strength of pub smoking restrictions. The Bureau of Labor Statistics' monthly state-level unemployment data is used in constructing a state-level unemployment rate variable, which is included in all regressions to control for spillover effects of unemployment beyond individual-level employment status. Pub smoke-free air law strength data was collected by the ImpacTeen project through the MayaTech consulting firm and is used to create an indicator variable representing the presence of any smoking restrictions in pubs.

[28] There are 10.1 ounces of ethanol in a 750-ml, 80-proof bottle and 3.6 ounces in a 6-pack of 12-ounce beers.
[29] Data was obtained from the NIAAA website. Data was accessed on November 27, 2011 at http://www.niaaa.nih.gov/Resources/DatabaseResources/QuickFacts/AlcoholSales/default.htm.

People living closer to the epicenters of the terrorist attacks may experience disproportionate stress (Smith et al., 1999; Stein et al., 2004; Schlenger et al., 2002). These people are more likely to have been directly impacted by the attacks, and this can cause negative emotions, such as stress, that can lead to HRAC. To test this hypothesis, distance data was calculated using ArcGIS software. Distances were measured from the centers of New York City, Washington DC, and Oklahoma City to the centers of each of the respective counties in the United States.[30] If county data was missing, as it was in 22.8% of cases, the average quarterly distance data for residents of the state was used instead.

Unfortunately, the BRFSS data does not provide employer information, which would be useful for identifying military personnel and analyzing any differential effect of terrorism on this population. Instead, county-level military pay data, provided by the Consolidated Federal Funds Report, a government expenditures report, is used.[31] The federal military pay for active duty and national guard/reservist soldiers in each county is divided by interpolated annual July Census population estimates by county to obtain county per capita military pay information, which is merged with the BRFSS data. State per capita military pay information was used for observations with missing county data. A benefit of this county-level data is that it captures family and community effects of terrorism.

People living in high population density areas may have greater stress following terrorism because terrorists are likely to target high population density centers. If this is true, then people living in counties with higher population densities may show larger increases in stress and HRAC following terrorism than people living in low population density counties. Interpolated

---

[30] Following 9/11, the distance measure used was the distance from New York City to the center of each county unless the distance to Washington DC was less than 100 miles, in which case only the distance to Washington DC was used.

[31] Data was obtained from the National Priorities Project website. Data was accessed on July 8, 2011 at http://nationalpriorities.org/en/tools/database/.

July Census population estimates and county land area data were used to determine population densities by county. If county data was missing in the BRFSS data, then the average quarterly population density for respondents in the state was used.

Data on military casualties, stock market valuation, and crime is used in sensitivity analysis to determine if these factors have the effect of weakening measured impacts of terrorism. The attacks of 9/11 were associated with substantial falls in stock market valuation (personal wealth) and a war in Afghanistan. The first causalities of Operation Enduring Freedom occurred in October of 2001. Casualty data for this operation[32] was used to generate a measure of military casualties over the past 30 days. A past 30-day moving average of the closing values for the Dow Jones Industrial Average was matched to the daily BRFSS data to control for financial stress and changes in wealth that could affect HRAC consumption. Finally, annual state-level violent and property crime data is summed and used for comparing terrorism with another form of violence related stress.[33]

## 13. SINGLE EQUATION MODELING WITH A REGRESSION DISCONTINUITY DESIGN

### 13.1 Model

The effect that terrorism has on stress and HRAC will first be explored using single equation modeling, with a regression discontinuity design, to observe the effect of terrorism on stress and HRAC over time. Imbens and Lemieux provide an excellent overview of this method

---

[32] Data was obtained from the Department of Defense Personnel & Procurement Statistics website. Data was accessed on July 8, 2011 at http://siadapp.dmdc.osd.mil/personnel/CASUALTY/castop.htm. Over the time period investigated, military casualties included in this measure are 105 casualties in Operation Enduring Freedom. Smaller involvements that resulted in casualties, including 2 casualties in the Kosovo conflict in 1999, are not included in this measure. The first casualties of Operation Iraqi Freedom were not until March of 2003, so this war does not overlap with the dates used in this study.

[33] Data was obtained from the Federal Bureau of Investigation's "Crime in the U.S." website. Data was accessed on July 8, 2011 at http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s.

(Imbens and Lemieux, 2008) and this method was used in one other study on the effect of 9/11 on stress and substance use (Ford et al., 2003). An algebraic representation of the single equation models is identified in equations 8-9:

$$\mathrm{stress}_{\mathrm{ist}} = \alpha + \beta_1 \emptyset_{\mathrm{st}} + \beta_2 \mathrm{X}_{\mathrm{ist}} + \beta_3 \mathrm{post}_{\mathrm{t}} + \beta_4 \mathrm{time}_{\mathrm{t}} + \beta_5 1999_t + \gamma_{\mathrm{s}} + \gamma_{\mathrm{day}} + \gamma_{\mathrm{season}} + \varepsilon_{\mathrm{ist}} \quad (8)$$

$$\mathrm{HRAC}_{\mathrm{ist}} = \alpha + \beta_1 \emptyset_{\mathrm{st}} + \beta_2 \mathrm{X}_{\mathrm{ist}} + \beta_3 \mathrm{post}_{\mathrm{t}} + \beta_4 \mathrm{time}_{\mathrm{t}} + \beta_5 1999_t + \gamma_{\mathrm{s}} + \gamma_{\mathrm{season}} + \varepsilon_{\mathrm{ist}} \quad (9)$$

The models control for a variety of factors that potentially influence alcohol use. The subscript *i* refers to the individual, *s* to the state, and *t* to the year. The estimated sample always contains observations from the year 1999 and from 1/1/2001-9/11/2001. The year 1999 is used, in part, to help control for seasonal determinants of HRAC. Months or quarters though the end of 2002 are iteratively added with replacement to this base sample. This extra month or quarter is individually captured by the $\mathrm{post}_t$ variable, making $\beta_3$ the coefficient of interest. This regression discontinuity design allows observation of the potential influence of terrorism over time.

The dependent variable $\mathrm{stress}_{ist}$ is an integer variable with values between 0-30 for days in the past month that mental health was not good. The $\mathrm{HRAC}_{ist}$ dependent variable is either a component of HRAC, the prevalence of any HRAC, or the intensity of HRAC.

In both equations, $\mathrm{X}_{ist}$ is a matrix of individual-level control variables (gender, race/ethnicity, household income, age, education attainment, marital status, and employment status).[34] This rich set of individual characteristics controls for demographic and socio-demographic shifts correlated with HRAC. Included in $\mathrm{X}_{ist}$ is an indicator variable for the highest category of household income to account for a downward bias when household income categories were converted into a continuous variable. Squared household income and age terms are also included in non-average marginal effect specifications to account for any non-linearity.

[34] Reference categories are male, White non-Hispanic, some high school, married, and employed.

$\emptyset_{st}$ is a matrix of state-level control variables (any smoking restrictions in pubs, ethanol prices, and unemployment rates) that vary across state and time.[35]

Several controls are used in the models to limit potential omitted variable biases. A linear monthly time trend, $time_t$, is used to account for national time-varying changes in HRAC over time. An indicator variable for the year 1999 is included to capture any effect caused by the discontinuity between years 1999 and 2001-2002.[36] Season indicator variables[37] are used to control for seasonal effects of HRAC, such as greater HRAC around winter holidays. State indicators are included to capture unobservable time-invariant differences across geographical regions (including differences in attitudes towards alcohol consumption). In the stress model, day fixed effects are included to control for any variation in stress reported depending on the day of the week the interview was conducted (e.g. Mondays are stressful days).

The dependent variable data type was considered when deciding on the estimation techniques for the single equation models. For the stress model, the mean of the dependent stress variable is 3.2 days and variance of the variable is 62.0 days, over 19 times greater. Parameters would be biased if using an OLS model because of the strong rightward skew of the data; therefore, this variable will be analyzed as a continuous count variable using a negative binomial distribution to account for the large over-dispersion. For the HRAC intensity model, an ordered logit model will be used to test the transition between multiple HRAC components. An ordered logit model is not estimated with a constant term and instead uses cut points. Logit estimation will be used for HRAC component and any HRAC models.

[35] In the single equation model for stress (1), any smoking restrictions in pubs and real after-tax ethanol prices are not included in $\emptyset_{st}$.
[36] Some of this discontinuity variation will also be controlled for by the monthly time trend, $time_t$, which ends at a value of 12 in December, 1999 and resumes at the value of 25 in the January, 2001.
[37] December, January, and February are winter months and all seasons have three months.

## 13.2 Determining the Effect of Terrorism Over Time

Stock charts of the average marginal effects on the quarterly post coefficients for equations 8-9 are presented in Figures 29-35. Figures 36-42 show the monthly effects for the same time period.

Results generated from equation 8 suggest that individuals experienced a sharp increase in stress in the fourth quarter of 2001, shown in Figure 29. The increase in stress returned to baseline immediately in subsequent quarters.

The three components of HRAC are initially analyzed separately, shown in Figures 30-32, to observe if any components increase following 9/11. There is no evidence of a quarterly increase in drinking excessive drinks on drinking days after 9/11, but an increase was found in April of 2002 at a 10% significance level. Excessive drinks per month increased at the 10% significance level in the fourth quarter of 2002. Unlike these other two HRAC components, any binge drinking substantially increases (at a 1% significance level) in all quarters following 9/11. Counterintuitively, the average marginal effect quarterly point estimates for this model increase over time. This may suggest a delayed stress response to 9/11 as opposed to a discounted stress response.

HRAC and HRAC intensity results (for predicted one component and two component HRAC drinkers) are shown in Figures 33-35. All three stock charts follow a similar pattern to that shown earlier for any binge drinking, with statistically significant increases in all quarters and increasing magnitudes of average marginal effect point estimates.

Based on earlier results, future analysis will use one of two time horizons. The fourth quarter of 2001 will be used to explore the short-term impact of terrorism on HRAC. Two added benefits of this short-term approach are that 1) post-9/11 data is used from the same annual sample as pre-9/11 data instead of introducing a new annual sample, and 2) there is no reduction in the number of states collecting information on stress. The full five quarters after 9/11 will be used to explore the effect of terrorism over a longer period of time.

Table XII shows the average marginal effect point estimates for the terrorism post variable from equations 8-9. Full results are provided in Tables XIII-XV.[38]

[38]Full results show that the real price per ounce of ethanol was a statistically significant negative. Depending on the time horizon used, a $1 increase in the real price per ounce of ethanol was found to reduce any HRAC by 5.7 to 7.2 percentage points. In years 1999 and 2001, not having any smoking restrictions was associated with a 2.4 percentage point reduction in any binge drinking and a 2.6 percentage point reduction in any HRAC. One possible explanation for this is that individuals avoiding pubs because of smoking restrictions may drink more at home. Another possible explanation is that individuals attend pubs more frequently and/or for longer periods of time because of less indoor smoke, drinking more in the process. Finally, depending on the time horizon used, a 1 percentage point increase in the state-level unemployment rate was found to reduce stress by a quarter of a day per 30 days and binge drinking between .4 to .8 percentage points, depending on the time horizon used. This procyclical relationship between employment and dangerous drinking is corroborated by another study (Ruhm and Black, 2002).

TABLE XII: SINGLE EQUATION MODELING

| | Independent Variable: 4Q of 2001 | Full Post 9/11 |
|---|---|---|
| Equation (1) - Stress | | |
| Negative Binomial | **0.4124*** ** | **0.2847*** ** |
| | (0.1214) | (0.0979) |
| Equation (2) - HRAC Component #2 - Any Binge Drinking | | |
| Logit | **0.0164*** ** | **0.0112*** ** |
| | (0.0049) | (0.0037) |
| Equation (2) - Any HRAC | | |
| Logit | **0.0170*** ** | **0.0112*** ** |
| | (.0053) | (0.004) |
| Equation (2) - HRAC Intensity, Predicted One Component HRAC Drinkers | | |
| Ordered Logit | **.0070*** ** | **0.0046** ** |
| | (.0024) | (0.0019) |
| Equation (2) - HRAC Intensity, Predicted Two Component HRAC Drinkers | | |
| Ordered Logit | **.0052*** ** | **0.0033** ** |
| | (.0018) | (0.0013) |

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with linearized standard errors.
[b] Each cell presents the result of interest from different regressions.
[c] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[d] Two-tailed t-statistics are reported.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

TABLE XIII: STRESS SINGLE EQUATION MODEL FULL RESULTS

| | Dependent Variable: | |
|---|---|---|
| | Stress | |
| State-Level Unemployment Rate | -25.1396*** | -25.4952*** |
| | (5.2095) | (4.0726) |
| Black non-Hispanic | 0.9404*** | 0.9664*** |
| | (0.0454) | (0.0406) |
| Asian non-Hispanic | -0.3761*** | -0.3354*** |
| | (0.0792) | (0.0752) |
| Native American non-Hispanic | -1.0304*** | -0.9854*** |
| | (0.1509) | (0.1288) |
| Hispanic | 0.8759*** | 0.7163*** |
| | (0.2688) | (0.2299) |
| Missing Race/Ethnicity | -0.4906*** | -0.551*** |
| | (0.0924) | (0.0796) |
| Age | 0.8564*** | 0.8415*** |
| | (0.179) | (0.1522) |
| Junior High | -0.0401*** | -0.0397*** |
| | (0.0021) | (0.0019) |
| Some High School | -0.0142 | 0.0217 |
| | (0.1746) | (0.1597) |
| High School | -0.5511*** | -0.4941*** |
| | (0.1576) | (0.144) |
| College | -0.4884*** | -0.4681*** |
| | (0.1599) | (0.1461) |
| Some College | -1.1278*** | -1.1003*** |
| | (0.1611) | (0.1468) |
| Missing Education | -0.1592 | -0.5133 |
| | (0.6974) | (0.5891) |
| Unemployed | 1.694*** | 1.7276*** |
| | (0.1278) | (0.1144) |
| Student | 0.001 | -0.0901 |
| | (0.1092) | (0.0937) |
| Not Student, Not in Labor Force | 0.9035 | 0.9616*** |
| | (0.0786) | (0.0709) |
| Missing Employed Status | -0.1598 | 0.625 |
| | (0.4163) | (0.5039) |

**(continued on next page)**

**(continued from previous page)**

| | | |
|---|---|---|
| Divorced | 1.4985*** | 1.5355*** |
| | (0.0785) | (0.0721) |
| Widowed | 0.4723*** | 0.556*** |
| | (0.1089) | (0.0987) |
| Unmarried and Other Marital Status | 0.5559*** | 0.6144*** |
| | (0.0687) | (0.0605) |
| Missing Marital Status | 1.5832** | 1.5522*** |
| | (0.7076) | (0.5946) |
| Real Household Income | -0.0392*** | -0.0394*** |
| | (0.0027) | (0.0024) |
| Top Household Income Category | -0.5694*** | -0.5457*** |
| | (0.1796) | (0.1591) |
| Year 1999 | -0.6735** | -0.7171*** |
| | (0.2772) | (0.1507) |
| Time (Month) | -0.0095 | -0.0118* |
| | (0.0113) | (0.0064) |
| 9/11 Terrorism Variable, 4Q of 2001 | 0.4124*** | |
| | (0.1214) | |
| 9/11 Terrorism Variable, Full Post 9/11 | | 0.2847*** |
| | | (0.0979) |
| State Fixed Effects | X | X |
| Season Fixed Effects | X | X |
| Day Fixed Effects | X | X |
| Observations | 332,729 | 439,130 |

[a] The average marginal effect (averaged for each weighted observation) for all variables are reported with linearized standard errors.
[b] Average marginal effects for factor variables of sex, race/ethnicity, education, employment, marital status, top household income category, 1999, and terrorism measure discrete changes from the base level.
[c] Each column presents full results from different regressions.
[d] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

TABLE XIV: ANY BINGE DRINKING AND ANY HRAC SINGLE EQUATION MODEL FULL RESULTS

| | Dependent Variable: HRAC Component #2 - Any Binge Drinking | | Any HRAC | |
|---|---|---|---|---|
| State-Level Unemployment Rate | -0.8333*** | -0.4325*** | -0.3555 | -0.0215 |
| | (0.2171) | (0.1535) | (0.2338) | (0.1643) |
| Real After-Tax Price per Ounce of Ethanol | 0.0200 | 0.0196 | -0.0717** | -0.057** |
| | (0.026) | (0.0221) | (0.0281) | (0.0236) |
| No Pub Smoking Restrictions | -0.0239** | 0.0210 | -0.0264** | 0.0233 |
| | (0.0099) | (0.0236) | (0.0108) | (0.0257) |
| Female | -0.135*** | -0.1378*** | -0.1191*** | -0.1211*** |
| | (0.0022) | (0.0017) | (0.0023) | (0.0018) |
| Black non-Hispanic | -0.06*** | -0.0653*** | -0.0717*** | -0.0757*** |
| | (0.0032) | (0.0025) | (0.0035) | (0.0027) |
| Asian non-Hispanic | -0.0892*** | -0.088*** | -0.1073*** | -0.104*** |
| | (0.0051) | (0.0044) | (0.0054) | (0.0046) |
| Native American non-Hispanic | 0.0155 | 0.0042 | 0.0109 | -0.0016 |
| | (0.0119) | (0.0088) | (0.0126) | (0.0093) |
| Hispanic | -0.0201*** | -0.0217*** | -0.0226*** | -0.0238*** |
| | (0.0041) | (0.0034) | (0.0044) | (0.0036) |
| Missing Race/Ethnicity | -0.0249*** | -0.0261*** | -0.0298*** | -0.0304*** |
| | (0.006) | (0.0047) | (0.0066) | (0.0051) |
| Age | -0.0039*** | -0.0038*** | -0.0041*** | -0.004*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Some High School | -0.0110 | -0.0082 | 0.0035 | 0.0041 |
| | (0.0093) | (0.0075) | (0.0094) | (0.0075) |
| High School | -0.0085 | -0.0017 | 0.0084 | 0.0106 |
| | (0.0086) | (0.007) | (0.0086) | (0.0069) |
| Some College | -0.0071 | -0.0010 | 0.0122 | 0.0132* |
| | (0.0087) | (0.007) | (0.0086) | (0.007) |
| College | -0.0294*** | -0.0239*** | -0.0101 | -0.0093 |
| | (0.0087) | (0.0071) | (0.0087) | (0.0071) |
| Missing Education | -0.0488* | -0.0201 | -0.0392 | -0.0223 |
| | (0.0253) | (0.0233) | (0.0273) | (0.0237) |

**(continued on next page)**

**(continued from previous page)**

| | | | | |
|---|---|---|---|---|
| Unemployed | 0.0028 | 0.0026 | 0.0009 | 0.004 |
| | (0.0054) | (0.0041) | (0.0058) | (0.0044) |
| Student | -0.0143*** | -0.0138*** | -0.0203*** | -0.0188*** |
| | (0.0051) | (0.0042) | (0.0056) | (0.0045) |
| Not Student, Not in Labor Force | -0.0438*** | -0.0447*** | -0.0422*** | -0.0427*** |
| | (0.0035) | (0.0027) | (0.0036) | (0.0028) |
| Missing Employed Status | -0.0367* | -0.0435*** | -0.0363 | -0.0463** |
| | (0.0221) | (0.0155) | (0.0264) | (0.0182) |
| Divorced | 0.0666*** | 0.0669*** | 0.0701*** | 0.0709*** |
| | (0.0034) | (0.0027) | (0.0036) | (0.0028) |
| Widowed | 0.0453*** | 0.0436*** | 0.0496*** | 0.047*** |
| | (0.0092) | (0.0068) | (0.0082) | (0.0062) |
| Unmarried and Other Marital Status | 0.0678*** | 0.0685*** | 0.0764*** | 0.0751*** |
| | (0.0031) | (0.0026) | (0.0034) | (0.0028) |
| Missing Marital Status | -0.0314** | -0.0074 | -0.0416** | -0.0124 |
| | (0.0157) | (0.0139) | (0.0169) | (0.0159) |
| Real Household Income | 0.0004*** | 0.0003*** | 0.0006*** | 0.0004*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Top Household Income Category | 0.0060 | 0.0113* | 0.0089 | 0.0143** |
| | (0.0086) | (0.0068) | (0.0092) | (0.0073) |
| Year 1999 | -0.0264* | 0.0118 | -0.0528*** | -0.008 |
| | (0.0141) | (0.0093) | (0.0152) | (0.0096) |
| Time (Month) | -0.0014*** | 0.0002 | -0.0017*** | 0 |
| | (0.0005) | (0.0002) | (0.0005) | (0.0002) |
| 9/11 Terrorism Variable, 4Q of 2001 | 0.0164*** | | 0.017*** | |
| | (0.0049) | | (0.0053) | |
| 9/11 Terrorism Variable, Full Post 9/11 | | 0.0112*** | | 0.0112*** |
| | | (0.0037) | | (0.004) |
| State Fixed Effects | X | X | X | X |
| Season Fixed Effects | X | X | X | X |
| Observations | 331,961 | 571,477 | 327,237 | 565,350 |

[a] The average marginal effect (averaged for each weighted observation) for all variables are reported with linearized standard errors.
[b] Average marginal effects for factor variables of no pub restrictions, sex, race/ethnicity, education, employment, marital status, top household income category, 1999, and terrorism measure discrete changes from the base level.
[c] Each column presents full results from different regressions.
[d] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

TABLE XV: HRAC INTENSITY SINGLE EQUATION MODEL FULL RESULTS

| | Dependent Variable: HRAC Intensity, Predicted One Component HRAC Drinkers | | HRAC Intensity, Predicted Two Component HRAC Drinkers | |
|---|---|---|---|---|
| State-Level Unemployment Rate | -0.15 | -0.0091 | -0.1095 | -0.0065 |
| | (0.1088) | (0.0766) | (0.0794) | (0.0549) |
| Real After-Tax Price per Ounce of Ethanol | -0.0292** | -0.0248** | -0.0213** | -0.0178** |
| | (0.013) | (0.0111) | (0.0095) | (0.008) |
| No Pub Smoking Restrictions | -0.0122** | 0.0102 | -0.0091** | 0.0072 |
| | (0.0048) | (0.0121) | (0.0037) | (0.0084) |
| Female | -0.0566*** | -0.0584*** | -0.0389*** | -0.0393*** |
| | (0.0012) | (0.001) | (0.0009) | (0.0007) |
| Black non-Hispanic | -0.0357*** | -0.0383*** | -0.0242*** | -0.0255*** |
| | (0.0018) | (0.0014) | (0.0011) | (0.0009) |
| Asian non-Hispanic | -0.0535*** | -0.052*** | -0.0344*** | -0.0332*** |
| | (0.003) | (0.0026) | (0.0017) | (0.0015) |
| Native American non-Hispanic | 0.0086 | 0.0026 | 0.0067 | 0.0019 |
| | (0.0061) | (0.0046) | (0.0049) | (0.0035) |
| Hispanic | -0.0092*** | -0.0106*** | -0.0068*** | -0.0077*** |
| | (0.0022) | (0.0018) | (0.0016) | (0.0013) |
| Missing Race/Ethnicity | -0.0135*** | -0.0143*** | -0.0098*** | -0.0102*** |
| | (0.0031) | (0.0024) | (0.0022) | (0.0017) |
| Age | -0.0019*** | -0.0019*** | -0.0014*** | -0.0014*** |
| | (0) | (0) | (0) | (0) |
| Some High School | 0.0031 | 0.0021 | 0.0023 | 0.0015 |
| | (0.0045) | (0.0037) | (0.0033) | (0.0027) |
| High School | 0.0044 | 0.0046 | 0.0032 | 0.0033 |
| | (0.0042) | (0.0035) | (0.003) | (0.0025) |
| Some College | 0.0049 | 0.0045 | 0.0036 | 0.0033 |
| | (0.0042) | (0.0035) | (0.003) | (0.0025) |
| College | -0.0073* | -0.0079** | -0.0052* | -0.0055** |
| | (0.0042) | (0.0035) | (0.003) | (0.0025) |
| Missing Education | -0.0219* | -0.0147 | -0.0148* | -0.01 |
| | (0.0132) | (0.0113) | (0.0085) | (0.0074) |

**(continued on next page)**

(continued from previous page)

| | | | | |
|---|---|---|---|---|
| Unemployed | 0.0017 | 0.0033 | 0.0012 | 0.0024 |
| | (0.0027) | (0.0021) | (0.002) | (0.0015) |
| Student | -0.0077*** | -0.0076*** | -0.0055*** | -0.0053*** |
| | (0.0028) | (0.0022) | (0.0019) | (0.0015) |
| Not Student, Not in Labor Force | -0.0203*** | -0.0209*** | -0.014*** | -0.0141*** |
| | (0.0018) | (0.0014) | (0.0012) | (0.0009) |
| Missing Employed Status | -0.0133 | -0.0184* | -0.0093 | -0.0125* |
| | (0.0151) | (0.011) | (0.0102) | (0.0071) |
| Divorced | 0.0346*** | 0.0351*** | 0.0247*** | 0.0246*** |
| | (0.0017) | (0.0013) | (0.0013) | (0.001) |
| Widowed | 0.0239*** | 0.0229*** | 0.0164*** | 0.0154*** |
| | (0.0038) | (0.0029) | (0.0028) | (0.0021) |
| Unmarried and Other Marital Status | 0.0363*** | 0.0367*** | 0.026*** | 0.0259*** |
| | (0.0016) | (0.0013) | (0.0012) | (0.001) |
| Missing Marital Status | -0.0195** | -0.0051 | -0.0118** | -0.0032 |
| | (0.0098) | (0.0084) | (0.0056) | (0.0051) |
| Real Household Income | 0.0003*** | 0.0002*** | 0.0002*** | 0.0001*** |
| | (0.0001) | (0.0001) | (0) | (0) |
| Top Household Income Category | 0.0037 | 0.0059* | 0.0027 | 0.0043* |
| | (0.0042) | (0.0034) | (0.0031) | (0.0025) |
| Year 1999 | -0.0192*** | -0.0013 | -0.0142*** | -0.001 |
| | (0.0069) | (0.0045) | (0.0052) | (0.0032) |
| Time (Month) | -0.0007*** | 0 | -0.0005*** | 0 |
| | (0.0002) | (0.0001) | (0.0002) | (0.0001) |
| 9/11 Terrorism Variable, 4Q of 2001 | 0.007*** | | 0.0052*** | |
| | (0.0024) | | (0.0018) | |
| 9/11 Terrorism Variable, Full Post 9/11 | | 0.0046** | | 0.0033** |
| | | (0.0019) | | (0.0013) |
| State Fixed Effects | X | X | X | X |
| Season Fixed Effects | X | X | X | X |
| Observations | 327,237 | 565,350 | 327,237 | 565,350 |

[a] The average marginal effect (averaged for each weighted observation) for all variables are reported with linearized standard errors.
[b] Average marginal effects for factor variables of no pub restrictions, sex, race/ethnicity, education, employment, marital status, top household income category, 1999, and terrorism measure discrete changes from the base level.
[c] Each column presents full results from different regressions.
[d] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Estimates suggest that 9/11 increased stress by about 10 extra hours per 30 days (13.3%) in the fourth quarter of 2001, but this estimate falls to 7 hours per 30 days (9.3%) in the five quarters following 9/11. The any binge drinking component of HRAC increased by 1.6 percentage points (12.2%) in the fourth quarter of 2001 or by 1.1 percentage points (7.7%) in the five quarters following 9/11. The probability of engaging in HRAC closely mirrored the results for any binge drinking, increasing by 1.7 percentage points (11.2%) in the fourth quarter of 2001 or by 1.1 percentage points (6.9%) in the five quarters following 9/11. Both predicted one component and two component HRAC drinking increased following terrorism, suggesting that terrorism causes both new HRAC consumption and more HRAC consumption for existing HRAC drinkers.

A similar analysis was attempted in the months following the Oklahoma City bombing on April 19, 1995. The alcohol module was mandatory in 1995, but was not for years 1994 or 1996. This hampered the author's ability to control for seasonal variation. A squared time variable was included in estimated equations to attempt to better capture seasonal variation. No increases in stress or HRAC were found.[39]

### 13.3 Sensitivity Analysis

The discontinuity from years 1999 to 2001 is concerning because it provides greater potential for time-varying omitted variables to bias estimates. This concern is addressed in sensitivity analysis by dropping the year 1999, using pre-9/11 observations in the year 2001 to fully control for spring and summer season fixed effects, and then using the reduced sample to reestimate equations 8 and 9 for only the second and third quarters of 2002. Estimates are

[39] There are some key differences between 9/11 and the Oklahoma City bombing that may contribute to no stress or HRAC increases. The Oklahoma City bombing had one-twentieth the number of casualties, the perpetrator of the attack was a US citizen and apprehended almost immediately after the attack, and popular air travel was not involved.

comparable to estimates shown in Figures 29-35, with results remaining statistically significant at 5% levels. The level of statistical significance for the third component of HRAC, excessive drinks per month, actually increases from insignificant to positively significant at the 10% level in the third quarter of 2002. This sensitivity analysis suggests that results are not attenuated by using the year 1999.

In creating any HRAC and HRAC intensity measures, observations with missing conditional alcohol drinks on drinking days, conditional alcohol binge drinking, conditional alcohol days, and/or missing pregnancy status were subset, even if information was present to determine at least one of the components of HRAC. Alternative treatments of these missings impact the magnitude of previously reported findings but not the statistical significance. Considering that known components of HRAC were between 2.6-3.7 times higher for individuals with some missing information than for individuals with full information, a more reasonable approach may be to treat these individuals as HRAC drinkers. If these individuals are treated as such, a 2.2 percentage point increase in any HRAC is found in the fourth quarter of 2001 and a 1.5 percentage point increase over the full period. These estimates are larger than the 1.7 and 1.1 percentage point estimates found in the base results generated after subsetting these individuals. Results become marginally smaller than base results if these individuals are treated as non-HRAC drinkers instead of being subset.

Sensitivity analysis was also conducted by separately investigating the impact of the following three stressors on post-9/11 estimates: military casualties over the past 30 days, 30-day moving average of the DOW Jones Industrial Average, and state-level crime per capita. Inclusion of these variables did not result in the post variables becoming statistically insignificant, but the variables themselves were occasionally associated with stress or HRAC.[40] Not including these variables in the base specifications does not appear to substantially influence results.

## 13.4 Costs of Terrorism-Induced HRAC

The effect of 9/11 on stress and HRAC is found to be economically significant. The most recent estimate of the economic costs of HRAC is $223.5 billion in 2006, or $18.6 billion monthly (Bouchery et al., 2011). Bouchery and colleague's definition of HRAC is slightly different than that used in this paper;[41] nevertheless, this estimate is reasonable to use for a back-of-the-envelope cost calculation. In 2006, BRFSS data suggests that 16.4% of the US adult population engaged in any HRAC over the past month, which when multiplied by the 2006 adult population estimate of 225 million is about 36.8 million adult HRAC drinkers each month. Dividing $18.6 billion over 36.8 million HRAC drinkers per month provides a cost estimate per HRAC drinker per month of $505.

Marginal effect point estimates reported earlier suggested a 1.7 percentage point increase in any HRAC in the fourth quarter of 2001 or a 1.2 percentage point increase in any HRAC over the five quarters after 9/11. Using estimated national adult populations of 212 million in 2001 and 215 million in 2002, the monthly terrorism-induced number of adult HRAC drinkers are 3.6 million per month in the fourth quarter of 2001 and 2.4 million per month through the five

[40] The inclusion of crime per capita had little impact on the post variable estimates. The crime per capita variable itself had a positive association with stress over the three years. However, it had a negative association with HRAC and HRAC intensity over this same period. Stock market valuation had the effect of reducing post estimates for all alcohol measures, but marginally increased post estimates for stress. All post variable associations remained significant at conventional levels when stock market valuation was included. The stock market valuation variable itself had a negative association with all drinking measures over the three years. Military casualties had no noteworthy impacts on previously reported estimates and was not itself statistically significant.

[41] In the study by Bouchery and colleagues, HRAC did not separately include excessive drinks on drinking days. It does include all drinking done by individuals under the age of 21, whereas this study, using an adult sample, only classifies HRAC for individuals aged 18-21 and only if they took part in one of the four components of HRAC.

quarters. Using the $505 monthly figure derived earlier, costs of terrorism-induced HRAC are found to be $5.5 billion in the fourth quarter of 2001 and $18.1 billion over the full time period. Bouchery and colleagues determined that 42.1% of the total economic cost is borne by the government (i.e. $2.3 billion and $7.6 billion), 41.5% is borne by the HRAC drinkers and their families ($2.3 billion and $7.5 billion), and others in society absorb the remainder. The federal government collected revenues of $8.4 billion from alcohol sales in 2002[42], and state/local governments collected revenues of $4.6 billion.[43] Even if all of these sales were used for HRAC, the best case scenario for the government would be revenue increases from terrorism-induced drinking of just $60 million in the fourth quarter of 2001 and $200 million over the full time period, or only 2.6% of the government costs from terrorism-induced HRAC. Further, this analysis does not consider costs associated with previous HRAC drinkers taking part in more components of dangerous drinking. For these reasons, costs calculations are thought to be underestimated.

## 14. INTERACTION VARIABLE MODELS

Interaction variables are created by interacting a post-9/11 measure with other measures to test if people who live closer to the epicenters of the terrorist attacks, are from a county with a higher military participation rate, or are from a county with a higher population density have disproportionate stress or HRAC increases following terrorism. Additionally, interaction variables will be created to test if people were differentially impacted by terrorism based on age

[42] Data was obtained from the Beer Institute's Brewers Almanac website. Data was accessed on May 4, 2012 at http://www.beerinstitute.org/statistics.asp?bid=200.

[43] Data was obtained from the Tax Center's website. Data was accessed on May 4, 2012 at http://www.taxpolicycenter.org/taxfacts/displayafact.cfm?Docid=399.

or education.[44] All constitutive terms of the interaction variables are included as stand-alone variables in the models (Brambor et al., 2005; Braumoeller, 2004). Results investigating differential responses to terrorism in the fourth quarter of 2001 are presented in Table XVI.

[44] An ordinal ranking of education is used. The education information was merged into a continuous education variable by assigning the following values for the highest level of education completed: 0 for junior high, 1 for some high school, 2 for high school, 3 for some college, and 4 for college. The average value, 2.6, was used for those with missing education information.

TABLE XVI: INTERACTION MODELS

| | Dependent Variable: | | | |
|---|---|---|---|---|
| | Stress | Any Binge Drinking | Any HRAC | HRAC Intensity |
| Interaction Variable: | | | | |
| Reverse County Distance * 4Q of 2001 | **0.0599** | **-.1206** | **0.1458*** | **0.1523*** |
| | (0.0623) | (.0880) | (0.0825) | (0.0861) |
| Reverse County Distance Squared * 4Q of 2001 | **-0.0436** | **-0.0698** | **-0.0651** | **-0.0981** |
| | (0.1145) | (.1668) | (0.1584) | (0.1571) |
| County Population Density * 4Q of 2001 | **0.0002** | **0.0034** | **0.0042** | **0.0039** |
| | (0.0028) | ( .0038) | (0.0036) | (0.0036) |
| County Population Density Squared * 4Q of 2001 | **0.0001** | **-0.0003** | **-0.0003** | **-0.0003** |
| | (0.0001) | (.0002) | (0.0002) | (0.0002) |
| County Per Capita Military Pay * 4Q of 2001 | **-0.0288** | **-0.0508** | **-0.0478** | **-0.0498** |
| | (0.0295) | (.0410) | (0.038) | (0.038) |
| County Per Capita Military Pay Squared * 4Q of 2001 | **0.0221**** | **0.0250***** | **0.0266***** | **0.0258***** |
| | (0.0091) | (.0087) | (0.0079) | (0.0078) |
| Age * 4Q of 2001 | **0.0009** | **0.0016** | **-0.0011** | **-0.0010** |
| | (0.0012) | (.0019) | (0.0016) | (0.0017) |
| Education * 4Q of 2001 | **0.0211** | **-0.0192** | **-0.0299** | **-0.0348** |
| | (0.0187) | (.0259) | (0.0242) | (0.0242) |

[a] Each cell presents the result of interest from different regressions.
[b] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[c] Added to the respective models (full controls) are any necessary constitutive terms.
[d] Two-tailed t-statistics are reported.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

It is hypothesized that people living closer to the 9/11 epicenters may have disproportionate stress and HRAC increases following terrorism than people living further away. This relationship is searched for in the continental United States, with Alaska subset to remove potential outliers (Hawaii is already subset due to missing prices). Two different specifications are used, a standard interaction specification and a second specification in which distance is squared and interacted with the terrorism variable to allow for nominal distances to be weighted more heavily closer to the terrorist attack epicenters than further away from it. When interacting ArcGIS county distance data with the terrorism measure, people living closer to the terrorist attack epicenters were found to have greater HRAC increases in the regular specification relative to those living further away. However, there is no evidence that proximity caused relative increases in stress, nor does this HRAC relationship hold in the distance squared specification.

There is some evidence that all four measures disproportionately increased in military communities. Statistically significant estimates are found for all four dependent variables when military pay squared is interacted with the fourth quarter of 2001; however, results are not duplicated in the non-squared specification. Squared specification findings suggest that individuals living in areas with high military pay per capita have a disproportionate increase in stress and HRAC. These increases are not sensitive to inclusion of the military casualties over the past 30 days variable, suggesting that 9/11 had an independent effect from the subsequent wars in these communities.

These results at first glance appear at odds with another study using cross sectional data of military respondents before and after 9/11, which found that mental health actually improved following 9/11 and there was no increase in alcohol use. These somewhat surprising findings may be due to greater support for the military following 9/11 and a clearer mission (Smith et al., 2004). The discrepancy between Smith and colleagues' study and this study suggests that family and friends of soldiers, as opposed to the soldiers themselves, reacted to 9/11 with stress and HRAC increases.

Results indicate that people of different age or education did not have differential stress or HRAC responses. Disproportionate changes were also not found depending on population density.

## 15: UNBIASED EFFECT OF STRESS ON HRAC

An instrumental variable approach, two-stage least squares (2SLS), is used to explore the unbiased effect that stress has on HRAC. Regressing HRAC on stress may result in biased estimates due to simultaneity between stress and HRAC, as individuals may engage in HRAC during times of high stress to decrease their stress. 2SLS purges the correlation between stress and the error term, using the instrument of 9/11 to isolate the variation in stress that is uncorrelated with the error term in the HRAC models. The 2SLS models are identified in equations 10-11:

$$\mathrm{stress}_{ist} = \alpha + \beta_1 \emptyset_{st} + \beta_2 X_{ist} + \beta_3 4Q\_2001_t + \beta_4 \mathrm{time}_t + \gamma_s + \gamma_{season} + v_{ist} \tag{10}$$

$$\mathrm{HRAC}_{ist} = \alpha + \beta_1 \emptyset_{st} + \beta_2 X_{ist} + \beta_3 \widehat{\mathrm{stress}}_{ist} + \beta_4 \mathrm{time}_t + \gamma_s + \gamma_{season} + \varepsilon_{ist} \tag{11}$$

Three forms of HRAC—any binge drinking, any HRAC, and HRAC intensity will be tested in the second-stage. Only the fourth quarter of 2001 will be used as the instrument instead of the five quarters after 9/11 to obviate potential problems related to partial collecting of stress information in year 2002. The predicted value for stress is generated from equation 10 and is then entered directly into the second-stage HRAC models in equation 11, with error correction in the second-stage.

2SLS estimation uses linear modeling. Consistency of 2SLS estimates does not depend upon linearity of the reduced form equations (Kelejian, 1971). Further, even though the second-stage uses dichotomous or ordered dependent variables, 2SLS results typically capture the local average treatment effect of interest (Angrist and Krueger, 2001). Therefore, little harm is done by using limited dependent variables in the respective stages of 2SLS.

Results are presented in Table XVII.

TABLE XVII: 2SLS ESTIMATES FOR UNBIASED EFFECT OF STRESS ON HRAC

| | | | |
|---|---|---|---|
| First Stage - Equation 3 | | | |
| Dependent Variable: | Stress | Stress | |
| Independent Variable: | 4Q of 2001 | 4Q of 2001 | |
| | **.362******* | **0.337******* | |
| | (0.010) | (.101) | |
| F-test | 13.19 (p-value=0) | 11.21 (p-value=0) | |
| | | | |
| Second Stage - Equation 4 | | | |
| Dependent Variable: | Any Binge Drinking | Any HRAC | HRAC Intensity |
| Independent Variable: | Stress_hat | Stress_hat | Stress_hat |
| | **.046******* | **0.051******* | **0.063**** |
| | (0.018) | (0.021) | (.033) |
| | | | |
| Number of Observations | 326,685 | 322,114 | |

[a] Survey features of the data are used in all regressions, producing robust standard errors that are cluster-corrected at both the state and the primary sampling unit levels.
[b] One-tailed t-statistics are reported in the second-stage because the unbiased effect of stress on HRAC is hypothesized to either have zero influence or a positive influence.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

In the first-stages, both *t*-statistics and *F*-statistics show that terrorism is strongly associated with stress. In both tests, the null hypothesis of weak instrumentation is rejected at a 5% significance level (Stock, Wright, and Yogo, 2002). In the second-stage, a one-tailed *t*-statistic is used to test the null hypothesis that the unbiased effect of stress has no positive impact on HRAC. In the fourth quarter of 2001, the hypothesis that the unbiased effect of stress on HRAC has no positive impact is rejected at a 1% confidence level for both any binge drinking and any HRAC. It is rejected at a 5% confidence level for HRAC intensity.

Evaluated at the means, results suggest that a 1 day increase in stress over 30 days has a 4.6 percentage point increase in any binge drinking, a 5.1 percentage point increase in any HRAC, and a .06 HRAC intensity level increase.[45] The first-stage suggests an increase in stress from 9/11 in the fourth quarter of 2001 of roughly a third of a day per 30 days, so assuming that stress is the only causal pathway through which terrorism influences binge drinking and HRAC, 2SLS estimates suggest that in the fourth quarter of 2001 terrorism caused a 1.7 percentage point increase in both any binge drinking and any HRAC, and an increase of .02 HRAC intensity levels. This effect size is virtually identical for estimates obtained from single equation modeling in the fourth quarter of 2001, shown in Table XII, suggesting that in the short run the entire increase in any binge drinking and any HRAC generated from terrorism is through stress rather than alternative causal pathways.

[45] While outside the main focus of this paper, a related question is if the unbiased effect of HRAC reduces stress. Real after-tax ethanol prices is a theoretically valid instrument for HRAC; however, this variable generate a low *F*-statistic in the first-stage that fails to reject the null hypothesis of weak instrumentation, thus preventing exploration of this question.

## 16. DISCUSSION AND CONCLUSION

This study suggests a large national increase in stress and HRAC from 9/11. To the best of the author's knowledge, this is the first study providing an unbiased estimate of the effect of stress on HRAC, finding that an extra day of stress per month increases any HRAC by 5.1 percentage points. Both HRAC initiation and expansion was associated with 9/11, with any binge drinking being a commonly chosen component of HRAC. An ethanol price increase of between $.20-.24 per ounce, or $.10-.12 per standard drink, would have been needed to have stopped the increase in HRAC stemming from terrorism. There is some evidence to suggest that disproportionate increases were found closer to the terrorist attack epicenters for HRAC and in heavy military participation communities for all measures. The costs of HRAC represent a large hidden cost of terrorism, totaling $18.1 billion in the five quarters following 9/11.

The study's primary limitation is that it is cross-sectional, which precludes causal inferences. Longitudinal analyses on associations between terrorism and HRAC may provide more robust findings. Future research could be useful to determine how minors are impacted by terrorism through alcohol use. Research would also be useful to explore if alcohol producers attempt to profit from terrorism through business practices such as changing pricing strategies or their mix of advertisements in response to terrorism. Finally, research should be conducted on the extent to which the findings of this study can be applied to other types of national disasters, such as Hurricane Katrina.

## 17. FIGURES

The following pages contain the figures referenced in this essay.

Figure 27: Stress and 9/11 Over Time, standard deviations from the mean

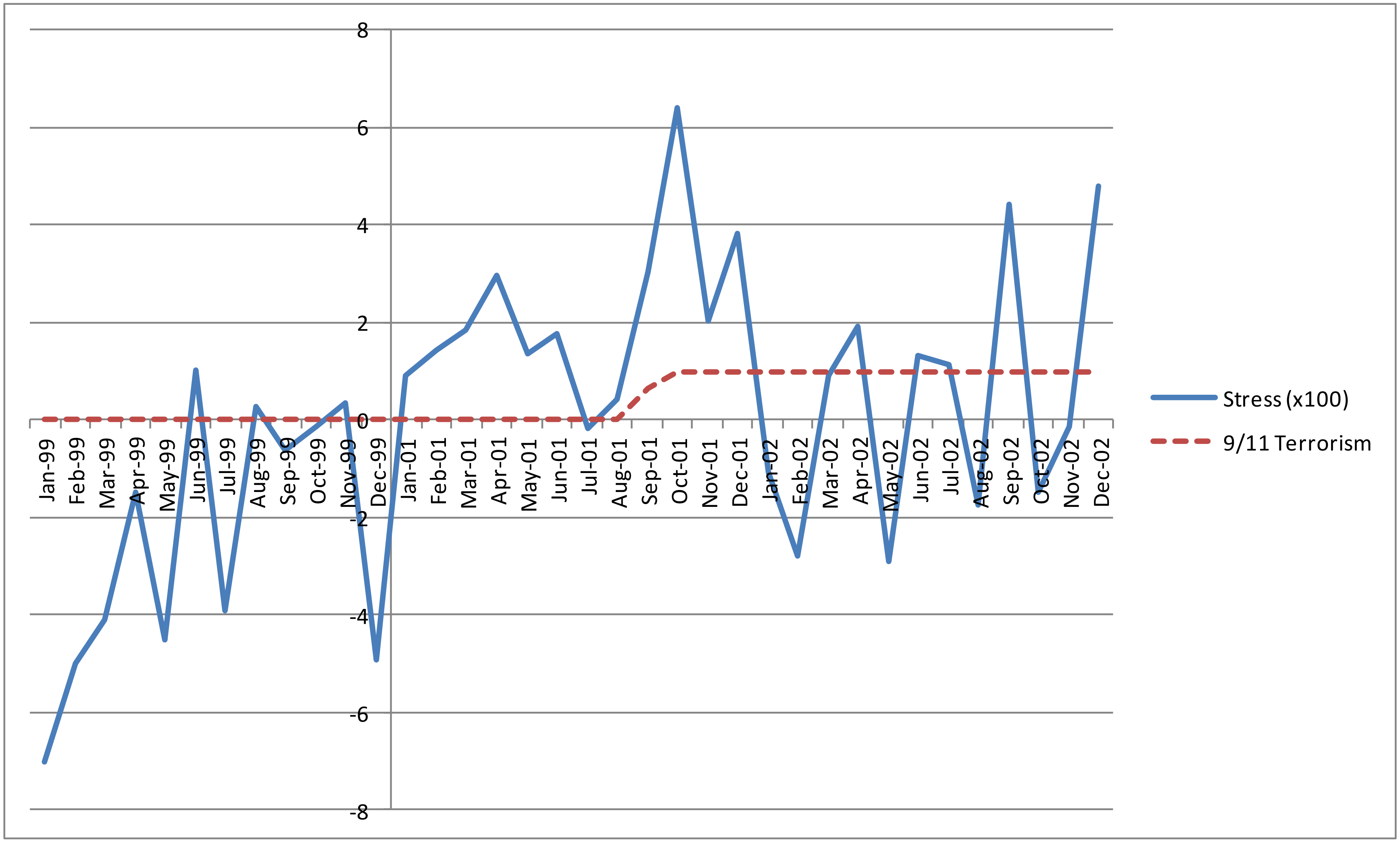


Figure 28: HRAC and 9/11 Over Time, standard deviations from the mean

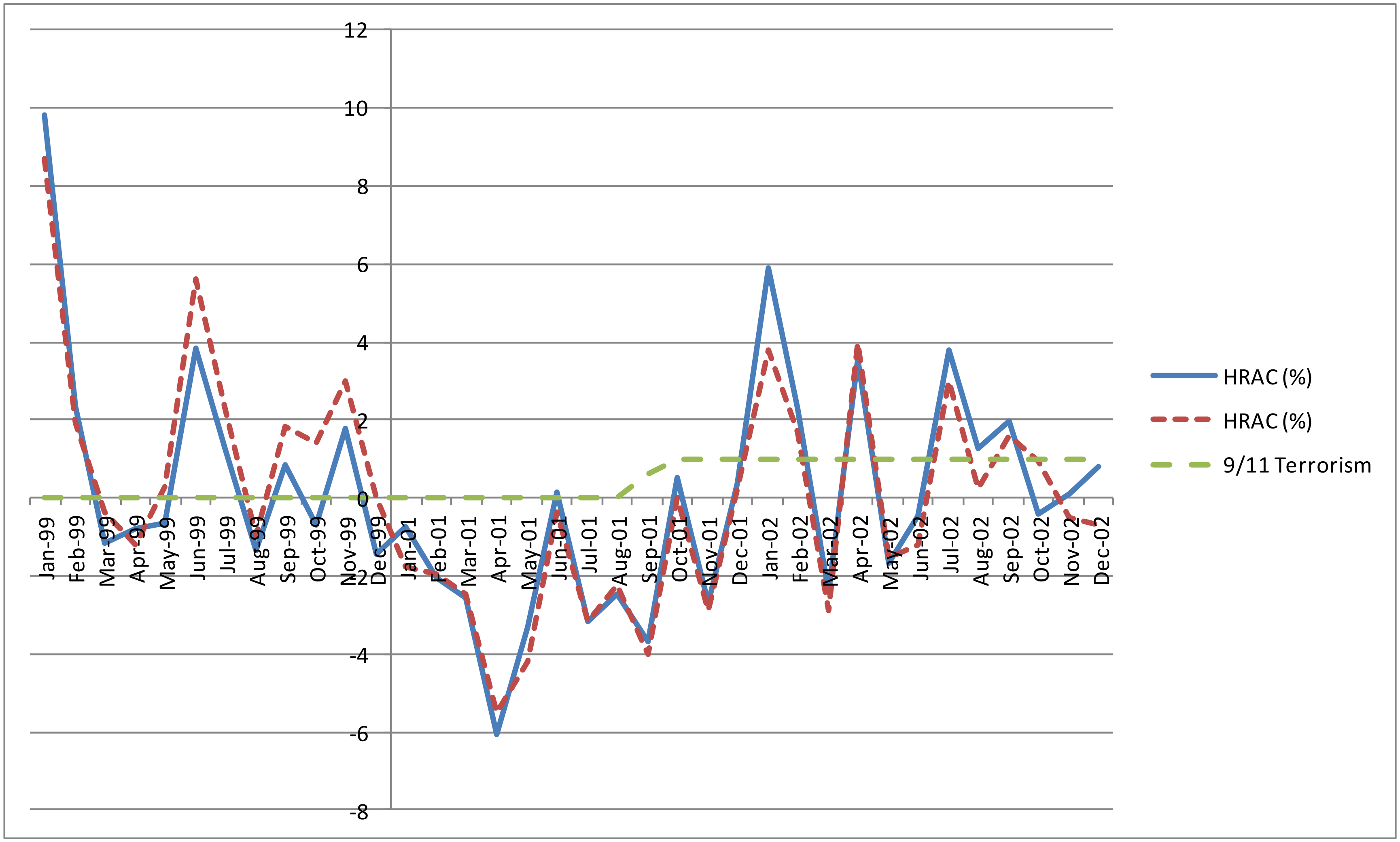
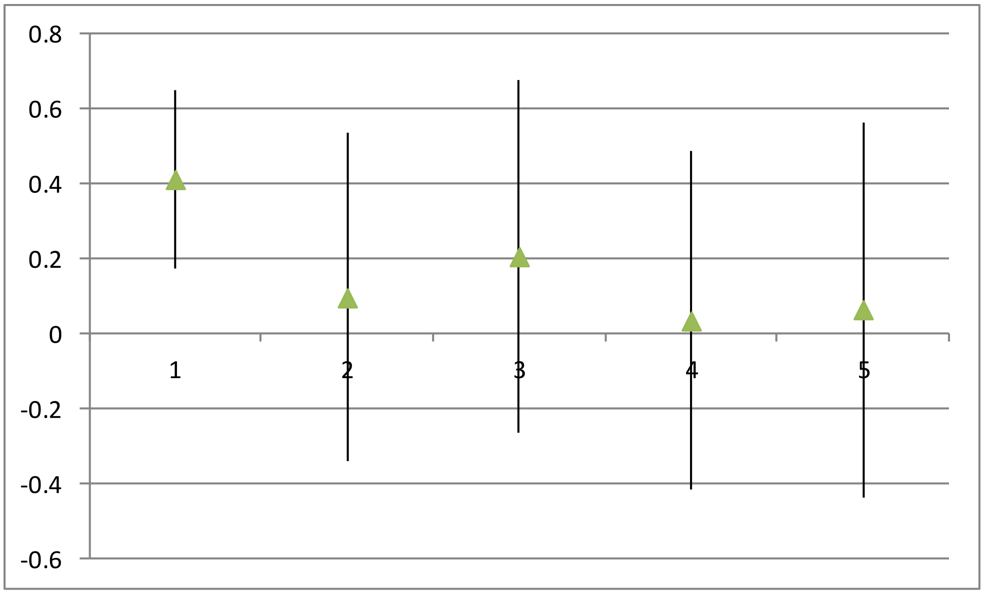
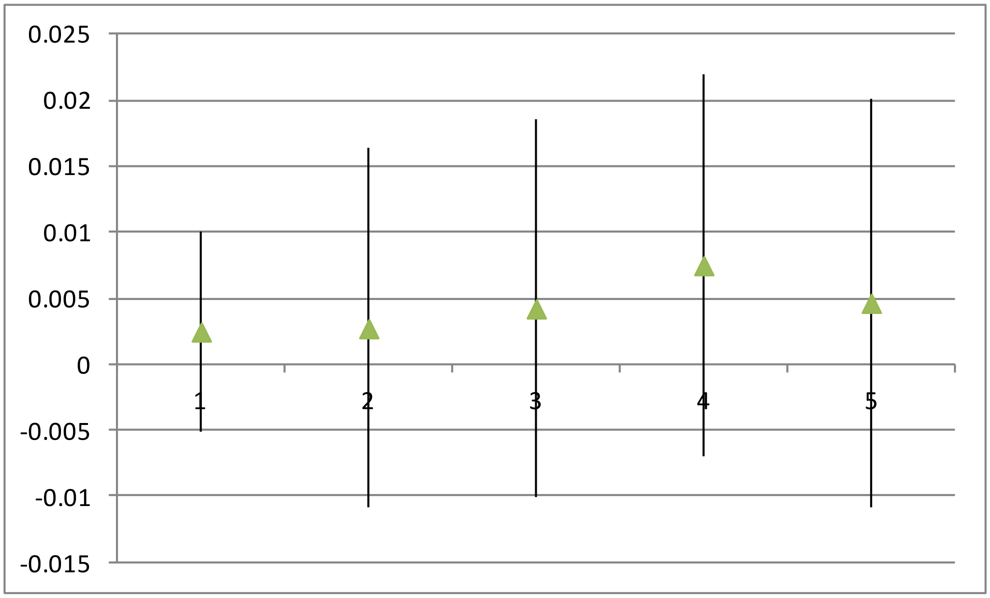


Figure 29: Influence of Time on Stress after 9/11, marginal effects of terrorism, quarterly



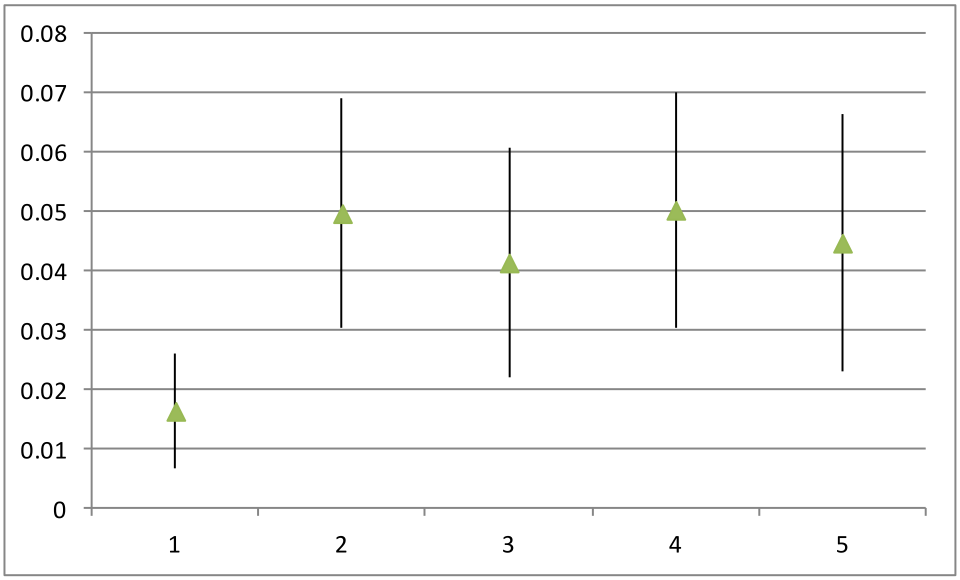

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 30: Influence of Time on HRAC Component #1 (excessive drinks on drinking days) after 9/11, marginal effects of terrorism, quarterly



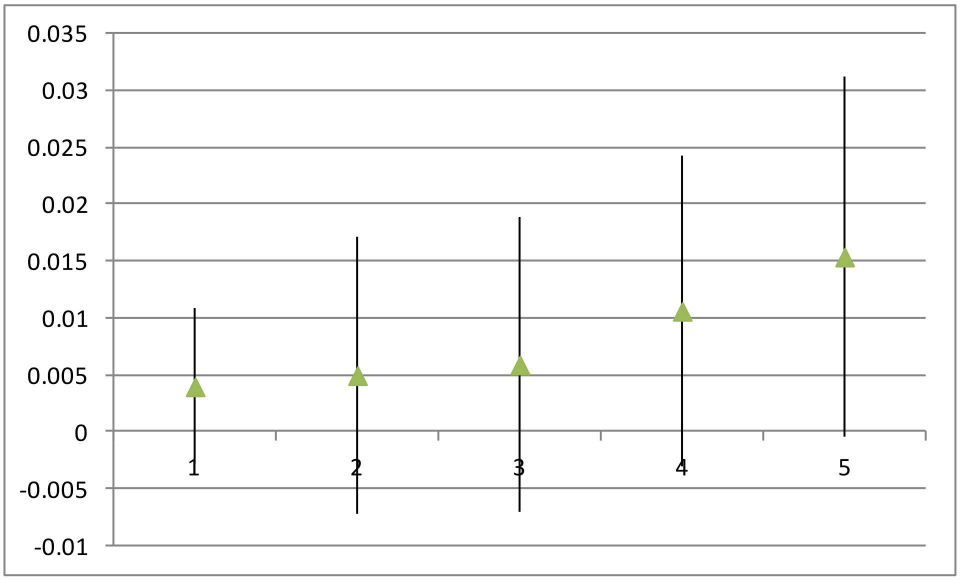

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 31: Influence of Time on HRAC Component #2 (any binge drinking) after 9/11, marginal effects of terrorism, quarterly



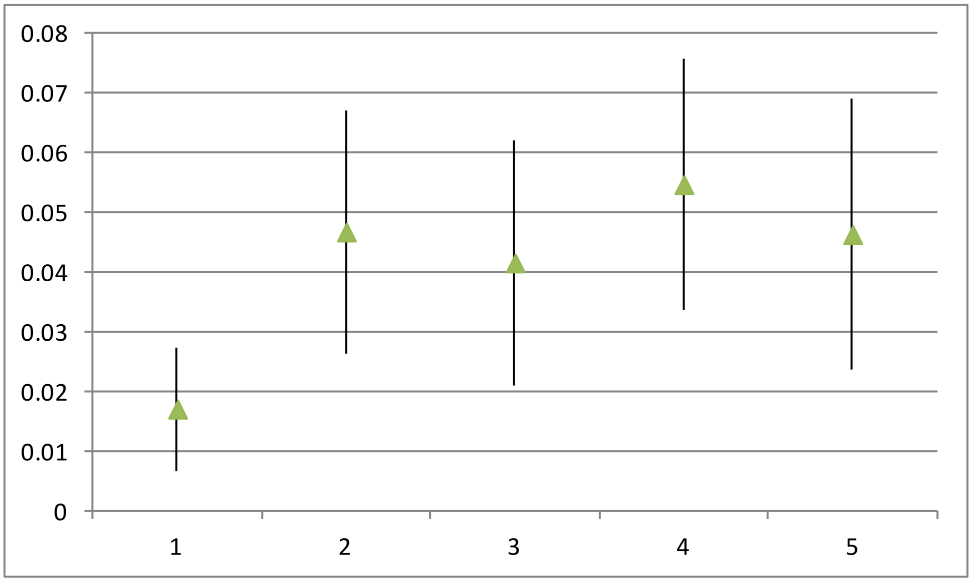

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 32: Influence of Time on HRAC Component #3 (excessive drinks per month) after 9/11, marginal effects of terrorism, quarterly



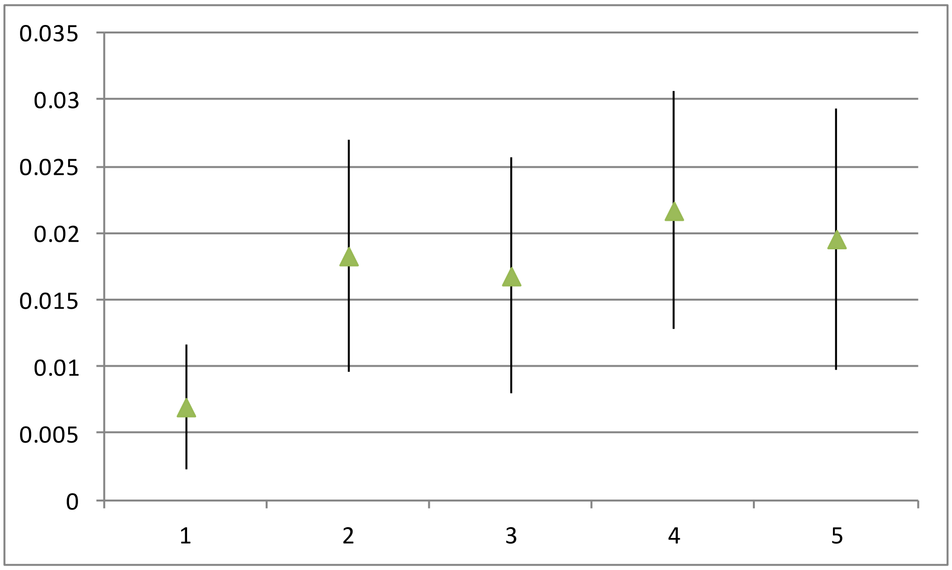

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 33: Influence of Time on any HRAC after 9/11, marginal effects of terrorism, quarterly



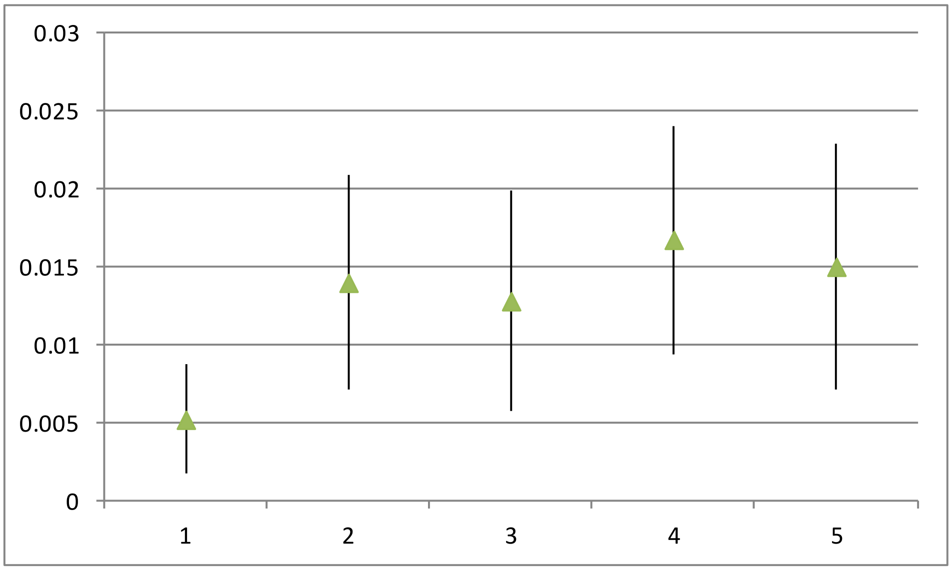

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 34: Influence of Time on HRAC Intensity after 9/11, marginal effects of terrorism for predicted one component HRAC drinkers, quarterly



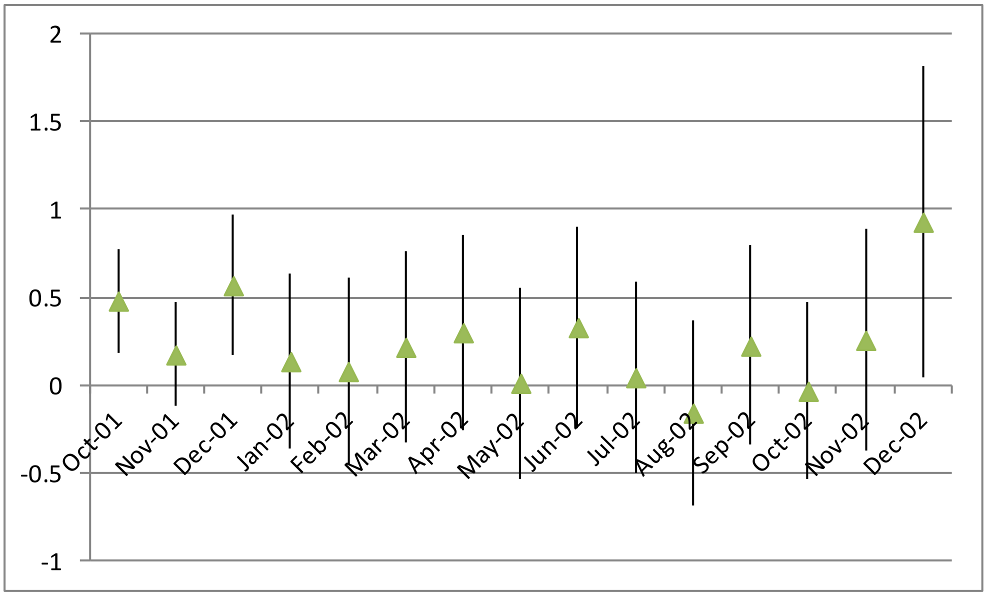

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 35: Influence of Time on HRAC Intensity after 9/11, marginal effects of terrorism for predicted two component HRAC drinkers, quarterly



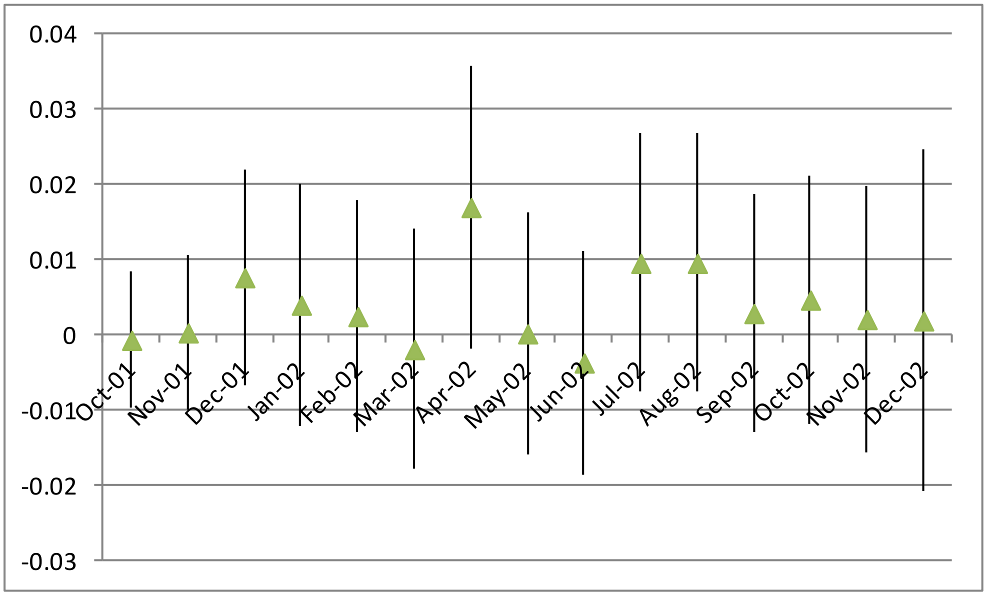

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a quarter at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 36: Influence of Time on Stress after 9/11, marginal effects of terrorism, monthly



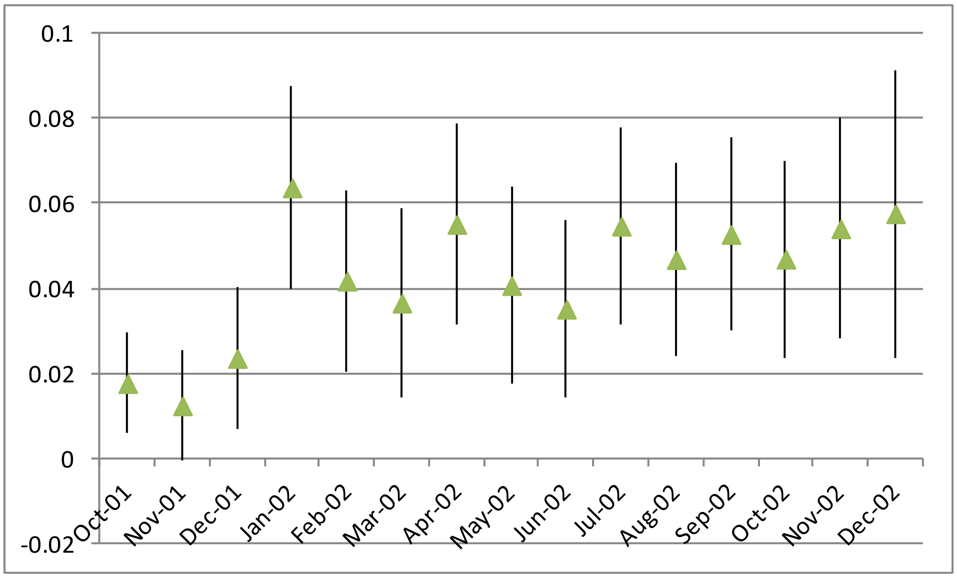

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 37: Influence of Time on HRAC Component #1 (excessive drinks on drinking days) after 9/11, marginal effects of terrorism, monthly



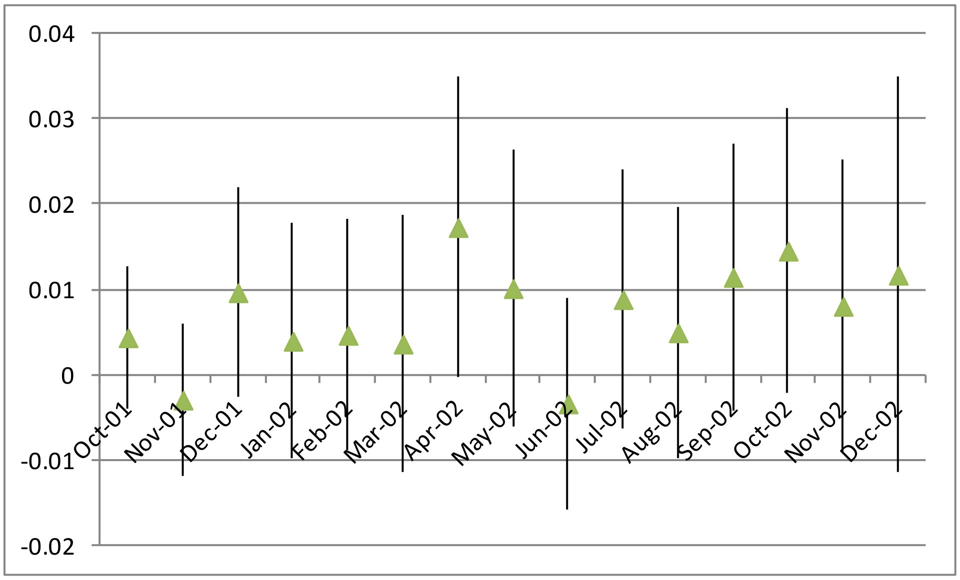

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 38: Influence of Time on HRAC Component #2 (any binge drinking) after 9/11, marginal effects of terrorism, monthly



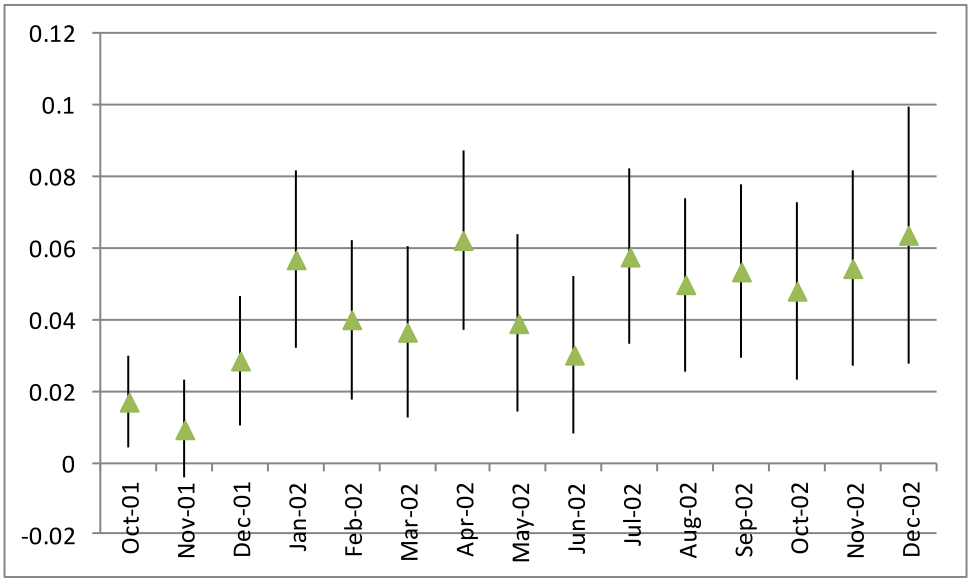

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 39: Influence of Time on HRAC Component #3 (excessive drinks per month) after 9/11, marginal effects of terrorism, monthly



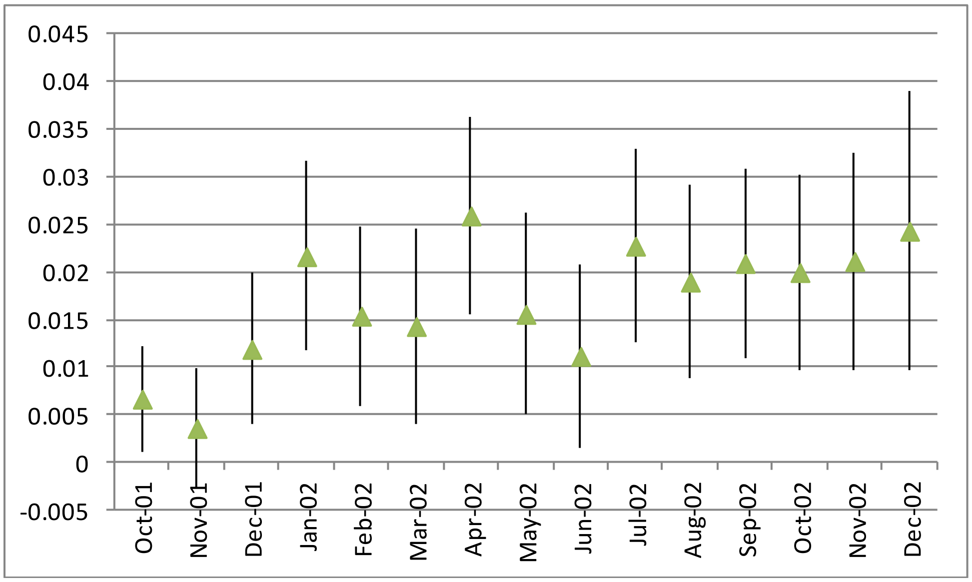

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 40: Influence of Time on any HRAC after 9/11, marginal effects of terrorism, monthly



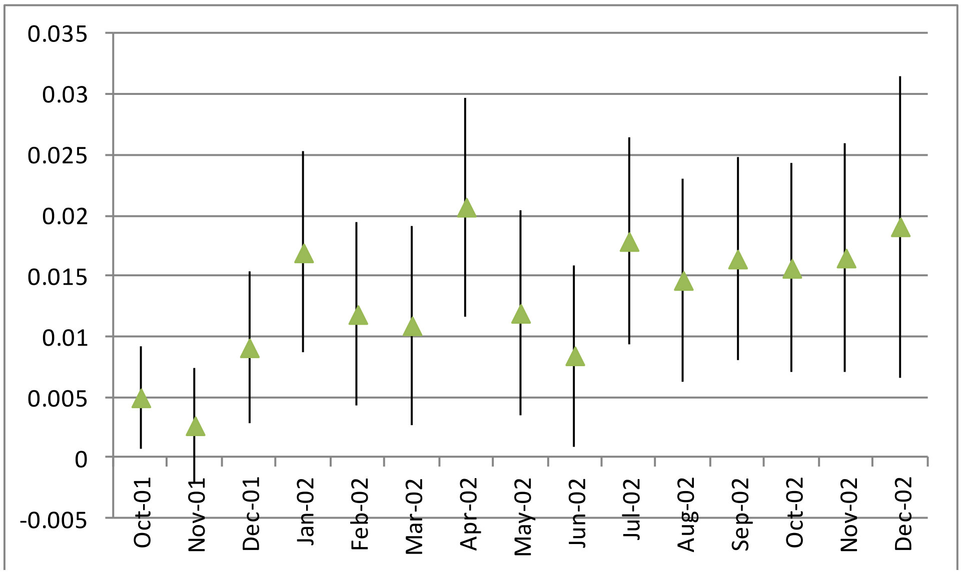

[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 41: Influence of Time on HRAC Intensity after 9/11, marginal effects of terrorism for predicted one component HRAC drinkers, monthly




[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

Figure 42: Influence of Time on HRAC Intensity after 9/11, marginal effects of terrorism for predicted two component HRAC drinkers, monthly




[a] The average marginal effect (averaged for each weighted observation) for the terrorism post variables are reported with 95% confidence intervals using linearized standard errors.
[b] Each point estimate and confidence interval is obtained from a different regression, with the sample iteratively adding a month at a time with replacement.
[c] Unused data was subset from the analysis to maintain the correct survey weighting.

# 18. CITED LITERATURE


Angrist, J. D., & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives*, *15*(4), 69-85.

Blalock, G., Kadiyali, V., & Simon, D. (2009). Driving fatalities after 9/11: a hidden cost of terrorism. *Applied Economics*, *41*(14), 1717-1729.

Bouchery, E. E., Harwood, H. J., Sacks, J. J., Simon, C. J., & Brewer, R. D. (2011). Economic Costs of Excessive Alcohol Consumption in the U.S., 2006. *American Journal of Preventive Medicine*, *41*(5), 516-524.

Brambor, T., Clark, W. R., & Golder, M. (2005). Understanding Interaction Models: Improving Empirical Analyses. *Political Analysis*, *14*(1), 63-82.

Braumoeller, B. F. (2004). Hypothesis Testing and Multiplicative Interaction Terms. *International Organization*, *58*(04), 807-820.

Burns, W. J., & Slovic, P. (2007). The Diffusion of Fear: Modeling Community Response to a Terrorist Strike. *The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology, 4*(4), 298-317.

CDC. (2004). Alcohol-Attributable Deaths and Years of Potential Life Lost--United States, 2001. *MMWR. Morbidity and Mortality Weekly Report*, *53*(37), 866-70.

CDC. (2010). Vital Signs: Binge Drinking among High School Students and Adults—United States, 2009. *MMWR. Morbidity and Mortality Weekly Report*, *59*.

Chaloupka, F. J., Grossman, M., & Saffer, H. (2002). The Effects of Price on Alcohol Consumption and Alcohol-Related Problems. *Alcohol Research and Health*, *26*(1), 22–34.

Ford, C. A., Udry, J. R., Gleiter, K., & Chantala, K. (2003). Reactions of young adults to September 11, 2001. *Archives of Pediatrics & Adolescent Medicine*, *157*(6), 572-8.

Imbens, G. W., & Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, *142*(2), 615-635.

Johnson, P. B., Richter, L., Carise, D., McLellan, a T., & Kleber, H. D. (2002). Alcohol use patterns before and after September 11. *American Clinical Laboratory, 21*(7), 25-27.

Kelejian, H. H. (1971). Two-Stage Least Squares and Econometric Systems Linear in Parameters but Nonlinear in the Endogenous Variables. *Journal of the American Statistical Association*, *66*, 373-374.

Knudsen, H. K., Roman, P. M., Johnson, J. A., & Ducharme, L. J. (2005). A changed America? The effects of September 11th on depressive symptoms and alcohol consumption. *Journal of Health and Social Behavior*, *46*(3), 260-73.

NIAAA. (2008). Tips for Cutting Down on Drinking. Retrieved from http://pubs.niaaa.nih.gov/publications/Tips/tips.pdf

Perrine, M. W. B., Schroder, K. E. E., Forester, R., McGonagle-Moulton, P., & Huessy, F. (2004). The Impact of the September 11, 2001, Terrorist Attacks on Alcohol Consumption and Distress: Reactions to a National Trauma 300 Miles from Ground Zero. *Journal of Studies on Alcohol*, *65*(1), 5-15.

Pfefferbaum, B., North, C. S., Pfefferbaum, R. L., Christiansen, E. H., Schorr, J. K., Vincent, R. D., & Boudreaux, A. S. (2008). Change in Smoking and Drinking after September 11, 2001, in a National Sample of Ever Smokers and Ever Drinkers. *The Journal of Nervous and Mental Disease*, *196*(2), 113-21.

Richman, J. A., Shannon, C. A., Rospenda, K. M., Flaherty, J. A., & Fendrich, M. (2009). The relationship between terrorism and distress and drinking: two years after September 11, 2001. *Substance Use & Misuse*, *44*(12), 1665-80.

Richman, J. A., Wislar, J. S., Flaherty, J. A., Fendrich, M., & Rospenda, K. M. (2004). Effects on alcohol use and anxiety of the September 11, 2001, attacks and chronic work stressors: a longitudinal cohort study. *American Journal of Public Health*, *94*(11), 2010-5.

Ruhm, C. J., & Black, W. E. (2002). Does drinking really decrease in bad times? *Journal of Health Economics*, *21*(4), 659-78.

Schlenger, W. E., Caddell, J. M., Ebert, L., Jordan, B. K., Rourke, K. M., Wilson, D., Thalji, L., et al. (2002). Psychological reactions to terrorist attacks: findings from the National Study of Americans' Reactions to September 11. *JAMA : the Journal of the American Medical Association*, *288*(5), 581-8.

Smith, D., Christiansen, E. H., Vincent, R., & Hann, N. E. (1999). Population Effects of the Bombing of Oklahoma City. *The Journal of the Oklahoma State Medical Association*, *92*(4), 193-198.

Smith, T. C., Smith, B., Corbeil, T. E., Riddle, J. R., & Ryan, M. A. K. (2004). Self-Reported Mental Health Among US Military Personnel Prior and Subsequent to the Terrorist Attacks of September 11, 2001. *Journal of Occupational and Environmental Medicine*, *46*(8), 775-782.

Stein, B. D., Elliott, M. N., Jaycox, L. H., Collins, R. L., Berry, S. H., Klein, D. J., & Schuster, M. A. (2004). A National Longitudinal Study of the Psychological Consequences of the September 11, 2001 Terrorist Attacks: Reactions, Impairment, and Help-Seeking. *Psychiatry: Interpersonal and Biological Processes*, *67*(2), 105–117.

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business and Economic Statistics*, *20*(4), 518-529.

Su, J. C., Tran, A. G. T. T., Wirtz, J. G., Langteau, R. a, & Rothman, A. J. (2009). Driving Under the Influence (of Stress): Evidence of a Regional Increase in Impaired Driving and Traffic Fatalities after the September 11 Terrorist Attacks. *Psychological Science*, *20*(1), 59-65.

U.S. DHHS. (2002). Impact of September 11 , 2001 Events on Substance Use and Mental Health in the New York Area.

USDA. (2010). Dietary Guidelines for Americans, 2010 - 7th Edition.

# **ESSAY THREE:** THE NATIONAL EFFECTS OF HURRICANE KATRINA ON RISK PERCEPTION AND SUBSTANCE ABUSE

## 19. INTRODUCTION

Hurricane Katrina made landfall on August 29, 2005. The hurricane and subsequent flooding caused 1,836 deaths, 86% of which were in Louisiana and 13% in Mississippi, making it the deadliest natural disaster in the United States in nearly a century and the costliest ever. According to Gallup polling, 93% of Americans believed Hurricane Katrina to be the worst natural disaster in their lifetime.[46] 96% of Americans said they followed the news about the hurricane very or somewhat closely, the third highest rating out of 150 events covered since the early 1990s. The natural disaster also affected mental health, with 98% of respondents feeling sadness, 78% shock, and 62% anger.[47]

People have incentives to respond to risks they know about. The 24/7 news coverage of Hurricane Katrina may have provided new information to individuals living in hurricane-prone areas of the dangers posed by hurricanes. Risk perception may have increased as a result. Associations between risk perception and feelings of worry and concern (e.g. stress) have been documented (Rundmo, 2002; Sjöberg, 1998). Further, associations between stress and smoking use (U.S. DHHS, 2012), and alcohol use (Colder, 2001; Greenfield and Harford, 2009; Hill and Angel, 2005; Rohrbach et al., 2009) have been found. Individuals may attempt to self-medicate higher stress with substance abuse. However, a primary limitation of these studies is that they do not address simultaneity because stress may cause substance abuse and/or substance abuse may cause stress (Parrott, 1998).

---

[46] Data was obtained from the article 'Public Skeptical New Orleans Will Recover,' found on the Gallup website. Data was accessed on June 6, 2012 at http://www.gallup.com/poll/18412/Public-Skeptical-New-Orleans-Will-Recover.aspx.

[47] Data was obtained from the article 'Public: Response to Katrina Better Now Than Just After Hurricane Hit,' found on the Gallup website. Data was accessed on June 6, 2012 at http://www.gallup.com/poll/18466/Public-Response-Katrina-Better-Now-Than-Just-After-Hurricane-Hit.aspx.

Using data from the continental United States and a difference-in-difference (DID) framework, this paper explores the possibility that the 24/7 news coverage of Hurricane Katrina generated increases in risk perception, stress, and substance abuse. Treatment groups consisting of individuals at-risk of hurricane activity, but not directly impacted by Hurricane Katrina, were created. Control groups are assigned for areas not at-risk of hurricane activity. Evidence for the hypothesis of substance abuse increases for at-risk residents is found. The author argues that this is likely attributable to these residents increasing their risk perceptions using new information provided by Hurricane Katrina.

This paper does not explore changes in stress and substance abuse in populations directly impacted by Hurricane Katrina. In New Orleans, for example, stress may have been generated from disaster-related disruptions rather than from increases in risk perception. Additionally, the disaster may have decreased the accessibility and increased the costs of cigarettes and alcohol in the short term. These confounding factors make exploration of stress and substance abuse changes in areas directly impacted by Hurricane Katrina outside the scope of this study.

## 20. LITERATURE

### 20.1 Risk Perception

Several economics studies suggest that environmental disasters, such as hurricanes, cause individuals to increase risk perceptions. This is shown by impacts of environmental disasters on property values in areas directly impacted by the disasters and in "near miss" areas, using hedonic valuation models and DID analysis. Kousky, 2010 reviews the literature and concludes that declines in property values following environmental disasters are suggestive of increases in risk perception. In Kousky's own empirical analysis, she finds evidence that following the 1993 flooding of the Missouri and Mississippi rivers, property prices in the special flood hazard areas (SFHA)[48] did not change, but property prices in the 500-year floodplain and along the rivers did. Regulations mandating notification for homebuyers in the SFHA may have contributed to the insignificant effect, as no new information was provided from the flood. However, a lack of this information (no notification mandate) in the 500-year floodplain and stigma associated with the river may have contributed to the property value declines in these areas (Kousky, 2010). An extension of this finding is that a proxy for risk perception, longevity expectations, declined for older Florida adults in Dade County, Florida due to a direct hit from Hurricane Andrew in 1992 (Smith, 2008), the most costly natural disaster before Hurricane Katrina.

Hallstrom and Smith investigated the impact of Hurricane Andrew on property values in Lee County, Florida, a “near miss” from Hurricane Andrew. DID findings suggested a 19% slowdown in property value increases for housing units in the SFHA due to the near-miss (Hallstrom and Smith, 2005). Slowdowns were more pronounced in the county experiencing the direct hit, Dade County, compared to Lee County (Carbone, Hallstrom, and Smith, 2006). While an environmental disaster may lead to an upward revision of risk perception in the short term, increases may be short-lived in the absence of additional reinforcement (e.g. more hurricanes). One study found the price differential for properties in the flood zone disappearing for housing prices in Pitt County, North Carolina five years after Hurricane Floyd in 1999 (Bin and Landry, 2011).

Additionally, following disasters, risk perceptions may increase disproportionately for lower educated individuals because they have less skill in matching subjective expectations of a future similar event with the objective reality (Becker and Rubinstein, 2010). Lower educated

[48] SFHAs are defined by the Federal Emergency Management Agency (FEMA) as areas with a 1% or greater chance of 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.

people may also disproportionately view the 24/7 coverage of Hurricane Katrina as "new information," whereas higher educated people may have been aware of the dangers all along. These explanations may contribute to lower educated individuals experiencing disproportionate increases in stress and/or substance abuse.

## 20.2 Hurricanes

Hurricanes present real risks that may be underestimated. Storm surge is often the greatest threat to life and property from a hurricane. Storm surge is generated 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 (Botts et. al, 2012). Storm surge associated with Hurricane Katrina was as high as 25-28 feet and pushed up to 20 miles inland. The United States is quite vulnerable to storm surge, as much of the United States' densely populated Atlantic and Gulf Coast coastlines are less than 10 feet above sea level. Gulf coastal counties are particularly vulnerable, as 72% of ports, 27% of major roads, and 9% of rail lines in this region are at or below 4 feet elevation. Despite this, Gulf coast counties have seen booming population growth of 32% from 1990-2008.[49] Further, residents may be unaware and uninsured against the dangers of coastal storm-surge flooding because FEMA flood zones are defined only for areas at-risk of fresh water flooding. The percentage of homes in storm surge zones, but not in SHFAs, is greater than 50% for 11 of 14 major coastal metro areas (Botts et al., 2012).

A secondary danger of hurricanes is wind damage. A model of the maximum inland wind speeds and penetration given hurricane category strengths has been developed and validated. This model shows that a strong enough storm can cause hurricane-force winds as far inland as

[49] Data was obtained from the article 'Storm Surge Overview,' found on the National Oceanic and Atmospheric Administration (NOAA) website. The article was accessed on June 6, 2012 at http://www.nhc.noaa.gov/surge/.

Oklahoma, Arkansas, and Tennessee (Kaplan and DeMaria, 1995). Hurricane-induced tornados are another form of wind damage that can result from hurricanes. Research has shown that tornadoes induced by tropical cyclones (e.g. hurricanes) are heavily concentrated in the immediate coastal areas, with 44% occurring within 50 kilometers (31 miles) of the coast and 79% within 200 kilometers (124 miles) of the coast. These tornadoes can touchdown as early as four days before and up to three days after the tropical cyclone makes landfall, although 84% occur between 12 hours before to 48 hours after landfall (Schultz and Cecil, 2009). Hurricane Katrina, for example, was found to have spawned 62 tornadoes in nine different states, 55 of which were in coastal states (NOAA, 2006).

Some coastal states are more prone to being hit by hurricanes than others. In the ten years prior to Hurricane Katrina, 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 Hurricane Katrina, the northeast states of New York, Connecticut, Massachusetts, and Rhode Island had not seen a hurricane since Hurricane Bob in 1991.[50]

## 21. DATA DESCRIPTION

### 21.1 Behavioral Risk Factor Surveillance System

This research uses the Behavioral Risk Factor Surveillance System (BRFSS) data.[51] State health departments and the Centers for Disease Control and Prevention (CDC) collect the BRFSS data on risky personal health behaviors via landline telephone surveys of individuals

---

[50] Data was obtained from the article ‘Chronological List of All Hurricanes which Affected the Continental United States: 1851-2007,’ found on the NOAA website. Data was accessed on June 6, 2012 at http://www.aoml.noaa.gov/hrd/hurdat/ushurrlist18512007.txt.
[51] Detailed information on the BRFSS data is available at http://www.cdc.gov/brfss/.

aged 18 years and older. A limitation of the data is that information about youth is not collected. The data is nation and state representative of the non-institutionalized population. The data has date, state, and county identifying information.[52]

The time period used in this study is one year before and after Hurricane Katrina's landfall on August 29, 2005. Data for only the continental United States is used, and the states of Mississippi and Louisiana are subset to avoid capturing disruption from the actual hurricane rather than changes in risk perception. A total of 645,364 observations are used for the 46 states and Washington DC. Information on stress, smoking, and alcohol usage is consistently collected as part of mandatory modules. Unweighted and weighted descriptive statistics for this data are provided in Table XVIII.

[52] County data is absent for 18.7% of observations over the study period.

TABLE XVIII: POPULATION DESCRIPTIVE STATISTICS - 8/29/2004-8/29-2006, CONTINENTAL UNITED STATES MINUS LOUISIANA AND MISSISSIPPI

| | Unweighted | | Weighted | |
|---|---|---|---|---|
| | Mean | Standard Deviation | Mean | Standard Deviation |
| BRFSS | | | | |
| Male (%) | 38.34 | 48.62 | 48.59 | 49.89 |
| Female (%) | 61.66 | 48.62 | 51.41 | 49.89 |
| White non-Hispanic (%) | 80.66 | 39.49 | 69.68 | 45.88 |
| Black non-Hispanic (%) | 7.16 | 25.78 | 9.02 | 28.59 |
| Asian non-Hispanic (%) | 1.24 | 11.09 | 2.84 | 16.57 |
| Native American non-Hispanic (%) | 1.42 | 11.83 | 1.01 | 9.99 |
| Hispanic (%) | 6.42 | 24.50 | 14.19 | 34.84 |
| Missing Race/Ethnicity (%) | 3.10 | 17.33 | 3.26 | 17.73 |
| Age | 52.05 | 17.35 | 45.82 | 17.87 |
| Junior High (%) | 3.57 | 18.55 | 4.55 | 20.80 |
| Some High School (%) | 6.74 | 25.07 | 7.55 | 26.37 |
| High School (%) | 30.63 | 46.10 | 29.60 | 45.57 |
| Some College (%) | 26.39 | 44.07 | 26.11 | 43.85 |
| College (%) | 32.41 | 46.80 | 31.81 | 46.49 |
| Missing Education (%) | 0.26 | 5.11 | 0.38 | 6.17 |
| Employed (%) | 56.52 | 49.57 | 61.43 | 48.59 |
| Unemployed (%) | 4.00 | 19.59 | 5.13 | 22.03 |
| Student (%) | 2.13 | 14.45 | 4.47 | 20.63 |
| Not Student, Not in Labor Force (%) | 37.05 | 48.29 | 28.48 | 45.05 |
| Missing Employed Status (%) | 0.30 | 5.51 | 0.49 | 6.96 |
| Married (%) | 55.24 | 49.73 | 59.35 | 49.03 |
| Divorced (%) | 16.32 | 36.96 | 11.09 | 31.34 |
| Widowed (%) | 12.34 | 32.89 | 6.50 | 24.60 |
| Unmarried and Other Marital Status (%) | 15.71 | 36.39 | 22.68 | 41.80 |
| Missing Marital Status (%) | 0.40 | 6.28 | 0.39 | 6.19 |
| Real Household Income (without imputation, in 1000s of dollars) | 30.10 | 17.83 | 31.86 | 18.22 |
| Real Household Income (with imputation, in 1000s of dollars) | 29.52 | 17.17 | 31.03 | 17.62 |
| Top Household Income Category (%) | 19.47 | 39.59 | 23.08 | 42.06 |
| Stress (Days Mental Health Not Good over Past 30 Days) | 3.39 | 7.66 | 3.37 | 7.44 |
| Every Day Smoker (%) | 14.77 | 35.48 | 14.83 | 35.47 |
| Some Day Smoker (%) | 4.77 | 21.31 | 5.48 | 22.72 |
| Former Smoker (%) | 28.11 | 44.95 | 24.23 | 42.77 |
| Never Smoker (%) | 52.35 | 49.94 | 55.46 | 49.61 |
| | | | | |

| | | | | |
|---|---|---|---|---|
| Alcohol High Risk Measure #1 - Excessive Drinks Per Drinking Day (%) | 4.77 | 21.31 | 7.06 | 25.58 |
| Alcohol High Risk Measure #2 – Any Binge Drinking (as % of men) | 18.52 | 38.84 | 21.83 | 36.63 |
| Alcohol High Risk Measure #3 - Excessive Drinks per Month (%) | 4.50 | 20.72 | 5.06 | 21.89 |
| Alcohol High Risk Measure #4 - Drinking During Pregnancy (%) | 0.10 | 3.09 | 0.12 | 3.43 |
| Alcohol High Risk Measure (Any) (%) | 11.17 | 31.49 | 14.66 | 35.33 |
| Alcohol High Risk Measure (Cumulative) | .16 | .50 | .22 | .60 |
| Reside in Counties Along Atlantic Ocean or Gulf of Mexico (%) | 12.24 | 32.77 | 13.31 | 33.91 |
| Reside in States Along Atlantic Ocean or Gulf of Mexico, but in Non-Coastal Counties (%) | 24.47 | 42.99 | 29.39 | 45.48 |
| Merged Outside Data | | | | |
| State-Level Unemployment Rate (%) | 4.80 | 0.98 | 4.99 | 0.87 |
| Real Price of 6-Pack of Heineken Beer (in dollars) | 4.95 | 0.26 | 4.94 | 0.24 |
| Real Price of Pack of Cigarettes (in dollars) | 2.64 | 0.49 | 2.62 | 0.48 |
| No Pub Smoking Restrictions (%) | 77.38 | 41.84 | 69.83 | 45.82 |
| Smoke-Free Air Law Index (scale of 1-9) | 2.87 | 3.05 | 3.36 | 3.39 |
| Reside in Counties At-Risk for Storm Surge from Category 1 Hurricane (%) | 22.76 | 41.93 | 24.39 | 43.31 |
| Reside in Counties At-Risk for Storm Surge from Category 3 Hurricane (%) | 22.81 | 41.96 | 24.50 | 43.38 |
| Reside in Counties At-Risk for Storm Surge from Category 5 Hurricane (%) | 22.88 | 42.01 | 24.61 | 43.45 |
| Reside in Counties At-Risk for Wind Damage from Category 1 Hurricane Only (%) | 38.94 | 48.76 | 37.52 | 48.83 |
| Reside in Counties At-Risk for Wind Damage from Category 3 Hurricane Only (%) | 46.52 | 49.88 | 47.93 | 50.39 |
| Reside in Counties At-Risk for Wind Damage from Category 5 Hurricane Only (%) | 48.57 | 49.98 | 51.08 | 50.42 |

Men, racial/ethnic minorities (except Native Americans), employed, married, younger, and high household income individuals are underrepresented in the unweighted data. The weighted data is used in all regression analyses.

## 21.2 BRFSS Data for Stress and Substance Abuse

Data on mental health, alcohol usage, and smoking is collected in the BRFSS survey. 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?" Survey respondents are also asked if they have smoked 100 or more cigarettes in their lifetime and, if so, the frequency of smoking days. Responses are categorized as every day smoker, some day smoker, former smoker, and never smoker. Four alcohol measures are consistently provided in the BRFSS data: 1) alcohol prevalence over the past 30 days, 2) number of drinking days over the past 30 days, 3) conditional number of drinks consumed on drinking days, and 4) conditional number of times having binge drank on any one occasion over the past 30 days. [53] The conditional questions were asked only to those answering in the affirmative to having used alcohol or reporting a positive number of drinking days. In 2004-2005, binge drinking was defined as 5 drinks for both genders and in 2006 this was reduced to 4 drinks for women.[54] Reporting was high for questions concerning stress and substance use.[55] The BRFSS

---

[53] In 2005 and 2006, to measure alcohol prevalence, respondents were directly asked if alcohol was consumed during the past 30 days. In contrast, in 2004, this information was imputed based on answers to a subsequent question asking how many days over the past week or month alcohol was consumed. In 2004, the definition of a drink is "1 can or bottle of beer, 1 glass of wine, 1 can or bottle of wine cooler, 1 cocktail, or 1 shot of liquor." The definition wording changes in 2005-2006 to "12-ounce beer, 1 5-ounce glass of wine, or a drink with one shot of liquor."

[54] This change may have contributed to an increase in the prevalence of binge drinking amongst women of 7.3% in 2004-2005 to 10% in 2006. This inconsistency is addressed in regression analysis by using only binge drinking data for men.

stress and smoking measures have been found to have high validity and estimates are comparable with other datasets (CDC, 1998, 2005). Self-reported alcohol measures are reasonable to view as a lower bound on true consumption (Cook and Moore, 2000).

Unlike the immediate harm caused by any amount of tobacco consumption, moderate amounts of alcohol consumption have health benefits (CDC, 2004; USDA, 2010). For this reason, this research will focus on the impact of Hurricane Katrina on high risk alcohol consumption (HRAC), as opposed to alcohol prevalence, because of the impact that HRAC has on public health.

There are at least four scientifically-established components of HRAC: 1) the consumption of four or more drinks on any day for men or three drinks on any day for women, 2) the consumption within 2 hours of 4 or more drinks for women and 5 or more drinks for men (i.e. binge drinking), 3) the consumption over the past week of more than two drinks per day for men or more than one drink per day for women, and 4) drinking during pregnancy (Bouchery et al., 2011; USDA, 2010). BRFSS data is used to construct measures similar to these definitions, denoting HRAC if individuals report 1) an average number of drinks on drinking days exceeding three for women and four for men, 2) any binge drinking for only men (due to the definition change for women in 2006) 3) consuming more than 60 alcoholic beverages over the past month for men or more than 30 for women, and 4) any alcohol usage during pregnancy for women.

There was overlap between the different components of HRAC,[56] but Pearson test statistics indicate differences between groups except for two tests involving drinking during

---

[55] In the survey period used in this study, 98.3% of survey participants provided logical responses to number of stressful days, 99.6% provided logical responses to smoking status, 99.7% provided logical responses to alcohol prevalence, and 98.0-98.4% provided logical responses to conditional measures of alcohol use.

[56] If people drank excessively on drinking days (HRAC component #1), 83.83% also binge drank, 39.02% also consumed excessive drinks per month, and .46% of women also drank during pregnancy. If people binge drank (HRAC component #2), 40.18% also drank excessively on drinking days, 26.17% also consumed excessive drinks per

pregnancy, likely due to the low sample size for this component of HRAC. Descriptive statistics for stress and substance abuse is available in Table XVIII.

21.3 BRFSS Data for Control Variables

Socio-demographic information is provided for all respondents and is used to control for other factors that can explain stress and substance abuse. These controls include indicator variables for gender, race/ethnicity, education attainment, marital status, and employment status. Household income information was provided as a categorical variable, and this was converted into a continuous variable using the median for each of the categories. Age is used as a continuous variable.

Missing indicator variables were set equal to one for respondents with missing race/ethnicity, education, employment, and marital status information. Household income information was not provided by 13.7% of survey respondents. Dropping these observations could bias the estimates; therefore, missing household income values were linearly imputed by regressing household income on variables likely to explain household income and then predicting missing values.[57] Additionally, a small number of observations were missing information on age and values were similarly imputed.[58]

month, and .43% of women also drank during pregnancy. If people consumed excessive drinks per month (HRAC component #3), 54.17% drank excessively on drinking days, 75.77% binge drank, and .27% of women drank during pregnancy. If women drank during pregnancy (HRAC component #4), 8.94% drank excessively on drinking days, 15.19% binge drank, and 4.93% consumed excessive drinks per month.

[57] Inflation-adjusted household income category values were used as a lower bound for any predictions.

[58] Age was imputed first and household income second. The age bounds of 18 and 99 were used for any predictions that fell outside the range.

## 21.4 Merged Data for Control Variables

Data that controls for determinants of smoking and drinking were collected from outside sources and merged onto the BRFSS data. The Tax Burden on Tobacco contains weighted price averages for a pack of 20 cigarettes, including pack, carton, and machine sales of both brand and generic cigarettes (Orzechowski and Walker, 2009). These prices are inclusive of federal and state excise taxes. These prices are disaggregated to a quarterly level by ImpacTeen and were further adjusted by the author for changes in state excise taxes occurring mid-quarter.[59]

The American Chamber of Commerce Researchers Association (ACCRA) Cost of Living Index quarterly beer data for select cities is used as a proxy for alcohol prices.[60] Price are collected for a six-pack of Heineken and prices are representative of prices paid in places where the top income quintile shops, so discount alcohol stores are likely to be underrepresented in the computation of these prices. Heineken prices are exclusive of sales taxes but inclusive of state and federal excise taxes. All price observations were averaged by state and quarter and matched to BRFSS state residency data. Past state alcohol prices were used for any missing prices, or future prices were used if there were no prices provided at an earlier point in time. No price data is provided for New Hampshire and until 2006 for Maine, so these states are subset from the analysis in models of HRAC.

All monetary data, including the cigarette and beer price data, is adjusted for inflation using the Bureau of Labor Statistic's consumer price index, city average for all consumers. The Bureau of Labor Statistics' monthly state-level unemployment data is used in constructing a

---

[59] In these instances, the weighted proportion of the increased cigarette excise tax (Orzechowski and Walker, 2009) was first removed from the average state price for that quarter. If the interview date was after the state excise tax increase came into effect, then the full state excise tax increase was added back to the adjusted price.

[60] While liquor prices were also collected by the ACCRA through 2004, this was discontinued in years 2005 and 2006.

state-level unemployment rate variable, which is included in all regressions to control for spillover effects of unemployment beyond individual-level employment status.

Smoke-free air law data was collected by the ImpacTeen project through the MayaTech consulting firm. This data measures the strength of each state's restaurant, workplace, and bar smoke-free air laws respectively (on a scale of 0-3, 3 being the strongest restrictions). This information is summed to create an index value of between 0-9 and is used in smoking models. Smoking restrictions in pubs may also particularly influence HRAC, so an indicator variable for the absence of any pub smoking restrictions is included in models of HRAC.

### 21.5 Merged Data for Treatment and Control Groups

At-risk hurricane areas are identified using two specifications. In the most basic specification, at-risk counties are simply coastal counties along the Gulf of Mexico and the Atlantic Ocean. The list of these counties is available in Table XIX.

TABLE XIX: COUNTIES ALONG THE COAST OF THE GULF OF MEXICO OR THE ATLANTIC OCEAN

| State | County |
|---|---|
| | |
| Alabama | Baldwin, Mobile |
| Connecticut | Fairfield, Middlesex, Ned London, New Haven |
| Delaware | Kent, New Castle, Sussex |
| Florida | Bay, Brevard, Broward, Charlotte, Citrus, Collier, Dixie, Duval, Escambia, Flagler, Franklin, Gulf, Hernando, Hillsborough, Indian River, Jefferson, Lee, Levy, Manatee, Martin, Miami-Dade, Monroe, Nassau, Palm Beach, Pasco, Pinellas, Santa Rose, Sarasota, St. Johns, St. Lucie, Taylor, Volusia, Wakulla, Walton |
| Georgia | Bryan, Camden, Charlton, Chatham, Glynn, Liberty, McIntosh |
| Louisiana | Cameron, Iberia, Jefferson, Lafourche, Orleans, Plaquemines, Saint Bernard, Vermilion, St. Mary, Terrebonne |
| Maine | Cumberland, Hancock, Knox, Lincoln, Sagadahoc, Waldo Washington, York |
| Maryland | Worcester |
| Massachusetts | Barnstable, Bristol, Dukes, Essex, Nantucket, Norfolk, Plymouth, Suffolk |
| Mississippi | Hancock, Harrison, Jackson |
| New Hampshire | Rockingham |
| New Jersey | Atlantic, Bergen, Cape May, Cumberland, Essex, Hudson, Middlesex, Monmouth, Ocean, Salem, Union, Passaic |
| New York | Kings, Nassau, New York, Queens, Richmond, Suffolk |
| North Carolina | Beaufort, Bertie, Brunswick, Camden, Carteret, Chowan, Currituck, Dare, Hyde, New Hanover, Onslow, Pamlico, Pasquotank, Pender, Perquimans, Tyrrell, Washington |
| Rhode Island | Bristol, Kent, Newport, Washington |
| South Carolina | Beaufort, Charleston, Colleton, Georgetown, Horry, Jasper |
| Texas | Aransas, Brazoria, Calhoun, Cameron, Chambers, Galveston, Jackson, Jefferson, Kennedy, Kleberg, Matagorda, Nueces, Orange, Refugio, Sabine, San Patricio, Willacy |
| Virginia | Gloucester, Hampton, Mathews, Norfolk, Northampton, Poquoson, Portsmouth, Virginia Beach, Williamsburg, York, Isle of Wight, Lancaster, Middlesex, Surry, Northumberland |

A more rigorous specification uses storm surge data from the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) system.[61] This system measures at-risk areas of storm surge depending on hurricane category strength,[62] taking into account land elevation, unique bay and river configurations, water depths, rainfall, and physical features such as bridges, roads, and levees. The SLOSH data was overlaid with county borders using ArcGIS to determine for each category of hurricane if any part of the county was in the SLOSH plain.[63] Coastal counties are always in the SLOSH plain, but the SLOSH plain also extends deeper inland.[64]

To address the concern of wind damage from hurricanes, including damage from hurricane-induced tornados, the inland wind decay model developed by Kaplan and DeMaria was used in this paper for purposes of generating a mild treatment group (Kaplan and DeMaria, 1995). This model takes into account increased penetration of dangerous wind speeds for stronger hurricanes, but 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 was overlaid with county borders using ArcGIS to determine for each category of hurricane[65] if any part of the county could be affected by strong gale strength wind damage of 47 miles per hour. This wind

---

[61] Detailed information on the SLOSH system is available at http://www.nhc.noaa.gov/ssurge/ssurge_slosh.shtml.

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

[63] The SLOSH data does not consider a category five hurricane north of South Carolina because the probability of this is extremely unlikely, so to maintain consistency with the data for the southern coastal states, these northern counties at-risk for a category 4 hurricane were assigned to be at-risk in the unlikely situation of a category 5 hurricane.

[64] The percentage of all counties with any part at-risk is 8.0% for a category 1 hurricane and is 8.3% for a category 5 hurricane, affecting 26.4% and 26.6% of the weighted sample respectively. Category 5 hurricanes also have slightly more impact in the non-coastal counties of coastal states, affecting 31.5% of this population compared to 30.6% for a category 1 hurricane. Any category of hurricane also has the potential to impact non-coastal states of Washington DC and two counties in Pennsylvania.

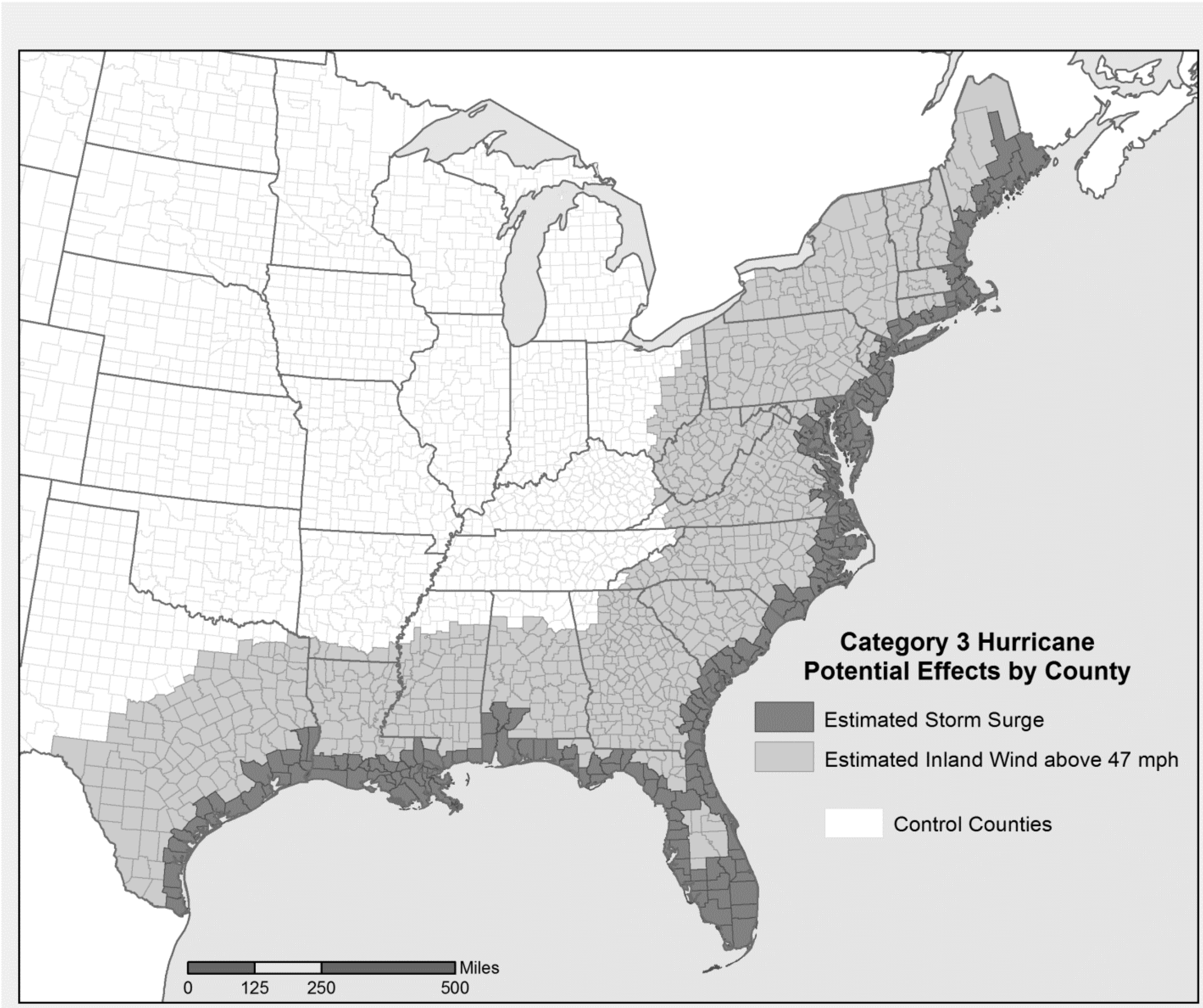
[65] The wind damage data does not consider the possibility of a category five hurricane north of North Carolina, so to maintain consistency with the data for the northern coastal states, counties at-risk for a category 4 hurricane were assigned to be at-risk in the unlikely situation of a category 5 hurricane.

strength category was chosen because this is the point at which winds begin to cause structural damage.[66] The wind speeds were generated based on average hurricane forward velocity for different regions. The wind data extends much further inland than in the SLOSH model and varies more greatly by hurricane category strength.[67]

A map showing counties at risk of storm surge and wind damage from a category 3 hurricane is presented in Figure 43.

[66] Data was obtained from a description of the Beaufort Wind Scale found on the NOAA website. Data was accessed on June 6, 2012 at http://www.spc.noaa.gov/faq/tornado/beaufort.html.
[67] The wind damage data suggests that a category 1 hurricane can impact 37.5% of the sample with strong gale force winds, whereas a category 5 hurricane can impact 51.1% of the sample.

Figure 43: Map of Counties Potentially Impacted by a Category 3 Hurricane



# 22. MODEL

DID analysis will be performed using a mild treatment group and a strong treatment group, which was done in two other studies investigating the impact of natural disasters on property prices (Carbone et al., 2006; Kousky, 2010). Two advantages of using a mild treatment group is that 1) mild treatment group effect sizes can be compared to effect sizes in the control group and strong treatment group to test for internal model validity, and 2) the model is estimated more parsimoniously because observations in the mild treatment group can be used rather than discarded. One specification of control and treatment groups simply uses political boundaries, hypothesizing that knowledge of political boundaries rather than actual hurricane risk informs risk perceptions. In this specification, individuals living in coastal counties along the Atlantic Ocean or the Gulf of Mexico are part of the strong treatment group. The mild treatment group contains individuals living in non-coastal counties in these same coastal states. Non-coastal states (including West Coast states) are the control group.

While there is strong correlation between the political boundaries approach outlined above and hurricane risk, true risk from hurricanes is better captured by a second specification using storm surge and wind damage data. In this specification, individuals living in counties that can be reached by storm surge from a category 3 hurricane are part of the strong treatment group and individuals living outside the storm surge plain, but in areas susceptible to wind damage for a category 3 hurricane are part of the mild treatment group.

This study will use data collected between one year before and after Hurricane Katrina's landfall in Louisiana and Mississippi on August 29, 2005. Respondents interviewed within 30 days after Hurricane Katrina are excluded because the survey asked about stress and substance use behaviors over the past 30 days. In all models, observations with missing county information are subset, as well as the states of Mississippi and Louisiana. Additionally, Maine and New Hampshire are subset in models of HRAC because of unknown beer prices.

The stress dependent variable is an integer variable with values between 0-30 for days in the past 30 days that mental health was not good. For the stress model, the mean of the dependent stress variable is 3.4 days and variance of the variable is 55.3 days, over 16 times greater. Parameters would be biased if using an OLS model because of the strong rightward skew of the data; therefore, this variable will be analyzed as a continuous count variable using a negative binomial distribution to account for the large over-dispersion.

Two dependent variables are used for smoking. A dichotomous dependent variable takes on the value of a 1 for a smoker and a 0 for former smokers. In an alternative specification of this information, a smoking intensity variable takes on the value of 2 for individuals that are every day smokers, 1 for individuals that are some day smokers, and 0 for individuals that are former smokers. Estimation will be performed using either logit or ordered logit. Never smokers are subset from the smoking analysis to focus on strictly migration between former smokers, some day smokers, and every day smokers following Hurricane Katrina.[68]

The HRAC dependent variable is either a component of HRAC, the prevalence of any HRAC, or the number of components of HRAC. Drinking during pregnancy is not used as a stand-alone dependent variable because of low sample size. Binge drinking is only explored for a subset of males because of a definition change mid-sample. The four components of HRAC are used to construct a dichotomous measure of *any* HRAC and an ordered measure of HRAC

[68] 88% of cigarette initiation occurs before the age of 18 (U.S. DHHS, 2012). Since never smoking adults do not have the same perception of the stress-reducing potential of cigarettes as former smokers, it made sense to focus on just smoking changes within the ever smoker population. Unfortunately, data is not available to identify ever drinking adults, so the full sample is used for HRAC, resulting in less precise estimates.

intensity that is a 0 for no HRAC and increases by 1 for each individual component of HRAC.[69] This variable can have a maximum value of 3 for a pregnant woman or a binge-drinking man. Both any HRAC and HRAC intensity are used as dependent variables in regression analysis. Estimation will be performed using either logit or ordered logit.

All estimated models control for socio-demographic variables of gender, race/ethnicity, household income, age, education attainment, marital status, and employment status. An indicator variable for the highest category of household income is also included to account for a downward bias when household income categories were converted into a continuous variable. Squared household income and age terms are also included to account for any non-linearity. Additionally, state-level control variables of unemployment rates are included in all models. Real after-tax cigarette prices and an ordinal ranking of smoke-free air law strengths are included in smoking models. Real after-tax beer prices and an indicator variable for no state-level pub smoking restrictions are included in the alcohol models. State and month fixed effects are used to control for such things as anti-smoking sentiment, anti-drinking sentiment, and seasonal/holiday motivations for substance use.

To test the hypothesis that lower-educated individuals may be more susceptible to increases in stress and substance abuse from Hurricane Katrina, this DID analysis is alternatively computed for just individuals with no higher than a high school education.[70] A difference-in-difference-in-difference (DIDID) model is also estimated interacting the post*treatment variable with a dichotomous indicator for if the person has only a high school or less education. The stratified model allows confounders to vary by education, whereas confounders are jointly

[69] In creating any HRAC and the HRAC intensity measure, observations with missing conditional alcohol drinks on drinking days, conditional alcohol days, conditional alcohol binge drinking for men, and/or missing pregnancy status were subset, even if information was present to determine at least one of the components of HRAC.

[70] This assigning of "low education" as those with no more than a high school education was done somewhat arbitrarily, but this specification has the benefit of roughly halving the sample.

estimated in the parsimonious DIDID model. Statistically significant impacts on either the post*treatment variable in the stratified model or the post*treatment*education variable in the DIDID model provides evidence that less educated people experienced disproportionate risk perception increases following Hurricane Katrina, which caused stress and/or substance abuse.

## 23. RESULTS

Table XX shows the percent change in the control and treatment groups between pre- and post-Hurricane Katrina means for three dependent variables of stress, HRAC intensity, and smoking intensity.[71]

[71] The intensity substance abuse dependent variables are reported rather than dichotomous indicators for any substance abuse to allow for more variation in the dependent variable, but sensitivity analysis suggests that results are similar either way.

TABLE XX: PERCENTAGE CHANGES IN MEANS OF DEPENDENT VARIABLES FROM PRE- TO POST-HURRICANE KATRINA

| Dependent Variable | Control Group | Mild Treatment | Strong Treatment |
|---|---|---|---|
| | Non-Coastal States | Non-Coastal Counties in Coastal States | Counties along Gulf of Mexico or the Atlantic Ocean |
| Stress | -0.89% | -3.44% | 1.22% |
| HRAC Intensity | -7.22% | -2.07% | -1.36% |
| Smoking Intensity | -1.70% | -0.48% | 0.92% |
| | | | |
| | Counties Outside Wind Damage Plain from Category 3 Hurricane | Counties At-Risk of Wind Damage from Category 3 Hurricane Only | Counties At-Risk of Storm Surge from Category 3 Hurricane |
| Stress | -0.70% | -2.36% | -1.26% |
| HRAC Intensity | -7.77% | -2.89% | -0.79% |
| Smoking Intensity | -1.65% | -0.99% | 0.55% |

The political border specification for control and treatment groups is provided on top, and the storm surge and wind damage specification is provided underneath. Changes in both measures of substance abuse increase as hurricane risk increases. HRAC intensity decreased 7.2% in the year following Hurricane Katrina in non-coastal states, but decreased by only 2.1% in non-coastal counties in coastal states and decreased by only 1.4% in counties along the coast. In this same specification, smoking intensity decreased by -1.7% in non-coastal states, but increased by .9% in counties along the coast. The same pattern was observed using the storm surge and wind damage specification. This data provides suggestive evidence that Hurricane Katrina may have increased substance abuse depending on hurricane risk; however, formal DID analysis will be used to control for other confounders.

Hurricane Katrina's impact on stress is ambiguous. While the change in stress from non-coastal states to coastal counties is greater in the political border specification, this relationship is reversed in the specification using storm surge and wind damage data. Further, the mild treatment groups in both specifications exhibit the greatest declines in stress. One possible explanation for this ambiguous relationship is that individuals using substances in response to increased risk perception may succeed in self-medicating higher stress. Another possible explanation is that potentially the BRFSS stress instrument does not adequately capture the type of stress stemming from the Hurricane Katrina disaster.[72] Moving forward, DID analysis will focus on just the impact of Hurricane Katrina on substance abuse.

Table XXI presents DID results using the political border specification for treatment and control groups. Table XXII presents DID results using the storm surge and wind damage specification.

---

[72] The question wording provided by BRFSS and used as a proxy for stress is "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"

TABLE XXI: REGRESSION RESULTS USING POLITICAL BORDER SPECIFICATION

| Sample | Base | | Low Education | |
|---|---|---|---|---|
| Dependent Variables | HRAC Intensity | Smoking Intensity | HRAC Intensity | Smoking Intensity |
| | | | | |
| State Level Unemployment Rate | 1.000<br>(0.034) | 0.946**<br>(0.026) | 0.957<br>(0.055) | 0.945<br>(0.039) |
| Real Price of 6-Pack of Heineken Beer | 0.806**<br>(0.069) | | 0.775**<br>(0.111) | |
| Real After-Tax Price per Pack of Cigarettes | | 0.993<br>(0.091) | | 0.913<br>(0.126) |
| No Pub Smoking Restrictions | 0.997<br>(0.050) | | 1.008<br>(0.089) | |
| Smoke-Free Air Law Index | | 0.998<br>(0.005) | | 1.002<br>(0.008) |
| Post-Katrina | 0.885***<br>(0.032) | 0.922***<br>(0.027) | 0.809***<br>(0.049) | 0.899**<br>(0.040) |
| Non-Coastal Counties in Coastal States | | | | |
| Post-Katrina*Non-Coastal Counties in Coastal States | 1.067<br>(0.055) | 1.079*<br>(0.046) | 1.105<br>(0.095) | 1.092<br>(0.071) |
| Coastal Counties | 1.141***<br>(0.052) | 1.022<br>(0.041) | 1.017<br>(0.086) | 0.940<br>(0.057) |
| Post-Katrina*Coastal Counties | 1.054<br>(0.059) | 1.095<br>(0.055) | 1.188*<br>(0.116) | 1.224***<br>(0.094) |
| | | | | |
| State Fixed Effects | X | X | X | X |
| Month Fixed Effects | X | X | X | X |
| Demographic Characteristics | X | X | X | X |
| Subpopulation Observations | 497,824 | 251,549 | 194,941 | 112,919 |

[a] Results are provided as proportional odds ratios and the numbers in parentheses are standard errors.

[b] Never smokers are subset from the smoking intensity models because never smoking adults rarely begin smoking and do not have the same perception of the stress-reducing potential of cigarettes.
[c] A constitutive variable for non-coastal counties in coastal states is omitted because the state fixed effects provide a smaller unit.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

TABLE XXII: REGRESSION RESULTS USING STORM SURGE AND WIND DAMAGE SPECIFICATION (FOR A CATEGORY 3 HURRICANE)

| Sample | Base | | Low Education | |
|---|---|---|---|---|
| Dependent Variables | HRAC Intensity | Smoking Intensity | HRAC Intensity | Smoking Intensity |
| | | | | |
| State Level Unemployment Rate | 1.000<br>(0.034) | 0.945**<br>(0.026) | 0.949<br>(0.055) | 0.945<br>(0.040) |
| Real Price of 6-Pack of Heineken Beer | 0.812**<br>(0.069) | | 0.741**<br>(0.108) | |
| Real After-Tax Price per Pack of Cigarettes | | 1.004<br>(0.094) | | 0.919<br>(0.131) |
| No Pub Smoking Restrictions | 0.994<br>(0.049) | | 0.975<br>(0.087) | |
| Smoke-Free Air Law Index | | 0.998<br>(0.005) | | 1.002<br>(0.008) |
| Post-Katrina | 0.883***<br>(0.034) | 0.916***<br>(0.029) | 0.767***<br>(0.052) | 0.900**<br>(0.045) |
| Wind Risk Counties | 1.127<br>(0.102) | 0.936<br>(0.090) | 1.226<br>(0.173) | 0.973<br>(0.155) |
| Post-Katrina* Wind Risk Only Counties | 1.050<br>(0.054) | 1.063<br>(0.045) | 1.150<br>(0.101) | 1.043<br>(0.068) |
| Storm Surge Risk Counties | 1.19*<br>(0.114) | 0.934<br>(0.093) | 1.121<br>(0.169) | 0.942<br>(0.157) |
| Post-Katrina*Storm Surge Risk Counties | 1.070<br>(0.055) | 1.113**<br>(0.051) | 1.220**<br>(0.112) | 1.211***<br>(0.086) |
| | | | | |
| State Fixed Effects | X | X | X | X |
| Month Fixed Effects | X | X | X | X |
| Demographic Characteristics | X | X | X | X |
| Subpopulation Observations | 497,824 | 251,549 | 194,941 | 112,919 |

[a] Results are provided as proportional odds ratios and the numbers in parentheses are standard errors.

[b] Never smokers are subset from the smoking intensity models because never smoking adults rarely begin smoking and do not have the same perception of the stress-reducing potential of cigarettes.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Coefficients for state fixed effects, month fixed effects, and socio-demographic characteristics are omitted for space considerations. In both tables, the first two columns provide results for the full sample, except former smokers are subset from all smoking intensity models. The second two columns provide results for individuals with at most a high school education. Results are provided as proportional odds ratios.

Odds ratios for control variables suggest that increases in the price of beer decreases the odds of engaging in HRAC. Cigarette prices were not found to have a deterrence effect in the ever smoker population. Increases in the state unemployment rate decrease the odds of smoking in the base sample, a countercyclical relationship between unemployment and smoking found in other studies (Ruhm, 2000, 2005). The post-Katrina parameter is less than even odds (<1), suggesting a decline in both HRAC and smoking intensity over time. HRAC intensity and smoking intensity are higher in coastal counties.

In the political border specification, Hurricane Katrina did not have any statistically significant increases on HRAC intensity in coastal counties or non-coastal counties in coastal states, although the odds ratios are greater than even. Hurricane Katrina did have a statistically significant impact on smoking intensity in non-coastal counties, but not for coastal counties, although the odds ratio in the latter case was larger. Results better conform to hypothesized predictions for low educated individuals. Statistically significant impacts of Hurricane Katrina in coastal counties were found for both HRAC intensity and smoking intensity. For low educated individuals, Hurricane Katrina in coastal counties was associated with an 18.8% increase in the odds of engaging in any HRAC and a 22.4% increase in the odds of a former smoker relapsing.[73]

---

[73] While results are most intuitive to analyze from the base level of the dependent variable, results were jointly determined from all integers of the ordered dependent variable, and interpretation applies to any other level. For example, one component HRAC drinkers also have an 18.8% increase in the odds of becoming two or more HRAC component drinkers, and some day smokers have a 22.4% increase in the odds of becoming an every day smoker.

While the impact of Hurricane Katrina on substance abuse in non-coastal counties of coastal states have greater than even odds, these odds were smaller than for individuals living in coastal counties, conforming to expectations.

The results presented in Table XXII, using storm surge and wind damage data, are fairly consistent with hypothesized predictions for both samples. Hurricane Katrina was associated with an 11.3% increase in the odds of a former smoker relapsing, but no statistically-significant impact on HRAC intensity was found. Again, odds were larger for lower educated individuals, suggesting statistically significant 22.0% and 21.1% increases in the odds of increasing HRAC or smoking levels. In all four models the mild treatment group odds ratios were greater than even odds, but smaller than for the strong treatment group, providing evidence of internal model validity.

The HRAC intensity increase for low educated individuals was further explored by separately analyzing the individual HRAC components using logit modeling. The increase in HRAC intensity appears to be due to increases in excessive drinks per drinking day and excessive drinks per month, but not due to increases in binge drinking in the male population. Additionally, the substance abuse increases appear to be accounted for entirely within the male population. Results calculated with just the sample of males in Table XXIII exhibit the same statistically significant coefficients as the results presented in Table XXII using both sexes.

TABLE XXIII: REGRESSION RESULTS FOR MALES USING STORM SURGE AND WIND DAMAGE SPECIFICATION (FOR A CATEGORY 3 HURRICANE)

| Sample | Base | | Low Education | |
|---|---|---|---|---|
| Dependent Variables | HRAC Intensity | Smoking Intensity | HRAC Intensity | Smoking Intensity |
| | | | | |
| State Level Unemployment Rate | 1.025 (0.043) | 0.905** (0.038) | 0.991 (0.070) | 0.907 (0.058) |
| Real Price of 6-Pack of Heineken Beer | 0.821* (0.088) | | 0.762 (0.137) | |
| Real After-Tax Price per Pack of Cigarettes | | 0.949 (0.132) | | 0.869 (0.190) |
| No Pub Smoking Restrictions | 0.966 (0.060) | | 0.918 (0.100) | |
| Smoke-Free Air Law Index | | 1.003 (0.008) | | 1.000 (0.012) |
| Post-Katrina | 0.889** (0.042) | 0.885** (0.044) | 0.775*** (0.064) | 0.888 (0.068) |
| Wind Risk Counties | 1.051 (0.120) | 0.955 (0.148) | 1.233 (0.211) | 1.037 (0.284) |
| Post-Katrina* Wind Risk Only Counties | 1.023 (0.066) | 1.073 (0.071) | 1.088 (0.116) | 1.044 (0.103) |
| Storm Surge Risk Counties | 1.123 (0.136) | 0.967 (0.156) | 1.083 (0.198) | 0.991 (0.282) |
| Post-Katrina*Storm Surge Risk Counties | 1.051 (0.068) | 1.153** (0.081) | 1.217* (0.138) | 1.360*** (0.149) |
| | | | | |
| State Fixed Effects | X | X | X | X |
| Month Fixed Effects | X | X | X | X |
| Demographic Characteristics | X | X | X | X |
| Subpopulation Observations | 189,450 | 110,646 | 71,064 | 49,892 |

[a] Results are provided as proportional odds ratios and the numbers in parentheses are standard errors.

[b] Never smokers are subset from the smoking intensity models because never smoking adults rarely begin smoking and do not have the same perception of the stress-reducing potential of cigarettes.
* significant at 10% level; ** significant at 5% level; *** significant at 1% level

Unlike males, the results for females (unreported) suggest no increases in substance abuse in the treatment groups from Hurricane Katrina.

Sensitivity analysis is performed of results from the storm surge and wind damage specification. First, results were not sensitive to using a logit model with a 0-1 dichotomous variable for the presence of any HRAC or smoking. Second, other than a minor attenuation of the odds ratios on the interaction variable between Hurricane Katrina and storm surge counties, results were not sensitive to using either category 1 or category 5 hurricanes to define treatment groups.

Third, rather than stratifying by low educated individuals, a parsimonious DIDID model was estimated that interacted post-Hurricane Katrina, the treatment groups, and a dichotomous indicator for low education. The interaction suggests that smoking disproportionately increased for low educated individuals in storm surge counties due to Hurricane Katrina, although the impact was attenuated somewhat from the stratified model, where other confounders were estimated for just low educated individuals rather than for the population as a whole. The interaction for HRAC intensity remained above even odds but was no longer statistically significant. However, the excessive drinks per month component of HRAC remained statistically significant. In general, DIDID findings are similar to reported DID findings for low educated individuals.

Finally, results were stratified by region to attempt to compensate for different probabilities of a state being struck by a hurricane. As was noted in the literature, historically hurricanes are more common in the Gulf coast region and are less frequent moving north along the Atlantic Ocean coastline. Statistically significant increases in smoking intensity in the storm surge region for a category 3 hurricane remained for the Gulf region (not including Louisiana and Mississippi), but not for the other two regions. HRAC intensity was no longer statistically significant for any region, which may be due to a reduction in the sample size of the treatment groups. These results suggest that the probability of a hurricane may be another factor informing risk perceptions. More research is needed to more formally test this hypothesis.

## 24. CONCLUSIONS

Results from this study suggest that Hurricane Katrina, with its 24/7 news coverage, was noticed by individuals, provided new information, raised risk perceptions, and contributed to substance abuse increases. Lower educated individuals, who may have less skill in matching subjective and objective risks, or who may have been less familiar with hurricane risks prior to Hurricane Katrina, were more impacted. While past research has focused on the locations directly affected by the disasters or “near misses,” this research suggests that the impact of “national” disasters extends far beyond the source. These findings should be of interest to public health advocates, as it documents a little understood pathway to substance abuse.

The results using actual hurricane risk data appeared more robust than results using political borders. This may suggest that following Hurricane Katrina, individuals learned accurate information about hurricane risk areas. While more awareness of objective risks is welcomed, irrational increases in risk perception that cause substance abuse is not. One policy response to prevent this is to better educate individuals of hurricane risks before hurricanes occur so that post-disaster responses are not as reactionary and drastic. This could be accomplished by mandating notification of home purchases in storm surge zones similar to what is done currently for home purchases in SFHAs. A secondary recommendation is to improve access to higher education. This has many secondary social and economic consequences, including, apparently, helping individuals better manage risk perceptions following national disasters.

There was some evidence to suggest that Hurricane Katrina contributed to HRAC increases for low-educated individuals. A limitation of the BRFSS data is that, unlike for smoking, individuals who have never drank alcohol were not distinguishable and could not be subset. This resulted in less precise estimates, as never drinking adults were not expected to start in response to Hurricane Katrina.

A limitation of this study is that it does not account for migration, including but not limited to migration to other states due to Hurricane Katrina. Hurricane Katrina evacuees may react with substance abuse due to disruption from the disaster in their personal lives, rather than because of increases in risk perception. However, this particular type of migration should not affect estimates if these evacuees made up a sufficiently small proportion of the national population and if evacuees proportionally dispersed to areas in the treatment and control groups.

In conclusion, there is some evidence that Hurricane Katrina raised perceived risk of a future deadly hurricane and increased smoking and HRAC as a result. To the best of the author’s knowledge, this is the first study to detect changes in substance abuse in areas not directly impacted by the natural disaster. The findings provide greater understanding of the influence of perceived risk on substance abuse.

**26. CITED LITERATURE**


Becker, G. S., & Rubinstein, Y. (2010). Fear and the Response to Terrorism : An Economic Analysis. *Working Paper*.

Bin, O., & Landry, C. (2011). Changes in Implicit Flood Risk Premiums : Empirical Evidence from the Housing Market. *Working Paper, 6383,* 1-41. Retrieved from http://ssrn.com/abstract=1850671

Botts, H., Jeffery, T., Kolk, S., & Suhr, L. (2012). *2012 CoreLogic Storm Surge Report - Residential Storm-Surge Exposure Estimates for U.S. Coastal Areas*.

Bouchery, E. E., Harwood, H. J., Sacks, J. J., Simon, C. J., & Brewer, R. D. (2011). Economic Costs of Excessive Alcohol Consumption in the U.S., 2006. *American Journal of Preventive Medicine*, *41*(5), 516-524.

CDC. (1998). Self-Reported Frequent Mental Distress Among Adults -- United States, 1993-1996. *MMWR. Morbidity and Mortality Weekly Report*, *47*(16), 325-331.

CDC. (2004). Alcohol-Attributable Deaths and Years of Potential Life Lost--United States, 2001. *MMWR. Morbidity and Mortality Weekly Report*, *53*(37), 866-70.

CDC. (2005). State-Specific Prevalence of Cigarette Smoking and Quitting Among Adults -- United States, 2004. *MMWR. Morbidity and Mortality Weekly*, *54*(44), 1124-27.

Carbone, J. C., Hallstrom, D. G., & Smith, V. K. (2006). Can Natural Experiments Measure Behavioral Responses to Environmental Risks? *Environmental & Resource Economics*, *33*(3), 273-297.

Colder, C. R. (2001). Life Stress, Physiological and Subjective Indexes of Negative Emotionality, and Coping Reasons for Drinking: Is there Evidence for a Self-Medication Model of Alcohol Use? *Psychology of Addictive Behaviors*, *15*(3), 237-245.

Cook, P., & Moore, M. (2000). Economics of Alcohol. *Handbook of Health Economics, 1*, 1629-1673.

Greenfield, T., & Harford, T. (2009). Modeling Cognitive Influences on Drinking and Alcohol Problems. *Journal of Studies on Alcohol and Drugs*, (January), 78-86.

Hallstrom, D. G., & Smith, V. K. (2005). Market responses to hurricanes. *Journal of Environmental Economics and Management*, *50*(3), 541-561.

Hill, T. D., & Angel, R. J. (2005). Neighborhood disorder, psychological distress, and heavy drinking. *Social Science & Medicine*, *61*(5), 965-75.

Kaplan, J., & DeMaria, M. (1995). A Simple Empirical Model for Predicting the Decay of Tropical Cyclone Winds after Landfall. *Journal of Applied Meteorology, 34*(November), 2499-2512.

Kousky, C. (2010). Learning from extreme events: risk perceptions after the flood. *Land Economics*.

NOAA. (2004). The Most Intense Hurricanes in the United States 1851-2004. Retrieved from http://www.nhc.noaa.gov/pastint.shtml

NOAA. (2006). *Service Assessment - Hurricane Katrina August 23-31, 2005*. Retrieved from http://www.nws.noaa.gov/om/assessments/pdfs/Katrina.pdf

Orzechowski and Walker. (2009). The Tax Burden on Tobacco: The Historical Compilation, Vol. 44. *Arlington, VA: Orzechowski and Walker*, *44*.

Parrott, A. C. (1998). Does Cigarette Smoking Cause Stress? *American Psychologist*, *54*(10), 817-820.

Rohrbach, L. A., Grana, R., Vernberg, E., Sussman, S., & Sun, P. (2009). Impact of Hurricane Rita on Adolescent Substance Use. *Psychiatry*, *72*(3), 222. NIH Public Access.

Ruhm, C. J. (2000). Are recessions good for your health? *Quarterly Journal of Economics, 115*(2), 617-650.

Ruhm, C. J. (2005). Healthy living in hard times. *Journal of Health Economics*, *24,* 341-363.

Rundmo, T. (2002). Associations between affect and risk. *Journal of Risk Research*, *5*(2), 119-135.

Schultz, L., & Cecil, D. (2009). Tropical cyclone tornadoes, 1950-2007. *Monthly Weather Review*, (1991), 3471-3484.

Sjöberg, L. (1998). Worry and Risk Perception. *Risk Analysis*, *18*(1), 85-93.

Smith, V. K. (2008). Risk Perceptions, Optimism, and Natural Hazards. *Risk Analysis*, *28*(6), 1763-7.

U.S. DHHS. (2012). Preventing Tobacco Use Among Youth and Young Adults: A Report of the Surgeon General.

USDA. (2010). Dietary Guidelines for Americans, 2010 - 7th Edition.

## VITA

| | |
|---|---|
| NAME: | Michael F. Pesko |
| EDUCATION: | B.A., Economics, Management, and English, Hamline University, St. Paul, Minnesota, 2007 |
| | M.A., Economics, University of Illinois at Chicago, Chicago, Illinois, 2010 |
| | Ph.D., Economics, University of Illinois at Chicago, Chicago, Illinois, 2012 |
| TEACHING: | Department of Economics, University of Illinois at Chicago, Chicago, Illinois: Principles of Macroeconomics |
| | Department of Economics, North Central College, Naperville, Illinois: Intermediate Macroeconomics |
| HONORS: | University Fellowship, University of Illinois at Chicago, Chicago, Illinois, 2008-2012 |
| | Houston H. Stokes Outstanding Thesis Award, University of Illinois at Chicago, Chicago, Illinois, 2012 |
| | Phi Beta Kappa, Hamline University, St. Paul, Minnesota, 2007 |
| | Presidential Scholarship, Hamline University, St. Paul, Minnesota, 2003-2007 |
| EXPERIENCE: | ORISE Fellow and Consultant, Centers for Disease Control and Prevention, Office on Smoking and Health, Atlanta, Georgia, 2011-2012 |
| | Consultant, Arkansas Office of the Attorney General, 2011-2012 |
| | Consultant, World Health Organization, Tobacco Free Initiative, Geneva, Switzerland, 2010 |
| PUBLICATIONS: | Michael F. Pesko, Judy Kruger, and Andrew Hyland. (2012). Cigarette Price Minimization Strategies Used by Adults. American Journal of Public Health. e-View Ahead of Print. doi: 10.2105/AJPH.2012.300861 |