The Effect Of Smoke-Free Air Laws On Various Short And Long Run Mortality Outcomes

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THESIS

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I dedicate this thesis to my parents, Mamuco and Karen; my sisters, Monica and Melany; and to Jessi Diaz.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
ARDI	Alcohol-Related Disease Impact
AMI	Acute Myocardial Infarction
BEA	Bureau of Economic Analysis
BIC	Bayesian Information Criterion
CDC	Center for Disease Control
CLRS	Chronic Lower Respiratory Disease
COPD	Chronic Obstructive Pulmonary Disease
EPA	Environmental Protection Agency
HHG	Hausman, Hall, and Griliches
HHS	U.S. Department of Health and Human Services
ICD	International Classification of Diseases
SFA	Smoke-Free air law
SGR	Surgeon General Report
SHS	Secondhand Smoke

Summary

This dissertation emphasizes the importance of implementing comprehensive smoke-free air laws (SFAs) that aim to protect 100% of the U.S. population. I define a comprehensive smoke-free air law as a law that specifically bans smoking in restaurants, bars, private and public workplaces. A ban that prohibits smoking in restaurants and not bars is not considered comprehensive; in the same manner, a ban that provides separately ventilated areas is also not considered comprehensive. Previous studies have shown that comprehensive smoke-free air laws have had a significant effect on reducing mortality due to acute myocardial infarction and strokes. This study confirms these earlier findings and shows that comprehensive SFAs has decreased mortality rates due to chronic lower respiratory disease, lung cancer, and cirrhosis. This study is the first to examine mortality outcomes at the U.S. county and state level over the past 24 years. Reductions in these six underlying causes of death range from 0.9 to 13.6 percent. These results provide further evidence to support the implementation and legislation of comprehensive SFAs to reduce exposure to secondhand smoke.

1. Introduction

Exposure to secondhand smoke (SHS) has been causally associated with cardiovascular and respiratory diseases. More specifically it has been linked to heart disease mortality, acute and chronic coronary heart disease morbidity, elevated risk of stroke, and lung cancer (California Environmental Protection Agency: Air Resources Board, 2005). Epidemiological studies consistently find a 25-30% increase in coronary heart disease from exposure to secondhand smoke while studies using serum cotinine as a biomarker find these estimates to be low and point to an even greater relative risk (HHS, 2006; Institute of Medicine & Committee on Secondhand Smoke Exposure and Acute Coronary Events, 2010).

Smoke-free policies have been an important and growing component of comprehensive tobacco control policies. As opposed to other tobacco policies that focus on discouraging smokers from smoking, SFAs are primarily enacted to protect non-smokers from the harm of SHS. In the United States, smoke-free policies have been implemented entirely in a bottom up fashion. As of this writing, there is not a nationwide federal smoking ban. Initially smoke-free policies focused on bans and restricted areas. In 1973, Arizona became the first state to restrict smoking in various public places. The same year, the Civil Aeronautics Board required no-smoking sections on all commercial air flights (Institute of Medicine & Committee on Secondhand Smoke Exposure and Acute Coronary Events, 2010). The first comprehensive ban, the focus of this dissertation, was enacted in 1990 in San Luis Obispo, California for bars and restaurants (American Nonsmokers' Rights Foundation, 2017a). At the state level, California was the first to pass a comprehensive workplace law (Institute of Medicine & Committee on Secondhand Smoke Exposure and Acute Coronary Events, 2010).

This dissertation focuses on comprehensive SFAs, not smoking bans and restrictions. A comprehensive SFA is one that specifically bans smoking at a 100 percent level. I exclusively focus on bar, restaurant, and private and public workplace bans. A ban that prohibits smoking in restaurants and not bars is not considered comprehensive and similarly a ban that only mandates separately ventilated areas is not considered comprehensive.

Over the past decade substantial research has demonstrated the effectiveness of implementing comprehensive smoke-free air laws. In particular, smokers and nonsmokers experience reduced exposure to SHS (Callinan, Clarke, Doherty, & Kelleher, 2010), reductions in smoking among youth and young adults (HHS, 2014), reductions in the prevalence of tobacco use, increases in the number of tobacco users who quit, reductions in initiation for youth (Guide to Community Preventive Services, 2013), reductions in the number of cigarettes smoked per day, increases in quitting attempts, and increases in smoking cessation rates (HHS, 2006). Given the effect that SHS has on the cardiovascular system a vast majority of research has also focused on reductions in hospital admissions for acute myocardial infarction.

The most recent meta-analysis identified 43 relevant studies, which provided a combined 86 risk estimates for: acute myocardial infarction (AMI), acute coronary syndrome, acute coronary events, ischemic heart disease, angina, coronary heart disease, sudden cardiac death, stroke, transient ischemic attack, chronic obstructive pulmonary disease, asthma, lung infections and spontaneous pneumothorax(Tan & Glantz, 2012). The meta-analysis finds a consistent decreases in hospitalization and mortality for all outcomes except transient ischemic attack, chronic obstructive pulmonary disease and spontaneous pneumothorax when comprehensive smoke-free laws are implemented (Tan & Glantz, 2012).

The evidence that smoke-free air laws have led to decreases in mortality is clear. This dissertation will provide further evidence in support of this notion and to promote the implementation and legislation of further comprehensive SFAs. Chapter 2 provides evidence that comprehensive smoke-free air laws in the short run have contributed to the decline in acute myocardial infarction (AMI), stroke and chronic lower respiratory disease (CLRD) mortality. Depending on the model and SFA specification used, I find an average decrease of 3.2 percent for AMI, 1.2 percent for strokes, and 2.1 for CLRD. As a counterfactual, I find that SFAs have no effect on mortality from appendicitis.

Chapter 3 provides evidence that comprehensive smoke-free air laws in the long run have contributed to the decline in lung cancer and cirrhosis mortality. Depending on the number of lags, the model, and the SFA specification used, I find a decrease of 4.4 to 10.7 percent for lung cancer after 11 lags, and 2.9 to 13.6 percent for cirrhosis after 11 lags.

1.1. Purpose and Contribution

This dissertation investigates the impact that smoke-free air laws have had on short term and long-term mortality outcomes. The short-term mortality outcomes are acute myocardial infarction (AMI), cerebrovascular diseases (more commonly known as strokes), and CLRD. The long-term mortality outcome focus on malignant neoplasms of the trachea, bronchus, and lung (more commonly known as lung cancer), and alcoholic liver disease and cirrhosis. From here on forward, I refer to cirrhosis as the combined mortality from cirrhosis and alcoholic liver disease.

The idea and hypothesis are not new, but the work advances the field and adds to the smoking ban literature in eight distinct ways:

1. To my knowledge, this is the longest time horizon study as I employ 24 years of data.
2. This is the only study that uses county and state level data for the continental United States; previous studies focus on certain localities or state level data.
3. This is the first national level study to investigate how mortality due to AMI and strokes has been affected by SFAs.
4. This is the first national level study to investigate how mortality due to CLRD, lung cancer, and cirrhosis has been affected by SFAs. In addition, it is the first study to look at these underlying causes of death.

5. Mortality data is more diverse than hospitalization data, as it diminishes the disparities in access to hospitals and income. Providing more accurate results as to the effects of SFAs.
6. This dissertation employs data from the Americans for Nonsmokers Rights Foundation to calculate the effective percentage of the population that is covered by a smoke-free air law. This measure is new and novel and seldom used; it better captures how populations are actually protected by various smoke-free air laws that exist across cities, municipalities, counties and across states.
7. I use both a conditional and unconditional negative binomial fixed-effects model to properly account for overdispersion in the data; to date, no previous study has addressed this data issue, nor attempted to correct for it.
8. Lastly, by using lung cancer and cirrhosis mortality data, this is the first study to look at the long-term effects of SFAs.

1.2. Economics and Smoke-Free Air Laws

One of the main areas of research in economics is the law of unintended consequences. While often not formally defined it encompasses the idea that laws, policies, and ideas may have unanticipated effects. SFAs are the only tobacco control measure that focuses on the health of non-smokers instead of aiding smokers. The main intention of SFAs is to protect both nonsmokers and smokers from the dangers of SHS. However, as this dissertation will prove, the implementation of SFAs has contemporaneously decreased mortality from AMI, strokes, and CLRD and over a longer time horizon, SFAs have decreased mortality in lung cancer and cirrhosis. The framework of unintended consequences tends to focus on negative unanticipated consequences, but not all unintended consequences should be viewed in this manner.

A second peculiarity of SFAs is the grassroots implementation they have had in the United States. In other countries it is more common to have one blanked Federal law, but not in the United States. Econometric speaking, this peculiarity lends itself to exploit panel data methods to calculate the true causal effect of SFAs on mortality.

1.3. Analytical Framework

As stated, the goal of this dissertation is to calculate the impact that SFAs have had on further reducing mortality from AMI, strokes, CLRD, lung cancer and cirrhosis. This requires distinguishing the role that SFAs have had in the short run, and long run, and to distinguish the causal links between these policies and these specific mortality outcomes. Over the years various Surgeon General Reports (SGR) have been dedicated to this subject. In 2004 the report focused on the health consequences of smoking, in 2006 it focused on the health consequences of exposure to secondhand smoke, in 2010 it focused on how tobacco smoke causes diseases, and in 2014 it further focused on the health consequences of smoking. These reports and various medical research papers appropriately summarize the background information needed to establish my analytical framework.

Comprehensive SFAs work by prohibiting smoking in all indoor areas, here I specifically focus on private and public workplaces, restaurants, and bars. The primary goal for enacting comprehensive SFAs is to protect nonsmokers from SHS, since exposure to SHS has been causally linked to cancer, respiratory, and cardiovascular disease (HHS, 2014). Furthermore, the evidence is now sufficient to conclude that SFAs are not only effective in reducing exposure to SHS, but they also lead to less smoking among those covered by an SFA (HHS, 2014). Therefore, SFAs work through two mechanisms. Implementing SFAs directly leads to less exposure to SHS, and secondarily SFAs lead to less smoking. Both this direct and indirect mechanism should lead to decreases in mortality of AMI, strokes, CLRD, lung cancer and cirrhosis. I will briefly review the epidemiological evidence of how these mechanisms work specifically for each mortality outcome.

In the short run epidemiologic evidence indicates that even minimal exposure to SHS increases the risk of an acute coronary event, such as an AMI and/or stroke (Institute of Medicine & Committee on Secondhand Smoke Exposure and Acute Coronary Events, 2010). In 2006 both the SGR and the Institute of Medicine concluded that there is a causal relationship between SHS and increased risk of morbidity and mortality from coronary heart disease (HHS, 2006; Institute of Medicine & Committee on Secondhand Smoke Exposure and Acute Coronary Events, 2010). Furthermore, SHS exposure is relevant for nonsmokers and smokers, as SHS increases the risk of having an AMI for both (Teo et al., 2006). Furthermore, cigarettes are a major causes of AMI and strokes (HHS, 2004), as smoking is one of the most relevant risk factors associated with AMI (HHS, 2010). Lastly, impaired delivery of oxygen to the heart due to SHS, can be especially damaging to people with cardiovascular disease, since it increases arrhythmia and causes ischemia leading to an increased risk of both fatal and non-fatal cardiac events (Glantz & Parmley, 1995).

With regards to strokes, in 2014 the previous finding was further reiterated in the SGR and the language changed from inferring a causal relationship to establishing one: Exposure to SHS increases the risk of having a stroke by 20-30% (HHS, 2014).

CLRD is the third leading cause of death in the United States (HHS, Centers for Disease Control and Prevention, & National Center for Health Statistics, 2016), for reference heart disease and cancer are number one and two, followed by strokes as the fifth leading cause. Three major diseases are included under CLRD: asthma, bronchiectasis, and chronic obstructive pulmonary disease (COPD). While each disease present in different manners, they all affect the lower lung and obstruct airways causing shortness of breath. The major risk factor to develop CLRD is exposure to tobacco smoke either as a smoker or from SHS ("CDC - COPD Home Page—Chronic Obstructive Pulmonary Disease (COPD)," 2016).

In 2004 the SGR concluded that “The evidence is sufficient to infer a causal relationship between smoking and lung cancer” (HHS, 2004). Studies have shown that the risk of developing lung cancer for nonsmokers has remained steady since the first SGR of 1964, however by 2000-2010 the risk for women and men smokers to develop cancer is 25.7 and 25 times more likely respectively. This relative risk has increased even though the prevalence of smoking and the number of cigarettes consumed has decreased over this period (HHS, 2014). In the long run the relationship between SHS and lung cancer is pretty clear; SHS is classified as a known human lung carcinogen.

The relationship between SHS and smoking and cirrhosis is less clear. I argue that since alcohol consumption and cigarette smoking are known complement activities, alcohol consumption is strongly associated with increased rates of smoking (McKee, Krishnan-Sarin, Shi, Mase, & O’Malley, 2006) and conversely, smoking increases alcohol consumption (Barrett, Tichauer, Leyton, & Pihl, 2006). Therefore in the long run one should observe a decrease in cirrhosis, given the decrease in alcohol consumption that occurs with reductions in smoking due to the implementation of SFAs.

1.4. Data

All analyses use a core compiled data set, which contains the number of deaths in a county from AMI, strokes, CLRD, lung cancer, and cirrhosis, the effective percentage of the population covered by all three comprehensive SFAs (restaurant, bar, and private or public workplaces) in a county, and the county level unemployment rate. To verify the validity of the results, various other controls such as the average price of a pack of cigarettes - including all taxes in each county - are used. In this section I will detail the source of the data and elaborate on caveats where applicable.

1.4.1. Core Data Set

All mortality data is from the Center for Disease Control and Prevention, National Center for Health Statistics, Compressed Mortality File. This data set contains mortality and population counts for all U.S. counties from 1968 to 2015, I specifically use data ranging from 1991 to 2014. The CDC Wonder Compressed Mortality file uses the World Health Organization International Classification of Disease and Related Disorders (ICD) codes; the 9th revision is used for the years 1991-1998 and the 10th revision is used for the years 1999-2014. Several revisions have occurred between ICD-9 and ICD-10 which I address specifically in the section below.

Acute Myocardial Infarction: Under ICD-9 AMI is coded as 410 (Acute myocardial infarction), under ICD-10 it is coded as the combined sum of I21.0 (Acute transmural myocardial infarction of anterior wall), I21.1 (Acute transmural myocardial infarction of inferior wall), I21.2 (Acute transmural myocardial infarction of other sites), I21.3 (Acute transmural myocardial infarction of unspecified site), I21.4 (Acute subendocardial myocardial infarction), I21.9 (Acute myocardial infarction, unspecified), I22.0 (Subsequent myocardial infarction of anterior wall), I22.1 (Subsequent myocardial infarction of inferior wall), I22.8 (Subsequent myocardial infarction of other sites), and I22.9 (Subsequent myocardial infarction of unspecified site). For AMI I focus my analysis on two age groups: the mortality for all adults over the age of 20 and for those aged 35-64.

As briefly mentioned above, the mortality data in my data set transitions from ICD-9 codes for years 1991-1998 to ICD-10 codes for years 1999-2014. It is important to keep in mind that when correlating ICD-9 to ICD-10, several challenges exist, mainly stemming from differences in definition. For AMI in particular, there are four main changes that occur when transitioning from ICD-9 to ICD-10 codes. The first change pertains to changes in the descriptive time frame. The time frame for AMI codes changes from 8 or less weeks when using ICD-9 codes to 4 or less when using ICD-10 codes; making the definition of an AMI event no longer standardized across time. The second change pertains to alterations in the definition of "acute"; in ICD-10 this definition does not necessarily exist. Acute can be thought of as referencing an initial or a subsequent AMI, but it does not define the time frame. The third change also pertains to a definition change, as the word "subsequent" is different between ICD-9 and ICD-10. Lastly, the ability to identify initial episodes of care in ICD-10 based on the code alone will no longer be possible (Workgroup for Electronic Data Interchange (WEDI), 2012).

Even though these changes are significant and make comparing years challenging, I follow the recommendations of the latest comparability study to group definitions from ICD-9 to be comparable with ICD-10. After each ICD revision, comparability studies are routinely performed as part of the implementation of a new ICD system. The main goal of a comparability study (also referred to as a bridge coding study), is to calculate the comparability ratio. This rate is calculated by dividing the number of deaths classified under the new revision by the number of deaths classified under the old revision using data from a single year(Anderson, Miniño, Hoyert, & Rosenberg, 2001). This rate then represents the net effect of the new revision on underlying cause-of-death statistics. A comparability ratio of 1.00 indicates perfect correspondence between the two revisions, or that any increase in the allocation of that specific code is completely offset by a decrease in the allocation of that specific code(Anderson et al., 2001). A ratio of less than 1.00 indicates that fewer causes-of-death are being classified to the new revision, a ratio greater than 1.00 indicates that more causes-of-death are being classified under the new revision (Anderson et al., 2001). For AMI the comparability ratio is 0.9887 with a standard error of 0.0003. This indicates that 1.13 percent fewer deaths are being classified under ICD-10 then would have been classified under ICD-9.

Strokes (Cerebrovascular disease): Under ICD-9 cerebrovascular disease is coded as: 430 (Subarachnoid hemorrhage), 431 (Intracerebral hemorrhage), 432.0 (Nontraumatic extradural hemorrhage), 432.1

(Subdural hemorrhage), 432.9 (Unspecified intracranial hemorrhage), 433.0 (Basilar artery), 433.1 (Carotid artery), 433.2 (Vertebral artery), 433.3 (Multiple and bilateral), 433.8 (Other specified precerebral artery), 433.9 (Unspecified precerebral artery), 434.0 (Cerebral thrombosis), 434.1 (Cerebral embolism), 434.9 (Cerebral artery occlusion, unspecified), 436 (Acute, but ill-defined, cerebrovascular disease), 437.0 (Cerebral atherosclerosis), 437.1 (Other generalized ischemic cerebrovascular disease), 437.2 (Hypertensive encephalopathy), 437.3 (Cerebral aneurysm, nonruptured), 437.4 (Cerebral arteritis), 437.5 (Moyamoya disease), 437.6 (Nonpyogenic thrombosis of intracranial venous sinus), 437.8 (Other), 437.9 (Unspecified), and 438 (Late effects of cerebrovascular disease). Under ICD-10 cerebrovascular diseases is coded as: I60 (Subarachnoid haemorrhage), I61 (Intracerebral haemorrhage), I62 (Other nontraumatic intracranial haemorrhage), I63 (Cerebral infarction), I64 (Stroke, not specified as haemorrhage or infarction), I67 (Other cerebrovascular diseases), and I69 (Sequelae or cerebrovascular disease).

The comparability ratio for strokes is 1.0588, indicating that 5.88 percent more deaths are being classified under ICD-10 then would have been classified under ICD-9. This increase is mostly attributable to changes in Rule 3[1], where some categories of cerebrovascular disease are chosen over pneumonia when both are listed on the death certificate (Anderson et al., 2001). For stroke mortality I focus on all adults over the age of 20.

Chronic Lower Respiratory Disease: For ICD-9 codes I use: 490 (Bronchitis, not specified as acute or chronic), 491.0 (Simple chronic bronchitis), 491.1 (Mucopurulent chronic bronchitis), 491.2 (Obstructive chronic bronchitis), 491.8 (Other chronic bronchitis), 491.9 (Unspecified chronic bronchitis), 492 (Emphysema), 493.0 (Extrinsic asthma), 493.1 (Intrinsic asthma), 493.9 (Asthma, unspecified), 494

[1] Rule 3 states the following: if the condition selected by the General Principle or by Rule 1 or Rule 2 is obviously a direct consequence of another reported condition, whether in Part I or Part II [of the medical certification portion of the death certificate], select this primary condition(*ICD-10*, 1992). The cause of death that is most affected by this change is pneumonia, mainly because it tends to be the consequence of another condition or injury.

(Bronchiectasis), and 496 (Chronic airway obstruction, not elsewhere classified). For ICD-10 codes I use: J40 (Bronchitis, not specified as acute or chronic), J41 (Simple and mucopurulent chronic bronchitis), J42 (Unspecified chronic bronchitis), J43 (Emphysema), J44 (Other chronic obstructive pulmonary disease), J45 (Asthma), J46 (Status asthmaticus), and J47 (Bronchiectasis).

The main reason I use CLRD data instead of COPD data is because of the regrouping that took place from ICD-9 codes to ICD-10 codes. Under ICD-10 COPD and allied conditions became CLRD (Anderson et al., 2001). The comparability ratio is 1.0478; this 4.78 percent classification increases is mainly due to Rule 3. Previously these deaths were coded as pneumonia, since pneumonia is a direct consequence of most chronic lower respiratory diseases (Anderson et al., 2001). Lastly, if I had simply used sub-categories of CLRD instead of the combined sum, the comparison between ICD-9 and ICD-10 is too extreme, for example bronchitis, chronic and unspecified has a comparability ratio of 0.3935. For CLRD mortality I focus on adults over the age of 20.

Lung Cancer (Malignant neoplasms of trachea, bronchus, and lung): Under ICD-9 I use the following codes to identify mortality from lung cancer: 162.0 (Trachea), 162.2 (Main bronchus), 162.3 (Upper lobe, bronchus or lung), 162.4 (Middle lobe, bronchus or lung), 162.5 (Lower lobe, bronchus or lung), 162.8 (Other parts of bronchus or lung), and 162.9 (Bronchus and lung, unspecified). For ICD-10 I use: C33 (Malignant neoplasm of trachea), C34.0 (Main bronchus - Malignant neoplasms), C34.1 (Upper lobe, bronchus or lung - Malignant neoplasms), C34.2 (Middle lobe, bronchus or lung - Malignant neoplasms), C34.3 (Lower lobe, bronchus or lung -Malignant neoplasms), C34.8 (Overlapping lesion of bronchus and lung - Malignant neoplasms), and C34.9 (Bronchus or lung, unspecified - Malignant neoplasms).

The major change in the categorization of lung cancer pertains to changes in the way the primary site of a malignant neoplasm is selected in the underlying cause of death certificate. In ICD-10 lung cancer has been added to the list of common sites of metastasis and is considered a secondary cause of death whenever it appears with any other metastasis sites in Part 1 of the U.S. Standard Certificate of Death (Anderson et al., 2001). For example, if cancer of the colon is listed in line (a) and cancer of the lung in line (b), then cancer of the colon is selected as the underlying cause of death; on the other hand if they were listed in reverse order cancer of the lung would be selected as the underlying cause of death (Anderson et al., 2001). These changes don't impact the malignant neoplasm category as a whole, but it does affect my lung cancer subcategory. The comparability ratio for lung cancer is 0.9837; indicating that 1.63 percent fewer deaths are being classified as lung cancer (Anderson et al., 2001). This decrease is vastly due to change in the categorization mentioned above. For lung cancer mortality I focus on all adults over the age of 20.

Cirrhosis (Alcoholic liver disease and cirrhosis): Under ICD-9 alcoholic liver disease is coded as the combined sum of 571.0 (Alcoholic fatty liver), 571.1 (Acute alcoholic hepatitis), 571.2 (Alcoholic cirrhosis of liver), and 571.3 (Alcoholic liver damage, unspecified). Liver cirrhosis is coded as 571.5 (Cirrhosis of liver without mention of alcohol), 571.6 (Biliary cirrhosis), 571.8 (Other chronic nonalcoholic liver disease), and 571.9 (Unspecified chronic liver disease without mention of alcohol). Under ICD 10 alcoholic liver disease is coded as the combined sum of K70.0 (Alcoholic fatty liver), K70.1 (Alcoholic hepatitis), K70.3 (Alcoholic cirrhosis of liver), K70.4 (Alcoholic hepatic failure), and K70.9 (Alcoholic liver disease, unspecified). Liver cirrhosis is coded as K74.3 (Primary biliary cirrhosis), K74.4 (Secondary biliary cirrhosis), K74.5 (Biliary cirrhosis, unspecified), K74.6 (Other and unspecified cirrhosis of liver), K76.0 (Fatty (change of liver, not elsewhere classified), K76.9 (Liver disease, unspecified). For these ICD codes I follow the ICD codes used by the Alcohol-Related Disease Impact (ARDI) report to classify alcohol-attributable mortality fractions ("CDC - ARDI - Alcohol-Related ICD Codes," n.d.).

Given that I used the ICD codes recommended by ARDI, specific comparability ratios are not available for these specific groupings, however for alcoholic liver disease the estimated comparability ratio is 1.0183.

This ratio indicates that 1.83% more deaths from alcoholic liver disease are being classified under the new revision. Some of this increase is due to changes in Rule 3, where chronic liver disease is chosen over pneumonia when both are listed on the death certificate (Anderson et al., 2001). The remaining portion can be partially attributed to ICD-10 having a new classification category, Alcoholic liver failure (K70.4)(*ICD-10*, 1992). For cirrhosis mortality I focus on all adults over the age of 20.

A condensed version of the ICD codes used for each mortality outcome can be found in table 27 in the appendix. In summary, three comparability ratios overstate the number of deaths, while two understate these figures. For all ratios there is no more than a 10 percent over or under attribution due to the change from ICD-9 definitions to ICD-10.

Lastly, one of the major disadvantages of using the CDC Wonder Compressed Mortality data set is the data restriction placed upon it per the Public Health Service Act (42 U.S.C. 242m(d)). This act stipulates that data contained in the CDC Wonder Compressed mortality dataset should not be presented nor published when death counts are nine or fewer. Given that my dataset is at the county level, data for smaller counties where less than nine people a year died is missing.

Smoke-Free Air Laws Measure: Two sources of data are used to construct this measure. State level SFAs are from MayaTech; city and county level SFA data are from the American Nonsmoker's Rights Foundation. Both datasets provide policy information for private and public workplaces, restaurants and bars. The data distinguishes when city level ordinances are stronger than county and state policies. The measure then shows the effective percentage of the population in each county that is covered by "No", "Some", "Qualified", and "100 Percent" smoke-free air policies, within each of the 4 venues mentioned above for a total of 16 variables. I only use the latter data and construct a measure that captures the effect percentage of the population in a county that is covered by all comprehensive bans (bar, restaurant, private/public workplaces).

Unemployment Rate: Data on annual county and state level unemployment rates are from the Local Area Unemployment Statistics from the United States Bureau of Labor Statistics. Only one small caveat is worth noting. The unemployment rates for Clifton Forge County (FIPS code 51560) and Alleghany County (FIPS code 51005) in Virginia are combined rates, since these counties merged together on July 1, 2001. The unemployment rate data is only available for all years merged, whereas the other data separates these two counties. Data for both counties were merged to match the Local Area Unemployment Statistics.

1.4.2. Control Data Set

Real Price of a Pack of Cigarettes: This data is originally constructed at the monthly level and includes the price of a pack of cigarettes with federal, state, and county level excise tax rates. State level data is constructed using data from the Tobacco Institute's Annual Tax Burden on Tobacco (Orzechowski & Walker, 2014). The county and city level data was constructed using data from Tobacco Free Kids. The price of a pack of cigarettes is for a generic brand with 20 cigarettes. All numbers have been updated to adjust for inflation and are reported in December 2014 dollars.

Real Per Capita Personal Income: This data is compiled from the Bureau of Economic Analysis (BEA). The BEA defines personal income as the income available to persons for consumption expenditures, taxes, interest payments, transfer payments to governments and the rest of the world, or for saving. The data is divided by the county population to make meaningful comparisons (US Department of Commerce, 2016). Lastly, the data is reported in nominal terms and is converted to real December 2014 dollar estimates using the U.S. city average of the Consumer Price Index.

County Business Patterns: This data is a series provided by the United States Census Bureau that provides, among other information, the number of establishments for most NAICS codes. I use the following eight establishments as controls: the total number of grocery stores and supermarkets; the total number of fruit and vegetable markets; the total number of beer, wine and liquor stores; the total number of recreation and fitness facilities; the total number of bars and drinking establishments; the total number of full-service restaurants; the total number of fast food restaurants; and the total number of all types of hospitals. State level measures are simple aggregates of the county variables. The main purpose behind these variables is to control for risk factors associated with the mortality outcomes of interest. For example, the number of fruit and vegetable markets is intended to control for the access (or lack thereof) to healthy food. In the same manner, the number of bars and drinking establishments is intended to control for the access to alcohol, a known risk factor for the mortality outcomes used.

Annual Particulate Matter 2.5: This data series is provided by CDC and is compiled from various sources. The primary source of data is from the U.S. Environmental Protection Agency's Air Quality System. For county level data the highest 24-hour daily average from multiple monitors is used. When monitors are not available the estimates rely on Community Multiscale Air Quality output. The data is provided as an annual average, which is further based on seasonal averages and daily measures (CDC, 2016).

Lastly, it is important to note that not all data sets are available for all years. Table 1 summarizes the name of the data point, the data source, and the years the data is available.

TABLE 1: VARIABLES, SOURCES AND YEARS AVAILABLE

Data	Source	Years Available
Mortality Outcomes (AMI, Strokes, CLRD, Lung Cancer, and Cirrhosis)	CDC National Center for Health Statistics, Compressed Mortality	1991-2014
Smoke-Free Air Laws	MayaTech and the American Nonsmoker's Rights Foundation	1991-2014
Unemployment Rate	Local Area Unemployment Statistics from the US Bureau of Labor Statistics	1991-2014
Real Price of a Pack of Cigarettes	Tobacco Institute's Annual Tax Burden on Tobacco and Tobacco Free Kids.	1991-2014
Real Per Capita Personal Income	Bureau of Economic Analysis	1991-2014
County Business Patterns: • Grocery stores and supermarkets • Fruit and vegetable markets • Beer, wine and liquor stores • Recreation and fitness facilities • Bars and drinking establishments • Full-service restaurants • Fast food restaurants • All types of hospitals.	Census Bureau	1998-2014
Annual Particulate Matter	CDC	2001-2014

2. The Short Run Impact of Smoke-Free Air Laws: Acute Myocardial Infarction, Strokes, and Chronic Lower Respiratory disease

2.1. Introduction

In this chapter, I will estimate what I call the short run impact of SFAs. I will focus on county and state-level AMI, stroke, and CLRD mortality. I specifically use the effective percentage of the population that is covered by all comprehensive SFAs (bar, restaurant, private/public workplace) at the county and state-level respectively as the exogenous variation. I find decreases in mortality in the range of 1.0 to 4.9 percent.

2.2. Background

2.2.1. Acute Myocardial Infarction

Several papers have examined the impact of SFAs on AMI, both by looking at hospital admission and mortality. This literature review will focus heavily on studies that have used mortality as their outcome of interest, though the following hospitalization results are worth mentioning. The first study to look at this relationship was Sargent, Shepard, and Glantz in 2004 were they reported a 40 percent reduction in hospital admission for AMI in Helena, Montana. This decrease was observed after the implementation of comprehensive SFA for public places and workplace (Sargent, Shepard, & Glantz, 2004). Since then numerous studies have been published along with seven meta-analysis that have demonstrated more attenuated results that range from three to 19 percent reductions (Glantz, 2008; Lightwood & Glantz, 2009; Meyers, Neuberger, & He, 2009; Mackay, Irfan, Haw, & Pell, 2010; Lee & Fry, 2011; Tan & Glantz, 2012; Lee, Fry, & Forey, 2014).

The first study to examine mortality from AMI is from 2010 and uses a Poisson regression model and data from Massachusetts. The period studied is from January 1, 1999 to December 31, 2006, and analyzes the impact of the July 2004 comprehensive smoking ban that took effect at the state level. The authors find that the ban led to a 7.4 percent reduction in AMI mortality rates. When controlling for gender the effect was greater for women than for men, with a 9.7 and 5.1 percent reduction respectively. The authors also analyzed the effect the state level ban had on various cities and towns in Massachusetts. Specifically, they focus on cities and towns that had established local comprehensive bans prior to July 2004. For these cities and towns the state level ban had no effect on mortality. However, for cities and towns with no prior ban in place, the state level ban lead to a reduction of AMI mortality of 9.2 percent. Lastly, when the authors analyzed the effect of the ban 12 months after its implementation a cumulative decrease of 18.6 percent was found, compared to only 1.6% when only analyzing the first 12 months of data after the state ban (Dove et al., 2010).

A second US study used fixed-effects modeling to compare AMI rates before and after the passage of a smoking ban to mortality rates of AMI in communities that did not pass bans (Shetty, DeLeire, White, & Bhattacharya, 2011). Using a sample of 467 counties from the multiple cause of death files for 1990 through 2004, Sherry and colleagues find that smoking restrictions did not affect short-term mortality from all-causes and from AMI in any age group. This study unfortunately only takes into account the effect of smoking bans in workplaces; restaurant and bar smoking bans are not included, which might explain why an effect was not found.

A third US study focuses on those aged 25 to 54 to assess the short-term impact of workplace SFAs for the time period of 2000 through 2005 (Adams, Cotti, & Fuhrmann, 2013). Adams and colleagues find a 16 percent reduction in AMI infarction for the younger age group, but no significant effect for those retired (55 years and older). The model is estimated by weighted least squares using state and year fixed-effects. Without justification, the authors use a logistic transformation of AMI fatality rate as their dependent variable. The results seem robust to alternative specifications such as unweighted Poisson and negative binomial fixed-effects models.

The last US study is a tobacco industry sponsored article (Rodu, Peiper, & Cole, 2011). Rodu and colleagues focus on 6 states that passed state level laws from 1995 to 2003 to test for the difference between two independent proportions and find that the ordinances had no effect on AMI mortality. This study is not included in the most recent meta-analysis performed by Glantz as the study uses non-standard methodology, the analysis uses few data points, and excludes California and New York from the analyses, which coincidentally had numerous comprehensive local laws enacted during the time period considered (Tan & Glantz, 2012).

There are five international studies that have analyzed the effect of smoke-free legislation on mortality from AMI, one from Flanders, Belgium (Cox, Vangronsveld, & Nawrot, 2014), two from Spain (Villalbí et al., 2011) (Agüero et al., 2013), and two from Italy (Cesaroni et al., 2008) (Gasparrini, Gorini, & Barchielli, 2009).

In Belgium smoke-free legislation was implemented in phases. The authors looked at all-cause mortality from 2000-2009 for the implementation of phase 1 and phase 2. Phase 1, passed on January 1, 2006 in all public places but excluded bars, cafes, restaurants, nightclubs and discotheques; phase 2 extended the bans to include restaurants. It is important to note that this is one of the first studies that analyzed the effect of smoke-free air laws on a longer time horizon, 3 years. Using a segmented Poisson regression and a binary indicator for the smoke-free ban, the authors find an immediate decrease of AMI mortality of 33.8 percent and 13.1 percent for women and men respectively under the age of 60. For women and men over the age of 60 the decreases were 7.9 and 9 percent respectively. When looking at the longer time horizon they find an annual decrease of 3.8 percent (Cox et al., 2014).

The first Spanish study uses Poisson regression models to compare adjusted AMI mortality rates by sex and age in 2004 and 2005 to those in 2006 after the SFA was imposed in January 2006. Villalbí and colleagues find a reduction of 9 and 8.7 percent for men and women; unfortunately, it is not clear if the authors use controls (other covariates) in their Poisson regression models (Villalbí et al., 2011). The second Spanish study, by Agüero and colleagues, uses a population based registry and negative binomial regression analysis. The authors find an overall reduction of 18 percent AMI mortality. Woman and people aged 65 years and older benefited the most from the partial ban on smoking that Spain passed on January 1, 2006, 27 percent and 26 percent respectively (Agüero et al., 2013). What is most remarkable about this study is the magnitude of the declines found, even after taking into account that only a partial ban on smoking was enacted.

The first Italian study looks at the declines in AMI mortality and hospital admissions in Rome after a comprehensive ban was passed on January 10, 2005. Cesaroni and colleagues also use Poisson regression to analyze the effect that a binary indicator for the comprehensive smoke-free ban has had on the number of daily episodes of AMI mortality and AMI hospital admission (jointly defined in the study as an acute coronary event). The authors find a reduction of 11.2 percent in acute coronary events for individuals aged 35-64 and for those aged 65-74 a 7.9 percent reduction was found. When taking into account socio-economic status, young people living in low socioeconomic census blocks benefited the most from the comprehensive ban (Cesaroni et al., 2008).

The second Italian study uses Poisson regression to compare AMI mortality incidence from 2000-2004 to 2005 for those 30 to 64 years old in the Tuscany area. The study focuses on both public and workplace SFAs. The results are sensitive to model specification: the model with a linear time trend indicates a 5.4 percent reduction in AMI rates, while the model without the time trend shows no reduction (Gasparrini et al., 2009).

2.2.2. STOKES

The first and only study that I am aware off to look at mortality reduction in stroke (in addition to respiratory mortality and COPD) is based on the national workplace smoking ban that took place in Ireland in 2004 (Stallings-Smith, Zeka, Goodman, Kabir, & Clancy, 2013). Stallings-Smith and colleagues use Poisson regression and find that all-cause mortality has an immediate decrease of 13 percent post ban, a 32 percent decrease in strokes, 26 percent decrease in ischemic heart disease, and 38 percent decrease in COPD (Stallings-Smith et al., 2013).

2.2.3. CHRONIC LOWER RESPIRATORY DISEASE

To my knowledge there are no studies to date that look specifically at the relationship of SFAs on mortality from CLRD. The only study that I am aware of that looks at a COPD, which is a subcomponent of CLRD, is the study mentioned in the previous section. To reiterate, Stallings-Smith and colleagues find a 38 percent decrease in Ireland.

There are four relevant studies that look at the impact of SFAs on hospitalizations for various subcategories of CLRD that are worth mentioning. The first study focuses on hospital admission in the Toronto area and finds a 33 percent reduction for the combined admission of Asthma, COPD, and pneumonia/bronchitis (Naiman, Glazier, & Moineddin, 2010). To my knowledge this is the only study to use an ARIMA model to isolate the effect of SFAs. Furthermore, they attribute most of the reduction to restaurant SFA policies.

The second study uses Medicare beneficiary data and looks at the impact of 938 local smoke-free laws passed between 1991-2008 had on COPD admissions in the United States (Vander Weg, Rosenthal, & Vaughan Sarrazin, 2012). The authors use Poisson regression and adjust for the increase patterns of COPD and find an 11 percent reduction in hospital admission due to workplace SFAs and a 15 percent reduction due to bar SFAs.

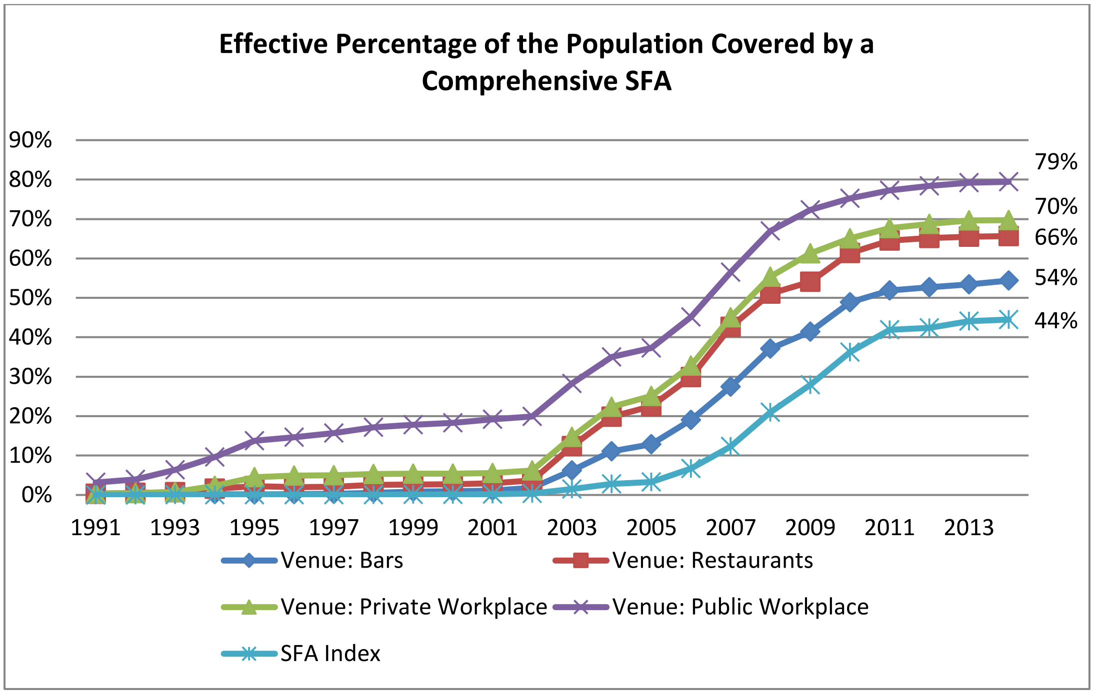
The third study to include hospital admission from exacerbations of COPD uses data from Ireland for the population aged 20 to 70 years old and finds no specific effect for COPD (Kent, Sulaiman, Nicholson, Lane, & Moloney, 2012). However, when the authors combine all pulmonary diseases rates (exacerbations of COPD, pneumonia, lower respiratory tract infection exacerbations of asthma, and spontaneous pneumothorax) they find a nine and 15 percent reduction when controlling for weather, pollution and influenza.

The final study to look at hospital admissions for COPD focuses on data from Geneva, Switzerland and finds a substantial decrease of 46 percent (Humair et al., 2014). The authors use Poisson regression and controls for period dummies, seasonality, influenza, age, gender, and a linear time trend.

2.3. Methods and Data

My analytical background can be found in section 1.2. As mentioned previously in this study I emphasize the importance of implementing comprehensive SFAs that protect 100 percent of the U.S. population. A comprehensive SFA is defined as one that specifically bans smoking in restaurants, bars, and private and public workplaces at a 100 percent level. A ban that prohibits smoking in restaurants, and not bars, is not considered comprehensive; likewise, a ban that provides separately ventilated areas is also not considered comprehensive. In the last two decades the percentage of people covered by a comprehensive SFA has vastly increased. As of December 2014, 54 percent, 66 percent, 70 percent, and 79 percent of the population in the continental United States is protected by either a state, county or city smoke-free air law in bars, restaurants, private, and public workplaces, respectively. Figure 1 below shows how the effective percentage of protected populations by a comprehensive SFA has increased since 1991.

FIGURE 1: EFFECTIVE PERCENTAGE OF THE POPULATION COVERED BY COMPREHENSIVE SFA, 1991-2014



Summary statistics are provided in table 2 and table 3. For the underlying cause of death, my outcome variable, I provide both the county mean number of deaths and the death rate. The mean number of deaths for AMI in a year in a county is 72, 67 for strokes, and 61 for CLRD. From 1991 to 2014 the SFA index annual average, the variable of interest, increased from zero to 44 percent. On average 12 percent of the population is protected by comprehensive laws that includes all venues of interest.

TABLE 2: SHORT RUN, COUNTY LEVEL SUMMARY STATISTICS

Variable		Mean	S.D.	Min	Max
Underlying Cause of Death - 20 Years and older					
AMI	Number of Deaths	72	177	10	5,773
	Death Rate	136	85	8	1,198
Strokes	Number of Deaths	67	154	10	4,430
	Death Rate	96	45	16	811
CLRD	Number of Deaths	61	123	10	3,057
	Death Rate	81	35	11	403
Underlying Cause of Death - 35-64 Year olds					
AMI	Number of Deaths	30	41	10	918
	Death Rate	60	46	4	452
SFA Index		12%	31%	0%	100%
SFA Dummy		11%	31%	0%	100%
Comprehensive Bar SFA - Annual Average		13%	33%	0%	100%
Comprehensive Restaurant SFA - Annual Average		17%	37%	0%	100%
Comprehensive Private Workplace SFA - Annual Average		20%	39%	0%	100%
Comprehensive Public Workplace SFA - Annual Average		28%	42%	0%	100%
County Level Unemployment Rate		6.3%	3.0%	0.7%	39.3%
County Level Real Price of a Pack of Cigarettes in 2014 Dollars		$ 3.83	$ 2.50	$ 0.91	$ 16.92
County Level Real Per Capita Income in 2014 Dollars		$ 33,523	$ 9,138	$ 7,668	$195,632
Average Fine Particulate Matter		10.26	2.50	3.70	30.30
Total Number of Grocery Stores and Supermarkets		21	80	0	2429
Total Number of Fruit and Vegetables Markets		1	5	0	186
Total Number of Beer, Wine and Liquor Stores		10	34	0	1158
Total Number of Number of Hospitals (All)		2	5	0	158
Total Number of Recreation and Fitness Facilities		9	28	0	845
Total Number of Full-Service Restaurants		68	224	0	7821
Total Number of Fast Food Restaurants		64	220	0	7798
Total Number of Bars and Drinking Establishments		15	46	0	1256
County Population		61,937	202,855	25	7,530,028

Summary statistics at the state level, shown in table 3 below, are similar to the county estimates.

TABLE 3: SHORT RUN STATE LEVEL SUMMARY STATISTICS

		Mean	S.D.	Min	Max
Underlying Cause of Death - 20 Years and older					
AMI	Number of Deaths	3487	3675	143	18844
	Death Rate	86	38	22	226
Strokes	Number of Deaths	2971	2967	186	18161
	Death Rate	74	17	36	133
CLRD	Number of Deaths	2486	2451	125	13578
	Death Rate	63	14	26	114
Appendicitis	Number of Deaths	19	10	10	64
	Death Rate	0.2	0.1	0.1	0.5
Underlying Cause of Death - 35-64 Year olds					
AMI	Number of Deaths	36	18	10	103
	Death Rate	692	659	11	3290
SFA Index		18%	35%	0%	100%
SFA Dummy		15%	35%	0%	100%
Comprehensive Bar SFA - Annual Average		19%	36%	0%	100%
Comprehensive Restaurant SFA - Annual Average		26%	40%	0%	100%
Comprehensive Private Workplace SFA - Annual Average		27%	41%	0%	100%
Comprehensive Public Workplace SFA - Annual Average		37%	41%	0%	100%
State Level Unemployment Rate		5.7%	1.9%	2.3%	13.7%
State Level Real Price of a Pack of Cigarettes in 2014 Dollars		$ 4.65	$ 1.52	$ 2.30	$ 10.74
State Level Real Per Capita Income in 2014 Dollars		$ 40,297	$ 7,659	$ 24,127	$ 72,812
Average Fine Particulate Matter		9.96	2.38	5.43	17.80
Total Number of Grocery Stores and Supermarkets		1347	1661	100	10323
Total Number of Fruit and Vegetables Markets		63	110	0	736
Total Number of Beer, Wine and Liquor Stores		618	685	14	3885
Total Number of Number of Hospitals (All)		144	121	14	692
Total Number of Recreation and Fitness Facilities		581	596	46	3709
Total Number of Full-Service Restaurants		4338	4738	501	29796
Total Number of Fast Food Restaurants		4078	4463	326	28292
Total Number of Bars and Drinking Establishments		947	1009	29	4208
State Population		3,960,821	4,399,957	47,424	28,600,000

Table 4 presents the mean number of deaths and the mean death rate by year for AMI, strokes, and CLRD mortality. The mean and death rate for AMI shows a clear decline for both those aged 20 years and older and those 35 to 64 years old. For strokes the mean number of deaths has remained steady, while the death rate has declined over time. For CLRD, both the mean and death rate have increased over time.

TABLE 4: COUNTY LEVEL MEAN DEATHS AND MEAN DEATH RATES FOR AMI, STROKES, AND CLRD MORTALITY

Year	AMI - 20 Years and Older		AMI - 35-64 Year Olds		Strokes - 20 Years and Older		CLRD - 20 Years and Older	
	Mean Number of Deaths	Mean Death Rate	Mean Number of Deaths	Mean Death Rate	Mean Number of Deaths	Mean Death Rate	Mean Number of Deaths	Mean Death Rate
1991	89	196	34	82	64	109	53	65
1992	87	189	33	76	65	107	54	65
1993	87	187	32	78	66	111	55	71
1994	85	178	32	73	68	110	56	70
1995	84	174	31	70	69	112	56	70
1996	83	167	31	66	69	111	57	70
1997	81	160	30	64	70	109	58	72
1998	81	156	30	61	69	107	58	74
1999	80	151	30	58	72	113	61	81
2000	77	145	30	57	73	109	61	79
2001	75	138	29	56	71	106	61	80
2002	74	135	29	56	71	104	61	81
2003	72	127	29	55	70	100	61	82
2004	67	115	29	53	68	94	61	78
2005	66	113	29	52	66	89	62	83
2006	63	107	27	52	64	84	61	79
2007	60	101	28	50	64	83	61	82
2008	60	103	28	52	63	81	65	90
2009	58	97	27	51	63	76	63	88
2010	57	94	27	51	62	77	63	88
2011	56	92	27	51	62	75	65	91
2012	55	93	27	52	63	74	65	91
2013	56	91	26	53	63	73	67	95
2014	54	90	27	54	65	74	66	94

2.4. Empirical Specification

I use a conditional negative binomial fixed-effects to estimate the causal effect that SFAs have had on AMI, strokes, and CLRD mortality. This panel data estimation method was originally developed by Hausman, Hall and Griliches (Hausman, Hall, & Griliches, 1984). I chose this model for several reasons. For one I have more than 20 panels of data, making the unconditional negative binomial fixed-effects model computationally difficult. In addition, having more than 20 panels of data can lead to the "incidental parameters problem[2]," leading to biased estimates as the number of panels increases (Hilbe, 2011). Furthermore, a negative binomial model, as opposed to a Poisson model, can be used to account for overdispersion. Overdispersion occurs when the conditional variance, for the dependent variable, is greater than the mean (Hilbe, 2011). This can be visually appreciated in the summary statistics, where the standard deviation is at least twice the size of the mean. Cameron and Trivedi argue that it is conceivable that including fixed-effects can control for some overdispersion in the data (Cameron & Trivedi, 2013). I tested this notion by running selective computationally intensive GLM models. The Pearson deviance statistics for the models that ran are close to 1.0 when a negative binomial model is used. On the other hand, Poisson models had Pearson deviance statistics that ranged between 2.0 and 4.0. For all model, except for the counterfactual, the Pearson dispersion statistic for the negative binomial was always smaller than the Poisson statistic, indicating that a negative binomial model did indeed correct for a substantial amount of overdispersion in the data, even in the presence of fixed-effects estimators. For available models, these results can be found in table 28 in the appendix. The appendix table also includes estimates for the SFA Index variable, confirming the validity of the unconditional and conditional fixed effects model results that will be presented in the following sections.

As a basic model, I use the following:

$$M_{it} = \beta_0 + \beta_1 SFA_{it} + \beta_2 U_{it} + \beta_3 ICD_t + \beta_4 X_{it} + \delta_t + \alpha_i + \varepsilon_{it}$$

M_{it} is a non-negative count variable for the number of deaths in county *i*, at year *t*. SFA_{it} is the key explanatory variable and it captures the effective percentage of the population in a county that are covered by a comprehensive bar, restaurant and private/public workplace. This effective percentage is a

[2] The "incidental parameters problem" is essentially a maximum likelihood problem. Since T_i is assumed fixed (and small) there will not be an asymptotic result that will provide consistency for the maximum likelihood estimator of α_i (Greene, 2012).

yearly average of people covered over 12 calendar months. This variable can be considered a lower bound measure of SFA coverage, as the population must be covered by all comprehensive bans (bar, restaurant, private/public workplaces) to be included in my measure. For example, the population in a county that is only covered by a comprehensive bar SFA, would not be included in this measure. I believe this measure captures the true nature of comprehensive coverage.

All models include a constant β_0; the county level unemployment rate, U_{it}; an ICD dummy to capture the change from ICD-9 to ICD-10 that occurred in 1999, ICD_t. *Xit* is a vector of further control variables: the real price of a pack of cigarettes (including taxes); real per capita personal income; the total number of grocery stores and supermarkets; the total number of fruit and vegetable markets; the total number of beer, wine and liquor stores; the total number of recreation and fitness facilities; the total number of bars and drinking establishments; the total number of full-service restaurants; the total number of fast food restaurants; the total number of all types of hospitals; and annual particulate matter which is a measure of outdoor pollution.

I also perform this analysis at the state level. All models include a year fixed-effects δ_t; a county (or state) fixed-effect, α_i; and an error term ε_{it}. County (or state) and year fixed-effects enter the model as dichotomous indicators for each county (or state) and each year. The model will exclude one county (or state) and one-year indicator. They are placed in the model to capture difference across counties (or states) and over time that are not captured by the other covariates in the model. To control for difference in county (or state) population size I use population as an exposure variable in all regressions. Lastly, all analyses are performed for the 48 continental states in the United States. Alaska and Hawaii were dropped from the analysis as to much data was missing to make any meaningful inference.

2.5. Results

2.5.1. Acute Myocardial Infarction

To make results comparable across cases, all models are restricted by years based on the availability of data. Table 5 presents the most basic results for those aged 20 and above and uses all years available of data, 1991-2014. The baseline specification includes SFAs, the unemployment rate, the ICD dummy, county, and year fixed-effects. Each specification adds a variable from the X_{it} vector. Therefore model 2 includes the real price of a pack of cigarettes; model 3 adds the real per capita personal income. Establishment data and particulate matter are not included in these results as data is not available for the years used. For ease of interpretation, all results are presented as incidence rate ratios.

TABLE 5: AMI RESULTS, 1991-2014 (BASELINE)

VARIABLES	(1)	(2)	(3)
SFA Index	0.937***	0.977***	0.977***
	(0.00335)	(0.00395)	(0.00398)
Unemployment Rate	0.991***	0.990***	0.989***
	(0.000662)	(0.000664)	(0.000676)
ICD Dummy	0.386***	0.447***	0.460***
	(0.00228)	(0.00400)	(0.00429)
Real Price of a Pack of Cigarettes in 2014 Dollars		0.978***	0.980***
		(0.000993)	(0.00101)
Real Per Capita Income in 2014 Dollars			1.000***
			(2.97e-07)
Constant	0.00116***	0.00121***	0.00134***
	(1.39e-05)	(1.48e-05)	(1.95e-05)
Observations	54,644	54,644	54,644
Number of Counties	2,741	2,741	2,741
Age	20plus	20plus	20plus
County FE	YES	YES	YES
Year FE	YES	YES	YES
Years Used	1991-2014	1991-2014	1991-2014
AIC	385,301	384,831	384,687
BIC	385,533	385,071	384,937

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

The baseline specification indicates that increasing comprehensive SFA protection from zero to 100 percent of the population leads to a 6.3 percent reduction in AMI deaths. Adding control variables decreases this reduction to 2.3 percent (model 3). Based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), model 3 is the preferred model. The AIC and BIC are general fit statistics. When using the AIC and BIC to compare models, one looks for the smallest value to assess the better-fitted model (Hilbe, 2011).

Table 6 presents results for years 1998-2014 and includes the data from County Business Patterns, again the years are restricted to accommodate the years of data that are available. These variables are intended to control for risk factors and behavior that affect AMI. The baseline specification indicates that increasing comprehensive SFA protection from zero to 100 percent of the population leads to a 3.8 (model 4) percent reduction in AMI deaths. Controlling for the presence of these various establishments reduces the main outcome variable to 2.8 percent (model 7). Based on the AIC and BIC statistic model 7, which includes all covariates, is the preferred model.

TABLE 6: AMI RESULTS, 1998-2014

VARIABLES	(4)	(5)	(6)	(7)
SFA Index	0.962***	0.980***	0.977***	0.972***
	(0.00364)	(0.00399)	(0.00402)	(0.00467)
Unemployment Rate	0.994***	0.993***	0.990***	0.990***
	(0.000911)	(0.000912)	(0.000962)	(0.00108)
ICD Dummy	0.482***	0.524***	0.536***	0.536***
	(0.00286)	(0.00479)	(0.00511)	(0.00626)
Real Price of a Pack of Cigarettes in 2014 Dollars		0.987***	0.989***	1.004***
		(0.00108)	(0.00110)	(0.00150)
Real Per Capita Income in 2014 Dollars			1.000***	1.000***
			(4.46e-07)	(5.58e-07)
Total Number of Grocery Stores and Supermarkets				0.999***
				(0.000116)
Total Number of Fruit and Vegetable Markets				0.994***
				(0.000519)
Total Number of Beer, Wine and Liquor Stores				0.998***
				(0.000188)
Total Number of Number of Hospitals (All)				0.997***
				(0.000662)
Total Number of Recreation and Fitness Facilities				1.000**
				(0.000173)
Total Number of Full-Service Restaurants				1.000***
				(5.35e-05)
Total Number of Fast Food Restaurants				1.000***
				(4.50e-05)
Total Number of Bars and Drinking Establishments				0.999***
				(0.000112)
Constant	0.00120***	0.00124***	0.00143***	0.00161***
	(1.85e-05)	(1.93e-05)	(3.01e-05)	(3.99e-05)
Observations	36,958	36,958	36,958	36,958
Number of Counties	2,600	2,600	2,600	2,600
Age	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Years Used	1998-2014	1998-2014	1998-2014	1998-2014
AIC	245,977	245,840	245,746	243,373
BIC	246,139	246,010	245,925	243,620

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

The last set of models is for years 2001-2014 and adds average particulate matter as a control variable. Given that ICD codes changed in 1999, these regressions do not include the ICD dummy. The baseline estimate indicates that increasing comprehensive SFA protection from zero to 100 percent of the population leads to a 3.4 (model 8) percent reduction in deaths. Controlling for all other covariates and adding the average particulate matter, the main outcome variable is reduced to 2.7 percent (model 12).

Based on the AIC and BIC statistic model 12, which now fully includes all covariates, is the preferred model specification.

TABLE 7: AMI RESULTS, 2001-2014

VARIABLES	(8)	(9)	(10)	(11)	(12)
SFA Index	0.966***	0.977***	0.975***	0.974***	0.973***
	(0.00397)	(0.00413)	(0.00416)	(0.00483)	(0.00483)
Unemployment Rate	1.001	1.000	0.998*	0.997***	0.997**
	(0.00113)	(0.00113)	(0.00119)	(0.00134)	(0.00135)
Real Price of a Pack of Cigarettes in 2014 Dollars		0.986***	0.988***	1.005***	1.004***
		(0.00119)	(0.00121)	(0.00163)	(0.00163)
Real Per Capita Income in 2014 Dollars			1.000***	1.000***	1.000***
			(4.99e-07)	(6.39e-07)	(6.41e-07)
Total Number of Grocery Stores and Supermarkets				0.999***	0.999***
				(0.000139)	(0.000138)
Total Number of Fruit and Vegetable Markets				0.994***	0.994***
				(0.000564)	(0.000565)
Total Number of Beer, Wine and Liquor Stores				0.998***	0.998***
				(0.000219)	(0.000218)
Total Number of Number of Hospitals (All)				0.999*	0.999**
				(0.000675)	(0.000676)
Total Number of Recreation and Fitness Facilities				0.999***	0.999**
				(0.000205)	(0.000205)
Total Number of Full-Service Restaurants				1.000***	1.000***
				(6.12e-05)	(6.11e-05)
Total Number of Fast Food Restaurants				1.000***	1.000***
				(5.29e-05)	(5.28e-05)
Total Number of Bars and Drinking Establishments				0.999***	0.999***
				(0.000127)	(0.000132)
Average Fine Particulate Matter					1.004***
					(0.00130)
Constant	0.0012***	0.0013***	0.0014***	0.0016***	0.0015***
	(2.32e-05)	(2.49e-05)	(3.73e-05)	(4.88e-05)	(5.22e-05)
Observations	29,694	29,694	29,694	29,694	29,694
Number of Counties	2,524	2,524	2,524	2,524	2,524
Age	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Years Used	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014
AIC	190,354	190,226	190,174	188,482	188,472
BIC	190,487	190,367	190,323	188,698	188,696

seEform in parentheses/unconditional model has county clustered se

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As expected, the real price of cigarettes, the unemployment rate, and real per capita income are significant predictors in the model. The results for the real price of cigarettes for models 11 and 12 are troublesome; the results for models 9 and 10 are in line with the finding of *Death and Taxes* (Moore, 1996). The results indicate that increasing the real price of cigarettes by one dollar will decrease AMI mortality by 1.4 and 1.2 percent. Moore finds that increasing tobacco taxes by 10 percent would save over 6,000 lives a year.

Theoretically the effect of unemployment on AMI mortality is ambiguous, but empirically it has led to a lively discussion. For one, job related stress could lead to increases in AMI, though not being employed could also lead to increases in stress and AMI mortality. The results for unemployment indicate that increases in the unemployment rate lead to decreases in AMI mortality (models 1, 2, 3, 4, 5, 6, 7, 10, 11, and 12; models 8 and 9 are not statically significant). A recent paper argues that this relationship is U-shaped, and mortality decreases for lower levels of unemployment and increase once unemployment is closer to 17 percent (Bonamore, Carmignani, & Colombo, 2015). This result support this notion, as the average county level unemployment level during this time period is 6.3 percent.

Next, I present results for what I call the "full sample." Given the restriction placed on the mortality outcome[3] these results restrict the data set to panels that include AMI death counts for all years. In other words, I only include panels that have mortality counts for all 24 years of data, effectively restricting my sample to large counties. For brevity, I only present the model number, the incident rate ratio for the SFA index, the standard error in parenthesis, AIC, and BIC statistics. These models replicate the models found in table 5,6, and 7.

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[3] As mentioned in section 1.3, one of the major disadvantages of using the CDC Wonder Compressed Mortality data set is the data restriction placed upon it per the Public Health Service Act (42 U.S.C. 242m(d)). This act stipulates that data contained in the CDC Wonder Compressed mortality dataset should not be presented nor published when death counts are 9 or fewer.

TABLE 8: AMI RESULTS, ALL MODELS WITH "FULL SAMPLE" RESTRICTED DATA

	(1)	(2)	(3)	(4)	(5)	(6)
SFA Index - Full Sample	0.940***	0.978***	0.977***	0.967***	0.982***	0.979***
	(0.00389)	(0.00456)	(0.00459)	(0.00415)	(0.00452)	(0.00456)
AIC	279,738	279,430	279,319	186,324	186,249	186,167
BIC	279,959	279,660	279,557	186,479	186,412	186,338
Covariates	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Full Sample	YES	YES	YES	YES	YES	YES
Years Used	1991-2014	1991-2014	1991-2014	1998-2014	1998-2014	1998-2014
	(7)	(8)	(9)	(10)	(11)	(12)
SFA Index - Full Sample	0.973***	0.969***	0.978***	0.976***	0.973***	0.973***
	(0.00499)	(0.00448)	(0.00465)	(0.00468)	(0.00513)	(0.00514)
AIC	184,527	147,685	147,612	147,558	146,395	146,388
BIC	184,764	147,813	147,747	147,701	146,602	146,603
Covariates	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Full Sample	YES	YES	YES	YES	YES	YES
Years Used	1998-2014	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

The results from tables 5-7 and table 8 don't vary drastically. Both model 12 of table 7 and model 12 of the restricted "full sample" estimate a 2.7 percent reduction in AMI, as seen in table 8.

The conditional negative binomial fixed-effect model that I use was originally developed by Hausman, Hall, and Griliches (HHG) in 1984 (Hausman et al., 1984). In this model, the conditional negative binomial fixed-effects estimator conditions the likelihood function for each panel by the sum of the counts for that panel, effectively eliminating panel-level heterogeneity (Poi, Sanchez, & MacDonald, 2012). In other words, the model is specifically derived by conditioning out the fixed-effects from the model estimation (Hilbe, 2011). This peculiarity allows the model to adjust for a near infinite number of panels (Hilbe, 2011). This last characteristic is important for my model, as I have data for 3,109 counties over 24 years.

However, conditional negative binomial fixed-effects models are somewhat controversial. In 2002, Allison and Waterman demonstrated that HHGs model is not a true fixed-effects model, as it does not control for all time invariant covariates (Allison & Waterman, 2002). In their paper they propose using an unconditional negative binomial model as an alternative estimation method. Unfortunately using an unconditional negative binomial is not easy, as it is computationally intensive[4] to enter each fixed-effect in the model. Furthermore, in the presence of a large number of fixed-effects (as is the case in my models) estimators may be inconsistent. The inconsistency stems from how the fixed-effects are built into the distribution of the gamma heterogeneity, α, instead of building them into the mean. This construction makes the incidental parameters problem hard to interpret; exactly how the estimators are inconsistent is also a matter of debate (Baltagi, 2013; Greene, 2012) .

I believe the debate should really center on what one considers to be a fixed-effect. Allison and Waterman argue that because in HHG's model the panel dummies and their coefficients do not have the same role as the other regressors in the model, it is therefore not a true fixed-effects model(Allison & Waterman, 2002). In other words, Allison and Waterman view fixed-effects models as extensions of pooled estimators that include a set of dummy variables that allow for panel-specific constant terms (Allison & Waterman, 2002). If, however one considers fixed-effect estimators as estimators that allow for panel-level heterogeneity then HHG's estimator is a valid fixed-effects estimator (Poi et al., 2012).

Even though the unconditional model is computationally intensive and suffers from the incidental parameters problem, I provide estimates of all 12 models for sensitivity purposes. For comparison purposes I also provide the estimates for the 12 conditional model estimates (tables 5, 6 and 7), and the 12 "full sample" conditional model estimates (results from table 8). As can be seen in table 9, the results don't vary drastically. As mentioned above, for model 12, the conditional negative binomial fixed-effects model and the "full sample" conditional negative binomial fixed-effects model estimate a 2.7 percent

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[4] As an example, one of my models ran for 11 days.

reduction. The unconditional version estimates a 3.1 percent reduction, while the unconditional "full sample" version estimates a 3.2 percent reduction. Based on AIC and BIC statistical estimates, the best model is the "full-sample" conditional negative binomial fixed-effects model.

TABLE 9: AMI RESULTS, 2001-2014, CONDITIONAL AND UNCONDITIONAL MODELS

VARIABLES	Conditional (12)	Conditional (12)	Unconditional (12)	Unconditional (12)
SFA Index	0.973***	0.973***	0.969***	0.968***
	(0.00483)	(0.00514)	(0.00906)	(0.0101)
Unemployment Rate	0.997**	0.997*	1.002	1.000
	(0.00135)	(0.00150)	(0.00226)	(0.00264)
Real Price of a Pack of Cigarettes in 2014 Dollars	1.004***	1.006***	0.996	0.999
	(0.00163)	(0.00172)	(0.00331)	(0.00358)
Real Per Capita Income in 2014 Dollars	1.000***	1.000***	1.000	1.000
	(6.41e-07)	(7.07e-07)	(1.05e-06)	(1.30e-06)
Total Number of Grocery Stores and Supermarkets	0.999***	1.000***	1.000	1.000
	(0.000138)	(6.20e-05)	(0.000197)	(0.000190)
Total Number of Fruit and Vegetable Markets	0.994***	1.001	1.002	1.002
	(0.000565)	(0.000728)	(0.00115)	(0.00114)
Total Number of Beer, Wine and Liquor Stores	0.998***	0.999***	0.999**	0.999**
	(0.000218)	(0.000188)	(0.000446)	(0.000434)
Total Number of Number of Hospitals (All)	0.999**	0.998***	1.001	1.001
	(0.000676)	(0.000594)	(0.00135)	(0.00132)
Total Number of Recreation and Fitness Facilities	0.999**	1.000*	1.000	1.000
	(0.000205)	(0.000178)	(0.000300)	(0.000303)
Total Number of Full-Service Restaurants	1.000***	1.000***	1.000	1.000
	(6.11e-05)	(5.25e-05)	(0.000158)	(0.000149)
Total Number of Fast Food Restaurants	1.000***	1.000***	1.000***	1.000***
	(5.28e-05)	(4.46e-05)	(0.000102)	(9.89e-05)
Total Number of Bars and Drinking Establishments	0.999***	0.999***	1.000	1.000
	(0.000132)	(0.000111)	(0.000328)	(0.000321)
Average Fine Particulate Matter	1.004***	1.004***	1.010***	1.008***
	(0.00130)	(0.00134)	(0.00266)	(0.00292)
Constant	0.00154***	0.00104***	0.000714***	0.000614***
	(5.22e-05)	(3.87e-05)	(3.75e-05)	(3.94e-05)
Observations	29,694	21,218	29,796	21,218
Number of Counties	2,524	1,516	2,524	1,516
Age	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Full Sample		YES		YES
Years Used	2001-2014	2001-2014	2001-2014	2001-2014
AIC	188,472	146,388	206,336	158,984
BIC	188,696	146,603	206,560	159,199

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

As a final sensitivity analysis, I rerun all the models in table 9 using an SFA dummy variable. The SFA dummy is a dichotomous variable that takes on the value of one when 100 percent of the population in a county is covered by all (bar, restaurant, private/public workplaces) SFAs, and zero otherwise. This measure is more restrictive than the SFA Index variable used above, as the whole county has to be protected by comprehensive SFAs. These results are presented in table 10; while smaller they are essentially the same.

TABLE 10: AMI RESULTS, 2001-2014, CONDITIONAL AND UNCONDITIONAL MODELS USING SFA DUMMY

VARIABLES	Conditional (12)	Conditional (12)	Unconditional (12)	Unconditional (12)
SFA Dummy	0.970***	0.971***	0.970***	0.969***
	(0.00448)	(0.00489)	(0.00814)	(0.00897)
Unemployment Rate	0.996***	0.997*	1.002	1.000
	(0.00132)	(0.00149)	(0.00226)	(0.00264)
Real Price of a Pack of Cigarettes in 2014 Dollars	1.004**	1.006***	0.996	0.999
	(0.00158)	(0.00172)	(0.00328)	(0.00354)
Real Per Capita Income in 2014 Dollars	1.000***	1.000***	1.000	1.000
	(6.29e-07)	(7.06e-07)	(1.05e-06)	(1.30e-06)
Total Number of Grocery Stores and Supermarkets	1.000***	1.000***	1.000	1.000
	(0.000117)	(6.11e-05)	(0.000197)	(0.000190)
Total Number of Fruit and Vegetable Markets	0.999	1.001	1.002	1.002
	(0.00155)	(0.000717)	(0.00115)	(0.00115)
Total Number of Beer, Wine and Liquor Stores	0.999***	0.999***	0.999**	0.999**
	(0.000215)	(0.000188)	(0.000446)	(0.000433)
Total Number of Number of Hospitals (All)	0.998***	0.998***	1.001	1.001
	(0.000615)	(0.000592)	(0.00135)	(0.00132)
Total Number of Recreation and Fitness Facilities	0.999***	1.000*	1.000	1.000
	(0.000183)	(0.000178)	(0.000299)	(0.000302)
Total Number of Full-Service Restaurants	1.000***	1.000***	1.000	1.000
	(5.33e-05)	(5.23e-05)	(0.000158)	(0.000149)
Total Number of Fast Food Restaurants	1.000***	1.000***	1.000***	1.000***
	(4.60e-05)	(4.47e-05)	(0.000101)	(9.88e-05)
Total Number of Bars and Drinking Establishments	0.999***	0.999***	1.000	1.000
	(0.000114)	(0.000111)	(0.000327)	(0.000320)
Average Fine Particulate Matter	1.004***	1.004***	1.010***	1.008***
	(0.00123)	(0.00134)	(0.00267)	(0.00293)
Constant	0.00150***	0.00104***	0.000714***	0.000613***
	(4.94e-05)	(3.87e-05)	(3.76e-05)	(3.94e-05)
Observations	29,694	21,218	29,796	21,218
Number of Counties	2,524	1,516		
Age	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Full Sample		YES		YES
Years Used	2001-2014	2001-2014	2001-2014	2001-2014
AIC	188,501	146,382	206,335	158,982
BIC	188,725	146,597	206,559	159,197

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

2.5.1.1. Acute Myocardial Infarction for those 35 to 64 years old

The hospitalization literature has heavily focused on the effects of SFAs on those 35 to 64 years old. Below I present the results for model 12, though instead of focusing on the adult population that is 20 years and older, I restrict the estimates to those 35 to 64 years old. The conditional negative binomial fixed-effects results indicate a 5.7 percent reduction, while the "full sample" results indicate a 4.5 percent reduction. For the unconditional models the decrease is 5.2 and 4.7 percent respectively. The results are consistent with the literature; SFAs protect this age group the most.

TABLE 11: AMI RESULTS, 2001-2014, CONDITIONAL AND UNCONDITIONAL MODELS FOR 35-64 YEAR OLDS

VARIABLES	Conditional (12)	Conditional (12)	Unconditional (12)	Unconditional (12)
SFA Index	0.943***	0.955***	0.947***	0.953**
	(0.00888)	(0.0119)	(0.0154)	(0.0202)
Unemployment Rate	0.995*	0.998	0.997	0.994
	(0.00261)	(0.00371)	(0.00437)	(0.00643)
Real Price of a Pack of Cigarettes in 2014 Dollars	0.992***	0.991**	0.984***	0.987*
	(0.00304)	(0.00397)	(0.00554)	(0.00692)
Real Per Capita Income in 2014 Dollars	1.000***	1.000***	1.000	1.000
	(1.16e-06)	(1.44e-06)	(1.91e-06)	(2.65e-06)
Total Number of Grocery Stores and Supermarkets	1.000**	1.000	1.000	1.000
	(7.63e-05)	(7.78e-05)	(0.000179)	(0.000152)
Total Number of Fruit and Vegetable Markets	0.999	1.001	1.000	1.000
	(0.000973)	(0.000972)	(0.00136)	(0.00131)
Total Number of Beer, Wine and Liquor Stores	0.999***	1.000	1.000	1.000
	(0.000253)	(0.000271)	(0.000489)	(0.000469)
Total Number of Number of Hospitals (All)	0.999	0.999	1.001	1.001
	(0.000822)	(0.000874)	(0.00146)	(0.00142)
Total Number of Recreation and Fitness Facilities	0.999***	0.999**	1.000	0.999
	(0.000265)	(0.000279)	(0.000403)	(0.000419)
Total Number of Full-Service Restaurants	1.000**	1.000	1.000	1.000
	(7.68e-05)	(7.79e-05)	(0.000165)	(0.000142)
Total Number of Fast Food Restaurants	1.000***	1.000***	1.000***	1.000***
	(6.34e-05)	(6.42e-05)	(0.000100)	(9.76e-05)
Total Number of Bars and Drinking Establishments	0.999***	1.000**	1.000	1.000
	(0.000162)	(0.000178)	(0.000327)	(0.000319)
Average Fine Particulate Matter	1.007***	1.002	1.010**	1.003
	(0.00228)	(0.00281)	(0.00439)	(0.00497)
Constant	0.00184***	0.000577***	0.000675***	0.00109***
	(0.000138)	(5.05e-05)	(6.42e-05)	(0.000124)
Observations	11,214	5,036	11,419	5,036
Number of Counties	1,221	360		
Age	35-64	35-64	35-64	35-64
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Full Sample		YES		YES
Years Used	2001-2014	2001-2014	2001-2014	2001-2014
AIC	60,311	31,858	68,993	34,982
BIC	60,509	32,034	69,192	35,158

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

2.5.1.2. State Level Results for Acute Myocardial Infarction

Lastly, I present state level results. The conditional and unconditional negative binomial fixed-effects results for both the SFA index variable and the SFA dummy variable are presented in table 12. These results also include the estimates for the population 20 years and older and for the subpopulation of those 35 to 64 years old. For the population 20 years and older, the SFA index and dummy indicates a 3.3 to 4.1 percent reduction. For those 35 to 64 years old, this range is 3.3 to 4.6 percent depending on the model. These results are very similar to the ones presented at the county level. This finding corroborates the validity of the county level estimates, as the state level data does not have missing data points as the county level data does.

TABLE 12: AMI RESULTS, 2001-2014, CONDITIONAL AND UNCONDITIONAL STATE LEVEL MODELS

VARIABLES	Conditional (12)	Unconditional (12)
SFA Index (Age 20 Plus)	0.967***	0.960***
	(0.00910)	(0.00792)
SFA Index (Age 35-64)	0.964**	0.967
	(0.0144)	(0.0309)
SFA Dummy (Age 20 Plus)	0.960***	0.959**
	(0.00792)	(0.0166)
SFA Dummy (Age 35-64)	0.954***	0.955*
	(0.0125)	(0.0238)
Covariates	YES	YES
State FE	YES	YES
Year FE	YES	YES
Years Used	2001-2014	2001-2014

seEform in parentheses/unconditional model has state clustered se
*** p<0.01, ** p<0.05, * p<0.1

2.5.2. Strokes

In this section I will present results for stroke mortality. The methodology is identical to the one presented in the AMI section. For brevity I will present condensed results and only for those individuals who are 20 years and older. The latter restriction is due to missing data given the CDC Underlying Cause of Mortality file data restriction, which suppresses data to zero when less than 9 people died in a county in a year.

Model 1 is analogues to model 12 from AMI. Columns 1, 2, and 4 present results for the conditional fixed-effects model; columns 3, 4, and 6 are the unconditional fixed-effects models. Columns 1, 2, 3 and 4 are for county level estimates, while 5 and 6 present state level estimates. Finally, column 2 and 4 are results for the county restricted “full sample.”

The first thing to note is that all results that use the unconditional fixed-effects model are statistically insignificant. When I use non-county/state clustered standard errors, these results are statistically significant (results not shown). When clustering the standard error at the county/state level the error term is twice the size, this can also be appreciated when comparing the standard errors of the conditional fixed-effects model to those of the unconditional fixed-effects model.

For statistically significant results, the estimates indicate that increasing comprehensive SFA protection from zero to 100 percent population coverage leads to a 0.9 to 1.7 percent reduction in stroke deaths for those 20 years and older.

TABLE 13: STROKE RESULTS, 2001-2014, COUNTY AND STATE, CONDITIONAL AND UNCONDITIONAL MODELS

VARIABLES	Conditional (12)	Conditional (12)	Un-conditional (12)	Un-conditional (12)	Conditional (12)	Un-conditional (12)
SFA Index	0.989***	0.989***	0.990	0.991	0.983**	0.991
	(0.00348)	(0.00390)	(0.00617)	(0.00658)	(0.00686)	(0.0131)
Unemployment Rate	0.999	0.998*	1.001	1.000	0.993***	0.995
	(0.000996)	(0.00115)	(0.00179)	(0.00202)	(0.00257)	(0.00460)
Real Price of a Pack of Cigarettes in 2014	1.003**	1.004***	1.001	1.003	1.004	0.995
Dollars	(0.00112)	(0.00125)	(0.00204)	(0.00210)	(0.00393)	(0.00826)
Real Per Capita Income	1.000***	1.000***	1.000	1.000	1.000***	1.000***
in 2014 Dollars	(4.20e-07)	(4.88e-07)	(7.50e-07)	(8.83e-07)	(1.44e-06)	(2.53e-06)
Total Number of Grocery	1.000***	0.996***	1.000**	1.000*	0.995**	0.992*
Stores and Supermarkets	(2.55e-05)	(0.000935)	(9.18e-05)	(8.84e-05)	(0.00220)	(0.00426)
Total Number of Fruit	1.000	1.000***	1.000	1.000	1.000	1.000
and Vegetable Markets	(0.000298)	(2.79e-05)	(0.000971)	(0.000961)	(9.24e-06)	(1.92e-05)
Total Number of Beer,	1.000	1.000	1.000	1.000	1.000**	1.000
Wine and Liquor Stores	(9.52e-05)	(0.000332)	(0.000262)	(0.000255)	(0.000134)	(0.000391)
Total Number of Number	1.000	1.000	1.001	1.001	1.000	1.000
of Hospitals (All)	(0.000264)	(0.000104)	(0.000714)	(0.000710)	(2.60e-05)	(5.45e-05)
Total Number of Recreation and Fitness	1.000	1.000	1.000	1.000	1.000***	1.000***
Facilities	(8.14e-05)	(0.000291)	(0.000197)	(0.000197)	(9.61e-05)	(0.000143)
Total Number of Full-	1.000***	1.000	1.000***	1.000***	1.000	1.000
Service Restaurants	(2.22e-05)	(9.04e-05)	(8.23e-05)	(7.78e-05)	(2.10e-05)	(3.23e-05)
Total Number of Fast	1.000***	1.000***	1.000	1.000*	1.000***	1.000**
Food Restaurants	(1.93e-05)	(2.48e-05)	(5.74e-05)	(5.66e-05)	(5.88e-06)	(1.25e-05)
Total Number of Bars and Drinking	1.000***	1.000***	1.000	1.000	1.000***	1.000**
Establishments	(5.75e-05)	(2.14e-05)	(0.000173)	(0.000170)	(5.41e-06)	(1.08e-05)
Average Fine Particulate	0.997***	1.000***	0.997	0.995**	1.000***	1.000
Matter	(0.000840)	(6.39e-05)	(0.00199)	(0.00214)	(1.29e-05)	(2.74e-05)
Constant	0.00540***	0.00252***	0.000820***	0.000859***	0.000555***	0.00146***
	(0.000295)	(0.000105)	(3.51e-05)	(4.22e-05)	(6.14e-05)	(0.000186)
Observations	27,979	19,412	28,112	19,412	683	683
Number of Counties/States	2,401	1,387				
Age	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES		
State FE					YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Full Sample		YES		YES		
Years Used	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014
AIC	163,287	124,643	181,081	136,102	7,212	7,855
BIC	163,510	124,856	181,304	136,314	7,334	7,977

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

Next, I present results using the SFA dummy instead of the SFA index (table 14). Whereas in the AMI results, where the change in SFA variable did not seem to matter, it does appear to matter for stroke mortality. In this case, not only are most of the results statistically significant, they are also larger. Depending on the specification used, SFA protection has led to anywhere from a 1.1 to a 1.6 percent reduction in stroke mortality for the population 20 years and older.

TABLE 14: STROKE RESULTS, 2001-2014, COUNTY AND STATE, CONDITIONAL AND UNCONDITIONAL MODELS, USING SFA DUMMY

	Conditional (12)	Conditional (12)	Unconditional (12)	Unconditional (12)	Conditional (12)	Unconditional (12)
SFA Dummy	0.987***	0.987***	0.989*	0.988*	0.984***	0.987
	(0.00330)	(0.00369)	(0.00588)	(0.00626)	(0.00600)	(0.0114)
Covariates	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES		
State FE					YES	YES
Full Sample		YES		YES		
Year FE	YES	YES	YES	YES	YES	YES
Years Used	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014

seEform in parentheses/unconditional model has county/state clustered se
*** p<0.01, ** p<0.05, * p<0.1

2.5.3. Chronic Lower Respiratory Disease

In this section I follow the same structure as the results presented for stroke mortality. To reiterate, column 1, 2, and 4 present results for the conditional fixed-effects model; columns 3, 4, and 6 are the unconditional fixed-effects models. Columns 1, 2, 3 and 4 are for county level estimates, while 5 and 6 present state level estimates. Finally, column 2 and 4 are results for the county restricted “full sample.”

For both models, the state level results are four times larger than the county level results. I believe this is due to the missing data present in the county file, given the CDC Underlying Cause of Mortality file data restriction. At the state level SFA protection has led to a 4.2 to 4.6 percent reduction in CLRD mortality.

TABLE 15: CLRD RESULTS, 2001-2014, COUNTY AND STATE, CONDITIONAL AND UNCONDITIONAL MODELS

VARIABLES	Conditional (12)	Conditional (12)	Un-conditional (12)	Un-conditional (12)	Conditional (12)	Un-conditional (12)
SFA Index	0.991**	0.996	0.988**	0.994	0.958***	0.954***
	(0.00358)	(0.00423)	(0.00594)	(0.00668)	(0.00818)	(0.0138)
Unemployment Rate	0.998*	0.997***	0.999	0.998	0.988***	0.989**
	(0.000991)	(0.00120)	(0.00162)	(0.00193)	(0.00292)	(0.00536)
Real Price of a Pack of Cigarettes in 2014 Dollars	0.991***	0.993***	0.988***	0.989***	0.992*	0.984
	(0.00112)	(0.00130)	(0.00211)	(0.00226)	(0.00475)	(0.0104)
Real Per Capita Income in 2014 Dollars	1.000***	1.000***	1.000***	1.000**	1.000***	1.000***
	(4.40e-07)	(5.31e-07)	(9.68e-07)	(1.14e-06)	(1.61e-06)	(2.30e-06)
Total Number of Grocery Stores and Supermarkets	1.000**	1.000**	1.000	1.000	1.009***	1.008
	(2.88e-05)	(3.38e-05)	(0.000126)	(0.000121)	(0.00274)	(0.00513)
Total Number of Fruit and Vegetable Markets	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000346)	(0.000414)	(0.000942)	(0.000913)	(1.43e-05)	(3.13e-05)
Total Number of Beer, Wine and Liquor Stores	1.000**	1.000**	1.000	1.000	1.000	1.000
	(0.000106)	(0.000119)	(0.000411)	(0.000400)	(0.000187)	(0.000330)
Total Number of Number of Hospitals (All)	1.000	1.000	1.001	1.001	1.000*	1.000
	(0.000302)	(0.000351)	(0.000916)	(0.000907)	(3.18e-05)	(6.24e-05)
Total Number of Recreation and Fitness Facilities	1.000	1.000	1.000	1.000	1.000	1.000
	(9.36e-05)	(0.000111)	(0.000225)	(0.000227)	(0.000126)	(0.000202)
Total Number of Full-Service Restaurants	1.000***	1.000***	1.000**	1.000**	1.000	1.000
	(2.68e-05)	(3.31e-05)	(0.000106)	(0.000104)	(2.87e-05)	(4.70e-05)
Total Number of Fast Food Restaurants	1.000***	1.000***	1.000	1.000*	1.000***	1.000***
	(2.24e-05)	(2.65e-05)	(6.49e-05)	(6.44e-05)	(7.75e-06)	(1.54e-05)
Total Number of Bars and Drinking Establishments	0.999***	0.999***	1.000	1.000	1.000	1.000
	(6.31e-05)	(7.19e-05)	(0.000223)	(0.000221)	(7.14e-06)	(1.54e-05)
Average Fine Particulate Matter	1.006***	1.006***	1.003	1.004	1.000***	1.000*
	(0.000887)	(0.00103)	(0.00220)	(0.00234)	(1.59e-05)	(2.89e-05)
Constant	0.00425***	0.00172***	0.000791***	0.000708***	0.000346***	0.00107***
	(0.000232)	(7.28e-05)	(3.70e-05)	(3.97e-05)	(3.97e-05)	(0.000136)
Observations	27,940	16,460	28,057	16,460	683	683
Number of Counties/States	2,402	1,176				
Age	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES		
State FE					YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Full Sample		YES		YES		
Years Used	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014
AIC	163,472	109,120	181,193	119,124	7,380	8,011
BIC	163,695	109,328	181,415	119,332	7,502	8,133

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

Using the SFA dummy variable instead, seems to closely reiterate the validity of my results. At the state level there appears to be a 4.7 to 4.9 percent reduction in CLRD mortality.

TABLE 16: CLRD RESULTS, 2001-2014, COUNTY AND STATE, CONDITIONAL AND UNCONDITIONAL EFFECTS MODELS, USING SFA DUMMY

	Conditional (12)	Conditional (12)	Unconditional (12)	Unconditional (12)	Conditional (12)	Unconditional (12)
SFA Dummy	0.987***	0.990**	0.987**	0.991	0.953***	0.951***
	(0.00337)	(0.00397)	(0.00549)	(0.00614)	(0.00692)	(0.0106)
Covariates	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES		
State FE					YES	YES
Full Sample		YES		YES		
Year FE	YES	YES	YES	YES	YES	YES
Years Used	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014	2001-2014

seEform in parentheses/unconditional model has county/state clustered se
*** p<0.01, ** p<0.05, * p<0.1

2.5.4. Sensitivity Analysis: Appendicitis

Given that SFA protection will not affect all types of mortality, I run a counterfactual model at the state level using appendicitis as my mortality outcome. Given the CDC Wonder Underlying Cause of Death file restriction I can only estimate this model at the state level, as most counties have missing data at the county level. This is a problem for me, not for society, as not a lot of individuals die of appendicitis. I use appendicitis as a counterfactual as one would not expect SFAs to affect this underlying cause of death. The results are below in table 17. As can be seen, these results are not statistically significant for either the SFA index or the SFA dummy; for that matter none of the variables, except for particulate matter, are statistically significant. For this specific model I used a Poisson regression (note the lack of a constant term), as the negative binomial version never converged and was not necessary given the lack of overdispersion in the data (these results can be found in the appendix in table 28). I believe these results validate the results obtained for AMI, strokes, and CLRD.

TABLE 17: APPENDICITIS STATE LEVEL RESULTS, 2001-2014, POISSON MODEL, USING SFA INDEX AND SFA DUMMY

VARIABLES	Index (12)	Dummy (12)
SFA	0.855	0.864
	(0.0848)	(0.0779)
Unemployment Rate	1.061	1.058
	(0.0459)	(0.0461)
Real Price of a Pack of Cigarettes in 2014 Dollars	1.024	1.016
	(0.0595)	(0.0590)
Real Per Capita Income in 2014 Dollars	1.000*	1.000
	(2.72e-05)	(2.73e-05)
Total Number of Grocery Stores and Supermarkets	1.000	1.000
	(0.000110)	(0.000112)
Total Number of Fruit and Vegetable Markets	1.000	1.000
	(0.00152)	(0.00152)
Total Number of Beer, Wine and Liquor Stores	1.000	1.000
	(0.000344)	(0.000343)
Total Number of Number of Hospitals (All)	1.001	1.001
	(0.00120)	(0.00120)
Total Number of Recreation and Fitness Facilities	1.000	1.000
	(0.000288)	(0.000287)
Total Number of Full-Service Restaurants	1.000	1.000
	(7.31e-05)	(7.29e-05)
Total Number of Fast Food Restaurants	1.000	1.000
	(6.70e-05)	(6.74e-05)
Total Number of Bars and Drinking Establishments	1.000	1.000
	(0.000170)	(0.000168)
Average Fine Particulate Matter	1.084**	1.081**
	(0.0356)	(0.0351)
Observations	182	182
Number of States	22	22
Age	20plus	20plus
State FE	YES	YES
Year FE	YES	YES
Years Used	2001-2014	2001-2014
AIC	842	842
BIC	925	925

seEform in parentheses/unconditional model has state clustered se
*** p<0.01, ** p<0.05, * p<0.1

2.6. Discussion

SFAs are one of many successful tobacco control policies. They are implemented with the intention of protecting nonsmokers from the harm associated with secondhand smoke, but their success extends beyond this initial goal. SFAs have led to decreases in smoking, increases in quits and quit attempts, decreases in initiation, decreases in hospitalization for certain conditions, and as this chapter has proven they have also lead to decreases in mortality from AMI, strokes, and CLRD.

My estimates show that at the county level AMI mortality has decreased by 2.7 to 3.2 percent for those 20 years and older, and 4.5 to 5.7 percent for those 35 to 64 years old. Stroke mortality has decreased by 1.1 to 1.3 percent, and CLRD mortality has decreased by 0.9 to 1.3 percent for those 20 years and older. At the state level the estimates are larger: 3.3 to 4.1 percent for AMI for those 20 years and older, 3.6 to 4.6 percent for AMI for those 35 to 64 years old, 1.6 to 1.7 percent for strokes for those 20 years and older, and 4.2 to 4.9 percent for CLRD for those 20 years and older.

All estimates appear to be small when compared with previous studies. For AMI, the previous literature finds a range of 3.8 (Belgium study) to 18 percent (Spanish study). For strokes, the only study available uses Irish data and provides an estimate of 38 percent, which is 22 times larger than my largest estimate of 1.7 percent. The results for CLRD are the first to be estimated, they are larger than those provided for AMI and strokes. However, my largest result of 4.9 percent is half the size of the lower bound estimate provided in the hospitalization literature, which ranges from 9 to 46 percent.

There are five drawbacks to this study that are worth noting. The main drawback is not being able to distinguish whether smokers or nonsmokers have benefited the most from the implementation of SFAs. In the same matter this study does not distinguish if certain age groups over the age of 20, or whether women or men benefited the most. Though as the results for AMI for the population 35-64 years old showed, this population appears to have an increased benefit. The main reason this study is not able to obtain these results is lack of mortality data for small counties. The CDC Wonder Underlying Cause of Death file has a restriction that does not provide data if less than 9 people died in a county. For some of these groups, upwards of 90 percent of the data was missing, making inference meaningless. Though as mentioned, I was able to estimate the impact of SFAs on AMI for those aged 35 to 64.

As in any study, it is possible that the effect of SFAs that I estimate is entirely due to unobserved heterogeneity. One would worry that healthy counties on average would tend to pass more comprehensive SFAs than unhealthy counties. I believe by using fixed-effects modeling to capture within and not across county variation in the data, has resolved this heterogeneity issue. Furthermore, I control for a majority of risk factors that may lead to increases or decreases in these underlying causes of death.

I acknowledged previously that the conditional negative binomial fixed-effect model proposed by HHG is not considered a true fixed-effects model by some. I estimated the unconditional negative binomial fixed-effect model proposed by Allison and Waterman as an alternative approach(Allison & Waterman, 2002). For the most, both models estimate similar results. In some cases, statistical significance was not achieved in the unconditional negative binomial fixed-effects model, which might be due to the incidental parameter problem. Neither model is considered superior; I believe between the two I have provided valid and robust estimates. If the estimates were wrong, then I would expect to find a decrease in an underlying cause of mortality that is not affected by SFAs. To test this, I estimated models using appendicitis and found no effect, further proving the validity of my estimates.

To capture the protective nature of comprehensive SFA I chose to use only bar, restaurant, private, and public workplace bans. In the last two years, more laws have been passed that include venues such as casinos and hotels, and have extended bans to include other tobacco products such as electronic cigarettes. My SFA variable does not capture the expansion in these venues, nor the type of tobacco use that is prohibited. Given that most adults over the age of 20 spend the at least 8 hours of their day at work (and to a lesser extent at restaurants and bars), I believe my measure is valid in capturing the protective nature of SFAs. While comprehensive bans in casinos, nightclubs, and hotel are important, most adults do not spend vast amounts of time in these establishments.

Lastly, I only analyzed the contemporaneous effect of SFAs on mortality from AMI, strokes, and CLRD. Future research should focus on whether these effects have any persistence over time. The hospitalization literature provides mixed results, though no one has studied the long-term effect of SFA on this specific underlying cause of death.

It is important to address the strengths of this study despite its drawbacks. This is the first study that has looked at 24 years of data at the county level for the continental United States. The length of time of this study, combined with the grassroots adoption of SFAs across counties, provides ample variation in time to estimate the true causal effect of SFAs. While my results are for the continental United States, I believe they are generalizable to other countries. No other study contains the amount of variation in SFA implementation, changes in comprehensive ban protection, and changes in underlying causes of mortality. Furthermore, this is the first study to address overdispersion, and provide various estimates for both conditional and unconditional negative binomial fixed-effects models. I address how these models treat fixed-effect estimation differently and find that both estimation techniques provide similar estimates. Missing from the literature is an explanation of why Poisson and OLS models are appropriate to use. To my knowledge not a single study addresses the issue of overdispersion which is quite common in count data and can only be addressed using negative binomial models.

Finally, I also created an SFA Index measure that better captures how populations are effectively protected by the implementation of bar, restaurant, private/public workplaces. My literature search indicates that an index like this has been rarely used. Since most studies prefer to use a dummy variable to capture the effect of SFAs I estimate models that also use one. For all models most estimates are similar.

The results of this paper emphasize the importance of enacting comprehensive SFAs. Not only do SFAs protect nonsmokers from the harmful effects of SHS, they have led to reductions in AMI, Strokes, and CLRD mortality in the adult population over the age of 20. For the population aged 35 to 64 years old the percent decreases in AMI deaths is double, 6 percent. These figures should not be ignored, as there is plenty of room to implement further SFAs. As of early April 2017 only 58 percent of the U.S. population is protected by a comprehensive bar, restaurant, and private/public workplace law (American Nonsmokers' Rights Foundation, 2017b).

3. The Long Run Impact of Smoke-Free Air Laws: Lung Cancer and Cirrhosis

3.1. Introduction

In this chapter, I will estimate what I call the "long run impact of SFAs." I will focus on county and state-level lung cancer and cirrhosis mortality. I specifically use the effective percentage of the population that is covered by all comprehensive SFAs (bar, restaurant, private and public workplace) at the county and state-level respectively as exogenous variation. Estimations use various distributional lag models in the SFA variable to show the relationship between SFAs and mortality from lung cancer and cirrhosis. These underlying causes of death develop over longer time horizons, so the aim specifically is to estimate if SFAs have a long run effect and have led to decreases in mortality. While the results are sensitive to the empirical estimation used, I find mortality decreases in the range of 2.2 to 13.6 percent.

3.2. Background

3.2.1. Lung Cancer

Men who smoke increase their risk of dying from lung cancer by more than 23 times and for women the risk is increased by more than 12 times (CDC's Office on Smoking and Health, 2015). Secondhand smoke not only causes cardiovascular disease such as AMI and strokes, it also leads to lung cancer in the long run. SHS causes 7,333 annual deaths from lung cancer (CDC's Office on Smoking and Health, 2015) furthermore, of these it is estimated that lung cancer kills 3,400 nonsmoking adults every year (Tynan, Babb, MacNeil, & Griffin, 2011). Even though there is a clear link between secondhand smoke and smoking, lung cancer and the protective nature of SFAs, there are no studies that have attempted to estimate whether SFAs lead to reductions in lung cancer mortality.

3.2.2. Cirrhosis

Alcohol consumption and cigarette smoking are known complement activities; that is, alcohol consumption is strongly associated with increased rates of smoking (McKee et al., 2006) and conversely, smoking increases alcohol consumption (Barrett et al., 2006) (Young-Wolff et al., 2013). Furthermore smokers are more than three times as likely as non-smokers to abuse or depend on alcohol (McKee, Falba, O'Malley, Sindelar, & O'Connor, 2007); among drinkers with alcohol use disorder, 35% are also nicotine dependent (Grant, Hasin, Chou, Stinson, & Dawson, 2004). Therefore, I postulate that as more counties adopt smoke-free air policies, especially those focusing on bars, the public health benefits of smoke-free air laws should affect heavy drinking and in the long run mortality from cirrhosis should decrease.

To date only a handful of studies have focused on this relationship, and no study to date has examined cirrhosis mortality at the county level. There are four relevant studies that are worth reviewing: Two use data from the United States, and two use data from the International Tobacco Control Four Country Survey. The first study examines the impact of smoke-free legislation on the likelihood of alcohol use disorders (AUDs) over time. The authors use logistic regressions and data from the National Epidemiological Survey on Alcohol and Related Conditions to determine whether the implementation of statewide smoke-free legislations in restaurants and bars leads to changes in remission, onset, and recurrence of alcohol use disorder. The authors find that states that implemented legislation for restaurants and bars had a higher likelihood of alcohol use disorder remission and a lower likelihood of onset (Young-Wolff et al., 2013).

A second study that uses United States data, employs difference-in-difference methodology to analyze SFA policy changes over time and their effect on state per capita consumption from 1980 to 2009. The authors use a three point scale to quantify the type of SFAs: zero indicates no policy, one indicates a non-comprehensive ban, and two indicates a comprehensive ban. The authors use this scale for workplaces, restaurants and bars. The final scale is the sum of these, ranging from zero to six. The authors find that a one point increase in the SFA policy scale (for example going from three to four) was associated with a 1.1 percent decrease in per capita total alcohol consumption. No significant effects were found for wine, but a one point increase in the scale was associated with a 0.7 and 1.9 percent decrease for beer and spirits respectively (Krauss, Cavazos-Rehg, Plunk, Bierut, & Grucza, 2014).

The two other studies on this topic use data from the International Tobacco Control Four Country Survey. The first study conducted in 2012 looks at changes in the frequency and amount of alcohol consumption in the presence of smoke-free bar policies over time. More specifically, the authors use generalized estimating equations to assess how changes in bar SFA policies have led to: i) changes in the frequency of alcohol consumption, ii) changes in the amount of alcohol typically consumed, and iii) changes in the frequency of binge drinking(Kasza, McKee, Rivard, & Hyland, 2012). The authors find that specific bar SFA policies are not associated with significant reduction in alcohol consumption among smokers in general. However, changes in these policies are associated with small reductions in the amount of alcohol consumed by hazardous drinkers, and with reductions in the frequency of alcohol consumed by heavy smokers (Kasza et al., 2012).

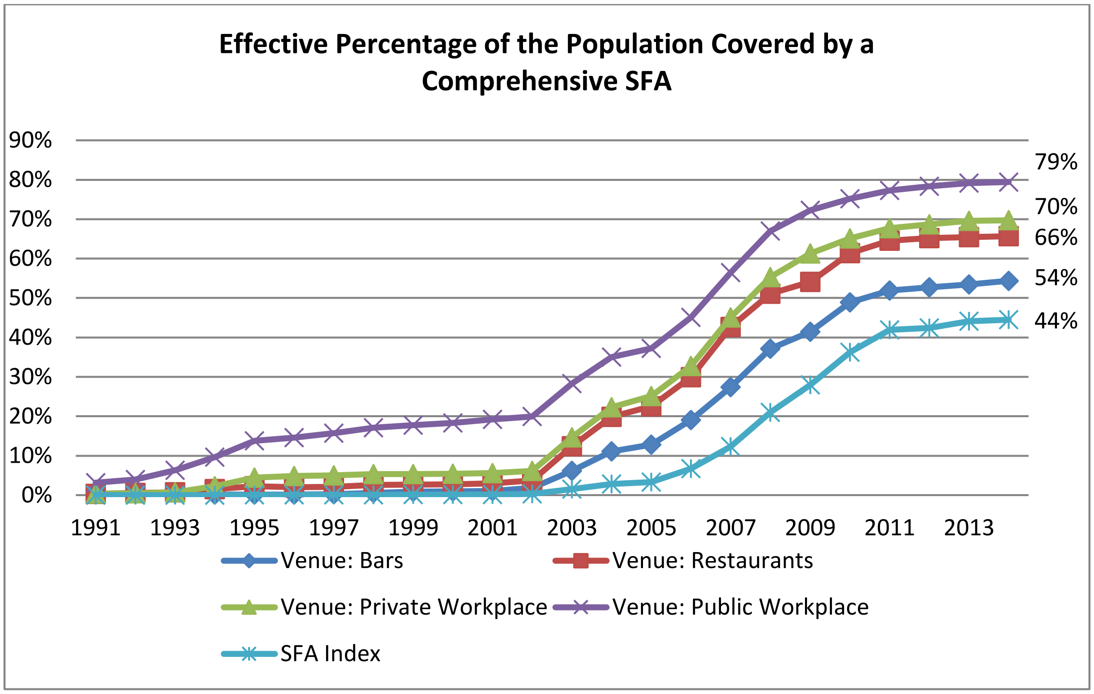
The second and last study focuses on Scotland and evaluates whether the 2006 smoke-free policies decreased drinking behaviors among smokers in public venues. The study is based on a telephone survey that took place before and after Scotland implemented a smoke-free policy prohibiting smoking in public venues, including bars and pubs(McKee et al., 2009). Data from the United Kingdom was used as a control. Overall, the authors find that drinking behaviors did not significantly change. However, when the results were stratified by location, Scottish smokers decreased their weekly consumption in pubs by about 4 drinks a week when compared to smokers in the United Kingdom (McKee et al., 2009). Furthermore, Scottish heavy-drinking smokers decreased their weekly alcohol consumption in pubs from 12.02 drinks to 6.31 (McKee et al., 2009). The authors theorized that drinking could have been moved from pubs to households, but the data did not support this notion.

3.3. Methods and Data

The methodology and data for this chapter is similar to that found in chapter 2. As before, my analytical background can be found in section 1.2. To reiterate this chapter focuses on the importance of implementing comprehensive smoke-free air laws (SFAs) that protect 100 percent of the U.S. population. A comprehensive SFA is defined as one that specifically bans smoking in restaurants, bars, and private and public workplaces at a 100 percent level. A ban that prohibits smoking in restaurants and not bars is not considered comprehensive; in the same manner, a ban that provides separately ventilated areas is also not considered comprehensive. In the last two decades the percentage of people covered by a comprehensive SFA has vastly increased.

As of December 2014, 54 percent, 66 percent, 70 percent and 79 percent of the population in the continental United States are protected by either a state, county or city smoke-free air law in bars, restaurants, private and public workplaces respectively. Figure 2 below shows how the effective percentage of protected populations by a comprehensive SFA has increased since 1991.

FIGURE 2: EFFECTIVE PERCENTAGE OF THE POPULATION COVERED BY COMPREHENSIVE SFA, 1991-2014



Summary statistics are provided in table 18. For the underlying cause of death, my outcome variable, I provide both the county mean number of deaths and the death rate. At the county over the time period of study, the mean number of lung cancer deaths is 71 and 41 for cirrhosis. From 1991 to 2014 the SFA index annual average, the variable of interest, has increased from zero to 44 percent from 1991 to 2014 (shown in figure 2). On average 12 percent of the population is protected by comprehensive laws that includes all venues of interest.

TABLE 18: LONG RUN, COUNTY LEVEL SUMMARY STATISTICS

		Mean	S.D.	Min	Max
Underlying Cause of Death - 20 Years and older					
Lung Cancer	Number of Deaths	71	152	10	3477
	Death Rate	97	34	8	392
Cirrhosis	Number of Deaths	41	70	10	1470
	Death Rate	19	12	4	340
SFA Index		12%	31%	0%	100%
SFA Dummy		11%	31%	0%	100%
Comprehensive Bar SFA - Annual Average		13%	33%	0%	100%
Comprehensive Restaurant SFA - Annual Average		17%	37%	0%	100%
Comprehensive Private Workplace SFA - Annual Average		20%	39%	0%	100%
Comprehensive Public Workplace SFA - Annual Average		28%	42%	0%	100%
County Level Unemployment Rate		6.3%	3.0%	0.7%	39.3%
County Level Real Price of a Pack of Cigarettes in 2014 Dollars		$ 3.83	$ 2.50	$ 0.91	$ 16.92
County Level Real Per Capita Income in 2014 Dollars		$ 33,523	$ 9,138	$7,668	$ 195,632
County Population		61,937	202,855	25	7,530,028

Summary statistics at the state level, shown below in table 19, are similar to the county estimates.

TABLE 19: LONG RUN, STATE LEVEL SUMMARY STATISTICS

		Mean	S.D.	Min	Max
Underlying Cause of Death - 20 Years and older					
Lung Cancer	Number of Deaths	3144	3013	170	13995
	Death Rate	77	16	21	117
Cirrhosis	Number of Deaths	629	767	31	5660
	Death Rate	15	4	6	41
SFA Index		19%	33%	0%	100%
SFA Dummy		15%	33%	0%	100%
Comprehensive Bar SFA - Annual Average		21%	38%	0%	100%
Comprehensive Restaurant SFA - Annual Average		22%	38%	0%	100%
Comprehensive Private Workplace SFA - Annual Average		33%	40%	0%	100%
Comprehensive Public Workplace SFA - Annual Average		6%	2%	2%	14%
State Level Unemployment Rate		$ 38,651	$ 7,255	$ 23,399	$ 70,615
State Level Real Price of a Pack of Cigarettes in 2014 Dollars		$ 10.23	$ 2.40	$ 5.82	$ 17.80
State Level Real Per Capita Income in 2014 Dollars		1,348	1,635	101	10,037
State Population		3,940,967	4,352,883	47,424	27,800,000

As seen in table 20, for both lung cancer and cirrhosis the number of deaths has remained relatively constant over the 24 years of data used. These lung cancer figures differ from those provided by the American Lung Cancer Association. I believe the difference stems from methodology differences. My figures are simple average county death rate figures, while the numbers provided by the American Lung Cancer Association are more precisely calculated by adjusting for age groups and gender.

TABLE 20: SUMMARY STATISTICS: MEAN DEATHS AND MEAN DEATH RATE AT THE COUNTY LEVEL FOR LUNG CANCER AND CIRRHOSIS

Year	Lung Cancer - 20 Years and Older		Cirrhosis - 20 Years and Older	
	Mean Number of Deaths	Mean Death Rate	Mean Number of Deaths	Mean Death Rate
1991	69	97	44	16
1992	70	98	43	16
1993	70	98	42	16
1994	70	98	41	16
1995	70	98	41	16
1996	71	98	40	15
1997	71	99	40	15
1998	71	98	41	15
1999	71	95	40	17
2000	71	98	40	17
2001	71	98	40	17
2002	72	98	41	17
2003	72	98	40	18
2004	72	97	39	18
2005	72	98	39	18
2006	72	97	40	18
2007	71	97	40	20
2008	71	96	39	20
2009	71	96	39	19
2010	71	96	40	21
2011	71	95	41	22
2012	71	94	42	23
2013	70	93	41	24
2014	70	93	42	25

3.4. Empirical Specification

Once more, I use a conditional negative binomial fixed-effect model to estimate the causal effect that SFAs have had on lung cancer and cirrhosis. To reiterate, this panel data estimation method was originally developed by Hausman, Hall and Griliches (Hausman et al., 1984). As in chapter 2, I use this model to control for overdispersion in the data. The Pearson Dispersion Statistic can be found in the appendix in table 28. While overdispersion seems to disappear with more lags in the SFA variable, and it does not appear to be as large as that found in the previous chapter, the GLM negative binomial results are better than those for the GLM Poisson models. In some instances there actually appears to be underdispersion, for which to date there is no correction for (Hilbe, 2011).

I use the following reduced form equation as a basic model:

$$M_{it} = \beta_0 + \beta_1 SFA_{it} + \beta_2 SFA_{it-1} + \ldots \beta_{10} SFA_{it-11} + \beta_{11} U_{it} + \beta_{12} ICD_t + \beta_{13} X_{it} + \delta_t + \alpha_i + \varepsilon_{it}$$

M_{it} is a non-negative count variable for the number of deaths in county *i*, at year *t*. As before, SFA_{it} is the key explanatory variable and captures the effective percentage of the population in a county that is covered by a comprehensive bar, restaurant and private/public workplace. This effective percentage is a yearly average of people covered over 12 calendar months. This variable can be considered a lower bound measure of SFA coverage, as the population must be covered by all comprehensive bans (bar, restaurant, private/public workplaces) to be included in my measure. For example, the population in a county that is only covered by a comprehensive bar SFA, would not be included in this measure. As before, I believe this measure captures the true nature of comprehensive coverage.

All models include a constant β_0; the county level unemployment rate, U_{it}; an ICD dummy to capture the change from ICD-9 to ICD-10 that occurred in 1999, ICD_t. *Xit* is a vector of further control variables: the real price of a pack of cigarettes, and real per capita personal income.

I perform this analysis at the state level as well. All models include a year fixed-effects δ_t; a county (or state) fixed-effect, α_i; and an error term ε_{it}. County (or state) and year fixed-effects enter the model as dichotomous indicators for each county (or state) and each year. The model will exclude one county (or state) and one-year indicator. They are placed in the model to capture difference across counties (or states) and over time that are not captured by the other covariates in the model. To control for difference in county (or state) population size I use population as an exposure variable in all regressions. Lastly, all analyses are performed for the 48 continental states in the United States. Alaska and Hawaii were dropped from the analysis as too much data was missing to make any meaningful inference.

3.4.1. Justification for Lagged SFA Variable

The major difference in this chapter is the estimation of the long run effect of the SFA_{it} index. There is expected to be a time interval between the implementation of a smoking ban and a change in the mortality from lung cancer and cirrhosis, due to the slow progression and onset of these diseases. This period is difficult to define, and beyond the scope of this dissertation, but given that it is relevant to the mechanism of transmission between secondhand smoke exposure and mortality due to these illnesses, at minimum an estimated range is needed.

Using a broad classification there are two types of lung cancer: non-small cell lung cancer and small cell lung cancer("Lung Cancer 101 | Lungcancer.org," n.d.). Non-small cell lung cancer has various types of tumors, among them adenocarcinoma and squamous cell carcinoma. Studies conducted through the 1960s concluded that squamous cell carcinoma was strongly associated with smoking and was the most common type of lung cancer. However, changes in cigarette design have led to more smokers developing adenocarcinoma (Thun, Henley, & Calle, 2002); though currently all histologic types of lung cancer are associated with smoking. Squamous cell carcinoma stars as an *in situ* lesion and develops to a clinically apparent tumor in three to four years (Stewart & Kleihues, 2003). I use this threshold as a starting point for my analysis.

There are three types of liver disease: Steatosis (simple uncomplicated fatty liver), Alcoholic Liver Disease, and Cirrhosis. As mentioned in the data section, I focus on alcoholic liver diseases and cirrhosis, both of which take a long time to develop and for the most are attributable to heavy and excessive drinking. About 10 to 35 percent of heavy drinkers will develop alcoholic hepatitis (a sub classification of alcoholic liver disease) and about 10 to 20 percent will develop cirrhosis. Alcoholic hepatitis is reversible and patients may recover completely provided they stop consuming alcohol. Cirrhosis on the other hand is irreversible. For liver cirrhosis to develop daily drinking should be around 80 grams of ethanol, and will take anywhere from 10 to 20 years. Eighty grams of ethanol constitutes about one liter of wine, eight beers or half pint of liquor (Richmond County Medical Society, 2011). I use this as guide to establish a lagging threshold. In other words, there should be an effect after approximately 9 lags of the SFA variable.

3.5. Results

3.5.1. Lung Cancer

All models use data from 1991 through 2014. I run models using the current SFA value and then continue to lag this variable from one to eleven periods. These conditional negative binomial fixed-effect model results are in table 21. Based on medical research, I predicted that an effect should be seen after three to four years, the first statistically significant decline occurs after 5 lags, and shows a 1.0 percent reduction in lung cancer. From there the declines become larger, with a decrease of 8.4 percent observed at the 11-lag mark. To be clear, the estimate should be interpreted as an 8.4 percent decline in lung cancer will be observed 11 years after increasing comprehensive SFA protection (in bars, restaurants, private/public workplaces) from zero to 100 percent of the population.

The contemporaneous effect of prices on mortality is negative and statistically significant for the first five models, implying that increasing the real price of cigarettes by $1 would lead to a 0.04 percent decrease in lung cancer mortality (first model). To a point this result makes sense, however it should be interpreted lightly. There are no studies to date that show that contemporaneous increases in cigarette prices lead to immediate decreases in lung cancer. Instead decreases in lung cancer occur over a longer time horizon. Ex-smokers don't experience an immediate reduction in their chances of getting lung cancer, instead these reductions occur years after they have quit smoking.

TABLE 21: LUNG CANCER RESULTS, 1991-2014

VARIABLES	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
SFA Index	1.014***	1.012***	1.008***	1.006**	1.001	0.990**	0.985***	0.975***	0.972***	0.972***	0.956***	0.916***
	(0.00270)	(0.00279)	(0.00293)	(0.00314)	(0.00348)	(0.00383)	(0.00434)	(0.00505)	(0.00610)	(0.00732)	(0.00898)	(0.0143)
Unemployment Rate	1.005***	1.005***	1.005***	1.004***	1.003***	1.003***	1.002***	1.002***	1.001*	1.001	1.001	1.000
	(0.000534)	(0.000550)	(0.000568)	(0.000589)	(0.000612)	(0.000636)	(0.000665)	(0.000703)	(0.000751)	(0.000798)	(0.000820)	(0.000841)
ICD Index	0.905***	0.900***	0.887***	0.887***	0.881***	0.874***	0.867***	0.860***				
	(0.00582)	(0.00573)	(0.00571)	(0.00578)	(0.00584)	(0.00587)	(0.00590)	(0.00589)				
Real Price of a Pack of	0.996***	0.997***	0.997***	0.998***	0.998**	1.000	1.001	1.001	1.001	1.000	1.000	0.999
Cigarettes in 2014 Dollars	(0.000688)	(0.000695)	(0.000710)	(0.000732)	(0.000769)	(0.000799)	(0.000826)	(0.000846)	(0.000868)	(0.000881)	(0.000885)	(0.000914)
Real Per Capita Income in	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
2014 Dollars	(2.19e-07)	(2.29e-07)	(2.39e-07)	(2.50e-07)	(2.66e-07)	(2.81e-07)	(2.97e-07)	(3.14e-07)	(3.28e-07)	(3.40e-07)	(3.53e-07)	(3.68e-07)
Constant	0.00739***	0.00805***	0.00862***	0.00966***	0.0107***	0.0122***	0.0139***	0.0160***	0.0181***	0.0242***	0.0347***	0.0504***
	(0.000378)	(0.000452)	(0.000518)	(0.000651)	(0.000801)	(0.00106)	(0.00141)	(0.00192)	(0.00256)	(0.00462)	(0.00985)	(0.0216)
Observations	49,695	47,734	45,751	43,736	41,714	39,659	37,628	35,562	33,497	31,459	29,367	27,287
Number of Counties	2,489	2,487	2,481	2,477	2,470	2,460	2,455	2,443	2,437	2,430	2,420	2,410
Age	NB	NB	NB	NB	NB	NB	NB	NB	NB	NB	NB	NB
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AIC	305,899	292,511	279,323	265,670	252,154	238,389	224,838	211,172	197,548	183,990	170,189	156,649
BIC	306,146	292,748	279,550	265,887	252,361	238,587	225,026	211,350	197,716	184,149	170,338	156,788

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*** p<0.01, ** p<0.05, * p<0.1

To confirm the robustness of the results presented: I use the unconditional negative binomial fixed-effects model, restrict both models to the "full-sample" dataset, and run all four models with the SFA dummy variable instead of the SFA index variable. All results can be found in table 22. The conditional negative binomial fixed-effects model is presented again for completeness. When using the SFA index variable, all results are remarkably similar; when using the more restrictive SFA dummy variable, the results are not as consistent, but still show a constant decline in lung cancer rates as the SFA variable is lagged further.

Some models show a statistically significant positive increase in lung cancer mortality for the initial lagged models, though this increase decreases as the SFA variables are further lagged. These variables are not statistically significant in the “full sample” unconditional negative binomial fixed-effect model. This model uses county clustered standard errors, which are not used in the conditional negative binomial fixed-effects model[5]. Clustering the error term provides more precise estimates. These results should be interpreted with caution, as the unconditional negative binomial fixed-effects models with large panels can provide inconsistent estimators due to the “incidental parameters problem.” The results that use the SFA dummy variable are also not consistent. This inconsistency could be due to the SFA dummy being more restrictive than the SFA index variable and may not capture the full extent of SFA policies.

[5] STATA only allows clustering standard errors for unconditional negative binomial fixed-effects models.

TABLE 22: LUNG CANCER COUNTY LEVEL ALL MODELS, 1991-2014

SFA Index	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
1: Conditional Model	1.014***	1.012***	1.008***	1.006**	1.001	0.990**	0.985***	0.975***	0.972***	0.972***	0.956***	0.916***
	(0.00270)	(0.00279)	(0.00293)	(0.00314)	(0.00348)	(0.00383)	(0.00434)	(0.00505)	(0.00610)	(0.00732)	(0.00898)	(0.0143)
2: Conditional Model - Full	1.014***	1.013***	1.009***	1.008**	1.003	0.993*	0.988**	0.979***	0.976***	0.976***	0.960***	0.922***
Sample	(0.00301)	(0.00310)	(0.00325)	(0.00348)	(0.00385)	(0.00421)	(0.00475)	(0.00551)	(0.00660)	(0.00786)	(0.00960)	(0.0153)
3: Unconditional Model	1.012**	1.010*	1.005	1.004	0.998	0.986**	0.979***	0.967***	0.962***	0.963***	0.948***	0.907***
	(0.00590)	(0.00585)	(0.00586)	(0.00597)	(0.00618)	(0.00643)	(0.00685)	(0.00808)	(0.00978)	(0.0117)	(0.0127)	(0.0177)
4: Unconditional Model - Full	1.010	1.009	1.005	1.004	0.999	0.988*	0.983**	0.973***	0.967***	0.968***	0.952***	0.913***
Sample	(0.00618)	(0.00611)	(0.00610)	(0.00618)	(0.00636)	(0.00662)	(0.00701)	(0.00826)	(0.00990)	(0.0119)	(0.0128)	(0.0178)
SFA Dummy	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
5: Conditional Model	1.024***	1.018***	1.017***	1.015***	1.007**	1.002	1.001	0.994	0.990	0.988	0.971***	0.974
	(0.00266)	(0.00275)	(0.00291)	(0.00316)	(0.00354)	(0.00391)	(0.00454)	(0.00528)	(0.00668)	(0.00796)	(0.0108)	(0.0428)
6: Conditional Model - Full	1.024***	1.019***	1.018***	1.016***	1.008**	1.004	1.004	0.997	0.992	0.990	0.972**	0.975
Sample	(0.00296)	(0.00305)	(0.00323)	(0.00350)	(0.00391)	(0.00430)	(0.00498)	(0.00576)	(0.00722)	(0.00856)	(0.0116)	(0.0462)
7: Unconditional Model	1.021***	1.016***	1.013**	1.012**	1.003	0.998	0.997	0.986*	0.983*	0.981*	0.966***	0.974
	(0.00579)	(0.00581)	(0.00576)	(0.00578)	(0.00608)	(0.00604)	(0.00677)	(0.00727)	(0.00948)	(0.0107)	(0.0127)	(0.0613)
8: Unconditional Model - Full	1.019***	1.015**	1.013**	1.013**	1.004	1.000	1.001	0.991	0.986	0.985	0.968**	0.978
Sample	(0.00604)	(0.00605)	(0.00599)	(0.00598)	(0.00628)	(0.00621)	(0.00694)	(0.00741)	(0.00962)	(0.0109)	(0.0129)	(0.0621)
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Years Used						1991-2014						

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*** p<0.01, ** p<0.05, * p<0.1

These eight county models are replicated at the state level and can be found in table 23. The results are consistent with the county level results and indicate an even greater decrease in mortality from lung cancer. After 11 lags, lung cancer mortality decreased in the range of 4.4 to 10.7 percent. For both the SFA index and the SFA dummy variables in the unconditional negative binomial fixed-effects models with clustered standard errors at the state level, the problematic positive results for the initial lags seem to have disappeared. This is not the case for the conditional negative binomial fixed-effects models. Lastly, it is important to point out that all estimates for all models are directionally negative and increase in magnitude as the SFA variable is lagged further. This consistency indicates that in the long run SFA policies have contributed to the decrease in lung cancer mortality.

TABLE 23: LUNG CANCER, STATE LEVEL ALL MODELS, 1991-2014

SFA Index	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
1: Conditional Model	1.025***	1.025***	1.019***	1.015**	1.008	0.995	0.989	0.979**	0.979*	0.983	0.964**	0.897***
	(0.00658)	(0.00655)	(0.00671)	(0.00698)	(0.00752)	(0.00811)	(0.00903)	(0.0104)	(0.0127)	(0.0151)	(0.0179)	(0.0298)
2: Unconditional Model	1.003	1.000	0.991	0.987	0.981	0.972*	0.969**	0.965*	0.965	0.967	0.944**	0.893***
	(0.0146)	(0.0137)	(0.0136)	(0.0131)	(0.0136)	(0.0146)	(0.0149)	(0.0176)	(0.0216)	(0.0249)	(0.0258)	(0.0370)
SFA Dummy	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
3: Conditional Model	1.023***	1.020***	1.019***	1.016**	1.007	1.001	1.001	0.995	0.997	0.997	0.977	0.963
	(0.00583)	(0.00587)	(0.00610)	(0.00644)	(0.00706)	(0.00774)	(0.00883)	(0.0104)	(0.0130)	(0.0151)	(0.0196)	(0.0791)
4: Unconditional Model	0.997	0.994	0.989	0.987	0.981	0.977*	0.981	0.980	0.981	0.983	0.965***	0.956***
	(0.0131)	(0.0125)	(0.0121)	(0.0115)	(0.0126)	(0.0132)	(0.0139)	(0.0160)	(0.0186)	(0.0149)	(0.0103)	(0.00919)
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Years Used						1991-2014						

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*** p<0.01, ** p<0.05, * p<0.1

3.5.2. Cirrhosis

The results for cirrhosis are presented in the same manner as those for lung cancer: the first table presents county level conditional negative binomial fixed-effects model results; the second table presents eight result: conditional negative binomial fixed-effects, unconditional negative binomial fixed-effects, "full sample" for both models, and these four models are replicated using the SFA dummy variable instead of the SFA index variable; the last table replicates these eight models using state level data.

Using the medical literature, I predicted that SFAs would have an effect about 10 years after their implementation. Table 24 shows that after nine lags the SFA variable becomes statistically significant and shows a 3.5 percent decline in cirrhosis. Like the results for lung cancer, as more time elapses the lagged SFA variable increases in magnitude, after 11 lags there is a 7.7 percent decline in cirrhosis. To be clear, the estimate should be interpreted as a 7.7 percent decline in cirrhosis will be observed 11 years after increasing comprehensive SFA protection (in bars, restaurants, and private/public workplaces) from zero to 100 percent of the population. As a precaution, the results for eight, 10, and 11 lags should be taken lightly as the equations did not actually converge.

The results in table 25 show statistically significant results for the models using the SFA index variable, but not for the models that use the more restrictive SFA dummy. Like the lung cancer results, these results also present the positive statistically significant results for some of the initial lags. The state level results, in table 26, no longer present these results.

TABLE 24: CIRRHOSIS RESULTS, 1991-2014

VARIABLES	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
SFA Index	1.004	1.001	1.003	1.012	1.020***	1.022***	1.016*	1.010	0.983	0.965**	0.954**	0.923***
	(0.00665)	(0.00670)	(0.00686)	(0.00720)	(0.00783)	(0.00847)	(0.00933)	(0.0108)	(0.0129)	(0.0154)	(0.0187)	(0.0281)
Unemployment Rate	0.999	0.999	0.998	0.996**	0.996***	0.995***	0.994***	0.993***	0.992***	0.991***	0.992***	0.993***
	(0.00138)	(0.00140)	(0.00142)	(0.00144)	(0.00147)	(0.00151)	(0.00156)	(0.00163)	(0.00171)	(0.00181)	(0.00187)	(0.00192)
ICD Index	1.783***	1.775***	1.753***	1.704***	1.719***	1.693***	1.653***	1.638***				
	(0.0289)	(0.0283)	(0.0280)	(0.0271)	(0.0277)	(0.0274)	(0.0268)	(0.0265)				
Real Price of a Pack of Cigarettes in 2014 Dollars	0.965***	0.966***	0.969***	0.970***	0.971***	0.974***	0.978***	0.980***	0.985***	0.988***	0.989***	0.992***
	(0.00165)	(0.00165)	(0.00167)	(0.00170)	(0.00176)	(0.00182)	(0.00186)	(0.00189)	(0.00195)	(0.00201)	(0.00205)	(0.00216)
Real Per Capita Income in 2014 Dollars	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
	(5.24e-07)	(5.44e-07)	(5.65e-07)	(5.88e-07)	(6.20e-07)	(6.52e-07)	(6.81e-07)	(7.12e-07)	(7.37e-07)	(7.67e-07)	(7.98e-07)	(8.32e-07)
Constant	0.00101***	0.00117***	0.00143***	0.00193***	0.00258***	0.00367***	0.00781***	0.0253**	211.5	287.1	3,106	18,028
	(6.95e-05)	(9.46e-05)	(0.000140)	(0.000244)	(0.000440)	(0.000892)	(0.00406)	(0.0434)	(0)	(41,977)	(0)	(0)
Observations	14,271	13,849	13,416	12,967	12,501	12,042	11,570	11,094	10,631	10,110	9,555	8,996
Number of Counties	991	989	988	987	986	984	982	981	976	975	972	969
Age	NB	NB	NB	NB	NB	NB	NB	NB	NB	NB	NB	NB
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AIC	82,162	79,130	76,034	72,848	69,648	66,561	63,377	60,297	57,394	54,048	50,599	47,127
BIC	82,374	79,333	76,229	73,035	69,826	66,731	63,539	60,451	57,532	54,185	50,721	47,240

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*** p<0.01, ** p<0.05, * p<0.1

TABLE 25: CIRRHOSIS, COUNTY LEVEL ALL MODELS, 1991-2014

SFA Index	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
1: Conditional Model	1.004	1.001	1.003	1.012	1.020***	1.022***	1.016*	1.010	0.983	0.965**	0.954**	0.923***
	(0.00665)	(0.00670)	(0.00686)	(0.00720)	(0.00783)	(0.00847)	(0.00933)	(0.0108)	(0.0129)	(0.0154)	(0.0187)	(0.0281)
2: Conditional Model - Full	0.989	0.990	0.994	1.008	1.017*	1.022*	1.023*	1.022	1.003	0.986	0.972	0.934*
Sample	(0.00881)	(0.00892)	(0.00915)	(0.00966)	(0.0105)	(0.0113)	(0.0123)	(0.0141)	(0.0165)	(0.0191)	(0.0227)	(0.0332)
3: Unconditional Model	1.010	1.006	1.006	1.009	1.012	1.011	1.005	0.999	0.973	0.958**	0.947**	0.919***
	(0.0140)	(0.0133)	(0.0123)	(0.0119)	(0.0128)	(0.0135)	(0.0147)	(0.0169)	(0.0191)	(0.0206)	(0.0228)	(0.0274)
4: Unconditional Model - Full	0.992	0.992	0.994	1.003	1.004	1.004	1.006	1.005	0.989	0.974	0.961	0.927**
Sample	(0.0182)	(0.0172)	(0.0159)	(0.0155)	(0.0163)	(0.0168)	(0.0185)	(0.0208)	(0.0228)	(0.0241)	(0.0264)	(0.0300)
SFA Dummy	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
5: Conditional Model	1.002	1.004	1.010	1.016**	1.030***	1.028***	1.032***	1.010	0.991	0.984	0.976	1.072
	(0.00643)	(0.00653)	(0.00675)	(0.00715)	(0.00794)	(0.00859)	(0.00985)	(0.0114)	(0.0147)	(0.0178)	(0.0243)	(0.0942)
6: Conditional Model - Full	0.991	0.995	1.005	1.016	1.032***	1.032***	1.051***	1.027*	1.020	1.005	0.988	1.054
Sample	(0.00857)	(0.00873)	(0.00906)	(0.00962)	(0.0107)	(0.0115)	(0.0131)	(0.0150)	(0.0190)	(0.0218)	(0.0293)	(0.116)
7: Unconditional Model	1.009	1.008	1.011	1.011	1.020	1.015	1.019	1.000	0.981	0.978	0.971	1.070
	(0.0132)	(0.0123)	(0.0113)	(0.0112)	(0.0123)	(0.0123)	(0.0148)	(0.0163)	(0.0199)	(0.0217)	(0.0258)	(0.0773)
8: Unconditional Model - Full	0.996	0.999	1.004	1.009	1.017	1.014	1.032*	1.014	1.008	0.997	0.981	1.051
Sample	(0.0172)	(0.0161)	(0.0147)	(0.0145)	(0.0156)	(0.0153)	(0.0189)	(0.0200)	(0.0244)	(0.0257)	(0.0301)	(0.0838)
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Years Used						1991-2014						

seEform in parentheses/unconditional model has county clustered se
*** p<0.01, ** p<0.05, * p<0.1

TABLE 26: CIRRHOSIS, STATE LEVEL ALL MODELS, 1991-2014

SFA Index	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
1: Conditional Model	0.997	0.986	0.984	0.987	0.992	0.995	0.987	0.984	0.961*	0.957**	0.938**	0.864***
	(0.0119)	(0.0117)	(0.0115)	(0.0117)	(0.0123)	(0.0131)	(0.0142)	(0.0165)	(0.0202)	(0.0197)	(0.0301)	(0.0393)
2: Unconditional Model	0.994	0.982	0.978	0.977	0.977	0.977	0.967	0.955	0.928*	0.915*	0.908**	0.868*
	(0.0337)	(0.0313)	(0.0282)	(0.0261)	(0.0263)	(0.0269)	(0.0295)	(0.0333)	(0.0376)	(0.0417)	(0.0410)	(0.0719)
SFA Dummy	No Lag	1 Year Lag	2 Year Lag	3 Year Lag	4 Year Lag	5 Year Lag	6 Year Lag	7 Year Lag	8 Year Lag	9 Year Lag	10 Year Lag	11 Year Lag
3: Conditional Model	0.987	0.983	0.988	0.990	0.997	0.996	1.000	0.992	0.978	0.976	0.977	1.042
	(0.0104)	(0.0104)	(0.0104)	(0.0107)	(0.0115)	(0.0123)	(0.0138)	(0.0163)	(0.0208)	(0.0248)	(0.0258)	(0.134)
4: Unconditional Model	0.984	0.977	0.979	0.980	0.980	0.978	0.975	0.960	0.950	0.952**	0.957***	1.029**
	(0.0282)	(0.0258)	(0.0238)	(0.0234)	(0.0236)	(0.0236)	(0.0277)	(0.0307)	(0.0320)	(0.0219)	(0.0158)	(0.0141)
Covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Age	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus	20plus
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Years Used						1991-2014						

seEform in parentheses/unconditional model has state clustered se
*** p<0.01, ** p<0.05, * p<0.1

One of the main econometric estimation problems for these models, is the lack of data at the county level due to the CDC Underlying Cause of Death File data restriction. To reiterate, if less than nine deaths occurred in one county in one year the data is suppressed to zero. This is one of the reasons why the state level results provide more robust and consistent estimates than those provided at the county level. Using the SFA Index a decline in cirrhosis mortality of 13.2-13.6 percent can be observed after 11 lags. The models that use the more restrictive SFA index variable are negative but statistically insignificant for the conditional fixed effects. In contrast the results are positive and statistically significant for the unconditional fixed effects model. Overall though, the state level results for cirrhosis show a clear decline over time.

3.6. Discussion

Although it depends on model specification and results vary by the number of lags used, overall this analysis indicates that implementing comprehensive SFAs has led to decreases in lung cancer and cirrhosis mortality. To recap, when using 11 lags lung cancer mortality has decreased in the range of 4.4 to 10.7 percent while cirrhosis mortality has decreased in the range of 2.9 to 13.6 percent.

When conceiving of this research question, my initial thoughts were that I would not see a statistically significant effect as I would need more than 30 years of data to appreciate the effect of SFAs on lung cancer and even more time for cirrhosis. However, after much consideration I believe these results presented are plausible and correct. Given that both smokers and drinkers must consistently smoke and drink over a long-time horizon to develop lung cancer or cirrhosis, I believe these observed decreases are for the individuals that would have otherwise continued to smoke, or inhale SHS, or drink excessively had SFAs not been implemented and would have otherwise developed and died of lung cancer or cirrhosis. In other words, we are only observing the beginning of adverted deaths, most likely from the distribution of older individuals. I believe these estimates are only plausible because SFAs have been implemented for over 20 years in some localities. A 20-year time lag provides sufficient time for lung cancer or cirrhosis deaths to be averted for older individuals that marginally decreased smoking, inhaling SHS, or drinking excessively when these laws were first enacted.

Let me further elaborate by employing lung cancer as an example. For a smoker to develop lung cancer s(he) must smoke steadily. Young smokers don't die of lung cancer, it is older smokers that die. For lung cancer rates to decrease, tobacco control policies must be in place for a considerable amount of time before the effects are apparent. The results I present here reflect this policy lag. Furthermore, I believe the results where an increase in lung cancer is observed, also reflects the effects of this policy lag.

This is the first study to look at the relationship of SFAs on lung cancer and cirrhosis and the long run impact that their implantation has had. SFAs are implemented with the intention of protecting nonsmokers from the harmful effects associated with SHS. We know that SHS leads to lung cancer in the long run, yet this direct relationship hadn't been proved empirically. Furthermore this is the first study to also look at the relationship of SFAs and cirrhosis. For both underlying causes of death I find consistent decreases in mortality that increase in magnitude as more time elapses.

These findings provide empirical evidence that SFAs not only provide immediate benefits. I expect these decreases to become larger with time. For one, and as mentioned, these conditions develop over time. Secondly, the SFA policy implantation that took place in later years still hasn't manifested itself in my results.

There are limitations to this study. As noted in the previous chapter it is impossible to distinguish if smokers, nonsmokers, women, men, or certain age groups benefit the most from these comprehensive smoking bans. As before, this drawback is mostly due to the fact that CDC Wonder Underlying Cause of Mortality file suppresses all data to missing variables if less than nine people died in a county. This is a big limitation for the cirrhosis portion of my research, since not a lot of people die of cirrhosis. However, I was able to find meaningful results both at the county and state level. I also provide results for various models that further validate these results.

While the overall results indicate decreases in lung cancer and cirrhosis, they are not at times consistent across lags. Some models present gaps from one lagged model to the next, especially with cirrhosis, where there are intervals of lags where the estimates are not statistically significant. While I can't explain why this occurs, it is clear that SFAs do decrease mortality from lung cancer and cirrhosis and that these decreases increase in magnitude over time. Of note is that these decreases are larger in magnitude as those found in the previous chapter for AMI, stroke, and CLRD.

Examining the relationship of cirrhosis and SFAs is not as straightforward as examining the relationship with lung cancer. I argue that decreases in cirrhosis occur indirectly by decreasing alcohol consumption. As mentioned before this decrease in drinking occurs as individuals concurrently decrease their smoking, as heavy drinkers tend to be heavy smokers and vice-versa. It is plausible that some individuals simply switch their smoking and alcohol consumption from restaurants and bars to their homes, and these decreases are due entirely to a different factor. I cannot think of another outcome that mimics the changes in SFA protection over the last 24 years that would lead to decreases in mortality from cirrhosis. With more data it would be possible to test a counterfactual such as ovarian cancer that is not affected by smoking. Unfortunately, this might not be a true counterfactual as recent studies have linked ovarian cancer to smoking.

Like the previous chapter, the results of this paper emphasize the importance of enacting comprehensive SFAs. Not only do SFAs protect nonsmokers from the harmful effects of SHS, in the long run they reduce lung cancer and cirrhosis mortality for those 20 years and older. These figures should not be ignored, as there is plenty of room to implement further SFAs. I reiterated, as of April 2017 only 58 percent of the

U.S. is protected by a comprehensive bar, restaurant, and private/public workplace law (American Nonsmokers' Rights Foundation, 2017b).

4. Conclusion

This dissertation has focused on the short and long run impacts that SFAs have had on mortality. I used a conditional and unconditional negative binomial fixed-effects model to estimate the contemporaneous effect of SFAs on AMI, stroke, and CLRD mortality. To estimate the long run effects of SFAs, I used various lags of the SFA variable and found that these comprehensive bans have also lead to decreases in lung cancer and cirrhosis. Using the most conservative estimate, SFAs save 6 annual lives per county: 4 from AMI, 1 from Strokes, and 1 from CLRD. Over the long run SFAs have saved an additional 4 lives from lung cancer and 6 lives from cirrhosis per county per year.

I used two variables to capture the protective nature of SFAs, an SFA index and an SFA dummy. The SFA index captured the effective percentage of the population covered by all four comprehensive SFAs at a 100 percent level; the SFA dummy, a dichotomous variable, captured when 100 percent of the population in a county/state was covered by all four venues. By construction the SFA dummy was more restrictive than the index. As constructed the index captured the cumulative effect local SFAs have as they are enacted.

The research presented here has its limitations. The main limitation stems from the missing data due to the CDC Wonder Compress Mortality file convention of not providing data for counties that have less than ten deaths in a year. Given the results presented at the state level, it appears that this limitation is not a problem and all results should be considered a lower bound estimate.

The second limitation steams from whether one considers a conditional negative binomial fixed-effects model, developed by HHG, a true fixed-effects model. To counter this I estimated an unconditional negative binomial fixed-effects model as proposed by Allison and Waterman (Allison & Waterman, 2002). In almost every model, SFAs lead to decreases in mortality. There does not appear to be a better or more accepted alternative estimation for non-negative count left hand side variables, that accounts for overdispersion in the data, and that further allows one to use fixed-effects. Thus, this study is an improvement on the previous studies in the field.

Overall, the estimates presented here are consistent with more conservative estimates provided in the literature. These results provide more robust estimates of the true effects of SFAs on mortality. Although the results are conservative, it provides support for the enactment of comprehensive SFAs in more localities and/or at federal level.

"If you're working on a problem you can solve in your own lifetime, you're not thinking big enough."
- Wes Jackson

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TABLE 27: ICD-9 AND ICD-10 UNDERLYING CAUSE OF DEATH CODES AND COMPARABILITY RATIO

Underlying Cause of Death	ICD-9	ICD-10	Comparability Ratio
AMI	410	I21.0, I21.1, I21.2, I21.3, I21.4, I21.9, I22.0, I22.1, I22.8, I22.9	0.9887
Strokes	430, 431, 432.0, 432.1, 432.9, 433.0, 433.1, 433.2, 433.3, 433.8, 433.9, 434.0, 434.1, 434.9, 436, 437.0, 437.1, 437.2, 437.3, 437.4, 437.5, 437.6, 437.8, 437.9, 438	I60, I62, I63, I64, I67, I69	1.0588
CLRD	490, 491.0, 491.1, 491.2, 491.8, 491.9, 493.0, 493.1, 493.9, 494, 496	J40, J41, J42, J43, J44, J45, J46, J47	1.0478
Appendicities	540-543	K35-K38	1.0347
Lung Cancer	162.0, 162.2, 162.3, 162.4, 162.5, 162.8, 162.9	C33, C34.0, C34.1, C34.2, C34.3, C34.8, C34.9	0.9037
Cirrhosis	571.0, 571.1, 571.2, 571571.8, 571.9.3, 571.5, 571.6,	K70.0, K70.1, K70.3, K70.4, K70.9, K74.3, K74.4, K74.5, K74.6, K76.0, K76.9	N/A - Used ICD codes for ARDI

TABLE 28: SHORT RUN, GLM POISSON AND NEGATIVE BINOMIAL RESULTS WITH PEARSON DISPERSION STATISTIC

County Level								
	AMI - 20 Plus		AMI - 35-64 Years Old		Strokes - 20 Plus		CLRD - 20 Plus	
	Poisson	NB	Poisson	NB	Poisson	NB	Poisson	NB
Model (3)	-0.0301***	-0.0399***						
	(0.00270)	(0.00535)						
Pearson Dispersion Statistic	2.786896	1.04349						
Model (7)	-0.0343***	-0.0346***						
	(0.00295)	(0.00538)						
Pearson Dispersion Statistic	2.342794	1.046087						
Model (12)	-0.0325***	-0.0312***	-0.0645***	-0.0540***	-0.0106***	-0.00973**	-0.00801**	-0.0120***
	(0.00321)	(0.00554)	(0.00819)	(0.0103)	(0.00324)	(0.00408)	(0.00329)	(0.00407)
Pearson Dispersion Statistic	2.134211	1.054548	1.420524	0.9806111	1.245041	0.9973781	1.243967	0.9928792
State Level								
	AMI - 20 Plus		AMI - 35-64 Years Old		Strokes - 20 Plus		CLRD - 20 Plus	
	Poisson	NB	Poisson	NB	Poisson	NB	Poisson	NB
Model (12)	-0.0379***	-0.0340***	-0.0465***	-0.0336*	-0.0162***	-0.00948	-0.0377***	-0.0467***
	(0.00380)	(0.0107)	(0.00861)	(0.0174)	(0.00385)	(0.00713)	(0.00395)	(0.00827)
Pearson Dispersion Statistic	6.282022	1.257063	3.704138	1.395106	3.368749	1.213397	4.458342	1.164778

Counterfactual		
	Appendicitis - 20 Plus	
	Poisson	NB
Model (12)	-0.157	-0.157
	(0.0993)	(0.0993)
Pearson Dispersion Statistic	0.5826399	0.5826396

TABLE 29: LONG RUN, GLM POISSON AND NEGATIVE BINOMIAL RESULTS WITH PEARSON DISPERSION STATISTIC

	County Level				State Level			
	Lung Cancer - 20 Plus		Cirrhosis - 20 Plus		Lung Cancer - 20 Plus		Cirrhosis - 20 Plus	
	Poisson	NB	Poisson	NB	Poisson	NB	Poisson	NB
No Lag	0.0136***	0.0119***	0.00499	0.00980	0.0186***	0.00284	-0.0163***	-0.0205**
	(0.00250)	(0.00328)	(0.00599)	(0.00756)	(0.00271)	(0.00561)	(0.00598)	(0.0104)
Pearson Dispersion Statistic	1.209884	0.9347888	1.272963	0.8932647	4.471497	1.085033	2.790033	1.145933
1 Year Lag	0.0112***	0.0100***	0.00248	0.00621	0.0150***	0.000461	-0.0182***	-0.0253**
	(0.00260)	(0.00339)	(0.00614)	(0.00766)	(0.00281)	(0.00569)	(0.00612)	(0.0104)
Pearson Dispersion Statistic	1.194764	0.9368132	1.237814	0.8937572	4.25	1.094746	2.637328	1.148062
2 Year Lag	0.00730***	0.00473	0.00429	0.00639	0.0111***	-0.00450	-0.0124*	-0.0218**
	(0.00275)	(0.00356)	(0.00637)	(0.00782)	(0.00294)	(0.00573)	(0.00634)	(0.0104)
Pearson Dispersion Statistic	1.186052	0.9394538	1.202	0.8958023	3.865996	1.099333	2.486773	1.149967
3 Year Lag	0.00597**	0.00385	0.0124*	0.00922	0.00816***	-0.00655	-0.0103	-0.0235**
	(0.00297)	(0.00381)	(0.00674)	(0.00814)	(0.00313)	(0.00587)	(0.00665)	(0.0107)
Pearson Dispersion Statistic	1.169857	0.9416478	1.16412	0.8946824	3.552676	1.109141	2.359387	1.137107
4 Year Lag	0.000861	-0.00195	0.0206***	0.0123	0.00252	-0.0119*	-0.00396	-0.0211*
	(0.00333)	(0.00423)	(0.00737)	(0.00876)	(0.00339)	(0.00616)	(0.00716)	(0.0111)
Pearson Dispersion Statistic	1.157668	0.9439013	1.133696	0.8977847	3.231536	1.116307	2.204744	1.145207
5 Year Lag	-0.00964***	-0.0137***	0.0219***	0.0110	-0.00501	-0.0176***	-0.00641	-0.0224*
	(0.00372)	(0.00468)	(0.00806)	(0.00944)	(0.00372)	(0.00653)	(0.00779)	(0.0117)
Pearson Dispersion Statistic	1.141969	0.945568	1.10591	0.9026033	2.940493	1.113423	2.09411	1.152642
6 Year Lag	-0.0155***	-0.0209***	0.0157*	0.00469	-0.00758*	-0.0189***	-0.0149*	-0.0320***
	(0.00426)	(0.00534)	(0.00907)	(0.0105)	(0.00421)	(0.00690)	(0.00879)	(0.0123)
Pearson Dispersion Statistic	1.128814	0.9498114	1.073751	0.904557	2.522909	1.116014	1.877139	1.15149
7 Year Lag	-0.0255***	-0.0336***	0.00963	-0.00101	-0.0157***	-0.0263***	-0.0206*	-0.0390***
	(0.00504)	(0.00627)	(0.0106)	(0.0121)	(0.00505)	(0.00794)	(0.0106)	(0.0146)
Pearson Dispersion Statistic	1.115774	0.9550939	1.054275	0.9061074	2.285774	1.119925	1.818399	1.150888
8 Year Lag	-0.0284***	-0.0391***	-0.0170	-0.0278*	-0.0199***	-0.0307***	-0.0606***	-0.0804***
	(0.00613)	(0.00762)	(0.0131)	(0.0148)	(0.00629)	(0.00952)	(0.0136)	(0.0180)
Pearson Dispersion Statistic	1.104575	0.9600219	1.042673	0.9118812	2.064652	1.12511	1.73736	1.15045
9 Year Lag	-0.0282***	-0.0373***	-0.0354**	-0.0429**	-0.0225***	-0.0319***	-0.0764***	-0.0960***
	(0.00740)	(0.00907)	(0.0160)	(0.0177)	(0.00793)	(0.0117)	(0.0177)	(0.0231)
Pearson Dispersion Statistic	1.087542	0.9622882	1.020886	0.9157294	1.885145	1.141587	1.693899	1.17169
10 Year Lag	-0.0453***	-0.0539***	-0.0471**	-0.0543**	-0.0391***	-0.0478***	-0.0755***	-0.0897***
	(0.00929)	(0.0111)	(0.0196)	(0.0215)	(0.0104)	(0.0148)	(0.0229)	(0.0292)
Pearson Dispersion Statistic	1.070392	0.9668652	1.00822	0.9190903	1.781197	1.170498	1.632616	1.193797
11 Year Lag	-0.0880***	-0.0978***	-0.0805***	-0.0840**	-0.0862***	-0.0880***	-0.107**	-0.108**
	(0.0155)	(0.0181)	(0.0304)	(0.0328)	(0.0199)	(0.0258)	(0.0428)	(0.0498)
Pearson Dispersion Statistic	1.058921	0.9715306	0.9919662	0.9231239	1.678742	1.213509	1.491182	1.213348

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Education

PhD in Economics, *University of Illinois at Chicago,* Chicago, IL, Expected 2017

Dissertation: "*The Effect of Smoke-Free Air Laws On Various Short And Long Run Mortality Outcomes.*" Advisor: Dr. John A. Tauras.

Areas of Concentration: Health Economics, Public Economics.

MA in Economics, *University of Illinois at Chicago,* Chicago, IL, 2011

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BA in Economics (Minor: Mathematics), *University of Illinois at Chicago,* Chicago, IL, 2009

Magna Cum Laude, Honors, Highest Distinction in Economics

Publications

Jidong, H., Chriqui, J.F., DeLong, H., Mirza, M., **Diaz, M.C.** & Chaloupka, F.J. 2016. Do State Minimum Markup/Price Laws Work? Evidence from Retail Scanner Data and TUS-CPS. T*obacco Control* 2016;25:i52-i59.

Reports

Diaz, M.C. The Effect Of Alcohol Excise Tax Increases On Sexual Assault. Addendum to The Effects of Alcohol Excise Tax Increases on Public Health and Safety in Texas. 2016 Report prepared for Texans Standing Tall.

Chaloupka F.J., Edwards, S.M., Ross, H., **Diaz, M.,** Kurti, M., Xu, X., Pesko, M., Merriman, D. & DeLong, H. 2015. Preventing and Reducing Illicit Tobacco Trade in the United States. Report prepared for National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health (CDC).

Diaz, M.C., Chaloupka F.J. & Jernigan D.H. 2015. The Effects of Alcohol Excise Tax Increases on Public Health and Safety in Texas. Report prepared for Texans Standing Tall.

Analytical work for Expert Testimony

Wal-Mart Stores, Inc., et al. v. Texas Alcoholic Beverage Commission, et al. Civil Action No. 1:15-cv-00134-RP. Export report filed March 18, 2016

Philip Morris Brands Sàrl, Philip Morris Products SA, and Philip Morris Limited v. the Secretary of State for Health, CO/2323/2015; JT International SA and Gallaher Limited v. the Secretary of State for Health, CO/2352/2015; British American Tobacco UK Limited, British American Tobacco (Brands) Inc., and British American Tobacco Investments) Limited v. the Secretary of State for Health, CO/2322/2015; Imperial

Tobacco Limited v. the Secretary of State for Health, CO/2601/2015; and Tann UK ltd, TannPapier GmbH, Benkert UK Ltd, and Deutsche Benkert GmbH KG v. the Secretary of State for Health, CO/2706/2015, on behalf of the United Kingdom. Expert report filed 13 September 2015; reply report filed 5 November 2015.

Papers under review

Tauras, J. A., Chaloupka, F.J. & **Diaz, M.C.** 2013. Economic Impact of Arkansas' Tobacco Tax Increase on Low-Income Households in Arkansas. Under review at *CDC.*

Diaz, M.C. Alcohol Excise Taxes and Their Effect on Alcohol-Attributable Cancer. Addendum to The Effects of Alcohol Excise Tax Increases on Public Health and Safety in Texas. 2016 Report prepared for Texans Standing Tall.

Working Papers

Diaz, M.C., Pesko M., Huang, J., Wada, R., & Chaloupka, F.J. 2016. Are Vaping Products Displacing Cigarettes? Evidence from Nielsen Retail Data, 2007-2013.

Presentations

Presentation: "Change on a Dime." Presented at Texans Standing Tall 2015 Statewide Summit to Create Healthier and Saver Communities, Austin, TX on September 2, 2015.

Presentation: "Smoke-Free Air Laws and their Effect on Various Mortality Outcomes, 1991-2012." Presented at IALHEA Diversity Dialogue and Research Forum, Chicago, IL on April 15, 2015.

Poster Presentation: "The Impact of Electronic Cigarette Sales on Cigarette Sales, 2007-2013." Presented at State and Community Tobacco Control (SCTC) Steering Committee Bi-Annual Meeting, Chicago, IL on September 18, 2014.

Work Experience

I. **Consultant**

Dr. Frank Chaloupka, McKing Consulting Corporation, OSH at CDC.

Responsibilities: In charge of gathering information and producing case studies related to illegal and illicit cigarette sales. Case studies focused on the use of encrypted tax stamps for the states of California, Massachusetts, and Michigan; and tribal legislation for the states of Arizona, Oklahoma, Washington, and Wisconsin. Two minor case studies were produced focused on Cost Benefit Analysis of Tax Reward programs for Chicago and Cook County.

December 2014 - Present

II. **Research Assistant**

Dr. Jidong Huang, Institute of Health Research and Policy (IHRP).

Responsibilities: Manage and prepare for analysis the Nielsen Tobacco scanner data, CPS-TUS survey data, and Twitter Fire-Hose Data. As needed perform statistical analysis using various techniques: Ordinary Least Squares (OLS), Fixed Effects, Marginal Analysis, Difference and Difference, Regression Discontinuity, and Instrumental Variables. Perform market analysis and presentations as needed for ANRF, Legacy, CDC, and FDA. Prepare and write literature reviews for papers and briefs as needed.
January 2013 – Present

Dr. John A, Tauras, Department of Economic, UIC
Project: Economic Impact of Arkansas' Tobacco Tax Increase on Low-Income Households in Arkansas.
Responsibilities: Leader in building architecture, implementation, maintenance, and analysis of database. Prepared data for cost benefit analysis, wrote descriptive portion of each organization that received funds under provisions of 2009 excise tax increase.
January 2012-June 2013

Dr. Helen Roberts, Center for Economic Education
Responsibilities: Develop and implement lesson plans to promote financial literacy for K-12 students, college students and teachers. Leader in building architecture and implementation, maintenance and analysis of databases in Access. Produce and organize teacher conference and professional development material. Assist in training teacher to use the Stock Market Game, buy providing market research and examples.
August 2009 – December 2012

III. Teaching Assistant

Professor: Helen Roberts, Department of Economics, UIC
Course: Independent Study – Undergraduate Federal Reserve Challenge
Fall 2009, Fall 2010, Fall 2011, Fall 2012.

Professor: Ali T. Akarca, Department of Economics, UIC
Course: Principle of Economics for Business
Fall 2010.

IV. Other Working Experience

Intern, Treasury Strategies, Chicago, IL
May 2012 – May 2013

Data Analyst, Alliance for Minority Participation Grant and Office Aid, Department of Mathematics, Statistics and Computer Science, University of Illinois at Chicago.
Summer Break and Winter Break 2011, and September 2007 to August 2009.

Assistant Dining Room Manager and Wine Steward, Emerson Inn by the Sea, Manasota Beach Club, Weekapaug Inn, and Hotel Iroquois on the Beach
June 2002 to August 2007

Statistical Software Proficiency

Proficient with STATA (data management, statistical analysis, and STATA programing), Excel, Power Point, and Word.
Experience with SAS, SPSS, Access, and Matlab.

Languages

English and Spanish (Native)
German (Basic reading, writing, and conversation, Deutsches Sprachdiplom-Stufe I)
French (Basic conversation)

Awards

Abraham Lincoln Fellowship (Graduate), AY 2009-2010 and AY 2013-2014.
Sylvia L. Saffrin Memorial Award (Undergraduate), Spring 2009.
Ronald Moses Memorial Award (Undergraduate), Spring 2009.
Martin Luther King, Jr. Scholarship (Undergraduate), Fall 2007 and Spring 2008.
The LAS Alumni Association of the UIC Merit Award (Undergraduate), Spring 2008

References

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