No News is Bad News: Mortality Effects of Inland Oil Spills Vary with News Coverage

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Abstract

Exploiting county-level variation in exposure to severe inland oil spills and their news coverage status, I estimate that oil spills raise ambient air pollution levels and mortality rates, but only when a spill is not reported in the news. The increases in mortality rates are caused by the elevated air pollution and are concentrated in the most susceptible group: elderly adults. When a spill is covered in the news, there are not only no changes in ambient air quality but also persistent decreases in county-level mortality rates. By exploring heterogeneous effects, I show that the decreases in mortality rates are due to out-migration. The differential effects on air pollution and mortality imply that information on environmental disasters is beneficial to the environment and human health.

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Oil spills, the release of liquid petroleum hydrocarbons into the environment due to human activity, constitute a considerable proportion of environmental disasters. Although laws governing oil spills in the United States date back to as early as the mid 19th century, the governance framework prior to the Exxon Valdez oil spill in 1989 was patchy, at best. The Exxon Valdez spill fundamentally changed the way the U.S. public thought about oil and resulted in a more comprehensive governance framework through the establishment of the Oil Pollution Act of 1990. However, even with comprehensive legislation, oil spills still occur frequently in the United States, both offshore and inland.

Oil spills not only pollute the environment but also pose threats to human health. Numerous studies in the medical literature have examined how oil spills impact health, causing respiratory symptoms, mental distress, infertility, and chromosome damage. Most of these studies focus on a small sample of coastal residents after an offshore oil spill. In the economics literature, to the best of my knowledge, there are only three studies on oil spills and health, two of which focus on birth outcomes and the other of which evaluates mental health. Offshore oil spills can only affect people in limited geographic areas, usually the closest coastal region. Moreover, depending on the amount spilled, the distance to the coast, and the wave conditions, the impacts on the coastal communities vary greatly. As a result, it is difficult to detect changes in mortality, an important but rare health outcome, after an offshore oil spill. This suggests that inland oil spills are more suitable for examining the mortality effects of oil spills. However, data on inland oil spills are not used by researchers due to poor quality. Despite its great importance, the mortality cost of oil spills is unknown due to the described challenges.

This paper conducts a new and informative quasi-experimental investigation of the effects of oil spills on mortality by exploiting severe inland oil spills ($\geq$ 100,000 gallons per incident) in the U.S. between 1990-2017. I overcome the challenges described above by cleaning a dataset on severe inland oil spills and combining the spill data with county-level mortality data. I separate counties that experienced severe inland oil spills into two groups by their news coverage status to inspect the function of information in cases of environmental shocks.[1] Using difference-in-differences designs, I estimate the causal relationship between oil spills and mortality. The unpredictability of the timing and location of a severe inland oil spill lends exogeneity to these environmental shocks. I also examine changes in ambient air pollution after a severe inland oil spill, since worsened air quality is the most likely channel through which inland spills affect mortality in a geographic area as large as a county.

This empirical analysis generates several key results. County-level ambient air quality deteriorates only after a spill that is not reported in the news, and this effect lasts for 12-14 months. The monthly all-cause age-standardized mortality rate in counties that experienced spills that did not receive news coverage increased by 1.03 deaths per 100,000 people for the entire population in the 12 months after a spill. These two results suggest that air pollution is the mechanism underlying the causal relationship between oil spills and mortality. To test this hypothesis, I use oil spills as an instrument for air pollution and find statistically significant impacts of air pollution on mortality. The overall mortality cost in these counties in the 12 months after a spill that is not reported in the news add up to $3.32 billion based on a back-of-the-envelope calculation.

Though county-level air quality remains the same after a spill that was reported in the news, I evaluate county-level mortality changes after spills that received news coverage in the paper because Chen (2021) finds significant decreases in labor market outcomes and significant increases in the gross out-migration of high-income individuals in these counties in the long run. The event study plot shows that the monthly mortality rate adjusts to a lower level within a year of the occurrence of a spill that received news coverage and stays at that level thereafter. This seemingly counterintuitive result can be fully explained by migratory responses. If the most susceptible and vulnerable individuals move away after learning of a severe inland oil spill in their county of residence, the mortality rate of that

[1] Exploiting the same set of severe inland oil spills, Chen (2021) shows that the mostly likely determinant of whether a spill receives news coverage is the number of newspapers in a county. Spills with and without news coverage and characteristics of counties that experienced spills with and without news coverage are comparable.

county will consequently decrease. In a heterogeneity analysis, I find that almost all of the mortality rate decreases are from counties with above-median out-migration responses, while the mortality effects in counties with below-median out-migration responses are close to zero and insignificant. Since the decline is due to out-migration rather than real improvements in health conditions, there are no health benefits associated with this mortality rate decrease. If counties with spills that do not receive news coverage are good counterfactuals for counties with spills that receive news coverage, the avoided costs of air pollution-caused mortality for spills that are covered in the news sum to $2.62 billion.

This work contributes to the literature in several ways. First, this paper provides new and important causal estimates of the effects of oil spills, one frequent type of environmental disaster, on mortality in a quasi-experimental setting at the national scale. Environmental disasters are not only catastrophic for the environment, but also harmful to human health. Previous literature finds that persistent exposure to nuclear radiation at a very low level damages cognitive abilities, lowers IQ scores, and has negative psychological effects (Almond, Edlund, & Palme, 2009; Danzer & Danzer, 2016; Black, Bütikofer, Devereux, & Salvanes, 2019); deforestation leads to more incidents of very low birth weight and extreme prematurity, rises mortality and morbidity rates, and increases the prevalence of malaria (Santos & Almeida, 2018; Jones, 2019; Carrillo, Branco, Trujillo, & Lima, 2019); and childhood exposure to the Dust Bowl increases the risks of being disabled and decreases future fertility (Arthi, 2018). Although oil spills account for a great proportion of environmental disasters, there is a lack of evidence on their health effects in economics. Existing economic studies on oil spills and health find that oil spills worsen birth outcomes and cause mental health problems (Beland & Oloomi, 2019; Marcus, 2021; Chong & Srebot, 2019). As a novel study that establishes the causal link between oil spills and mortality in the general population, the findings of this paper furthers the understanding of the health impacts and costs of oil spills.

This paper's findings also contribute to the understanding of how the public responds to information on environmental shocks. Several studies find that pollution information can trigger avoidance behavior (e.g., Banzhaf & Walsh, 2008; Neidell, 2009; Graff Zivin, Neidell, & Schlenker, 2011; Moulton, Sanders, & Wentland, 2018). Other studies examine the relationship between media attention and the environmental performance of firms. For example, Saha and Mohr (2013) find that toxic releases decrease significantly among establishments that receive newspaper coverage compared to companies that do not receive such coverage. My results indicate that information on spills affects both cleanup responses and individual behavioral responses after an oil spill. The finding of an increase in air pollution at the county level after spills that are not reported in the news, but not after those that are covered provides suggestive evidence that the disclosure of environmental disasters results in faster cleanup responses. The decreased mortality rate due to increased out-migration in counties that experienced spills that are publicized by news shows that information on environmental disasters can induce extreme avoidance behavior, i.e., migration, regardless of the actual pollution caused by the disaster.

Third, this paper joins a handful of studies that investigate the mortality effects for the overall population (e.g. Graff Zivin & Neidell, 2009; Deschênes & Greenstone, 2011; Deschênes, Greenstone, & Shapiro, 2017), rather than concentrating on any single age group. The majority of studies on pollution and mortality focus on infant deaths (e.g. Chay & Greenstone, 2003; Currie & Neidell, 2005; Knittel, Miller, & Sanders, 2016) because newborns do not have pre-exposure to any pollution and can provide a clean estimate of the treatment effect. Many other studies examine mortality in elderly adults, since they are more vulnerable and susceptible to environmental shocks, and mortality changes are more likely to be observed in this group (e.g. Miller, Molitor, & Zou, 2017; Deryugina, Heutel, Miller, Molitor, & Reif, 2019; Hollingsworth & Rudik, in press). Unlike these studies, I examine how oil spills influence the mortality of the overall population and then detail the age-specific changes in the mortality rates in the analysis.

The rest of the paper is structured as follows. Section 1 provides information on oil spill-related air pollution and health consequences and provides the background on inland oil spills and the governance framework in the United States. Section 2 describes the data. Section 3 specifies the empirical strategy used in the analysis. Sections 4 and 5 present and discuss the results, respectively. Section 6 presents the conclusion.

1 Background

Oil spills—releases of liquid petroleum hydrocarbon into the environment due to human activities—constitute a considerable proportion of environmental disasters. Among all types of oils, petroleum-based oil is the most common. The Clean Water Act specifically names petroleum and fuel oil in its definition of oil. According to the Chemical Hazards Response Information System, there are 98 crude oil and refined petroleum products, such as gasoline, jet fuel, and naphtha. I focus on these 98 products in this paper.

1.1 Oil Spill-Induced Air Pollution and Health Consequences

Petroleum oil spills and the cleanup process can release many chemicals that are harmful to human health into the atmosphere. Petroleum products contain hundreds of chemicals, many of which are volatile organic compounds (VOCs) that can evaporate and form toxic vapors in the air. Some VOCs are classified as hazardous air pollutants that have serious human health effects. For example, benzene can cause cancer, hexane can affect the nervous system, and toluene has been linked to chromosomal abnormalities. Although they are not directly linked to oil spills, recovery and cleanup operations emit nitrogen oxides (NO_x), which strongly affect the respiratory system (Middlebrook et al., 2012). Furthermore, in the presence of sunlight, VOCs react with NO_x to create ozone, which is a main component of smog. Breathing ozone can trigger a series of respiratory symptoms, including coughing, throat irritation, airway inflammation, and reduced lung function. Ground-level ozone can also increase the risk of premature death in individuals with heart or lung disease.[2] In addition, NO_x is also a precursor of fine particulate matter, which can cause both lung and heart issues, as numerous scientific studies have shown.[3]

A considerable number of medical studies have demonstrated the health effects of oil spills, but, to the best of my knowledge, there are only three papers in the economics literature examining how oil spills affect human health. Exposure to oil spills of large amount may cause adverse health events and affect health conditions in the long-run through biomedical mechanisms. The medical literature has shown that oil spills are associated with the following issues: 1) increased risk of headache, dizziness, wheezing, sore throat and eyes, and itchy skin (Lee et al., 2010; Peres et al., 2016); 2) respiratory symptoms, such as asthma and lung diseases (Ramirez, Arevalo, Sotomayor, & Bailon-Moscoso, 2017; Noh et al., 2019); 3) mental distress, depression, anxiety, PTSD, and suicidal ideation (Janjua et al., 2006; Rung et al., 2016; Choi et al., 2016; Osofsky, Osofsky, Weems, Hansel, & King, 2016; Nugent et al., 2019); 4) increased risk of miscarriage and fertility issues (Ramirez et al., 2017; Harville, Shankar, Zilversmit, & Buekens, 2018); and 5) DNA and chromosome damage and increased risks of cancer (Hildur et al., 2015; Kim et al., 2017; Ramirez et al., 2017). Additionally, the Michigan Department of Community Health reports that approximately 30% of households living near a spill site choose to relocate (Stanbury et al., 2010). Two of the three economics papers of which I am aware focus on birth outcomes. Beland and Oloomi (2019) and Marcus (2021) find that pollution from petroleum results in poorer birth outcomes, including lower birth weight, a greater likelihood of prematurity, and lower APGAR scores. Marcus (2021) also finds that highly educated white mothers are 2.5% more likely to move after learning about a spill. Chong and Srebot (2019) report significantly higher probability of psychological distress.

[2] Basic information on ground-level ozone pollution from the EPA: https://www.epa.gov/ground-level-ozone-pollution/ground-level-ozone-basics.

[3] Basic information on particulate matter pollution from the EPA: https://www.epa.gov/pm-pollution/health-and-environmental-effects-particulate-matter-pm.

1.2 Oil Spill Governance in the United States

Oil spill governance in the U.S. started in the mid-19th century, but all the laws before the 1989 Exxon Valdez oil spill provided only limited safeguards against the hazards of oil spills. The first law relating to oil spills is the Limitation of Liability Act of 1851, which, in an attempt to protect the shipping industry, states that the liability of vessel owners for incident-related costs is limited to the post-incident value of their vessel .[4] Examples of some other statutes that govern oil spills prior to the 1989 Exxon Valdez oil spill include the Oil Pollution Act of 1924, the Federal Water Pollution Act of 1965 (which later became the Clean Water Act of 1972), the Hazardous Liquid Pipeline Act of 1979, and the Comprehensive Environmental Response, Compensation, and Liability Act of 1980. Despite the existence of these laws, the governance framework lacked proper consolidation and was inadequate for spill prevention and responses. Congress attempted to establish more encompassing and elaborate oil pollution laws several times, but conflicts among interest groups hindered all the efforts, with the attempts ending in stalemates.

On March 24, 1989, the Exxon Valdez oil tanker struck a reef off the coast of Alaska and spilled 10.8 million gallons of crude oil into Prince William Sound. In the wage of the incident, "'Big oil' was suddenly seen as a necessary evil, something to be feared and mistrusted" (National Research Council, 2003). Due to growing pressure from the public and the apparent shortcomings of the patchy governance framework, a more comprehensive legislation, the Oil Pollution Act of 1990 (OPA), was passed. The OPA enforces the removal of spilled oil, requires specific operating procedures for the cleanup and measurement of damage, defines responsible parties and their financial liability for the damage and cleanup costs, and establishes a fund for damages and cleanup and removal costs.

[4] Two high-profile examples in which this statute was invoked to limit the liability of certain responsible parties are the sinking of the RMS Titanic in 1912 and the Deepwater Horizon oil spill in 2010.

1.3 Inland Oil Spills since 1990

Although this comprehensive governance framework, the OPA, was established and took effect in 1990, inland oil spills still happen frequently with large spill amount in the United States. Figure 1 shows the number of inland oil spills and the total spill amount in the U.S. from 1990 to 2018. The annual number of spills increased from approximately 10,000 in the 1990's to a steady 12,000 since 2000. The total spill amount displays a downward trend, with an annual average of approximately 4 million gallons from 1990 to 2018. Figure 2 displays the number of spills and spill amounts for each state between 1990 and 2018. There is significant geographic variation in both the number of spills and the spill amounts among the states. The Gulf Coast has the most oil spill incidents, and the East and West Coasts have more spills than the Midwest and Mountain States. Among all the states, Texas is one of the states with the most spill incidents, and it has the highest total spill amount.

2 Data

In this paper, I use data from various sources and combine the datasets by matching counties. This section describes the datasets and the key variables used in the analysis.

2.1 Inland Petroleum Oil Spills

I identify counties that experienced inland oil spills using reports from the U.S. Coast Guard National Response Center (NRC). As the sole point of contact within the National Response System, the NRC records all discharges of various substances into the environment, as well as maritime and railroad incidents, in the United States. The unit of observation in the dataset is a reported incident. Each observation reports, whenever available, the incident date and location (city, county, and state), the name and amount of the spilled material, and whether the spill is offshore. Approximately 325,000 reported inland incidents involved the 98 petroleum products occurred between 1990 and 2018 in 3,031 out of the 3,141 counties and county equivalents in the U.S. The amount of spilled oil is measured in various volume and mass units, such as barrels, cubic feet, pounds, etc. I convert all the spill amounts to gallons.

Figure 3 plots the density of the spill amount per incident in logs and summarizes the spill amount per incident in gallons. The density of the spill amount is extremely right-skewed and a density plot of the raw spill amount in gallons is not informative. The density plot of the logged spill amount roughly follows a normal distribution. The lower x-axis displays the logged spill amount, and the upper x-axis displays the summary statistics of the spill amount in gallons. The vertical dashed lines represent the logged values of the summary statistics on the upper x-axis. The smallest spill amount is 1.66e-06 gallons, which is almost zero. The unit of measure for this spill is a "drop." It appears in the dataset because responsible parties are required by law to report all incidents to the NRC. The 1st percentile is only 0.009 gallons and there is a great portion of spills smaller than 1 gallon ($\log(1) = 0$). The median and mean spill amounts are 20 and 676 gallons, respectively. This plot illustrates that the majority of the spills are of small amount, although the largest spills are enormous. Because small spills are unlikely to have any impact at the county level, Chen (2021) identifies a threshold of 100,000 gallons through a semiparametric analysis and classifies the 139 spills with amounts equal to or above the threshold as "severe." Following this definition, I focus on these 139 severe inland oil spills in this paper.

Table 1 summarizes all the severe inland oil spills that occurred between 1990 and 2018. Panel A of Table 1 shows that between 1990 and 2018, there are 139 severe spills with an average spill amount of 336,000 gallons. Panel B categorizes the severe spills by news coverage status. I check whether there is newspaper coverage for each of the severe spills in the newspaper archives introduced in the next subsection. Despite the large spill amounts, there are more spills not covered by any newspaper articles than spills that are covered. On average, news-covered severe spills release 32,000 more gallons of oil into the environment than those not covered in the news, although this difference is not statistically significant.[5] Exploiting the same set of severe inland oil spills, Chen (2021) shows that the mostly likely determinant of whether a spill receives news coverage is the number of newspapers in a county. There are more newspapers in counties with spills covered in the news than in counties with spills not covered in the news, and the difference is statistically significant. Characteristics, including population and average wage, of counties in these two groups are comparable. Panel C lists the summary statistics of the severe spills by type of incident. Among all the types, pipeline ruptures are the most common cause of severe spills, accounting for 55.4% of all severe spills. Next are incidents happened in fixed facilities, which make up 22.3% of all severe spills. The remaining 22.3% consists of spills caused by vessel collisions, storage tank leakages, and train derailments. One feature shared by all spill types is that the nature of all severe spills is accidental. The unpredictability of the time and location of severe spills renders them exogenous. In other words, I assume that conditional on the location and year, the occurrence of a severe spill is uncorrelated with other unobserved economic shocks. Panel D reports the spills by news coverage and type of incident. The number of news-covered severe spills is very similar to that of spills not covered by news across all types except for those happened in fixed facilities. Among the 31 severe spills happened in fixed facilities, only 3 were reported in newspaper articles. This suggests that fixed facilities probably have some power to conceal information on spills from local media, although they are obligated to report such incidents to authorities.[6]

2.2 Newspaper Data

To determine whether a spill receives news coverage, I use three newspaper archives, Newspaper.com, NewsLibrary.com, and Access World News. Newspapers.com is a comprehensive newspaper archive consisting of over 21,700 newspapers from across the United States and

[5]The p-value of the difference is 0.69 and the t statistic is 0.399.

[6]In a robustness check, I exclude fixed facility spills from the analysis, and the results remain similar to the main estimates in the paper.

beyond; it primarily covers the 19th and 20th centuries but goes back to as early as the 1700s. NewsLibrary.com is an online news archive of over 3,500 newspapers in the U.S. that dates back to 1948. Access World News is a collection of over 600 U.S. newspapers that goes back to 1978. To be comprehensive, I search the dates and locations of severe spills in all three archives to determine whether a spill is covered by news. The combination of the archives provides extensive coverage of information and perspectives at various geographic levels, including many hard-to-find regional and local newspaper articles. Access to local newspaper sources is the key to determining whether residents and employers could have learned about a severe inland oil spill occurred in their county.[7]

2.3 Mortality Data

The restricted county-by-month Multiple Cause of Death Data between 1982 and 2017 are from the National Vital Statistics System (NVSS) of the Centers for Disease Control and Prevention, and the county-by-year population estimates are from the National Cancer Institute's Surveillance, Epidemiology, and End Result (SEER) program. The mortality dataset represents the universe of deaths in the U.S. and reports the following information at the individual level for each death: cause of death,[8] age at death, county, month, and year of death, and county residence. I use the county of residence to identify whether a decedent lived in a county in which a spill occurred. The main outcome variable is the age-standardized mortality rate (ASMR) per 100,000 people at the month-county level. Since the spill dataset starts in 1990, I use the age distribution of the U.S. population in 1989 as the reference to standardize mortality rates.[9] The advantage of the ASMR is that it accounts for differences

[7] In a robustness check, I exclude fixed facility spills from the analysis, and the results remain similar to the main estimates in the paper.

[8] The cause of death is specified by the 9th revision of the International Classification of Diseases (ICD-9) codes up to 1998 and by the 10th revision of the International Classification of Diseases (ICD-10) codes afterwards.

[9] ASMR is defined as a weighted average of the age-specific mortality rates per 100,000 people, where the weights are the proportions of people in the different age groups of a reference population. Specifically, I calculate the ASMRs as follows: first, I split the overall population into 10 age groups, < 1, 1-14, 15-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, and 85 above. For each year, I divide the number of deaths in

in the age structure of the population over time. I report the mortality rates for the overall population and then by age group to identify the group(s) that drives the changes. To explore the causal channel, I show changes in all-cause mortality as well as deaths from internal and external causes. Furthermore, I estimate the impacts of spills on cardiovascular- and respiratory-related deaths to examine whether air pollution is a channel. Table 2 presents summary statistics for the county-level monthly ASMR by cause of death and population for each age group. The ASMR of elderly age group is the highest, and deaths from internal causes account for over 90% of the all-cause mortality.

2.4 Air Pollution Data

Ambient air pollution data are from the EPA's Air Quality System (AQS) database. I use ground monitor readings from the pre-generated daily summary data for the four EPA criteria gases–ozone (O_3), carbon monoxide (CO), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2)–as well as the fine and coarse particulate matter ($PM_{2.5}$ and PM_{10}). Comprehensive data for the four criteria gases are available in years 1980-2018, while particulate matter was not monitored extensively until later (1986 for PM_{10} and 1999 for $PM_{2.5}$). To make the results consistent with mortality rates, I convert the daily monitor readings to the county-by-month level. Specifically, I take a weighted average of the mean monthly concentration levels for each pollutant from monitors that are within 25 miles of a county centroid, where the weights are the inverse of the distance between each monitor and the county centroid. Since the number of active monitors is limited during the sample period, I include all of the monitors, which creates an unbalanced panel, in this computation. If there are no monitors within 25 miles of a county, the pollution measure is missing for that county; if all monitors within 25 miles of a county are turned off in a given month (e.g., many O_3 monitors are only active during March through October), the pollution measure for that

each age group by the corresponding population of that age group and then multiply the result by 100,000 to obtain age group-specific mortality rates. I then multiply the age group-specific mortality rates by the percentage of that age group in the 1989 population and add the products for all of the age groups to obtain the ASMR for each year.

county and that month is missing. In the analysis, I use a balanced panel of counties for each pollutant. Data availability differs by pollutants because monitors for some pollutants are more prevalent than others. Summary statistics of the monthly levels of air pollutants at the county level are shown in Table 3.

I focus mainly on NO_2 and O_3 because their concentrations are expected to increase after oil spills. Though levels of $PM_{2.5}$ are also anticipated to increase, the late introduction of $PM_{2.5}$ monitoring and the balanced panel significantly decrease the number of treated counties available for the analysis and render the estimates noisy. I include CO, SO_2, and PM_{10} as placebo tests because oil spills should not affect the concentrations of these pollutants.

2.5 Weather Data

Weather could be an environmental confounder of the oil spill-mortality relationship in the unlikely event that weather conditions differ by treatment status. To flexibly control for weather patterns, I obtain daily station-level temperature (maximum and minimum) and precipitation data from the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information for 1980-2018. To obtain county level values, I average the readings from all stations that fall within a 25-mile radius of each county centroid with weights equal to the inverse of the distance between the station and the county centroid. To construct monthly measures, for temperature, I compute the fraction of each month that the daily mean temperature (calculated as the average of maximum and minimum daily temperatures) falls into one of eight 10-degree Fahrenheit bins (< 30, 30-40, 40-50, 50-60, 60-70, 70-80, and > 80); for precipitation, I add the daily readings for each month to obtain a monthly precipitation measure.

3 Empirical Strategy

To estimate the causal effects of severe inland oil spills on air pollution and mortality rates, I use difference-in-differences specifications. The treatment group comprises counties that experienced severe spills, and the control group comprises counties with centroids more than 100 miles away from the centroid of any spill county. The identification assumption is that the outcomes of the treatment and control groups would have evolved along parallel trajectories had spills not occurred. In other words, the causal estimates are identified based on the assumption of a parallel trend between the treatment and control groups.

3.1 Treatment and Control Groups

Figure 4 plots the geographic distribution of the treatment and control groups. Following Chen (2021), which studies the effects of inland oil spills on local labor markets, I define a county as treated if it experienced at least one severe inland oil spill between 1990 and 2018; if a county experienced multiple spills during this period, I focus on the first spill. There are 113 counties that experienced spills in total. Among these counties, 55 experienced spills that received news coverage and 60 experienced spills that did not receive news coverage. To avoid the issue of artificial entries into and exits from the treatment group due to an unbalanced panel, I use a panel of severe spills balanced in event time in the estimation. Following the definition of Chen (2021), the control group consists of the 1,318 counties whose centroids are more than 100 miles away from the centroid of any spill county. Counties within 100 miles of a spill county are dropped in case of spillover effects.

3.2 Econometric Specifications

I estimate two panel fixed effect specifications, both of which exploit variation in the timing and geographic location of the severe spills, to determine how severe inland oil spills affect air quality and mortality rates. The identifying assumption is that counties with severe inland oil spills would have evolved in a manner similar to that of the non-affected counties had the spills not occurred. To understand how the effects of severe spills evolve over time, I perform an event study to flexibly trace the dynamic treatment effects. The estimation equation takes the following form:

$$y_{cmy} = \sum_{d=-D,\, d\neq -1}^{D} \beta_d Spill_{cd} + \beta_{-(D+1)} Spill_{c,-(D+1)} + \beta_{D+1} Spill_{c,D+1} + \gamma' W_{cmy} + \alpha_{cm} + \omega_{sy} + \epsilon_{cmy}, \tag{1}$$

where y_{cmy} is some outcome for county c in month m of year y, such as the level of some air pollutant or the mortality rate. The variable $Spill_{cd}$ is a spill indicator that equals 1 if county c experienced a severe inland oil spill d months ago as of month m of year y. The variables $Spill_{c,-(D+1)}$ and $Spill_{c,D+1}$ are group indicators that equals 1 if, as of month m of year y, county c is $\geq (D+1)$ months before or after a spill. That is , I focus on a window of $\pm D$ months around a spill. W_{cmy} is a vector of monthly weather conditions for each county including the percentage of time that the daily mean temperature falls into one of eight Fahrenheit temperature bins (< 30, 30-40, 40-50, 50-60, 60-70, 70-80, and > 80) and precipitation and precipitation squared. I include county-by-month of year and state-by-year fixed effects, denoted as α_{cm} and ω_{sy} respectively. The county-by-month of year fixed effects control for any county-level time-invariant characteristics in the same month of the year across years. This captures any effects caused by county-specific seasonality. Since policies regarding pollution emissions and healthcare may vary by state, the state-by-year fixed effects flexibly control for time trends that are common to all counties in each state. The error term, ϵ_{cmy}, represents unobserved county-by-month shocks to the outcomes that are assumed to be uncorrelated with the regressors of interest, $Spill_{c,d}$. To adjust for arbitrary serial correlation within a county, I cluster standard errors at the county level. I do not use weighting for ambient air pollution, while I weight regressions for mortality rates by the 1989 age group-specific populations.

Despite its flexibility, the event study is inefficient for summarizing the overall treatment effect. For the sake of brevity, I employ a difference-in-differences model to compare the outcomes in the D months before and after a severe spill using a post-spill indicator. In other words, I use the D months prior to a spill as the reference period and measure the difference in the temporal changes between the treatment and control counties. Specifically, I estimate the following equation:

$$y_{cmy} = \beta_{post} Spill_{c,post} + \beta_{-(D+1)} Spill_{c,-(D+1)} + \beta_{D+1} Spill_{c,D+1} + \gamma' W_{cmy} + \alpha_{cm} + \omega_{sy} + \epsilon_{cmy}, \quad (2)$$

where $Spill_{c,post}$ is an indicator that equals 1 in the month that the spill occurred and D months afterward for spill county c, and equals 0 otherwise. All the other variables are defined the same way as in Equation (1). The parameter of interest, β_{post}, is interpreted as the change in the outcome variables of county c caused by a severe oil spill. The regression uses no weighting for air pollution and is weighted by the 1989 age group-specific populationss for mortality rates.

4 Results

4.1 Ambient Pollution

Figure 5 plots the event study estimates of the effects of severe spills on the six criteria air pollutants, CO, O_3, NO_2, SO_2, $PM_{2.5}$, and PM_{10}, in the 12 months after a severe inland oil spill. For counties with spills that received news coverage, compared to the control group, the event study plots do not show obvious changes in any of the ambient air pollutant in the 12 months after a spill. The difference-in-differences estimates in Panel A of Table 4 also suggest that there are no statistically significant changes in any of the pollutants. This may seem somewhat strange given the scientific evidence that oil spills are likely to result in increased levels of NOx, ozone, and fine particulate matter. One potential reason is that the effects last only over a much shorter period, e.g., weeks rather than months. To investigate this, I estimate the effects of spills on air pollution using weekly data. Specifically, I estimate the effects in the first week, the first two weeks, and the first four weeks after a spill. The estimated effects are reported in Appendix Table A.1. Again, there are no apparent changes in any of the pollutants. A possible explanation is that news coverage draws public attention, which leads to faster responses to spills and faster cleanup. As a result, oil spills that are reported in the news do not cause detectable changes in air quality at the county level, though there could be increases in ambient pollution in smaller geographical areas.

Unlike counties with spills that receive news coverage, there is a jump in the level of NO_2 immediately after a spill that is not covered by any newspaper articles, and the ambient NO_2 level stays higher in those counties for the next 12 months. The magnitude of this increase is a statistically significant 0.839 ppm at the county level. Relative to the pre-spill NO_2 level of 14.869 ppm, this is a 5.64% increase. The NO_2 level returns to the pre-spill level 14-18 months after a spill that does not receive news coverage. Although the changes in ozone and particulate matter shown in Panel B of Table 4 are positive, the estimates are imprecise and the event study plots in Figure 5 do not display evident increases. As expected, the levels of ambient CO and SO_2 do not change. In contrast to the situation for spills that receive news coverage, the 12-month increase in NO_2 after a spill that is not covered in the news indicates that the response time and the cleanup process take much longer when a spill does not receive public attention. This is consistent with the finding of Saha and Mohr (2013) that toxic releases decrease significantly among establishments that receive attention from newspapers.

4.2 Mortality Rates

The previous section shows that the ambient air quality worsens only in counties with a severe inland oil spill that is not reported by news, and not in counties with spill that is reported in the news. In this section, I report the effects of oil spills on the monthly ASMR per 100,000 people at the county level by news coverage status.

4.2.1 Spills Without News Coverage

Results — I begin with event study graphs that focus on the same window, ± 12 months around a spill, that is used for ambient air pollution. Figure 6 plots the estimated effects of a spill that does not receive news coverage on the monthly all-cause ASMR of the overall population at the county level. The ASMR increases by approximately 3 (i.e., the age-standardized number of deaths increases by approximately 3 per 100,000 people) in the month of the spill and it remains high for 12 months afterwards. To determine the types of deaths and the population groups that are most affected, I further investigate the changes in ASMR by cause of death and age group. Appendix Figure A.1 shows the event study estimates by internal- and external-cause ASMR for the overall population. The internal-cause ASMR graph is identical to the all-cause ASMR graph shown in Figure 6, while the external-cause ASMR graph depicts precise null effects. This indicates that the increase is the result of internal-cause deaths, which suggests that air pollution is a likely channel. The null effect of external-cause deaths, which are primarily due to accidents, serves as a placebo test. Appendix Figure A.2 divides the population into four age groups: infants (age < 1), children ($1 \leq$ age ≤ 15), working age population ($15 <$ age < 65), and elderly adults (age ≥ 65). The shape of the event study graph for the ASMR of elderly adults is basically the same as that depicted in Figure 6, which means that the increase in deaths among elderly adults drives the main result.

Table 5 reports the difference-in-differences estimates by cause of death and age group. Column (1) in Panel A suggests that the all-cause, all-age mortality rate increases by a statistically significant 1.033 deaths per 100,000 people, which is a 1.668% increase, in the 12 months after a spill without news coverage. This increase is mainly driven by the ASMR of the elderly population, which increases by a statistically significant 8.293 (2.240%). Though not statistically significant, the ASMR of children increases by 6.983 %, which is considerable. Panels B and C detail the changes in ASMR due to internal and external causes. In Panels A to C, it is apparent that changes in internal-cause deaths account for almost all of the changes in the overall mortality rate across the age groups. The internal-cause ASMR of the entire population grows by 1.091 (1.886%), primarily due to the increase in internal-cause ASMR among elderly adults. The effects of spills on externally caused deaths are all small and insignificant. These estimates support the mechanism by which worsened air quality leads to more deaths, since air pollution will increase the number of internal-cause deaths but will not impact the external-cause (accidental) deaths.

To further probe whether the increase in deaths is due to air quality deterioration, I follow the convention in the pollution-health literature and examine cardiovascular and respiratory mortality rates. Column (1) of Panels D and E shows that the age-standardized number of deaths increased by statistically significant 0.369 and 0.303 per 100,000 people for cardiovascular- and respiratory-related deaths in the overall population, respectively. Once again, most of the increases are in elderly adults. Increases in cardiovascular and respiratory ASMR account for 65% of all-cause deaths. This provides strong support of the mechanism by which air pollution worsens mortality outcomes. Moreover, the effects on infants (column (2)) are all negative except for respiratory-related deaths, which shows a considerable increase of 0.689 (41.189%), a value that is significant at the 5% level. Since newborns are very vulnerable and do not have previous exposure to other shocks, the substantial increase in respiratory-caused mortality in this age group supports the air pollution channel as a cause.

Mechanism — The preceding section measures the reduced-form effects of spills that do not receive news coverage on mortality and suggests taht air pollution is a potential mechanism. I now turn to an instrumental variable (IV) approach to directly examine the effects of air pollution on mortality. The results in Section 4.1 suggest that only NO_2 levels significantly increased; therefore, I focus on NO_2 here and use oil spills as an instrument variable for NO_2. Figure 7 shows the changes in NO_2 and all-cause, all-age ASMR from 12 months before to 18 months after a spill that is not covered in the news. These two event study graphs have similar shapes, and the effects on both NO_2 and ASMR return to zero around the same time. This further strengthens the evidence of air pollution as the causal channel. NO_2 is an important precursor of both O_3 and $PM_{2.5}$, both of which negatively affect health (e.g., Graff Zivin & Neidell, 2009; Moretti & Neidell, 2011; Ward, 2015; Deryugina et al., 2019).[10] Elevated NO_2 concentrations could result in increases in O_3 and $PM_{2.5}$.[11] Therefore, I emphasize that the IV estimates of the effects of NO_2 should be interpreted cautiously because they may reflect the impact of not only NO_2, but also O_3 and $PM_{2.5}$.

Table 6 reports the ordinary least squares (OLS) estimates and the IV estimates. As the main specification, I include county-by-month of year and state-by-year fixed effects and cluster the standard errors at the county level. The regressions are weighted by the 1989 age group-specific populations. Since weather conditions can affect both mortality and ambient pollution, to avoid omitted variable bias, I control for monthly precipitation and the fraction of each month that the daily average temperature falls into the eight 10-degree Fahrenheit bins. The OLS results in Panel A indicate that NO_2 has a statistically significant relationship with all-cause mortality rates across the age groups. A 1-ppm increase in the monthly average NO_2 concentration is associated with a modest increase of 0.100 all-cause deaths per 100,000 people, or an increase of 0.163%. The largest absolute increases occur in the most vulnerable groups: elderly adults and infants, though the effect on infants is not statistically significant.

When I take the IV approach, I find that the estimates are 3 to 5 times larger than the OLS estimates. The considerably larger estimates in Panel B imply that a 1 ppm increase in

[10] The correlation between NO_2 and $PM_{2.5}$ is 0.748, and the correlation between NO_2 and O_3 is -0.379. It is well-documented in the literature that O_3 is negatively correlated with other pollutants that affect mortality (Currie & Neidell, 2005; Deryugina et al., 2019).

[11] One potential reason for the finding of no significant changes in O_3 and $PM_{2.5}$ reported in Section 4.1 is poor data quality. Ambient ozone is not emitted, but is determined by interactions between NO_x and VOCs under exposure to sunlight and heat. Because ozone is more likely to be formed in warm weather, many ozone monitors are turned on only from March to October each year. Ozone concentrations in cold weather in many counties are unmonitored and unknown. A comprehensive monitoring system of $PM_{2.5}$ did not exist until 1999, and monitors are sparsely distributed. Moreover, the balanced panel requirement (i.e., county-level air pollution data cannot be missing for the $\pm$ 12 months around a spill) leaves even fewer counties in the analysis.

monthly average NO_2 leads to an additional 0.421 all-cause deaths per 100,000 people, which is an increase of 0.7%. As before, the ASMR for elderly adults and infants increase the most since they are the most sensitive and vulnerable groups. Although the increase is not as large in absolute size, the ASMR for the working age population also rises by approximately 0.8%. These results illustrate that NO_2, potentially in combination with O_3 and $PM_{2.5}$, severely worsens health outcomes and results in more deaths. Since the standard errors are clustered, I report the Kleibergen-Paap rk Wald F statistic from the first stage. The large first stage F statistics suggest that the instrument is strong.[12]

Oil spills not only cause air pollution, but can also pollute water and affect local labor markets. This raises concerns regarding whether the instrument meets the exclusion restriction since both water pollution and labor market conditions impact mortality. To inspect whether oil spill-induced water pollution invalidates the IV estimates, I repeat the exercise by only including spills that do not reach water. The results are reported in Appendix Table A.2. The IV estimates for the land-only spills are close to the IV estimates in Table 6 Panel B both quantitatively and qualitatively, and the first stage F statistics become even larger. Using the same data, Chen (2021) finds precise null effects on labor market outcomes in counties that experienced a spill not reported in the news. Hence, neither water pollution nor labor market conditions invalidate the exclusion restriction of the IV.

4.2.2 Spills With News Coverage

Results — Although I find no effects on air pollution, Chen (2021) manifests that county-level labor market outcomes (including employment, wages, the number of establishments, and labor force) deteriorate in the five years after a spill that is covered in the news and that gross out-migration significantly increases. Since both labor market conditions and migration can affect mortality, I examine how county-level mortality rates respond to spills with news coverage. To be consistent with Chen (2021), I focus on the same time window,

[12] The critical values for the Stock-Yogo weak identification test are 13.91 for the 5% maximal IV relative bias and 22.30 for the 10% maximal IV size (Stock and Yogo, 2005).

which spans the ± 5 years, or ± 60 months in my setting, around a spill.

Figure 8 plots the estimated effects of a spill that is reported in the news on the monthly all-cause ASMR of the overall population at the county level. There is a clear level shift in ASMR in the 60 months after a severe spill. The ASMR adjusts to a lower level in the first 6-12 months after a spill, and then stabilizes around the lower level. Appendix Figure A.3 plots the event study graphs by cause of death. The internal-cause ASMR graph appears to be almost identical to the all-cause ASMR event study graph in Figure 8, while the external-cause ASMR graph depicts precise null effects. This signals that the decline in internal-cause deaths drives the overall effect.

Table 7 details the difference-in-differences estimates by cause death and age group. Column (1) of Panel A reports that, compared to the control counties, the county-level monthly all-cause, all-age mortality rate reduces by a statistically significant 1.300 deaths per 100,000 people, a 1.786% decrease, in the 60 months after a spill that is reported in the news. The ASMR of all age groups, except for children, decrease. The largest decreases in absolute value are from infants and elderly adults, which are the most vulnerable groups. In terms of percent changes, the largest reductions are from infants and the working age population. Hence, almost all age groups contribute to the overall decrease in ASMR. Comparing Panels B and C to each other and to Panel A, it is clear that the reductions in internal-cause deaths account for almost all of the reduction in the all-cause ASMR across age groups. All age groups experience decreases in internal-cause mortality rates. For external-cause deaths, the effects are small and imprecise, though the percent changes for some age groups are considerable.

Mechanism — It is both intriguing and, to some extent, counterintuitive to observe a decline in mortality rates after an environmental shock. To identify the mechanism underlying the decrease, I investigate changes in the following factors as potential channels: 1) labor market outcomes, wages, employment, and employment rate; 2) government transfers in general, and then medical benefits in particular; 3) out-migration; and 4) individual behavioral responses. Figure 9 plots the changes in the potential channels after a spill that is covered in the news.[13]

Previous research has demonstrated that mortality rates are pro-cyclical (Ruhm, 2000), and individuals' behaviors become healthier when economic conditions weaken (e.g., Ruhm, 2005; Gruber & Frakes, 2006; Xu, 2013). According to these findings, the weakening of labor market conditions in counties with spills that are reported in the news, as reported in Chen (2021), might result in lower mortality rates in these counties. Panel A in Figure 9 displays changes in wages, employment, and employment to working age population ratio after a severe inland oil spill that receives news coverage. Though all three labor market outcomes decrease in the long term, there is no effect in the year of the spill and the effects in year 1 are small and insignificant for all three outcomes. However, Figure 8 shows that the ASMR starts to decline almost immediately and reaches a lower level within a year. The ASMR then stabilizes at the lower level in the long term. This suggests that the weakening of labor market outcomes happens after the decrease in ASMR and cannot be the cause.

Non-disaster government transfers may increase after an environmental disaster to help people cope with the shock (Deryugina, 2017). Medical benefits, which include Medicare, public assistance medical care, and military medical insurance, may also increase after an environmental disaster, especially when the media publicize the disaster and potential health concerns. Panel B depicts the changes in overall government transfers and medical benefits. There is no change in either general government transfers or medical benefits, which means that they cannot trigger the decrease in ASMR.

News of deterioration of the quality of the environment can result in out-migration and encourage people to stay away. For instance, information on the introduction of a Toxics Release Inventory facility induces migratory response (Banzhaf & Walsh, 2008) and reduces house prices near the plants (Moulton et al., 2018). Values of residential properties near hazardous waste sites stay low, and the population level stays the same, even after the

[13] Panels A and C in Figure 9 are reproduced from Chen (2021).

cleanup process (McCluskey & Rausser, 2003; Greenstone & Gallagher, 2008), which serves as evidence of low influx. Regarding oil spills, Marcus (2021) finds that highly educated white mothers are 2.5% more likely to move after learning about a spill. Similarly, Chen (2021) finds that the gross out-migration rate increases significantly by 0.2 percentage points in the year in which a spill that is reported in the news occurs, and by 0.3 percentage points for the entire post-spill period, as shown in the figures reproduced in Panel C. If individuals who are vulnerable and susceptible to pollution move out immediately after learning that a severe oil spill has occurred, regardless of the real changes in pollution levels, there will be a rapid decrease in the mortality rate. Moreover, the mortality rate should stabilize at a lower level after the most vulnerable people leave. These two predictions match the observed changes in ASMR shown in Figure 8. In addition, in the first year after a spill, the magnitude of the average increase in the number of out-migrated individuals in a county is much greater than the magnitude of the average county-level decrease in the number of deaths, 503.48 individuals v.s. -56.71 deaths, based on simple back-of-the-envelope calculations. Hence, out-migration is the most likely cause of the morality decrease in counties with spills that are reported in the news.

To further inspect whether out-migration causes the decrease in ASMR, I estimate the mortality effects of oil spills based on the magnitude of the out-migration effects. If out-migration is the channel for this change, i.e., if vulnerable people move out in response to the information that a severe oil spill has occurred nearby, then there should be larger decreases in ASMR in counties with large out-migration effects. To test this hypothesis, I divide the counties that experienced a spill that received news coverage into two groups, those with an above- and below-median out-migration effect, and then implement the difference-in-differences estimation specified in Equation (2) on each group. The out-migration effects of the above- and below-median groups are statistically significant at 0.0042 (SE 0.0006), i.e., 0.42 percentage points, and insignificnat at -0.0002 (SE 0.0007), i.e., -0.02 percentage points, respectively.[14] The estimates of the mortality changes in these two groups are presented in Panels B and C of Table 8. To facilitate comparison, I report in Table 8 Panel A the estimated all-cause ASMR effects on all the age groups from Table 7 Panel A. The estimated mortality effect in counties with an above-median out-migration effect is a statistically significant decrease of 1.948 deaths per 100,000 people (-2.626%), while the decrease is only of 0.188 deaths per 100,000 people (-0.269%) in counties with a below-median out-migration effect. These two estimates fall on the two sides of the overall effect, which is a decline of 1.300 deaths per 100,000 people. These heterogeneous effects align with the prediction that there are larger mortality decreases in counties with larger migratory responses. Almost all of the decreases in the overall mortality rates come from the above-median out-migration effect group, the group from which all of the migration effect comes from. When the out-migration response is indistinguishable from zero, the magnitude of the mortality decrease is also close to zero. This confirms that out-migration is the mechanism underlying the morality rate decline in counties with spills that are reported in the news.

Though I do not observe behavioral responses, I discuss and disprove the plausibility of individual behavioral responses as the channel for the reduction in mortality. Many studies have found that pollution information induces behavioral responses. For example, short-term increases in ambient air pollution make people spend more time indoors (Graff Zivin & Neidell, 2009; Neidell, 2009) and purchase face masks (Zhang & Mu, 2018) and air purifiers (Ito & Zhang, 2020), and water quality violations significantly increase bottled water consumption (Graff Zivin et al., 2011). It is possible that local residents, especially those who are susceptible to pollution, will take preventative actions to reduce health risks after learning of an oil spill in their county . If this is the case, then we can expect to see some decrease in mortality rates. However, it is unlikely that behavioral responses can last half a decade. Graff Zivin and Neidell (2009) and Neidell (2009) both find that smog alerts significantly reduce outdoor activities. However, Graff Zivin and Neidell (2009) also find that when

[14] The estimation of 0.0042 (SE 0.0006) is statistically significant at the 1% level, while the estimation of -0.0002 (SE 0.0007) is not significant at all.

alerts are issued on two consecutive days, people alter their behaviors only on the first day and not on the second day, which suggests that the disclosure of environmental information cannot induce long-term intertemporal avoidance behaviors. Admittedly, oil spills can be more severe and last longer than smog, which may result in avoidance behaviors continuing over a longer time period. Nonetheless, most of the spills that are reported in news are cleaned up in a couple of weeks to several months, which makes it hard to imagine that behavioral responses would persist for five years. Therefore, I rule out behavioral responses as a potential channel for the declines in mortality rates.

5 Discussion

5.1 Robustness Checks

I conduct a number of robustness checks to test whether the results are sensitive to variation in the control variables and the treatment and control groups, or to the transformation of the outcome variables. The robustness check results are in reported the Appendix.

First, I examine whether the results are stable when different control variables are included. Recall that the main specification includes county-by-month of year and state-by-year fixed effects as well as monthly weather conditions. In one robustness check, I change the fixed effects to county, month of year, and year fixed effects. The county fixed effect captures county-level time-invariant characteristics; the month of year fixed effect captures seasonality; and the year fixed effect captures the nationwide secular trend. In another robustness check, I exclude the weather variables from the main specification. The estimates are in Appendix Tables A.3-A.5 for the use of different fixed effects and in Appendix Tables A.6-A.8 for the omission of the weather controls. Overall, the point estimates and significance levels are very similar between these two alternative specifications and those of the main analysis.

I also probe the robustness of the air pollution and mortality rate estimates to a variation in the treatment and control groups. As discussed in the Data section, the number of spills between the groups with and without news coverage are comparable for all spills of different types except for fixed facility spills. There are many more fixed facility spills not reported in the news than spills that are reported: 28 vs. 3; and fixed facility spills make up a much larger proportion of spills not covered in the news than spills that are covered: 35% vs. 5%. To examine of fixed facility spills drive the overall results, I exclude all such spills and re-run the main analysis. The estimates shown in Appendix Tables A.9-A.11 are very similar to the main estimates in both magnitudes and significance levels, which invalidates the hypothesis that fixed facility spills drive the overall effects. Following Chen (2021), the control group is defined as counties whose centroid is more than 100 miles away from the centroid of any treated county. To determine whether the results are robust to different definitions of the control group, I use counties within 100 miles of the spill counties as the control group and re-estimate the effects. I report the results from this exercise in Appendix Tables A.12-A.14. The estimates are quantitatively and qualitatively similar to the main results, which validates the robustness of the estimates and alleviates the concern about a violation of the Stable Unit Treatment Value Assumption.

In addition, I test whether the results are robust to transformations of the outcome variables. Specifically, I transform the outcome variables from raw levels to logs for air pollutants and take the inverse hyperbolic sine for mortality rates.[15] The coefficient estimates under both transformations yield an interpretation of percent changes. The estimated effects and imputed level changes are shown in Appendix Tables A.15-A.17. It is clear that the magnitude of the effects in both percents and levels and the statistical significance levels are very similar to the main results.

[15] I use the inverse hyperbolic sine transformation rather than logs for mortality rates because there are many zero observations in mortality rates. The inverse hyperbolic sine of a variable is defined as arsinh $= \ln(x + \sqrt{x^2 + 1})$. The formula shows that zero is well defined in the inverse hyperbolic sine function.

5.2 Mortality Costs of Spills

I now consider the mortality costs of severe inland oil spills. One way to monetize the social costs of mortality is to multiply the estimated number of lives lost by the value of a statistical life (VSL). The pitfall of this approach is that applying the same VSL in the evaluation may overstate the economic cost, since not all deceased individuals have the same life expectancy, e.g., a prime-aged person vs. an elderly person, and people who die as a result of oil spills might have been sicker prior to the oil spills than those who do not die. Alternatively, one could measure the life-years lost (LYL) rather than the lives lost and then use the value of a statistical life-year to monetize the mortality costs. This overcomes the shortcoming of using the same VSL for all decedents across different age groups. Hence, I rely on the LYL approach in this exercise.

The value of the mortality costs is measured by the product of the LYL and the value of a statistical life-year. The LYL is estimated using changes in the number of deaths and the counterfactual life expectancy for each age group. The changes in the number of deaths for each age group in counties with a spill that is not reported in the news are taken from Table 5 Panel A. Following the standard approach used in the empirical literature, I approximate counterfactual life expectancy using population life tables (Gardner & Sanborn, 1990; Fontaine, Redden, Wang, Westfall, & Allison, 2003; Centers for Disease Control and Prevention, 2008; Deschênes & Greenstone, 2011; Rapsomaniki et al., 2014).[16] Since people who die prematurely from oil spills are likely to be weaker and have shorter life expectancies, I follow Deryugina et al. (2019) and deflate the number of LYL by 31% to account for possible harvesting effects. If I assign each life-year a standard value of approximately $140,000 in 2019 dollars (Cutler, 2004), the total mortality cost of severe inland oil spills that are not reported in the news is approximately $3.49 billion in the post 12-month period.[17]

[16] I use the United States Life Tables of 2017 (Arias & Xu, 2019) to estimate the life expectancy, which is evaluated in the middle of the age range for each age group. The counterfactual life expectancy for the four age categories is 78.6 for infants (age $<$1 year), 71.6 for children (age 1-15 years), 42.0 for the working age population (age 16-64 years), and 12.4 for the elderly adults (age $\geq$65 years).

[17] In the oil spill scenario, using the same VSL across age groups will significantly overestimate the mortality

As discussed in the results section, the rapid downward level shift in mortality rates in counties with spills that are covered by news is most likely due to out-migration. Since there is no change in ambient air quality, the extreme avoidance behavior, out-migration does not reduce mortality but simply relocate more susceptible and vulnerable people. In other words, there is a general equilibrium effect, and no real changes in mortality occur in these counties. Had no information about an oil spill provided, air pollution would have worsened, and mortality rates would have increased in counties with spills that receive news coverage. Assuming counties with spills not reported in the news can serve as good counterfactuals for counties with spills that are reported in the news, the avoided mortality costs in all counties with spills that receive news coverage total \$2.62 billion. This can be interpreted as the mortality benefits of providing information about spills.

5.3 Provision of Spill Information as a Policy Option

The tradeoffs associated with the provision of information about spills determine whether it is ideal to consider providing information about spills as a policy option. Chen (2021) finds that spill information triggers sorting, which places the burden of avoidance costs on individuals, degrades labor markets in spill counties, and has distributional consequences that may aggravate environmental injustice. When spill information is made publicly available, high-income people are the ones who respond with migration. This implies that individuals are bearing avoidance costs, but only the high-income group can afford them. Changes in the composition of migrant groups weaken labor markets in counties with spills that receive news coverage and have distributional effects. People who cannot afford to leave face degraded labor market conditions during the post spill period. The composition of the remaining population in counties with spills that receive news coverage also becomes poorer over time,

cost. The VSL in the U.S. is in the range of \$4 to \$10 million according to an emerging consensus in the literature (e.g., Kniesner, Viscusi, Woock, & Ziliak, 2012; Robinson & Hammitt, 2016; Kniesner & Viscusi, 2019). Multiplying the number of lives lost by these VSL estimates without considering age differences will result in an estimated cost ranging from \$8.6 to \$20.2 billion. I do not use age-specific VSL estimates, which are available from several studies (e.g., Viscusi & Aldy, 2003; Blomquist, Dickie, & O'Conor, 2011; Aldy & Smyth, 2014), because these estimates do not cover all age groups.

which could exacerbate the inequality of exposure to pollution and environmental injustices. However, Chen (2021) suggests that it is possible to alleviate or even avoid these negative impacts by providing more complete information on the cleanup process and the surrounding environmental conditions and by formulating more targeted preventive regulations.

The results reported in this paper suggest that the provision of information about oil spills benefits the environment and human health. County-level ambient air quality deteriorates and mortality rates rise only when spill information is not made publicly available. This suggests that providing information about spills encourages faster cleanup responses, and consequently saves lives. The avoided air pollution and increases in mortality rates are far from a full accounting of the benefits of providing information about spills. Due to limited data availability, the effects of severe spills on water and soil conditions are not discussed in this paper. Given that ambient air quality does not change when information about spills is made publicly available, it is very likely that water and soil conditions will not be affected, at least not for a long time, when there information is available. Moreover, the provision of spill information may benefit other dimensions of human health. The provision of information will likely prevent an increase in the number of hospital admissions related to respiratory and cardiovascular problems, since changes in air quality due to spills are not detectable. When oil is released into water, spill information could prevent residents from developing diseases, such as digestive cancer, that are linked to drinking contaminated water (Ebenstein, 2012). Spill information may also lower the effects of spills on birth outcomes, such as low birth weight, premature birth, and abnormalities, which have long-term effects on cognitive development, educational attainment, and earnings (Black, Devereux, & Salvanes, 2007; Figlio, Guryan, Karbownik, & Roth, 2014; Oreopoulos, Stabile, Walld, & Roos, 2008).

Taking all of these factors into account, it is likely that the benefits of providing information about spills outweigh the costs, and the provision of spill information could serve as a policy tool. Note that the benefits of the use of providing information about spills as a policy tool are maximized only when policymakers also provide more complete environmental information and implement preventive regulations.

6 Conclusion

Using county-level variation in severe inland oil spills and their news coverage status, this paper examines how inland oil spills affect mortality rates when the public has different degrees of access to information. A lack of publicly available information about spills results in statistically significant increases in county-level air pollution levels and consequently increases in mortality rates for the entire population in the 12 months after a spill. Most of the increase in mortality rates comes from the most susceptible group: elderly adults. When a spill is reported in the news, there are not only no detectable changes in ambient air quality, but also long-lasting significant declines in mortality rates for the overall population in the incident counties. The mortality rate for almost every age group decreases in the five years after a spill. Using an analysis of heterogeneity, I demonstrate that the persistent decreases in mortality rate are because an increase in gross out-migration.

The findings of this paper imply that the provision of spill information is beneficial to the environment and human health. Ambient air quality worsens only when a spill is not reported in the news, suggesting that public attention induces faster cleanup. When air quality remains unchanged, mortality rates also do not change. The avoided increases in air pollution and the mortality rate provide a lower bound for the benefits of providing oil spill information to the public. The increased speed of cleanup induced by providing spill information would likely reduce the impacts of spills on other aspects of the environment, such as water and soil, and on the ecosystem. In addition to reducing mortality, faster cleanup will protect people from diseases related to oil spills.

While this paper considers the context of inland oil spills, the lessons obtained from this work and that of Chen (2021) could offer important guidance regarding the use of information as a policy tool for other environmental disasters, such as chemical spills and smog. Direct preventative regulations and remediation efforts will prevent environmental disasters and limit the impacts of such disasters when they do occur. The provision of information about environmental disasters can act as a complementary tool, because it will attract public attention, trigger faster cleanup, and protect the environment and human health. Complete and transparent information on the cleanup process and environmental conditions is essential to alleviate potential distributional consequences and environmental injustice associated with the provision of information.

Figures and Tables

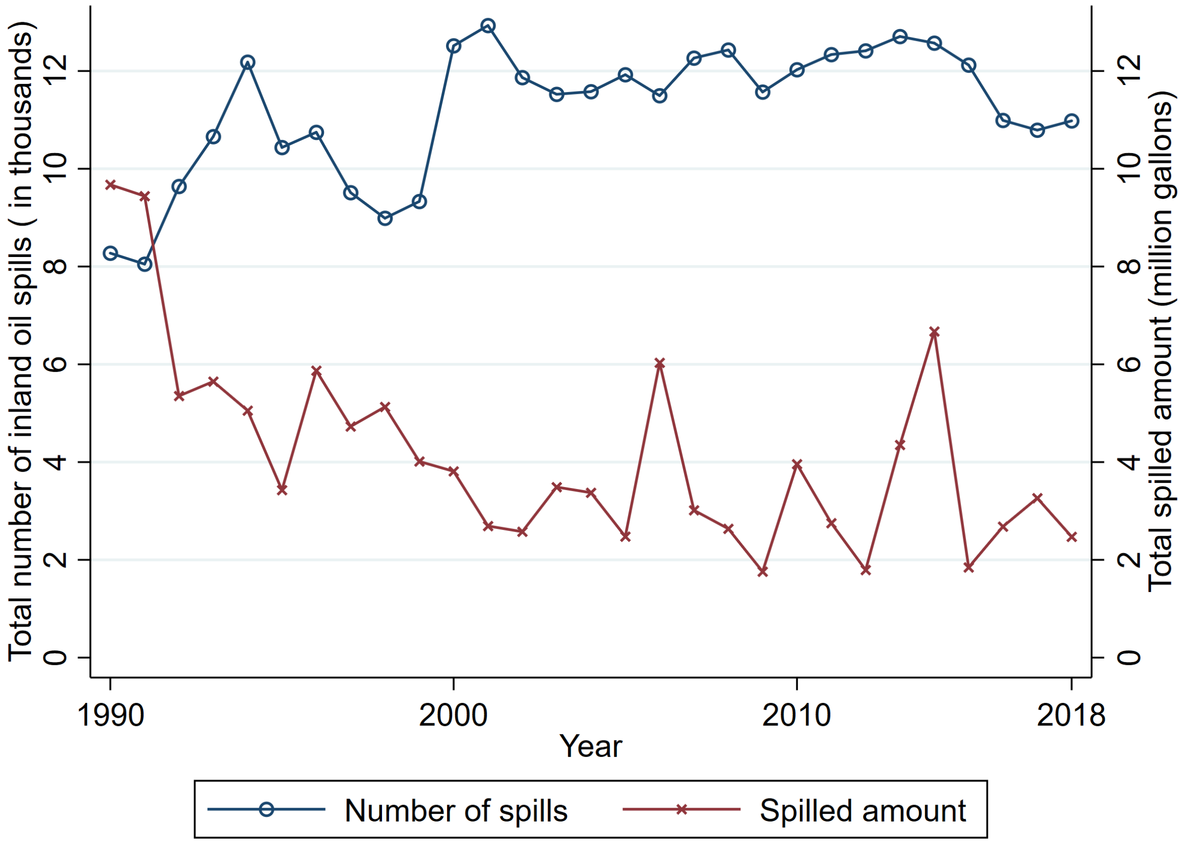
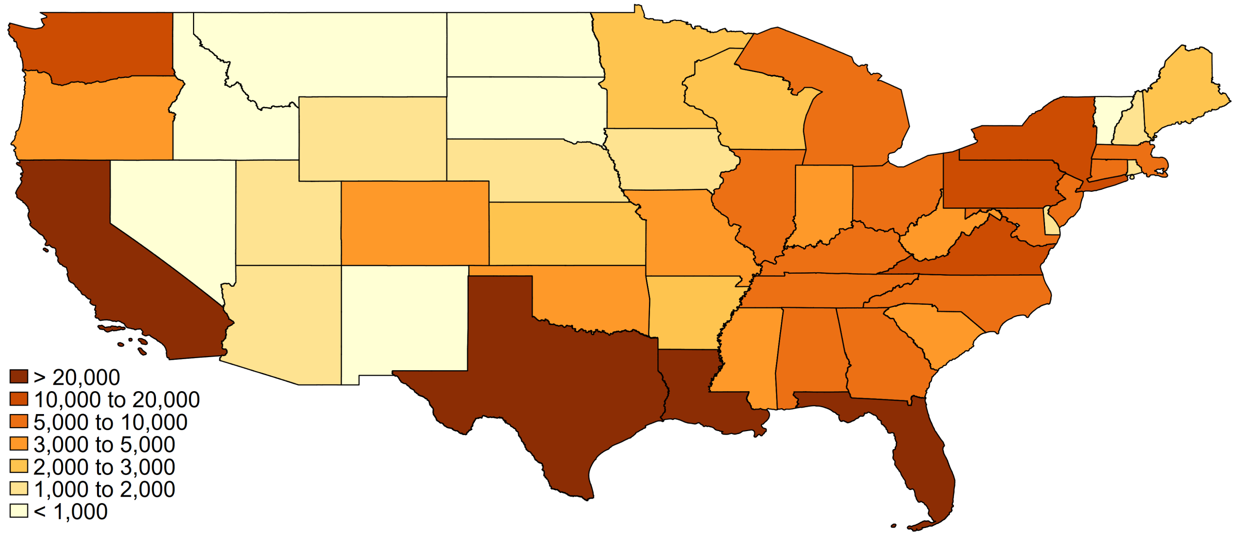
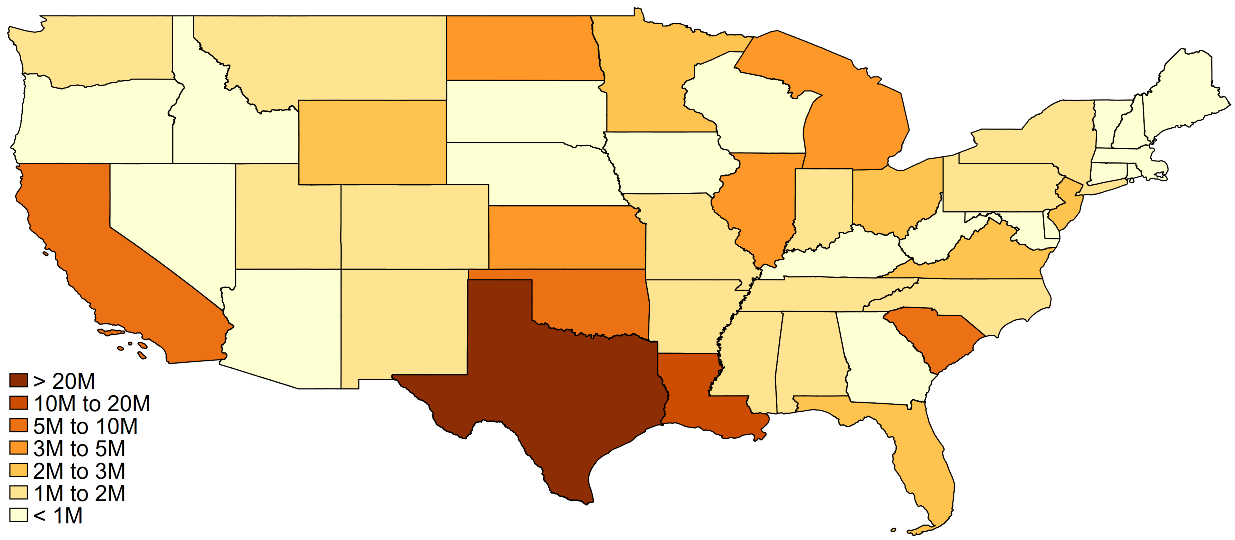


Figure 1: Total Numer of Inland Petroleum Oil Spills and Total Spilled Amount

Source: The National Response Center of the U.S. Coast Guard.



(a) Total Number of Incidents



(b) Total Spilled Amount (Gallons)

Figure 2: Number of Oil Spill Incidents and Spilled Amount of Each State in 1990-2018

Source: The National Response Center of the U.S. Coast Guard.

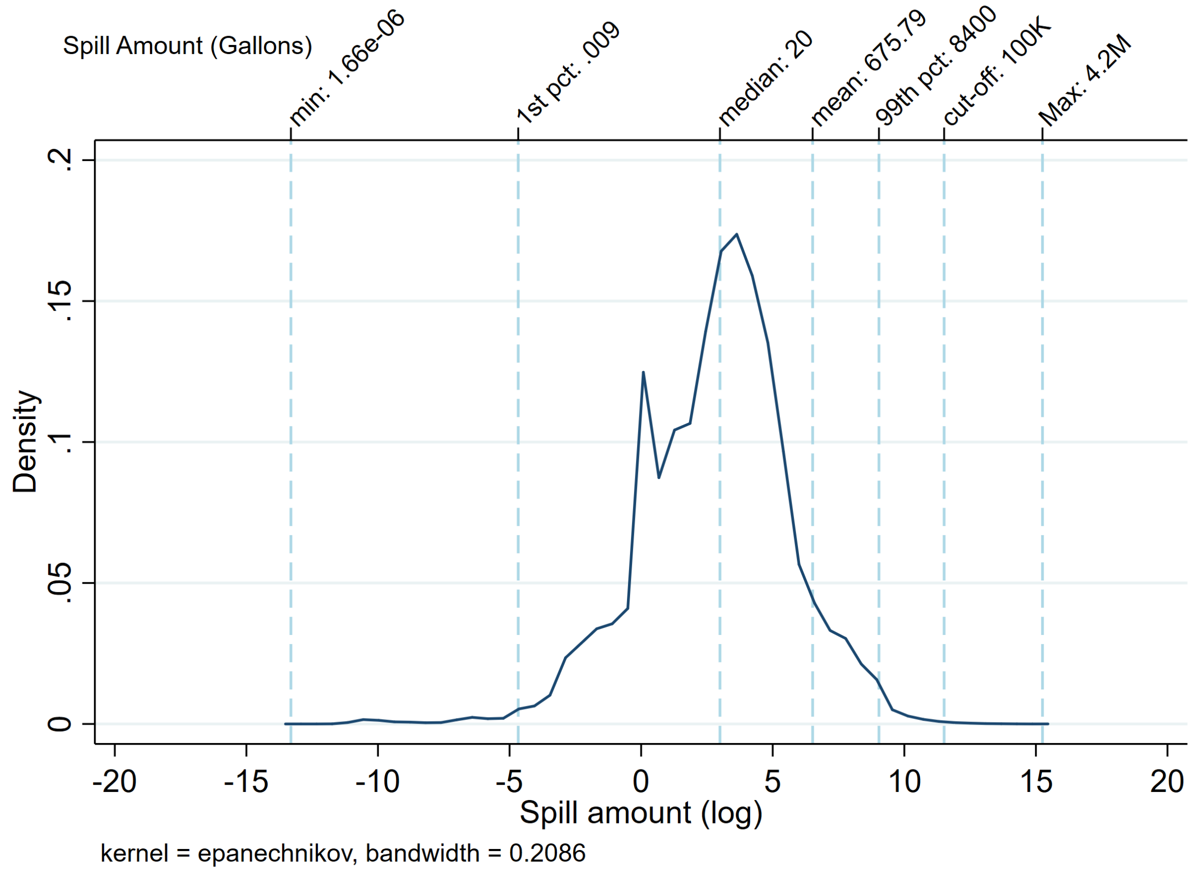


Figure 3: Density Plot of Spill Amount (log)

Note: The lower x-axis displays the logged spill amount, and the upper x-axis displays the summary statistics of the spill amount in gallons. The vertical dashed lines represent the logged values of the summary statistics on the upper x-axis.

Source: The National Response Center of the U.S. Coast Guard.

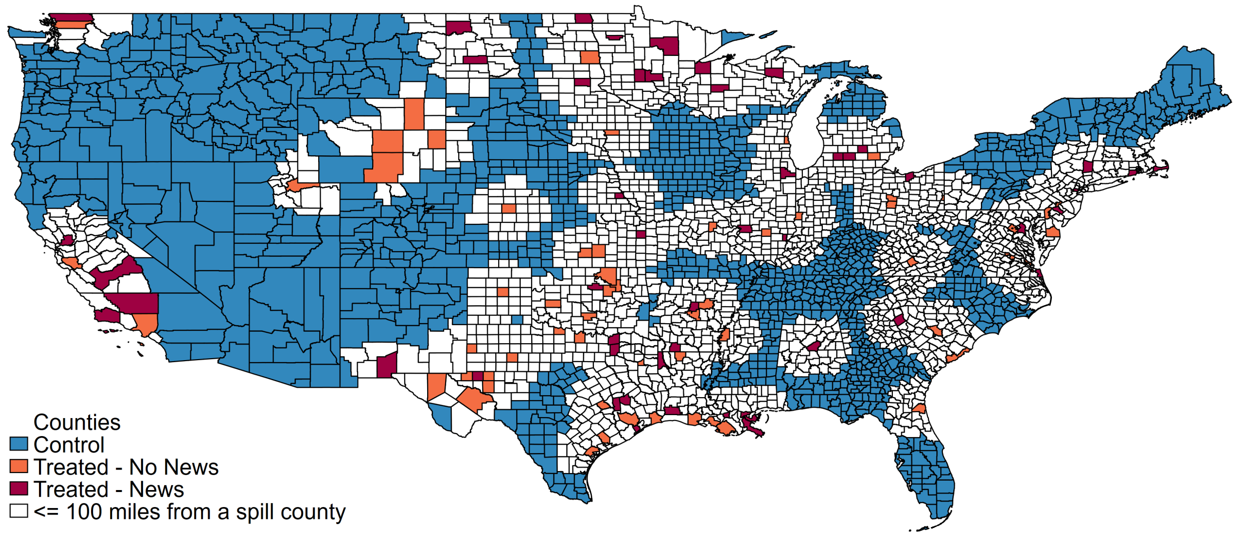
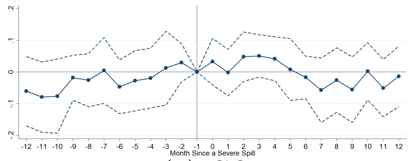


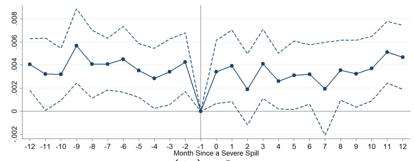
Figure 4: Treatment and Control Groups

Source: The National Response Center of the U.S. Coast Guard.

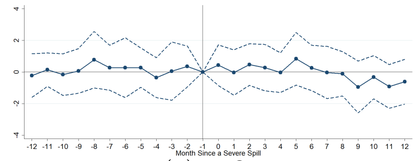
Panel A. With News Coverage



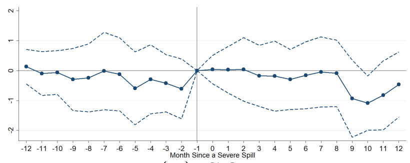
(a) CO



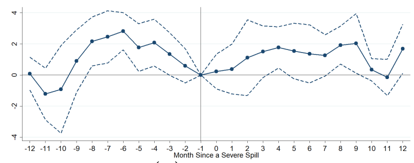
(b) O_3



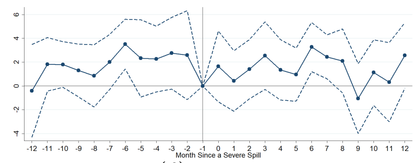
(c) NO_2



(d) SO_2

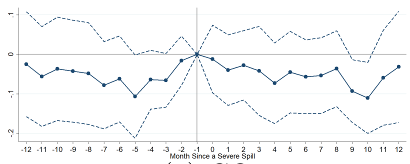


(e) $PM_{2.5}$

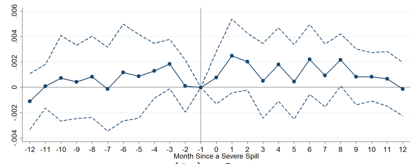


(f) PM_{10}

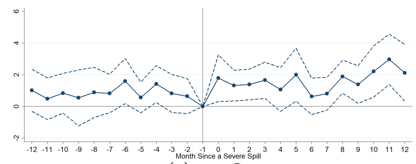
Panel B. Without News Coverage



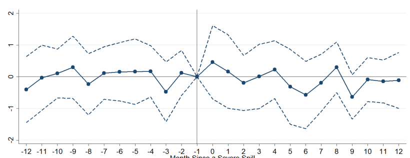
(g) CO



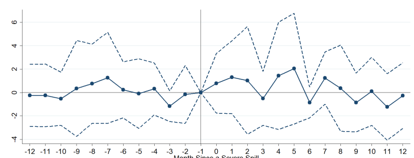
(h) O_3



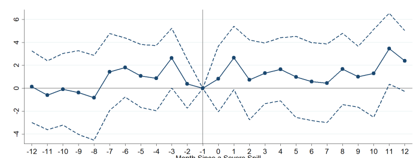
(i) NO_2



(j) SO_2



(k) $PM_{2.5}$



(l) PM_{10}

Figure 5: Effects of Severe Inland Oil Spills on Ambient Pollution

Note: These are event study plots created by regressing outcome variables of the spill counties on a set of event time indicators, county-by-month of year and state-by-year fixed effects as specified in Equation (1). The outcome variables are displayed below the corresponding plots. The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95% confidence intervals. Standard errors are clustered at county level. Time is normalized relative to the month in which a severe inland oil spill occurs and the coefficients are normalized to zero in the month prior to a spill.
Source: EPA's AQS.

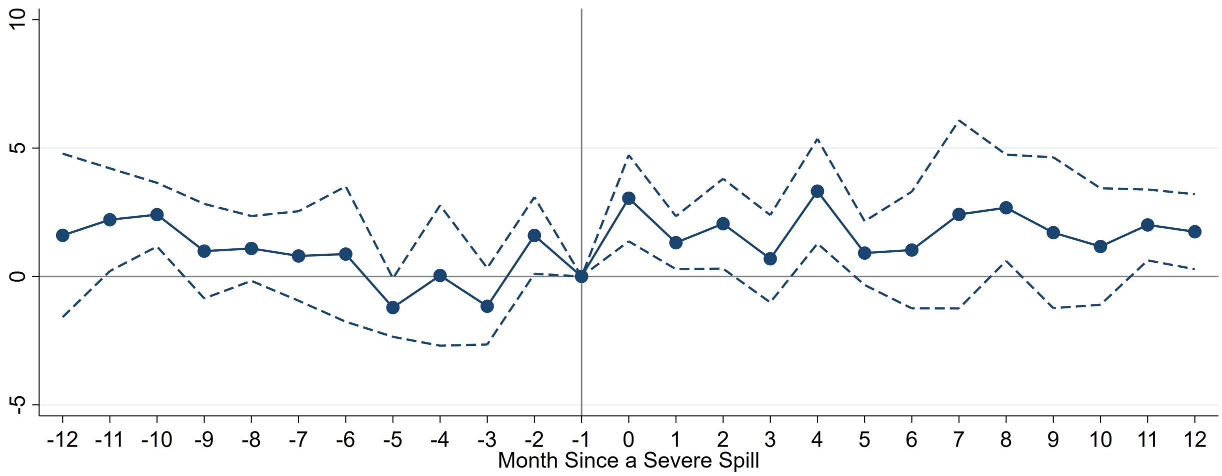
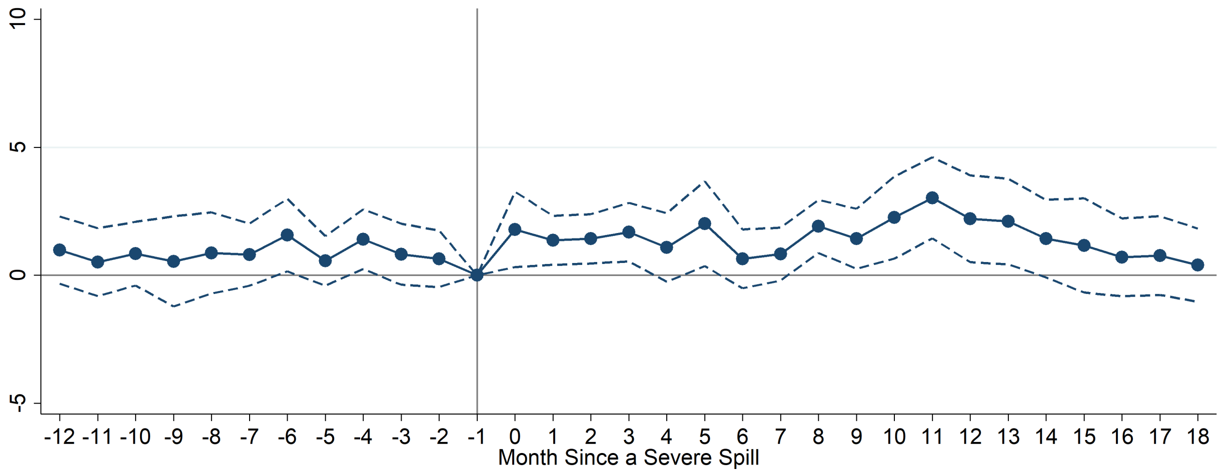
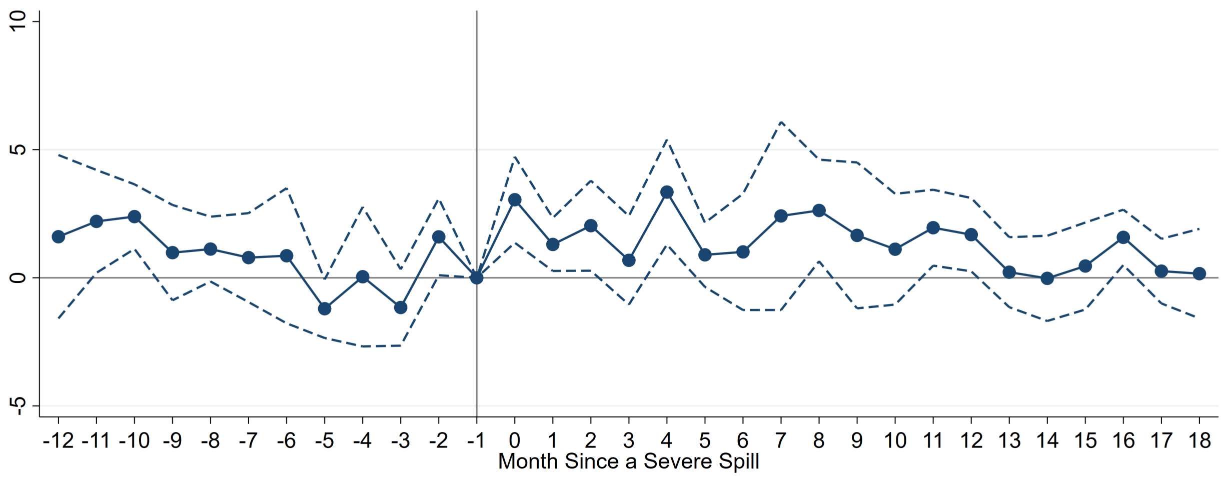


Figure 6: Effects of Spills Without News Coverage on Monthly ASMR

Note: This figure plots the estimates of the event study coefficients specified in Equation (1). The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95% confidence intervals. Standard errors are clustered at the county level. Time is normalized relative to the month in which a severe inland oil spill occurs and the coefficients are normalized to zero in the month prior to a spill.
Source: NVSS.



(a) NO_2



(b) All-Cause ASMR

Figure 7: Effects of Spills Without News Coverage on NO_2 and Monthly All-Cause ASMR

Note: This figure plots the estimates of the event study coefficients specified in Equation (1). The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95% confidence intervals. Standard errors are clustered at the county level. Time is normalized relative to the month in which a severe inland oil spill occurs and the coefficients are normalized to zero in the month prior to a spill.
Source: AQS and NVSS.

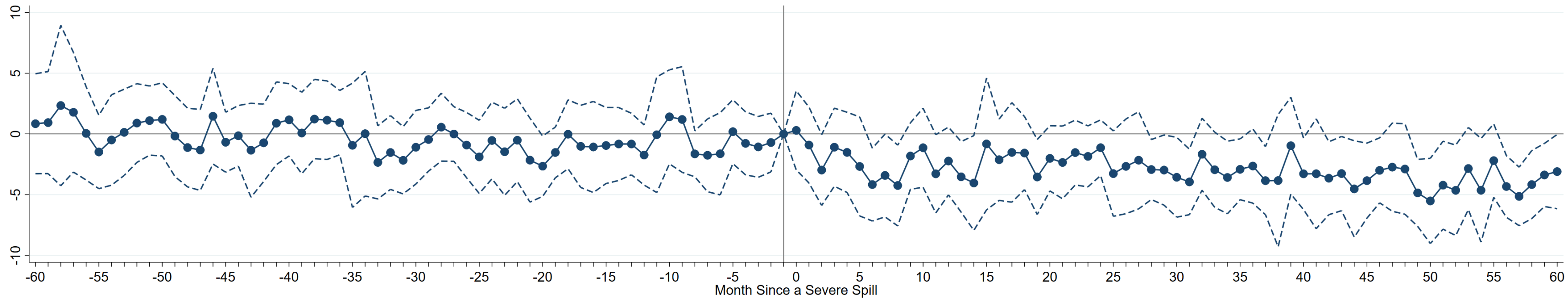
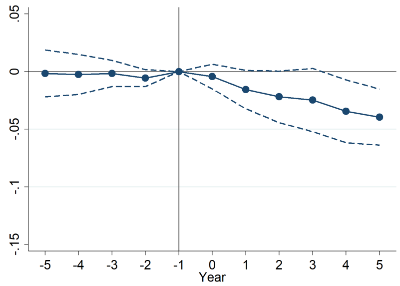


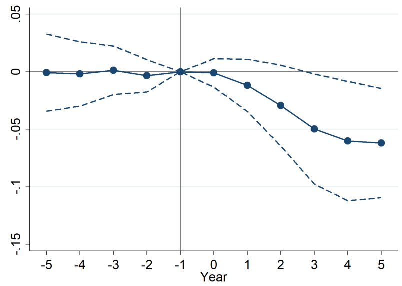
Figure 8: Effects of Spills with News Coverage on Monthly ASMR

Note: This figure plots the estimates of the event study coefficients specified in Equation (1). The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95% confidence intervals. Standard errors are clustered at the county level. Time is normalized relative to the month in which a severe inland oil spill occurs and the coefficients are normalized to zero in the month prior to a spill.
Source: NVSS.

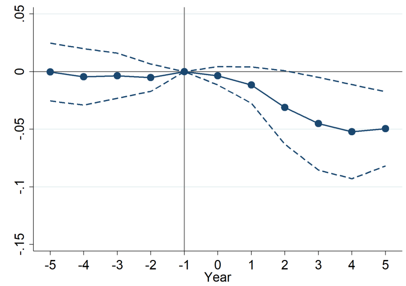
Panel A. Labor Market Outcomes



(a) Average wage per job (log)

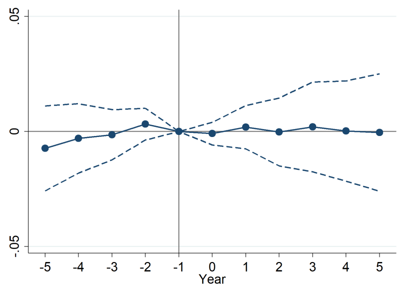


(b) Employment (log)

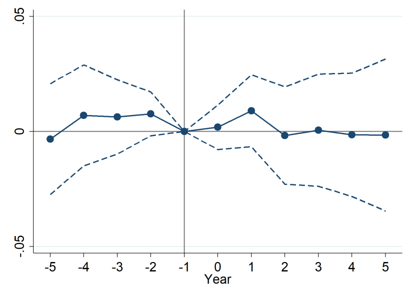


(c) Emp/working age pop ratio

Panel B. Government Transfers

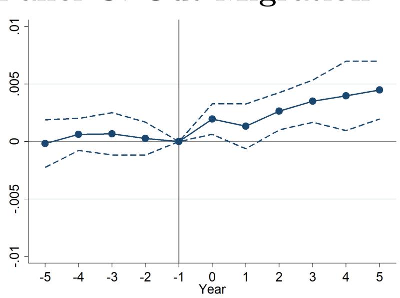


(d) Government transfers (log)



(e) Medical benefits (log)

Panel C. Out-Migration



(f) Gross out-migration rate

Figure 9: Changes in Potential Channels: Labor Outcomes, Transfers, and Out-Migration

Note: These event study plots are created by regressing outcome variables of the spill counties on a set of event time indicators, county fixed effects, and state-by-year fixed effects. The names of the outcome variables are displayed below each plot. The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95 percent confidence intervals. Standard errors are clustered at county level. Time is normalized relative to the year in which a severe inland oil spill occurs and the coefficients are normalized to zero in the year prior to a spill. Panels A and C are regenerated from Chen (2021).
Source: QCEW, IRS, and REIS.

Table 1: Summary Statistics of Severe ($\geq$ 100K gallons) Inland Oil Spills (in 1000 gallons)

	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Median	(6) Max
Panel A. All Severe Spills						
Spill Amount	139	335.67	465.35	100	200	4200
Panel B. Severe Spills by News Coverage						
With News	59	354.04	584.78	100	223	4158
Without News	80	322.12	523.71	100	164.77	4200
Panel C. Severe Spills by Type of Incident						
Pipeline	77	311.01	279.10	100	212.10	1680
Fixed Facility	31	222.34	282.06	100	130.20	1512
Vessel	14	401.47	366.95	100	226	1260
Storage Tank	13	718.00	1199.5	100	186.90	4200
Railroad	4	215.75	179.90	100	140	483
Panel D. Severe Spills by News Coverage and Type of Incident						
With News						
Pipeline	42	353.93	303.63	100	244	1680
Fixed Facility	3	171.13	66.407	126	140	247.38
Vessel	8	299.25	234.39	100	226	828
Storage Tank	5	603.20	936.72	100	168	2268
Railroad	1	100	-	100	100	100
Without News						
Pipeline	35	259.52	240.72	100	200.30	1449
Fixed Facility	28	227.83	296.23	100	128.10	1512
Vessel	6	537.77	483.91	105	426.80	1260
Storage Tank	8	789.74	1396.4	100	269.85	4200
Railroad	3	254.33	199.04	120	160	483

Note: The data span 1990-2018. The mean amount of spills with and without news coverage in Panel B are not statistically different: the p-value is 0.69 and the t-stat is 0.3989.
Source: The U.S. Coast Guard National Response Center.

Table 2: Summary Statistics of Monthly County-Level Mortality Rates and Population

	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Max
Panel A. Monthly Age-Standardized Mortality Rate					
All Causes					
Overall Population	1,320,613	65.63	14.88	0	1,638.87
Infant (age $<$ 1)	1,320,704	66.76	87.22	0	100,000
Children	1,320,806	2.05	4.31	0	4,000
Working Age Pop	1,320,798	25.12	9.81	0	1,512
Elderly (age $\geq$ 65)	1,320,578	382.00	89.19	0	10,742.59
Internal Causes					
Overall Population	1,320,613	60.67	14.07	0	1,620.96
Infant (age $<$ 1)	1,320,704	63.73	85.23	0	100,000
Children	1,320,806	1.07	2.66	0	1,388.89
Working Age Pop	1,320,798	19.76	8.17	0	1,512
Elderly (age $\geq$ 65)	1,320,578	372.69	88.06	0	10,438.58
External Causes					
Overall Population	1,320,613	4.96	3.37	0	648.79
Infant (age $<$ 1)	1,320,704	3.03	17.90	0	7,142.86
Children	1,320,806	0.98	3.36	0	4,000
Working Age Pop	1,320,798	5.36	4.24	0	874.79
Elderly (age $\geq$ 65)	1,320,578	9.31	10.74	0	4,836.24
Panel B. Annual Population					
Overall Population	1,329,697	90,165.24	292,623.8	61	10,163,507
Infant (age $<$ 1)	1,329,588	1,254.88	4,429.21	1	185,654
Children	1,329,680	17,466.45	57,849.95	5	2,116,663
Working Age Pop	1,329,697	59,808.17	197,427.4	46	6,983,106
Elderly (age $\geq$ 65)	1,329,497	11,637.8	34,370.62	14	1,343,960

Note: The summary statistics are for all U.S. counties in 1982-2017. Age-standardized mortality rates are defined as the number of deaths per 100,000 people.
Source: NVSS for Panel A and SEER for Panel B.

Table 3: Summary Statistics of Monthly County-Level Ambient Air Pollution

	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Max
CO (ppb)	215,054	0.753	0.571	0.000	6.579
O_3 (ppb)	482,780	0.031	0.010	0.000	0.089
NO_2 (ppm)	211,304	13.328	8.254	0.000	125.400
SO_2 (ppm)	342,951	4.914	4.837	0.000	437.390
$PM_{2.5}$ (μg/m3)	268,131	10.720	4.300	0.300	88.020
PM_{10} (μg/m3)	340,512	23.733	10.550	0.067	423.420

Note: The summary statistics for CO, O_3, NO_2, and SO_2 are from 1980 to 2018, for $PM_{2.5}$ are from 1999 to 2018, and for PM_{10} are from 1986 to 2018.
Source: EPA's AQS.

Table 4: Effects of Severe Inland Oil Spills on County-Level Monthly Ambient Air Pollution

	CO (ppb)	O_3 (ppb)	NO_2 (ppm)	SO_2 (ppm)	$PM_{2.5}$ (μg/m3)	PM_{10} (μg/m3)
Panel A. With News Coverage						
0-12 months after spill	0.022	-0.000	-0.152	-0.121	0.191	-0.126
	(0.020)	(0.001)	(0.211)	(0.259)	(0.194)	(0.692)
Percent change	3.532	-0.459	-1.025	-2.673	1.937	-0.541
Mean of dep. var.	0.611	0.028	14.826	4.530	9.834	23.333
N	77,352	180,261	68,045	125,043	100,841	141,944
Panel B. Without News Coverage						
0-12 months after spill	-0.003	0.001	0.839**	-0.054	0.393	0.849
	(0.020)	(0.000)	(0.423)	(0.285)	(0.405)	(0.626)
Percent change	-0.436	1.948	5.640	-1.053	3.133	3.400
Mean of dep. var.	0.738	0.028	14.869	5.129	12.529	24.978
N	78,212	178,318	68,288	126,439	100,800	141,114

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of the severe inland oil spills on criteria air pollutants at the county-by-month level in the 12 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. Standard errors are clustered at the county level.
Source: EPA's AQS.

Table 5: Effects of Spills Without News Coverage on County-Level Monthly ASMR

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-12 months after spill	1.033**	−3.344*	0.123	0.004	8.293**
	(0.431)	(1.900)	(0.082)	(0.133)	(2.911)
Percent change	1.668	-5.497	6.983	0.018	2.240
Mean ASMR	61.917	60.837	1.766	22.688	370.214
Panel B. Internal-Cause ASMR					
0-12 months after spill	1.091**	-2.459	0.085	0.135	8.047**
	(0.464)	(1.568)	(0.058)	(0.165)	(3.082)
Percent change	1.886	-4.207	8.441	0.743	2.218
Mean ASMR	57.842	58.451	1.012	18.178	362.848
Panel C. External-Cause ASMR					
0-12 months after spill	-0.058	-0.885	0.038	-0.131	0.245
	(0.079)	(0.582)	(0.065)	(0.090)	(0.264)
Percent change	-1.419	-37.101	5.026	-2.905	3.332
Mean ASMR	4.075	2.386	0.754	4.511	7.366
Panel D. Cardiovascular ASMR					
0-12 months after spill	0.369**	-0.365	0.025	-0.025	2.865**
	(0.188)	(0.246)	(0.027)	(0.084)	(1.382)
Percent change	1.458	-22.398	24.225	-0.400	1.668
Mean ASMR	25.332	1.628	0.104	6.243	171.788
Panel E. Respiratory ASMR					
0-12 months after spill	0.303*	0.689**	0.015	0.037	2.091*
	(0.155)	(0.294)	(0.022)	(0.041)	(1.180)
Percent change	5.190	41.189	15.352	3.719	5.032
Mean ASMR	5.840	1.673	0.096	0.995	41.563
N	555,433	555,474	555,527	555,527	555,406
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of estimates of the effects of severe inland oil spills not reported in the news on ASMR at the county-by-month level in the 12 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: NVSS.

Table 6: Effects of NO_2 on County-Level Monthly ASMR: OLS and IV

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. OLS					
NO_2	0.100**	0.091	0.004**	0.045**	0.552**
	(0.041)	(0.084)	(0.002)	(0.023)	(0.206)
Percent change	0.163	0.146	0.209	0.193	0.152
Mean ASMR	60.124	57.262	1.616	22.007	359.947
Panel B. IV					
NO_2	0.421***	0.292	0.015*	0.217***	2.215***
	(0.072)	(0.234)	(0.008)	(0.036)	(0.585)
Percent change	0.700	0.511	0.939	0.986	0.615
Mean ASMR	60.124	57.262	1.616	22.007	359.947
First stage F statistics (Kleibergen-Paap rk Wald)	48.497	44.736	47.084	49.274	46.541
N	56,787	56,787	56,787	56,787	56,787
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the OLS and IV estimates of the effects of NO_2 on ASMR at the county-month level. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: AQS and NVSS.

Table 7: Effects of Spills with News Coverage on County-Level Monthly ASMR

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-60 months after spill	-1.300^{**}	-3.724	0.030	-1.177^{**}	-4.937^{**}
	(0.408)	(3.020)	(0.088)	(0.408)	(1.915)
Percent change	-1.786	-4.922	1.339	-3.969	-1.192
Mean ASMR	72.801	75.668	2.264	29.650	414.149
Panel B. Internal-Cause ASMR					
0-60 months after spill	-1.180^{**}	-3.844	-0.001	-1.001^{**}	-4.862^{**}
	(0.366)	(3.015)	(0.065)	(0.334)	(1.906)
Percent change	-1.749	-5.273	-0.086	-4.241	-1.199
Mean ASMR	67.469	73.888	1.215	23.593	405.568
Panel C. External-Cause ASMR					
0-60 months after spill	-0.120	0.119	0.031	-0.176	-0.075
	(0.113)	(0.286)	(0.042)	(0.157)	(0.185)
Percent change	-2.247	4.287	2.990	-2.909	-0.875
Mean ASMR	5.332	2.780	1.049	6.057	8.581
N	547,807	547,848	547,901	547,901	547,780
Pct. in the pop	100	1.352	19.858	65.568	13.222

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimated effects of severe inland oil spills that are reported in the news on ASMR at the county-by-month level in the 60 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: NVSS.

Table 8: Effects of Spills with News Coverage on County-Level Monthly ASMR by Out-Migration

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-60 months after spill	-1.300^{**}	-3.724	0.030	-1.177^{**}	-4.937^{**}
	(0.408)	(3.020)	(0.088)	(0.408)	(1.915)
Percent change	-1.786	-4.922	1.339	-3.969	-1.192
Mean ASMR	72.801	75.668	2.264	29.650	414.149
N	547,807	547,848	547,901	547,901	547,780
Pct. in the pop	100	1.352	19.858	65.568	13.222
Panel B. Counties With Above Average Out-Migration Effect					
0-60 months after spill	-1.948^{***}	-4.640	-0.093	-1.788^{***}	-7.086^{***}
	(0.328)	(2.873)	(0.104)	(0.405)	(2.056)
Percent change	-2.626	-6.157	-4.006	-5.792	-1.685
Mean ASMR	74.163	75.366	2.332	30.877	420.491
N	540,931	540,972	541,025	541,025	540,904
Pct. in the pop	100	1.375	20.392	65.250	12.983
Panel C. Counties With Below Average Out-Migration Effect					
0-60 months after spill	-0.188	-3.466	0.292^{***}	0.047	-1.648
	(0.645)	(5.842)	(0.073)	(0.499)	(3.215)
Percent change	-0.269	-4.546	13.667	0.175	-0.411
Mean ASMR	70.017	76.244	2.134	27.111	400.446
N	539,197	539,238	539,291	539,291	539,170
Pct. in the pop	100	1.331	19.400	65.841	13.427

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimated effects of severe inland oil spills that are reported in the news on ASMR at the county-by-month level in the 60 months after a spill by changes in out-migration. All regressions include county-by-month of year and state-by-year fixed effects. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: NVSS.

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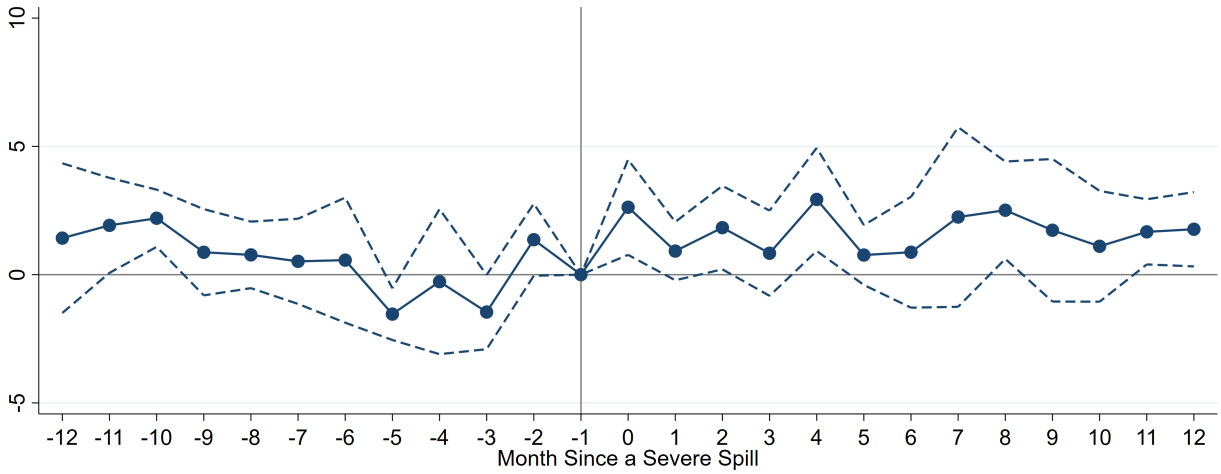
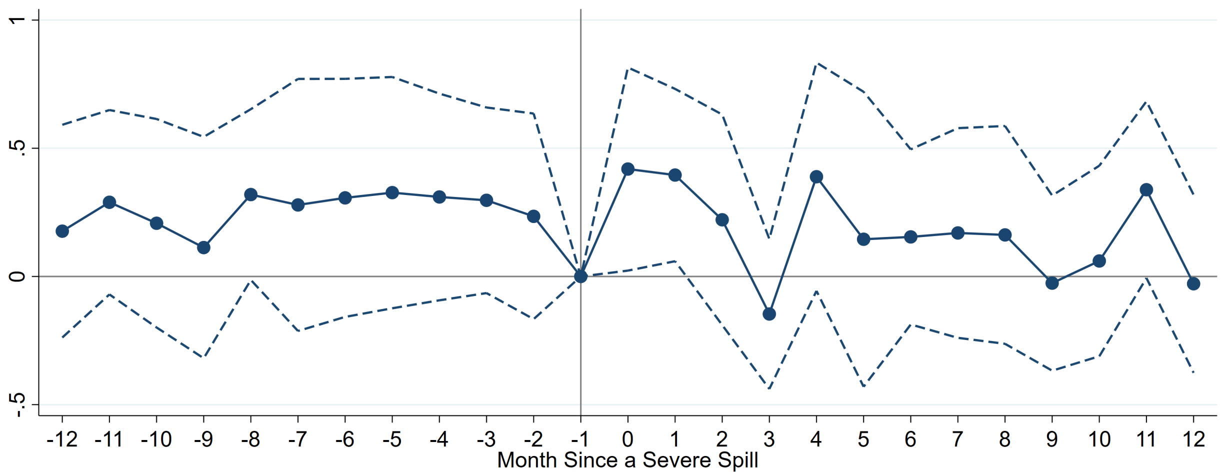
Appendix

A Figures and Tables



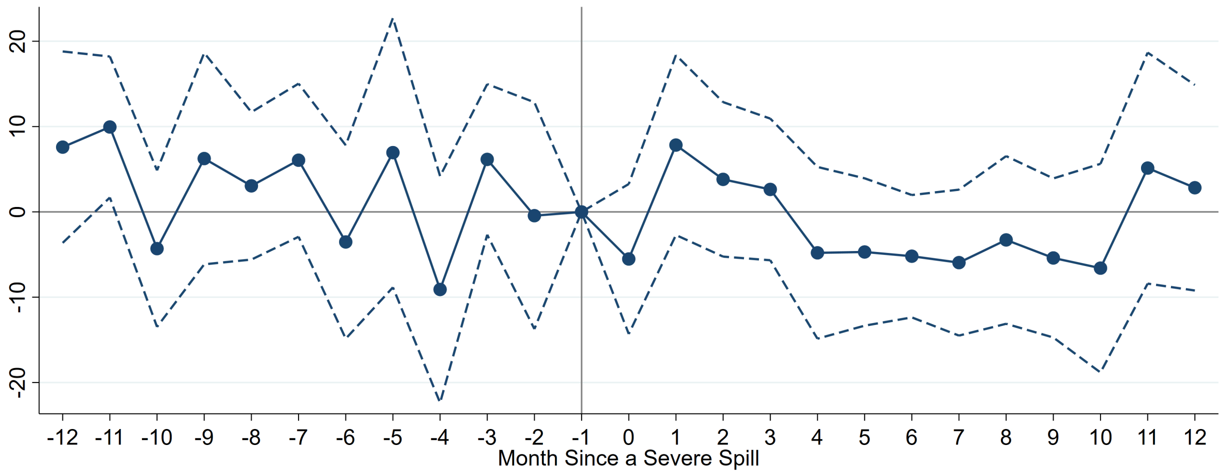
(a) Internal-Cause ASMR



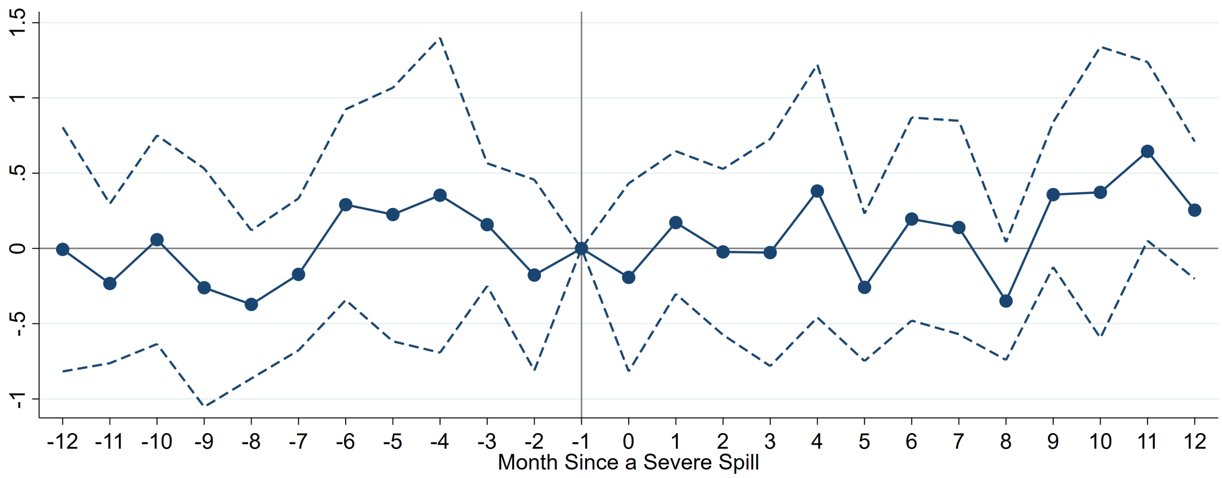
(b) External-Cause ASMR

Figure A.1: Effects of Not News-Covered Spills on Monthly Internal- and External-Cause ASMR

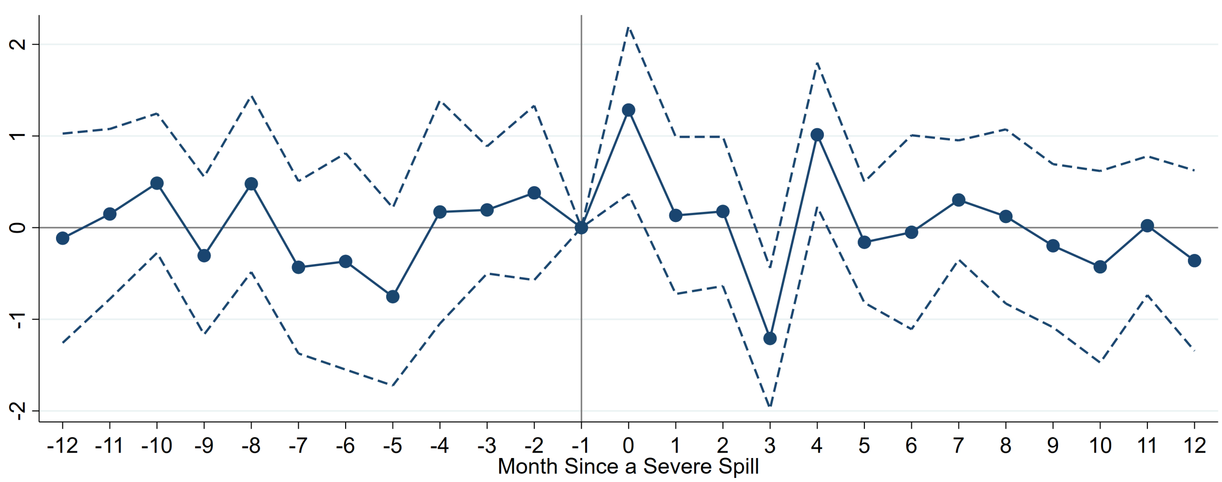
Note: This figure plots the estimates of the event study coefficients specified in Equation (1). The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95% confidence intervals. Standard errors are clustered at the county level. Time is normalized relative to the month in which a severe inland oil spill occurs and the coefficients are normalized to zero in the month prior to a spill.
Source: NVSS.



(a) Infants

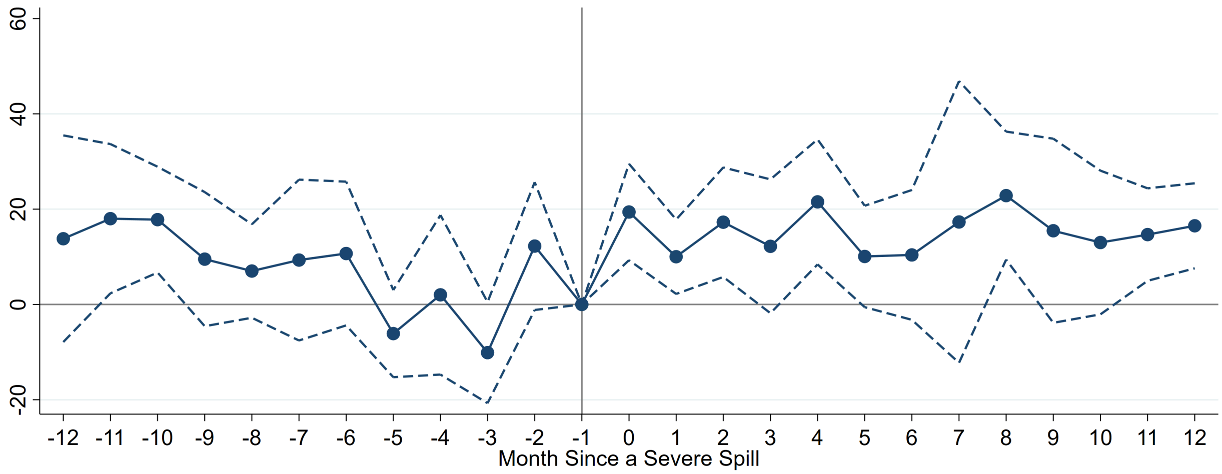


(b) Children



(c) Working Age Population

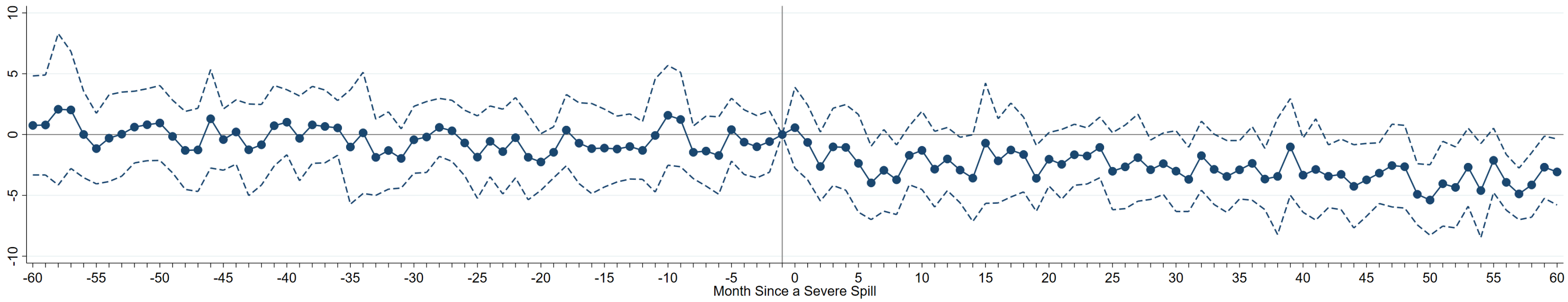
Figure A.2: Effects of Not News-Covered Spills on Monthly All-Cause ASMR by Age Groups



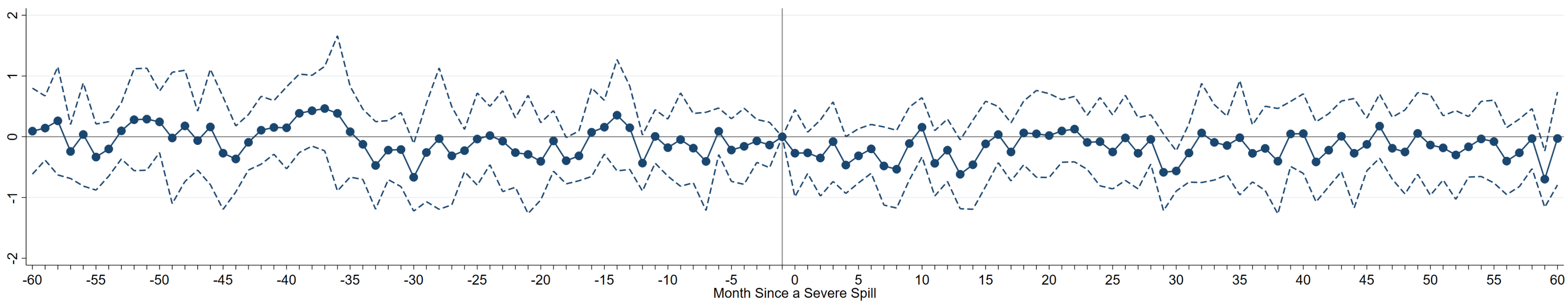
(d) Elderly

Figure A.2: Effects of Not News-Covered Spills on Monthly All-Cause ASMR by Age Groups (cont.)

Note: This figure plots the estimates of the event study coefficients specified in Equation (1). The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95% confidence intervals. Standard errors are clustered at the county level. Time is normalized relative to the month in which a severe inland oil spill occurs and the coefficients are normalized to zero in the month prior to a spill.
Source: NVSS.



(a) Internal-Cause ASMR



(b) External-Cause ASMR

Figure A.3: Effects of Spills with News Coverage on Monthly Internal- and External-Cause ASMR

Note: This figure plots the estimates of the event study coefficients specified in Equation (1). The points on the connected lines represent the estimated effects at each event time. The dashed lines represent the 95% confidence intervals. Standard errors are clustered at the county level. Time is normalized relative to the month in which a severe inland oil spill occurs and the coefficients are normalized to zero in the month prior to a spill.
Source: NVSS.

Table A.1: Effects of Severe Inland Oil Spills on County-Level Weekly Ambient Air Pollution

	CO (ppb)	O_3 (ppb)	NO_2 (ppm)	SO_2 (ppm)	$PM_{2.5}$ (μg/m3)	PM_{10} (μg/m3)
Panel A. First Week After a Spill						
With News	-0.105	0.001	-0.249	-0.137	-0.572	-1.726
	(0.086)	(0.001)	(0.499)	(0.413)	(2.063)	(1.838)
N	334,114	762,082	291,980	539,061	430,358	593,736
Without News	-0.040	-0.000	1.868	-1.009	2.406	0.386
	(0.049)	(0.001)	(1.351)	(0.675)	(2.466)	(3.344)
N	338,671	753,742	291,916	545,311	428,823	592,999
Panel B. First Two Weeks After a Spill						
With News	-0.079	0.001	-0.817	-0.213	-0.462	-2.008
	(0.080)	(0.001)	(0.640)	(0.387)	(1.706)	(1.749)
N	334,114	762,082	291,980	539,061	430,358	592,233
Without News	-0.057	-0.001	1.866**	-0.962	1.955	0.983
	(0.041)	(0.001)	(0.947)	(0.631)	(2.243)	(2.598)
N	338,671	753,742	291,916	545,311	428,823	592,999
Panel C. First Four Weeks After a Spill						
With News	-0.043	0.001	-0.627	-0.217	0.700	-2.882*
	(0.050)	(0.001)	(0.522)	(0.287)	(0.776)	(1.725)
N	334,114	758,912	291,666	539,061	430,358	592,233
Without News	-0.086	0.000	1.648**	-0.882**	0.126	0.825
	(0.053)	(0.001)	(0.801)	(0.378)	(2.006)	(1.670)
N	338,671	749,760	290,762	545,311	427,786	592,999

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of the severe inland oil spills on criteria air pollutants at the county-by-week level in the first week, the first two weeks, and the first four weeks after a spill. All regressions include county-by-week of year, and state-by-year fixed effects and weather controls. Standard errors are clustered at the county level.
Source: EPA's AQS.

Table A.2: Effects of NO_2 on County-Level Monthly ASMR After a Spill not Reached Water: OLS and IV

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. OLS					
NO_2	0.110**	0.103	0.003	0.050**	0.599**
	(0.041)	(0.088)	(0.002)	(0.025)	(0.201)
Percent change	0.188	0.190	0.165	0.237	0.169
Mean ASMR	58.638	54.040	1.549	21.015	353.652
Panel B. IV					
NO_2	0.374***	0.389**	0.009	0.196***	1.911***
	(0.042)	(0.130)	(0.007)	(0.028)	(0.364)
Percent change	0.638	0.720	0.607	0.931	0.540
Mean ASMR	58.638	54.040	1.549	21.015	353.652
First stage F statistics (Kleibergen-Paap rk Wald)	80.413	73.530	73.318	79.220	85.088
N	54,849	54,849	54,849	54,849	54,849
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the OLS and IV estimated effects of NO_2 on ASMR at the county-month level. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: AQS and NVSS.

Table A.3: Effects of Severe Inland Oil Spills on County-Level Monthly Ambient Air Pollution with Fixed Effects Different from the Main Specification

	CO (ppb)	O_3 (ppb)	NO_2 (ppm)	SO_2 (ppm)	$PM_{2.5}$ (μg/m3)	PM_{10} (μg/m3)
Panel A. With News Coverage						
0-12 months after spill	0.014	-0.000	0.028	0.053	0.209	-0.184
	(0.018)	(0.001)	(0.173)	(0.213)	(0.259)	(0.610)
Percent change	2.310	-1.490	0.187	1.166	2.123	-0.787
Mean of dep. var.	0.611	0.028	14.826	4.530	9.834	23.333
N	77,822	180,771	68,659	125,608	101,097	142,577
Panel B. Without News Coverage						
0-12 months after spill	-0.034	0.001	0.607**	-0.027	0.272	0.691
	(0.022)	(0.000)	(0.245)	(0.291)	(0.242)	(0.431)
Percent change	-4.642	2.035	4.080	-.526	2.169	2.765
Mean of dep. var.	0.738	0.028	14.869	5.129	12.529	24.978
N	78,686	178,827	68,902	126,999	101,057	141,749

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of the severe inland oil spills on criteria air pollutants at the county-by-month level in the 12 months after a spill. All regressions include county, month of year, and year fixed effects and weather controls. Standard errors are clustered at the county level.
Source: EPA's AQS.

Table A.4: Effects of Spills Without News Coverage on County-Level Monthly ASMR with Fixed Effects Different from the Main Specification

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-12 months after spill	1.054	−3.235	0.104	0.081	8.235*
	(0.649)	(2.242)	(0.070)	(0.174)	(4.279)
Percent change	1.703	-5.317	5.882	0.359	2.224
Mean ASMR	61.917	60.837	1.766	22.688	370.214
Panel B. Internal-Cause ASMR					
0-12 months after spill	1.063	-2.285	0.106**	0.166	7.798*
	(0.699)	(1.888)	(0.046)	(0.230)	(4.394)
Percent change	1.838	-3.909	10.482	0.911	2.149
Mean ASMR	57.842	58.451	1.012	18.178	362.848
Panel C. External-Cause ASMR					
0-12 months after spill	-0.008	−0.950*	0.002	-0.084	0.436*
	(0.093)	(0.558)	(0.062)	(0.110)	(0.247)
Percent change	-0.206	-39.802	-0.291	-1.868	5.920
Mean ASMR	4.075	2.386	0.754	4.511	7.366
Panel D. Cardiovascular ASMR					
0-12 months after spill	0.506*	-0.230	0.020	0.140	3.274
	(0.298)	(0.205)	(0.025)	(0.099)	(2.112)
Percent change	1.999	-14.105	19.418	2.247	1.906
Mean ASMR	25.332	1.628	0.104	6.243	171.788
Panel E. Respiratory ASMR					
0-12 months after spill	0.281**	0.515	0.016	0.026	2.083**
	(0.112)	(0.313)	(0.020)	(0.039)	(0.841)
Percent change	4.806	30.760	17.173	2.631	5.013
Mean ASMR	5.840	1.673	0.096	0.995	41.563
N	555,435	555,476	555,529	555,529	555,408
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills not reported in the news on ASMR at the county-month level in the 12 months after a spill. All regressions include county, month of year, and year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.

Source: NVSS.

Table A.5: Effects of Spills with News Coverage on County-Level Monthly ASMR with Fixed Effects Different from the Main Specification

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-60 months after spill	-1.591^{***}	-2.827	-0.056	-1.434^{**}	-5.429^{**}
	(0.449)	(3.221)	(0.132)	(0.650)	(1.654)
Percent change	-2.185	-3.735	-2.472	-4.836	-1.311
Mean ASMR	72.801	75.668	2.264	29.650	414.149
Panel B. Internal-Cause ASMR					
0-60 months after spill	-1.373^{***}	-3.044	-0.068	-1.112^{**}	-5.400^{**}
	(0.295)	(3.168)	(0.087)	(0.372)	(1.720)
Percent change	-2.035	-4.177	-5.610	-4.714	-1.331
Mean ASMR	67.469	73.888	1.215	23.593	405.568
Panel C. External-Cause ASMR					
0-60 months after spill	-0.218	0.218	0.012	-0.322	-0.029
	(0.248)	(0.218)	(0.051)	(0.348)	(0.187)
Percent change	-4.089	7.841	1.162	-5.311	-0.340
Mean ASMR	5.332	2.780	1.049	6.057	8.581
N	547,809	547,850	547,903	547,903	547,782
Pct. in the pop	100	1.352	19.858	65.568	13.222

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills reported in the news ASMR at the county-by-month level in the 60 months after a spill. All regressions include county, month of year, and year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific population. Standard errors are clustered at the county level.
Source: NVSS.

Table A.6: Effects of Severe Inland Oil Spills on County-Level Monthly Ambient Air Pollution Without Weather Controls

	CO (ppb)	O_3 (ppb)	NO_2 (ppm)	SO_2 (ppm)	$PM_{2.5}$ (μg/m3)	PM_{10} (μg/m3)
Panel A. With News Coverage						
0-12 months after spill	0.020	-0.000	-0.185	-0.122	0.184	-0.228
	(0.020)	(0.001)	(0.218)	(0.245)	(0.203)	(0.723)
Percent change	3.334	-0.940	-1.246	-2.697	1.869	-0.979
Mean of dep. var.	0.611	0.028	14.826	4.530	9.834	23.333
N	77,379	180,629	68,111	125,180	101,054	142,152
Panel B. Without News Coverage						
0-12 months after spill	-0.003	0.001	0.794*	-0.071	0.336	0.874
	(0.020)	(0.000)	(0.412)	(0.281)	(0.444)	(0.669)
Percent change	-0.420	1.920	5.343	-1.392	2.678	3.498
Mean of dep. var.	0.738	0.028	14.869	5.129	12.529	24.978
N	78,686	178,827	68,902	126,999	101,057	141,749

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of the severe inland oil spills on criteria air pollutants at the county-by-month level in the 12 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects. Standard errors are clustered at the county level.
Source: EPA's AQS.

Table A.7: Effects of Spills Without News Coverage on County-Level Monthly ASMR Without Weather Controls

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-12 months after spill	1.053**	−3.482*	0.138*	0.031	8.188**
	(0.462)	(1.936)	(0.080)	(0.136)	(3.134)
Percent change	1.701	-5.724	7.793	0.135	2.212
Mean ASMR	61.917	60.837	1.766	22.688	370.214
Panel B. Internal-Cause ASMR					
0-12 months after spill	1.075**	-2.565	0.087	0.113	7.926**
	(0.487)	(1.587)	(0.056)	(0.163)	(3.218)
Percent change	1.858	-4.389	8.623	0.623	2.184
Mean ASMR	57.842	58.451	1.012	18.178	362.848
Panel C. External-Cause ASMR					
0-12 months after spill	-0.021	-0.917	0.050	-0.083	0.262
	(0.074)	(0.581)	(0.065)	(0.086)	(0.255)
Percent change	-0.527	-38.439	6.679	-1.831	3.557
Mean ASMR	4.075	2.386	0.754	4.511	7.366
Panel D. Cardiovascular ASMR					
0-12 months after spill	0.378*	-0.363	0.024	-0.029	2.872**
	(0.199)	(0.246)	(0.027)	(0.087)	(1.421)
Percent change	1.494	-22.270	23.262	-0.458	1.672
Mean ASMR	25.332	1.628	0.104	6.243	171.788
Panel E. Respiratory ASMR					
0-12 months after spill	0.300*	0.690**	0.014	0.030	2.073*
	(0.158)	(0.294)	(0.022)	(0.042)	(1.208)
Percent change	5.131	41.244	14.189	3.029	4.987
Mean ASMR	5.840	1.673	0.096	0.995	41.563
N	562,736	562,811	562,864	562,864	562,709
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills not reported in the news on ASMR at the county-by-month level in the 12 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: NVSS.

Table A.8: Effects of Spills with News Coverage on County-Level Monthly ASMR Without Weather Controls

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-60 months after spill	-1.336^{**}	-3.704	0.037	-1.183^{**}	-5.160^{**}
	(0.412)	(2.999)	(0.090)	(0.409)	(1.833)
Percent change	-1.836	-4.895	1.635	-3.991	-1.246
Mean ASMR	72.801	75.668	2.264	29.650	414.149
Panel B. Internal-Cause ASMR					
0-60 months after spill	-1.214^{***}	-3.845	-0.000	-1.006^{**}	-5.053^{**}
	(0.365)	(2.995)	(0.065)	(0.335)	(1.820)
Percent change	-1.800	-5.275	0.024	-4.263	-1.246
Mean ASMR	67.469	73.888	1.215	23.593	405.568
Panel C. External-Cause ASMR					
0-60 months after spill	-0.122	0.140	0.037	-0.178	-0.107
	(0.113)	(0.282)	(0.043)	(0.157)	(0.183)
Percent change	-2.290	5.045	3.501	-2.932	-1.246
Mean ASMR	5.332	2.780	1.049	6.057	8.581
N	555,094	555,169	555,222	555,222	555,067
Pct. in the pop	100	1.352	19.858	65.568	13.222

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills reported in the news on ASMR at the county-by-month level in the 60 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects. The regressions are weighted by the 1989 age group-specific population. Standard errors are clustered at the county level.
Source: NVSS.

Table A.9: Effects of Severe Inland Oil Spills on County-Level Monthly Ambient Air Pollution Without Fixed Facility Spills

	CO (ppb)	O_3 (ppb)	NO_2 (ppm)	SO_2 (ppm)	$PM_{2.5}$ (μg/m3)	PM_{10} (μg/m3)
Panel A. With News Coverage						
0-12 months after spill	0.018	-0.000	-0.196	-0.137	0.220	-0.302
	(0.020)	(0.001)	(0.199)	(0.267)	(0.195)	(0.725)
Percent change	3.011	-.405	-1.369	-3.159	2.235	-1.293
Mean of dep. var.	0.598	0.028	14.349	4.322	9.834	23.343
N	76,884	179,793	67,577	124,575	100,841	141,548
Panel B. Without News Coverage						
0-12 months after spill	0.057	0.000	1.316***	-0.246	0.532	1.185
	(0.044)	(0.001)	(0.495)	(0.577)	(0.369)	(0.901)
Percent change	7.725	1.092	11.348	-6.117	4.656	5.142
Mean of dep. var.	0.733	0.028	11.599	4.028	11.417	23.040
N	74,125	175,570	64,920	122,050	100,563	137,284

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of the severe inland oil spills on criteria air pollutants at the county-by-month level in the 12 months after a spill. Fixed facility spills are excluded from the analysis. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. Standard errors are clustered at the county level. *Source:* EPA's AQS.

Table A.10: Effects of Spills Without News Coverage on County-Level Monthly ASMR Without Fixed Facility Spills

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-12 months after spill	1.324**	−7.332*	0.141	-0.042	10.053**
	(0.543)	(4.252)	(0.197)	(0.266)	(3.987)
Percent change	1.944	-9.201	6.007	-0.161	2.518
Mean ASMR	68.098	79.682	2.355	26.041	399.159
Panel B. Internal-Cause ASMR					
0-12 months after spill	1.403**	-3.527	0.087	0.201	9.301**
	(0.476)	(3.929)	(0.124)	(0.273)	(3.740)
Percent change	2.228	-4.750	7.207	0.979	2.388
Mean ASMR	62.975	74.268	1.203	20.576	389.441
Panel C. External-Cause ASMR					
0-12 months after spill	-0.080	−3.804**	0.055	-0.243	0.752
	(0.186)	(1.155)	(0.182)	(0.223)	(0.556)
Percent change	-1.554	-70.263	4.749	-4.454	7.734
Mean ASMR	5.122	5.414	1.153	5.465	9.718
Panel D. Cardiovascular ASMR					
0-12 months after spill	0.093	-0.091	0.077	-0.064	0.913
	(0.324)	(0.754)	(0.047)	(0.145)	(2.551)
Percent change	0.348	-4.293	51.524	-0.886	0.513
Mean ASMR	26.670	2.217	0.149	7.209	178.144
Panel E. Respiratory ASMR					
0-12 months after spill	0.354	0.912	0.084*	0.119	1.885
	(0.249)	(0.765)	(0.050)	(0.132)	(1.488)
Percent change	5.817	42.889	73.038	9.453	4.437
Mean ASMR	6.078	2.126	0.115	1.255	42.484
N	546,794	546,835	546,888	546,888	546,767
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills not reported in the news on ASMR at the county-by-month level in the 12 months after a spill. Fixed facility spills are excluded from the analysis. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: NVSS.

Table A.11: Effects of Spills with News Coverage on County-Level Monthly ASMR Without Fixed Facility Spills

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-60 months after spill	-1.221^{**}	-3.650	0.029	-1.141^{**}	-4.659^{**}
	(0.404)	(3.065)	(0.089)	(0.411)	(1.898)
Percent change	-1.685	-4.974	1.274	-3.848	-1.129
Mean ASMR	72.498	73.382	2.280	29.653	412.505
Panel B. Internal-Cause ASMR					
0-60 months after spill	-1.101^{***}	-3.743	-0.005	-0.969^{**}	-4.569^{**}
	(0.358)	(3.061)	(0.065)	(0.335)	(1.886)
Percent change	-1.640	-5.310	-0.441	-4.115	-1.131
Mean ASMR	67.141	70.497	1.211	23.547	403.988
Panel C. External-Cause ASMR					
0-60 months after spill	-0.120	0.093	0.034	-0.172	-0.090
	(0.115)	(0.290)	(0.043)	(0.159)	(0.185)
Percent change	-2.242	3.227	3.215	-2.817	-1.059
Mean ASMR	5.356	2.885	1.069	6.106	8.517
N	547,375	547,416	547,469	547,469	547,348
Pct. in the pop	100	1.352	19.858	65.568	13.222

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills reported in the news on ASMR at the county-by-month level in the 60 months after a spill. Fixed facility spills are excluded from the analysis. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: NVSS.

Table A.12: Effects of Severe Inland Oil Spills on County-Level Monthly Ambient Air Pollution by Using ≤ 100-mile Counties as Control Group

	CO (ppb)	O_3 (ppb)	NO_2 (ppm)	SO_2 (ppm)	$PM_{2.5}$ (μg/m3)	PM_{10} (μg/m3)
Panel A. With News Coverage						
0-12 months after spill	0.012	-0.000	-0.071	0.047	0.100	-0.597
	(0.017)	(0.001)	(0.158)	(0.218)	(0.134)	(0.596)
Percent change	1.945	-0.466	-0.479	1.041	1.020	-2.557
Mean of dep. var.	0.611	0.028	14.826	4.530	9.834	23.333
N	133,688	293,423	138,320	212,142	157,732	195,376
Panel B. Without News Coverage						
0-12 months after spill	-0.022	0.001*	0.784**	0.073	0.300	0.532
	(0.014)	(0.000)	(0.306)	(0.244)	(0.420)	(0.514)
Percent change	-2.964	2.618	5.275	1.423	2.392	2.129
Mean of dep. var.	0.738	0.028	14.869	5.129	12.529	24.978
N	134,552	291,479	138,562	213,534	157,692	194,548

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of the severe inland oil spills on criteria air pollutants at the county-by-month level in the 12 months after a spill. The control group consists of counties the centroids of which are within 100 miles from the centroid of any spill county. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. Standard errors are clustered at the county level.
Source: EPA's AQS.

Table A.13: Effects of Spills Without News Coverage on County-Level Monthly ASMR by Using ≤ 100-mile Counties as Control Group

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
	Panel A. All-Cause ASMR				
0-12 months after spill	0.961*	−1.863	0.067	-0.036	8.064**
	(0.582)	(1.422)	(0.080)	(0.143)	(4.060)
Percent change	1.551	-3.062	3.783	-0.157	2.178
Mean ASMR	61.917	60.837	1.766	22.688	370.214
	Panel B. Internal-Cause ASMR				
0-12 months after spill	0978	-0.954	0.057	0.046	7.722*
	(0.636)	(1.271)	(0.051)	(0.202)	(4.147)
Percent change	1.690	-1.631	5.669	0.252	2.128
Mean ASMR	57.842	58.451	1.012	18.178	362.848
	Panel C. External-Cause ASMR				
0-12 months after spill	-0.017	−0.909*	0.009	-0.081	0.341
	(0.088)	(0.533)	(0.064)	(0.108)	(0.235)
Percent change	-0.419	-38.104	1.253	-1.803	4.634
Mean ASMR	4.075	2.386	0.754	4.511	7.366
	Panel D. Cardiovascular ASMR				
0-12 months after spill	0.341	-0.109	0.012	0.016	2.572
	(0.188)	(0.246)	(0.027)	(0.084)	(1.382)
Percent change	1.345	-6.689	11.667	0.256	1.497
Mean ASMR	25.332	1.628	0.104	6.243	171.788
	Panel E. Respiratory ASMR				
0-12 months after spill	0.259**	0.500*	0.006	0.000	2.062**
	(0.122)	(0.267)	(0.020)	(0.037)	(0.948)
Percent change	4.440	29.913	5.922	0.036	4.961
Mean ASMR	5.840	1.673	0.096	0.995	41.563
N	753,200	753,218	753,264	753,264	753,196
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills not reported in the news on ASMR at the county-month level in the 12 months after a spill. The control group consists of counties the centroids of which are within 100 miles from the centroid of any spill county. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.

Source: NVSS.

Table A.14: Effects of Spills with News Coverage on County-Level Monthly ASMR by Using $\leq$ 100-mile Counties as Control Group

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
	Panel A. All-Cause ASMR				
0-60 months after spill	-1.046^{*}	-2.410	0.102	-1.016^{*}	-2.900^{*}
	(0.408)	(3.020)	(0.088)	(0.408)	(1.915)
Percent change	-1.436	-3.185	-4.486	-3.425	-0.700
Mean ASMR	72.801	75.668	2.264	29.650	414.149
	Panel B. Internal-Cause ASMR				
0-60 months after spill	-0.899^{**}	-2.660	-0.071	-0.757^{**}	-3.104^{*}
	(0.424)	(2.709)	(0.083)	(0.383)	(1.641)
Percent change	-1.333	-3.650	-5.862	-3.208	-0.765
Mean ASMR	67.469	73.888	1.215	23.593	405.568
	Panel C. External-Cause ASMR				
0-60 months after spill	-0.146	0.250	0.030	-0.259	0.204
	(0.175)	(0.275)	(0.053)	(0.230)	(0.205)
Percent change	-2.740	9.001	2.892	-4.271	-2.373
Mean ASMR	5.332	2.780	1.049	6.057	8.581
N	547,807	547,848	547,901	547,901	547,780
Pct. in the pop	100	1.352	19.858	65.568	13.222

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills not reported in the news on ASMR at the county-by-month level in the 60 months after a spill. The control group consists of counties the centroids of which are within 100 miles from the centroid of any spill county. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific population. Standard errors are clustered at the county level.
Source: NVSS.

Table A.15: Effects of Severe Inland Oil Spills on County-Level Monthly Ambient Air Pollution (Logged)

	CO (ppb)	O_3 (ppb)	NO_2 (ppm)	SO_2 (ppm)	$PM_{2.5}$ (μg/m3)	PM_{10} (μg/m3)
Panel A. With News Coverage						
0-12 months after spill	-0.023	0.003	0.005	0.090	0.026	0.022
	(0.034)	(0.033)	(0.016)	(0.076)	(0.019)	(0.025)
Level change	-0.014	0.000	0.075	0.408	0.258	0.509
Mean of dep. var.	0.611	0.028	14.826	4.530	9.834	23.333
N	77,247	180,140	67,994	123,911	100,840	141,937
Panel B. Without News Coverage						
0-12 months after spill	-0.009	0.028	0.056**	-0.007	0.040	0.036
	(0.050)	(0.017)	(0.025)	(0.086)	(0.027)	(0.026)
Level change	-0.007	0.001	0.833	-0.037	0.506	0.900
Mean of dep. var.	0.738	0.028	14.869	5.129	12.529	24.978
N	78,106	178,197	68,232	125,292	100,799	141,107

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of the severe inland oil spills on criteria logged air pollutants at the county-by-month level in the 12 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. Standard errors are clustered at the county level.

Source: EPA's AQS.

Table A.16: Effects of Spills Without News Coverage on County-Level Monthly ASMR (IHS Transformed)

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-12 months after spill	0.017**	−0.021	0.056	-0.001	0.023**
	(0.008)	(0.036)	(0.035)	(0.008)	(0.009)
Level change	1.026	-1.247	0.100	-0.033	8.628
Mean ASMR	61.917	60.837	1.766	22.688	370.214
Panel B. Internal-Cause ASMR					
0-12 months after spill	0.019**	-0.021	0.059*	0.009	0.023**
	(0.009)	(0.037)	(0.033)	(0.011)	(0.009)
Level change	1.117	-1.214	0.060	0.170	8.412
Mean ASMR	57.842	58.451	1.012	18.178	362.848
Panel C. External-Cause ASMR					
0-12 months after spill	-0.016	-0.118	0.010	-0.026	0.020
	(0.019)	(0.080)	(0.038)	(0.020)	(0.033)
Level change	-0.065	-0.281	0.007	-0.119	0.150
Mean ASMR	4.075	2.386	0.754	4.511	7.366
Panel D. Cardiovascular ASMR					
0-12 months after spill	0.018**	−0.179**	0.007	-0.003	0.021**
	(0.009)	(0.068)	(0.018)	(0.022)	(0.009)
Level change	0.466	-0.291	0.001	-0.018	3.634
Mean ASMR	25.332	1.628	0.104	6.243	171.788
Panel E. Respiratory ASMR					
0-12 months after spill	0.043*	0.248*	0.012	0.011	0.036
	(0.022)	(0.149)	(0.019)	(0.022)	(0.026)
Level change	0.249	0.415	0.001	0.011	1.493
Mean ASMR	5.84	1.673	0.096	0.995	41.563
N	555,433	555,474	555,527	555,527	555,406
Pct. in the pop	100	1.440	20.980	64.677	12.902

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills not reported in the news on IHS transformed ASMR at the county-by-month level in the 12 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific populations. Standard errors are clustered at the county level.
Source: NVSS.

Table A.17: Effects of Spills with News Coverage on County-Level Monthly ASMR (IHS Transformed)

	(1) Overall	(2) Infant	(3) Children	(4) Working Age	(5) Elderly
Panel A. All-Cause ASMR					
0-60 months after spill	-0.012^{**}	-0.025	-0.008	-0.031^{**}	-0.009^{*}
	(0.006)	(0.059)	(0.041)	(0.015)	(0.005)
Level change	-0.877	-1.858	-0.018	-0.907	-3.557
Mean ASMR	72.801	75.668	2.264	29.650	414.149
Panel B. Internal-Cause ASMR					
0-60 months after spill	-0.012^{**}	-0.028	-0.018	-0.035^{**}	-0.009^{*}
	(0.005)	(0.062)	(0.045)	(0.016)	(0.005)
Level change	-0.816	-2.050	-0.022	-0.820	-3.679
Mean ASMR	67.469	73.888	1.215	23.593	405.568
Panel C. External-Cause ASMR					
0-60 months after spill	-0.012	0.090^{**}	-0.021	-0.015	-0.015
	(0.023)	(0.042)	(0.026)	(0.027)	(0.027)
Level change	-0.063	0.250	0.022	-0.093	-0.126
Mean ASMR	5.332	2.780	1.049	6.057	8.581
N	547,807	547,848	547,901	547,901	547,780
Pct. in the pop	100	1.352	19.858	65.568	13.222

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the difference-in-differences estimates of the effects of severe inland oil spills reported in the news on IHS transformed ASMR at the county-by-month level in the 60 months after a spill. All regressions include county-by-month of year and state-by-year fixed effects and weather controls. The regressions are weighted by the 1989 age group-specific population. Standard errors are clustered at the county level.
Source: NVSS.