Labor Market Effects of Environmental Disasters and Information Shocks: Evidence from Inland Oil Spills

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Abstract

This paper provides causal estimates on how inland oil spills, one major type of environmental disaster, affect local labor markets. By exploiting severe inland petroleum oil spills and their news coverage status, I find that spills negatively affect county-level labor markets, but only when a spill is in the news. In the five years after a severe inland spill that receives news coverage, employment, wages, the number of establishments, and the labor force all decrease significantly. Severe inland spills not reported in the news yield no such effects. Exposure to spill information induces composition changes in county-level gross migration, weakening labor market conditions in low-tradability industries, such as retail and food services. Information on environmental disasters triggers sorting, which has distributional effects and degrades labor markets in counties with spills that receive news coverage. Back-of-the-envelope calculations suggest that compared to the control group, counties with spills that receive news coverage lost 407,000 jobs, the monetary value of which is equivalent to \$41.4B, and \$27.1B in foregone wages in aggregate during the post period.

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Environmental disasters impose significant economic consequences.[1] Damages to ecosystems and economies following a large environmental disaster can extend for years, sometimes even decades. High-profile examples include the Dust Bowl in the 1930s, the Chernobyl disaster in 1986, and the Deepwater Horizon oil spill in 2010, which all had lasting impacts on human health, education, food safety, and labor markets. The process of industrialization makes environmental disasters more ubiquitous despite existing regulations. Understanding the economic impacts of environmental disasters is thus of great importance because it helps design more efficient preventative regulations and formulate more targeted and effective response mechanisms.

Most studies evaluating the consequences and effects of disasters in the economics literature cover natural disasters.[2] Affected outcomes include migration, mortality, fiscal costs, income, education, and labor markets (e.g., Kahn, 2005; Boustan, Kahn, & Rhode, 2012; Deryugina, 2017; Kirchberger, 2017; Nguyen & Minh Pham, 2018; Karbownik & Wray, 2019; Deryugina & Molitor, 2020; de Oliveira, Lee, & Quintana-Domeque, in press). Although environmental disasters also occur frequently with severe consequences, there are fewer studies on this type of disasters. Due to limited data availability, almost all causal research on environmental disasters is case studies of a single environmental disaster. The majority focus on health impacts, such as mental health and birth outcomes, of environmental disasters (e.g., Danzer & Danzer, 2016; Beland & Oloomi, 2019; Jones, 2019; Marcus, 2021). I contribute to this literature by studying how such disasters impact local labor markets.

This paper provides new and informative causal estimates of the short- and long-term effects of oil spills, a frequent type of environmental disaster, on local labor markets in a quasi-experimental setting. I leverage a novel source of incident-level data on oil spills in the U.S. between 1990 and 2018, and link them to labor market outcomes at the county level. I focus on employment and wages, the equilibrium quantity and price in a labor market, and

[1]Environmental disasters are catastrophic events regarding the natural environment caused by human activities.

[2]Natural disasters are calamitous events resulting from the natural processes of the earth.

the number of establishments and the labor force, which I use as imperfect measures of labor demand and supply. I focus on inland oil spills of 100,000 gallons or more which I classify as "severe."[3] I estimate the impacts of such spills on county-level labor markets in the 5 years following a spill by employing three versions of panel fixed effect methods: an event study, a difference-in-differences estimation, and a concise event study. The unpredictability of the time and location of spills lends exogeneity to the environmental shocks.

Previous literature has shown that individuals respond to pollution information by altering their behavior (e.g., Banzhaf & Walsh, 2008; Graff Zivin, Neidell, & Schlenker, 2011; Moulton, Sanders, & Wentland, 2018). To inspect the role played by information in labor market responses to environmental disasters, I use local newspaper coverage as a proxy for whether information on a spill is available to the public. I separate counties that experienced severe inland oil spills into two groups: one with news coverage, and one without. If news is determined endogenously, the news coverage status of a spill is not a good indicator for information. Through various balance tests, I show that the two groups' distributions of spills and county demographics, such as pre spill population and wage, are comparable. This is consistent with the finding in Saha and Mohr (2013): there is no statistically significant correlation between the likelihood of a Toxics Release Inventory-listed facility being reported in newspaper articles and characteristics of a community. The most likely determinant of news coverage of a spill is the number of local newspapers in a county. Campa (2018) finds that the likelihood of an industrial plant's emissions being featured in newspapers rises with the plant's proximity to newspaper agencies. In the same spirit, I find that the number of local newspapers in incident counties with news coverage is higher than that in counties without news coverage. Together, these results suggest that news coverage is not determined endogenously by spill characteristics or county demographics, and can serve as a good proxy for information.

[3]Since it is difficult to define which counties are affected by an offshore oil spill, I include only inland oil spills in my analysis. I select 100,000 gallons as the threshold through a semiparametric analysis, which I discuss in detail later in the paper.

I find county-level labor markets do respond after a severe spill, but only when the spill is in the news. Employment, wages, the number of establishments, and the labor force all experience statistically and economically significant declines following a spill that receives news coverage. Difference-in-differences estimates find that employment decreases by 3.4%, wages decrease by 2.1%, the number of establishments decreases by 2.9%, and the labor force decreases by 3.7%. Concise event studies show that the immediate responses (0-1 year after a spill) are insignificant and small in magnitude and the overall effects are driven by longer-run responses (2-5 years after a spill) . Back-of-the-envelope calculations suggest that in aggregate, counties with spills covered in the news lost 407,000 jobs, $27.1 billion in wages, 20,000 establishments, and 402,000 people in the labor force in the entire post period. The foregone wage estimates count only the total changes in wages for all workers still employed after a spill, but not the wage losses for people who became unemployed after the spill, and do not capture the monetary value of lost jobs. The local wage loss for workers who became unemployed in all counties with spills that receive news coverage in all the post years sums to $41.4 billion. In contrast, when a severe inland oil spill is not reported in news articles, labor market outcomes in the incident counties show no difference from those in the control counties. Combined, these results suggest that severe inland oil spills themselves are not influential enough to affect labor markets at the county level, but that information on severe spills ignites labor market responses at a much larger scale.

It is surprising that a one-time oil spill could have long-lasting negative impacts of large magnitudes on all aspects of labor markets in counties with spills that are reported in the news but no effect when there is no news on the spills. To understand the mechanism behind the results, I investigate several potential channels. One potential mechanism is that spill information induces population shrinkage, which shifts labor demand and supply, and the equilibrium point. Another potential mechanism is that certain industries that are most likely to be affected drive the overall labor market effects. By directly estimating population changes and heterogeneous labor market effects by industry, I show that neither of these mechanisms has empirical support. The most plausible mechanism is that spill information triggers changes in migration composition and negatively shocks low-tradability industries, such as restaurants and retail. After a spill that receives news coverage, more high-income individuals leave and fewer high-income individuals enter an incident county. Both these compositional changes in migration negatively shock the demand of goods and services from low-tradability industries and hurt the associated labor market conditions. This intensifies the compositional changes, and the affected labor markets stumble. The county-level migration effects and labor market effects by industry tradability are consistent with the predictions of this mechanism.

This paper makes several contributions to the literature. First, it advances the understanding of labor market impacts of disasters. Most of the existing studies in this literature focus on natural disasters, such as hurricanes/typhoons (Belasen & Polachek, 2008; Gröger & Zylberberg, 2016; Groen, Kutzbach, & Polivka, 2020), earthquakes (Yuan & Zhu, 2016; Kirchberger, 2017; Ager, Eriksson, Hansen, & Lønstrup, 2020), floods (Boustan et al., 2012; Hornbeck & Naidu, 2014), and tornados (Ewing, Kruse, & Thompson, 2009). Several case studies examine environmental disasters. Lehmann and Wadsworth (2011) and Yemelyanau, Amialchuk, and Ali (2012) evaluate the long-term effects of Chernobyl on the health and labor market outcomes of affected individuals. Aldy (2014) estimates the short-run effects of the 2010 Deepwater Horizon oil spill on wages and employment in the Gulf Coast region. Hoang, Le, Nguyen, and Vuong (2020) study the short-term labor market impacts of the 2016 Formosa industrial marine disaster in Vietnam on the fishery industry in the affected area. Unlike these case studies, this paper exploits numerous instances of the same type of environmental disaster over a long period of time, 1990-2018. Through a quasi-experimental investigation, I provide new and informative causal estimates of the labor market effects of severe inland oil spills. The short- and long-term causal estimates of severe spills on a comprehensive set of outcomes paint a complete picture of the post disaster labor market dynamics.

This paper's findings also contribute to the literature on pollution information. Previous literature has shown that exposure to pollution information can induce avoidance behaviors among information recipients (Graff Zivin & Neidell, 2009; Neidell, 2009; Zabel & Guignet, 2012; Moulton et al., 2018) and aggravate environmental injustice (Banzhaf & Walsh, 2008; Wang, Deltas, Khanna, & Bi, 2021; Marcus, 2021). Consistent with this literature, this paper finds compositional changes in migration immediately after a severe spill that is covered in the news, indicating that spill information induces avoidance behavior among individuals to the detriment of environmental justice. In addition, firms will underestimate the costs of pollution when individuals bear the burden of avoidance costs. Moreover, the migratory responses from high-income people and the negative labor market effects imply that the spill information-induced compositional changes in migration have distributional consequences. People who stay in counties with spills that receive news coverage are of lower income and have to face degraded county-level labor markets. Note that, these findings should *not* be interpreted as information is detrimental and should be concealed from the public. Using the same empirical setting, Chen (2021) finds that information on spills is beneficial to the environment and human health. Severe inland oil spills increase air pollution levels and mortality rates at the county level only the spills are not reported in the news.

In addition, this paper speaks to the literature on labor markets and migration. In theory, when labor markets perform poorly, people move to places with better employment opportunities (Schultz, 1961; Sjaastad, 1962). Empirically, individuals do not migrate out when their local labor markets perform poorly even though labor markets with better prospects exist (Monras, 2020). The observed low migration might be a result of optimal decision-making, but also might be due to budget constraints or incomplete information on job opportunities (Wilson, 2021). The finding that population size does not change after spills that are covered in the news despite labor market weakening provides another piece of evidence that people do not always move out when labor markets falter. Only a small group of high-income people leaving the incident counties supports the notion that budget constraints and incomplete information on job opportunities limit migration.

As a further consideration, the findings in this paper provide insights into the impacts of the current transition toward remote work. The elevated potential for remote work due to technology development was not exploited extensively until the COVID-19 pandemic (Bloom, Liang, Roberts, & Ying, 2015; Bartik et al., 2020). Jobs that can be done remotely typically pay higher and are more likely to be held by highly educated workers (Dingel & Neiman, 2020; Bick, Blandin, & Mertens, 2020). As high-income high-skill workers transition to remote work, many of them choose to migrate out of cities, which endangers the local consumer service economies that depend greatly on demand from these workers (Althoff, Eckert, Ganapati, & Walsh, 2021). Given that this transition is recent, long-run effects have not yet been observed. This paper's results can provide some insights into the long-run migration and overall labor market effects of remote work. The observed weakening of low-tradability industries that form local consumer economies may undermine overall labor market conditions in affected places. This could intensify out-migration and lessen in-migration of high-income high-skill workers, which hurts local labor markets even more. These changes would worsen all labor market outcomes, and result in fewer high-income high-skill workers in towns in the long run until a new equilibrium is reached.

The rest of the paper proceeds as follows. Section 1 provides background on oil spills and the governance framework in the United States. Section 2 describes the data. Section 3 introduces the empirical strategies used in the analysis. Sections 4 and 5 present and discuss the results, respectively. Section 6 concludes.

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 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 related 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 wake 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

[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.

costs, and establishes a fund for damages and cleanup and removal costs.

1.2 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 exploit a novel data source to acquire information on inland oil spills in the United States between 1990 and 2018. I also use data on the newspaper coverage status of the spills, county-level labor market outcomes, and migration from various sources. My analysis relies on the geographic linkage of all these datasets at the county level in the United States. This section describes the different datasets and the key variables in my 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. Small spills are unlikely to have any impact on local labor markets at the county level. In this paper, I focus on the 139 inland oil spills with spill amounts greater than or equal to 100,000 gallons, which I classify as "severe." The threshold of 100,000 gallons is selected through a semiparametric analysis, which I discuss in detail later.

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, severe spills that are covered in the news 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] 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 severe spills that are covered in the news is very similar to that of spills not covered in the 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.

The number of newspapers in each county comes from the U.S. News Deserts Database, a project created and maintained by the Center for Innovation and Sustainability in Local Media at the UNC Hussman School of Journalism and Media.[7] This database provides the names of local newspapers in each county in the U.S. in 2004, 2014, 2016, and 2020. Using this information, I count the total number of newspapers in each county.

2.3 Labor Market Data

I use annual county-level economic outcome data from three datasets, all of which are national in scope. Annual county-level data on wages, employment, and the number of establishments between 1975 and 2018 are from the Quarterly Census of Employment and Wages (QCEW) published by the Bureau of Labor Statistics. The county-by-industry data are from 1990 to 2018 because 1990 is the first year that the industry data, which aggregate North American Industry Classification System (NAICS) industries to a higher level, are available from the QCEW.[8] Annual data on the labor force from 1990 to 2018 at the county level come from the Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) program. The annual total population and population by age in 1975-2018 are from the Census Bureau

[7] The Expanding News Desert: https://www.usnewsdeserts.com/.

[8] The QCEW-NAICS crosswalk is available on the QCEW's website: https://www.bls.gov/cew/classifications/industry/industry-supersectors.htm. I recreate the crosswalk in Table A.1 in the appendix.

Population and Housing Unit Estimates. Panels A-C of Table 2 provide summary statistics of the labor market outcomes and population.

To understand how inland oil spills affect local labor markets, I mainly focus on the following outcomes (in logs): employment, wages, the number of establishments, and the labor force. The first two are the equilibrium quantity and price in a county-level labor market, and the latter two imperfectly measure labor demand and supply. I also look at changes in the county-level working age population, unemployment rate, ratio of employment to working age population, and labor force participation rate to better understand other aspects of the affected local labor markets at the county level. Changes in all these outcome variables depict a comprehensive picture of the responses of local labor markets in counties that experienced severe spills.

2.4 Migration Data

To explore whether oil spills lead to changes in migratory behavior, I use annual county-to-county migration data from the Internal Revenue Services (IRS) that span the years 1990-2017. The IRS data use individual income tax returns to extract year-to-year address changes as a proxy for migration into and out of each county. The total adjusted gross income of all in- and out-migrants is also available. The data on gross migration from and into the spill counties help to pin down the mechanism and speak to avoidance behavior and environmental justice. Panel D of Table 2 provides summary statistics of county-level gross out- and in-migration.

3 Empirical Strategy

To estimate the effects of severe inland oil spills, I employ panel fixed effect models with propensity score weighting. The unpredictability of the time and location of severe spills renders them exogenous. The identification strategy relies on the assumption that the treatment and control groups would have evolved on parallel trajectories had the spills not occurred. In other words, the causal estimates are identified based on the parallel trend assumption.

3.1 Treatment and Control Groups

This section describes the treatment and control groups in my analysis. Figure 4 plots the geographic distribution of these two groups. I define a county as treated if it experienced at least one severe inland oil spill during 1990-2018 regardless of whether the spill was reported in the news. Though not the focus of this paper, one question that naturally arises is what determines news coverage of a spill. To check if the difference in coverage is caused by differences in spill amounts or county characteristics, I directly compare these measures for these two groups. One may think that larger spills would be more likely to receive news coverage. Panel B of Table 1 shows that as discussed earlier, the means of severe spills with and without news coverage are not significantly different. To further demonstrate that these spills are comparable, I plot their densities in Figure 5. The densities of these two groups overlap for almost all spill amounts, which provides more evidence that the difference in news coverage status is not due to the difference in spill amounts.

Another possibility is that the spill counties are different in their demographics, which results in some counties reporting severe spills while others do not. Panels A and B in Table 3 provide tests on whether county characteristics differ between these two groups. Since the spill data start in 1990, to avoid capturing the effects of the spills, I test whether the county characteristics are significantly different in the five years before, i.e., in 1985-1989, for datasets that go back to 1985 or before. For characteristics only available starting from 1990, I use the 1990 data to perform the tests. Most of the characteristics are not significantly different between counties with spills that are covered and not covered in the news. This suggests that the difference in news coverage is not caused by intrinsic differences between the two groups of counties. This result is consistent with the finding in the literature: the likelihood of a TRI facility being reported in newspaper articles is not significantly correlated with characteristics of nearby communities (Saha & Mohr, 2013).

The most likely determinant of a spill receiving news coverage is the number of newspapers within a county. Campa (2018) finds that the likelihood of a plant's emissions being reported in newspapers increases with the plant's proximity to newspaper agencies. Similar to this finding, I find that counties with spills that receive news coverage have more newspapers than counties that experienced spills not covered in the news, and this difference is statistically significant. The density plot of the number of newspapers by news coverage is in Figure 6, and the test of the mean numbers is in Panel C of Table 3. Together, these results indicate that news coverage is not determined endogenously by spill characteristics or county demographics, and can serve as a good proxy for information. The difference in news coverage status of spills reflects different availability of information on spills to the public.

There are 115 treated counties, i.e., counties with at least one severe spill, for the 1990-2018 sample period. For counties with multiple severe spills, I only look at their first spill. Since an unbalanced panel may affect coefficient estimates in unexpected ways purely due to its mechanical structure, I use the same set of severe spills in the analysis. In other words, I use a panel of severe spills balanced in event time in the estimation process to avoid artificial entries into and exits from the treatment group. This means that I need to choose a time window wide enough to estimate the labor market impacts of the spills but not so wide that the number of treated counties drops dramatically. In practice, I use a window that spans from five years before to five years after a spill, which leaves me with 96 treated counties, among which 43 experienced spills with news coverage and 53 experienced spills without coverage.

I use the 1,318 counties with centroids more than 100 miles away from the centroid of any spill county as the control group. The main identifying assumption of the panel fixed effect methods is that counties with severe inland oil spills would have evolved following a trajectory parallel to that of the *unaffected* counties had the spills not occurred. Although counties close to spill counties are more likely to be similar in characteristics to the spill counties, they are also more likely to absorb spillover effects, if there are any, of severe oil spills. As a result, nearby counties are potentially affected as well and may not serve as a valid control group. Therefore, I use counties whose centroids are more than 100 miles away from any spill county centroids as my control group. Though not contaminated by potential leakages, faraway counties may not share similar economic conditions and demographics to the spill counties. To construct a credible counterfactual group, I use propensity score weighting in my analysis.

3.2 Econometric Specifications

I estimate three panel fixed effect specifications, all of which exploit variation in the timing and geography of severe spills, to determine how severe inland oil spills affect local labor markets. To understand how the effects of severe spills evolve over time, I perform an event study to flexibly trace out the dynamic treatment effects. The estimation equation takes the following form:

$$y_{ct} = \sum_{d=-5,\, d\neq-1}^{5} \beta_d Spill_{cd} + \beta_{-6} Spill_{c,-6} + \beta_6 Spill_{c,6} + \alpha_c + \omega_{st} + \epsilon_{ct}, \tag{1}$$

where y_{ct} is some outcome for county c in year t, such as logged employment or average wage per job. The variable $Spill_{cd}$ is a spill indicator equal to 1 if county c experienced (will experience) a severe inland oil spill d years ago (in d years) as of year t. The variables $Spill_{c,-6}$ and $Spill_{c,6}$ are group indicators equal to 1 if, as of year t, county c is $\geq$ 6 years before or after a spill. That is, I focus on a window of $\pm$ 5 years around a spill. I include county and state-by-year fixed effects, denoted by α_c and ω_{st}, respectively. The county fixed effects control for any county-level time-invariant characteristics over time. Since economic and labor market conditions vary from state to state, the state-by-year fixed effects flexibly control for time trends common to all counties in each state. The error term, ϵ_{ct}, represents unobserved county-by-year shocks to the outcomes that are assumed to be uncorrelated with the regressors of interest, $Spill_{cd}$. To adjust for arbitrary serial correlation within a county, I cluster standard errors at the county level.

The parameters of interest are the β_ds, which capture the effects of a severe spill on some outcome y_{ct} relative to the difference in the same outcome between the treated and control counties 1 year before the spill. The validity of the coefficient estimates relies on there being no differential trends between the treatment and control groups in the periods before the treatment. Since the treatment and control groups are geographically distant, they may not share similar economic conditions and demographics. To make the control group more comparable to the treatment group, I use propensity score weighting when running the regressions, with weights equal to 1 for the treated counties and $\frac{pscore}{1-pscore}$ for the control counties.[9] Though propensity score weighting makes the treatment and control groups more comparable, it does not eliminate pre-trends. To address the issue of pre-trends, I follow Dobkin, Finkelstein, Kluender, and Notowidigdo (2018) and Goodman-Bacon (2021a, 2021b) to fit a linear trend with the data, remove the trend from the outcomes in all periods, and estimate the regression with the transformed outcomes.

Despite its flexibility, the event study is inefficient in summarizing the overall treatment effect. To achieve brevity, I employ a difference-in-differences model to compare the labor market outcomes 5 years before and after a severe spill using a single post-spill indicator. In other words, I use the 5 years prior to a spill as the reference period and assume that there is no differential trend between the treated and control counties in this period. Specifically, I estimate the following equation:

$$y_{ct} = \beta_{post} Spill_{c,post} + \beta_{-6} Spill_{c,-6} + \beta_6 Spill_{c,6} + \alpha_c + \omega_{st} + \epsilon_{ct}, \tag{2}$$

where $Spill_{c,post}$ is an indicator equal to 1 for the year that the spill happened and the 5 years afterward for a spill county c and 0 otherwise. All the other variables are defined the

[9] I use a logit regression and the outcomes in the pre-treatment period (i.e., before 1990) to compute the propensity scores. The dependent variable is an indicator variable of the treatment status.

same as those in Equation (1). The regression is propensity score weighted. The parameter of interest is β_{post}, which can be interpreted as the change in the outcome variables of county c in the post period caused by a severe oil spill.

Though concise, the difference-in-differences estimates reveal nothing about the trajectory of the effects. To efficiently summarize the impacts while still depicting the evolution of the effects of a severe spill to some extent, I implement another specification that groups post-spill years 0-1 and 2-5 and assume that there is no difference in trends between the treated and control counties in the 5 years before a spill. The specific estimation equation is:

$$y_{ct} = \beta_{0-1} Spill_{c,0-1} + \beta_{2-5} Spill_{c,2-5} + \beta_{-6} Spill_{c,-6} + \beta_{6} Spill_{c,6} + \alpha_c + \omega_{st} + \epsilon_{ct}, \tag{3}$$

where $Spill_{c,0-1}$ and $Spill_{c,2-5}$ indicates whether county c is 0-1 year or 2-5 years after a severe spill as of year t. The remaining variables and the standard error clustering are the same as in the previous two specifications. Again, the regression is weighted by propensity score weights. The coefficient β_{0-1} reflects the immediate response, and β_{2-5} reflects the longer-term response to a severe spill in some outcome y_{ct}.

4 Results

4.1 Semiparametric Estimates

As discussed in the Data section, almost all counties experience at least one inland oil spill between 1990 and 2018 and the majority of the spills are small. It is unlikely for a small spill of, for example, 20 gallons to have any impact on labor market outcomes at the county-by-year level. Hence, I focus on spills above a certain amount. To determine this threshold, I estimate the gradient of the labor market outcomes with respect to the spill amount semiparametrically. Since most of the counties experience spills in consecutive years, a difference-in-differences estimate on the whole sample captures not only the effect of a targeted spill, but also spills in the following years, which could lead to bias. To evaluate the effect of an individual spill and that spill only, the ideal setting is to focus on counties that experienced one and only one spill and use counties experienced no spills as the control group. However, through out the sample period for the spills, there are only 166 counties with one and only one spill. These 166 spills do not cover the full spectrum of the spill amounts and there are an insufficient number of observations to conduct a semiparametric analysis. To overcome this issue, I use counties with one and only one spill of at least 1,000 gallons as the treatment group and counties with spills of fewer than 1,000 gallons or with no spills as the control group. There are 747 counties with one and only one spill of at least 1,000 gallons, and the number of observations with different spill amounts allows me to semiparametrically estimate the effects of oil spills.[10]

I estimate an equation slightly different from Equation (2):

$$y_{ct} = \sum_{a} \beta_{post} Spill_{c,post} \times \mathbb{1}(\text{Amount} = a) + \beta_{-6} Spill_{c,-6} + \beta_6 Spill_{c,6} + \alpha_c + \omega_{st} + \epsilon_{ct}, \quad (4)$$

where the post-spill indicator $Spill_{c,post}$ is interacted with indicators of different spill amount bins $\mathbb{1}(\text{Amount} = a)$. To ensure that there are enough observations within each bin, I use 6 bins to represent the spill amount levels. Subfigure (a) of Figure 7 plots the semiparametric effects of an oil spill on the ratio of employment to working age population. The estimates on all bins are close to zero and insignificant.[11] This suggests that spills of up to 10,000 gallons have no labor market effect at the county level. While the estimate on the at-least-10,000-gallon bin is also small and insignificant, it reveals nothing about the effects of extremely large oil spills. The last bin consists of 70 spills, among which 42 are between 10,000 and 20,000 gallons and 14 are between 20,000 and 40,000 gallons. It could be that spills not

[10] I have tested lower thresholds, such as 50 gallons, 100 gallons, and 500 gallons, but there are not enough number of observations with different spill amounts for a semiparametric analysis.

[11] The county-level labor market effect on the employment to working age population ratio of oil spills of fewer than 1,000 gallons in comparison to counties with no oil spills is 0.0001 with a standard error of 0.0020.

much larger than 10,000 gallons have minimal impacts while much larger spills significantly affect labor market outcomes. When all spills of at least 10,000 gallons are grouped together into one bin with the majority being just above the 10,000-gallon threshold, I cannot deduce much about the extremely large spills.

To further investigate the effects of the large spills, I compare counties with one and only one spill of at least 10,000 gallons to counties with spills of fewer than 1,000 gallons. This yields more observations of spills of at least 10,000 gallons to increase the statistical power and allows me to use finer bins for this analysis. Subfigure (b) of Figure 7 plots the semiparametric estimates of spills of at least 10,000 gallons using 7 bins. The employment to working age population ratio gradient is close to zero for spills of between 10,000 to 100,000 gallons and drops by approximately 2% for spills of at least 100,000 gallons. The semiparametric plots of all the other labor market outcomes are in Figure A.1 in the Appendix. These semiparametric estimates are either noisy and do not suggest a clear cutoff or suggest a cutoff larger than 100,000 gallons. Hence, to be conservative, I use 100,000 gallons as the threshold and focus only on spills with an amount above this threshold in the later analysis.

4.2 Impacts of Spills on County-Level Labor Market Outcomes

I present the labor market effects of severe inland oil spills by news coverage status in this section. Figure 8 plots event study estimates of the effects of severe spills on employment, wages, the number of establishments, and the labor force. Employment and wages are the equilibrium quantity and price of a labor market, and the number of establishments and the labor force imperfectly represent labor demand and supply. The event study graphs illustrate that spill counties with and without news coverage exhibit sharp contrasts in labor market responses to a spill. Compared to those in the control group, employment in counties with spills that are reported in the news drops slightly in the first two years after a spill, experiences larger decreases in years 2-3, and stabilizes in years 4-5. By year 5, employment is about 6% lower. The average wage per job keeps decreasing since the year of a spill. By year 5, wages are about 4% lower than those of the control group. Both the number of establishments and the size of the labor force start to decline after a spill and they are about 6% and 7% lower, respectively, in year 5. Assuming that the number of establishments and the labor force imperfectly measure labor demand and supply, these results suggest that labor demand and supply in counties with spills that are covered in the news decrease dramatically and the equilibrium quantity and price fall as a result. All these changes are both economically and statistically significant. For counties with severe spills not covered by news, the estimated effects are consistently close to zero in the post period for all of these outcomes. The drastic differences in labor market changes after spills that receive news coverage and those that do not indicate that spill information ignites much larger labor market responses than the spills themselves.

Table 4 reports the difference-in-differences (Equation (2)) and concise event study (Equation (3)) estimates of the effects of severe spills. For counties with severe spills covered in the news, the former estimation finds that relative to the outcomes for the control group, employment decreases by 3.4%, wages decrease by 2.1%, the number of establishments decreases by 2.9%, and the labor force decreases by 3.7%. All four estimates are significant in both economic and statistical senses. Counties with severe spills not covered by news, on the other hand, experience no changes in any of these outcomes in the post period. The estimates in Panel B summarize the immediate (0-1 year after) and a longer-term (2-5 years after) responses to a severe spill. The immediate responses in spill counties with news coverage are all small in magnitude and none are statistically significant. The longer-term responses of counties with severe spills reported in the news are a 4.9% drop in employment, a 2.8% drop in wages, a 4.2% drop in the number of establishments, and a 5.3% drop in the labor force. This means that the overall effects in Panel A are driven by the longer-term responses. For counties with spills not reported in any newspaper articles, the immediate and longer-term responses are both close to 0 and statistically insignificant.

4.3 Potential Mechanisms

It is surprising that a one-time oil spill could have long-lasting negative impacts of large magnitudes on all aspects of labor markets in counties with spills that receive news coverage but no effect when there is no news on the spills. In this section, I investigate potential mechanisms that could drive the above results.

4.3.1 Working Age Population Shrinks

One possibility for both labor demand and supply to decrease dramatically after a spill that receives news coverage is that people leave the affected counties at a large scale when they are well-informed of spills and the population shrinks. To check if this is the case and to further examine the labor market situations, I investigate how the working age population and employment statistics respond in the spill counties.

Figure 9 presents the event study plots of the working age population, unemployment rate, employment to working age population ratio, and labor force participation rate by news coverage. For counties with spills not covered by news, none of the estimated effects are significant, and the magnitudes are close to zero in the post period for all four outcomes. For counties with spills reported in the news, in comparison to the control group, the estimated effects on the working age population are insignificant and close to zero after a spill. This suggests that a severe inland oil spill does not affect the county-level population size even when the spill is well publicized.[12] The effects on the unemployment rate are close to zero and insignificant. For the employment to working age population ratio and labor force participation rate, the event study graphs are of a similar shape: in the first two years after a spill, the effects are negative and small; the magnitude of the decrease grows larger in the next couple of years, and stabilizes in years 3-5 with a significant decline of about 5 percentage points.

[12]The effect on the overall population is also zero and insignificant. The event study plot of the effect on the overall population is in Figure A.2 in the appendix.

The difference-in-differences (Equation (2)) and concise event study (Equation (3)) estimates of the effects of severe spills are shown in Table 5. Panel A presents the difference-in-differences estimates. For counties with severe spills that are reported in the news, relative to those in the control group, the difference-in-differences estimates on the working age population and unemployment rate are close to zero and insignificant, consistent with the event study graphs. The employment to working age population ratio and labor force participation rate on average decline by a statistically significant 2.9 and 2.8 percentage points, respectively. The difference-in-differences estimates on these four outcomes from counties with spills not reported in the news are all close to zero and not statistically significant. The concise event study estimates, which summarize the immediate (0-1 year) and a longer-term (2-5 years) responses, are in Panel B. Both the immediate and longer-term responses in the working age population and unemployment rate after a severe spill with news coverage are minimal and statistically insignificant. The immediate responses in the ratio of employment to the working age population and the labor force participation rate are small and insignificant, while the estimates for years 2-5 are both large and very statistically significant. In regard to severe inland spills without news coverage, neither the short- nor the long-run response is statistically distinguishable from zero for any of the outcomes.

The event study graphs in Figure 9 and the estimates in Table 5 demonstrate that the county-level working age population does not change after a news-reported severe spill. This invalidates the hypothesis that the labor market effects in counties with spills reported in the news are due to population shrinkage. Moreover, these results suggest that when labor market conditions worsen, people choose to stay at where they are, even if they are out of the labor force. Since the trajectories of the decreases in the labor force and employment in Figure 8 are very similar, the unemployment rate does not change much. In other words, in this circumstance, the unemployment rate alone does not reflect the worsening of county-level labor markets.

4.3.2 Industries that Could Cause Spills Drive the Results

It is also possible that after an oil spill, industries that might cause severe inland oil spills are severely impacted by the incident, and then these industry-specific negative effects lead to a worsening of overall county-level labor market outcomes. I perform an industry heterogeneity analysis to formally test this potential mechanism. Given that I detect labor market effects only when there is news, I focus on counties with spills reported in the news.[13] Data on employment and wages at the county-by-industry level in 1990-2018 are available from the QCEW.[14] Figure 10 plots the treatment effects by industry, and Table 6 summarizes the outcomes by industry in the 5 years before a severe oil spill that is covered in the news.

The first industry that comes to mind in discussions of oil spills is almost always the oil and gas production industry (NAICS 211 oil and gas extraction and NAICS 213111 drilling oil and gas wells), which is part of the natural resources and mining industry. Both the employment and wage estimates for natural resources and mining are indistinguishable from zero, which means that labor market conditions in this industry do not change after a severe spill. These estimates indicate that it is very unlikely that this industry affects overall county-level labor markets. Additionally, the null effects in the natural resources and mining industry align with the fact that severe spills that receive news coverage are caused not by oil production but by accidents during transportation.

As mentioned in the Data section, most of the spills are due to pipeline ruptures, which suggests that industries related to pipelines might drive the results. Oil and gas pipeline construction (NAICS 237120) is part of the construction industry, and pipeline transportation of crude oil (NAICS 486110) and refined petroleum product pipeline transport (NAICS

[13] A heterogeneous analysis spills without news coverage is in Appendix Figure A.3. Almost all of the industry-level effects on employment and wage are insignificant.

[14] QCEW industries are aggregations of the NAICS industries. Appendix Table A.1 presents the QCEW-NAICS industry crosswalk. I use the QCEW county-by-industry data instead of the NAICS data for two reasons. First, the QCEW industry data start in 1990, while the NAICS data are first available from 1998. Second, the 2-digit NAICS data for many counties in many years are unavailable due to disclosure restrictions. Using the QCEW county-by-industry data allows me to include all U.S. counties with almost no missing observations over a longer time period in the analysis.

486910) are part of the trade, transportation, and utilities industry. The estimated wage effect on the construction industry is approximately 2.5% but insignificant. This industry has the largest negative effect, about 10%, in employment. Despite the large decreases in employment, this industry makes up only a very small portion of the entire labor market. In the 5 years before a spill, the average number of employees in the construction industry is 4,443, representing only 4.7% of the overall employment. It would be impossible for this industry alone to drag overall employment down by 3.4%, as estimated in Table 4. The trade, transportation, and utilities industry includes not only the transportation and warehousing industry, but also the wholesale trade, retail trade, and utilities industries, as listed in Appendix Table A.1. Within this industry, transportation and warehousing makes up only 16.8% of all employment. Although the estimated employment and wage effects in the trade, transportation, and utilities industry are statistically significant with large magnitudes of 6% and 4%, respectively, these effects are not large enough to make this industry the sole driver of the overall estimated effects, let alone the transportation and warehousing industry within it.

Therefore, these results invalidate the hypothesis that the labor market effects are driven by industries that could cause severe oil spills. Besides, if this hypothesis were to hold, then all counties would experience decreases in labor market outcomes regardless of news coverage status, since the spills and county characteristics are comparable between these two groups as aforementioned. The fact that I observe large declines only when a spill receives news coverage and no changes when there is no news provides further evidence that the effects are not solely driven by industries that could cause spills.

4.3.3 News Coverage Tarnishes County Reputation

Another possible explanation for the large effects after a spill that is reported in the news and the difference in effects between counties with different news coverage status is a reputation channel. Place-based reputation can be viewed as a form of capital asset that produces an income stream by stimulating demand for regional goods and services (Larkin, Huffaker, & Clouser, 2013). Suppose that all the incident counties have a good reputation for industries that rely on the environment, such as tourism and fishery, and that this reputation draws non-local demand. When a severe inland spill is reported in the news, these industries' reputation in the incident county becomes tarnished, while their reputation remains intact if a severe spill is not publicized. As a result, demand for goods and services from these industries in spill counties with news coverage decreases, while demand in spill counties with no news coverage stays constant. Since labor demand is an induced demand, when demand for goods and services decreases (is unchanged), labor demand in sectors that rely on a good reputation also falls (stays the same).

One industry that relies heavily on a good environmental reputation is tourism and recreation, part of the leisure and hospitality industry. If a county's environmental reputation is ruined by a spill, the local leisure and hospitality industry could suffer substantial losses, resulting in lower employment and wages. Figure 10 shows that the employment effect on the leisure and hospitality industry is an insignificant -4%, and the wage effect is a significant -6%. The average number of employees in leisure and hospitality accounts for 10% of overall employment in the 5 years before a spill, according to Table 6. The size of the effects combined with the proportion of this industry in overall employment suggests that the decreases in county-level labor market outcomes are not attributable solely to the leisure and hospitality industry.

If severe inland oil spills pollute the soil or water, industries whose production relies heavily on the environment, such as agriculture and fishery, could be affected to a large extent when the reputation of the environment is tarnished. The natural resources and mining industry includes all industries that require the environment as an input in their production, including agriculture, forestry, fishing, and hunting. As discussed in the previous subsection, the employment and wage effects for the natural resources and mining industry are close to zero and statistically insignificant, which means that the worsening of overall labor market conditions is not driven by this industry. Hence, the reputation mechanism cannot explain the main results.

4.3.4 News Coverage Affects Migration and Low-Tradability Industries

The most plausible mechanism is that spill information triggers changes in migration composition and negatively shocks industries of low tradability, i.e., industries whose productions are mostly consumed locally. Though the overall population level remains unaffected after a spill reported in the news, people still move into and out of the incident counties. When information on a severe spill is publicly available, people who care about environmental amenities avoid an incident county. However, migration and a change in the destination of a planned migration in a short time are feasible only for individuals with resources, such as wealth, high education, and the ability to locate another job in a different county. In other words, it is likely that there are more high-income people leaving and fewer high-income people entering an incident county. Both of these compositional changes in migration put downward pressure on demand for goods and services from low-tradability industries, such as restaurants, real estate, construction, and retail. Since labor demand is an induced demand, the decrease in the demand for goods and services would lead to a decrease in labor demand in industries with low tradability. Consequently, employment and wage levels in these industries would decrease. When this happens, workers in low-tradability industries have incentives to shift to high-tradability industries. However, different skill requirements for jobs in low- and high-tradability industries generate transitional frictions and block most low-tradability industry workers from entering high-tradability industries. As a result, low-tradability industries suffer considerable losses in terms of employment and wages, whereas high-tradability industries are affected only slightly. These compositional changes in migration and worsening of outcomes in the low-tradability industries results in a vicious circle: poor performance of low-tradability industries weakens overall county-level labor markets, which escalates the compositional changes in migration and hurts low-tradability industries even further. This vicious circle explains the long-lasting negative effects of spills that receive news coverage on local labor markets. When there is no news, a severe spill does not trigger compositional changes in migration, and the incident county does not fall into this vicious circle. This explains why no labor market effects are detected after a spill that receives no news coverage.

The empirical examination of this mechanism consists of two parts: an analysis of county gross out- and in-migration and a heterogeneity analysis of labor market outcomes by industry tradability level. To analyze migration flows, rather than just focusing on the population stock, I evaluate the effects of severe spills on the average per capita income of migrants and the migration rate using county-to-county migration data from the IRS.[15] Event study plots on migrants' per capita income and gross migration rates are in Figure 11 by news coverage status. The event study graphs show that, among out-migrants, there is an immediate increase in average per capita income after a spill with news coverage, and the effect stays higher in the entire post period. For spills without news coverage, there are no clear changes in the average per capita income among the migrant outflow, and the estimates are imprecise. As for the out-migration rate, there is a significant jump in the year in which a spill with news coverage happens and the effect grows even larger in the post period, whereas there is no change detected after a spill that is not in the news. Regarding in-migration, migrants' average per capita income decreases, and the migration rate slightly increases after a spill with news coverage, while there are no significant changes after a spill without news coverage.

Table 8 summarizes the effects more concisely. For spills with news coverage, the average income of the migrant outflow in comparison to that in the control group increases by 3.3%, and the gross out-migration rate increases by 0.3 percentage points. Average income of the migrant inflow decreases by 1.8%, and the gross in-migration rate increases by 0.2 percentage points. Because the magnitudes of the changes in the out- and in-migration rates

[15] I use the lagged population as the base when computing the migration rate, following Strobl (2011).

are very small and similar to each other, the overall change in population size is negligible and insignificant, as shown in Table 5. The immediate and longer-run responses in average income among migrant outflows and the out-migration rate are both statistically significant after a spill that is covered in the news. The immediate and longer-run effects on average income among migrant inflows and the in-migration rate after a spill with news coverage are not as significant as the effects on outflows. These out- and in-migration effects suggest that there are larger and quicker migratory responses from local residents than individuals who plan to move in. For spills without news coverage, the average effects and the immediate and longer-run responses on all outcomes are all insignificant. Although some of the income effects of a spill without news coverage are large, the estimates are noisy and do not have adequate statistical power.

The migration results align perfectly with the predictions based on the first component of the mechanism. These results provide evidence that information on severe oil spills does change the composition of migration. Moreover, the compositional changes in migration are not temporary but long-lasting. This new migratory pattern speaks to the migration literature to some extent. Out-migration and changes to the destination of a planned in-migration in a short time are feasible for people with resources, not for everyone. In theory, when labor markets perform poorly, people move to other places with better employment opportunities (Schultz, 1961; Sjaastad, 1962). However, practically speaking, moving or switching the destination of a planned migration are not universally feasible because of budget constraints or incomplete information on job opportunities (Monras, 2020; Wilson, 2021). As a result, people who do move out and switch destinations are on average with high income, as I observe here.

The long-lasing compositional changes—more high-income people leaving and fewer high-income people entering—act as a persistent negative shock to demand for non-tradable goods. According to the prediction of this mechanism, the demand decrease will translate into sustained employment and wage declines in the labor market of low-tradability industries.

To verify the validity of the second part of this mechanism, I compute the tradability for each QCEW industry and check if industries with lower tradability experience larger decreases in labor market outcomes than more tradable industries. Tradability of a industry is defined as the percent of total employment that is engaged in the production of tradable goods and services, following the literature (e.g., Jensen, Kletzer, Bernstein, & Feenstra, 2005).[16] The heterogeneous effects by industry in Figure 10 and the industry tradability measures in Table 7 lend some support to the prediction that non-tradable industries suffer considerably whereas the tradable industries are affected only slightly. There are significant decreases in low-tradability industries, such as construction and trade, transportation, and utilities. On the other hand, the estimated effects for industries with high tradability, such as natural resources and mining and manufacturing, are small and statistically insignificant.

To inspect the labor market effects by tradability more succinctly, I split the county-by-industry data into halves by tradability: high-tradability and low-tradability industries.[17] I then estimate the treatment effects of spills that receive news coverage on employment and wages by tradability. I focus only on spills with news coverage because there are no migration composition changes after spills without news coverage. The event study graphs are in Figure 12 and the estimates are in Table 9. For low-tradability industries, the event study graphs show that there are clear decreases in employment and wages after spills that are reported in the news, with average effects of -5.4% and -3.7%, respectively. For high-tradability industries, the employment and wage effects are small in magnitude and statistically insignificant.

[16] I compute these tradability measures using the percent of traded employment for each 2-digit NAICS industry from Delgado, Bryden, and Zyontz (2014) Table 2. As mentioned earlier, each QCEW industry consists of one or more 2-digit NAICS industries. When a QCEW industry contains only one 2-digit NAICS industry, the tradability of this QCEW industry is the same as that of the 2-digit NAICS industry. When a QCEW industry contains two or more 2-digit NAICS industries, the tradability of this QCEW industry is the weighted sum of the tradability of each 2-digit NAICS industry, with the weights being the employment share within the QCEW industry for each 2-digit NAICS industry.

[17] I divide the ten industries into halves by tradability, with each half consisting of five industries. According to the tradability measures, high-tradability industries include the natural resources and mining industry, manufacturing industry, information industry, financial activities industry, and professional and business services industry, and low-tradability industries include the construction industry, trade, transportation, and ttilities industry, education and health services industry, leisure and hospitality industry, and other services industry.

This matches the prediction of the second part of the mechanism exactly: with the spill information-induced changes in migration composition, demand for goods and services from low-tradability industries drops, and labor markets in these industries weaken, whereas high-tradability industries are not impacted. Together, the results on migration and heterogeneity by industry tradability provide empirical support to this mechanism.

5 Discussion

5.1 Robustness Checks

5.1.1 No Propensity Score Weighting

I use propensity score weighting to make the control group more comparable to the treatment group in the main analysis since the treatment and control groups are comprised of counties at least 100 miles apart and not similar to each other. To examine whether the main results are driven by the propensity score weighting, I rerun the analysis for the main result without weighting. The event study graphs in appendix Figure A.4 show that the dynamics of the effects on all the labor market outcomes are the same as those in the main analysis. The difference-in-differences and concise event study estimates in Appendix Table A.2 are quantitatively and qualitatively similar to the main results. Hence, the use of propensity score weighting does not drive the main findings in the paper.

5.1.2 Variation in Treatment Timing

Recent literature has shown that conventional two-way fixed effect (TWFE) estimates may be biased when there is variation in the treatment timing (e.g., Goodman-Bacon, 2021a; Callaway & Sant'Anna, 2020; Borusyak, Jaravel, & Spiess, 2021). Multiple methods and estimators have been developed to address this issue (e.g., Cengiz, Dube, Lindner, & Zipperer, 2019; De Chaisemartin & d'Haultfoeuille, 2020; Sun & Abraham, 2020), and it has been shown that these estimators all perform equally well.[18] To inspect whether the TWFE estimates in this paper suffer from issues caused by variation in the treatment timing, I estimate the labor market effects of severe spills using the interaction weighted (IW) estimator developed by Sun and Abraham (2020). Appendix Figure A.5 plots the IW estimates against the TWFE estimates without propensity score weighting.[19] The IW and TWFE estimates are almost identical to each other in all the event study graphs, which suggests that the conventional TWFE estimates in this paper do not suffer from issues caused by variation in treatment timing. The most likely reason for the almost identical estimates is that there is a considerably large number of never-treated control counties in the analysis.

5.1.3 Counties Within 100 Miles as the Control Group

In the main analysis, I use counties whose centroids are more than 100 miles away from the centroids of the treated counties as the control group in case the surrounding counties are affected by the spills and cannot serve as valid controls. In this section, I directly use counties within 100 miles as the control group to inspect whether the main results are stable. The event study plots and the difference-in-differences estimates based on the control group of counties within 100 miles are in Appendix Figure A.6 and Table A.3. For every outcome variable, these event study graphs are of the same shape as the event study plots in the main analysis, and the difference-in-differences and concise event study estimates have magnitudes and statistical significance similar to those of the main results. This exercise suggests that the main results are robust to different definitions of the control group and lessens concerns over a violation of the Stable Unit Treatment Value Assumption.

[18]For a summary of the recent developments in the Difference-in-Differences literature, see https://asjadnaqvi.github.io/DiD/. A comparison of six recently developed estimators is provided in this Stata project: https://github.com/pietrosantoleri/staggered_did.

[19]The IW estimator does not allow weights.

5.1.4 Exclusion of Spills in Fixed Facilities

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), which suggests that factories may have some power to conceal spill information from the public. In terms of proportion, fixed facility spills make up 35% of spills not covered in the news, but only 5% of spills covered in the news. The large differences in the number and proportion of fixed facility spills might be the reason behind the differences in the estimated labor market effects. To probe whether the differences in the estimated effects are driven by fixed facility spills, I drop all such spills and re-run the main analysis. Appendix Figure A.7 and Table A.4 present the results without fixed facility spills. The event study graphs are basically the same as those in the main analysis, and the difference-in-differences and concise event study estimates are of similar magnitudes and statistical significance to the main estimates. These quantitatively and qualitatively similar results disprove the conjecture that the differences in the estimated effects between the groups with and without news coverage are driven by fixed facility spills.

5.1.5 Employment from the BEA Regional Economic Accounts

Since the QCEW assigns employment to a county based on the place of work, the decreases in county-level employment could be a result of employment reallocation rather than real job losses. In other words, it could be that, after a severe spill with news coverage, workers in the incident counties commute to another county to work instead of working in their county of residence. If this were the case, then the effects of severe spills on employment would reflect a change in work location rather than real unemployment. To examine whether there are real declines in the number of employed residents in counties with spills covered in the news, I reanalyze the employment effects using data from the BEA Regional Economic Accounts

(REA)[20], which assigns employment according to the place of residence. The event study plots in Appendix Figure A.8 show that the trajectory, magnitudes, and confidence intervals of the estimated employment effects based on the REA data are very close to the main results based on the QCEW data. This provides evidence that the decreases are not due to reallocation of economic activities, but reflect real employment losses in counties experienced spills with news coverage.

5.2 Labor Market Losses and Welfare Changes in Amenities

5.2.1 Total Labor Market Losses in Spill Counties

I now compute the total labor market losses in spill counties using back-of-the-envelope calculations. Specifically, I consider the losses in employment, wages, the number of establishments, and the size of the labor force in spill counties in the year in which the spill happened and the 5 years after. Since the effects on all four outcomes are precise zeros for counties experienced spills not covered in the news, there are no labor market losses in these aspects for these counties. In other words, the calculation is based only on the estimated effects of spills that are reported in the news. For employment, the number of establishments, and the labor force, I use the average outcome level in the 5 years before a spill as the baseline and compute the changes using the year 5 estimates. To compute the total wage loss, I multiply the average wage level in the pre period by the average wage decrease estimated from the difference-in-differences specification, and then multiply the average number of employees in the post period. The total losses per county and in aggregate for all counties with spills reported in the news are summarized in Appendix Table A.5 Panels A and B. The aggregate numbers from Panel B show that there are 407,000 lost jobs, $27.1B in foregone wages, 20,000 fewer establishments, and 402,000 fewer people in the labor force in all counties with spills reported in the news in the entire post period. The foregone wages in the table account only for the aggregate wage changes for all workers still employed after

[20] Previously called the Regional Economic Information System.

a spill, but not for wage losses from people who became unemployed because of the spill. In other words, the monetary value of the lost jobs is not reflected in the foregone wages. The total wage loss for workers who became unemployed due to spills in all the spill counties with news coverage in all the post years, i.e., the monetary value of all lost jobs, sums to $41.4 billion.

Note that, the focus here is on the losses in counties that experienced spills with news coverage, not on labor market conditions in a broader area. It is possible that there is a general equilibrium effect such that the lost jobs and establishments are re-created in other counties and the total number of jobs and establishments in the U.S. does not change. In other words, there may be no aggregate losses in employment and establishments if we look at the U.S. as a whole. However, geographic relocation of jobs and establishments is not observed in the county-level datasets and is not the focus of this paper.

5.2.2 Welfare Changes in Amenities in Spill Counties

There are many components in the welfare evaluation of severe spills, and labor market losses account for only one of them. Another component that is often discussed in the literature is changes in amenities. To evaluate how severe spills affect people's valuation of local amenities, I build a dynamic spatial model following Artuç, Chaudhuri, and McLaren (2010), Caliendo, Dvorkin, and Parro (2019), and Rudik, Lyn, Tan, and Ortiz-Bobea (2021). Details of the model are in Appendix B. The basic idea is that an individual will leave an incident county after learning a spill occurs if the expected present discounted value (PDV) of the stream of future utilities generated from amenities and wages that the individual can gain from the current county of residence is smaller than the expected PDV of all future utilities that the individual can acquire from another county net of the moving cost. The model is estimated by panel fixed effect regressions–event study and difference-in-differences to be specific–using the county-level wage and out-migration data. Appendix Figure A.9 and Table A.6 show the results. The estimates are measured in percent changes in wage and should be interpreted as effects of severe spills on the valuation of local amenities. There are no clear changes in the post period in the event study graphs and the difference-in-differences estimates are all close to zero in size and statistically insignificant regardless of the news coverage status of the spills. These results indicate that, regardless of news, there are no welfare changes in amenities at the county level on average. This provides further evidence that the long-run negative labor market effects after a news-reported spill are not caused by a degradation of amenities.

However, note that, the finding of no changes in the valuation of local amenities at the county level does not mean that the valuation of amenities does not change at a more granular level. It is possible, and likely, that the significant increase in out-migration in the year of a spill with news coverage as shown in Figure 11 (b) is from people whose valuation of local amenities declined. However, this increased out-migration makes up only 3.6% of the gross out-migration.[21] Even if utilities from environmental amenities for this group of people declined considerably, the average change could be negligible since people who migrate out for this reason account for only a very small portion of total out-migration. Thus, there may be no changes in local amenities detected on average even when individual valuations of amenities for some people decrease significantly. Individual-level data are needed to assess changes in the valuation of local amenities for people who migrated out due to a spill, which is beyond the scope of this paper.

5.3 Information on Environmental Disasters as a Policy Lever

The results in this paper suggest that information on environmental disasters could have distributional effects and aggravate environmental justice. When spill information is available to the public, there are migratory responses from a group of people who have higher income than the usual out- and in-migrants in the pre period. This implies that the burden of avoidance costs is borne by individuals, but only people who have resources can afford

[21] The increase in the year of spill is 0.166 percentage points and the gross out-migration rate is 4.568%.

it. Moreover, the compositional changes in migration are long-lasting. The changes in migration composition result in labor market weakening in counties with spills that receive news coverage. This has distributional consequences because the people remaining in the counties with spills reported in the news have lower income in the first place and have to face degraded county-level labor markets after spills. The decrease in the number of high-income people also makes the composition of the population in spill counties with news coverage poorer over time, which exacerbates environmental injustice.

Despite the distributional effects, degraded labor markets, and worsened environmental justice, information on environmental disasters brings benefits to other perspectives. In a study closely related to this paper and relying on the same county-level dataset of severe inland oil spills, Chen (2021) finds that ambient air quality worsens only in counties with spills not reported in the news in the 12 months after a spill, but not in counties where a spill is covered in the news. This indicates that spill information encourages faster cleanup responses, likely due to public attention. In other words, spill information is beneficial to the environment, though the monetary value of this benefit is unobserved. Because of the elevated air pollution level, county-level mortality rates also increase in the 12 months after a spill not reported in the news, but there are no such changes when a spill receives news coverage. By assuming counties with spills not covered in the news are good counterfactuals, the avoided mortality costs in spill counties with news coverage in the 12 months after spills total \$2.62 billion.

The mortality benefit alone is far from a full accounting of the benefits of environmental disaster information. First, the monetary value of the benefit to the environment from spill information-induced faster cleanup can be enormous but is not observed here. Additionally, it is very likely that spill information generates benefits on other dimensions of human health. The faster cleanup response induced by spill information likely reduces the number of hospital admissions for respiratory and cardiovascular problems. If a spill is released into water, information on the spill could prevent residents from diseases, such as digestive cancer, linked to drinking contaminated water (Ebenstein, 2012). Spill information may also lower the effects of spills on infant birth outcomes, such as low birth weight, premature birth, and abnormality, which have longer-term effects on cognitive development, educational attainment, and earnings (Black, Devereux, & Salvanes, 2007; Figlio, Guryan, Karbownik, & Roth, 2014; Oreopoulos, Stabile, Walld, & Roos, 2008).

It is highly likely that provision of environmental disaster information has positive welfare effects overall, but policymakers still should take complementary actions to moderate labor market costs induced by information provision. With the knowledge that labor market losses are ignited by more high-income people leaving and fewer high-income people entering incident counties after learning the occurrence of a spill, governments could take actions to maintain the number of high-income residents. For example, frequent full disclosures on the cleanup process and water and air conditions is one way to lessen current local residents' and potential future residents' concerns over pollution and a deterioration in environmental amenities. With complete, rather than incomplete, information, local residents and potential in-migrants may find it less critical to migrate out or avoid incident counties. If there are no compositional changes in migration, there are no ripple effects that weaken labor markets after a spill that receives news coverage in the long-run.

Understanding the effects of spills and spill information can help policymakers not only formulate more targeted response mechanisms to minimize labor market costs ex post, but also design more efficient and more effective regulations to prevent the occurrence of spills ex ante. As aforementioned, most of the severe spills are due to pipeline ruptures. Though accidental, many pipeline ruptures are due to corrosion, deformations, and cracking, and they are preventable through inspections and maintenance. Frequent pipeline inspections and maintenance are not required by law in the U.S.[22] Whether to increase pipeline inspection and maintenance frequency to prevent severe spills depends the magnitudes of the inspection and maintenance costs and the labor market costs. The total foregone wages after severe spills

[22] A background on pipeline inspection and maintenance frequency is in Appendix C.

that receive news coverage are \$27.1B, according to the back-of-the-envelope calculation.[23] The pipeline inspection and maintenance costs are \$150,000 per mile.[24] The total foregone wages are equivalent to the inspection costs for 180,700 miles of liquid petroleum pipelines, which is close to the mileage of all liquid petroleum pipelines in the U.S.[25] Because not all pipelines are susceptible to failure, the focus should be on segments with a higher possibility of resulting in a spill, such as the aging pipelines. Doing so would make it possible to increase pipeline inspection and maintenance frequency to prevent spills, and the expenses would be cheaper than the total labor market costs from spills. Moreover, there would be two benefits from such a regulation. First, requiring more frequent inspections would put the costs on potential polluters than burden individuals with the avoidance costs, which would not worsen environmental injustice. Second, increasing inspection frequency would make firms value both pollution and social costs, which would incentivize firms to make efficient risk reducing investments (Boyd, 1997).

6 Conclusion

This paper examines the labor market effects of environmental disasters with and without public accessibility to information. I find that county-level labor markets suffer from severe inland oil spills, but only when a spill is in the news. In the year in which a spill that is covered in the news occurs and the five years after, employment, wages, the number of establishments, and the labor force all decrease significantly in both economic and statistical senses. When a spill is not in the news, all the estimated effects are precise zeros. The mechanism underlying the labor market effects is that spill information triggers migration

[23] I do not consider lost jobs here because of the potential general equilibrium effects discussed earlier.

[24] According to Brito and Sheshinkski (1997), inspection and maintenance costs are 3% of pipeline construction costs. Average pipeline construction costs are approximately \$5 million per mile, as reported by the American Petroleum Institute. Hence, the average inspection and maintenance costs are \$150,000 per mile.

[25] According to the American Petroleum Institute, the total mileage of liquid petroleum pipelines traversing the U.S. is 190,000 miles: https://www.api.org/oil-and-natural-gas/wells-to-consumer/transporting-oil-natural-gas/pipeline/where-are-the-pipelines.

composition changes, i.e., more high-income people leave and fewer high-income people enter an incident county, which hurts low-tradability industries, such as retail and restaurants, and the overall county-level labor market. When there is no information on a spill, there are no changes in migration composition and no labor market effects. Analyses of county-level gross migration and labor market performance by tradability validate this mechanism.

The results in this paper suggest that information on environmental disasters leads to migration and sorting, which has distributional effects and hurts environmental justice. The migratory responses from high-income people after a spill that is reported in the news have distribution consequences. Individuals who do not, or cannot, move away from a county that experiences a spill that is reported in the news have to face degraded local labor markets. Moreover, the individual-level migratory responses suggest that local residents bear avoidance costs. With the decline in the number of high-income people, the composition of communities in counties experienced spills with news coverage gradually grows poorer, which exacerbates environmental injustice.

The findings in this paper have implications for the use of environmental disaster information as a policy tool. Though this paper finds that provision of spill information could trigger labor market responses with considerable costs, Chen (2021) finds that exposure to spill information benefits air quality and prevents mortality. Provision of spill information may also have benefits on other aspects, such as general human health and the environment and ecosystem, that are unaccounted for in these two studies. It is very likely that the overall welfare effects of providing spill information to the public is positive. To optimally exploit provision of environmental disaster information as a policy tool, governments should take complementary actions to minimize labor market costs ex post. For example, issuing frequent full disclosures on the cleanup process and environmental conditions can alleviate people's concerns and lower out-migration. Establishment of more effective and more efficient regulations, such as requirements of more frequent inspections and maintenance, can prevent the occurrence of oil spills ex ante and avoid all the negative consequences identified in this paper.

Figures and Tables

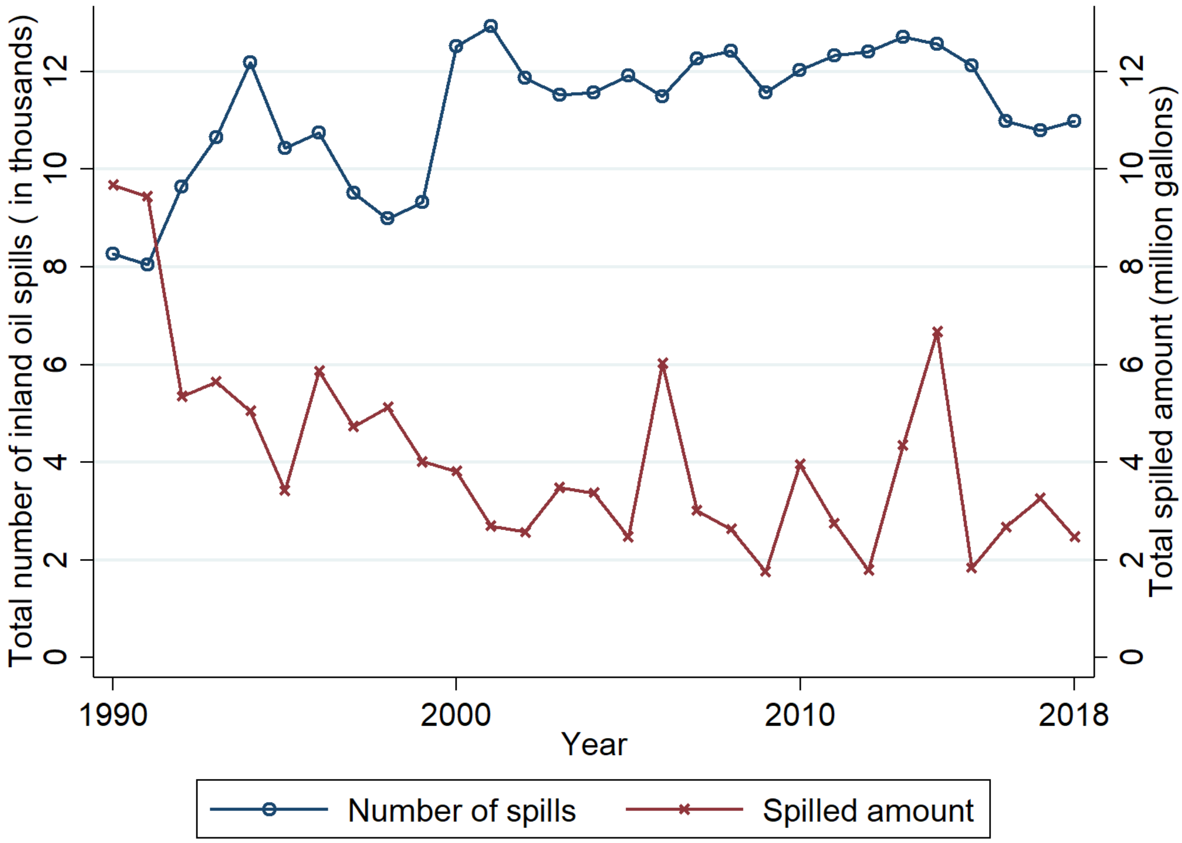
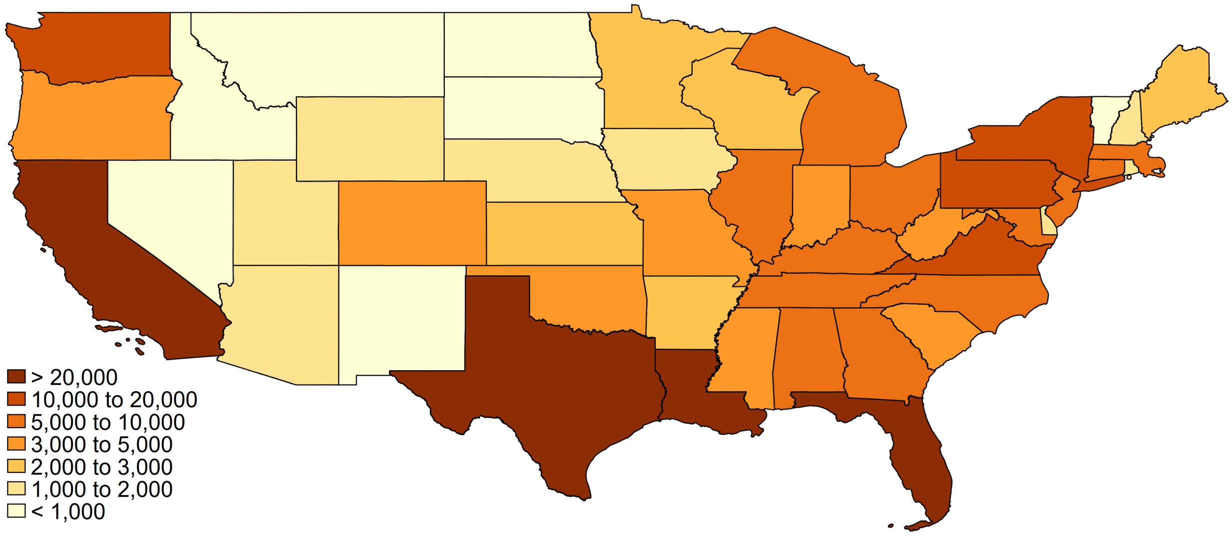
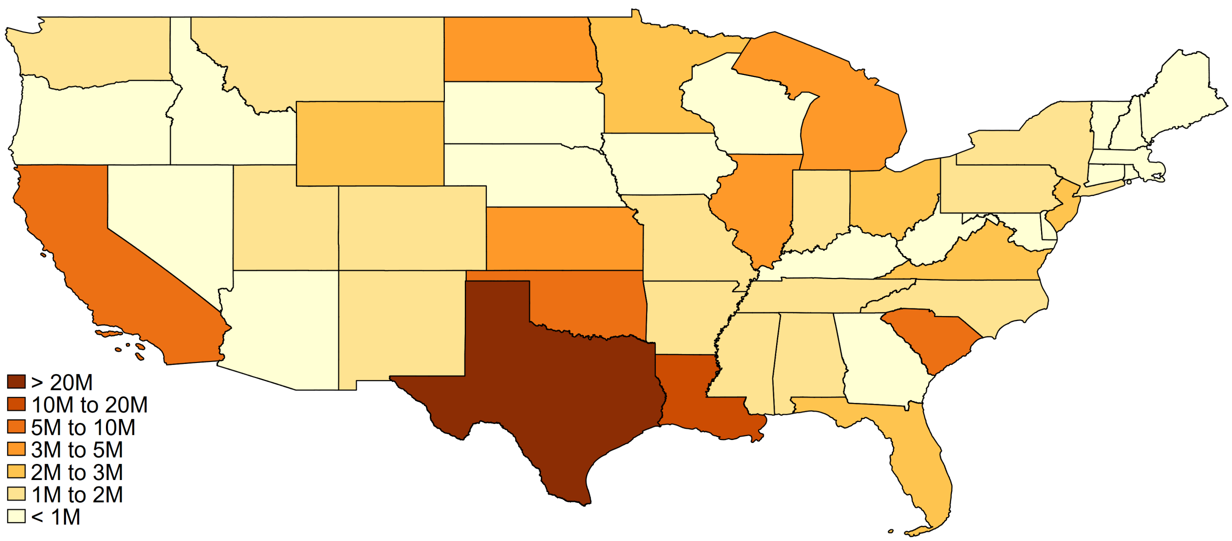


Figure 1: Total Numer of Inland Petroleum Oil Spills and Total Spilled Amount

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.

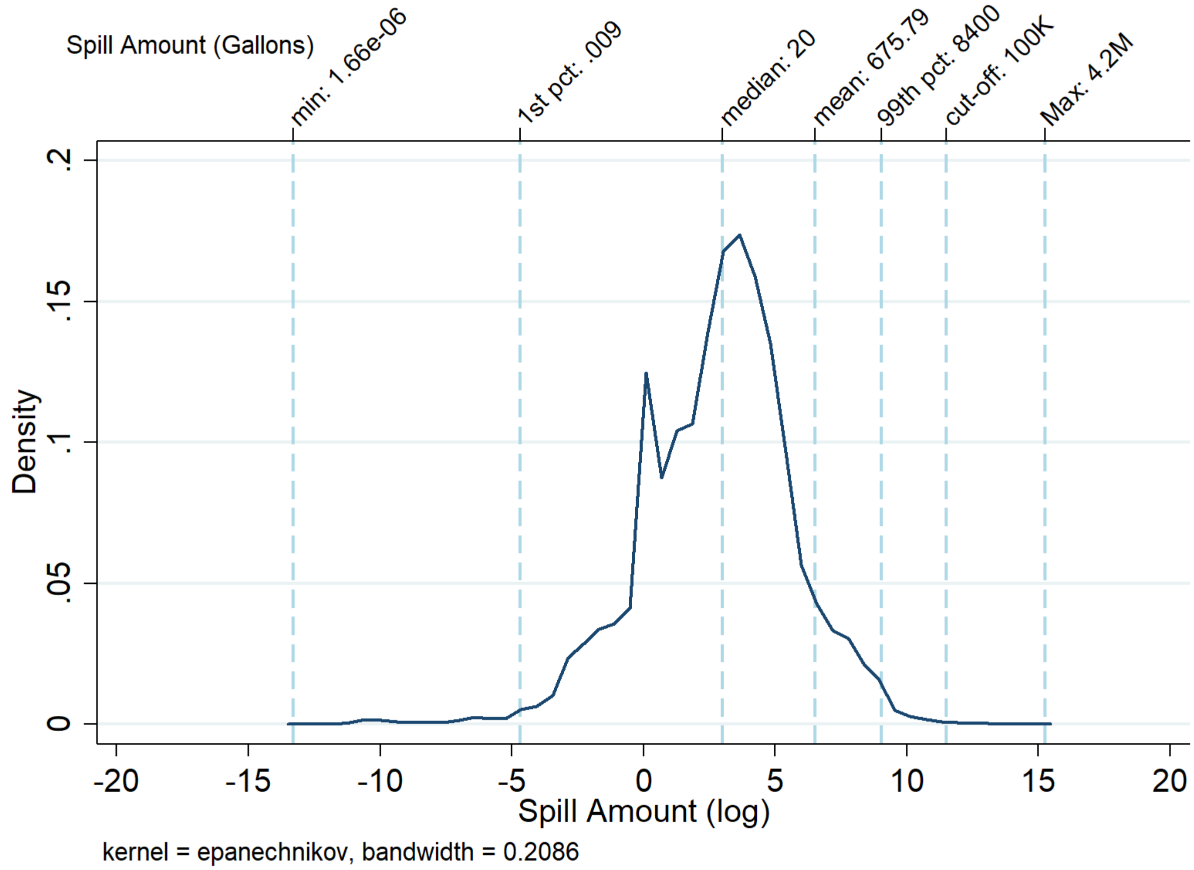


Figure 3: Density Plot of All Spill Amount (log)

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.

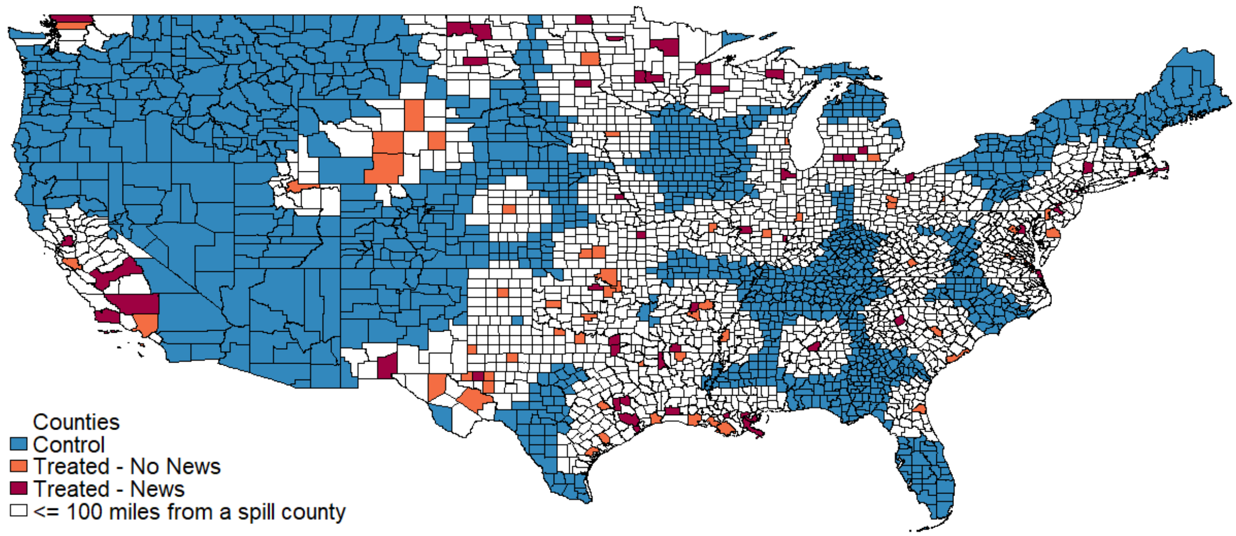


Figure 4: Treatment and Control Groups

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

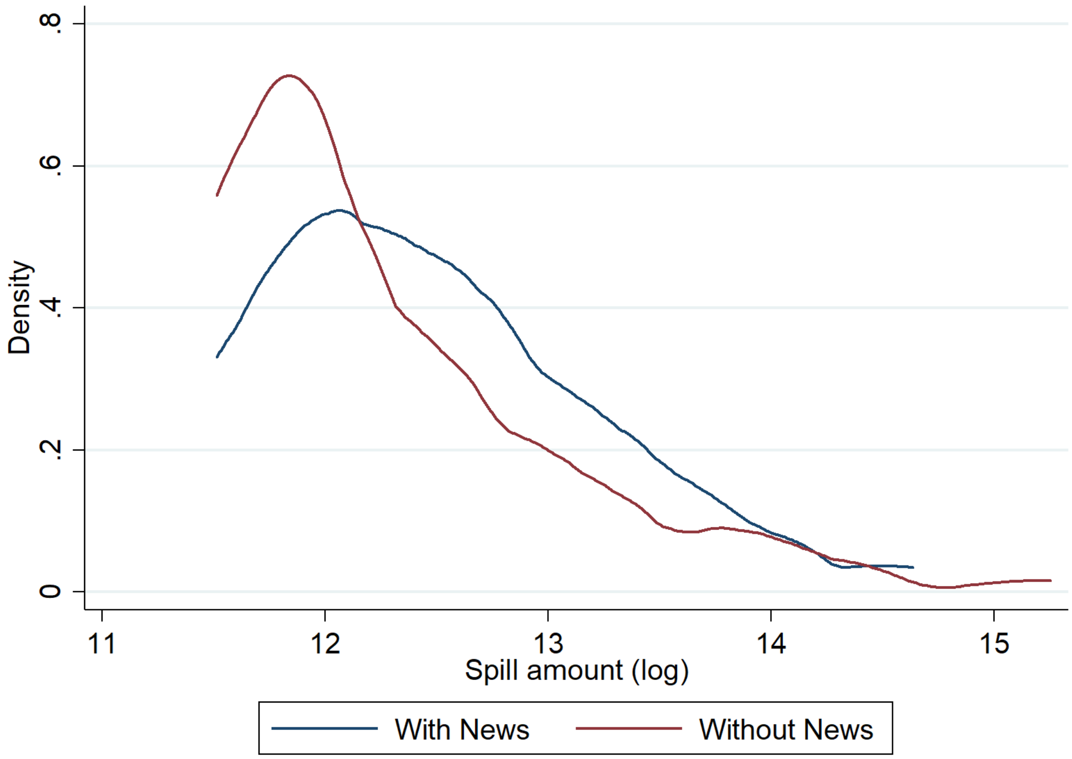


Figure 5: Density Plot of Severe Spill Amount (log)

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

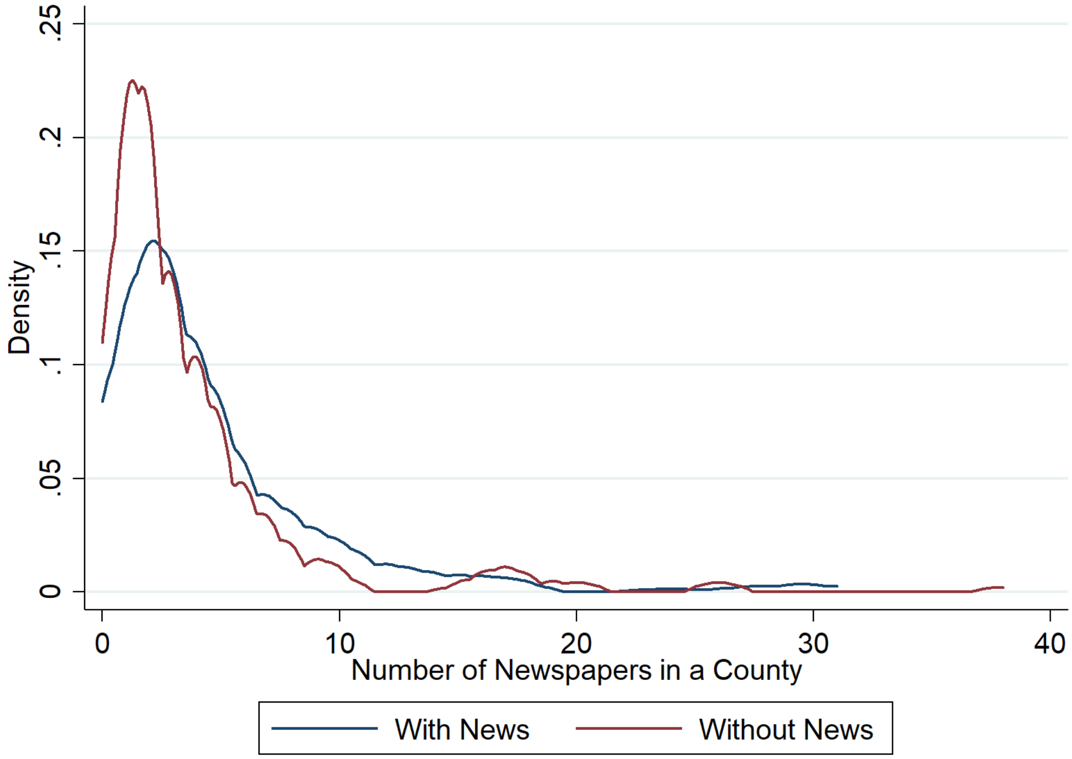
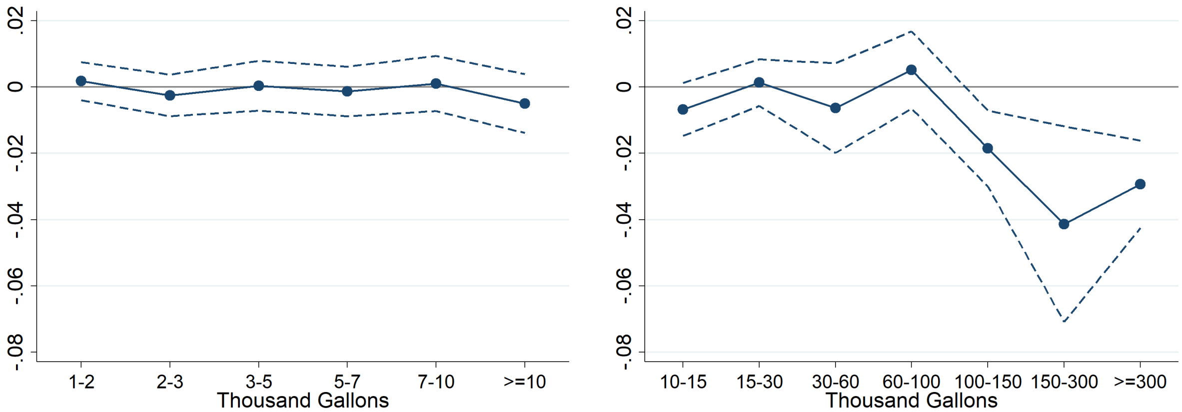


Figure 6: Density Plot of Number of Newspapers in a County

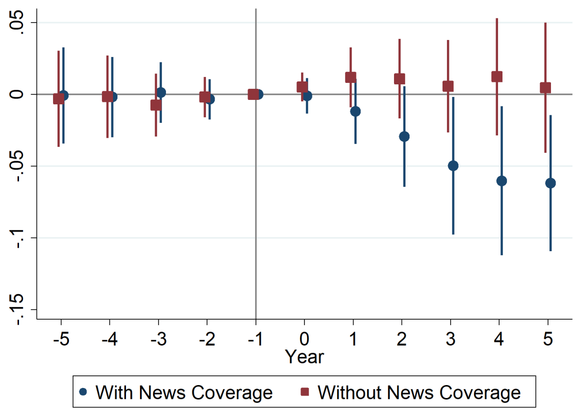
Source: UNC Hussman School of Journalism and Media.



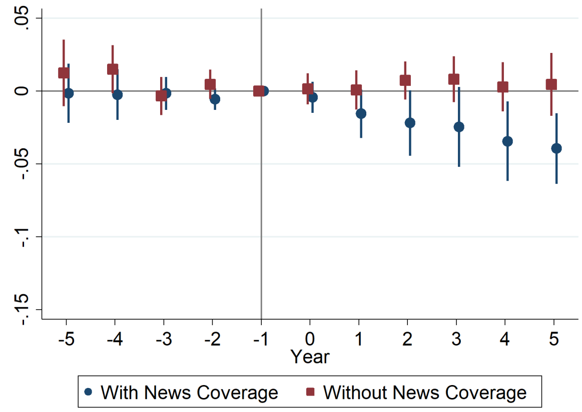
(a) Only 1 spill $\geq$ 1K gallons (b) Only 1 spill $\geq$ 10K gallons

Figure 7: Semiparametric Estimates of Inland Oil Spills on Employment to Population Ratio

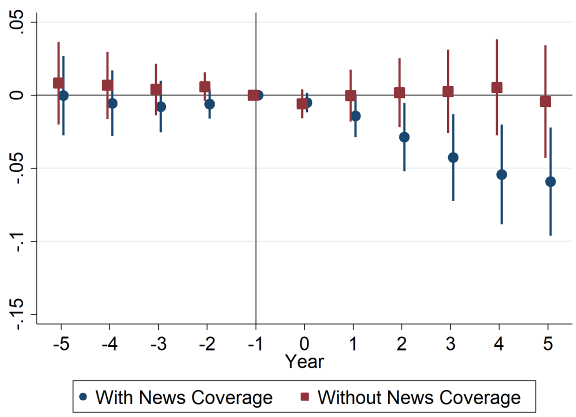
Note: The points on the connected lines represent the estimated effect of each bin. The dashed lines represent the 95% confidence intervals, where standard errors are clustered at the county level. The control group consists of counties without a spill and counties with spills < 1,000 gallons. The effect on counties with spills < 1,000 gallons compared to counties without a spill is .0001 (S.E. = .0020).
Source: QCEW.



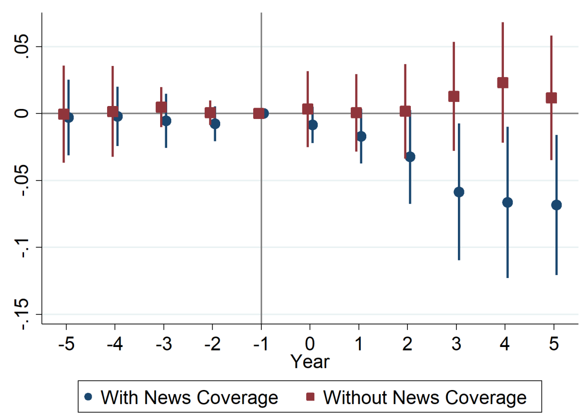
(a) Employment (log)



(b) Average wage per job (log)



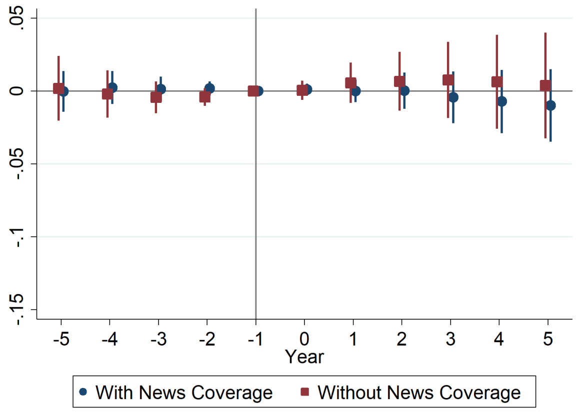
(c) Number of establishments (log)



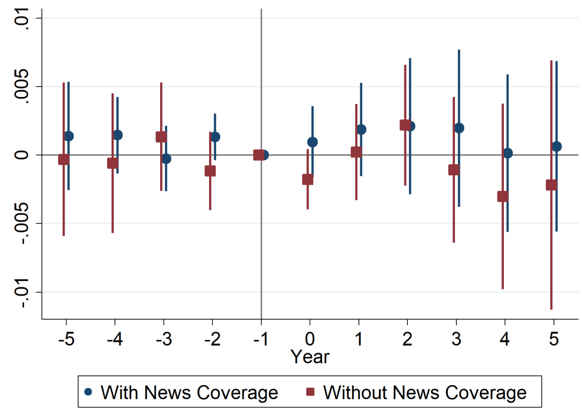
(d) Labor force (log)

Figure 8: Effects of Severe Inland Oil Spills on Labor Demand and Supply

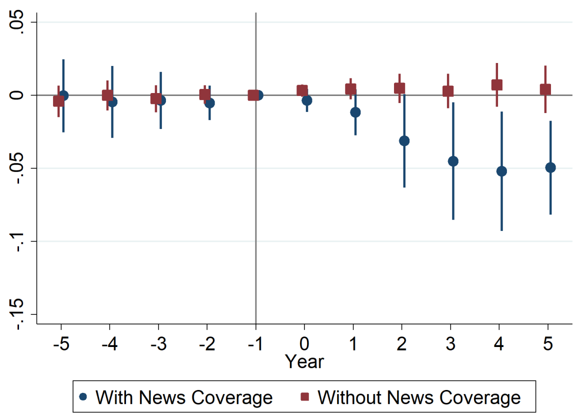
Note: These are event study plots created by regressing outcome variables of the spill counties on a set of event time indicators, county fixed effects, and state-by-year fixed effects as specified in Equation (1) with propensity score weights. The outcome variables are displayed below the corresponding plots. The dots (squares) represent the estimated effects at the event time. The spikes represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW and LAUS.



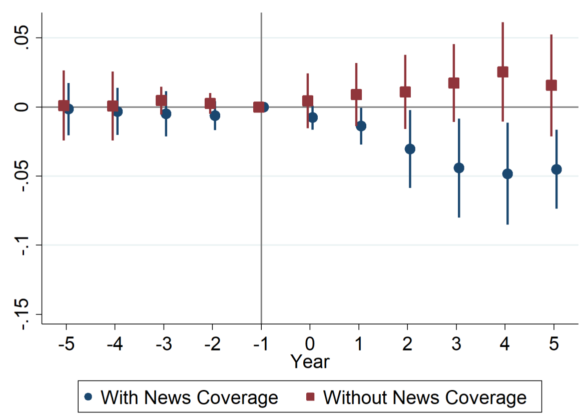
(a) Working age population (log)



(b) Unemployment rate



(c) Emp/working age population ratio

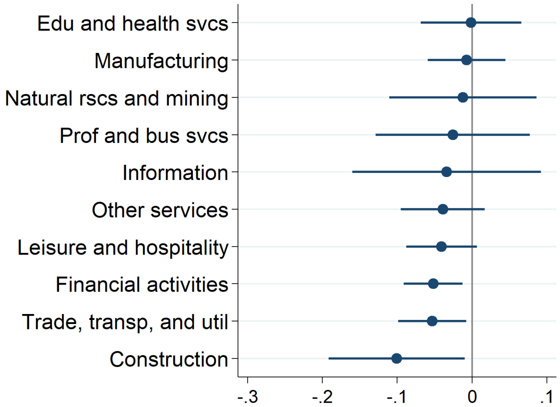


(d) Labor force participation rate

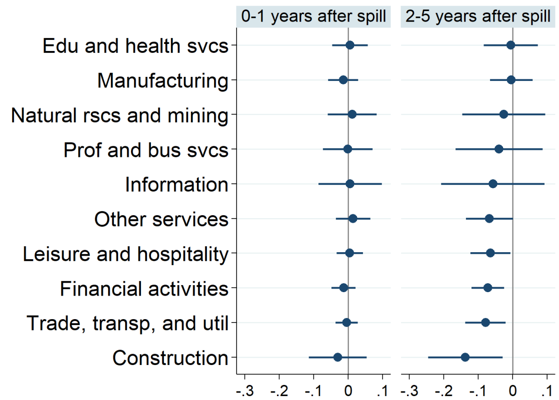
Figure 9: Effects of Severe Inland Oil Spills on Population and Employment Statistics

Note: These are event study plots 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 as specified in Equation (1) with propensity score weights. The outcome variables are displayed below the corresponding plots. The dots (squares) represent the estimated effects at the event time. The spikes represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW, LAUS, and the Census.

Panel A. Employment

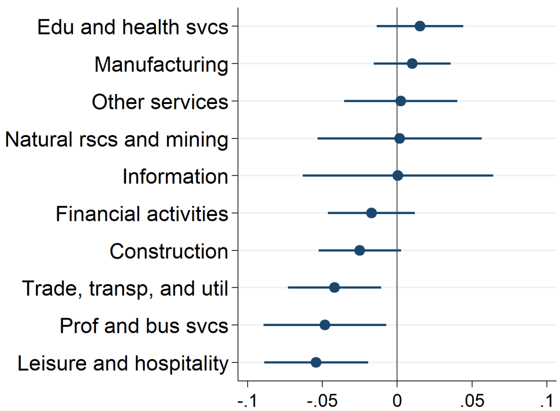


(a) Diff-in-diff estimates on emp (log)

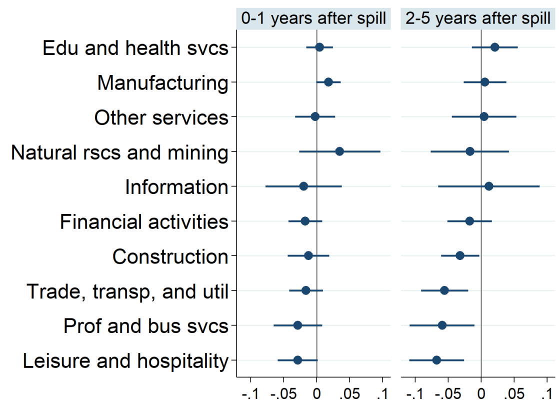


(b) Concise event study estimates on emp (log)

Panel B. Wage



(c) Diff-in-diff estimates on wage (log)

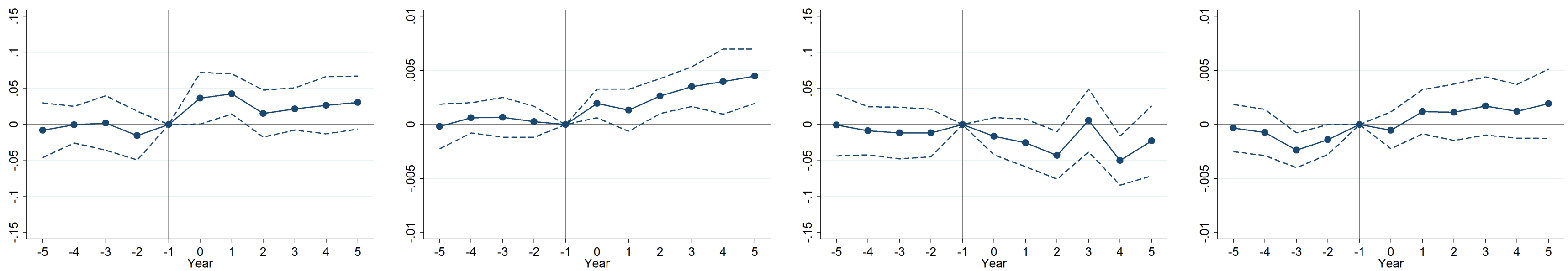


(d) Concise event study estimates on wage (log)

Figure 10: Heterogeneous Treatment Effects of Severe Spills with News Coverage by Industry

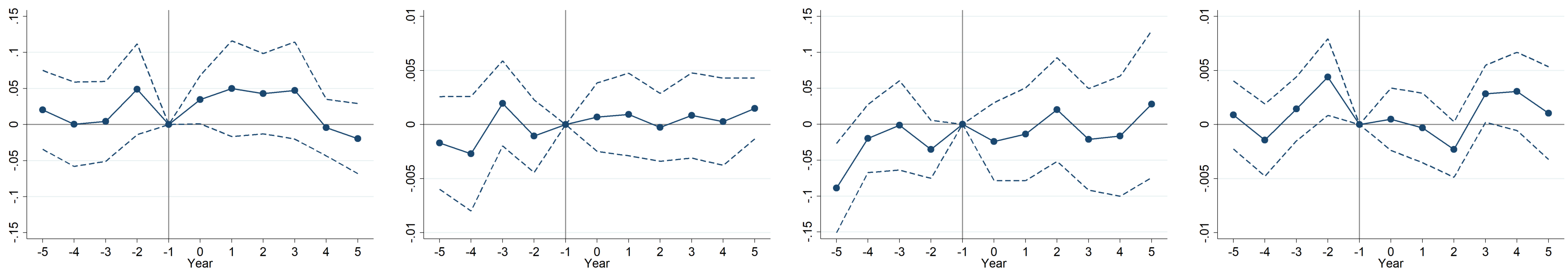
Note: These plots report the difference-in-differences (Equation (2)) and concise event study (Equation (3)) estimates of the effects of the severe inland oil spills on labor market outcomes at county-by-year level for each industry. All regressions include county and state-by-year fixed effects and are weighted by propensity score weights. Standard errors are clustered at the county level.
Source: QCEW.

Panel A. With News



(a) Avg outflow income (log) (b) Gross out-migration rate (c) Avg inflow income (log) (d) Gross in-migration rate

Panel B. Without News

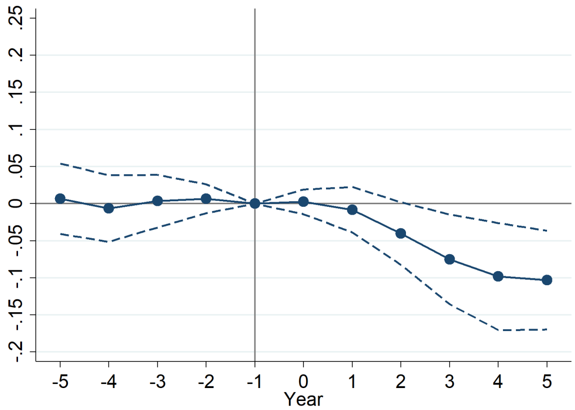


(e) Avg outflow income (log) (f) Gross out-migration rate (g) Avg inflow income (log) (h) Gross in-migration rate

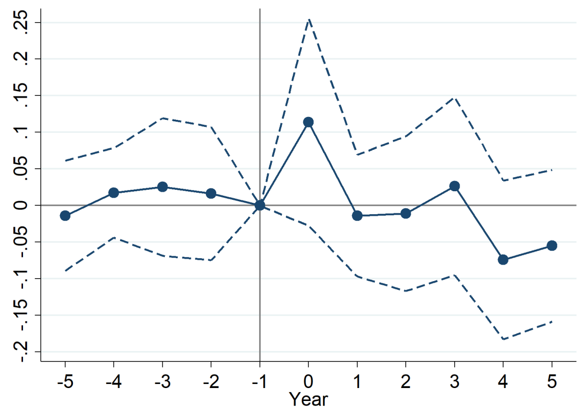
Figure 11: Event Study Results of the Effects of Severe Inland Oil Spills on Gross Migration

Note: These plots report the event study estimates of the severe inland oil spills on out- and in-migration outcomes at the county-by-year level. All regressions include county and state-by-year fixed effects. The points on the connected lines represent the estimated effects at the event time. The dashed lines represent the 95% confidence intervals, where standard errors are clustered at the 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.

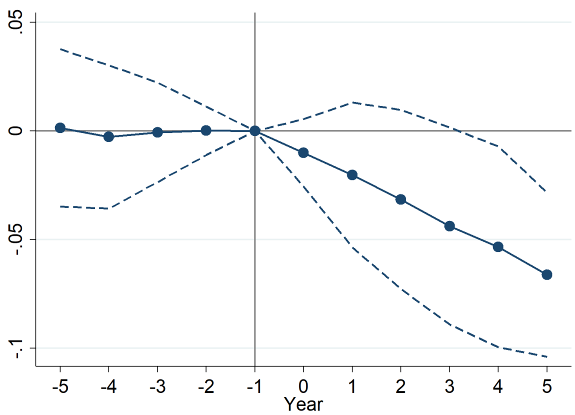
Source: IRS.



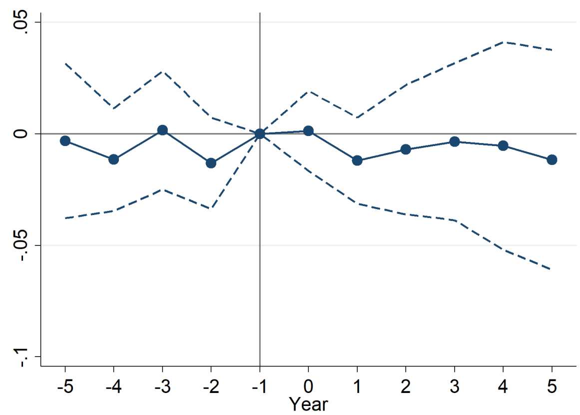
(a) Low Tradability: Employment



(b) High Tradability: Employment



(c) Low Tradability: Wages



(d) High Tradability: Wages

Figure 12: Effects of Severe Inland Oil Spills with News Coverage by Industry Tradability

Note: These are event study plots created by regressing employment and wages of the spill counties on a set of event time indicators, county fixed effects, and state-by-year fixed effects as specified in Equation (1) with propensity score weights. The points on the connected lines represent the estimated effects at the event time. The dashed lines represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW.

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 to 2018. The mean amounts 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 Labor Market Outcomes, Population, and Gross Migration

	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Median	(6) Max
Panel A. Labor Market Outcomes from QCEW 1980-2018						
Average wage per job	121155	25246.7	10642.9	5689	23601	134619
Employment	121155	37686.7	138776.8	16	7323	4443084
Emp/working age pop ratio	121114	0.4165	0.1694	0.06597	0.3982	6.9272
Number of establishments	121155	2302.0	8872.5	5	558	497026
Panel B. Labor Market Outcomes from LAUS 1990-2018						
Labor force	90219	46829.9	151692.8	38	11596	5136341
Labor force participation	90179	0.6049	0.08527	0.1787	0.6095	1.5789
Unemployment	90219	2772.9	10447.9	1	716	615101
Unemployment rate	90219	0.0614	0.0289	0.0038	0.0553	0.4044
Panel C. Population 1980-2018						
Population	121271	89254.9	290240.5	55	24308	10120540
Working age population	121327	59137.34	195693	43	15480	6946383
Pct working age pop	121225	0.6375	0.0384	0.3169	0.6387	0.8635
Percent black	117028	0.09105	0.1459	0.00004944	0.02024	0.8690
Panel D. Gross Out- and In-Migration 1990-2017						
Out-Migration						
Number of individuals	86759	4360.8	11961.8	5	1142	341832
Migration rate	85133	0.04950	0.01768	0.0001330	0.04648	0.4231
Adjusted gross income	80527	137675.1	465615.8	6.2800	23720.3	14339604.6
AGI per capita	80527	22998.1	8259.3	19.323	21414.6	484719.5
In-Migration						
Number of individuals	86708	4389.3	10896.6	13	1179	230559
Migration rate	86683	0.05099	0.02086	0.003885	0.04707	0.8720
Adjusted gross income	80472	137905.4	416647.3	82.000	25044.4	10849187.4
AGI per capita	80472	23344.2	9746.1	758.95	21372.5	741223.4

Note: All monetary amounts have been converted to 2019 dollars using the Consumer Price Index.
Source: QCEW, LAUS, Census, and IRS.

Table 3: Spill County Characteristics by News Coverage

	(1) With News	(2) Without News	(3) Difference	(4) p-value
Panel A. QCEW Outcomes and Population 1985-1989				
Average wage per job	18724.353	18725.442	1.090	0.997
Employment	101616.851	147175.525	45558.674	0.185
Emp/WA pop ratio	0.533	0.561	0.028	0.023
Number of establishments	5024.229	7135.461	2111.232	0.208
Population	244635.898	305509.677	60873.779	0.396
Working age population	164409.331	206354.747	41945.416	0.390
Pct working age pop	0.648	0.645	-0.003	0.346
Percent black	0.111	0.109	-0.002	0.852
Panel B. LAUS Outcomes and Gross Migration 1990				
Labor force	126470.327	161998.767	35528.439	0.678
Labor force participation	0.626	0.623	-0.003	0.837
Num of outflow indiv	12926.109	18109.465	5183.356	0.535
Outflow AGI per capita	22491.59	23416.29	924.70	0.484
Num of inflow indiv	10103.479	13428.742	3325.263	0.506
Inflow AGI per capita	22267.43	22506.11	238.679	0.871
Panel C. Number of Newspapers 2004, 2014, 2016, 2020				
Number of newspapers	4.67	3.75	0.92	0.047
Num of counties	55	60		

Note: All monetary amounts have been converted to 2019 dollars using the Consumer Price Index.
Source: QCEW, LAUS, Census, and IRS.

Table 4: Effects of Severe Inland Oil Spills on Labor Market Outcomes

	(1) Employment (log)	(2) Average wage per job (log)	(3) Number of establish-ments (log)	(4) Labor force (log)
Panel A. Difference-in-Differences Estimates (Equation (2))				
With News				
0-5 years after spill	-0.034*	-0.021**	-0.029**	-0.037**
	(0.018)	(0.009)	(0.012)	(0.015)
Without News				
0-5 years after spill	0.009	-0.005	-0.008	0.007
	(0.018)	(0.008)	(0.018)	(0.021)
Panel B. Concise Event Study Estimates (Equation (3))				
With News				
0-1 year after spill	-0.005	-0.007	-0.005	-0.008
	(0.012)	(0.006)	(0.010)	(0.010)
2-5 years after spill	-0.049**	-0.028**	-0.042***	-0.053**
	(0.022)	(0.011)	(0.015)	(0.021)
Without News				
0-1 year after spill	0.008	-0.006	-0.011	0.000
	(0.014)	(0.007)	(0.013)	(0.015)
2-5 years after spill	0.009	-0.004	-0.007	0.011
	(0.021)	(0.009)	(0.021)	(0.025)
Num of obs (with News)	56650	56650	56650	38202
Num of obs (without News)	57162	57162	57162	37914

Standard errors in parentheses

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

Note: This table reports the difference-in-differences and concise event study estimates of the effects of the severe inland oil spills on labor market outcomes at the county-by-year level. All regressions include county and state-by-year fixed effects and are weighted by propensity score weights. Standard errors are clustered at the county level.
Source: QCEW and LAUS.

Table 5: Effects of Severe Inland Oil Spills on Population and Employment Statistics

	(1) Working age population (log)	(2) Unemployment rate	(3) Emp to working age population ratio	(4) Labor force participation rate
Panel A. Difference-in-Differences Estimates (Equation (2))				
With News				
0-5 years after spill	-0.004	0.001	-0.029***	-0.028***
	(0.010)	(0.002)	(0.009)	(0.008)
Without News				
0-5 years after spill	0.006	-0.001	0.003	0.012
	(0.014)	(0.002)	(0.006)	(0.017)
Panel B. Concise Event Study Estimates (Equation (3))				
With News				
0-1 year after spill	0.000	0.001	-0.004	-0.007
	(0.006)	(0.001)	(0.007)	(0.005)
2-5 years after spill	-0.006	0.000	-0.042***	-0.039***
	(0.012)	(0.003)	(0.013)	(0.012)
Without News				
0-1 year after spill	0.004	-0.001	0.002	0.005
	(0.009)	(0.002)	(0.005)	(0.012)
2-5 years after spill	0.007	-0.001	0.004	0.016
	(0.017)	(0.003)	(0.008)	(0.020)
Num of obs (With News)	56650	38202	56650	38202
Num of obs (Without News)	57162	37914	57162	37914

Standard errors in parentheses

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

Note: This table reports the difference-in-differences and concise event study estimates of the effects of the severe inland oil spills on labor market outcomes at the county-by-year level. All regressions include county and state-by-year fixed effects and are weighted by propensity score weights. Standard errors are clustered at the county level.
Source: QCEW and LAUS.

Table 6: Summary Statistics by Industry in the 5 Years before a Spill with News Coverage

	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Median	(6) Max
Panel A. Employment by Industry						
Natural resources and mining	158	2828.9	9477.2	13	409	59853
Construction	166	4442.7	5880.6	47	2102	26589
Manufacturing	155	8482.7	8961.9	184	4225	43622
Trade, transportation, and utilities	170	16870.3	23188.3	253	7208	96052
Information	155	1851.5	3466.9	13	592	18120
Financial activities	169	4680.8	9460.3	47	1253	52331
Professional and business services	163	9905.7	17959.3	44	3996	86636
Education and health services	170	12777.4	28413.9	106	5117.5	170430
Leisure and hospitality	169	8969.0	13668.4	59	4612	62528
Other services	164	3411.9	5329.6	39	1323	23691
Overall	170	89986.7	137097.2	1111	39196	666957
Panel B. Average Wage Per Job by Industry						
Natural resources and mining	158	46600.2	27832.4	18377.5	36719.6	160068.8
Construction	166	51503.3	12524.4	29385.5	50972.0	85219.7
Manufacturing	155	58610.5	13201.0	36650.1	57935.4	133907.6
Trade, transportation, and utilities	170	38217.4	9398.9	24305.8	36530.4	85153.6
Information	155	49028.9	15513.2	12329.7	48493.3	86846.1
Financial activities	169	46956.6	13014.4	26060.7	44883.1	94991.7
Professional and business services	163	46302.7	16024.7	20712.5	43094.3	96302.1
Education and health services	170	39032.7	8832.5	20545.5	38509.1	57415.3
Leisure and hospitality	169	16341.1	5753.5	7575.7	15712.8	33996.6
Other services	164	29884.9	8814.8	13338.4	29834.7	60926.4
Overall	170	32550.4	9246.4	16002	31744.5	78363

Note: All monetary amounts have been converted to 2019 dollars using the Consumer Price Index.
Source: QCEW.

Table 7: QCEW Industry Tradability

QCEW Industry	% Traded Employment
Natural resources and mining	100%
Manufacturing	93%
Professional and business services	56.6%
Information	53%
Financial activities	45.3%
Trade, transportation, and utilities	28.5%
Leisure and hospitality	21.4%
Education and health services	10.2%
Construction	8%
Other services	2%

Note: The QCEW industry tradabilities are computed based on the percent of traded employment for each 2-digit NAICS sector from Delgado et al. (2014). Specifically, for each QCEW industry, I multiply the tradability of each 2-digit NAICS industry that falls under that QCEW industry by its share within the QCEW industry, and then sum this product for all the 2-digit NAICS industries within the same QCEW industry.

Table 8: The Effects of Severe Inland Oil Spills on Gross Migration

	(1) Avg outflow income (log)	(2) Gross out-migration rate	(3) Avg inflow income (log)	(4) Gross in-migration rate
Panel A. Difference-in-Differences Estimates (Equation 2)				
With News				
0-5 years after spill	0.033***	0.003***	-0.018*	0.002*
	(0.012)	(0.001)	(0.011)	(0.001)
Without News				
0-5 years after spill	0.010	0.001	0.023	-0.000
	(0.020)	(0.002)	(0.023)	(0.001)
Panel B. Concise Event Study Estimates (Equation 3)				
With News				
0-1 year after spill	0.043***	0.001*	-0.013	0.001
	(0.012)	(0.001)	(0.011)	(0.001)
2-5 years after spill	0.028*	0.003***	-0.020	0.002*
	(0.015)	(0.001)	(0.013)	(0.001)
Without News				
0-1 year after spill	0.027	0.001	0.011	-0.001
	(0.019)	(0.002)	(0.019)	(0.001)
2-5 years after spill	0.003	0.001	0.029	0.000
	(0.022)	(0.002)	(0.027)	(0.001)
Num of obs (With News)	33809	36414	33795	36408
Num of obs (Without News)	33679	36274	33664	36268

Standard errors in parentheses

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

Note: This table reports the difference-in-differences and concise event study estimates of the effects of the severe inland oil spills on gross out- and in-migration outcomes at the county-by-year level. All regressions include county and state-by-year fixed effects. Standard errors are clustered at the county level.

Source: IRS.

Table 9: Effects of Severe Inland Oil Spills with News Coverage by Industry Tradability

	(1) Employment (log)	(2) Average wage per job (log)
Panel A: Difference-in-Differences Estimates (Equation 2)		
Low Tradability		
0-5 years after spill	-0.054***	-0.037***
	(0.020)	(0.014)
High Tradability		
0-5 years after spill	-0.010	-0.001
	(0.036)	(0.016)
Panel B: Concise Event Study Estimates (Equation 3)		
Low Tradability		
0-1 year after spill	-0.004	-0.014
	(0.017)	(0.011)
2-5 years after spill	-0.081***	-0.048***
	(0.025)	(0.016)
High Tradability		
0-1 year after spill	0.041	-0.000
	(0.043)	(0.010)
2-5 years after spill	-0.037	-0.002
	(0.045)	(0.020)
Num of obs (Low Tradability)	38898	38898
Num of obs (Upper Half)	38281	38281

Standard errors in parentheses

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

Note: This table reports the difference-in-differences and concise event study estimates of the effects of the severe inland oil spills on county-level annual employment and wages by industry tradability. All regressions include county and state-by-year fixed effects. Standard errors are clustered at the county level.

Source: QCEW.

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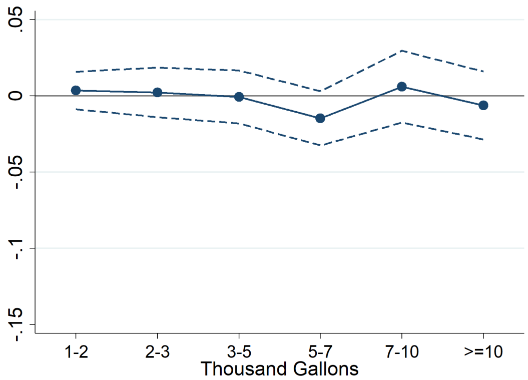
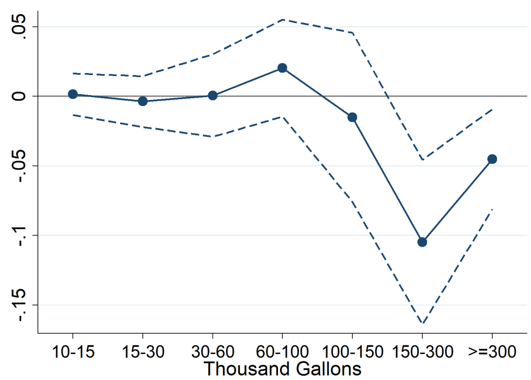
Appendix

A Figures and Tables

Panel A. Employment (log)

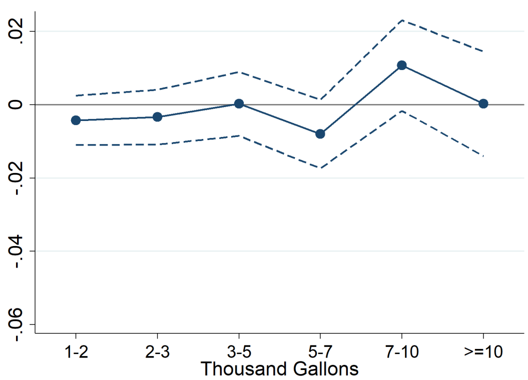


(a) Only 1 spill ≥ 1K gallons

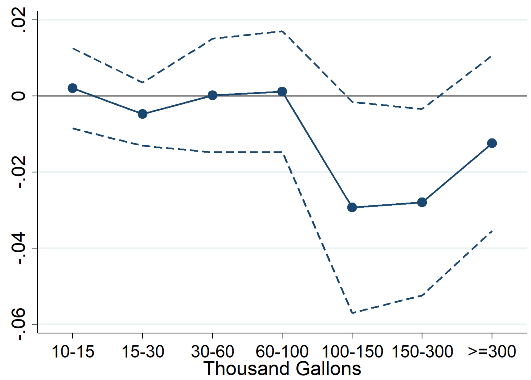


(b) Only 1 spill ≥ 10K gallons

Panel B. Wage (log)

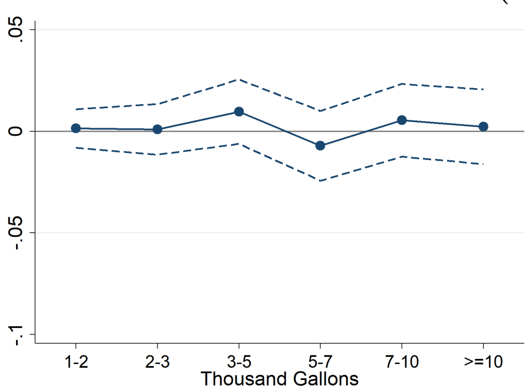


(c) Only 1 spill ≥ 1K gallons

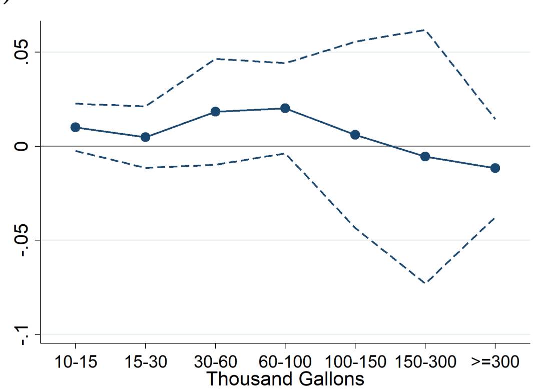


(d) Only 1 spill ≥ 10K gallons

Panel C. Number of Establishments (log)



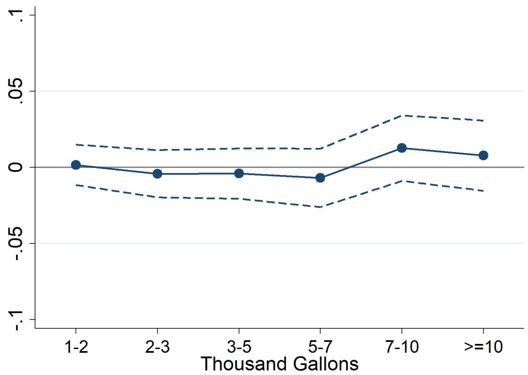
(e) Only 1 spill ≥ 1K gallons



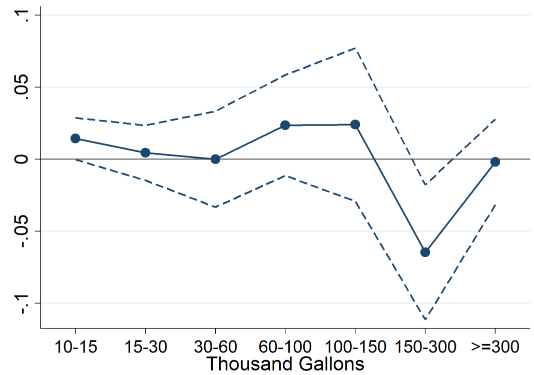
(f) Only 1 spill ≥ 10K gallons

Figure A.1: Semiparametric Estimates of Inland Oil Spills on Labor Market Outcomes

Panel D. Labor Force (log)

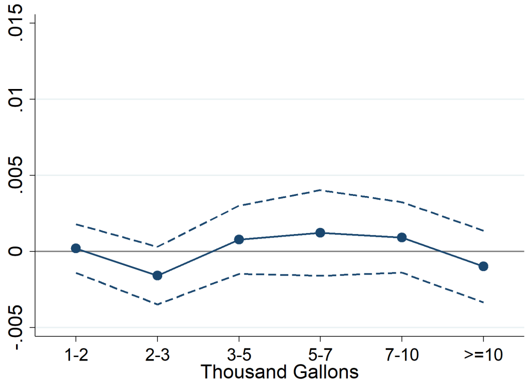


(g) Only 1 spill $\geq$ 1K gallons

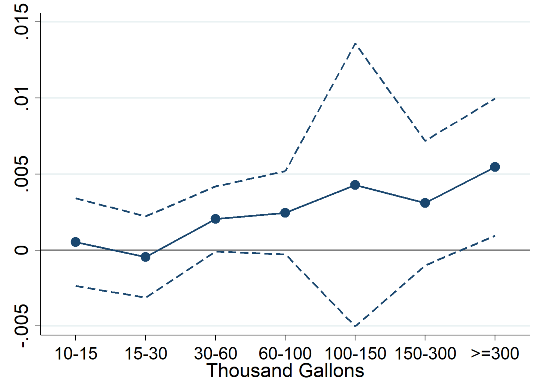


(h) Only 1 spill $\geq$ 10K gallons

Panel E. Unemployment Rate

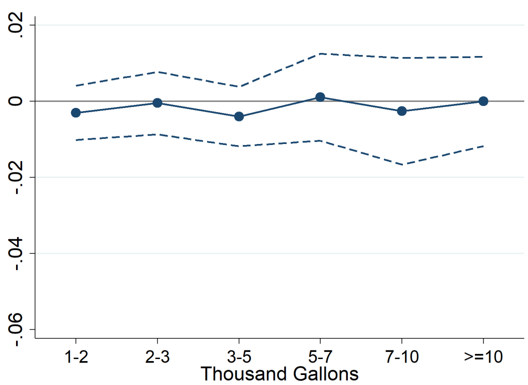


(i) Only 1 spill $\geq$ 1K gallons

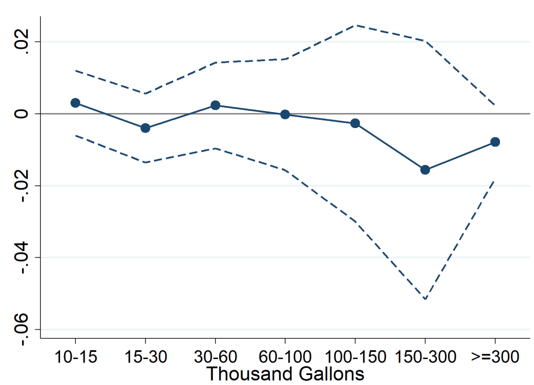


(j) Only 1 spill $\geq$ 10K gallons

Panel F. Labor Force Participation Rate



(k) Only 1 spill $\geq$ 1K gallons



(l) Only 1 spill $\geq$ 10K gallons

Figure A.1: Semiparametric Estimates of Inland Oil Spills on Labor Market Outcomes (cont.)

Note: The points on the connected lines represent the estimated effect of each bin. The dashed lines represent the 95% confidence intervals, where standard errors are clustered at the county level. The control group consists of counties without a spill and counties with spills < 1,000 gallons. The effects of spills < 1,000 gallons compared to no spills are (standard errors in parentheses): 0.002 (0.005) on employment, -0.000 (0.002) on wages, -0.002 (0.004) on the number of establishments, -0.002 (0.004) on the labor force, -0.000 (0.000) on unemployment rate, and 0.001 (0.002) on labor force participation rate.
Source: QCEW and LAUS.

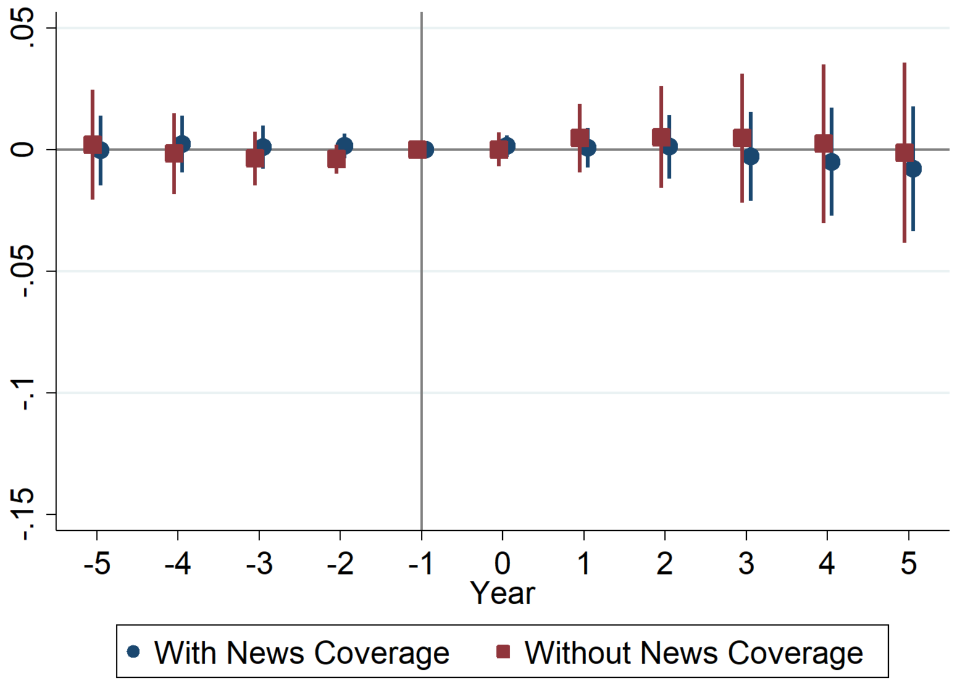
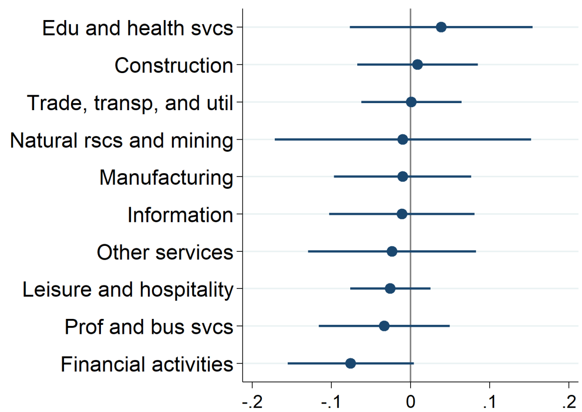


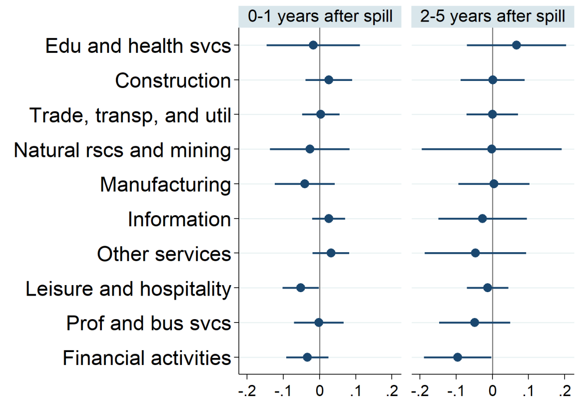
Figure A.2: Effects of Severe Inland Oil Spills on Overall Population (log)

Note: This event study plot is created by regressing logged overall population in the spill counties on a set of event time indicators, county fixed effects, and state-by-year fixed effects as specified in Equation (1) with propensity score weights. The dots represent the estimated effects at the event time. The spikes represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: Census.

Panel A. Employment

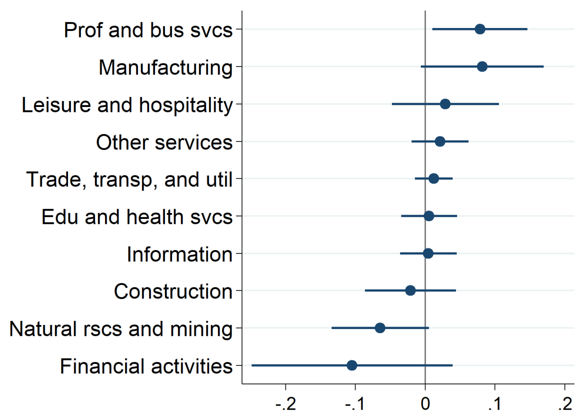


(a) Diff-in-diff estimates on emp (log)

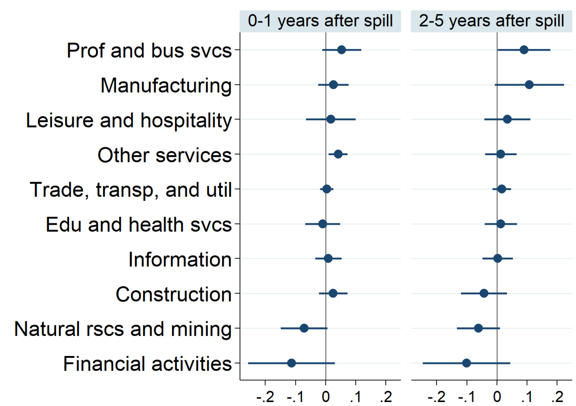


(b) Concise event study estimates on emp (log)

Panel B. Wage



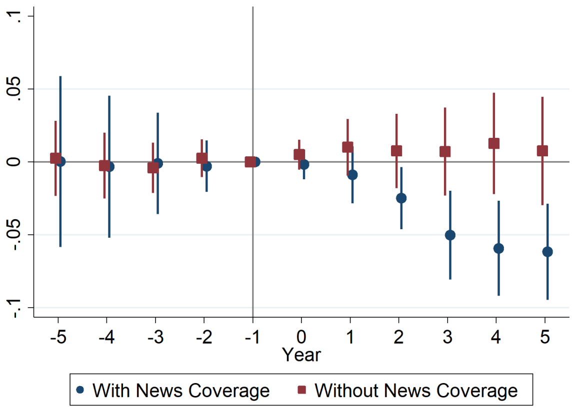
(c) Diff-in-diff estimates on wage (log)



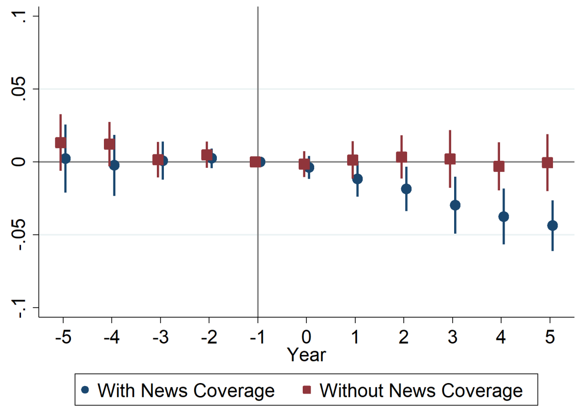
(d) Concise event study estimates on wage (log)

Figure A.3: Heterogeneous Treatment Effects of Severe Spills Without News Coverage by Industry

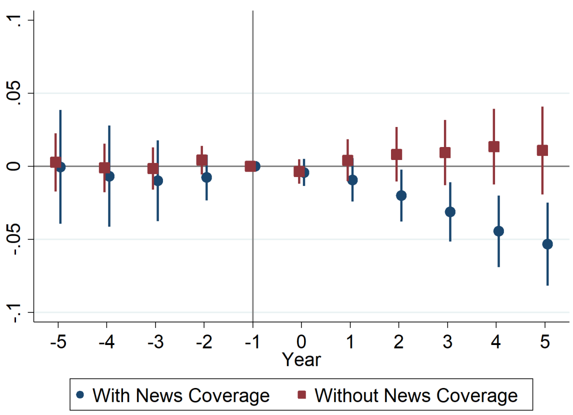
Note: These plots report the difference-in-differences (Equation (2)) and concise event study (Equation (3)) estimates of the effects of the severe inland oil spills on labor market outcomes at the county-by-year level for each industry. All regressions include county and state-by-year fixed effects and are weighted by propensity score weights. Standard errors are clustered at the county level.
Source: QCEW.



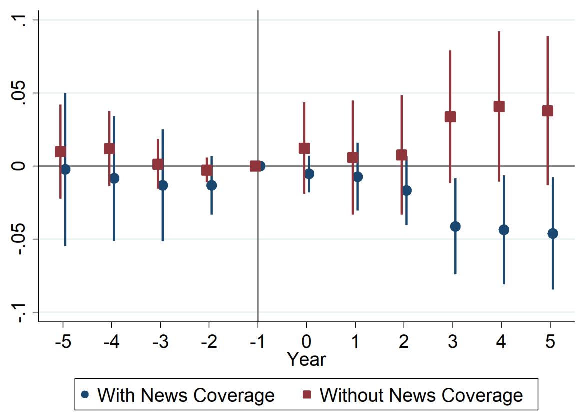
(a) Employment (log)



(b) Average wage per job (log)



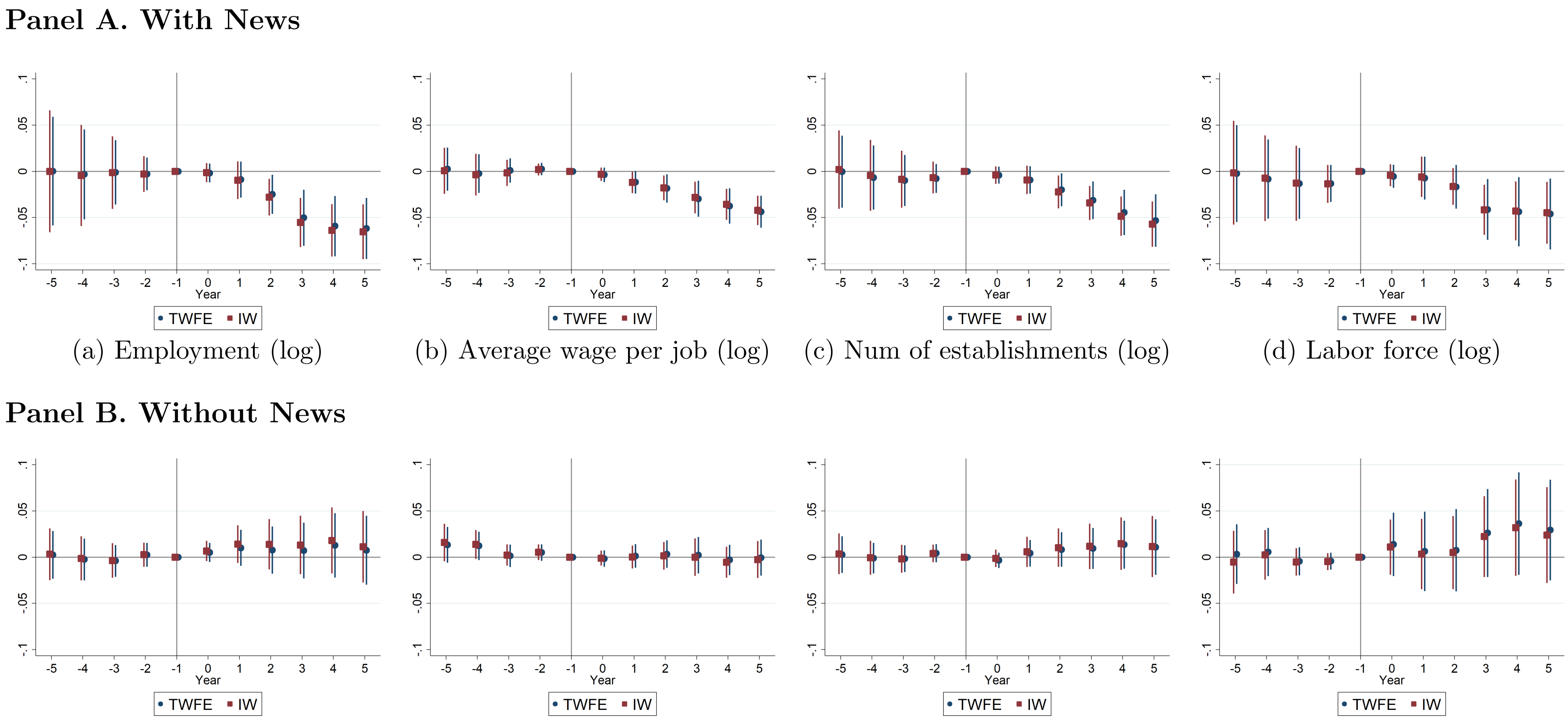
(c) Number of establishments (log)



(d) Labor force (log)

Figure A.4: Effects of Severe Inland Oil Spills on Labor Demand and Supply without Propensity Score Weighting

Note: These are event study plots 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 as specified in Equation (1) without propensity score weights. The outcome variables are displayed below each plot. The dots (squares) represent the estimated effects at the event time. The spikes represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW and LAUS.

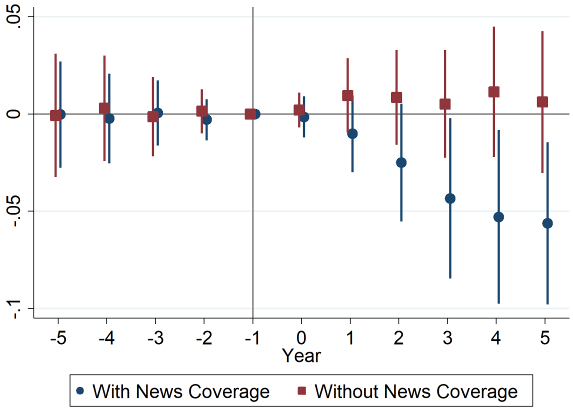


(a) Employment (log) (b) Average wage per job (log) (c) Num of establishments (log) (d) Labor force (log)

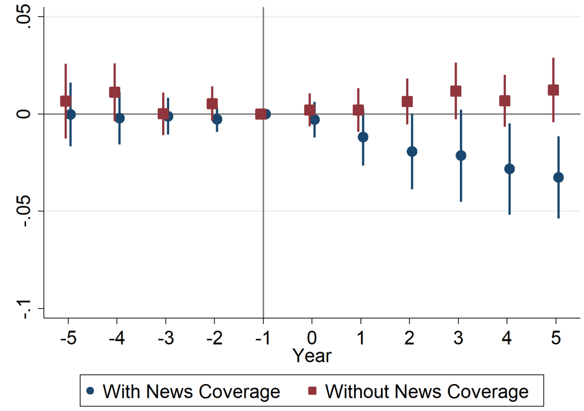
(e) Employment (log) (f) Average wage per job (log) (g) Num of establishments (log) (h) Labor force (log)

Figure A.5: Effects of Severe Inland Oil Spills on Labor Market Outcomes: Interaction Weighted vs. Two-Way Fixed Effect

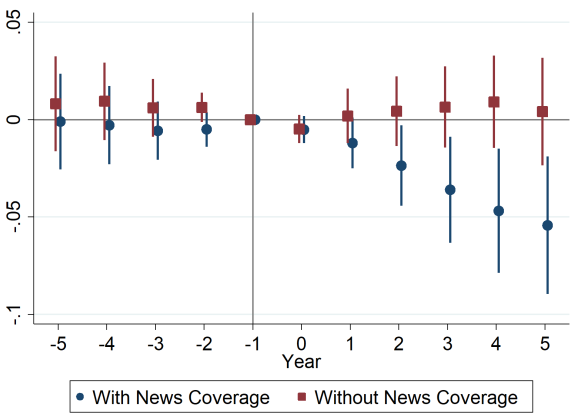
Note: These are event study plots created by estimating Equation (1) with the interaction weighted method and the traditional two-way fixed-effect method without propensity score weights. The outcome variables are displayed below each plot. The dots (squares) represent the estimated effects at the event time. The spikes represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW and LAUS.



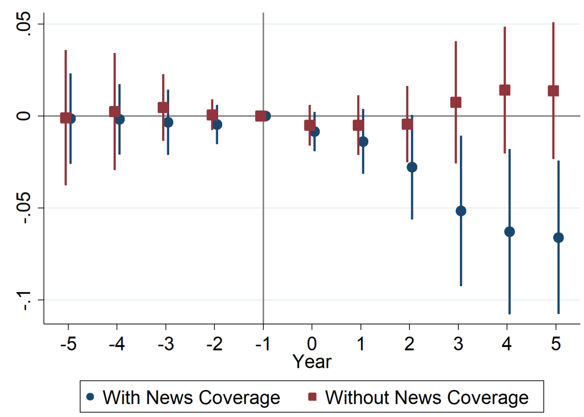
(a) Employment (log)



(b) Average wage per job (log)



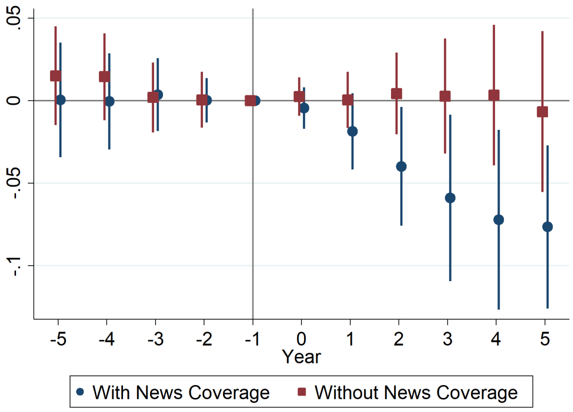
(c) Number of establishments (log)



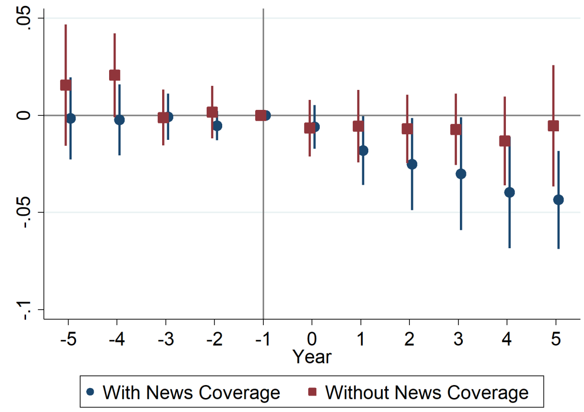
(d) Labor force (log)

Figure A.6: Effects of Severe Inland Oil Spills on Labor Demand and Supply with $\leq$ 100-mile Counties as Control Group

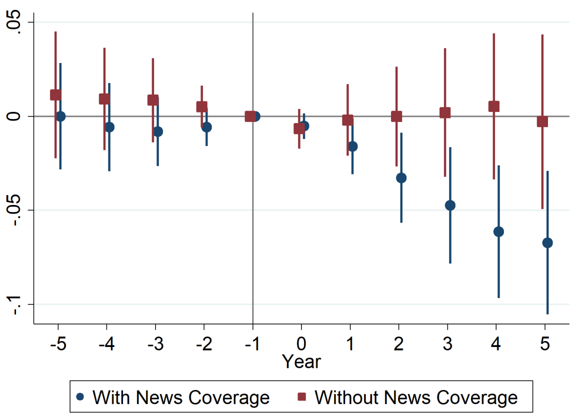
Note: These are event study plots created by regressing outcome variables of the spill counties on a set of event time indicators, county fixed effects, and state-by-year fixed effects as specified in Equation (1) with propensity score weights using counties within 100 miles as the control group. The outcome variables are displayed below each plot. The dots (squares) represent the estimated effects at the event time. The spikes represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW and LAUS.



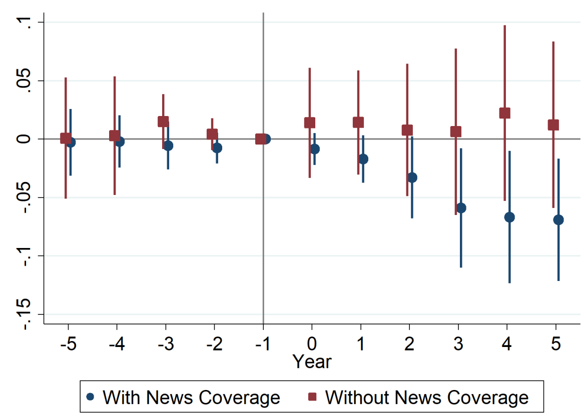
(a) Employment (log)



(b) Average wage per job (log)



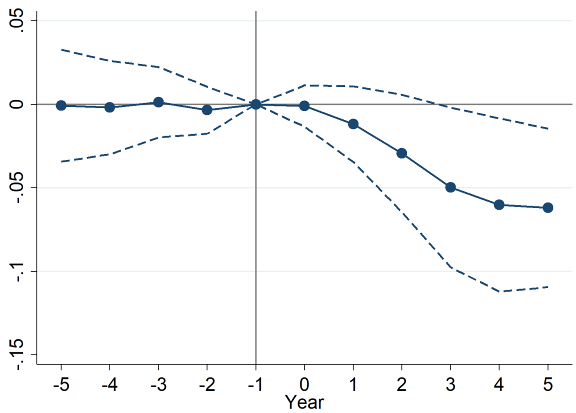
(c) Number of establishments (log)



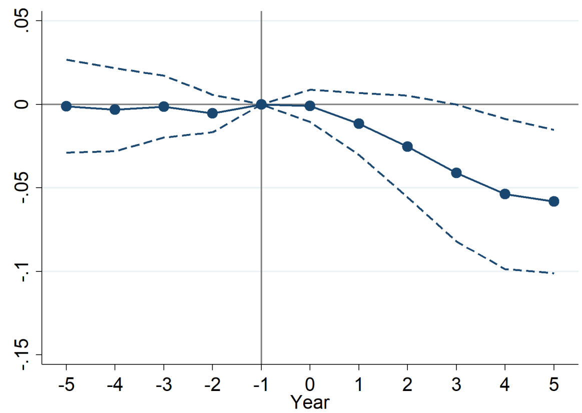
(d) Labor force (log)

Figure A.7: Effects of Severe Inland Oil Spills on Labor Demand and Supply without Fixed Facility Spills

Note: These are event study plots 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 as specified in Equation (1) with propensity score weights. The outcome variables are displayed below each plot. The dots (squares) represent the estimated effects at the event time. The spikes represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW and LAUS.



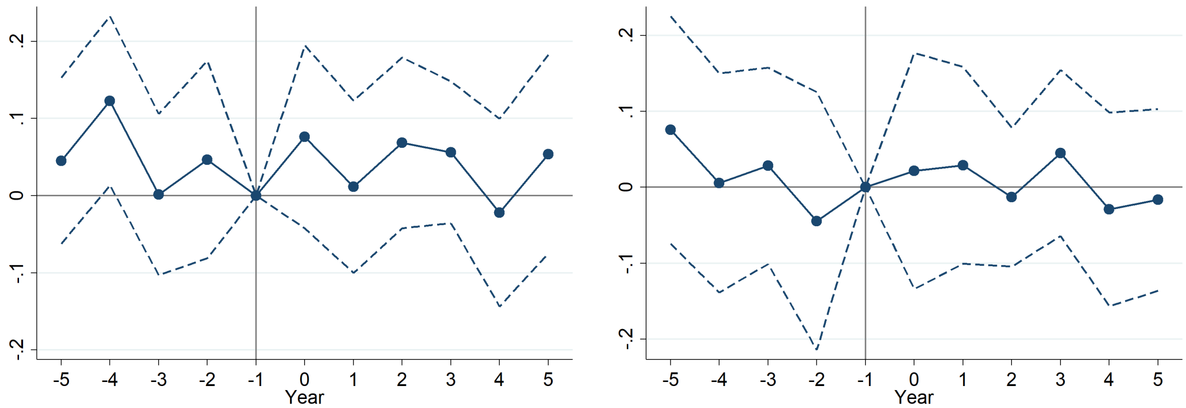
(a) QCEW employment



(b) REA employment

Figure A.8: Effects of Severe Inland Oil Spills on Employment

Note: These are event study plots 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 as specified in Equation (1) with propensity score weights. The points on the connected lines represent the estimated effects at the event time. The dashed lines represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW and REA.



(a) With News (b) Without News

Figure A.9: Effects of Severe Inland Oil Spills on County-Level Amenities

Note: These are event study plots 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 following the estimation equation in Appendix B. β is calibrated to 0.96 and ν is calibrated to 2.02 following Caliendo et al. (2019). The points on the connected lines represent the estimated effects at the event time. The dashed lines represent the 95% confidence intervals, where standard errors are clustered at the 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.
Source: QCEW and IRS.

Table A.1: QCEW Industry-NAICS Industry Crosswalk

QCEW	NAICS
Natural resources and mining	NAICS 11 Agriculture, Forestry, Fishing, and Hunting NAICS 21 Mining
Construction	NAICS 23 Construction
Manufacturing	NAICS 31-33 Manufacturing
Trade, transportation, and utilities	NAICS 42 Wholesale Trade NAICS 44-45 Retail Trade NAICS 48-49 Transportation and Warehousing NAICS 22 Utilities
Information	NAICS 51 Information
Financial activities	NAICS 52 Finance and Insurance NAICS 53 Real Estate and Rental and Leasing
Professional and business services	NAICS 54 Professional, Scientific and Technical Services NAICS 55 Management of Companies and Enterprises NAICS 56 Administrative and Waste Services
Education and health services	NAICS 61 Educational Services NAICS 62 Health Care and Social Assistance
Leisure and hospitality	NAICS 71 Arts, Entertainment, and recreation NAICS 72 Accommodation and Food Services
Other services	NAICS 81 Other Services

Note: This table is recreated based on the crosswalk from QCEW (https://www.bls.gov/cew/classifications/industry/industry-supersectors.htm).

Table A.2: Effects of Severe Inland Oil Spills on Labor Demand and Supply without Propensity Score Weighting

	(1) Employment (log)	(2) Average wage per job (log)	(3) Number of establish- ments (log)	(4) Labor force (log)
Panel A. Difference-in-Differences Estimates (Equation 2)				
With News				
Post-spill indicator	-0.034*	-0.025***	-0.022	-0.019
	(0.019)	(0.007)	(0.017)	(0.019)
Without News				
Post-spill indicator	0.009	-0.006	0.006	0.020
	(0.017)	(0.009)	(0.013)	(0.023)
Panel B. Concise Event Study Estimates (Equation 3)				
With News				
0-1 year after spill	-0.004	-0.008	-0.002	0.001
	(0.021)	(0.007)	(0.016)	(0.021)
2-5 years after spill	-0.048**	-0.033***	-0.032*	-0.030
	(0.019)	(0.008)	(0.017)	(0.020)
Without News				
0-1 year after spill	0.008	-0.006	-0.000	0.010
	(0.012)	(0.007)	(0.009)	(0.020)
2-5 years after spill	0.010	-0.006	0.010	0.025
	(0.019)	(0.010)	(0.016)	(0.026)
Num of obs (With News)	57332	57332	57332	38379
Num of obs (Without News)	57844	57844	57844	38091

Standard errors in parentheses

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

Note: This table reports the difference-in-differences and concise event study estimates of the effects of the severe inland oil spills on labor market outcomes at the county-by-year level without propensity score weighting. All regressions include county and state-by-year fixed effects and are weighted by propensity score weights. Standard errors are clustered at the county level.
Source: QCEW and LAUS.

Table A.3: Effects of Severe Inland Oil Spills on Labor Demand and Supply with ≤ 100-mile Counties as Control Group

	(1) Employment (log)	(2) Average wage per job (log)	(3) Number of establish- ments (log)	(4) Labor force (log)
Panel A. Difference-in-Differences Estimates (Equation 2)				
With News				
Post-spill indicator	-0.030**	-0.018**	-0.026**	-0.036***
	(0.015)	(0.007)	(0.012)	(0.013)
Without News				
Post-spill indicator	0.007	0.002	-0.002	0.002
	(0.017)	(0.007)	(0.014)	(0.016)
Panel B. Concise Event Study Estimates (Equation 3)				
With News				
0-1 year after spill	-0.004	-0.006	-0.005	-0.008
	(0.010)	(0.005)	(0.009)	(0.009)
2-5 years after spill	-0.043**	-0.024***	-0.037**	-0.050***
	(0.018)	(0.009)	(0.015)	(0.017)
Without News				
0-1 year after spill	0.005	-0.002	-0.007	-0.007
	(0.014)	(0.006)	(0.011)	(0.014)
2-5 years after spill	0.007	0.005	0.000	0.006
	(0.020)	(0.008)	(0.017)	(0.019)
Num of obs (With News)	75324	75324	75324	50363
Num of obs (Without News)	75801	75801	75801	50075

Standard errors in parentheses

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

Note: This table reports the difference-in-differences and concise event study estimates of the effects of the severe inland oil spills on labor market outcomes at the county-by-year level by using counties within 100 miles as the control group. All regressions include county and state-by-year fixed effects and are weighted by propensity score weights. Standard errors are clustered at the county level. *Source:* QCEW and LAUS.

Table A.4: Effects of Severe Inland Oil Spills on Labor Demand and Supply without Fixed Facility Spills

	(1) Employment (log)	(2) Average wage per job (log)	(3) Number of establish-ments (log)	(4) Labor force (log)
Panel A. Difference-in-Differences Estimates (Equation 2)				
With News				
Post-spill indicator	-0.045**	-0.025***	-0.034***	-0.038**
	(0.018)	(0.009)	(0.012)	(0.015)
Without News				
Post-spill indicator	-0.005	-0.015	-0.008	0.008
	(0.019)	(0.009)	(0.021)	(0.032)
Panel B. Concise Event Study Estimates (Equation 3)				
With News				
0-1 year after spill	-0.012	-0.010	-0.006	-0.008
	(0.013)	(0.007)	(0.010)	(0.010)
2-5 years after spill	-0.063***	-0.033***	-0.048***	-0.053**
	(0.023)	(0.011)	(0.016)	(0.021)
Without News				
0-1 year after spill	-0.005	-0.013	-0.011	0.009
	(0.012)	(0.009)	(0.014)	(0.021)
2-5 years after spill	-0.005	-0.015	-0.006	0.007
	(0.023)	(0.010)	(0.026)	(0.041)
Num of obs (With News)	56563	56563	56563	38173
Num of obs (Without News)	56195	56195	56195	37653

Standard errors in parentheses

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

Note: This table reports the difference-in-differences and concise event study estimates of the effects of the severe inland oil spills on labor market outcomes at the county-by-year level using counties within 100 miles as the control group. All regressions include county and state-by-year fixed effects and are weighted by propensity score weights. Standard errors are clustered at the county level. *Source:* QCEW and LAUS.

Table A.5: Labor Market Losses in Counties with Spills Covered in the News

	(1)	(2)	(3)	(4)	(5)
				95% Confidence Interval	
	Total Losses	S.E.	p-value	Lower Bound	Upper Bound
Panel A. Labor Market Losses in One County					
Employment	-7406.177	2852.001	0.010	-13001.16	-1811.189
Wage	-4.92e+08	2.14e+08	0.022	-9.13e+08	-7.19e+07
Number of establishments	-359.8746	119.745	0.003	-594.7875	-124.9617
Labor force	-7316.451	2622.572	0.005	-12461.33	-2171.577
Panel B. Labor Market Losses in All Counties					
Employment	-407339.7	156860	0.010	-715064.1	-99615.37
Wage	-2.71e+10	1.18e+10	0.022	-5.02e+10	-3.95e+09
Number of establishments	-19793.1	6585.974	0.003	-32713.31	-6872.894
Labor force	-402404.8	144241.5	0.005	-685372.9	-119436.7

Standard errors in parentheses

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

Note: This table reports the back-of-the-envelope calculations on losses in employment, wages, the number of establishments, and the labor force in all counties with spills that receive news coverage in the year in which the spill occurs and the 5 years after. The total wage loss only represents total changes in wages for all workers still employed after a spill, but not foregone wages from people who became unemployed because of the spill. The total wage loss for workers who became unemployed due to spills in the entire post period in one county with a spill that receives news coverage is $753.04 million and in all counties with spills that receive news coverage sum to $41.42 billion.
Source: QCEW and LAUS.

Table A.6: Effects of Severe Inland Oil Spills on County-Level Local Amenities

	(1) $\nu = 1$	(2) $\nu = 1.5$	(3) $\nu = 2.02$	(4) $\nu = 2.5$	(5) $\nu = 3$
Panel A. With News					
$\beta = 0.96$	-0.008	-0.005	-0.002	0.000	0.003
	(0.007)	(0.010)	(0.013)	(0.015)	(0.018)
$\beta = 0.9$	-0.008	-0.006	-0.003	-0.001	0.002
	(0.007)	(0.010)	(0.013)	(0.016)	(0.019)
Panel B. Without News					
$\beta = 0.96$	-0.009	-0.007	-0.005	-0.003	-0.002
	(0.006)	(0.010)	(0.013)	(0.017)	(0.021)
$\beta = 0.9$	-0.009	-0.007	-0.005	-0.003	-0.002
	(0.007)	(0.010)	(0.014)	(0.018)	(0.022)
Num of obs (With News)	34736				
Num of obs (Without News)	34601				

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 on local amenities at the county-by-year level following the estimation equation in Appendix B. Caliendo et al. (2019) calibrates β to 0.96 and ν to 2.02. To check the sensitivity of the estimates to different parameter values, I set β to 0.9 and ν to 1, 1.5, 2.02, 2.5, and 3 as well. The effects are measured in percent changes in wages. All regressions include county and state-by-year fixed effects. Standard errors are clustered at the county level.
Source: QCEW and IRS.

B A Dynamic Spatial Model of Spills and Local Amenities

The theoretical framework for the welfare analysis is built upon the dynamic forward-looking setting of Artuç et al. (2010) and Caliendo et al. (2019), and the effects of spills on local amenities are added to the model following Rudik et al. (2021). To begin with, I define the consumption decisions of the individuals. Suppose that individuals value consumption and local amenity of the county, and their preferences are captured by a Cobb-Douglas utility function:

$$U(C_{i,t}, A_{i,t}) = \log\big(C_{i,t}A_{i,t}\big),$$

where $C_{i,t}$ is consumption and $A_{i,t}$ is local amenities. In each time period t, which is discrete and represents one year, residents in each county i either supply their one unit of labor inelastically, or stay fully unemployed. If an individual is employed, she earns a competitive wage $w_{i,t}$ and consumes $C_{i,t} = w_{i,t}/P_{i,t}$ units of goods, where $P_{i,t}$ is the price index. If an individual is unemployed, she receives a level of consumption $C_{i,t} = c_i^0 > 0$ that is county-specific and time-invariant. In other words,

$$C_{i,t} = \begin{cases} w_{i,t}/P_{i,t} & \text{if employed,} \\ c_i^0 & \text{if unemployed.} \end{cases}$$

Local amenities $A_{i,t}$ is assumed to be multiplicatively separable in spill indicator $Spill_{id}$, which indicates whether county i experienced a spill d years ago (in d years):

$$A_{i,t} = \bar{A}_{i,t}\exp\big(f(Spill_{id}; \xi_d)\big),$$

where $\bar{A}_{i,t}$ represents the average amenity level exogenous of a spill, $\exp\big(f(Spill_{id}; \xi_d)\big)$ captures the effects of a spill on amenities, f is an arbitrary function of $Spill_{id}$, and ξ_d is the parameter that governs how a spill affects local amenities.

I now consider the migration decisions of the individuals over time. Individuals are forward-looking with a common discount rate of $\beta \in (0,1)$ on the future periods. In each period, individuals observe the conditions of the economy, whether a county experienced an severe inland oil spill, and the realization of their own idiosyncratic shock $\mu_{i,t}$. At the end of each period, individuals decide whether to stay in the current county, or migrate out. In Artuç et al. (2010), Caliendo et al. (2019), and Rudik et al. (2021), migration is origion-destination specific. In this paper, the migration data come from IRS. Due to the disclosure restriction, many cells of the county-to-county migration data are suppressed, which generates a considerable number of missing observations. Because of this, the panel for most counties are discontinuous and there are many counties with no observations at all. Due to this data limitation, I simplify the model and assume that migration is a binary decision: an individual either remains in the current county i or migrate out, which I denote by $-i$. In other words, I do not distinguish the destination of the migration. With this modification, I can focus on the total gross out-migration of each county in the empirical estimation. Migration decisions are subject to the economic conditions, local amenities, the realization of the idiosyncratic shock, and migration costs m_{-i}, which are county-specific, time-invariant, measured in terms of utility, and additive. The migration cost is zero if the individual does not migrate, i.e. $m_i = 0$. Individuals will choose to live in the county with the highest expected present value of the utility stream net of moving costs. Formally, the dynamic optimization problem for a household in county i at time t is:

$$v_{i,t} = U(C_{i,t}, A_{i,t}) + \max_{l \in \{i,-i\}} \Big\{ \beta \mathbb{E}_t \big[\mathbb{E}_\mu [v_{l,t+1}] \big] - m_l + \mu_{l,t} \Big\}, \tag{1}$$

where $\mathbb{E}_t[\cdot]$ is the expectation taken over future state variables which capture the effects of policies, technology shocks, environmental shocks, and the like conditional on all the information available at time t. $\mathbb{E}_\mu[\cdot]$ is the expectation over future realizations of the idiosyncratic shocks for the individual.

As is common in dynamic discrete choice models, I assume that the idiosyncratic shock $\mu_{l,t}$ is independently and identically distributed and follows a Type-I Extreme Value distribution with parameters $(-\gamma\nu, \nu)$. With this parameter specification, the mean of $\mu_{l,t}$ is zero. This assumption allows for simple aggregation of idiosyncratic decisions made by individuals in a closed-form. Denoting $V_{i,t} \equiv \mathbb{E}_\mu[v_{i,t}]$ and taking an expectation of the above equation with respect to μ yields:

$$V_{i,t} = U(C_{i,t}, A_{i,t}) + \nu \log\left(\sum_{l\in\{i,-i\}} \exp\left\{\left[\beta\mathbb{E}_t[V_{l,t+1}] - m_l\right]/\nu\right\}\right).$$

Under the assumption that $\mu_{l,t} \overset{iid}{\sim} \text{EV1}(-\gamma\nu, \nu)$, the migration share also has a closed-form analytical expression:

$$s_{i,t} = \frac{\exp\left\{\left[\beta\mathbb{E}_t[V_{-i,t+1}] - m_{-i}\right]/\nu\right\}}{\sum_{l\in\{i,-i\}} \exp\left\{\left[\beta\mathbb{E}_t[V_{l,t+1}] - m_l\right]/\nu\right\}},$$

where $s_{i,t}$ represents the share of people who move out of county i in time t. This expression has an intuitive interpretation: all else being equal, the higher the net lifetime utility of migration, the more individuals will move out.

Following Artuç et al. (2010) and Rudik et al. (2021), I estimate the effects of a severe inland oil spill on local amenities by exploiting variation in migration, wages, and spill status. To estimate the effects, I first take expectation of equation (1) with respect to μ and rearranging terms:

$$V_{i,t} = U(C_{i,t}, A_{i,t}) + \beta\mathbb{E}_t[V_{i,t+1}] + \mathbb{E}_\mu\left[\max_{l\in\{i,-i\}}\{\mu_{l,t} + \bar{\mu}_{li,t}\}\right], \tag{2}$$

where $V_{i,t} \equiv \mathbb{E}_\mu[v_{i,t}]$ and $\bar{\mu}_{li,t} \equiv \beta\mathbb{E}_t[V_{l,t+1} - V_{i,t+1}] - m_l$. Equation (2) indicates that the average value of being in county i can be decomposed into three terms: 1) the current period utility that an individual receives, i.e. $U(C_{i,t}, A_{i,t})$; 2) the base value of staying in county i in next period, i.e. $\beta\mathbb{E}_t[V_{i,t+1}]$; and 3) the value of having the option to move out of county i should prospects look better elsewhere, i.e. $\mathbb{E}_\mu\left[\max_{l\in\{i,-i\}}\{\mu_{l,t} + \bar{\mu}_{li,t}\}\right]$. Denote $\mathbb{E}_\mu\left[\max_{l\in\{i,-i\}}\{\mu_{l,t} + \bar{\mu}_{li,t}\}\right]$ by $\Omega_{i,t}$. Using equation (2), $\bar{\mu}_{li,t}$ can be rewritten as

$$
\begin{aligned}
\bar{\mu}_{li,t} + m_l &= \beta \mathbb{E}_t[V_{l,t+1} - V_{i,t+1}] \\
&= \beta \mathbb{E}_t[U(C_{l,t}, A_{l,t}) - U(C_{i,t}, A_{i,t}) + \beta \mathbb{E}_{t+1}[V_{l,t+2} - V_{i,t+2}] + \Omega_{l,t} - \Omega_{i,t}]
\end{aligned}
$$

or

$$\bar{\mu}_{li,t} + m_l = \beta \mathbb{E}_t[U(C_{l,t}, A_{l,t}) - U(C_{i,t}, A_{i,t}) + \bar{\mu}_{li,t+1} + m_l + \Omega_{l,t} - \Omega_{i,t}] \tag{3}$$

Artuç et al. (2010) show that, under the assumption that $\mu_{l,t}$ follows a Type-I Extreme Value distribution,

$$\bar{\mu}_{li,t} \equiv \beta \mathbb{E}_t[V_{l,t+1} - V_{i,t+1}] - m_l = \nu[\ln s_{l,t} - \ln s_{i,t}]$$

and

$$\Omega_{i,t} = -\nu \ln s_{i,t}.$$

Plugging in the Cobb-Douglas utility function and the two expressions above into equation (3), we arrive at

$$\mathbb{E}_t \left[\frac{\beta}{\nu} \ln \left(\frac{C_{l,t} A_{l,t}}{C_{i,t} A_{i,t}} \right) + \beta \ln \left(\frac{s_{i,t}}{1 - s_{l,t}} \right) - \ln \left(\frac{s_{i,t+1}}{1 - s_{i,t+1}} \right) + \frac{\beta - 1}{\nu} m_l \right] = 0$$

This moment condition can be interpreted as a linear regression. Because migration decision is binary in my setting, l becomes $-i$, which indicates out-migration in general without specifying a destination. Substituting in the expressions for consumption C and amenities A delivers:

$$
\begin{aligned}
\ln\left(\frac{s_{i,t}}{1-s_{i,t}}\right) =& \frac{\beta}{\nu}\ln\left(\frac{w_{-i,t+1}}{w_{i,t+1}}\right) + \frac{\beta}{\nu}\ln\left(\frac{P_{-i,t+1}}{P_{i,t+1}}\right) \\
&+ \frac{\beta}{\nu}\ln\left(\frac{\bar{A}_{-i,t+1}}{\bar{A}_{i,t+1}}\right) + \frac{\beta}{\nu}\Big[f(Spill_{-i,d+1};\xi_{d+1}) - f(Spill_{i,d+1};\xi_{d+1})\Big] \\
&+ \beta\ln\left(\frac{s_{i,t+1}}{1-s_{-i,t+1}}\right) + \frac{\beta-1}{\nu}m_l + \tau_{t+1}.
\end{aligned}
\tag{4}
$$

where τ_{t+1} is news revealed in period $t+1$.

Equation (4) suggests that the current ratio of the share of people that migrate out of to the share of people that remain in county i can be explained by four components. The first component is the difference in one period ahead consumption between staying and moving, which is captured by the first line of the equation. The second component is the difference in local amenity levels between staying and moving in the next period, which is represented by the terms in the second line. The third component is the first term in the third line, which is the future migration-to-staying ratio that captures the difference in option value in county i to all destination counties for an individual migrated out of county i. The last component is the unobserved moving cost, the second term in the third line.

The goal of the current exercise is to estimate the effects of severe inland oil spills on local amenities, ξ_{d+1}. Since the values of β and ν are not parameters of interest, I calibrate $\beta = 0.96$ and $\nu = 2.02$ annually following Caliendo et al. (2019). The purpose of the spill response function $f(Spill_{i,d};\xi_d)$ is to allow for non-linear impacts of spills happened d years ago (in d years) on local amenities. To make it consistent with the event-study framework in the main analysis, I construct the response function as $f(Spill_{i,d};\xi_d) = \xi_d Spill_{i,d}$. Because there are only 113 spill counties (out of a total of 3,143 counties) in the almost thirty year time span, the probability of moving to a spill county within a ten year window around the occurrence of a severe spill is very small. Hence, I assume that $Spill_{-i,d} = 0$ and $f(Spill_{-i,d};\xi_d) = \xi_d Spill_{-i,d} = 0$ all the time. Under this assumption, $f(Spill_{-i,d+1};\xi_{d+1}) - f(Spill_{i,d+1};\xi_{d+1}) = -\xi_{d+1}Spill_{i,d+1}$. Now, with the calibration and the construction of

$f(Spill_{i,d};\xi_d)$, I rewrite equation (4) by shifting the subscript from t to $t-1$ and deliver the following event-study specification for estimating the effect of a severe inland oil spill on county-level local amenities:

$$\ln\left(\frac{s_{i,t-1}}{1-s_{i,t-1}}\right) - \beta\ln\left(\frac{s_{i,t}}{1-s_{-i,t}}\right) - \frac{\beta}{\nu}\ln\left(\frac{w_{-i,t}}{w_{i,t}}\right)$$
$$= -\left(\sum_{d=-5,\, d\neq -1}^{5} \xi_d Spill_{i,d} + \xi_{-6}Spill_{c,-6} + \xi_6 Spill_{c,6}\right) + \alpha_i + \omega_{st} + \tau_t,$$

where α_i is a county fixed effect and ω_{st} is a state-by-year fixed effect. I include the fixed effects to fully capture the difference in price indices $\ln(P_{-i,t+1}/P_{i,t+1})$, the difference in local amenities exogenous to spills $\ln(\bar{A}_{-i,t+1}/\bar{A}_{i,t+1})$, and the migration costs m_{-i}. I cluster the standard errors at the county level to account for serial correlation in shocks within a county over time. The treatment and control groups are defined the same as in the main analysis: spill counties comprise the treatment group and counties that are more than 100 miles away comprise the control group.

The outcome variable on the left-hand side of the equation is directly available from data. The annual out-migration rates of a county are available in the IRS data. To obtain the out-migration rate for counties that individuals from county i migrated to is more complicated. The IRS data reports the number of migration to the destination counties if the total number of migrants are larger than ten. If the number is below the threshold, it does not meet the disclosure requirement and neither the destination county nor the number of migrants is reported. Instead, the IRS aggregates these county-to-county migration to five regions, within state, northeast, midwest, south, and west, and report the total out-migration number for each region. To compute the out-migration rate for the destination counties, I take a weighted average of the out-migration shares of all the destination counties with the number of migrants being the weight. For the five regions, I first calculate the out-migration rate for each region, and then apply the the weighted average. In this way, the average out-migration rate for the destination regions is specific to each origin county. Data on average county-by-year wage come from QCEW. The average wage for the destination counties of out-migration is constructed in a similar fashion as the out-migration rate for the destination counties.

To concisely estimate the effect of spills on local amenities, I create a single dummy variable $Spill_{i,post}$ to indicate that the current period is the period that a spill happened or within 5 years after a spill, i.e. $Spill_{i,post} = 1$ if $0 \leq d \leq 5$. The specification now becomes

$$\begin{aligned}
&\ln\left(\frac{s_{i,t-1}}{1-s_{i,t-1}}\right) - \beta \ln\left(\frac{s_{i,t}}{1-s_{-i,t}}\right) - \frac{\beta}{\nu}\ln\left(\frac{w_{-i,t}}{w_{i,t}}\right) \\
&= -\big(\xi_{post} Spill_{i,post} + \xi_{-6} Spill_{c,-6} + \xi_{6} Spill_{c,6}\big) + \alpha_i + \omega_{st} + \tau_t.
\end{aligned}$$

Everything else is defined the same as in the event study specification above.

C Background on Pipeline Inspection and Maintenance Frequency

The Pipeline and Hazardous Materials Safety Administration (PHMSA) is the agency within the Department of Transportation that responsible for enforcing regulations and conducting inspections of pipeline transportation. The PHMSA is not required by law to examine all the pipelines at regular intervals, but rather schedules federal inspections on a case by case basis. The frequency of the inspections is determined by various factors, such as the conditions of the pipelines, the features of the surrounding area, and the infraction history of the operator. In general, PHMSA prioritizes inspections on pipelines that have leakage history, present excessive risk to the environment, and near densely populated areas. Besides the PHMSA inspections, pipeline-operating companies are also required by law to perform inspection and maintenance at intervals not exceeding five years for pipelines that could affect a high-consequence area (HCA), which is an area of large population, or has commercially navigable waterways, or contain sensitive habitats. For pipelines that will not affect an HCA, they are inspected at a frequency specified by their written inspection plan approved by the PHMSA.