Pollution Risk and Business Activity*

George Zhe Tian† Buvaneshwaran Venugopal‡ Vijay Yerramilli§

June 2023

Abstract

We use major toxic chemical spills as shocks to the pollution risk of their local neighborhoods and examine the consequent effects on local small businesses. A key finding is that pollution shocks contribute to increases in business concentration in their local economy because of their disproportionate adverse effects on smaller establishments compared to larger establishments. Specifically, in every sector, establishments in the smallest size quartile experience large reduction in sales, modest reduction in employment, and significant increase in likelihood of exit following exposure to major spills, whereas those in the largest size quartile experience increase in sales and employment. Business exposed to major spills obtain lower amounts through Small Business Administration (SBA) loans, and consistent with tightening of supply of credit, these loans have lower SBA guarantees and feature higher interest rates. Counties exposed to major spills experience decline in aggregate sales, increase in establishment exits, and increase in the number of bankruptcies among small businesses. There is a significant and persistent migration of population and income away from counties that experience major toxic spills, which may explain the persistent adverse effects on local small businesses.

Keywords: Pollution Risk, Toxic Chemical Spills, Small Business

*We thank David De Angelis, Antonio Gargano, Tom George, Stuart Gillan, Kevin Roshak, Dimuthu Ratnadiwakara, and seminar participants at the University of Houston and the University of North Texas for their helpful comments and discussions on issues examined in this paper.

†C. T. Bauer College of Business, University of Houston, Houston, TX. Email: george.zhe.tian@gmail.com

‡College of Business, University of Central Florida, Orlando, FL. Email: eshwar@ucf.edu

§C. T. Bauer College of Business, University of Houston, Houston, TX. Email: vyerramilli@bauer.uh.edu

Introduction

The recent toxic chemical spill following a train derailment in East Palestine, Ohio has once again highlighted the adverse effects of spikes in environmental pollution on nearby populations and businesses. The accident caused the leakage of many chemicals– including a known carcinogen, vinyl chloride– into the air, ground and creeks leading to the Ohio River, and resulted in property damage and business disruptions. News reports indicate that residents continue to face significant concerns regarding their health and safety several weeks after the incident, and local business establishments face substantial uncertainty regarding their future prospects.[1] An interesting anecdote that highlights the uncertainty faced by local businesses features a major grocery chain which had to pull water that was bottled 25 miles from the crash site off of store shelves out of an "abundance of caution" three weeks after the spill.[2] Despite this anecdotal evidence about the immediate aftermath of toxic chemical spills, we know little about their long-term effects on small business activity. This is the question we examine in this paper. We focus on small businesses because they are the life blood of the US economy and account for a sizeable share of employment (e.g., see Neumark et al. 2011; Haltiwanger et al. 2013; Decker et al. 2014). We show that major toxic chemical spills have persistent adverse effects on local small businesses in all but a few sectors of the economy, and may contribute to increases in business concentration in their local economy because of their disproportionate adverse effects on smaller establishments compared to larger establishments.

There are two broad reasons why we expect accidental toxic chemical spills to have long-term effects on business activity. First, the dramatic nature of these accidents and the ensuing media coverage have an adverse effect on the health risk perceptions of the local population. The clean-up effort from major spills can last several years as chemicals seep

[1] For example, see coverage of the aftermath of this accident in the Wall Street Journal (https://www.wsj.com/articles/after-ohio-train-derailment-toxic-chemicals-and-distrust-remain-ebd9c846) and the New York Times (https://www.nytimes.com/2023/02/14/climate/ohio-train-derailment-chemical-spill-health.html).

[2] See https://time.com/6258825/giant-eagle-water-east-palestine-ohio/ in the Time magazine.

into the ground and water supplies, and the threat to human health and uncertainty can linger long after the emergency has been dealt with.[3] The stigma of the spill can also last a long time because, as per the availability heuristic (Tversky and Kahneman 1973), people who remember the media coverage of the spill will tend to overestimate the health risks. Hence, the local area may become less attractive for residential and commercial activity following a toxic chemical spill, making it harder for businesses to attract customers and retain employees. Second, these accidents are also likely to lead to new environmental/safety regulations and tougher enforcement of existing regulations, which increases the regulatory risk of businesses in the local area (including those that did not cause the accident), especially those in polluting industries. We refer to these risk factors collectively as "pollution risk." Our empirical strategy is to use major toxic chemical spills as *shocks* to the pollution risk of businesses in the vicinity of the spill, and examine the consequent effect of these shocks on local small business activity. The spills we examine are the result of unexpected accidents that cause the leakage of pollutants (e.g., crude oil and chemicals) and lead to large-scale evacuations in the affected area. Although accidental spills are more likely to occur near chemical factories, pipelines or railway tracks, we focus on large-scale accidents that are relatively uncommon and whose precise locations, and the set of business establishments exposed to these accidents, are hard to predict. Therefore, large toxic chemical spills provide a quasi-natural experiment framework to identify the effect of pollution risk on small business activity.

We collect data on small businesses – defined as those with 500 or fewer employees across all their establishments – across the U.S. from Mergent Intellect, a business intelligence aggregator of company profiles. Our sample includes 4.18 million small business establishments over the 2010-2018 period for which we have information on sales, employment and industry classification.[4] We retrieve data on toxic chemical spills from the U.S. Coast Guard's Na-

[3] See https://www.vox.com/science/23612128/ohio-train-derailment-east-palestine-chemical-spill-cleanup-norfolk-southern.

[4] We exclude businesses with fewer than 5 employees because these are likely to be sole proprietor-employee type businesses for which data vendors impute sales and employee numbers.

tional Response Center (NRC). Among other details, the database contains each incident's date of occurrence, location, responsible party, pollution medium, and the number of evacuations, injuries and fatalities. For our main analysis, we define major toxic chemical spills as those that cause evacuations of at least 900 people, which is close to the 99^{th} percentile value of number of evacuations among spills that lead to evacuations. As per our definition, there are 24 major toxic spills across 15 states that occurred over the 2010-2018 period. We define a small business as treated (i.e., exposed to a major toxic spill) in year t if it is located within a 25-mile radius of a major toxic spill that occurred before or during year 't'; otherwise, the business is classified as untreated. Our qualitative results are robust to alternative evacuation thresholds for defining major toxic spills, and alternative choices of treatment radius.

We estimate a difference-in-differences (DiD) model using the "stacked regression" approach (e.g., see Gormley and Matsa 2011; Cengiz et al. 2019) to identify the effect of these pollution shocks on the sales, employment and likelihood of exit of local small businesses. In contrast to the standard two-way fixed effects (TWFE) DiD regression, the stacked regression approach allows for comparison of treated firms with better comparable control firms, and provides valid estimates of the average treatment effect on the treated in settings with staggered treatment timing and treatment effect heterogeneity where the TWFE DiD model may encounter problems (Callaway and Sant'Anna 2021; Goodman-Bacon 2021; Sun and Abraham 2021). We estimate the DiD regressions separately for each sector so that we are able to account for the heterogeneous effects of major toxic spills on businesses in different industry groups.

The average treatment effect of pollution shocks on small business sales varies significantly across sectors: the effect is negative in manufacturing & mining, retail and services sectors, but is small and positive in the construction and wholesale sectors. When we sort small business establishments into four quartiles based on size, we uncover a striking contrast in how the effect of pollution shocks on small business establishments vary across the size categories. The effect on sales is negative and significant for establishments in the two smallest size quartiles across all sectors, whereas the effect is positive and significant for establishments in the largest size quartile across all sectors. These contrasting results highlight the redistributive effects of pollution shocks on small business activity: the smallest establishments experience large, and often persistent, declines in sales possibly because they are not well-equipped to deal with the disruptions brought about by the spills, and this works to the advantage of larger establishments which actually experience an increase in sales. The redistributive effect is economically significant across all industries: for instance, in the services sector, businesses in the smallest size quartile experience a 17.1% reduction in sales whereas those in the largest size quartile experience a 8.8% increase in sales after being exposed to major toxic chemical spills.

Pollution shocks have a positive, but economically modest, effect on small business employment across all sectors. However, when we further sort small business establishments into four quartiles by size, we find that establishments in the smallest size quartile in all sectors reduce their employment after being exposed to major toxic chemical spills, whereas those in the two largest size quartiles in all sectors experience increase their employment. An important caveat is that we only have information on the number of employees at each establishment, but do not have information on hours of employment or wages. Hence, we are unable to rule out the possibility that small business establishments decrease their hours of employment without lowering the employee count following exposure to major toxic chemical spills.

Pollution shocks have a significant positive effect on the likelihood of exit of small business establishments across all sectors, where the exit may occur due to multiple reasons that we cannot distinguish: bankruptcy, business closure, or acquisition by another business. This effect is economically significant and persistent, and highlights the vulnerability of small businesses to transitory shocks. Moreover, across all sectors, the positive effect of pollution shocks on the likelihood of small business exit is strongest for establishments in the smallest size quartile and is small or statistically insignificant for establishments in the largest size quartile. Thus, pollution shocks have a disproportionately adverse effect on the smallest business establishments, and are likely to contribute to increase in business concentration in their local economies.

We use a loan-level database of Small Business Administration (SBA) 7(a) loans to examine the effect of major toxic chemical spills on the availability and price of SBA loans to small businesses located in the vicinity of these spills. We find that SBA loans made to treated small businesses have significantly lower amounts, which may reflect either lower demand for credit by treated small businesses or lower supply of credit to treated small businesses, or both. However, we also find that loans made to treated borrowers have smaller fractions guaranteed by the SBA and feature modestly higher interest rates, which are consistent with tightening of supply of credit to treated small businesses. In terms of loan performance, we find that SBA loans made to treated borrowers are more likely to be charged off ex post, but we do not find any significant effects on the charge-off amounts.

In light of the contrasting effects of major toxic chemical spills on small business establishments across the size categories, a natural question that arises is: what happens to the *aggregate* small business activity in the vicinity of these spills? If the only effect of major toxic chemical spills is to redistribute sales and employment from the smallest to larger small businesses, then there should not be any affect of these spills on aggregate small business activity. On the other hand, if the reductions at the smallest businesses are not offset by the gains at larger small businesses, then there may be a negative effect on aggregate small business activity. To address this question, we examine the effect of major toxic chemical spills on countywide measures of aggregate small business activity. Formally, we create a county-year panel dataset of small business activity by aggregating establishment-level data at the county level. We label a county as treated if it contains any business establishment that is located within a 5-mile radius of a major toxic chemical spill. Apart from the county in which the spill occurred, this definition also picks up neighboring counties if a portion of these counties is close to the location of the spill.

We find that counties exposed to major toxic chemical spills experience a 10.8% decline in aggregate small business sales in the years following the spill, and most of the decline occurs in 3-year period following the spill. In other words, the reduction in sales at the smallest businesses exposed to major spills (which we documented above) are not offset by the gains at larger small businesses. We fail to detect any effect of major toxic chemical spills on aggregate small business employment of treated counties. (As we noted above, an important caveat is that we do not have information on hours of employment.) We find that treated counties experience a significant increase in the number of small business exits, a smaller increase in the number of small business births that is not enough to offset the increase in exits, and a significant increase in small business bankruptcy filings. Moreover, treated counties experience a significant decline in the quantum of SBA lending in the 3-year period following the spill, both in terms of the number of loans approved and the aggregate amount lent.

As we noted above, one potential channel through which toxic chemical spills may have persistent adverse effects on local business activity is that the health risk perceptions and stigma associated with these spills cause an out-migration of people from surrounding areas, especially higher-income households. To test this hypothesis, we collect data on the U.S. population migration between counties from the Internal Revenue Service (IRS) Statistics of Income (SOI) database, which allows us to observe the number of tax-filing residents leaving a county and their destination counties. Consistent with this hypothesis, we find that counties exposed to major toxic chemical spills suffer large and persistent declines in the number of tax filings, number of tax-paying individuals, and the aggregate net adjusted gross income in the years following the spill compared to similar control counties.

Our paper contributes to the growing literature on the economic effects of environmental pollution. The adverse health effects from pollution are well established in the literature, and pollution been shown to lead to lower labor supply and lower worker productivity (Graff Zivin and Neidell 2012), migration of top executives and increase in CEO compensation (Levine et al. 2018; Deng and Gao 2013; Wang et al. 2021), and lower house prices (Chay and Greenstone 2005; Currie et al. 2015) in affected areas. Industrial pollution can represent a source of systematic risk (Hsu et al. 2022) and polluting firms are associated with higher cost of capital (Heinkel et al. 2001; Chava 2014). Chu et al. (2021) show that firms alter their green innovation activities and strategies in response to toxic chemical spills occurring near their headquarters. We contribute to this literature by highlighting the effects of pollution on small business activity. An important takeaway is that pollution shocks may contribute to increase in business concentration in their local economy because of their disproportionate adverse effects on smaller establishments compared to larger establishments. This is similar to the finding that import competition shocks following trade liberalization lead to increase in concentration among US firms due to reallocation from small inefficient firms to large firms (Amiti and Heise 2021).

Our findings are also relevant to debates surrounding environmental and safety regulations, which is often framed as a trade-off between the benefits of improving safety and environmental quality versus the costs imposed on businesses and workers. That is, on the one hand, environmental regulations are widely credited for curbing emissions and improving health outcomes (Chay and Greenstone 2003; Currie and Neidell 2005; Schlenker and Walker 2016; Isen et al. 2017). On the other, critics contend that these regulations are costly for businesses and workers, distort the production and investment decisions of affected firms (Becker and Henderson 2000) and impose significant transitional wage losses for affected workers (Walker 2013). Indeed, Walker (2013) notes that the distinction between "jobs versus the environment" is one of the more politically salient aspects of these regulations. However, we show that pollution shocks have persistent adverse effects on small businesses in most sectors of the economy, and this should be relevant to the debate surrounding the costs and benefits of environmental and safety regulations.

1 Data

1.1 Data Sources

Toxic Chemical Spills: We retrieve data on toxic chemical spill incidents from the U.S. Coast Guard's National Response Center (NRC) database. First-hand information on toxic chemical spills is entered into the NRC database when a responsible party or a third party reports an oil, chemical, radiological, biological, or etiological discharge into the environment within the United States by calling the NRC hotline. Among other information, the database contains each incident's time of occurrence, physical address, responsible party, pollution medium, number of people evacuated, and the number of injuries or fatalities. While the NRC data span the 1994–2020 period, we focus on incidents that occurred during the 2010–2018 period for which we have information on small business establishments. There were 245,709 toxic chemical spills across the United States over this period, but the vast majority of these spills did not result in any evacuations, injuries or fatalities. Only 2,163 toxic chemical spills (or 0.88% of total spills) resulted in any evacuations.

Small Businesses: We collect data on small business establishments across the U.S. from Mergent Intellect, a business intelligence aggregator of company profiles. Mergent Intellect contains information on nearly 97 million active and inactive business establishments in the U.S., for both public and private companies. An establishment is defined as a business or industrial unit at a single physical location that produces or distributes goods or provides services; e.g., a single store or factory. This information is put together by combining data from the widely used Dun & Bradstreet database and Mergent's own products which rely on public filings, yellow pages, credit inquiries, and direct telephone calls. Establishment-level information in Mergent Intellect includes name, a unique identifier, location (latitude and longitude), Standard Industrial Classification (SIC) code, founding year, names of company executives, and sales and employment at an annual frequency.

Following the definition used by the Office of Advocacy of the U.S. Small Business Administration (SBA), we define a company as a small business if it employs 500 or fewer employees across all its establishments.[5] We exclude businesses with fewer than 5 employees because of concerns relating to data quality; specifically, due to concerns that data vendors are more likely to impute sales and employee numbers for sole proprietor-employee type businesses (Crane and Decker (2019)). Thus, we download establishment-level data for all private companies with at least 5 employees and no more than 500 employees. The extract of Mergent Intellect which we downloaded provides information on establishment-level sales and employment only for the nine year period from 2010 to 2018. Hence, we are forced to restrict our analysis to this time period. We are able to assemble an establishment-year panel data which spans the 2010–2018 period and includes information on 4.18 million small business establishments.

Small Business Administration 7(a) Loan Guarantee Program: The 7(a) loan guarantee is the Small Business Administration's (SBA) flagship loan program designed to help small businesses that are creditworthy but struggle to get financing (Kalmenovitz and Vij (2022)).[6] Banks and other financial institutions verify the creditworthiness of borrowers, and issue and administer the loans. The SBA offers a government guarantee to repay 50% to 90% of the loan in the event of borrower default. The rate of SBA guarantee is determined by multiple factors including the loan size. We obtain data on 494,385 small business loans guaranteed by the SBA from `data.sba.gov`. For each loan, we observe the identity of the borrower, the lender, and loan characteristics such as loan amount, interest rate, term, the amount guaranteed by the SBA, and the charge-off amount if any.

[5] This is the simplest definition of a small business because it uses the same employee threshold across all industries. There are alternative industry-level definitions of small business that are used for government programs and contracting, and which rely on both revenue and employment cutoffs that vary across industries and over time. Please see `https://www.sba.gov/sites/default/files/advocacy/SB-FAQ-2016_WEB.pdf` for details.

[6] The other relevant SBA programs are the 504 loans—provides financing for long-term capital expenditures— and the Disaster Loan Assistance program—provides assistance for small businesses affected by events declared as disasters by the President, SBA Agency, or Secretary of Agriculture.

Migration and Individual Income: We collect data on the county-level income tax filings and U.S. population migration between counties during our sample period from the Internal Revenue Service (IRS) Statistics of Income (SOI) database. The county-level income tax statistics include information on the number of tax filings, adjusted gross income (AGI), and a breakdown of the number of filings and AGI across income brackets.We construct three types of measures from the county-year tax files: (i) Adjusted Gross Income/# Filings, which represents the average income of a tax filer in a county, (ii) variables that capture the # Tax Filings in the following income brackets—AGI≤\$50K, \$50K<AGI≤\$100K, and AGI>\$100K, and (iii) three more variables that capture the Total AGI of tax filers in the aforementioned income brackets.

The migration data is based on address changes reported on individual income tax returns filed with the IRS. This data set allows us to observe the number of residents leaving a county and their destination counties during our sample period. Using this data, we construct two net migration (inflow-outflow from a county) variables: (i) Net # Tax Filings, which approximates the year-over-year net gain/loss in the number of households and (iii) Net Adjusted Gross Income, which approximates the year-over-year net gain/loss in the total taxable income of a county.

Other data sources: We collect data on county gross domestic product from the Bureau of Economic Analysis. We use this series to control for the county business environment in all our analyses. We also collect data on bankruptcies from the Federal Judicial Center's (FJC) Integrated Database, which includes information on all court cases reported to the Administrative Office of the U.S. Courts. We observe the filing entity type (personal/business), the date of filing, the date of the final decision, and the location of each filing during our sample period. We identify small businesses that file for bankruptcy in each county each year and aggregate the data to the county-year level for our analyses.

1.2 Shocks to Pollution Risk

Our empirical strategy is to use major toxic chemical spills as shocks to the pollution risk of their local neighborhoods, and examine the consequent effects on small business establishments located in the vicinity of such spills. In this section, we define major toxic chemical spills and the treatment variables that capture shocks to pollution risk.

We define major toxic chemical spills as those that lead to large-scale evacuations because such spills are more likely to be associated with adverse health effects and business disruptions, and are also more likely to attract media coverage that increases the pollution risk perceptions of the local population. For our main analysis, we define major toxic chemical spills as those that cause evacuations of at least 900 people. We use 900 evacuations as the threshold because, as we show below in Table 1, 900 is just below the 99^{th} percentile value of number of evacuations among spills that lead to evacuations. As per our definition, there are 24 major toxic chemical spills across 15 states that occurred over the 2010-2018 period.

We define "treated" establishments as those that are located in the vicinity of major toxic chemical spills. Accordingly, we geocode the physical addresses of toxic chemical spills provided by the NRC database into coordinates and use the map with establishment coordinates supplied by Mergent Intellect to calculate the distance between business establishments and the spills. For our main analysis, we use a 25-mile radius around the spills to define treated establishments. Formally, we define the indicator variable $Spill_{k,t-}$ which takes the value of 1 for establishment k in year t if the establishment is located within 25-mile radius of a major toxic chemical spill that occurred in year t or before, and the value of 0 otherwise. We also define two indicator variables that identify treatment at different time intervals: (i) $Spill_{k,t-3:t}$ is an indicator variable equal to one when the establishment k is located within a 25-mile radius of a major toxic chemical spill that occurred between t and $t-3$, and zero otherwise; (ii) $Spill_{k,t-4+}$ is an indicator variable equal to one when the establishment k is located within a 25-mile radius of major toxic chemical spills that occurred four years or more before year t, and zero otherwise. As will become apparent below, we use $Spill_{k,t-3:t}$ and

$Spill_{k,t-4+}$ to separately identify the short-run and long-run effects, respectively, of major toxic chemical spills on surrounding small businesses.

1.3 Descriptive Statistics

Toxic Chemical Spills

As noted above, the vast majority of toxic chemical spills in the NRC database do not result in any serious consequences, such as evacuations, injuries or fatalities. Only 2,163 spills (or 0.88% of total spills) over the 2010–2018 period resulted in any evacuations. We provide descriptive statistics for these spills in Table 1. Panel A provides the descriptive statistics for the number of evacuations, injuries and fatalities. As can be seen, the distribution of the number of evacuations is highly skewed: the median is 25, whereas the 95^{th} and 99^{th} percentile values are 408 and 938, respectively. Moreover, injuries and fatalities are relatively uncommon.

Panel B provides a breakdown of the 2,163 toxic chemical spills by incident type, pollution medium, responsible party, and the aftermath. Examining the incident type, we find that most of these spills occur at fixed facilities (63.7%), followed by storage tanks (10.6%) and pipelines (9.3%). In terms of pollution medium, most of these spills involve chemical releases into the air (65%), and a few lead to land pollution (8.5%) and water pollution (5.4%). However, in 20.1% of incidents, we do not have specific information on the pollution medium. Private enterprises are responsible for 68.5% of the incidents, whereas public utilities and government entities account for only 5.9% of these incidents. Examining the aftermath, we find that 13.3% of the spills result in injuries and 1.6% result in fatalities. In addition to physical damage to individuals, many spills cause disruptions to public infrastructure: 12.3% result in road closures, and 5.0% involve railroad track closures.

As per our definition, there are 24 major toxic chemical spills that occurred over the 2010-2018 period. We provide a detailed description of these major toxic chemical spills in Panel C, and provide a spatial distribution in Figure 1 where centers of dots indicate the spill locations and sizes of the dots are proportional to the number of people evacuated. We observe that these 24 major toxic chemical spills are spread across 15 states. While most of these toxic chemical spills are geographically distant from each other, some places did experience multiple incidents: for example, the greater New York city area experienced four major spills in three consecutive years 2014-2016.

Small Business Establishments

We provide descriptive statistics for the small business establishment data in Table 2. Panel A provides information on the number of establishments, total sales over the 2010-2018 period, average employment, and the number of treated establishments separately for each industry group or sector, where each sector is a collection of similar 2-digit SIC industries. (We group mining with manufacturing because there are very few small business establishments in the mining industries). For each of these variables, we also report (in square brackets) the sector's percentage contribution to the aggregate total across all small business establishments.

We have information on over 4.18 million small business establishments across all sectors, which generated aggregate sales of $44.78 trillion and average annual employment of 41.76 million over the 2010–2018 period. In comparison, the total US civilian employment over the 2010–2018 period varied from 138.44 million to 156.82 million (see https://www.bls.gov/charts/employment-situation/civilian-employment.htm). The services sector accounts for the largest share of establishments (49.2%), sales (39.1%) and employment (49.5%). The retail sector has the second largest share of establishments and employment, whereas the manufacturing sector has the second largest share in terms of sales.

The last column in Panel A reports the number of establishments that are exposed to a major toxic chemical spill within a 25-mile distance (i.e., treated establishments) during the 2010–2018 period. Overall, 349,009 establishments (or 8.35% of all establishments) are exposed to major toxic chemical spills during this time period. The proportions of treated establishments in the various sectors are in line with their percentage shares of establishments reported in column (1). For instance, the services sector accounts for 49.2% of all establishments and 49.3% of treated establishments, and similarly for other industry groups.

Panel B provides summary statistics for the establishment-year panel data, which spans the 2010–2018 period, includes information on 4.18 million small business establishments, and has one observation for each establishment-year combination. The distribution of annual sales and employees is highly skewed: while the median establishment has $0.5 million in sales and 8 employees, the average values of sales and number of employees are $1.67 million and 13.99, respectively. Roughly 5% of establishments exit the panel each year. Recall that exit may be due to bankruptcy, business closure, or acquisition by another business.

Small Business Loans

We summarize our small business loan data in Table 3. The average 7(a) loan amount is $374,760 and the SBA guaranteed amount is $277,230 (74% of loan amount). The average interest rate on these loans is 6.43% and the average maturity is just over 10 years. A loan is charged off after best efforts to recover unpaid balances. In our sample, the charge-off rate is 5% and the average balance that the taxpayer is responsible for on the charged-off loans is about $130,650.

2 Empirical Methodology

Our empirical framework uses major toxic chemical spills as shocks to the pollution risk of surrounding small businesses and examines the consequent effect of these shocks on sales and employment of these businesses. Because our setting involves staggered treatment timing and treatment effect heterogeneity, we employ the "stacked regression" difference-in-differences (DiD) approach (e.g., see Gormley and Matsa 2011; Cengiz et al. 2019) to identify the effect of these pollution shocks on local small businesses. This approach allows for comparison of treated establishments with a matched sample of comparable control establishments, and can account for heterogeneity arising from differences in treatment timing and treatment severity. The stacked regression approach involves the following steps.

First, we match each treated small business establishment that experienced a major spill in year 't' with five control establishments that are very similar to the treated establishment in the year prior to its treatment. Specifically, each control establishment must satisfy the following criteria: (i) it did not experience a major spill during the 2010–2018 period, and is not part of a multi-establishment company that experienced a major spill in year 't'; (ii) it is in the same 2-digit SIC industry as the treated establishment; (iii) it is located in a county with a similar GDP and similar GDP growth as the treated establishment's county; and (iv) it is similar to the treated establishment in terms of sales, employment, and age in year 't-1'. We use the nearest-neighbor matching approach for conditions (iii) and (iv) with a caliper of 0.1. Henceforth, we refer to the grouping of a treated establishment and its five control establishments as a "cohort".

Using the criteria outlined above, we are able to identify matches for 154,159 establishments out of the 349,009 treated establishments in our sample.[7] In Table A.2, we analyze the quality of our matched treated and control samples for the six industry sectors by examining the Standardized Mean Difference (SMD) and Variance Ratios (VR). As a rule of thumb, SMD of matching variables should be less than 0.25 and VR should be in the interval (0,2) and ideally be close to one (Austin (2009); Rubin (2001)). The SMD of covariates in our matching equation is between -0.05 and 0.02 and the VR is between 0.36 and 0.85 which suggests that our matched samples are well-balanced.

Second, for all the treated and control firms in each cohort, we construct firm-year panels over the ±5-year period around the year 't' in which the treated establishment experienced

[7] We can identify matches for a higher percentage of treated establishments by loosening the caliper in the nearest-neighbor matching procedure or by matching on fewer characteristics, but doing so will dilute the quality of the matching procedure.

the major spill. These panels span the 2010–2018 period but they are unbalanced in terms of the number of pre- and post-event observations because these vary depending on the year of treatment. However, we do require that treated and control establishments have at least one pre-event and one post-event observation. We then create a stacked panel data set by pooling the data across cohorts, and estimate the average treatment effect using the following DiD regression on the stacked panel data set:

$$Y_{k,e,t} = \alpha + \beta Spill_{k,t-} + \mu_{e,k} + \mu_{e,t} + X'_{k,e,t-1} \cdot \delta + \varepsilon_{k,e,t} \tag{1}$$

where 'k' refers to an establishment, 'e' indexes the treatment-control cohort, and 't' denotes the year. Recall that $Spill_{k,t-}$ is an indicator variable that identifies the treated establishments, that is, establishments which are located within a 25-mile radius of a major toxic chemical spill that occurred before or during year 't'. We include cohort-establishment fixed effects ($\mu_{e,k}$) to control for unobserved heterogeneity across establishments and spill events; and cohort-year fixed effects ($\mu_{e,t}$) to account for common time-varying factors within each cohort. We control the regressions for establishment age and the GDP of the county in which the establishment is located. We estimate the DiD regressions separately for each sector listed above so that we are able to account for the heterogeneous effects of major toxic chemical spills on businesses in different sectors of the economy. The heterogeneity may arise because while all local businesses are exposed to the adverse health effects and disruptions brought about by these spills, businesses in polluting industries may also be exposed to the increase in environmental regulatory risk following these major accidents. Throughout the analyses, we winsorize all variables except dummy variables at the 1st and 99th percentiles to reduce possible impacts of extreme outliers.

We also estimate a variant of equation (1) after replacing $Spill_{k,t-}$ with two separate indicator variables: $Spill_{k,t-3:t}$ to identify establishments that were exposed to a major toxic chemical spill that occurred during the past three years (i.e, between t and $t-3$); and

$Spill_{k,t-4+}$ to identify establishments that were exposed to a major toxic chemical spill that occurred four years or more before year t. Hence, the coefficient estimates on $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ allow us to separately identify the short-run and long-run effects, respectively, of major toxic chemical spills on surrounding small businesses.

We also implement the following dynamic version of regression (1) to estimate the year-by-year treatment effects in the years prior to and after treatment:

$$Y_{k,e,t} = \alpha + \sum_{\tau=5,\tau\neq-1}^{\tau=-5} \beta_\tau Spill_{k,t+\tau} + \mu_{e,k} + \mu_{e,t} + X'_{k,e,t-1} \cdot \delta + \varepsilon_{k,e,t} \tag{2}$$

In the equation above $\{Spill_{k,t+\tau}\}$ are ten dummy variables that identify pre-treatment and post-treatment years for establishments in cohort e, where $\tau = 0$ represents the year of the spill around which we build the treatment-control cohort panel. The omitted year in the regression above is $\tau = -1$ (i.e., the year prior to treatment) so that β_τ captures the change in the outcome variable for the treated establishment between years $t+\tau$ and $t-1$, compared to compared to control establishments in the cohort.

We use the stacked regression DiD approach instead of the standard two-way fixed effects DiD model,[8] because recent advances in econometric theory (e.g., Callaway and Sant'Anna 2021; Goodman-Bacon 2021; Sun and Abraham 2021) suggest that the two-way fixed effects DiD model may not provide valid estimates of the average treatment effect on the treated in settings with staggered treatment timing and treatment effect heterogeneity. And recent empirical works in the finance literature demonstrate that these biases are relevant for research settings in finance that rely on staggered treatment timing (e.g., Karpoff and Wittry 2018; Baker et al. 2022).

[8] The two-way fixed effects model is: $Y_{kt} = \alpha + \beta Spill_{k,t-} + \mu_k + \mu_t + X'_{k,t-1} \cdot \delta + \varepsilon_{k,t}$, where μ_k and μ_t denote establishment fixed effects and year fixed effects, respectively.

3 Effects of Pollution Shocks on Small Businesses

In this section, we use regression (1) to examine the effects of pollution shocks resulting from major toxic chemical spills on individual small business establishments. The outcome variables of interest are: $log(Sales_{k,e,t})$ which is the natural logarithm of sales of establishment k in cohort e and year t; $log(\#Employees_{k,e,t})$ which is the natural logarithm of the number of employees of establishment k in cohort e and year t; and $Exit_{k,e,t}$ which is an indicator variable to identify if establishment k exits our panel in cohort e and year t. We also examine the effects on sales growth ($log(Sales_{k,e,t}/Sales_{k,e,t-1})$) and employment growth ($log(\#Employees_{k,e,t}/\#Employees_{k,e,t-1})$) but present these results in the internet appendix to conserve space.

3.1 Effects on Small Business Sales

We present the results of regression (1) with $log(Sales_{k,e,t})$ as the dependent variable in Table 4. We estimate the regression separately for each sector so that we are able to account for the heterogeneous effects of pollution shocks on businesses in different industries.

We present the sector-wise break-up of results in Panel A, where each row corresponds to a sector. In each row, columns (1) through (3) present the coefficient on the $Spill_{k,t-}$ treatment dummy (with standard errors reported in parentheses below), the R^2 of the regression, and the number of observations, respectively, for that sector. Columns (4) and (5) present the results of a variant of regression (1) in which we replace $Spill_{k,t-}$ with $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ to distinguish between the short-run and long-run effects of pollution shocks. We only report the coefficients on $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ because R^2 and N are similar to those in the baseline regression.

We find that the effects of pollution shocks on small business sales vary substantially across sectors. The negative and significant coefficients on $Spill_{k,t-}$ in case of manufacturing & mining, retail, and services indicate that small businesses in these sectors experience a significant reduction in sales in the years after they are exposed to major toxic chemical spills, compared to similar control establishments that were not exposed to such spills. The decline in sales in these sectors are economically significant: 2.5% in manufacturing & mining which translates to $81,000 for the average establishment; 2.2% decline in retail or $23,540 for the average establishment; and 2.7% in services or $35,640 for the average establishment. Moreover, the negative and significant coefficients on both $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ in these sectors indicate that the decline in sales for establishments in these sectors following major toxic chemical spills is not reversed in the long run. By contrast, small businesses in finance and real estate do not experience any significant changes in sales after being exposed to major toxic chemical spills.

A surprising result in Panel A is that the coefficient on $Spill_{k,t-}$ is positive and significant for the construction and wholesale sectors, which indicates that small businesses in these sectors actually experience a modest increase in sales following major toxic chemical spills. Moreover, the positive and significant coefficients on $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ indicate that these patterns persist in the long run. One potential explanation for this result is that businesses in the construction and wholesale sectors benefit from the post-spill repair and cleanup efforts.[9] Another potential explanation is that it is driven by larger establishments in construction and wholesale sectors which are more likely to survive in the long run and benefit from the decline in sales of their smaller competitors after being exposed to major spills. We explore this angle further in our analysis below.

Next, we sort establishments within each sector into four size quartiles (based on sales), and estimate regression (1) separately for these different size categories. We report the coefficient on $Spill_{k,t-}$ for each sector and size category in Panel B, where Q1 and Q4 denote the smallest and largest size quartile, respectively. The results in Panel B point to a striking contrast in how the effect of pollution shocks on small business establishments varies across the size categories. In each sector the coefficient on $Spill_{k,t-}$ increases monotonically from

[9] Wholesalers in our sample include distributors of chemicals, lumber, shoe, glass, etc., as well as large distributors of retail products.

category Q1 to Q4. More interestingly, the coefficient on $Spill_{k,t-}$ is large and negative for establishments in the two smallest size quartiles across all sectors (with the exception of the size Q2 group in the construction sector), whereas the effect is positive and significant for establishments in the largest size quartile across all sectors. These contrasting results highlight the redistributive effects of pollution shocks on small business activity: the smallest establishments experience large reduction in sales possibly because they are not well-equipped to deal with the disruptions brought about by the spills, and this works to the advantage of larger establishments which actually experience an increase in sales. The redistributive effect is economically significant across all industries: for instance, in the services sector, establishments in the smallest size quartile experience a 17.1% reduction in sales whereas those in the largest size quartile experience a 8.8% increase in sales after being exposed to major toxic chemical spills.

The size quartile results for the construction and wholesale sectors also explain the positive average treatment effect which we found for these sectors in panel A. In the construction sector, for instance, the coefficient on $Spill_{k,t-}$ is negative and significant for the smallest size category Q1, insignificant for category Q2, and positive and significant for the two largest size categories, Q3 and Q4. Examining the magnitudes of these coefficients, it is not surprising that the average treatment effect across all these categories (i.e., the coefficient on $Spill_{k,t-}$ for the sector as a whole) would be modestly positive and significant, which is in line with what we found in Panel A. There is a similar explanation for the positive average treatment effect in the wholesale sector.

We find qualitatively similar results when we estimate regression (1) with sales growth – defined as $log(Sales_{k,e,t}/Sales_{k,e,t-1})$ – as the dependent variable. To conserve space, we present these results in Panel A of Table A.1 in the internet appendix. As with the sales results above, we find a striking contrast in how the effect of pollution shocks on sales growth of small business establishments varies across the size categories: across all sectors, the effect is negative for establishments in the smallest size quartile but is positive for establishments in the largest size quartile.

Finally, we estimate regression (2) with $log(Sales_{k,e,t})$ as dependent variable to estimate the year-by-year treatment effects on small business sales in the years prior to and after treatment. We estimate the regression separately for each sector and size quartile combination, and plot the coefficient estimates of dynamic indicators (i.e., β_τ) around the spill event year along with their 95% confidence intervals indicated by the error bars in Figure 2. To conserve space we provide the plots for only the smallest and largest size category (i.e., Q1 and Q4) for each sector. The plots are broadly consistent with the findings in Panel B of Table 4, and indicate that pollution shocks have more adverse effects on Q1-establishments compared to Q4-establishments in each sector. There are some notable differences in persistence of effects across sectors: Q1-establishments in retail and services sectors experience persistent decline in sales following pollution shocks and do not fully recover even 5 years after the shock, whereas Q1-establishments in the wholesale sector experience a short-lived decline in sales which is reversed within 2 years after the shock. Q1-establishments in manufacturing & mining fall in between these polar cases: they experience medium-term persistent decline in sales which are reversed by the fourth year following the spill.[10]

3.2 Effects on Small Business Employment

We present the results of regression (1) with $log(\#Employees_{k,e,t})$ as the dependent variable in Table 5. The organization and presentation of results in this table is similar to that in Table 4. We first present a sector-wise break-up of results in Panel A, where we present both the average treatment effect (coefficient on $Spill_{k,t-}$), and its breakdown into a short-run and long-run effect (coefficients on $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$) in Panel A. Then, in Panel B, we present the average treatment effect separately for each sector and size category.

[10]Note that β_τ coefficients for manufacturing & mining in the pre-treatment years are different from zero and are positive, which highlights the difficulty in finding comparable control establishments. Nonetheless, the sharp switch from positive β_τ coefficients in the pre-treatment years to negative β_τ coefficients in the post-treatment years captures the adverse effects of major toxic chemical spills on sales of small business manufacturing establishments.

Turning to Panel A, a somewhat surprising finding is that the coefficient on $Spill_{k,t-}$ is positive and significant, albeit small, for all sectors except the retail sector where it is statistically insignificant. For instance, the point estimate for manufacturing & mining in the first row indicates a 0.7% increase in employment (equivalent to an increase of 0.14 employees, on average) for small businesses exposed to major toxic chemical spills. Moreover, the coefficients on both $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ are positive and significant which indicates that this effect, though small, is persistent.

The explanation for this surprising result is in Panel B where we find evidence of a redistributive effect similar to what we found with sales in Table 4. Specifically, establishments in the smallest size quartile (i.e., category Q1) across all sectors experience reduction in employment after being exposed to exposure to major toxic chemical spills, with the strongest effects in services, retail and construction. By contrast, establishments in the two largest size quartiles (i.e., Q3 and Q4) in all sectors experience increases in employment after being exposed to major toxic chemical spills. Examining the magnitudes of these coefficients, it is not surprising that the average treatment effect across all size categories (i.e., the coefficient on $Spill_{k,t-}$ for the sector as a whole) would be modestly positive and significant, which is in line with what we found in Panel A.

Figure 3 presents the results of regression (2) with $log(\#Employees_{k,e,t})$ as dependent variable aimed at estimating the year-by-year treatment effects on small business employment in the years prior to and after treatment. To conserve space we provide the plots of the β_τ coefficients (along with their 95% confidence intervals indicated by the error bars) for only the smallest and largest size category (i.e., Q1 and Q4) for each sector. Consistent with the results in Panel B of Table 5, we find that the effects of pollution shocks on small business employment are modest in size, and that the effects are more negative for Q1-establishments compared to Q4-establishments in each sector. Q1-establishments in the retail and services sectors experience more persistent declines in employment following pollution shocks, whereas Q1-establishments in manufacturing & mining, wholesale, and finance, real estate & insurance sectors experience short-lived decline in employment which is reversed within 2 years after the shock.

3.3 Effects on Small Business Exit

We present the results of regression (1) with $Exit_{k,e,t}$ as the dependent variable in Table 6. Recall that $Exit_{k,e,t}$ is an indicator variable to identify that establishment k exited our sample in year t. The exit may be due to bankruptcy, business closure, or acquisition by another business. The organization and presentation of results in this table is similar to that in Table 4. We first present a sector-wise break-up of results in Panel A, where we present both the average treatment effect (the coefficient on $Spill_{k,t-}$), and its breakdown into a short-run and long-run effect (coefficients on $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$). Then, in Panel B, we present the average treatment effect separately for each industry group and size category.

In Panel A we find that the coefficient on $Spill_{k,t-}$ in column (1) is positive and significant for all sectors, which indicates that pollution shocks have a significant positive effect on the likelihood of exit of small business establishments in all sectors. These effects are economically significant: the coefficient for manufacturing & mining indicates that small businesses in this industry are 0.6% more likely to exit after being exposed to a major toxic chemical spill which is large in comparison to the average unconditional likelihood of exit of 5% for this industry (see Panel B of Table 2). This effect is also persistent in all sectors as evidenced by the positive and significant coefficients on the $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ dummies in columns (4) and (5).

The results in Panel B indicate that the positive effect of pollution shocks on the likelihood of small business exit is stronger for establishments in the smallest size quartile (Q1) compared to establishments in the largest size quartile (Q4) across all sectors. The coefficient on $Spill_{k,t-}$ is positive and significant in the Q1 column across all sectors with the exception of finance, insurance and real estate. By contrast, the coefficient on $Spill_{k,t-}$ is statistically insignificant in the Q4 column for most sectors, with the exception of manufacturing

& mining and services sectors for which the coefficient is positive but small in magnitude. These results are consistent with our earlier findings relating to sales and employment and highlight that establishments in the smallest size quartile are most adversely affected by pollution shocks. An interesting implication of these findings is that major toxic chemical spills may lead to increase in business concentration in the surrounding areas.

Figure 4 presents the results of regression (2) with $Exit_{k,e,t}$ as dependent variable aimed at estimating the year-by-year treatment effects on small business exit in the years prior to and after treatment. To conserve space we provide the plots of the β_τ coefficients (along with their 95% confidence intervals indicated by the error bars) for only the smallest and largest size category (i.e., Q1 and Q4) for each sector. Consistent with the results in Panel B of Table 6, we find that the positive effect of pollution shocks on small business exit is stronger among Q1-establishments compared to Q4-establishments in all sectors. Q1-establishments in the manufacturing & mining, retail and services sectors experience more persistent increases in likelihood of exit following pollution shocks, whereas the corresponding effect is more short-lived for Q1-establishments in the construction and wholesale sectors. In the finance, insurance & real estate sector, neither Q1-establishments nor Q4-establishments experience an increase in likelihood of exit following pollution shocks.

3.4 Robustness

Recall that we use a 900+ evacuation threshold to define major toxic chemical spills, and a 25-mile radius to define our treatment indicators. In this section, we examine how our establishment-level results vary as we vary the treatment radius and evacuation threshold. To conserve space we present the results of the robustness analysis only for the manufacturing & mining industry because similar patterns hold in other industry groups.

Effect of varying treatment radius: Figure 5 provides plots of how the average treatment effect (coefficient on $Spill_{k,t-}$ in equation (1)) varies as we vary the treatment radius for defining $Spill_{k,t-}$ from 10 miles to 50 miles, while using the 900+ evacuation threshold to define major toxic chemical spills. We present plots for $log(Sales_{k,e,t})$, $log(\#Employees_{k,e,t})$ and $Exit_{k,e,t}$ as dependent variables in panels (a), (b) and (c), respectively. Plots (a) and (c) show that the adverse effect of major toxic chemical spills on sales and likelihood of exit, respectively, is strongest when we use a shorter treatment radius but the effect is significant even at the 50-mile treatment radius. Indeed, plot (c) shows that the average treatment effect with $Exit_{k,e,t}$ as dependent variable is monotonically decreasing in the treatment radius. On the other hand, plot (b) shows that the average treatment effect with $log(\#Employees_{k,e,t})$ as dependent variable is positive, albeit small, and does not vary significantly with the treatment radius.

Effect of varying evacuation threshold: Figure 6 provides plots of how the average treatment effect (coefficient on $Spill_{k,t-}$ in equation (1)) varies as we vary the evacuation threshold for defining major toxic chemical spills from 400 to 1600, while using the 25-mile treatment radius for defining $Spill_{k,t-}$. We present plots for $log(Sales_{k,e,t})$, $log(\#Employees_{k,e,t})$ and $Exit_{k,e,t}$ in panels (a), (b) and (c), respectively. Plots (a) and (c) show that the average treatment effect for sales and likelihood of exit is stronger for higher evacuation thresholds, but the relation is not monotonic. On the other hand, plot (b) shows that the average treatment effect with $log(\#Employees_{k,e,t})$ as dependent variable is positive, albeit small, and does not vary significantly with the evacuations threshold.

3.5 Effects on Small Business Lending

In this section, we use the loan-level database of SBA 7(a) loans to examine the effect of major toxic chemical spills on the availability and price of SBA loans to small businesses located in the vicinity of these spills. Each observation in the database corresponds to a loan made to a small business, and only a small set of borrowers have more than one loan. Hence, we estimate the effect of the pollution shock on loan outcomes using variants of the

the following fixed effects regression:

$$Y_{lt} = \alpha + \beta Spill_{l,t-} + \mu_{industry,t} + \mu_{bank,t} + X'_{k,t-1} \cdot \delta + \varepsilon_{l,t}, \tag{3}$$

where $Spill_{l,t-}$ is a dummy variable to identify that the borrower obtained the loan after one of its establishments was exposed to (i.e., was in a 25-mile radius of) a major toxic chemical spill. We also estimate variants of regression (3) after replacing $Spill_{l,t-}$ with two dummy variables: (i) $Spill_{l,t-3:t}$ identifies that the borrower was exposed to a major toxic chemical spill between years $t-3$ and t, where t is the year in which the loan is originated; and (ii) $Spill_{l,t-4+}$ identifies that the borrower was exposed to a major toxic chemical spill four or more years before year t. We control the regression for the logarithm of the lagged GDP of the borrower's county, and include NAICS-3×Year fixed effects and Bank×Year fixed effects.[11]

The outcome variable of interest ($Y_{l,t}$) is one of the following: log of the loan amount, fraction of loan guaranteed by the SBA, interest rate, log of the maturity, a dummy to identify that the loan was subsequently charged off by the bank, and the log of the charge-off amount for loans that were charged off. We present the results of these regressions in Table 7 where each row corresponds to a different outcome variable of interest. The first three columns report the coefficient on $Spill_{l,t-}$, the R^2 of the regression, and number of observations, respectively. Columns (4) and (5) report the coefficients on $Spill_{l,t-3:t}$ and $Spill_{l,t-4+}$ for the variant of regression (3) described above.

The negative coefficient on $Spill_{l,t-}$ in the first row of Table 7 indicates that small businesses obtain 2.8% less amounts through SBA loans, which translates to a \$10,493 reduction for the average loan, following exposure to major toxic chemical spills. The coefficient estimates in columns (4) and (5) indicate that treated small businesses experience large reductions in SBA loan amounts (8.5%) in the three-year period following the spill, but there

[11]We use NAICS-3 to define industry in this regression because the SBA loan database only provides the NAICS classification.

are no significant effects in the long run.

The reduction in SBA loan amounts may reflect either lower demand for credit by treated small businesses or lower supply of credit to treated small businesses, or both. To distinguish between the demand versus supply of credit, we next examine the effect of major toxic chemical spills on the fraction of the loan guaranteed by the SBA. The negative coefficient on $Spill_{l,t-}$ in the second row indicates a modest reduction in the fraction of loan guaranteed by the SBA, and is consistent with tighter supply of credit to treated small businesses. The coefficient estimates in columns (4) and (5) indicate that the treated small businesses experience a 0.7% reduction in the loan fraction guaranteed by the SBA in the three-year period following the spill, but there are no significant effects in the long run.

The results in rows 3 and 4 indicate that small businesses pay persistently higher interest rates and obtain loans of shorter maturity after being exposed to major toxic chemical spills. Both these results are consistent with tightening of credit supply to treated small borrowers. However, both these effects are very modest in economic terms: the 0.052% increase in interest rate is small in comparison to the average interest rate of 6.43%, and the 2% reduction in maturity corresponds to a reduction in maturity of 2.4 months.

In terms of loan performance, we find that SBA loans made to small businesses that have been exposed to major toxic chemical spills are more likely to be charged off ex post. The coefficient on $Spill_{l,t-}$ indicates that SBA loans made to treated borrowers are 0.6% more likely to be charged off, which is economically significant in comparison to the unconditional charge off rate of 5%. Moreover, the coefficients on $Spill_{l,t-3:t}$ and $Spill_{l,t-4+}$ indicate that the increase in charge off rate for treated borrowers materializes only in the long-run period following exposure to the major toxic chemical spills. In the final row, we examine the effect on log of charge-off amount for the subsample of SBA loans that are charged off. Within this subsample, we do not find any differences in loan charge-off amounts between treated and untreated borrowers.

4 Countywide Effects of Pollution Shocks

In the previous section, we examined the effect of pollution shocks on the sales, employment, and likelihood of exit for individual small business establishments. Our results highlighted the redistributive effects of pollution shocks on individual small business establishments. Specifically, establishments in the smallest size quartile are most adversely affected by pollution shocks, and experience large reduction in sales, modest reduction in employment, and significant increase in the likelihood of exit. By contrast, establishments in the largest size quartile experience increase in sales and employment, and are significantly less likely to exit following exposure to pollution shocks.

A natural question that arises is: what happens to the *aggregate* small business activity in the vicinity of major toxic chemical spills? If the only effect of major spills is to redistribute sales and employment from the smallest businesses to larger small businesses then there should not be any affect of these spills on aggregate small business activity. On the other hand, if the reductions at the smallest businesses are not offset by the gains at larger small businesses, then there may be a negative effect on aggregate small business activity. We address this question in this section by examining the effect of major toxic chemical spills on countywide measures of aggregate small business activity.

We modify the matching methodology and stacked regressions discussed in section 2 as follows: We label a county as treated, denoted using the $Spill_{c,t-}$ dummy, if it contains a small business establishment that is located within a 5-mile radius of a major toxic chemical spill. Apart from the county in which the spill occurred, this definition also picks up neighboring counties if a portion of these counties is close to the location of the spill. We match each treated county in the year 't' with five control counties which did not experience a major spill during the 2010–2018 period and are most similar to the treated county in terms of aggregate sales, aggregate employment, GDP, and GDP growth in year 't-1'. Next, we construct a $\pm$ 5-year panel around each treatment-controls cohort and stack them to create our county-level stacked panel. We use a county-year level version of regression (1) to estimate average treatment effects for countywide measures of small business activity.

4.1 Effects on Countywide Small Business Activity

We focus on the following outcome variables ($Y_{c,e,t}$) all of which are defined at the county-year level: *Log*(*Aggregate Sales*) which is the logarithm of the aggregate sales of all small business establishments; *Log*(*Aggregate #Employees*) which is the logarithm of the aggregate number of employees of all small business establishments; *# of Establishment Entries* which denotes the number of new small business establishments which started their operations during the year; *# of Establishment Exits* which denotes the number of new small business establishments which exited during the year; and *# of Establishment Bankruptcies* which denotes the number of small business establishments which filed for bankruptcy during the year. We use the Poisson regression specification instead of OLS for examining the effects on establishment entries, exits and bankruptcies because these variables may have zero values for many county-year pairs. We report the results of these regressions in Table 8 where each row corresponds to a different outcome variable of interest. The first three columns report the coefficient on $Spill_{c,t-}$, the R^2 of the regression, and number of observations, respectively. Columns (4) and (5) report the coefficients on $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$ for a variant of regression (1) that allows us to distinguish between the short-run and long-run effects of major toxic chemical spills.

The negative and significant coefficient on $Spill_{c,t-}$ in row 1 indicates that counties exposed to major toxic chemical spills experience a 10.8% decline in aggregate small business sales in the years following the spill. In other words, the reduction in sales at the smallest businesses exposed to major spills (which we documented above) is not offset by the gains at larger small businesses. The coefficients on $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$ indicate that the decline in aggregate small business sales occurs in the 3-year period following the spill, but the effect is not persistent beyond year 4. However, we fail to detect any effect of major toxic chemical spills on aggregate small business employment of treated counties, as evidenced by the insignificant coefficients on all the treatment indicators in row 2.

The positive and significant coefficient on $Spill_{c,t-}$ in row 3 indicates that counties exposed to major toxic chemical spills experience a significant increase in the number of small business exits in the subsequent years. The coefficients on $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$ indicate that the increase in exits occur in the 3-year period following the spill, but this effect is not persistent beyond year 4. Recall that the exits may be due to business closures, bankruptcies, or acquisitions by other businesses. We specifically focus on the number of small business bankruptcy filings in the row 4. The coefficients on the treatment dummies indicate that counties exposed to major toxic chemical spills experience a significant increase in the number of small business bankruptcy filings in subsequent years, and this effect is highly persistent.

We examine the effect on new business creation in the last row. Consistent with creative destruction at work, we find a positive effect of major toxic chemical spills on number of small business entries in subsequent years (positive and significant coefficient on $Spill_{c,t-}$), and this effect is concentrated in the 3-year period following the spill. However, the positive effect on entries is not large enough to offset the positive effect on exits.

4.2 Effects on Countywide SBA Lending

Next, we examine the effects of pollution shocks on countywide measures of SBA lending. To do this, we use the information from the loan-level database of SBA 7(a) loans to create measures of aggregate SBA lending at the county-year level. We then use a county-year level version of regression (1) to estimate average treatment effects for countywide measures of SBA lending.

We focus on the following outcome variables ($Y_{c,e,t}$) all of which are defined at the county-year level: log of number of SBA loan approvals, log of total amount of SBA lending, log of the aggregate charge-off amount, and the number of charge-offs. We use the Poisson regression specification instead of OLS for examining the effects on number of charge-offs because this variable has zero values for many county-year pairs. We report the results of these regressions in Table 9 where each row corresponds to a different outcome variable of interest. The first three columns report the coefficient on $Spill_{c,t-}$, the R^2 of the regression, and number of observations, respectively. Columns (4) and (5) report the coefficients on $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$ for a variant of regression (1) that allows us to distinguish between the short-run and long-run effects of major toxic chemical spills.

The results in the first two rows indicate that counties exposed to major toxic chemical spills experience significant reductions in the number of SBA loans and the total amount of SBA lending. These effects materialize in the 3-year period following the spills, and do not persist beyond year 4. In terms of SBA loan performance, we do not find any significant effect of major toxic chemical spills on either the number of charge-offs or the aggregate charge-off amount at the county-year level.

4.3 Effects on Countywide Tax Base

As we noted above, one potential channel through which toxic chemical spills may have persistent adverse effects on local business activity is that the health risk perceptions and stigma associated with these spills cause an out-migration of people from surrounding areas, especially higher-income households. To test this hypothesis, we examine the effects of major toxic chemical spills on changes in the tax base of counties. Formally, we use the county-year level version of regression (1) described above to estimate average treatment effects for the following net migration (inflow minus outflow of tax-paying residents) measures at the county-year level which we constructed using the IRS-SOI data: *Net # Tax Filings*, which approximates the year-over-year net gain/loss in the number of households; and *Net Adjusted Gross Income*, which approximates the year-over-year net gain/loss in the total taxable income of a county. The number of tax filings is expressed in thousands and the gross income is expressed in millions. The results of these regressions are presented in Table 10.

The negative and significant coefficient of $Spill_{c,t-}$ in the first row indicates that counties exposed to major toxic spills experience a decline of 12,322 tax filings each year, on average, in the post-spill period compared to similar counties that were not exposed to toxic spills. The negative and significant coefficients in columns (4) and (5) indicate that this decline occurs both in the short and the long run. Indeed, the long-run effect seems to be larger than the short-run effect which may be because migration of population takes longer to materialize.

The results in the second row indicate that counties exposed to major toxic chemical spills experience a decline in aggregate (i.e., countywide) net adjusted gross income of \$1.95 billion each year, on average, in the post-spill period compared to similar counties that were not exposed to toxic spills. The decline occurs both in the short- and the long-run period following the spill, and the long-run effect seems to be larger than the short-run effect.

Next, we examine the effect of toxic spills on the number of filers and aggregate income across income brackets. The results show that, compared to unexposed counties, in counties that experienced a major toxic spill, there is a small but statistically insignificant decrease in the number of tax filings for the lowest income bracket (AGI≤\$50K); there is a 5.6% increase in the number of tax filings (equivalent to 5,106 filings) for the middle-income bracket (\$50K<AGI≤\$100K); and there is an 8.1% decrease in the number of tax filings (equivalent to 5,201 filings) for the top income bracket (AGI≥100K). An analysis of the aggregate AGI across income brackets shows a similar pattern. The top income bracket coefficient implies that the aggregate AGI of top earners in counties affected by major toxic spills declines by 7.1% (equivalent to \$1.28 billion) compared to top earners in unexposed counties. This effect is significant and larger in the long run. The last row shows that the AGI per filing is lower after a spill in counties exposed to a major toxic spill compared to unexposed ones.

Overall the results in Table 10 indicate that there is a significant and persistent exodus of the population (especially among high-income individuals) and income from counties that experience major toxic chemical spills, and this may explain the persistent adverse effects on local small business activity which we documented in the previous section.

5 Concluding Remarks

In this paper, we use major toxic chemical spills as shocks to the pollution risk of their local neighborhoods and examine the consequent effects on local small business. The effects of these pollution shocks on small business activity vary significantly across industries and size categories. Establishments in the smallest size quartile experience large reduction in sales, modest reduction in employment, and significant increase in likelihood of exit following exposure to pollution shocks, whereas those in the largest size quartile experience increase in sales and employment. These contrasting findings highlight the redistributive effects of pollution shocks on small business activity: the smallest businesses experience a persistent reduction in sales possibly because they are not well-equipped to deal with the disruptions brought by the spills, and this works to the advantage of larger small businesses which actually experience an increase in sales. These findings also suggest that pollution shocks contribute to increase in business concentration in their local economy.

Business exposed to major toxic chemical spills obtain lower amounts through the SBA 7(a) loan program. Moreover, consistent with tightening of supply of credit following exposure to toxic chemical spills, we find that loans made to treated borrowers have smaller fractions guaranteed by the SBA and feature modestly higher interest rates. In terms of loan performance, we find that SBA loans made to treated borrowers are more likely to be charged off ex post, but there is no significant effect on the charge-off amount.

Counties exposed to major toxic chemical spills experience a reduction in aggregate small business sales, increase in the number of small business exits, a smaller increase in the number of small business births that is not enough to offset the increase in exits, and an increase in the number of small business bankruptcy filings. We also find that there is a significant and persistent exodus of population and income from counties that experience major toxic spills, and this may explain the persistent adverse effects on local small business activity.

References

Amiti, M. and S. Heise (2021). Us market concentration and import competition.

Austin, P. C. (2009). Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples. *Statistics in medicine 28*(25), 3083–3107.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics 144*, 370–395.

Becker, R. and V. Henderson (2000). Effects of air quality regulations on polluting industries. *Journal of Political Economy 108*, 379–421.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*, 200–230.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The effect of minimum wages on low-wage jobs. *Quarterly Journal of Economics 134*, 1405–1454.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science 60*, 2223–2247.

Chay, K. Y. and M. Greenstone (2003). The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. *Quarterly Journal of Economics 118*(3), 1121–1167.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? Evidence from the housing market. *Journal of Political Economy 113*, 376–424.

Chu, Y., A. Y. Liu, and X. Tian (2021). Environmental risk and green innovation: Evidence from evacuation spills. *Available at SSRN 3740551*.

Crane, L. D. and R. A. Decker (2019). Business Dynamics in the National Establishment Time Series (NETS). *Finance and Economics Discussion Series 2019-034. Washington: Board of Governors of the Federal Reserve System.*

Currie, J., L. Davis, M. Greenstone, and R. Walker (2015). Environmental health risks and housing values: Evidence from 1,600 toxic plant openings and closings. *American Economic Review 105*, 678–709.

Currie, J. and M. Neidell (2005). Air pollution and infant health: What can we learn from California's recent experience? *Quarterly Journal of Economics 120*, 1003–1030.

Decker, R., J. Haltiwanger, R. Jarmin, and J. Miranda (2014). The Role of Entrepreneurship in US Job Creation and Economic Dynamism. *Journal of Economic Perspectives 28*, 3–24.

Deng, X. and H. Gao (2013). Nonmonetary benefits, quality of life, and executive compensation. *Journal of Financial and Quantitative Analysis 48*, 197–218.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*, 254–277.

Gormley, T. A. and D. A. Matsa (2011). Growing out of trouble? Corporate responses to liability risk. *Review of Financial Studies 24*, 2781–2821.

Graff Zivin, J. and M. Neidell (2012). The impact of pollution on worker productivity. *American Economic Review 102*, 3652–73.

Haltiwanger, J. C., R. S. Jarmin, and J. Miranda (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics 95*, 347–361.

Heinkel, R., A. Kraus, and J. Zechner (2001). The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis 36*, 431–449.

Hsu, P.-H., K. Li, and C.-Y. Tsou (2022). The pollution premium. *Journal of Finance, Forthcoming*.

Isen, A., M. Rossin-Slater, and W. R. Walker (2017). Every breath you take—every dollar you'll make: The long-term consequences of the Clean Air Act of 1970. *Journal of Political Economy 125*, 848–902.

Kalmenovitz, J. and S. Vij (2022). Regulatory risk perception and small business lending. *Working Paper*.

Karpoff, J. M. and M. D. Wittry (2018). Institutional and legal context in natural experiments: The case of state antitakeover laws. *Journal of Finance 73*, 657–714.

Levine, R., C. Lin, and Z. Wang (2018). Toxic emissions and executive migration. *Available at SSRN 3134194*.

Neumark, D., B. Wall, and J. Zhang (2011). Do Small Business Create More Jobs? New Evidence for the United States from the National Establishment Time Series. *Review of Economics and Statistics 93*, 16–29.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: Application to the tobacco litigation. *Health Services and Outcomes Research Methodology 2*, 169–188.

Schlenker, W. and W. R. Walker (2016). Airports, air pollution, and contemporaneous health. *Review of Economic Studies 83*, 768–809.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*, 175–199.

Tversky, A. and D. Kahneman (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology 5*, 207–232.

Walker, W. R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *Quarterly Journal of Economics 128*, 1787–1835.

Wang, L., Y. Dai, and D. Kong (2021). Air pollution and employee treatment. *Journal of Corporate Finance 70*, 102067.

Figure 1: Spatial Distribution of Major Toxic Chemical Spills

This figure visualizes the spatial distribution of major toxic chemical spills in the US over the period 2010-2018. Each dot represents a major spill with its size proportional to the number of people evacuated.

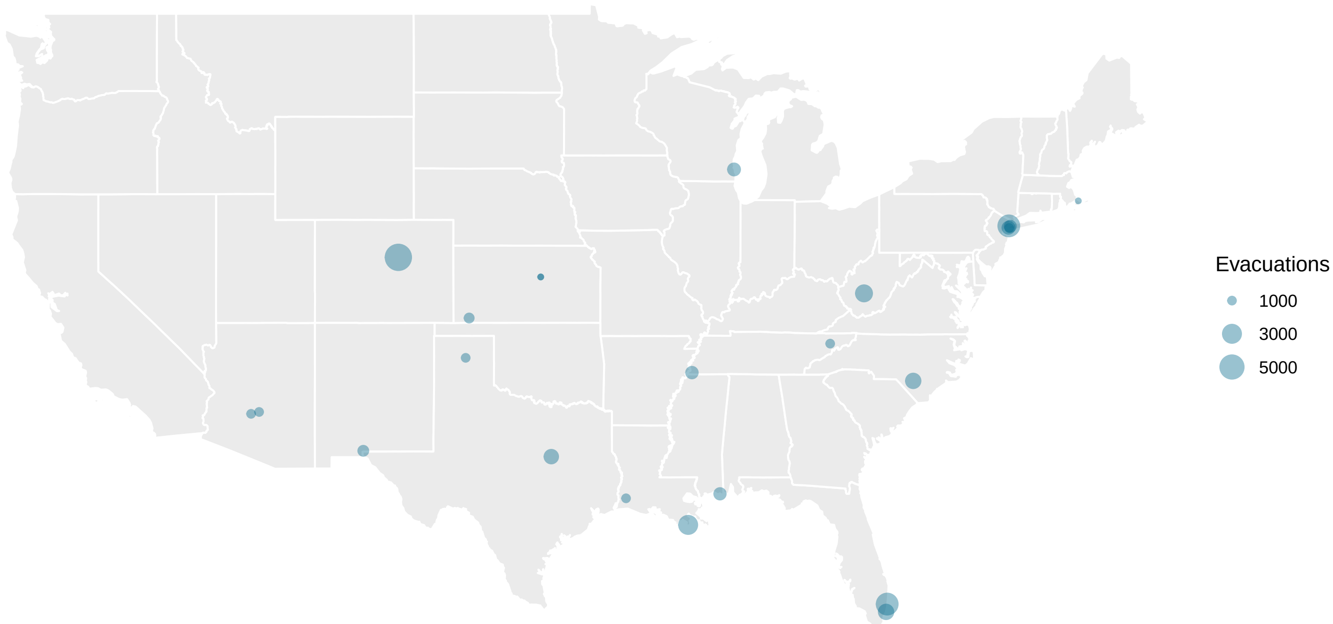
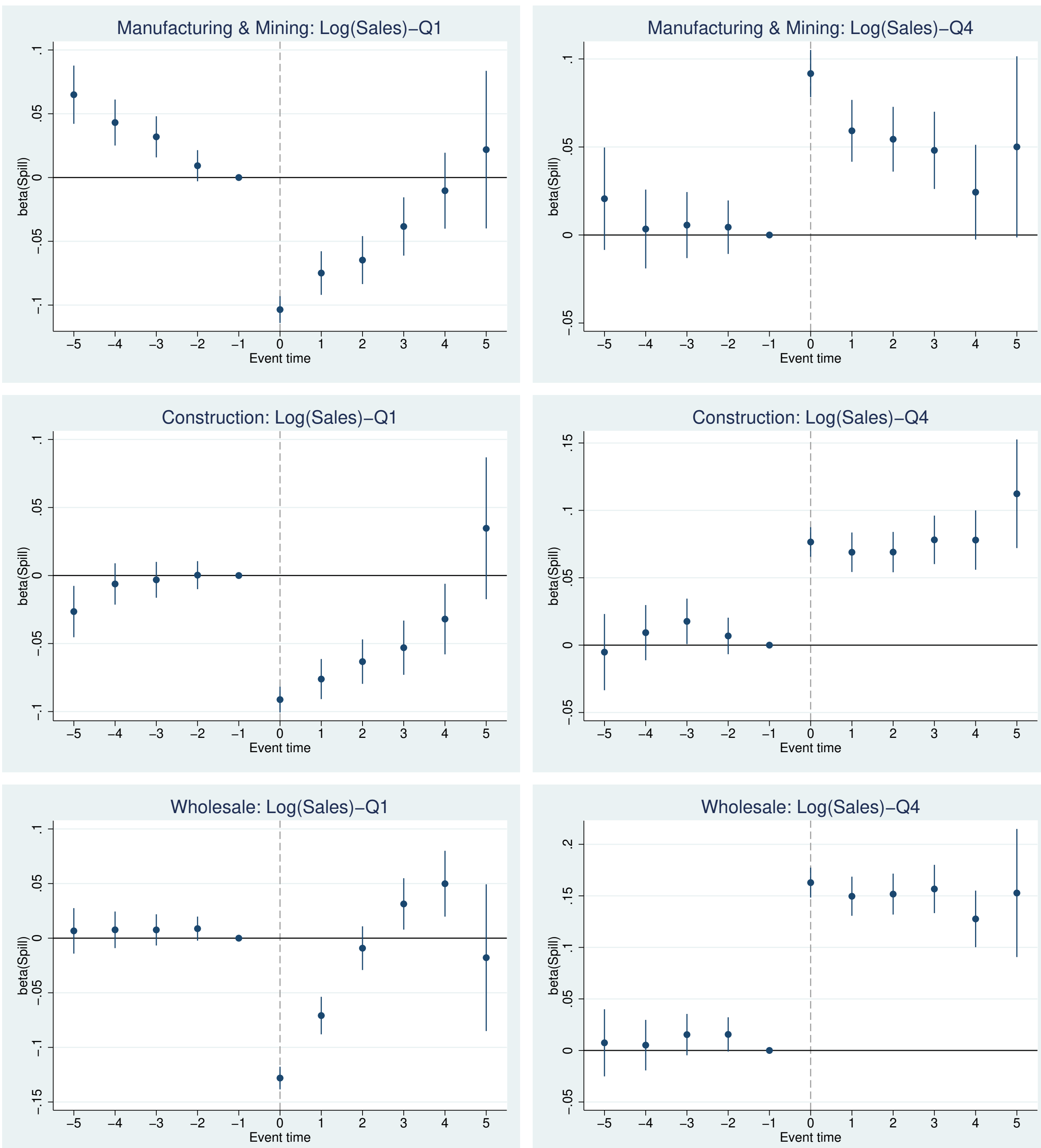


Figure 2: Effect of Pollution Shocks on Small Business Sales: Dynamic Effect by Sector and Size Quartile

This figure reports the results of regression (2) with $log(Sales_{k,e,t})$ as dependent variable to estimate the year-by-year treatment effects in the years prior to and after treatment. We estimate the regression separately for each sector-size quartile combination, and plot the coefficient estimates of dynamic indicators (i.e., β_τ) around the spill event year along with their 95% confidence intervals indicated by the error bars. To conserve space we provide the plots for only the smallest and largest size category (i.e., Q1 and Q4) for each sector.

Dependent Variable = Log(Sales)



Dependent Variable = Log(Sales) *[Continued]*

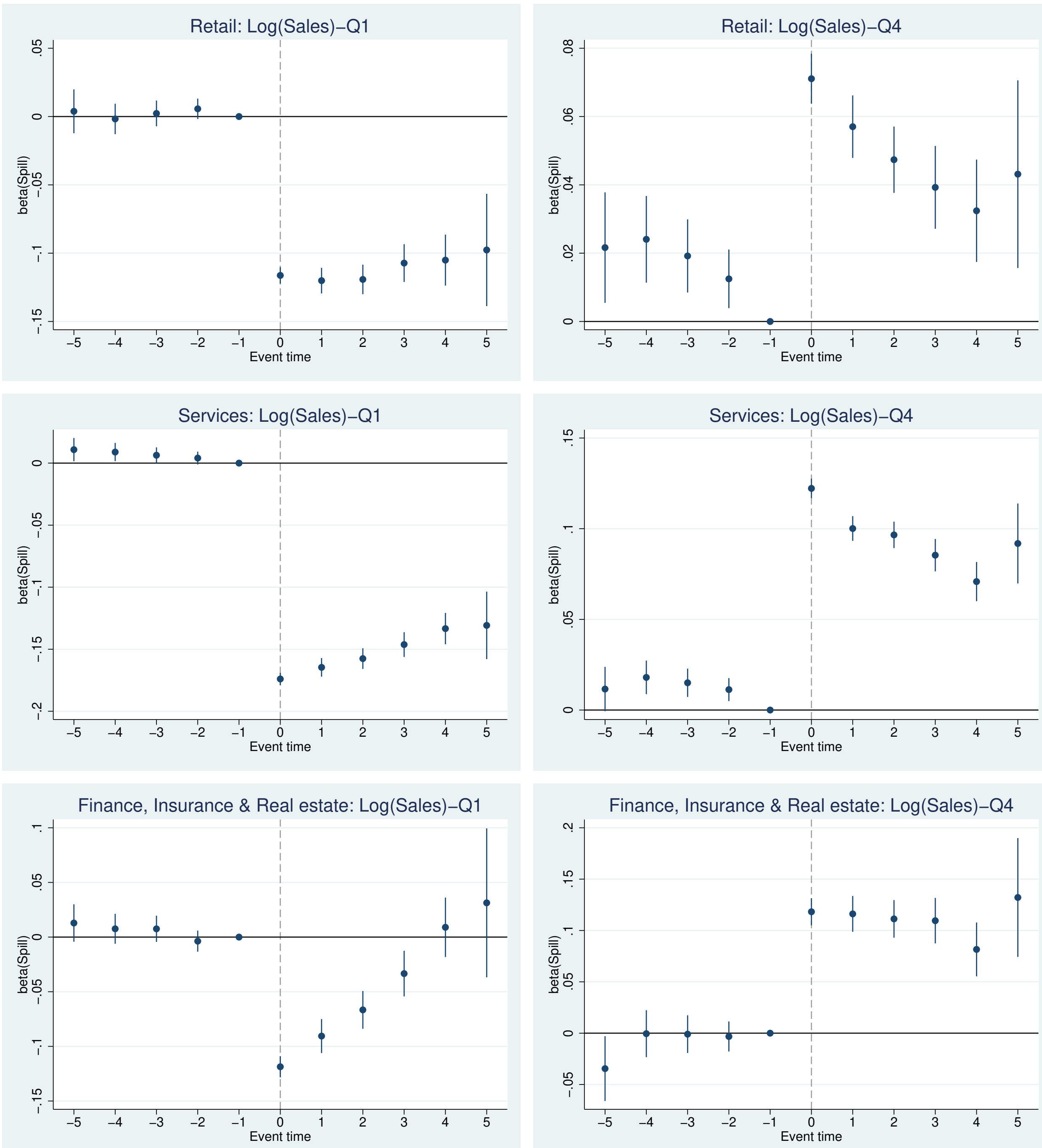
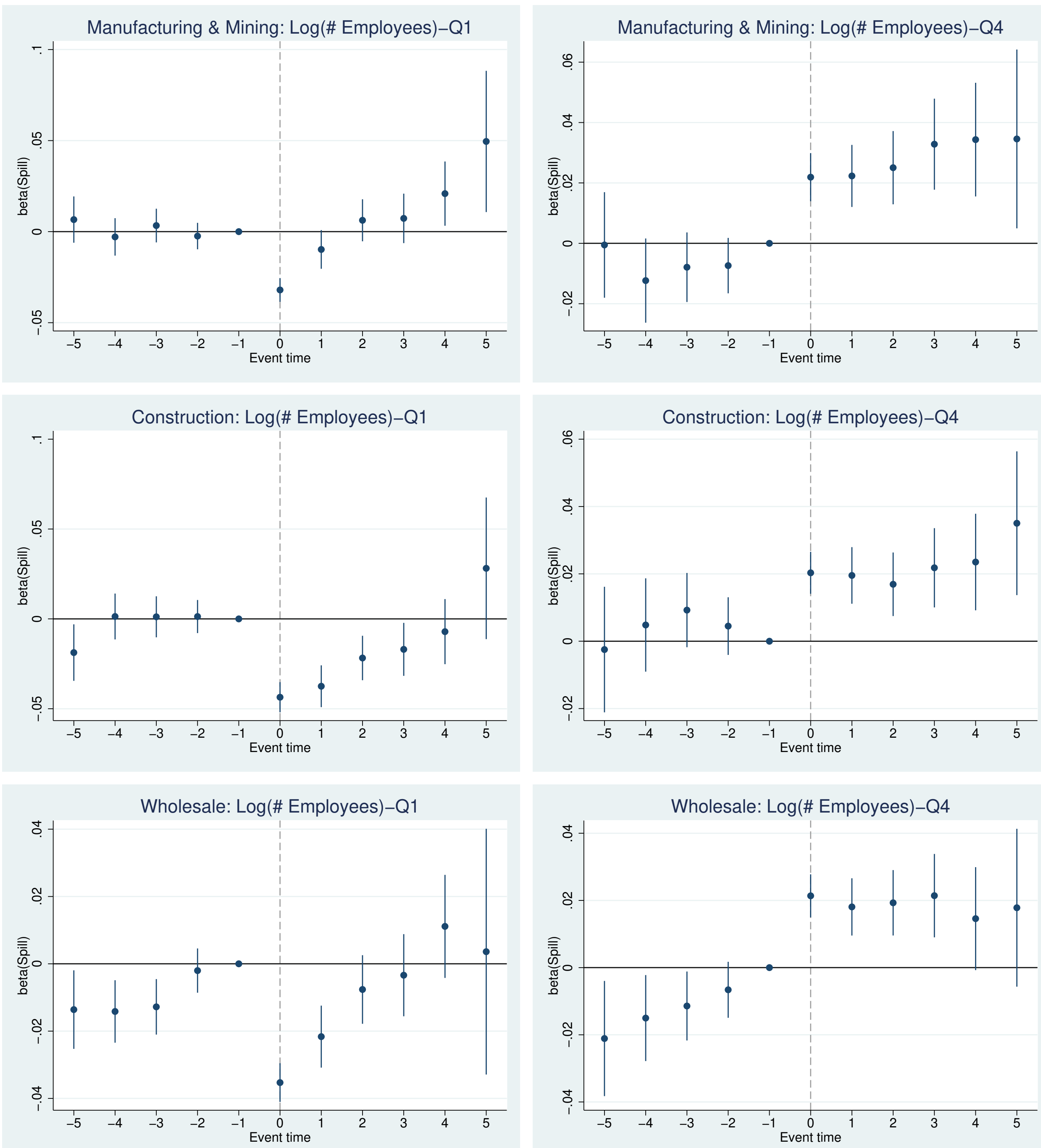


Figure 3: Effect of Pollution Shocks on Small Business Employment: Dynamic Effect by Sector and Size Quartile

This figure reports the results of regression (2) with $log(\#Employees_{k,e,t})$ as dependent variable to estimate the year-by-year treatment effects in the years prior to and after treatment. We estimate the regression separately for each sector-size quartile combination, and plot the coefficient estimates of dynamic indicators (i.e., β_τ) around the spill event year along with their 95% confidence intervals indicated by the error bars. To conserve space we provide the plots for only the smallest and largest size category (i.e., Q1 and Q4) for each sector.

Dependent Variable = Log(#Employees)



Dependent Variable = Log(#Employees) *[Continued]*

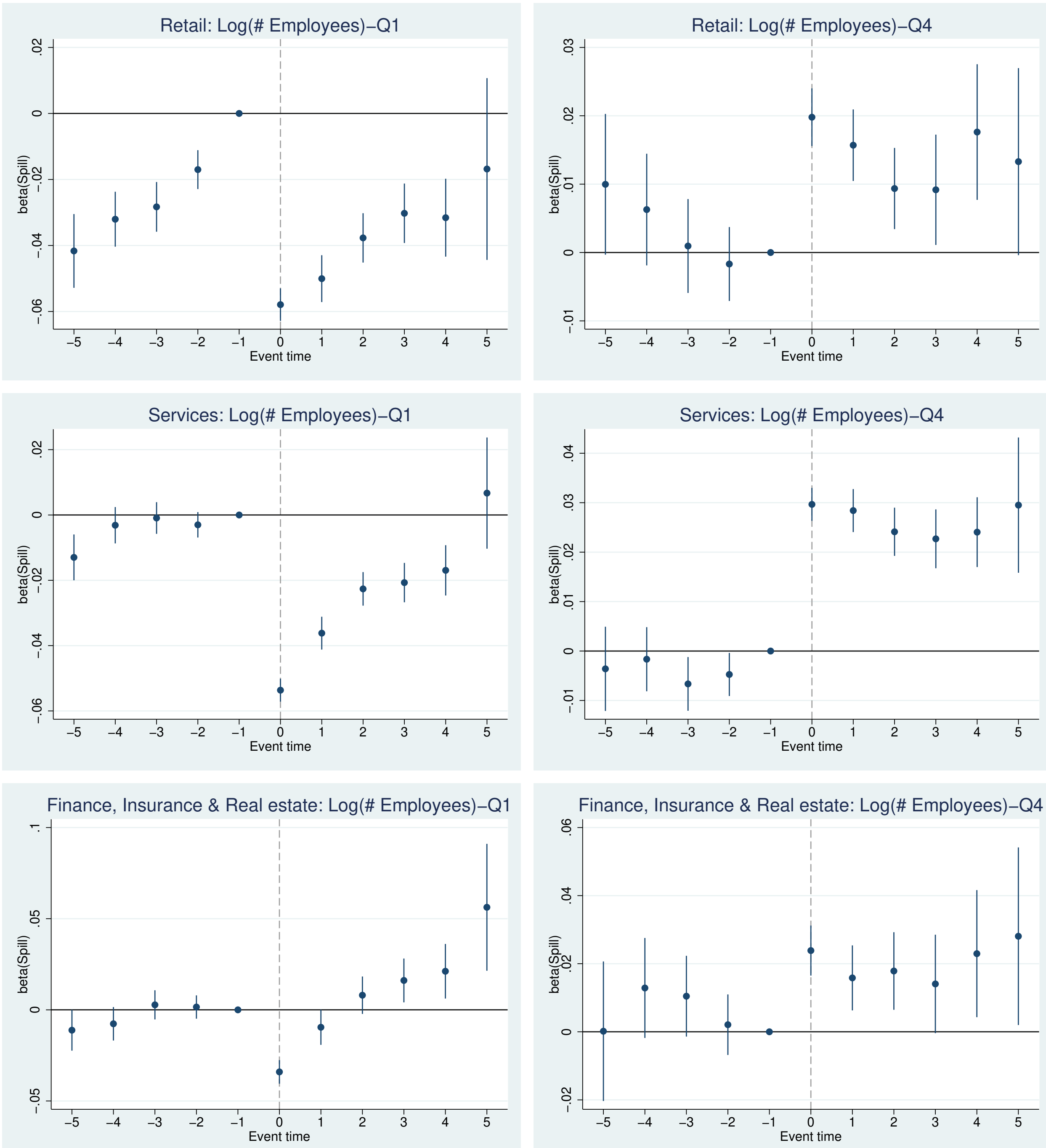
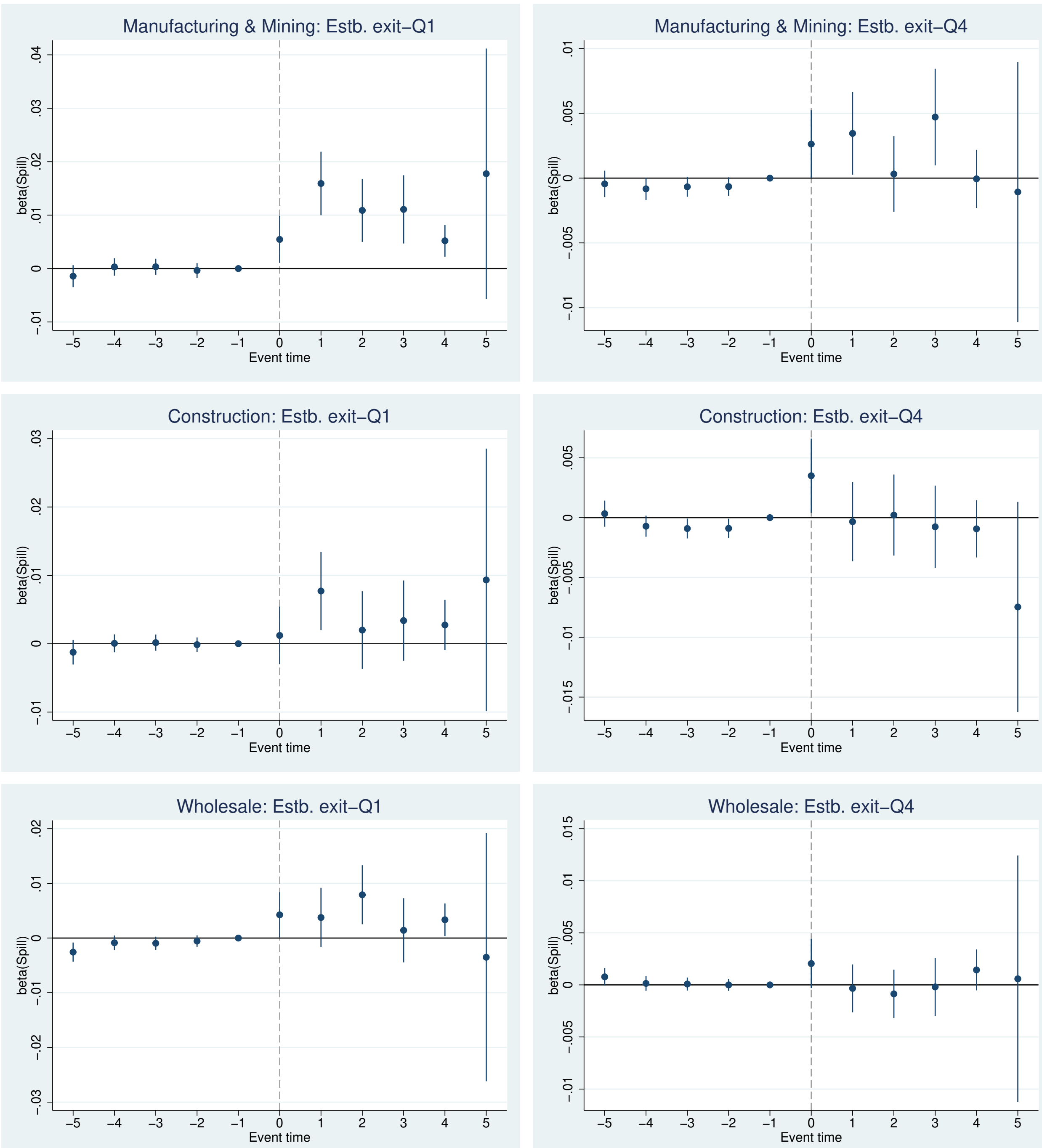


Figure 4: Effect of Pollution Shocks on Small Business Exit: Dynamic Effect by Sector and Size Quartile

This figure reports the results of regression (2) with $Exit_{k,e,t}$ as dependent variable to estimate the year-by-year treatment effects in the years prior to and after treatment. We estimate the regression separately for each sector-size quartile combination, and plot the coefficient estimates of dynamic indicators (i.e., β_τ) around the spill event year along with their 95% confidence intervals indicated by the error bars. To conserve space we provide the plots for only the smallest and largest size category (i.e., Q1 and Q4) for each sector.

Dependent Variable = Exit



Dependent Variable = Exit *[Continued]*

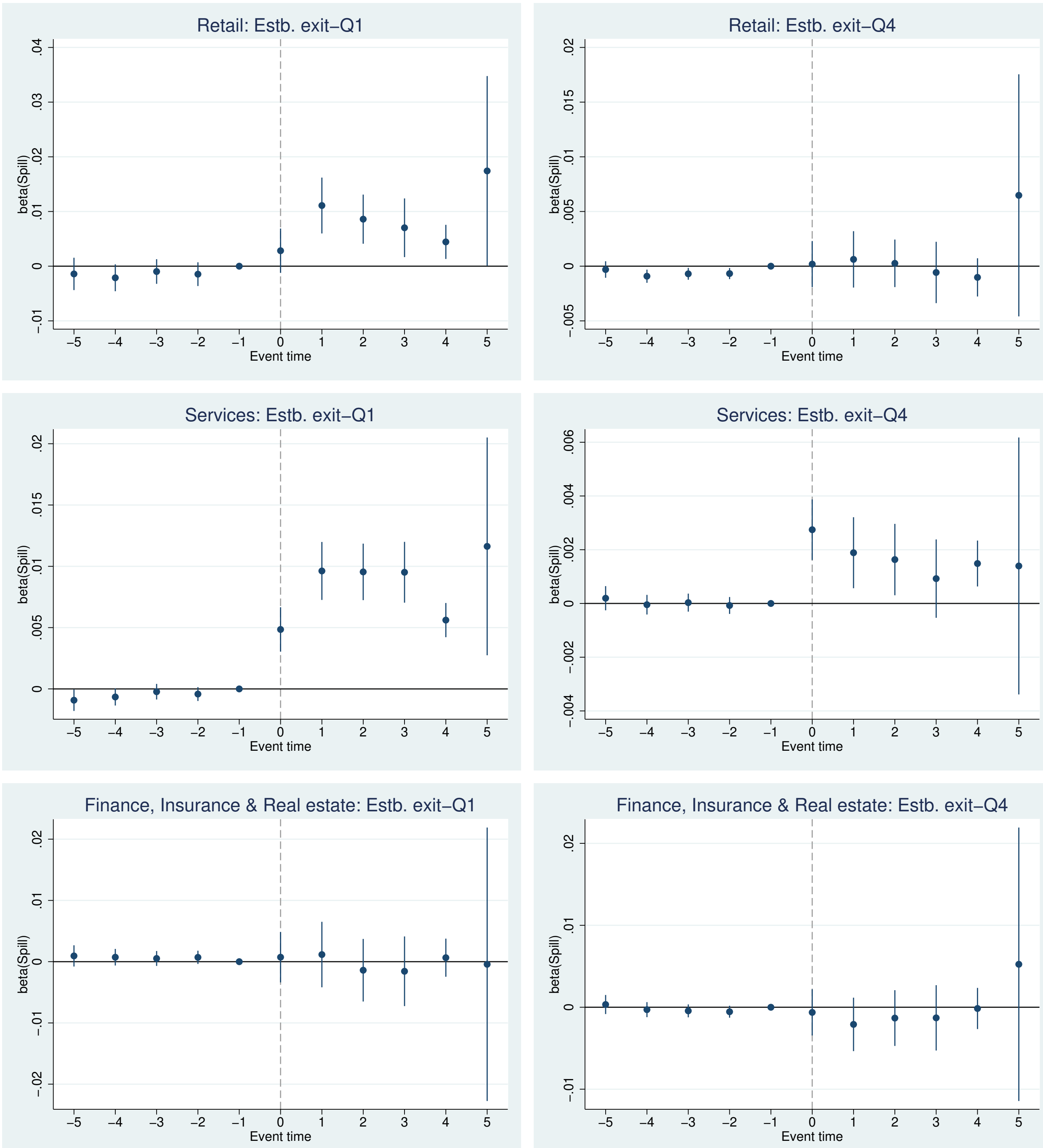
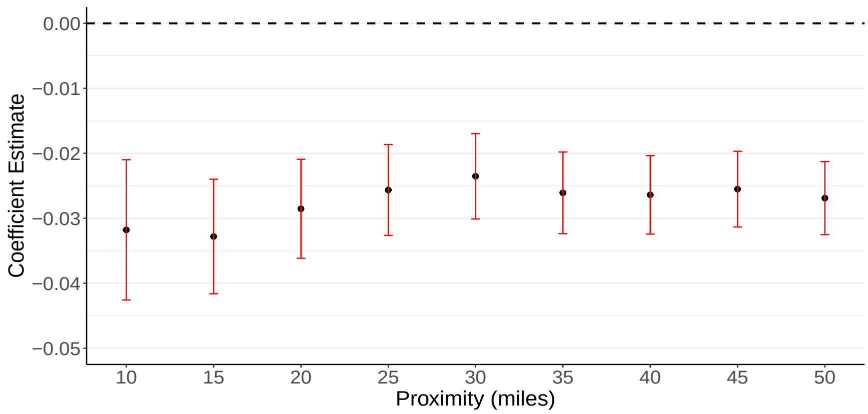


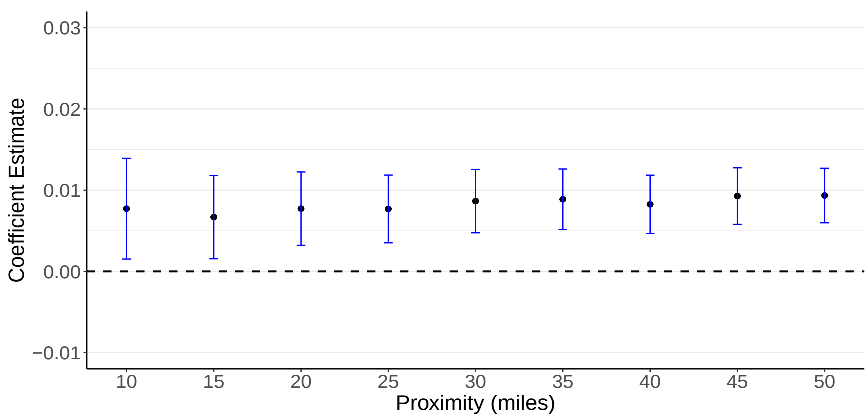
Figure 5: Effects of Pollution Shocks on Small Businesses: Varying Treatment Radius

This figure shows how the effect of major toxic chemical spills on sales, employment, establishment exit of small manufacturing and mining businesses varies with treatment radius centered around incident locations. We estimate regression (1) and report the coefficient estimates on $Spill_{k,t-}$ with respect to a range of treatment radius from 10 miles to 50 miles with their 95% confidence intervals represented by the error bars. The dependent variables are Log(Sales), Log(#Employees), and Exit in Panel (a), (b), and (c), respectively.

(a) Sales



(b) Employment



(c) Establishment Exit

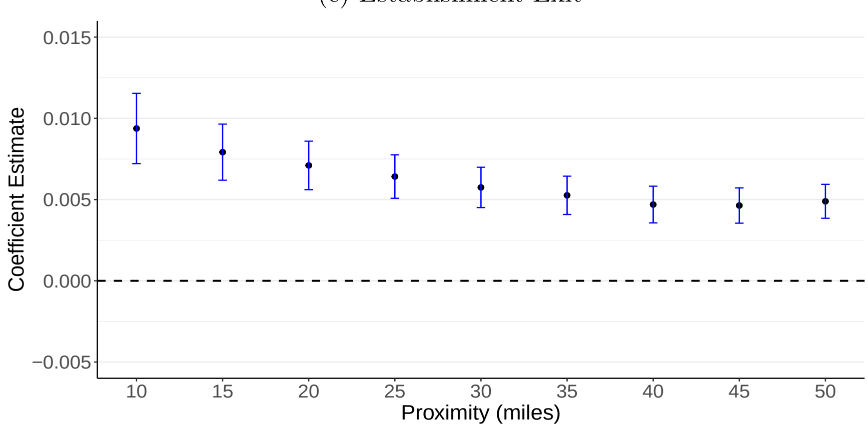


Figure 6: Effects of Pollution Shocks on Small Businesses: Varying Treatment Evacuations

This figure shows how the effect of toxic chemical spills on sales, employment, establishment exit of small manufacturing and mining businesses within a 25-mile radius varies with the number of people evacuated associated with the toxic chemical spills. We estimate regression (1) and report the coefficient estimates on $Spill_{k,t-}$ with respect to a range of number of evacuations from 400 to 1600 with their 95% confidence intervals represented by the error bars. The dependent variables are Log(Sales), Log(#Employees), and Exit in Panel (a), (b), and (c), respectively.

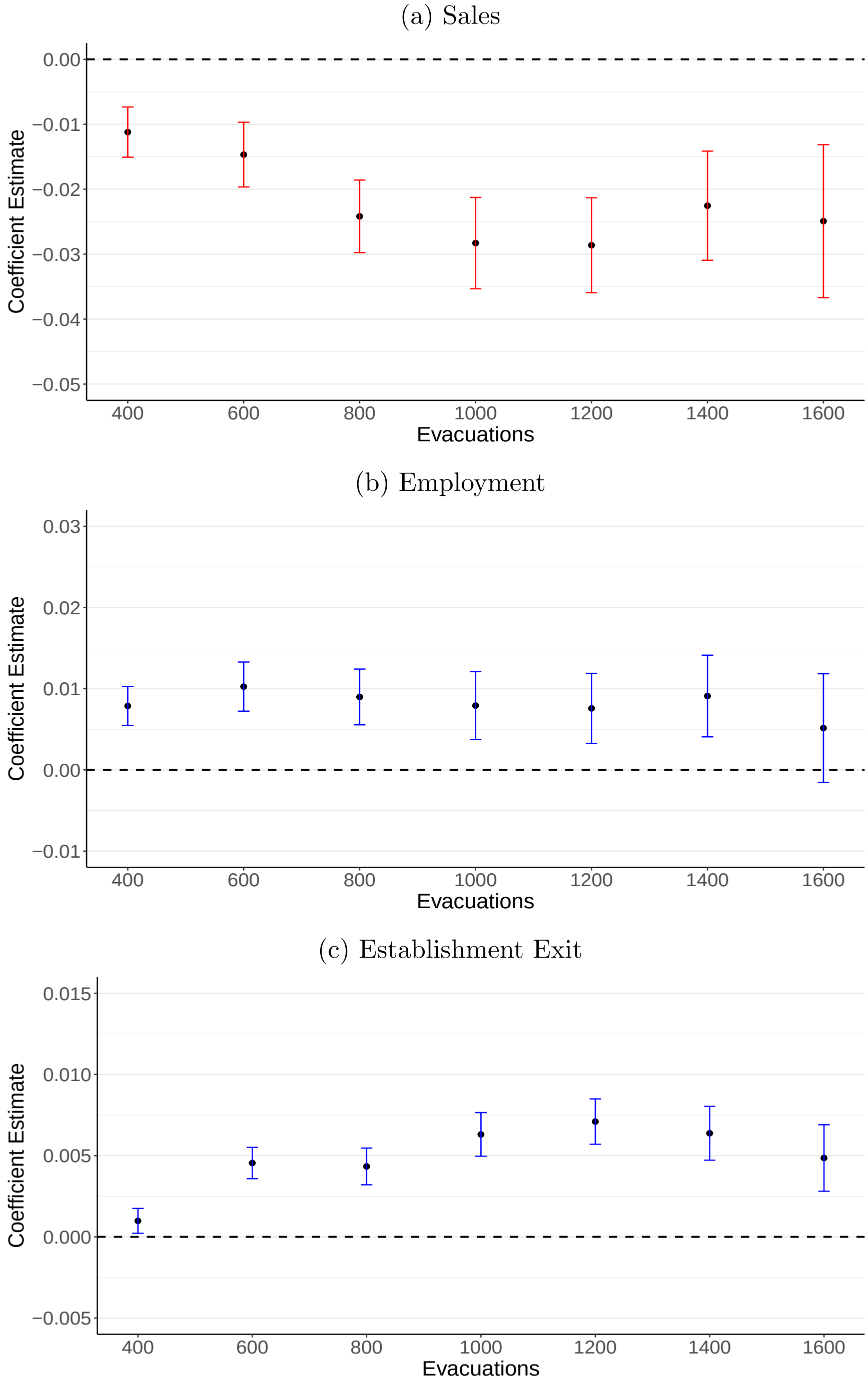


Table 1: Summary Statistics– Toxic Chemical Spills

This table reports summary statistics of toxic chemical spills. Panel A reports summary statistics of toxic chemical spills that caused evacuations (evacuation spills hereafter). Panel B separately reports the proportion of evacuation spills by the type of installation from which the spill occurred, the party who is held responsible for the incident, the pollution propagation medium of the spill, and the physical aftermath of incidents. Panel C reports characteristics of "major toxic chemical spills", defined as spills that led to the evacuation of at least 900 people. There are 24 major toxic chemical spills in the U.S. during the period 2010-2018. For each of them, we report the incident date, location, number of people evacuated, casualties (collective number of injuries or fatalities), pollution medium, type of facility at which the incident occurs, and responsible party type.

Panel A: Summary Statistics of Evacuation Spills

	Mean	P10	Median	P90	P95	P99	N
# evacuations	89.86	3	25	200	408	938	2,163
# injuries	0.44	0	0	1	2	7	2,163
# fatalities	0.02	0	0	0	0	1	2,163

Panel B: Characteristics of Evacuation Spills

Incident Type	Proportion
Fixed Facility	63.7%
Storage Tank	10.6%
Pipeline	9.3%
Mobile	4.0%
Railroad	2.9%
Vessel	2.4%
Unknown/Other	7.1%

Responsible Party	Proportion
Private Enterprise	68.5%
Public Utility	3.0%
Government	2.9%
Private Citizen	2.1%
Unknown/Other	23.5%

Medium	Proportion
Air	65.0%
Land	8.5%
Water	5.4%
Soil	1.0%
Unknown/Other	20.1%

Aftermath	Proportion
Injuries	13.3%
Fatalities	1.6%
Road Closure	12.3%
Major Artery Closure	2.5%
Track Closure	5.0%

Panel C: List of Major Toxic Chemical Spills							
No.	Date	Location	Evacuated	Casualties	Medium	Type	Responsible Party
1	2010-12-16	PASCAGOULA, MS	1400	0	AIR	FIXED	PRIVATE ENTERPRISE
2	2011-01-03	CUDAHY, WI	1500	0	AIR	FIXED	PRIVATE ENTERPRISE
3	2011-03-24	PARKER, CO	6000	0	LAND	FIXED	UNKNOWN
4	2011-04-03	SATANTA, KS	1100	0	OTHER	FIXED	UNKNOWN
5	2011-11-14	EAST SANDWICH, MA	900	1	AIR	FIXED	PRIVATE ENTERPRISE
6	2012-11-13	SALINA, KS	900	0	AIR	FIXED	PRIVATE ENTERPRISE
7	2013-04-17	WEST, TX	1800	151	OTHER	STORAGE TANK	UNKNOWN
8	2013-06-24	CHRISTIANSTED, VI	1000	0	AIR	MOBILE	PRIVATE ENTERPRISE
9	2014-04-23	MEMPHIS, TN	1425	0	OTHER	PIPELINE	UNKNOWN
10	2014-05-02	QUEENS, NY	1350	0	OTHER	RAILROAD	UNKNOWN
11	2014-05-27	ANTHONY, NM	1200	0	LAND	FIXED	PRIVATE ENTERPRISE
12	2014-06-17	TAR HEEL, NC	2000	0	AIR	FIXED	PRIVATE ENTERPRISE
13	2014-08-02	MIAMI, FL	2000	0	AIR	FIXED	UNKNOWN
14	2015-02-16	MT. CARBON, WV	2400	1	WATER	RAILROAD	PRIVATE ENTERPRISE
15	2015-05-28	BORGER, TX	1000	2	AIR	FIXED	PRIVATE ENTERPRISE
16	2015-11-11	NEW YORK, NY	4000	0	OTHER	RAILROAD	PRIVATE ENTERPRISE
17	2016-09-30	BROOKLYN, NY	1000	0	RAIL	RAILROAD	OTHER
18	2016-10-27	BROOKLYN, NY	1500	0	RAIL	RAILROAD	UNKNOWN
19	2017-03-08	SULPHUR, LA	1000	0	AIR	FIXED	UNKNOWN
20	2017-04-19	MIDWAY, TN	1000	0	AIR	FIXED	PRIVATE ENTERPRISE
21	2017-09-20	GOLDEN MEADOW, LA	3000	0	SOIL	MOBILE	PRIVATE ENTERPRISE
22	2018-02-06	AVONDALE, AZ	1000	1	AIR	FIXED	PRIVATE ENTERPRISE
23	2018-04-02	PORT EVERGLADES, FL	4000	0	OTHER	FIXED	UNKNOWN
24	2018-08-11	SCOTTSDALE, AZ	1000	0	WATER	FIXED	UNKNOWN

Table 2: Summary Statistics– Small Business Data

This table provides descriptive statistics for the small business establishment data. Panel A provides information on the number of establishments, total sales over the 2010-2018 period (in $ million), average annual employment (in '000), number of establishment exits, and the number of treated establishments separately for each industry group. For each of these variables, we also report (in square brackets) the industry group's percentage contribution to the aggregate total across all small business establishments. Panel B provides summary statistics for the establishment-year panel data, which spans the 2010-2018 period, includes information on 4.18 million small business establishments, and has one observation for each establishment-year combination. We provide these summary statistics separately for each industry group.

Panel A: Summary of Industry Groups

Variable	Establishments [%]	Total Sales [%]	Avg. Employment [%]	Estb. exit [%]	Treated Estb. [%]
All sectors	4,178,210	44,778,368	41,763,508	1,303,019	349,009
Manufacturing & Mining	345,413	6,910,925	4,679,291	100,813	24,617
(SIC 20-39, 10-14)	[8.27]	[15.43]	[11.20]	[7.74]	[7.05]
Construction	345,639	4,904,769	3,897,820	108,608	23,454
(SIC 15-17)	[8.27]	[10.95]	[9.33]	[8.34]	[6.72]
Wholesale	214,135	5,720,721	2,406,745	64,797	23,494
(SIC 50-51)	[5.13]	[12.78]	[5.76]	[4.97]	[6.73]
Retail	975,029	6,515,554	7,758,404	308,973	81,767
(SIC 52-59)	[23.34]	[14.55]	[18.58]	[23.71]	[23.43]
Services	2,055,716	17,502,780	20,682,584	639,265	171,970
(SIC 40-49, 70-89)	[49.20]	[39.09]	[49.52]	[49.06]	[49.27]
Finance, Insurance & Real estate	242,278	3,223,622	2,338,665	80,563	23,707
(SIC 60-65)	[5.80]	[7.20]	[5.60]	[6.18]	[6.79]

Panel B: Summary Statistics for Establishment-Year Panel

Variable	Mean	p25	Median	p75	SD	N
All sectors						
Sales	1.67	0.22	0.50	1.20	3.88	26,882,399
Employees	13.99	5.00	8.00	15.00	19.25	26,882,399
Estb. exit	0.05	0.00	0.00	0.00	0.21	27,084,204
Manufacturing & Mining						
(SIC 20-39, 10-14)						
Sales	3.24	0.45	1.00	3.00	5.70	2,130,552
Employees	19.76	6.00	10.00	21.00	25.48	2,130,552
Estb. exit	0.05	0.00	0.00	0.00	0.21	2,146,000
Construction						
(SIC 15-17)						
Sales	2.05	0.42	0.78	1.80	3.95	2,388,152
Employees	14.66	5.00	8.00	15.00	18.42	2,388,152
Estb. exit	0.05	0.00	0.00	0.00	0.21	2,407,043
Wholesale						
(SIC 50-51)						
Sales	3.86	0.65	1.40	3.80	6.17	1,482,596
Employees	14.62	5.00	8.00	15.00	18.55	1,482,596
Estb. exit	0.04	0.00	0.00	0.00	0.20	1,495,043
Retail						
(SIC 52-59)						
Sales	1.07	0.14	0.34	0.80	3.00	6,067,899
Employees	11.50	5.00	7.00	12.00	15.26	6,067,899
Estb. exit	0.05	0.00	0.00	0.00	0.22	6,112,412
Services						
(SIC 40-49, 70-89)						
Sales	1.32	0.20	0.43	0.96	3.24	13,256,645
Employees	14.06	5.00	7.00	14.00	19.84	13,256,645
Estb. exit	0.05	0.00	0.00	0.00	0.21	13,354,404
Finance, Insurance & Real estate						
(SIC 60-65)						
Sales	2.07	0.35	0.62	1.40	4.51	1,556,555
Employees	13.51	5.00	7.00	14.00	18.18	1,556,555
Estb. exit	0.05	0.00	0.00	0.00	0.22	1,569,302

Table 3: Summary statistics– Small Business Loans

This table summarizes the 7(a) small business loans approved and guaranteed by the Small Business Administration during the period 2010-2018. Loan amounts and guaranteed amounts are in thousands of dollars, the interest rate is in percentage, and the loan term is in months.

Variable	Mean	p25	Median	p75	SD	N
Loan characteristics						
Loan amount	374.76	40.00	125.00	357.70	669.09	494,385
SBA guaranteed amt.	277.23	21.30	80.07	270.00	513.39	494,385
Interest rate	6.43	5.50	6.00	7.25	1.50	494,385
Loan Term	121.25	84.00	84.00	120.00	79.89	494,385
Revolving	0.32	0.00	0.00	1.00	0.47	494,385
# jobs supported	10.73	2.00	4.00	11.00	20.27	494,385
Charge-off	0.05	0.00	0.00	0.00	0.22	494,385
Charge-off amt.	130.65	19.54	49.94	135.67	252.64	25,960
Borrower type						
Sole proprietor	0.11	0.00	0.00	0.00	0.31	494,385
Partnership	0.02	0.00	0.00	0.00	0.13	494,385
Corporation	0.87	1.00	1.00	1.00	0.33	494,385

Table 4: Effect of Pollution Shocks on Small Business Sales

This table reports the results of regressions investigating the effect of major toxic chemical spills on the sales of small business establishments located in the vicinity of the spills. Panel A presents the results of regression (1) with $log(Sales_{k,e,t})$ as dependent variable, estimated separately for each industry group. In each row, the first three columns present the coefficient on the $Spill_{k,t-}$ treatment dummy (with standard errors reported in parentheses below), the R^2 of the regression, and the number of observations, respectively, for that industry group. Columns (4) and (5) report the coefficients on the $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ dummies in a variant of regression (1) where we replace the $Spill_{k,t-}$ treatment dummy with these two dummies. In Panel B we sort establishments within each industry group into four size quartiles based on lagged sales, where Q1 (Q4) denotes the smallest (largest) size quartile, and estimate regression (1) separately for these different size categories. In each row, columns (1) through (4) report the coefficient on the $Spill_{k,t-}$ treatment dummy for size quartiles Q1 through Q4, respectively. We include cohort-establishment fixed effects and cohort-year fixed effects in all regressions, and control for firm age and lagged county-level GDP but suppress the coefficients on these control variables to conserve space. Standard errors reported in parentheses are clustered at the cohort-establishment level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Average Treatment Effects by Industry

	Log(Sales)				
	$\beta(Spill_{k,t-})$ (1)	R^2 (2)	Obs (3)	$\beta(Spill_{k,t-3:t})$ (4)	$\beta(Spill_{k,t-4+})$ (5)
Manufacturing & Mining	-0.025***	0.948	1,017,443	-0.026***	-0.019***
	(0.004)			(0.004)	(0.006)
Construction	0.010***	0.946	982,037	0.009**	0.027***
	(0.003)			(0.003)	(0.006)
Wholesale	0.019***	0.929	1,266,895	0.017***	0.046***
	(0.004)			(0.004)	(0.007)
Retail	-0.022***	0.955	2,046,408	-0.021***	-0.032***
	(0.002)			(0.002)	(0.004)
Services	-0.027***	0.937	6,336,707	-0.027***	-0.035***
	(0.002)			(0.002)	(0.003)
Finance, Insurance & Real estate	-0.001	0.940	1,098,767	-0.001	0.006
	(0.004)			(0.004)	(0.006)

Panel B: Average Treatment Effects by Industry and Size Quartile

	Log(Sales)			
	$\beta(Spill_{k,t-})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	-0.101***	-0.043***	-0.014**	0.056***
	(0.007)	(0.006)	(0.007)	(0.009)
Construction	-0.069***	0.007	0.032***	0.068***
	(0.007)	(0.006)	(0.007)	(0.008)
Wholesale	-0.062***	-0.022***	0.017**	0.141***
	(0.007)	(0.007)	(0.008)	(0.010)
Retail	-0.122***	-0.037***	0.012***	0.038***
	(0.005)	(0.003)	(0.003)	(0.005)
Services	-0.171***	-0.046***	0.009***	0.088***
	(0.003)	(0.002)	(0.003)	(0.004)
Finance, Insurance & Real estate	-0.087***	-0.032***	0.008	0.113***
	(0.007)	(0.006)	(0.007)	(0.009)

Table 5: Effect of Pollution Shocks on Small Business Employment

This table reports the results of regressions investigating the effect of major toxic chemical spills on the employment of small business establishments located in the vicinity of the spills. Panel A presents the results of regression (1) with $log(\#Employees_{k,e,t})$ as dependent variable, estimated separately for each industry group. In each row, the first three columns present the coefficient on the $Spill_{k,t-}$ treatment dummy (with standard errors reported in parentheses below), the R^2 of the regression, and the number of observations, respectively, for that industry group. Columns (4) and (5) report the coefficients on the $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ dummies in a variant of regression (1) where we replace the $Spill_{k,t-}$ treatment dummy with these two dummies. In Panel B we sort establishments within each industry group into four size quartiles based on lagged sales, where Q1 (Q4) denotes the smallest (largest) size quartile, and estimate regression (1) separately for these different size categories. In each row, columns (1) through (4) report the coefficient on the $Spill_{k,t-}$ treatment dummy for size quartiles Q1 through Q4, respectively. We include cohort-establishment fixed effects and cohort-year fixed effects in all regressions, and control for firm age and lagged county-level GDP but suppress the coefficients on these control variables to conserve space. Standard errors reported in parentheses are clustered at the cohort-establishment level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Average Treatment Effects by Industry

	Log(#Employees)				
	$\beta(Spill_{k,t-})$ (1)	R^2 (2)	Obs (3)	$\beta(Spill_{k,t-3:t})$ (4)	$\beta(Spill_{k,t-4+})$ (5)
Manufacturing & Mining	0.007***	0.959	1,017,443	0.006***	0.014***
	(0.002)			(0.002)	(0.004)
Construction	0.010***	0.947	982,037	0.009***	0.016***
	(0.002)			(0.002)	(0.004)
Wholesale	0.007***	0.950	1,266,895	0.007***	0.014***
	(0.002)			(0.002)	(0.003)
Retail	-0.001	0.959	2,046,408	0.000	-0.001
	(0.001)			(0.001)	(0.002)
Services	0.003***	0.944	6,336,707	0.003***	0.002
	(0.001)			(0.001)	(0.002)
Finance, Insurance & Real estate	0.006***	0.953	1,098,767	0.006***	0.011***
	(0.002)			(0.002)	(0.004)

Panel B: Average Treatment Effects by Industry and Size Quartile

	Log(#Employees)			
	$\beta(Spill_{k,t-})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	-0.013***	0.003	0.008**	0.029***
	(0.004)	(0.003)	(0.004)	(0.005)
Construction	-0.032***	0.021***	0.032***	0.016***
	(0.005)	(0.004)	(0.004)	(0.005)
Wholesale	-0.013***	0.008***	0.007**	0.027***
	(0.004)	(0.003)	(0.004)	(0.005)
Retail	-0.034***	0.005**	0.010***	0.011***
	(0.003)	(0.002)	(0.002)	(0.003)
Services	-0.037***	-0.004**	0.019***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)
Finance, Insurance & Real estate	-0.009**	0.001	0.019***	0.013**
	(0.004)	(0.003)	(0.004)	(0.005)

Table 6: Effect of Pollution Shocks on Small Business Exit

This table reports the results of regressions investigating the effect of major toxic chemical spills on the employment of small business establishments located in the vicinity of the spills. Panel A presents the results of regression (1) with $Exit_{k,e,t}$ as dependent variable, estimated separately for each industry group. In each row, the first three columns present the coefficient on the $Spill_{k,t-}$ treatment dummy (with standard errors reported in parentheses below), the R^2 of the regression, and the number of observations, respectively, for that industry group. Columns (4) and (5) report the coefficients on the $Spill_{k,t-3:t}$ and $Spill_{k,t-4+}$ dummies in a variant of regression (1) where we replace the $Spill_{k,t-}$ treatment dummy with these two dummies. In Panel B we sort establishments within each industry group into four size quartiles based on lagged sales, where Q1 (Q4) denotes the smallest (largest) size quartile, and estimate regression (1) separately for these different size categories. In each row, columns (1) through (4) report the coefficient on the $Spill_{k,t-}$ treatment dummy for size quartiles Q1 through Q4, respectively. We include cohort-establishment fixed effects and cohort-year fixed effects in all regressions, and control for firm age and lagged county-level GDP but suppress the coefficients on these control variables to conserve space. Standard errors reported in parentheses are clustered at the cohort-establishment level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Average Treatment Effects by Industry

	Estb. exit				
	$\beta(Spill_{k,t-})$ (1)	R^2 (2)	Obs (3)	$\beta(Spill_{k,t-3:t})$ (4)	$\beta(Spill_{k,t-4+})$ (5)
Manufacturing & Mining	0.006***	0.343	1,017,443	0.007***	0.004***
	(0.001)			(0.001)	(0.001)
Construction	0.003***	0.341	982,037	0.003***	0.001
	(0.001)			(0.001)	(0.001)
Wholesale	0.004***	0.341	1,266,895	0.004***	0.002***
	(0.001)			(0.001)	(0.001)
Retail	0.004***	0.393	2,046,408	0.004***	0.003***
	(0.001)			(0.001)	(0.001)
Services	0.004***	0.349	6,336,707	0.004***	0.003***
	(0.000)			(0.000)	(0.000)
Finance, Insurance & Real estate	0.001**	0.337	1,098,767	0.001**	0.002**
	(0.001)			(0.001)	(0.001)

Panel B: Average Treatment Effects by Industry and Size Quartile

	Estb. exit			
	$\beta(Spill_{k,t-})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	0.010***	0.008***	0.005***	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
Construction	0.003**	0.004***	0.003*	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Wholesale	0.005***	0.006***	0.003***	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Retail	0.008***	0.007***	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Services	0.008***	0.004***	0.002***	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
Finance, Insurance & Real estate	-0.001	0.006***	0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)

Table 7: Effect of Pollution Shocks on Small Business Lending

This table reports the results of regression (3) aimed at investigating the effect of major toxic chemical spills on the availability and price of SBA loans to small businesses located in the vicinity of these spills. Each row in the table corresponds to a different outcome variable of interest ($Y_{l,t}$). The first three columns report the coefficient on the $Spill_{l,t-}$ treatment dummy, the R^2 of the regression, and number of observations, respectively. Columns (4) and (5) report the coefficients on the $Spill_{l,t-3:t}$ and $Spill_{l,t-4+}$ dummies in a variant of regression (3) where we replace the $Spill_{l,t-}$ treatment dummy with these two dummies. We include NAICS-3×Year fixed effects and Bank×Year fixed effects in all regressions, and control for the logarithm of lagged county-level GDP but suppress the coefficient on this variable to conserve space. Standard errors in parentheses are clustered at the borrower and year level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\beta(Spill_{l,t-})$ (1)	R^2 (2)	Obs (3)	$\beta(Spill_{l,t-3:t})$ (4)	$\beta(Spill_{l,t-4+})$ (5)
Log(Loan amt.)	-0.028***	0.400	482,043	-0.085***	0.002
	(0.008)			(0.020)	(0.009)
SBA guaranteed fraction	-0.004***	0.492	482,043	-0.007**	-0.001
	(0.001)			(0.002)	(0.001)
Interest	0.052***	0.427	482,043	0.084**	0.029***
	(0.010)			(0.028)	(0.008)
Term	-0.020***	0.300	481,891	-0.043***	-0.006
	(0.004)			(0.012)	(0.004)
Charge-off	0.006***	0.058	482,043	0.007	0.005***
	(0.001)			(0.004)	(0.001)
Log(Charge-off amt.)	0.014	0.491	23,294	0.004	0.015
	(0.016)			(0.049)	(0.014)

Table 8: Effect of Pollution Shocks on Countywide Small Business Activity

This table reports the results of regressions investigating the effects of major toxic chemical spills on aggregate small business activity at the county-year level. Accordingly, we estimate a variant of regression (1) on a stacked county-year matched panel data set, where the $Spill_{c,t-}$ treatment indicator identifies counties that are exposed to major toxic chemical spills. Each row in the table corresponds to a different outcome variable of interest ($Y_{c,e,t}$). The first three columns report the coefficient on the $Spill_{c,t-}$ treatment dummy, the R^2 of the regression, and number of observations, respectively. Columns (4) and (5) report the coefficients on the $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$ dummies in a variant of regression (1) where we replace the $Spill_{c,t-}$ treatment dummy with these two dummies. We include cohort-county fixed effects and cohort-year fixed effects in all regressions, and control the regression for lagged county GDP but suppress the coefficient on this variable to conserve space. Standard errors in parentheses are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\beta(Spill_{c,t-})$ (1)	R^2 (2)	Obs (3)	$\beta(Spill_{c,t-3:t})$ (4)	$\beta(Spill_{c,t-4+})$ (5)
OLS:					
Log(Aggregate Sales)	-0.108*	0.994	1,236	-0.117**	-0.047
	(0.058)			(0.056)	(0.104)
Log(Aggregate #Employees)	-0.002	0.999	1,236	-0.011	0.062
	(0.020)			(0.020)	(0.053)
Poisson:					
# Estb. exits	0.115***	0.985	1,122	0.115***	0.075
	(0.038)			(0.038)	(0.076)
# Bankruptcies	0.344***	0.892	1,159	0.322***	0.494***
	(0.090)			(0.084)	(0.182)
# Estb. entries	0.085*	0.971	1,092	0.104**	-0.014
	(0.047)			(0.046)	(0.098)

Table 9: Effect of Pollution Shocks on Countywide SBA Lending

This table reports the results of regressions investigating the effects of major toxic chemical spills on aggregate SBA lending at the county-year level. Accordingly, we estimate a variant of regression (1) on a stacked county-year matched panel data set, where the $Spill_{c,t-}$ treatment indicator identifies counties that are exposed to major toxic chemical spills. Each row in the table corresponds to a different outcome variable of interest ($Y_{c,t}$). The first three columns report the coefficient on the $Spill_{c,t-}$ treatment dummy, the R^2 of the regression, and number of observations, respectively. Columns (4) and (5) report the coefficients on the $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$ dummies in a variant of regression (1) where we replace the $Spill_{c,t-}$ treatment dummy with these two dummies. We include cohort-county fixed effects and cohort-year fixed effects in all regressions, and control the regression for lagged county GDP but suppress the coefficient on this variable to conserve space. Standard errors in parentheses are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\beta(Spill_{c,t-})$ (1)	R^2 (2)	Obs (3)	$\beta(Spill_{c,t-3:t})$ (4)	$\beta(Spill_{c,t-4+})$ (5)
Log(1+# approvals)	-0.122**	0.984	1,236	-0.121**	-0.127
	(0.055)			(0.057)	(0.078)
Log(Total amt.)	-0.649*	0.851	1,236	-0.654*	-0.616
	(0.350)			(0.363)	(0.478)
Log(Charge-off amt.)	-0.191	0.793	642	-0.197	-0.141
	(0.231)			(0.236)	(0.316)
# Charge-offs	0.173	0.678	861	0.154	0.272
	(0.118)			(0.108)	(0.191)

Table 10: Effect of Pollution Shocks on Countywide Tax Base

This table reports the results of regressions investigating the effects of major toxic spills on the tax filing population at the county-year level. Accordingly, we estimate a variant of regression (1) on a stacked county-year matched panel data set, where the $Spill_{c,t-}$ treatment indicator identifies counties that are exposed to major toxic spills. Each row in the table corresponds to a different outcome variable of interest ($Y_{c,e,t}$). The first three columns report the coefficient on the $Spill_{c,t-}$ treatment dummy, the R^2 of the regression, and the number of observations, respectively. Columns (4) and (5) report the coefficients on the $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$ dummies in a variant of regression (1) where we replace the $Spill_{c,t-}$ treatment dummy with these two dummies. We include cohort-county fixed effects and cohort-year fixed effects in all regressions, and control the regression for lagged county GDP but suppress the coefficient on this variable to conserve space. Standard errors in parentheses are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\beta(Spill_{c,t-})$ (1)	R^2 (2)	Obs (3)	$\beta(Spill_{c,t-3:t})$ (4)	$\beta(Spill_{c,t-4+})$ (5)
Net County-to-County Migration					
Net # Tax Filings ('000)	-12.322***	0.810	1,236	-11.313***	-19.302**
	(4.429)			(4.204)	(8.442)
Net Adj. Gross Income ($M)	-845.355**	0.855	1,236	-806.245**	-1115.966
	(400.184)			(367.701)	(782.950)
Aggregate County-level Income					
Log(# Tax Filings in Income Bracket)					
$AGI \leq \$50,000$	-0.006	1.000	1,236	-0.009	0.011
	(0.012)			(0.012)	(0.016)
$\$50,000 < AGI \leq \$100,000$	0.056*	0.998	1,236	0.054	0.068
	(0.033)			(0.033)	(0.044)
$AGI > \$100,000$	-0.081*	0.988	1,236	-0.076*	-0.119
	(0.044)			(0.041)	(0.079)
Log(Total AGI in Income Bracket ('000))					
$AGI \leq \$50,000$	-0.071	0.997	1,230	-0.078	-0.024
	(0.052)			(0.053)	(0.038)
$\$50,000 < AGI \leq \$100,000$	0.057*	0.998	1,236	0.056*	0.067
	(0.033)			(0.032)	(0.046)
$AGI > \$100,000$	-0.071**	0.996	1,236	-0.069**	-0.089**
	(0.030)			(0.029)	(0.039)
Adj. Gross Income (AGI) in ('000)/# Filings	-2.166**	0.983	1,236	-2.031**	-3.101**
	(0.932)			(0.937)	(1.249)

A Appendix

Table A.1: Effect of Pollution Shocks on Small Business Sales and Employment Growth

This table reports the results of regressions investigating the effect of major toxic chemical spills on the sales and employment growth of small business establishments located in the vicinity of the spills. Panel A presents the results of regression (1) with $log(Sales_{k,e,t}/Sales_{k,e,t-1})$ as the dependent variable, estimated separately for each industry group. We sort establishments within each industry group into four size quartiles based on lagged sales, where Q1 (Q4) denotes the smallest (largest) size quartile, and estimate the regression. In each row, columns (1) through (4) report the coefficient on the $Spill_{k,t-}$ treatment dummy for size quartiles Q1 through Q4, respectively. Panel B presents the results of regression (1) with $log(\#Employees_{k,e,t}/\#Employees_{k,e,t-1})$ as the dependent variable. We include cohort-establishment fixed effects and cohort-year fixed effects in all regressions, and control for firm age and lagged county-level GDP but suppress the coefficients on these control variables to conserve space. Standard errors reported in parentheses are clustered at the cohort-establishment level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Treatment Effects on Sales Growth by Industry and Size Quartile

	$log(Sales_{k,e,t}/Sales_{k,e,t-1})$			
	$\beta(Spill_{k,t-})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	-0.010***	-0.002	0.000	0.005*
	(0.003)	(0.002)	(0.003)	(0.003)
Construction	-0.007***	-0.002	-0.001	0.010***
	(0.003)	(0.002)	(0.002)	(0.003)
Wholesale	-0.003	0.005**	0.017***	0.033***
	(0.003)	(0.003)	(0.003)	(0.003)
Retail	-0.031***	-0.011***	0.004***	0.012***
	(0.002)	(0.001)	(0.001)	(0.002)
Services	-0.028***	-0.007***	0.004***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)
Finance, Insurance & Real estate	-0.015***	-0.001	0.002	0.018***
	(0.002)	(0.002)	(0.002)	(0.003)

Panel B: Treatment Effect on Employment Growth by Industry and Size Quartile

	$log(\#Employees_{k,e,t}/\#Employees_{k,e,t-1})$			
	$\beta(Spill_{k,t-})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	0.004**	0.002	0.002	0.006***
	(0.002)	(0.001)	(0.001)	(0.002)
Construction	0.010***	0.001	-0.004**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Wholesale	0.003*	0.002**	0.003**	-0.002
	(0.002)	(0.001)	(0.001)	(0.002)
Retail	-0.008***	-0.002*	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Services	0.004***	0.003***	0.001*	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Finance, Insurance & Real estate	0.002*	0.006***	0.004***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)

Table A.2: Balance Tests

This table reports balance tests that examine the closeness of treated and control establishments in our sample obtained via the nearest-neighbor matching method. We report the Standardized Mean Difference (SMD) and Variance Ratios (VR) of covariates in our matching equation. We report the average SMD and VR across the industries in our sample; the standard deviation of these statistics is reported in parentheses.

Covariate	Standardized Mean Difference (SD)	Variance Ratio (SD)
Log(Sales$_{k,e,t-1}$)	-0.05	0.80
	(0.03)	(0.14)
Log(#Employees$_{k,e,t-1}$)	-0.03	0.83
	(0.02)	(0.09)
Log(Age$_{k,e,t-1}$)	0.02	0.85
	(0.04)	(0.04)
GDP$_{k,e,t-1}$	-0.01	0.67
	(0.24)	(0.10)
GDP growth$_{k,e,t-1}$	-0.01	0.36
	(0.09)	(0.04)