Environmental Pollution and Business Activity: Evidence From Toxic Chemical Spills*

George Zhe Tian† Buvaneshwaran Venugopal‡ Vijay Yerramilli§

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Abstract

We use major toxic chemical spills as pollution shocks to their local neighborhoods and examine the consequent effects on local business activity. A key finding is that pollution shocks contribute to increases in business concentration in their local economy because of their disproportionate adverse effect on smaller establishments which works to the advantage of larger establishments. Specifically, in every sector, establishments in the smallest size quartile experience significant increases in the likelihood of exit, a large reduction in sales, and a modest reduction in employment following exposure to major spills, whereas those in the largest size quartile actually experience increases in sales and employment, and do not face an increased likelihood of exit. We identify two likely explanations for these persistent adverse effects on local business activity: worsening of credit frictions and migration of population and income away from counties exposed to major toxic chemical spills.

Keywords: Pollution, Toxic Chemical Spills, Business Concentration, Credit Frictions, Business Exits

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†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 local business activity. In this paper, we show that major toxic chemical spills have persistent adverse effects on local business activity, and may contribute to increase in business concentration in their local economy because of their disproportionate adverse effects on smaller establishments which actually work to the advantage of 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 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

[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.

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

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. Moreover, given these risks, banks may reduce their lending in areas affected by toxic chemical spills. 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 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 business activity.

We collect data on business establishments across the U.S. from Mergent Intellect, a business intelligence aggregator of company profiles. Our sample includes over 5.3 million 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 National Response Center (NRC). Among other details, the database contains each incident's date of occurrence, location, responsible party, pollution medium,

[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.

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 business establishment 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 likelihood of exit, sales, and employment of local businesses. In contrast to the standard two-way fixed effects (TWFE) DiD regression, the stacked regression approach allows for comparison of treated business establishments with better comparable control establishments, 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.

We begin by examining the effect of toxic chemical spills on the *extensive margin* of business activity, that is, the likelihood of exit of local business establishments, where the exit may occur due to the following reasons that we cannot distinguish: bankruptcy, closure, or acquisition by another business. We find that these pollution shocks have an economically significant and persistent positive effect on the likelihood of exit of local business establishments across all sectors, which highlights the long-term adverse effects of these transitory accidental shocks on local business activity. When we sort business establishments within each sector into four quartiles based on size, we find that the positive effect of pollution shocks on the likelihood of exit decreases monotonically with size in all sectors: it is strongest for establishments in the smallest size quartile, and is either absent or economically insignificant for establishments in the largest size quartile. Thus, pollution shocks have a disproportionately adverse effect on the survival of smaller business establishments, and are likely to contribute to increase in business concentration in their local economies.

Turning to the *intensive margin* of business activity, we uncover a striking contrast in how establishments of different sizes are affected differently by major toxic chemical spills. Across all sectors, establishments in the two smallest size quartiles experience large reduction in sales following exposure to major toxic chemical spills, whereas establishments in the largest size quartile actually experience increase in sales. These contrasting results highlight the redistributive effects of pollution shocks on local business activity: the smallest establishments experience large adverse effects 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 sectors: for instance, in the services sector, establishments in the smallest size quartile experience a 27.5% reduction in sales whereas those in the largest size quartile experience a 2.7% increase in sales after being exposed to major toxic chemical spills. We find similar redistributive effects, albeit smaller in size, when we examine the effects of these pollution shocks on establishment-level employment.

We hypothesize that there are two potential channels through which the effects we document above may arise. First, banks may reduce their lending in areas affected by toxic chemical spills, which leads to a disproportionate adverse effect on smaller businesses that rely more on bank credit (the "credit friction" channel). Second, the health risk perceptions and stigma associated with these spills may cause an out-migration of households, especially higher-income households, from surrounding areas which leads to persistent adverse effects on local businesses (the "population exodus" channel). We find empirical support for both these channels in our setting.

We find support for the credit friction channel in two ways. First, we use a loan-level database of Small Business Administration (SBA) 7(a) loans to show that loan characteristics (other than amount) change in a manner that is consistent with a tighter supply of credit to treated small business borrowers. Specifically, all else equal, loans to treated borrowers have a smaller fraction guaranteed by the SBA, higher interest rates, and shorter maturity. Second, we show that toxic chemical spills have more adverse effects on treated businesses that face stronger credit market frictions ex-ante. For this test, we rely on findings in prior research that private businesses face stronger credit frictions if they are located in banking markets dominated by large banks (e.g., Berger et al. 2005) and if they are located farther away from bank branches (Degryse and Ongena 2005; Agarwal and Hauswald 2010).

To test for the population exodus channel, we measure the net gain/loss in the number of tax filings and aggregate adjusted gross income (AGI) at the county-year level using data from the Internal Revenue Service's (IRS) Statistics of Income (SOI) database. 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.) Consistent with the population exodus hypothesis, we find that treated counties suffer large and persistent declines in the number of tax filings and aggregate AGI in the post-treatment years compared to similar control counties. Moreover, the treated counties also experience strong and persistent declines in the average taxable income per filing (i.e., the ratio of aggregate AGI to the number of tax filings in the county) in the post-treatment years, especially in the higher-income brackets, which indicates that there is greater out-migration of higher-income residents than lower-income residents from the affected counties.

Given our evidence that major toxic chemical spills redistribute sales and employment from smaller to larger business establishments, it is natural to ask: what happens to the *aggregate* business activity and business concentration in counties exposed to such spills? To address this question, we create a county-sector-year panel dataset of business activity by aggregating establishment-level data within each sector and year at the county level. We find that, compared to similar control counties that were not exposed to major toxic chemical spills, treated counties experience large declines in aggregate sales in all sectors, and significant increases in business concentration in many sectors. We also find evidence of decreases in aggregate employment and increase in business exits in a few sectors in the post-spill period.[5] These pollution shocks have no significant effects on new business entries, except in the retail sector where we detect a positive effect. Finally, using data collected under the Community Reinvestment Act (CRA), we show that treated counties experience a significant decline in aggregate small business lending compared to similar control counties in the post-spill period.

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 has 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 business activity. An important takeaway is that pollution shocks 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

[5] An important caveat to the weaker effect on aggregate employment compared to aggregate sales is that we only have information on the number of employees at each establishment but do not have information on hours of employment. Hence, we cannot rule out the possibility that there was a decline in the aggregate hours of employment in treated counties.

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 also have implications for the debate 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 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.

Business Establishments: We collect data on 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.

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 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)). We are able to assemble an establishment-year panel data which spans the 2010–2018 period and includes information on over 5.3 million business establishments.

Small Business Lending: We obtain information on small-business lending from two sources. We obtain loan-level information from the Small Business Administration (SBA)

7(a) Loan Guarantee Program, which is the SBA's 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.

To examine lending outcomes at the county level, we leverage small business lending data collected under the Community Reinvestment Act (CRA). The CRA defines small business loans as commercial and industrial loans of $1 million or less. All depository institutions above a certain asset threshold (e.g., $1.252 billion in 2018) must report the geographic distribution of their small business loans. The CRA data is the most comprehensive data on small business lending and covers approximately 86% of all loans under $1 million (Greenstone et al. 2020).

Bank Branches and Deposits: We obtain branch-level bank deposits data from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) data which is collected through an annual survey of all FDIC-insured depository institutions. The survey collects information on branch characteristics such as total deposits, information on parent banks, and detailed addresses as of June 30th of each year. The data covers the universe of US bank branches and spans from 1994 until 2018.

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

[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.

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.

The migration data is based on address changes reported on individual income tax returns filed with the IRS. This allows us to measure the net gain/loss in the number of tax filings and aggregate AGI at the county-year level.

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 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 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 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.

Business Establishments

We provide descriptive statistics for the 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. For instance, we group finance, insurance & real estate (henceforth, FIRE) industries together because of their similarity. (We group mining with manufacturing because there are very few 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 business establishments.

We have information on over 5.33 million business establishments across all sectors, which generated aggregate sales of $74.13 trillion and average annual employment of 56.82 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 (48.5%), sales (40%) and employment (49.7%). 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, 434,388 establishments (or 8.14% of all establishments) are exposed to major toxic chemical spills during this time period. The proportions of treated establishments in the various sectors are roughly in line with their percentage shares of establishments reported in column (1). For instance, the services sector accounts for 48.5% of all establishments and 49% of treated establishments, and similarly for other industry groups.

The establishments in our sample may belong to either publicly listed firms or private firms. Moreover, private firms can be further subdivided into two categories: those that employ 500 or fewer employees across all their establishments, which is a commonly-used definition of a "small business";[7] and those that employ more than 500 employees. We

[7]This definition, which is used by the Office of Advocacy of the U.S. Small Business Administration (SBA), 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

provide this three-way break-up of our sample in Panel B. As can be seen, across all sectors combined, only 1.1% of establishments belong to publicly-listed firms, 62.2% belong to private firms that are commonly classified as small businesses, and 36.7% belong to private firms that employ more than 500 people (although some of these may also be classified as small businesses based on alternative industry-specific definitions employed by SBA and other government agencies).

We use the Mergent data to create an (unbalanced) establishment-year panel data set, which spans the 2010–2018 period, includes information on 5.33 million establishments, and has one observation for each establishment-year combination. We provide sector-wise summary statistics for this panel data set in Panel C. As expected, the distribution of annual sales and employees is highly skewed: while the median establishment has \$0.48 million in sales and 7 employees, the average values of sales and number of employees are \$2.27 million and 15.67, respectively. 6.27% of establishments exit the panel each year. Recall that exit may be due to bankruptcy, business closure, or acquisition by another business.

2 Empirical Methodology

Our empirical framework uses major toxic chemical spills as shocks to the pollution risk of their local neighborhoods and examines the consequent effect of these shocks on local business activity. 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 business activity. 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.

and over time. Please see https://www.sba.gov/sites/default/files/advocacy/SB-FAQ-2016_WEB.pdf for details.

First, we match each treated business establishment that is exposed to a major toxic chemical 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 and employment, and is similar to the treated firm (in case of multi-establishments firms) in terms of overall firm 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 315,547 establishments out of the 434,388 treated establishments in our sample.[8] In Table A.1 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 establishments in each cohort, we construct establishment-year panels over the ±5-year period around the year 't' in which the treated establishment experienced 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

[8]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.

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:

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

where 'k' refers to an establishment, 'e' indexes the treatment-control cohort, and 't' denotes the year. The outcome variable of interest, $Y_{k,e,t}$, is one of the following: $Exit_{k,e,t}$ which is an indicator variable to identify if establishment k exits our panel in cohort e and year t; $log(Sales_{k,e,t})$ which is the natural logarithm of sales of establishment k in cohort e and year t; and $log(\#Employees_{k,e,t})$ which is the natural logarithm of the number of employees of establishment k in cohort e and year t.

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. 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 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,[9] 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).

[9]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 Business Activity

In this section, we use regression (1) to examine the effects of pollution shocks resulting from major toxic chemical spills on individual business establishments.

3.1 Effects on Likelihood of Exit

We begin by examining the effects of major toxic chemical spills on the *extensive margin* of business activity, namely, the likelihood of exit of establishments located in the vicinity of the spill. Accordingly, we estimate regression (1) with $Exit_{k,e,t}$ as the dependent variable. Recall that $Exit_{k,e,t}$ is an indicator variable to identify that establishment k exited our sample in year t, where the exit may be due to bankruptcy, business closure, or acquisition by another business. 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 results of these regressions in Table 3.

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 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 local business establishments in all sectors. These effects are economically significant: for instance, the coefficient estimate for the services sector indicates that business establishments are 1.6% 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 C of Table 2). This effect is also persistent in the long run in all sectors as evidenced by the positive and significant coefficients on the $Spill_{k,t-4+}$ dummy in column (5).

Next, we sort establishments within each sector into four size quartiles (based on sales) one year before the treatment year, 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 indicate that the effect of pollution shocks on the likelihood of small business exit is strongest for establishments in the smallest size quartile (Q1), and the effect decreases monotonically as we move from column Q1 to column Q4. Indeed, in most sectors, there is no effect of these pollution shocks on the likelihood of exit for establishments in the largest size quartile (Q4); the only exceptions are the services sector where the effect is positive but small, and the finance, insurance & services sector for which the effect is negative but small. These findings imply that toxic chemical spills have a disproportionately adverse effect on the survival of smallest business establishments, and are likely to contribute to increase in business concentration in the surrounding areas.

Figure 2 presents the results of regression (2) with $Exit_{k,e,t}$ as dependent variable aimed at estimating the year-by-year treatment effects on the likelihood of 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 3, we find that the positive effect of pollution shocks on the likelihood of exit is stronger among Q1-establishments compared to Q4-establishments in all sectors. Moreover, in most sectors, the increase in likelihood of exit for Q1-establishments after exposure to major toxic chemical spills is highly persistent over time; e.g., it is evident that the likelihood of exit for treated Q1-establishments in the retail sector and the services sector remains high even

5 years after exposure to the spill. By contrast, the effect is comparatively short-lived for Q1-establishments in the wholesale sector and the finance, insurance & real estate sector.

3.2 Effects on Sales and Employment

Next, we examine the effects major toxic chemical spills on the *intensive margin* of business activity, namely, the sales and employment of establishments located in the vicinity of the spill. Accordingly, we estimate regression (1) with $log(Sales_{k,e,t})$ and $log(\#Employees_{k,e,t})$, respectively, as the dependant variable of interest. We have already established that the effects of pollution shocks vary substantially across the four size quartiles within each sector. Therefore, to conserve space and avoid repetition, we omit the presentation of average treatment effects at the sector level and only present the average treatment effects separately for each size quartile within each sector (i.e., similar to the presentation in Panel B of Table 3).

We present the results of regression (1) with $log(Sales_{k,e,t})$ as the dependent variable in Panel A of Table 4. The results point to a striking contrast in how the effect of pollution shocks on establishment-level sales varies across the size categories. In each sector the coefficient on $Spill_{k,t-}$ increases monotonically from 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 major toxic chemical spills on the sales of local business establishments: 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 sectors: for instance, in the services sector, establishments in the smallest size quartile experience a 27.5% reduction in sales whereas those in the largest size quartile experience a 2.7% increase in sales after being exposed to major toxic chemical spills.

We also estimate the dynamic regression (2) with $log(Sales_{k,e,t})$ as dependent variable to estimate the year-by-year treatment effects on establishment-level 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 3. 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 A 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 all other sectors experience medium-term persistent decline in sales which are reversed by either the third or the fourth year following the spill.[10]

We present the results of regression (1) with $log(\#Employees_{k,e,t})$ as the dependent variable in Panel B of Table 4. As can be seen, the effects on employment are significantly weaker compared to the effects on sales which we documented in Panel A. Even among the smallest size category (Q1), we find that toxic chemical spills lead to no significant reduction in employment in the construction and FIRE sectors, and only lead to modest reductions in employment in the other sectors. By contrast, establishments in the two largest size quartiles (i.e., Q3 and Q4) in all sectors experience modest increases in employment after being exposed to major toxic chemical spills. Overall, these is evidence of a redistributive effect similar to, but weaker in magnitude than, what we found with sales in Panel A. One

[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 business manufacturing establishments.

potential explanation for the weak effects on employment among the smallest businesses is that these businesses may respond to pollution shocks by decreasing the hours worked instead of laying off employees. Unfortunately, as noted above, we only observe the total employee count and do not have any information on hours worked.

3.3 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. We present the results of the robustness analysis in Table A.2. To conserve space we present the results of the robustness analysis only for the services sector because it is the largest sector in terms of number of establishments, sales, and employment. We note that similar patterns hold in other sectors.

Changing the Treatment Radius: To examine how the effects of major toxic chemical spills (defined using the 900+ evacuation threshold) vary with distance from the site of the spill, we define treatment indicators similar to $Spill_{k,t-}$ to identify establishments that are located in different distance bands from the spill site: 0-10 miles, 10-15 miles, 15-20 miles, 20-25 miles, 25-30 miles, and 30-35 miles. Specifically, $Spill_{k,t-}(10-15)$ identifies establishments that are located more than 10 miles away but less than or equal to 15 miles from the site of a major toxic chemical spill; other distance band treatment indicators are defined similarly.

We then estimate a variant of regression (1) where we include all these non-overlapping treatment indicators. The results of this regression are presented in Panel A. As can be seen, the adverse effects of toxic chemical spills are generally stronger for establishments located closer to the spill site compared to those located farther away, although the effects are not monotonic across the distance bands.

Changing the Evacuation Threshold: To examine how the effects of major toxic chemical spills (defined using the 25-mile treatment radius) vary with the evacuations caused by the spill, we define treatment indicators similar to $Spill_{k,t-}$ to identify establishments that are located close to spills of varying evacuation levels: less than or equal to 500, 500-1000, 1000-1500, and 1500+. Specifically, $Spill_{k,t-}(500-1000)$ identifies establishments that are located close to a spill that causes 500 or more evacuations but less than 1000 evacuations; the other evacuation treatment indicators are defined similarly.

We then estimate a variant of regression (1) where we include all these non-overlapping treatment indicators. The results of this regression are presented in Panel B. As can be seen, the adverse effects of toxic chemical spills are generally stronger for establishments located closer to spills with higher evacuation counts although the effects do not increase monotonically with the evacuation level. This may be because the number of treated establishments in the 1500+ evacuation threshold category may be significantly smaller than in other categories due to the relative rarity of such spills.

4 Economic Channels

We showed above that toxic chemical spills have persistent adverse effects on smaller business establishments located in the vicinity of the spills, which work to the advantage of larger business establishments. In this section, we explore two potential channels through which these effects may arise.

First, banks may reduce their lending in areas affected by toxic chemical spills, which leads to a disproportionate adverse effect on smaller businesses that rely more on bank credit (the "credit friction" channel). Second, the health risk perceptions and stigma associated with these spills may cause an out-migration of households, especially higher-income households, from surrounding areas which leads to persistent adverse effects on local businesses (the "population exodus" channel). We note that these two channels are not independent, and may actually reinforce each other: banks may reduce lending in affected areas in anticipation of the population exodus, and the population exodus may be more intense in affected areas with less availability of bank credit.

4.1 The Credit Friction Channel

The main empirical challenge in testing the credit friction channel is the difficulty in delineating between the demand for and supply of bank credit. That is, reduction in the quantity of bank lending to treated businesses may be driven by either lower demand for credit by treated businesses or lower supply of credit by banks to treated businesses, and it is hard to differentiate between these two effects. We overcome this challenge in two ways: First, we use a loan-level database of small business loans to show that loan characteristics (other than amount) change in a manner that is more consistent with tighter supply of credit to treated small business borrowers. Second, we show that toxic chemical spills have more adverse effects on treated businesses that face stronger credit market frictions ex ante.

Effects on Loan Contract Terms

We summarize the SBA 7(a) loan database in Table A.3. 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. 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.

Because this is a loan-level database with few repeat borrowers, we use variants of the following fixed effects regression to examine the effect of major toxic chemical spills on the loan terms offered to small businesses located in the vicinity of the spills:

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

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 5 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 5 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 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.

Effect of Ex-Ante Credit Frictions

Next, we examine how the effects of toxic chemical spills on treated establishments vary with the ex ante credit market frictions faced by the firms to which these establishments belong. We use two measures of credit frictions that have been shown to be relevant for credit provision to private firms, which constitute the bulk of our sample: (i) the deposit market share of "large" banks – defined as banks with total assets exceeding $100 billion – in the borrowing firm's county because past research highlights that large, nationwide banks do not specialize in relationship-based lending to small business (e.g., see Berger et al. 2005, and references therein);[12] and (ii) distance to nearest bank branch because borrower proximity facilitates the bank's collection of soft information (e.g., Degryse and Ongena 2005; Agarwal and Hauswald 2010).

Formally, we use information from FDIC's Summary of Deposits (SOD) database to compute the total deposit market share of large banks within each county. We then define the indicator variable, *High Large Bank Share*, to identify firms that are headquartered in counties which are in the top quartile across all counties in terms of the deposit market share of large banks. Similarly, after computing the distance between each firm's headquarter (HQ) and its nearest bank branch, we define the dummy variable, *High HQ-Branch Distance*, to identify firms that are in the top quartile in terms of distance to their nearest bank branch.[13] These two dummies serve as proxies for high credit frictions. Note that, unlike *High Large Bank Share* which is defined at the county level, *High HQ-Branch Distance* is a firm-specific measure of credit frictions.

We then estimate regression (1) after augmenting it with either the *High Large Bank Share* dummy or the *High HQ-Branch Distance* dummy and its interaction with $Spill_{k,t-}$.

[12] We use the $100 billion threshold because the Federal Reserve defines large financial institutions to include U.S. firms with assets of $100 billion or more and foreign banking organizations with combined U.S. assets of $100 billion or more (see `https://www.federalreserve.gov/supervisionreg/large-financial-institutions.htm`).

[13] In our sample, the top quartile cutoff for the distance between firm HQ and nearest bank branch is about 1 mile. Hence, *High HQ-Branch Distance* identifies firms whose HQ are located more than a mile away from the nearest bank branch.

We estimate this regression separately for each sector and size quartile combination. As per the bank channel hypothesis, the coefficient on the interaction term should be positive, especially for the smallest establishments. The results of these regressions are presented in Table 6. We present the coefficient on $Spill_{k,t-} \times$ *High Large Bank Share* for each sector-size quartile combination in Panel A; and the coefficient on $Spill_{k,t-} \times$ *High HQ-Branch Distance* in Panel B.

We find that the coefficient on $Spill_{k,t-} \times$ *High Large Bank Share* in Panel A is positive and economically significant for Q1 establishments in all sectors except manufacturing and wholesale, which indicates that the smallest establishments are significantly more likely to exit following exposure to toxic chemical spills if they belong to firms that are headquartered in counties dominated by large banks. The corresponding effect for Q4 establishments is mixed and economically insignificant.

Similarly, we find in Panel B that in the manufacturing, retail and services sectors, the coefficient on $Spill_{k,t-} \times$ *High HQ-Branch Distance* is positive and economically significant for firms in the smallest size quartile (column Q1), which indicates that the effect of toxic chemical spills on the likelihood of exit is significantly stronger for establishments belonging to firms that are located farther away from bank branches. By contrast, the coefficient is either negative or insignificant for Q4 establishments.

Overall, the results in Table 6 are consistent with the credit friction channel because the smallest firms are more heavily reliant on bank credit, and thus, should be most affected by credit market frictions.

4.2 The Population Exodus Channel

To test for the population exodus channel, we examine the effects of major toxic chemical spills on changes in the tax base of counties. 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 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 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 construct 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 adjusted gross income (AGI) or taxable income of a county. The number of tax filings is expressed in thousands and the AGI is expressed in millions of dollars. The results of these regressions are presented in Table 7.

The negative and significant coefficient on $Spill_{c,t-}$ in the first row indicates that counties exposed to major toxic spills experience a net 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 net decline in aggregate (i.e., countywide) AGI of $845 million each year, on average, in the post-spill period compared to similar counties that were not exposed to toxic spills. The coefficient estimates in columns (4) and (5) suggest that the decline is persistent and stronger in the long-run period following the spill, although the long-run coefficient is not statistically significant at the conventional 10% level.

The dependent variable of interest in the third row is the ratio of countywide AGI to number of tax filings; i.e., the average taxable income per filing in the county (expressed in thousands of dollars). The negative and significant coefficient on $Spill_{c,t-}$ indicates that counties exposed to major toxic chemical spills experience a decline of $2,166 in taxable income per filing, which suggests that there is greater out-migration of higher-income residents than lower-income residents from the affected counties. The coefficient estimates in columns (4) and (5) suggest that the decline in taxable income per filing is highly persistent.

In the remaining rows of Table 7, we examine changes in average taxable income per filing in three separate income categories: $AGI \leq \$50,000$, $\$50,000 < AGI \leq \$100,000$, and $AGI > \$100,000$. As can be seen, the decline in average taxable income per filing following exposure to toxic chemical spills is mainly driven by households in the highest income bracket.

Overall the results in Table 7 indicate that there is a significant and persistent exodus of the population and income, especially of higher-income households, from counties that experience major toxic chemical spills. This may explain the persistent adverse effects on local business activity which we documented in the previous section.

5 Countywide Effects of Pollution Shocks

We showed above that major toxic chemical spills have a disproportionate adverse effect on smaller business establishments to the advantage of larger business establishments: in every sector, establishments in the smallest size quartile experience significant increase in likelihood of exit, large reduction in sales, and modest reduction in employment, whereas those in the largest size quartile actually experience increase in sales and employment, and do not face increased likelihood of exit. It is natural to ask: what happens to the *aggregate* business activity and business concentration in the vicinity of major toxic chemical spills?

If the only effect of major spills is to redistribute sales and employment from small to large establishments, then there should be increase in business concentration but no effect on aggregate sales and employment. On the other hand, if the reductions at the smallest establishments are not offset by the gains at larger establishments, then aggregate sales and employment should also decline. In this section, we use a county-year level version of regression (1), as described in Section 4.2, to examine the effects of major toxic chemical spills on countywide measures of aggregate business activity, business concentration, and small business credit.

5.1 Effects on Countywide Business Activity and Concentration

We focus on the following outcome variables ($Y_{c,e,t}$) all of which are defined at the county-sector-year level: *Log*(*Aggregate Sales*) which is the logarithm of the aggregate sales of all business establishments; *HHI* which is the Herfindahl-Hirschman Index computed using market shares based on sales, and serves as a proxy for business concentration; *Top Q Market Share* which is the cumulative market share of establishments in the largest size quartile, and serves as another proxy for business concentration; *Log*(*Aggregate Employment*) which is the logarithm of the aggregate number of employees of all business establishments; *# of Establishment Exits* which denotes the number of business establishments which exited during the year; and *# of Establishment Entries* which denotes the number of new business establishments which started their operations during the year. We use the Poisson regression specification instead of OLS for examining the effects on establishment exits and entries because these variables may have zero values for many county-sector-year combinations. We report the results of these regressions in Table 8 where each column corresponds to a different outcome variable of interest. For each outcome variable, we report the coefficient on $Spill_{c,t-}$ separately for each sector.

The dependent variable in column (1) is *Log*(*Aggregate Sales*). The negative and significant coefficients across all rows in column (1) indicate that counties exposed to major toxic chemical spills experience decline in aggregate sales in all sectors in the post-spill period. 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 businesses. These effects are economically significant, and range from a 4.4% decline in the retail sector to a 14.3% decline in the manufacturing & mining sector.[14]

The dependent variables in column (2) and (3) are *HHI* and *Top Q Market Share*, respectively, both of which serve as proxies of business concentration. The results in these two columns indicate that counties exposed to major toxic chemical spills experience an increase in business concentration in the manufacturing & mining, retail, services, and FIRE sectors in the post-spill period. We find consistent results with both these measures of business concentration, except that the coefficient in column (3) for the FIRE sector is not statistically significant at the conventional 10% level. These effects are particularly striking in the retail and services sectors: as per the coefficient estimates in column (3), the cumulative countywide market share of firms in the top size quartile increases by 10.9% in the retail sector and by 16.9% in the services sector following exposure to major toxic chemical spills.

The dependent variable is *Log*(*Aggregate Employment*) in column (4). Consistent with our results in Table 4, we find that the effects of major toxic chemical spills on countywide employment are weaker compared to those on countywide sales. We find that counties exposed to major toxic chemical spills experience decline in aggregate employment in manufacturing & mining and wholesale sectors only, but not in the other sectors.

The results in column (5) indicate that counties exposed to major toxic chemical spills experience a significant increase in the number of business exits in manufacturing & mining, wholesale, and services sectors, but we do not find similar effects in other sectors. The results in column (6) indicate that maor toxic chemical spills do not have a significant effect on new business entries, except in the retail sector where we detect a positive effect.

[14] In an unreported test, we estimate a variant of regression (1) which allows us to distinguish between the short-run and long-run effects of major toxic chemical spills, by separately estimating coefficients on $Spill_{c,t-3:t}$ and $Spill_{c,t-4+}$. We find that the decline in aggregate sales is persistent in the retail and FIRE sector, but not in other sectors. We omit these results from the paper in order to conserve space.

Recall that exits may occur due to business closures, bankruptcies, or acquisitions by other businesses. We have information on the number of business bankruptcy filings at the county-year level, but we do not have a breakup of bankruptcy filings by sectors. In an unreported test, we find that counties exposed to major toxic chemical spills experience a significant increase in the number of business bankruptcy filings in subsequent years, and this effect is highly persistent.

5.2 Effects on Countywide Small Business Lending

We use small business lending data collected under the Community Reinvestment Act (CRA) to examine aggregate small business lending at the county level. The CRA defines small business loans as commercial and industrial loans of \$1 million or less. As noted above, the CRA data is the most comprehensive data on small business lending and covers approximately 86% of all loans under \$1 million. We use the CRA data to create a county-year panel of small business lending, which we use to examine the effects of major toxic chemical spills on aggregate small business lending in the affected counties. The results of our estimation are presented in Table 9.

Examining the results with *Log(Total #Loans)* as dependent variable, we find that counties exposed to major toxic chemical spills experience significant and persistent reductions in the total number of small business loans compared to similar control counties. These declines are found in all loan size categories: loans of less than \$100,000, loans for amounts greater than \$100,000 but less than or equal to \$250,000, and loans for amounts greater than \$250,000 but less than or equal to \$1 million.

Examining the results with *Log(Total Loan Amount)* as dependent variable, we find that counties exposed to major toxic chemical spills experience significant and persistent reductions in the total amount of small business lending. However, this decline is mainly driven by large declines in the total amount of lending through small-denomination loans of less than \$100,000. By contrast, there is no significant effect of major toxic chemical spills on the total amount of lending through large-denomination loans where the amount is greater than \$250,000 and up to \$1 million. Because business establishments in the smallest (largest) size quartile are more likely to obtain small-denomination (large-denomination) loans, these contrasting effects are consistent with our findings above that major toxic spills have disproportionate adverse effects on smaller business establishments.

6 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 business activity. We find that, in every sector, establishments in the smallest size quartile experience significant increase in likelihood of exit, large reduction in sales, and modest reduction in employment following exposure to major spills, whereas those in the largest size quartile actually experience increase in sales and employment, and do not face increased likelihood of exit. These contrasting findings highlight the redistributive effects of pollution shocks: 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 businesses which actually experience an increase in sales. An immediate implication of these findings, which we verify, is that pollution shocks contribute to increase in business concentration in their local economy.

We identify two likely explanations for these persistent adverse effects on local business activity. The first explanation, which we term the credit friction channel, posits that banks reduce their lending in areas affected by toxic chemical spills, which leads to a disproportionate adverse effect on smaller businesses that rely more on bank credit. Consistent with tightening supply of credit, we show that SBA loans to treated borrowers have smaller fraction guaranteed by the SBA, higher interest rates, and shorter maturity. Moreover, we show that toxic chemical spills have more adverse effects on treated businesses that face stronger credit market frictions ex ante.

The second explanation, which we term the population exodus channel, posits that the health risk perceptions and stigma associated with these spills cause an out-migration of households, especially higher-income households, from surrounding areas which leads to persistent adverse effects on local businesses. Consistent with this hypothesis, we find that treated counties suffer large and persistent declines in the number of tax filings and aggregate adjusted gross income in the post-treatment years compared to similar control counties. Moreover, the treated counties also experience strong and persistent declines in the average taxable income per filing in the post-treatment years, especially in the higher-income brackets, which indicates that there is greater out-migration of higher-income residents than lower-income residents from the affected counties.

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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.

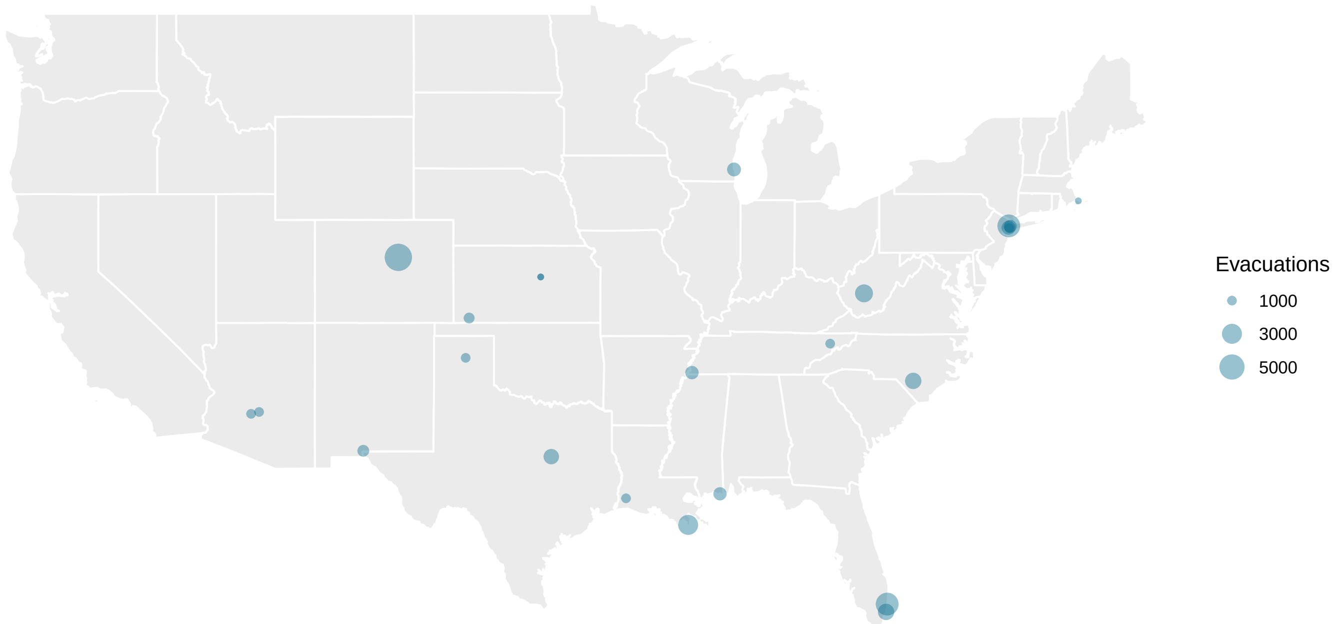
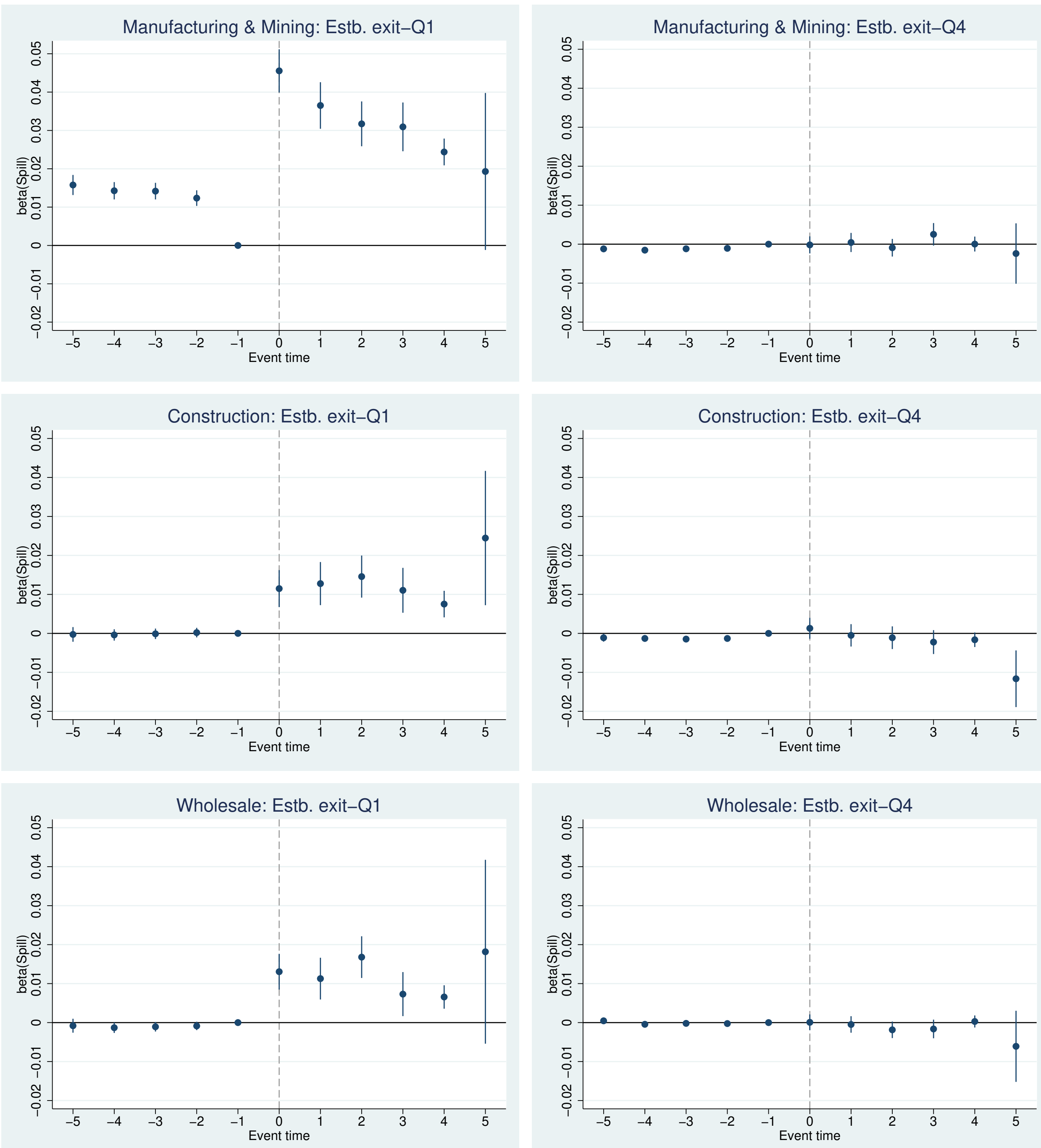


Figure 2: Effect of Pollution Shocks on Likelihood of Exit: Dynamic Effects by Sector and Size Quartile

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]*

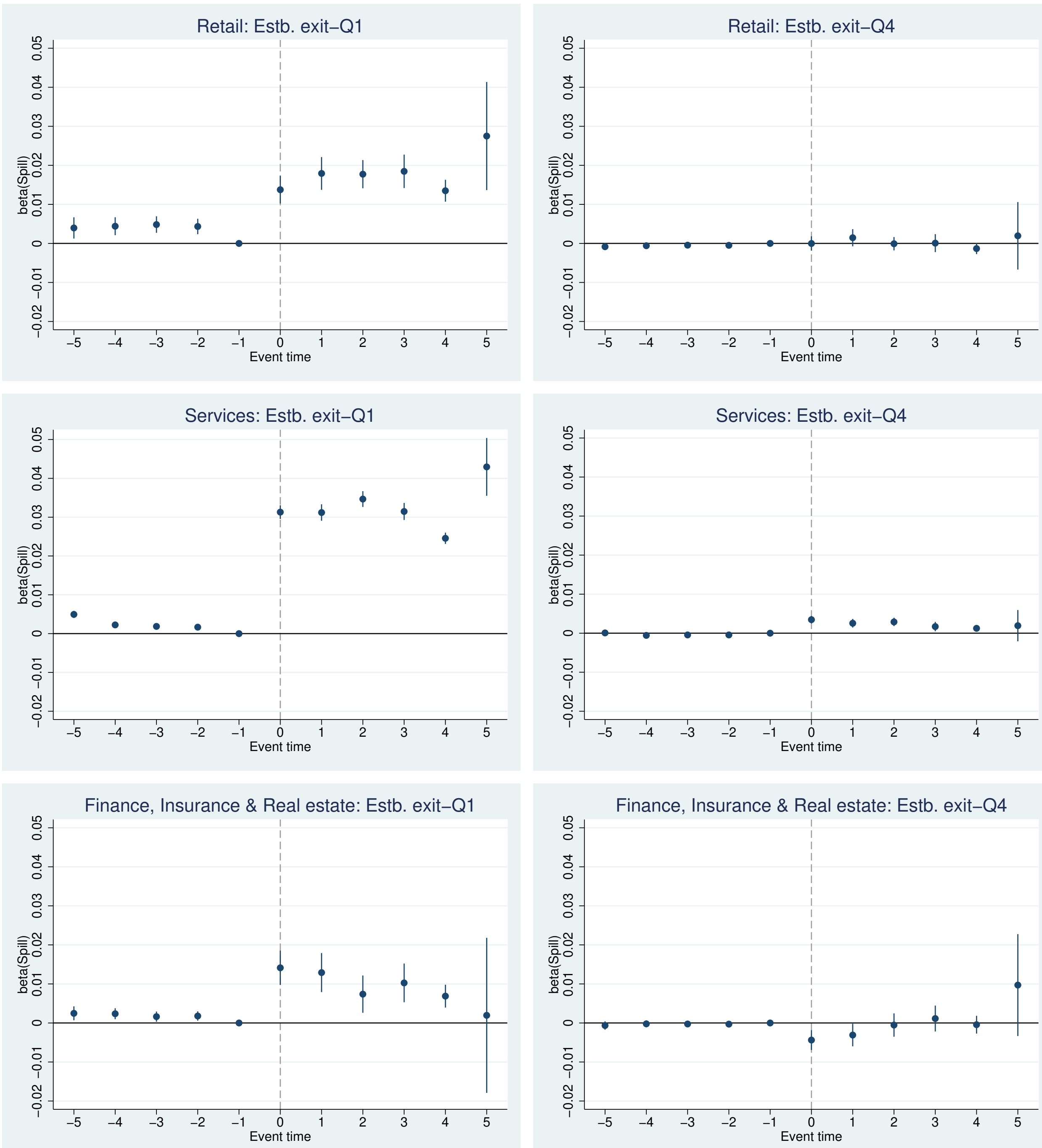
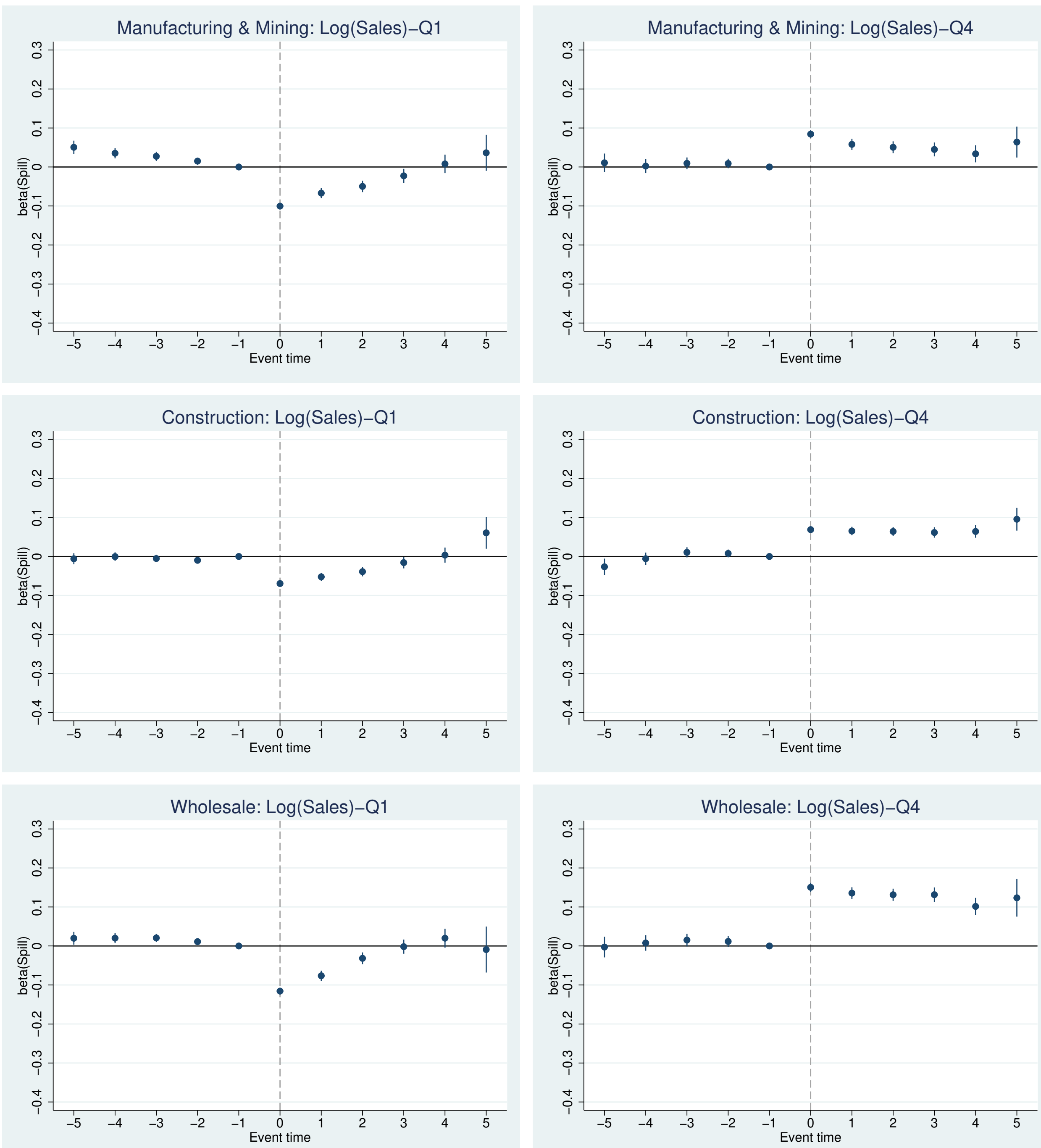


Figure 3: Effect of Pollution Shocks on Establishment-Level Sales: Dynamic Effect by Sector and Size Quartile

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]*

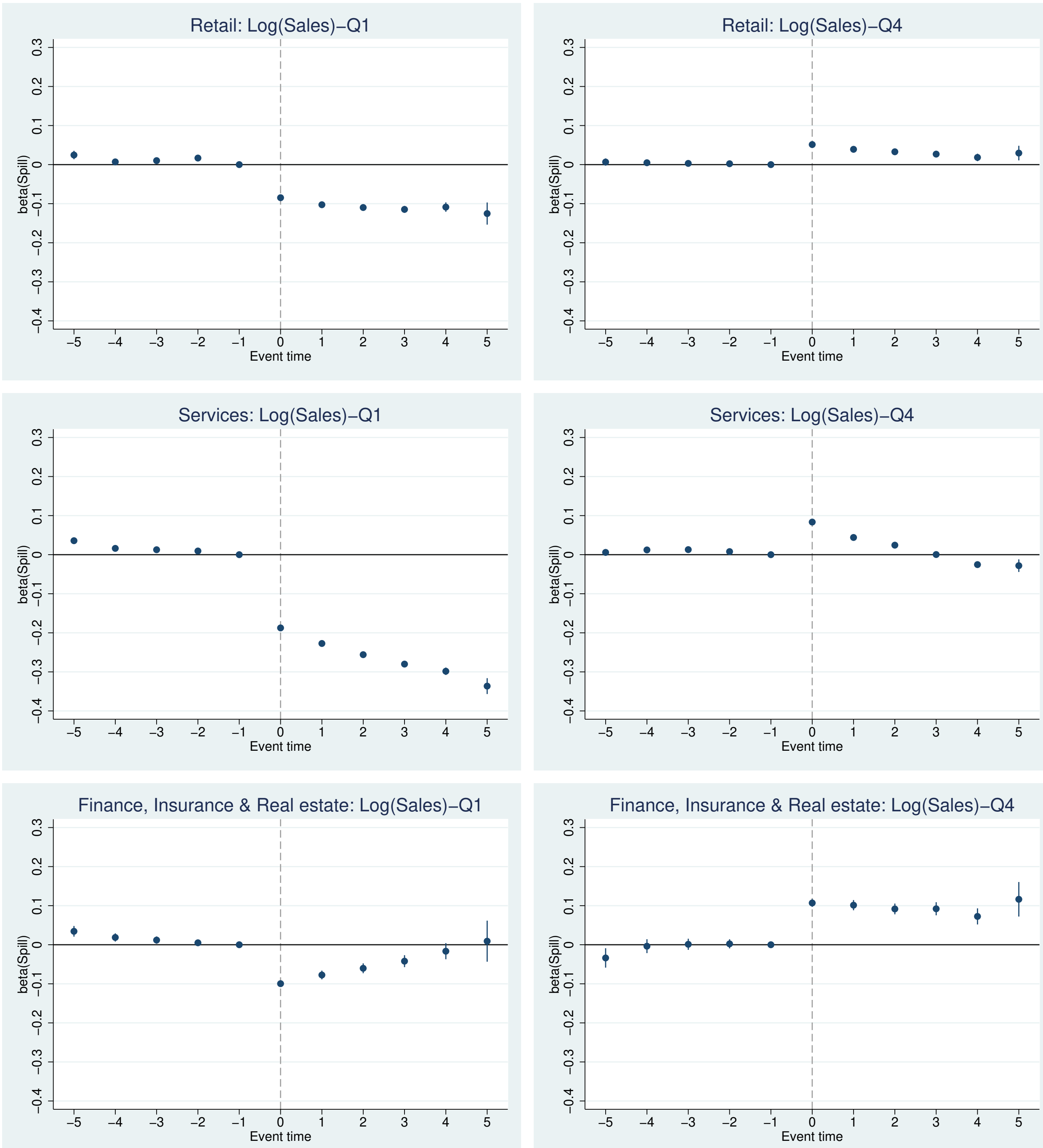


Table 1: Summary Statistics– Toxic Chemical Spills

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– Business Data

This table provides descriptive statistics for the 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 business establishments. In Panel B we further divide companies in our sample into three groups: (i) private companies with 500 or fewer employees, (ii) private companies with more than 500 employees, and (iii) listed companies. Panel C provides summary statistics for the establishment-year panel data, which spans the 2010-2018 period, includes information on 5.33 million 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	5,331,695	74,132,864	56,815,000	1,687,813	434,388
Manufacturing & Mining	523,202	13,404,021	7,436,455	172,470	33,503
(SIC 20-39, 10-14)	[9.81]	[18.08]	[13.09]	[10.22]	[7.71]
Construction	394,005	6,774,851	4,820,051	122,172	26,943
(SIC 15-17)	[7.39]	[9.14]	[8.48]	[7.24]	[6.20]
Wholesale	251,398	8,961,587	3,256,573	76,592	27,227
(SIC 50-51)	[4.72]	[12.09]	[5.73]	[4.54]	[6.27]
Retail	1,253,390	9,556,690	9,733,297	399,527	103,777
(SIC 52-59)	[23.51]	[12.89]	[17.13]	[23.67]	[23.89]
Services	2,588,160	29,671,442	28,249,996	807,312	212,719
(SIC 40-49, 70-89)	[48.54]	[40.02]	[49.72]	[47.83]	[48.97]
Finance, Insurance & Real estate	321,540	5,764,276	3,318,629	109,740	30,219
(SIC 60-65)	[6.03]	[7.78]	[5.84]	[6.50]	[6.96]

Panel B: Private vs. Listed Establishments by Industry Groups

Variable	Establishments [%]			Total Sales [%]			Avg. Employment [%]		
	Employees $\leq$ 500	Employees > 500	Listed	Employees $\leq$ 500	Employees > 500	Listed	Employees $\leq$ 500	Employees > 500	Listed
All sectors	3,315,532	1,957,559	58,604	49,351,284	22,646,446	2,135,138	38,117,960	38,997,560	884,941
	[62.19]	[36.72]	[1.10]	[66.57]	[30.55]	[2.88]	[67.09]	[68.64]	[1.56]
Manufacturing & Mining	277,788	238,957	6,457	7,771,636	4,856,058	776,327	4,555,590	4,790,186	234,541
(SIC 20-39, 10-14)	[53.09]	[45.67]	[1.23]	[57.98]	[36.23]	[5.79]	[47.55]	[50.00]	[2.45]
Construction	262,687	130,194	1,124	4,941,334	1,786,571	46,945	3,459,164	3,478,388	19,176
(SIC 15-17)	[66.67]	[33.04]	[0.29]	[72.94]	[26.37]	[0.69]	[49.72]	[50.00]	[0.28]
Wholesale	178,469	70,531	2,398	6,567,418	2,238,763	155,406	2,307,872	2,352,320	44,226
(SIC 50-51)	[70.99]	[28.06]	[0.95]	[73.28]	[24.98]	[1.73]	[49.06]	[50.00]	[0.94]
Retail	783,090	443,329	26,971	6,882,947	2,510,270	163,473	6,632,888	6,900,872	276,530
(SIC 52-59)	[62.48]	[35.37]	[2.15]	[72.02]	[26.27]	[1.71]	[48.03]	[49.97]	[2.00]
Services	1,613,171	958,209	16,780	19,666,314	9,384,649	620,479	19,018,490	19,251,898	231,283
(SIC 40-49, 70-89)	[62.33]	[37.02]	[0.65]	[66.28]	[31.63]	[2.09]	[49.40]	[50.00]	[0.60]
Finance, Insurance & Real estate	200,327	116,339	4,874	3,521,633	1,870,136	372,507	2,143,956	2,223,898	79,186
(SIC 60-65)	[62.30]	[36.18]	[1.52]	[61.09]	[32.44]	[6.46]	[48.21]	[50.01]	[1.78]

Panel C: Summary Statistics for Establishment-Year Panel

Variable	Mean	p25	Median	p75	SD	N
All sectors						
Sales	2.27	0.20	0.48	1.20	6.94	32,601,086
Employees	15.67	5.00	7.00	15.00	26.58	32,601,086
Estb. exit	0.05	0.00	0.00	0.00	0.22	32,845,815
Manufacturing & Mining						
(SIC 20-39, 10-14)						
Sales	4.92	0.38	0.96	3.50	10.80	2,722,782
Employees	24.47	6.00	10.00	24.00	38.35	2,722,782
Estb. exit	0.06	0.00	0.00	0.00	0.24	2,742,718
Construction						
(SIC 15-17)						
Sales	2.49	0.42	0.78	1.89	6.13	2,725,653
Employees	15.89	5.00	8.00	15.00	23.38	2,725,653
Estb. exit	0.04	0.00	0.00	0.00	0.21	2,747,254
Wholesale						
(SIC 50-51)						
Sales	5.17	0.65	1.40	4.11	10.32	1,732,263
Employees	16.94	5.00	9.00	16.00	26.29	1,732,263
Estb. exit	0.04	0.00	0.00	0.00	0.20	1,747,016
Retail						
(SIC 52-59)						
Sales	1.29	0.11	0.30	0.75	4.82	7,421,115
Employees	11.75	5.00	7.00	12.00	18.22	7,421,115
Estb. exit	0.05	0.00	0.00	0.00	0.22	7,475,100
Services						
(SIC 40-49, 70-89)						
Sales	1.84	0.18	0.40	0.95	6.17	16,113,969
Employees	15.80	5.00	7.00	14.00	27.48	16,113,969
Estb. exit	0.05	0.00	0.00	0.00	0.22	16,232,814
Finance, Insurance & Real estate						
(SIC 60-65)						
Sales	3.06	0.33	0.61	1.50	8.54	1,885,304
Employees	15.84	5.00	7.00	14.00	27.11	1,885,304
Estb. exit	0.06	0.00	0.00	0.00	0.23	1,900,913

Table 3: Effect of Pollution Shocks on Likelihood of Exit

This table reports the results of regressions investigating the effect of major toxic chemical spills on the likelihood of exit of business establishments located in the vicinity of the spills. Panel A presents the results of regression (1) with $Exit_{k,t}$ as the 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	0.011***	0.379	1,739,665	0.011***	0.006***
	(0.001)			(0.001)	(0.001)
Construction	0.006***	0.376	1,721,872	0.006***	0.004***
	(0.001)			(0.001)	(0.001)
Wholesale	0.006***	0.374	1,949,325	0.007***	0.004***
	(0.001)			(0.001)	(0.001)
Retail	0.010***	0.432	4,364,998	0.010***	0.007***
	(0.000)			(0.000)	(0.001)
Services	0.016***	0.366	12,746,819	0.017***	0.013***
	(0.000)			(0.000)	(0.000)
Finance, Insurance & Real estate	0.006***	0.376	1,968,987	0.006***	0.004***
	(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	0.026***	0.011***	0.006***	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Construction	0.012***	0.009***	0.004***	0.000
	(0.002)	(0.001)	(0.001)	(0.001)
Wholesale	0.013***	0.008***	0.006***	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Retail	0.012***	0.018***	0.011***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Services	0.029***	0.023***	0.012***	0.003***
	(0.001)	(0.001)	(0.000)	(0.000)
Finance, Insurance & Real estate	0.009***	0.011***	0.006***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)

Table 4: Effect of Pollution Shocks on Sales and Employment

This table reports the results of regressions investigating the effect of major toxic chemical spills on the sales and employment of business establishments located in the vicinity of the spills. The dependent variable is $log(Sales_{k,t})$ in Panel A, and $log(Sales_{k,t})$ in Panel B. In each panel, 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 on Sales, by Industry and Size Quartile

	Log(Sales)			
	$\beta(Spill_{k,t-})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	-0.101***	-0.055***	-0.015***	0.053***
	(0.006)	(0.004)	(0.005)	(0.007)
Construction	-0.051***	0.004	0.011**	0.063***
	(0.005)	(0.004)	(0.005)	(0.006)
Wholesale	-0.086***	-0.039***	0.000	0.123***
	(0.006)	(0.005)	(0.006)	(0.008)
Retail	-0.129***	-0.057***	-0.022***	0.033***
	(0.003)	(0.002)	(0.002)	(0.003)
Services	-0.275***	-0.138***	-0.072***	0.027***
	(0.002)	(0.002)	(0.002)	(0.002)
Finance, Insurance & Real estate	-0.095***	-0.034***	-0.012**	0.098***
	(0.005)	(0.004)	(0.005)	(0.007)

Panel B: Average Treatment Effects on Employment, by Industry and Size Quartile

	Log(# Employees)			
	$\beta(Spill_{k,t-})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	-0.007**	-0.001	0.017***	0.033***
	(0.003)	(0.003)	(0.003)	(0.005)
Construction	-0.003	0.017***	0.026***	0.022***
	(0.004)	(0.003)	(0.003)	(0.004)
Wholesale	-0.016***	-0.003	0.009***	0.022***
	(0.003)	(0.002)	(0.003)	(0.004)
Retail	-0.036***	-0.004***	0.005***	0.014***
	(0.002)	(0.001)	(0.001)	(0.002)
Services	-0.042***	-0.022***	0.003**	0.023***
	(0.002)	(0.001)	(0.001)	(0.002)
Finance, Insurance & Real estate	-0.004	0.002	0.013***	0.019***
	(0.003)	(0.002)	(0.003)	(0.004)

Table 5: Effect of Pollution Shocks on Loan Contract Terms

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 6: Ex-Ante Credit Market Frictions and Effect of Pollution Shocks

This table reports the results of regressions investigating the how the effect of major toxic chemical spills on likelihood of exit varies with ex-ante credit market frictions faced by the parent firms. We estimate a variant of regression (1) with $Exit_{k,t}$ as the dependent variable, after augmenting it with a measure of high credit frictions and its interaction with $Spill_{k,t-}$. In Panel A we proxy for high credit frictions using the *High Large Bank Share* dummy which identifies firms that are located in counties that are in the top quartile among all counties in terms of the deposit market share of large banks (defined as bank with assets exceeding $100 billion). In Panel B we proxy for high credit frictions using the *High HQ-Branch Distance* dummy which identifies firms that are in the top quartile in terms of distance to their nearest bank branch.

In each panel, we sort establishments within each sector into four size quartiles based on lagged sales, where Q1 (Q4) denotes the smallest (largest) size quartile, and estimate the regression separately for each sector and size quartile. We then report the coefficient on the interaction of $Spill_{k,t-}$ with the proxy for high credit frictions for each sector-size quartile combination. 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: Effect of Local Market Share of Large Banks

	Estb. exit			
	$\beta(Spill_{k,t-} \times HQ\ High\ Large\ FI\ Share_{c,t-1})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	-0.006	0.002	0.018***	0.001
	(0.005)	(0.004)	(0.003)	(0.002)
Construction	0.017***	0.007	0.003	0.006**
	(0.006)	(0.005)	(0.004)	(0.003)
Wholesale	-0.004	0.008**	0.010***	0.000
	(0.004)	(0.003)	(0.003)	(0.002)
Retail	0.010***	0.005*	-0.003	-0.004**
	(0.003)	(0.003)	(0.002)	(0.002)
Services	0.007***	0.013***	0.009***	0.003***
	(0.002)	(0.001)	(0.001)	(0.001)
Finance, Insurance & Real estate	0.017***	0.012***	0.001	-0.005**
	(0.004)	(0.003)	(0.003)	(0.002)

Panel B: Effect of Distance to Nearest Bank Branch

	Estb. exit			
	$\beta(Spill_{k,t-} \times 1\, mile{+}_{c,t-1})$			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Manufacturing & Mining	0.071***	-0.009	-0.011**	0.001
	(0.012)	(0.007)	(0.005)	(0.003)
Construction	-0.002	0.007	0.003	-0.005
	(0.007)	(0.006)	(0.005)	(0.003)
Wholesale	0.012	-0.009	-0.004	-0.007**
	(0.009)	(0.007)	(0.005)	(0.003)
Retail	0.014*	0.011	0.001	0.001
	(0.008)	(0.008)	(0.007)	(0.004)
Services	0.015***	-0.004	-0.003	-0.006***
	(0.004)	(0.003)	(0.003)	(0.002)
Finance, Insurance & Real estate	-0.001	0.001	0.025*	0.006
	(0.010)	(0.012)	(0.015)	(0.011)

Table 7: 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)
County-level Adj. Gross Income (AGI) in '000s/# Filings					
Total AGI/# Filings	-2.166**	0.983	1,236	-2.031**	-3.101**
	(0.932)			(0.937)	(1.249)
AGI/# Filings: $AGI \leq \$50K$	-0.521	0.942	1,236	-0.544	-0.359
	(0.539)			(0.531)	(0.636)
AGI/# Filings: $\$50K \geq AGI \leq \$10K$	-0.157	0.984	1,236	-0.126	-0.374
	(0.447)			(0.428)	(0.636)
AGI/# Filings: $AGI \geq \$100K$	-20.542**	0.961	1,236	-19.857**	-25.280**
	(9.718)			(9.636)	(12.411)

Table 8: Effect of Pollution Shocks on Business Activity by County and Industry

This table reports the results of regressions investigating the effects of major toxic chemical spills on aggregate business activity at the county-industry-year level. Accordingly, in Panel A, we estimate a variant of regression (1) on a stacked county-industry-year matched panel data sets created separately for each industry group. We match each treated county-industry observation with five control county-industry observations that are similar to the treated in terms of sales, HHI, employment, GDP, and GDP growth one year before the treatment. The $Spill_{c,t-}$ treatment indicator identifies county-industry combinations that are exposed to major toxic chemical spills. Each column in the table corresponds to a different outcome variable of interest ($Y_{c,e,t}$). 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.

	$\beta(Spill_{c,t-})$					
	Log(Aggr. Sales) (1)	HHI (2)	Top Q Sales Share (3)	Log(Aggr. Employment) (4)	# Estb. Exits (5)	# Estb. Entries (6)
Manufacturing & Mining	-0.143***	0.130***	0.022**	-0.114***	0.243***	-0.030
	(0.037)	(0.048)	(0.010)	(0.033)	(0.086)	(0.064)
Construction	-0.079**	-0.005	-0.011	-0.047	0.019	-0.060
	(0.035)	(0.027)	(0.007)	(0.031)	(0.060)	(0.048)
Wholesale	-0.051**	0.029	0.011	-0.055***	0.244***	-0.006
	(0.022)	(0.033)	(0.009)	(0.017)	(0.055)	(0.034)
Retail	-0.044**	0.116**	0.109**	0.062	0.018	0.101*
	(0.020)	(0.053)	(0.045)	(0.041)	(0.035)	(0.060)
Services	-0.051**	0.164***	0.169**	0.000	0.103*	0.044
	(0.020)	(0.063)	(0.067)	(0.023)	(0.057)	(0.029)
Finance, Insurance & Real estate	-0.089**	0.075**	0.015	-0.050	-0.007	0.060
	(0.044)	(0.037)	(0.009)	(0.035)	(0.092)	(0.048)

Table 9: Effect of Pollution Risk on Countywide CRA Lending

This table reports the results of regressions investigating the effects of major toxic chemical spills on the county-level aggregate loans issued by depository institutions covered by the Community Reinvestment Act (CRA) 1997. Accordingly, we estimate a variant of regression (1) on a stacked county-year matched county 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(Total # Loans)					
#Loans to Comps. Gross Rev. $<$ \$ 1 *mil.*	-0.314***	0.980	1,282	-0.289***	-0.574***
	(0.096)			(0.094)	(0.140)
Loan Amt. $\leq$ \$100,000	-0.174***	0.989	1,325	-0.161***	-0.311***
	(0.055)			(0.055)	(0.084)
\$100,000 $<$ *Loan Amt.* $\leq$ \$250,000	-0.230***	0.960	1,168	-0.239***	-0.138*
	(0.068)			(0.070)	(0.082)
\$250,000 $<$ *Loan Amt.* $\leq$ \$ 1*mil.*	-0.103**	0.969	1,149	-0.104**	-0.088
	(0.046)			(0.045)	(0.077)
Log(Total Loan Amount)					
\$*Loans Amt. to Comps. Gross Rev.* $<$ \$ 1*mil.*	-0.427***	0.915	1,331	-0.429***	-0.416*
	(0.160)			(0.159)	(0.215)
Loan Amt. $\leq$ \$100,000	-0.315***	0.942	1,331	-0.336***	-0.183
	(0.097)			(0.086)	(0.203)
\$100,000 $<$ *Loan Amt.* $\leq$ \$250,000	-0.177	0.885	1,331	-0.206	0.005
	(0.202)			(0.201)	(0.352)
\$250,000 $<$ *Loan Amt.* $\leq$ \$ 1*mil.*	-0.045	0.902	1,331	-0.080	0.176
	(0.204)			(0.208)	(0.233)

A Internet Appendix

Table A.1: 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$_{k,t-1}$)	-0.06	0.81
	(0.04)	(0.03)
Log(# Employees$_{k,t-1}$)	-0.04	0.82
	(0.02)	(0.02)
Log(Firm Sales$_{k,t-1}$)	-0.04	0.39
	(0.02)	(0.02)
Log(# Firm Employees$_{k,t-1}$)	-0.06	0.73
	(0.08)	(0.05)
Log(Age$_{k,t-1}$)	0.04	0.93
	(0.04)	(0.06)
GDP$_{k,t-1}$	0.10	0.99
	(0.06)	(0.09)
GDP growth$_{k,t-1}$	0.03	0.86
	(0.03)	(0.02)

Table A.2: Effects of Pollution Shocks on Local Business Activity: Robustness to Treatment Radius and Evacuation Thresholds

This table shows how the effect of major toxic chemical spills on sales, employment, and establishment exit varies with distance from the incident locations and the intensity of evacuations for establishments in the Services sector. We estimate a variation of regression (1) with concentric band indicators for the distance of treated establishments from the spill location and report the coefficient estimates of $Spill_{k,t-}$ interacted with the band indicators. In Panel (a), we report the estimated impact on Services sector establishments that are located within 0-10, 10-15, 15-20, 20-25, 25-30, and 30-35 miles mutually exclusive distance bands. We fixed the evacuation threshold as 900 for analysis in this panel. In panel B, we report the estimated impact on Services sector establishments that are located within 25 miles of the spill location but face different evacuation intensities. 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: Effect across Distance Bands

	(1) Estb. exit	(2) Log(Sales)	(3) Log(# Employees)
$\beta(Spill_{k,t-})$ across Distance Bands:			
0-10	0.020***	-0.127***	-0.008***
	(0.000)	(0.002)	(0.001)
10-15	0.016***	-0.149***	-0.023***
	(0.001)	(0.002)	(0.001)
15-20	0.014***	-0.141***	-0.018***
	(0.001)	(0.003)	(0.002)
20-25	0.011***	-0.127***	-0.010***
	(0.001)	(0.003)	(0.002)
25-30	0.012***	-0.125***	-0.008***
	(0.001)	(0.003)	(0.002)
30-35	0.011***	-0.123***	-0.006***
	(0.001)	(0.003)	(0.002)
Obs.	15,626,303	15,626,303	15,626,303
R^2	0.365	0.937	0.940
Cohort-Estb. FE.	✓	✓	✓
Cohort-Year FE	✓	✓	✓

Panel B: Effect across Evacuation Bands

	(1) Estb. exit	(2) Log(Sales)	(3) Log(# Employees)
$\beta(Spill_{k,t-})$ across Evacuation Buckets:			
< 500	0.021***	-0.196***	-0.046***
	(0.000)	(0.001)	(0.001)
$500 - 1000$	0.013***	-0.179***	-0.025***
	(0.000)	(0.001)	(0.001)
$1000 - 1500$	0.024***	-0.211***	-0.028***
	(0.000)	(0.002)	(0.001)
1500+	0.021***	-0.256***	-0.059***
	(0.000)	(0.002)	(0.001)
Obs.	34,108,549	34,108,549	34,108,549
R^2	0.379	0.925	0.933
Cohort-Estb. FE.	✓	✓	✓
Cohort-Year FE	✓	✓	✓

Table A.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