Firm Behavior and Pollution in Small Geographies*

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Abstract

We consider the relationship between the location choices of potentially polluting firms and local income. Unlike previous research in the area of environmental justice, we distinguish between pollution potential and actual releases of toxic substances in the locality. We explore the relationship between the profit maximizing behavior of potentially polluting firms in their choice of both location and expenditures to influence the likelihood of toxic releases and their expected financial costs. We proxy the expenditures on prudential behavior by observing the co-localization of waste remediation activities. Evidence supports the conclusion that firms behave rationally in managing risk of toxic release, which may result in disparities in exposure to toxic releases faced by certain population groups.

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1 Introduction

Analysis of industrial localization and concentration has been of considerable interest since, at least, Marshall in 1920 and spawned a broad literature. However, there is a narrower question of whether the localization and distribution of polluting activities in the production of tradeables is the result of firms' strategic decisions based on local demographic characteristics. This more nuanced question falls within the strand of literature in the realm of environmental justice as well as the broader context of industrial organization.

From the perspective of environmental justice, the question is, "Are low income areas or areas with larger fractions of minorities disproportionately affected by potential health risk associated with exposure to toxic releases?" A concomitant question is then, "Are polluting firms more likely to locate in lower income or higher minority areas?" On the other hand, there is the alternative question as to whether or not households self-select locally or regionally by income due, in part, to a correlation between housing prices and local environmental quality? If so, the correlation is *ex post.* Or, is there some combination of these circumstances at work to create the circumstances the literature reports?

This paper primarily analyzes the first question while showing that this effect is not the result of changes in demographic characteristics. Much of the literature has focused on actual or observed localized toxic releases and the demographic characteristics of the surrounding areas. In our view, the issue has two dimensions. The first dimension is whether demographic characteristics – in particular, income – of the local area influences potentially polluting firms' location choices. Then, importantly, we consider the second dimension as to whether the potentially polluting firms' choices on prudential expenditures that result in different likelihoods of toxic release are influenced by local demographic characteristics. That is, even though the previous literature has found correlation between toxic releases and lower income levels in the surrounding areas, it does not necessarily mean that potentially polluting firms are more likely to locate in lower income areas, but rather that potentially polluting firms in those lower income areas are more likely to realize that pollution potential because they take fewer costly precautions in terms of waste management.

Therefore, in this paper, we take a different approach, one that has the potential to add a critical understanding of location decisions of potentially polluting firms and their decisions that influence the likelihood of toxic releases. That is, we don't restrict the analysis to reported toxic releases, but we consider the universe of firms in industries that are represented in the Environmental Protection Agency's Toxic Release Inventory (TRI), the potentially polluting firms,[1] and analyze the demographic characteristics of the local area where these firms are located or locate. More importantly, we use the location decisions of firms belonging to the waste management and remediation industry as a proxy for the demand for prudential expenditure arising from firms concerned about the liability of toxic release in terms of their expected profits.

To clarify the relationship between the location and toxic waste management choices of potentially polluting firms and local income levels, we first provide a theoretical framework. A potentially polluting firm seeking to maximize profits will be concerned about the liability of toxic releases and the threat such releases pose to its financial results. As the firms' exposure to pollution-related financial risk increases with income (due to higher property values or higher probability of collective actions by residents and other businesses), a prudential response is to manage that risk by limiting the release of hazardous waste in the environment. A potential channel through which firms can reduce their toxic releases is by employing more waste management and remediation services. Two otherwise identical firms, one in a high income neighborhood and the other in a low income neighborhood, would be expected to

[1] A potentially polluting (TRI-type) firm is defined as any firm, regardless of size or reporting requirements, that is in the same NAICS code as a firm that had to report a toxic release to the Environmental Protection Agency's Toxic Release Inventory (TRI), excluding NAICS 562 Hazardous Waste. However, only firms in these NAICS codes that employ at least 10 FTEs and exceed EPA threshold limits in terms of their processing or usage of designated hazardous or toxic chemicals are subject to mandatory reporting within the TRI (https://www.epa.gov/toxics-release-inventory-tri-program). The firms subject to mandatory reporting are denoted in this paper as TRI-reporting firms. TRI-reporting firms responsible for toxic releases that exceed TRI limits are identified and treated in this paper as TRI-polluters.

demand different levels of waste management and remediation services, positively correlated to the surrounding incomes.

Like any firm choosing a location, a firm engaged in a potentially polluting activity needs to consider the array of attributes of any particular location in terms of their importance for profitability,[2] including the financial risk of release and the necessary costs of managing the likelihood of toxic release. Recognizing that the incentives faced by a representative firm result in the realization of a localized aggregation of similar (potentially polluting) firms, we derive some conditions that can lead to either a positive or negative (or both) relationship between local income and the total level of potentially polluting activities in a neighborhood.

We then investigate empirically the predictions of our theoretical framework by looking at the relationship between the location choices of potentially polluting firms, waste management and remediation firms, pollution hazards and local income levels. In this analysis, we consider the demand for remediation or waste management services as a demand that arises from firms concerned about the impact of toxic release on their expected profits. Although not perfectly correlated with localized firms' demand for environmental quality, waste management/remediation is the only clearly identified industry involved in pollution mitigation in the regional non-tradeables sector for which entry and employment data are available.

By and large, the potentially polluting activities considered here result from industrial activities whose output is not dependent on the local market, i.e., production of tradeables. Firms in these activities are free to choose any location, subject to zoning restrictions. One might naturally think of household demand for localized environmental quality to be expressed collectively through the political process and reflected in a regulatory or statutory framework that restricts the nature, location and technologies of productive activities. By restricting our analysis to a single state, Texas, we control for an otherwise heterogeneous regulatory

[2]Economists have long been interested in explaining what factors motivate profit-maximizing firms when they choose to open a new plant or expand an existing facility. There have been studies on the theory of plant location, including the role of taxes and agglomeration economies. Shadbegian and Wolverton (2012) review the theory, evidence, and implications of the role of environmental regulations in plant location decisions.

framework.[3] There are few local environmental restrictions imposed in the State of Texas, beyond local zoning laws, and the state itself takes a relatively light hand to regulation. Thus, jurisdictions in the state are largely subject to a practically identical regulatory environment. Differences in local demand for waste management services must arise from the consumers of those environmental services, i.e., local firms responding to localized conditions, and we largely eliminate any localized version of the pollution haven hypothesis due to regulatory heterogeneity.

In addition to the analysis of potentially polluting industry localization and household income, we consider the probability of entry of a potential polluter in and across the given geographies. By also focusing on entry, we avoid the question of inter-jurisdictional population sorting that might occur in the years following a potentially polluting firm's entry. Residential mobility and regional sorting by income due to the presence or absence of an environmental hazard, if they occur, would already be reflected in observed household incomes in the areas proximate or distant to the pre-existing industrial concentrations (demographic characteristics are given at the time of entry). We conduct a similar analysis of likelihood of entry of waste management/remediation firms into those geographies while controlling for the presence of potentially polluting firms. In both cases, we control for agglomeration economies that might serve to attract firms into existing industrial concentrations (Glaeser et al., 1992; Henderson et al. 1995; Combes, 2000; Rosenthal and Stange, 2003).

Working at the census tract-level, we find that locations and entry probabilities of potentially polluting firms are positively correlated with local income over only the lower range of income. These firms' demands for measures to reduce the likelihood of toxic release, as proxied by the presence and entry of waste management/remediation firms, show a similar, but amplified, pattern and are positively correlated with the presence of potentially polluting

[3]Texas is an attractive setting to consider given its size. It is the second-largest state in the U.S. both geographically and economically (with a gross state product of $1.6 trillion dollars in 2016). Its economy would rank 14th in the world when its gross state product is considered relative to national gross domestic products. It contains significant geo-physical diversity and is home to 25 separate metropolitan statistical areas (MSAs).

firms. We also find very persuasive evidence that the relative frequency of toxic release, i.e., the ratio of toxic releases to the number of potentially polluting firms, is negatively correlated with proximate household income. Taken together, our results lead us to conclude that the inverse U-shaped relationship between income and toxic release is, at least partially, the product of potentially polluting firms seeking to maximize their expected profits by balancing the financial risk associated with a toxic release and the costs of waste management and remediation services.

The firm-level profit-maximization approach used in this paper has been common to economists investigating firm siting choices in relation to environmental issues. For example, List and Co (2000) used a conditional logit model to investigate in which states multinational firms make investments, leveraging variation in state environmental policies to consider whether foreign direct investment is, in part, driven by environmental standards. Likewise, Keller and Levinson (2002) investigated the number of new foreign-owned plants as a function of abatement costs to determine the effect of environmental-related compliance costs on the location of foreign direct investments. List et al. (2003) analyzed plant relocation choices made by firms, and found that differences in environmental factors (in this case, air quality regulations) significantly alter location choices. In our paper, by restricting the analysis to a single state, Texas, we control for an otherwise heterogeneous regulatory framework and focus on non-regulatory environmental factors and how these factors affect firms' siting and location choices.

Our empirical finding at small geographical scale is novel in the field of environmental economics and has clear application to the literature on environmental justice. The early environmental justice literature has primarily focused on the relationship between local income and pollution exposure (Arora and Cason, 1999 and, Brooks and Sethi, 1997). While these papers find some empirical evidence of an inverted U-shaped curve, the theoretical relationship between levels of undesirable localized emissions and regional or local income or the role of the remediation industry have not been investigated.

Understanding the mechanisms leading to the correlations between income, race and pollution is crucial to draw policy implications. Several papers in the environmental justice literature try to identify the relative importance of the various causal mechanisms. Banzhaf and Walsh (2008) and Depro et al. (2015) show that residential mobility and sorting by income can explain the observed correlations. On the other hand, Been and Gupta (1997) and Pastor et al. (2001) find that disproportionate siting by polluting firms seems to matter more than residential mobility.

Modelling entry decisions and using more economic factors as control variables, De Silva et al. (2016) find evidence that polluting firms choose to locate disproportionately in poor or high minority areas. However, in their analysis, they consider only firms in the TRI which have actually reported a toxic release. While these results might well portray an effective reality, we find that limiting the analysis to TRI firms that have a release on record is overly narrow and may miss a useful, broader picture. Our paper contributes to the environmental justice literature by considering *potentially* polluting firms and exploring how their location and waste management decisions, proxied by the presence of waste management and remediation firms, can explain the disparities in pollution exposure in different household income localities.

The structure of the article is as follows: in the next section, we present our theoretical framework. We then develop our empirical approach. In the section that follows, we explain the patterns of entry and exit in the remediation industry. Lastly, we summarize and conclude.

2 Theoretical analysis

The question of residents' exposure to local pollution has two dimensions: (1) polluting firms location choices, and (2) their pollution level decisions. To motivate the structure of our empirical analysis, we develop a profit-maximization framework (Levinson, 1996) that illustrates how local characteristics, including local income, are likely to affect both the number of potentially-polluting firms in a locality and their efforts to avoid releases of hazardous waste in the environment.

A potentially-polluting firm is considering the location of a new plant in one of the L local areas, indexed by $l \in \{1, ..., L\}$. This new plant is a price taker in the output and input markets and is characterized by its use of toxic chemicals that produce hazardous wastes, x. The use of hazardous substances varies across facilities because they may use different pollution prevention technologies (or P2 activities that reduce the production of waste ex ante), belong to different sectors, etc. From an individual polluter's perspective, releasing toxic chemicals in the environment is costly because the firm will have to implement a clean-up program, pay penalties and compensate the local residents for damages.[4] To avoid legal and/or clean up costs associated with toxic releases, firms handling hazardous substances can undertake efforts to prevent these releases through costly waste management practices such as treatment and recycling. As opposed to P2 activities, waste management prevents releases once hazardous wastes have been generated during the production process.

Conditional on its location decision in local area l, a facility of type x chooses quantities of outputs and inputs and a level of investment in waste management practices to maximize their profit function (where the output price is normalized to 1):

$$\max_{\mathbf{q},e} \quad f(\mathbf{q}, \mathbf{v}_l, x) - \mathbf{p}_l.\mathbf{q} - h(e, m_l) - p(x - e)$$

where $\mathbf{q}$ is a vector of input quantities and e is the amount of the hazardous substances that is released in the local area (posing a threat to the environment and human health). $\mathbf{p}_l$ is a vector of input prices (e.g. wages, rents...) in area l. Output is given by $f(\mathbf{q}, \mathbf{v}_l, x)$, which depends on the type of the facility and the characteristics of the local area, $\mathbf{v}_l$ (other than input prices) that can affect a facility's profit (e.g. number of roads and railroads, number of amenity establishments...).

Among these local characteristics, household median income is of particular interest. Here

[4] Indeed, most disposal or other release practices are subject to a variety of regulatory requirements designed to minimize potential harm to human health and the environment.

we make the distinction between the median income of household living in the local area (m_l) and the wages paid by the facility (included in vector $\mathbf{p}_l$) because the local areas considered in the empirical analysis are relatively small, so facilities located in one area can attract workers from other areas. Guerrieri et al. (2013) show that local housing price dynamics suggest local amenities respond to the income levels of residents. Handbury (2013) shows that cities with higher income per capita offer wider varieties of high quality groceries. Based on those results, it seems that the quality of some local amenities endogenously responds to the types of residents who choose to live in the local areas. Higher income neighborhoods tend to have better physical and social infrastructure and this may contribute to lower logistical costs and help to retain workers or to attract workers from other areas with higher marginal product of labor (quality of workforce). We therefore hypothesize (and we will investigate this question in the empirical analysis) that there are some potential offsetting benefits available in higher income areas that might attract and retain firms. We rewrite $\mathbf{v}_l = (\mathbf{Z}_l, m_l)$, where m_l is the household median income and $\mathbf{Z}_l$ represents other local characteristics.

The last two terms of the above expression capture the pollution cost. The cost of release is $h(e, m_l)$, with $h_e(e, m_l) > 0$ and $h_m(e, m_l) > 0$ for all $e, m_l \geq 0$.[5] Higher incomes (and associated higher property values) are expected to increase the costs of release in a local area (Hamilton, 1995) since, in litigation, injured parties recover damages based on reduced property values or, in the case of impacts that limit work or productive ability, lost income (Mastromonaco, 2015). Also, a higher-income area might be associated with a higher probability of collective actions or higher bargaining power for local residents to force the firm to implement a more thorough clean-up program in case of release or adopt stricter environmental standards above any broader regulatory requirements (Timmins and Vissing, 2017).[6] Residents can also lobby the government for indirect regulatory intervention towards those

[5] We assume that $h(e, 0) > 0$ for all $e \geq 0$. There is a basic, obligatory clean-up program that must be undertaken by firms, in case of toxic release, regardless of citizens demand for or willingness to pay for a better environment.

[6] In the context of shale gas leases, Timmins and Vissing (2017) show evidence that negotiated lease terms vary with some local demographic characteristics, including income and minority ratio.

facilities (Earnhart, 2004). Their ability to do so will depend on their income and willingness to bear the costs of the effort to achieve a cleaner environment. Let $a = x - e$ be the amount of hazardous waste that is treated or recycled to avoid releases. Avoidance activities don't cause any damage but have an increasing and convex cost $p(a)$ (with $p(0) = 0$, $p'(a) > 0$ and $p''(a) > 0$ for all $0 \leq a \leq x$).[7]

The indirect profit of a facility of type x in a local area l can then be written as:

$$\pi(\mathbf{p}_l, m_l, \mathbf{Z}_l, x) - c(m_l, x)$$

with $\pi_m > 0$ (due to the offsetting benefits of locating in higher-income neighborhood) and $\pi_{p^i} < 0$, where p^i is an element of the input prices vector $\mathbf{p}_l$. The indirect cost of pollution $c(m_l, x)$ is increasing in m_l and x: $c_m = h_m(e^*, m_l) > 0$ and $c_x = p'^*) > 0$, where e^* represents the profit-maximizing level of release.

Local income and individual releases. Firms will release toxic chemicals in the environment at a level e^* such that the marginal cost of releases, $h_e(e^*, m_l)$, is equal to the marginal cost of waste management, $p'^*)$. As a result, if $h_{em}(e^*, m_l) > 0$, i.e. the marginal cost of releases is increasing in income, the optimal level of release will be decreasing in income m_l, $\frac{de^*}{dm} = \frac{-h_{em}(e^*, m_l)}{h_{ee}(e^*, m_l) + p''^*)} < 0$. Lower income areas will be disproportionately subject to localized releases, although not necessarily more densely populated by potentially polluting firms.

Local income and number of firms. In a profit-maximization framework, a potentially-polluting firm considering the location of a new plant will choose the neighborhood with the attributes $(\mathbf{p}_l, m_l, \mathbf{Z}_l)$ that lead to the highest expected profit, $\pi(\mathbf{p}_l, m_l, \mathbf{Z}_l, x) - c(m_l, x)$, given its type x. We denote by E_{lx} the binary indicator that equals 1 if facility of type x locates in area l, and equals 0 otherwise. The probability that a facility of type x is located in area l is

[7] To guarantee that we have an interior solution for e and that the first-order conditions are sufficient for a maximum, we further assume that $h_e(0, m_l) - p'(x) < 0$, $h_e(x, m) - p'(0) > 0$, and $h_{ee}(e, m_l) + p''(x - e) > 0$ for all $e, m_l \geq 0$.

then given by:

$$Pr(E_{lx} = 1) = Pr[\pi(\mathbf{p}_l, m_l, \mathbf{Z}_l, x) - c(m_l, x) > \pi(\mathbf{p}_k, m_k, \mathbf{Z}_k, x) - c(m_k, x) \quad k \neq l]$$

For a given x, because we hypothesized that $\pi_m > 0$ and $c_m > 0$, the effect of local income on the probability to choose a local area l, and so on the total number of firms in the area, is *a priori* ambiguous.

Local income and total pollution. We now investigate the relationship between total pollution in area l and local income m_l. As suggested earlier, if $h_{em} > 0$, individual releases will be decreasing in local income. Total pollution will depend on how the function $Pr(E_{lx} = 1)$ varies with income.

First, note that, if the number of firms in a given location is decreasing in local income (i.e. firms always prefer to locate in low-income areas), total pollution will be decreasing, *ceteris paribus*, for all levels of local income, as predicted by the environmental justice literature.

However, it is very likely that at relatively low levels of income, the benefits of locating in an area with better quality workforce and physical infrastructure can outweigh the higher costs of pollution such that the equilibrium number firms in a local area is increasing with the local income. If that is the case and if for some income levels, the increase in the number of firms more than offsets the reduction in individual releases, then total pollution will be increasing for those income levels.

Local income and waste management. Another important insight from the model is that individual releases might decrease for two reasons. First, for a given x, as income increases, the cost of releasing toxic chemicals also increases. Firms will respond to this higher financial risk by spending more on avoidance activities. We should therefore observe that potentially-polluting firms' demand for waste management services (recycling, treatment...) is higher in wealthier neighborhoods.

Second, the composition of polluting activities in a local area may also vary with income. Indeed, an increase in local income is costlier for firms in sectors relying more on toxic chemicals:

$$c_{mx} = \frac{h_{em}(e^*, m_l)p''^*)}{h_{ee}(e^*, m_l) + p''^*)} > 0$$

In a profit-maximizing framework, this may lead to a sorting of potentially polluting firms: Firms with a high x (belonging to sectors relying more on toxic chemicals or without alternative clean technologies) will prefer lower-income areas, while firms with low x (cleaner firms) will prefer higher-income areas. In that case, individual releases will be decreasing in income, not because firms invest more in waste management activities but because they are cleaner and don't produce hazardous waste.

3 Empirical analysis

We now turn to the empirical analysis of the relationship between local income, industrial localization and local environmental quality. For our purposes, a local area is the census tract. Census tracts in populous areas are relatively small. Thus, it represents the locality closely adjacent to any potentially polluting firm located in the tract. It also closely represents the population that bears the immediate environmental impact in case of toxic release. Most chemicals included in the TRI Program have very localized impacts. Using individual level data, Currie et al. (2015) show that the openings or closings of toxic plants (i.e. plants reporting a release to the TRI Program) have an impact on housing prices and birth outcomes within a 1-mile radius of the plant location. A census tract is generally larger than a 1-mile-radius circle, thereby the demographic characteristics of the population outside the circle may add noise to the estimation. It might still be an appropriate scale of measurement if we consider the spillover effects of the toxic pollutants on the residents a little further away from the facility.[8] These spillover effects can enlarge the source of community pressure. Moreover,

[8] Currie and Schmeider (2009) identify health effects of some TRI chemicals at the county level.

surveying more than 100 Environmental Justice studies, Baden et al. (2007) provide evidence that racial and income inequalities become stronger when the unit of analysis is smaller. Our results can therefore be seen as conservative estimates of the impact of income on local levels of pollution.

As previously noted, the analysis is limited to the State of Texas. Jurisdictions in the state are largely subject to a practically identical regulatory environment. One example of the state's interference in local regulatory efforts was the widely reported lawsuit brought by the State against the City of Denton that banned hydraulic fracturing by referendum with 59% of the vote. The state sought to limit the municipality's ability to regulate oil and gas activities, to allow the state to pre-empt local regulations, and to ensure that all local efforts to impose regulations be "commercially reasonable" (See the Texas Tribune, September 18, 2015 for reporting of the city's failure to block oil and gas activities). Differences in pollution and clean-up requirements at the local level should then be explained by local characteristics either through litigation/compensation costs or through the ability of the local residents to negotiate stricter clean-up programs with the potentially polluting firms. Aside from the benefit of a homogeneous regulatory environment, we are able to take advantage of access to detailed establishment-level data from the Texas Quarterly Census of Employment and Wages, as described below.

3.1 *Establishment-level data*

All establishment- and industry-level data are derived from the Texas Quarterly Census of Employment and Wages (QCEW) for the years 2000–2006 as provided by the Texas Workforce Commission.[9] The QCEW reports data at the establishment level, including exact address,

[9]The main data used in this study were collected and provided by the Texas Workforce Commission. These data are fully-disclosed (tax ID, locations, wages, and employment) and are not available to the general public. We were able to acquire them under the terms of non-disclosure agreement. We can only provide the data under the terms of this agreement either in terms of establishment-level aggregation at the NAICS-6 or some industry aggregation of NAICS-6 establishment-level data at the county level. We can report total county-level data at NAICS-6 if there are at least four establishments in the county with no establishment representing more than 60% of the the total county employment in the given NAICS-6 industry. Interested researchers can

geographical coordinates, age, parent company, monthly employment, and quarterly payroll for all establishments in Texas subject to reporting under the Unemployment Insurance (UI) program. Different establishments within the same firm are identified by unique identification numbers and reported separately.

Recognizing that the data are at the establishment level, we use the more usual terminology of the firm to indicate a specific productive facility or plant.

3.2 *TRI data*

The TRI is a mandatory reporting program managed by the U.S. Environmental Protection Agency for a set of industries that use or produce certain toxic or dangerous chemicals. The EPCRA (Emergency Planning and Community Right to Know Act) Section 313 requires owners and operators of facilities that meet all of the following criteria, to file an annual TRI report detailing how much of certain chemicals is released to the environment or managed through recycling, energy recovery and treatment:

- The facility has 10 or more full-time employee equivalents (FTE);
- The facility is included in a given subset of the North American Industry Classification System (NAICS); and
- The facility manufactures (defined to include importing), processes, or otherwise uses any EPCRA Section 313 chemical in quantities greater than the established threshold in the course of a calendar year.[10]

As pointed out in Footnote 1, we define three sets of TRI-related firms. First, firms for which reporting is mandatory, i.e. that meet the three reporting requirements mentioned above, but excluding firms in the NAICS 562 Waste Management and Remediation Services

contact the Texas Workforce Commission for data requests.

[10]See https://www.epa.gov/toxics-release-inventory-tri-program for details on on NAICS codes, listed chemicals, and chemical thresholds required for reporting.

(this sub-sector group includes establishments engaged in the collection, treatment, and disposal of hazardous waste materials, see details below), are called TRI-reporting firms. There are 2,355 unique TRI reporters in our dataset. Second, TRI-reporting firms are not necessarily firms that experienced a toxic release. Firms that actually report toxic chemical releases are treated as TRI-polluters for the year in which the release is reported. As such, a firm can be a polluter in year t, but not a polluter in year $t+i$. There are 795 unique firms that report a release over the period of this analysis. Finally, we refer to all firms located in a NAICS code that contains a TRI-polluter, regardless of whether reporting is mandatory for the firm, as a TRI-type firm or potentially polluting firm. Our objective in this study is to analyze the co-location of remediation firms, as a proxy for pollution risk management by firms in industries known to pollute. We are working at sufficient industry detail, six-digit NAICS, that a reasonable level of homogeneity in activity can be assumed. If establishments in a given industry have been identified as having experienced a release via TRI reporting, we are assuming that other establishments in the same industry have largely similar activities and could potentially experience a similar release. There are 36,553 unique potentially polluting firms in our dataset (see Figure 1). For our analysis, we also identify 18,252 firms in the dataset that are located in NAICS codes covered by the TRI Program, and which have 10 or more FTEs (i.e. they meet two of the reporting criteria).

All other industries are treated as either non-TRI-type industries (i.e. they are not in a NAICS code identified by the TRI Program) or remediation industries (NAICS 562). There are 508,113 unique non-TRI-type firms, and 598 unique remediation firms in the dataset. Table A.1 provides a definition of all the categories of firms used in this paper.

If firms don't report toxic releases, it might be because they successfully manage their hazardous wastes in different ways, e.g. treatment or recycling. This type of activity (even if the waste is treated on-site) is not carried out by the polluting firms because it requires an extensive and potentially costly government permitting process or requires transport to an approved treatment, storage or disposal facility. Thus, they are usually carried out by specialized firms belonging to the remediation industry. The services supplied by these companies are local and often very specialized (depending on the type of polluting industry, pollutants, etc.) and typically require highly skilled/trained workers.

We restrict the waste management/remediation sector to four industry sub-sectors in NAICS 562 Waste Management and Remediation Services. Specifically, we consider establishments in NAICS 562112 Hazardous Waste Collection, 562211 Hazardous Waste Treatment and Disposal, 562910 Remediation Services, and 562920 Materials Recovery Facilities (recycling). We shall refer to these four NAICS codes collectively as either waste management or remediation industries (for our purposes, these two terms refer to the same set of industries).

The EPA also provides toxicity weights for each toxic chemical listed in the TRI Program which allows us to compute a tract-level toxicity index by aggregating all TRI-polluters' releases, measured in pounds of toxicity, within a tract. Even though this index only takes into account toxic releases from TRI-polluters, we believe it constitutes a good proxy for the level of pollution in a local area. First, while some papers (de Marchi and Hamilton, 2006; and Koehler and Spengler, 2007) point to some underreporting, overall compliance was nevertheless high. Second, we believe it likely that releases by small firms (with less than 10 employees) probably represent a relatively small portion of total toxicity.

3.3 *Census-tract data*

Median income and population statistics at the census tract level are taken from the U.S. Census Bureau. For Census-based data, we linearly interpolate co-variates from Census 2000 and Census 2010 to generate yearly observations at the tract level. The realizations of the variables we use from Census 2000 and Census 2010 are of course highly correlated with each other. For example, the correlation between median income in 2000 and 2010 is 0.95. A few Census 2000 tracts are divided in Census 2010. We aggregate variables (or construct population-weighted averages, where appropriate) to obtain corresponding Census 2000 tract information. We also consider some measures of local infrastructure (and, by that proxy, transportation costs) using the number of roads, number of rail roads, road construction expenditures.

3.4 *Summary Statistics*

To motivate the cubic and spline specifications used in the next section, we plot a bar graph for average actual shares of toxic releases, TRI-type, and remediation firms per tract by median income in Figure 2. To construct this figure, we first normalize toxic releases, TRI-type, and remediation firms in a given tract for a given year by the corresponding yearly totals of toxic releases, TRI-type firms, and remediation firms. Next, we plot these normalized average shares by income bins of $10,000. Toxic releases (the first bar in each bin) are higher in low-income tracts and we do not observe any reported releases beyond the income level of $100,000. However, TRI-type (the second bar in each bin) and remediation firms (the last bar in each bin) are distributed in low and high-income tracts. This figure also indicates that the downturn in toxic releases starts around $60,000.[11]

Based on the 2000 US Census, there are 4,388 tracts in Texas. In our analysis, we only use tracts with commercial activity, i.e. in which there is at least one TRI-type or remediation establishment in at least one year of our sample period. Summary statistics for all the 4,302 tracts with commercial activity, are reported in Table 1 (column 1).[12] In Table 1 (columns 2-4), we provide summary statistics for three income intervals (based on the observed downturn in Figure 2). Out of 4,302 tracts with commercial activity, 3,797 tracts have a median income below $66,700. Only 125 tracts have a median income above $100,000. The average toxicity index for all tracts is about 0.010 million toxic pounds per year. Toxic releases drop dramatically when income increases and we don't observe reported releases in tracts with average median income above $100,000. There are only 0.084 incumbent waste remediation firms per tract. For a representative tract, there are 4.018 TRI-type firms while the number

[11] Note this figure is censored at $150,000 to be consistent with Figure 3 and the last bin represents all shares above $150,000.

[12] A description of these variables is provided in Table A.2 in Appendix A.

of firms that are required to report to the TRI Program (TRI reporting firms) is about 0.677. The average numbers of TRI type, TRI reporting firms, and remediation firms drop as median income increases, but they are not zero in tracts with income above \$100,000. The insights from Table 1 and Figure 2 could be interpreted as consistent with our conjecture that firms in high income tracts invest more in remediation technologies compared to firms located in low income tracts.

Average median household income for all tracts is about \$43,930 and the average wage paid by establishments in each tract is about \$38,250 per year. The median income refers to the residents of a particular tract (i.e. local standard of living), while wage refers to the wage paid by establishments located in this tract to their workers (i.e. cost of labor). Because tracts are relatively small (especially in urban areas), local residents are not necessarily working for the facilities located in their resident tract. In our data the correlation between median income and wage is only 0.2288. For a given tract, the average population is about 5,088 and the average unemployment rate is about 4.468 percent. The average house value is about \$114,230.

Not surprisingly, in higher income tracts, wage, college educated population, amenities, and housing value increase. We also observe that as income increases, the minority ratio drops from about 30 percent in tracts with median income of less than \$66,700 to about 15 percent or below in tracts with median income of at least \$66,700.

3.5 *Results*

To test the predictions of the theoretical analysis, we estimate an empirical model that takes the following form:

$$y_{lt} = \mathbf{X}_{lt}\mathbf{\Delta} + \tau_t + \mu_{lt} \tag{1}$$

where y, depending on the specification, is total toxicity in pounds in each tract, the total number of firms in the TRI-type sectors per tract,[13] the relative frequency of toxic releases in each tract, or the total number of firms in the remediation industry per tract at a given time. $\mathbf{X}_l = (\mathbf{p}, m, \mathbf{Z})'_l$ contains the tract-l specific characteristics treated as median income m, average wage, college ratio, number of amenity-type establishments, infrastructure, population density, unemployment rate, housing rental ratio, and housing prices in the year, t. Additionally, De Silva et al. (2016) show that high polluting firms locate in high minority areas. As rent and income are correlated with race, we also use the minority ratios as a control variable. We include a dummy variable to control for tracts that are in counties bordering nearby states and Mexico. Reporting thresholds and chemicals listed in the TRI Program may change over time. That was the case for reporting thresholds for lead and lead compounds in 2002. This might affect the number of TRI-polluters and the toxicity per tract. To control for this, we use year dummies.[14]

The TRI Program only requires firms with more than 10 FTEs to submit a report every year, while the definition of TRI-type firms used in this section does not have any size requirement. To ensure that our results are not driven by small firms, which are likely to face different regulatory constraints, we perform the same analysis as the one detailed in this section, but using only TRI-type firms with at least 10 FTEs. Estimation results are presented in Appendix B. Employment at the firm level is not constant over our sample period. It is therefore possible that a firm has less than 10 employees at the beginning of our sample period, but more than 10 employees at the end. To account for a firm's potential growth, our analysis in Appendix B considers as a potentially polluting firm, any firm in a qualifying NAICS that has at least 10 FTEs during at least one year of our sample period.[15] One potential issue

[13] We also estimate the effect of local income on the total number of employees in the TRI-type sectors per tract (as a proxy for output) and the results (available upon request) are qualitatively the same as with the number of firms.

[14] We also estimate our basic siting models for before 2002 and after 2002 samples. We report these results in Table A.3 and show that they are qualitatively the same.

[15] We also estimate our model when we don't allow for firms' growth, i.e. when considering TRI-type firms with at least 10 FTEs in all sample periods. The results (available upon request) remain qualitatively the

with this approach is that we miss about 10 percent of the firms that entered at the end of our sample period with fewer than 10 FTEs, but have the potential to grow in the future. As shown in Appendix B, all the results with this narrower definition of TRI-type firms are very similar to the results obtained when considering all TRI-type firms (Tables 2, 3, 4 and 6).

Local income and total pollution. Estimation results for the total toxicity per tract, where we employ a cubic specification for income, are reported in Table 2. The results for income are then graphed, *ceteris paribus*, in Figure 3. An inverted U-shaped curve is present for the relationship between total toxicity and median income, peaking at median income of approximately $65,000, as in De Silva et al. (2016). Figure 3 is also consistent with Figure 2.

In Table 3, using the observed turning points in Figures 2 and 3, we re-estimate this relationship for the same set of correlates. However, in these estimations, we identify three intervals for median income in order to estimate linear splines, or piecewise linear relationships between the independent variable and median income. We find a positive relationship over the median income range $0-66,700, and a negative relationship for the highest range of median income with respect to toxicity. In Table A.4 in Appendix A, we show that the results are similar when we use the natural log of toxicity as our dependent variable. The lowest possible value for total toxicity per tract at a given time is 0. Hence the dependent variable is censored and equation (1) is estimated via maximum likelihood, assuming a normal distribution for the errors and accounting for censoring. We base all inferences on robust standard errors for parameters and marginal effects are reported in Table A.4.

Local income and number of firms. Total pollution in a local area has two dimensions: (1) potentially-polluting firms siting decisions, and (2) their behavior toward the pollution risk. We first investigate siting decisions using the total number of firms in the TRI-type sectors in a tract as our explanatory variable. As shown in Tables 2 and 3 (column 2), this number increases and then levels off at higher income levels, suggesting that there are benefits

same.

of locating a new plant in higher-income areas that offset the legal/clean-up costs related to potential toxic releases.[16]

The sectors covered by the TRI Program generally do not depend on local markets. However, some sectors might rely on natural resources that are not available everywhere in Texas. This is particularly relevant for the oil and gas industry. In column 3 of Tables 2 and 3, we show that our results don't change if we exclude the oil and gas industries from the set of TRI-type firms.[17]

Local income and individual releases. Second, according to our theoretical framework, firms will adjust their pollution behavior to the local demographic characteristics. To explore this prediction, we estimate the relative frequency of toxic releases (above the EPA threshold) reported to the TRI Program as a function of local income. Given the nature of our dependent variable, we estimate this fractional model using the method proposed by Papke and Wooldridge (1996). This is intended to capture the behavioral outcomes of TRI-type firms as a function of income. Results in Table 4 confirm that local income has a stronger impact on the relative frequency of toxic releases in higher-income tracts, indicating that the relative frequency of firm-level releases decreases at a lower rate at relatively low income levels than for higher income levels. This seems to suggest that the marginal cost of increasing releases is larger in higher-income areas.[18]

One concern might be that the result of a decreasing frequency of TRI polluters arises because of self-sorting by TRI-type firms. If those industries that have a higher likelihood of release tend to cluster in lower income areas, and those industries that have a lower likelihood of release are more likely to be found in higher income neighborhoods, then this result

[16] A potential issue may be that our demographic variables are contemporaneous. Therefore, we re-estimate these localization regressions with demographic characteristics lagged by a period. Our results (available upon request) are consistent and robust.

[17] In column 3, we exclude two NAICS codes related to the oil and gas industry: 213111 (Drilling, Oil and Gas Wells) and 324110 (Petroleum Refineries).

[18] If we consider that property values in a given tract are a good proxy for the legal costs associated with releases (in case compensations have to be paid to local residents), we can also look at the relationship between income and property values in a given geography. Our data show that the relationship is indeed convex (see Figure A1 in Appendix A).

will emerge. To address this issue, we separated three industries at NAICS-3 for individual analysis. We chose industries that represent a high, medium and low proportion of our set of TRI-type firms. Specifically, we chose chemicals, fabricated metal, and miscellaneous n.o.s. Note that, the chemical industry represents one of the main sources of releases reported annually to the TRI Program, while fabricated metal, and miscellaneous n.o.s. account for a small proportion of annual releases reported. As shown in Table 5, the relative frequency of firms reporting toxic releases in these three sectors retain a similar appearance to the relative frequency that appears for all the TRI-type industries. The value of the coefficient for local income decreases for higher income intervals. In other words, local income has a stronger negative impact on the likelihood of releases in higher income tracts.

Local income and waste management. Finally, we explore the channels through which TRI-type firms reduce their releases. To this end, we analyze how the number of firms in the waste remediation industry evolves with income. The services offered by these companies are very localized and will only be used by firms that handle or produce hazardous wastes. We use the number of remediation firms as a proxy for the demand in waste management services. In Table 6 and Figure 3, we show that the number of firms in the waste remediation industry rises with income level as does the TRI-type sectors, indicating that potentially-polluting firms in higher income tracts tend to utilize more remediation services. There is also substantial correlation in Column 2 between the number of remediation firms and the number of TRI-type firms in each tract. Remediation firms are more likely to locate in areas where a high number of potentially-polluting firms are present. These results suggest that a potential channel through which TRI-type firms manage the higher pollution-related financial risk in wealthier neighborhood is by investing more in waste management services provided by the remediation sector.

Overall, our findings suggest that the inverted U-shape relationship between local pollution and income is a consequence of firm location and production decisions in a profit-maximizing context. Everything else being equal, potentially polluting firms will tend to prefer higher income areas. For relatively low levels of income, the increase in the number of potentially polluting firms more than offsets the reduction in individual releases, and total pollution is increasing. However, to compensate for the increasing legal/clean-up costs associated with toxic releases, profit-maximizing firms located in high income areas will invest more in waste management practices, leading to a reduction in total pollution.

Other covariates. Beyond these observations of interest to us, we also see from the results in Tables 2, 3 and 6 that transportation networks (roads and rail roads) play an important role in driving firm siting decisions. In accordance with the environmental justice literature, we also find that TRI-type firms are likely to locate in areas where there is a large percentage of non-white residents. However, the larger the share of a tract's population with college degrees, the less likely a firm is to locate in that area. TRI-type and remediation firms are also more likely to choose areas of industrial concentration in which incumbent firms are paying higher wages. Higher wage rates reflect higher marginal products of labor (quality of workforce) and, in the case of firms that require high skill labor inputs, reflect the availability of a workforce that matches their hiring needs.

3.6 *Robustness Checks*

Self-sorting by TRI-type firms. The cost of choosing a higher-income area (and so the probability to locate in this area) may depend on a firm's characteristics (denoted by x in the theoretical framework), e.g. production technology, investment in P2 activities, size of the plant... In that respect, the reduction in the frequency of releases observed in Table 4 could be a consequence of firms sorting across locations according to their technologies or other characteristics, rather than the result of successful waste management practices. To this point, we might note that this is not inconsistent with our theoretical analysis and results so far. Rather it would tend to reinforce the environmental justice argument. Nevertheless, we address this concern in different ways.

First, firms' probability of releasing toxic chemicals depends on their investment in P2 activities. Previous studies (Harrington, 2012, 2013; Khanna et al 2009; Florida and Davison, 2001) show that local community characteristics, such as local income, have limited impact on P2 activities. Moreover, the effectiveness of P2 activities in achieving environmental targets or reducing pollution has shown to be limited only to some toxic chemicals and some industries (Sam, 2010; Gamper-Rabindran, 2006).

Second, as different sectors might use technologies producing different amounts of hazardous wastes, there may be a self-sorting by TRI-type sectors, with the most polluting sectors located in poorer neighborhood. To address this issue, we restrict our analysis to two sectors, which account for a large proportion of releases reported to the TRI: chemicals and oil and gas. As shown in Table A.5 (columns 1 and 2) of Appendix A, our main finding that the number of TRI-type firms is increasing with income for low income tracts holds for the chemical and oil/gas sectors. For the oil and gas industry, the number of TRI-type firms increases with income up to \$100,000. The coefficient is then negative but non significant. For the chemical industry, the number of potential polluters increases with income except over the interval [\$67,000–\$100,000], where it slightly decreases.

Other facilities' characteristics are likely to affect the probability of releases. There may be a self-sorting by age or size of the plants, with older and/or larger plants primarily located in low-income tracts. In Appendix B, we show that the results remain unchanged when we consider only TRI-type firms with at least 10 FTEs. In Table A.5 (column 3) of Appendix A, we also show that our results are robust if we restrict the analysis to TRI-type firms that are more than 10 years old. The number of TRI-type firms is increasing over the income interval [\$0–\$100,000] and then decreases for median incomes higher than \$100,000.

One other sorting issue may be that firms change locale to leave demographic conditions for a more suitable neighborhood in terms of financial risk associated with a release. During the course of the data, fewer than one-tenth of one percent of firms (90 TRI-type firms, of which 17 were TRI-reporting firms, out of a total of 36,553 TRI-type establishments) changed census tract. We do not find this issue to be important in this case.[19]

Causality. It may be the case that a tract's demographic characteristics (including income) change over time precisely because of firms' location decisions: residents express their preferences for environmental attributes by moving across jurisdictions. We deal with this endogeneity issue in different ways.

First, we look at the correlations between ranking of tracts in 2000 and 2006. These results are reported in Table A.6. Our results indicate that ranking of tracts based on income, education, and population are highly correlated between 2000 and 2006 and the correlation coefficient is more than 96 percent for all variables. To the extent that industrial concentrations in 2000 probably represent the cumulative effects of perhaps several decades, we might assume that sorting effects at the beginning or our sample period represent a population location equilibrium, or *ex post* sorting equilibrium.

Another way to deal with this reverse causality issue is to look at firms' entry models. Insofar as entrant's locational calculus is concerned, demographic characteristics of the potential localities are largely given. With this in mind, we utilize an entry model for TRI-type firms by focusing only on new entrants in our sample period (2000-2006). Entry is defined as the appearance of a new Entreprise Identification Number in our QCEW data. Controlling for other relevant factors, we should observe entrants' preferences with respect to local incomes without the issue of costly relocation that affects incumbent firms.

Due to the large number of new entrants (11,752), it is not possible to estimate this entry model using a conditional logit. Instead, we use the Poisson Pseudo Maximum Likelihood (PPML) method with time fixed effects. Compared to the standard Poisson estimation, the

[19] Additionally, one might be concerned that firms with multiple establishments may locate their manufacturing plant in a low income neighborhood while their sales office may be located in an affluent area. This does not seem to be the case in our sample as the average firm has only 1.3 branches. This number is computed excluding industries as such as retail gasoline, commercial printing, and food processing which represent less than 5 percent of the sample. If we include these industries this number is about 2.6.

PPML estimation does not assume that the data are distributed with the mean equal to the variance of the event count. The data need not even come from a Poisson process and may be either under or over-dispersed. Note that the estimated coefficients are nevertheless identical to the Poisson regression estimates. All that is required for PPML consistency is that the conditional mean function be correctly specified.[20] Here, the dependent variable is the number of TRI-type entrants (y) for a given tract (l) for a given year (t). Tract-level independent variables are as described before. The basic model is as follows:

$$E[y_{lt}|X_{lt}] = \exp(X_{lt}^{'}\psi + \tau_t) \tag{2}$$

These entry results are presented in Table 7. We observe a clear correlation between TRI-type entrants and income as in our localization models. This exercise is consistent with our theoretical prediction that local income drives firms' location decision behavior. The presence of incumbent TRI-type firms has a positive impact on the probability of entry of new TRI-type firms, indicating the presence of localization economies. The transportation-based effects, wage rates and share of the population with a college degree follow a pattern similar to what we found in the siting models in Tables 2 and 3. In the last column of Table 7, we find that the average house value has no impact on entry decisions of TRI-type firms.[21]

The results of the entry models also show that to understand firms' pollution and location decisions, it is important to consider the universe of firms in industries that are represented in the TRI. When considering only firms reporting a release to the TRI Program (i.e. TRI-polluters), De Silva et al. (2016) find that entry of TRI-polluters follows an inverted U-shape pattern, while Wolverton (2009) observes a negative impact of income on TRI-polluters' location decisions.

[20] For a more detailed discussion of this reasoning, see Gourieroux et al. (1984) and Santos Silva and Tenreyro (2006, 2011).

[21] We don't include median income and average house value in the same regression because these two variables are highly correlated.

Additional Robustness Checks. In Appendix C, we present a series of robustness checks to show that our results are not driven by some particular tracts (MSA vs. non-MSA) or firms (TRI-type firms excluding TRI-polluters, TRI-type firms which are at least 10 years old, TRI-reporters...). We also show that our results remain valid if we use a more restrictive definition of TRI-type industries based on their probability to pollute.

4 Entry and exit patterns in the remediation industry

An important insight from the previous section is that local median income affects both firms' location and pollution decisions. Potentially polluting firms seem to locate in both lower and higher income areas, while the frequency of firms that actually pollute decreases with local median income. This seems to suggest that potentially polluting firms in lower income areas are more likely to realize their pollution potential because they take fewer costly precautions. Waste management activities have been used as a proxy for local demand for environmental quality. Results in Table 6 suggest that there is a substantial correlation between the number of waste management firms and the number of TRI-type firms at the tract level. Waste remediation firms supply pollution risk management services in response to the demand for those services posed by potentially polluting firms. Given the importance of these activities to explain the relationship between local income, location and pollution, we investigate further the structure of the industry supplying these remediation/waste management services.

4.1 *Entry*

In this section, we estimate the entry process of waste remediation establishments by census tract in Texas on an annual basis over the years 2000-2006. Establishment entry in any year is defined as the appearance (initial UI liability) of a new Enterprise Identification Number (EIN). We estimate the number of entrants in a particular location (tract) as a function of location characteristics. These characteristics include the number of remediation firms already present in that county (localization effects), the number of establishments in TRI-related industries in that tract, median personal income, level of education attainment, amenities, infrastructure, population density, unemployment rate, and controls for housing ownership. We also include a dummy variable to control for tracts that are in counties bordering nearby states and Mexico. We present the distributions of incumbent and entrant firms for the waste remediation industry in Table 8.

The most common year of firm entry was 2002. This coincides with a TRI rule making which lowered reporting thresholds for lead and lead compounds.[22] De Silva et al. (2016) show that, in 2002, the number of TRI reports involving lead or lead compounds increased six-fold compared to 2001. Also note that the aggregate announced toxic weight increased by a factor greater than four in 2002 relative to 2001. We argue that, with this threshold change, demand for waste remediation increased in 2002 and, hence, we see an increase in entrants in 2002. We control for this by using year dummies. There is an average of about 0.013 remediation entrants per tract over the entire period of the sample.

We empirically model a firm's (i) location (l - tract) choice of entry at time t in order to maximize expected profits using a conditional Logit model (see McFadden, 1974). Results for the likelihood of entry are reported in Table 9. In all model specifications, the localization of remediation activity is important, all else equal. The estimated coefficient of the variable that uses the number of existing remediation firms as a measure of industrial concentration is positive and significant at the .01 level. In other words, the presence of incumbent remediation firms has a positive impact on the likelihood of additional entry of remediation firms. This is consistent with the presence of localization economies, or economies of scale from industrial concentration, that enhance the attractiveness of a given location for a start-up or relocating establishment. Not surprisingly, the presence of TRI-type firms matters with consistently and highly significant coefficient estimates across all models.

[22]See Title 40, Part 372 of the Code of Federal Regulations which is summarized in volume 66, number 11 of the Federal Register.

This indicates that industries with a history of polluting firms are an important factor in the presence of remediation firms. The estimated coefficient on median income is also significant and positive and there is some evidence that the second derivative on the median income variable may be negative or the relationship is concave. We also conclude that population matters, as does land area. The signs of the coefficients for both variables, *ceteris paribus*, imply that greater population density, as would be expected, results in a higher likelihood of entry of remediation establishments. Of further interest is the estimated coefficient on the ratio of college-educated residents. These results suggest that higher levels of education correlate to lower remediation firm entry probabilities.

As a robustness check, we estimate the entry process using a count data model with time fixed effects, specifically a Poisson model estimated by Pseudo Maximum Likelihood (PPML). Our dependent variable is the number of waste management entrants for a given tract (l) for a given year (t). Estimation results for these PPML regressions are contained in Table 10. No qualitative differences are observed between these two models. As before, there is evidence of localization effects and demand-side factors associated with a larger TRI-type firm sector on the likelihood of remediation firm entry. In summary, the above findings support our earlier conjecture that remediation firms will locate closer to TRI-type firms.

4.2 *Entry at random locations*

As an additional robustness check, we look at entry by establishments in the remediation industries into random locations that are not dependent on legal jurisdictional boundaries. The locations are defined as non-overlapping rings of one-mile radius centered on establishments that are not in the defined set of remediation industries –that is, establishments in either a TRI-type or a non-TRI-type industries, excluding the remediation sector.

This brings an additional level of spatial acuity into the analysis. We center the rings on existing establishments because we want to limit the analysis to areas where there is commercial activity in order to ensure that the chosen areas are actually potential choices for locating a new establishment. Not doing so might result in choosing locations in which there is virtually no population, such as remote rural or agricultural land with no industrial or commercial infrastructure, or no commercial or industrial activity due to, say, zoning restrictions. Any non-remediation industry establishment that existed at any point during the time frame of the study is a potential center point, thus allowing for the possibility of new areas of commercial activity that came into existence during the course of the analysis and the possibility that a remediation firm is the first to enter the area.

By maximizing the number of potential rings while imposing the non-overlapping condition, we get 8,142 rings. Table 11 provides summary statistics for these non-overlapping rings. We see 231 out of 395 entrants enter into these random locations. Figure 4 shows these locations.

The specific industry containing the firm that is used to center the random location ring does not matter –it only serves to locate a ring in an area that allows commercial activity. It is, rather, the industrial content captured in the ring that matters. In this analysis, the variables of interest are remediation industry establishments and TRI-type firms contained in the random rings. We are unable to measure non-establishment variables, such as household income or other population characteristics, at the spatial division of the rings. Hence, the other variables in the model are still measured at the census tract level and reflect the census tract in which the ring center is located. In general, this represents measures for the census tract variable values that reflect the tract in which the majority of the area of the ring is located.

The results of the PPML estimation in Table 12 are quite similar to those based on establishments at the census tract. That is, localization is, as before, an important determinant of the likelihood of remediation establishment entry. Further, the presence of TRI-type establishments in the rings is an important factor in location decisions of remediation industry establishments. Of interest, higher wages in the surrounding census tract are significantly associated with higher entry probabilities which can reflect the industry's demand for higher skilled labor.

4.3 *Exit*

Thinking about establishment exits, we have in mind a theoretical model involving a threshold rule that is analogous to the profit maximization problem considered in our entry analysis. In this case, if firms do not make a sufficient level of profit, they choose to exit the industry. In order to consider the question of remediation industry establishment exit, we estimate logit models in which the dependent variable is coded one if the firm exits during a given period or as zero if the firm continues operation through the entire period.

Exit is identified as having taken place if the firm EIN disappears from the data set at the outset of a given calendar year and is treated as having occurred during the last year in which the firm is present in the data (year previous to disappearance). The time to failure is relative to the year in which the firm entered the market. That is, we only consider firms that enter during the time frame of the analysis, i.e., entry in years 2000-2006, and consider the exit event relative to the number of years since entry. The observed number of years to failure, therefore, ranges from a low of one (failure in year of entry) to a high of seven (no failure observed) across the establishments in the sample. Table 13 illustrates exit patterns. To interpret Table 13, note that in year 2002, there were 98 entrants. By 2006, or over the course of the following five years, 69 of them exited the market.

Overall, there were 395 entrants of which 214 had exited by 2006. Table 14 provides establishment-level summary statistics. About 36% of the establishments have past experience in the market. On average, these establishments have an additional branch or are part of a multi-establishment firm. Additionally, these establishments pay about $49,000 per year in wages and employ about 19 workers. This indicates that this labor force is highly skilled and limited to a given area. Hence, we conjecture that firms will compete for the same resources and this will affect the survival rate. In this case, we expect agglomeration to increase the likelihood of exit.

Estimation results are reported in Table 15. In the case of localization effects, the presence of other remediation firms increases the likelihood of failure for these new establishments. On the other hand, the numbers of local area TRI-type firms appear to have no influence on exit probabilities. Not surprisingly, like firms in most industries, the age of the firm and firm size (employment) are negatively correlated with probability of failure in any given period. Local income appears to have no statistically significant effect on exit.

5 Conclusion

We have employed detailed data for small geographies to analyze the posited theoretical relationship between the localization of potentially polluting firms, toxic releases, and local-area incomes. Our model suggests that profit-maximizing, potentially polluting firms behave rationally toward the financial risk inherent in a toxic release. Our conjecture is that, as risk exposure increases with incomes within spatial proximity to those firms, the firms will take measures to manage that risk. We utilized the localization of the waste management industry as a means of observing evidence of demand for risk-reducing options. In this context, firms can vary their utilization of waste management services as an additional means of managing pollution risk across the spectrum of locations in lower income, lower risk exposure areas to location in higher income, higher risk exposure areas.

We find our results to be persuasive. We find evidence consistent with our hypotheses, both in terms of potentially polluting firms' localization, the localization of waste remediation firms, and in terms of the relative frequency of these firms' reported releases. Since the analysis was made within a single state, we have largely controlled for heterogeneity in regulatory structures that, under the traditional pollution haven argument, would lead to a similar result in terms of realized releases if polluting firms were to exploit opportunities to locate in lower income areas anxious to attract employers by providing relatively lax regulatory environments. While both explanations will lead to a similar outcome, ours is driven by non-policy related incentives, although it does depend on enforcement of a common set of laws. That is to say, the traditional economic paradigm of profit-maximizing behavior in the presence of risk can explain disparities in exposition to toxic releases among different population groups independent of any differences across regulatory regimes.

Our results bear implications for policies that aim to enhance environmental justice, but also speaks to policies that can exploit the incentives inherent in the standard paradigm of profit-maximization. One of the objectives of the TRI Program was to create a strong incentive for companies to take measures to reduce their toxic release and be good neighbors in their communities. During our sample period 2000–2006, overall toxic releases in the US decreased by about 34% with a further decline of about 21% since 2006. However, our paper shows that this decline might not be uniformly distributed because firms respond rationally to local demographic characteristics (including local income). In trying to implement the lowest-cost response to the publication of the TRI data, firms will tend to reduce releases through waste management when local opposition is the highest.

Our analysis suggests that without further actions, the disparities in exposure to toxic release faced by certain population groups will not be reduced by simply requiring that firms report their releases. If the attainment of greater environmental justice across population groups is a policy goal, serious thought should then be given to the regulations on compensation schemes, designed to offset the costs of potential environmental risk.

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Figure 1: Locations of waste remediation and TRI firms

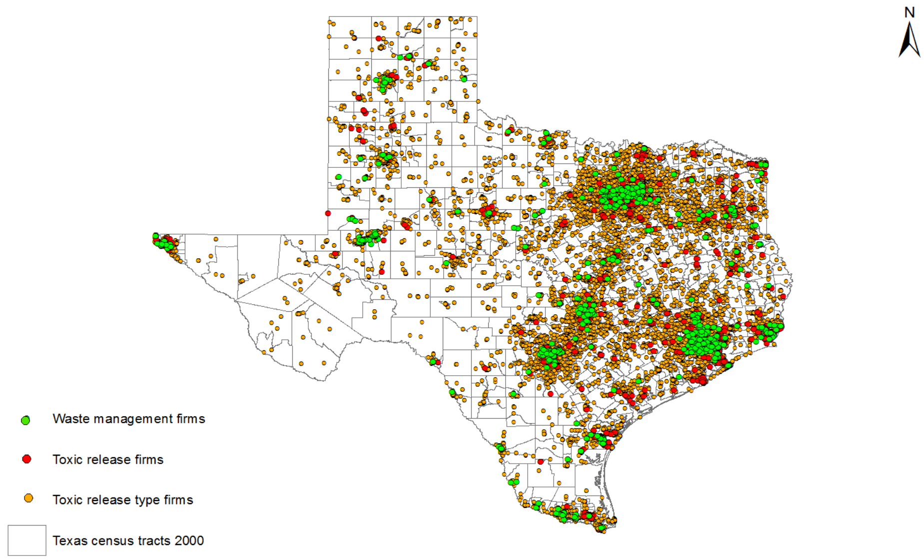


Figure 2: Average shares of toxic pounds, TRI type, and remediation firms per tract by median income

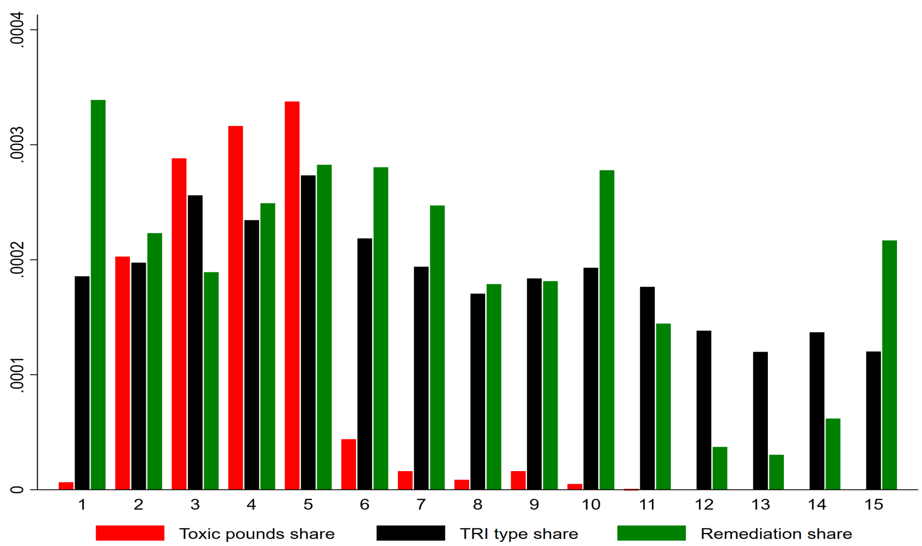
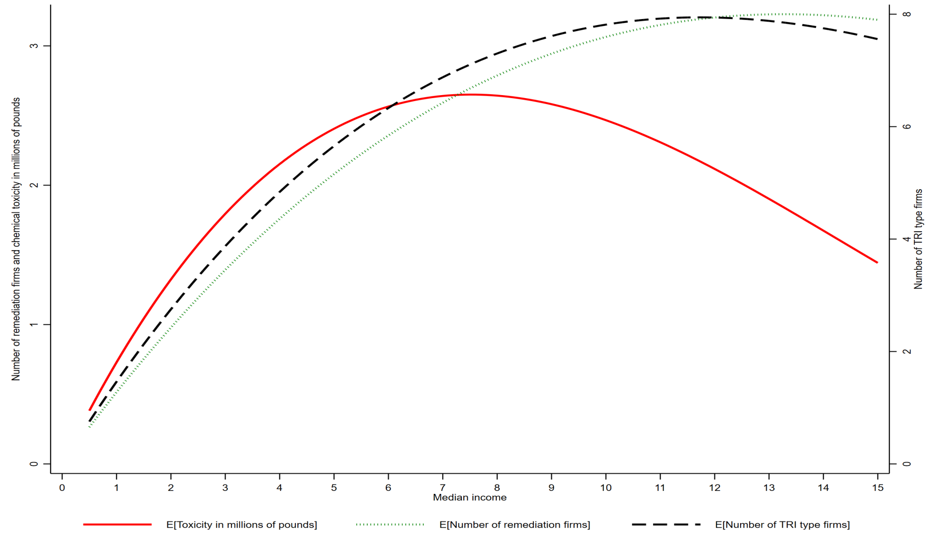


Figure 3: Estimated cubic functions relating to median income



The coefficients used for the cubic specification in toxicity pounds are reported in Column 1 in Table 2 and for TRI type, the coefficients are reported in Column 2 in Table 2. We use estimates reported in Table 6 Column 1 to draw the expected line for remediation firms.

Figure 4: Non-overlapping one mile rings – Dallas area

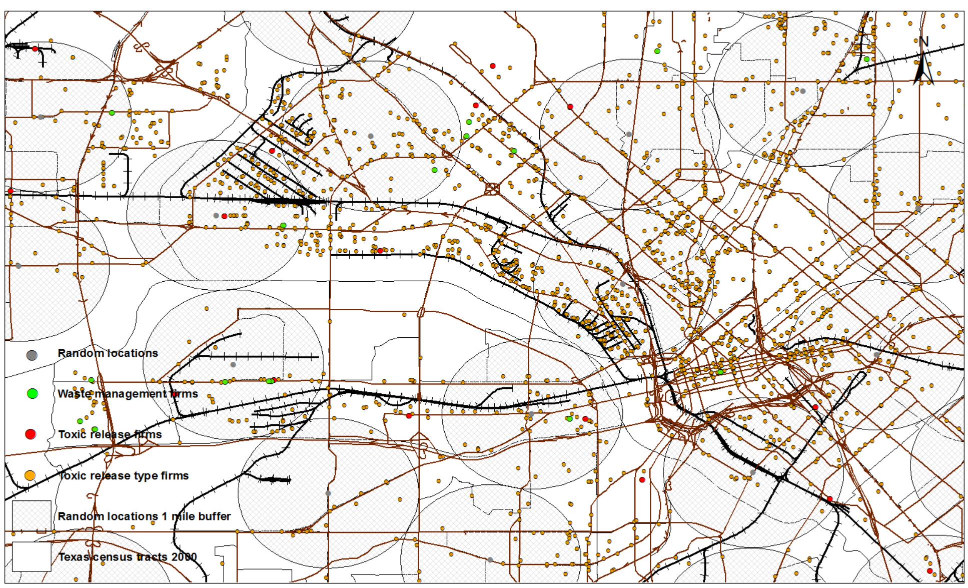


Table 1: Summary statistics by tract

Variable	Mean (Standard deviation)			
	All	Average median income (in \$10,000)$_{lt}$		
		\$0 – \$66.7	>\$66.7 – \$100	>\$100
Number of tracts	4,302	3,797	380	125
Average toxicity in pounds$_{lt}$ (in millions)	0.010	0.011	0.001	0.000
	(0.180)	(0.194)	(0.013)	(0.000)
Average number of environmental remediation firms$_{lt}$	0.084	0.087	0.082	0.049
	(0.342)	(0.351)	(0.317)	(0.241)
Average number of TRI type firms$_{lt}$	4.018	4.146	3.234	2.501
	(9.994)	(10.415)	(6.504)	(3.030)
Average number of TRI reporting firms$_{lt}$	0.677	0.682	0.724	0.383
	(1.667)	(1.619)	(2.236)	(0.860)
Median income (in \$10,000)$_{lt}$	4.393	3.762	7.937	12.767
	(2.278)	(1.237)	(0.972)	(2.971)
Average wage (in \$10,000)$_{lt}$	3.825	3.550	5.247	7.836
	(4.470)	(3.596)	(7.080)	(10.868)
Percentage nonwhite residents$_{lt}$	0.290	0.309	0.157	0.107
	(0.186)	(0.187)	(0.089)	(0.081)
College ratio$_{lt}$	0.094	0.078	0.200	0.264
	(0.078)	(0.064)	(0.064)	(0.050)
Number of amenity establishments$_{lt}$	5.478	5.500	5.009	6.227
	(12.878)	(13.487)	(5.436)	(9.550)
Number of roads$_{lt}$	13.150	13.712	9.024	8.640
	(12.022)	(12.292)	(7.942)	(10.532)
Number of rail roads$_{lt}$	2.153	2.339	0.850	0.488
	(4.154)	(4.305)	(2.526)	(1.569)
Unemployment rate$_{lt}$	4.468	4.703	2.790	2.434
	(3.204)	(3.261)	(1.139)	(3.483)
Population (in 1,000)$_{lt}$	5.088	4.910	6.696	5.584
	(2.884)	(2.618)	(3.995)	(4.521)
Land area (in 100 square miles)$_{lt}$	0.622	0.694	0.092	0.045
	(2.200)	(2.331)	(0.213)	(0.071)
Population density (in 1,000 per 100 square miles)$_{lt}$	285.518	288.251	264.699	265.799
	(317.324)	(331.210)	(180.403)	(180.185)
Housing rental ratio$_{lt}$	0.315	0.337	0.167	0.100
	(0.201)	(0.199)	(0.121)	(0.094)
TxDOT expenditures (in \$1,000,000)$_{lt}$	9.068	9.918	3.127	1.305
	(23.076)	(24.322)	(7.291)	(2.380)
Average house value (in \$10,000)$_{lt}$	11.423	9.485	19.937	44.380
	(9.619)	(5.127)	(8.925)	(26.902)

Table 2: Explaining variation in the number of toxic pounds and TRI type firms at tract level

Variable	Toxicity in pounds$_{lt}$	Number of firms in TRI type$_{lt}$	
		All	Without oil and gas
	(1)	(2)	(3)
Median income (in \$10,000)$_{lt}$	0.799***	1.553***	1.553***
	(0.105)	(0.178)	(0.177)
Median income (in \$10,000)$^2_{lt}$	-0.072***	-0.091***	-0.092***
	(0.015)	(0.022)	(0.022)
Median income (in \$10,000)$^3_{lt}$	0.002***	0.001*	0.001*
	(0.001)	(0.001)	(0.001)
Average wage (in \$10,000)$_{lt}$	0.034***	0.078***	0.077***
	(0.003)	(0.013)	(0.013)
Percentage nonwhite residents$_{lt}$	1.568***	3.606***	3.594***
	(0.169)	(0.409)	(0.409)
College ratio$_{lt}$	-5.342***	-11.859***	-11.859***
	(0.689)	(1.245)	(1.243)
Number of amenity establishments$_{lt}$	-0.005*	0.114***	0.114***
	(0.003)	(0.004)	(0.004)
Number of roads$_{lt}$	0.007***	0.158***	0.158***
	(0.002)	(0.005)	(0.005)
Number of rail roads$_{lt}$	0.064***	0.364***	0.362***
	(0.003)	(0.015)	(0.015)
Unemployment rate$_{lt}$	0.004	-0.014	-0.014
	(0.005)	(0.019)	(0.019)
Population density$_{lt}$	-0.002***	-0.001***	-0.001***
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	0.769***	3.194***	3.197***
	(0.178)	(0.447)	(0.447)
Border county effects$_{lt}$	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Number of observations	30,114	30,114	30,114
Log likelihood	-3,189	-109,737	-109,691
Uncensored observations	833	29,968	29,962

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Explaining variation in the number of toxic pounds and TRI type firms at tract level – alternate specification

Variable	Toxicity in pounds$_{lt}$	Number of firms in TRI type$_{lt}$	
		All	Without oil and gas
	(1)	(2)	(3)
Median income \$0 – \$66,700$_{lt}$	0.275***	0.873***	1.045***
	(0.029)	(0.065)	(0.056)
Median income >\$66,700 – \$100,000$_{lt}$	0.016	0.244**	0.321***
	(0.069)	(0.112)	(0.095)
Median income >\$100,000$_{lt}$	-0.627	-0.122	-0.150*
	(0.482)	(0.093)	(0.081)
Average wage (in \$10,000)$_{lt}$	0.034***	0.078***	0.043***
	(0.003)	(0.013)	(0.011)
Percentage nonwhite residents$_{lt}$	1.387***	3.482***	3.711***
	(0.165)	(0.408)	(0.350)
College ratio$_{lt}$	-5.732***	-12.085***	-12.618***
	(0.693)	(1.252)	(1.081)
Number of amenity establishments$_{lt}$	-0.005*	0.114***	0.080***
	(0.003)	(0.004)	(0.004)
Number of roads$_{lt}$	0.007***	0.159***	0.111***
	(0.002)	(0.005)	(0.004)
Number of rail roads$_{lt}$	0.063***	0.362***	0.275***
	(0.003)	(0.015)	(0.012)
Unemployment rate$_{lt}$	0.002	-0.022	0.016
	(0.005)	(0.019)	(0.016)
Population density$_{lt}$	-0.002***	-0.001***	-0.001***
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	0.825***	3.208***	2.881***
	(0.178)	(0.448)	(0.384)
Border county effects$_{lt}$	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Number of observations	30,114	30,114	30,114
Log likelihood	-3,202	-109,742	-86,458
Uncensored observations	833	29,968	29,962

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Relative frequency of toxic release firms reported at tract level

Variable	(TRI polluters / TRI type)$_{lt}$	
	(1)	(2)
Median income \$0 – \$66,700$_{lt}$	-0.036***	-0.013
	(0.011)	(0.014)
Median income >\$66,700 – \$100,000$_{lt}$	-0.038	-0.033
	(0.040)	(0.042)
Median income >\$100,000$_{lt}$	-0.259*	-0.287*
	(0.138)	(0.157)
Average wage (in \$10,000)$_{lt}$		0.014***
		(0.002)
Percentage nonwhite residents$_{lt}$		0.289***
		(0.102)
Number of amenity establishments$_{lt}$		-0.019***
		(0.003)
Number of roads$_{lt}$		-0.001
		(0.001)
Number of rail roads$_{lt}$		0.024***
		(0.002)
Unemployment rate$_{lt}$		0.000
		(0.004)
Population density$_{lt}$		-0.000***
(in 1,000 per 100 square miles)		(0.000)
Housing rental ratio$_{lt}$		0.225*
		(0.117)
Year effects	Yes	Yes
Border county effects$_{lt}$	Yes	Yes
Number of observations	30,114	30,114
Log likelihood	-1,215	-1,177

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Relative frequency of toxic release firms reported by industry at tract level

Variable	(Chemical polluters / total chemical firms)$_{lt}$	(Fabricated metal polluters / total fabricated metal)$_{lt}$	(Miscellaneous manuf. polluters / total miscellaneous manuf.)$_{lt}$
	(1)	(2)	(3)
Median income \$0 – \$66,700$_{lt}$	0.048***	0.093***	0.057**
	(0.013)	(0.014)	(0.026)
Median income >\$66,700 – \$100,000$_{lt}$	0.003	-0.169***	0.000
	(0.037)	(0.044)	(0.050)
Median income >\$100,000$_{lt}$	-0.532***	-0.147***	-0.000
	(0.186)	(0.051)	(0.057)
Average wage (in \$10,000)$_{lt}$	0.018***	0.008***	0.008***
	(0.002)	(0.001)	(0.002)
Percentage nonwhite residents$_{lt}$	0.690***	0.853***	0.340**
	(0.098)	(0.097)	(0.169)
Number of amenity establishments$_{lt}$	0.001*	0.002***	0.003***
	(0.001)	(0.000)	(0.001)
Number of roads$_{lt}$	0.002	0.005***	0.010***
	(0.001)	(0.001)	(0.001)
Number of rail roads$_{lt}$	0.042***	0.017***	0.007
	(0.003)	(0.003)	(0.004)
Unemployment rate$_{lt}$	0.014***	0.007**	-0.011
	(0.003)	(0.003)	(0.016)
Population density$_{lt}$	-0.001***	-0.001***	-0.000
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	0.522***	0.037	0.616***
	(0.089)	(0.094)	(0.143)
Year effects	Yes	Yes	Yes
Border county effects$_{lt}$	Yes	Yes	Yes
Number of observations	30,114	30,114	30,114
Log likelihood	-3,258	-2,630	-1,005

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Explaining variation in the number of remediation firms at tract level

Variable	Number of firms in remediation$_{lt}$			
	(1)	(2)	(3)	(4)
Median income \$0 – \$66,700$_{lt}$	0.378***	0.332***		
	(0.031)	(0.030)		
Median income >\$66,700 – \$100,000$_{lt}$	0.040	0.021		
	(0.055)	(0.053)		
Median income >\$100,000$_{lt}$	0.016	0.027		
	(0.045)	(0.044)		
Median income (in \$10,000)$_{lt}$			0.541***	0.465***
			(0.087)	(0.084)
Median income (in \$10,000)$^2_{lt}$			-0.027**	-0.023**
			(0.011)	(0.011)
Median income (in \$10,000)$^3_{lt}$			0.000	0.000
			(0.000)	(0.000)
Number of TRI type incumbent establishments$_{lt}$		0.028***		0.028***
		(0.002)		(0.002)
Average wage (in \$10,000)$_{lt}$	0.023***	0.021***	0.023***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)
Percentage nonwhite residents$_{lt}$	0.512***	0.277	0.483**	0.239
	(0.197)	(0.193)	(0.198)	(0.195)
College ratio$_{lt}$	-4.744***	-4.168***	-4.632***	-4.065***
	(0.620)	(0.604)	(0.619)	(0.603)
Number of amenity establishments$_{lt}$	0.011***	0.008***	0.011***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Number of roads$_{lt}$	0.016***	0.008***	0.016***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Number of rail roads$_{lt}$	0.046***	0.032***	0.046***	0.032***
	(0.005)	(0.005)	(0.005)	(0.005)
Unemployment rate$_{lt}$	0.013*	0.015**	0.014*	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)
Population density$_{lt}$	-0.000***	-0.000***	-0.000***	-0.000***
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	2.084***	1.922***	2.086***	1.924***
	(0.209)	(0.204)	(0.209)	(0.204)
Border county effects$_{lt}$	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Number of observations	30,114	30,114	30,114	30,114
Log likelihood	-9,630	-9,492	-9,639	-9,502
Uncensored observations	2,104	2,104	2,104	2,104

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Models of aggregate entry counts for TRI type firms at tract level

Variable	Number of entrants$_{lt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of TRI type incumbents$_{ilt}$	0.013***	0.012***	0.012***	0.012***	0.012***	0.013***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median income \$0 – \$66,700$_{lt}$		0.074***		0.145***	0.207***	0.184***	
		(0.015)		(0.019)	(0.020)	(0.022)	
Median income >\$66,700 – \$100,000$_{lt}$		-0.145***		-0.088**	-0.025	0.001	
		(0.038)		(0.041)	(0.041)	(0.041)	
Median income >\$100,000$_{lt}$		-0.044		-0.040	-0.036	-0.027	
		(0.030)		(0.030)	(0.029)	(0.030)	
Average wage (in \$10,000)$_{lt}$		0.018***	0.019***	0.019***	0.019***	0.019***	0.019***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Percentage nonwhite residents$_{lt}$		0.108	-0.174*	0.089	-0.319**	-0.165	-0.540***
		(0.112)	(0.101)	(0.110)	(0.130)	(0.133)	(0.131)
College ratio$_{lt}$			-1.115***	-2.276***	-3.581***	-4.135***	-1.324***
			(0.239)	(0.364)	(0.395)	(0.407)	(0.296)
Number of amenity establishments$_{lt}$				0.005***	0.004***	0.005***	0.004***
				(0.000)	(0.000)	(0.001)	(0.000)
Number of roads$_{lt}$		0.002	0.002	0.001	0.001		0.000
		(0.002)	(0.002)	(0.002)	(0.002)		(0.002)
Number of rail roads$_{lt}$		0.028***	0.026***	0.026***	0.026***		0.026***
		(0.003)	(0.003)	(0.003)	(0.003)		(0.003)
Unemployment rate$_{lt}$					0.004	-0.002	0.008*
					(0.004)	(0.005)	(0.005)
Population density$_{lt}$		0.051***	0.055***	0.042***	0.041***	0.054***	0.056***
(in 1,000 per 100 square miles)		(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
Housing rental ratio$_{lt}$					0.876***	0.887***	0.393***
					(0.136)	(0.135)	(0.125)
TxDOT expenditures (in \$1,000,000)$_{lt}$						0.001	
						(0.001)	
Average house value$_{lt}$							0.000
							(0.002)
Border county effects$_{lt}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	30,114	30,114	30,114	30,114	30,114	30,114	30,114
Log likelihood	-23,851	-23,029	-23,060	-22,887	-22,812	-23,074	-22,953

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Entry patterns

Entry year	Remediation firm	
	Entrants	Incumbents
2000	43	203
2001	47	241
2002	98	277
2003	54	362
2004	58	367
2005	50	368
2006	45	375

Table 9: Conditional logit results for remediation firm entry at tract level

Variable	Firm entry$_{ilt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of environmental remediation	1.048***	0.985***	0.996***	0.950***	0.918***	0.921***	0.979***
incumbents$_{lt}$	(0.059)	(0.062)	(0.062)	(0.064)	(0.065)	(0.064)	(0.063)
Number of TRI type incumbents$_{ilt}$	0.008***	0.006***	0.007***	0.005***	0.006***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Median income \$0 – \$66,700$_{lt}$		0.180***		0.340***	0.439***	0.409***	
		(0.042)		(0.055)	(0.059)	(0.061)	
Median income >\$66,700 – \$100,000$_{lt}$		-0.058		0.028	0.137	0.126	
		(0.090)		(0.095)	(0.097)	(0.096)	
Median income >\$100,000$_{lt}$		-0.030		-0.017	-0.016	-0.009	
		(0.088)		(0.086)	(0.085)	(0.086)	
Average wage (in \$10,000)$_{lt}$			0.309	1.036***	0.404	0.312	-0.071
			(0.325)	(0.348)	(0.380)	(0.382)	(0.376)
Percentage nonwhite residents$_{lt}$		0.013*	0.015**	0.014**	0.013*	0.013*	0.013*
		(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
College ratio$_{lt}$			0.796	-3.244***	-5.312***	-5.334***	-0.157
			(0.765)	(1.111)	(1.222)	(1.230)	(0.940)
Number of amenity establishments$_{lt}$				0.004***	0.003***	0.003***	0.004***
				(0.001)	(0.001)	(0.001)	(0.001)
Number of roads$_{lt}$		0.004	0.002	0.003	0.003		0.001
		(0.003)	(0.003)	(0.004)	(0.004)		(0.004)
Number of rail roads$_{lt}$		0.014	0.011	0.014	0.013		0.012
		(0.009)	(0.009)	(0.009)	(0.009)		(0.009)
Unemployment rate$_{lt}$					0.004	0.003	0.014
					(0.010)	(0.010)	(0.011)
Population density$_{lt}$		-0.000*	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***
(in 1,000 per 100 square miles)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$					1.642***	1.593***	0.506
					(0.355)	(0.354)	(0.335)
TxDOT expenditures (in \$1,000,000)$_{lt}$						-0.007	
						(0.004)	
Average house value$_{lt}$							0.011**
							(0.005)
Border county effects$_{lt}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of entrants	395	395	395	395	395	395	395
Number of tratcs	4,302	4,302	4,302	4,302	4,302	4,302	4,302
Log likelihood	-3,180	-3,161	-3,170	-3,147	-3,136	-3,136	-3,162
χ^2	249.1	288.7	269.3	316.0	338.7	337.8	284.8

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Models of aggregate entry counts for remediation firms at tract level

Variable	Number of entrants_{lt}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of environmental remediation	1.048***	0.969***	0.996***	0.950***	0.918***	0.921***	0.979***
incumbents_{lt}	(0.059)	(0.064)	(0.062)	(0.066)	(0.066)	(0.065)	(0.063)
Number of TRI type incumbents_{ilt}	0.008***	0.006***	0.007***	0.005***	0.006***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median income \$0 – $\$66{,}700_{lt}$		0.248***		0.340***	0.439***	0.409***	
		(0.048)		(0.058)	(0.061)	(0.062)	
Median income >\$66,700 – $\$100{,}000_{lt}$		-0.052		0.028	0.137	0.126	
		(0.095)		(0.104)	(0.106)	(0.105)	
Median income $>\$100{,}000_{lt}$		-0.026		-0.017	-0.016	-0.009	
		(0.083)		(0.082)	(0.081)	(0.081)	
Average wage (in $\$10{,}000)_{lt}$		0.012***	0.015***	0.014***	0.013***	0.013***	0.013***
		(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Percentage nonwhite residents_{lt}		1.146***	0.309	1.036***	0.404	0.312	-0.071
		(0.330)	(0.320)	(0.335)	(0.363)	(0.364)	(0.357)
College ratio_{lt}			0.796	-3.244**	-5.312***	-5.334***	-0.166
			(0.810)	(1.356)	(1.391)	(1.406)	(0.986)
Number of amenity $\text{establishments}_{lt}$				0.004***	0.003***	0.003***	0.004***
				(0.001)	(0.001)	(0.001)	(0.001)
Number of roads_{lt}		0.004	0.002	0.003	0.003		0.001
		(0.004)	(0.004)	(0.004)	(0.004)		(0.004)
Number of rail roads_{lt}		0.014	0.011	0.014	0.013		0.012
		(0.011)	(0.011)	(0.010)	(0.011)		(0.010)
Unemployment rate_{lt}					0.004	0.003	0.014
					(0.013)	(0.013)	(0.015)
Population density_{lt}		-0.000**	-0.000**	-0.000*	-0.000***	-0.000***	-0.000***
(in 1,000 per 100 square miles)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Housing rental ratio_{lt}					1.642***	1.593***	0.507
					(0.368)	(0.367)	(0.359)
TxDOT expenditures (in $\$1{,}000{,}000)_{lt}$						-0.007	
						(0.005)	
Average house value_{lt}							0.011***
							(0.004)
Border county effects_{lt}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	30,114	30,114	30,114	30,114	30,114	30,114	30,114
Log likelihood	-1,987	-1,962	-1,977	-1,954	-1,942	-1,943	-1,969

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Summary statistics for randomly chosen non-overlapping locations

Variable	Non-overlapping locations
Number of non-overlapping locations	8,142
Number of environmental remediation entrants	231
Average number of environmental remediation entrants$_{lt}$	0.004
	(0.072)
Average number of environmental remediation incumbents$_{lt}$	0.024
	(0.173)
Average number of TRI type firms$_{lt}$	1.212
	(5.708)

Standard deviation are in parentheses.

Table 12: Aggregate entry counts at a random location for remediation firms

Variable	Number of entrants$_{lt}$		
	(1)	(2)	(3)
Number of environmental remediation	1.105***	1.065***	1.117***
incumbents within 0-1 mile$_{lt}$	(0.115)	(0.113)	(0.116)
Number of TRI type incumbents within 0-1 mile$_{lt}$	0.011***	0.010***	0.011***
	(0.002)	(0.002)	(0.002)
Median income \$0 – \$66,700$_{lt}$	0.490***	0.411***	
	(0.086)	(0.089)	
Median income >\$66,700 – \$100,000$_{lt}$	0.083	0.055	
	(0.131)	(0.131)	
Median income >\$100,000$_{lt}$	-0.050	-0.061	
	(0.232)	(0.231)	
Average wage(in \$10,000)$_{lt}$	0.022***	0.022***	0.021***
	(0.007)	(0.007)	(0.006)
Percentage nonwhite residents$_{lt}$	2.462***	2.137***	2.036***
	(0.482)	(0.474)	(0.536)
College ratio$_{lt}$	0.149	0.171	5.100***
	(1.628)	(1.640)	(1.294)
Number of amenity establishments$_{lt}$	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Number of roads$_{lt}$	-0.001		-0.001
	(0.005)		(0.005)
Number of rail roads$_{lt}$	0.017		0.016
	(0.011)		(0.011)
Unemployment rate$_{lt}$	0.083***	0.079***	0.085***
	(0.016)	(0.016)	(0.020)
Population density$_{lt}$	0.001***	0.001***	0.001***
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	2.334***	2.129***	1.022*
	(0.521)	(0.534)	(0.551)
TxDOT expenditures (in \$1,000,000)$_{lt}$		-0.022**	
		(0.010)	
Average house value$_{lt}$			0.012
			(0.008)
Border county effects$_{lt}$	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Number of obs.	56,994	56,994	56,994
Log likelihood	-1,337	-1,330	-1,357

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The dependent variable is the number of environmental remediation
firms in a random location (within 0-1 mile.)

Table 13: Exit patterns for exiting firms

Entry year	Total entrants	Exit year							Total
		2000	2001	2002	2003	2004	2005	2006	
2000	43	0	2	2	5	6	3	2	20
2001	47		5	6	16	6	3	3	39
2002	98			4	29	18	11	7	69
2003	54				7	11	10	5	33
2004	58					13	10	9	33
2005	50						9	7	16
2006	45							5	5
Total	395	0	7	12	57	54	46	38	214

Table 14: Establishment level summary statistics for exiting remediation firms

Variable	Mean (Standard deviation)
Establishments with past experience	0.364
	(0.481)
Average number of branches	1.021
	(2.334)
Age (in months)	42.702
	(22.532)
Average wage (in $10,000)	4.908
	(11.619)
Size	18.872
	(37.543)

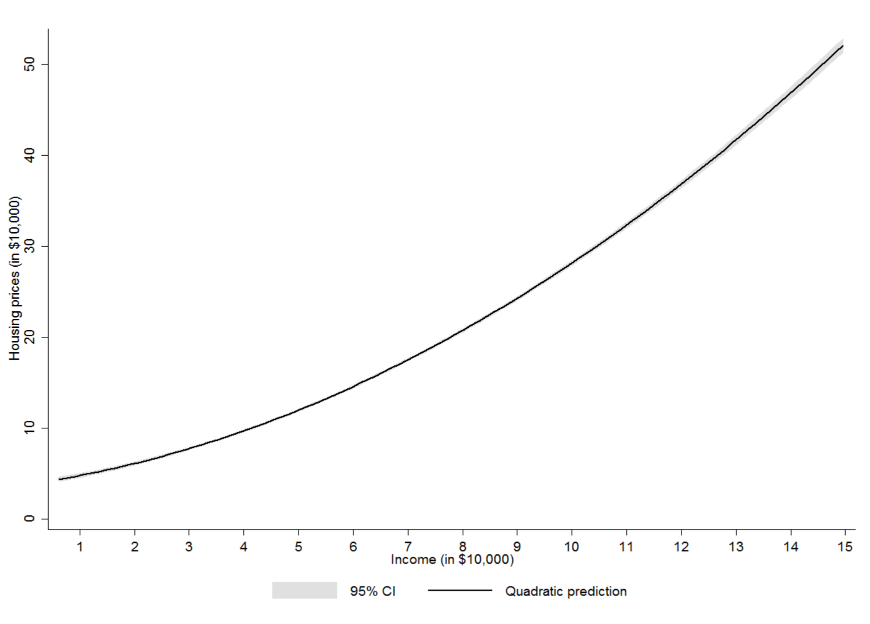
Table 15: Logit results for remediation firm exit

Variable	Exit					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of environmental remediation	0.076***	0.076***	0.076***	0.077***	0.077***	0.077***
incumbents$_{ilt}$	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Number of TRI type incumbents$_{ilt}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Establishments with past experience$_i$	-0.016	-0.017	-0.017	-0.016	-0.018	-0.017
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Number of branches$_{it}$	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age$_{it}$	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median income \$0 – \$66,700$_{lt}$	-0.003		-0.002	0.008	0.008	
	(0.008)		(0.010)	(0.011)	(0.011)	
Median income >\$66,700 – \$100,000$_{lt}$	-0.002		-0.002	0.005	0.007	
	(0.013)		(0.014)	(0.014)	(0.015)	
Median income >\$100,000$_{lt}$	0.014		0.014	0.016	0.016	
	(0.012)		(0.012)	(0.012)	(0.012)	
Average wage (in \$10,000)$_{lt}$	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Size$_{it}$	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
College ratio$_{lt}$		-0.017	-0.033	-0.222	-0.209	-0.260
		(0.127)	(0.182)	(0.212)	(0.207)	(0.199)
Number of amenity establishments$_{lt}$			-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Number of roads$_{lt}$	-0.000	-0.000	-0.000	-0.000		-0.000
	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
Number of rail roads$_{lt}$	-0.002	-0.002	-0.002	-0.001		-0.001
	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
Unemployment rate$_{lt}$				-0.002	-0.002	-0.002
				(0.003)	(0.002)	(0.002)
Population density$_{lt}$	0.000	0.000	0.000	-0.000	0.000	-0.000
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$				0.108*	0.115**	0.119**
				(0.055)	(0.057)	(0.055)
MSA	-0.007	-0.009	-0.007	-0.011	0.005	-0.012
	(0.036)	(0.036)	(0.037)	(0.038)	(0.046)	(0.037)
TxDOT expenditures (in \$1,000,000)$_{lt}$					0.001	
					(0.001)	
Average house value$_{lt}$						0.003
						(0.002)
Border county effects$_{lt}$	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,346	1,346	1,346	1,346	1,346	1,346
Log likelihood	-421.481	-422.408	-421.363	-419.779	-420.188	-420.055

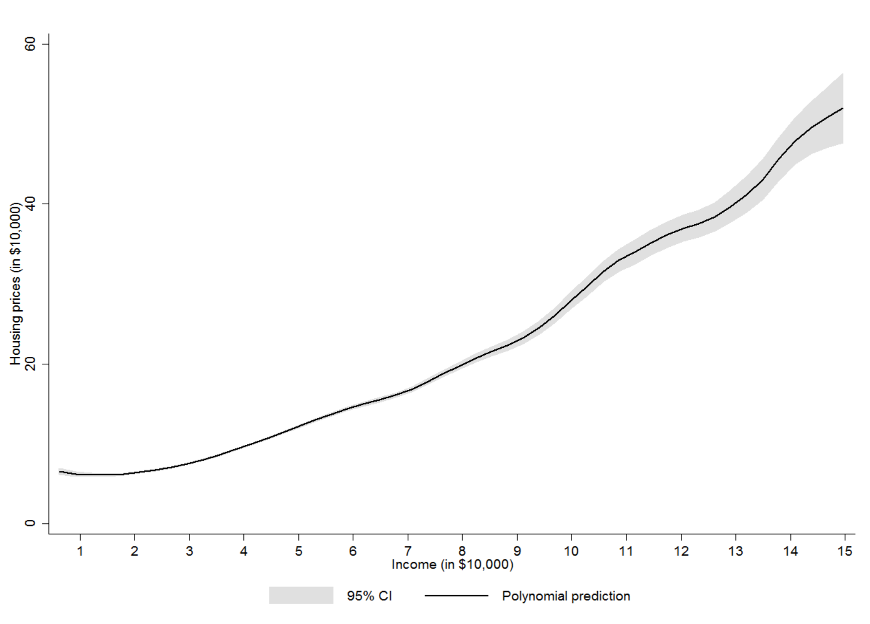
Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The dependent variable takes the value of 1 for exit and 0 otherwise.

Appendix A



Panel A



Panel B

Figure 1: Relationship between housing prices and median income

Table A.1: Categories of plants

Firm type	Number of firms	Definition
TRI-reporters	2,355	Plants for which reporting to the TRI Program is mandatory, i.e. that meet the three requirements outlined in page 14, excluding firms in the NAICS 562 - "Waste Management and Remediation Services."
TRI-polluters	795	Plants for which reporting to the TRI Program is mandatory and that reported a pollutant release in year t.
TRI-type plants	36,553	Plants located in the same six-digit NAICS code as TRI-polluters, whether reporting is mandatory or not
TRI-type plants with at least 10 FTEs observed in one period.	18,252	Firms located in the same six-digit NAICS code as TRI-polluters, whether reporting is mandatory or not, and that have at least 10 FTEs during at least one year of our sample period.
Remediation facilities	598	Firms in the NAICS 562 - "Waste Management and Remediation Services."
Non-TRI-type firms	508,113	Firms that are not located in a NAICS code identified by the TRI Program.

Table A.2: Variable descriptions

Variable	Description
Number of environmental remediation firms$_{lt}$	Number of environmental remediation per tract per year. NAICS codes: 562112, 562211, 562910, and 562920
TRI type establishments$_{lt}$	Number of TRI type firms per tract per year.
TRI reporting establishments$_{lt}$	Number of TRI reporting firms per tract per year.
Tract-level toxicity (in pounds)	The EPA provides toxicity weights for each chemical reported in the TRI which allows for aggreating heterogeneous releases. We then aggregate total release per tract for a given year.
Age$_{it}$	Establishment's age in months
Number of employees$_{it}$	Establishment or tract level number of employees per year.
Employement ratio$_{it}$	This is the establishment's employment divided by the total employees in the industry in TX at a given year.
Wage$_{it}$	Establishment level wage per year.
Plant with past experience$_{i}$	This is a plant with past experience in the industry
Number of branches in TX$_{it}$	Number of branches in TX
Number of roads$_{lt}$	We use the U.S. Census Bureau's Census Feature Class Codes (CFCC) to identify roads. These road maps are provided by ESRI Data & Maps (2000) at census tract level. We use all major highways to small roads that provide access to businesses, facilities, and rest areas along limited-access highways.
Number of rail roads$_{lt}$	As in roads we use the U.S. Census Bureau's Census Feature Class Codes (CFCC) and ESRI Data & Maps (2000) to identify rail roads. We use all major and minor rail tracks identified by ESRI Data & Maps.
Median income (\$)$_{lt}$	Census tract level median income.
Poverty ratio$_{lt}$	Census tract level percentage of the population under the poverty rate.
College ratio$_{lt}$	Census tract level college graduates as percentage of the population.
Number of amenity establishments$_{lt}$	To measure the relative local presence of amenities, we compute the tract level number of establishments in NAICS 71, Arts, Entertainment, and Recreation, and NAICS 721110 (hotels and motels), 722110 (full service restaurants), and 722410 (drinking places, alcoholic beverages) as reported in the QCEW data.
Housing rental ratio$_{lt}$	Tract level percentage of housing stock rented.
Unemployment rate$_{lt}$	Census tract level unemploymentrate.
Population$_{lt}$	Census tract level total population.
Land area$_{l}$	Census tract level land area in square miles.
TxDOT expenditures$_{lt}$(in \$1,000,000)	We construct tract level road construction expenditures by weighting county totals by tact level population.
Average house value$_{lt}$	Census tract level average house value.
Percent nonwhite residents	Census tract-level share of nonwhite population per year.

Table A.3: Explaining variation in the number of toxic pounds, TRI type, and remediation firms at tract level before and after 2002

Variable	Before 2002			Since 2002		
	Toxicity	Number of firms in		Toxicity	Number of firms in	
	in pounds$_{lt}$	TRI type$_{lt}$	Remediation$_{lt}$	in pounds$_{lt}$	TRI type$_{lt}$	Remediation$_{lt}$
	(1)	(2)	(3)	(4)	(5)	(6)
Median household income \$0 – \$66,700$_{l,t}$	0.258***	0.785***	0.169***	0.279***	0.912***	0.381***
	(0.063)	(0.130)	(0.061)	(0.032)	(0.075)	(0.035)
Median household income >\$66,700 – \$100,000$_{l,t}$	-1.424	0.105	-0.167	0.026	0.303**	0.056
	(1.633)	(0.230)	(0.129)	(0.073)	(0.128)	(0.059)
Median household income >\$100,000$_{l,t}$	-0.078	-0.168	0.049	-0.747	-0.104	0.027
	(75.841)	(0.212)	(0.112)	(0.529)	(0.103)	(0.047)
Average wage (in \$10,000)$_{lt}$	0.020***	0.054**	0.019**	0.038***	0.088***	0.021***
	(0.006)	(0.024)	(0.010)	(0.004)	(0.015)	(0.006)
Percentage nonwhite residents$_{lt}$	0.709**	2.592***	0.081	1.623***	4.210***	0.402
	(0.277)	(0.653)	(0.313)	(0.197)	(0.532)	(0.245)
Number of TRI type incumbent establishments$_{lt}$			0.020***			0.031***
			(0.003)			(0.002)
Other tract controls$_{lt}$	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,604	8,604	8,604	21,510	21,510	21,510
Log likelihood	-467.8	-31,633	-31,617	-2,724	-78,087	-7,261

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Censored linear regression results for log of toxic pounds at tract level

Variable	Log(toxic pounds)$_{lt}$
Median income \$0 – \$66,700$_{lt}$	0.095***
	(0.011)
Median income >\$66,700 – \$100,000$_{lt}$	-0.004
	(0.024)
Median income >\$100,000$_{lt}$	-0.241
	(0.162)
Log(average wage)$_{lt}$	0.314***
(in \$10,000)	(0.020)
Percentage nonwhite residents$_{lt}$	0.513***
	(0.066)
College ratio$_{lt}$	-1.967***
	(0.240)
Log (number of amenity establishments)$_{lt}$	0.008
	(0.010)
Log (umber of roads)$_{lt}$	0.083***
	(0.014)
Log (umber of rail roads)$_{lt}$	0.200***
	(0.013)
Unemployment rate$_{lt}$	0.001
	(0.002)
Log(population density)$_{lt}$	-0.025***
(in 1,000 per 100 square miles)	(0.005)
Housing rental ratio$_{lt}$	0.024
	(0.065)
Border county effects$_{lt}$	Yes
Year effects	Yes
Number of observations	30,114
Log likelihood	-5,340.402
Uncensored observations	833

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.5: Explaining variation of TRI type firms by industry and by age at tract level

Variable	Oil and gas$_{lt}$	Chemicals$_{lt}$	$>$ 10 years old
	(1)	(2)	(3)
Median income \$0 – \$66,700$_{lt}$	0.196	0.389***	1.045***
	(0.130)	(0.024)	(0.056)
Median income >\$66,700 – \$100,000$_{lt}$	0.765***	-0.127***	0.321***
	(0.233)	(0.044)	(0.095)
Median income >\$100,000$_{lt}$	-1.516	0.145***	-0.150*
	(1.088)	(0.034)	(0.081)
Average wage (in \$10,000)$_{l,t}$	0.064***	0.005	0.043***
	(0.012)	(0.005)	(0.011)
Percentage nonwhite residents$_{lt}$	1.403*	1.728***	3.711***
	(0.804)	(0.146)	(0.350)
College ratio$_{l,t}$	-8.356***	-5.267***	-12.618***
	(2.968)	(0.472)	(1.081)
Number of amenity establishments$_{l,t}$	0.006	0.004***	0.080***
	(0.004)	(0.001)	(0.004)
Number of roads$_{l}$	0.000	0.007***	0.111***
	(0.007)	(0.002)	(0.004)
Number of rail roads$_{l}$	0.100***	0.126***	0.275***
	(0.015)	(0.005)	(0.012)
Population (in 1,000)$_{l,t}$	-0.039	0.022***	0.016
	(0.037)	(0.006)	(0.016)
Unemployment rate$_{l,t}$	-0.000***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{l,t}$	1.921**	1.358***	2.881***
	(0.826)	(0.160)	(0.384)
Border county effects$_{l}$	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Number of obs.	30,114	30,114	30,114
Log likelihood	-815.0	-27,275	-86,458
Uncensored observations	116	7,645	23,669

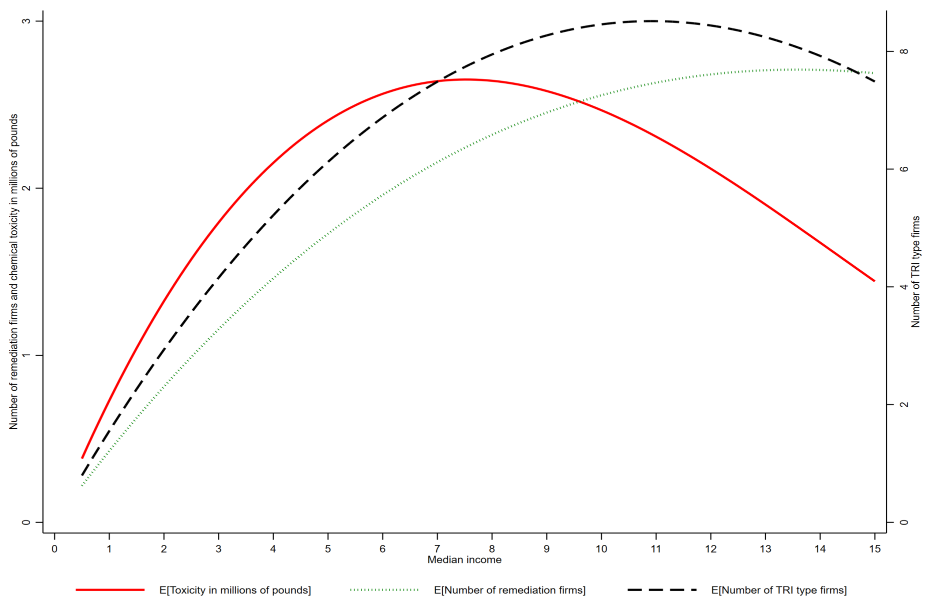
Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Tract ranking

Variable		2006		
		Income	Education	Population
	Income	0.964		
2000	Education		0.990	
	Population			0.960

Appendix B

Figure 1: Estimated cubic functions relating to median income



The coefficients used for the cubic specification in toxicity pounds are reported in Column 1 in Table 2 and for TRI type, the coefficients are reported in Column 2 in Table B.1. We use estimates reported in Table B.3 Column 2 to draw the expected line for remediation firms.

Table B.1: Explaining variation in the number TRI type firms at tract level

Variable	Number of TRI type firms$_{lt}$			
	All		Without oil and gas	
	(1)	(2)	(3)	(4)
Median income (in \$10,000)$_{lt}$	1.635***		1.630***	
	(0.175)		(0.175)	
Median income (in \$10,000)$^2_{lt}$	-0.085***		-0.085***	
	(0.022)		(0.022)	
Median income (in \$10,000)$^3_{lt}$	0.001		0.001	
	(0.001)		(0.001)	
Median income \$0 – \$66,700$_{lt}$		0.946***		0.943***
		(0.062)		(0.062)
Median income >\$66,700 – \$100,000$_{lt}$		0.319***		0.322***
		(0.110)		(0.110)
Median income >\$100,000$_{lt}$		-0.360***		-0.358***
		(0.101)		(0.101)
Average wage (in \$10,000)$_{lt}$	0.144***	0.145***	0.142***	0.143***
	(0.012)	(0.012)	(0.012)	(0.012)
Percentage nonwhite residents$_{lt}$	4.540***	4.383***	4.538***	4.380***
	(0.387)	(0.385)	(0.386)	(0.385)
College ratio$_{lt}$	-19.282***	-19.469***	-19.265***	-19.449***
	(1.193)	(1.198)	(1.192)	(1.197)
Number of amenity establishments$_{lt}$	0.095***	0.095***	0.095***	0.095***
	(0.004)	(0.004)	(0.004)	(0.004)
Number of roads$_{lt}$	0.153***	0.154***	0.153***	0.154***
	(0.005)	(0.005)	(0.005)	(0.005)
Number of rail roads$_{lt}$	0.375***	0.373***	0.373***	0.371***
	(0.013)	(0.013)	(0.013)	(0.013)
Unemployment rate$_{lt}$	-0.022	-0.031*	-0.022	-0.031*
	(0.018)	(0.018)	(0.018)	(0.018)
Population density$_{lt}$	-0.000***	-0.000***	-0.000***	-0.000***
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	6.617***	6.619***	6.615***	6.616***
	(0.422)	(0.423)	(0.422)	(0.423)
Border county effects$_{lt}$	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Number of observations	30,114	30,114	30,114	30,114
Log likelihood	-74,732	-74,742	-74,664	-74,674
Uncensored observations	19,372	19,372	19,355	19,355

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the number of TRI-type facilities with at least 10 employees observed in one period.

Table B.2: Relative frequency of toxic release firms reported at tract level

Variable	(TRI polluters / TRI type)$_{lt}$	
	(1)	(2)
Median income \$0 – \$66,700$_{lt}$	-0.036***	-0.019
	(0.013)	(0.015)
Median income >\$66,700 – \$100,000$_{lt}$	-0.041	-0.033
	(0.044)	(0.046)
Median income >\$100,000$_{lt}$	-0.184*	-0.204*
	(0.098)	(0.108)
Average wage (in \$10,000)$_{lt}$		0.015***
		(0.002)
Percentage nonwhite residents$_{lt}$		0.214**
		(0.107)
Number of amenity establishments$_{lt}$		-0.021***
		(0.003)
Number of roads$_{lt}$		0.000
		(0.002)
Number of rail roads$_{lt}$		0.023***
		(0.003)
Unemployment rate$_{lt}$		0.000
		(0.004)
Population density$_{lt}$		-0.000***
(in 1,000 per 100 square miles)		(0.000)
Housing rental ratio$_{lt}$		0.188
		(0.121)
Year effects	Yes	Yes
Border county effects$_{lt}$	Yes	Yes
Number of observations	30,114	30,114
Log likelihood	-1,709	-1,651

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The number of TRI-type plants represents facilities with at least 10 employees observed in one period.

Table B.3: Explaining variation in the number of remediation firms at tract level

Variable	Number of remediation firms$_{lt}$	
	(1)	(2)
Median income \$0 – \$66,700$_{lt}$	0.323***	
	(0.030)	
Median income >\$66,700 – \$100,000$_{lt}$	0.015	
	(0.053)	
Median income >\$100,000$_{lt}$	0.028	
	(0.043)	
Median income (in \$10,000)$_{lt}$		0.449***
		(0.084)
Median income (in \$10,000)$^2_{lt}$		-0.022**
		(0.011)
Median income (in \$10,000)$^3_{lt}$		0.000
		(0.000)
Number of TRI type incumbent establishments$_{lt}$	0.043***	0.043***
	(0.002)	(0.002)
Average wage (in \$10,000)$_{lt}$	0.020***	0.019***
	(0.005)	(0.005)
Percentage nonwhite residents$_{lt}$	0.210	0.170
	(0.193)	(0.194)
College ratio$_{lt}$	-4.005***	-3.902***
	(0.602)	(0.600)
Number of amenity establishments$_{lt}$	0.007***	0.007***
	(0.001)	(0.001)
Number of roads$_{lt}$	0.007***	0.007***
	(0.002)	(0.002)
Number of rail roads$_{lt}$	0.028***	0.028***
	(0.005)	(0.005)
Unemployment rate$_{lt}$	0.015**	0.016**
	(0.007)	(0.007)
Population density$_{lt}$	-0.000***	-0.000***
(in 1,000 per 100 square miles)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	1.853***	1.855***
	(0.203)	(0.203)
Border county effects$_{lt}$	Yes	Yes
Year effects	Yes	Yes
Number of observations	30,114	30,114
Log likelihood	-9,475	-9,484
Uncensored observations	2,104	2,104

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
The number of TRI-type incumbents represents facilities with at least 10 employees observed in one period.

Appendix C: Additional Robustness Checks

MSA vs. Non-MSA. De Silva et al. (2016) find that the siting decision of TRI-polluters is most strongly related to race in rural communities, while the results for income still exhibit an inverted U-shape. In Table C.1, we show that siting decisions of TRI-type firms are related to median income in both rural areas and MSAs and that siting is positively correlated with income for lower-income areas. We extend this analysis to remediation firms and the toxicity index and find that for lower income levels, the number of remediation firms increases faster with income in MSA areas while for toxic releases, the coefficient of median income is larger in non-MSA areas.

TRI-type firms without TRI-polluters. Next we check whether our results are driven by TRI-polluters. We reestimate our siting models where the dependent variable is the TRI-type firms without TRI-polluters. That is, we define a category of TRI-type firms that contains only firms that have not reported a release. The findings in Table C.2 indicate that results are not driven by pollution-reporting firms. Note also Column 2 that indicates that results for location choices of remediation firms are unaffected by the subtraction of TRI-polluters. The demand for waste management services seems to be driven by firms that do not report releases, but are likely to use other types of waste management services, e.g. waste treatment, recycling...

Number of TRI-reporters. Our objective in this study is to analyze the co-location of remediation firms, as a proxy for pollution risk management by firms in industries known to pollute. We are working at sufficient industry detail, six-digit NAICS, that a reasonable level of homogeneity in activity can be assumed. If establishments in a given industry have been identified as having experienced a release via TRI reporting, we are assuming that other establishments in the same industry have largely similar activities and could potentially experience a similar release. For this reason, we believe that TRI-type firms is a good representation of a tract's potential toxicity. However, as a robustness check, we estimate equation (1) using TRI reporting firms instead of TRI-type as our dependent variable. Results are reported in Table C.3 and are consistent with those in Tables 2 and 3.

Non-TRI-type firms. It is natural to wonder if the increasing and concave relationship between the number of TRI-type firms and local income is not also observed in the case of non-TRI-type firms. That is, is this result specific to TRI-type firms or does industrial localization more generally exhibit this same pattern? To answer this question, we conducted a similar regression to analyze the localization of non-TRI-type firms. As can be seen in Table C.4, there is a positive relationship between income and localization of firms, *ceteris paribus*, over the two lower income splines and then the relationship flattens out. Regardless of pollution exposure and regulatory risk, high income census tracts are areas that remain strategic locations for production activities.

TRI *probable* Industries. We finally test whether using a narrower set of industries (those where TRI-polluters are relatively common) would change the results presented in Table 2.

To this end, we define a TRI-type firm as a firm that is located in the same NAICS code as a TRI-polluter (as before) but we exclude all the industries that have not polluted every year during our sample period and have less than seven pollution incidents. This allows us to drop industries with few polluters and keep the industries that are likely to report a release in Texas (*TRI probable industries*). The results in Table C.5 remain qualitatively the same as those in Table 2 (using the broader definition of TRI-type firms).

Table C.1: Explaining variation in TRI type firms, remediation firms, and toxicity levels by MSA and non-MSA

Variable	Number of firms in					
	TRI type$_{lt}$		Remediation$_{lt}$		Toxicity in pounds$_{lt}$	
	MSA	Non-MSA	MSA	Non-MSA	MSA	Non-MSA
	(1)	(2)	(3)	(4)	(5)	(6)
Median income \$0 – \$66,700$_{lt}$	0.549***	0.780***	0.217***	0.199*	0.161***	0.722***
	(0.083)	(0.066)	(0.034)	(0.116)	(0.027)	(0.182)
Median income >\$66,700 – \$100,000$_{lt}$	0.184	-0.880	-0.003	-327.930	0.041	0.258
	(0.123)	(0.631)	(0.054)	(31,532.365)	(0.057)	(1.011)
Median income >\$100,000$_{lt}$	-0.149		0.021		-0.535	
	(0.101)		(0.043)		(0.404)	
Number of TRI type incumbent establishments$_{lt}$			0.025***	0.212***		
			(0.002)	(0.020)		
Average wage (in \$10,000)$_{lt}$	0.067***	0.262***	0.018***	0.004	0.026***	0.191***
	(0.014)	(0.021)	(0.005)	(0.038)	(0.003)	(0.033)
Percentage nonwhite residents$_{lt}$	3.007***	2.535***	0.020	-0.964	0.940***	5.058***
	(0.475)	(0.437)	(0.203)	(0.806)	(0.145)	(1.214)
College ratio$_{lt}$	-8.717***	-1.818	-3.260***	-4.230	-4.598***	1.924
	(1.430)	(1.534)	(0.624)	(2.761)	(0.614)	(4.156)
Number of amenity establishments$_{lt}$	0.108***	0.144***	0.007***	0.019	-0.005**	-0.002
	(0.005)	(0.009)	(0.001)	(0.013)	(0.003)	(0.024)
Number of roads$_{lt}$	0.207***	0.038***	0.008***	0.004	0.006***	0.014*
	(0.007)	(0.003)	(0.002)	(0.005)	(0.002)	(0.008)
Number of rail roads$_{lt}$	0.462***	0.098***	0.041***	-0.052***	0.055***	0.075***
	(0.018)	(0.009)	(0.006)	(0.016)	(0.003)	(0.018)
Unemployment rate$_{lt}$	-0.058***	0.069***	0.011	-0.012	0.001	0.034
	(0.022)	(0.020)	(0.007)	(0.036)	(0.005)	(0.076)
Population density$_{lt}$	-0.000	-0.000***	-0.000***	0.000	-0.000***	-0.001**
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	1.505***	3.654***	1.527***	0.700	0.583***	0.235
	(0.521)	(0.530)	(0.213)	(0.918)	(0.155)	(1.562)
Border county effects$_{lt}$	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	24,654	5,460	24,654	5,460	24,654	5,460
Log likelihood	-91,860	-13,189	-8183	-1202	-2494	-605.5
Uncensored observations	24,534	5,434	1,843	261	708	125

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.2: Explaining variation in TRI type firms (without TRI), and remediation firms at tract level

Variable	Number of firms in	
	TRI type$_{lt}$	Remediation$_{lt}$
	(1)	(2)
Median income \$0 – \$66,700$_{lt}$	0.856***	0.333***
	(0.065)	(0.030)
Median income >\$66,700 – \$100,000$_{lt}$	0.243**	0.021
	(0.112)	(0.053)
Median income >\$100,000$_{lt}$	-0.121	0.027
	(0.093)	(0.044)
Number of TRI type (without TRI) incumbent establishments$_{lt}$		0.027***
		(0.002)
Average wage (in \$10,000)$_{lt}$	0.076***	0.021***
	(0.013)	(0.005)
Percentage nonwhite residents$_{lt}$	3.492***	0.276
	(0.407)	(0.194)
College ratio$_{lt}$	-11.791***	-4.187***
	(1.250)	(0.605)
Number of amenity establishments$_{lt}$	0.115***	0.008***
	(0.004)	(0.001)
Number of roads$_{lt}$	0.160***	0.008***
	(0.005)	(0.002)
Number of rail roads$_{lt}$	0.350***	0.033***
	(0.015)	(0.005)
Unemployment rate$_{lt}$	-0.022	0.015**
	(0.019)	(0.007)
Population density$_{lt}$	-0.000***	-0.000***
(in 1,000 per 100 square miles)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	3.082***	1.930***
	(0.448)	(0.204)
Border county effects$_{lt}$	Yes	Yes
Year effects	Yes	Yes
Number of observations	30,114	30,114
Log likelihood	-109,686	-9,495
Uncensored observations	29,968	2,104

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.3: Explaining variation in the number of TRI reporting firms at tract level

Variable	Number of firms in TRI reporters$_{lt}$			
	All	Without oil and gas	All	Without oil and gas
	(1)	(2)	(3)	(4)
Median income (in \$10,000)$_{lt}$	1.956***	1.951***		
	(0.085)	(0.084)		
Median income (in \$10,000)$^2_{lt}$	-0.112***	-0.112***		
	(0.011)	(0.011)		
Median income (in \$10,000)$^3_{lt}$	0.001***	0.001***		
	(0.000)	(0.000)		
Median income \$0 – \$66,700$_{lt}$			1.097***	1.093***
			(0.028)	(0.028)
Median income >\$66,700 – \$100,000$_{lt}$			0.275***	0.272***
			(0.046)	(0.046)
Median income >\$100,000$_{lt}$			-0.289***	-0.287***
			(0.051)	(0.051)
Average wage (in \$10,000)$_{lt}$	0.025***	0.024***	0.026***	0.025***
	(0.005)	(0.005)	(0.005)	(0.005)
Percentage nonwhite residents$_{lt}$	2.417***	2.414***	2.221***	2.219***
	(0.170)	(0.170)	(0.168)	(0.168)
College ratio$_{lt}$	-15.111***	-15.037***	-15.510***	-15.433***
	(0.551)	(0.551)	(0.554)	(0.553)
Number of amenity establishments$_{lt}$	0.004**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Number of roads$_{lt}$	0.036***	0.036***	0.037***	0.037***
	(0.002)	(0.002)	(0.002)	(0.002)
Number of rail roads$_{lt}$	0.189***	0.188***	0.187***	0.186***
	(0.005)	(0.005)	(0.005)	(0.005)
Unemployment rate$_{lt}$	-0.041***	-0.041***	-0.051***	-0.051***
	(0.008)	(0.008)	(0.008)	(0.008)
Population density$_{lt}$	-0.002***	-0.002***	-0.002***	-0.002***
(in 1,000 per 100 square miles)	(0.000)	(0.000)	(0.000)	(0.000)
Housing rental ratio$_{lt}$	3.500***	3.487***	3.559***	3.546***
	(0.182)	(0.182)	(0.182)	(0.182)
Border county effects$_{lt}$	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Number of observations	30,114	30,114	30,114	30,114
Log likelihood	-35,218	-35,176	-35,241	-35,199
Uncensored observations	10,291	10,291	10,291	10,291

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.4: Explaining variation of non–TRI type firms at tract level

Variable	Number of firms$_{lt}$	
	(1)	(2)
Median income \$0 – \$66,700$_{lt}$	1.892***	0.845***
	(0.074)	(0.076)
Median income >\$66,700 – \$100,000$_{lt}$	2.419***	1.632***
	(0.127)	(0.124)
Median income >\$100,000$_{lt}$	-0.371***	-0.000
	(0.106)	(0.104)
Average wage (in \$10,000)$_{lt}$	0.156***	0.163***
	(0.014)	(0.014)
Percentage nonwhite residents$_{lt}$	-0.962**	-3.107***
	(0.463)	(0.450)
College ratio$_{lt}$	18.137***	31.204***
	(1.421)	(1.418)
Number of amenity establishments$_{lt}$	0.375***	0.360***
	(0.005)	(0.005)
Number of roads$_{lt}$	0.233***	0.235***
	(0.006)	(0.006)
Number of rail roads$_{lt}$	-0.052***	0.054***
	(0.017)	(0.016)
Unemployment rate$_{lt}$	0.068***	0.111***
	(0.022)	(0.021)
Population density$_{lt}$	-0.000***	
(in 1,000 per 100 square miles)	(0.000)	
Population (in 1,000)$_{lt}$		0.892***
		(0.022)
Land area (in 100 square miles)$_{lt}$		-0.310***
		(0.030)
Housing rental ratio$_{lt}$	20.816***	16.482***
	(0.509)	(0.467)
Border county effects$_{lt}$	Yes	
Year effects	Yes	
Number of observations	30,114	30,114
Log likelihood	-114,000	-113,192
Uncensored observations	30,114	30,114

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C.5: Explaining variation in the number of TRI type firms at tract level

Variable	Number of firms in TRI type$_{lt}$	
	(1)	(2)
Median income (in \$10,000)$_{lt}$	1.536***	
	(0.177)	
Median income (in \$10,000)$^2_{lt}$	-0.090***	
	(0.022)	
Median income (in \$10,000)$^3_{lt}$	0.001*	
	(0.001)	
Median income \$0 – \$66,700$_{lt}$		0.867***
		(0.065)
Median income >\$66,700 – \$100,000$_{lt}$		0.245**
		(0.111)
Median income >\$100,000$_{lt}$		-0.121
		(0.093)
Average wage (in \$10,000)$_{lt}$	0.077***	0.078***
	(0.013)	(0.013)
Percentage nonwhite residents$_{lt}$	3.584***	3.462***
	(0.407)	(0.406)
College ratio$_{lt}$	-11.770***	-11.994***
	(1.239)	(1.245)
Number of amenity establishments$_{lt}$	0.114***	0.114***
	(0.004)	(0.004)
Number of roads$_{lt}$	0.157***	0.158***
	(0.005)	(0.005)
Number of rail roads$_{lt}$	0.361***	0.360***
	(0.015)	(0.015)
Unemployment rate$_{lt}$	-0.014	-0.022
	(0.019)	(0.019)
Population density (in 1,000 per 100 square miles)$_{lt}$	-0.000***	-0.000***
	(0.000)	(0.000)
Housing rental ratio$_{lt}$	3.186***	3.200***
	(0.445)	(0.446)
Border county effects$_{lt}$	Yes	Yes
Year effects	Yes	Yes
Number of observations	30,114	30,114
Log likelihood	-109521	-109525
Uncensored observations	29,944	29,944

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The dependent variable excludes all industries that have not polluted all years and have less than seven pollution incidents.