Entry and Exit Patterns of "Toxic" Firms*

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Abstract

We pair an establishment-level dataset from Texas with public information available in the Toxics Release Inventory (TRI) to evaluate the standing of dirty industries in Texas census tracts with a focus on environmental justice concerns. The share of nonwhite residents in a tract is positively correlated with the number of TRI-reporting firms and an inverse-U-shaped relationship characterizes the number of TRI-reporting firms and a tract's median income. Even after controlling for factor prices and other covariates which might drive firm location decisions, entrants that report to the TRI are more likely to locate in areas with a higher share of nonwhite residents. Firms that report to the TRI are also more likely to enter areas with a low share college graduates. In contrast, the number of entrants from industries which do not have TRI reporters is negatively related to the percent of nonwhite residents in a tract. Firms in these non-reporting industries are also more likely to enter areas with a high share of college graduates. Polluters appear to agglomerate, raising concerns about both chemical releases being concentrated in certain tracts and also affecting nonwhite-dense areas disproportionately. The strength of these effects often depend on an urban/rural classification, with rural areas experiencing the most pronounced concerns. Moreover, TRI-reporting firms are less likely to exit the market relative to their peers which operate in the same industry but do not need to file TRI reports, suggesting releases may affect a region in the long-run.

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On December 3, 1984 a plant producing pesticides in Bhopal, India leaked methyl isocyanate gas and chemicals which resulted in thousands of deaths for those living in the area around the plant. This tragedy led to demand for increased awareness from citizens all over the world and the passing of the Emergency Planning and Community Right-to-Know Act of 1986 in the U.S. The act (along with later expansions and legislation) requires companies to publicly report releases of chemicals thought or known to be toxic (Section 313). In the U.S., polluting firms are mandated to report chemical emissions or disposals to the Environmental Protection Agency (EPA), which then provides the public with this knowledge through its annual Toxics Release Inventory (TRI) report. Many of these chemicals are unregulated; however, Kahn (2006) noted that the TRI receives media attention and its release is considered a "day of shame" for the largest polluters. Hamilton (1995a) showed that, in 1989, the publishing of the TRI resulted in substantial statistically-significant losses for publicly-held firms required to report—nearly 75% of reporting firms were publicly traded and the total losses were about $4.1 million on average. Konar and Cohen (1997) provided evidence that this poor stock performance may provide proper incentives for firms to reduce toxic emissions, suggesting public disclosure can be an effective way of reducing environmental contaminants.[1] Khanna, Quimio, and Bojilova (1998) showed that repeated reports allow investors to understand a firm's environmental effects and draw comparisons over time and across firms given the annual provision of environmental information, which leads to negative abnormal returns.

Researchers concerned with environmental justice have noted a disturbing finding: areas with a high concentration of minorities also have a higher concentration of firms which engage in pollution. As such, race is often found to be correlated with the location of TRI firms. Hamilton (1995b) provided an empirical investigation of decisions made by hazardous waste facilities and found that areas in which expansion is targeted have a higher percentage of minorities. Brooks and Sethi (1997) also found communities across the U.S. with a high proportion of black residents had greater exposure to air toxics in the early 1990s. Wolverton (2009) took an important step in clarifying this discussion by contributing in two important ways: first, she matched firm location decisions with an area's characteristics at the time of siting. Second, Wolverton recognized that canonical economic factors had not been controlled for in previous research. Shadbegian and Wolverton (2010) provided a recent survey and discussion of issues involving the location decisions of firms that pollute, from both a theoretical and empirical perspective. The current stance in the literature is somewhat mixed but seems to be leaning towards the conclusion that once economic factors are controlled for, race is no longer significant.

We investigate three primary questions in our research. First, is there a positive relationship between the number of TRI-reporting firms in an area and the area's share of nonwhite residents? To consider this, we highlight important trends in the data that can be gleaned from simple summary statistics and spatial patterns. We then estimate econometric models to explain variation in the number of observed TRI reporters given variation in the share of nonwhite residents as well as other tract-level characteristics. Second, do new entrant firms that report to the TRI choose to locate in areas with higher concentrations of nonwhite residents, even after accounting for variables that should drive firm location decisions? In maximizing profits firms consider the price of labor, transportation, and land, among other things. To consider this, we write down a profit maximization problem that leads to a conditional logit framework which can be taken to data. Lastly, we ask if TRI-reporting firms are more or less likely to exit the industry, and whether that effect might differ based on the share of nonwhite residents in a region. To consider this, we estimate the probability of a firm leaving the industry based on its status as a TRI-reporter relative to a reasonable group of peers—those firms that operate in the same industries as the TRI-reporters, but who are not required to file TRI reports.

All of our research questions relate to the industry structure of TRI-reporting firms and its relationship with the share of nonwhite residents living in an area. Our data concerns the state of Texas over the years 1999–2006. Texas is an attractive setting to consider given its size (with 261,231 square miles of land it is the second-largest state in the U.S.), economic importance (with a gross state product of $1.3 trillion dollars in 2012, its economy ranks second in the U.S. and 14th in the world if its gross state product is considered against national gross domestic products), and diversity (the Census 2010 reported that 70% of Texans are white and 12% are black—values consistent with national proportions, though the share of Texans that identify as Hispanic vastly exceeds the national share). Texas also includes many urban and rural areas allowing us to see if environmental justice concerns differ based on the development and land uses of given locations. The Tax Foundation ranked Texas 10th in its 2015 State Business Tax Climate Index while all other contiguous states had rankings that exceeded 30. Since corporate tax rates typically vary across states, it seems natural that firms might choose a state to locate in based on the corporate tax rate (perhaps among other things), but then choose a location within a state for different reasons. It is this second decision that we focus on in our entry analysis. As such, we model firms as choosing to locate in any census tract in Texas and assume this choice set is fixed and common to all firms.[2]

When considering the relationship between the number of TRI-reporting firms in a tract and its share of nonwhite residents, we find a strong positive relationship. Other economic variables such as income, wages, and transportation networks also have significant correlations with the number of TRI-reporting firms. There is a large literature concerned with the environmental Kuznets curve (EKC) which typically relates income per capita to the concentration of some pollutant in a region. Grossman and Krueger (1995) first found that an inverse-U-shaped function characterized the relationship between income per capita and the concentration of pollutants in a region. Since their work, many researchers have found that this pattern holds for various regions over time as well as across regions at a given time for a number of different pollution measures. In our data, the EPA provides toxicity weights for each chemical reported in the TRI which allows for aggregating heterogeneous releases. Constructing these hazard estimates affords us the ability to bridge a connection between the environmental justice literature and the EKC literature. Specifically, we show that both these aggregated releases and the number of TRI-reporting firms generate an inverse-U-shaped relationship with income. Moreover, TRI entrants are almost always locating on the uphill portion of these functions. In contrast, firms that enter industries in which TRI firms are not present locate throughout the income distribution.

Our entry analysis shows that tracts with a larger share of nonwhite residents are more likely to see a TRI-reporting firms enter their region. Arora and Cason (1999), using data from the 1990 U.S. Census to consider toxic releases in 1993, found evidence of environmental injustice in certain geographic areas. The authors concluded "This result seems confined to nonurban areas, which contain high concentrations of minority residents mainly in the South." Following up on this, we partition our sample into various subsamples and find that the siting decision is most strongly related to race in rural communities, but that the results hold for all but the Dallas–Fort Worth and Houston areas—something that is consistent with Wolverton (2009). Our results carry through if we estimate aggregate entry counts using other econometric specifications. We believe we are the first to complement our entry analysis of TRI-reporting firms with estimates of entry models specifically concerning firms that do not belong to TRI-reporting industries. We find that, disturbingly and regardless of how non-TRI firms are defined, these firms are less likely to enter tracts with a high share of nonwhite residents, deepening the environmental justice concerns. Consistent with our results characterizing the inverse-U-shaped relationship between income and the number of TRI-reporting firms, entry of TRI firms follows the EKC-like pattern while entry of non-TRI firms does not.

While most researchers have focused solely on location decisions, we consider site choice as well as the ability of firms to survive in the industry—something that is important given the inverse-U-shaped relationship between income and the number of TRI firms which suggests that fewer firms will exist in communities with higher incomes. TRI-reporting firms are less likely to exit an industry on average, but this effect is not significantly exacerbated given a region's share of nonwhite residents. Even so, because TRI-reporters are less likely to exit there may be long-run consequences for communities that allow these firms to site in their area.

We should also note that our data enable us to construct cumulative variables to account for agglomeration effects that might involve other TRI-reporting firms or other firms in TRI-reporting industries (who may not report to the TRI). Agglomeration might result because one region's willingness to accept a noxious facility signals to other polluting firms that they have a better chance of siting a plant in the area (though we try to address zoning concerns), if there are knowledge spillovers, or if an area has a labor force that is prepared to work at these facilities. We find that TRI-based agglomeration effects often do play a role. That is, TRI reporters are more likely to enter a tract once another polluting firm has located in the tract. In addition, TRI firms are even less likely to exit the industry if other TRI firms are present in the tract.

Our findings are concerning when viewed together: if polluting firms are more likely to locate in regions with a higher share of nonwhite residents, the siting of one firm attracts others (through agglomeration), and these firms are less likely to exit the industry, then environmental justice concerns could be even more concentrated in nonwhite areas and persist in the long-run. Of course, concessions are often made in allowing the siting of pollution facilities. Mastromonaco (2011) looks at housing decisions of whites and minorities and finds that both tend to trade-off higher pollution exposure for lower housing prices.[3] Kunreuther and Kleindorfer (1986) and Kunreuther, Kleindorfer, Knez, and Yaksick (1987) considered an auction mechanism in which communities submit bids which represent payments to be received in exchange for allowing a polluting firm to locate within its borders. Neighboring areas, which likely enjoy employment benefits, could make compensating payments to the host site for absorbing the environmental cost. Nonetheless, the phrase (and acronym) "not-in-my-backyard" (NIMBY) suggests that people would like to avoid such externalities whenever possible. Still, the increased propensity to enter into nonwhite areas, agglomeration effects, and lower likelihood of exiting the industry paint a concerning picture that suggest regulators and community development boards need to consider seriously the consequences of allowing such enterprises to open shop.

Our article is organized as follows: in the next section, we discuss our data. We then investigate how a tract's characteristics relate to the number of TRI-reporting firms present. In doing so, we link our analysis to the EKC literature and show that entry by TRI-reporting firms is consistent with this underlying inverse-U-shaped relationship. In the section that follows, we propose a firm profit maximization problem and use data on location choices to investigate the siting decisions of TRI-reporting entrants. By studying the location decisions of firms, we can hold the sorting of a tract's residents constant and look at the decisions of newly located firms. In doing so, we control for factor prices such as wages, transportation costs, and the cost of land, along with other tract-specific and industry-specific covariates. Having a higher share of nonwhite residents increases the chances that a TRI-reporting firm will locate in a given tract. We complement this with some evidence that firms that do not belong to industries harboring TRI-reporters are *less* likely to enter areas with larger shares of nonwhite residents. We then consider the corresponding end-of-life-cycle decision to exit the industry for TRI-reporting firms, finding TRI-reporting firms are less likely to exit the industry. Lastly, we summarize and conclude.

Data

Our empirical strategy involves merging data from various sources to control for a number of important factors identified by social scientists. Specifically, any firm that produces more than 25,000 pounds of toxic chemicals is required to report such pollution and this information is provided to the public via the TRI. We identify TRI-reporting firms located in Texas and marry these data with firm-level panel data obtained from the Quarterly Census of Employment and Wages (QCEW). All establishments which report to the unemployment insurance programs of the U.S. are part of the data. Our QCEW data covers all Texas establishments and spans the years 1999–2006, involving quarterly observations. These data allow us to identify each establishment's physical location, industry in which the firm competes, start-up date, as well as its monthly employment and wage bill.[4] Though the QCEW data is quarterly, we collapse observations to the year level (by aggregating quarterly variables) given the TRI data is yearly. We define locations according to the U.S. census tracts which allows us to bring in tract-level demographic data (race, gender, poverty, population density, etc.).

During the years 1999–2006, we identified 817 establishments that reported to the TRI. Of these we were able to correctly match 752 to the QCEW database given the name and address of the firm as noted in the TRI data.[5] Of these these 752 matched firms, 166 were new entrants—which we identify by the appearance of a new record in our QCEW data. Specifically, any new employer identification number assigned to a firm with a liability date after July 1, 1999 is considered a new entrant. Pairing firms with QCEW data allows us to identify which industry the firm competes in as defined by the North American Industry Classification System (NAICS) 2002 definition. We present the distributions of incumbent and entrant firms across the NAICS three-digit industry codes in table 1. NAICS industries with many incumbents also see the vast majority of entrants so that the distribution of incumbents and entrants across these NAICS industries are not drastically different. Chemical Manufacturing is clearly the most common TRI-reporting type of firm, accounting for about a third of our incumbent and entrant firms. After that, Fabricated Metal Product Manufacturing, Food Manufacturing, and Plastics and Rubber Products Manufacturing together constitutes about a third of these observations.

In table 2, we present an upper-triangular matrix representing the firms' year of entry and first year of TRI reporting. Most observations lie on the main diagonal of the matrix—representing instances where firms enter the industry and immediately begin reporting to the TRI. Observations off the diagonal of this matrix correspond to firms who enter the industry one year, but do not report to the TRI until later in their lifespan. Firms who don't report in their initial year might be likely to appear off the diagonal if they enter late in a given year or experience growth which leads to TRI-thresholds being exceeded in subsequent years. The most common year of first reporting was 2002 which coincides with a TRI rulemaking which lowered reporting thresholds for lead and lead compounds.[6] Consistent with this, the number of reports involving lead or lead compounds increased sixfold in 2002 relative to 2001 while the aggregate weight announced increased more than four times the prior year's amount.

The industry definition is helpful in that it allows us to investigate other firms with similar industrial output that are located nearby—even if they are not listed in the TRI. Thus, we can maintain records and construct variables that document the number of TRI-reporting firms as well as the number of firms in each industry from which a TRI report is filed to account for potential agglomeration effects. We also lever data from the 2000 and 2010 U.S. Census to bring in tract-level demographic and economic data. Economists might argue that firms should locate in tracts which allow the firm to produce output in the most cost effective way possible. As such, the cost of various input factors may drive location decisions. We include things like average wages paid by firms in each tract at a given point in time (constructed using our QCEW as a weighted average of payments made by firms present in the tract at a the time of siting), the unemployment rate of the tract which might capture availability of labor in a tract, the employment ratio of the siting firm's industry in a tract at a point in time (constructed as the incumbents' share of the state's employment in that industry), measures of transportation costs such as the number of miles of federal, state, and city-maintained roads as well as the number of railroad tracks in each tract (as well as Texas Department of Transportation expenditures within a tract), the size of the tract to account for whether there might be open space given the current composition of the area, and the average house value to represent the cost of land.[7,8]

Summary statistics of some important tract-level variables are presented in table 3 and formal definitions of all variables we employ are provided in table 10 of the appendix. For Census-based data, we linearly interpolate covariates from the Census 2000 and Census 2010 to generate yearly observations at the tract level.[9] We present the summary statistics across all Texas census tracts as well as conditional on whether the tract is considered part of an urban or rural area. Specifically, we separate out tracts belonging to the Dallas–Fort Worth (DFW) and Houston Metropolitan Statistical

Areas (MSAs), tracts in any Texas MSA (including DFW and Houston), and tracts that are strictly not part of an MSA in Texas (non-MSA tracts).[10] The partitions allow us to consider how results change when considering mostly urban or rural areas as well as to understand which areas are driving results at the state level.

First, consider the columns labeled "All" which detail the summary statistics of all tracts in Texas or all tracts within the relevant subsample of the data. In general, there are slightly more TRI firms (entrants and incumbents) per tract the more urban the area and the statewide average is consistent with that of the sample of all MSAs. If we define TRI-like firms to be firms that operate in the same three-digit NAICS industry in which TRI reporters are active, then we observe there a similar pattern concerning the number of TRI-like firms per tract.[11] The Census 2000 and Census 2010 officially considered race and Hispanic origin to be two distinct concepts and elicited this information from every individual living in the U.S. through different questions. To be explicitly clear, for the purposes of this article, when we refer to nonwhite populations we mean all respondents who did not indicate "White" as the response to the question "What is this person's race?" We compute the share of residents who indicate white as their race and subtract this from one to get the share of nonwhite residents.[12] Again, there is a ranking across the subsamples with the highest share of minorities in the Houston and Dallas MSAs, then in the full set of MSAs, and the rural tracts are the ones that have the lowest share nonwhite residents. Such a monotonic pattern characterizes most variables when viewed along this urban-rural spectrum in which the DFW and Houston MSAs sample is the most urban and the non-MSA sample the most rural. For example, the more urban the subsample the higher the populations per tract. But this ranking holds for many variables—the more urban subsamples have larger incomes, lower poverty, more renters, more college graduates, but also more unemployment. Because populations are already somewhat homogenized by the U.S. Census Bureau's definition of a tract which puts bounds on a given region's population, the land area (in 100 square miles) is far smaller for the MSA-member tracts than that of rural tracts (and hence the average tract) in Texas. Transportation-wise, the more urban tracts have fewer road and railroad miles and see less TxDOT spending (again likely due to the size differences of the average tract in these subsamples).

We have also provided summary statistics for tracts belonging to each of these areas conditional on the presence of a TRI-reporting firm. By definition, the number of TRI reporters and entrants is the same for this subset of tracts as it is for all tracts. Note that the share of nonwhite residents is higher for each set of tracts in which TRI-reporting firms are present, relative to the respective full samples. Though wages are higher for employees in these areas, residents' incomes are typically lower and unemployment higher (the exception is the non-MSAs sample). Urban tracts with at least one TRI-reporting firm have higher poverty rates, a lower share of the population with college degrees, a larger number of other TRI-like establishments, and about the same number of amenities. Tracts that are home to TRI-reporters also appear to have much richer transportation networks and are typically larger in geographic size.

We used geo-coded QCEW data to construct maps of Texas. First, in figure 1, we depict each firm we observe in the data as well as the TRI-reporting firms. In general, the DFW and Houston MSAs are firm-concentrated, both with firms at large and TRI-reporting firms. However, there are clearly other pockets of high economic activity within Texas in which we also see a high concentration of TRI-reporting firms. Most of these are in population-concentrated areas such as around San Antonio and Austin as well as El Paso. There are also many of these firms located nearby Dallas and Houston, but outside of the respective MSAs. For example, many TRI-reporting firms are located in northeast Texas and along the southeast coast line. In figure 2 we retain only the TRI-reporting firms and shade the census tracts to depict the share of nonwhite residents living in a given tract. When viewing Texas as a whole, TRI-reporting firms do appear to be mostly concentrated in the darker-shaded areas, indicating those with a higher share of nonwhite residents. However these areas are also centers of economic activity. As an example of other factors that may be driving firm location, we provide blown-up snapshots of the DFW and Houston MSAs in figure 3 and 4, respectively. The maps of the MSAs again suggest that, at least on the surface, there appears to be a positive correlation between the share of nonwhite residents and the number of TRI-reporting firms sited within a tract. Perhaps more remarkable from these MSA-specific maps is how the locations of the TRI-reporting firms align with the railroad network which are the dark lines included in the figures. This suggests that transportation factors will be important to account for in going forward.

While our discussion has highlighted some summary statistics of our data, to understand the relationship between the number of TRI-reporting firms and a tract's characteristics, formal econometric models are needed. In the next section, we investigate various relationships by recognizing that these firms are polluting firms and that, beyond the environmental justice literature lies an enormous body of research (both empirical and theoretical) that has related pollution measures with income per capita. We leverage some of the insights from these environmental economists while maintaining a focus on environmental justice concerns. These relationships are not independent of each other, especially if the distribution of income for nonwhite residents differs from that of white residents.

The Number of TRI Reporters and Tract Characteristics

In this section, we are interested in explaining variation in the number of observed TRI reporters in a given tract, at a given point in time, given variation in the share of nonwhite residents as well as other tract-level characteristics. Since Grossman and Krueger (1995) researchers concerned with economic growth and the environment have debated whether measures of environmental quality exhibit an inverted-U-shaped relationship with income per capita.[13] We consider whether a nonlinear relationship might be relevant to characterizing salient relationships between income per capita and toxic releases as well as the number of TRI-reporting facilities within a tract.

Firms must file a TRI report should they exceed the release thresholds of numerous various chemicals, making comparison across them difficult. We provide a listing of the 25 most frequently reported chemicals in the table 11 of the appendix in which we summarize the average plant-level toxicity (for both entrants and incumbents). As can be expected, while all of the listed chemicals are hazardous, their toxicities vary substantially. The EPA provides toxicity weights which reflect the relative toxicity of each chemical (per unit of relevant measurement), which can be used with reported emissions and aggregated to understand the toxic releases a given area incurs. Thus, multiplying the reported emissions by the toxicity weights and summing, we construct an aggregate weight of these pollutants.

In our specifications, we do not impose an inverse-U-shaped relationship but rather allow for one to emerge by fitting regression models involving cubic polynomials of the median income for a census tract to help explain variation in these aggregate weights. A relationship consistent with an EKC would involve a positive coefficient on the median income term, a negative coefficient on the squared term involving median income, and a negligible effect from the cubic term. Because this dependent variable must be non-negative, we considered a standard Tobit model. In table 4, we present in column (1) coefficient estimates and standard errors from this regression. There are 34,416 observations which comprise 4,302 tracts each observed for eight years in our data.[14] The econometric specification includes many other covariates along with the cubic polynomial, such as the share of nonwhite residents which is our primary variable of interest, and year fixed effects to control for economic changes over time as well as changes in the TRI reporting thresholds.[15,16] Note that the coefficient on the share of nonwhite residents is significant and implies that tracts with a higher share of nonwhite residents also incur higher releases of toxic chemicals on average. The median income terms are statistically significant and appear to be consistent with an EKC-like relationship.

To our knowledge, researchers interested in the possibility of the EKC have traditionally always considered the dependent variable to be some measure of emissions or pollution concentration. Given our focus on the industry structure of TRI-reporting firms, we wondered whether the number of TRI-reporting firms in a given tract might also respect such a relationship. The correlation between aggregate toxic releases per tract and the number of firms in a tract is 0.92. If an inverse-U-shaped relationship characterizes a pollutant and income per capita, it is likely appropriate for the number of firms in a tract—especially in industries with increasing marginal costs and/or capacity constraints as then more effluent byproduct is consistent with production increasing because of more firms in the industry. While communities in which income per capita is low might allow for toxic firms to locate in their areas because of the prospects of jobs or higher salaries, those with sufficiently high income per capita may push back against toxic firms citing in their areas if environmental quality is a normal good.[17] Fischel (2005) described how homeowners promote municipal governance and regulations. Glaeser, Gyourko, and Saks (2005) suggested that higher incomes induce more stringent zoning laws—at least with regards to the construction of new housing units, though regulations concerning exposure to pollution have been noted since zoning ordinances first came into use in the late 19th century.[18] Together these arguments suggest the potential for an inverse-U-shaped relationship between income per capita and the number of polluting firms in an area. In column (2), we estimate an econometric model which corresponds to that of column (1) but using the number of TRI-reporters in a tract as the dependent variable. The coefficients are now interpreted as the effect of a unit increase of each respective variable on the expected number of TRI firms in a tract. Indeed, the results are remarkably similar qualitatively and the relationships between the number of TRI-reporting firms and the share of nonwhite residents as well as the income terms remains.

In addition, because the number of TRI reporters is by definition a count variable, in column (3) we present results from estimating a Poisson model. Researchers who adopt a standard Poisson model assume the dependent variable y is independently distributed and the distribution of y is a Poisson distribution. A consequence of adopting this assumption is that it imposes equality between the mean and variance of the dependent variable, conditional on explanatory variables; i.e., $\mathbb{E}(y|\mathbf{x}) = \mathbb{V}(y|\mathbf{x})$. We follow Santos Silva and Tenreyro (2006) and estimate the model via Poisson pseudo-maximum likelihood (PPML). The PPML estimator is optimal when the conditional variance is proportional to the conditional mean, allowing for both under and overdispersion. In contrast, a negative binomial model could be used to address overdispersion but would only be consistent if the conditional distribution of the dependent variable is in fact negative binomial. With that concern in mind, the Poisson model is very robust in this aspect: Gourieroux, Monfort, and Trognon (1984) showed that a consistent and asymptotically normal estimator can be obtained without specifying the probability density function of disturbances representing specification error in the parameter of the Poisson distribution. Even if the conditional variance is not proportional to the conditional mean, the PPML will still be consistent and is generally well behaved as shown by Santos Silva and Tenreyro (2011), who also demonstrated that the PPML estimator works very well even when the proportion of zeros is large. As such, we employ the PPML strategy with inference being based on an Eicker–White robust covariance matrix. In column (3) of table 4, we report results from the model estimated via PPML. The results again suggest a positive correlation between the number of TRI reporters and the share of nonwhite residents in an area. Note, too, there appears to be an important nonlinear dependence characterizing the relationship between income and the number of TRI-reporting firms in a tract.

In figure 5, we plot the cubic functions of median income estimated from models (1) and (2) of table 4. The average median income across the sample is \$43,536 with a minimum at \$6,141 and a maximum at \$230,000. The functions depicted concerning the number of firms and aggregate toxic releases peak at \$61,990 and \$69,663, respectively, different by just about one standard deviation of the median income per tract. Note that the EKC is typically documented using an example of a local pollutant that remains in the atmosphere for relatively short periods of time (an extreme example would be noise). In the case we consider, the pattern concerns the number of firms established in polluting industries and filing TRI reports during our data period. Regardless of whether these firms belong to "footloose" industries (where a pollution haven hypothesis might hold), the entry and exit of manufacturing firms involves extensive fixed costs. As such, the irreversibility of this trend for a given region—that is, once a region attracts firms, whether it is even capable of undoing this harm, is questionable. It would be surprising if regional changes in development, planning, and zoning laws could change in a way such that situated firms would be forced to leave, as they would likely be protected under some kind of grandfathering clause. Therefore, it is likely that firms must exit voluntarily for the toxic releases of a given tract to decrease. This motivates an investigation of firm exit patterns, something we consider later in this article.

Before considering firm exit, and as a way of motivating the investigation of plant location decisions, we complement figure 5 with some relative histograms in figure 6 which partitions the median income variable into \$10,000-bins. The bars represent the share of three variables that are contained in each of the income bins. Specifically, we document the entry patterns of two types of firms: those that enter and report to the TRI at some point in our sample (TRI entrants, whose distribution is the left-most one plotted in each income bin) and those firms that enter into a NAICS industry which is not the primary industry of a firm we observe filing a TRI report (whose distribution corresponds with the middle bar within each income bin). This latter group is meant to at least proxy for entry into non-TRI relevant industries. Note that the entry of TRI reporters is far more concentrated in tracts with low median income and the mode of the distribution obtains below the average median income per tract observed in our data. In contrast, the distribution of entry into the non-TRI relevant industries has higher variance and a mean that is consistent with the average median income per tract. The difference between these two relative histograms is apparent from the figure alone and tests for the equality of these distributions (both Komogorov–Smirnov and Wilcoxen–Mann-Whitney U tests) are rejected at any conventional level. TRI-reporters locate disproportionately into low income tracts. Relative to figure 5, about 90% of TRI reporters that we observe enter lie on the uphill-portion of the inverse-U-shaped relationship concerning the number of TRI-reporting firms conveyed in figure 5, reinforcing the concerns we had about this relationship and its persistence. The final histogram plotted (to the far right of each income segment) reflects the share of Texas census tracts with median income relevant for the respective $10,000-bin. This is meant to show that tracts are not overly concentrated among the lower income levels (relative to the entry distributions) and that there are some tracts with higher median incomes. Non-TRI firms are entering into tracts with higher income levels and there is a clear turning point in the entrant distributions coinciding with the income bin containing the median incomes at which the functions depicted in figure 5 peak. Beyond this level of income, tracts begin seeing more non-TRI entrants and fewer TRI entrants.

Plant Location Choice

The results of the previous section document a correlation between the number of toxic firms and the share of nonwhite residents in an area as well as highlight the nonlinear role income may play. Sill, it's not clear whether nonwhite residents might choose to live in these areas after a plant has sited or whether firms target nonwhite areas. In this section, we investigate the siting decisions of TRI-reporting firms that we see enter during our sample period which allows us to control for the composition of each tract as well as tract- and time-specific factor prices which should be important to firm location decisions. As such, to consider entry of the TRI-reporting firms, we model firms as choosing a location (tract) to enter which maximizes their profits. This specification generates a conditional logit model which allows us to control for factors that researchers in the environmental justice literature suggest are important, covariates other economists have found to be important, and then we expand the set of variables by using other reasons economists have found are important in driving firm location like agglomeration (c.f., Deltas, De Silva, and McComb (2014)), the availability of amenities (c.f., Gottlieb (1995)), transportation networks (c.f., Chandra and Thompson (2000)), and other socioeconomic and demographic variables. Because we are interested in how these characteristics of an area affect the location of a firm, our approach is in the spirit of Bartik (1985).

Specifically, we empirically model a firm's location choice during a certain period as the result of an attempt to maximize expected profits by using a conditional logit framework (see, for example, McFadden (1974)). Firm i's profit from siting in tract ℓ at time t can be written as follows:

$$\pi_{i,\ell,t} = V'_{\ell,t}\beta + W'_{\ell}\gamma + X'_{i,\ell,t}\delta + \epsilon_{i,\ell,t}. \tag{1}$$

where $V_{\ell,t}$ collects the tract-ℓ specific characteristics at time t such as the share of nonwhite residents, terms involving median income, and the percentage of the region's population with a college education. W_ℓ captures tract-specific factors which do not change over the data period such as the number of roads and railroads (though we do see variation in procurement spending over time when we use that to capture a tract's infrastructure), the land area of a tract, as well as indicators for whether the tract is part of a county that borders another state. The vector $X_{i,\ell,t}$ contains covariates that are firm-, tract-, and time-specific. For example, agglomeration effects might obtain from locating near other TRI-reporting and TRI-like firms. As such, we include variables which capture the number of firms that have reported to the TRI and the number of other TRI-like firms in tract ℓ. Remember, these other firms have the same NAICS codes as TRI firms but never reported to the TRI. Moreover, these variables are firm-specific in the sense that they represent counts of the respective types of firms within the same three-digit NAICS industry as firm i. We assume that the disturbance $\epsilon_{i,\ell,t}$ is independent and identically distributed according to a Type-I extreme value distribution. We also assume that each firm knows their private costs and expected profits.

The firm profit maximization objective is particularly attractive in this context: Wolverton (2012) found the primary reason for dirty firm location decisions was profit maximization among competing alternative hypotheses. More broadly, this approach 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 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, List, McHone, and Millimet (2003) considered plant *relocation* choices made by firms, again finding differences in environmental factors (in this case, air quality regulations) significantly alter location choices.

This setup enables us to convert the discrete actions of competitors into continuous location choice probabilities. We can specify the conditional logit model as follows:

$$\Pr(E_{i,\ell,t} = 1 | V_{\ell,t}, W_\ell, X_{i,\ell,t}) = \Pr(\pi_{i,\ell,t} > \pi_{i,k,t} \text{ for all } \ell \neq k) \tag{2}$$

where $E_{i,\ell,t}$ is an indicator variable which equals one if firm i chooses location ℓ at time t and zero otherwise. Firm i will choose location ℓ if $\pi_{i,\ell,t} > \pi_{i,k,t}$ for all $k \neq \ell$. Therefore, conditional on the decision to open a new plant, the probability that firm i will choose particular location ℓ at time t can be written as follows:

$$\Pr(E_{i,\ell,t} = 1) = \frac{\exp\left(V'_{\ell,t}\beta + W'_{\ell}\gamma + X'_{i,\ell,t}\delta\right)}{\sum_{k=1}^{m}\exp\left(V'_{k,t}\beta + W'_{k}\gamma + X'_{i,k,t}\delta\right)}. \tag{3}$$

In Texas, there are 4302 tracts which are home to at least one firm that operates in an industry for which we see some firm also operate and file a TRI report. We observe 166 TRI-reporting firms enter as new firms in our sample period. In table 5, we present the coefficient estimates from various specifications of the conditional logit model. A positive coefficient means that an increase in that variable for a given tract (holding values for others constant), makes the tract more likely to be chosen. First, in agreement with the concerns of the environmental justice literature, all models suggest a positive, statistically significant relationship between a firm's propensity to locate in a given tract and the share of nonwhite residents.[19] Second, agglomeration effects appear only to matter if the firms present in a tract are TRI reporters. That is, firms with more incumbent TRI reporting firms are more likely to attract new firms but such a relationship does not hold based on the number of like TRI firms (non-reporters but also operating in the same industry). Third, based on our EKC findings we allow income to enter the models in a flexible way. Though the sign of each polynomial coefficient is consistent with the EKC relationship, these effects are not statistically significant. Beyond these observations of interest to us, we also see from the results that, as the maps presented earlier suggested, transportation networks play an important role in driving firm location decisions (but TxDOT spending does not). TRI firms are also more likely to enter areas with higher wages. Remember that average wages are the wages paid by firms in the area and so this result reflects the fact that TRI firms are locating in areas of industrial concentration which have higher wages (as shown even in the summary statistics presented in table 3). The larger the share of a tract's population holding college degrees, the less likely a firm is to locate in that area. Controls for the physical size of a tract and the housing rental ratio really don't play much of a role.

In table 6, we consider various subsets of tracts in our data to try and understand where the concerns of the environmental justice literature are most prevalent. To begin, in column (1) we revisit the two locations that were the focus of Wolverton's (2009) work. Doing so, cuts our entrant sample in half (there are 84 entrants) and retains about 44 percent of the tracts in the location choice set (there are 1910 tracts in DFW and Houston MSAs that house at least one firm in an industry from which we see TRI reports filed). There are a few changes that we observe relative to our statewide investigation. First, a higher share of nonwhite residents is no longer associated with a higher chance of a firm locating in a given tract. Second, the agglomeration effects stemming from the presence of other TRI reporters continue to hold (though, again, agglomeration of TRI-like firms is not important). The income, transportation-based effects, and negative relationship between entry and the share of the population with a college degree follow a pattern similar to what we found in the full sample. In column (2), we consider the complement to the DFW and Houston case by focusing only on the entry of TRI firms outside of these two MSAs. As expected given the full sample results, the environmental justice concerns are much stronger in this sample of tracts—as are the agglomeration effects of TRI reporters. Here, having a large share of college educated residents is not significantly related with the entry of a TRI reporting firm.

Building on the partition across columns (1) and (2), we repeat this slicing of the data but group tracts according to whether the tract is part of any Texas MSA (not just the DFW and Houston ones) or not. When focusing on either of these groups, the share of nonwhite residents is significant, though the magnitude of the effect is far larger in the non-MSA setting. Arora and Cason (1999) noted that environmental justice concerns are primarily confined to nonurban areas. These results seem to speak to an almost monotonic relationship in that sense as well. The DFW and Houston

MSAs are each about three times as large as any other Texas MSA. The results in this table suggest that the share of nonwhite residents becomes increasingly important once you consider Texas MSAs as a group (column (3)), the set of all non-DFW or Houston tracts (column (2)), or all non-MSA tracts at large (column (4)). In general, for most covariates significance is far harder to achieve in the non-MSA setting for most of the effects because there are only 24 entrants observed. As such, we see a similar magnitude for the TRI-reporting agglomeration effect across columns (3) and (4), though the standard errors are too large in the smaller non-MSA sample for the effect to be significant.[20]

In table 7 we present estimates from two other models concerning the full sample of data in which we aggregate over NAICS industries to see if our findings hold more generally and whether an alternative econometric specification might lead to different results. Specifically, we consider a count model in the spirit of Keller and Levinson (2002) who 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. Some theoretical justification of this model can be found in the application of Becker and Henderson (2000) who consider a supply and demand relationship concerning new plant "births" in a given area to better understand how the status of attainment and nonattainment of air quality standards (which perhaps induces differences the stringency of regulation) affect new firms' location decisions. In column (1), we show that when estimating a model involving the number of TRI-reporting entrants via PPML, the sign and significance of all covariates is largely unchanged. That is also true if we consider a Tobit model in which the dependent variable is the number of entrants that report to the TRI, as presented in column (2). In general, the higher the percent of nonwhite residents, the higher the expected number of TRI entrants in a tract. Agglomeration effects are important for TRI reporters, but not for other TRI-like firms and the results here align with the conditional logit results.[21]

Considering these other models also makes our analysis more amenable to a comparison of the relationships characterizing entry patterns of non-TRI reporters as well, something feasible given our QCEW data. We consider non-TRI reporters to be the firms that enter into a three-digit NAICS industry for which no TRI-reporting firm in our data belongs. This of course, involves far more firms—we see 320,230 non-TRI entrants which amounts to about 9.3 per tract over our sample period. Estimating a conditional logit model with this many entrants would prove challenging computationally but the PPML and Tobit models are fairly simple to estimate with such data. We present the results of such estimates in columns (3) and (4) of table 7. Note that the sign of the coefficient on the share of nonwhite residents flips sign and becomes significantly negative—that is, a higher percent of nonwhite residents is negatively related with non-TRI firm entry. This deepens the concern of the environmental justice literature if it implies non-polluting firms are locating disproportionately in white-concentrated tracts. There are no agglomeration benefits from the presence of TRI reporting firms (perhaps not surprising since these entrants are not TRI reporters). The terms involving income no longer reflect an inverse-U-shaped relationship. In contrast to the results concerning TRI-reporting firms, these firms are more likely to locate in regions with a high share of college graduates. Road networks seem important, though not railroad networks and the firms locate in population-dense areas (given the coefficient on population is positive and the land area coefficient is negative).

Survival of Firms

We complement our entry analysis with a look at a firm's ability to survive once they've reported to the TRI. The TRI is a type of environmental policy that can be considered an accountability program—many of the chemicals that are required to be reported are not regulated directly. The idea is that requiring firms to report such effluents might induce community or consumer-driven pressure to reduce unregulated pollutants. Or, simply, requiring the firms to make such reports might induce the firm to internalize some toxic releases that would be quite cheap to reduce when public reporting is required. Specifically, all firms emitting the threshold level of various pollutants are required to report, but the firms pay no direct penalties. The idea is that by making the reporters' waste public information, that will deter firms from emitting to the fullest extent. We felt it would be interesting to see if, after reporting, the firms are able to survive in the industry relative to other non-reporters.

Wolverton (2009) begins her research by consulting the TRI and seeing which firms are listed. She then looks backwards to try and find when the firms entered the industry. In contrast, our approach is the opposite: we take data on entry of *all* firms and match them to the TRI, then focused our analysis thus far on those firms that existed prior to or entered during our sample period. However, our approach also allows us to consider the end of the life-cycle. Specifically, a challenge for Wolverton was that she did not know whether a firm left the industry entirely, or whether the emissions of pollutants fell below the required threshold for reporting. Our data allow us to see whether the firm exited the industry entirely given we can track the disappearance of an establishment-specific employer identification number across quarters of the QCEW data. Once a firm no longer appears in a given quarter, we assume the firm exited the market in the prior quarter (corresponding to the last period in which the firm was observed to be active).

To consider exit we compute a firm's age in months and report some summary statistics in table 8. For this part of the analysis, we restrict our sample to involve only establishments that open by 2005 because we want to be able to allow for exits to be observed—something not possible for firms that enter in the final data year. The summary statistics here are partitioned into two types of firms over the period 1999–2005: TRI-reporting firms, considered in the first two data-related columns, and TRI-like firms, described in the last two data columns. The total number of TRI-reporting firms is 155—referencing back to table 2, we can reconcile this with the full sample size of 166 TRI-reporting firms by seeing that 11 firms entered in 2006. We see 21 TRI-reporting firms in our sample both enter and exit the industry. TRI-reporting firms are larger on average, have higher wages, and those that do not exit are older, while those that do exit do so at a younger age. The summary statistics for the covariates considered in our earlier analysis are again presented but are restricted to tracts which have TRI-reporting or TRI-like firms, respectively. On average, tracts with TRI-reporting firms have a higher share of nonwhite residents, lower median income and an higher poverty rate for the tracts (despite higher wages for the employees), about half the number of amenities, and a lower population, relative to the tracts with TRI-like firms.

We have in mind a theoretical model involving a threshold rule that is analogous to the profit maximization problem considered in our entry analysis. Here if firms do not make a sufficient level of profit, they choose to exit the industry. To consider this empirically, we estimate logit models in which the dependent variable is a zero if the firm chooses to remain active in a given year, and a one if the firm chooses to exit. The year the firm exists is considered to be relative to the year they entered. For example, if we see two firms, one that entered in 2000 and one that entered in 2002, when we evaluate data from 2004, it will be the fourth year for the year-2000 entering firm and the second year for the year-2002 firm. Because our data span the years 1999–2006, we have at most six observations (2000, 2001, ..., 2005) for each entering firm and as few as one observation for a given firm (that would correspond to a firm that enters one year and exits the following year).

In table 9, we consider the subsample of firms which we observe entering and are either TRI-reporters or TRI-like firms, and present the estimated marginal effects of various logit models. Since the dependent variable takes on a value of one when a firm exits, positive coefficient estimates suggest firms are more likely to exit while negative ones imply the firm is less likely to exit. There are some notable trends across the host of models presented.[22] First, the share of nonwhite residents living in a firm's tract is not significant. Second, on average TRI reporters are less likely to exit by about 20% relative to firms that are the same industries, but not filing TRI reports. This effect however, is not asymmetrically different based on the share of the host tract's nonwhite residents.[23] Still, the fact that TRI reporters are less likely to exit deepens environmental justice concerns about polluters not only excessively locating in nonwhite-dense regions, but continually exposing these residents to pollution in the long-run. Typically the downhill portion of the inverse-U-shaped relationship characterizing the number of TRI-reporting firms is driven by increased demand for environmental-related goods (like cleaner air and water) stemming from increased incomes. However, if TRI reporters are unlikely to exit it could mean the reversibility of these firm sitings is compromised in the long-run. Third, agglomeration effects are again at play—firms located in tracts with other TRI incumbents are even less likely to exit. As such, a given tract could see a disproportionate share of toxic releases in the short- and long-run. Estimates of the coefficients corresponding to other covariates seem consistent with intuition and other results from the industrial organization literature. For example, the higher the unemployment rate in a tract, the less likely a firm is to exit. Like Dunne, Klimek, and Roberts (2005), we find firms that are bigger (based on employment size or the firm's share of the industry's employment), older, or have had prior ownership are less likely to exit.[24]

Summary and Conclusion

We considered the industry structure, location decision, and propensity to survive of TRI-reporting firms in Texas over the years 1999 through 2006. Our focus on Texas is an important one given many researchers have pointed to California and Texas as regulatory leaders (c.f., Figlio, Kolpin, and Reid (1999), Berman and Bui (2001), Fredriksson and Millimet (2002)) with Texas having a reputation as a state with lax environmental policies. We hope to have contributed to the literature concerning environmental justice in a few ways. First, a strong positive correlation exists between the number of firms that report to the TRI and the percent of nonwhite residents within a tract, even after controlling for a number of other important economic factors. In considering how the number of these firms relates to tract-specific covariates, we also bridged the gap between the environmental justice literature and the literature focused on the environmental Kuznets curve. To do this, we documented an inverse-U-shaped relationship between per-capita income and the aggregate toxic emissions in an tract as well as the number of TRI establishments. This pattern reflects that a nonlinear relationship might best characterize these two variables—we do not feel this implies that economic growth will "solve" the associated environmental problems (as evidenced by our firm exit analysis).

We also investigated whether firms observed to enter during our sample period selected into tracts with a high share of nonwhite residents, given important variables which account for the factor prices in a given tract. Indeed, for our data and for all but the Dallas and Houston MSAs subsample, firms are more likely to enter tracts with a larger share of nonwhite residents. The result is robust in that significance remains for both our main conditional logit model as well as using other specifications concerning the number of TRI entrants. We also documented at various points that our findings do not go through when considering entry patterns of firms that less likely to be TRI reporters. Specifically, we determined all three digit NAICS for which there are no TRI reporters present and looked at entry in these industries. Disturbingly, these firms are significantly *less* likely to enter tracts with a high share of nonwhite residents.

Lastly, when it comes to the survival of TRI-reporting firms as compared to other firms in the NAICS industries which harbor the TRI-reporting firms, TRI reporters are, on average, less likely to exit their industries. In all entry and exit models we also show that TRI-industry-based agglomeration effects are important. Specifically, the presence of incumbent TRI-reporting firms further increases the chances that a new TRI-reporting firm enters a tract and decreases the probability that a TRI-reporting firm exits the industry.

As a whole, our data seem to suggest some serious concerns remain from an environmental justice perspective. Polluters are disporportionately locating in areas with a high share of nonwhite residents, while the complement set of firms avoids these areas. Agglomeration is important which means exposing an area to an even larger share of releases and these TRI reporters are less likely to exit relative to firms in the same industries who do not emit enough to require reporting, meaning the effects may persist in the long-run. There may need to be policy intervention to reverse some of these trends, but increased awareness about the consequences we document such as the agglomeration potential and presence of these firms in the long-run might help policymakers in communities reconsider their decision to allow polluting firms the ability to locate in their areas.

References

Arora, S., and T.N. Cason. 1999. "Do Community Characteristics Influence Environmental Outcomes? Evidence from the Toxics Release Inventory." *Southern Economic Journal* 65:691–716.

Bartik, T.J. 1985. "Business Location Decisions in the United States: Estimates of the Effects of Unionization, Taxes, and Other Characteristics of States." *Journal of Business & Economic Statistics* 3:14–22.

Becker, R., and V. Henderson. 2000. "Effects of Air Quality Regulations on Polluting Industries." *Journal of Political Economy* 108:379–421.

Berman, E., and L.T.M. Bui. 2001. "Environmental Regulation And Productivity: Evidence From Oil Refineries." *Review of Economics and Statistics* 83:498–510.

Brooks, N., and R. Sethi. 1997. "The Distribution of Pollution: Community Characteristics and Exposure to Air Toxics." *Journal of Environmental Economics and Management* 32(2):233–250.

Bui, L. 2005. "Public Disclosure of Private Information as a Tool for Regulating the Environment: Firm-Level Responses by Petroleum Refineries to the Toxics Release Inventory. Working paper, Brandeis University." Unpublished.

Bui, L.T., and C.J. Mayer. 2003. "Regulation and Capitalization of Environmental Amenities: Evidence from the Toxic Release Inventory in Massachusetts." *Review of Economics and Statistics* 85:693–708.

Chandra, A., and E. Thompson. 2000. "Does Public Infrastructure Affect Economic Activity?: Evidence from the Rural Interstate Highway System." *Regional Science and Urban Economics* 30:457–490.

Dasgupta, S., B. Laplante, H. Wang, and D. Wheeler. 2002. "Confronting the Environmental Kuznets Curve." *Journal of Economic Perspectives* 16(1):147–168.

Deltas, G., D.G. De Silva, and R.P. McComb. 2014. "Agglomeration Spillovers and Industry Dynamics: Firm Entry, Growth, and Exit in the Software Publishing Industry." Working paper, University of Illinois.

Dinda, S. 2004. "Environmental Kuznets Curve Hypothesis: A Survey." *Ecological Economics* 49:431–455.

Dunne, T., S.D. Klimek, and M.J. Roberts. 2005. "Exit from Regional Manufacturing Markets: The Role of Entrant Experience." *International Journal of Industrial Organization* 23:399–421.

Figlio, D.N., V.W. Kolpin, and W.E. Reid. 1999. "Do States Play Welfare Games?" *Journal of Urban Economics* 46:437–454.

Fischel, W.A. 2005. *The Homevoter Hypothesis: How Home Values Influence Local Government Taxation, School Finance, and Land-Use Policies*. Harvard University Press.

Fredriksson, P.G., and D.L. Millimet. 2002. "Is There a California Effect in US Environmental Policymaking?" *Regional Science and Urban Economics* 32:737–764.

Glaeser, E.L., J. Gyourko, and R.E. Saks. 2005. "Why Have Housing Prices Gone Up?" *American Economic Review* 95:329–333.

Gottlieb, P.D. 1995. "Residential Amenities, Firm Location and Economic Development." *Urban Studies* 32:1413–1436.

Gourieroux, C., A. Monfort, and A. Trognon. 1984. "Pseudo Maximum Likelihood Methods: Applications to Poisson Models." *Econometrica* 52:701–20.

Grossman, G.M., and A.B. Krueger. 1995. "Economic Growth and the Environment." *Quarterly Journal of Economics* 110:353–77.

Hamilton, J.T. 1995a. "Pollution as News: Media and Stock Market Reactions to the Toxics Release Inventory Data." *Journal of Environmental Economics and Management* 28(1):98–113.

—. 1995b. "Testing for Environmental Racism: Prejudice, Profits, Political Power?" *Journal of Policy Analysis and Management* 14:107–132.

Helland, E., and A.B. Whitford. 2003. "Pollution Incidence and Political Jurisdiction: Evidence from the TRI." *Journal of Environmental Economics and Management* 46(3):403–424.

Kahn, M.E. 2006. *Green Cities: Urban Growth and the Environment*. Brookings Institution Press: Washington, D.C.

Keller, W., and A. Levinson. 2002. "Pollution Abatement Costs and Foreign Direct Investment Inflows to U.S. States." *Review of Economics and Statistics* 84:691–703.

Khanna, M., W. Quimio, and D. Bojilova. 1998. "Toxics Release Information: A Policy Tool for Environmental Protection." *Journal of Environmental Economics and Management* 36(3):243–266.

Konar, S., and M.A. Cohen. 1997. "Information as Regulation: The Effect of Community Right to Know Laws on Toxic Emissions." *Journal of Environmental Economics and Management* 32(1):109–124.

Kunreuther, H., P. Kleindorfer, P.J. Knez, and R. Yaksick. 1987. "A Compensation Mechanism for Siting Noxious Facilities: Theory and Experimental Design." *Journal of Environmental Economics and Management* 14(4):371–383.

Kunreuther, H., and P.R. Kleindorfer. 1986. "A Sealed-Bid Auction Mechanism for Siting Noxious Facilities." *American Economic Review* 76:295–99.

List, J.A., and C.Y. Co. 2000. "The Effects of Environmental Regulations on Foreign Direct Investment." *Journal of Environmental Economics and Management* 40(1):1–20.

List, J.A., W.W. McHone, and D.L. Millimet. 2003. "Effects of Air Quality Regulation on the Destination Choice of Relocating Plants." *Oxford Economic Papers* 55:657–678.

Mastromonaco, R. 2015. "Do Environmental Right-to-Know Laws Affect Markets? Capitalization of Information in the Toxic Release Inventory." *Journal of Environmental Economics and Management* 71:54–70.

—. 2011. "Dynamic General Equilibrium Analysis of the Equity Implications and Welfare Effects of Disproportionate Exposure. University of Oregon Working Paper." Unpublished.

McFadden, D. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In P. Zarembka, ed. *Frontiers in Economics*. New York: Academic Press.

Oberholzer-Gee, F., and M. Mitsunari. 2006. "Information Regulation: Do the Victims of Externalities Pay Attention?" *Journal of Regulatory Economics* 30:141–158.

Sanders, N.J. 2014. "Toxic Assets: How the Housing Market Responds to Environmental Information Shocks." Working paper, College of William and Mary.

Santos Silva, J.M., and S. Tenreyro. 2011. “Further Simulation Evidence on the Performance of the Poisson Pseudo-Maximum Likelihood Estimator.” *Economics Letters* 112:220–222.

—. 2006. “The Log of Gravity.” *Review of Economics and Statistics* 88:641–658.

Selden, T.M., and D. Song. 1995. “Neoclassical Growth, the J Curve for Abatement, and the Inverted U Curve for Pollution.” *Journal of Environmental Economics and Management* 29(2):162–168.

Shadbegian, R.J., and A. Wolverton. 2010. “Location Decisions of U.S. Polluting Plants: Theory, Empirical Evidence, and Consequences. National Center for Environmental Economics, U.S. Environmental Protection Agency, Working Paper #10–05.” Unpublished.

Wolverton, A. 2009. “Effects of Socio-Economic and Input-Related Factors on Polluting Plants’ Location Decisions.” *The B.E. Journal of Economic Analysis & Policy* 9:1–32.

—. 2012. “The Role of Demographic and Cost-Related Factors in Determining Where Plants Locate: A Tale of Two Texas Cities.” In S. Banzhaf, ed. *The Political Economy of Environmental Justice*. Stanford University Press, chap. 8.

Table 1: TRI Industry Distribution

NAICS Title	NAICS-3	Incumbents		Entrants	
		n	%	n	%
Oil and Gas Extraction	211	1	0.17		
Utilities	221	7	1.19		
Construction of Buildings	236	2	0.34	3	1.81
Food Manufacturing	311	47	8.02	15	9.04
Beverage and Tobacco Product Manufacturing	312	6	1.02	2	1.20
Textile Mills	313	1	0.17	1	0.60
Leather and Allied Product Manufacturing	316	2	0.34	1	0.60
Wood Product Manufacturing	321	17	2.90	8	4.82
Paper Manufacturing	322	4	0.68	1	0.60
Petroleum and Coal Products Manufacturing	324	25	4.27	12	7.23
Chemical Manufacturing	325	221	37.71	47	28.31
Plastics and Rubber Products Manufacturing	326	41	7.00	12	7.23
Nonmetallic Mineral Product Manufacturing	327	14	2.39	3	1.81
Primary Metal Manufacturing	331	22	3.75	5	3.01
Fabricated Metal Product Manufacturing	332	55	9.39	19	11.45
Machinery Manufacturing	333	20	3.41	8	4.82
Computer and Electronic Product Manufacturing	334	22	3.75	7	4.22
Electrical Equipment, Appliance, and Component Manufacturing	335	4	0.68	2	1.20
Transportation Equipment Manufacturing	336	19	3.24	4	2.41
Furniture and Related Product Manufacturing	337	2	0.34		
Miscellaneous Manufacturing	339	7	1.19	2	1.20
Merchant Wholesalers, Durable Goods	423	1	0.17		
Merchant Wholesalers, Nondurable Goods	424	39	6.66	12	7.23
Electronics and Appliance Stores	443	1	0.17		
Waste Management and Remediation Services	562	6	1.02	2	1.20
Total		586	100.00	166	100.00

Table 2: Census Tract-Level Breakdown of Entry Year vs. First-Report Year

Entry Year	Total	TRI report year							
		1999	2000	2001	2002	2003	2004	2005	2006
1999	30	10	2		17			1	
2000	13		4		8			1	
2001	18			7	8			3	
2002	26				24	1		1	
2003	23					23			
2004	22						20	2	
2005	23							22	1
2006	11								11
Total	166	10	6	7	57	24	20	30	12

Table 3: Census Tract-Level Summary Statistics

Variable	All of Texas		DFW & Houston MSAs		MSAs Only		Non-MSAs Only	
	All	TRI firms ≥ 1	All	TRI firms ≥ 1	All	TRI firms ≥ 1	All	TRI firms ≥ 1
Number of tracts	4302	328	1910	149	3,522	226	780	62
Number of TRI reporters	752	752	305	305	670	670	182	182
Number of TRI entrants	166	166	84	84	142	142	24	24
Percent nonwhite	0.292	0.326	0.340	0.389	0.311	0.347	0.207	0.238
residents$_{l,t}$	(0.196)	(0.205)	(0.222)	(0.223)	(0.201)	(0.211)	(0.139)	(0.149)
TRI incumbents$_{i,l,t}$	0.031	0.406	0.037	0.470	0.031	0.415	0.029	0.367
	(0.260)	(0.857)	(0.332)	(1.099)	(0.272)	(0.906)	(0.196)	(0.602)
Other TRI-like	5.561	12.974	6.453	18.180	5.751	14.211	4.704	7.663
establishments$_{i,l,t}$	(29.185)	(53.359)	(34.933)	(78.071)	(27.341)	(59.068)	(6.443)	(7.750)
Number of roads$_l$	13.150	20.250	10.986	18.725	11.666	19.237	19.853	24.597
	(12.022)	(17.279)	(11.388)	(19.977)	(11.315)	(17.637)	(12.813)	(14.901)
Number of railroads$_l$	2.153	6.091	1.582	6.081	1.785	6.086	3.815	6.113
	(4.154)	(8.429)	(3.901)	(9.890)	(3.958)	(8.941)	(4.588)	(5.745)
Median income (\$)$_{l,t}$	43,535.80	39,279.41	51,518.78	41,452.82	45,915.14	40,240.82	32,792.17	35,154.65
	(22,589.71)	(14,752.87)	(26,790.60)	(15,403.98)	(23,997.65)	(15,404.70)	(8,553.04)	(10,611.19)
Average wage (\$)$_{l,t}$	37,350.27	46,445.20	44,450.49	50,482.31	39,361.92	48,121.18	28,266.87	39,254.69
	(44,234.28)	(21,664.64)	(54,462.64)	(22,053.27)	(47,951.11)	(22,235.92)	(17,574.25)	(17,281.69)
Poverty ratio$_{l,t}$	0.143	0.151	0.118	0.151	0.139	0.151	0.165	0.150
	(0.106)	(0.091)	(0.096)	(0.094)	(0.109)	(0.095)	(0.088)	(0.072)
College ratio$_{l,t}$	0.097	0.070	0.118	0.068	0.105	0.070	0.062	0.068
	(0.082)	(0.060)	(0.096)	(0.063)	(0.088))	(0.064)	(0.034)	(0.039)
Number of amenity	5.053	5.215	5.177	5.551	5.250	5.455	4.164	4.183
establishments$_{l,t}$	(12.240)	(7.168)	(15.723)	(8.621)	(13.346)	(7.717)	(4.604)	(3.883)
Housing rental ratio$_{l,t}$	0.319	0.309	0.351	0.362	0.342	0.330	0.218	0.224
	(0.204)	(0.191)	(0.226)	(0.206)	(0.212)	(0.198)	(0.120)	(0.123)
Average house value (\$)$_{l,t}$	125,072.00	110,771.60	151,661.00	118,035.50	133,025.20	113,987.50	89,160.05	96,974.17
	(75,067.58)	(49,050.55)	(89,094.57)	(51,182.54)	(7,9731.41)	(51,206.98)	(28,287.60)	(35,307.33)
Population$_{l,t}$	5,036.913	5,157.921	5,474.035	5,267.283	5,271.369	5,230.089	3,978.257	4,848.298
	(2,824.293)	(2,715.314)	(3,030.338)	(2,917.577)	(2,914.326)	(2,863.148)	(2,067.731)	(1,930.209)
Unemployment rate$_{l,t}$	4.373	4.851	4.523	5.778	4.483	5.131	3.875	3.647
	(3.420)	(4.592)	(4.057)	(6.274)	(3.552)	(4.981)	(2.693)	(1.825)
Land area$_l$	0.623	0.814	0.121	0.420	0.214	0.538	2.465	2.000
(in 100 square miles)	(2.200)	(2.626)	(0.924)	(3.123)	(1.001)	(2.538)	(4.245)	(2.671)
TxDOT expenditures$_{l,t}$	8.473	9.443	2.033	3.257	3.715	4.963	29.955	28.663
(in \$1,000,000)	(21.923)	(18.273)	(6.069)	(9.249)	(9.493)	(11.310)	(40.994)	(27.628)

Standard deviations are in parentheses.

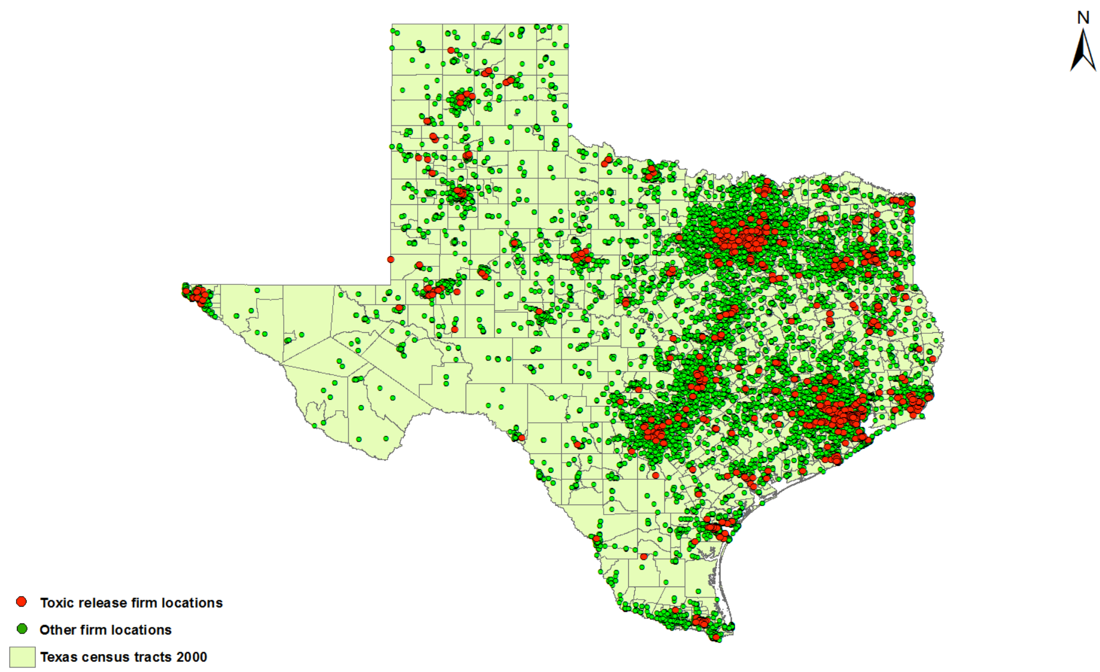

Figure 1: Locations of TRI and other firms

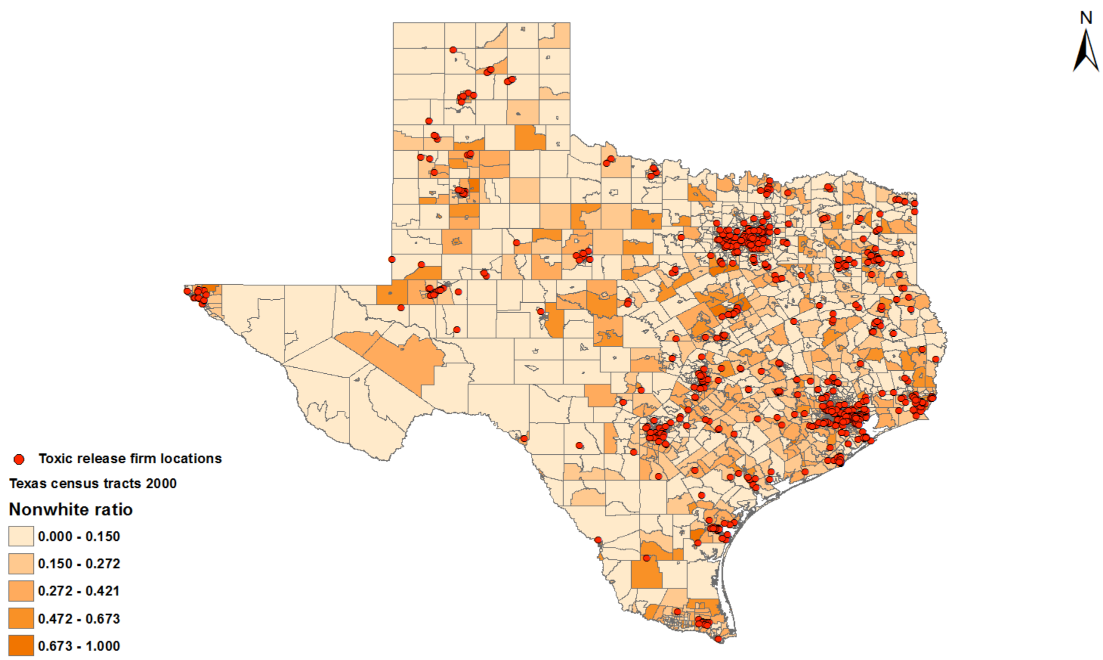

Figure 2: Locations of TRI firms and concentration of nonwhite population

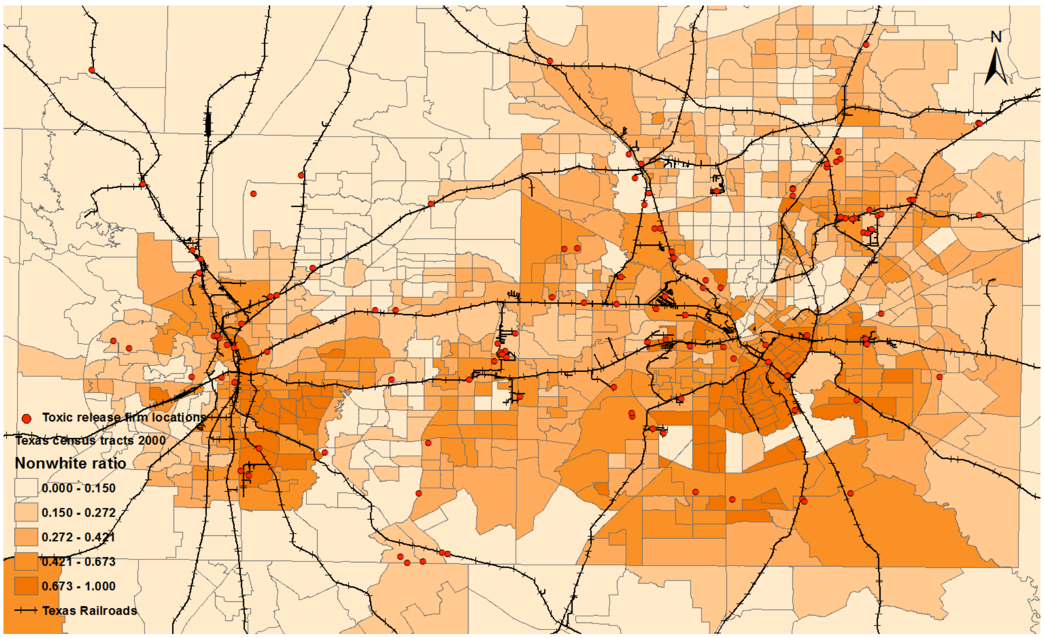

Figure 3: Distribution of TRI firms in Dallas–Fort Worth MSA

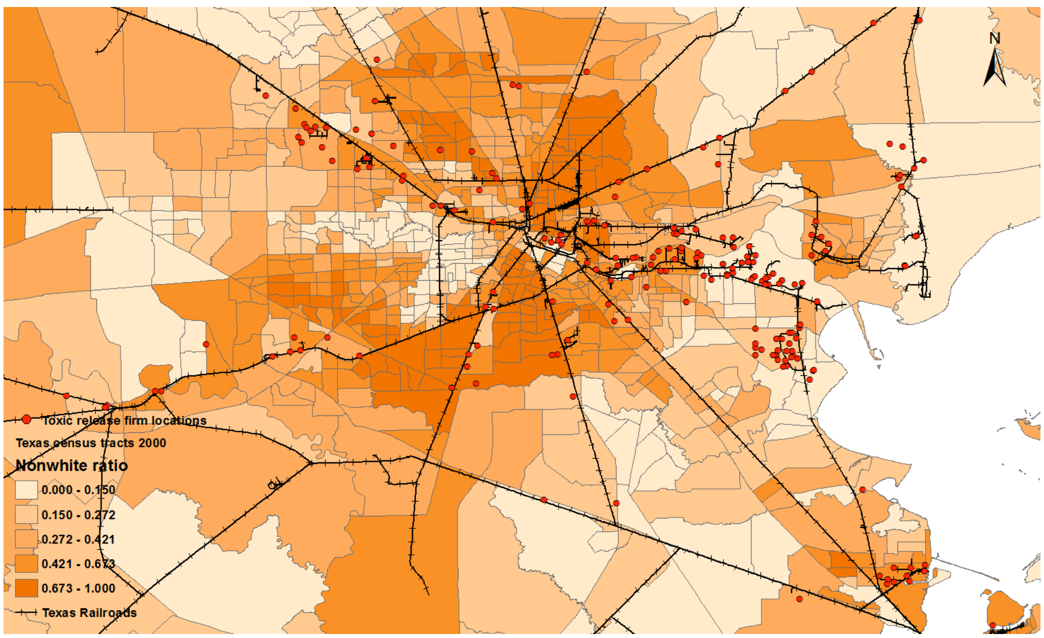

Figure 4: Distribution of TRI firms in Houston MSA

Table 4: Explaining Variation in Aggregate Toxicity and the Number of TRI Firms

Variable	Tobit		PPML
	Total number of pounds$^{a}_{l,t}$	Total number of TRI firms$_{l,t}$	Total number of TRI firms$_{l,t}$
	(1)	(2)	(3)
Percent nonwhite residents$_{l,t}$	0.96143***	1.21805***	0.81329***
	(0.15524)	(0.23213)	(0.18703)
Median income (in \$10,000)$_{l,t}$	0.85136***	1.06862***	1.03213***
	(0.13331)	(0.17733)	(0.15164)
Median income (in \$10,000)$^{2}_{l,t}$	-0.08067***	-0.10969***	-0.10641***
	(0.01683)	(0.02553)	(0.02306)
Median income (in \$10,000)$^{3}_{l,t}$	0.00187***	0.00253***	0.00255***
	(0.00055)	(0.00095)	(0.00088)
Average wage(in \$10,000)$_{l,t}$	0.03849***	0.06142***	0.03084***
	(0.00645)	(0.00802)	(0.00386)
Number other TRI-like establishments$_{l,t}$	0.00071	0.00175	0.00026
	(0.00128)	(0.00110)	(0.00032)
College ratio$_{l,t}$	-5.89364***	-6.59933***	-6.09433***
	(1.00047)	(1.04780)	(0.98014)
Number of amenity establishments$_{l,t}$	-0.00799**	-0.02262***	-0.02788***
	(0.00379)	(0.00670)	(0.00674)
Number of roads$_{l}$	0.01566***	0.01775***	0.01858***
	(0.00214)	(0.00340)	(0.00259)
Number of railroads$_{l}$	0.08332***	0.12985***	0.06388***
	(0.01041)	(0.01055)	(0.00362)
Population (in 1,000)$_{l,t}$	0.00080	-0.01190	-0.07367***
	(0.00851)	(0.01659)	(0.02649)
Unemployment rate$_{l,t}$	0.01728***	0.01637	0.01230*
	(0.00427)	(0.01082)	(0.00742)
Land area (in 100 square miles)$_{l}$	-0.04073***	-0.06659**	-0.10458***
	(0.01406)	(0.02662)	(0.03976)
Border county effects$_{l}$	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Number of obs.	34,416	34,416	34,416
Log likelihood	-3,860.064	-5,230.485	-4,992.117
Uncensored obs.	941	980	

Statistical significance levels: *** =1%, ** = 5%, * = 10%.
[a]In millions of pounds.

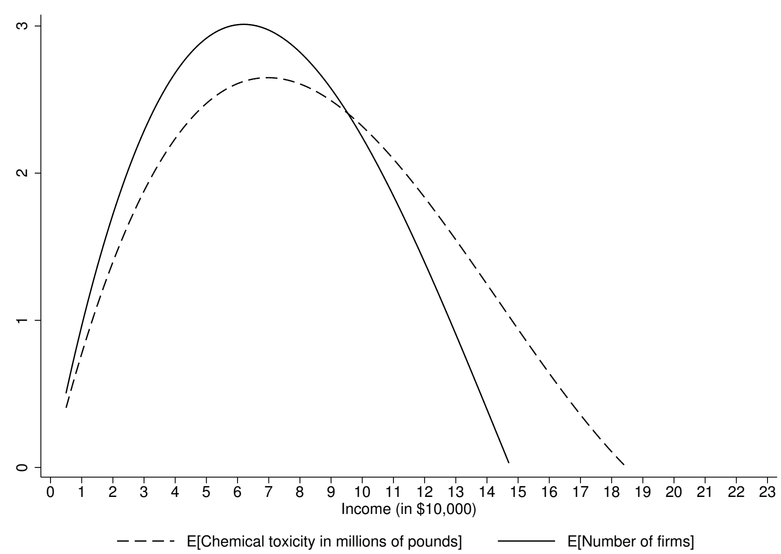

Figure 5: Estimated cubic functions relating toxicity measures to median income in a region

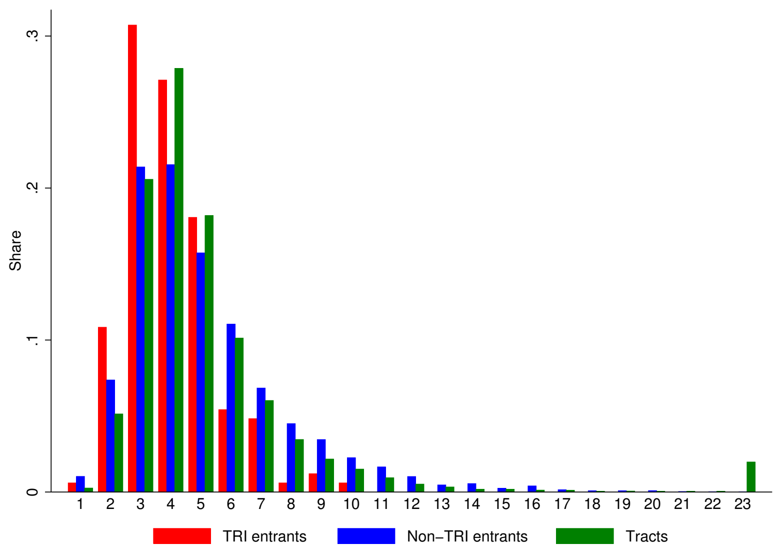

Figure 6: The shares of TRI entrants and non-TRI entrants siting in regions with various income levels

Table 5: Conditional Logit Results: All Tracts

Variable	TRI firm entry					
	(1)	(2)	(3)	(4)	(5)	(6)
Percent nonwhite residents$_{l,t}$	1.622***	0.902**	1.619***	1.435***	1.243***	0.992**
	(0.432)	(0.394)	(0.431)	(0.465)	(0.457)	(0.452)
TRI incumbents$_{i,l,t}$	0.374***	0.386***	0.347***	0.347***	0.479***	0.375***
	(0.042)	(0.041)	(0.042)	(0.043)	(0.037)	(0.042)
Number of other TRI type establishments$_{i,l,t}$	-0.001	-0.001	-0.001	-0.001	0.001**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Median income (in \$10,000)$_{l,t}$	0.636		0.663	0.720*	0.702	
	(0.395)		(0.456)	(0.404)	(0.444)	
Median income (in \$10,000)$^2_{l,t}$	-0.078		-0.047	-0.056	-0.062	
	(0.065)		(0.081)	(0.069)	(0.077)	
Median income (in \$10,000)$^3_{l,t}$	0.002		0.000	0.001	0.001	
	(0.003)		(0.004)	(0.003)	(0.004)	
Average wage (in \$10,000)$_{l,t}$	0.028***	0.030***	0.031***	0.031***	0.031***	0.030***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
College ratio$_{l,t}$		-4.499***	-6.945***	-6.575***	-7.684***	-5.043**
		(1.482)	(2.071)	(2.187)	(2.219)	(2.047)
Number of amenity establishments$_{l,t}$			-0.016	-0.019	0.002	-0.018
			(0.011)	(0.012)	(0.004)	(0.012)
Number of roads$_l$	0.018***	0.017***	0.022***	0.023***		0.022***
	(0.004)	(0.004)	(0.005)	(0.005)		(0.005)
Number of railroads$_l$	0.047***	0.044***	0.045***	0.046***		0.046***
	(0.007)	(0.007)	(0.007)	(0.007)		(0.007)
Population (in 1,000)$_{l,t}$	-0.012	0.002	-0.020	-0.011	-0.011	0.010
	(0.032)	(0.030)	(0.032)	(0.032)	(0.031)	(0.030)
Unemployment rate$_{l,t}$				0.023*	0.019	0.019
				(0.014)	(0.014)	(0.015)
Land area (in 100 in square miles)$_l$				-0.013	0.039	-0.015
				(0.033)	(0.025)	(0.033)
Housing rental ratio$_{l,t}$				0.215	-0.327	-0.097
				(0.519)	(0.504)	(0.521)
TxDOT expenditures (in \$1,000,000)$_{l,t}$					-0.000	
					(0.005)	
Average house value$_{l,t}$						0.017
						(0.017)
Border county effects$_l$	Yes	Yes	Yes	Yes	Yes	Yes
Number of entrants	166	166	166	166	166	166
Number of tracts	4,302	4,302	4,302	4,302	4,302	4,302
Log likelihood	-1,300.507	-1,299.112	-1,290.994	-1,289.396	-1,319.45	-1,295.525
χ^2	176.780	179.570	195.800	199.000	138.890	186.740

Statistical significance levels: *** =1%, ** = 5%, * = 10%.

Table 6: Conditional Logit Results: Subsamples of Texas

Variable	TRI firm entry			
	DFW and Houston	Non-DFW or Houston	MSAs	Non-MSAs
	(1)	(2)	(3)	(4)
Percent nonwhite residents$_{l,t}$	0.701	2.270***	1.178**	4.304**
	(0.651)	(0.796)	(0.501)	(1.740)
TRI incumbents$_{i,l,t}$	0.340***	0.709***	0.329***	0.258
	(0.053)	(0.194)	(0.043)	(0.651)
Number of other TRI type establishments$_{i,l,t}$	-0.001	0.005	-0.001	0.028
	(0.001)	(0.003)	(0.001)	(0.022)
Median income (in $10,000)$_{l,t}$	0.567	-0.018	0.672	-4.455
	(0.489)	(0.873)	(0.432)	(6.100)
Median income (in $10,000)$^2_{l,t}$	-0.057	0.056	-0.049	1.564
	(0.071)	(0.170)	(0.072)	(1.986)
Median income (in $10,000)$^3_{l,t}$	0.001	-0.004	0.001	-0.176
	(0.003)	(0.010)	(0.004)	(0.207)
Average wage (in $10,000)$_{l,t}$	0.030***	0.040***	0.031***	0.065
	(0.009)	(0.012)	(0.007)	(0.049)
College ratio$_{l,t}$	-7.878***	-3.009	-7.600***	14.599
	(2.943)	(3.510)	(2.287)	(9.414)
Number of amenity establishments$_{l,t}$	-0.029*	-0.000	-0.016	-0.061
	(0.017)	(0.015)	(0.012)	(0.057)
Number of roads$_l$	0.031***	0.017**	0.024***	0.028*
	(0.007)	(0.008)	(0.005)	(0.014)
Number of railroads$_l$	0.031***	0.067***	0.042***	0.047
	(0.012)	(0.011)	(0.007)	(0.038)
Population (in 1,000)$_{l,t}$	-0.056	0.027	-0.049	0.176*
	(0.049)	(0.043)	(0.036)	(0.094)
Unemployment rate$_{l,t}$	0.016	-0.064	0.010	0.051
	(0.016)	(0.069)	(0.015)	(0.098)
Land area (in 100 in square miles)$_l$	0.042	-0.084	0.050*	-0.110
	(0.033)	(0.066)	(0.031)	(0.102)
Housing rental ratio$_{l,t}$	-0.079	-0.530	0.167	-2.679
	(0.693)	(0.928)	(0.546)	(2.589)
Border county effects$_l$	No	Yes	Yes	Yes
Number of entrants	84	82	142	24
Number of tracts	1,910	2,392	3,522	780
Log likelihood	-562.905	-598.076	-1,064.193	-145.020
χ^2	143.410	79.750	190.980	29.600

Statistical significance levels: *** =1%, ** = 5%, * = 10%.

Table 7: Models of Aggregate Entry Counts

Variable	Number of TRI entrants		Number of non-TRI entrants	
	PPML	Tobit	PPML	Tobit
	(1)	(2)	(3)	(4)
Percent nonwhite residents$_{l,t}$	1.436***	1.542***	-0.796***	-3.778***
	(0.468)	(0.446)	(0.046)	(0.420)
TRI incumbents$_{l,t}$	0.347***	0.545***	-0.014	-0.090
	(0.046)	(0.081)	(0.026)	(0.246)
Number of other TRI-like establishments$_{l,t}$	-0.001	-0.000	0.001***	0.056**
	(0.001)	(0.001)	(0.000)	(0.024)
Median income (in \$10,000)$_{l,t}$	0.720**	0.670*	0.080***	-0.413*
	(0.336)	(0.352)	(0.020)	(0.212)
Median income (in \$10,000)$^2_{l,t}$	-0.056	-0.052	0.008***	0.240***
	(0.055)	(0.058)	(0.002)	(0.026)
Median income (in \$10,000)$^3_{l,t}$	0.001	0.000	-0.001***	-0.010***
	(0.002)	(0.003)	(0.000)	(0.001)
Average wage(in \$10,000)$_{l,t}$	0.031***	0.039***	0.009***	0.158***
	(0.004)	(0.006)	(0.001)	(0.023)
College ratio$_{l,t}$	-6.574***	-5.193**	1.890***	24.601***
	(2.483)	(2.319)	(0.125)	(1.846)
Number of amenity establishments$_{l,t}$	-0.019	-0.016	0.006***	0.366***
	(0.012)	(0.012)	(0.001)	(0.053)
Number of roads$_l$	0.023***	0.022***	0.017***	0.220***
	(0.005)	(0.005)	(0.001)	(0.016)
Number of railroads$_l$	0.046***	0.070***	-0.001	0.044**
	(0.007)	(0.010)	(0.002)	(0.021)
Population (in 1,000)$_{l,t}$	-0.011	0.006	0.067***	0.939***
	(0.031)	(0.029)	(0.002)	(0.034)
Unemployment rate$_{l,t}$	0.023	0.026	0.004	0.042
	(0.014)	(0.016)	(0.004)	(0.033)
Land area (in 100 square miles)$_l$	-0.013	-0.021	-0.053***	-0.322***
	(0.045)	(0.044)	(0.009)	(0.042)
Housing rental ratio$_{l,t}$	0.215	-0.080	1.916***	16.676***
	(0.572)	(0.533)	(0.049)	(0.639)
Border county effects$_l$	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Number of Obs.	34,416	34,416	34,416	34,416
Log likelihood	-948.794	-1,071.080	-146,879.510	-121,940.730

Statistical significance levels: *** =1%, ** = 5%, * = 10%.

Table 8: Firm-Level Summary Statistics

Variable	Entry sample only (1999-2005)			
	TRI firms		TRI type firms	
	Non-exits	Exits	Non-exits	Exits
Number of firms	134	21	8,775	4,154
Average number of employees$_{i,t}$	243.785	109.904	38.799	25.931
	(603.158)	(252.140)	(156.793)	(87.487)
Employment ratio$_{i,t}$	0.007	0.001	0.002	0.001
	(0.017)	(0.003)	(0.023)	(0.012)
Average wage (\$)$_{i,t}$	59,515.27	91,959.54	45,028.44	45,975.64
	(48,005.17)	(137,917.70)	(107,742.30)	(72,297.66)
Age$_{i,t}$ (in months)	27.713	14.558	22.239	22.085
	(21.596)	(12.769)	(18.759)	(17.441)
Plant with past experience$_i$	0.352	0.084	0.207	0.155
	(0.478)	(0.279)	(0.406)	(0.362)
Number of branches in TX$_{i,t}$	5.859	12.684	10.003	9.967
	(17.332)	(25.009)	(26.948)	(26.511)
TRI incumbents$_{j,l,t}$	1.571	1.274	0.076	0.066
	(2.517)	(1.292)	(0.608)	(0.464)
Percent nonwhite residents$_l$	0.341	0.385	0.300	0.296
	(0.237)	(0.236)	(0.199)	(0.193)
Other TRI-like establishments$_{j,l,t}$	2.076	1.579	4.418	6.384
	(4.598)	(3.283)	(13.664)	(16.342)
Median income (\$)$_{l,t}$	40,421.30	37,614.84	43,625.78	43,336.71
	(16,806.92)	(12,781.16)	(20,304.21)	(18,848.67)
College ratio$_{l,t}$	0.075	0.058	0.091	0.090
	(0.068)	(0.042)	(0.079)	(0.071)
Poverty ratio$_{l,t}$	0.155	0.156	0.145	0.143
	(0.098)	(0.089)	(0.105)	(0.102)
Number of amenity establishments$_{l,t}$	4.907	5.095	11.257	11.947
	(7.851)	(6.730)	(28.500)	(29.219)
Number of roads$_l$	19.557	17.411	21.777	22.799
	(18.518)	(10.667)	(26.371)	(31.125)
Number of railroads$_l$	6.764	9.474	4.547	4.822
	(8.749)	(9.040)	(8.026)	(8.811)
Population$_{l,t}$	4,685.354	5,816.432	5,700.884	5,728.765
	(2,588.224)	(3,574.619)	(3,419.800)	(3,457.318)
Unemployment rate$_{l,t}$	5.494	4.330	4.506	4.362
	(6.486)	(1.777)	(4.346)	(4.448)
Rental housing ratio$_{l,t}$	0.327	0.277	0.326	0.325
	(0.222)	(0.178)	(0.207)	(0.206)
Border county$_l$	0.172	0.147	0.326	0.115
	(0.377)	(0.356)	(0.336)	(0.321)

Standard deviations are in parentheses.

Table 9: Logit Results for Exit: All Entrants

Variable	Exit					
	(1)	(2)	(3)	(4)	(5)	(6)
Percent nonwhite residents$_{l,t}$	-0.00056	0.00044	-0.00025	-0.00559	-0.01364	-0.01341
	(0.01132)	(0.01128)	(0.01130)	(0.01130)	(0.01265)	(0.01266)
TRI firm$_i$		-0.17575***	-0.20590***	-0.22330***	-0.20100***	-0.20110***
		(0.02359)	(0.04247)	(0.04236)	(0.04261)	(0.05265)
Percent nonwhite residents$_{l,t}$ $\times$ TRI firm$_i$			0.08315	0.08700	0.08426	0.07491
			(0.09147)	(0.09076)	(0.09097)	(0.09032)
Median income (in $10,000)$_{l,t}$	0.02944***	0.02972***	0.02982***	0.02854***	0.02289***	0.02308***
	(0.00757)	(0.00752)	(0.00752)	(0.00756)	(0.00751)	(0.00751)
Median income (in $10,000)$^2_{l,t}$	-0.00405***	-0.00404***	-0.00405***	-0.00392***	-0.00334***	-0.00336***
	(0.00102)	(0.00101)	(0.00101)	(0.00102)	(0.00101)	(0.00101)
Median income (in $10,000)$^3_{l,t}$	0.00014***	0.00014***	0.00014***	0.00014***	0.00012***	0.00012***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
College ratio$_{l,t}$	0.03402	0.02547	0.02524	0.02486	0.01460	0.01444
	(0.03102)	(0.03095)	(0.03095)	(0.03077)	(0.03929)	(0.03930)
Number of TRI incumbents$_{i,l,t}$					-0.00810**	-0.00847**
					(0.00348)	(0.00351)
Number of other TRI-like establishments$_{i,l,t}$					0.00117***	0.00117***
					(0.00012)	(0.00012)
Age$_{i,t}$	-0.00150***	-0.00147***	-0.00147***	-0.00155***	-0.00146***	-0.00145***
	(0.00011)	(0.00012)	(0.00012)	(0.00012)	(0.00011)	(0.00011)
Average employment$_{i,t}$	-0.00023***	-0.00019***	-0.00019***			
	(0.00004)	(0.00004)	(0.00004)			
Employment ratio$_{i,t}$				-1.15481*	-0.76252	-0.75453
				(0.61071)	(0.47915)	(0.47736)
Wage (in $10,000)$_{i,t}$					0.00008	0.00009
					(0.00015)	(0.00015)
Plant with past experience$_i$					-0.04452***	-0.04448***
					(0.00531)	(0.00530)
Number of branches in TX$_{i,t}$					0.00016***	0.00016***
					(0.00006)	(0.00006)
Number of amenity establishments$_{l,t}$	0.00013**	0.00012**	0.00012**	0.00011*	0.00009	0.00009
	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)	(0.00006)
Number of roads$_l$	0.00016*	0.00014	0.00014	0.00014	0.00001	0.00001
	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)	(0.00009)
Number of railroads$_l$	0.00046*	0.00059**	0.00060**	0.00055**	0.00048	0.00046
	(0.00028)	(0.00027)	(0.00027)	(0.00028)	(0.00029)	(0.00029)
Population (in 1,000)$_{l,t}$	0.00053	0.00042	0.00041	0.00052	0.00094	0.00095
	(0.00060)	(0.00060)	(0.00060)	(0.00061)	(0.00060)	(0.00060)
Unemployment rate$_{l,t}$	-0.00185***	-0.00178***	-0.00178***	-0.00180***	-0.00155**	-0.00156**
	(0.00070)	(0.00068)	(0.00068)	(0.00069)	(0.00066)	(0.00066)
Housing rental ratio$_{l,t}$					0.00051	0.00075
					(0.01350)	(0.01350)
Exit within 18 months after TRI report$_i$						0.06401
						(0.06477)
Exit between 18 to 36 months after TRI report$_i$						0.19346***
						(0.05834)
Exit between 36 to 48 months after TRI report$_i$						-0.06416
						(0.06040)
Border county effects$_l$	Yes	Yes	Yes	Yes	Yes	Yes
Trend$_t$	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	32,110	32,110	32,110	32,110	32,110	32,110
Log likelihood	-12,175.963	-12,134.153	-12,133.834	-12,156.719	-12,054.012	-12,048.669
χ^2	409.560	463.280	464.160	466.530	627.710	620.280

Statistical significance levels: *** =1%, ** = 5%, * = 10%.

Appendix

Table 10: Variable Descriptions

Variable	Description
Number TRI entrants	Number of TRI entrants by three-digit NAICS codes per tract per year.
TRI incumbents	Number of TRI incumbents by three-digit NAICS code per tract per year.
Other TRI-like establishments	Number of other TRI-like firms by three-digit NAICS codes per tract per year.
TRI firm	A dummy variable that takes the value 1 if the firm is identified as a TRI firm and 0 otherwise.
Percent nonwhite residents	Census tract-level share of nonwhite population per year.
Age	Establishment's age in months.
Number of employees	Establishment-level number of employees per year.
Employment ratio	This is the establishment's employment divided by the total number of employees in the industry in Texas at a given year.
Wage	Establishment-level wage per year (in $10,000).
Average wage	Census tract-level average wage paid by employers within tract per year (in $10,000).
Plant with past experience	A dummy variable to indicate if the establishment identification number is new or was previously assigned.
Number of branches in TX	Number of sister branches in Texas that an establishment has.
Number of roads	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 the 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 roads.
Number of railroads	As in roads we use the U.S. Census Bureau's Census Feature Class Codes (CFCC) and ESRI Data & Maps (2000) to identify railroads. We use all major and minor rail tracks identified by ESRI Data & Maps.
Median income	Census tract-level median income per year (in $10,000).
Poverty ratio	Census tract-level percentage of the population under the poverty rate per year.
College ratio	Census tract-level college graduates as percentage of the population per year.
Number of amenity establishments	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	Census tract-level percentage of housing stock rented per year.
Population	Census tract-level total population per year.
Unemployment rate	Census tract-level unemployment rate per year.
TxDOT expenditures (in $1,000,000)	We construct tract-level road construction expenditures by weighting county totals by the tract-level population per year.
Average house value	Census tract-level average house value per year.
Land area	The size of the census tract (in 100 square miles).
Exit within 18 months after TRI report	A dummy variable that takes the value 1 if the TRI firm exit within 18 months after its initial TRI report and 0 otherwise.
Exit between 18 to 36 months after TRI report	A dummy variable that takes the value of 1 if the TRI firm exit between 18 and 36 months after its initial TRI report and 0 otherwise.
Exit between 36 to 48 months after TRI report	A dummy variable that takes the value of 1 if the TRI firm exit between 36 and 48 months after its initial TRI report and 0 otherwise.

Table 11: Average Plant-Level Toxicity for 25 Most Frequently Reported Chemicals

Chemical	Average plant level toxicity (in pounds)			
	Entrants		Incumbents	
	Mean	(Standard deviation)	Mean	(Standard deviation)
1,2,4-TRIMETHYLBENZENE	297,512.90	(478,248.20)	521,915.80	(729,632.70)
1,3-BUTADIENE	1,147,218.00	(1,912,368.00)	975,234.60	(1,029,670.00)
AMMONIA	383,601.20	(1,410,532.00)	814,664.30	(2,096,981.00)
BENZENE	676,719.30	(1,765,092.00)	1,284,997.00	(2,703,369.00)
CERTAIN GLYCOL ETHERS	57,692.26	(75,383.92)	410,803.60	(922,960.70)
CHLORINE	759,340.10	(1,601,147.00)	1,226,669.00	(2,598,924.00)
CYCLOHEXANE	836,257.7	(1,978,939.00)	786,845.90	(990,737.00)
ETHYLBENZENE	506,913.9	(685,163.70)	740,435.30	(1,147,305.00)
ETHYLENE	709,064.5	(1,818,787.00)	877,409.70	(1,199,091.00)
ETHYLENE GLYCOL	595,501.00	(2,241,682.00)	533,873.50	(1,052,055.00)
FORMALDEHYDE	833,621.60	(946,450.90)	987,951.30	(1,206,138.00)
HYDROCHLORIC ACID	647,474.600	(2,124,008.00)	1,056,486.00	(1,502,220.00)
LEAD	110,619.00	(179,204.20)	279,445.00	(595,501.00)
LEAD COMPOUNDS	906,130.90	(1,917,242.00)	825,152.90	(1,154,142.00)
METHANOL	564,747.60	(1,614,826.00)	802,263.70	(2,078,398.00)
N-BUTYL ALCOHOL	338,317.30	(617,986.70)	741,603.00	(1,035,010.00)
N-HEXANE	787,708.40	(1,755,695.00)	693,414.70	(1,090,815.00)
NAPHTHALENE	342,718.40	(527,334.20)	809,542.40	(1,222,746.00)
NITRATE COMPOUNDS	1,846,038.00	(2,422,544.00)	1,707,722.00	(3,024,060.00)
POLYCYCLIC AROMATIC COMPOUNDS	1,136,584.00	(2,184,348.00)	698,514.80	(752,776.50)
PROPYLENE	663,708.70	(1,893,600.00)	1,204,809.00	(2,613,973.00)
STYRENE	341,568.90	(604,319.80)	595,021.40	(1,125,544.00)
SULFURIC ACID	370,905.90	(624,756.40)	1,168,186.00	(1,206,139.00)
TOLUENE	479,393.10	(1,434,397.00)	595,021.40	(1,125,544.00)
XYLENE (MIXED ISOMERS)	224,910.50	(382,592.60)	1,168,186.00	(1,206,139.00)
ZINC COMPOUNDS	887,485.00	(2,285,989.00)	570,414.90	(1,071,977.00)
All other chemicals	839,178.40	(2,009,554.00)	1,272,003.00	(2,437,158.00)

Notes

[1]We should note that Bui (2005) argued that while toxic emissions might have declined for petroleum refineries, it's not clear that such improvements are due to the TRI per se, or whether they might just be spillover benefits from investments intended to abate other pollutants that face heavy regulation. We recognize that there are often complementaries in various pollutants and, for our work, primarily use the TRI as a means of identifying firms that might reasonably be considered significant polluters—having released enough pollutants so as to exceed EPA-established thresholds.

[2]Though in parts of our analysis we partition Texas into various rural or urban areas. Furthermore, as will be clear, we do restrict the set of tracts in which firms can locate in a way that we feel mitigates concerns about zoning laws.

[3]There is an important literature that focuses its attention on the TRI and its relationship with housing prices. Bui and Mayer (2003) as well as Oberholzer-Gee and Mitsunari (2006) found that housing prices did not respond to initial TRI reports. However, Sanders (2014) found that when other industries were added to the TRI in 1998, this led to price drops of 2–3 percent in housing prices. Likewise, Mastromonaco (2015) found information about the types of chemicals on-site for polluting firms does impact housing prices. We control for average house value in some of our empirical specifications.

[4]Throughout, we use the term "firm" interchangeably with the word "establishment" or "plant" but to be clear, we observe establishment-level reporting and QCEW data; thus, if a firm has multiple establishments but only a subset reports to the TRI, then we know exactly which report and which do not. Though we use the word "firm" our analysis is based on establishment-level data. When establishments are related to a common parent firm, we identify such a distinction.

[5]Unmatched observations include operations affiliated with the U.S. armed forces and events such as railway spills.

[6]See Title 40, Part 372 of the Code of Federal Regulations which is summarized in volume 66, number 11 of the *Federal Register*. Aside from this, the document "Changes to the TRI List of Toxic Chemicals" which can be accessed at http://www2.epa.gov/sites/production/files/2015-03/documents/tri_chemical_list_changes_2_27_15.pdf shows that some chemicals were added to the TRI list in 2000, but that is the only other change to the chemicals that require reporting or their associated thresholds during our sample period.

[7]We use the number of tracks as opposed to the number of or distance to rail stations as some trains seem to pass through tracts and stop at industrial plants without formal stations to load/unload cargo. This measure avoids confusion between between passenger and industrial stations.

[8]The procurement contract spending data from the Texas Department of Transportation (TxDOT) is at the county level. We then allocate expenditures across tracts within each county based on the tract's share of the county's population in each year.

[9]The realizations of a given variable we use from the Census 2000 and the Census 2010 are highly correlated with each other. For example, the correlation between median income in 2000 and 2010 is 0.95, the share of nonwhite residents is 0.74, the poverty rate is 0.79, the share of the population with a college degree is 0.94. Census 2000 tracts are occasionally divided in Census 2010. We aggregate variables (or construct population-weighted averages when appropriate) to obtain corresponding Census 2000 tract information.

[10]Wolverton (2009) restricts attention to the DFW and Houston MSAs and considers firms that report to the TRI at least once between 1988 and 1993.

[11]We maintain this definition throughout but, as a robustness check, we also considered definitions of TRI-like firms based on the share of employment in an industry that is accounted for by TRI reporters. For example, if at least $x\%$ of the employees in an industry work for TRI-reporting firms, then firms in that industry would be classified as TRI-like establishments. Our core results do not change when considering such alternative definitions such as when $x = 1\%$, 10%, or even 50%.

[12]Over the Census 2000 and Census 2010, 2.6% of Texas residents indicated multiple races though, because we have only aggregate data, we do not know which races the respondents indicated.

[13]An overview of this literature with additional insights into the root causes and perspectives from pessimists and optimists is provided by Dasgupta, Laplante, Wang, and Wheeler (2002). We have also found the survey by Dinda (2004) does a great job summarizing this literature. Kahn (2006) describes how prices, technology, and government actions can affect the shape and location of the EKC. Note, too, that unlike sulfur dioxide emissions which might

cross borders easily and result in acid rain being incurred by neighbors, the release of toxic chemicals is likely borne by the region in which the firm is located.

[14]There are 4,388 total tracts and we focus on the ones that have allowed at least one firm in TRI-reporting industries to operate at some point during our sample period (including tracts in which incumbents may have entered before our data begin). This helps mitigate concerns that tracts without these firms have zoning laws which prohibit such entry.

[15]Remember, some chemicals were added to the TRI listing in 2000 and thresholds changed for lead and lead compounds in 2002.

[16]Using TRI data from 1987–1996, Helland and Whitford (2003) found the emissions into the air and water are systematically higher in counties that border other states, perhaps because jurisdictional considerations mean the negative effects of pollution are partially incurred by those outside of a given state. Because of this, we include in all of our analysis, a variable that equals one if the tract borders another state (and is zero otherwise).

[17]A number of researchers have provided theoretical models under which various assumptions are employed in order for the model to predict an inverse-U-shaped relationship between income per capita and pollution. For example, Selden and Song (1995) provided a fairly simple model in which economic growth of an area initially leads to an increase in emissions, after which other factors (perhaps which are correlated with education or political involvement) cause an eventual downturn.

[18]See, for example, the United States National Commission on Urban Problems' 1969 report "Building the American City."

[19]Marginal effects can be computed from the coefficient estimates along with the implied probabilities of each tract being selected given the realizations of the covariates for each tract. Doing so, allows us to make comparisons across variables. For example, using the results in column (6), imagine all variables are fixed at their mean values (as presented in table 3). If an alternative tract had a share of nonwhite residents that was 10% above the average share of nonwhite residents (and all other variables were at their means), this tract would have a 1.5% greater chance of being selected. To put this in perspective, to achieve an equivalent increase of 1.5% in the chance of being selected, a tract would need to have 1.6% fewer college graduates. Or, using the TRI-based agglomeration terms, the tract would need to have an additional 0.25 firms.

[20]Additionally we considered conditional logit models with nonlinear specifications concerning agglomeration effects. For example, if the number of TRI firms or like-TRI firms involves quadratic terms they do occasionally appear significant, but the results we focus on are qualitatively similar.

[21]The results concerning partitions of our tract space according to DFW and Houston MSA membership or the Texas MSA definition (as presented in the conditional logit models of table 6) are also robust in reflecting the same pattern under the PPML and Tobit specifications.

[22]As a robustness check, we also considered definitions of TRI-like firms based on the share of employment in an industry that is accounted for by TRI reporters. As examples, if at least 1%, or 10%, or 50% of the employees in an industry work for TRI-reporting firms, then firms in that industry would be classified as TRI-like establishments. Our core results do not change when considering such alternative definitions.

[23]Though the coefficient on the interaction of the share of nonwhite residents with the TRI dummy firm is positive, it is statistically insignificant and about one third of the size of the coefficient on the TRI indicator variable itself.

[24]We also considered models involving quadratic terms for the age of the establishment as well as the establishment's size (average employment or share of industry employment). The quadratic terms are significant but our qualitative results for the main variables of concern to us do not change. We also investigated whether the first TRI report triggered firm exit from the industry after a certain amount of time (like the additional variables included in model (6) of table 9) but did not find anything notable to report or changes to our main results.