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Do Industries Pollute More in Poorer Neighborhoods? Evidence From Toxic Releasing Plants in Mexico

Importante

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Abstract

Studies on industrial pollution and community pressure in developing countries are rare. We employ previously unused, self-reported toxics pollution data from Mexico to show that there exists some evidence of environmental justice concerns and community pressure in explaining industrial pollution behavior. We obtain historical data on toxic releases into water and land for the time period 2004 to 2012. We focus on 7 major pollutants including heavy metals and cyanide. To address endogeneity concerns of socioeconomic demographic variables, we use data from 2000 Census of Population and Housing and 2005 count data. Our results show that the immediate local population might be affected more by on-site land pollution than end-of-pipe discharges into waterbodies as the latter affects only downstream communities. Among our consistent results, increase in percent of households with telephone leads to lower land (and water) pollution; while increase percent of households with computer leads to increase in water pollution only. Similarly, vulnerable population as captured by percent of population over 65 years and higher unemployment rate leads to higher water pollution only. Other proxies for income and poverty have expected signs but not consistently across all models.

Keywords: Industrial Pollution, Local Income and Unemployment Effects, Informal Regulation, Environmental Justice, Community Pressure, Toxic Releases

Resumen

Los estudios sobre la contaminación industrial y la presión de la comunidad en los países en vías de desarrollo son raras. Empleamos, datos previamente no utilizadas de contaminación de tóxicos de auto-reporte de México para demostrar que existe alguna evidencia de las preocupaciones de justicia ambiental y la presión de la comunidad para explicar el comportamiento de la contaminación industrial. Obtenemos los datos históricos sobre las emisiones tóxicas en el agua y la tierra para el período 2004 a 2012. Nos centramos en 7 contaminantes más importantes, incluyendo metales pesados y cianuro. Para hacer frente a las preocupaciones de endogeneidad de las variables demográficas socioeconómicas, utilizamos los datos de 2000 del Censo de Población y Vivienda de 2005 y los datos de recuento. Nuestros resultados muestran que la población local inmediata podría ser afectado más por la contaminación de la tierra en el sitio de descargas de final de tubería en los cuerpos de agua ya que esta última afecta a las comunidades aguas abajo solamente. Entre nuestros resultados consistentes, aumento en el porcentaje de hogares con teléfono conduce a la disminución de la tierra (y agua) de la contaminación; mientras por ciento de aumento de los hogares con computadora lleva a un aumento en la contaminación del agua solamente. Del mismo modo, la población vulnerable como capturado por ciento de la población de 65 años y mayor tasa de desempleo lleva a sólo la contaminación del agua superior. Otros sustitutos de los ingresos y la pobreza han esperado signos pero no de manera consistente a través de todos los modelos.

Palabras claves : La contaminación industrial, efectos renta y de desempleo local, la regulación informal, la justicia ambiental, la presión de la comunidad, las emisiones tóxicas

Introduction

A key question that most environmental justice studies want to answer is whether industries pollute more in poorer neighborhoods where community pressure to improve environmental performance is lower. Empirical evidence on the relationship between community characteristics and firm level pollution needs to be interpreted with caution. Higher emissions in poorer neighborhoods might be due to less community pressure on polluters or due to low income population moving into more polluted neighborhoods because households pay for cleaner air or water. To address this problem of households sorting behavior, we use temporally lagged socio-economic characteristics of the community. Community characteristics prevailing prior to the pollution decisions are made, are pre-determined-- i.e. firms decide how much to pollute based on given community characteristics (or pressure). By definition, this time-invariant community data avoids any household level sorting arising due to richer households paying for less pollution.

Evidence on informal regulation for toxics pollution is important in the context of a developing country because it is likely to be the principal pollution control mechanism that determines toxics releases. Poor enforcement of regulations often due to weak institutional capacity is cited as a major factor in poor environmental performance of industries in developing countries. When citizens are made aware of the toxic releases of their nearby industries, the negative publicity imposed on the firms incentivizes them to reduce their toxic pollution. Armed with knowledge of hazardous wastes produced in their local neighborhood, community members can either decide to put pressure on polluters to reduce their pollution or choose to move away to reduce exposure (Saha and Mohr, 2013).

Studies on community pressure or informal regulation are rare in developing countries and in Latin America, in particular. Dasgupta, Lucas and Wheeler (2002) find that particulate matter emissions are higher in higher wage (urban) municipalities in Brazil and mostly generated by large plants. By contrast, Seroa de Motta (2006) uses survey data of large manufacturing plants in Brazil, for the year 1997, to conclude that pressure from communities and NGOs are important factors in explaining environmental performance of manufacturing firms in Brazil. Feres and Reynaud (2012) confirm that informal regulation and more specifically community pressure influence formal regulatory actions such as inspections and sanctions. They capture informal regulation by using the count of citizen complaints about pollution at a given plant or in a given location and the number of meetings organized with environmental NGOs, local community or political representatives. In Bogota, Colombia, Cruz

(2004) finds that formal regulation as opposed to community pressure determines environmental performance of industries. Community pressure is measured by number of complaints filed by the locals against the industrial enterprises. However, his results show that higher income and education are significant in explaining complaints filed by the local population.

Evidence on informal regulation from Mexico comes mostly from survey data. Dasgupta, Hettige and Wheeler (2000) and Gangadharan (2006) use survey data from 1995 to investigate whether local community pressure drives environmental management decisions of major polluters in Mexico. More recently, Blackman and Kildegaard (2010) do not find any evidence of informal regulatory pressure in the small and medium enterprises sector, captured through membership of tanneries in a trade association promoting clean technologies in Leon, Guanajuato. We hope to fill this gap by investigating environmental justice concerns and/or community pressure by using the most up-to-date self-reported pollution data of major toxics generating facilities in Mexico.

To address the question of whether plants pollute more in poorer neighborhoods, we match the RETC plant level pollution data with socioeconomic, demographic characteristics obtained from Mexico's Census of Population and Housing. In contrast to Mexico's RETC database, the Toxic Release Inventory (TRI) of the US that was started in 1987 has been heavily studied. Majority of the initial studies use zipcode level socio-economic demographic characteristics to explain TRI pollution e.g. Brooks and Sethi (1997) study air emissions while Arora and Cason (1998) study aggregate air, water and land emissions. Helland and Whitford (2003) is an exception as they investigate the impact of county level community factors on air, water and land emissions separately. Mexico's Census data is not available at the zipcode level, so we choose AGEB (Área Geoestadística Básica Urbana) as our definition of neighborhood or affected population which is roughly comparable to census tracts in the US. We use GIS (Geographical Information Systems) to match the RETC plant location data and the corresponding AGEB in which the plant is located.

To address endogeneity of community variables we focus on Census data for the year 2000 and 2005 count data, since the pollution data is from 2004 to 2012. Our premise is that 2000 (and 2005) community characteristics are most likely exogenous to the post-2005 firm decisions (Arora and Cason, 1998). We know that plant specific factors such as size and age are likely to explain plant level environmental performance e.g. larger plants have higher toxic emissions. Since we could not obtain such plant specific data, we refined our pooled OLS models with plant level fixed effects. To incorporate variability over time, we assign community characteristics from the 2000 Census data to pollution over the years 2004 until 2008 and 2005 count data to pollution over the years 2009 until 2012. Following recent studies such as Gray et al (2012), we check sensitivity of the results by constructing aggregate measures of community variables that include all AGEBs that are within 1, 2 or 5km of each facility (based on centroid calculations).

A Typical Model of Firm-Level Pollution

Under mandatory reporting of toxic releases above thresholds, the firm's objective is to minimize its costs of pollution abatement i.e. reduce its current level of releases to different media and expected costs of non-compliance with the regulation. Its costs of pollution abatement depend on plant specific factors such as age of the plant i.e. vintage of the abatement technology, size of the plant i.e. the scale of its manufacturing operations. Its expected costs of violation, either due to non-reporting or under-reporting emissions, depends on the stringency of regulation i.e. thresholds in the case of toxic releases and monitoring and enforcement efforts of the implementing agencies. Increased inspection activities raises the expected costs of violation. To the extent that there is regulatory targeting of inspections e.g. bigger plants are inspected more, plant size captures expected costs of violation. Increased enforcement activities either on the firm itself or on firms in the same industry also increase the expected costs of non-compliance. The firm's costs of non-compliance are also affected by location specific factors such as pressure from the affected community due to their adverse impact on health and the environment in general (aesthetics). The underlying economic incentive to reduce pollution is the negative impact of this news on their stock market returns () or boycott of their manufactured products by the consumers. Hence, a typical reduced form model explains firm level pollution with plant specific factors, such as size of its productions operation, age of the plant, type of manufacturing facility, that determine its costs of abatement, formal regulatory factors, and informal factors such as community pressure.

$$Pollution_{it} = f(size_i, age_i, type_i, regulation, community\ factors) \quad (1)$$

Previous studies have found empirical evidence on at least one or a combination of the above mentioned factors in determining environmental performance of firms. We focus on toxics pollution as conventional pollutants present different level of risk factors for the affected community. Gray et al (2012) use Census of Manufacturers data to control for plant characteristics such as facility age and size. Helland and Whitford (2003) control for regulatory stringency by including total number of inspections on firms in the state. As will be discussed in the section on empricial model, much of the literature on the distributional effect of pollution have focused on how community chracteristics determine firm level pollution (abatement).

In order to identify causality of community factors on current pollution behavior, we need to address the reverse causality of ambient pollution levels determining the resultant community characteristics. Helland and Whitford (2003) use contemporaneous sociodemographics conceding to the possibility that reverse causality of higher pollution levels causing wealthier people to leave the county and hence the remaining population has a higher poverty level. Our strategy to address this problem is to utilize temporally lagged community data that are time-invariant and hence by definition not influenced by household level sorting of richer people moving out of more polluted neighborhoods.

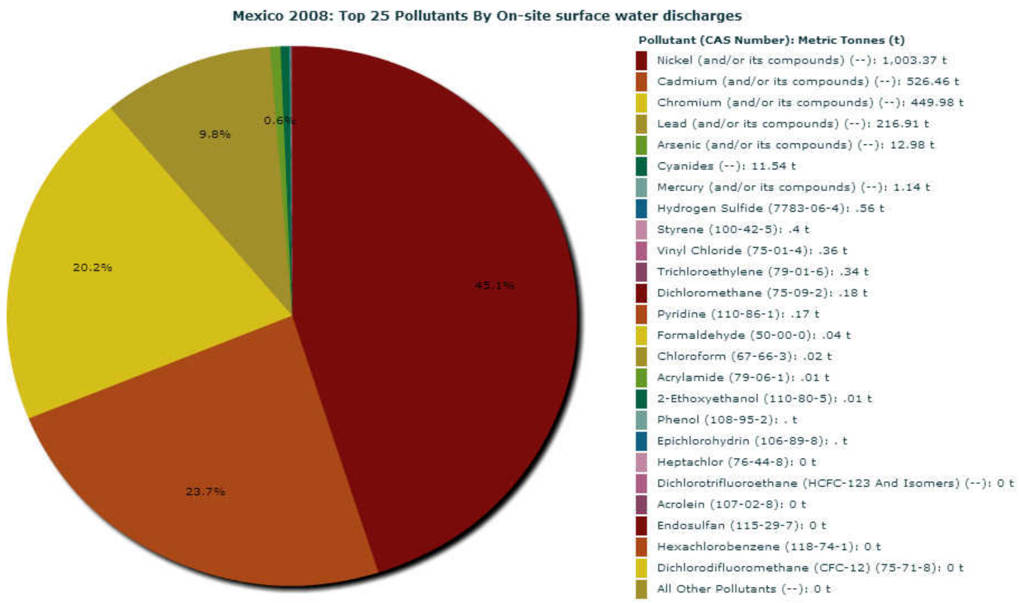
Data

Pollution Data

In Mexico, the toxic releases (RETC) data is maintained by the Mexican Secretariat of the Environment and Natural Resources (SEMARNAT) and firms report out-of-stack air emissions and end-of-pipe water pollutant discharges, land releases and transfers to wastewater or other forms of treatment/management. In June 2004, Mexico adopted mandatory reporting of 104 toxic pollutants by industries (Bravo-Álvarez et al 2005). The focus was on the following industries-- chemicals, petroleum and petrochemicals, paints and pigments, automobiles, cellulose and paper, metallurgical, glass, electricity generation, asbestos, cement and related products, and plants processing toxic wastes; plants that discharge wastewater directly into Mexico's waters; and plants that generate more than 10 tons annually of toxic pollutants. The companies report all the information through their annual operation certificates (COA) in an electronic format (Eicker et al 2010). Based on the information provided by the facilities, SEMARNAT prepares public reports presenting data on annual emissions (e.g. SEMARNAT 2009). The information is updated yearly and is freely available to the public on the Internet, since 2006. A SEMARNAT official mentions that "[C]ommon errors found in the reports are errors in the conversion of units and errors in the selection of the appropriate substance for report (substances with similar names are often interchanged)" (p11-12).

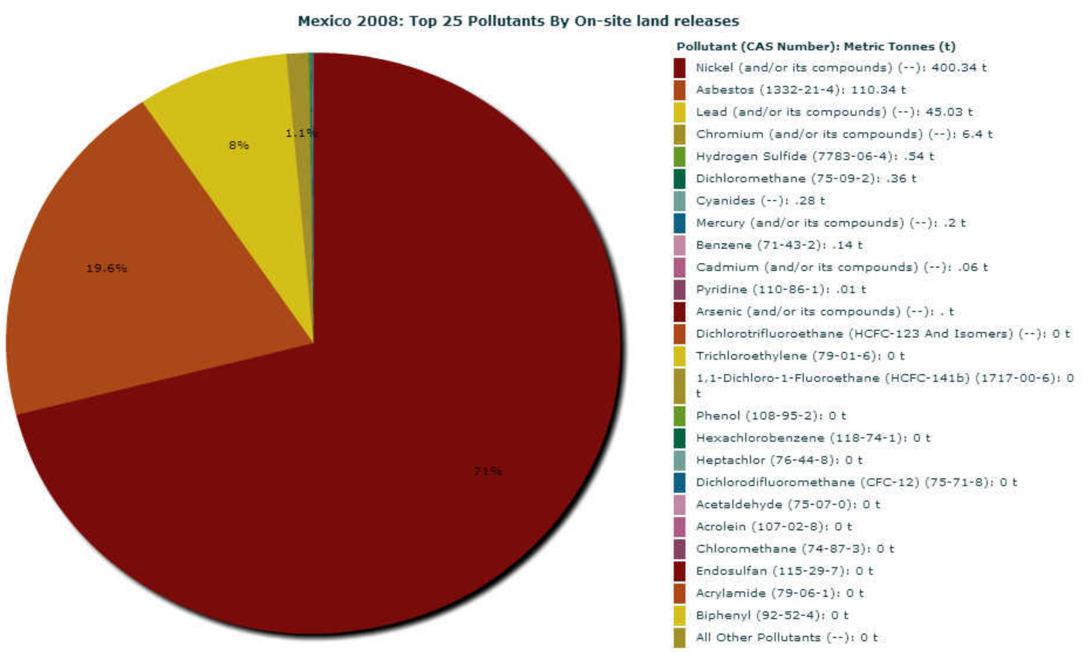
We focus on 7 major toxic pollutants based on frequency of reporting over 2004 to 2012. We estimate our model on water and land pollution data as air emissions data for these toxic pollutants span across only 3 years from 2007 to 2009. These are Arsenic and its compounds, Cadmium and its compounds, Cyanide (organic and inorganic), Chromium and its compounds, Lead and its compounds, Mercury and its compounds, and Nickel and its compounds. According to the CEC (2009) report, these heavy metals pose the greatest threat to health from exposure. Figures 1 and 2 show that these pollutants were among the top 25 pollutants for both on-site water and land releases. Hence, we expect the affected community to be concerned about the releases of these pollutants in their neighborhood.

FIGURE 1



Source: Taking Stock Online Report, CEC (2011)

FIGURE 2



Source: Taking Stock Online Report, CEC (2011)

Our dataset has 5104 RETC facilities that report at least once, over 2004-2012, its pollutant emissions or transfers on any one of the 7 toxic substances.[1] [2] Of the 5104 facilities, there are 3278 plants that discharge 7 pollutants (6 metals and cyanide) into the water and 2456 plants that discharge 7 pollutants (6 metals and cyanide) into land.

Majority of these plants are located in the State of Mexico (14 percent), Nuevo Leon (10 percent), Chihuahua (9 percent), Tamaulipas (8 percent), Mexico City (7 percent) and Jalisco (6 percent). Note that the three biggest metropolitan statistical areas (MSAs) of Mexico City, Monterrey and Guadalajara are included in these states covered. Majority of these plants are in the chemical (21 percent), metallurgy (13 percent), automobiles and related (9 percent), other (9 percent), electronics and related (8 percent), and petroleum and petrochemicals (7 percent).

Table 1 presents the summary statistics on water and land pollution data.[3] Across the 6 heavy metals, plants on average discharged into water 0.16 tons per year of heavy metals, over 2004-2012; while plants on average released 0.03 tons per year of metals on land. Compared to the threshold of 0.001 tons per year, water pollution of heavy metals was higher than land emissions. For organic and inorganic cyanide, water discharges on average (0.06) are again higher than land emissions of 0.01 on average compared to the threshold of 0.1 tons per year. Unlike heavy metals, both water and land releases are lower than the threshold.

As discussed in the literature (Decker et al 2005), toxic releases data exhibit a lot of variability (over time) and for Mexico there is additional variability in terms of the sample of polluters reporting annually to SEMARNAT. For land emissions, coverage essentially starts from 2007 (to 2012). For on-site water discharges, the coverage is from 2004 to 2012. For both land and water, annual reports drop in the year 2010. [4] Over time, annual average water pollution of the same 6 metals and cyanide peak in year 2008 with subsequent decline (Figure 3). Figure 4 shows that annual average land emissions peak in the year 2011 to drop beyond that. These trends are representative when we track each pollutant separately.

[1] We identify a RETC facility with its "NRA" code in the database. We had to manually consolidate the number of 'unique' RETC facilities as the same physical plant/business can have multiple NRAs if it has multiple activities e.g. generation of electricity, treatment of toxic residuals; it undergoes a name change; it undergoes a sector change; different address; different years, etc.

[2] Multiple observations for a plant and the same substance and year are aggregated.

[3] For the discussion of the pollution data, we drop suspect outliers/data entry errors from the sample. However, we include all observations in the regression as we log transform the pollution data. For water discharges, we drop 2 observations in mercury, 1 in lead and 1 in nickel. For land pollution, we drop 2 observations in nickel and 2 in lead.

[4] We were unable to confirm whether variability inherent in toxic emissions could explain this decline in 2010 or whether firms are really cleaning up and hence not required to report emissions or whether changes in regulation or reporting problems might explain this attrition in the data.

FIGURE 3

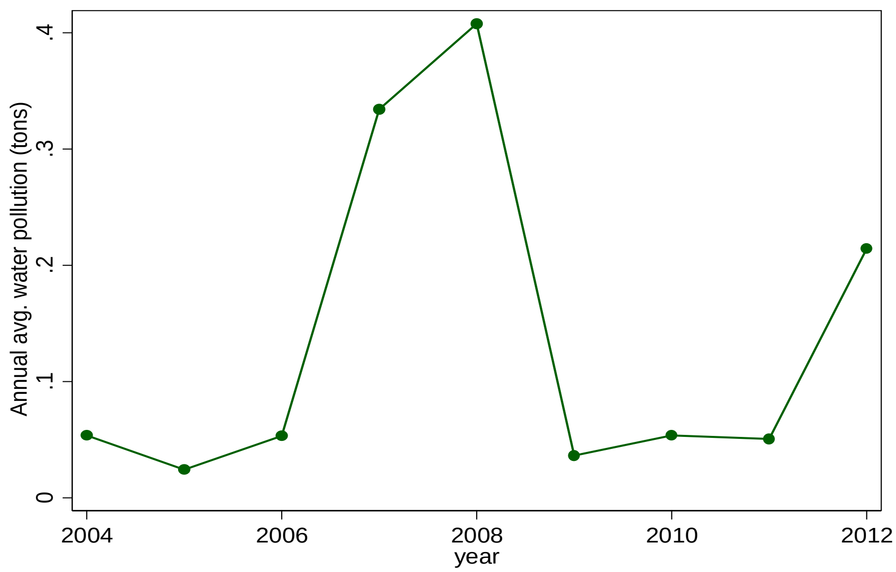
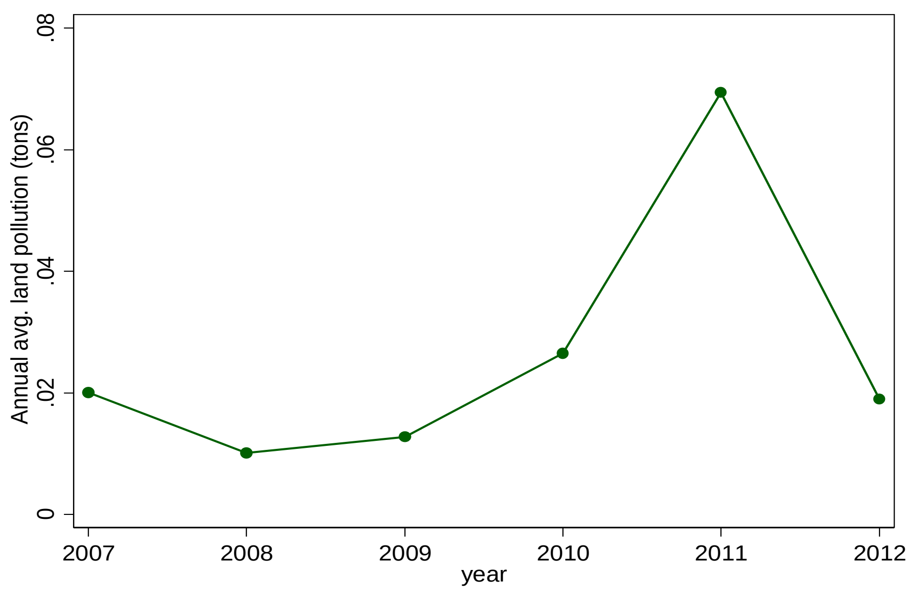


FIGURE 4



Census Data

We match the pollution data to the census data using GIS. We use information on latitude and longitude to match the facility location with the Census characteristics of the neighborhood. Of the 5104 facilities that had latitude, longitude and reported either air, water or land pollution, we could match the location of 2638 facilities to 1513 Census AGEBs (for the year 2000). AGEBs are urban areas that are based on topographical features that are identifiable and permanent and they are homogenous according to geographical, economic, and social features on population count.[5] [6] We consider alternative definitions of a neighborhood by calculating the distance between each plant and the centroid of each AGEB to determine which AGEBs falls within 1, 2 or 5 km(s) of the plant. AGEB values for each population characteristic are then aggregated to get the overall value for each plant. Based on the distance between each facility and the AGEB centroid, we could match 3236 facilities to 6657 AGEBs that are within 1km radius, 3807 facilities to 13550 AGEBs that are within 2km radius, and 4408 facilities to 21256 AGEBs that are within 5km radius.

We rely on the literature heavily to identify the community factors that might explain environmental performance of facilities nearby. Hamilton (1995) provides a detailed categorization of these community variables into race/gender based discrimination, economic discrimination and willingness to engage in collective action. We report the summary statistics for 4408 facilities based on the aggregate AGEB characteristics that are within 5kms radius.[7] To capture education, we include percent of the population over 15 years of age with post-primary education.[8] Table 1 shows that on average 61 percent of the population over 15 years had post primary education. To capture income effect and/or quality of labor force, we include percent of households that have computer. On average, 12 percent of households had computer. Higher population density might capture higher exposure or the income effect i.e. more urban areas have higher incomes.[9] On average, the population per square km is 60. To capture poverty, we include percent of households with telephone and percent of households with female heads. On average, 46 percent of households had telephone and 20 percent of households had female heads. To capture propensity to engage in collective action, due to vulnerable population, we include percent of population under 4 years and percent over 65 years. On average, 10.6 percent of the population was 4 years and below while only 4 percent was 65 years and above. Alternately, we expect industries to face less pressure in communities where a

[5] Census data for non-urban areas are not available at a spatial scale comparable to the AGEB for urban areas.

[6] AGEBs can be larger than census tracts in the United States – more than 10,000 people in some cases – but are mostly similar in size, with 2,500 people in each on average. Unlike US census tracts, AGEBs are only defined for urban areas and towns.

[7] The community variables are similar under different definitions of neighborhood.

[8] Ideally we would capture income effect through education indicators such as population over 18 years with higher education. This data is not available for the 2005 count data so we had to choose a more basic indicator such as percent over 15 years with post primary education which might be capturing more of a poverty impact rather than income. For example, upon including higher education indicators that are available in 2000 and 2010 Censuses, we find the expected negative sign (for land pollution only).

[9] Although, too dense population might lead to rich people migrating out.

significant proportion of the local population is employed by the industries, hence we include percent of workers employed in the manufacturing sector. On average, 37 percent of the workers were employed by the industries. Lastly, higher local unemployment might mean less pressure on industries to start or expand their operations due to the income generating possibilities. On average, only 1.3 percent of the working age population (labor force) was unemployed.

Empirical Strategy

We estimate the empirical model based on equation (1) and depending on the availability of relevant data for Mexico's toxics releasing plants. As mentioned before, plant specific information such as size, and age could not be obtained for our RETC facilities. Neither can facility level inspections nor enforcement activities be readily obtained for Mexico. To the extent that regulators target larger, more polluting firms, controlling for size would capture variations in regulatory stringency/presence. For community factors, Mexico's Census of Population and Housing does not directly ask questions on the income or poverty status of households hence we consider proxies that might capture economic status of the population. In addition, we include variables that might capture propensity to engage in collective action or exert community pressure (e.g. higher population density) and factors that capture less pressure on polluters as the local population is expected to favor the income/employment generating potential of industries (e.g. higher unemployment rate).

First, we estimate an OLS model of the log of annual toxic releases to water and land, during 2004-2012. Our explanatory variables of interest are our proxies for income and poverty, propensity to engage in collective action, and income generating potential of industries, obtained from the 2000 Census. In order to avoid endogeneity problem of local community characteristics, we regress annual pollution from 2004 to 2012 on community data from 2000, controlling for some important factors that might explain pollution behavior. Following the same logic, we try 2005 count data on pollution data from 2004 to 2012. We include state level controls to capture variations in enforcement and monitoring of regulation, among other things, controls for the type of pollutant, yearly variations, and type of industry—chemicals, metallurgy, automobiles, electronics, petroleum and petrochemicals, etc. Finally, we report standard errors clustered within plants, for each pollutant, as we expect pollution reported for the same plant to be correlated over the years.

$$lPoll_{ist} = \alpha + \sum_{d=1}^{9} \beta_d dem_{id} + tox_s + type_i + state_i + year_t + \varepsilon_{ist}$$

(2)

In equation (2), the dependent variable is the log of toxic emission of substance s, by plant i and in year t, $lPoll_{ist}$. We cover 7 toxic substances for water and land pollution, over 2004-2012. We estimate the model keeping the toxic substances disaggregated, because residents might perceive different levels of environmental risks (on health) from different toxics and hence might react differently to knowledge of different toxic substances in their neighborhood.

We consider 9 different socioeconomic demographic variables, for the year 2000. These are population density, percent of higher educated population, percent of households with computer, percent of households with telephone, percent of households with female heads, percent of population under 4 years, percent of population over 65 years, percent of workers in the manufacturing sector and unemployment rate. In equation (2), dem_{id} represents census data on variable d for the AGEB in which plant i is located or for the aggregate AGEB characteristics within 1, 2 or 5 km(s) radius of the plant i. The substance s is captured by tox_s. The type of industry or manufacturing facility of plant i is captured by $type_i$. Finally, $state_i$ is the state in which plant i is located, and yearly controls are $year_t$ in which the plant i reported pollution of substance s.

Next, we refine our pooled OLS estimations, by estimating a plant level fixed effects model. Plant fixed effects capture all time-invariant factors that explain why some plants pollute more than others.[10] It would also control for other time-invariant location specific factors such as number of plants (RETC facilities) located in the neighborhood. More toxic releasing facilities would capture the effect of either greater pressure on polluters to reduce emissions due to higher ambient pollution or network externalities. Another location feature might be variations in transportation costs, for example if the factory is located near major highways.

However, our community data based on the distance between each plant to the AGEB centroid is essentially plant specific information. The only case where the community data is not plant specific is the community characteristics for the AGEB in which the plant(s) is located. Even then, plant fixed effects can be included only when the corresponding community characteristics are time varying (rather than using data from only the year 2000 or 2005). So, we estimate an unbalanced panel model by assigning community data from Census 2000 to pollution data from 2004 to 2008 and count data from 2005 to pollution data for the years 2009 to 2012.[11] We could not identify a variable equivalent to the percent of workers employed by the manufacturing sector or unemployment rate in the 2005 count data. So, our final number of community characteristics fell to 7. As a robustness test, we estimate the fixed effects model on the sample of plants which have at least 4 out of the 9 annual reports (50% time series) to check if our results hold. Finally, we estimate the unbalanced panel models with imputed community data for neighborhoods within 1, 2 and 5 km(s) radius of the plant.

[10] Other than employing panel data techniques we could not include plant level dummy variables in the OLS models due to the short panel problem.
[11] We estimated the models using 2000 and 2010 Census data. Our main conclusions and results remain unchanged.

Conclusions

We find two consistent results on the evidence of environmental injustice and/or community pressure. Higher percent of telephones as capturing declining poverty, leads to lower on-site land releases (and water pollution). On the other hand, higher percent of households with computer leads to higher water pollution (only). We understand that mechanisms of exposure differ across the 2 media of pollution considered—water and land. The characteristics of the immediate neighborhood might matter more for on-site land releases than water pollution. For water, the downstream community is expected to be affected by plant´s discharges rather than the upstream communities. The community variables themselves are often highly correlated with each other and are essentially plant specific calculations that are correlated with plant fixed effects.

Table 2 presents the pooled OLS model for water and land pollution, using 2000 socioeconomic data for the (single) AGEB in which the plant(s) is located (column(1)) and for all the AGEBs within 1, 2 and 5 km(s) of the plant in columns (2), (3) and (4), respectively. A few of the interesting results are discussed below. Higher manufacturing employment has the expected (positive) coefficient in all four definitions of local community for the water pollution model. Higher manufacturing employment means less pressure on polluters to reduce emissions due to local income/employment generating potential. The coefficient in column (1) can be interpreted as, if percent employed by the manufacturing sector increase by 1 percent, then a typical facility increases its water pollution by 0.01 percent. The coefficient in column (3) can be interpreted as if manufacturing employment increases by 1 percent in the AGEBs within 2 kms of the facility then water pollution is increased by 0.03 percent.

Another result indicating possible plant level environmental justice concerns is that the coefficient on percent of working age population that is unemployed has a positive sign for all four definitions of neighborhood. Higher unemployment rates means lesser pressure on firms to reduce pollution. The coefficient in column (2) can be interpreted as, if unemployment rate in the AGEBs within 1 km of the facility increases by 1 percent, then water discharges of a typical facility increase by 0.2 percent. The coefficient in column (4) can be interpreted as, if unemployment in the AGEBs within 5 kms of the facility increases by 1 percent than water pollution of the nearby facility increases by as much as 0.4 percent.[12]

We find some evidence of pressure due to higher proportion of vulnerable population as captured by higher percent of population under 4 years. The coefficients in columns (1) and (2) can be interpreted as, if population 4 years of age and below increase by 1 percent, in the AGEB where the facility is located and in AGEBs within 1 km of the

[12] Upon estimating a fixed effects model with annual imputed data, using 2000 and 2010 Censuses, higher unemployment rate leads to higher on-site land releases only.

facility, then a typical facility reduces its water discharges by 0.1 percent, respectively. Areas with higher population density face lower water pollution, but only for two definitions of neighborhood. Higher density means higher exposure to pollution and hence increased pressure and/or increased regulatory stringency because past studies find that greater regulatory efforts are directed towards larger industries (and hence more polluting) as well as in poorer and dense neighborhoods (Escobar and Chavez, 2013). The coefficient in columns (1) and (2) of Table 2 can be interpreted as a 1 percent increase in density leads firms to reduce water pollution by 0.4 and 0.2 percent, respectively.

The results of on-site land releases are presented in columns (5) through (8) of Table 2. Land pollution affects groundwater contamination hence the immediate community might be more affected by on-site releases than end-of-pipe discharges into rivers/streams. Some of the interesting results/departures from water pollution are discussed below. First, the share of manufacturing employment has the reverse (negative) sign for land releases, compared to water pollution. The results in columns (5) through (8) show that increased share of manufacturing employment, surprisingly, leads to lower land pollution of nearby facilities. The coefficients can be interpreted as, an increase in manufacturing employment by 1 percent in the AGEB in which the plant is located and in AGEBs within 1, 2 and 5 km(s) of the facility, leads firms to actually reduce on-site releases between 0.004 and 0.007 percent. The only possible explanation is that polluting firms are concerned about the health impact of toxic releases on their labor force.

Second, higher population density leads to increased land pollution in contrast to water pollution. The positive coefficient implies that since higher population density areas are also poorer (in Mexico), polluters feel less pressure to reduce their on-site releases. The coefficients in columns (5) through (8) can be interpreted as, if population density in the AGEB in which the facility is located or in AGEBs within 1, 2 and 5 km(s) of the facility increase by 1 percent then the nearby facility increases its land releases between 0.06 and 0.2 percent.

Table 3 presents the OLS model with community data from 2005 rather than the 2000 Census. We could not identify an indicator for either share of manufacturing employment or the unemployment rate in the 2005 data. Among the consistent results for water pollution (presented in columns (1) through (4) of Table 3), increased share of younger children exerts a negative impact on water pollution, but only when considering the aggregate AGEB characteristics within 1,2 and 5 kms of the facility. Similarly, higher population density exerts a negative impact on water pollution for all definitions of the local community.

Surprisingly, areas with higher percent of population over 15 years with post primary education face higher water pollution for all four definitions of the neighborhood. The coefficient in column (1) can be interpreted as, if population over 15 years with post primary education increase by 1 percent in the AGEB in which the facility is located, then a typical facility increases its water discharges by 0.02 percent. The coefficient in column (4) shows that if the post primary educated population increase by 1 percent in the AGEBs within 5 kms of the facility, then a typical polluter increases its water pollution by as much as 0.1 percent. A possible explanation is that this variable is capturing the quality of work force as opposed to the income effect.

Among the other income/poverty indicators, percent of households with computer, which could proxy for increasing income, has the expected (negative) sign. Households with computer are likely to be richer and hence more likely to exert pressure on firms to reduce pollution. The coefficient in column (3) can be interpreted as, if number of households with computer increase by 1 percent then water discharges of a typical facility reduces by 0.06 percent. Percent of households with telephone, which could proxy for declining poverty, has the expected (negative) sign, only for 2 definitions of neighborhood. Households with telephones are less poor and hence likely to exert more pressure on firms to reduce pollution. The coefficient in column (1) can be interpreted as, if number of households with telephone increase by 1 percent then water discharges of a typical facility reduces by 0.02 percent.

The land pollution results are presented in columns(5) through (8) of Table 3. Among the consistent results, higher population density leads to increased on-site land releases (similar to land pollution in columns (5) through (8) of Table 2). Higher percent of post primary educated population leads to higher land pollution (similar to water pollution in columns (1) through (4) of Table 3). While, increased percent of households with computer leads to lower land releases that is statistically significant only for 2 definitions of neighborhood.

Fixed Effects Model

Table 4 presents the fixed effects estimation results for water and land pollution. We briefly discuss some of the interesting results and/or departures from the pooled OLS estimations. We interpret the results with caution because the aggregate AGEB characteristics based on distance to AGEB centroids to each plant are essentially plant specific data. Interesting departures/results are discussed below.

Upon including plant fixed effects, higher percent of households with computer leads to higher water pollution (columns (1) through (4) of Table4). As mentioned before, our variables are representing one among the multiple possible aspects such as income/poverty or quality of labor force effect and willingness to engage in action due to vulnerable population or inequity in the burden of pollution due to higher age dependency. The coefficients in columns (1) through (4) of Table 4 can be interpreted as, if percent with computer increases by 1 percent, then the nearby facility increases water pollution between 0.03 and 0.06 percent. On the other hand, percent of households with telephone has the expected negative sign for all four definitions of neighborhood. An increase in percent with telephone in the AGEB in which the facility is located leads to lower water pollution by 0.06 percent.

Increased percent of older population seem to increase water pollution for 2 out of the 4 definitions of neighborhood (that are statistically significant). It can be interpreted as capturing the impact of less community pressure and hence evidence of environmental injustice in communities with higher age dependent population, which implies increased pressure on income earners. Lastly, unlike the OLS specifications, higher population density leads to higher water pollution that is significant for at least 2 of the 4 definitions of neighborhood in Table 4.

Among the highlights, for the fixed effects land pollution models (presented in columns (5) through (8) of Table 4)—increased percent of households with telephone leads to lower on-site releases, in line with the declining poverty effect argument--at least 3 of the 4 definitions of local community are statistically significant. Percent over 15 years with post primary education changes sign from positive to negative (compared to OLS in Table 3) but is rarely statistically significant.

Robustness

Finally, Table 5 presents the results upon estimating the unbalanced panel models restricting our sample to facilities that have pollution data for at least 4 out of the maximum possible 9 annual reports. Similar to the fixed effect models in Table 4, percent of households with computer leads facilities to increase water pollution (columns (1) through (4)). As mentioned before, a possible explanation is that this variable is capturing the quality of labor force effect rather than the income effect. The other consistent result, is the negative coefficient on percent of households with telephone. As expected, increased households with telephone means less poor communities and hence increased pressure on polluters. Compared to fixed effects estimation on the entire sample, higher percent of post primary educated population leads to increased water pollution that is statistically significant for 3 of the 4 definitions of neighborhood—capturing the quality of labor force effect, more basic educated population, rather than richer neighborhoods.

Lastly, columns (5) through (8) of Table 5 present the fixed effects estimation of land pollution for the sample of facilities with at least 4 out of total possible 9 annual reports. Among the results similar to the fixed effects estimated on the entire sample, higher percent of households with telephone leads to lower on-site releases that is statiscally significant for 3 of the 4 definitions of community.

Policy Implications and Potential Extensions

To conclude, we find some evidence of community pressure and willingness to engage in collective action from industrial pollution data in Mexico. Our results also present some evidence of environmental justice concerns as poorer communities might face a disproportionately higher share of pollution burden. As part of our empirical strategy, we first estimate OLS specifications to address endogeneity concerns of community factors by using data that are determined before almost all of our pollution data (June 2004 started mandatory reporting). In the OLS models, we find that higher population density leads to lower water and air pollution but higher on-site land pollution. Higher unemployment rate leads to higher water pollution (only). Increased proportion employed by manufacturing sector leads to higher water but surprisingly lower on-site land releases. Higher percent of households with telephone (capturing declining poverty) leads to lower water pollution, while higher percent of households with computer leads to lower land pollution.

Next part of our empirical strategy was to fit unbalanced panel data models since unobserved plant specific effects are likely to significantly influence pollution behavior. We use imputed community data using information from the 2000 Census and the 2005 count data. Upon controlling for all time-invariant plant specific factors, percent of households with telephone continue to have a negative impact on water (though not always significant) and land releases. Percent of households with computer leads to higher water pollution, possibly capturing the quality of labor force effect while increased proportion of older population leads to higher water pollution, capturing the pressure on income earners of a higher age-dependent population.

Overall, since pollution dispersion/exposure mechanisms differ across the 2 media considered, immediate local community might be more affected by groundwater pollution through on-site land releases (storage in lagoons or treatment ponds or put in landfills) and to a lesser extent by downstream water pollution. Lessons can be drawn for regulators in terms of problem medium of pollution like end-of-pipe water discharges that affect the downstream population more rather than the immediate community surrounding the facility as this includes population that are upstream to the factory location. By contrast, community pressure might exist at small scales of the immediately affected community for on-site land releases.

The empirical model could be enriched upon availability of more direct measures of data on income and/or poverty, census data for non-urban areas at a more disaggregated level than municipalities, geocoded census data for older years (1995 or earlier), obtaining dates of establishment of firms to explicitly investigate the concerns of endogeneity of community characteristics, investigating proxies for plant size, e.g. number of employees, investigating availability of data on regulatory efforts such as inspections and enforcement directed towards these industries—to name a few.

Appendix

I. TABLES

TABLE 1: SUMMARY STATISTICS OF ANNUAL POLLUTION AND 2000 CENSUS DATA

Variable	Obs.	Mean	Standard Deviation	Min	Max
Annual Emissions in tons/yr, 2004-2012					
water discharges of metals	40209	0.16	4.99	0	450.6
land emissions of metals	24218	0.03	0.79	0	68.34
water discharges of cyanide	6927	0.065	2.29	0	180.58
land emissions of cyanide	3971	0.01	0.25	0	11.9
2000 aggregate AGEB characteristics					
percent over 15 yrs with post primary education	4408	61.38	11.66	0	96.25
population density (per sq. km)	4408	60.06	41.27	0.08	463.52
percent of households with computer	4408	12.28	8.89	0	62.84
percent of households with telephone	4408	46.20	19.08	0	100
percent of households with female heads	4408	20.15	4.92	0	37.80
percent of population 4yrs and below	4408	10.62	1.94	0	27.27
percent of population 65yrs and above	4408	4.22	1.83	0	16.44
percent employed in manufacturing	4408	37.42	13.01	0	82.02
unemployment rate (%)	4408	1.27	0.63	0	10.28

TABLE 2: OLS OF WATER AND LAND POLLUTION—2000 CENSUS DATA AND STANDARD ERRORS CLUSTERED WITHIN PLANTS

	On-site water discharges				On-site land releases			
explanatory variables	(1) single AGEB	(2) all AGEBs within 1km	(3) all AGEBs within 2km	(4) all AGEBs within 5km	(5) single AGEB	(6) all AGEBs within 1km	(7) all AGEBs within 2km	(8) all AGEBs within 5km
density	-0.007***	-0.004***	-0.001	-0.001	0.001*	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
education	-0.000	-0.022***	-0.009	0.009	0.001	-0.007**	0.002	-0.001
	(0.008)	(0.007)	(0.007)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
telephone	-0.015***	-0.005	-0.008	0.010	0.010***	0.005**	0.002	-0.007**
	(0.005)	(0.005)	(0.006)	(0.007)	(0.002)	(0.002)	(0.003)	(0.003)
computer	0.006	0.015**	0.025***	-0.029***	-0.011***	-0.009***	-0.003	0.013**
	(0.005)	(0.006)	(0.008)	(0.011)	(0.003)	(0.003)	(0.005)	(0.006)
unemployment	0.083	0.212***	0.329***	0.414***	-0.072**	-0.003	0.003	0.020
	(0.054)	(0.061)	(0.072)	(0.073)	(0.035)	(0.024)	(0.024)	(0.033)
female head	0.024***	0.006	-0.015	-0.029*	-0.007**	0.006	-0.000	-0.002
	(0.009)	(0.011)	(0.012)	(0.016)	(0.003)	(0.004)	(0.005)	(0.007)
under 4yrs	-0.109***	-0.100***	-0.165***	-0.143***	-0.014*	-0.016	0.017	-0.004
	(0.019)	(0.020)	(0.027)	(0.034)	(0.008)	(0.010)	(0.011)	(0.021)
over 65yrs	-0.019	0.036	0.015	0.030	-0.009	-0.022**	-0.017	-0.036*
	(0.021)	(0.023)	(0.031)	(0.040)	(0.008)	(0.010)	(0.013)	(0.019)
manufacturing	0.007*	0.017***	0.028***	0.022***	-0.006***	-0.004*	-0.007***	-0.007***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	-8.448***	-7.305***	-7.467***	-11.629***	-1.762	-1.181	-1.462	-5.228***
	(1.064)	(1.036)	(1.082)	(1.142)	(1.274)	(1.216)	(0.916)	(0.703)
R^2	0.24	0.22	0.21	0.19	0.80	0.81	0.81	0.81
N	21,651	27,334	33,066	39,201	11,750	14,928	18,686	23,122

Note: Standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01

TABLE 3: OLS OF WATER AND LAND POLLUTION—2005 COUNT DATA AND STANDARD ERRORS CLUSTERED WITHIN PLANTS

	On-site water discharges				On-site land releases			
explanatory variables	(1) single AGEB	(2) all AGEBs within 1km	(3) all AGEBs within 2km	(4) all AGEBs within 5km	(5) single AGEB	(6) all AGEBs within 1km	(7) all AGEBs within 2km	(8) all AGEBs within 5km
density	-0.008***	-0.007***	-0.004***	-0.003*	0.001*	0.002***	0.004***	0.001**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
education	0.016*	0.016**	0.039***	0.085***	0.007**	0.009***	0.016***	0.006
	(0.009)	(0.008)	(0.009)	(0.011)	(0.003)	(0.003)	(0.004)	(0.005)
telephone	-0.017*	-0.019***	0.014	0.031**	0.013***	0.003	0.002	-0.010
	(0.010)	(0.005)	(0.012)	(0.014)	(0.005)	(0.002)	(0.005)	(0.006)
computer	-0.015	-0.046***	-0.063***	-0.124***	-0.004	-0.016***	-0.016***	-0.009
	(0.011)	(0.008)	(0.010)	(0.012)	(0.004)	(0.004)	(0.005)	(0.006)
female head	0.032***	0.019**	0.006	0.002	-0.002	0.001	-0.008	-0.006
	(0.011)	(0.010)	(0.011)	(0.014)	(0.004)	(0.005)	(0.005)	(0.006)
under 4yrs	0.092**	-0.117***	-0.053*	-0.317***	-0.014	-0.018	-0.013	-0.059**
	(0.045)	(0.027)	(0.029)	(0.049)	(0.015)	(0.012)	(0.014)	(0.025)
over 65yrs	0.002	0.010	0.046*	-0.140***	-0.013	0.004	-0.009	-0.028**
	(0.021)	(0.017)	(0.024)	(0.030)	(0.009)	(0.010)	(0.010)	(0.013)
constant	-10.134***	-7.236***	-11.025***	-11.675***	-5.748***	-4.829	-3.884***	-4.523***
	(1.349)	(1.007)	(1.202)	(1.584)	(1.100)	(7,417.627)	(1.074)	(0.975)
R^2	0.24	0.22	0.21	0.19	0.82	0.81	0.81	0.81
N	20,043	27,083	33,030	39,177	10,689	14,785	18,623	23,113

Note: Standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01

TABLE 4: FIXED EFFECTS OF WATER AND LAND POLLUTION—2000 AND 2005 CENSUS DATA (STANDARD ERRORS CLUSTERED WITHIN PLANTS)

	On-site water discharges				On-site land releases			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
explanatory variables	single AGEB	all AGEBs within 1km	all AGEBs within 2km	all AGEBs within 5km	single AGEB	all AGEBs within 1km	all AGEBs within 2km	all AGEBs within 5km
density	0.040**	0.003	0.039**	-0.023	-0.005	0.003	0.017*	-0.017
	(0.016)	(0.008)	(0.016)	(0.020)	(0.007)	(0.004)	(0.009)	(0.011)
education	-0.025	0.054***	0.006	0.031**	-0.018**	-0.002	0.007	-0.014
	(0.018)	(0.013)	(0.012)	(0.014)	(0.007)	(0.006)	(0.007)	(0.009)
telephone	-0.061***	-0.023	-0.013	-0.076***	-0.022**	-0.013**	-0.017***	-0.009
	(0.017)	(0.015)	(0.014)	(0.015)	(0.008)	(0.007)	(0.006)	(0.008)
computer	0.031**	0.059***	0.050***	0.050***	0.008	-0.012**	0.004	-0.010
	(0.014)	(0.013)	(0.016)	(0.019)	(0.007)	(0.006)	(0.008)	(0.013)
female head	0.041	-0.031	0.046*	0.055	0.011	-0.016	-0.007	-0.026
	(0.026)	(0.023)	(0.025)	(0.036)	(0.011)	(0.011)	(0.013)	(0.020)
under 4yrs	0.360***	0.207***	-0.001	-0.339***	0.072**	-0.021	-0.025	-0.191***
	(0.068)	(0.043)	(0.044)	(0.076)	(0.028)	(0.020)	(0.023)	(0.048)
over 65yrs	0.408***	0.061	0.763***	-0.043	-0.002	0.065***	0.062	-0.254***
	(0.107)	(0.066)	(0.103)	(0.170)	(0.054)	(0.023)	(0.056)	(0.088)
constant	-11.650***	-13.905***	-16.945***	-1.206	0.566	-0.927	-3.827***	1.836
	(2.009)	(1.819)	(1.942)	(2.798)	(1.291)	(0.883)	(1.095)	(1.318)
R^2	0.08	0.07	0.06	0.05	0.79	0.79	0.79	0.79
N	19,579	27,227	33,050	39,192	10,473	14,859	18,637	23,117

Note: Standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01

TABLE 5: FIXED EFFECTS OF WATER AND LAND POLLUTION—AT LEAST 50% DATA, 2000 AND 2005 CENSUS DATA (CLUSTERED STANDARD ERRORS)

	On-site water discharges				On-site land releases			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
explanatory variables	single AGEB	all AGEBs within 1km	all AGEBs within 2km	all AGEBs within 5km	single AGEB	all AGEBs within 1km	all AGEBs within 2km	all AGEBs within 5km
density	-0.049***	-0.024***	0.063***	0.005	-0.018	-0.002	0.033*	-0.025
	(0.018)	(0.007)	(0.022)	(0.023)	(0.043)	(0.007)	(0.018)	(0.017)
education	0.000	0.066***	0.027*	0.047***	-0.037**	-0.013	0.003	-0.018
	(0.016)	(0.013)	(0.015)	(0.017)	(0.017)	(0.014)	(0.013)	(0.015)
telephone	-0.036**	-0.006	-0.011	-0.065***	-0.074**	-0.033**	-0.054***	-0.022
	(0.016)	(0.017)	(0.018)	(0.021)	(0.029)	(0.013)	(0.014)	(0.014)
computer	0.037***	0.083***	0.048**	0.062***	-0.002	-0.017	-0.031**	-0.014
	(0.014)	(0.014)	(0.019)	(0.022)	(0.023)	(0.014)	(0.015)	(0.020)
female head	0.023	0.016	0.042	0.104**	0.021	-0.031	0.035	-0.026
	(0.030)	(0.025)	(0.029)	(0.048)	(0.036)	(0.023)	(0.029)	(0.041)
under 4yrs	0.328***	0.268***	-0.033	-0.217**	0.062	-0.074**	0.073	-0.279***
	(0.072)	(0.052)	(0.053)	(0.098)	(0.080)	(0.035)	(0.044)	(0.085)
over 65yrs	0.331***	-0.013	1.067***	0.085	-0.164	0.029	-0.172	-0.590***
	(0.113)	(0.068)	(0.161)	(0.203)	(0.120)	(0.089)	(0.106)	(0.182)
constant	-9.921***	-15.775***	-18.927***	-7.010**	7.461*	1.254	-2.383	4.537**
	(1.746)	(1.757)	(2.526)	(3.010)	(4.032)	(1.912)	(1.667)	(2.219)
R^2	0.06	0.06	0.05	0.04	0.80	0.80	0.80	0.80
N	9,023	12,623	15,645	18,803	2,363	3,515	5,132	7,194

Note: Standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01

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