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Moser, Mathias; Zwickl, Klara

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Informal Environmental Regulation of Industrial Air Pollution: Does Neighborhood Inequality Matter?

Klara Zwickl
Mathias Moser

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Informal environmental regulation of industrial air pollution: Does neighborhood inequality matter?¹

Klara Zwickl²

Mathias Moser³

klara.zwickl@wu.ac.at

matmoser@wu.ac.at

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Abstract

This paper analyzes if neighborhood income inequality has an effect on informal regulation of environmental quality, using census tract-level data on industrial air pollution exposure from EPA's Risk Screening Environmental Indicators and income and demographic variables from the American Community Survey and EPA's Smart Location Database. Estimating a spatial lag model and controlling for formal regulation at the states level, we find evidence that overall neighborhood inequality – as measured by the ratio between the fourth and the second income quintile or the neighborhood Gini coefficient – increases local air pollution exposure, whereas a concentration of top incomes reduces local exposure. The positive coefficient of the general inequality measure is driven by urban neighborhoods, whereas the negative coefficient of top incomes is stronger in rural areas. We explain these findings by two contradicting effects of inequality: On the one hand, overall inequality reduces collective action and thus the organizing capacities for environmental improvements. On the other hand, a concentration of income at the top enhances the ability of rich residents to negotiate with regulators or polluting plants in their vicinity.

Keywords: Informal Regulation; Income Inequality; Collective Action; Industrial Air Pollution Disparities, Risk-Screening Environmental Indicators, Spatial Lag Model

JEL codes: D3, H4, Q5, R2

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²Institute for Ecological Economics, Department of Socio-Economics, Vienna University of Economics and Business.

³Institute of Macroeconomics, Department of Economics, Vienna University of Economics and Business.

1 Introduction

This paper analyzes if neighborhoods with higher levels of income inequality are less successful in advocating for informal environmental regulation and suffer higher air pollution exposure as a consequence. Theoretical and empirical evidence suggests that where formal regulation of pollution is less than one hundred percent effective, affected communities can bargain for environmental clean-up with local regulators and polluting plants in their vicinity (Pargal and Wheeler, 1996; Pargal et al., 1997). Informal regulation has been found to depend on neighborhood characteristics, especially neighborhood education levels or average income, since wealthier, better educated neighborhoods have superior organizing capacities. However, so far the relationship between neighborhood income inequality and informal environmental regulation has been neglected.

The effect of within-group inequality on individual and collective outcomes has become an important field of research in behavioral economics. Previous evidence suggests that group inequality reduces the group members' willingness to pay for the provision of local public goods (Durlauf, 1996; Benabou, 1996; Alesina et al., 1999) and affects the group's ability to engage in collective action to preserve the local commons (Baland and Platteau, 2007; Akbulut and Soylu, 2012). This argument can be extended to informal regulation of air pollution. However, the effect of inequality on air quality is not as clear as the effect of inequality on other local public goods, since it is not directly the local tax payers, but the polluting firms who pay for its provision, for example through installing additional pollution mitigation technology.¹ On the one hand, one can thus expect that local inequality reduces organizing capacities and therefore informal environmental regulation and lead to higher local air pollution exposure as a consequence. On the other hand, a concentration of income at the top enhances the ability of rich residents to advocate for improvements in environmental quality that benefit the entire neighborhood.

We will test the relationship between inequality and informal regulation empirically using a similar approach as Pargal et al. (1997), estimating air pollution as a function of neighborhood characteristics, controlling for formal regulation at a broader geographical scale. However, instead of using the volume of emissions as a dependent variable, we will use census tract-level industrial air pollution exposure data from EPA's Risk Screening Environmental Indicators (RSEI). Using exposure instead of raw emissions data has the advantage that it takes into account the variation in damage to the local environment depending on various factors such as stack heights, wind patterns, or geographical properties, which Pargal et al. (1997) discuss as an important factor to include. We merge the RSEI data with income and demographic characteristics from the American Community Survey and EPA's Smart Location Database. Due to strong spatial correlation in the dependent variable, which can lead to a serious bias in the estimates due to spatial spill-over effects, we

¹Firms might then pass on (parts of) the costs through price increases, so the total costs are likely to spread out across society.

estimate a spatial lag model. We thereby improve the methodology on explaining variation in environmental quality across U.S. neighborhoods.

We find that, on the one hand, overall income inequality – as measured by the q4/q2 ratio or the neighborhood Gini coefficient – is associated with higher local air pollution exposure. Since state fixed-effects capture most of the variation in formal regulation, our findings suggest that neighborhood income inequality reduces informal environmental regulation. This effect is driven by urban neighborhoods. On the other hand, a concentration of income at the top – as measured by the income ratio between the top 5 percent of the tract and the top 20 percent of the county – is associated with lower air pollution exposure, suggesting that top incomes increase informal regulation. The latter effect is particularly strong in rural tracts. This suggests that the degree of urbanization has an effect on how inequality affects informal environmental regulation and thus environmental outcomes.

The remainder of the paper is organized as follows. After a literature review in section 2, section 3 describes the data and presents summary statistics and maps, and the spatial model. Section 4 reports regression results and section 5 concludes.

2 Literature Review

As opposed to formal regulation, which includes both command and control and market-based environmental policy, informal regulation refers to local environmental improvements that have been achieved by residents' bargaining with firms and regulators. Informal regulation depends strongly on the organizing capacity of the neighborhood, i.e. the neighborhood's ability to threaten the polluter with negative publicity, consumer boycotts, compensation demands, up to the threat of physical violence (Pargal et al., 1997, p. 433f). When informal regulation is effective, from the perspective of the firm, the expected penalty for polluting is high enough to at least partly reduce the pollution externalities by installing mitigation technology, and at most shut down the polluting plant.

While Pargal and Wheeler (1996) provide evidence for substantial degrees of informal regulation for Indonesia, Pargal et al. (1997) find that informal regulation also plays an important role in the U.S., a country with high levels of formal regulation. In fact, the two pre-requisites for informal environmental regulation are, first, a gap between formal regulation and local environmental preferences, and second, a community's ability to exert political, social, or economic pressure. Education and average income have been found to increase a community's leverage to achieve local environmental improvements. It is likely that income inequality is also important in this context.

This paper builds upon two strands of literature: First, the literature on the behavioral consequences of group- or neighborhood-inequality, especially the effects of inequality on collective action. Second, analyses explaining variations in environmental quality by socio-economic characteristics.

2.1 Inequality and Collective Action

Previous research has emphasized that successful collective action depends on the group’s ability to cooperate, which in turn is affected by the composition of the group (Janssen and Ostrom, 2007). Table 1 provides an overview of how inequality can affect communities’ organizing capacities, both through altering individual incentives, as well as by changing social norms and social capital formation.

At the level of individual incentives, Olson (1971) argues that inequality can improve collective action if it enables a few rich group members to agree on an action — such as providing an additional public school — independent of the behavior of the rest of the group. The argument can be extended to pollution, if rich residents bargain with the regulators and firms to avoid facility siting or demand pollution mitigation technologies. By contrary, Durlauf (1996), Benabou (1996) and Alesina et al. (1999) find that inequality reduces collective action as the increased heterogeneity in the group negatively affects the group’s decision making power, e.g. by deciding on a tax rate to finance the public school. Individual incentives can also play a role in the conservation of the local commons. If the famous “tragedy of the commons” (Hardin, 1968) — a scenario where missing property rights result in over-use and subsequent depletion — is extended to a situation where the group is heterogeneous, individual incentives to agree to common rules will depend on one’s own relative economic position, as well as whether the use of the resource increases or declines with income and wealth (Baland et al., 2007.) It is likely that the demand for clean air increases with income and wealth, since there is evidence that rich people move to cleaner neighborhoods (Banzhaf and Walsh, 2008). However, the lack of opportunities to do so could give poor people a higher interest in the environmental conservation of a specific neighborhood. On the contrary, it is also possible that the rate of home-ownership, which is increasing with income, reduces geographic mobility and therefore increases the rich peoples interest in the conservation of a specific location. In sum, individual incentives for environmental conservation across the income spectrum can be ambiguous. The effects can be further complicated due to heterogeneity in environmental demand (Phaneuf, 2013).

In recent years, a thriving behavioral economics literature has emphasized effects of inequality on collective action that go beyond individual incentives. This literature argues that inequality can reduce social capital and trust, and thus affect the group members’ attitudes towards each other. The effect of inequality on social capital formation has been demonstrated by Putnam (2000), who distinguishes between “bridging” versus “bonding” social capital, where the former refers to the case when individuals participate in heterogeneous groups and get into contact with people with very different socio-economic backgrounds, whereas “bonding” social capital refers to participation in relatively homogeneous groups. In theory, heterogeneity could improve social capital and group collective action, if people with different economic backgrounds pool their strengths, or reduce it if people predominantly interact within relatively homogeneous groups and heterogeneity reduces overall participation.

Table 1: Inequality and Collective Action

	Individual Incentives	Social Behavior
Inequality increases collective action	Incentives to contribute are increasing with income and wealth; if some individuals are rich enough, they can provide the public good independent of the action of others (Olson)	Bonding Social Capital (Putnam), diversity within the group could increase the chances of success if resources and knowledge are pooled
Inequality reduces collective action	Incentives to contribute are declining with group heterogeneity (Durlauf, Benabou, Alesina et al.); the use of a the common pool resource is a function of income/wealth (Baland and Platteau)	Bridging Social Capital (Putnam), inequality reduces trust and thus impedes cooperation (Janssen and Ostrom, Baland and Platteau)

Empirically there is a lot of evidence that inequality reduces a group’s ability to cooperate due to the decline in trust, and negative effects from inequality aversion in general. Exploring state–year variation in levels of income inequality and social capital (Putnam, 2000, Chapter 22) finds a strong negative correlation. Using data from the General Social Survey from the 1970s to 1990s, Alesina and Ferrara (2000) demonstrate that higher income inequality and racial/ethnic fragmentation at the city level are associated with lower participation in social activities, such as church groups, school service groups, sports groups and political groups. They find the strongest negative effects of inequality on group membership for groups where members interact directly and excludability is low. In a follow up study also using General Social Survey data, Alesina and Ferrara (2002) find that trust is lower amongst historically disadvantaged group members (women and minorities) and in groups with high levels of income inequality. Fehr and Schmidt (1999) show experimentally that group members care about equitable outcomes and that the economic environment — including the level of income inequality — reduces group members’ willingness to cooperate. Conducting trust experiments, Anderson et al. (2006) demonstrate that group heterogeneity reduces trust, although the findings are sensitive towards the experimental setting.

Based on this evidence, we hypothesize that inequality has a predominantly negative effect on collective action, with the consequence that unequal neighborhoods are less successful to achieve informal regulation and therefore suffer higher local industrial air pollution exposure. However, this could be counter–acted by the effect described by Olson (1971), if rich individuals use their political power to achieve higher environmental quality, which benefits the entire neighborhood. To capture these ambiguous effects, we include two different inequality measures in the specification: first, a measure of overall income inequality, such as the neighborhood Gini coefficient; and second a measure of top income concentration, such as the income ratio of the top 5 percent of the neighborhood to the top 20 percent of the county.

2.2 Environmental Disparities by Socio–Economic Status

There is widespread evidence that low–income households and racial/ethnic minorities suffer disproportionate pollution exposure in the US. Measures of the distribution of environmental quality across the US suggest that environmental inequality is much higher than income inequality (Boyce et al., 2014). A number of studies have found empirical evidence that industrial facilities with toxic releases (Perlin et al., 1995; Brooks and Sethi, 1997; Arora and Cason, 1999), toxic storage and disposal facilities (Anderton et al., 1994; Been and Gupta, 1997; Mohai and Saha, 2007; Bullard et al., 2008) and other environmental hazards (Hird and Reese, 1998; Mohai et al., 2009) are disproportionately located in poor and minority neighborhoods. More recent studies have used modelled exposure data instead of proximity to environmental hazards, arguing that the latter rely on somewhat arbitrary assumptions on the distance of the pollution effect. Exposure data are mainly obtained from two sources: EPA’s Risk–Screening Environmental Indicators model (see for example Ash and Fetter, 2004; Downey and Hawkins, 2008; Abel and White, 2011; Zwickl et al., 2014) and EPA’s National Air Toxics Assessment model (Pastor et al., 2005; Morello–Frosch and Jesdale, 2005).

Previous studies on environmental disparities by socio-economic status have typically estimated pollution exposure as a function of income, race/ethnicity and some non–discriminatory control variables such as population density. Most studies found statistically significant effects of both income and race/ethnicity (Mohai et al., 2009; Bell and Ebisu, 2012; Zwickl et al., 2014). In these studies, the coefficients for race/ethnicity remained significant even after controlling for income. Furthermore, some studies have found that the extent of segregation at a specific location is positively associated with pollution exposure at this location (Lopez, 2002; Morello–Frosch and Jesdale, 2005; Cole et al., 2013).

In theory, the correlation between industrial pollution exposure and neighborhood characteristics could arise in both directions: On the one hand, industrial firms can site hazards disproportionately in disadvantaged communities or use less clean technologies in these communities because they face less regulatory pressure. On the other hand, poor and minority households can move into areas with lower air quality because of lower property values or due to housing market discrimination. The dominant causal pathway is difficult to obtain, since most studies have used very detailed geographic micro–databases with large cross-sectional, but no time dimension. While this strong regional disaggregation is necessary to avoid wrong inference due to the so called ‘ecological fallacy’², it impedes longitudinal analysis.³ The few studies that have established causality by tracking facility sitings or facility emissions over time, have found that discriminatory siting practices in poor and minority communities play an important role (Pastor et al., 2001), and there is evidence

²The problem of ‘ecological fallacy’ refers to the situation where spatial patterns observed at a broader geographical scale such as the county or zip–code level cannot be replicated for finer geographic resolutions (Anselin, 2002).

³Most recent studies on environmental inequality use census tracts as unit of observation. Census tract boundaries are changed as a consequence of population growth or decline. Since population changes could be correlated with changes in demographic characteristics of interest for explaining environmental quality, census boundary changes cannot be assumed to be exogenous. For that reason it is difficult to create a longitudinal census tract–level database to control for pre–siting dynamics.

that firms reduce their toxic emissions in response to media-coverage (Saha and Mohr, 2013). Thus, even though it is likely that the causal relationship also runs from pollution to socio-economic characteristics (Been and Gupta, 1997; Banzhaf and Walsh, 2008), a significant part of the relationship between pollution and neighborhood characteristics is due to industrial siting/clean-up based on neighborhood characteristics. This goes in line with the view that informal regulation is an important predictor of environmental quality.

The importance of this causal pathway is also supported by the fact that controlling for income, other demographic characteristics of a neighborhood, such as the percentages of minorities, are still significant predictors of air quality (Pastor et al., 2005; Mohai et al., 2009; Bell and Ebisu, 2012) and that race/ethnicity are stronger predictors of air quality in the poorer half of U.S. cities (Zwickl et al., 2014), in neighborhoods with the lowest organizing capacities for informal regulation. Furthermore, previous studies have found that besides racial/ethnic minority status, racial fragmentation is an important predictor for poor air quality (Morello-Frosch and Jesdale, 2005; Cole et al., 2013). They explain this by arguing that fragmentation reduces a community’s ability to engage in collective action.

However, the relationship between income inequality and pollution exposure has not been examined empirically at the neighborhood level. By explaining environmental quality at a fine geographic resolution, we will thus start with a similar model as the literature on environmental disparities by socio-economic status. We will then add measures of neighborhood inequality to test for the effect of inequality on the neighborhood’s ability to organize for local environmental improvements, controlling for variations in environmental quality at a broader geographical scale.

3 Data and Methodology

3.1 Data

We use the geographic micro-data from EPA’s Risk Screening Environmental Indicators (RSEI) 2010, which we merge with the American Community Survey 2006–2010 and EPA’s Smart Location Database to obtain income and demographic variables at the census tract-level. Census tracts are geographic units that were created by the Census Bureau and local officials for social analyses of neighborhoods. The Census 2010 defines tracts as areas of around 4,000 people that are split by legal and geographical boundaries, the entire US consisting of around 74,000 tracts, including Alaska and Hawaii. Our sample includes 68512 blockgroups in the 48 contiguous states, for which income inequality measures are available.⁴ Census tracts have been used to analyze neighborhood-effects in various other fields such as unemployment (Topa, 2001), sub-prime lending (Richter and Craig, 2013) or housing markets and segregation (Brueckner and Rosenthal, 2009).

⁴Most missing observations lie in very rural areas with a low population density and too little survey responses for reliable income inequality estimates.

RSEI is based on a model by the Environmental Protection Agency, which uses information on releases from over 400 chemicals from more than 25,000 industrial facilities, that have to report their emissions to the Toxic Release Inventory (TRI), as well as a fate-and-transport model⁵ to estimate ambient air pollution for grid cells of 810 meters square. The chemicals are weighted by toxicity, which is defined as chronic human health hazard from inhalation exposure, and then the toxicity-weighted exposure from each chemical is added.⁶ The resulting variable, that was merged with census data at the block-level and then aggregated to the census tract-level using area weights⁷, is a good measure of residential exposure to air pollution from industrial facilities, as it depends both on the number and activity of facilities in an area, as well as the technology used by the facilities to reduce hazardous releases (e.g. production methods, stack heights or the installation of scrubbers). The variable thus reflects variations in informal regulation at the neighborhood level.⁸

We obtain census tract-level demographic and income variables from the 5-year average estimates of the American Community Survey (ACS) 2006–2010. Summary statistics for the variables included are reported in section 3.4. Since 2005, the ACS has replaced the Census long form, which was last conducted in 2000 and has been the most widely used source for socio-economic variables at detailed geographic resolution down to the census block (for demographic variables) and block group (for income variables). ACS is a continuous survey that is conducted for a smaller sample every year, based on which 1-year, 3-year and 5-year averages are estimated, where the latter are considered most reliable for fine geographic resolutions. Since our dependent variable is from 2010, we use ACS 5-year average estimates from 2006–2010⁹ The main advantage of the American Community Survey is that, compared to the census long form, it includes some additional variables of interest for explaining environmental disparities, such as variables on the distribution of income at the census tract-level.¹⁰

⁵Which includes stack heights, exit gas velocities, wind patterns and chemical decay rates

⁶RSEI hereby ignores cumulative health effects, which could be larger than the sum of toxicity-weighted exposure.

⁷We thank Michael Ash for providing access to the census tract-level RSEI data.

⁸Even though the RSEI model was peer-reviewed repeatedly (US EPA, 2012) and is at present the best available source to obtain census tract-level industrial air pollution exposure data, it is important to mention three shortcomings. First, RSEI could be biased because of mis-reporting by TRI firms if monitoring is insufficient. If mis-reporting itself is a function of neighborhood characteristics, because firms are less likely to under-report their emissions in communities with less access to information, this could lead to wrong inference. However, if it is more likely that firms under-report their emissions in poor and minority neighborhoods due to less regulatory oversight in line with the informal regulation hypothesis, the bias is against our hypothesis of unequal exposure. Second, since RSEI is derived from a model, the results depend on various assumptions of the model, including the relative toxicity of chemicals or their atmospheric dispersion. However, since the model is reviewed periodically by expert groups, the estimates reflect state-of-the art scientific knowledge on the environmental damage and human health hazard from these chemicals. Third, RSEI only captures industrial point sources and excludes air pollution from other sources (such as agriculture or mobile sources from cars or air planes), which could be positively or negatively correlated with industrial pollution. However, inequality could also affect informal regulation of other sources of air pollution.

⁹The small lag between demographics and pollution, is in fact a good way to focus on pollution as outcome variable and reduce problems of reverse causality of median or average neighborhood income.

¹⁰Two shortcomings of the ACS are worth emphasizing: First, the ACS has been criticized for non-random variations in model uncertainty, specifically regional and demographic variation in the margin of errors of the income variables. Especially low-income inner-city census tracts, and census tracts in the South and Southwest have higher margins of errors than others (Folch et al., 2014). Second, the time period from 2006 to 2010 was characterized by the final stage of the boom and subsequent burst of the U.S. housing market bubble and the following Great Recession. It is thus a very heterogeneous time period, where households' characteristics changed dramatically and therefore the results could be sensitive to timing (whether a household

We add the share of industrial employment, as well as other employment, population density and land-use variables from EPA’s block group-level Smart Locations Database, that we aggregated to the census tract-level.

3.2 Empirical Strategy

The following model specification is commonly used in analyses of environmental disparities at the neighborhood level, which is also the basis for our empirical analysis:

$$\mathbf{EXPOSURE}_i = \beta_0 + \beta_1 \times \mathbf{minority}_i + \beta_2 \times \mathbf{medinc}_i + \beta_z \times \mathbf{z}_i + \delta_s + \epsilon_i \quad (1)$$

The dependent variable, $\mathbf{EXPOSURE}_i$ is the measure of industrial air pollution exposure in the census tract i and captures both variation in facility siting and pollution mitigation technology. $\mathbf{minority}_i$ is a vector of variables indicating the percent of African Americans, Hispanics and other minorities in the population of the tract. Since minorities are disproportionately exposed to pollution, compared to the omitted group non-Hispanic whites, the coefficients of these variables are expected to be positive. \mathbf{medinc}_i is the median household income in the tract. In general, this coefficient is expected to be negative in line with the informal regulation hypothesis: as income increases, demand for environmental quality and organizing capacities increase and pollution exposure declines. We additionally control for industrial activity by including the percent of industrial jobs in total employment, as well as urbanization. \mathbf{z}_i is a vector of these additional control variables.

It is important to note that income can be endogenous, if wealthier residents move out of polluted areas (e.g. [Pargal et al., 1997](#), p. 440), and industrial activity can be an intermediate variable, since it can explain both pollution and socio-economic characteristics of a neighborhood. However, the fact that the race/ethnicity coefficients are still statistically significant even when controlling for income and industrial activity, strengthens the case for discriminatory industrial siting as the dominant causal pathway, since income controls for housing affordability and industrial activity for job availability, both of which cause people to move to more polluted areas.

We further include state fixed effects δ_c to control for variation in formal regulation between states. The inclusion of fixed-effects also controls for other important variables explaining the dependent variable at a broader scale, such as the availability of skilled workers, infrastructure, transport and logistics, or the availability of natural resources.

To test the hypothesis that income inequality affects environmental quality through reducing informal

was surveyed in 2006 or 2010). For this reason, we do not include some of the most sensitive variables with this respect, such as housing values. Since the variables from the ACS represent residential — as opposed to workplace — socio-economic characteristics, we are estimating exposure disparities at the residential location. However, overall exposure disparities, that also take into account outdoor air pollution at the workplace location, could differ substantially.

regulation, we add measures of income inequality to the above equation as additional explanatory variables.

$$\mathbf{EXPOSURE}_i = \beta_0 + \beta_1 \times \mathbf{minority}_i + \beta_2 \times \mathbf{medinc}_i + \beta_3 \times \mathbf{inequal}_i + \mathbf{z}_i \times \beta_z + \delta_s + \epsilon_i \quad (2)$$

$\mathbf{inequal}_i$ stands for a vector of these variables: We will add both overall measures of inequality, such as the Q4/Q2 ratio, or the Gini coefficient, as well as measures of top income concentration, measured by the ratio between the top 5 percent of the tract to the top 20 percent of the county. We expect the overall inequality measures to have positive coefficients, since higher inequality reduces collective action and therefore the environmental quality. The top income shares are expected to have negative coefficients, since an income concentration enhances the ability of the rich to demand environmental improvements.

Controlling for median or average incomes, the causal pathway of the overall inequality measure is likely to run from inequality to pollution, in line with the informal regulation hypothesis, since there is no straight forward way how pollution might affect the level of inequality when holding average incomes constant. However, the top income variable can be endogenous if rich people move out of polluted areas. We therefore consider the coefficient of the overall inequality measures as reliable, the coefficients of the top income shares – similar to the coefficients of median income – have to be interpreted with more caution.

3.3 Estimation Approach

Most previous studies in the field have assumed that the dependent variable and the error term in equation 1 are independently distributed and not correlated across space, and have thus estimated OLS. However, if one or both of these assumptions are violated, it can seriously bias coefficients and standard errors of OLS estimations. In our analysis, we are especially concerned with spatial correlation in the dependent variable due to spatial spillovers, which can lead to biased estimates. Spillovers arise from the very nature of air pollution as an externality, that does not stop at neighborhood borders. Moreover, since the air quality variable is obtained from a fate-and-transport model, which explicitly models spillovers at the 810×810 meter grid-cell level, it is likely that even after aggregating the grid-cell pollution score to the census tract-level, there will still be a substantial amount of modelled spill-overs. Figure 1 shows a choropleth map of the dependent variable, which is very concentrated across space. While a large part of tracts have rather low levels of industrial air pollution, several pollution hot-spots can be identified with very high levels.

Since we aim at separating the direct effects of inequality on environmental quality from the indirect effects that result from spatial spillovers, we estimate a spatial lag model which distinguishes between direct and indirect effects by controlling for pollution exposure in neighboring tracts (see Brueckner, 2003). We will present robustness tests estimating a spatial error model (for a discussion of spatial models see Anselin,

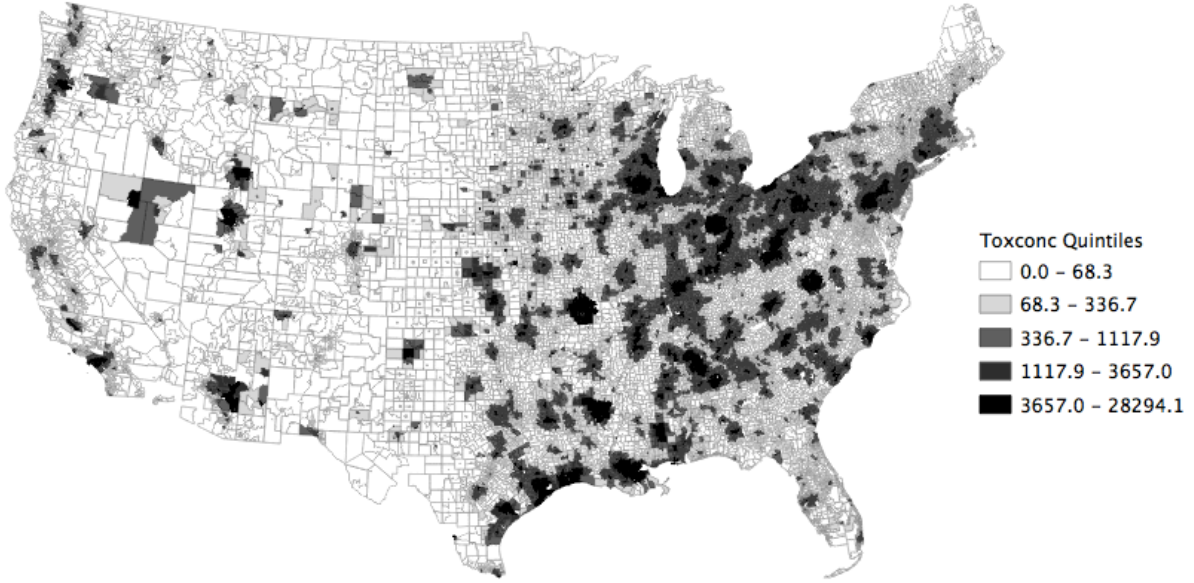


Figure 1: Air Pollution Exposure (censored toxconc) Choropleth Map

1988).

Both spatial lag and spatial error models can be written in a nested form as

$$y_i = \rho \mathbf{W} y_i + \beta \mathbf{X} + \gamma \delta_s + \nu \quad \nu = \lambda \mathbf{W} \nu_i + \epsilon_i \quad (3)$$

where \mathbf{W} is a $N \times N$ spatial weight matrix, $\mathbf{W} y_i$ is the spatially-lagged dependent variable, \mathbf{X} a matrix of explanatory variables and δ_s are state fixed effects. Due to the spillover-structure of our variable of interest, we will put an emphasis on the lag model. For the lag model it is assumed that $\lambda = 0$, so that there is no spatial pattern in the error structure. The lag model thus simplifies to

$$y_i = \rho \mathbf{W} y_i + \beta \mathbf{X} + \gamma \delta_s + \epsilon_i \quad \epsilon_i = N(0, \sigma_i^2)$$

We loosen the assumption of $\lambda = 0$ by additionally estimating a spatial error model, which sets $\rho = 0$ in equation 3 to focus on the spatial structure in the error term. To control for potential heteroscedasticity, we estimate White heteroscedasticity-robust standard errors.

Choosing the structure of \mathbf{W} is crucial for detecting and controlling for spatial autocorrelation. \mathbf{W} defines a set of neighbours for each observation, so that its elements w_{ij} are positive if two observations are related

and zero otherwise. However, choosing an appropriate spatial weights matrix is not trivial. If the assumed weight matrix does not reflect the true drivers of autocorrelation correctly, the model may (still) be subject to misspecification (Bivand et al., 2013). Since there is no broadly agreed choice for \mathbf{W} in the context of our data¹¹, we use a series of different matrix specifications, but mainly focus on so-called *k-nearest neighbors* (KNN), with $k = 5$. This implies that every census tract is assumed to be correlated with its five nearest neighbours, measured via tract centroids.¹²

The estimation procedure for equation 3 follows Kelejian and Prucha (1998) and more specifically the implementation of these methods in the *R spdep* library described in Bivand et al. (2005). In essence, the estimation of this model can be based on the spatial two stage least squares estimator (S2SLS) (Anselin et al., 1980; Kelejian and Prucha, 1998; Kelejian et al., 2004) where the spatially lagged dependent variables serve as instruments for the lagged endogeneous variable. An overview of the estimation procedure is given e.g. by Anselin (2011).

3.4 Summary Statistics

Table 2 reports summary statistics for the variables used. Because TOXCONC, the pollution exposure score obtained from RSEI, is skewed to the left — since many tracts have little or no industrial air pollution — we add 1 to include observations with zero values and take its logarithm. To reduce the influence of outliers we censor TOXCONC at the 97th percentile. Our dependent variable thus is the censored log of TOXCONC.

	Min.	Median	Mean	Max.	Std. Dev.
Toxconc	0.00	613.57	2995.93	28294.13	5972.51
Censored ln(Toxconc)	0.00	6.42	6.12	10.25	2.43
% African American	0.00	0.03	0.13	1.00	0.22
% Hispanic	0.00	0.06	0.14	1.00	0.21
% Other Minority	0.00	0.02	0.05	0.99	0.09
Median Income	5.82	49.86	55.78	250.00	26.93
Mean Income	8.60	60.78	69.64	561.13	35.34
Share Industrial Employment	0.00	0.17	0.25	1.00	0.22
Majority Urbanized	0.00	1.00	0.71	1.00	0.46
Tract Gini	0.18	0.40	0.41	0.78	0.06
County Top 5%	0.16	1.35	1.59	13.20	0.92
Q4/Q2 Ratio	1.15	2.32	2.42	43.66	0.54

Table 2: Descriptive Statistics for Variables

Independent variables included in different specifications are the following: the percentage of African

¹¹The biggest challenge is the unequal shape and size-distribution of tracts, outlined in figure 1. Since every census tract has roughly 4000 residents, low-populated tracts in the center of the US are much larger than the high-populated tracts especially in the eastern part of the US. Furthermore, some tracts are “islands” within other tracts. These properties make distance-based spatial weights infeasible and contiguity-based spatial weights unreliable

¹²Additionally we provide robustness checks of this choice by assuming varying numbers of nearest neighbours. We also consider alternative methods for creating the weights matrix such as the Queen-style contiguity criterion as well as distance-based measures. Distance-based weights are chosen in such a way, that each observation has at least one neighbour. In general, our results are very robust. Results are available upon request.

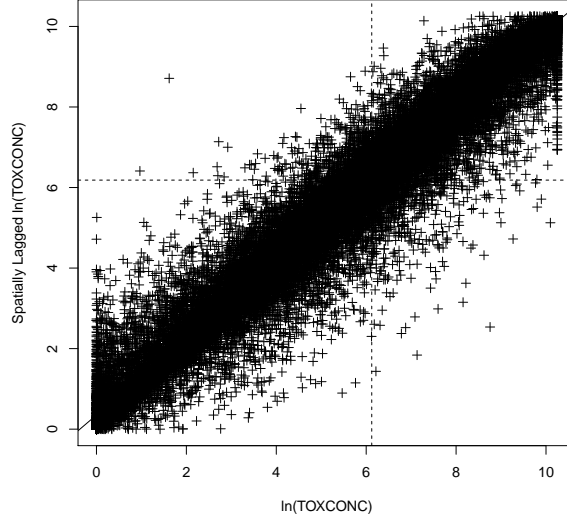


Figure 2: Moran Scatterplot of TOXCONC (ln)

Note: Horizontal axis: $\ln(\text{toxconc})$, vertical axis: spatially lagged $\ln(\text{toxconc})$ using KNN-5 spatial weights

Americans, the percentage of Hispanics and the percentage of other minorities, each ranging from zero to one; the median annual household income of the tract ranging from below \$5800 to \$250,000, which is the value at which ACS censors some income variables for confidentiality reasons; mean income ranging from \$8600 to over \$560,000, the share of industrial employment ranging from 0 to 1, a dummy variable indicating whether the majority of the census tract's population lives in an urbanized area (which is the case for 71% of tracts); and three measures of income inequality. While the Tract Gini and the Q4/Q2 ratio measure general tract-level inequality, the Tract Top5/County Q5 variable measures the ratio between the top 5% of the tract to the top20% of the county, and thus whether a tract has a concentration of top incomes in relation to the corresponding county. The median value of this variable is 1.35, suggesting that in half of the tracts there is no strong income concentration in comparison to the county according to our measure. However, the maximum is over over 13, thus the top 5 percent in this tract have an income that is more than thirteen times as high as the average income of the top 20 percent of the county. The Gini coefficient ranges from 0.18 to 0.78 with a median that is close to the mean and around 0.4. The Q4/Q2 ratio ranges from slightly above 1 to over 43. In the median tract the Q4/Q2 ratio is 2.3, suggesting that the average family income of the top 40 percent are more than twice as high as the corresponding income of the bottom 40 percent.

Regarding the spatial autocorrelation in our dependent variable, we present a global *Moran Scatterplot* in Figure 2, which describes the correlation in air pollution exposure levels between a tract and its spatial lag

Table 3: Baseline Regressions

	OLS	Spatial Lag	Spatial Error
Constant	4.848*** (0.062)	0.191*** (0.034)	5.030*** (0.164)
% African American	1.158*** (0.041)	0.130*** (0.010)	0.166*** (0.025)
% Hispanic	1.316*** (0.048)	0.143*** (0.012)	0.234*** (0.031)
% Other Minority	1.661*** (0.092)	0.161*** (0.028)	-0.026 (0.049)
Median Income	0.003*** (0.000)	-0.000*** (0.000)	-0.000* (0.000)
Urbanized	2.083*** (0.019)	0.267*** (0.012)	0.357*** (0.013)
% Industrial Empl.	0.652*** (0.035)	0.110*** (0.011)	0.111*** (0.012)
ρ		0.933*** (0.006)	
λ			0.948*** (0.005)
Observations	68512	68512	68512
Pseudo R^2	0.39	0.98	0.366
Moran's I	0.90	0.11	0.95

***: Significant at 0.1%; **: Significant at 1%; *: Significant at 5%

(i.e. the weighted level of the neighboring tracts according to the weights matrix). As can be seen there is a strong spatial correlation measured using the default KNN-5 weights with a high number of observations in the lower left quadrant (*Low-Low*) as well as the upper right corner (*High-High*). This is also indicated by the highly significant Moran's I statistic for this variable with a value of 0.93.

4 Estimation Results

In the first step, before testing the relationship between neighborhood inequality and industrial air pollution exposure, we estimate a standard model explaining environmental disparities by socio-economic status as discussed in section 2.2 and compare OLS with the spatial lag and the spatial error models (see table 3). All three equations include state fixed-effects and White-standard errors. In all specifications, the percentages African Americans, Hispanics, and other minorities are positive and statistically significant, so are the dummy for urbanized neighborhoods and the percentage of industrial employment, however in the latter two models the coefficients drop in size, due to the spatial structure in our data.

In the OLS estimation (column 1 of table 3) a coefficient of 1.16 for African Americans suggests that a 10 percentage point increase in African American residents coupled with a 10 percentage point decrease of Whites (the omitted category) is associated with a 11.6 percent increase in pollution exposure within the state. However, due to spatial correlation in the dependent variable, this effect could be over-estimated, or in

Table 4: Baseline Regressions inc. Inequality

	OLS	Spatial Lag	Spatial Error
Constant	4.795*** (0.075)	0.127*** (0.035)	4.985*** (0.164)
% African American	1.145*** (0.041)	0.119*** (0.010)	0.160*** (0.025)
% Hispanic	1.308*** (0.048)	0.140*** (0.012)	0.235*** (0.031)
% Other Minority	1.631*** (0.092)	0.139*** (0.029)	-0.033 (0.049)
Median Income	0.004*** (0.000)	0.000 (0.000)	-0.000 (0.000)
Urbanized	2.079*** (0.020)	0.264*** (0.012)	0.356*** (0.013)
% Industrial Empl.	0.651*** (0.035)	0.112*** (0.011)	0.112*** (0.012)
Q4/Q2	0.028 (0.015)	0.026*** (0.004)	0.018*** (0.005)
County Top 5%	-0.025* (0.010)	-0.015*** (0.002)	-0.011** (0.004)
ρ		0.933*** (0.006)	
λ			0.948*** (0.005)
Observations	68512	68512	68512
Pseudo R^2	0.39	0.98	0.367

***: Significant at 0.1%; **: Significant at 1%; *: Significant at 5%

fact could be a combination between a direct and an indirect effect. In the spatial lag model the coefficient of 0.13 suggests that a 10 percentage point increase in African American residents is associated with an increase in total pollution exposure by 1.3 percent, controlling for indirect pollution spill-overs from neighboring tracts. The coefficients for Hispanics and other minorities are roughly of the same magnitude. This also suggest that the majority of the effect of the OLS estimates is due to spatial spill-overs. However, since part of the spill-overs might be an unintended by-product of facility-siting or clean-up in a nearby community, the finding of prevailing positive coefficients in the lag model strengthens the case for environmental injustice.

The coefficient of median income is statistically significant but close to zero in all three specifications and switches signs between OLS and the spatial models. The urbanization dummy and the percentage of industrial employment are positive and statistically significant in all three specifications, suggesting higher pollution exposure in urbanized tracts and tracts with higher industrial activity.

The results of the error model are generally very robust, the size of the coefficients for most variables lie between OLS and the lag model. The circumstance that the coefficients are still statistically significant when controlling for spatial correlation in the error gives us the confidence, that our results are not only obtained with the theoretical assumptions of the lag model.

Table 4 adds two measures of income inequality: the ratio between Q4/Q2 of the tract and ratio between the tract top 5 percent and the county top 20. Both variables try to capture different aspects of social

interaction: While the quantile ratio serves as a measure of overall inequality, the second measure focuses on the relative importance of high income earners in a tract. The variables already included in table 3 are robust towards adding these two variables. The signs of the inequality variables are robust across all three specifications, and similar in size, however the Q4/Q2 ratio is only significant in the spatial models. The results are in line with our hypotheses about the effect of inequality on pollution levels. On the one hand, the overall inequality measures are associated with higher pollution levels, and therefore measure the effect of social cohesion discussed earlier. On the other hand, we find that a concentration of high income earners is correlated with lower levels of pollution. This finding supports the assumption, that rich individuals may have different preferences for pollution or are able to back their demands through economic resources (e.g. through campaigns).

Table 5 finally reports various robustness checks of the spatial lag-model in table 4. In column 1 we control for mean income instead of median income. This is done as mentioned above to reduce reverse-causality, as it is unlikely that at a given level of average income, changes in air quality affect the neighborhood's income distribution. Our results are very robust towards this change. In column 2 we replace Q4/Q2 by the neighborhood Gini coefficient, which is another *general* inequality measure, although non-linear by construction. This variable also has a positive and statistically significant sign — a ten percentage-point increase in the Gini can be related to a 3.8% increase in pollution levels. In column 3 we add the Q5/Q2 ratio instead of the Q4/Q2 ratio, which is a more extreme measure of top income earners. In principal this substitution confirms the robustness of the inequality effect, although the coefficient of Q5/Q2 is smaller, probably a result of its narrower definition. In column 4 we drop the share of top income earners in relation to the county (county top 5%), which does not have an effect on the coefficient of Q4/Q2.

It can be argued that the effect of inequality may vary between urban and rural areas, due to what [Pargal et al. \(1997\)](#) refer to as the “visibility effect” of a polluting plant, that is lower in urban areas, where average levels of pollution are higher. However, neighborhood organizing capacities could also vary by population density, and the influence of rich individuals on individual regulations could be stronger in rural areas. In the last two columns, we therefore interact Q4/Q2 and the Gini with the urbanization measure as dummy to test if the effect of inequality on informal regulation varies by the degree of urbanization. We find that the effect of the overall inequality measure differs between urban and rural areas: whereas in urban areas, overall inequality is associated with an increase in pollution exposure using both Q4/Q2 and the Gini as inequality measure. In rural areas, Q4/Q2 turns negative, and the Gini turns zero and not statistically significant. The top income measure is negative in both urban and rural areas, however the coefficients are larger in rural areas. As we noted, the results for the overall inequality measures are more reliable, since the top income measures can be endogenous. The “move-out” effect could be even stronger in rural areas, where people are more mobile, already take long commuting distances to their workplace into account, and might be less

Table 5: Spatial Lag Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
ρ	0.932*** (0.006)	0.935*** (0.006)	0.934*** (0.006)	0.934*** (0.006)	0.947*** (0.006)	0.943*** (0.006)
Constant	0.126*** (0.035)	0.038 (0.039)	0.153*** (0.036)	0.130*** (0.035)	0.260*** (0.044)	0.188*** (0.049)
% African American	0.125*** (0.010)	0.113*** (0.010)	0.118*** (0.010)	0.124*** (0.010)	0.117*** (0.010)	0.110*** (0.010)
% Hispanic	0.147*** (0.012)	0.139*** (0.012)	0.139*** (0.012)	0.146*** (0.012)	0.136*** (0.012)	0.137*** (0.012)
% Other Minority	0.135*** (0.028)	0.127*** (0.029)	0.134*** (0.029)	0.152*** (0.028)	0.135*** (0.028)	0.124*** (0.029)
% Industrial Empl.	0.112*** (0.011)	0.114*** (0.011)	0.111*** (0.011)	0.114*** (0.011)	0.096*** (0.010)	0.104*** (0.011)
Urbanized	0.262*** (0.012)	0.260*** (0.012)	0.260*** (0.012)	0.266*** (0.012)		
Mean Income	0.000*** (0.000)					
Q4/Q2	0.028*** (0.004)			0.020*** (0.004)		
County Top 5%	-0.021*** (0.003)	-0.031*** (0.003)	-0.023*** (0.004)			
Median Income		0.001*** (0.000)	0.000* (0.000)	-0.000** (0.000)	0.000 (0.000)	0.000*** (0.000)
Tract Gini		0.380*** (0.039)				
Q5/Q2			0.009*** (0.002)			
Q4/Q2 Urban					0.034*** (0.005)	
Q4/Q2 Rural					-0.024** (0.008)	
Cty Top5 Urban					-0.006** (0.002)	-0.028*** (0.003)
Cty Top5 Rural					-0.057*** (0.007)	-0.050*** (0.010)
Gini Urban						0.486*** (0.038)
Gini Rural						0.000 (0.070)
Observations	68512	68512	68512	68512	68512	68512
Pseudo R^2	0.98	0.98	0.98	0.98	0.98	0.98

***: Significant at 0.1%; **: Significant at 1%; *: Significant at 5%

likely to move away from environmental hazards. Furthermore, since over 70 percent of US census tracts are classified as urbanized, where we found that inequality has a predominantly negative effect, we conclude that local inequality increases environmental pollution by reducing neighborhoods' organizing capacities in line with the informal regulation hypothesis.

As [LeSage and Pace \(2010\)](#) point out, the immediate interpretation of coefficients in the lag model can cause erroneous interpretations, and they suggest to consider partial derivatives instead, to distinguish between direct and indirect effects. This is due to the fact that a change in inequality may influence the tract's own pollution level but through the spatial spillover there could also exist a feedback effect from the neighbouring tracts. We follow the approach of [LeSage and Pace](#) and simulate these effects from the variance-covariance matrix to draw inference. The results from this exercise are presented in [table 6](#). Both direct and indirect effects are found to have similar signs as compared to the total effects presented before. Especially the direct effects are of similar size and magnitude (see [table 5](#)) and therefore our conclusions remain valid.

5 Conclusion

This paper investigates if the degree of neighborhood inequality matters for informal regulation of industrial air pollution in the United States. Using data on industrial air pollution exposure from EPA's Risk Screening Environmental Indicators model and income and demographic data as well as control variables from the American Community Survey and EPA's Smart Location Database, we estimate a spatial lag model explaining air pollution exposure and controlling for variation in regulation and environmental quality at a broader geographical scale. We find that general income inequality measures, such as the neighborhood Gini coefficient, or the Q4/Q2 ratio, are associated with higher pollution exposure, suggesting weaker informal environmental regulation in unequal neighborhoods. However, a concentration of top incomes, as measured by the tract top 5 % to the county top 20 % ratio is associated with a reduction in air pollution. While the former effect is driven by urban neighborhoods, the latter effect is especially strong in rural neighborhoods, suggesting that wealthy rural residents are most likely to achieve environmental improvements by bargaining with firms or regulators. Since over 70% of U.S. neighborhoods are classified as urban, we conclude that inequality has a predominantly negative effect on the neighborhoods ability to achieve local environmental improvements.

Our findings contribute both to the literature on informal regulation, by identifying an additional factor that determines communities' organizing capacities and thus the variation of environmental quality at a smaller geographical scale, as well as to the literature on the behavioral effects of income inequality. Specifically, we show that it can be useful to distinguish between different forms of inequality – overall inequality and top income concentration – and between different behavioral effects in urban and rural areas.

References

- Abel, T. D. and White, J. (2011). Skewed riskscape and gentrified inequities: environmental exposure disparities in Seattle, Washington. *American Journal of Public Health*, 101(S1):S246–54.
- Akbulut, B. and Soyly, C. (2012). An inquiry into power and participatory natural resource management. *Cambridge Journal of Economics*, 36(5):1143–1162.
- Alesina, A., Baqir, R., and Easterly, W. (1999). Public goods and ethnic divisions. *The Quarterly Journal of Economics*, (November):1243–1284.
- Alesina, A. and Ferrara, E. L. (2000). Participation In Heterogeneous Communities. *The Quarterly Journal of Economics*, 115(3):847–904.
- Alesina, A. and Ferrara, E. L. (2002). Who trusts others? *Journal of Public Economics*, 85(2):207 – 234.
- Anderson, L., Mellor, J., and Milyo, J. (2006). Induced heterogeneity in trust experiments. *Experimental Economics*, 9(3):223–235.
- Anderton, D. L., Anderson, A. B., Oakes, J. M., and Fraser, M. R. (1994). Environmental equity: the demographics of dumping. *Demography*, 31(2):229–48.
- Anselin, L. (1988). *Spatial econometrics: methods and models*, volume 4. Springer.
- Anselin, L. (2002). Under the hood. Issues in the specification and interpretation of spatial regression models. *Agricultural Economics*, 27(3):247–267.
- Anselin, L. (2011). GMM estimation of spatial error autocorrelation with and without heteroskedasticity. *Note (GeoDa Center, Arizona State University, 2011)*.
- Anselin, L. et al. (1980). Estimation methods for spatial autoregressive structures. *Regional Science Dissertation & Monograph Series, Program in Urban and Regional Studies, Cornell University*, (8).
- Arora, S. and Cason, T. N. (1999). Do Community Characteristics Influence Environmental Outcomes? Evidence from the Toxics Release Inventory. *Southern Economic Journal*, 65(4):691–716.
- Ash, M. and Fetter, T. R. (2004). Who Lives on the Wrong Side of the Environmental Tracks? Evidence from the EPA’s Risk-Screening Environmental Indicators Model. *Social Science Quarterly*, 85(2):441–462.
- Baland, J.-M., Bardhan, P., Das, S., Mookherjee, D., and Sarkar, R. (2007). Inequality, Collective Action, and the Environment: Evidence from Firewood Collection in Nepal. In Baland, J.-M., Bardhan, P., and Bowles, S., editors, *Inequality, cooperation, and environmental sustainability*. Princeton Univ. Press, Princeton, NJ [u.a.].
- Baland, J.-M. and Platteau, J.-P. (2007). Collective action on the commons: The role of inequality. In Baland, J.-M., Bardhan, P., and Bowles, S., editors, *Inequality, cooperation, and environmental sustainability*. Princeton Univ. Press, Princeton, NJ [u.a.].
- Banzhaf, H. and Walsh, R. (2008). Do people vote with their feet? An empirical test of Tiebout’s mechanism. *American Economic Review*, 98(3):843–863.
- Been, V. and Gupta, F. (1997). Coming to the nuisance or going to the barrios? A longitudinal analysis of environmental justice claims. *Ecology Law Quarterly*, 24(1):1–56.
- Bell, M. L. and Ebisu, K. (2012). Environmental inequality in exposures to airborne particulate matter components in the United States. *Environmental Health Perspectives*, 120(12):1699–704.
- Benabou, R. (1996). Equity and Efficiency in Human Capital Investment: The Local Connection. *The Review of Economic Studies*, 63(2):237–264.

- Bivand, R., Bernat, A., Carvalho, M., Chun, Y., Dormann, C., Dray, S., Halbersma, R., Lewin-Koh, N., Ma, J., Millo, G., et al. (2005). The spdep package. *Comprehensive R Archive Network, Version 0.3-13*.
- Bivand, R. S., Pebesma, E., and Gomez-Rubio, V. (2013). *Applied spatial data analysis with R, Second edition*. Springer, NY.
- Boyce, J. K., Zwickl, K., and Ash, M. (2014). Three Measures of Environmental Inequality. *INET Working Paper, Working Group on the Political Economy of Distribution*, (4).
- Brooks, N. and Sethi, R. (1997). The distribution of pollution: Community characteristics and exposure to air toxics. *Journal of Environmental Economics and Management*, 32(2):233–250.
- Brueckner, J. and Rosenthal, S. (2009). Gentrification and neighborhood housing cycles: Will America’s future downtowns be rich? *The Review of Economics and Statistics*, 91(4):725–743.
- Brueckner, J. K. (2003). Strategic interaction among governments: An overview of empirical studies. *International Regional Science Review*, 26(2):175–188.
- Bullard, R. D., Mohai, P., Saha, R., and Wright, B. (2008). Toxic Wastes and Race at Twenty: Why Race still matters after all of these years. *Environmental Law*, 38:371–411.
- Cole, M. a., Elliott, R. J., and Khemmarat, K. (2013). Local exposure to toxic releases: Examining the role of ethnic fractionalization and polarisation. *Ecological Economics*, 93:249–259.
- Downey, L. and Hawkins, B. (2008). Single-Mother Families and Air Pollution : A National Study. *Social Science Quarterly*, 89(2):523–536.
- Durlauf, S. (1996). A Theory of Persistent Income Inequality. *Journal of Economic Growth*, 93(1986):75–93.
- Fehr, E. and Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics*, 114(3):817–868.
- Folch, D. C., Arribas-Bel, D., Koschinsky, J., and Spielman, S. E. (2014). Uncertain Uncertainty: Spatial Variation in the Quality of American Community Survey Estimates. *Arizona State University Working Paper*, (01).
- Hardin, G. (1968). The tragedy of the commons. *Science*, 162(3859):1243–1248.
- Hird, J. A. and Reese, M. (1998). The Distribution of Environmental Quality: An Empirical Analysis. *Social Science Quarterly*, 79(4):639–716.
- Janssen, M. A. and Ostrom, E. (2007). Adoption of a new regulation for the governance of common-pool resources by a heterogenous population. In Baland, J.-M., Bardhan, P., and Bowles, S., editors, *Inequality, cooperation, and environmental sustainability*. Princeton Univ. Press, Princeton, NJ [u.a.].
- Kelejian, H. H. and Prucha, I. R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *The Journal of Real Estate Finance and Economics*, 17(1):99–121.
- Kelejian, H. H., Prucha, I. R., and Yuzefovich, Y. (2004). Instrumental variable estimation of a spatial autoregressive model with autoregressive disturbances: Large and small sample results. *Advances in econometrics*, 18:163–198.
- LeSage, J. and Pace, R. K. (2010). *Introduction to spatial econometrics*. CRC press.
- Lopez, R. (2002). Segregation and black/white differences in exposure to air toxics in 1990. *Environmental Health Perspectives*, 110(S2):289–95.

- Mohai, P., Lantz, P. M., Morenoff, J., House, J. S., and Mero, R. P. (2009). Racial and socioeconomic disparities in residential proximity to polluting industrial facilities: evidence from the Americans' Changing Lives Study. *American Journal of Public Health*, 99(S3):S649–56.
- Mohai, P. and Saha, R. (2007). Racial Inequality in the Distribution of Hazardous Waste : A National-Level. *Social Problems*, 54(3):343–370.
- Morello-Frosch, R. and Jesdale, B. M. (2005). Separate and Unequal: Residential Segregation and Estimated Cancer Risks Associated with Ambient Air Toxics in U.S. Metropolitan Areas. *Environmental Health Perspectives*, 114(3):386–393.
- Olson, M. (1971). *The logic of collective action: Public goods and the theory of groups*. Harvard University Press, second printing, Cambridge MA.
- Pargal, S., Hettige, H., Singh, M., and Wheeler, D. (1997). Formal and Informal Regulation of Industrial Pollution: Comparative Evidence from Indonesia and the United States. *The World Bank Economic Review*, 11(3):pp. 433–450.
- Pargal, S. and Wheeler, D. (1996). Informal Regulation of Industrial Pollution in Developing Countries: Evidence from Indonesia. *Journal of Political Economy*, 104(6):pp. 1314–1327.
- Pastor, M., Morello-Frosch, R., and Sadd, J. L. (2005). The air is always cleaner on the other side: race, space and ambient air toxics exposure in California. *Journal of Urban Affairs*, 27(2):127–148.
- Pastor, M., Sadd, J., and Hipp, J. (2001). Which Came First? Toxic Facilities, Minority Move-In, and Environmental Justice. *Journal of Urban Affairs*, 23(1):1–21.
- Perlin, S. A., Setzer, R. W., Creason, J., and Sexton, K. (1995). Distribution of industrial air emissions by income and race in the United States: an approach using the toxic release inventory. *Environmental Science & Technology*, 29(1):69–80.
- Phaneuf, D. J. (2013). Heterogeneity in environmental demand. *Annu. Rev. Resour. Econ.*, 5(1):227–244.
- Putnam, R. D. (2000). *Bowling alone: The collapse and revival of American community*. Simon and Schuster, New York.
- Richter, F. G.-C. and Craig, B. R. (2013). Lending patterns in poor neighborhoods. *Journal of Economic Behavior & Organization*, 95:197–206.
- Saha, S. and Mohr, R. D. (2013). Media attention and the Toxics Release Inventory. *Ecological Economics*, 93:284–291.
- Topa, G. (2001). Social Interactions, Local Spillovers and Unemployment. *Review of Economic Studies*, 68(235):261–295.
- US EPA (2012). *EPA 's Risk-Screening Environmental Indicators (RSEI) Methodology (RSEI Version 2.3.1)*. US Environmental Protection Agency.
- Zwickl, K., Ash, M., and Boyce, J. K. (2014). Regional Variation in Environmental Inequality: Industrial Air Toxics exposure in U.S. cities. *Ecological Economics*, 107:494–509.

A Appendix

Table 6: Direct & Indirect Effects for Lag Specifications

	(1)		(2)		(3)		(4)		(5)		(6)	
	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
% African American	0.190***	1.314***	0.173***	1.210***	0.180***	1.257***	0.190***	1.323***	0.185***	1.424***	0.173***	1.290***
% Hispanic	0.225***	1.551***	0.213***	1.491***	0.213***	1.484***	0.223***	1.552***	0.216***	1.659***	0.215***	1.602***
% Other Minority	0.206***	1.423***	0.194***	1.360***	0.205***	1.433***	0.232***	1.617***	0.214***	1.647***	0.195***	1.454***
% Industrial Empl.	0.171***	1.182***	0.174***	1.221***	0.171***	1.191***	0.175***	1.215***	0.153***	1.174***	0.164***	1.222***
Urbanized	0.400***	2.760***	0.398***	2.788***	0.399***	2.782***	0.406***	2.825***				
Mean Income	0.001***	0.003***										
Q4/Q2	0.042***	0.292***					0.030***	0.210***				
County Top 5%	-0.032***	-0.222***	-0.048***	-0.338***	-0.035***	-0.242***						
Median Income			0.001***	0.005***	0.000*	0.003*	-0.000**	-0.002**	0.000	0.000	0.001***	0.006***
Tract Gini			0.582***	4.082***								
Q5/Q2					0.014***	0.097***						
Q4/Q2 Urban									0.053***	0.410***		
Q4/Q2 Rural									-0.038**	-0.296**		
Cty Top5 Urban									-0.009**	-0.068**	-0.044***	-0.329***
Cty Top5 Rural									-0.091***	-0.696***	-0.079***	-0.588***
Gini Urban											0.763***	5.690***
Gini Rural											0.000	0.003

***: Significant at 0.1%; **: Significant at 1%; *: Significant at 5%