Segregation, Bargaining Power and Environmental Justice

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Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
2017

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Acknowledgements

I would like to thank my faculty advisor Dr. Christopher Timmins without whom this thesis would not be possible. I am extremely grateful for his continual guidance, advice and feedback. I would also like to thank my honors thesis seminar advisor Dr. Tracy Falba, whose initial guidance and comments led me to pursue the work in this honors thesis. I am also grateful to the staff at the National Historical Geographic Information System (NHGIS) and the Bureau of Labour Statistics as well as fellow student Anne Driscoll, whose help in extraction, clarification and clean-up of datasets made this work possible. Special thanks to the staff at Data and Visualizations Services for their technical assistance and expertise.

Abstract

Under efficient Coasian bargaining, the recipients of an environmental harm are compensated by the polluter for every unit of the nuisance that they bear. When those doing the negotiation are also those bearing the costs of the environmental harm, this will lead to an efficient outcome in which the benefits and social costs of the polluting activity are equalized on the margin. Transaction costs frequently lead to bargaining being conducted by government representatives on behalf of their constituents; e.g., county officials may bargain with polluting firms over payments in exchange for siting facilities within their borders. When populations are highly segregated, representatives can more easily target the costs of polluting facilities to a politically weak minority while the majority enjoys the Coasian compensation. We test this theory using information on three decades of county-level polluting employment and a measure of racial/ethnic dissimilarity. Results confirm the hypothesis that segregation facilitates the siting of polluting facilities, suggesting an important source of procedural environmental injustice.

Keywords: Environmental Justice, Coasian Bargaining, Dissimilarity Index, Siting, Segregation, Procedural Justice, Toxic Release Inventory

JEL codes: Q52, Q53, Q56, R3, R58

1 Introduction

"Environmental justice is the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies... It will be achieved when everyone enjoys the same degree of protection from environmental and health hazards, and equal access to the decision-making process to have a healthy environment in which to live, learn, and work".[1]

The concept of environmental justice (EJ) emerged in the late 1970s and early 1980s in response to North Carolina's attempt to dispose of 120 million pounds of polychlorinated biphenyls in Warren County, the county with the highest proportion of African Americans in the state at that point in time. This sparked a study by the US General Accounting Office of major facilities in the South (GAO, 1983), leading to a national study sponsored by the United Church of Christ's Commission for Racial Justice (United Church of Christ, 1987). The rise of environmental justice issues to prominence saw President Bill Clinton issue an executive order requiring federal agencies to make environmental justice considerations in all decision making. Since then, environmental justice has grown into an expansive and multi-disciplinary field of research.

The definition and scope of EJ varies substantially in the literature. Some consider aspects such as intent (of policy makers and firms), others focus on regulation or broader concerns with environmentalism, however, a recurring theme is the disproportionate exposure of disadvantaged groups (defined by one or a combination of race, ethnicity and class) to environmental nuisances. Much of the existing literature therefore seeks to identify the relationship between racial or class characteristics and exposure to environmental risk. Notable studies which have found evidence in support of race-based disproportionate exposure include the United Church of Christ (1987), Been (1995), Ringquist (1997), Perlin et al. (1995) and Sadd et al. (1999). There have also been studies which found no evidence of disproportionate exposure including Anderton et al. (1994) and Bowen et al. (1995)[2], but overall the evidence

[1] https://www.epa.gov/environmentaljustice. Accessed 1/19/2017.

[2] The discrepancy in results could have arisen due to differing choices of geographic unit of measurement and the relative importance of proximity measures as compared to risk-based measures,

has typically supported the existence of environmental inequity.

Often documented sources of environmental risk include (but are not limited to): proximity to hazardous/toxic sites, air pollution, water pollution, soil pollution and noise pollution. There are obvious direct costs which are imposed by environmental risk such as negative health outcomes which need to be treated, lowered earning power due to negative health outcomes and loss of livestock/produce. Besides these direct costs, areas of low environmental quality could also be subject to economic disinvestment from 'clean' industries. The presence of environmental nuisances could also be attractive to additional environmental nuisances that are seeking to capitalize on economies of agglomeration. Firms seeking to pollute a natural resource might seek out other polluting firms so as to work together to overcome legal and institutional barriers. Some polluting firms also produce inputs for other polluting firms as a by-product and co-locating in a single area allows for minimization of transport costs. This agglomeration mechanism leaves an at-risk community further exposed to environmental risk.

Whilst the EJ field has already progressed considerably, it is insufficient to document the existence of such inequities. In order for research to best inform policy decisions, it is paramount that the source of documented disproportionate exposure to environmental harms is uncovered. The most commonly proposed explanations found in the current literature include:

1. Siting: where environmental nuisances are placed into neighbourhoods of the disadvantaged group because of certain attributes which are attractive to firms such as lowered resistance or smaller expected liability costs

2. Sorting: where low-income (and often racial minority) persons move into polluted neighbourhoods in response to discounted housing prices, a result of the departure of wealthier persons who choose to avoid the environmental nuisance (i.e., hedonic house price theory)

3. Government (In)action: where governments are negligent in inspecting and enforcing regulation in disadvantaged communities

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both of which are actively debated.

4. Neighbourhood Effects: where persistent health consequences from exposure to pollution cause an intergenerational transfer of poverty as subsequent generations have limited education, lowered incomes and higher healthcare spending

This paper focuses on the siting mechanism, paying particular attention to a potential failure of the Coasian bargaining paradigm. Coasian bargaining states that an efficient allocation of resources will result from unregulated interaction of polluter and victim. Viewed from a Coasian bargaining framework, when an economic activity imposes environmental risk (a social cost) on communities, the party upon which that cost is imposed should be adequately compensated. Coase's theorem holds that, given some assumptions, negotiation between parties (in this case the polluter and the community) ensures an efficient outcome.

The EPA definition cited at the start of this thesis includes the "meaningful involvement" of all peoples in environmental policy, a reference to one form of procedural justice which must be present for environmental justice. Procedural justice is also a condition required for the efficient bargaining which leads to satisfaction of the Coase theorem. Lack of a proper avenue to express individual preferences could result in consequences for the efficiency of eventual bargaining outcomes. This paper tests the idea that in a world with transaction costs and government failure, procedural justice can easily break down. If so, Coasian bargaining is prone to failure, particularly in areas of higher racial segregation, as the group conducting the bargaining is able to reap the compensation whilst simultaneously shifting part of (if not all) the costs onto a segregated community. The eventual outcome is that the segregated community then faces a higher than optimal level of pollution.

Anecdotal cases of this mechanism have appeared over the years. Cole and Foster (2001) tell the story of Kettleman City, a small farmworker community located in King's County, California.[3] While already the site of the largest toxic waste dump west of Alabama, Kettleman City was faced with the siting of a new toxic waste incinerator in 1988. Located in predominantly white Kings County, Kettleman City is roughly thirty miles south west of the county seat Hanford. At the time, the town was almost exclusively Latino and nearly half of the residents spoke only Spanish.[4]

[3] Another relevant example also highlighted by Cole and Foster is that of Chester, Pennsylvania.
[4] Today, the ethnic and linguistic disparities are no less extreme.

Under California state law, government agencies were required to provide public notice regarding the establishment of such facilities; in the case of Kettleman City, this entailed printing a notice (written in English) in a newspaper published in another part of the county, erecting a signed fence post four miles outside of town, and sending notices to the large corporations who were adjacent landowners. The residents were never able to adequately express their need for compensation – either individually, collectively, or through their county officials. At the same time, the benefits of the facility, such as increased tax revenues were spread among all residents of the county, not just those of Kettleman City.

Given this phenomena, I expect that the failure of Coasian bargaining will result in the disproportionate siting of environmental nuisances in segregated communities. I measure segregation with the index of dissimilarity; formally defined in Section 4.1, the index of dissimilarity measures the spatial homogeneity of two groups across a geographic area (i.e., county). I conduct regressions of employment in industries reporting to the Toxics Release Inventory (TRI) on the index of dissimilarity and find that higher levels of segregation indeed result in subsequent increasing employment in TRI-reporting industries. I find this result not only in the cross-section, but also in changes over time.

This paper proceeds as follows. Section 2 conducts a review of the existing literature on the topic, Section 3 covers the theoretical underpinnings of how environmental injustice might arise due to the failure of Coasian bargaining. Section 4 introduces the data sets utilized in the study. Section 5 explains the econometric methodology and presents the results from the various models. Section 6 covers the implications of the work presented, future research avenues and concludes this paper.

2 Literature Review

The existing literature on environmental justice is varied, with work ranging from determining if environmental nuisances are disproportionately distributed, identifying aspects of environmental burden and qualitative and quantitative descriptions of the effects of environmental injustice. However, the literature reviewed in this section will largely focus on work that has been done to identify the causes of environmental injustice. In particular, I review previous research relevant to the siting mechanism.

Hamilton (1995) identifies three categories of economic and political theory that might result in the distribution of pollution which he describes as "environmental racism". The first possibility is pure discrimination and is based on the notion that the decision makers (be it the firm itself or a governing body) gain utility from discriminatory siting of environmental nuisances based on the racial composition of the host community. Hamilton also suggests that operating under the conditions of Coase's theorem, polluting plants try to site locations where they impose the least external cost as doing so would minimize the amount of compensation to be paid (Jenkins and Maguire, 2004). Finally, Hamilton puts forward an argument based on Olson's theory of collective action (1965). Acknowledging that in reality transaction costs are neither absent nor negligible, Hamilton argues that the ability of a group to collectively voice its valuation of environmental amenities is just as, if not more, important than the actual valuation itself. By identifying predictor variables which belonged to one of the three theories, Hamilton came to the conclusion that firms consider the likelihood of collective action affecting their siting costs when making plans for capacity expansion.

Boyce (1995) also considers the negative externality of environmental degradation. He states that microeconomic theory would suggest that examination of social costs and benefits should suffice to reach an efficient outcome, but then argues that outcomes are affected by a "power-weighted social decision rule". Relating his theory to Coase's Theorem, Boyce suggests that parties who are better able to bear the transaction costs of a negotiation are more powerful as it is necessary to bear these costs when either rejecting a polluting facility or obtaining adequate compensation.

Been (1994) reviews earlier studies by the US General Accounting Office (GAO) (1983) and by Bullard (1983), both of which appeared to find evidence of disproportionate siting of what she terms locally undesirable land uses (LULUs). Been describes the sorting mechanism, a process in which market dynamics might result in racial minorities moving nearer to LULUs to take advantage of lower land and housing prices, which could also cause the same eventual observable outcome: a disproportionate number of racial minorities around LULUs. Been attempts to improve on the work done by GAO and Bullard by tracing the effect on host communities some time after the siting and finds mixed results. Revisiting the GAO study, she finds that market dynamics did not cause the distribution of burden, but a similar extension of studies by Bullard suggest that free market economics played a substantial role in the outcomes observed.

Multiple studies exist in the current EJ literature that attempt to correlate socioeconomic characteristics with environmental outcomes, but there is less work that specifically tries to identify the causal mechanism through which persons of color and the poor end up with a disproportionate burden is still somewhat lacking. In particular, the commonly used socioeconomic characteristics of percentage minority race and income are not suitable for finer work beyond identifying correlation between race and income and environmental outcomes. I attempt to tackle this by utilizing a quantitative metric of segregation which I believe to be a key point in determining whether an efficient outcome can be reached via Coasian bargaining, or if policy treatments might be required.

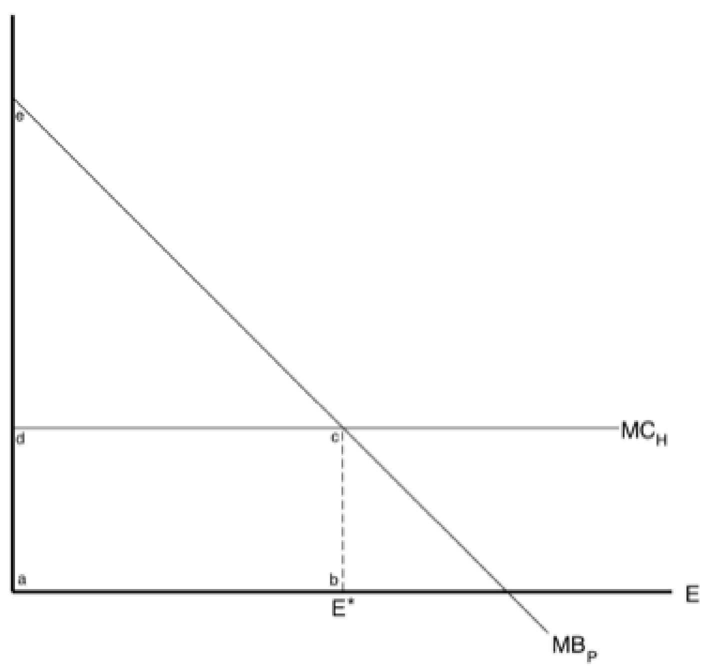
3 Economic Theory

In 'The Problem of Social Cost', Coase argued that in the absence of wealth effects on demand and transaction costs and with well-defined property rights, negotiations between involved parties would result in an efficient outcome. However, in the same paper Coase suggested that real-world transaction costs are rarely sufficiently low that the assumption is met. In the scenario of siting an environmental nuisance, conducting negotiations between the polluter and each individual who might be affected would require a prohibitive amount of time and effort, hence a small group negotiates on behalf of the collective. County officials, for example, typically bargain on behalf of county residents, with compensation coming in the form of tax revenues and money to support construction of other public goods and infrastructure (Jenkins and Maguire 2004). However, this process could be hindered if the negotiators have interests that are misaligned with the group upon which the social cost is imposed. This situation is further described below.

In the model that follows I refer to the community receiving a polluting site as the "host" of the pollution and designate that agent with the subscript "H"; the polluter is designated with the subscript "P". MC_H denotes the marginal cost of another unit of pollution emissions (E) to the host, while MB_P indicates the marginal benefit of another unit of pollution emissions to the polluter.

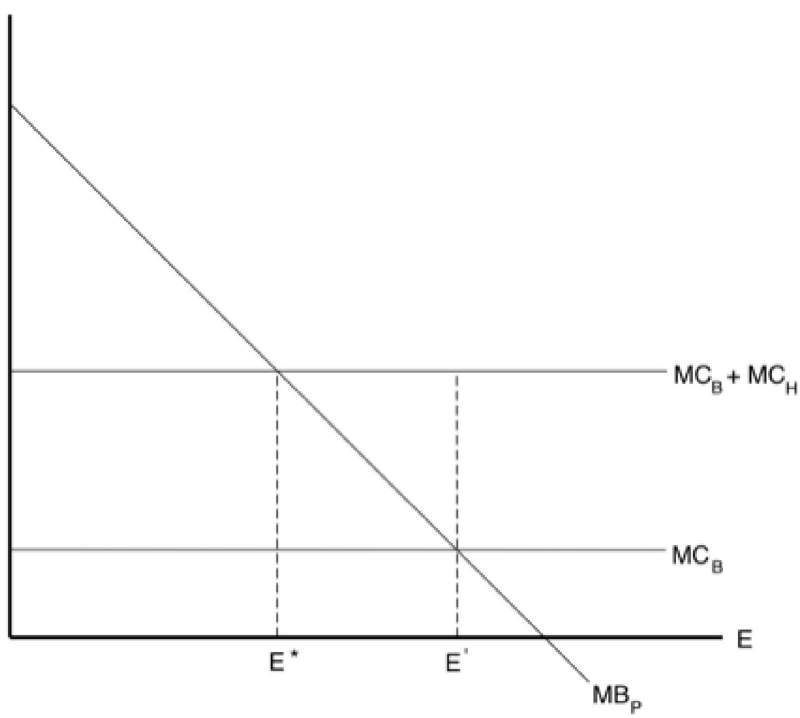
In the classic Coasian framework, if the host has property rights (i.e., in the absence of an agreement, the host is entitled to a pollution-free environment), the polluter will pay an amount equal to or greater than the victim's marginal cost suffered from each unit of pollution. In Figure 1, that payment is measured by the rectangle (abcd) along with, possibly, some portion of the triangle (cde). This leads to an efficient level of pollution emissions (E*), where social surplus is maximized.

Figure 1: Classic Coasian Framework



The above assumes that the negotiators have successfully obtained compensation for the social cost imposed on the host. However, a problem arises if those doing the bargaining (such as representatives of county government) are able to shift the costs of pollution to a poorly represented subgroup (or otherwise avoid the social cost that would be imposed). This might be the case if a minority group with little political representation were geographically segregated and made to bear the brunt of the environmental nuisance while the well-represented majority benefits from the compensation. As the costs of the environmental nuisance are incurred only by those in geographical proximity to the it, when a nuisance is sited in a disadvantaged host community, only the host community incurs the cost while the bargainers themselves are able to avoid it. If so, the costs suffered by the bargainer, MC_B, are lower than those suffered by the host community. The bargainers thus decide to bargain to an inefficient level of emissions (E' in Figure 2); the cost of each unit of emissions beyond E* exceeds the benefits to the polluter, but the decision is made because the true costs of the pollution are not internalized by the agent bargaining on behalf of the victim because of the ability to geographically isolate the pollution with the politically weak group.

Figure 2: Coasian Framework with misaligned bargainer and host interests



It is theorized that areas that are more racially segregated are more likely to see a greater extent of polluting economic activity as the polluter and bargainer are able to reap benefits while imposing the cost of exposure to environmental risk on a separate group. More specifically, I might expect to see that, in racially segregated areas, minority communities that are geographically separate from the larger county population are underrepresented (or unrepresented altogether) in the Coasian bargaining process and as such receive little or no recompense for the environmental risk they face. This causes a disproportionate amount of environmental risk to be shifted onto such communities.

The testable implication of this result is that in locations where bargainers are better able to isolate pollution sources in communities comprised of poorly represented individuals, Coasian bargaining will lead to more pollution siting. I would therefore expect to see more pollution in segregated counties where minority groups are more geographically isolated.

4 Data and Empirical Model

In order to test this hypothesis, two metrics are utilized. The first measures the level of segregation of a geographic area, while the second measures the extent of the environmental nuisance. Three main data sources are employed: (i) the EPA's Toxics Release Inventory records, (ii) summary census data from the National Historic Geographic Information System (NHGIS), and (iii) employment data from the Bureau of Labour Statistics.

4.1 Data on racial segregation

The measurement of racial segregation used in this study is the index of dissimilarity. The index of dissimilarity is a demographic measure of the spatial homogeneity of two racial or ethnic groups distributed across a geographic area. In the context of this study, the geographic area is a county that is comprised of census tracts. The index of dissimilarity is widely utilized and accepted as a summary statistic of residential segregation (Weinberg *et al.*, 2002).

The index of dissimilarity (D) for a particular county can be calculated using the following equation:[5]

$$D = \frac{1}{2}\sum_{i=1}^{n}\left(\frac{a_i}{A} - \frac{b_i}{B}\right) \tag{1}$$

where:

a_i refers to the population of the first racial group in the i^{th} census tract in the county

A refers to the total population of the first racial group in the county

b_i refers to the population of the second racial group in the i^{th} census tract in the county

B refers to the total population of the second racial group in the county

Decennial census data of population by race at census tract and county levels were obtained from the University of Minnesota, Minnesota Population Center's National Historic Geographic Information System (NHGIS) for the years 1990, 2000 and 2010.[6] It is a nominally integrated dataset that is available at both county and census tract levels. Nominally integrated datasets are ones in which geographic units are linked across time via their name and/or identification code and are not necessarily identical in their spatial definition. For the purposes of this work, I assume any minor changes in county spatial definitions to be negligible. Additionally, changes in census tract definitions over time are unimportant as tracts are merely used as a tool in calculating the index of dissimilarity for each county, which is comparable over time. For a small number of counties, no census tract data were available and an index of dissimilarity could not be calculated.

Of note for this dataset, persons of Spanish/Hispanic origin are not explicitly identified. Instead, they fall under the category "Some other race". This is a limitation of

[5]This equation places equal weight on each census tract in the calculation of segregation, in reality, census tracts vary in geographical size and population. However, since census tracts are chosen by design to cover approximately the same population, the absence of weights for actual population is acceptable

[6]NHGIS is managed by the Minnesota Population Center at the University of Minnesota and is funded by grants from the National Science Foundation and the Eunice Kennedy Shriver National Institute of Child Health and Human Development. It provides free on-line access to summary statistics for U.S. censuses beginning in 1790. The dataset retrieved was Table B08: Persons by Detailed Race.

the data available as the Persons by Hispanic or Latino Origin by Race table is only available beginning in 2000.

The index of dissimilarity was then calculated for each county by utilizing the white population as the first racial group and combining the population of all other race groups to form the second racial group. In this study, I sum up the populations of all non-white race groups and assume this to be a single "minority" group. In approximately 8% of all observations, the total population of all non-white race groups exceeds that of the white population. These cases were excluded from consideration.

In order to provide a general understanding of the range of values for the index of dissimilarity, summary statistics are included below in Table 1. Additionally, these indices are also summarized graphically in Appendix A.

Table 1: Table of summary statistics for index of dissimilarity

Year	Mean	Standard Deviation	Minimum[1]	Maximum
1990	0.28212	0.15404	0.0000909	0.8600452
2000	0.25649	0.14700	0.0010712	0.8682151
2010	0.24851	0.13708	0.0004423	0.8294279
All	0.26237	0.14688	0.0000909	0.8682151

[1] For a small subset of counties (in particular those with very small populations), a single census tract spans the entire county. In these instances, the index of dissimilarity is calculated to be 0; these counties are dropped from the calculation of these summary statistics.

4.2 Data on exposure to environmental risk

The metric that I use to quantify exposure to environmental risk or environmental nuisances is "dirty" employment. The data utilized in identifying polluting or dirty industries comes from the TRI, a publicly available database published and maintained by the EPA. TRI data are self-reported, meaning that they are likely have a conservative bias.[7] Additionally, there have been changes in the coverage and criteria

[7] Firms have an incentive to appear as though their level of emissions is lower than it actually is and given that the level of emissions is self-reported, firms will likely under-report the level of

for reporting associated with this program over time. Given the way in which I use these data, these issues are not likely to cause a problem. In particular, I use the data to identify what is and what is not a polluting industry. To this end, I apply Currie *et al.*'s (2015) approach of ignoring the relative magnitudes of the releases and instead use the TRI simply to identify industries in which a firm has ever been required to report to the index. In particular, I identify a firm as "polluting" if it ever reports to the TRI, and then similarly label all firms in that firm's industry as "polluting" as well. This approach is conservative, in that some industries that are not polluting may be identified as such, but would not be likely to locate in segregated counties under my maintained hypothesis. As such, this makes it more difficult for us to find a statistical effect of segregation on polluting employment.

I define industries based on the North American Industry Classification System (NAICS), which is the standard used by most Federal agencies in classifying business establishments since 1997. Specifically, each industry is defined by its 6 digit NAICS code.[8] I will further assume that if an industry is polluting during the time period of the TRI data retrieved (2000-2014), then it was polluting before as well.

The Bureau of Labour Statistics' (BLS) Quarterly Census on Employment and Wages (QCEW) data is used to calculate total employment along with employment specifically in dirty industries, as defined above. The Bureau of Labour Statistics provides annual average employment levels for industries specified at various levels based on their NAICS industry code. In some cases, data are obtained for a time period before the implementation of the NAICS system. These data are crosswalked to a matching 6 digit NAICS code by the BLS. The data made available through the BLS' QCEW are not entirely complete. In particular, the more in-depth an industry code, the higher the likelihood that those data will not be available (that is to say, data are more likely to be missing for an industry identified with a 6 digit code as opposed to industries identified with a 3 digit code). As such, I are unable to observe employment levels for a small portion of the industries identified from the TRI data. Further, some data are unavailable as they have been suppressed for confidentiality

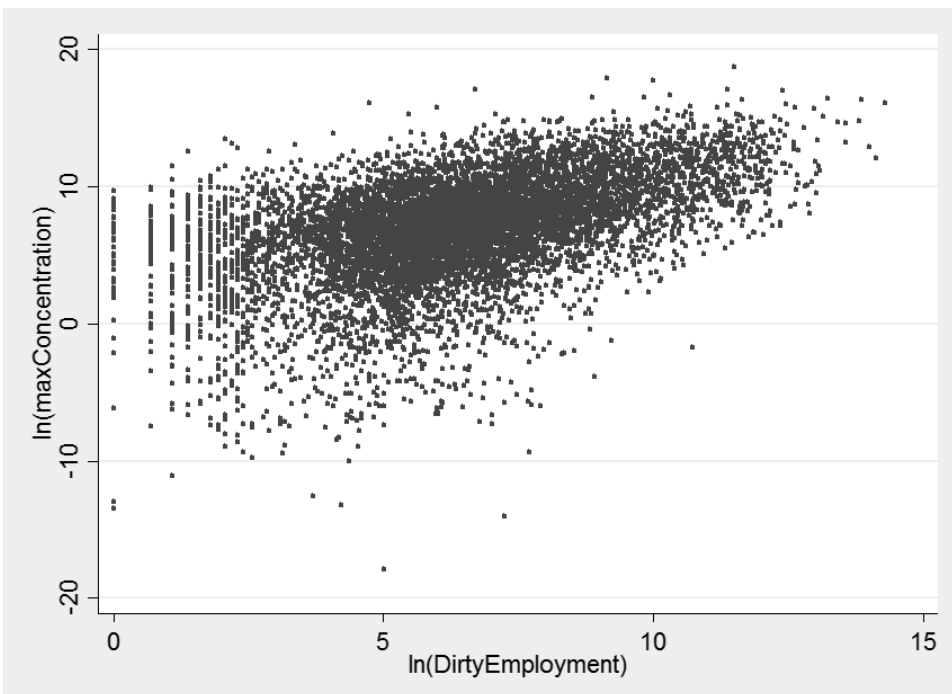
emissions. Alternatively, mistakes that lead to over-reporting are more likely to be corrected by firms than mistakes that lead to under-reporting.

[8]For further information about NAICS refer to http://www.census.gov/eos/www/naics/ or http://www.bls.gov/bls/naics.htm

reasons. Heat maps of the logarithm of the level of dirty employment in each county are provided for illustrative purposes in Appendix A.

As a final check on the relevance of my measure of dirty employment, I demonstrate that it is, in fact, correlated with toxicity at the county level. In order to do so, I employ data from the EPA's Risk Screening Environmental Indicators (RSEI) data set. The RSEI uses data on toxic emissions collected by the Toxic Release Inventory, fate and transport models, and detailed information about the toxicity of each individual pollutant to generate a detailed measure of toxicity for each of a set of 810 x 810 meter grid cells covering the United States. I use the RSEI in each of the three census years to determine the maximum toxicity concentration in each county. Figure 3 compares the log of this measure to the log of dirty employment in the county (pooling across years). The two data series yield a correlation of 0.4953.

Figure 3: Scatter Plot of ln(maximum toxicity) against ln(DirtyEmployment)



4.3 Covariates

In order to control for other possible determinants of changes in employment, additional data were retrieved from NHGIS – county level statistics for Persons by Age, Per Capita Income, Occupied Housing Units by Tenure and Mortgage Status and Educational Attainment of Persons above 25. For these variables, the data are available for the three decades under study (1990, 2000, 2010) with the exception of Per Capita Income and Educational Attainment where the 5-year moving average data (2008-2012) from the 2012 American Community Survey were used in place of data for 2010. These data were also nominally integrated.

5 Results & Discussion

Before presenting the results, it is important to frame their interpretation. The coefficient on the index of dissimilarity (β_1 in the equations below) gives us (approximately) the percentage change in dirty employment for an increase of 1 in the index of dissimilarity. However, the index of dissimilarity is an index that ranges from 0 to 1, and an increase in the dissimilarity index by 1 is extremely unlikely. Instead it might be more useful to examine the effect on $\ln(DirtyEmp_{i,t})$ of a 1 standard deviation change in the index of dissimilarity (from Table 1, σ_D=0.147). $0.147\beta_1$ would thus provides a better intuition of the impact of segregation on the exposure to environmental risk.

5.1 Cross-Sectional Regression Model

I first run a cross-sectional regression of ln(DirtyEmployment) against the index of dissimilarity across the full dataset. Two control variables, %Non-white and ln(PerCapitaIncome) are also added. The equation for this model is:

$$\ln(DirtyEmp)_i = \beta_0 + \beta_1 D_i + \ln(\%NonWhite)_i + \ln(PerCapInc)_i + \epsilon_i \qquad (2)$$

where D_i is the index of dissimilarity. Additional regressions are also run for each decade of data individually with the same controlling variables. The results of these regressions are shown in Table 2. Despite some variation in magnitude, the coefficient of the index of dissimilarity is positive and statistically significant at the 1% level in all six regressions. This is true even in the regressions which controlled for county-wide race and income measures. The mean of the coefficient from the three single decade regressions is 0.603. This means the model predicts that a change of 1 standard deviation in the index of dissimilarity leads to an approximately 9% increase in the level of dirty employment.

While the cross-sectional results may be biased as the model does not control for many other county and time variables that might be correlated with both the index of dissimilarity and the level of dirty employment, they do provide an indication of the long-run impact of segregation on exposure to environmental nuisances.

Table 2: Results of Cross-Sectional Regression

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		All Years		Year 1990	Year 2000	Year 2010
Index of Dissimilarity	6.770***	-0.0465	0.667***	0.372**	0.603***	0.834***
	(0.174)	(0.0946)	(0.0930)	(0.166)	(0.173)	(0.127)
Percentage Minority			-0.354***	-0.122	-0.373**	-0.0911
			(0.0948)	(0.177)	(0.179)	(0.133)
ln(PerCapitaIncome)			1.039***	1.326***	1.270***	1.474***
			(0.0339)	(0.127)	(0.129)	(0.0862)
ln(TotalPopulation)		1.606***	1.471***	1.549***	1.525***	1.263***
		(0.0106)	(0.0108)	(0.0256)	(0.0237)	(0.0148)
Constant	4.739***	-10.21***	-19.03***	-22.34***	-22.00***	-21.24***
	(0.0446)	(0.107)	(0.313)	(1.041)	(1.138)	(0.800)
Observations	7,906	7,906	7,906	2,692	2,632	2,582
R-squared	0.195	0.780	0.805	0.791	0.796	0.855

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

5.2 Panel Data Regression Model

A key challenge in the literature when trying to identify the siting mechanism is the issue of causality. In particular, it is difficult to determine if toxic facilities are sited in an area because of pre-existing attributes of that area, or if toxic facilities (directly or indirectly) cause the area around it to evolve, changing its demographic characteristics.

Regressions in the previous subsection revealed a clear cross-sectional relationship between racial segregation and employment in polluting industries; however, this correlation could just as easily be explained as a case of reverse-causality. In fact, the sorting mechanism described in Section 1 fits such a scenario rather well. It could be suggested that toxic facilities site themselves in some unknown, arbitrary manner, and that racial and low-income minorities move into the surrounding areas to take advantage of discounted house prices whilst the higher-income and racial majority moves away from the surrounding area, giving rise to the increased segregation that I observe above.

In order to address this concern, I conduct a series of panel data regressions. Instead of regressing the level of dirty employment on county attributes in the same time period, I regress the level of dirty employment on county attributes from an earlier time period (including the lagged level of dirty employment). Because I have three decades of decennial data, the level of dirty employment in each of the latter two decades was regressed against attributes from the previous decade along with a county fixed effect ($\beta_{0,i}$) that controls for all county attributes that do not vary over time. The details of the exact specification are as follows:

$$\ln(DirtyEmp_{i,t+1}) = \beta_{0,i} + \beta_1 D_{i,t} + \beta_2 \ln(DirtyEmp_{i,t}) + \beta X_{i,t} + \gamma_t + \epsilon_{i,t} \tag{3}$$

Since it is reasonable to assume that the level of dirty employment in a future period time cannot cause any 'sorting' mechanism in a previous period, this regression tests the hypothesis that it is segregation that causes the increase in dirty employment and not vice versa.

Three different specifications are tested, with each specification being carried out twice (with and without a time fixed effect). Specifications (1) and (2) are basic regressions with no control variables included. The coefficient on the index of dissimilarity in specification (1) is negative, however, applying a time fixed effect (specification (2)) results in a finding that the index of dissimilarity has no significant effect on future dirty employment.

Next, basic control variables are added. I control for the population of the county, the per capita income as well the the percentage of the county that is non-white. Addition of these controls (specifications (3) & (4)) result in a statistically significant and positive impact of the index of dissimilarity on future dirty employment.

Finally, I include additional possible covariates such as education level (percentage of persons above 25 with at least a bachelor's degree) as well as several 'collective action' variables (percentage of housing units which were rented, percentage of residents above 65 and percentage of residents under 5) which measure the propensity of a community towards collective action (Hamilton, 1995). The inclusion of these additional covariates in specifications (5) & (6) gives us results that again indicate that the index of dissimilarity has a positive and significant effect on future dirty employment.

Based on the model represented in specification (6), which includes all control variables as well as a time and county fixed effects, I predict that a 1 standard deviation increase in the dissimilarity index results in an approximately 8% increase in the level of future dirty employment.

As a check on the model, I look at the coefficients for each of the various control variables included in the model. The signs are reasonable. Communities with more young children are more susceptible to negative health effects – hence, a higher propensity for collective action against environmental hazards and a negative effect on future dirty employment. Similarly, communities with more elderly residents have a greater propensity for collective action and a similar negative effect on future dirty employment. Communities with more residents renting rather than owning a house are likely to have a smaller propensity for collective action – hence, a positive effect on future dirty employment. Finally, as the education level of the community rises, residents are more likely to be aware of the full costs imposed on them by environmental hazards and thus a negative effect on future dirty employment.

As an extension, additional regressions were carried out by census regions and divisions. These results are included in Section 5.4.

Table 3: Results of lagged fixed effects regression model

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			$\ln(DirtyEmployment_{i,t+1})$			
ln(DirtyEmployment)	0.413***	0.134***	-0.0360	-0.0196	-0.0568	-0.0393
	(0.0357)	(0.0477)	(0.0533)	(0.0542)	(0.0529)	(0.0534)
Index of Dissimilarity	-1.051***	-0.0959	0.454**	0.561***	0.385**	0.525***
	(0.190)	(0.214)	(0.190)	(0.188)	(0.186)	(0.185)
Percentage Minority			-4.087***	-4.988***	-3.565***	-4.658***
			(0.314)	(0.399)	(0.333)	(0.425)
ln(PerCapitaIncome)			0.963***	0.140	1.237***	0.328
			(0.0581)	(0.219)	(0.0817)	(0.225)
ln(TotalPopulation)			0.499***	0.582***	0.754***	0.798***
			(0.114)	(0.116)	(0.129)	(0.132)
% Degree Holder					-4.255***	-4.241***
					(0.557)	(0.550)
% Renters					1.207*	0.790
					(0.718)	(0.726)
% Above 65					-3.630***	-4.509***
					(1.190)	(1.287)
% Under 5					-4.969**	-3.079
					(1.999)	(1.931)
2000.year		0.213***		0.390***		0.447***
		(0.0218)		(0.101)		(0.103)
Constant	6.110***	8.244***	-5.037***	1.753	-9.310***	-1.113
	(0.363)	(0.442)	(1.146)	(2.141)	(1.654)	(2.637)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,174	5,174	5,174	5,174	5,174	5,174
R-squared	0.137	0.204	0.272	0.277	0.301	0.307
Number of area_fips	2,630	2,630	2,630	2,630	2,630	2,630

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

5.3 Robustness models

In order to test the results for robustness, two additional specifications were run: (1) using a ‘placebo’ model and (2) using 5-digit NAICS codes.

5.3.1 'Placebo' model

My hypothesis suggests that more segregated counties are likely to have more employment in dirty industries in the future. The 'placebo' model is one in which I attempt to determine the effect of segregation on future total employment in the county. This allows us to verify that the level of segregation affects future dirty employment specifically and not just total employment.

I find that the effect of the index of dissimilarity of a county on the future total employment in that county is statistically insignificant, which my determination that the effect of segregation is restricted to future dirty employment and not future total employment. This result was consistent across all the specifications.

Table 4: Results of 'Placebo' model

	(1)	(2)	(3)	(4)	(5)
Variables			$\ln(TotalEmployment_{i,t+1})$		
ln(TotalEmployment)	0.402***	0.448***	0.0867**	0.0730*	0.0643
	(0.0318)	(0.0324)	(0.0414)	(0.0403)	(0.0397)
Index of Dissimilarity	0.0514	0.101	0.0614	0.0713	0.0480
	(0.0651)	(0.0664)	(0.0579)	(0.0570)	(0.0564)
ln(PerCapitaIncome)		-0.252***	-0.224***	-0.271***	-0.215***
		(0.0695)	(0.0619)	(0.0599)	(0.0622)
% Minority		-0.486***	-0.709***	-0.786***	-0.647***
		(0.133)	(0.126)	(0.134)	(0.138)
% Renters				-0.624***	-0.377
				(0.228)	(0.242)
% Above 65					0.862*
					(0.470)
% Under 5					-1.257**
					(0.628)
% Degree Holder				0.498**	0.482**
				(0.222)	(0.220)
2000.year	-0.0869***	0.0372	0.0353	0.0357	-0.00239
	(0.00708)	(0.0313)	(0.0279)	(0.0281)	(0.0307)
ln(TotalPopulation)			0.580***	0.541***	0.577***
			(0.0553)	(0.0568)	(0.0561)
Constant	6.869***	8.812***	5.617***	6.795***	5.813***
	(0.355)	(0.674)	(0.725)	(0.728)	(0.804)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	5,230	5,230	5,230	5,230	5,230
R-squared	0.243	0.255	0.355	0.366	0.373
Number of area_fips	2,653	2,653	2,653	2,653	2,653

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

5.3.2 5-digit NAICS definitions

A key point of contention commonly raised in the EJ literature is that of the definition of pollution/environmental risk. As noted in Section 4, this study utilizes 6 digit NAICS codes to define each industry. As a test of the robustness of the results above to varying definitions of polluting industries, the same series of regressions from Section 5.2 were run utilizing 5 digit NAICS codes to define industries instead. The results of these regressions are presented in Table 5.

Table 5: Results from fixed effects model using 5 digit NAICS definitions

	(1)	(2)	(3)	(4)	(5)	(6)
Variables			$\ln(DirtyEmployment_{i,t+1})$			
ln(DirtyEmployment)	0.293***	0.173***	-0.0230	-0.0202	-0.0493	-0.0461
	(0.0420)	(0.0497)	(0.0496)	(0.0502)	(0.0510)	(0.0516)
Index of Dissimilarity	-0.993***	-0.314	0.492**	0.511**	0.476**	0.500**
	(0.236)	(0.267)	(0.232)	(0.234)	(0.237)	(0.237)
ln(TotalPopulation)			0.673***	0.687***	1.104***	1.112***
			(0.135)	(0.134)	(0.162)	(0.162)
ln(PerCapitaIncome)			0.911***	0.765***	1.324***	1.148***
			(0.0694)	(0.277)	(0.0947)	(0.305)
% Minority			-5.742***	-5.899***	-4.680***	-4.873***
			(0.396)	(0.507)	(0.437)	(0.576)
% Degree Holder					-6.370***	-6.378***
					(0.643)	(0.643)
% Renters					1.326	1.234
					(0.998)	(0.995)
% Above 65					-5.467***	-5.631***
					(1.581)	(1.662)
% Under 5					-4.900*	-4.562*
					(2.637)	(2.578)
2000.year		0.123***		0.0689		0.0858
		(0.0237)		(0.129)		(0.142)
Constant	7.663***	8.544***	-5.806***	-4.608*	-13.05***	-11.46***
	(0.458)	(0.507)	(1.321)	(2.755)	(2.080)	(3.570)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,189	5,189	5,189	5,189	4,726	4,726
R-squared	0.063	0.086	0.182	0.182	0.231	0.231
Number of area_fips	2,638	2,638	2,638	2,638	2,400	2,400

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

These results corroborate those presented in Section 5.2, the coefficients for the index of dissimilarity are similar in magnitude and are still statistically significant. This result implies that the study is indeed robust to some variation in the definition of a polluting industry.

5.4 Extended results by Census Regions and Divisions

Additional county and time fixed effect regressions were run by census regions and divisions.[9] The results for the regressions by census region are shown in Table 6 and the results for the regressions by census divisions are shown in Tables 7 & 8. When broken down by census regions and divisions, the coefficient on the index of dissimilarity is positive and statistically significant at the 1% level in 2 out of 4 census regions. However, when carried out on census divisions, only 1 division retains statistical significance at a 1% level. As the fixed-effects model is carried out on individual regions or divisions, the number of counties used to identify each regression coefficient drops substantially; this could be the reason that some parameters begin to lose statistical significance. In particular, the regressions on the Northeast and West regions (that have less than 500 counties observed) yield parameters that are not statistically significant. On the other hand, the Midwest and the South (that have upwards of 1000 counties observed) yield parameters that are statistically significant at the 1% level.

[9] Details of how the US is broken down into regions and divisions can be found at: https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf

Table 6: Results of regression by census region

Variables	(1) Northeast	(2) Midwest	(3) South	(4) West
ln(DirtyEmployment)	0.197	-0.0115	-0.103	0.118
	(0.139)	(0.0740)	(0.0811)	(0.0769)
Index of Dissimilarity	0.217	0.831***	0.817**	-0.0314
	(0.463)	(0.265)	(0.338)	(0.533)
ln(PerCapitaIncome)	0.890	0.906**	0.313	-0.486
	(0.669)	(0.408)	(0.407)	(0.443)
Percentage Minority	-1.266	-6.121***	-4.244***	-4.796***
	(1.008)	(0.758)	(0.664)	(0.843)
% Degree Holder	-3.435***	-1.803	-4.122***	-4.249***
	(1.204)	(1.192)	(0.981)	(1.296)
% Renters	6.139***	-2.659**	1.237	-0.0963
	(1.625)	(1.168)	(1.176)	(1.121)
% Above 65	3.490	-12.23***	-4.097**	-4.421*
	(2.574)	(2.301)	(2.007)	(2.406)
% Under 5	-12.75***	2.595	-4.712	-7.725*
	(3.595)	(4.160)	(3.951)	(4.098)
ln(TotalPopulation)	0.544*	0.0287	1.068***	0.318
	(0.305)	(0.260)	(0.227)	(0.248)
2000.year	-0.0491	0.178	0.465**	0.733***
	(0.282)	(0.186)	(0.196)	(0.215)
Constant	-7.956	3.004	-4.063	12.81**
	(7.678)	(4.516)	(4.570)	(5.115)
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	414	1,855	2,293	612
R-squared	0.458	0.300	0.325	0.393
Number of area_fips	209	934	1,172	315

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

Table 7: Results of regression by census division

Variables	(1) New England	(2) Middle Atlantic	(3) East North Central	(4) West North Central
ln(DirtyEmployment)	0.0211	0.254	0.0309	-0.0105
	(0.119)	(0.174)	(0.0967)	(0.110)
Index of Dissimilarity	0.0426	0.393	0.619	0.670
	(0.834)	(0.534)	(0.389)	(0.425)
ln(PerCapitaIncome)	1.380**	0.171	0.854	1.249**
	(0.654)	(0.954)	(0.577)	(0.589)
% Minority	-0.845	-1.600	-5.504***	-6.569***
	(1.256)	(1.493)	(1.144)	(1.065)
% Degree Holder	-0.647	-4.749**	-3.246**	-1.770
	(1.632)	(1.842)	(1.489)	(1.533)
% Renters	5.836***	3.796	-1.170	-3.044*
	(1.827)	(2.369)	(1.582)	(1.707)
% Above 65	5.432	-0.321	-14.46***	-5.304
	(4.367)	(3.368)	(3.271)	(3.390)
% Under 5	-17.78***	-11.43**	12.66**	1.655
	(4.031)	(4.960)	(5.181)	(6.540)
ln(TotalPopulation)	0.0364	0.474	0.324	-0.594*
	(0.504)	(0.417)	(0.360)	(0.324)
2000.year	-0.442*	0.331	0.240	0.186
	(0.252)	(0.431)	(0.262)	(0.258)
Constant	-4.824	0.675	-0.806	5.629
	(9.540)	(10.73)	(6.102)	(6.559)
County Fixed Effects	Yes	Yes	Yes	Yes
Observations	133	281	854	1,001
R-squared	0.601	0.463	0.306	0.353
Number of area_fips	67	142	430	504

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

Table 8: Results of regression by census division (Cont'd)

Variables	(1) South Atlantic	(2) East South Central	(3) West South Central	(4) Mountain	(5) Pacific
ln(DirtyEmployment)	-0.170	-0.0377	-0.244*	0.102	-0.0593
	(0.148)	(0.108)	(0.126)	(0.0924)	(0.127)
Index of Dissimilarity	0.598	-0.667	1.939**	0.604	-0.821
	(0.447)	(0.626)	(0.953)	(0.726)	(0.890)
ln(PerCapitaIncome)	0.130	0.702	-1.591**	-0.633	-0.184
	(0.578)	(0.914)	(0.792)	(0.513)	(0.562)
% Minority	-3.777***	-5.957***	-9.079***	-6.457***	-0.155
	(0.741)	(1.857)	(1.774)	(1.042)	(1.399)
% Degree Holder	-1.572	-4.561*	-2.635	-3.716*	-5.583***
	(1.233)	(2.360)	(2.916)	(1.917)	(1.832)
% Renters	2.030	-1.291	0.228	2.350	-3.427*
	(1.621)	(2.254)	(2.515)	(1.724)	(1.948)
% Above 65	-1.551	-7.319*	-8.130**	-8.417***	3.509
	(2.127)	(4.187)	(3.467)	(2.661)	(4.103)
% Under 5	-7.057	11.80	-7.494	-7.426	-5.110
	(4.769)	(9.858)	(10.52)	(5.714)	(6.790)
ln(TotalPopulation)	1.059***	0.925**	1.457***	0.158	1.159***
	(0.296)	(0.401)	(0.501)	(0.312)	(0.399)
2000.year	0.366	0.249	1.636***	1.033***	0.211
	(0.265)	(0.437)	(0.428)	(0.251)	(0.312)
Constant	-2.263	-6.354	11.85	15.67***	0.900
	(5.841)	(10.21)	(8.242)	(5.311)	(7.079)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	966	626	701	391	221
R-squared	0.287	0.314	0.470	0.478	0.433
Number of area_fips	493	317	362	199	116

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

6 Conclusion

The debate surrounding the causes and consequences of environmental injustice is varied and complex, with researchers, politicians and activists each adopting different stances on the scale, impact and cause of the disproportionate exposure to environmental hazards. Indeed, even defining an environmental hazard is a challenging process. This paper attempts to examine and test a single mechanism causing the disproportionate incidence of environmental risk - segregation and its effect on the siting of environmental nuisances. The reasoning is based on the economic theory described by Coase (1960) which explains that through a bargaining process, an efficient outcome can be achieved despite the imposition of an external cost on host communities by polluting facilities. However, the challenges associated with real-world bargaining, caused by the existence of transaction costs (which necessitates the use of proxies in negotiation) and government failure, result in a breakdown of this bargaining process.

The results presented above show evidence that, even after controlling for county-level measures of income, racial mix, education and propensity for collective action, counties of greater racial segregation have higher levels of employment in industries that report emissions in the TRI. This bolsters the belief that in counties where there exist racial minority groups that are segregated, Coasian bargaining fails to achieve an efficient outcome. More specifically, in such counties, the resulting level of exposure to environmental hazard is higher than efficient level.

This result has implications for EJ policymaking. Specifically, finding that it is a failure of the bargaining process that results in the dispropotionate burden of exposure to environmental hazards suggests that policies aiming to rectify this should attempt to ensure that host communities are able to express their desire for compensation. If host communities are indeed able to do so, then firms making siting decisions would respond in a manner such that an efficient outcome is achieved. There are various ways in which host communities could better express their compensation requirement – this could be done by requiring firms to bargain more directly with a host community rather than with a group situated in a different geographic area within the county, or by implementing failsafes to ensure that the group bargaining on behalf of the host community provides a fair representation of the preferences of the host community. Either of those suggestions would provide a greater level of procedural justice in the siting process.

While this paper tackles the specific issue of the failure of Coasian bargaining, it does not reject the existence of other mechanisms that could also result in the current disproportionate exposure of environmental hazards. It does however, highlight a lack of procedural justice that is in contrast to the EPA's stance of "equal access to the decision-making process to have a healthy environment in which to live, learn, and work". Subsequent policy making should consider the issue of procedural justice and the role of Coasian bargaining in determining if equitable exposure to nuisances is achieved.

Further work could attempt to more explicitly identify the causal relationship between segregation and siting. One possible avenue for this is to narrow the scope under consideration and conduct an in-depth geospatial analysis of the location of TRI facilities relative to the location of segregated communities. An alternative would be to directly verify if the geographic area (census tract) in which a segregated community is located faces a level of environmental risk disproportionately higher than that of other geographic areas in the same county. The siting mechanism I have described would imply that the toxic facilities are sited in/near to the area with a segregated community, causing that area to have a higher level of environmental risk. It would also be interesting to see further analysis utilizing different definitions of environmental risk and different choices of geographic unit of measurement yield similar conclusive results.

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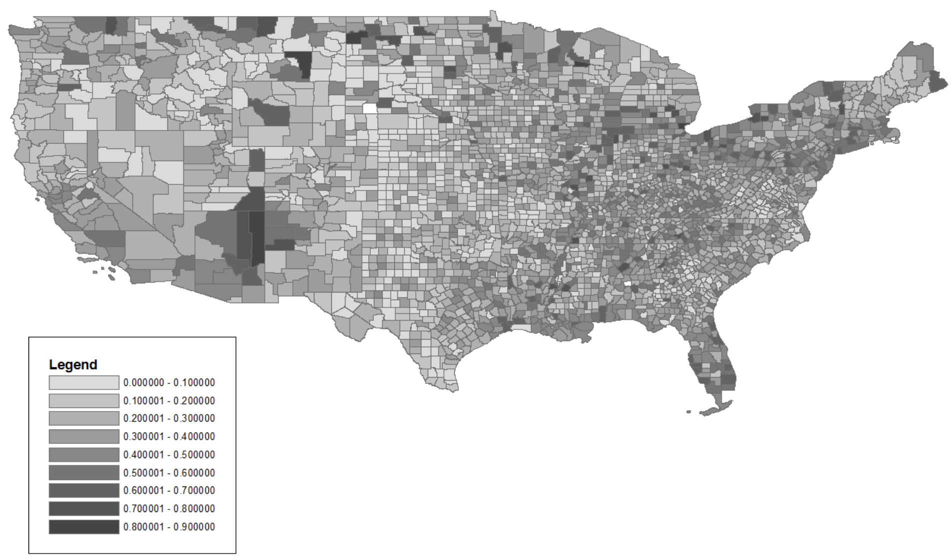
A Summary Data Figures

Figures 4, 5 and 6 are figures illustrating the index of dissimilarity in each county in the years 1990, 2000 and 2010 respectively. Figure 7 provide an additional illustration of the relative change in the indices between 1990 and 2010.

Figures 8, 9 and 10 are heat maps of $\ln(DirtyEmp)$ in 1990, 2000 and 2010

Figure 4: Heat map of index of dissimilarity in 1990



respectively. Figure 11 further provides a heat map of the relative change from 1990 to 2010.

Figure 5: Heat map of index of dissimilarity in 2000

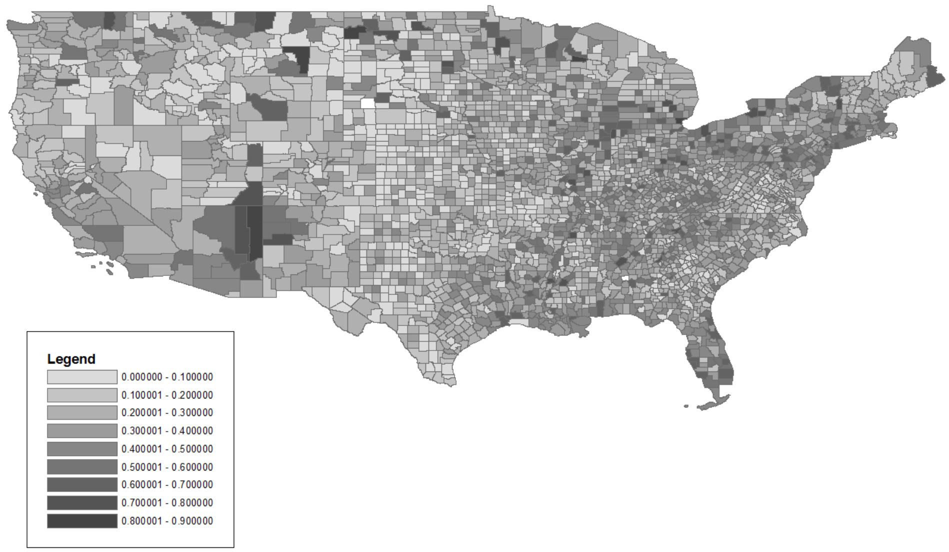


Figure 6: Heat map of index of dissimilarity in 2010

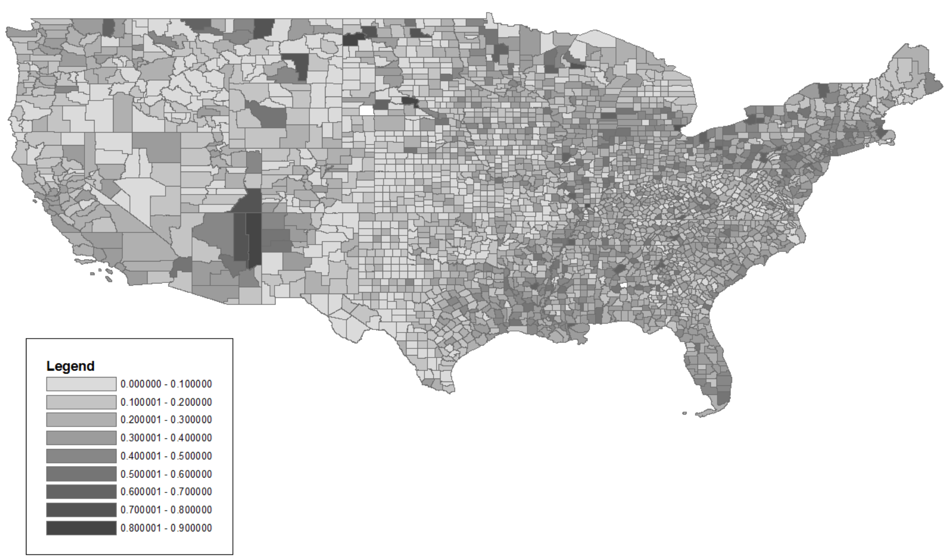


Figure 7: Heat map of change in index of dissimilarity between 1990 and 2010

Figure 8: Heat map of ln(DirtyEmp) in 1990

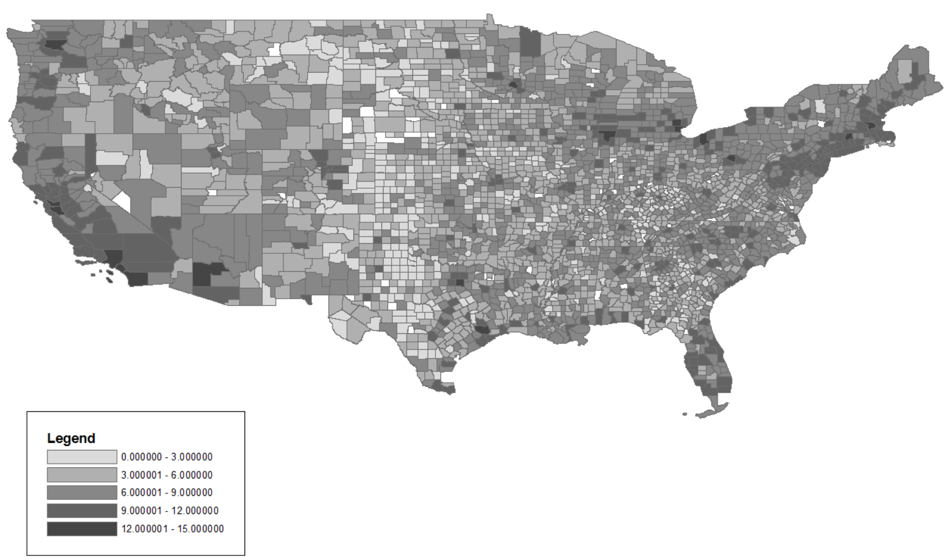


Figure 9: Heat map of ln(DirtyEmp) in 2000

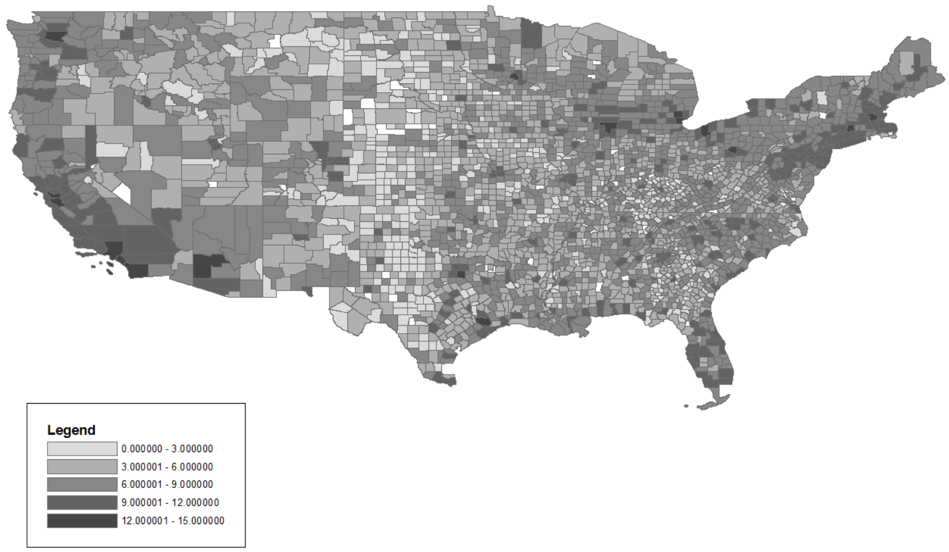


Figure 10: Heat map of ln(DirtyEmp) in 2010

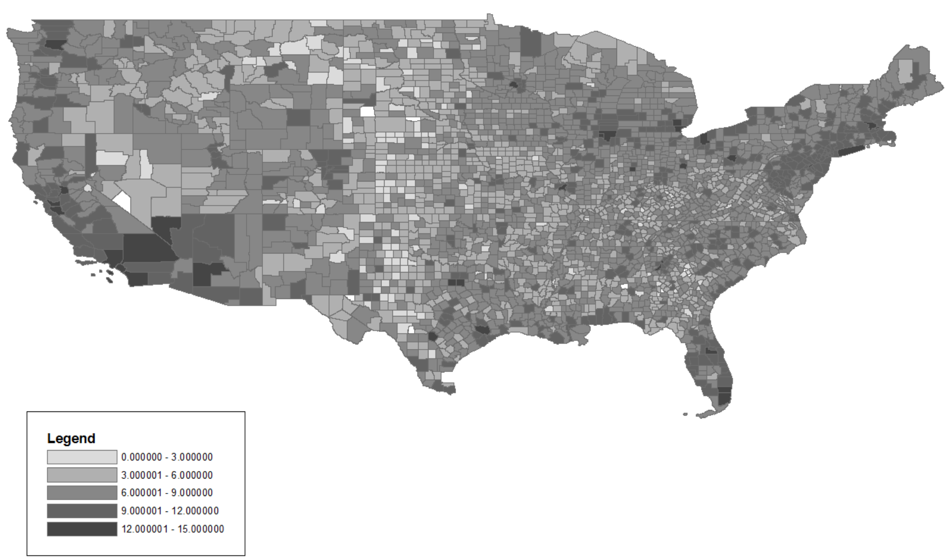


Figure 11: Heat map of change in ln(DirtyEmp) between 1990 and 2010