White Flight and Coming to the Nuisance: Can Residential Mobility Explain Environmental Injustice?

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Abstract: Effective environmental justice (EJ) policy requires an understanding of the economic and social forces that determine the correlation between race, income, and pollution exposure. We show how the traditional approach used in many EJ analyses cannot identify nuisance-driven residential mobility. We develop an alternative strategy that overcomes this problem and implement it using data on air toxics from Los Angeles County, California, USA. Differences in estimated willingness to pay for cleaner air across race groups support the residential mobility explanation. Our results suggest that Hispanics may dislike cancer risk but be less willing to trade other forms of consumption to avoid it. As a result, household mobility responses may work against policies designed to address inequitable siting decisions for facilities with environmental health risks.

JEL Codes: C33, D63, Q53, R21, R23

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THE ENVIRONMENTAL JUSTICE (EJ) movement in the United States is generally acknowledged to have grown out of the events following the illegal dumping of 31,000 gallons of PCB-contaminated oil along 240 miles of North Carolina highways

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in 1978.[1] Subsequent to the prosecution of those responsible for the dumping, the government of North Carolina was tasked with disposing of over 40,000 cubic yards of contaminated soil. The contentious process that ensued resulted in the creation of a landfill site in Warren County, which was (and continues to be) predominantly low income and black, despite the availability of arguably better sites elsewhere in the state. The protests that followed the siting decision led to influential studies by the General Accounting Office (US GAO 1983) and the United Church of Christ's Commission on Racial Justice (UCC 1987), which demonstrated that poor and minority communities were disproportionately exposed to hazardous wastes in many parts of the United States. The momentum from these studies led to President Bill Clinton's issuing of Executive Order 12898 in 1994, requiring all federal agencies to take environmental justice concerns into consideration when making rules. A consequence of this order is that federal agencies require some understanding of the nature of and causes behind inequitable exposure to pollution sources. The research community has subsequently followed with a large (and growing) EJ literature.

EJ policy concerns have not dissipated since Clinton's executive order—in fact, they have recently gained renewed attention from the US Environmental Protection Agency (EPA).[2] Moreover, research continues to show that disproportionate exposure to pollution is still an issue. Two decades after its historic EJ analysis, the United Church of Christ (UCC 2007) reported that 43.7% of residents within 1 kilometer of a hazardous waste facility were African American or Hispanic, whereas that number falls to only 19% outside of a 5 kilometer buffer. Given the persistence of this outcome, EJ researchers have continued to gather evidence for and against the competing explanations for the observed correlations between race, income, and pollution. Is it the result of inequitable (possibly discriminatory) siting of landfills, hazardous waste facilities, sources of toxic emissions, and other "locally undesirable land uses" (LULU's)? Is it the result of disproportionate or discriminatory application of enforcement activities? Alternatively, is it the result of residential mobility that follows the siting of a nuisance? Residential mobility presents a challenge for some EJ policies since it suggests that the policy goal of equitable exposure may be undermined when residents with the means to do so move away from a LULU and their homes are repopulated by lower-income residents (see, e.g., Been 1994). It is this final question that we seek to address.

Economic models of housing demand provide a useful framework for understanding how environmental injustice is related to residential mobility. Each year, more than 30 million people move from one home to another (Ihrke 2014). Common

1. For a general discussion of the Ward Transformer case and the events that followed, see Exchange Project (2006).

2. See the details of the EPA's "Plan EJ 2014" at www.epa.gov/compliance/ej/plan-ej.

reasons given for moving are housing related (48%), family related (30%), and employment related (19%). Within-county moves are more likely to be driven by housing-related reasons, while between-county moves are more likely to be brought about by job-related factors (Ihrke 2014).

Although improved housing can be purchased or rented by reallocating expenditures toward housing structure and neighborhood quality and reducing consumption of other goods, home buyers and renters do have alternatives. For example, a mover might choose a home that is located near a hazardous waste site or other LULU—this behavior has typically been referred to as "coming to a nuisance" (Been 1994) or "minority move-in" (Morello-Frosch et al. 2002). A model of utility-maximizing households trading off housing stock, neighborhood quality, and other (dis)amenities is at the heart of most residential sorting models (see Kuminoff, Smith, and Timmins [2013] for an overview) and could explain "coming to the nuisance" as a rational response to opportunities in the housing marketplace. Measuring the trade-offs made by different groups of home buyers and renters requires knowing their circumstances both before and after their moves. Without individual "before and after" information, finding evidence of the residential mobility hypothesis (both "fleeing the nuisance" by some groups and "coming to the nuisance" by others) is difficult.

EJ researchers have historically turned to readily available geographically aggregated (e.g., census tract) data describing population flows in order to look for evidence of nuisance-driven residential mobility. That approach, however, has drawbacks. Our paper shows how those traditional empirical models are unidentified but offers an alternative. Applying that alternative approach to data from Los Angeles County, California, we find evidence that residential mobility plays an important role in determining the observed correlations between income, race, and pollution exposure while the traditional model continues to discount the role of residential mobility. The results raise questions about the strength of the existing evidence against residential mobility and the effectiveness of commonly proposed EJ policies. Our results support suggestions (e.g., Banzhaf 2012) that dealing with environmental injustice may require addressing income disparities.

This paper proceeds as follows. Section 1 reviews the EJ literature that has sought to distinguish the competing roles of housing market dynamics and inequitable siting and explains why the approach typically used to recover the role of residential mobility is not actually able to do so. Section 2 describes the data sets that we use to model residential decisions and neighborhood sociodemographics and discusses how we measure the "nuisance" in our empirical application—in particular, total cancer risk taken from the EPA's National Air Toxics Assessment. Section 3 uses those data to estimate both a traditional EJ model of residential mobility and our alternative model. Results are reported and contrasted with one another. Section 4 concludes and discusses policy implications.

1. UNRAVELING THE CAUSES OF RACE-INCOME-POLLUTION CORRELATION

1.1. Previous Research

A number of early longitudinal studies found little or no evidence of nuisance-driven residential mobility, concluding instead that significant demographic changes had not occurred after the siting of hazardous waste storage and disposal facilities (Oakes, Anderton, and Anderson 1996; Been and Gupta 1997; Shaikh and Loomis 1999; Pastor, Sadd, and Hipp 2001; Morello-Frosch et al. 2002). Like our analysis, the study by Pastor et al. (2001) focuses on Los Angeles County. Similar to most other studies, it adopts a geographically aggregated (census tract) approach and uses multivariable regression and simultaneous equation methods to conclude that disproportionate facility siting provides a better explanation for the correlation between race and proximity to toxic storage and disposal facilities.

There have been assessments of residential choice behavior that do provide some evidence in favor of housing market dynamics. Been (1994), for example, finds evidence in favor of both the disproportionate siting and residential mobility hypotheses in her study of the areas surrounding the sites used by Bullard (1983) and US GAO (1983). Using geographically aggregated choices, Cameron and McConnaha (2006) examine environmentally motivated migration near four Superfund sites and find evidence in favor of nuisance-driven residential mobility for some of them. Banzhaf and Walsh (2008) use a model based on Epple, Filimon, and Romer (1984) to predict that communities experiencing reductions in TRI (Toxics Release Inventory) emissions will see increases in total population, and they confirm this prediction with data from California. Additionally, they predict that increases in air pollution levels will encourage higher-income households to exit a community, whereas lower-income households will be more likely to enter. However, Banzhaf and McCormick (2007) demonstrate that similar predictions cannot be made about neighborhood-level race variables when home buyers have heterogeneous preferences. Banzhaf and Walsh (2013) demonstrate that predictions become even more complicated when home buyers have preferences for the race of their neighbors.

Crowder and Downey (2010) conduct one of the only analyses in the EJ literature that uses individual residential location choice data to examine proximity to pollution (toxic emissions measured at the census tract level), propensity to move, and the neighborhoods chosen by black and Latino households. Their study finds that, when they move, black and Latino households tend to move into neighborhoods with significantly higher emissions measured by the Toxics Release Inventory than comparable white households, suggesting a population dynamic that would lead to disproportionate pollution exposure by race. While their paper provides significant insights, it is important to note that their analysis does not assess how an individual's pollution exposure changes when she moves from one house to another. Seeing a purchase of a house 2 miles from a toxic site implies something very different depending on where the home buyer moved from. For example, if the buyer comes from a house that is 1 mile from a site, the purchase would result in reduced exposure; it would result in increased exposure, however, if the buyer comes from a house 10 miles from a site.

Although data describing individual residential choices are a welcome addition to the EJ literature, use of such data is generally limited by availability, coverage, and other practical (e.g., confidentiality) constraints. Analysis of geographically aggregated choices will continue to be a popular and practical method until more (larger) individual panel applications are developed. Next, we show why methods typically used to examine aggregated choices are unidentified.

1.2. Nonidentification in the Traditional Model of Residential Mobility

In the absence of clear theoretical predictions about the response of race to pollution (Banzhaf and McCormick 2007), assessing the role of residential mobility becomes an empirical question. However, geographically aggregated population statistics (e.g., changes in census tract demographics) cannot be used as evidence for or against the hypotheses of "white flight" or that people of color "come to the nuisance" to meet housing needs. To illustrate why, we work through the following simple example.

Consider a housing market with just three locations (j = 1, 2, 3) observed in each of two time periods (t = A, B). We use pop_j^t to measure the population in location j in period t.[3] The term $P_{j,k}$ is used to denote the probability that an individual in location k in period A chooses to reside in location j in period B. The market dynamics associated with this collection of locations are described by the following system of equations:

$$\begin{pmatrix} P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,1} & P_{3,2} & P_{3,3} \end{pmatrix} \begin{pmatrix} pop_1^A \\ pop_2^A \\ pop_3^A \end{pmatrix} = \begin{pmatrix} pop_1^B \\ pop_2^B \\ pop_3^B \end{pmatrix}. \tag{1}$$

A traditional EJ analysis like Pastor et al. (2001) considers the change in the population of a particular subgroup in each location j (i.e., $\Delta pop_j = pop_j^B - pop_j^A$) and compares it to the initial exposure to the environmental amenity associated with the location (α_j^A). The expression $\partial \Delta pop_j / \partial \alpha_j^A > 0$ is taken as evidence that members of the subgroup in question "flee the nuisance" (or, alternatively, "come to the amenity" denoted by α_j^A). Unfortunately, the interpretation is not that simple. The individual behavior of "coming to" or "fleeing from" the nuisance is instead described by the elements of the matrix $[P_{j,k}]$ and the way in which $P_{j,k}$ covaries with the change in exposure associated with the move from k to j $\left(\Delta\alpha_{j,k}^{A,B}\right)$. The elements of $[P_{j,k}]$ provide a true measure of how the change in exposure associated with a move affects the tendency of individuals to make that move.

3. In most EJ analyses, pop_j^t will refer to the population of a particular race or income subgroup. Without loss of generality, we refer to a single population group in this example.

The empirical challenge is that the vector of changes in population over time does not identify the matrix $[P_{j,k}]$. Recognizing that

$$\sum_j P_{j,k} = 1 \ \forall \ k = 1, 2, 3, \tag{2}$$

equations (1) and (2) constitute a system of six equations with nine unknown values of $P_{j,k}$. The system is, therefore, underidentified. Put differently, without additional structure, there is not a unique $[P_{j,k}]$ matrix that can explain the observed changes in aggregate populations. We expand upon this idea with a series of numerical examples. In each, we consider a different $[P_{j,k}]$ matrix; for simplicity, in each example we maintain the same distribution of amenity levels in both periods: $\alpha_1^A = \alpha_1^B = \alpha_1 = 0$, $\alpha_2^A = \alpha_2^B = \alpha_2 = 0.5$, and $\alpha_3^A = \alpha_3^B = \alpha_3 = 1$.[4]

In the first two numerical examples, $[P_{j,k}]$ is constructed to yield the same changes to population in each location: $\Delta pop_1 : 3 \rightarrow 1.8$, $\Delta pop_2 : 2 \rightarrow 2.2$, $\Delta pop_3 : 1 \rightarrow 2$. As a result, both examples are characterized by the same aggregate population dynamics. Although a traditional EJ analysis would interpret these population dynamics as “fleeing the nuisance” (i.e., population falls in the low-amenity community and rises in the high-amenity community), a regression of $P_{j,k}$ on the change in the amenity associated with a move from k to j, $\Delta\alpha_{j,k}^{A,B}$, and an intercept shows that the true individual market dynamics in each example are different. The estimated parameter on $\Delta\alpha_{j,k}^{A,B}$ in example 1, -0.0583, reflects “coming to the nuisance” (i.e., an improvement in the amenity makes a particular move less likely), while the estimated parameter in example 2, 0.0833, provides evidence of “fleeing the nuisance” (i.e., an improvement in the amenity makes the move more likely). *P*-values are reported in brackets.[5]

Example 1:

$$\begin{pmatrix} 0.00 & 0.60 & 0.60 \\ 0.50 & 0.25 & 0.20 \\ 0.50 & 0.15 & 0.20 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1.8 \\ 2.2 \\ 2.0 \end{bmatrix} \quad \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}.$$

Slope coefficient = -0.0583 [0.666] (coming to the nuisance).

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4. In our application, amenities do change over time. However, in this example (and in the rest of the EJ literature), we do not model individuals as having foresight with respect to how amenities will evolve in the future. Bayer et al. (2011) estimate a model of forward-looking residential home buyers. For the purposes of an EJ analysis, that approach is impractical both in terms of computational and data requirements.

5. In each case, we use observations where $j \neq k$, noting that the elements in each column of $[P_{j,k}]$ must sum to 1. Only two of the three elements in each column can

Example 2:

$$\begin{pmatrix} 0.50 & 0.10 & 0.10 \\ 0.30 & 0.50 & 0.30 \\ 0.20 & 0.40 & 0.60 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1.8 \\ 2.2 \\ 2.0 \end{bmatrix} \quad \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}.$$

Slope coefficient = 0.0833 [0.276] (fleeing the nuisance).

Our third numerical example shows that nuisance-based sorting can still occur at the individual level even when the aggregate distribution does not change. In example 3, the aggregate population distribution remains constant between periods A and B; however, the correlation between $P_{j,k}$ and $\Delta\alpha_{j,k}^{A,B}$ reveals residential mobility consistent with "coming to the nuisance" (an estimated coefficient of −0.0833). This example suggests that previous EJ research may have therefore overlooked nuisance-based sorting after determining that the population distributions do not exhibit economically and statistically significant responses to the placement of environmental harms.

Example 3:

$$\begin{pmatrix} 0.80 & 0.20 & 0.20 \\ 0.10 & 0.70 & 0.30 \\ 0.10 & 0.10 & 0.50 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} \quad \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}.$$

Slope coefficient = −0.0833 [0.061] (coming to the nuisance).

All three examples make clear that aggregate population dynamics alone are not able to distinguish the change in circumstances that individuals face when moving.

2. DATA

2.1. The National Air Toxics Assessment (NATA)

EPA designed the National Air Toxics Assessment to provide a "better understanding" of air toxic pollution risk at different geographic scales (state, county, and census tract). It includes a measure of total cancer risk associated with all assessed carcinogens (expressed in cases per million over and above a baseline), in addition to hazard indices for two noncancer risks (respiratory and neurological). NATA total cancer risk is important to the EPA given its important role in influential EJ analyses. Morello-Frosch et al. (2000), for example, consider census-tract lifetime cancer risk as part of the EPA's Cumulative Exposure Project. Other EJ analyses have also used NATA to evaluate the correlation of race or ethnicity and exposure to toxics at the tract level (Apelberg, Buckley, and White 2005; Pastor, Morello-Frosch, and

therefore be considered as independent observations. This leaves us with a small sample size of just n = 6 in each regression.

Sadd 2005; Morello-Frosch and Jesdale 2006; Chakraborty 2009, 2012; Hun et al. 2009). Given the high correlations between total cancer risk measure and respiratory (0.7766) and neurological (0.8194) indices, we focus on total cancer risk in our analysis; this simplifies the analysis, but the reader should be cautioned against interpreting our parameter estimates as measures of marginal willingness to pay (MWTP) for reduced total cancer risk alone.

Finally, one may question whether home buyers have direct knowledge of NATA total cancer risk. With updates to NATA in 2002 and 2005, the public's attention to the risk measures should have increased. In particular, the last NATA update addressed some of the EPA's 2001 Science Advisory Board Review recommendations associated with communicating results to the public and to urban community groups. For example, EPA added color-coded symbols to distributed materials to convey their confidence in exposure estimates.[6] EPA also provides a searchable "MyEnvironment" application with coarse county-level cancer risk information based on the user's location and links to additional NATA details, including census tract-level data used in our analysis.[7] Finally, one might expect NATA pollution to be associated with LULU's that are readily apparent to home buyers and renters.[8]

2.2. Census Tract Data

We use historical census tract–level statistics to determine the population share for each race group living in each census tract in 2000 and 2010. The census also provides tract-level information on median household income, median housing value, age distribution (e.g., percentage under 18 years), educational attainment (e.g., percentage college graduates or with less than high school), and a number of variables describing the housing stock (e.g., percentage of units detached or built before 1980). Table 1 describes the characteristics of 1,989 Los Angeles County tracts for which we have no missing observations in either decennial census.

6. See EPA's response to the Science Advisory Board Peer Review at http://www.epa.gov/ttn/atw/nata/sab/sabrev.html.

7. http://www.epa.gov/myenvironment/.

8. One might still be legitimately skeptical that movers are aware of the NATA figures. In response, we note that even if households were completely unaware of the cancer risk they faced, but rather made residential location decisions based on some neighborhood attribute that is both unobserved by the econometrician and highly correlated with NATA total cancer risk, the implications of our estimates for the distinction between siting and sorting explanations for environmental injustice (which depends only upon ex post correlations) would be the same. In that case, the reader would not want to give our parameter estimates strict MWTP interpretations, but rather treat the model as simply a test of sorting behavior, for which it would still be valid.

Table 1. Summary Statistics—Los Angeles County Census Tracts

Variables	Mean	Standard Deviation	Minimum	Maximum
Year = 2000:				
Household income, median ($)	47,579	24,426	9,451	200,000
Housing, median value ($)	230,356	144,329	10,000	1,000,000
% 1 unit detached	53	29	0	100
% built before 1980	81	17	0	100
% population under 18	28	8	1	58
% ed attainment < high school	32	22	0	86
% ed attainment college	15	11	0	49
CA API	618.4	124.3	378	924
Violent crime rates	628.0	306.3	113.2	1,484.3
NATA total cancer risk (1999)	95.0	31.0	32.9	555.8
TRI facilities	1.7	3.0	0	29.0
% Hispanic	44.1	29.3	2.3	98.3
% white	33.7	29.6	.2	93.4
% black	9.8	14.4	<.1	83.0
% Asian	12.5	16.0	<.1	94.2
Year = 2005:				
CA API	743.9	79.6	562.7	960.3
Violent crime rates	510.1	223.0	117.9	1183.1
NATA total cancer risk	108.2	30.2	24.2	270.5
Average TRI facilities (2004–6)	1.6	2.9	0	27
Trends 1990–2000:				
Δ% Hispanic	7.5	8.1	−20.4	41.1
Δ% white	−8.5	8.5	−42.7	19.3
Trends 2000–2010:				
Δ% Hispanic	3.2	2.0	−5.2	11.8
Δ% white	−1.8	2.1	−11.3	2.9

Note.—CA API = CA Academic Performance Index; NATA = National Air Toxics Assessment; TRI = Toxics Release Inventory.

Hispanics constitute a plurality in Los Angeles County in 2000, and their overall share grows by 3.2% between 2000 and 2010. Whites and Hispanics make up more than 75% of the population of Los Angeles in 2000. They also constitute the two groups with the largest disparities in income and pollution exposure. Blacks and Asians make up less than a quarter of the population, fall in the middle of the income and pollution exposure distributions, and tend to be more geographically concentrated in particular neighborhoods. Given all of these factors, we focus on whites and Hispanics in our empirical application. Their geographic distributions in 2000 are described in figure 1. Figure 2 illustrates the spatial distribution of the 1999 NATA total cancer risk measure.

2.3. Other Census Tract Attributes

We use a number of noncensus variables to describe the observable differences among census tracts. First, we use a measure of school quality produced by the California Department of Education. The department uses the results from the Standardized Testing and Reporting (STAR) program and California High School Exit Exam (CAHSEE) to calculate an Academic Performance Index (API; California Department of Education 2012a). The API is a single number that ranges between a low of 200 and a high of 1,000, which is used by the department to rank individual schools. Information guides provided to parents highlight California's API target of 800 for all schools; schools that fall below 800 are required to meet annual API growth targets designed to achieve that goal (California Department of Education 2012b). For each elementary school, we collect the base API data in 2000 and 2005 and calculate each census tract's school quality measure using the average of the three elementary schools closest to the census tract centroid.[9]

Second, we collected data from FBI crime statistics that describe the incidence of violent crimes in 2000 and 2005. Data are provided with a subscription to RAND California (ca.rand.org). They are organized by "city" and measure the number of incidents per 100,000 residents. Examples of cities inside Los Angeles County include Pico Rivera, Long Beach, and Huntington Park. Violent crime is defined as "crimes against people including homicide, forcible rape, robbery, and aggravated assault." We impute crime rates for each census tract using an inverse-distance weighted average of the crime rate in each city.

Finally, we control for the presence of productive activities in areas with air toxics by including the count of the average number of Toxics Release Inventory facilities within 1 mile of the border of each census tract between 2004 and 2006.[10] Polluting activities often generate employment opportunities and can be an indicator of general economic activity (all of which may be attractive to home buyers). Failing to account for this confounding factor can lead to an understatement of the costs associated with the pollution.

9. This recognizes Los Angeles Unified School District's open enrollment policy. Particular catchment zones may not be relevant, but commute time would make the quality of nearby elementary schools most relevant.

10. The US Environmental Protection Agency maintains a national database associated with the reports, the Toxics Release Inventory (TRI), and provides the public with access (http://www.epa.gov/tri/index.htm).

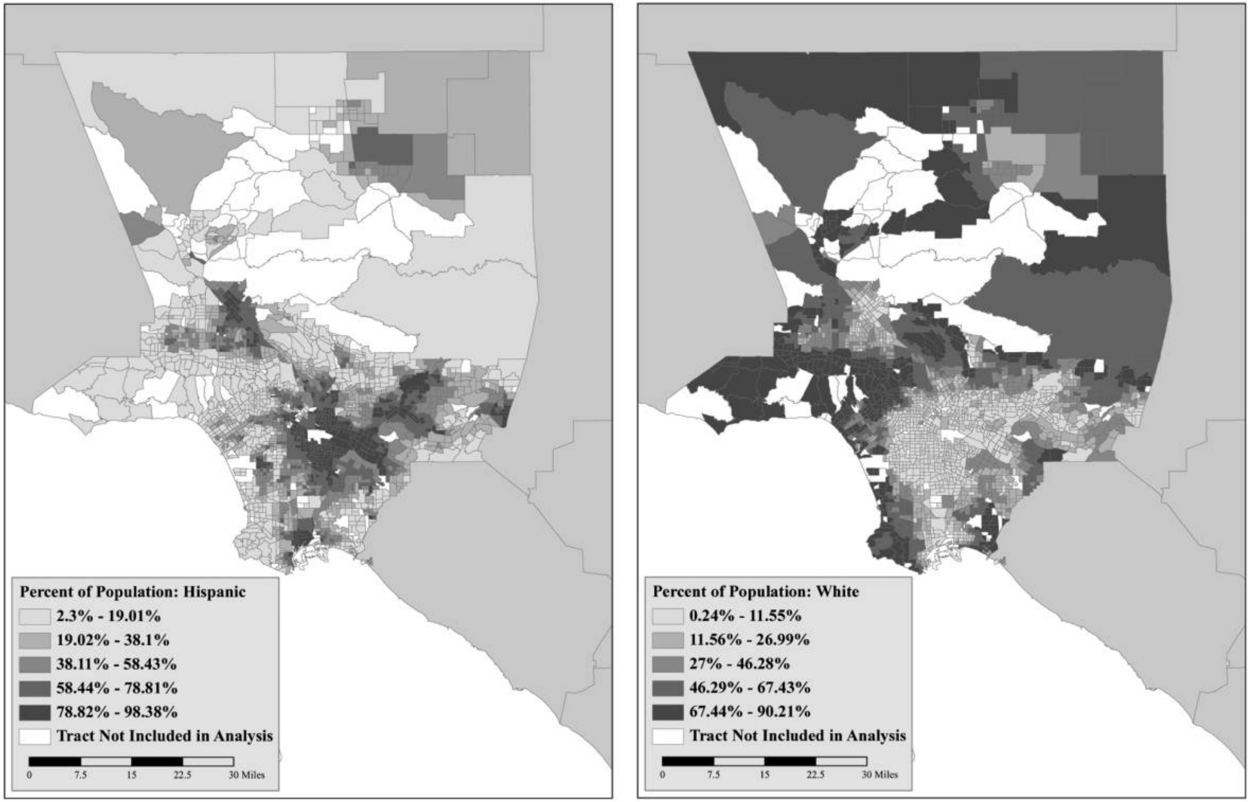

Figure 1. Maps of population distribution

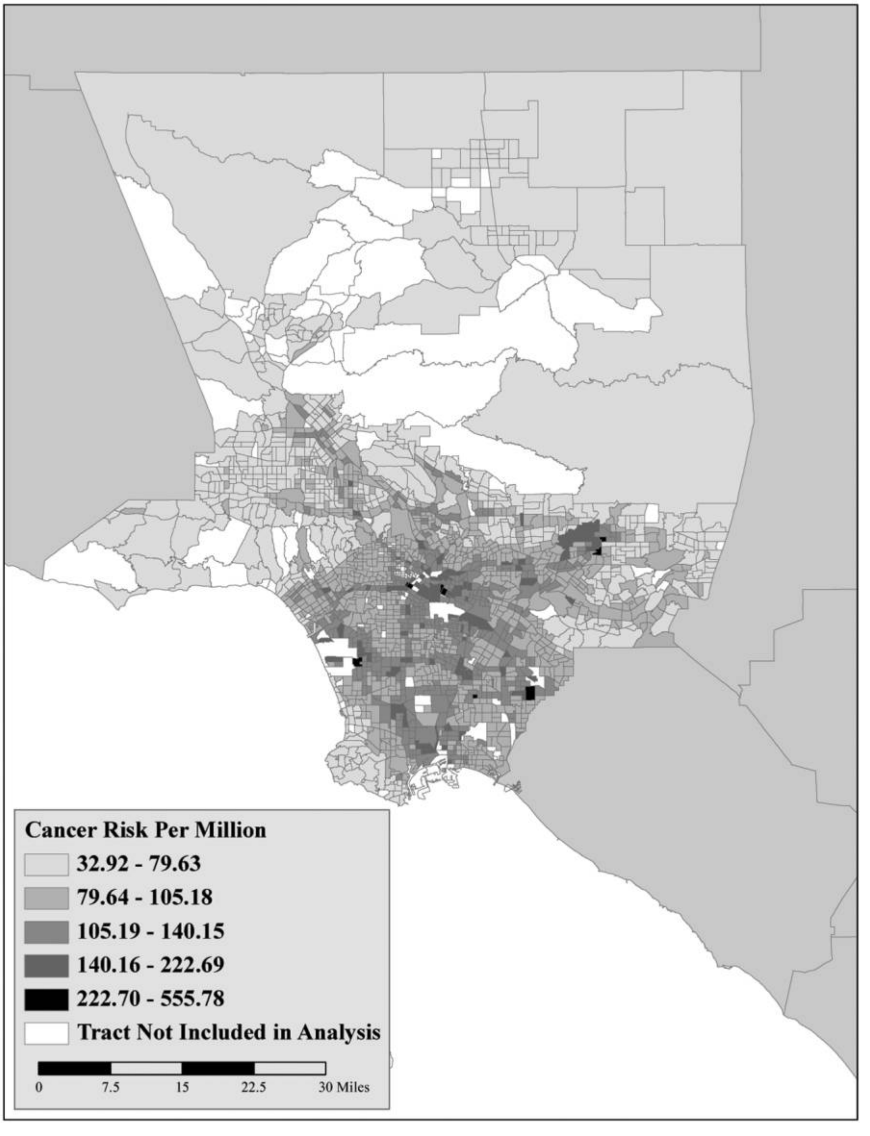

Figure 2. Map of NATA total cancer risk distribution

2.4. Moving Costs

Moving costs represent an important component of our model of individual residential decisions. This is both because they help explain why a large fraction of people do not move, even over the course of a decade, and because accounting for moving costs provides us with a tool with which we can recover the marginal utility of income. The marginal utility of income will prove useful when it comes time to compare our estimates between race groups. We use an approach for measuring actual moving costs, consisting of the physical costs of moving, closing costs, search costs associated with finding a new home, and financial costs associated with realtor payments; we derive these measures using raw data compiled and graciously provided by Bieri, Kuminoff, and Pope (2014). Using a time horizon of 37 years and a discount rate of 2.5%, we find that a representative move within Los Angeles County incurs an annualized cost of $134.38 in terms of physical moving costs in 2005. If the individual is moving from an owned house to another owned house, the assumption is that they pay 3% of the median housing value in both the starting and ending census tracts.[11] To account for the fact that renters do not pay this additional cost, we weight these payments by the percentage of residents in each tract who are homeowners.[12] Using the same data and methodology, we calculate the annualized cost associated with a move outside of Los Angeles County (i.e., into our "catch-all" category described below) to be approximately $600.

Measuring moving costs is a complicated exercise, and there are many factors that we may not adequately account for. We find, however, that qualitative results are not sensitive to variations in our assumptions about moving costs; we demonstrate in sensitivity analyses, for example, that our conclusions become even stronger if we incorporate additional "psychological" costs of moving.

3. EMPIRICAL ANALYSIS

3.1. Establishing the Correlation between Race and Pollution

Researchers commonly use correlation analysis to support claims of environmental injustice. In table 2, we report the correlation between the within-tract percentages of each race group and NATA total cancer risk for the 1,989 census tracts in our sample. While our focus is on whites and Hispanics, we report correlations for all four race groups. There are stark differences in correlation comparing the two largest groups—whites (−0.4676) and Hispanics (0.3967)—that raise questions about environmental injustice and confirm correlation patterns found elsewhere in the literature. We now look to the ability of the residential mobility hypothesis to explain the differences between these two groups.

11. During our sample period, the standard fee paid to a realtor in the US housing market is 6% of the price of the house being sold. We assume that this fee is effectively split evenly between the buyer and the seller.

12. Since we do not observe housing tenure by race at the tract level, we cannot control for tenure differentially by race.

Table 2. Correlation between Race and NATA Total Cancer Risk (Year 2000)

	NATA Cancer	% Asian	% Black	% Hispanic	% White
NATA cancer	1.000				
% Asian	.0254	1.000			
% black	.1156	−.2249	1.000		
% Hispanic	.3967	−.3167	−.0800	1.000	
% white	−.4676	−.0507	−.3509	−.7936	1.000

Note.—NATA = National Air Toxics Assessment.

3.2. Traditional Analysis of Residential Mobility

A traditional EJ residential mobility model explains these exposure patterns by comparing changes in aggregate tract-level demographics over the period 2000–2010 with a variety of year 2000 tract attributes (including NATA total cancer risk). Our traditional model corresponds to that found in Pastor et al. (2001) and is similar to those found elsewhere in the EJ literature. The traditional model is also the model underlying our nonidentification discussion in subsection 1.2. Our baseline specification relies on timing to help identify the causal effect of each variable on the change in each race group. In particular, we consider how changes in racial percentages between 2000 and 2010 are driven by 2000 tract-level attributes, assuming those attributes are predetermined and uncorrelated with unobservable determinants of migration. However, covariates such as year 2000 tract-level racial percentages could be proxies for race-specific unobservables and should be interpreted in that context.

Our baseline specification employs a rich set of covariates describing neighborhood attributes in an attempt to address this possibility. In our first alternative specification, we add a vector of neighborhood dummy variables that control directly for spatial unobservables. Working within a single county and using the census tract as our spatial unit of observation, there are not readily available neighborhood definitions for us to use for spatial dummies. The *Los Angeles Times* has, however, defined 16 regions within Los Angeles County as part of its “Mapping L.A.” portal.[13] The portal provides readers with information about demographics, income, schools, and news from each region. For our purposes, it provides one way to define spatial fixed effects that control for unobservable neighborhood characteristics. The map in the *Los Angeles Times* “Mapping L.A.” website describes the 16 neighborhoods.

Our second alternative specification addresses the possibility that race dynamics between 2000 and 2010 could simply be a reflection of the continuation of previous racial dynamics; racial pre-trends were found to be important determinants of race dynamics in Pastor et al. (2001). To test for this possibility, we add a control for the change in the own-race percentage in the census tract between 1990 and 2000 to our baseline specification.

13. See http://projects.latimes.com/mapping-la/neighborhoods/.

Results are described in table 3. Focusing on NATA total cancer risk, there is strong statistical evidence in the baseline and own-race pre-trend specifications that whites "come to the nuisance" (the same surprising result appears to be true for violent crimes as well), although this effect is economically modest—taking the result in the baseline specification (7.69×10^{-5}), increasing NATA total cancer risk from its lowest value to its highest value in 2000 (i.e., 32.9 to 555.8) would increase change in percentage white in the census tract by just over 4%. For Hispanics, we find evidence of the opposite sign but similar magnitudes in all three specifications—that is, "fleeing the nuisance" with respect to NATA total cancer risk. While these estimates are small, their significance allows us to statistically reject any support for the residential mobility hypothesis as an explanation for the correlations found in table 2. In the absence of such evidence, we would be left to conclude that disproportionate siting and/or enforcement of nuisances drives the observed correlation between cancer exposure and race.

3.3. A Structural Model of Neighborhood Dynamics

To better understand the neighborhood dynamics underlying the observed changes in aggregate demographics, we build on the model described in subsection 1.2, placing some structure on $P_{j,k}$ (the probability that a member of a particular group in tract k will choose to move to tract j) so that we can identify the role of NATA total cancer risk in driving residential mobility. Equations (1) and (2) represented a system of six equations with nine unknown $P_{j,k}$'s, leading to an identification problem. We overcome this problem by parameterizing $P_{j,k}$ as a function of location attributes. Start with the predicted population in neighborhood j in period B:

$$pop_j^B = \sum_{k=1}^{N} P_{j,k} pop_k^A. \tag{4}$$

Next, specify the mean utility from living in location k (δ_k) as a function of observable attributes of that location (X_k), a scalar attribute that is unobserved by the econometrician (ξ_k), and a vector of parameters (β):

$$\delta_k = f(X_k, \xi_k; \beta). \tag{5}$$

The utility an individual i receives from living in location k is given by

$$U_{i,k} = \delta_k + \eta_{i,k}, \tag{6}$$

where $\eta_{i,k}$ refers to the idiosyncratic utility specific to that individual and location. The change in utility an individual i currently living in location k receives from moving to location j is therefore given by

$$U_{i,j} - U_{i,k} = (\delta_j - \delta_k) - \mu MC_{j,k} + (\eta_{i,j} - \eta_{i,k}), \tag{7}$$

where $MC_{j,k}$ is our measure of moving costs described in section 2.4. If $j = k$, $MC_{j,k} = 0$, meaning that the change in utility from staying in one's current location is zero.

Table 3. Traditional Housing Market Dynamics Model

Variable	White			Hispanic		
	Baseline	FE Neighborhood	Own-Race Pre-trend	Baseline	FE Neighborhood	Own-Race Pre-trend
NATA total cancer risk	**7.69e−05*** **	**4.20E−05**	**6.48e−05*** **	**−9.84e−05*** **	**−6.61e−05** **	**−4.24e−05* **
TRI facilities	−3.07e−04*	−2.48E−04	−3.13e−04*	−5.19e−04***	−3.33e−04*	−3.45e−04**
API	−7.64E−06	−1.50e−05*	−8.15E−06	−1.75e−05**	2.29E−06	−6.12E−06
Violent crime rate	5.04e−06**	7.85e−06***	5.09e−06**	3.25E−06	1.43E−06	1.95E−06
Median income	1.49E−08	5.35E−08	1.77E−08	−1.77e−07***	−1.88e−07***	−1.86e−07***
% built before 1980	−1.23e−04***	−8.02e−05*	−1.14e−04***	1.11e−04***	4.52E−05	8.03E−06
Median home value	5.54E−09	3.05E−10	1.87E−09	6.41E−09	3.62E−09	1.61e−08**
% detached	−2.54E−05	−4.89e−05*	−4.07E−05	−1.70E−05	2.34E−05	3.85E−05
% under 18	5.84E−05	1.09E−04	1.48E−04	6.75e−04***	6.36e−04***	2.02e−04*
% high school dropout	4.30e−04***	4.08e−04***	2.94e−04***	−4.12e−04***	−4.95e−04***	−5.40E−05
% college graduate	1.05E−04	1.75E−04	2.94E−05	−3.62e−04***	−5.41e−04***	−1.68E−04
% white	1.45e−02***	1.55e−02**	9.81e−03*	−2.05e−02***	−3.10e−02***	−6.41E−03
% Asian	6.47e−02***	6.67e−02***	6.49e−02***	−1.25e−02**	−2.60e−02***	4.98E−03
% black	6.50e−02***	6.60e−02***	5.91e−02***	6.18E−03	−1.09e−02*	1.74e−02***
Δ% white (1990–2000)			2.47e−02***			
Δ% Hispanic (1990–2000)						9.67e−02***
Constant	−5.10e02***	−4.98e−02***	−4.13e−02***	5.90e−02***	6.17e−02***	3.34e−02***
N	1,989	1,989	1,989	1,989	1,989	1,989

Note.—Cancer risk = Total cancer risk, NATA 2005 read *X* in a million; violent crime = violent crime rate per 100,000 inhabitants, three nearest areas to centroid 2005; TRI facilities = average number of facilities with TRI emissions 2004–6 within 1 mile tract buffer; API = CA Academic Performance Index, API Base, three nearest elementary schools to centroid in 2005. FE = fixed effects.

* $p = .10$.

** $p = .05$.

*** $p = .01$.

If $\eta_{i,k}$ is independently and identically distributed Type I extreme value, then the probability that an individual in location k would find it optimal to move to location j is given by the familiar logit functional form. Applying this probability to all individuals in location k yields an equation for the share who move to each location j:

$$s_{j,k} = \frac{e^{(\delta_j - \delta_k - \mu MC_{j,k})}}{\sum_{l=1}^{N} e^{(\delta_l - \delta_k - \mu MC_{l,k})}}. \tag{8}$$

Similarly, the share of individuals in location k who would find it optimal to remain in that location is given by

$$s_{k,k} = \frac{1}{\sum_{l=1}^{N} e^{(\delta_l - \delta_k - \mu MC_{l,k})}}. \tag{9}$$

3.3.1. Open Migration Systems

The model of migration becomes complicated when we recognize that many of the observed changes in the distribution of population may actually reflect broader migration patterns into and out of the "system" being considered. The problem of the "open system" is common across papers looking for evidence of residential mobility, and it exacerbates the problem of not knowing all individuals' starting locations and ending destinations. It arises whenever the researcher considers a subset of locations, allowing movements into and out of that subset. Been (1994), for example, considers only those census tracts surrounding the nuisances used by Bullard (1983) and US GAO (1983). Oakes et al. (1996) use only tracts containing hazardous waste treatment, storage, and disposal facilities (TSDFs) and a small subset of control tracts. Been and Gupta (1997) use 544 communities that hosted active TSDFs in 1994, and Morello-Frosch et al. (2002) use census tracts in the South Coast Air Quality Management District. In analyses of the Superfund program, Greenstone and Gallagher (2008) use a set of census tracts in buffers surrounding the set of several hundred sites that were assigned Hazard Ranking System (HRS) scores by EPA in 1982; Gamper-Rabindran and Timmins (2011) use a similarly defined set of census blocks.

In the estimation below, we consider movements between Los Angeles County census tracts ($k = 1, 2, \ldots, N$) and a single "catch-all" location ($k = N + 1$) that captures all other locations. We discuss below why this simplification and, in particular, the number of individuals assumed to be in the catch-all location, does not present a problem when it comes to identification and estimation.

3.3.2. Timing

We use data from the 2000 and 2010 censuses to define periods A and B, respectively. In our primary specification, we model individuals as choosing to move from their year 2000 residences based on cancer risk and neighborhood amenities (i.e., school quality, violent crime, and TRI facility counts) revealed in 2005. The timing assumption is that residential locations observed in 2000 were the result of moves made from 1990 locations based on the realization of 1995 tract-level data; we take the year 2000 locations as given, treating them as an equilibrium that is "upset" by changes in neighborhood attributes that occur by 2005. The year 2010 represents a new equilibrium that will subsequently be upset in 2015. In sensitivity analyses, we show that qualitative results are robust to assuming that movements between 2000 and 2010 are instead based on year 2000 amenities and 1999 NATA total cancer risk.

3.3.3. *Estimation*

Estimation is carried out in two stages and separately for each race group (we suppress race group subscripts in the following discussion for the sake of brevity). The first stage is a mathematical exercise in which we solve an exactly identified system of equations. The second stage is a traditional statistical exercise.

We begin by finding the vector of $\{\delta_k\}_{k=1}^{N+1}$ and μ for each race group that best fits the system of equations described above. Of course, without additional information, this system contains $N + 2$ unknowns and only $N + 1$ equations describing the mapping of populations from 2000 to 2010 in each location. It is therefore still unidentified. We do, however, have access to an additional piece of information that solves the problem. In particular, we observe the share of households in each race group in Los Angeles County that do not move between 2000 and 2010.[14] These percentages, described in table 4, provide us with an additional equation that must hold for each race group:

$$\frac{\sum_{k=1}^{N} s_{k,k} pop_k^{2000}}{\sum_{k=1}^{N} pop_k^{2010}} = \%Stay. \tag{10}$$

Practically, solving for $\{\delta_k\}_{k=1}^{N+1}$ and μ is made simple by noting that, if we divide both sides of equation (4) by $TOTPOP = \sum_{k=1}^{N+1} pop_k^{2000} = \sum_{k=1}^{N+1} pop_k^{2010}$, we get

$$\sigma_j^{2010} = \sum_{k=1}^{N+1} \left(\frac{e^{(\delta_j - \delta_k - \mu MC_{j,k})}}{\sum_{l=1}^{N+1} e^{(\delta_l - \delta_k - \mu MC_{l,k})}} \right) \sigma_k^{2000}, \tag{11}$$

14. Using the 2010 American Community Survey, we find the percentage of households in 2010 who moved into their current house on or before 2000. Available data therefore measure the decision to "stay" defined in terms of staying in the same house, which we use to approximate the definition used in our model (i.e., in terms of staying in the same census tract). We demonstrate in sensitivity analyses that our results are robust to alternative assumptions about the definition of "stay."

Table 4. Stayer Probabilities and Fitted Moving Cost Parameters

Group	% Not Moving	μ
Hispanic	39.30	.05298
White	45.06	.05193

where $\sigma_j^t = pop_j^t / TOTPOP$.[15] Conveniently, given a guess at μ, equation (11) represents a contraction mapping in $\{\delta_k\}_{k=1}^{N+1}$. We can solve for those values by first taking a guess ($\overline{\delta}^0$) subject to a suitable normalization.[16] We then use that guess in conjunction with the observed population shares in 2000 ($\overline{\sigma}^{2000}$) to calculate predicted population shares in 2010 ($\tilde{\sigma}_j^{2010,0}$) $\forall$ j. We then update the $\overline{\delta}$ guess according to the following rule (Berry 1994):

$$\delta_j^1 = \delta_j^0 + (\ln \sigma_j^{2010} - \ln \tilde{\sigma}_j^{2010,0}). \tag{12}$$

The vector $\overline{\delta}^1$ is used to generate predictions of $\tilde{\sigma}_j^{2010,1}$ $\forall j$, which in turn are used to generate a new vector $\overline{\delta}^2$. This process is repeated until the difference between $\delta_j^{m+1} - \delta_j^m < \varepsilon\ \forall\ j(\varepsilon = 10^{-8})$. With the converged values of δ_k and the guess at μ, we then calculate the predicted percentage of the 2010 population who did not move from their tract in 2000, and we check to see how that value compares with *%Stay* for the appropriate racial group. We use a bisection method to search over values of μ that equate predicted *%Stay* to actual *%Stay*, solving for the values of $\{\delta_k\}_{k=1}^{N+1}$ at each step.

15. Note that, by introducing the "catch-all" location $k = N + 1$, we effectively make this into a closed system, where anyone entering Los Angeles County comes from location $N + 1$ and anyone leaving it moves to location $N + 1$. Of course, the size of the mean utility we ascribe to the catch-all location will be determined by the number of people we assume to be in location $N + 1$ to begin with. This does not present a problem as long as we do not attempt to interpret the mean utility of that location. What is important is that the values of the mean utilities associated with the other locations ($k = 1, 2, \ldots, N$) are not affected by the assumed population of $N + 1$. We find this to indeed be the case, with our results concerning relative willingnesses to pay of different race groups being essentially identical regardless of whether we define the population of $N + 1$ to be 2, 4, or 6 times the net change in population in ($k = 1, 2, \ldots, N$) between 2000 and 2010.

16. In general, there is no scale associated with the vector of utility indices (i.e., one could add an arbitrary constant value to all of them and not affect the behavioral shares). As such, a normalization is required. We normalize the values such that they are mean zero.

Moving to the second stage of the estimation procedure, we note that, because each race group's vector of mean utilities is separately normalized so that its average value is zero, values of δ_k are not directly comparable across race groups. However, normalizing by the marginal utility of income for each race group converts these mean utilities into dollar values that are directly comparable. Using race-specific estimates of μ_R as our measure of the marginal utility of income, we define $\hat{\delta}_{k,R} = \delta_{k,R}/\mu_R$.[17]

Finally, we use a simple least-squares regression technique to decompose $\{\hat{\delta}_{k,R}\}_{k=1}^{N}$.[18] Consider a linear specification of equation (5) for each race group:

$$\begin{aligned}\hat{\delta}_{k,H} &= \psi_H + \varphi_k + X_k'\beta_H + \xi_{k,H},\\ \hat{\delta}_{k,W} &= \psi_W + \varphi_k + X_k'\beta_W + \xi_{k,W},\end{aligned} \tag{13}$$

where φ_k is a fixed effect that measures the contribution to utility of all census tract attributes that enter similarly for both race groups. The term X_j includes all variables that are allowed to enter the utilities of the two race groups differently. In our baseline specification, X_j includes 2005 values of NATA total cancer risk, violent crime rate, API school quality, and the 2004–6 average TRI facility count. In an alternative specification, we also include white and Hispanic race pre-trends.

Stacking the dependent variables, these two equations can be combined into a single equation:

$$\hat{\delta}_{k,R} = \lambda_1 + \varphi_k + X_k'\pi_1 + \lambda_2 HISP_R + (HISP_R \times X_k)'\pi_2 + (1 - HISP_R) \times \xi_{k,W} + HISP_R \times \xi_{k,H}, \tag{14}$$

where $HISP_R$ is a dummy variable that takes the value 1 if $R = H$, and

$$\lambda_1 = \psi_W, \quad \lambda_1 + \lambda_2 = \psi_H, \quad \pi_1 = \beta_W, \quad \pi_1 + \pi_2 = \beta_H. \tag{15}$$

We combine data to create a new fixed effect, $\theta_k = \lambda_1 + \varphi_k + X_k'\pi_1$, and we estimate the following equation using the XTREG command in STATA:

$$\hat{\delta}_{k,R} = \theta_k + \lambda_2 HISP_R + (HISP_R \times X_k)'\pi_2 + (1 - HISP_R) \times \xi_{k,W} + HISP_R \times \xi_{k,H}. \tag{16}$$

Parameter estimates reveal the differences in willingness to pay between race groups:

$$\lambda_2 = \psi_H - \psi_W, \quad \pi_2 = \beta_H - \beta_W. \tag{17}$$

---

17. Note that estimates of μ_R are also not directly comparable across race groups, given the arbitrary normalizations of indirect utility. The normalization cancels out when we take the ratio $\delta_{k,R}/\mu_R$, allowing for cross-race comparisons.

18. Note that we do not have X_j data for the "catch-all" location $N + 1$, and the value of δ_{N+1} depends upon the assumed population of that location. We therefore drop location $N + 1$ from the second stage of the estimation procedure, meaning that we rely on within–Los Angeles County variation in X_j for identification.

3.4. Applying the Structural Model to Stylized Examples

Before reporting our results, we apply the structural model described above to the three examples used in section 1 to illustrate that the traditional EJ model does not identify nuisance-induced residential mobility. It is a simple matter to show that the structural model is able to successfully identify those dynamics. We assume $MC_{j,k} = 1$ if $j \neq k$ (= 0 otherwise); this assumption scales the differences between the mean utilities (δ_j) recovered for each location but does not affect our ability to compare their relative values. Figure 3*a*–*c* plots these mean utilities for each of the three locations versus the level of the nuisance for each of the three examples. A simple linear fit applied to those points shows that the structural model is indeed able to recover "coming to the nuisance" behavior in examples 1 and 3, and "fleeing the nuisance" behavior in example 2.

3.5. Structural Model Results

The first stage of our structural estimation procedure recovers each race group's vector of $\{\delta_{k,R}\}_{k=1}^{N}$ along with the coefficient on moving costs (μ_R); the latter are reported in table 4. Note that this stage of the procedure is the mathematical solution of a just-identified system of equations rather than an econometric procedure; there are no standard errors associated with μ_R.

The results from the second stage of our sorting model are reported in table 5. We find economically and statistically significant differences in Hispanic and white annual MWTP to avoid the risk of one additional case of cancer per million people (i.e., a unit of NATA total cancer risk). Relative to whites, Hispanics' observed residential location choices reveal a smaller willingness to give up other consumption in exchange for lower NATA total cancer risk—our results suggest that the difference between the two groups' MWTP is over 30¢ for a reduction of one unit of cancer risk. These MWTP differences are consistent with a residential mobility explanation for observed race and pollution correlations, contrary to the results of the traditional EJ analysis.

One way to quantify the influence of MWTP heterogeneity on sorting outcomes is with a counterfactual simulation. Given the sequential nature of our equilibrium, we are not able to easily simulate what Los Angeles County would look like if Hispanics had always had the same MWTP to avoid NATA total cancer risk as whites.[19] It is a simple matter, however, to ask how the distribution of population in 2010 would differ if we gave Hispanics the same MWTP to avoid cancer risk as whites when

19. In particular, our concept of equilibrium takes the distribution of population in 2000 as given and models individuals' decisions about where to live in 2010 based on data realized in 2005. Therefore, to model a world in which Hispanics had always had the same MWTP to avoid cancer risk as whites would require us to formally go back to the beginning of time (or, practically, to the point when cancer risk became relevant in Los Angeles County) and model the sequence of all move decisions from that point onward.

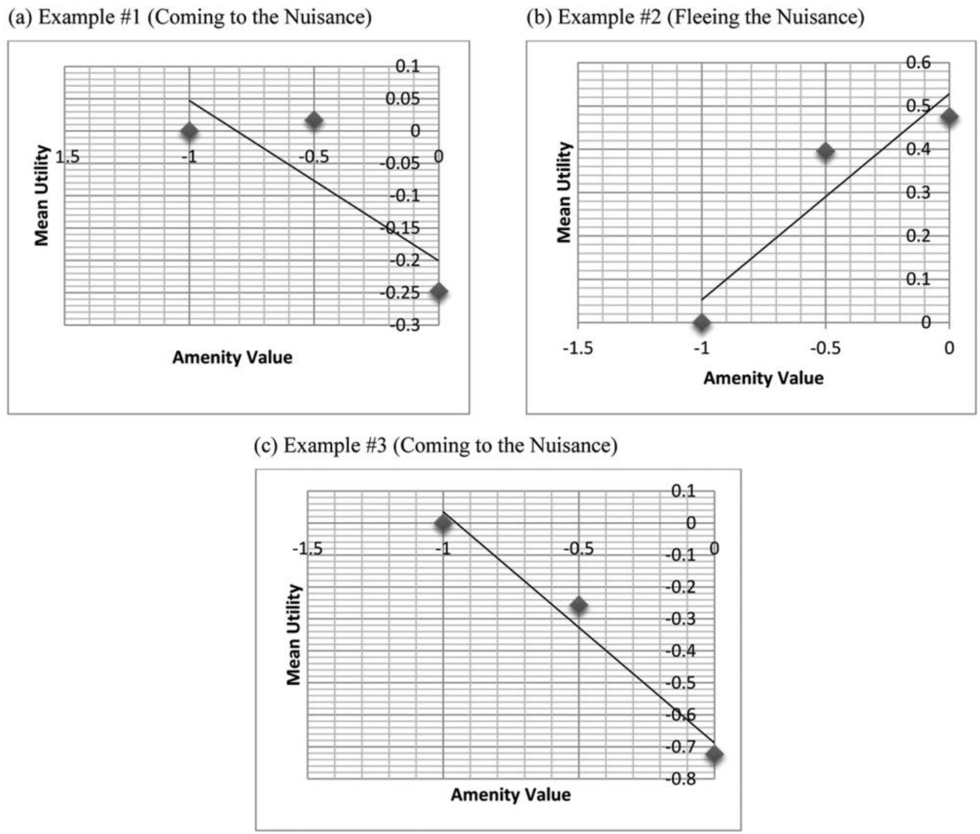

Figure 3. Mean utilities and amenity values from stylized examples. (*a*) Example 1 (coming to the nuisance); (*b*) Example 2 (fleeing the nuisance); (*c*) Example 3 (coming to the nuisance).

Table 5. Sorting Model

	2005 Amenity Values		2005 Amenity Values with Higher Stay %		2005 Amenity Values with Psychological Moving Costs		2000 Amenity Values	
NATA total cancer risk × Hispanic	.310***	.335***	.230***	.253***	.772***	.834***	.166***	.184***
	(.0176)	(.0173)	(.0139)	(.0136)	(.0437)	(.0431)	(.0170)	(.0167)
Violent crime × Hispanic	−.0103***	−.0166***	−.00902***	−.0140***	−.0255***	−.0414***	.00462**	.000430
	(.00250)	(.00244)	(.00197)	(.00192)	(.00622)	(.00608)	(.00180)	(.00180)
API × Hispanic	−.294***	−.253***	−.224***	−.190***	−.733***	−.629***	−.197***	−.175***
	(.00722)	(.00767)	(.00569)	(.00604)	(.0180)	(.0191)	(.00449)	(.00484)
TRI × Hispanic	1.380***	1.409***	1.089***	1.111***	3.433***	3.506***	1.155***	1.185***
	(.164)	(.157)	(.129)	(.124)	(.408)	(.391)	(.171)	(.166)
Hispanic intercept dummy	188.4***	157.4***	144.7***	118.6***	468.9***	391.7***	101.2***	88.47***
	(6.717)	(7.085)	(5.301)	(5.584)	(16.71)	(17.63)	(3.919)	(4.151)
Δ % white (2000–1990) × Hispanic		76.01***		58.37***		189.1***		64.20***
		(6.607)		(5.207)		(16.44)		(7.004)
Δ % Hispanic (2000–1990) × Hispanic		93.37***		76.30***		232.3***		76.30***
		(7.391)		(5.826)		(18.39)		(7.627)
Constant	.222	.220	.233	.231	.204	.200	.222	.220
	(.322)	(.308)	(.254)	(.243)	(.801)	(.766)	(.330)	(.321)
Observations	3,978	3,976	3,978	3,976	3,978	3,976	3,978	3,976

Note.—Standard errors in parentheses are calculated using the conventionally derived variance estimator for generalized least-squares regression. Cancer risk = total cancer risk, NATA 2005 read *X* in a million; violent crime = violent crime rate per 100,000 inhabitants, three nearest areas to centroid 2005; TRI = average number of facilities with TRI emissions 2004–6 within 1 mile tract buffer; API = CA Academic Performance Index API Base, three nearest elementary schools to centroid in 2005.

* $p = .10$.

** $p = .05$.

*** $p = .01$.

they make their 2005 residential location decisions (taking as given the distribution of population in 2000, which was based on decades of sorting subject to heterogeneous MWTP). Carrying out this exercise, we first find that the simulated correlation between Hispanic population count in 2010 and 2005 NATA total cancer risk after residential location decisions have been made based on estimated MWTP is 0.368 (similar to the correlation of 0.3967 that is found in the data in 2000).[20] For the counterfactual, begin by recalling that

$$\delta_{k,H} = \mu_H(\psi_H + \varphi_k + X'\beta_H + \xi_{k,H}) \tag{18}$$

and

$$\beta_W = \beta_H - \pi_2; \tag{19}$$

we can arrive at counterfactual mean utility values ($\delta_{k,H}$) according to

$$\delta_{k,H} = \mu_H\left[(\psi_H + \varphi_k + X'\beta_H + \xi_{k,H}) - \pi_2 NATA_k\right], \tag{20}$$

where $NATA_k$ is one of the elements of X_k and π_2 is our estimate on the interaction between $NATA_k$ and *HISP* (i.e., 0.310). This converts the coefficient on $NATA_k$ (and *only* the coefficient on $NATA_k$) to be equal to that for whites, and then (after multiplying by μ_H) rescales mean utilities back into their original units. Counterfactually ascribing Hispanics the same MWTP to avoid *NATA* as whites, the new simulated correlation falls to −0.079.

We estimate a number of alternative specifications to see if these conclusions are robust; results appear in the remaining columns of table 5 and in tables 6 and 7. First, we repeat the analysis and increase each group's stayer probability by a factor of 1.5.[21] With higher stay percentages for both groups, the disparity between white and Hispanic willingness to pay to avoid cancer risk is smaller but still statistically significant (i.e., 23¢ to 25¢ per unit reduction). Next, we repeat the analysis allowing for additional "psychological" costs brought about by the dislocation and hassle associated with moving by adding $200 to the annual costs associated with any move. With these additional psychological costs of moving, the disparity between white and Hispanic willingness to pay to avoid cancer risk grows even larger (77¢ to 83¢ for a one-unit reduction in cancer risk). Finally, we assume that households decide to relocate between 2000 and 2010 using information about tract attributes observed in 2000 (and 1999 NATA total cancer risk) rather than the mid-decade

20. There is no 2010 NATA total cancer risk measure to use here, so we assume that 2005 pollution levels will persist.

21. Recall that our definition of "stay" in available data referred to individuals staying in the same house as opposed to the same census tract. The data, therefore, likely understate the size of the "stay" probability from the point of view of our model.

Table 6. Sorting Model (Stayer Percentage Sensitivity Analysis)

	2005 Amenity Values					
	Hispanic and White Stay Percentage × 1.5		Hispanic Stay Percentage × 1.5		White Stay Percentage × 1.5	
NATA total cancer risk × Hispanic	.230***	.253***	.261***	.293***	.279***	.295***
	(.0139)	(.0136)	(.0151)	(.0149)	(.0165)	(.0163)
Violent crime × Hispanic	−.00902***	−.0140***	−.0131***	−.0182***	−.00622***	−.0125***
	(.00197)	(.00192)	(.00215)	(.00210)	(.00235)	(.00229)
API × Hispanic	−.224***	−.190***	−.254***	−.215***	−.265***	−.228***
	(.00569)	(.00604)	(.00621)	(.00658)	(.00679)	(.00721)
TRI × Hispanic	1.089***	1.111***	1.265***	1.283***	1.204***	1.237***
	(.129)	(.124)	(.141)	(.135)	(.154)	(.148)
Hispanic intercept dummy	144.7***	118.6***	165.2***	133.3***	167.8***	142.8***
	(5.301)	(5.584)	(5.777)	(6.080)	(6.323)	(6.657)
Δ % white (2000–1990) × Hispanic		58.37***		54.61***		79.77***
		(5.207)		(5.669)		(6.207)
Δ % Hispanic (2000–1990) × Hispanic		76.30***		87.37***		82.30***
		(5.826)		(6.343)		(6.944)
Constant	.233	.231	.233	.231	.222	.220
	(.254)	(.243)	(.277)	(.264)	(.303)	(.289)
Observations	3,978	3,976	3,978	3,976	3,978	3,976

Note.—Standard errors in parentheses are calculated using the conventionally derived variance estimator for generalized least-squares regression. Cancer risk = total cancer risk, NATA 2005 read *X* in a millionl; violent crime = violent crime rate per 100,000 inhabitants, three nearest areas to centroid 2005; TRI = average number of facilities with TRI emissions 2004 to 2006 within 1 mile tract buffer; API= CA Academic Performance Index API Base, three nearest elementary schools to centroid in 2005.

* $p = .10$.

** $p = .05$.

*** $p = .01$.

Table 7. Sorting Model (Psychological Cost Sensitivity Analysis)

	2005 Amenity Values					
	White and Hispanic with Psychological Moving Costs		White with Psychological Moving Costs		Hispanic with Psychological Moving Costs	
NATA total cancer risk × Hispanic	.772***	.834***	.609***	.600***	.473***	.569***
	(.0437)	(.0431)	(.0394)	(.0384)	(.0279)	(.0270)
Violent crime × Hispanic	−.0255***	−.0414***	−.00145	−.0168***	−.0343***	−.0412***
	(.00622)	(.00608)	(.00560)	(.00541)	(.00397)	(.00381)
API × Hispanic	−.733***	−.629***	−.536***	−.471***	−.491***	−.411***
	(.0180)	(.0191)	(.0162)	(.0170)	(.0115)	(.0120)
TRI × Hispanic	3.433***	3.506***	2.831***	2.937***	1.982***	1.978***
	(.408)	(.391)	(.367)	(.348)	(.261)	(.245)
Hispanic intercept dummy	468.9***	391.7***	329.2***	296.6***	328.1***	252.5***
	(16.71)	(17.63)	(15.05)	(15.70)	(10.67)	(11.04)
Δ % white (2000–1990) × Hispanic		189.1***		222.7***		42.47***
		(16.44)		(14.64)		(10.30)
Δ % Hispanic (2000–1990) × Hispanic		232.3***		151.5***		174.2***
		(18.39)		(16.37)		(11.52)
Constant	.204	.200	.204	.200	.222	.220
	(.801)	(.766)	(.721)	(.682)	(.511)	(.480)
Observations	3,978	3,976	3,978	3,976	3,978	3,976

Note.—Standard errors in parentheses are calculated using the conventionally derived variance estimator for generalized least-squares regression. Total cancer risk = total cancer risk, NATA 2005 read *X* in a million, violent crime = violent crime rate per 100,000 inhabitants, three nearest areas to centroid 2005; TRI = number of facilities with more than 0 TRI emissions 2000 within 1 mile tract buffer; API = CA Academic Performance Index API Base, three nearest elementary schools to centroid in 2005.

* p = .10.

** p = .05.

*** p = .01.

levels of these variables. While smaller than in our baseline specification, the disparity between white and Hispanic willingness to pay to avoid cancer risk is still statistically significant (i.e., 17¢ to 18¢ per unit reduction).

In tables 6 and 7, we estimate several different specifications to allow for heterogeneity in stay percentages and psychological costs (e.g., whites are given larger stayer probabilities or psychological costs but Hispanics are not, and vice versa). While the magnitudes of the differences in willingness to pay between the two race groups differ, our conclusions are robust to these variations in modeling assumptions and continue to support the residential mobility hypothesis.

Unfortunately, the residential mobility explanation for patterns of environmental injustice is often misinterpreted as an implicit argument that minorities derive utility from pollution. We do not make this claim. Rather, Hispanics can dislike cancer risk but be less willing to trade other forms of consumption to avoid it—both groups can view pollution as a nuisance, but differences in MWTP to avoid it, applied to repeated residential location decisions, can easily lead to discrepancies in exposure at the aggregate level over time. There is a simple economic explanation for this result. US Census data for 1999 show the extent of the income disparity between whites and Hispanics—whites in Los Angeles County had a per capita income of $35,785, while Hispanic per capita income was only $11,100. Given these differences and an assumption of diminishing marginal utility of income, whites, on average, would place less value on a marginal unit of "other consumption" (in a standard utility maximization model) and hence be willing to sacrifice more of those consumption goods in exchange for cancer risk reductions. In contrast, additional consumption may be more valuable to the lower-income Hispanic group, raising the opportunity cost of avoiding cancer risk.

4. CONCLUSIONS

With the Environmental Protection Agency's reaffirmed commitment to environmental justice in its Plan EJ 2014, learning about the causes and consequences of environmental injustice has taken on a renewed sense of importance. We show how the traditional approach used in many EJ analyses cannot identify nuisance-driven residential mobility. Put another way, the traditional approach does not provide compelling evidence for or against "coming to" or "fleeing from" the nuisance. To overcome this problem, we develop a structural model that uses aggregate census-tract data observed at different points in time to recover evidence of nuisance-driven residential mobility. It is a practical approach that can be replicated in future studies by EJ researchers with access to commonly available public data sources.

In an application to NATA total cancer risk in Los Angeles County, we find that the traditional EJ model yields evidence counter to a residential mobility explanation for observed race-pollution correlations. Hispanics exhibit a high positive correlation with cancer risk but show evidence of fleeing from that nuisance in the traditional model. Whites exhibit a strong negative correlation, but the traditional model suggests that they "come to" the nuisance. By default, the traditional model therefore suggests that disproportionate siting of nuisances or unequal enforcement of their cleanup must be responsible for the observed patterns of minority pollution exposure. Our analysis does not rule out these alternative explanations, but it does suggest that residential mobility plays a role.

In particular, our structural model shows that whites exhibit a larger MWTP to avoid NATA total cancer risk than do Hispanics—a result that corresponds to and can explain the observed differences between these groups in correlations with pollution. Over the long run, individuals making sorting decisions with systematically different marginal willingnesses to pay for neighborhood attributes will yield residential patterns that reflect those differences. A counterfactual simulation indicates a dramatic reduction in Hispanic correlation with cancer risk simply by giving Hispanics the white MWTP for the 2000–2010 moving decision. We emphasize that differences in MWTP can be easily explained by differences in economic circumstances and diminishing marginal utility of income rather than heterogeneity in concern over health consequences.

These conclusions highlight important questions about overall policy design and constraints faced by environmental policy makers. Our results suggest that residential mobility based on willingness to pay for different neighborhood amenities is likely to counteract the effects of policy targeting equitable site placement. As a result, "solutions" for environmental injustice problems may be more complex than simply changing zoning rules for the siting of pollution sources. Pollution exposure patterns can be explained by other sources of inequality—in particular, income inequality—which is where one may need to look to address environmental injustice.

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