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

by

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ABSTRACT

Effective environmental justice policy involves understanding 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 the problem and implements it using data on air toxics from L.A. County. Differences in estimated willingness-to-pay for cleaner air across race groups support residential mobility explanation. Our results suggest that household mobility responses eventually work against policies designed to address equitable siting decisions for facilities with environmental health risks.

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1. INTRODUCTION

Two decades after its historic environmental justice (EJ) analysis (UCC 1987), the United Church of Christ (2007) reported that over five million people of color live within one mile of a hazardous waste facility. Since the outcomes persist, EJ researchers continue 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 follows the siting of a nuisance? Residential mobility presents some challenges for some EJ policies since it suggests that the policy goal may be undermined when residents with the means to move away from a LULU leave neighborhoods and their homes are re-populated by lower income residents (see for example, Been 1994).

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 (US Bureau of the Census 2011a). The most common reason given for changing homes is the need for more living space or a better neighborhood; this is especially true for moves made within a county (US Census Bureau 2011b). Although additional living space and better neighborhoods can be purchased or rented by reallocating expenditures toward housing structure and neighborhood quality and reducing consumption of other goods, homebuyers 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 tradeoffs made by different groups of homebuyers 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.

Although EJ researchers have historically turned geographically aggregated (e.g. census tract) data describing population flows to look for evidence of nuisance-driven residential mobility, the approach has drawbacks. Our paper shows how traditional empirical models are unidentified and address the problem by describing a different approach. After applying the new approach to Los Angeles County, we find 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, the effectiveness of common EJ policies, and supports suggestions (e.g. Banzhaf, 2012) that dealing with environmental injustice may require addressing income disparities.

This paper proceeds as follows. Section 2 reviews the EJ literature that has sought to distinguish the competing roles of 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 3 describes how we measure the "nuisance" in our empirical application – in particular, the risk of cancer, respiratory and neurological diseases taken from the EPA's National Air Toxics Assessment. Section 4 describes the data sets that we use to model residential decisions and neighborhood sociodemographics. Section 5 uses those data to estimate both a traditional EJ model of residential mobility along with our alternative model. Section 6 concludes.

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

2.1 Previous Research

A number of early longitudinal studies found little or no evidence of nuisance-driven residential mobility, finding 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, Sadd, and Hipp (2001) focuses on L.A. 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.

Crowder and Downey (2010) conducted one of first analysis in the EJ literature to use individual-level 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 found that, when they move, black and Latino households tend to move into neighborhoods with significantly higher emissions measured by the Toxic Release Inventory than comparable white households, suggesting a population dynamic that would lead to disproportionate pollution exposure by race. While the paper provides important insights, their analysis cannot assess how an individual's pollution exposure changes when they move to from one house to another. Seeing a purchase a house two miles from a toxic site can be interpreted in different ways depending on where the household started. If the household comes from a house that is one mile from a site, the homeowner could be reducing exposure. If the household comes from a house ten miles from a site, the homeowners could be increasing exposure. Examining the attributes of either individual houses purchases or comparing houses sold by different groups still does not address the exposure changes generated by household moves. Although individual-choice data is welcome addition to the EJ literature, analysis of geographically aggregated choices will continue to be a popular and practical method until more individual panel applications are developed.

There are some assessments of residential choice behavior that do provide evidence in favor of housing market dynamics. 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 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 homebuyers have heterogeneous preferences. Banzhaf and Walsh (2010) demonstrate that predictions become even more complicated when homebuyers have preferences for the race of their neighbors.

2.2 Non-Identification in the Traditional Model of Residential Mobility

In the absence of clear theoretical predictions about the response of race to pollution, 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 city 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.[1] $s_{j,k}$ is used to denote the share of individuals in location k in period A who choose 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:

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

A traditional EJ analysis considers the change in the population of a particular sub-group 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 (α_j^A). $\frac{\Delta pop_j}{\alpha_j^A} > 0$ is taken as evidence that members of the sub-group in question "flee the nuisance" (or, alternatively, "come to the amenity"). 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 $[s_{j,k}]$ and the way in which $s_{j,k}$ co-varies with the change in exposure

[1] In most EJ analyses, pop_j^t will refer to the population of a particular race or income sub-group (e.g., low-income minorities). Without loss of generality, we refer to a single population group in this example.

associated with the move from k to j $(\Delta\alpha_{j,k})$. The elements of $[s_{j,k}]$ provide a true measure of how the change in exposure associated with a move affects the tendency of individuals to make that move.

The problem is that the change in population vectors over time does not identify $[s_{j,k}]$. Recognizing that

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

equations (1) and (2) constitute a system of six equations with nine unknown values of $s_{j,k}$. The system is, therefore, under-identified. Put differently, without additional structure, there is not a unique $[s_{j,k}]$ 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 $[s_{j,k}]$ matrix, but maintain the same distribution of amenity levels: $\alpha_1^A = 0$, $\alpha_2^A = 0.5$, $\alpha_3^A = 1$. In terms of timing, we model movements between periods A and B assuming that individuals observe the amenity levels in period A. Between periods B and C, individuals might move again after realizing updated amenity values, $\bar{\alpha}^B$.[2]

[2] As is the case in the rest of the EJ literature, we assume that individuals lack foresight with respect to how amenities will evolve in the future. Bayer, McMillan, Murphy and Timmins (2011) estimate a model of forward looking residential homebuyers. For the purposes of the present analysis, that approach is impractical both in terms of computational and data requirements. It would also require modeling the housing tenure decision (i.e., ownership versus renting), which is beyond the scope of the current literature.

In the first two numerical examples, $[s_{j,k}]$ 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 the 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 $s_{j,k}$ on $\Delta\alpha_{j,k}$ and an intercept shows that the true individual market dynamics in each example are different. The estimated parameter on $\Delta\alpha_{j,k}$ in example #1, -0.8805, 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, 3.409, reflects "fleeing the nuisance" (i.e., an improvement in the amenity makes the move more likely). P-values are reported in brackets.[3]

<u>Example #1</u>:

$$\begin{pmatrix} 0.00 & 0.60 & 0.60 \\ 0.50 & 0.25 & 0.20 \\ 0.50 & 0.15 & 0.20 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1.8 \\ 2.2 \\ 2.0 \end{bmatrix} \qquad \begin{bmatrix} \alpha_1^A \\ \alpha_1^A \\ \alpha_1^A \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}$$

Slope coefficient = - 0.8805 [0.666] (Coming to the Nuisance)

<u>Example #2</u>:

$$\begin{pmatrix} 0.50 & 0.10 & 0.10 \\ 0.30 & 0.50 & 0.30 \\ 0.20 & 0.40 & 0.60 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1.8 \\ 2.2 \\ 2.0 \end{bmatrix} \qquad \begin{bmatrix} \alpha_1^A \\ \alpha_1^A \\ \alpha_1^A \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}$$

Slope coefficient = 3.409 [0.276] (Fleeing the Nuisance)

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[3] In each case, we use observations where $j \neq k$, noting that the elements in each column of $[s_{j,k}]$ must sum to 1. Only two of the three elements in each column can therefore be considered as independent observations. This leaves us with a small sample size of just six observations in each regression.

Our third numerical example shows 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 1 and 2; however, the correlation between $s_{j,k}$ and $\Delta\alpha_{j,k}$ reveals residential mobility consistent with "coming to the nuisance" (an estimated coefficient of -7.50). 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: No Change in Aggregate Population Distribution

$$\begin{pmatrix} 0.80 & 0.20 & 0.20 \\ 0.10 & 0.70 & 0.30 \\ 0.10 & 0.10 & 0.50 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} \qquad \begin{bmatrix} \alpha_1^A \\ \alpha_1^A \\ \alpha_1^A \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}$$

Slope coefficient = - 7.50 [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 individuals face when moving.

3. DATA

3.1 The National Air Toxics Assessment (NATA)

NATA is an assessment published by the Environmental Protection Agency (EPA) that provides risk levels for cancer and other non-cancer respiratory and neurological effects at the census tract level, based on chronic exposure to air toxics.[4] Included in the dataset is the amount of risk that results from "on-road", "not-on-road", and "background" sources of pollution (i.e., the estimated risk would be without any human contributions). In order to calculate these values, the EPA first collects emissions data in the form of the National Emissions Inventory. Air dispersion models are then used to estimate ambient concentration of the emitted toxins. Those concentrations are combined with known natural sources of toxins. Local monitoring devices are then used to check the accuracy of the model's predictions. Ambient concentration is then converted to an exposure concentration, which measures the amount of each pollutant that people actually breath. This number can vary across individuals based on lifestyle (e.g. how much time is spent being active outside) but is a key metric in determining health risk. Based on the known health effects of the measured toxins, the EPA quantifies the risk for the defined community assuming lifetime exposure at the emissions levels measured at that time.

The 1999 NATA uses information on concentrations of 177 toxic substances (in addition to diesel particulate matter) to measure health risk at the census-tract level from breathing the pollutants. NATA ignores criteria pollutants (PM, NOx, SOx, O3, and CO) except for lead, which is also classified as a toxic. Measurements of health effects are expressed in terms of the amount by which the rate of incidence (out of one million people) exceeds the normal rate that would be experienced by the population in the absence of the toxic pollution.

Our use of NATA follows upon earlier work in the EJ literature that has focused on lifetime cancer risk measured at the tract level as part of the EPA's Cumulative Exposure Project (Morello-

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[4] Toxic (or hazardous) air pollutants are substances that are "known or suspected to cause cancer or other serious health effects, such as reproductive effects or birth defects, or adverse environmental effects…Examples of toxic air pollutants include benzene, which is found in gasoline, perchloroethylene, which is emitted from some dry cleaning facilities, and methyl chloride, which is used as a solvent and a paint stripper by a number of industries. Examples of other listed air toxics include dioxin, asbestos, toluene, and metals such as cadmium, mercury, chromium, and lead compounds." (http://www.epa.gov/oar/toxicair/newtoxics.html). A list of 187 hazardous air pollutants can be found at http://www.epa.gov/ttn/atw/188polls.html.

Frosch et al. 2000). Other EJ analyses that have used NATA data include Apelberg et al (2005), Pastor et al. (2005), Morello-Frosch and Jesdale (2006), Chakraborty (2009), Hun et al. (2009), and Chakraborty (2012), each of which evaluates the correlation of race or ethnicity and exposure to toxics at the tract-level.

Figures 1 and 2 describe the spatial distribution of four race groups (Asian, black, Hispanic, white) and the three NATA risk measures, respectively, for L.A. County. A clear pattern of correlation between minority status and pollution is evident, particularly for blacks and Hispanics considering respiratory and neurological risk.

3.2 Census Tract Data

We use data provided by the U.S. Census Bureau describing tract-level demographic and economic statistics. The 2005-2009 American Community Survey 5–year averages provide information about the share of the population in each race group living in each census tract during that period. We use more information from the 2000 Decennial Census, which, like the ACS, provides information on a 5% sample of the total population. Variables include population by race/ethnicity, the percentage of the population receiving public assistance, median household income, the percentage of the population under age 18 and over age 65, and the percentage of the population who are high school dropouts or college graduates. Census data also describe attributes of the housing stock, including the percentage of units with different numbers of bedrooms, the percentage built in different decades, and the percentage of detached units. Table 1 describes the characteristics of 1,921 L.A. County tracts for which we have no missing observations in either the decennial census or the ACS. Notable amongst these figures is the fact that Hispanics, for whom we will find important EJ impacts, constitute a plurality in Los Angeles county in 2000, and that their overall share grew between 2000 and 2005-2009.

3.3 Other Census Tract Attributes

We use a number of different statistics to determine the 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 (low of 200 to a high of 1,000) and helps the Department rank individual schools. Information guides provided to parents highlight California's API target of 800 for all schools and schools that fall below the target are required to meet annual API growth targets to achieve the 800 goal (California Department of Education, 2012). For each elementary school, we collected the Base API data in 2000 and calculated each census tract's school quality measure using the average of the three elementary schools (API Elementary) closest to the census tract centroid.

Second, we use data from RAND California describing the incidence of violent crimes in 2000. Data are organized by "city" and measure the number of incidents per 100,000 residents. Examples of cities inside L.A. 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 number of Toxic Release Inventory facilities within 1 mile of the border of each census tract in 2000.[5] Polluting activities often generate employment opportunities. Failing to account for this confounding factor can lead to an understatement of the costs associated with the pollution.

3.4 Moving Costs

Moving costs represent an important component of our model of individual moving decisions. This is both because they help explain why a majority of individuals do not move, even over a seven-year period, and because properly accounting for moving costs provides us with a tool to recover the marginal utility of income. The latter will prove useful when it comes time to compare our estimates across different 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, described by Bieri, Kuminoff, and Pope (2012).[6] Using a time horizon of 37 years, a discount rate of 2.5%, and their raw data, we find that a representative move within L.A. County incurs an annualized cost of $118.50 in terms of physical moving costs. 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.[7] 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 home owners.[8] Using

[5] Under Federal law, certain industries report disposal, other releases, and other waste management activities associated with selected chemicals. The U.S. 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).

[6] The authors graciously provided us with access to their raw data and calculations for constructing our moving cost measures.

[7] 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 seller.

[8] This is a conservative assumption; minority groups in Los Angeles are more likely to be renters, but assuming they are just as likely to be home owners leads us to understate our estimate of their marginal utility of income and subsequently

Bieri, Kuminoff and Pope's data and methodology, we calculate the annualized cost associated with a move outside of LA county (i.e., into our "catch-all" category described below) to be $528.71. Results are not sensitive to reasonable variations on these assumptions.

4. EMPIRICAL ANALYSIS

4.1 Establishing the Correlation Between Race and Pollution

We begin by examining census tract correlations between race and NATA risk, since correlation analysis is commonly used to support claims of environmental injustice. In Table 2, we report the correlation between race and our three NATA risk measures for the 1,921 census tracts.[9] Since white and Hispanic groups constitute three quarters of the population of Los Angeles and we focus on the correlations for each group. %White exhibits the strongest negative correlation with each of the three measures, while %Hispanic exhibits the strongest positive correlation. The remaining two groups – blacks and Asians – fall in between whites and Hispanics in terms of pollution exposure. %Black consistently exhibits a stronger positive correlation than %Asian, and in the case of respiratory risk, their correlation is similar to that of Hispanics.

Race groups exhibit negative correlations with one another – i.e., a higher percentage of race group X leads to a lower percentage of race group Y. From Table 2, we also see that %Asian exhibits the weakest negative correlation with %white, while %black and %Hispanic similarly exhibit a smaller negative correlation with one another.

Next, we report the the correlation between race and NATA risk using multivariate regression to control for potentially confounding factors (Table 3). We use the sociodemographic

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overstate their willingness to pay for avoiding air toxics. Since we do not observe housing tenure by race at the tract level, we cannot control for tenure differentially by race.

[9] The EJ literature has tended to focus on the percentage minority within each tract as the dependent variable when analyzing residential mobility. Looking at the absolute counts of each race group in each tract yields similar results.

and neighborhood attributes described above as controls. Results for cancer risk are similar to the corresponding bivariate correlations, with whites exhibiting the least exposure amongst the four groups, Hispanics the most, and Asians and blacks falling in between.[10] Respiratory risk results are also similar, with whites experiencing the least exposure, followed by Asians, with blacks and Hispanics showing the most. For all race groups, correlation with respiratory risk exposure is weak after controlling for potentially confounding variables. Neurological risk results differ most from the bivariate case, with whites exhibiting the least exposure, followed by blacks, and then by Asians and Hispanics, who have very similar conditional correlations. Finally, note that TRI site counts are significant determinant of each source of exposure risk. Since TRI sites can also be important sources of employment, it is important that we control for this potential confounding factor in the subsequent analyses.

These simple correlation analyses demonstrate that there are clear and robust EJ patterns for whites and Hispanics – the two largest population groups in L.A. County. Asians generally exhibit patterns similar to those of whites (although with somewhat greater risk exposure), except in the case of neurological risk where there exposure is much greater. Depending upon the specification (in particular, with or without controls for other neighborhood attributes), blacks may exhibit strong correlations with certain measures of NATA risk (i.e., respiratory and neurological). We now look to the ability of the residential mobility hypothesis to explain these patterns.

4.2 Traditional Analysis of Residential Mobility

The traditional EJ residential mobility model would seek to explain these exposure patterns by comparing changes in aggregate tract-level demographics with a variety of year 2000 tract

[10] % Other, a small catch-all group of the remaining race categories, is omitted from these regressions to avoid perfect collinearity.

attributes and NATA risk. This analysis corresponds to, for example, that found in Pastor, Sadd and Hipp (2001). It is also the model underlying our non-identification discussion in subsection 2.2. In addition to NATA risk, we include the following variables – TRI facility counts, sociodemographic controls (% public assistance, median household income, age and education distribution variables), housing attributes (numbers of bedrooms, housing age, and % detached) and neighborhood attribute (e.g., school quality, violent crime rate). As in the rest of the EJ literature, we rely on timing to help identify the causal effect of each variable on the change in each race group. In particular, we consider how movements between 2000 and 2007 are driven by 2000 tract-level attributes, which are pre-determined. However, variables like racial percentages could be proxy for race-specific unobservables, and pollution measures could be correlated with (and serve as proxies for) unobserved tract characteristics. We rely on a rich set of covariates describing neighborhood attributes to address this possibility, and demonstrate in an appendix that results are robust to the inclusion of spatial dummy variables to control for neighborhood-level unobservables.

Our dependent variable measures the change in the percentage of each race group in each tract. Results are reported in Tables 4-6. In the case of cancer risk, NATA's only statistically significant impact is on whites, where the model predicts that whites *come to* the nuisance. In the case of respiratory risk, the model again predicts that whites *come to* the nuisance while it predicts that Asians and Hispanics *flee* it. Similarly in the case of neurological risk, the model predicts that whites *flee* the risk while Hispanics *come to* it. Taken together, these results would suggest that the residential mobility hypothesis can do little to explain the exposure disparities found above. In the absence of such evidence, the literature typically concludes that correlation must be driven by disproportionate siting of nuisances.

4.3 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 2.2, placing some structure on $s_{j,k}$ (the share of individuals of a particular group in tract *k* who choose to move to tract *j*) so that we can identify the role of NATA risk in driving residential mobility. Equations (1) and (2) represented a system of six equations with nine unknown $s_{j,k}$'s, leading to an identification problem. By parameterizing $s_{j,k}$ as a function of location attributes, we overcome the identification problem. Start with the predicted population in neighborhood *j* in period B:

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

Next, specify the mean utility from living in location *k* (δ_k) as a function of observable attributes of that location (X_k), attributes that are 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 3.4. If $j = k$, $MC_{j,k} = 0$, meaning that the change in utility from staying in one's current location is zero.

If $\eta_{i,k}$ is distributed i.i.d. Type I extreme value, then the share of individuals in location *k* who find it optimal to move to location *j* is given by the familiar logit functional form:

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

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

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

4.3.1 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 and ending locations. 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 GAO (1983) and Bullard (1983). Oakes, Anderton, and Anderson (1996) use only tracts containing TSDF's and a small subset of control tracts. Been and Gupta (1997) use 544 communities that hosted active TSDF's 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 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 within L.A. County census tracts (k = 1, 2, …, 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, is innocuous when it comes to identification and estimation.

4.3.2 Time periods

We use data from the 2000 decennial census to define period A, and data from the 2005-2009 5-year American Community Survey sample to define period B. Both data sets take 5% samples of the total population. We will refer to the two periods as 2000 and 2007.

4.3.3 Estimation

Estimation is carried out in two stages. We begin by finding the vector of $\{\delta_k\}_{k=1}^{N+1}$ and μ that best fit the data. Of course, without additional information, this system contains N+2 unknowns and only N+1 equations describing the mapping of populations from 2000 to 2007 in each location. It is therefore still unidentified. We do have access, however, to an additional piece of information that solves this problem. In particular, we observe the share of households in each race subgroup in L.A. county that *do not move* between 2000 and 2007.[11] These percentages, described in Table 4, provide us with an additional equation that must hold for each race group *R*:

$$\frac{\sum_{k=1}^{N} s_{k,k} pop_k^{2000,R}}{\sum_{k=1}^{N} pop_k^{2007,R}} = \%Stay_R \tag{10}$$

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 $TOTPOP = \sum_{k=1}^{N+1} pop_k^{2000} = \sum_{k=1}^{N+1} pop_k^{2007}$, we get:

$$\sigma_j^{2007} = \sum_{k=1}^{N+1} \left(\frac{e^{(\delta_j - \delta_k - \mu MC_{j,k})}}{\sum_{l=1}^{N+1} e^{(\delta_l - \delta_k - \mu MC_{l,k})}} \right) \sigma_k^{2000} \tag{11}$$

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[11] Specifically, the 2007 3-year ACS describes the year in which each household moved into its current residence. We find the percentage of households who moved into their current house in or before 2000. Note that, in our model, not moving corresponds simply to remaining in the same census tract, while in our data, not moving corresponds to remaining in the same house. Within-tract moves are not common (i.e., 7% of all moves), meaning that this difference should not have a significant effect on our results.

where $\sigma_j^t = \frac{pop_j^t}{TOTPOP}$.[12] 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 ($\bar{\delta}^0$) subject to a suitable normalization.[13] We then use that guess in conjunction with the observed population shares in 2000 ($\bar{\sigma}^{2000}$) to calculate predicted population shares in 2007 ($\tilde{\sigma}_j^{2007,0}$) $\forall\, j$. We then update the $\bar{\delta}$ guess according to the following rule (Berry 1994):

$$\delta_j^1 = \delta_j^0 + (\ln \sigma_j^{2007} - \ln \tilde{\sigma}_j^{2007,0}) \tag{12}$$

The vector $\bar{\delta}^1$ is used to generate predictions of $\tilde{\sigma}_j^{2007,1}$ $\forall\, j$, which in turn are used to generate a new vector $\bar{\delta}^2$. This process is repeated until the difference between $\left|\delta_j^{m+1} - \delta_j^m\right| < \varepsilon \;\; \forall \;\; j \quad (\varepsilon = 10^{-8})$.

With the converged values of δ_j and the guess at μ, we then calculate the predicted percentage of the 2007 population who did not move from their tract in 2000, and check to see how that value compares with $\%Stay_R$ for the appropriate racial group. We use a bisection method to search over

[12] Note that, by introducing the "catch-all" location k = N+1, we effectively make this into a closed system, where anyone entering L.A. 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,…, N) are not affected by the assumed population of N+1. We find this to indeed be the case, with our results 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,…, N) between 2000 and 2007.

[13] 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 impact the behavioral shares). As such, a normalization is required. We normalize the values such that they are mean zero.

values of μ that equate predicted $\%Stay_R$ to actual $\%Stay_R$, solving for the values of $\{\delta_k\}_{k=1}^{N+1}$ at each step.

4.3.4 Complication: Zero Shares

The methodology described above assumes a positive population share (σ_j) in each location in each period. In our EJ application, we apply this procedure to different racial groups. Using a high-resolution definition of geography (e.g., census tracts), it is possible to observe tracts containing no members of a particular group. This is, in fact, the case in L.A. County, where 3.3% of tracts contain no whites, 14.9% contain no blacks, 10.0% contain no Asians, and 0.1% contain no Hispanics. This creates a practical difficulty, as equation (12) is not defined for a particular value of j if $\sigma_j^{2007} = 0$.

We deal with this problem by adding a "patch" – i.e., a small positive artificial population ρ (e.g., $\rho = 10^{-3}$) to each location; all locations will then have positive shares and the procedure described above will be computationally feasible. However, the value of δ_j associated with zero-share locations will become increasingly negative as the value of ρ becomes smaller and smaller $(\delta_j \to \infty$ as $\rho \to 0)$. This would create a problem using a simple least-squares regression technique to decompose $\{\delta_k\}_{k=1}^{N}$.[14] Consider a linear specification of equation (5):

$$\delta_k = X_k'\beta + \xi_k \tag{13}$$

[14] Note that we do not have X_j data for the "catch-all" location N+1, and the value of δ_k, k = N+1 depends upon the assumed population of that location. We therefore drop location N+1 from the second stage of the estimation procedure.

In particular, OLS estimates of β will vary with the choice of ρ. However, if fewer than half of all locations have positive population shares, we can decompose $\{\delta_k\}_{k=1}^{N}$ into its component parts using median regression. Median regression is a particular case of quantile regression (Koenker 2005) that is robust to the choice of ρ. With fewer than half of the locations having zero true population shares for any race group, median regression results are invariant to the choice of ρ. Table 7 illustrates this point for blacks – the race group with the most severe spatial segregation (i.e., a zero population share in nearly fifteen percent of tracts in 2007). Median regression estimates of the effect of NATA cancer risk on δ_j are invariant to the choice of ρ, while OLS estimates are highly sensitive.

As was the case for the traditional EJ specification, we use 2000 sociodemographics to model the determinants of movements between 2000 and 2007. The simplification is that residents will decide to move at some point between those two years based on the attributes they see in 2000, and the new 2007 values of variables like % Public Assistance and Median Household Income will be determined by that sorting process. Using the 2000 values is a more conservative approach that avoids problems of reverse causality; it is also the approach typically adopted in the EJ literature.[15]

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[15] Another concern may arise with respect to the possibility that NATA risk is correlated with unobservable neighborhood attributes. One solution to this problem would be to employ quantile IV strategies in the second-stage decomposition of δ_j (Hansen and Chernozhukov 2005), although this is computationally difficult with a large number of endogenous regressors. Another solution would be to use time variation in NATA risk and control for time-invariant tract unobservables with fixed effects. Doing so is complicated in our setting because (i) the NATA algorithm changes with each subsequent wave, making risk exposures incomparable over time, and (ii) fixed effect estimation is not easily implemented in the median regression context. One could imagine other empirical contexts (e.g., with time-varying disamenities and without the zero-share problem) where exploiting time variation would be easy. Instead, we address the concern of correlated unobservables by incorporating a vector of spatial dummy variables to control directly for neighborhood level unobservables. The definition of these spatial dummies and the results when we employ them are described in the appendix. In general, results are robust to their inclusion.

We consider the median regression for each race group separately. Note that, because each race group's δ_j is normalized so that its mean value is zero, parameter estimates are not directly comparable across race groups; however, the relative tradeoffs individuals make between tract attributes can be compared. A simple comparison can be made considering the tradeoff between NATA risk and other consumption. This can be found by using μ as our measure of the marginal utility of income. β_{NATA} / μ can thus be interpreted as the willingness to pay to avoid NATA exposure. We therefore report all results normalized by the marginal utility of income to facilitate comparisons across groups.

4.4 Applying Structural Model to Stylized Examples

Before reporting our results, we apply the structural model described above to the three examples used in Section 2 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. Figures 2 (a) - (c) plot these mean utilities for each of the three locations versus the level of the nuisance in each 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.

4.5 Structural Model Results

The first stage of our structural estimation procedure recovers each race group's vector of $\{\delta_j\}$ along with values of the marginal utility of income (μ) that make the group's predicted "stay" percentages exactly equal to observed "stay" percentages. These results are described in Table 8. Tables 9, 10, and 11 summarize the NATA coefficient results for specifications using cancer, respiratory, and neurological risk, respectively. Note that, before carrying out the second stage regression, we normalize each group's $\{\delta_j\}$ vector by its marginal utility of income (μ), meaning that all parameter estimates can be interpreted as annual marginal willingnesses to pay (MWTP). Considering NATA cancer risk, annual MWTP's to avoid an additional case range between 32¢ (whites), 23¢ (Asians), 7¢ (blacks) and 3¢ (Hispanics). While the willingness to pay estimates for blacks and Hispanics are statistically insignificant, both are significantly smaller than the estimate for whites. For respiratory risk, MWTP's are \$1.84 (whites), \$1.73 (Asians), 43¢ (blacks) and 20¢ (Hispanics), although the estimate for blacks only has a p-value of 0.156. For neurological risk, MWTP's are \$119.24 (whites), \$26.41 (Asians), \$6.03 (blacks) and \$16.52 (Hispanics).[16]

The first thing to notice about these results (in contrast to the results of the traditional EJ model) is that MWTP's mirror the relative correlations in Tables 2 and 3. It is important to note that this is not a mechanical result of the 2000 correlations – our estimates of MWTP are based on imputed migration flows (i.e., coming to or fleeing the nuisance) between 2000 and 2007. In contrast to the results of the traditional EJ regression, these results provide strong evidence in favor of the residential mobility hypothesis as an explanation for the observed correlations between race and pollution.

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[16] The estimated willingness to pay for blacks to avoid neurological risk is statistically insignificant; its confidence interval includes values in excess of Hispanic and Asian willingnesses to pay.

The second important point to note is that NATA risk enters negatively into the utility of each race group; i.e., each group has a positive (although sometimes not statistically significant) willingness to pay to avoid NATA risk. Contrary to many interpretations of the residential mobility hypothesis, it is not necessary for minority groups to "like" pollution in order for their sorting decisions to lead to environmental injustice. Rather, they need only be less willing to make tradeoffs in other dimensions to avoid it.

It is important to interpret this last point in its full social context – especially as it relates to income inequality and the marginal utility of income. We collect per capita income by race in L.A. County in 1999 from the U.S. Census Bureau American Factfinder.[17] Under diminishing marginal utility of income, we would expect whites, with a per capita income of $35,785, to place less value on a marginal unit of "other consumption" and be willing to sacrifice more of that other consumption to get less pollution exposure. The Asian group comes next, with a per capita income of $20,595, followed by blacks ($17,341) and Hispanics ($11,100). Falling per capita income suggests that the underlying marginal utility of income will rise as one moves from white to Asian to black to Hispanic, which is indeed what we find in Table 8. The fact that the marginal unit of "other" consumption may be more valuable to minority groups can help explain why those groups may be less willing to give up that consumption in exchange for reduced air toxics in comparison with whites.

[17] http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml.

5. CONCLUSIONS

With the Environmental Protection Agency's reaffirmed commitment to environmental justice in its Plan EJ 2014,[18] 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 (i.e., "coming to" or "fleeing from" the nuisance). To overcome the problem, we describe 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 and EJ researchers with access to publicly available census data can replicate our approach for additional studies.

In an application to air toxics in L.A. County, we find that the traditional approach yields evidence counter to the residential mobility hypothesis. The traditional model results are also inconsistent; for example, Hispanics exhibit a high correlation with every NATA risk measure but flee from the nuisance. Whites have the lowest correlation with every risk measure but come to the nuisance. These and other correlations produced by the traditional model suggest that disproportionate siting of nuisances or unequal enforcement of their cleanup explain the observed patterns of minority pollution exposure. In contrast, our structural model show that whites exhibit a larger marginal willingness to pay to avoid NATA exposure than do minority groups. Hispanics have the smallest MWTP estimates and exhibit the strongest correlations with NATA risks. We emphasize that differences in MWTP are driven in large part by the differences in the economic circumstances (e.g. low versus high income) in which households make choices versus indifference to health consequences. Over the long run, residential dynamics helps explain the disproportionate

[18] See description at http://www.epa.gov/environmentaljustice/plan-ej/.

exposure of minority groups (particularly Hispanics) to toxics as well its persistence over time. A similar story is not evident using traditional empirical models found within the EJ literature.

The conclusions highlight important questions about overall policy design and constraints environmental policy makers may face. For example, 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, policy "solutions" for environmental injustice may be more complex than changing zoning rules for the siting of pollution sources. Pollution exposure patterns are the result of other sources of inequality – in particular, income inequality.

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Table 1. Summary Statistics: Los Angeles County Tract-Level Data

Variable	Mean	Std. Dev.	Min	Max
2000 Covariates:				
NATA (Cancer)	95.8660	30.6950	32.9233	555.7834
NATA (Respiratory)	23.2118	8.6758	1.7215	80.9603
NATA (Neurological)	0.3041	0.1069	0.0448	1.7941
TRI	2.2514	3.7464	0	29
Med Household Income	46196.27	23181.65	7796	200001
% Public Assistance	0.0712	0.0596	0	0.4273
Median House Value	237718.10	149263.10	9999	1000001
% # Bedrooms > 2	0.3102	0.2427	0.0000	0.9673
% Built Before 1980	0.4141	0.2388	0.0067	0.9598
%Detached Units	0.4122	0.2660	0.0000	0.9830
API Elementary	614.47	122.76	378	924
Violent Crime Rate	613.13	375.49	0	1599
%Under 18	0.2788	0.0817	0.0092	0.6220
%Over 65	0.1009	0.0519	0	0.4259
%HS Dropout	0.1090	0.1041	0	0.6875
%College Graduate	0.2282	0.1831	0	0.7885
%Asian	0.1190	0.1409	0	0.8175
%Black	0.0923	0.1530	0	0.8967
%Hispanic	0.4444	0.2928	0.0230	0.9838
%White	0.3140	0.2795	0.0024	0.9021
Change Between 2000 – 2007:				
Δ % Asian	0.0114	0.0407	-0.1418	0.2349
Δ % Black	-0.0094	0.0382	-0.2002	0.2226
Δ % Hispanic	0.0294	0.0658	-0.4009	0.3464
Δ % White	-0.0246	0.0640	-0.5852	0.2086

NATA indices observed in 1999 and measure the expected number of cases per 1 million residents.

Table 2. Bivariate Correlations Between NATA and Race

	NATA Cancer	NATA Respiratory	NATA Neurological	% Asian	% Black	% Hispanic	% White
NATA Cancer	1						
NATA Respiratory	0.7726	1					
NATA Neurological	0.8105	0.8115	1				
% Asian	0.0015	-0.0330	-0.0086	1			
% Black	0.1085	0.2879	0.1468	-0.2334	1		
% Hispanic	0.3846	0.3705	0.4197	-0.3423	-0.0816	1	
% White	-0.4511	-0.5133	-0.5028	-0.0282	-0.3431	-0.7917	1

Table 3. Multivariate Correlations, NATA Between NATA, Race, and Neighborhood Attributes

	NATA (Cancer)		NATA (Respiratory)		NATA (Neurological)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
TRI	1.0979	6.40	0.0862	2.07	0.0026	4.76
Med Household Income	2.00E-05	0.26	3.65E-05	1.97	-9.63E-08	-0.40
% Public Assistance	40.7460	2.36	11.9335	2.85	0.2231	4.13
Median House Value	1.75E-05	2.05	6.23E-06	2.99	1.15E-07	4.30
% # Bedrooms > 2	-15.6560	-1.92	-11.4928	-5.78	-0.0592	-2.31
% Built Before 1980	34.4298	6.45	10.7264	8.26	0.0985	5.89
% Detached Housing	-26.3896	-3.41	-5.9036	-3.14	-0.1061	-4.37
API Elementary	0.0158	1.73	0.0058	2.59	0.0000	-0.94
Violent Crime Rate	0.0129	6.56	0.0056	11.68	0.0001	9.56
% Under 18	-46.8396	-2.76	-21.7412	-5.27	-0.2227	-4.19
% Over 65	-2.8485	-0.16	7.1648	1.65	0.0127	0.23
% HS Dropout	-5.2984	-0.71	-3.5563	-1.97	-0.0015	-0.07
% College Graduate	25.0525	2.37	9.1176	3.55	0.0686	2.07
% White	-166.876	-3.87	-13.720	-1.31	-0.433	-3.20
% Asian	-114.004	-2.67	2.823	0.27	-0.236	-1.77
% Black	-128.346	-3.05	8.035	0.78	-0.318	-2.41
% Hispanic	-96.718	-2.40	9.778	1.00	-0.215	-1.71
Constant	198.238	5.00	16.115	1.67	0.596	4.79
Adjusted R^2	0.3208		0.4970		0.4500	

Coefficients are ordinary least squares regression estimates.

Table 4. Traditional Model: NATA Cancer

	Δ%*Asian*		Δ%*Black*		Δ%*Hispanic*		Δ%*White*	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Cancer)	-4.41E-05	-1.27	-8.45E-06	-0.28	-4.64E-05	-0.88	9.38E-05	2.00
TRI	-3.56E-05	-0.14	2.20E-04	0.97	4.13E-04	1.04	-6.16E-04	-1.74
Med Household Income	1.44E-07	1.25	1.80E-07	1.80	-4.28E-07	-2.45	1.50E-07	0.96
% Public Assistance	-6.40E-02	-2.45	-6.21E-02	-2.76	-1.17E-01	-2.96	2.75E-01	7.77
Median House Value	-2.85E-08	-2.20	-3.56E-08	-3.18	-1.53E-08	-0.78	9.99E-08	5.70
% # Bedrooms > 2	-4.47E-02	-3.61	2.12E-02	1.98	7.29E-02	3.89	-6.00E-02	-3.58
% Built Before 1980	9.76E-03	1.20	-6.47E-03	-0.92	-7.56E-04	-0.06	-9.93E-03	-0.90
% Detached Housing	-3.23E-03	-0.28	-2.56E-02	-2.53	-7.79E-03	-0.44	4.74E-02	2.98
API Elementary	4.75E-05	3.43	9.59E-06	0.80	-9.71E-06	-0.46	-5.33E-05	-2.84
Violent Crime Rate	3.63E-06	1.20	9.44E-06	3.63	-1.93E-06	-0.42	-1.31E-05	-3.21
% Under 18	3.11E-02	1.21	2.49E-02	1.12	2.06E-01	5.29	-2.53E-01	-7.27
% Over 65	-1.06E-02	-0.39	7.59E-02	3.25	-4.00E-02	-0.98	1.99E-02	0.54
% HS Dropout	3.25E-02	2.90	3.26E-03	0.34	-6.17E-02	-3.64	2.83E-02	1.86
% College Graduate	-5.08E-02	-3.18	7.07E-04	0.05	-1.17E-01	-4.85	1.55E-01	7.13
% White	0.3254	4.97	-0.1387	-2.45	0.2165	2.18	-1.2544	-14.14
% Asian	0.3854	5.97	-0.1421	-2.55	0.0960	0.98	-1.1857	-13.56
% Black	0.2929	4.59	-0.2579	-4.68	0.2171	2.25	-1.1099	-12.85
% Hispanic	0.2653	4.35	-0.1440	-2.73	0.1045	1.13	-1.0524	-12.74
Constant	-0.2924	-4.84	0.1236	2.37	-0.1130	-1.24	1.0969	13.41
Adjusted R^2	0.1149		0.2503		0.2256		0.3445	

Table 5. Traditional Model: NATA Respiratory

	Δ%*Asian*		Δ%*Black*		Δ%*Hispanic*		Δ%*White*	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Respiratory)	-2.43E-04	-1.70	1.53E-05	0.12	-7.88E-04	-3.67	9.57E-04	4.98
TRI	-6.31E-05	-0.24	2.09E-04	0.93	4.30E-04	1.10	-5.96E-04	-1.70
Med Household Income	1.52E-07	1.31	1.79E-07	1.80	-4.01E-07	-2.30	1.17E-07	0.75
% Public Assistance	-6.29E-02	-2.41	-6.26E-02	-2.78	-1.10E-01	-2.78	2.67E-01	7.59
Median House Value	-2.78E-08	-2.14	-3.58E-08	-3.20	-1.12E-08	-0.57	9.56E-08	5.47
% # Bedrooms > 2	-4.68E-02	-3.75	2.15E-02	2.00	6.46E-02	3.43	-5.05E-02	-3.01
% Built Before 1980	1.08E-02	1.32	-6.92E-03	-0.98	6.10E-03	0.49	-1.70E-02	-1.53
% Detached Housing	-3.50E-03	-0.30	-2.53E-02	-2.50	-1.12E-02	-0.63	5.06E-02	3.20
API Elementary	4.82E-05	3.48	9.37E-06	0.78	-5.90E-06	-0.28	-5.74E-05	-3.07
Violent Crime Rate	4.42E-06	1.43	9.25E-06	3.47	1.88E-06	0.40	-1.73E-05	-4.15
% Under 18	2.79E-02	1.08	2.56E-02	1.15	1.91E-01	4.90	-2.37E-01	-6.80
% Over 65	-8.74E-03	-0.32	7.58E-02	3.24	-3.42E-02	-0.84	1.28E-02	0.35
% HS Dropout	3.19E-02	2.84	3.36E-03	0.35	-6.43E-02	-3.80	3.12E-02	2.06
% College Graduate	-4.97E-02	-3.10	3.55E-04	0.03	-1.11E-01	-4.61	1.48E-01	6.86
% White	0.3294	5.05	-0.1370	-2.43	0.2134	2.17	-1.2569	-14.30
% Asian	0.3911	6.07	-0.1412	-2.54	0.1035	1.06	-1.1991	-13.81
% Black	0.3005	4.72	-0.2570	-4.67	0.2294	2.39	-1.1296	-13.18
% Hispanic	0.2720	4.47	-0.1434	-2.73	0.1167	1.27	-1.0708	-13.05
Constant	-0.2972	-4.95	0.1217	2.35	-0.1095	-1.21	1.1000	13.60
Adjusted R^2	0.1155		0.2503		0.2307		0.3516	

Table 6. Traditional Model: NATA Neurological

	Δ%*Asian*		Δ%*Black*		Δ%*Hispanic*		Δ%*White*	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Neurological)	-8.38E-03	-0.76	-5.80E-03	-0.61	-3.67E-02	-2.20	4.88E-02	3.26
TRI	-6.26E-05	-0.24	2.26E-04	1.00	4.56E-04	1.16	-6.38E-04	-1.81
Med Household Income	1.42E-07	1.23	1.79E-07	1.80	-4.33E-07	-2.48	1.56E-07	1.00
% Public Assistance	-6.39E-02	-2.44	-6.12E-02	-2.71	-1.11E-01	-2.80	2.68E-01	7.56
Median House Value	-2.83E-08	-2.18	-3.51E-08	-3.12	-1.18E-08	-0.60	9.59E-08	5.46
% # Bedrooms > 2	-4.45E-02	-3.59	2.10E-02	1.96	7.15E-02	3.82	-5.86E-02	-3.50
% Built Before 1980	9.06E-03	1.11	-6.19E-03	-0.88	1.26E-03	0.10	-1.15E-02	-1.04
% Detached Housing	-2.96E-03	-0.25	-2.60E-02	-2.56	-1.05E-02	-0.59	5.01E-02	3.15
API Elementary	4.66E-05	3.37	9.30E-06	0.78	-1.14E-05	-0.55	-5.05E-05	-2.70
Violent Crime Rate	3.56E-06	1.17	9.68E-06	3.67	-3.57E-07	-0.08	-1.48E-05	-3.58
% Under 18	3.13E-02	1.22	2.40E-02	1.08	2.00E-01	5.13	-2.46E-01	-7.07
% Over 65	-1.04E-02	-0.38	7.60E-02	3.25	-3.94E-02	-0.96	1.90E-02	0.52
% HS Dropout	3.28E-02	2.92	3.30E-03	0.34	-6.15E-02	-3.63	2.78E-02	1.84
% College Graduate	-5.14E-02	-3.21	8.93E-04	0.06	-1.16E-01	-4.80	1.54E-01	7.10
% White	0.3291	5.03	-0.1398	-2.47	0.2083	2.11	-1.2489	-14.12
% Asian	0.3885	6.02	-0.1425	-2.56	0.0926	0.95	-1.1849	-13.59
% Black	0.2959	4.64	-0.2587	-4.70	0.2113	2.19	-1.1064	-12.84
% Hispanic	0.2678	4.39	-0.1445	-2.75	0.1011	1.10	-1.0509	-12.76
Constant	-0.2961	-4.91	0.1254	2.41	-0.1003	-1.10	1.0864	13.32
Adjusted R^2	0.1144		0.2504		0.2272		0.3468	

Table 7. Estimates for Blacks Under Alternative "Patch" Assumptions

	$\rho = 10^{-3}$		$\rho = 10^{-6}$		$\rho = 10^{-9}$	
	OLS	Median Regression	OLS	Median Regression	OLS	Median Regression
NATA (Cancer)	-0.3654	-0.0702	-0.5584	-0.0702	-0.7516	-0.0702
	(-1.92)	(-0.97)	(-1.92)	(-0.97)	(-1.92)	(-0.97)
Controls:						
TRI	Yes		Yes		Yes	
Housing Attributes	Yes		Yes		Yes	
Neighborhood Sociodemographics	Yes		Yes		Yes	
Other Neighborhood Attributes	Yes		Yes		Yes	
Neighbors Race	Yes		Yes		Yes	

Table 8. Stayer Probabilities and Fitted Moving Cost Parameters

Group	% Not Moving	μ
Asian	32.48	0.01469
Black	35.90	0.01955
Hispanic	32.64	0.02161
White	42.20	0.01349

Table 9. Sorting Model: NATA Cancer

	δ_{Asian}		δ_{Black}		$\delta_{Hispanic}$		δ_{White}	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Cancer)	-0.2302	-2.53	-0.0702	-0.97	-0.0300	-1.20	-0.3210	-5.09
TRI	-1.5422	-2.25	0.2167	0.40	0.5426	2.89	0.1006	0.21
Med Household Income	-6.59E-05	-0.22	8.01E-04	3.33	-3.11E-04	-3.72	7.48E-04	3.57
% Public Assistance	-654.3239	-9.59	-162.3281	-3.01	-181.7812	-9.63	-553.0737	-11.70
Median House Value	-8.56E-05	-2.53	4.95E-06	0.18	-8.34E-05	-8.87	1.15E-04	4.96
% # Bedrooms > 2	36.0875	1.11	25.5698	1.00	7.9380	0.88	37.9871	1.70
% Built Before 1980	73.9507	3.47	67.3254	4.01	27.7200	4.67	22.5680	1.54
% Detached Housing	-9.4323	-0.31	-28.7546	-1.18	45.3599	5.34	45.6372	2.18
API Elementary	0.0435	1.20	-0.1281	-4.45	0.0067	0.67	0.0431	1.72
Violent Crime Rate	-0.0183	-2.32	0.0266	4.25	-0.0053	-2.43	-0.0169	-3.09
% Under 18	-160.7567	-2.38	318.4292	6.01	96.5585	5.17	-69.8988	-1.50
% Over 65	-139.8656	-1.99	-249.9847	-4.51	-98.3197	-5.01	-24.2070	-0.49
% HS Dropout	-47.5464	-1.62	58.1861	2.52	-26.6035	-3.26	-37.0179	-1.84
% College Graduate	-58.4975	-1.40	48.1738	1.45	-5.7901	-0.50	-2.0564	-0.07
% White	-1059.238	-6.20	-227.562	-1.68	31.955	0.68	-1309.498	-11.10
% Asian	-708.700	-4.21	-291.512	-2.18	-0.530	-0.01	-1459.769	-12.54
% Black	-1152.370	-6.93	-69.365	-0.52	19.088	0.42	-1546.958	-13.46
% Hispanic	-1100.300	-6.93	-454.080	-3.59	48.055	1.10	-1470.561	-13.39
Constant	1206.236	7.67	320.145	2.56	-15.758	-0.36	1387.712	12.77
Pseudo R^2	0.2622		0.1514		0.2211		0.5529	

Table 10. Sorting Model: NATA Respiratory

	δ_{Asian}		δ_{Black}		$\delta_{Hispanic}$		δ_{White}	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Respiratory)	-1.7258	-4.43	-0.4322	-1.42	-0.2046	-1.64	-1.8496	-6.26
TRI	-1.3202	-1.86	0.0902	0.16	0.4740	2.11	0.3213	0.60
Med Household Income	1.09E-04	0.35	8.70E-04	3.52	-3.01E-04	-2.99	7.88E-04	3.29
% Public Assistance	-632.8804	-8.88	-170.2657	-3.06	-182.4731	-8.01	-511.7855	-9.51
Median House Value	-8.08E-05	-2.29	2.31E-05	0.83	-8.06E-05	-7.10	1.34E-04	4.99
% # Bedrooms > 2	17.4712	0.51	24.6880	0.93	3.7176	0.34	30.2658	1.18
% Built Before 1980	89.6975	4.00	70.1945	4.04	29.4826	4.09	27.0375	1.61
% Detached Housing	-21.0050	-0.65	-34.0396	-1.36	45.3527	4.43	45.4958	1.91
API Elementary	0.0500	1.32	-0.1159	-3.92	0.0077	0.64	0.0579	2.02
Violent Crime Rate	-0.0126	-1.50	0.0297	4.51	-0.0043	-1.61	-0.0154	-2.40
% Under 18	-204.2801	-2.89	295.0260	5.40	96.2728	4.25	-134.5613	-2.52
% Over 65	-135.0650	-1.83	-264.8258	-4.65	-91.5968	-3.86	-22.6657	-0.41
% HS Dropout	-30.3868	-0.99	58.7413	2.48	-26.0672	-2.66	-42.9608	-1.85
% College Graduate	-67.1728	-1.54	31.5659	0.92	-7.5075	-0.54	-3.3297	-0.10
% White	-985.132	-5.52	-256.664	-1.85	27.186	0.48	-1310.195	-9.76
% Asian	-617.882	-3.50	-314.202	-2.30	-4.041	-0.07	-1448.710	-10.93
% Black	-1063.366	-6.10	-82.429	-0.61	17.808	0.32	-1508.564	-11.53
% Hispanic	-1017.073	-6.10	-472.642	-3.66	45.188	0.85	-1445.361	-11.54
Constant	1140.764	6.95	341.351	2.68	-12.544	-0.24	1383.774	11.21
Pseudo R^2	0.2640		0.1515		0.2211		0.5560	

Table 11. Sorting Model: NATA Neurological

	δ_{Asian}		δ_{Black}		$\delta_{Hispanic}$		δ_{White}	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Neurological)	-26.4143	-0.90	-6.0258	-0.26	-16.5163	-1.83	-119.2423	-6.08
TRI	-1.3149	-1.88	0.2012	0.37	0.5884	2.80	0.0731	0.16
Med Household Income	-1.72E-04	-0.56	7.52E-04	3.14	-3.22E-04	-3.44	6.92E-04	3.38
% Public Assistance	-659.1290	-9.42	-164.2448	-3.06	-179.9431	-8.46	-520.2657	-11.22
Median House Value	-8.92E-05	-2.61	1.28E-06	0.05	-7.94E-05	-7.49	1.25E-04	5.45
% # Bedrooms > 2	4.01E+01	1.21	2.75E+01	1.08	6.74E+00	0.67	4.02E+01	1.83
% Built Before 1980	68.5383	3.16	64.1430	3.82	31.1868	4.68	22.2434	1.54
% Detached Housing	-6.9910	-0.22	-24.5694	-1.01	43.0288	4.50	40.9795	1.96
API Elementary	0.0414	1.12	-0.1245	-4.36	0.0058	0.52	0.0450	1.84
Violent Crime Rate	-0.0222	-2.72	0.0258	4.08	-0.0043	-1.72	-0.0162	-3.00
% Under 18	-130.4528	-1.89	333.8658	6.32	95.0362	4.52	-95.0147	-2.09
% Over 65	-134.5285	-1.87	-242.4493	-4.39	-92.5214	-4.19	-29.4301	-0.62
% HS Dropout	-30.3323	-1.01	58.9793	2.55	-22.9260	-2.51	-42.9234	-2.18
% College Graduate	-49.2343	-1.15	57.7299	1.74	-8.2577	-0.63	0.5004	0.02
% White	-1025.527	-5.89	-240.145	-1.79	35.672	0.67	-1306.394	-11.27
% Asian	-677.254	-3.95	-309.529	-2.33	4.531	0.09	-1449.155	-12.67
% Black	-1119.977	-6.60	-81.979	-0.63	21.930	0.43	-1535.824	-13.58
% Hispanic	-1078.350	-6.65	-466.594	-3.72	51.628	1.05	-1457.410	-13.49
Constant	1162.520	7.24	321.415	2.59	-18.130	-0.37	1389.940	12.99
Pseudo R^2	0.2616		0.1513		0.2213		0.5539	

Figure 1. Maps of Population Distribution

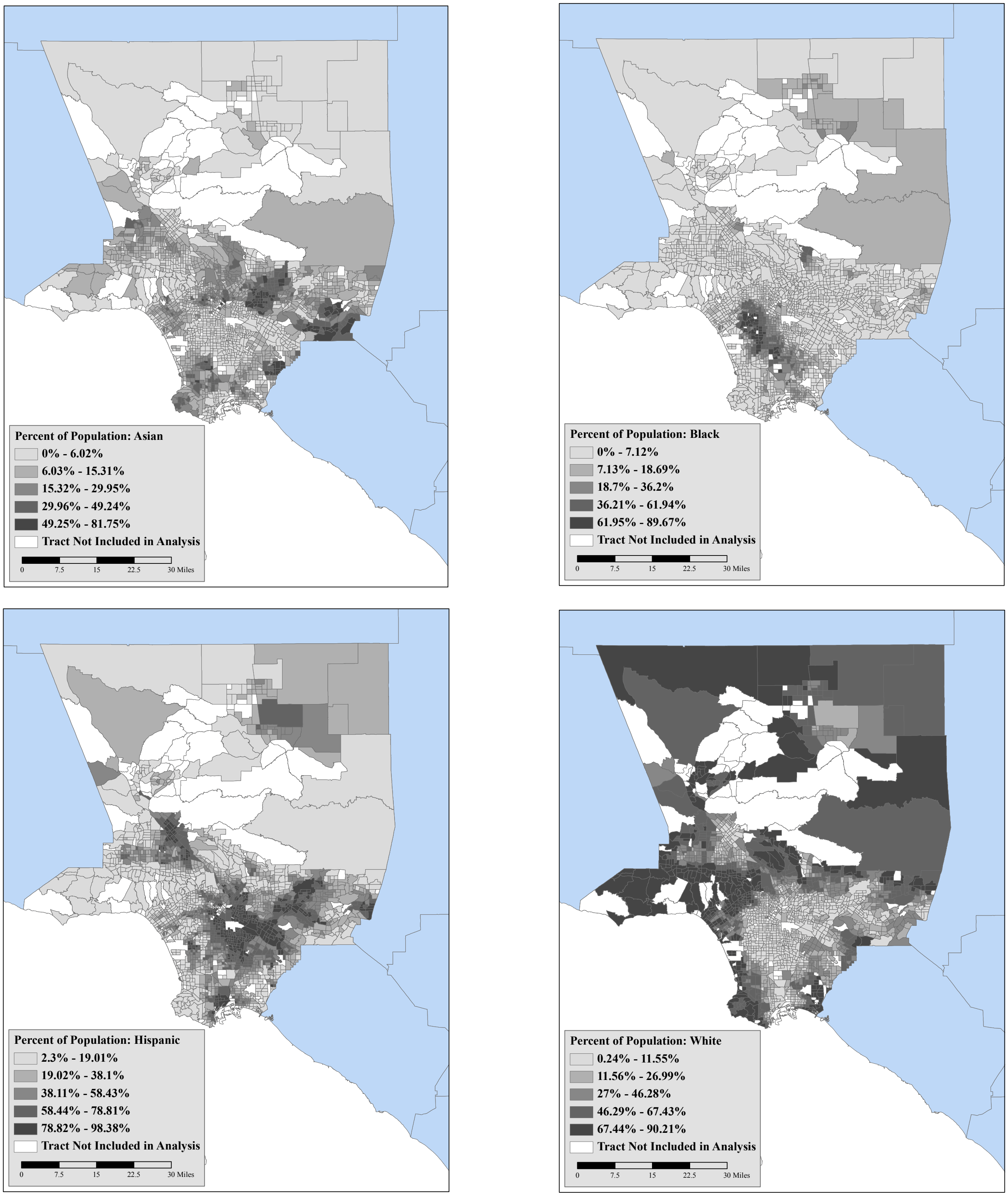


Figure 2. Maps of NATA Risk Distribution

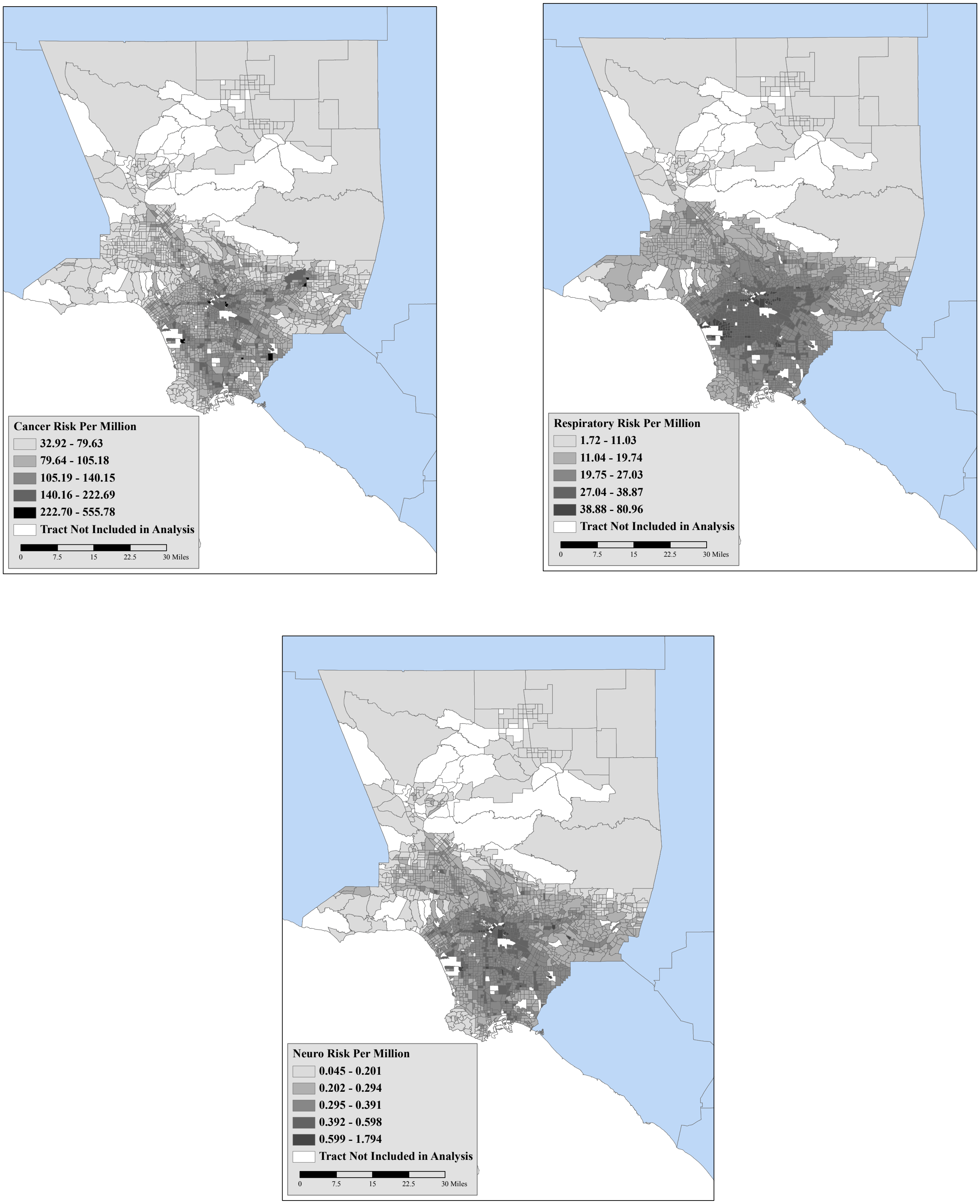
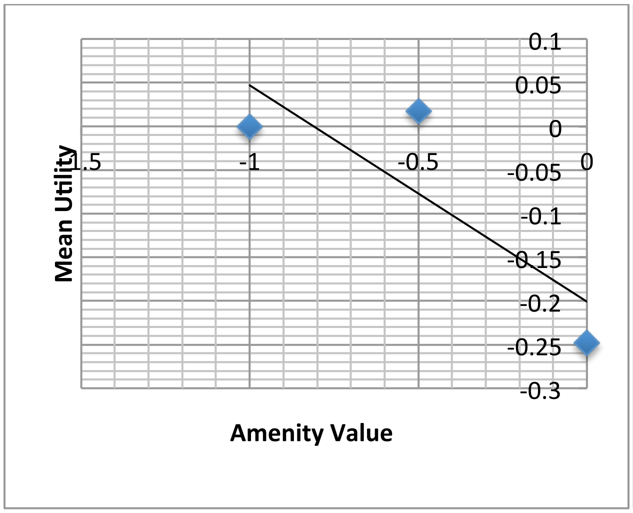
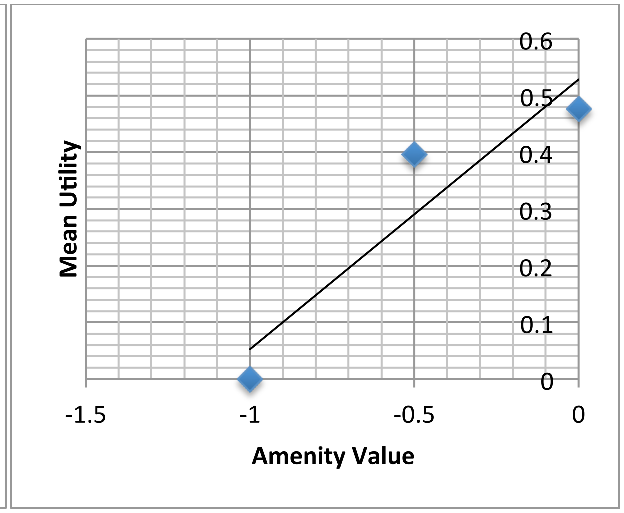


Figure 3. Mean Utilities and Amenity Values From Stylized Examples

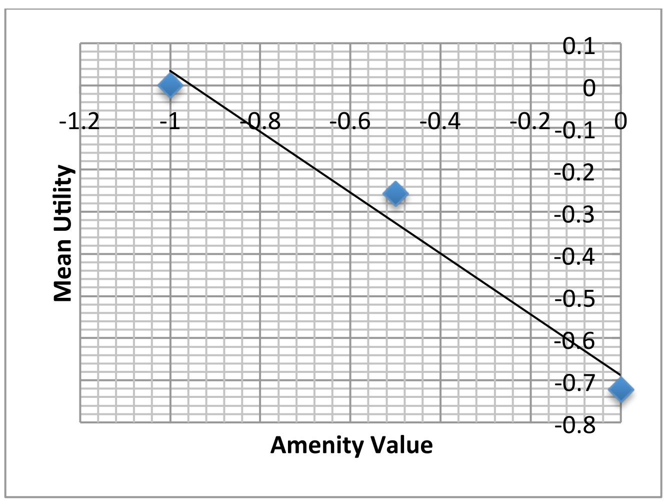
(a) Example #1 (Coming to the Nuisance)



(b) Example #2 (Fleeing the Nuisance)



(c) Example #3 (Coming to the Nuisance)



Appendix – Inclusion of Regional Dummies

In this appendix, we demonstrate that our results are robust to the inclusion of spatial dummies that control for unobserved neighborhood attributes that might be correlated with observed determinants of migration behavior. Working within a single county and using census tract as our spatial unit of observation, there are not readily available neighborhood definitions for us to use for spatial dummies. Fortunately, the Los Angeles Times has defined 16 regions within L.A. County as part of its "Mapping L.A." portal.[19] The portal provides readers with information about demographics, income, schools and news from each region. For our purpose, it provides a convenient way to group tracts and define spatial fixed effects that control for neighborhood characteristics for which we do not have data. The map in Figure A1, taken from the L.A. Times "Mapping L.A." website, describes the sixteen regions.

We repeat our estimation procedure underlying our structural model, but add a vector of dummy variables indicating in which of the first fifteen regions each census tract is included (the indicator for the Westside region is excluded). Results follow below in Tables A1 (a), (b) through A3 (a), (b) – (a) tables report results for the main covariates, and (b) tables report the regional dummy coefficients. Identification is based on *within-region* variation in 18 different covariates (including NATA risk). In each case, the differences in willingness to pay across race groups found in simpler specifications are confirmed in these richer specificaitons. Specifically in Table A1 (a), results are similar to those found without regional dummies. Willingness to pay for blacks remains statistically insignificant. Whites have the largest willingness to pay, followed by Asians, and then by Hispanics. A few differences between the specifications emerge when looking at respiratory risk in Table A2 (a); in particular, the difference between white and Asian willingness to pay is smaller (in fact, the Asian point estimate is now slightly higher than that of whites). Blacks' willingness to pay remains statistically insignificant, though, and the willingness to pay of Hispanics remains significantly lower than that of whites and Asians. Finally, considering neurological risk in Table A3 (a), we obtain similar results. Willingness to pay for whites greatly exceeds that of the other three race groups. Willingness to pay for Asians and blacks is again statistically insignificant, while willingness to pay for Hispanics remains small but significant. The only effect of including regional dummies is to slightly contract the difference in willingness to pay between whites and Hispanics.

[19] See http://projects.latimes.com/mapping-la/neighborhoods/.

While they do not completely rule out the influence of correlated unobservable neighborhood attributes, the stability of our results with respect to the inclusion of regional dummy variables goes a long way to alleviating this concern. In particular, results for whites and Hispanics, the two largest racial groups who are also the least geographically segregated, are remarkably stable.

Figure A1

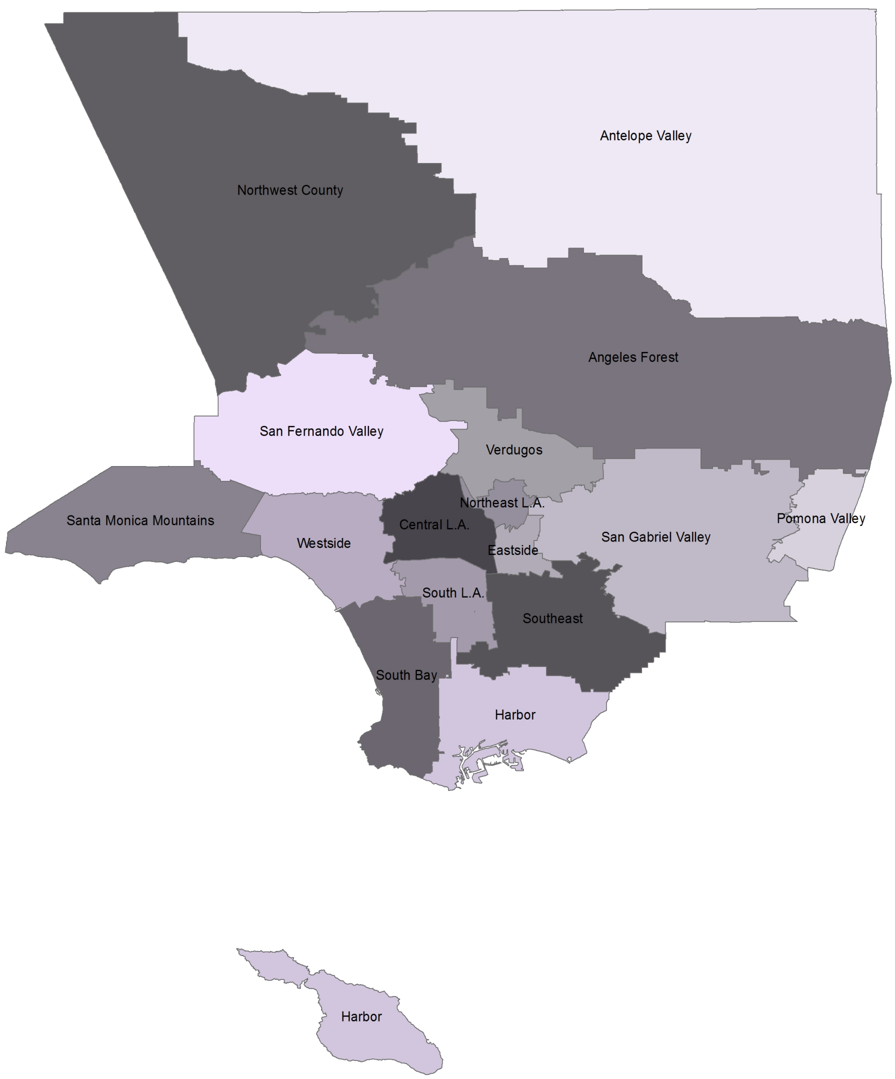


Table A1(a). Sorting Model With Regional Fixed Effects: NATA Cancer

	δ_{Asian}		δ_{Black}		$\delta_{Hispanic}$		δ_{White}	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Cancer)	-0.1324	-1.35	-0.0036	-0.04	-0.0478	-1.69	-0.2053	-3.43
TRI	-0.6129	-0.82	-0.2489	-0.39	0.3266	1.53	0.9618	2.19
Med Household Income	-3.54E-04	-1.10	1.45E-04	0.52	-5.35E-04	-5.86	6.08E-04	3.21
% Public Assistance	-530.2558	-7.23	-168.2738	-2.63	-164.0670	-7.88	-531.1397	-12.33
Median House Value	-8.22E-05	-2.23	1.85E-05	0.57	-7.14E-05	-6.73	1.25E-04	5.81
% # Bedrooms > 2	17.2451	0.49	86.6757	2.84	19.6594	1.98	47.7244	2.31
% Built Before 1980	71.6651	2.91	52.2939	2.46	13.8653	1.98	27.4235	1.91
% Detached Housing	18.7199	0.57	-23.9072	-0.85	54.2011	5.80	37.6356	1.95
API Elementary	0.0221	0.52	-0.0132	-0.35	-0.0048	-0.40	0.0285	1.13
Violent Crime Rate	-0.0173	-1.84	0.0157	1.90	-0.0027	-1.00	-0.0279	-4.99
% Under 18	-91.0065	-1.24	278.5255	4.34	31.3019	1.50	-71.2324	-1.65
% Over 65	-137.6360	-1.82	-167.6415	-2.53	-97.0330	-4.49	-10.7422	-0.24
% HS Dropout	-49.3718	-1.60	8.2041	0.30	-19.5918	-2.23	-48.7715	-2.65
% College Graduate	-37.4907	-0.83	82.4968	2.08	5.9308	0.46	-1.8396	-0.07
% White	-562.665	-2.87	-66.176	-0.39	-10.219	-0.19	-1007.833	-8.71
% Asian	-238.190	-1.22	-121.020	-0.71	-40.745	-0.75	-1166.922	-10.18
% Black	-624.271	-3.24	95.681	0.57	-26.625	-0.49	-1173.363	-10.33
% Hispanic	-627.585	-3.39	-217.172	-1.35	14.677	0.28	-1168.281	-10.69

Results continued on Table A1(b)

Table A1(b). Sorting Model With Regional Fixed Effects: NATA Cancer

Continued from Table A1(a)

Angeles Forest	3.9382	0.16	-1.4173	-0.07	22.4762	3.30	-2.4146	-0.17
Antelope Valley	-52.8469	-2.19	10.7043	0.50	9.8877	1.43	11.4889	0.80
Central L.A.	-4.6533	-0.33	11.6151	0.93	5.8146	1.44	5.4768	0.65
Eastside	-74.2063	-3.96	-514.0705	-31.36	21.5325	4.05	-52.4733	-4.75
Harbor	-10.8028	-0.70	34.1733	2.53	25.6479	5.84	-4.1218	-0.45
Northeast L.A.	-5.2484	-0.25	9.0888	0.48	25.0541	4.15	19.8909	1.60
Northwest County	-9.9148	-0.41	-3.7113	-0.17	33.2713	4.80	-14.7038	-1.03
Pomona Valley	-0.6017	-0.03	23.5257	1.23	27.7423	4.47	18.1088	1.40
San Fernando Valley	-18.7220	-1.25	7.9323	0.60	21.3523	4.98	1.7370	0.19
San Gabriel Mountains	-5.8950	-0.38	-33.1222	-2.41	23.9358	5.38	7.6706	0.83
Santa Monica Mountains	-10.8476	-0.31	-66.0431	-2.17	41.6604	4.24	32.3043	1.57
South Bay	-16.4793	-1.07	13.4081	0.99	26.5588	6.08	-13.9375	-1.54
Southeast	-74.5166	-4.65	0.7373	0.05	25.9357	5.69	-10.0184	-1.06
South L.A.	-181.6730	-10.07	35.1411	2.22	24.9765	4.87	-100.0724	-9.36
Verdugos	1.7707	0.09	-3.1900	-0.18	15.9311	2.82	26.6241	2.26
Constant	736.7450	4.03	69.9376	0.44	26.3025	0.51	1098.5320	10.20
Pseudo R^2	0.2891		0.1851		0.2301		0.5697	

Table A2(a). Sorting Model With Regional Fixed Effects: NATA Respiratory

	δ_{Asian}		δ_{Black}		$\delta_{Hispanic}$		δ_{White}	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Respiratory)	-1.3301	-3.07	-0.0700	-0.17	-0.4208	-3.47	-1.3149	-4.64
TRI	-0.5494	-0.83	-0.2359	-0.37	0.2448	1.29	0.5698	1.30
Med Household Income	-4.49E-04	-1.56	1.57E-04	0.58	-5.24E-04	-6.44	5.30E-04	2.80
% Public Assistance	-539.4248	-8.20	-162.9034	-2.60	-163.1801	-8.80	-494.7454	-11.47
Median House Value	-8.25E-05	-2.48	2.08E-05	0.65	-6.81E-05	-7.22	1.33E-04	6.14
% # Bedrooms > 2	9.6673	0.31	85.9061	2.88	16.8452	1.91	39.3306	1.90
% Built Before 1980	68.3066	3.08	52.1798	2.51	12.0135	1.92	28.3587	1.98
% Detached Housing	29.4154	1.00	-23.4644	-0.85	56.1835	6.76	50.3934	2.62
API Elementary	0.0299	0.78	-0.0122	-0.33	-0.0065	-0.60	0.0205	0.81
Violent Crime Rate	-0.0135	-1.57	0.0159	1.93	-0.0015	-0.61	-0.0240	-4.22
% Under 18	-80.0740	-1.21	275.4843	4.38	33.0399	1.78	-68.2377	-1.58
% Over 65	-127.3816	-1.86	-164.9315	-2.54	-100.7579	-5.23	-2.2769	-0.05
% HS Dropout	-63.7353	-2.29	9.7144	0.37	-24.7368	-3.16	-54.2588	-2.97
% College Graduate	-43.4846	-1.06	80.9739	2.08	2.3232	0.20	7.8124	0.29
% White	-488.445	-2.77	-85.685	-0.51	8.469	0.17	-1012.356	-8.79
% Asian	-166.258	-0.95	-140.088	-0.85	-23.660	-0.48	-1171.591	-10.26
% Black	-530.268	-3.06	75.606	0.46	-8.204	-0.17	-1167.932	-10.33
% Hispanic	-553.249	-3.32	-235.599	-1.49	32.658	0.70	-1170.199	-10.76

Results continued on Table A1(b)

Table A2(b). Sorting Model With Regional Fixed Effects: NATA Respiratory

Continued from Table A1(a)

Angeles Forest	-7.6584	-0.35	-1.9718	-0.09	18.2541	2.97	-9.2231	-0.64
Antelope Valley	-78.5590	-3.40	10.1682	0.46	3.7411	0.58	-8.4660	-0.56
Central L.A.	-6.4689	-0.51	12.0764	0.99	5.9823	1.66	5.1961	0.62
Eastside	-62.8693	-3.71	-512.9003	-31.65	22.8909	4.80	-50.3830	-4.51
Harbor	-16.6841	-1.20	33.9238	2.57	25.6212	6.53	-7.9459	-0.87
Northeast L.A.	-10.0387	-0.52	9.7885	0.53	24.0958	4.47	18.7738	1.49
Northwest County	-27.7988	-1.25	-3.8321	-0.18	28.2432	4.52	-19.0677	-1.31
Pomona Valley	-12.7673	-0.64	23.1845	1.22	24.4258	4.37	6.9892	0.54
San Fernando Valley	-26.2785	-1.92	7.5318	0.58	19.8827	5.15	-2.2567	-0.25
San Gabriel Mountains	-15.4647	-1.09	-33.1345	-2.46	23.3063	5.84	3.6376	0.39
Santa Monica Mountains	-18.2139	-0.58	-67.7779	-2.28	39.7710	4.54	32.2042	1.57
South Bay	-14.4453	-1.03	14.8496	1.11	29.0446	7.38	-8.2868	-0.89
Southeast	-80.4211	-5.60	1.6818	0.12	25.7323	6.34	-10.2541	-1.08
South L.A.	-189.5822	-11.68	35.5313	2.30	25.3211	5.54	-102.5397	-9.59
Verdugos	-5.9202	-0.33	-4.9262	-0.29	14.7104	2.91	20.7444	1.76
Constant	682.6754	4.17	88.0198	0.57	15.7135	0.34	1110.1930	10.38
Pseudo R^2	0.2902		0.1851		0.2311		0.5710	

Table A3(a). Sorting Model With Regional Fixed Effects: NATA Neurological

	δ_{Asian}		δ_{Black}		$\delta_{Hispanic}$		δ_{White}	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
NATA (Neurological)	-16.6598	-0.43	8.6365	0.33	-18.9331	-2.11	-93.4963	-4.89
TRI	-0.8320	-1.01	-0.3347	-0.52	0.3502	1.79	0.6339	1.53
Med Household Income	-3.49E-04	-0.98	1.36E-04	0.49	-5.87E-04	-6.97	6.12E-04	3.42
% Public Assistance	-520.2607	-6.35	-174.0499	-2.74	-168.4285	-8.75	-499.4416	-12.32
Median House Value	-8.14E-05	-1.98	1.56E-05	0.49	-5.94E-05	-6.07	1.29E-04	6.26
% # Bedrooms > 2	21.2720	0.54	81.7052	2.71	22.2831	2.43	41.5384	2.15
% Built Before 1980	67.7985	2.47	51.4131	2.45	16.4203	2.54	23.8575	1.77
% Detached Housing	20.5111	0.56	-21.8121	-0.78	51.1391	5.92	45.2044	2.50
API Elementary	0.0218	0.46	-0.0093	-0.25	-0.0038	-0.34	0.0306	1.29
Violent Crime Rate	-0.0190	-1.80	0.0185	2.26	-0.0023	-0.94	-0.0261	-4.92
% Under 18	-83.9801	-1.03	288.7618	4.55	33.4239	1.74	-71.4835	-1.77
% Over 65	-132.4554	-1.57	-177.7958	-2.71	-98.5756	-4.95	-9.2188	-0.22
% HS Dropout	-38.9049	-1.13	6.6685	0.25	-18.8952	-2.33	-58.8339	-3.42
% College Graduate	-42.2327	-0.84	80.8604	2.08	3.6398	0.30	-9.0378	-0.36
% White	-527.562	-2.42	-55.618	-0.33	-6.679	-0.13	-1025.018	-9.48
% Asian	-212.914	-0.98	-115.086	-0.69	-37.969	-0.75	-1185.547	-11.07
% Black	-589.801	-2.75	95.696	0.58	-23.349	-0.47	-1190.116	-11.22
% Hispanic	-602.240	-2.92	-215.673	-1.36	18.622	0.39	-1183.491	-11.59

Results continued on Table A1(b)

Table A3(b). Sorting Model With Regional Fixed Effects: NATA Neurological

Continued from Table A1(a)								
Angeles Forest	3.0346	0.11	-1.6521	-0.08	20.0618	3.15	-16.4631	-1.22
Antelope Valley	-55.2804	-1.97	10.1220	0.47	7.4274	1.12	-7.1812	-0.51
Central L.A.	-6.9385	-0.44	12.2439	0.99	4.5756	1.22	3.3680	0.43
Eastside	-82.3675	-3.99	-511.0182	-31.62	20.7415	4.24	-58.3608	-5.62
Harbor	-13.4192	-0.79	36.3372	2.73	24.1619	5.95	-10.7396	-1.25
Northeast L.A.	-5.4679	-0.23	10.8161	0.58	23.6514	4.24	13.0125	1.11
Northwest County	-13.6431	-0.50	-2.0468	-0.10	33.3171	5.17	-24.5566	-1.81
Pomona Valley	-2.7465	-0.11	27.1512	1.43	25.9819	4.52	5.8858	0.48
San Fernando Valley	-19.7322	-1.18	10.1918	0.77	19.7769	4.94	-5.0710	-0.60
San Gabriel Mountains	-7.8792	-0.45	-30.1122	-2.21	22.2441	5.38	-1.4043	-0.16
Santa Monica Mountains	-15.1730	-0.39	-62.3718	-2.07	38.1308	4.19	24.5073	1.27
South Bay	-18.3418	-1.07	14.1725	1.06	24.3560	6.02	-18.9605	-2.22
Southeast	-76.0768	-4.29	2.6582	0.19	25.0149	5.95	-15.2079	-1.71
South L.A.	-184.9558	-9.24	37.5013	2.40	23.4498	4.94	-104.6600	-10.42
Verdugos	-0.1082	0.00	-2.8841	-0.17	15.0753	2.89	14.3332	1.30
Constant	700.5254	3.45	57.3586	0.37	24.2331	0.51	1127.2060	11.20
Pseudo R^2	0.2885		0.1851		0.2304		0.5702	