Superfund Taint and Neighborhood Change: Ethnicity, Age Distributions, and Household Structure

by

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ABSTRACT

Certain sociodemographic groups often seem to be relatively more concentrated near environmental hazards than in the surrounding community. It is well-known that snapshot cross-sectional statistical analyses cannot reveal how residential mobility for these different groups reacts to changing public perceptions of environmental hazards. Decennial panel data over four census periods, for census tracts surrounding seven different urban Superfund localities, allow us to examine how ethnicities, the age distribution and family structure vary over time with distance from these major environmental disamenities. If the slope of the distance profile decreases over time, the group in question could be argued to be "coming to the nuisance." We find a lot of statistically significant movement, including some evidence of minority move-in and increasing relative exposure of children, especially those in single-parent households. However, it appears to be hard to make generalizations, across localities, about the mobility patterns for different groups. This heterogeneity may account for the difficulty other researchers have experienced in identifying systematic effects in data that are pooled across different environmental hazards. Changes over time in the sociodemographic mix near Superfund sites may also help explain differences in the extent to which housing prices rebound after cleanup commences.

Keywords: environmental justice, neighborhood dynamics, Superfund, environmental taint, children's environmental health.

1. Introduction

Advocates for environmental justice have long been concerned that snapshots of the demographics surrounding environmental hazards often seem to reveal a disproportionate share of low-income and minority groups living in these areas. However, the degree to which we should be concerned about this observation depends upon the dynamic process that leads to this result. Do industries or governments, when seeking to locate hazardous facilities, purposely choose low income or minority neighborhoods? Or does the tendency of these facilities to reduce the prices of nearby properties attract lower income home-buyers over time, and is ethnicity sufficiently correlated with income to produce this observed spatial inequity? If some types of victims are adequately compensated (subjectively, in the form of cheaper housing) for the disutility they experience by living closer to the site, they may be inclined to live closer to the site than would otherwise be optimal. This has been called "coming to the nuisance" (see Cooter and Ulen (1997)).

There has been a considerable amount written about environmental justice (EJ) across many different social science disciplines. Bowen (2002) offers a critical review of the existing EJ literature, and Been (1994) , Liu (1997) and Been and Gupta (1997) explain why we need to understand how neighborhoods change over time, both close to environmental disamenities and elsewhere, in order to understand the dynamics of neighborhood adaptation to these problems.

Been and Gupta (1997) study the demographics of 544 different communities that contained active commercial hazardous waste treatment, storage, and disposal facilities (TSDFs) in 1994. They examine the demographics of each community at the time of the census just prior to the opening of the TSDF, how those demographics change in each subsequent decade, and the demographics of these communities as of 1990. They find no substantial evidence that facilities which opened between 1970 and 1990 were sited in areas that were disproportionately African American, or in sites with unusually large proportions of poor households, although they were sited in areas with relatively more Hispanics. There was little evidence that the siting of a facility led to substantial changes in a neighborhood's socioeconomic status or racial or ethnic composition, although areas around TSDFs in 1990 were disproportionately populated by African Americans and Hispanics. Their analysis "provides little support for the theory that market dynamics following the introduction of the TSDF into a neighborhood might lead it to become poorer and increasingly populated by racial and ethnic minorities."

Existing empirical studies related to EJ, even those focusing on the possibility of "coming to the nuisance," have tended to discriminate only between neighborhoods which are "near" or "far" from an environmental disamenity. Additional work on the siting of TSDFs has been conducted for Los Angeles County by Pastor, et al. (2001). These authors use census tract data for the 1970, 1980 and 1990 census years, conformed to the 1990 configuration of tracts. In contrast to Been and Gupta, however, they consider "near" to consist of all census tracts within one-quarter mile, or within one mile, of the TSDF. They assess changes in demographics near TSDF sites and farther away from them, using a model that assumes that the effects of different TSDFs on the underlying processes are all the same.

Been and Gupta (1997) offer a very thorough and helpful assessment of the advantages and limitations of census tracts as the geographical unit of analysis. However, the choice of an appropriate comparison group of census tracts is a key consideration in attempting to model the effects of environmental disamenities on neighborhood composition over time.[1] The best census tracts to use as controls will be other tracts *in the same locality* at greater distances from the *same disamenity*. This choice allows the researcher to control implicitly for a host of other unobserved local conditions that could affect the sociodemographic mix near a site. Using randomly drawn census tracts from around the country does not control for these unobserved local conditions. Pastor et al. (2001) limit their analysis to Los Angeles, which is helpful, but they pool their data across all TSDFs in this region which suppresses information about heterogeneity across sites.

The greatest benefit from using other local census tracts as controls, however, is that the continuously measured *distance* of a tract from the site of the environmental disamenity is a particularly valuable variable to use in explaining changes in local patterns in sociodemographic characteristics over time. Rather than asking whether there are significant differences-in-differences (across time, between "near" and "far" census tracts), we can examine comprehensive local distance profiles for selected sociodemographic characteristics.

While the EJ literature does not seem to have taken advantage of the opportunity to consider continuous distance profiles, the hedonic property value (HPV) literature has done so routinely. However, the HPV literature generally fails to consider adequately the neighborhood dynamics that may accompany variations in the level of a point-source environmental disamenity when attempting to discern the effect on housing prices of changes over time in the level of that disamenity.

In the HPV literature, Michaels and Smith (1990) and Kohlhase (1991) have found that distance from Superfund sites in Boston and Houston had a positive effect on house prices. The suite of papers by Kiel and her coauthors all control for distance to Superfund sites or hazardous waste incinerators and focus on a number of different sites in Massachusetts (Kiel (1995), Kiel and McClain (1995), Kiel and Zabel (2001)). Dale, et al. (1999) emphasize housing prices over time as a function of distance from a lead smelter in Dallas, focusing explicitly on what happens to housing prices following cleanup of toxic sites. They find evidence of market rebound, but emphasize that "a continuous price/distance relationship fails to capture the entire effect of proximity to the smelter." McMillen and Thorsnes (2003) investigate the effect of Superfund listing and cleanup for a copper smelter in Tacoma, Washington. They find that prices more than completely rebound, while Dale, et al. (1999) uncover an anomaly in that "proximity to the RSR location in 1987-1990 is actually desirable, *ceteris paribus.*" We suspect that these results may reflect, in part, endogeneity of sociodemographic characteristics around Superfund sites during the cleanup phase.

While HPV models have begun to address time patterns in distance effects, they have controlled only crudely for contemporaneous changes in the sociodemographic mix in each neighborhood. Kiel and Zabel (2001) use only the proportion of unemployed workers and log of median household income for the relevant census tract "from decennial censuses," citing their importance based on Kiel and Zabel (1996). They do not, however, use any of the other sociodemographic neighborhood characteristics explored in that earlier study. Thus, their approach cannot fully address whether neighborhood dynamics, including any possible “coming to the nuisance” spawned by their Massachusetts Superfund sites, may have contributed to an increase in environmental inequity during this period. Dale, et al. (1999) control for just three census tract sociodemographic variables: percent below the poverty line, percent Hispanic, and percent African-American. These variables are interpolated between 1980 and 1990, and extrapolated at the 1980-1990 growth rate for the period 1991-1995. In all cases, these variables are assumed to be exogenous.

The likelihood of joint determination of housing prices and neighborhood sociodemographics is mentioned in Graham, et al. (1999). These authors explore the siting of coke plants and oil refineries. They conclude that market and non-market mechanisms, such as redlining, block-busting and other legal and illegal activities may dominate the original coke plant and oil refinery siting decisions as explanations for the 1990 proportion of non-white residents near these facilities. These authors cite “market dynamics theory” as predicting, over time, that hazardous or unattractive residential areas will lose high-income residents and attract low-income residents (due to the relatively depressed property values in these areas).

The present paper has a very specific focus. We are seeking evidence of systematic shifts over time in the spatial distribution of several different sociodemographic groups relative to the location of a significant environmental disamenity. In contrast to previous papers in the environmental justice literature, we employ continuously measured distance to construct a proxy for perceived risk. In contrast to previous papers in the hedonic property value literature, we specifically examine sociodemographic processes that may accompany changes in property values precipitated by a localized environmental problem. We are not undertaking to construct a comprehensive joint model of housing prices and “minority move-in.” Instead, we are attempting to characterize changes in the spatial distribution of the concentration of certain key sociodemographic categories, over time, relative to the locations of selected urban Superfund sites. We find some evidence of movements of the type that concern environmental justice advocates, but these tendencies are difficult to generalize across the different sites in our sample.

Section 2 of this paper describes the data available for our analysis, both sociodemographic and spatial. Section 3 outlines the empirical specifications we will use to examine changes in distance profiles of group proportions over time. Section 4 reviews our results and their interpretation, focusing on just the key results concerning changes in distance profiles over time, for the more than 150 regression models involved. Detailed numeric parameter estimates and other relevant comments on each model are offered in appendices. Section 5 outlines some directions for future research and Section 6 concludes.

2. Data

For our analysis, we require examples of significant environmental contamination that are readily apparent to the population in a particular local area. We have selected a set of seven Superfund sites on the presumption that the listing of a site on the National Priorities List (NPL) is likely to be well-publicized in the local community and knowledge of its existence should be available to realtors and property managers as well as to a large share of homeowners, home-buyers, and renters.

We limit our analysis to Superfund sites which were listed in the interval between 1980 and 1990 and which had not been cleaned up completely as of 2000. The seven sites we have chosen are distinguished by the relatively uniform and small geographic sizes of the surrounding census tracts and the relative absence of certain potentially confounding geographical features, such as major rivers, or other nearby Superfund sites.[2] Three of these sites are landfill sites or involve landfills:

1. Sayreville Landfill (NJ)
2. Cinnaminson Landfill (NJ)
3. Bethpage Landfill (NY)

Four are predominantly non-landfill problems, being mostly cases of industrial waste having contaminated groundwater:

4. CTS Printex Inc. (CA)
5. Montrose Chemical (CA)
6. Chem Central (MI)
7. Havertown PCP (PA)

Census data offer the only broad-based and reliable information on local-scale changes in demographics. We utilize a data set made available by GeoLytics, Inc., called the CensusCD Neighborhood Change Data Base (NCDB). In the NCDB, "short form" census data at the level of census-tracts has been linked across the last four decennial censuses.[3] To be able to use census tract data effectively as our unit of analysis, it is important to choose Superfund sites that are in heavily populated areas. Only then will there be sufficient numbers of census tracts within close proximity of the Superfund site. We need many nearby observations to be able readily to identify nearby distance profiles. The analyses we report are limited to a twelve kilometer radius, which should be more than sufficient to exhaust any proximity effects.[4]

We use the distance from the geographic centroid of each census tract to the nearest Superfund site in that locality as a proxy for perceived risk from Superfund contaminants. The expected effect of this perceived risk will depend on the nature of the contamination, so we cannot expect the effect of distance on the demographic mix of neighborhoods (census tracts) to be the same across all types of Superfund sites. Thus we will model the dynamics of neighborhood change separately for each locality.

We used GIS software (ESRI's ArcView 3.2) to geolocate each Superfund site and the centroid of each census tract for which any portion of the tract lies within our pre-defined distance from the local Superfund site. We also employ ESRI's available shapefiles to identify a number of other major geographic features that may be perceived as either amenities or disamenities: we use point data for the nearest major or minor central business district(s) and retail centers (malls); lines for major roads and railroad tracks; and polygons for airports and transit terminals. ESRI's ArcMap 8.1 software is then used to compute the distance in kilometers from each census tract centroid to the nearest entity in a particular class. We need to assume that the characteristics of these other geographic features have remained essentially constant over the 1970-2000 time period, since detailed historical data on these features is not available.

3. Empirical Models

We wish to examine what happens, over time, to the distance profile for the proportion of each census tract's population in each of a number of categories. We have data for local census tracts $i = 1, \ldots, N$ and for census years 1970 through 2000, denoted as $t = 0,1,2,3$. The impact of differences in proximity to a Superfund site on the characteristics of a census tract should diminish with distance from the Superfund site. Thus, we model the proportion of the population in a particular category, $\%X_{it}$, as a function of the *logarithm* of distance from the site, $\ln(d_{it})$. Our baseline distance profile is:

$$\%X_{it} = \beta_0 + \beta_1 \ln(d_{it}) + \varepsilon_{it} \tag{1}$$

The magnitude of the β_1 coefficient determines how quickly or slowly the profile flattens out.

If we were simply looking for current-period patterns around our Superfund sites in the percentages of census tract populations in particular sociodemographic groups (such as the percentages of African-Americans or Hispanics, or the percentage of children or seniors) we would be looking for nonzero estimates of the simple scalar parameter β_1. However, we wish to know how these spatial patterns *change* over time in response to *changes* in the (perceived) level of an environmental risk. This question requires spatial data collected over time, as perceived risks change.

We have noted that each of our Superfund sites was listed on the National Priorities List during the 1980-1990 window. If one imagines that this interval corresponds to the first publicly available information about the hazard associated with the site, one would expect that there should be little movement of a particular group relative to the site prior to its listing. However, local area residents may have been well aware of the hazards prior to listing, and environmental advocacy groups in each area may have publicized the need to have the site listed. None of the Superfund sites in our sample had been delisted by the year 2000. Officially, therefore, all of these sites were still contaminated at the time of the 2000 census. However, cleanup will have been proceeding to different degrees at each site, and people may have begun making longer-term housing decisions in anticipation of delisting at some time in the near future. Thus, we need to allow for bi-directional, as well as just uni-directional, shifts in our distance profiles over time.

The model in (1) implies that the distance profile is constant across all four decades in our sample. To explore the possibility that the coefficient β_1 is not a simple constant, but a nonlinear function of time t, where $t = 0,\ 1,\ 2,\ \text{and}\ 3$, that has the flexibility to both increase and then decrease (or vice-versa) over the census years in our study, the slope parameter can be generalized to a quadratic function of t:

$$
\begin{aligned}
\%X_{it} &= \beta_0 + (\beta_{10} + \beta_{11}t + \beta_{12}t^2)\ln(d_{it}) + \varepsilon_{it} \\
&= \beta_0 + \beta_{10}\ln(d_{it}) + \beta_{11}t\ln(d_{it}) + \beta_{12}t^2\ln(d_{it}) + \varepsilon_{it}
\end{aligned}
\tag{2}
$$

Given our definition of t, the coefficient β_{10} dictates the shape of the distance profile in 1970, since $t = t^2 = 0$ for that year. The key feature of the distance profile, for our research questions, may be summarized by the derivative of equation (2) with respect to log-distance: $\beta_{10} + \beta_{11}t + \beta_{12}t^2$.

A special case of the model in equation (2) allows the log-distance coefficient to change only monotonically over time, so that the model is simply:

$$
\%X_{it} = \beta_0 + \beta_{10}\ln(d_{it}) + \beta_{11}t\ln(d_{it}) + \varepsilon_{it} \tag{3}
$$

This is the minimal model wherein we can test statistically for any pattern of "coming to the nuisance." If $\beta_{11} > 0$, the distance profile is becoming more positively sloped over time (i.e. the profile is rotating *counterclockwise* so that the relative concentration of X_i near the site is falling). If $\beta_{11} < 0$, the distance profile is getting less positively sloped over time (i.e. the profile is rotating *clockwise* so that the relative concentration of X_i near the site is increasing). If this parameter is zero, the distance profile is unaffected by the passage of time. While we cannot track the movement of individuals, these changes in relative concentration suggest the overall net effect of geographic mobility in this locality.

In the more general quadratic-parameter specification in equation (2), the sign of β_{12} determines whether the distance profile becomes first more positively sloped and then less positively sloped over time, or vice-versa. There is likely to be considerable heterogeneity across our seven Superfund sites in terms of what probably happened to the subjective risks posed by the site (or sites) over time. In some cases, the hazards of the site were well-known prior to its listing, and the process of listing may have increased optimism about the long-term prospects of healthier conditions near the site. In other cases, the hazards represented by the site may have been less well-known prior to listing, and the process of listing the site may have created public information that sparked considerable fear about the site's hazards.

Our dependent variables are proportions. They are census-tract averages of (0,1) variables that capture whether each individual (or household) in the population has a certain characteristic, X_i. When using an average as a dependent variable, it is important to reflect the size of the sample used to compute that average. The variance of an average depends inversely on the size of the sample used to compute it. We therefore weight the data for each census tract by the number of individuals (or households) in the census tract, as appropriate.[5]

If data on proportions are regressed linearly on a range of explanatory variables, it is possible that some of the fitted proportions may fall outside the (0,1) range. To preclude this outcome, researchers often utilize a log-odds transformation of the dependent variable: $\log\left(\%X_i/[1-\%X_i]\right)$. In our case, however, the observed proportions in a handful of cases are either zero or one. Given the extreme minority of cases where this is a concern, we adjust the data by first converting each proportion according to $\%X_i^* = 0.9998\,(\%X_i) + 0.0001$.[6]

The data for each of our seven Superfund localities constitute panels with four time-series observations per census tract. Models with fixed or random effects are often appropriate when panel data are available, since these models are so valuable for controlling for unobserved sources of heterogeneity across groups (where the groups, in this application, are census tracts). However, models with tract fixed effects cannot estimate the effects of variables that are constant over time within each cross-sectional group. Our key variable, distance of the census tract from the Superfund site, is such a variable. Dummy variables for each census tract (fixed effects) are therefore inappropriate in this model.

Nevertheless, there are still a number of stochastic considerations relevant to cross-section/time-series data. Our number of time-series observations for each group is very small and the number of groups is large relative to the overall numbers of observations. Thus we are limited to specifications that employ time-wise fixed effects (dummy variables for each census year), heteroscedasticity across census tracts, and a common AR(1) error process shared by all census tracts. This appears to be the greatest level of generality for the error structure permitted by the quantities of data we have available.[7,8]

We generalize the basic quadratic model with timewise heterogeneity in equation (2) to include the logs of the distances to a number of other geographic features that may represent local amenities or disamenities:[9]

- the primary regional central business district (*ldc1*)
- the secondary regional central business district, if applicable (*ldc2*)
- the nearest retail center (*ldrt*)
- the nearest airport, if applicable (*ldap*)
- the nearest railroad (*ldrr*)
- the nearest major road (*ldrd*)
- the nearest transit terminal (*ldtt*)

We denote these variables generically as $\ln(d_{ki})$. We also allow for monotonic changes over time in the effects of proximity to these other features, $t\ln(d_{ki})$, resulting in a set of up to fourteen additional coefficients in our models, ($\gamma_{k0}, \gamma_{k1},$ k=1,...,7), depending upon which of these seven distance variables are relevant for a particular locality.

Finally, Cameron (2003) describes how failure to recognize directional heterogeneity in distance effects can obscure what might otherwise be statistically significant distance effects. Figure 1 summarizes this concern in the special case where there are only two directions. The distance effect may be systematically larger in one direction than in another, say, if the pollutant in question produces an odor that travels farther downwind than upwind. Ignoring direction amounts to collapsing all distance effects into a single direction, as illustrated by reflecting the upwind (left) distance profile around the axis. The resulting relationship may then exhibit heteroscedasticity and potentially larger standard errors than could be achieved if directional effects were accommodated.

In order that the models used in this paper be minimally sufficient to allow us to consider directional effects as we assess changes in the distance profiles of various sociodemographic characteristics over time, we restrict the directional effects to be constant over time. Let θ_i be the direction, in radians, from the Superfund site to the centroid of census tract i. With time-wise fixed effects, controls for other time-varying distance effects, and directional heterogeneity, the model in equation (2) can be generalized to achieve the specification that produces the empirical results we discuss in the next section:

$$
\begin{aligned}
\log\left[\frac{\%X_{it}^{*}}{(1-\%X_{it}^{*})}\right] &= \beta_0 + \left[\beta_{10} + \gamma_1 \cos(\theta_i) + \gamma_2 \sin(\theta_i)\right]\ln\left(d_i\right) \\
&+ \beta_{11} t \ln\left(d_i\right) + \beta_{12} t^2 \ln\left(d_i\right) \\
&+ \beta_2 D_{80t} + \beta_3 D_{90t} + \beta_4 D_{00t} \\
&+ \sum_{k=1}^{7}\left[\gamma_{k0}\ln(d_{ki}) + \gamma_{k1} t \ln(d_{ki})\right] + \varepsilon_{it}
\end{aligned}
\tag{4}
$$

4. Results and Interpretation

In the body of this paper, we will focus on just the two key parameters in equation (4) (β_{11} and β_{12}) and their implications for changes over time in the distance profiles of the population share of different sociodemographic groups. We must distill these core results from a very large number of regressions. We have three sociodemographic dimensions to consider (ethnicity, age, and household structure). These are captured by fourteen population shares. For ethnicity, we consider "White," "Black," and "Hispanic" population shares. For age, our shares are for "Under 6," "Kids 6-17," "Adults 18-64," and "Seniors (>65)." Household structure will be divided into two categories—those with children present and those without children. In the category with children, we look at shares for "Married couples with kids," "Male head with kids (single dads)," and "Female head with kids (single moms)." Finally for households without children, we consider the shares for "Married couples," "Male head," "Female head" and "Non-family" households (e.g. room-mates). Thus there are fourteen share variables for each of our seven sites, which means 98 unique dependent variables.

Recall that in any time period, if the distance profile for a particular socioeconomic variable pivots counter-clockwise (i.e. if its slope increases over time), then the group in question is becoming relatively less concentrated nearer the site. It has been "moving out." If the distance profile pivots clockwise (i.e. if its slope decreases over time), the group has become relatively more concentrated nearer the site. An increasing concentration near a particular site is consistent with members of that group moving closer to the site over time. They may be "coming to the nuisance."

For each sociodemographic share variable and for each site, the first model we estimate in each case allows the derivative of the transformed share with respect to the log of distance to the site to take the quadratic form, $\beta_{10} + \beta_{11}t + \beta_{12}t^2$. If the coefficient β_{12} on the quadratic term in that model is not statistically significantly different from zero, we drop the quadratic time-interaction term by restricting β_{12} to zero and revert to a simpler specification where the distance effect is simply $\beta_{10} + \beta_{11}t$. We refer to this model as one where the "distance profile is linear in time." This model is estimated *only* when β_{12} turns out to be statistically insignificant, and supplants the "quadratic in time" model in that case. If the coefficient β_{11} turns out *also* to be statistically insignificant, we confirm this result by reporting it as well.

It is important to be very clear about what we are looking for in our fitted models. We wish to know whether particular groups are becoming relatively more concentrated, or relatively less concentrated, near a Superfund site over time. In answering this question, we are less concerned with whether the distance profile is positively or negatively sloped at any specific point in time. Those time-isolated slopes correspond to the "snapshot" sociodemographic patterns mentioned in the introduction that environmental justice advocates find so provocative. What matters for our question is the *change over time* in the slope of the distance profile.[10] The only really important coefficients from the perspective of identifying possible patterns of "coming to the nuisance" among different groups are the β_{11} and β_{12} coefficients on the interaction terms $t\ln(d_i)$ and $t^2\ln(d_i)$.

In our most abbreviated summaries of results, displayed in Tables I through IV, we use a shorthand set of symbols to summarize the different types of statistically significant time patterns in distance profiles that we find in our data. Table I covers our ethnicity shares and Table II covers the different age group shares. Household structure is divided between two tables. Table III covers structures with children and Table IV covers structures without children. If there is no statistically significant effect, we signify this result as a horizontal line. In the quadratic-in-time models, a horizontal line composed of three dashes signifies no statistically significant quadratic time effect. In the linear-in-time models, a horizontal line consisting of a single dash depicts no statistically significant linear time effect.

If the quadratic-in-time specification reveals statistically significant quadratic effects, we identify five possible classes of outcomes for each of the two possible signs on β_{12} according to the time interval wherein the minimum or maximum of the quadratic time effect lies. The intervals include pre-1970, 1970-1980, 1980-1990, 1990-2000 and post-2000. For example, if the quadratic-in-time term that shifts the distance profile is *positive* and statistically significant at the 5% level, we summarize the time trend in the slope of the distance profile as one of "/", "u/", "u", "\u", or "\" according to whether the minimum of the fitted quadratic form falls in each of these five time intervals (see the symbol key preceding Tables I through IV).

In a set of intermediately detailed tables of results in Appendix B, we report the key parameter estimates and their standard errors, as well as the directional coefficients, for each of the population shares that make up our set of dependent variables. We suppress the other regression parameters for each specification, but note the number of other slope coefficients that are statistically significant at the 5% and 10% levels, as well as the extent of the multicollinearity between all of the different distances employed in each model. This statistic is the R^2 value for an auxiliary regression of the variable measuring the distance to the nearest Superfund site on the levels of the other distance variables used in each model, and is labeled "Distance Aux-R2".[11]

Table I in the body of this paper, for our ethnicity variables, shows some evidence of what could be construed as the types of local migration patterns that concern environmental justice researchers. However, the trends are not uniform across all sites. If local knowledge of the environmental problems associated with each site preceded the NPL listing event sufficiently in each case, we might expect to see, predominantly, that the slopes of the distance profiles for whites had been increasing (i.e. becoming less negative or more positive) over the four census years ("/", "u/", or at least "u", signifying an increase in the latter half of the time period) whereas the distance profiles for the two non-white groups had been decreasing (i.e. becoming more negative or less positive) over the four census years ("\" "n\", or at least "n", signifying a decrease in the latter half of the time period). Table I reveals limited systematic evidence of these patterns, although it is possible to discern at least some evidence of these patterns for one or more groups in many cases. First, we will consider the information contained in the columns of Table I, then we will consider the rows.

For the share of whites, the slope of the distance profile has been increasing monotonically over time for sites 3 and 7, implying that whites have been moving steadily *away* from these two Superfund sites. However, this same slope has been monotonically decreasing for sites 2 and 4, suggesting that whites have been moving steadily *toward* Superfund sites in these localities. For site 5, whites appear to have been moving toward the site prior to the listing decade, but away from the site after that point. For site 6, however, whites appear to have moved away from the site until the last intercensal decade in the sample (1990-2000). In one case, site 1, there is no statistically significant change in the distance profile for white population shares over time. Thus there is evidence of "white flight" from environmentally compromised areas in some cases, but there is arguably almost as much evidence for the opposite in other cases.

In two cases, sites 5 and 7, the slope of the black share distance profile has been decreasing monotonically over time, becoming either less positive or more negative, suggesting that blacks have grown relatively more numerous in the vicinity of the Superfund site. However, for site 2, the distance profile has gotten steeper over time, suggesting a tendency for blacks to move farther away. In one case, site 4, the relative concentration of blacks near the site declined until the decade when the site was listed, then grew afterward. In three cases (sites 1, 3 and 6), there is no evidence of any significant change in the distance profile for blacks.

The time patterns in distance profiles for Hispanics are different again. Hispanics show some evidence of moving towards the Superfund site for site 1, but they have tended to move away from sites 3 and 5. For site 2, this group seems to have moved toward the site until the listing decade, then away again, but for site 4, the pattern is just the opposite. For site 7, the predominant tendency is movement away from the site. In one case (site 6) there is no statistically significant time pattern in the distance profile.

We can now turn to considering each row of Table I, looking site-by-site for evidence of the types of patterns that have concerned environmental justice researchers. For site 1 (the Sayreville Landfill, NJ), the only significant ethnic trend we uncover is a tendency for Hispanics to move toward the landfill site. This might be construed as "minority move-in," although there is no evidence of this pattern for blacks in this case.

For site 2 (the Cinnaminson Landfill, NJ), the pattern is at odds with environmental justice concerns. Whites have tended to move toward the landfill over the entire time period, blacks to move away, and Hispanics moved closer in the pre-listing decade, but farther away in the post-listing decade. Perhaps this pattern means that prospective improvements in environmental quality ensuing from cleanup have led to the opposite of the "minority move-in" phenomenon, which might be termed "non-minority move-back."

For the remaining landfill, site 3 (the Bethpage Landfill, NY), both whites and Hispanics have tended to move away from the site, but there has been no time-wise change in the relative concentrations of blacks near the site. Perhaps this configuration suggests only "non-minority move-out," although Hispanics have tended to move away as well.

We can now turn to the non-landfill sites. For site 4 (CTS Printex Inc., CA), whites have tended to move toward the site. Both blacks and Hispanics appear to have been moving away from the site prior to listing, but their relative concentrations have been increasing subsequent to listing. The pattern among blacks and Hispanics would be consistent with "minority move-in" post-listing, but not the pattern for whites. In California, of course, there are significant numbers of other ethnic groups in some areas (notably Asian groups) and time trends in the shares of whites, blacks and Hispanics could be simultaneously affected by increasing trends in the numbers of these other groups, although we have no information about how Asians have moved relative to these Superfund sites.

Site 5 (Montrose Chemical, CA) shows whites moving towards the site in the first intercensal interval in the sample, prior to listing, but away from the site after the listing decade. Blacks have been moving steadily towards the site, but Hispanics have been moving steadily away from it, relatively. For blacks, this pattern is consistent with “minority move-in,” but not for Hispanics. Again, the growing Asian population in this area cannot be assessed due to an absence of conformable data on this group.

Site 6 (Chem Central, MI) exhibits no statistically significant changes in the distance profiles over time for either blacks or Hispanics. Whites, however, were becoming relatively less numerous in the vicinity of the site over the first two intercensal intervals, although in the final interval, this trend moderated, perhaps reflecting the effects of the cleanup process ensuing from listing.

Finally, for Site 7 (Havertown PCP, PA), whites have moved systematically farther away from the site, and blacks have moved systematically closer to the site. Hispanics have moved predominantly farther from the site, at least over the last two intercensal decades. This seems to suggest greater evidence of minority move-in than in some other cases.

Admittedly, we do not have the whole picture. Blacks and Hispanics do not constitute the entire spectrum of minority groups in all cases, and we do not incorporate income heterogeneity within each of these groups. This paper addresses only sociodemographic variables, rather than economic variables, and is limited by the variables that can be conformed across the last four census years.

Tables II through IV present analogous profiles for the shares of other sociodemographic categories. In Table II, describing age group trends, we note some evidence that children under 6 have tended to move closer to sites 6 and 7 throughout the time period we cover, and closer to sites 3 and 5 during the last intercensal decade, after listing. This may somewhat troubling, given public concern for children’s exposure to environmental contaminants. Recall that clean-up was not yet complete at any of these sites by the year 2000. In the other three cases, however, there were no significant spatial shifts in the relative concentration of very young children nearer to the site. There is likewise some evidence that older children, aged 6-17, have been moving closer to site 7 throughout the time span of our study, and closer to site 5 during the post-listing period (but predominantly farther away from site 3 during most of the 1970-2000 time period).

The results for adults are mixed, but adults are not generally classified as a “vulnerable population.” We scrutinize the results for seniors somewhat more closely. Three sites display no time pattern for seniors. However, seniors seem to be moving systematically farther away from site 6, but systematically closer to site 3 and perhaps to site 5. Their relative numbers have increased near site 2 since listing.

Again, we can alternatively explore the age patterns for each site, taken row by row. Site 1 (Sayerville Landfill, NJ) and site 2 (Cinnaminson Landfill, NJ), as well as site 4 (CTS Printex Inc., CA) display little evidence of any relative changes in the numbers of exposed children over time. Site 3 (Bethpage Landfill, NY) evidences movement toward the landfill, post-listing, for both of the children’s age groups and for seniors, and a relative movement away for adults 18-64. This suggests that relatively more environmentally vulnerable populations are exposed to the site during the listing and cleanup process, which is probably when housing prices in this area are the most depressed.

Site 4 (CTS Printex Inc., CA) shows little in the way of age patterns except a movement of adults away from the site prior to listing and back towards it afterwards. Site 5 (Montrose Chemical, CA), on the other hand, shows the two children’s age groups moving relatively farther away from the site prior to listing, then relatively closer to it after listing. The pattern for adults is the opposite. Seniors have tended to move closer throughout the time period, although they may have begun to move away during the final intercensal period in the sample.

In summary, for the different age groups, there seems to be some cause for concern that children are being moved disproportionately into proximity with some Superfund sites, especially post-listing and prior to clean-up. This pattern does not prevail across all sites, however.

Statistically significant differences in distance profiles over time for household structures with children are more sparse. For four of our seven sites, married couples with kids have tended to move predominantly *toward* the Superfund site over most or all of the time period in question. In two cases, they have tended to move predominantly *away*.

The cases of single dads and single moms, however, are more provocative. Where there are statistically significant trends, these two groups have tended to move *away* from the site in the first intercensal decade but *toward* the site in the last intercensal decade, after the site has been listed on the NPL. These patterns are present at four sites for single dads (although this group is a very small portion of the population in early years). Single moms are a larger and growing proportion of the population in general over this time period. For site 5 (Montrose Chemical, CA) and site 7 (Havertown PCP, PA), single moms and their children have tended to react to the listing of the local Superfund site by moving relatively closer. This is most likely in response to the local declines in housing prices in these areas as a result of publicity surrounding the listing of the Superfund site and the clean-up process. The potential for a "single parent effect" to contribute to greater childhood exposure to environmental contaminants suggests that children in these types of households may suffer additional disadvantages beyond simply those imposed on them by family structure.

Table IV describes our results for households without children, which are perhaps the most mixed. For married couples without children, four of the five sites with significant effects suggest movement towards the site prior to listing with some evidence of movement away from the site at some point post-listing, although the pattern is the opposite for site 4. There is very little evidence of systematic patterns in distance profiles over time for either the Male-headed or Female-headed households without kids (e.g. childless couples, empty-nesters, young singles, or widows and widowers), or for non-family households.

5. Directions for future research

Additional forthcoming data from GeoLytics will include census tract "long-form" data on median house values, median gross rents, and household incomes by Census tract, converted to a panel across the four census years. In- or out-migration from a Superfund area will also be affected by the time pattern of housing prices and rental rates near those areas, as opposed to farther away. These changes in market prices of housing will interact with the demand elasticity for housing of these different sociodemographic groups. Individual households will assess their marginal disutility from changes in proximity to a Superfund site relative to their marginal utility from differences in housing prices to be obtained from moving toward or away from the site.

Each of the Superfund sites in our sample is located in an urbanized area, so there are assumed to be many jobs and other attractants that might lead individuals to wish live in the vicinity of the Superfund site, were there no environmental hazard at that location. If housing prices were uniform across this region, households would choose to live farther away. A complementary paper, to be initiated when long-form Census economic data become available in the Neighborhood Change Database, will address patterns in household income, median house values and median rental rates.

6. Conclusions

The Superfund sites we examine are just a small fraction of all the sites on the National Priorities List, yet they represent an important subset of these sites. They are in heavily populated areas, so they may contribute a relatively large share to aggregate Superfund human exposure.

Our current empirical models describe what has happened to different population subgroups over time in the vicinity of these seven urban Superfund sites. Our models are descriptive models, rather than models that attempt to reveal causality or the mechanisms underlying these changes. They do contribute significantly to the complement of stylized facts to be accommodated by researchers who are concerned with modeling the spatial distribution of different sociodemographic groups in light of the processes that accompany the discovery and cleanup of hazardous waste sites. We conclude that there is no widespread and pervasive standard pattern over time of different socioeconomic groups "coming to the nuisance" with respect to urban Superfund sites. Time patterns are statistically significant in many cases, but vary rather widely in their direction and magnitude. No doubt this heterogeneity accounts, at least in part, for the difficulty that even very careful researchers have had in establishing any single overall tendency for the sociodemographic mix to change in any particular way when an environmental threat emerges. The heterogeneity noted by Bowen (2002) seems to be more than just regional. The effects may be unique to each site. This makes it very, very difficult to generalize about the environmental justice consequences of changes in environmental quality.

With this heterogeneity duly noted, however, there do seem to be at least a few patterns worth highlighting, for at least some Superfund sites:

1. Some minority groups may tend to move closer to working Superfund sites. However, others may fail to respond to the presumably cheaper housing that results, or may tend to move away (e.g. sites 1, 5, and 7);
2. Traditional minority groups (i.e. Blacks and Hispanics) may not always dominate "minority move-in." There are instances where the distance profiles of Black and Hispanic population shares do not change over time, but white shares exhibit a relative decline near the Superfund site, suggesting that other groups may be replacing them (e.g. site 3 and site 6).
3. There has been little previous work done specifically on the exposure of children to environmental hazards in the environmental justice literature or the hedonic property value literature. We have uncovered perhaps the first systematic evidence that Superfund taint, operating through its effects on the housing market, may result in increased relative exposure of children (and in some cases seniors) to environmental hazards, at least over the near term.
4. Previous work has not considered family structures either. We present what seems to be the first evidence that policy-makers may need to be concerned about households with children, and especially about single-parent households, responding disproportionally to the housing price signals that accompany information about environmental hazards.

Our original impetus for an investigation of the time patterns in distance profiles for sociodemographics around Superfund sites stemmed from concerns about papers that attempt to estimate "rebound" patterns in housing prices, such as Kiel and Zabel (2001) and Dale, et al. (1999). In some cases, distance profiles for housing prices seem to recover completely when the Superfund site is remediated. In other cases, the price recovery is incomplete. In yet others, it might be termed "overcomplete," as for the McMillen and Thorsnes (2003) study of Tacoma. Our current results may help to explain these seemingly inconsistent findings. In some areas, the property "taint" associated with identification and cleanup activities at a Superfund site appears to be accompanied by changes in sociodemographic patterns in the vicinity of the site. In some cases, younger families, minorities, or other housing-market constrained groups, such as single parents, appear to be attracted by the lower housing prices precipitated by the taint. Ceteris paribus, we would expect remediation to eliminate the taint on properties. To the extent that the presence of these groups also decreases housing prices (as suggested by the work of Kiel and Zabel (1996)), remediation of the Superfund site may not be enough to immediately restore pre-taint housing prices.

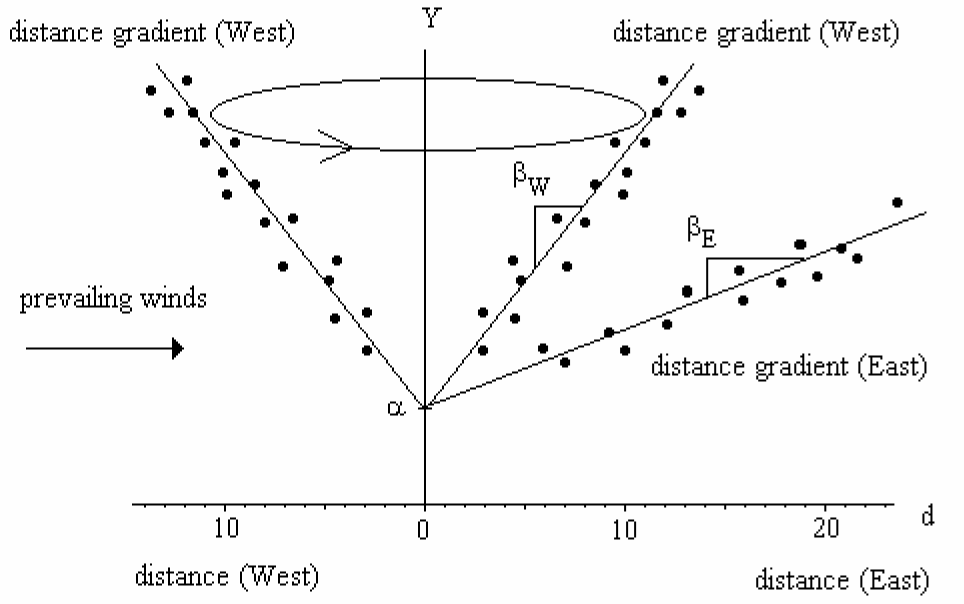

Figure 1

Interpretation of Tables

Only statistically significant (5% level) time patterns in distance profiles are reported.

KEY	Interpretation
---	Quadratic term not significant in model with quadratic-in-time distance profile
-	Linear term in linear model for time pattern of distance profile is statistically insignificant=slope of distance profile is not changing over time (no statistically significant migration apparent)
\	Slope of distance profile declines over time = group becomes relatively more abundant near site
/	Slope of distance profile increases over time = group becomes relative less abundant near site
u	Group becomes first more abundant, then less abundant near site (turning point in 1980-1990 time interval)
n	Group becomes first less abundant, then more abundant near site (turning point in 1980-1990 time interval)
\u	Group has become more abundant near site, but begins to become less abundant in 1990-2000 time interval
/n	Group has become less abundant near site, but begins to become more abundant in the 1990-2000 time interval
u/	Initially increasing but, starting in 1970-1980 time interval, group becomes relatively less abundant near site
n\	Initially decreasing but, starting in 1970-1980 time interval, group becomes relatively more abundant near site

Table I

How slope of distance profile varies over time: ethnic groups

	White		Black		Hispanic	
	quadratic	**linear**	**quadratic**	**Linear**	**quadratic**	**linear**
1. Sayreville Landfill (NJ)	---	-	---	-	---	\
2. Cinnaminson Landfill (NJ)	\		/		u	
3. Bethpage Landfill (NY)	---	/	---	-	/	
4. CTS Printex Inc. (CA)	---	\	n		n	
5. Montrose Chemical (CA)	u		\		---	/
6. Chem Central (MI)	/n		---	-	---	-
7. Havertown PCP (PA)	---	/	---	\	u/	

Table II

How slope of distance profile varies over time: age group

	Under 6		Kids 6-17		Adults 18-64		Seniors (>65)	
	quadratic	**linear**	**quadratic**	**linear**	**quadratic**	**linear**	**quadratic**	**Linear**
1. Sayreville Landfill (NJ)	---	-	---	-	---	/	---	-
2. Cinnaminson Landfill (NJ)	---	-	---	-	---	\	n	
3. Bethpage Landfill (NY)	n		/n		U		---	\
4. CTS Printex Inc. (CA)	---	-	---	-	N		---	-
5. Montrose Chemical (CA)	n		n		U		\u	
6. Chem Central (MI)	---	\	---	-	---	-	---	/
7. Havertown PCP (PA)	\		---	\	---	/	---	-

Table III

How slope of distance profile varies over time: family composition (with kids)

	Married couples with kids		**Male head with kids (single dads)**		**Female head with kids (single moms)**	
	quadratic	**Linear**	**quadratic**	**linear**	**quadratic**	**linear**
1. Sayreville L'fill (NJ)	---	\	n		---	-
2. Cinnaminson L'Fll (NJ)	---	-	---	-	---	-
3. Bethpage L'fill (NY)	/n		---	-	---	-
4. CTS Printex Inc. (CA)	\		---	-	---	-
5. Montrose Chemical (CA)	/		---	\	n	
6. Chem Central (MI)	---	\	---	\	---	-
7. Havertown PCP (PA)	n\		n		n	

Table IV

How slope of distance profile varies over time: family composition (no kids)

	Married couple, no kids		**Male head, no kids**		**Female head, no kids**		**Non-family**	
	quadratic	**linear**	**quadratic**	**linear**	**quadratic**	**linear**	**quadratic**	**linear**
1. Sayreville Landfill (NJ)	u		---	-	---	/	n	
2. Cinnaminson Landfill (NJ)	\u		---	-	u		n	
3. Bethpage Landfill (NY)	\u		---	-	\u		---	\
4. CTS Printex Inc. (CA)	/n		/		---	-	/	
5. Montrose Chemical (CA)	---	-	\u		/n		u	
6. Chem Central (MI)	---	-	---	-	---	-	---	-
7. Havertown PCP (PA)	u		---	-	---	-	---	/

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Endnotes

[1] Been and Gupta draw five one-percent samples of all the tracts identified in the 1970 census and five one-percent samples of all the tracts in the 1980 census. They then reconcile the tracts within each of those samples and compared demographic variables for the resulting reconciled areas across decades. However, they acknowledge that their TSDFs are often located at the edges of tracts, since they are often near transportation such as major roads or railways and these features often bound census tracts. They note that "data and time constraints" prevented them from analyzing the demographics of areas adjacent to host tracts.

[2] A brief description of each site, its listing date, types of contaminants, etc., is contained in Appendix A.

[3] For each census, the geographic definition of a number of tracts in any local area will change. Most commonly a tract is split into two or more tracts as the population it contains increases. In the NCDB, census tracts active in the 1970, 1980 and 1990 Census windows have been apportioned according to documented formulas to conform to the 2000-year Census tracts.

[4] Maps of the census tracts surrounding each of these sites are included in Appendix A.

[5] We discard any tract for which the population is less than 100 in any of the four Census years on the grounds that this appears to provide insufficient precision in calculating the shares of different sociodemographic groups. In these heavily urbanized areas, tracts with fewer than 100 people are probably anomalous in a number of ways.

[6] The transformed proportions lie between 0.0001 and 0.9999, so that they can be subjected to a log-odds transformation without difficulty. As log-odds transformations of slightly attenuated proportions, the dependent variables used in our estimations are free to range over the entire real line, and could therefore be approximately conditionally normally distributed.

[7] We rely on the xtgls command in Stata8, with weights to reflect the different sizes of each census tract ([aweight=trctpop]), i(trct) t(year) panels(h) and corr(a).

[8] We do not pursue corrections for spatially autocorrelated errors. This decision may have milder consequences in the case of census tract data than in the case of individual hedonic property value data, for example, but we treat the "spatial error" issue as a second-order problem in this paper. Subsequent research may pursue this aspect of the empirical problem.

[9] Variable names employed in our detailed regression results in Appendix C are given in parentheses.

[10] This subtlety is especially important when we entertain models with directional heterogeneity in distance effects. For particular values of the γ_1 and γ_2 coefficients, the overall coefficient on $\ln(d_i)$ may well be negative in some directions, even though its average value (using the assumption of zero means for $\cos(\theta)$ and $\sin(\theta)$) may be positive. Is it of any real consequence for our research questions if the actual distance profile in some directions is negatively sloped, even when it is positively sloped in the "average" direction? The answer seems to be no.

[11] Full regression results are relegated to Appendix C.