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Timewise and Directional Heterogeneity in Distance Profiles reflecting Superfund Taint: the Dynamics of Neighborhood Change

by

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ABSTRACT

Certain sociodemographic groups often seem to be relatively more concentrated near environmental hazards than in the surrounding community. However, snapshot statistical analyses cannot reveal how residential mobility for these different groups reacts to public perceptions of environmental hazards. Panel data for census tracts for sixteen different Superfund localities allow us to examine how ethnicities, the age distribution and family structure vary over time with proximity to these major environmental disamenities. For any particular group, a distance profile with a slope that decreases over time suggests the group may have been "coming to the nuisance." We find many statistically significant time patterns in distance profiles. However, there appears to be no way to generalize the mobility patterns for different groups in the face of evolving environmental hazards. This heterogeneity may account for the difficulty other researchers have experienced in identifying such systematic effects.

Our secondary theme concerns directional heterogeneity in externalities generated by point sources of pollution. In the context of an airborne pollutant, we explain how to let distance effects vary systematically with direction. Failure to allow for directional heterogeneity can obscure otherwise statistically significant distance effects. The "downwind" direction can be estimated, or the true downwind direction can be imposed upon the model using information about prevailing winds in the area. If appropriate, the downwind direction can be allowed to vary seasonally. We find frequent evidence of statistically significant directional effects in our sixteen data sets.

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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? This has been called "coming to the nuisance" (see Cooter and Ulen (1997)). 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 will be inclined to live closer to the site than would otherwise be optimal.

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 concludes (on the basis of studies that he identifies to be of relatively high quality) that "…it appears to be that hazardous sites are located in white working-class neighborhoods with residents heavily concentrated in industrial occupations, living in somewhat less expensive than average homes." He acknowledges the possible presence of other patterns at the subnational level, but that these vary in their character from region to region. In the present paper, we pursue this heterogeneity, with the finding that patterns may vary in their character not just from region to region, but from community to community.

Single cross-sections of data do not afford an opportunity to discern which came first, the low-income/minority neighborhood, or the hazardous waste site. We need to see how neighborhoods change over time, both close to the hazardous facility and elsewhere. A discussion of the issues is presented in Been (1994) , in Liu (1997) and in Been and Gupta (1997). More broadly, however, we must consider the simultaneity between housing prices and sociodemographics and how neighborhood dynamics, along both these dimensions, are influenced by environmental disamenities.

A. Environmental justice: "near" versus "far" and time, but not "distance"

A number of specific ideas have induced us to pursue the research program outlined in this paper. The first is a concern that 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 "near" or "far" from an environmental disamenity.

Been and Gupta (1997) is an example of EJ research that is relatively very sophisticated in its analysis. These authors 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 last census prior to the opening of the TSDF, how those demographics change in each subsequent decade, and the demographics of these communities as of 1990.

Been and Gupta 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."

Been and Gupta offer a very thorough and helpful assessment of the advantages and limitations of census tracts as the geographical unit of analysis. In addition to the unit of analysis, however, the identity of the appropriate comparison group is another key consideration in attempting to model the effects of environmental disamenities on neighborhood composition over time. Been and Gupta drew 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 reconciled 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.

The empirical approach taken in this paper is an outgrowth of concern about the approach taken by Been and Gupta to controlling for variation in other census tracts when assessing demographic changes in those tracts containing a significant localized environmental disamenity. To best understand the geographic movement of different sociodemographic groups relative to the location of a disamenity, the best census tracts to use as controls would seem to be other tracts *in the same locality* at greater distances from the disamenity. By using other local census tracts as controls, we also 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. All sorts of factors besides the presence of an environmental disamenity could account for different evolution over time of the sociodemographic mix near the disamenity and the mix in these other randomly selected tracts.

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 complete local distance profiles for selected sociodemographic characteristics.

B. Hedonic property value models: distance and time, but limited neighborhood change

While the EJ literature does not seem to have taken advantage of the opportunity to consider 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 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) offer the econometric innovation of time-varying average derivatives as a modeling strategy for use with hedonic property values as a function of distance. Their study investigates the effect of Superfund listing and cleanup for a copper smelter in Tacoma, Washington. They find that prices more than completely rebound. Finally, in some of our own work, Cameron and Crawford (2002), we have looked very carefully for evidence of housing price rebound effects and have found mixed results. When we control for a wide variety of shifts in sociodemographic characteristics around sites, we find it difficult to discern any remaining positive distance effect in any period. Dale, et al. (1999) also uncover an anomaly in that "proximity to the RSR location in 1987-1990 is actually desirable, *ceteris paribus.*" We suspect that these results reflect, in part, endogeneity of sociodemographic characteristics around Superfund sites.

The econometric innovations in McMillen and Thorsnes (2003) are offered in part because "[s]tandard regression estimators produce highly volatile gradient estimates with high standard errors in times with few sales." We propose an alternative model for distance effects that can accommodate differences in directional gradients. If substantial directional effects are present, but are ignored, one would expect the simple gradient estimate to exhibit a higher than necessary standard error and volatility in times with few sales, especially if the directional distribution of observed sales is non-uniform. Directional effects can be a particular concern when point-source toxic pollutants are airborne and there are significant prevailing winds. Given the olfactory insults associated with the Tacoma site, this issue may be relevant.

While HPV models have begun to address the 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 the 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 injustice 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.

One other class of studies should be mentioned explicitly. Point sources of pollution that produce noticeable odors will be especially relevant for the directional models we develop. Industrial hog farming is an important regional example that has been addressed in both the HPV literature and the EJ literature. Palmquist, et al. (1997) explain rural house prices in part by the quantity of swine operation manure generated within three different distance intervals from each house in their sample. The EJ dimensions of industrial hog-farming have been considered by Taquino, et al. (2002) and Wilson, et al. (2002).

C. Market dynamics

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 hear 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.) This insight coincides with our interest in exploring in the time variation in sociodemographic patterns around Superfund sites as an additional contributor to housing price variability over time and with distance and direction from the environmental disamenity.

2. Data

A. Superfund Sites

We require examples of significant environmental contamination that are readily apparent to the population in a particular local area. We have selected 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. 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 have limited our set of Superfund sites to sixteen individual or compound sites which were listed in the interval between 1980 and 1990 and which had not been cleaned up completely as of 2000. A brief description of each site, its listing date, types of contaminants, etc., is contained in Appendix A. Half of these sites are landfill sites or involve landfills (localities 1 though 8), and half are predominantly non-landfill problems, being mostly cases of industrial waste contaminating groundwater (localities 9 through 16).

We combine individual sites for which the areas of influence might overlap. This occurs in five of our sixteen Superfund localities. It may prove appropriate, in later work, to distinguish different distance profiles relative to each of the individual Superfund sites in a particular locality, especially if the perceived risks from each site are likely to be very different.[1] In the current study, we measure distance from each Census tract to the nearest Superfund site in the area. When considering direction, we also consider direction only from the nearest Superfund site.

To be able to use census tract data as our unit of analysis, it is important to choose Superfund sites in heavily populated areas. Only then will there be sufficient numbers of census tracts within close proximity of the Superfund site. We need nearby observations to be able to identify nearby distance profiles. It is likely that by the time one reaches a distance of 6 or more kilometers (about 3.6 miles) from a site, perceived risk will have diminished to the point that further increases in distance beyond that point can be expected to have very little effect. To ensure adequate geographical coverage, we have collected data to a distance of about nine miles or more from each Superfund site, but most of the analyses we report are limited to a twelve kilometer radius. This seems sufficient to exhaust any plausible proximity effects.

B. Sociodemographic Data

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, data at the level of census-tracts has been linked across the last four decennial censuses. 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 with the 2000-year Census tracts.[2]

We will assume that the apportioning formulas are sufficiently accurate so as not to compromise the analyses we conduct here. There appear to be no alternatives, other than eliminating from our analysis any tracts that do not match up across all four census years. It comes down to a tradeoff between the possibility of errors from inexact apportioning after the splitting of tracts, or throwing away data on tracts that have experienced the greatest population growth, and are therefore likely to be some of the most interesting tracts in any analysis of demographic shifts.

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 sites. Thus we will model the dynamics of neighborhood change separately for each locality.

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[1] In earlier work Cameron and Crawford (2002), we learned that collinearities among the distances from nearby Superfund sites can render these separate effects difficult to identify. Kiel and Zabel (2001) seem to have experienced similar difficulties with their analysis of the Woburn, MA sites.

[2] As of mid-May, 2003, only the short form Census data have been made available in the NCDB. The long-form component, with its critically important income, property value, rental rate, and housing tenure data, were scheduled for release in late January, but are still pending release. These data will form the basis of an important portion of our final roster of models. In the meantime, we offer the results for the sociodemographic, rather than economic characteristics of each census tract.

C. Spatial Data

We used GIS software (ESRI's ArcView) to geolocate each Superfund site, as well as the centroid of each of each census tract for which any of the tract lies within our pre-defined distance from the local Superfund site(s). We also employ ESRI's shapefiles to identify a number of other major geographic features: 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.

We use ESRI's ArcMap software to compute the distance from each census tract centroid to the nearest entity in a particular class. If there is more than one local Superfund site, we compute the distance to the nearest one, making the heroic assumption that distance from either site has the same effect on people's perceptions of risk and therefore on their mobility. We also need to assume that the characteristics of these other geographic features have remained constant over the 1970-2000 time period, since historic data on the presence or absence of these features is not available.

3. Empirical Models

A. Distance Profiles as a Function of Time

We wish to examine what happens, over time, to the distance profile of 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. 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:

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

The derivative of $\%X_{it}$ with respect to distance will be β_1 / d_{it}. If the profile is increasing with distance, it will increase more steeply at first and then flatten out. If the profile is decreasing with distance it will first decrease most sharply then flatten out. The magnitude of the β_1 coefficient determines how quickly or slowly the profile flattens out.

If we were simply looking for current patterns around our Superfund sites in the percentages of census tracts 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. If $\beta_1 = 0$, the proportion of the population in category X does not vary with distance from the Superfund site. If $\beta_1 > 0$, the proportion in category X increases with distance from the site, but at a decreasing rate. This means category X is relatively less abundant near the Superfund site. If $\beta_1 < 0$, the proportion of the population in category X declines with distance from the site, but at a decreasing rate. There are relatively more people in category X close to the site.

These patterns, when the exist, can be the result of many interacting factors including the other characteristics of the neighborhood and the history of development of the area. What we need is a natural experiment that holds constant everything else about a neighborhood while we vary the presence of an environmental hazard and observe the consequences for the spatial patterns of sociodemographic groups. Since this sort of controlled experiment is intractable, we need to find enough data to allow us to control for variations in these other characteristics by including them specifically in our econometric models.

What we need to know is how these spatial patterns *change* over time in response to *changes* in the (perceived) level of an environmental risk. We assume, as do many other researchers, that perceived risk is correlated with distance. So our question requires spatial data collected over time.

(a.) Distance Profile Quadratic in Time

Each of our Superfund sites was listed on the National Priorities List during the 1980-1990 window. If one imagined that this interval corresponded 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.

Furthermore, none of the Superfund sites in our sample had been delisted by the year 2000. Officially, therefore, at the time of the 2000 census, all of these sites were still contaminated. 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.

What does this imply for our priors concerning the time pattern in distance profiles? We need to allow for bi-directional, as well as just uni-directional shifts in these distance profiles over time. People with an aversion to proximity to these sites, ceteris paribus, may have begun to move away from the sites even prior to their date of listing. These same types of people may have begun to move back closer to these sites, ceteris paribus, before the site has been delisted.

The model in (1) implies that the distance profile is constant across all four decades in our sample. We can estimate a separate profile for each of the four time periods, and have explored the consequences of doing so. However, in this study there is a premium on being able to capture, parsimoniously, general patterns in the distance profile over time. We explore the possibility that the coefficient β_1 is not a simple constant, but a function of time t, where $t = 0,\ 1,\ 2,\ \text{and}\ 3$ correspond to $year = 1970,\ 1980,\ 1990,\ \text{and}\ 2000$. We make β_1 a quadratic function of t, so that the slope of the distance profile has the flexibility to both increase and then decrease (or vice-versa) over the census years in our study. The model becomes:

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

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 distance profile may be summarized best by the derivative with respect to log-distance:

$$\frac{\partial(\%X_{it})}{\partial\ln(d_{it})} = \frac{\partial(\%X_{it})}{\partial d_{it}/d_{it}} = \beta_{10} + \beta_{11}t + \beta_{12}t^2 \tag{3}$$

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.

(b.) Distance Profile Linear in Time

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

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

This is the minimal model wherein we can test statistically for a 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 this group 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 this group 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, any change in relative concentration (i.e. $\beta_{11} \neq 0$) suggests the overall net effect of geographic mobility in this locality.

(c.) Other Control Variables

As in all studies of environmental equity, the models we describe here can only demonstrate the *pattern* of geographic mobility in sociodemographic groups over time. Causality is yet a problem in this study, as in others. We cannot attribute these variations unambiguously and exclusively to the effects of information about the Superfund sites. For example, suppose the Superfund site lies near a central business district (CBD). Collinearity between the distances to these two features will be present. A 30-year pattern of suburbanization (i.e. out-migration from the urban area) may be picked up by our model as a 30-year pattern of directional mobility in response to Superfund risks if we fail to control for distance to the CBD.

To control for movements over time of households relative to other locational amenities and disamenities, we control in our models for time-varying distance profiles with respect to our other geocoded features: one or two central business districts, all major roads, retail centers, railroad, and transit terminals. For localities where airports are also relevant, we include an analogous set of terms for airport distances. It is important also to control for neighborhood dynamics that may reflect changing attitudes towards the amenities or disamenities embodied in these other geographic features. To accommodate such changing attitudes in our working specifications, all other log(distance) variables enter both alone and interacted with time. These control variables serve to reduce the chance that any apparent demographic shifts relative to the status of the Superfund site are actually due to monotonically changing attitudes towards proximity to these other features.

B. Distance Profiles as a Function of Direction

When some of the pollutants associated with a point source are airborne, it is possible that the presence of prevailing winds will mean that the distance profile of variables affected by this pollution will not be the same in all directions. Downwind from the site, we would expect the distance profile to be flatter. The critical distance beyond which discernible distance effects essentially disappear will be farther away from the site. Upwind from the site, since fewer of the contaminants are blown in this direction, the distance profile may well be steeper. The critical distance beyond which there are no further discernible distance effects will be closer to the site in the upwind direction.

Most hedonic property value models that consider proximity to some feature employ a distance variable only, with no attention to direction. There appear to be only two considerations of direction in any form in the hedonic literature. Gillen, et al. (2001) relegate directional considerations to the nature of spatial autocorrelation in the error terms in their model of isotropic versus anisotropic autocorrelation in house prices. There is no point-source environmental disamenity in their data from which distances are being measured; the only distances in the model are the distances between individual houses in the sample. In their study of the effects of industrial hog-farming operations on house prices, Palmquist, et al. (1997) mention the problem of prevailing winds as an area for future research. However, confidentiality of specific locational data concerning hog farms prevents them from pursuing these issues. Certainly, the McMillen and Thorsnes (2003) work concerning the "aroma of Tacoma" would appear to be a prime example of a Superfund point source of airborne pollutants for which prevailing winds would be an important consideration in modeling distance effects. They do not consider direction either.

Consider the case illustrated in Figure 1. Ignoring heterogeneity in distance effects around the points of the compass, relative to the Superfund site, can potentially obscure what might otherwise be a clear price-distance relationship. Figure 1 illustrates just two different directions, East and West, rather than the full 360° of the compass. In this case, the observations for the dependent variable, Y_i, are depicted as lying very close to the directionally-specific $E[Y_i]$. Each of these two directional distance profiles is depicted as a different linear function of distance, d, with a common intercept, α, but different slopes.[3]

The diagram is drawn under the assumption that prevailing winds are from the west. If the researcher was careful to control for direction before estimating the parameters of the distance gradient, the data in the example would yield very precise estimates of the common intercept, α, and two separate slopes, β_E and β_W. The steeper profile to the west indicates that the prevailing winds limit the westward diffusion of the pollutant. In contrast, the flatter profile to the east captures the fact that the prevailing winds carry the pollutant much farther in that direction. Ignoring direction is equivalent to superimposing the two different distance profiles in the right-hand quadrant of the diagram and fitting one common distance profile to the pooled data. We illustrate the effect of ignoring direction by also showing the western distant profile rotated around the vertical axis. The more heterogeneous the distance profiles in different directions, the greater will be the dispersion around the common "average" distance profile that the researcher attempts to fit to the data when direction is ignored.

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[3] Contrast this form of heterogeneity with the type commonly assumed in fixed effects models for panel data. There, we typically assume a common slope, but different intercepts across groups.

Consider Figure 2 and Figure 3, where we have added a set of points (open dots) for the intermediate North and South profiles, assumed to be symmetric since the prevailing winds are from due west. If the range of *distances* at which transactions are observed varies systematically with direction, heterogeneity bias can be sufficient to severely distort or obscure the resulting distance profile estimates. In hedonic property value studies, researchers typically consider the "extent of the market" for proximity effects to consist of all housing transactions within a particular radius of an environmental hazard. Or, the market may consist of all census tracts or zip codes with some or all of their area within a particular absolute distance from the site. If the researcher recognizes the potentially greater influence of the environmental amenity downwind, and therefore collects data to a greater distance in that direction, the consequences can be particularly perverse.

In Figure 2, the researcher knows that the prevailing winds are from the West, so she is less worried about the effect of pollution on housing prices in that direction, but more worried about the possible effect of pollution on housing prices to the east. Thus, she collects data out to a greater distance to the east. However, she fails to control for direction in the estimation process. When data to the west are limited to shorter distances (d_W^*) than the data to the east (d_E^*), it is possible to find no statistically significant relationship at all between Y and distance, despite strong relationships in each direction considered separately. The empirical estimates could suggest a negligible and statistically insignificant distance effect, when in fact distance effects are substantial and easy to discern when controlling for direction.

Figure 3 shows that even if the researcher collects data on Y within a constant radius, regardless of prevailing winds, it is possible that observations are not identically distributed with respect to distance from the Superfund site in all directions. This is a particular concern with data such as housing price information. In the downwind direction, there may simply be fewer nearby houses, or fewer nearby transactions. The minimum distances at which transactions are observed are depicted in Figure 3 as $d_W^{'}, d_{N,S}^{'}$, and $d_E^{'}$. If the nearest distance at which observations occur is greater in the downwind direction, slope distortions are also possible.

When direction is presumed not to matter, the spatial level curves of the $E[Y_i]$ are implicitly assumed to be circular. With directional diffusion of airborne pollutants, one would expect the iso-risk contours of the dispersal pattern to be non-circular. Ignoring the direction while estimating a distance gradient in these cases can significantly compromise the precision with which distance gradients are measured, and precision will be compromised more, the more different are the effects of the pollution in different directions from its source.

To accommodate directional heterogeneity in distance effects, we propose two alternative strategies. Each relaxes the implicit assumption of circular contours in the two-dimensional distance gradient function. They also allow the researcher to estimate the direction of the main axis of a more general set of elliptical level curves. The simple case, illustrated in Figures 1 and 2, assumes that the main axis of these ellipses is due West to due East. Any appropriate empirical model needs to allow for arbitrary directions for this axis, either to accommodate historical average wind directions, or to allow the main axis to be estimated empirically based on patterns in the dependent variable.

(a.) Simplest directional distance effect model

With GIS software, one can readily identify point locations of houses or census tracts in decimal degrees (conventionally, to six decimal places). The simplest specification for a generic dependent variable Y_i involves overlaying a direction-independent distance profile with some tilted plane defined over longitude and latitude. The combination of the lat/long effects on the dependent variable and symmetric distance effects can readily mimic distance effects that are non-constant around the points of the compass. Begin with a linear-in-distance specification:

$$Y_i = \alpha + \left(\gamma_1 long_i + \gamma_2 lat_i\right) + \beta_0 d_i + \varepsilon_i \qquad (4)$$

One degree of latitude is not the same distance as one degree of longitude. The length of one degree of longitude depends upon the latitude at which that distance is being calculated. In general one degree of longitude = cos(latitude)* 111.325 kilometers. In contrast, one degree of latitude is well approximated by 110.6 kilometers. This complicates the task of determining the direction of steepest descent when longitude and latitude are used directly as explanatory variables. It is preferable to compute location in (x,y)-space in common units in each direction.

Fortunately, it is not necessary to use the Greenwich Meridian and the equator as the origins of measurement for the absolute spatial location of each census tract. We recommend expressing both longitude and latitude in kilometers and shifting the origin of measurement to coincide with the Superfund site in question. Denote the longitude and latitude of the Superfund site as (x_s, y_s). Let x_i be the east-west coordinate of the census tract, using this origin, and let y_i be the north-south coordinate. Then

$$Y_i = \alpha + \left(\gamma_1 x_i + \gamma_2 y_i\right) + \beta_0 d_i + \varepsilon_i \qquad (5)$$

Here we assume that the longitude-to-kilometers conversion factor can be approximated for both the census tract and the Superfund site by the latitude correction corresponding to their average latitude, so that

$$\begin{aligned} x_i &= (111.325)\left(long_i - long_s\right)\cos\left[\left(lat_i + lat_s\right)/2\right] \\ y_i &= (110.6)\left(lat_i - lat_s\right) \end{aligned} \qquad (6)$$

In model (5), both the x_i and y_i distances are measured in kilometers, as is the distance d_i.[4] The parameters γ_1 and γ_2 in equation (5) will be different from their counterparts in equation (4) due to the change of location and scale.

It is convenient to convert equation (5) so that it is expressed entirely in terms of polar coordinates. Recall that $x_i = d_i \cos(\theta_i)$ and $y_i = d_i \sin(\theta_i)$ where θ_i is the direction from the Superfund site to the centroid of census tract i (measured in radians counter-clockwise from due east). Making this substitution, equation (5) becomes:

$$Y_i = \alpha + \left(\gamma_1 d_i \cos(\theta_i) + \gamma_2 d_i \sin(\theta_i)\right) + \beta_0 d_i + \varepsilon_i \qquad (7)$$

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[4] In implementing these transformations, it is crucial to remember that cartographers measure latitude in degrees from the equator, rather than in radians. The map measures of latitude must first be converted into the equivalent number of radians before using econometric software to calculate the cosine of the term in square brackets in the formulas in (6).

Collecting the terms in distance, we get:

$$Y_i = \alpha + \left(\beta_0 + \gamma_1 \cos(\theta_i) + \gamma_2 \sin(\theta_i)\right) d_i + \varepsilon_i \tag{8}$$

Instead of having a constant distance effect, the distance effect depends upon the direction in which it is being calculated.

(b.) Alternative directional distance effect model

Except for (i) changes of location and scale, (ii) the slight local approximation involving $\cos\left[\left(lat_i^* + lat_s\right)/2\right]$, and (iii) conversion exclusively polar coordinates, the model in equation (8) is identical to that involving the simple longitude and latitude variables in equation (4). However, there is nothing to mandate using only the functional form employed in equations (4) or (5). In fact, this form has the unappealing characteristic that in any particular direction, the marginal effect of distance remains constant as distance increases. In the case of environmental hazards, we generally expect the effect to diminish with distance until any incremental effect of distance essentially disappears. To approximate this pattern, researchers often resort to models that are linear in the logarithm of distance.

We can adapt the model in equation (5) to allow for diminishing marginal effects of distance, but still allow the marginal effect at any given distance to vary systematically and smoothly with direction by altering the model to:

$$Y_i = \alpha + \left(\beta_0 + \gamma_1 \cos(\theta_i) + \gamma_2 \sin(\theta_i)\right) \ln d_i + \varepsilon_i \tag{9}$$

To test statistically for the presence of directional differences in the distance effect, one would test the joint hypothesis that $\gamma_1 = \gamma_2 = 0$. Compared to a model with no directional effects, the parameter β_0 can be estimated more precisely by the specification in (9) if $\gamma_1 = \gamma_2 = 0$ does not hold in the data.

It is customary in describing fitted models involving heterogeneous parameters to simplify the results by reporting key varying derivatives calculated at the "means of the data." While the average angle $\overline{\theta}$ in any sample will depend upon the observations in that sample, it will usually be more convenient to note that the average values of both $\cos(\theta)$ and $\sin(\theta)$ would be zero if this angle was uniformly distributed around the circle. Evaluating the distance effect at these "averages" means considering just the β_0 coefficient.

The extrema of the distance effect over all possible directions, either for the model in (4) and (5) or for the alternative model in (9), occur where the derivative with respect to θ_i of the systematically varying coefficient, $\beta_0 + \gamma_1 \cos(\theta_i) + \gamma_2 \sin(\theta_i)$, goes to zero. Making use of the facts that $\partial \sin(\theta)/\partial\theta = \cos(\theta)$, $\partial \cos(\theta)/\partial\theta = -\sin(\theta)$, and $\cos(\theta)/\sin(\theta) = \tan(\theta)$, the predicted extrema occur at $\theta^* = \arctan(\gamma_2/\gamma_1)$. There are two solutions, one at θ^* (the maximum distance effect), and one at $\theta^{**} = \theta^* + \pi$ (the minimum distance effect). If we are considering a hedonic property value model using equation (9), housing prices would be predicted to increase most slowly as one moves away from the Superfund site in the direction

$$\theta^{**} = \arctan(\gamma_2 / \gamma_1) + \pi \tag{10}$$

which depends upon the estimated parameters γ_1 and γ_2. This direction (measured in radians counterclockwise from due east) can be converted to compass degrees (measured clockwise from due north) by computing $\phi^{**} = -180(\theta^{**}/\pi) + 90$. If airborne pollution levels were all that influenced housing prices by distorting the level curves of the price distribution away from just simple circles, this direction would be interpreted as the apparent downwind direction.

One potential problem with the specification in equation (9) is that it will allow the data to tell us which direction is downwind. In a property value model, the price gradient may appear to differ systematically with direction. Suppose the underlying true distance effect relative to Superfund taint is overlaid, for example, by a larger-scale distance gradient relative to the nearest city center. This component of the variation in housing prices over space could actually be due to differences in accessibility relative to the central business district, rather than downwind differences in the transport of pollutants from the local environmental disamenity.

Once the model in equation (9) has been estimated, therefore, it will be important to test whether the estimated "downwind" direction, ϕ^{**} coincides with the meteorological facts.[5] This statistical test of the estimated wind direction would involve constructing a point estimate and standard error for the estimated direction θ^{**} from the point estimates of parameters γ_1 and γ_2 and testing whether this direction could be equal to the actual downwind direction, θ^0. Historical prevailing wind directions for major cities in the US are provided by NOAA (1998).

(c.) Imposing the "downwind" direction

In some cases, the downwind direction should not be estimated, but should be determined from meteorological data and imposed upon the model. Assume initially that the direction of prevailing winds is constant over the seasons. Let the actual downwind direction from the Superfund site be θ^0 radians. If we wish to impose this downwind direction as a constraint on our estimation, it will translate into a restriction on the admissible values of γ_1 and γ_2. Solve equation (10) for the admissible relationship between γ_1 and γ_2:

$$\gamma_2 = \gamma_1 \tan(\theta^0 + \pi) \tag{11}$$

Substitute this restriction into equation (9) to yield

$$\begin{aligned} Y_i &= \alpha + \left(\beta_0 + \gamma_1 \cos(\theta_i) + \left[\gamma_1 \tan(\theta^0 + \pi)\right] \sin(\theta_i)\right) \ln d_i + \varepsilon_i \\ &= \alpha + \beta_0 \log d_i + \gamma_1 \left[\cos(\theta_i) + \tan(\theta^0 + \pi) \sin(\theta_i)\right] \ln d_i + \varepsilon_i \end{aligned} \tag{12}$$

[5] Recall that meteorologists report wind direction based on the direction from which the wind is coming, rather than the vector describing the direction in which it is blowing. Thus, a NW wind would be blowing "out of the NW, in a SE direction."

To test whether there is evidence of a directional effect in the dependent variable that coincides with wind direction (or other natural flows that may affect waterborne contaminants, for example), one would simply test whether $\gamma_1 = 0$ can be rejected.

This model can be estimated using conventional least-squares-based methods since all terms inside the square brackets are observed data. This specification allows for directional asymmetry in the distance effect, but admits for distortions only in a direction known to be consistent with prevailing winds. We might desire such a restriction. Without it, there is no requirement that the direction in which housing prices (say) increase most slowly with distance actually coincides with the direction in which pollution travels the farthest. Allowing the distance profile implied by the model to "tilt" in any arbitrary direction will court omitted variables bias. There may be other underlying factors which account for an overarching trend in housing prices, such as a temperature gradient, for example, or distance from a nearby city center or coastline or other amenity or disamenity for which we have not controlled.

(d.) Seasonal directional distance effects

A more interesting model may be appropriate when there are regular seasonal differences in the direction of prevailing winds. The term in equation (12) that carries the coefficient γ_1 captures the direction from the Superfund site to the census tract centroid, θ_i, which will be constant over time but will vary across observations. It also captures the direction of prevailing winds, θ^0. This model assumes that the direction of the prevailing winds is fixed across observations. A richer model might employ data on the dependent variable and on θ^0 that are subscripted by time. For example, selling prices of houses are understood to vary seasonally for a variety of reasons. If they also vary seasonally with respect to the seasonal pattern of dispersion of some point source pollutant, this information can also be employed to enhance estimation. The model could be generalized to:

$$Y_{it} = \alpha + \beta_0 \ln d_i + \gamma_1 \left[\cos(\theta_i) + \tan(\theta_t^0 + \pi) \sin(\theta_i) \right] \ln d_i + \varepsilon_{it} \tag{13}$$

As before, θ_t^0 is not a parameter to be estimated, but additional data on seasonal wind directions to be employed in the estimation process.

(e.) Level curves

For any of these directional models, it may be also be useful to derive the implied level curves for the overall distance profile. Once the unknown parameters of the model have been estimated, solve for the latitude and longitude coordinates of locations that lie along level curves for fitted Y_i. The geo-coded level curves can then be displayed using mapping software. Implementation proceeds as follows. Assume $\varepsilon_i = 0$ and solve the fitted model for the values of d_i^* that correspond to each of the observed directions (θ_i) represented in the sample if Y_i is held constant at Y^*. The set of polar coordinates satisfying this condition will be:

$$\left(d_i^*, \theta_i\right) = \left(\exp\left[\frac{\left(Y^* - \alpha\right)}{\beta + \gamma_1 \cos(\theta_i) + \gamma_2 \sin(\theta_i)} \right], \theta_i \right) \tag{14}$$

Convert these points expressed in terms of polar coordinates back into Cartesian coordinates using

$$\begin{aligned} x_i^* &= d_i^* \cos(\theta_i) \\ y_i^* &= d_i^* \sin(\theta_i) \end{aligned} \tag{15}$$

Then convert these simple Cartesian coordinates back into latitude and longitude by reversing the transformations in (6), remembering to convert latitude from radians to degrees in the process.

$$\begin{aligned} lat_i^* &= lat_s + (y_i^* / 110.6) \\ long_i^* &= long_s + \left(x_i^* / \left[(111.325) \cos\left[\left(lat_i^* + lat_s \right) / 2 \right] \right] \right) \end{aligned} \tag{16}$$

If the observations are first sorted in order of θ_i, the graphing routines in one's estimation software can be used to connect all of the points and draw a smooth curve. Saving the latitudes and longitudes and mapping these pairs of points will produce an elliptical pattern of points, one in the direction of each observed census tract in the sample. Alternatively, to produce an ellipse consisting of an arbitrarily dense pattern of points, one could discard the observed directions, θ_i, simulate as many evenly spaced values as desired between 0 and 2π and perform the transformations in equations (14) through (16) using these simulated values instead.

C. Stochastic Structure and Estimation

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. 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.[6]

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 $\%X_i^* = 0.9998\,(\%X_i) + 0.0001$. The transformed proportions lie between 0.0001 and 0.9999, so that they can be subjected to a log-

[6] We discard any tract for which the population is less than 100 in any of the four Census years. In these heavily urbanized areas, tracts with fewer than 100 people are probably anomalous in a number of ways.

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]

The data for each of our sixteen Superfund localities constitute panels with four time-series observations per census tract. Models with fixed or random effects automatically come to mind when panel data are available, since these models are so valuable for controlling for unobserved sources of heterogeneity across groups (which are census tracts in this application). 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 our data.[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.

(a.) Timewise heterogeneity

Our basic quadratic model with timewise heterogeneity was set out in equation (2). We now generalize it to include the logs of the distances to a number of other geographic features that may represent local amenities or disamenities:

- the primary regional central business district
- the secondary regional central business district, if applicable
- the nearest retail center
- the nearest airport, if applicable
- the nearest railroad
- the nearest major road
- the nearest transit terminal

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

Our most general estimating specification *without* directional effects takes the following form, where the variable t=0,1,2 and 3, for each of the census years from 1970 through 2000:

[7] Before reporting fitted proportions, of course, we undo this transformation.
[8] 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).

$$\log\left[\frac{\%X_{it}^*}{(1-\%X_{it}^*)}\right] = \beta_0 + \beta_{10}\ln\left(d_i\right) + \beta_{11}t\ln\left(d_i\right) + \beta_{12}t^2\ln\left(d_i\right) + \beta_2 D_{80t} + \beta_3 D_{90t} + \beta_4 D_{00t} + \sum_{k=1}^{7}\left[\gamma_{k0}\ln(d_{ki}) + \gamma_{k1}t\ln(d_{ki})\right] + \varepsilon_{it} \tag{17}$$

Fitted values of the log-odds for the transformed shares in each of the four years of the sample are calculated using the sample means of each of the d_{ki} variables. The four implied year-specific formulas are:

$$\log\left[\frac{\%X_{i70}^*}{(1-\%X_{i70}^*)}\right] = \left\{\beta_0 + \sum_{k=1}^{7}\left[\gamma_{k0}\ln(\bar{d}_k)\right]\right\} + \beta_{10}\ln\left(d_i\right) \tag{18}$$

$$\log\left[\frac{\%X_{i80}^*}{(1-\%X_{i80}^*)}\right] = \left\{\beta_0 + \beta_2 + \sum_{k=1}^{7}\left[(\gamma_{k0} + \gamma_{k1})\ln(\bar{d}_k)\right]\right\} + (\beta_{10} + \beta_{11} + \beta_{12})\ln\left(d_i\right)$$

$$\log\left[\frac{\%X_{i90}^*}{(1-\%X_{i90}^*)}\right] = \left\{\beta_0 + \beta_3 + \sum_{k=1}^{7}\left[(\gamma_{k0} + 2\gamma_{k1})\ln(\bar{d}_k)\right]\right\} + (\beta_{10} + 2\beta_{11} + 4\beta_{12})\ln\left(d_i\right)$$

$$\log\left[\frac{\%X_{i00}^*}{(1-\%X_{i00}^*)}\right] = \left\{\beta_0 + \beta_4 + \sum_{k=1}^{7}\left[(\gamma_{k0} + 3\gamma_{k1})\ln(\bar{d}_k)\right]\right\} + (\beta_{10} + 3\beta_{11} + 9\beta_{12})\ln\left(d_i\right)$$

These formulas have been simplified to emphasize that each log-odds is a linear function of the log of the distance from each tract centroid to the relevant Superfund site, $\ln(d_i)$. The slope of the function depends upon time, as does the intercept. Undoing the log-odds transformation will produce the familiar S-shaped curve bounded by zero and one. For each sociodemographic group, we will be examining this set of four fitted distance profiles as a function of d_i for each site. For all but a very few cases in our applications, the bounding of the fitted population proportion is not an issue.

(b.) Adding directional heterogeneity

For the models used in this paper to 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. The model in equation (17) can be generalized to:

$$\log\left[\frac{\%X_{it}^*}{(1-\%X_{it}^*)}\right] = \beta_0 + \left[\beta_{10} + \gamma_1 \cos(\theta_i) + \gamma_2 \sin(\theta_i)\right]\ln\left(d_i\right)$$
$$+ \beta_{11} t \ln\left(d_i\right) + \beta_{12} t^2 \ln\left(d_i\right)$$
$$+ \beta_2 D_{80t} + \beta_3 D_{90t} + \beta_4 D_{00t} \tag{19}$$
$$+ \sum_{k=1}^{7}\left[\gamma_{k0} \ln(d_{ki}) + \gamma_{k1} t \ln(d_{ki})\right] + \varepsilon_{it}$$

If we wish to allow only for variation in directional effects that is consistent with the known directions of prevailing winds in the direction of the site, but still constant over time, we could use:

$$\log\left[\frac{\%X_{it}^*}{(1-\%X_{it}^*)}\right] = \beta_0 + \beta_{10}\ln\left(d_i\right) + \gamma_1\left[\cos(\theta_i) + \tan(\theta_t^0 + \pi)\sin(\theta_i)\right]\ln d_i$$
$$+ \beta_{11} t \ln\left(d_i\right) + \beta_{12} t^2 \ln\left(d_i\right)$$
$$+ \beta_2 D_{80t} + \beta_3 D_{90t} + \beta_4 D_{00t} \tag{20}$$
$$+ \sum_{k=1}^{7}\left[\gamma_{k0} \ln(d_{ki}) + \gamma_{k1} t \ln(d_{ki})\right] + \varepsilon_{it}$$

If we can assume that the direction of prevailing winds has remained constant over the 31 year time-span of our data, one would expect that the parameters γ_1 and γ_2, which imply the directions of steepest and flattest ascent away from the Superfund site, should remain essentially unchanged.

It is easiest to understand the differences around the compass in the distance profile by considering as benchmarks the values of $\cos(\theta)$ and $\sin(\theta)$ in each of the "main" directions. East corresponds to $\theta = 0$, North to $\theta = \pi/2$ and so on. To the east of the Superfund site, the 1970 coefficient on the $\ln(d_i)$ term will be $\beta_{10} + \gamma_1\cos(\theta_i) + \gamma_2\sin(\theta_i) = \beta_{10} + \gamma_1$. To the north, it will be $\beta_{10} + \gamma_2$. To the west, the effective coefficient will be $\beta_{10} - \gamma_1$, and to the south, it will be $\beta_{10} - \gamma_2$.

With the insight from Figures 1 through 3 (that failing to control for directional heterogeneity in distance effects can obscure and also potentially distort apparent distance effects), we have estimated all of our models using the model in equation (19). If the distance domain is similar at all points of the compass, simpler models which ignore direction should produce unbiased estimates of the average distance effect around the compass, but the standard errors can be larger than necessary if there is unrecognized directional heterogeneity. Under these conditions, controlling for direction should merely allow us to better discriminate the magnitude of the distance effect. It should be more likely that we find an "average" distance effect that is statistically significantly different from zero if we use equation (19) rather than equation (17).

(c.) Further pending enhancements

Critical data for this study, not yet in public distribution as of the issuance of this report, include information on median house values, median gross rents, and household incomes by Census tract. In a way, we are still "waiting for the other shoe to drop." A critical factor that can be expected to affect the in- or out-migration from the Superfund site area will be the different time pattern of housing prices and rental rates in those areas. These changes in market prices of housing will interact with the demand elasticity for housing of different sociodemographic groups. Households will assess their marginal disutility from changes in proximity to a Superfund site and their marginal utility from differences in housing prices as they consider moving toward or away from the site.

When lower housing prices near a Superfund site serve to compensate victims for the increased risk associated with greater proximity, we can expect to see the phenomenon known as "coming to the nuisance." In general, if households are compensated for the disutility of proximity by lower housing prices, they will, in general, choose to live closer to the site than they would otherwise. Each of the Superfund sites 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 probably choose to live farther away.

An additional task awaits the publication of the census "long form" variables for the Neighborhood Change Database. We need to see if there is also evidence of patterns over time in the distance gradient for median house values, gross rental rates, and occupancy status. We might expect, ceteris paribus, that house values and rents will increase more sharply with distance the greater the perceived risk from proximity to the site. However, possible Superfund taint is not the only factor affecting housing prices. If lower housing prices make a neighborhood relatively more attractive to certain sociodemographic groups than to others, and neighborhood composition (by age group, family structure, ethnicity, or income levels) also affects housing prices, then the sociodemographic mix and housing prices are jointly endogenous. There is extant empirical evidence that neighborhood composition affects housing prices (e.g. Kiel and Zabel (1996)).

Our strategy to convert this simultaneous system into a simpler recursive system is to exploit the fact that migration in response to depressed housing prices resulting from Superfund taint may occur only with a lag. (Annual rather than decadal data would be preferable, of course. But homeowners tend to move with much lesser frequency than do renters.) We plan to specify neighborhood composition in 1980 and subsequent years as dependent upon housing prices in that tract in the previous period (a predetermined variable). However, housing prices in the current period will be modeled as depending only on the current sociodemographic characteristics of the neighborhood and the various proximity measures for the Superfund site and other local amenities and disamenities. In such a recursive system, if we are willing to assume that the off-diagonal elements of the cross-equation error correlations are zero, the parameters of each structural equation are identified even without omitted exogenous variables.

4. Results and Interpretation

Discussion of our results will focus on the key parameters β_{11} and β_{12} and their implications for changes over time in the distance profiles of the share of different sociodemographic groups. We have the results of a very large number of regressions to consider, so it is important to distill the key results of each regression as fully as possible. We have fourteen sociodemographic variables and sixteen sites, which means 224 unique dependent variables.

A. The Distance Effect

The key log-distance derivative (conveying the distance profile for each site) takes the form

$$\frac{\partial\left(\log\left[\frac{\%X_{it}^{*}}{(1-\%X_{it}^{*})}\right]\right)}{\partial\ln(d_{it})} = \beta_{10} + \beta_{11}t + \beta_{12}t^{2} \quad \text{for } t = 0,1,2,3 \tag{21}$$

where

$$\%X_i^* = 0.9998(\%X_i) + 0.0001$$

We refer to this model as one where the "distance profile is quadratic in time."

In any time period, if the distance profile for a particular socioeconomic variable pivots counter-clockwise, then the group in question is becoming relatively less concentrated nearer the site. If the distance profile pivots clockwise, the group had 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 attempt in each case allows the derivative of the transformed share with respect to the log of distance to the site to take the form shown in equation (21) above. 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 and revert to a simpler specification where the distance effect is:

$$\frac{\partial\left(\log\left[\frac{\%X_{it}^{*}}{(1-\%X_{it}^{*})}\right]\right)}{\partial\ln(d_{it})} = \beta_{10} + \beta_{11}t \quad \text{for } t = 0,1,2,3 \tag{22}$$

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 report this linear-in-time model anyway.

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 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. 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, 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 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. The only really important coefficients from the perspective of identifying possible patterns of "coming to the nuisance" among different groups are the coefficients on $t\ln(d_i)$ and $t^2\ln(d_i)$. These estimates will be highlighted with bold type in our tables of parameter estimates.

B. Interpreting Tabular Summaries of Distance Profiles

In our most abbreviated summaries of results, displayed in Tables 1 through 4, we use symbols to summarize the different types of statistically significant time patterns in distance profiles that we find in our data. We include tables for each of our four dimensions of sociodemographic variability: Table 1 - ethnicity; Table 2 – age groups; Table 3 - family structure with children; and Table 4 – family structure without children. If there is no statistically significant effect, we capture 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, either.

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 this coefficient 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 "/" (see the symbol key preceding Tables 1 through 4).

We report results for models without directional heterogeneity and for models that include directional effects. As expected, the number of statistically significant time effects in distance profiles increases. It is easier to discern time-varying distance effects when controlling for directional heterogeneity. For ethnic groups, the number of statistically significant time-profile coefficients increases from 25 to 36. For age groups, the number of such significant coefficients increases from 34 to 38, for households with kids from 20 to 23, and for households without kids, from 27 to 40.

Additional more-detailed tables of the empirical results are presented in the Appendices. We report the key parameter estimates and their standard errors, as well as the directional coefficients. We suppress the other regression parameters for each specification, but note the number of other slope coefficients that were statistically significant at the 5% and 10% levels, as well as the extent of the multicollinearity between different distances for the active dataset. This statistic is the R^2 value for an auxiliary regression of the variable measurings the distance to the nearest Superfund site variable on the levels of the other distance variables used in each model, and is labeled "Distance Aux-R2". Quadratic estimates are reported for all variables, and linear models are provided when quadratic terms are statistically insignificant.

C. Preliminary Results

Symbolic results are provided for four types of sociodemographic categories, for models without, and with, directional effects. We will only describe in detail the time patterns in distance profiles for the three ethnicity categories (denoted as Share White, Share Black, and Share Hispanic). For the share of whites, the slope of the distance profile has been increasing monotonically over time for four of our 16 localities; whites have been moving steadily away from Superfund sites in these localities. The slope of the distance profile has been monotonically decreasing in four other localities, suggesting that whites have been moving steadily toward Superfund sites in these localities. In two cases, whites have moved first towards the sites, then away from them, with the turning point during the interval when the Superfund sites were listed. In one case, whites were moving away from the Superfund site prior to listing, but toward them after listing. In two cases, whites moved away from Superfund sites for much of the time period, but began to move back towards them in the period from 1990-2000. Given the wide variety of statistically significant results evidenced in Table 1, it is not surprising that other researchers have had difficulty estimating one consistent and significant pattern.

Perusal of Tables 2 through 4 as well drives home the finding that conflicting patterns are the rule, rather than the exception. These results hold for the age distribution and the distribution of family structures. We conclude that there is no 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 widely in their direction and magnitude.

On the matter of directional heterogeneity in distance profiles, our more-detailed results reported in Appendix B for the ethnicity case reveal that distance profiles vary with direction in almost all instances. The only exceptions are for the share of whites at site 12, and for the shares of Hispanics at sites 13, 15, and 16. All of these sites are non-landfill sites, so that airborne transport of odors, for example, may be much less relevant. (Results constraining directional effects to coincide precisely with the known direction of prevailing winds await a subsequent revision of this paper.)

5. Caveats and Directions for Future Research

This project will not be complete until we can incorporate the pending data on median house values, median gross rents, household incomes and housing tenure status. All of these additional long-form census variables are crucial to our bigger story. While they are available separately for each census, they have not yet been amalgamated using conformable tract definitions in order to form a reasonable panel of data over all four census years.

As soon as the long-form panel data are published, we will be incorporating tract-specific data on median house values, median gross rental rates, and household incomes. Median house values and median gross rental rates will depend upon current sociodemographic characteristics of the census tract and upon distances to the Superfund sites and to other local amenities and disamenities, where the sociodemographic characteristics are recognized to be endogenous. However, for a tract's sociodemographic characteristics, we postulate that there may be statistically useful lags in adjustment to changing housing prices. The transactions costs of moving may prevent neighborhood sociodemographic characteristics from depending as much on contemporaneous housing prices. We will assess whether current sociodemographic characteristics are better explained by contemporaneous housing prices or by lagged (by a decade) housing prices.

Making current census tract sociodemographic characteristics depend upon lagged housing prices, but modeling current housing prices as depending upon current sociodemographic characteristics offers a way to work around identification issues in this context. The model we have in mind is one where neighborhood characteristics define baseline housing prices. Then a shock in the form of a "new" environmental hazard lowers housing prices. All socioeconomic groups would be inclined to move away from this "local public bad" if housing prices and all other conditions remained unchanged. However, decreased demand for housing in the vicinity of the hazard results in lower housing prices there, and these lower housing prices have an effect similar to that which would accompany monetary compensation for exposure to this risk. The compensation increases the net benefit from locating closer to the hazardous site, and some people will be induced to move closer than they would prefer to live if there had been no such compensation in the form of lower prices. Changes in housing prices can precipitate "coming to the nuisance." A number of other authors have recognized the potential for this process.

We plan to build upon this idea by recognizing that the change in sociodemographics in a locality can then feed back into housing prices. Of course, there is a long tradition of hedonic property value models in the environmental literature. For a careful review of empirical studies that assess the negative effects on property values of locally undesirable land uses (LULUs) such as waste sites, hazardous manufacturing facilities, and electric utility plants, see Farber (1998). Many papers in this literature recognize that neighborhood characteristics other than just LULUs affect housing prices and a respectable number control for sociodemographic characteristics. However, most of these models do not pursue the fact that these sociodemographics, if not the presence of the LULU itself, are potentially endogenous variables rather than purely exogenous variables. If low income households or minority groups are relatively more attracted by the lower housing prices ensuing from Superfund taint, and this taint is long-lived, turnover in occupancy over a ten-year horizon will attract new types of households to the area.

When the Superfund site is fully remediated and pronounced "clean," one might expect housing prices to rebound to their pre-event levels as quickly as they fell with the appearance of the environmental hazard. There is indeed some evidence that property values that have been temporarily depressed by the announcement of Superfund status can rebound fully after cleanup. What processes account for this apparent rebound effect? McCluskey and Rausser (2001) utilize a dynamic, discrete-time model to analyze the evolution of perceived risk around a hazardous waste site and its effect on property values. Gayer and Viscusi (2002) also explore media coverage (newspaper stories) and their effect on property value changes in the vicinity of Superfund sites.

McCluskey and Rausser's results suggest that media coverage and high prior risk perception increase current perceived risk which in turn lowers property values. However, the pattern of evolution of these imputed perceived risks over time is derived from a specification that controls for distance from the site, but not for any changes in demographics, which could also account for systematic shifts in housing prices. Perceived risk is inferred to remain high if housing prices remain low. But if housing prices remain depressed near the site because of changes in neighborhood sociodemographics precipitated by the Superfund identification and remediation, such a model could falsely conclude that perceived risk remains high. There has been little or no discussion of the collateral neighborhood dynamics that can also influence housing price patterns. Our larger research project will incorporate these neighborhood dynamics explicitly.

A further dimension of Superfund cleanup that seems not to have been explored in the literature concerns the distributional consequences of the cleanup. People who own houses in the Superfund area prior to publicity about the problem suffer capital losses if they must sell their house before the clean-up process is complete. They may also lose money on the sale of their house if it is sold even after the clean-up is complete, if neighborhood changes results in delayed recovery of housing prices following the cleanup. We would expect to see homeowners rent their houses long-term, if they can afford to do so, until housing prices fully recover. Homeowners who face capital market constraints may not have this option, and rental income from a dwelling near a Superfund site is also likely to be lower than the rents that could be charged in the absence of Superfund taint. However, low-income or minority groups who may be attracted to housing in a Superfund area because of its temporarily lower price may exchange a perceived or real health risk for the opportunity to realize capital gains when local housing prices rebound following cleanup. There is a clear need for a careful accounting of the distributional consequences of property value changes resulting from environmental hazards.

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 much larger share to aggregate Superfund human exposure.

Our current empirical results 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. The key lesson is that there seems to be *no* systematic pattern of ethnic groups or different age groups or different family structures moving closer to the hazardous site or farther away from it. 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.

The 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), Dale, et al. (1999), and some of our own work, Cameron and Crawford (2002). 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 others, it might be termed "overcomplete," as for the McMillen and Thorsnes (2003) study of Tacoma. Our current results may 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, lower-income, minority, or other housing-market constrained groups appear to be attracted by the lower housing prices precipitated by the taint. 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 restore pre-taint housing prices. Ceteris paribus, we would expect remediation to eliminate the taint on properties, but ceteris paribus is violated in the data.

A second significant contribution in this paper is the development and demonstration of a new empirical specification for spatial data concerning variables that may be affected by proximity to environmental hazards. We introduce *direction* as a potentially important determinant of distance (proximity) effects. We include a special case of this empirical model that can accommodate additional data about the direction of prevailing winds. This special case involves a restriction on the parameter estimates that can still be accommodated within a conventional least-squares-based estimation framework. If there are seasonal patterns in prevailing winds that may lead to seasonal differences in the spatial pattern of the level of the disamenity from the environmental hazard, these data can also be exploited.

We have developed this new empirical model quite generally. The dependent variable may be data on individual house selling prices, which would lead to a hedonic property value model that would also include all of the other usual variables for such models. The dependent variable may also be the proportion of the population in different sociodemographic groups. These models are relevant to the environmental justice/equity literature. The current empirical results in this draft of the paper reflect specifications that do not impose "prevailing wind" constraints on the estimated directional effects. There is statistically significant directional heterogeneity in distance effects from Superfund sites for a majority of our sociodemographic variables, even as we control for other distances to a wide range of other amenities and disamenities and allow these other distance effects also to change over time.

If direction is important, yet it is ignored, the best case result is that the researcher is limited to measuring the average distance effect, around the compass, with lesser precision that would be possible in a directional model. A worst case result is that the distance distribution of observations is systematically correlated with direction (an omitted variable) so that distance effects estimates are biased, as well as less precise than necessary. The implication of the insights from this model is that in some instances, prior research that has ignored substantial directional effects may have failed to identify statistically significant distance effects that are in fact present.

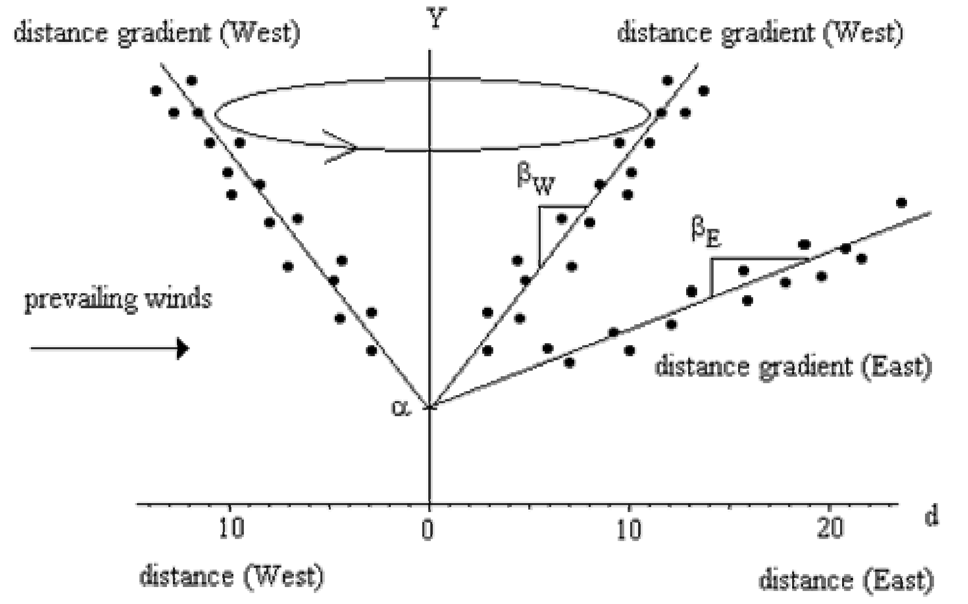

Figure 1

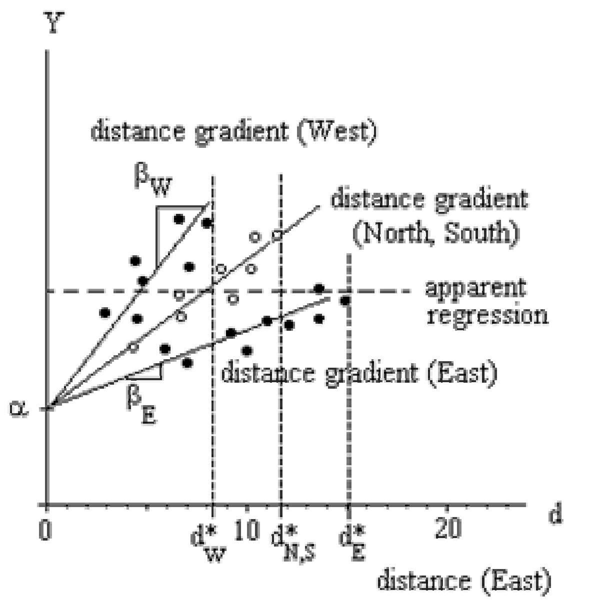

Figure 2

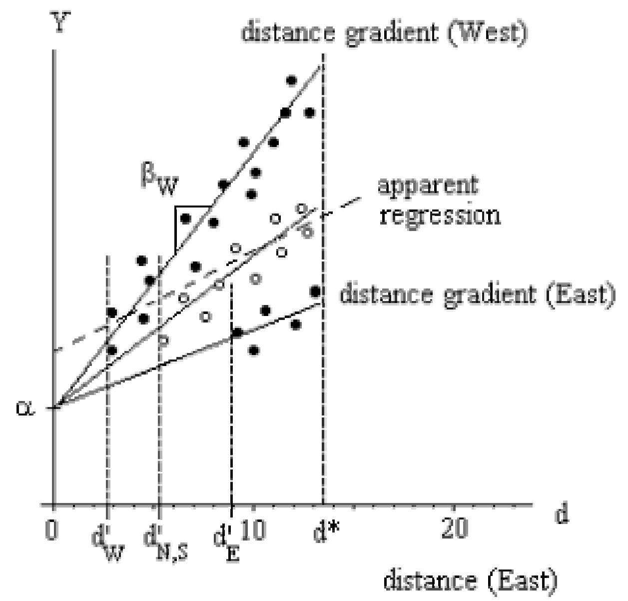

Figure 3

Interpretation of Tables

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

Each cell captures the results of one cross-section/time-series regression model with common AR(1) error structure across census tracts, time fixed effects, controls for monotonic time patterns in distance profiles relative to other local amenities/disamenities (CBDs, airports, railroads, roads, retail centers, transit terminals).

Models where the slope of the distance profile relative to the Superfund site is allowed to be quadratic in time are estimated first. If significant, only that result is reported. Linear-in-time distance profile models are not estimated. If the quadratic term in time is insignificant, a simpler linear-in-time model is estimated and 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 ("coming to the nuisance" throughout)
/	Slope of distance profile increases over time = group becomes relative less abundant near site (group moves away, throughout time period)
u	Group becomes first more abundant, then less abundant near site (turning point in 1980-1990 time interval) ("coming to the nuisance," followed by moving away)
n	Group becomes first less abundant, then more abundant near site (turning point in 1980-1990 time interval) ("coming to the nuisance" only post-1980-90)
\u	Group has become more abundant near site, but begins to get less abundant in 1990-2000 time interval ("coming to the nuisance" in the first two decades)
/n	Group has become less abundant near site, but begins to get more abundant in the 1990-2000 time interval ("coming to the nuisance" only in the last decade)
u/	Initially increasing, but starting in 1970-1980 time interval, group becomes relatively less abundant near site ("coming to the nuisance only in the first decase)
n\	Initially decreasing, but starting in 1970-1980 time interval, group becomes relatively more abundant near site ("coming to the nuisance" except in the first decade)
*	Compound-site locality, distance to closest site used for distance variable

Table 1a –

How slope of distance profile varies over time: ethnic groups
<u>Without</u> directional heterogeneity

	White		Black		Hispanic	
	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	u		---	-	---	-
2. MDS/Cork Landfill (MI)	---	-	n\		---	-
3. PJP Landfill/etc. (NJ) *	\u		---	/	u/	
4. Sayreville L'fill (NJ)	u		---	-	---	\
5. Cinnaminson L'Fll (NJ)	---	\	---	-	---	-
6. Bethpage L'fill (NY)	---	-	---	-	---	-
7. Ramapo Landfill (NY)	---	-	---	-	---	/
8. Silresim/IronHrse (MA) *	---	-	---	-	---	-
9. CTS Printex Inc. (CA)	n\		---	-	---	-
10. Montrose Chemical (CA)	n	-	---	\	u	
11. Chem Central (MI)	/n		\u		---	-
12. Kurt/McGillis (MN) *	---	\	---	-	u	
13. Mercury Refining (NY)	---	\	---	-	u	
14. NIMO Sarasota Sp (NY)	---	-	---	/	---	-
15. Havertown PCP (PA)	---	/	u		u/	
16. North Penn (PA) *	---	-	u		n	-

Table 1b –

How slope of distance profile varies over time: ethnic groups
<u>With</u> directional heterogeneity

	White		Black		Hispanic	
	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	---	/	n	-	\u	
2. MDS/Cork Landfill (MI)	---	-	n\		---	-
3. PJP Landfill/etc. (NJ) *	---	/	---	\	\	
4. Sayreville L'fill (NJ)	---	-	---	-	---	\
5. Cinnaminson L'Fll (NJ)	\		/		u	
6. Bethpage L'fill (NY)	---	/	---	-	/	
7. Ramapo Landfill (NY)	---	-	u		---	/
8. Silresim/IronHrse (MA) *	n		---	\	---	-
9. CTS Printex Inc. (CA)	---	\	n		n	
10. Montrose Chemical (CA)	u		\		---	/
11. Chem Central (MI)	/n		---	-	---	-
12. Kurt/McGillis (MN) *	u		---	\	u	
13. Mercury Refining (NY)	---	\	---	-	u	
14. NIMO Sarasota Sp (NY)	---	\	---	/	---	-
15. Havertown PCP (PA)	---	/	---	\	u/	
16. North Penn (PA) *	/n		---	\	---	-

Table 2a

How slope of distance profile varies over time: age group
No directional heterogeneity

	Under 6		Kids 6-17		Adults 18-64		Seniors (>65)	
	quadratic	linear	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	---	-	---	-	---	\	u	
2. MDS/Cork Landfill (MI)	---	-	---	-	n		u	
3. PJP Landfill/etc. (NJ) *	---	\	---	\	---	-	---	/
4. Sayreville L'fill (NJ)	---	\	---	-	n		u/	
5. Cinnaminson L'Fll (NJ)	---	-	n		u		---	-
6. Bethpage L'fill (NY)	---	-	---	-	u		---	\
7. Ramapo Landfill (NY)	---	-	---	\	---	-	---	-
8. Silresim/IronHrse (MA) *	u		u		n		---	-
9. CTS Printex Inc. (CA)	u/		---	-	---	\	---	/
10. Montrose Chemical (CA)	---	-	---	\	---	-	---	/
11. Chem Central (MI)	---	\	n		---	-	---	-
12. Kurt/McGillis (MN) *	n		u		---	-	---	-
13. Mercury Refining (NY)	---	-	---	/	---	-	---	-
14. NIMO Sarasota Sp (NY)	---	-	n\		---	-	\u	
15. Havertown PCP (PA)	---	-	---	-	u		---	\
16. North Penn (PA) *	---	-	---	-	---	\	---	/

Table 2b

How slope of distance profile varies over time: age group
<u>With</u> directional heterogeneity

	Under 6		Kids 6-17		Adults 18-64		Seniors (>65)	
	quadratic	linear	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	---	-	/n		---	\	u/	
2. MDS/Cork Landfill (MI)	---	-	---	-	n		u	
3. PJP Landfill/etc. (NJ) *	\u		\		/n		u	
4. Sayreville L'fill (NJ)	---	-	---	-	---	/	---	-
5. Cinnaminson L'Fll (NJ)	---	-	---	-	---	\	n	
6. Bethpage L'fill (NY)	n		/n		u		---	\
7. Ramapo Landfill (NY)	---	-	---	-	---	-	---	-
8. Silresim/IronHrse (MA) *	u		---	-	n		u	
9. CTS Printex Inc. (CA)	---	-	---	-	n		---	-
10. Montrose Chemical (CA)	n		n		u		\u	
11. Chem Central (MI)	---	\	---	-	---	-	---	/
12. Kurt/McGillis (MN) *	n		---	/	u		---	\
13. Mercury Refining (NY)	---	-	---	/	---	-	---	\
14. NIMO Sarasota Sp (NY)	---	-	n\		---	-	\u	
15. Havertown PCP (PA)	\		---	\	---	/	---	-
16. North Penn (PA) *	---	-	---	-	n		---	-

Table 3a

How slope of distance profile varies over time: family composition (with kids)
No directional heterogeneity

	Married couples with kids		Male head with kids (single dads)		Female head with kids (single moms)	
	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	---	-	---	-	u	
2. MDS/Cork Landfill (MI)	---	-	---	-	---	-
3. PJP Landfill/etc. (NJ) *	---	-	---	-	---	-
4. Sayreville L'fill (NJ)	---	\	---	-	---	-
5. Cinnaminson L'Fll (NJ)	n		---	-	---	-
6. Bethpage L'fill (NY)	/n		u/		---	-
7. Ramapo Landfill (NY)	---	-	---	-	---	-
8. Silresim/IronHrse (MA) *	---	-	---	\	---	/
9. CTS Printex Inc. (CA)	\u		---	-	---	-
10. Montrose Chemical (CA)	/n	/	---	\	n	
11. Chem Central (MI)	---	\	---	\	n	
12. Kurt/McGillis (MN) *	---	-	---	-	---	-
13. Mercury Refining (NY)	---	-	---	-	---	/
14. NIMO Sarasota Sp (NY)	/n		---	-	n	
15. Havertown PCP (PA)	---	-	---	-	u	
16. North Penn (PA) *	n		---	-	---	-

Table 3b

How slope of distance profile varies over time: family composition (with kids)
<u>With</u> directional heterogeneity

	Married couples with kids		Male head with kids (single dads)		Female head with kids (single moms)	
	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	---	-	---	-	---	-
2. MDS/Cork Landfill (MI)	---	-	u		---	-
3. PJP Landfill/etc. (NJ) *	\u		---	\	---	\
4. Sayreville L'fill (NJ)	---	\	n		---	-
5. Cinnaminson L'Fll (NJ)	---	-	---	-	---	-
6. Bethpage L'fill (NY)	/n		---	-	---	-
7. Ramapo Landfill (NY)	---	-	---	-	---	-
8. Silresim/IronHrse (MA) *	u		\		---	/
9. CTS Printex Inc. (CA)	\		---	-	---	-
10. Montrose Chemical (CA)	/		---	\	n	
11. Chem Central (MI)	---	\	---	\	---	-
12. Kurt/McGillis (MN) *	---	/	---	-	---	-
13. Mercury Refining (NY)	---	-	---	-	---	/
14. NIMO Sarasota Sp (NY)	/n		---	-	n	
15. Havertown PCP (PA)	n\		n		n	
16. North Penn (PA) *	---	-	---	-	---	-

Table 4a

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

No directional heterogeneity

	Married couple, no kids		Male head, no kids		Female head, no kids		Non-family	
	quadratic	linear	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	---	\	---	-	---	-	---	-
2. MDS/Cork Landfill (MI)	---	\	n		---	-	---	-
3. PJP Landfill/etc. (NJ) *	n		---	-	---	-	---	/
4. Sayreville L'fill (NJ)	---	/	n		---	/	---	-
5. Cinnaminson L'Fll (NJ)	u		---	-	---	-	---	-
6. Bethpage L'fill (NY)	---	\	---	-	---	-	---	-
7. Ramapo Landfill (NY)	---	\	---	-	---	-	---	-
8. Silresim/IronHrse (MA) *	n		---	-	n		---	-
9. CTS Printex Inc. (CA)	/n		---	/	---	-	---	-
10. Montrose Chemical (CA)	n		u		/n		---	/
11. Chem Central (MI)	---	-	---	-	---	-	---	-
12. Kurt/McGillis (MN) *	---	-	---	-	---	-	---	-
13. Mercury Refining (NY)	---	\	u		---	-	---	-
14. NIMO Sarasota Sp (NY)	---	\	---	-	---	\	u	
15. Havertown PCP (PA)	\u		---	-	---	\	---	-
16. North Penn (PA) *	---	-	---	-	---	-	u	

Table 4b

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

No directional heterogeneity

	Married couple, no kids		Male head, no kids		Female head, no kids		Non-family	
	quadratic	linear	quadratic	linear	quadratic	linear	quadratic	linear
1. G&H Landfill/LDI (MI) *	---	\	u		---	-	---	-
2. MDS/Cork Landfill (MI)	---	\	n		---	/	n	
3. PJP Landfill/etc. (NJ) *	u/		---	-	---	/	---	/
4. Sayreville L'fill (NJ)	u		---	-	---	/	n	
5. Cinnaminson L'Fll (NJ)	\u		---	-	u		n	
6. Bethpage L'fill (NY)	\u		---	-	\u		---	\
7. Ramapo Landfill (NY)	---	\	---	-	---	-	---	-
8. Silresim/IronHrse (MA) *	n		---	-	n\		---	-
9. CTS Printex Inc. (CA)	/n		/		---	-	/	
10. Montrose Chemical (CA)	---	-	\u		/n		u	
11. Chem Central (MI)	---	-	---	-	---	-	---	-
12. Kurt/McGillis (MN) *	u		---	-	u		---	\
13. Mercury Refining (NY)	---	\	\u		---	-	---	-
14. NIMO Sarasota Sp (NY)	---	\	---	-	---	\	u	
15. Havertown PCP (PA)	u		---	-	---	-	---	/
16. North Penn (PA) *	n		---	-	n		u	

APPENDIX A – Site Descriptions

When more than one site clearly affects the same area, we use for our distance variable the "distance to the nearest Superfund site"

#	Site Name	NPL Listing History	Site Type	Site Contaminants	Site Location	Site Status
1	G & H Landfill Operating from 1955 to 1974 Landfill was used as a waste oil recovery facility from 1955 to 1967, and as an industrial and municipal landfill from 1955 to 1974	Proposed: 12/30/1982 Final: 09/08/1983	60-acre landfill and approx. 10-20 acres of adjacent property, waste oil containing (PCBs) was dumped into unlined ponds on-site, waste solvents, paint sludge were disposed of along with municipal refuse	Soil and Groundwater: contaminant plume (containing benzene, toluene, xylene, and trichloroethene) exists beneath the site as well as a PCB-laden oil seep	Located in Macomb Co. between Utica and Rochester; site is bordered by the Clinton River and a State Recreational Area to the south and west, and by residential areas to the north and east	Constructed a landfill cover (cap), a slurry wall, and a groundwater extraction and treatment system that will be operated for at least 30 years; created new wetland areas to replace wetlands that have been contaminated; site is now in O&M phase
1	Liquid Disposal, Inc. Operating dates unavailable	Proposed: 12/30/1982 Final: 09/08/1983	7-acre commercial liquid waste incineration facility, accepted waste from major auto manufacturers, chemical companies and other industries around the state	Soil and Groundwater: VOCs, PCBs, PAHs, numerous heavy metals including barium, cadmium and lead	Located in Shelby Township, Macomb Co., MI; site is bordered by wetlands, the Clinton River and an auto junkyard; Rochester-Utica State Recreational Area and the Shadbush Tract Nature Study Area are within one mile of the site	Removed lagoon wastes, contaminated sediments, liquid waste, heavy metal sludge and drums from the site; in 1992 35 major PRPs signed a Consent Decree with EPA for final cleanup of the site, construction complete
2	Michigan Disposal (Cork Street Landfill) Operating from 1925 to 1992	Proposed: 10/15/1984 Final: 02/21/1990	68-acre landfill, from 1925 to 1961 the site operated as a waste disposal facility, in 1961 used for municipal waste disposal and until 1968 waste was burned in an on-site incinerator, ash was	Groundwater: VOCs including toluene, xylene, and benzene, heavy metals arsenic and lead detected in on-site monitoring wells, creek adjacent to the site showed elevated levels of lead and iron	Located in Kalamazoo, MI; predominantly in an industrial/commercial area; closest residence is located ½-mile from the site; approx. 30 private water wells and two municipal water wells operate within	Remedy includes placing solid waste cap on the entire site, pumping and treating contaminated groundwater and discharging it to a publicly-owned wastewater treatment facility; remedial

			buried in the landfill until 1981, when the site was used as a Type III landfill		two miles of the landfill; Davis Creek flows along a portion of the eastern site boundary	activities were planned for completion by the end of 2002
3	PJP Landfill Operating from 1968 to unknown closure date	Proposed: 12/01/1982 Final: 09/01/1983	87-acre landfill; may have been used to dispose of an unknown quantity of chemical, industrial wastes; also received solid wastes	Soil: chromium, phenols, pesticides, VOCs Leachate: contaminated with VOCs (benzene, chlorobenzene), lead	Located in Jersey City, NJ; high-rise apartment complex and a park are within ½ mile; site is bordered by Hackensack River on the west	Installed gas venting system; drum removal phase complete; activities associated with capping remaining landfill area initiated
3	Industrial Latex Corp. Operating from 1951 to 1983	Proposed: 06/24/1988 Final: 03/30/1989	Manufactured chemical adhesives, natural and synthetic rubber compounds	Soil: contaminated primarily with PCBs	Located in the Borough of Wallington, NJ; site is located in residential and industrial area; approximately 10,000 people live within ½ mile of the site	Contaminated buildings and other debris removed and disposed of off-site; soil cleanup completed in June 2000; EPA plans to propose deletion of the site from the NPL
3	Chemical Control Corporation Operating from 1970 to 1978	Proposed: 10/01/1981 Final: 09/01/1983	2-acre parcel of land; operated as a hazardous waste storage, treatment and disposal facility	Soil/Sediment: VOCs, pesticides, acid and base/neutral extractables and metals	Located in the city of Elizabeth, NJ; adjacent to the Elizabeth River; surrounding area mostly industrial although densely populated neighborhoods are located across the Elizabeth River	Removed debris and solidified soil to prevent further containment migration; constructed slurry wall around perimeter of site; currently being monitored
4	Sayreville Landfill Operating from 1970 to 1977	Proposed: 12/01/1982 Final: 09/01/1983	Municipal landfill covering approx. 30 acres; received municipal and light industrial waste; allegedly received hazardous waste during operations and after closure	Soil/Sediment: toluene, trichloroethylene (TCE), benzene, arsenic and chloroform Groundwater: Phenol, heavy metals including iron and manganese, VOCs, PAHs, cadmium and	Located in Sayreville, NJ; along tidal South River, part of site is in a wetland adjacent to South River; nearest resident is ½ mile away; municipal wells are in the vicinity	Removed drums, capped site, installed stormwater control and methane collection system; five year groundwater monitoring program implemented; Five Year Review completed May 2002

				lead		
5	Cinnaminson Township Landfill Operating from 1950s to 1980	Proposed: 10/01/1984 Final: 06/01/1986	400-acre site consisting of landfill, residential, light to heavy industrial properties; municipal, institutional, industrial wastes, including hazardous substances were deposited	Groundwater: arsenic and VOCs including chloroform, benzene, tetrachloroethylene and vinyl chloride	Located in Cinnaminson and Delran Townships of Burlington Co., NJ; the Delaware River is located approximately 5,000 feet to the northwest and U.S. Route 130 passes about 2,000 feet southwest of the site	Groundwater pump and treatment system completed in January 2000; groundwater treatment ongoing
6	Old Bethpage Landfill Operating from 1957 to 1986	Proposed: 10/01/1981 Final: 09/01/1983	65-acre inactive municipal landfill that is part of a sanitary landfill complex; primarily used for disposing incinerator residue, then accepted garbage, trash, solid industrial process wastes, damaged drums	Groundwater: heavy metals including iron and manganese, VOCs Leachate: same heavy metals as above	Located in Oyster Bay, NY; situated above the Magothy Aquifer, which supplies many public wells; approx. 10,000 residents live within a mile of site	Installed methane gas and leachate collection systems; fully capped landfill; groundwater treatment system completed; treatment ongoing
7	Ramapo Landfill Operating from 1972 to 1978	Proposed: 12/01/1982 Final: 09/01/1983	96-acre municipal landfill; reportedly received cosmetic, pharmaceutical and automotive sludge-like wastes in violation of codes and permits; unknown wastes also found near landfill	Soil: heavy metals, VOCs Groundwater: VOCs, mercury, lead, chromium, cadmium Surface water: heavy metals, semi-VOCs and phenols	Located in Rockland Co. along Route 59, 1 mile east of the Village of Hillburn; four public water supply wells serving the Spring Valley Water Authority systems, which provide water to 200,000 users, are located within 1,500 feet west of the site, just across the Ramapo River	Capped the landfill; EPA conducted preliminary evaluation and determined no immediate cleanup actions were required while further investigations leading to the final remedy selection are taking place
8	Silresim Chemical Corp. Operating from 1971 to 1977	Proposed: 07/23/1982 Final: 09/08/1983	5-acre plot in industrial area, reclaimed chemical wastes including	Soil: VOCs, semi-volatile organic compounds, pesticides, PCBs,	Located in city of Lowell, MA; 1 mile south of the central business district of	Construction of groundwater extraction and treatment system

			waste oil, solvents and sludge containing heavy metals	dioxin Groundwater: VOCs, semi-volatile organic compounds, pesticides, PCBs, heavy metals	Lowell and several hundred feet from the nearest residential area	complete in 1995, continues to operate; removal of VOC soil and groundwater contamination ongoing
8	Iron Horse Park Operating since 1913	Proposed: 09/08/1983 Final: 09/21/1984	553-acre industrial complex, includes manufacturing and rail yard maintenance facilities, open storage areas, landfills and wastewater lagoons	Soil: PCBs, petrochemicals, arsenic, cadmium, lead, selenium Groundwater: organic chemical, inorganic chemicals, asbestos, same heavy metals as found in soil	Located in city of North Billerica, MA; Middlesex Canal runs along the length of the northern boundary of site; Shawseen River is east of the site; Richardson Pond lies to north of the site	Asbestos materials removed; installed cap to control odors and eliminate migration of contaminants into the surface/groundwater on and off site; removed contaminated soils; further cleanup activities being planned
9	CTS Printex, Inc. Operating from 1966 to 1985	Proposed: 06/24/1988 Final: 02/21/1990	5.5-acre site, manufactured printed circuit boards	Soil: copper, lead Groundwater: VOCs, heavy metals	Located in city of Mountain View, CA; 2.5 miles south of San Francisco Bay	Excavation/disposal of contaminated soil complete; groundwater treatment ongoing
10	Montrose Chemical Corp. Operating from 1947 to 1982	Proposed: 10/15/1984 Final: 10/04/1989	13-acre plant property, manufactured technical grade pesticide (DDT)	Soil: DDT, chlorobenzene, benzene hexachloride (BHC) Groundwater: DDT, chlorobenzene	Located in city of Torrance, CA; within the Harbor Gateway between Los Angeles proper and the Los Angeles Harbor	Some areas having DDT contaminated sediments have been removed or capped; site studies are ongoing; final cleanup activities being planned
11	Chem Central (Grand Rapids) Operating since 1957	Proposed: 12/3019/82 Final: 09/08/1983	2-acre facility, distributed industrial chemicals	Soil: phthalates, VOCs, PCBs Groundwater: VOCs and semi-VOCs	Located in city of Wyoming, MI; ½ mile south of Plaster Creek; one-tenth mile from the nearest residence	Five Year Review completed in 1999, found that remedy is still protective of human health and environment

12	Kurt Manufacturing Company Operating since 1960	Proposed: 10/14/1984 Final: 06/10/1986	Site covers tens of acres; produces precision computer equipment	Soil and Groundwater: tetrachloroethene, trichloroethane, cis-1,2-dichloroethylene and trichloroethene	Located in Fridley, MN; site is an industrial, commercial and residential area; company is located one mile from the Mississippi River	Shaving bin sump was excavated and capped to prevent further seepage; pump-and-treat system installed in 1986; groundwater monitoring ongoing
12	MacGillis & Gibbs Co. / Bell Lumber & Pole Co. Operating since the early 1920's	Proposed: 09/08/1983 Final: 09/21/1984	Adjoining properties compose the 68-acre site; both companies are wood treatment plants	Soil and Groundwater: polycyclic aromatic hydrocarbons (PAHs), PCP, and heavy metals such as copper, chromium, and arsenic	Located in New Brighton, MN; closest residence is within several hundred feet	Removed abandoned process tanks, sludge, residues and metals-contaminated soils; installed groundwater collection and treatment facilities; ongoing
13	Mercury Refining, Inc. Operating from 1956 to 1998, continues operating as transfer facility	Proposed: 12/01/1982 Final: 09/01/1983	½-acre site in light industrial and commercial area, used for reclaiming mercury from batteries	Soil/Sediment: heavy metals including mercury, zinc and lead, PCBs Ground/Surface water: mercury, zinc and lead	Located in Colonie, NY; a tributary to Patroons Creek, which flows to the Hudson River, runs next to the site	Removed and disposed contaminated soil; constructed a new furnace building w/state-of-the-art pollution control equipment; clay cap yet to be evaluated; investigation ongoing
14	Niagara Mohawk Power Corp. (Saratoga Springs Plant) Operating from 1853 to present	Proposed: 06/24/1988 Final: 02/21/1990	7-acre site used for coal gas manufacturing until late 1940s, hazardous by-product materials were stored at various locations on site; in 1950s began operating as a multi-purpose service center	Soil/Sediment: polynuclear aromatic hydrocarbons (PAHs), VOCs associated w/coal tars, low levels of DDT Groundwater: PAHs and VOCs	Located in Saratoga Springs, NY; situated in a primarily residential area; approx. 10,000 live within a mile of the site and receive drinking water from the city; Loughberry Lake is the drinking water supply reservoir for the city and is located 2,000 feet upgradient of the site	Installed water-tight barrier wall around perimeter; construction of permanent water treatment facility is on-going; excavation/off-site treatment, disposal of sediments in Spring Run Creek is on-going; remediation of storm sewer, wetlands are expected to be begin this summer
15	Havertown PCP	Proposed:	Wood treatment	Soil/Ground/Surface	Located near the	Soils are now clean

	Operating from 1947 to 1981	12/30/1982 Final: 09/08/1983	facility; reportedly disposed primarily oil contaminated with pentachlorophenol (PCP) into a well leading to the groundwater under the plant, spilled liquid wastes on surface	water: PCP, arsenic, dioxins, VOCs, petroleum hydrocarbons	Haverford Township in Delaware Co., PA; situated along Naylor's Run, a small stream that flows through a residential area and eventually into the Delaware River	and safe; groundwater treatment plant constructed; treatment ongoing
16	North Penn Area 2 Operating from 1963 to 1986	Proposed: 01/22/1987 Final: 10/04/1989	350+ acre area; facility used to manufacture precision springs, reels, measuring and controlling apparatus; used up to 4,500 gallons per week of trichloroethylene (TCE) as a degreasing solvent	Soil/Groundwater: VOCs including trichloroethene (TCE)	Located in Hatfield, PA; site setting consists of a mixture of residential, commercial and industrial areas	Contaminated soils treated/removed; monitoring residential wells; ongoing investigation into sources of groundwater contamination; preparing feasibility study to evaluate various cleanup options
16	North Penn Area 6	Proposed: 01/22/1987 Final: 03/31/1989	Site is largely a groundwater contamination problem encompassing the area in and around the Borough of Lansdale, Pennsylvania; resulting primarily from the chemical components of solvents and degreasers used in the general vicinity	Groundwater: Trichloroethene (TCE) and perchloroethene (PCE) are the primary contaminants, although several other contaminants are present	Located in Lansdale, PA; an unnamed tributary to Towamencin Creek is about a mile from the site; approximately 100,000 people obtain drinking water from public and private wells within three miles of the site; the closest home is next to the site and the nearest well is 200 feet away	Temporary groundwater and extraction facility operating; constructing long-term groundwater extraction and treatment facility; installing two wells to prevent further movement of plume until treatment system is complete

Appendix B – Key Parameter Estimates and Regression Details

Location 1: G&H Landfill/Liquid Disposal Inc. (MI)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.093

N=368, tracts=92	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.0739	-0.2785	0.5008		0.9558	
	(0.39)	(1.91)*	(1.13)		(2.52)**	
ln(d)*t	**-0.2339**	**0.1420**	**1.3056**		**-1.0256**	
	(1.07)	**(2.12)****	**(2.66)*****		**(2.40)****	
ln(d)*t2	**0.0993**	**-**	**-0.5117**		**0.2451**	
	(1.57)		**(3.62)*****		**(1.99)****	
ln(d)*cos(theta)	0.1512	0.1623	-0.7481		-0.2597	
	(1.60)	(1.72)*	(4.81)***		(1.74)*	
ln(d)*sin(theta)	0.1682	0.1889	-0.3705		-0.2971	
	(1.47)	(1.64)	(1.54)		(1.49)	
mean Y	4.27	4.27	-6.74		-5.59	
st.dev. Y	2.03	2.03	2.41		1.94	
other 5% sig:	8	7	6		8	
other 10% sig:	0	1	1		1	
Min/Max yr:	1982	0	1983		1991	
AR1 rho	0.1955	0.1991	0.1137		0.1585	
Log L	-321.31	-320.79	-602.94		-511.90	
1. G&H Landfill/LDI (MI) profile code	222	123	131		4212	

Location 2: Michigan Disposal /Cork Street Landfill (MI)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.12

N=176, tracts=44	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.7896	-0.8114	0.7485		-0.0353	-0.0064
	(3.97)***	(3.99)***	(2.42)**		(0.13)	(0.03)
ln(d)*t	**0.0666**	**0.1082**	**0.4114**		**0.0752**	**-0.0535**
	(0.41)	**(1.11)**	**(1.31)**		**(0.22)**	**(0.43)**
ln(d)*t2	**0.0128**	**-**	**-0.2485**		**-0.0474**	**-**
	(0.29)		**(2.69)*** **		**(0.46)**	
ln(d)*cos(theta)	-0.2164	-0.2197	0.6836		-0.3361	-0.3322
	(2.23)**	(2.23)**	(3.26)***		(1.99)**	(1.94)*
ln(d)*sin(theta)	0.0760	0.0768	0.0584		0.0846	0.0818
	(1.48)	(1.47)	(0.68)		(1.03)	(0.99)
mean Y	2.67	2.67	-3.55		-4.75	-4.75
st.dev. Y	1.69	1.69	2.49		1.58	1.58
other 5% sig:	7	7	9		4	4
other 10% sig:	1	2	1		2	1
Min/Max yr:	1944	0	1978		1978	0
AR1 rho	0.3713	0.3861	0.2107		0.0846	0.0941
Log L	-89.55	-88.09	-194.28		-195.83	-195.48
2. MDS/Cork Landfill (MI)						
profile code	222	111	3431		222	111

Location 3: PJP Landfill/Industrial Latex/Chemical Control (NJ)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.195

N=3708, n=927	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.7621	-0.7698	1.0413	1.0887	-0.1697	
	(8.59)***	(8.67)***	(7.17)***	(7.55)***	(2.58)***	
ln(d)*t	**0.0859**	**0.1154**	**-0.1845**	**-0.3018**	**-0.3422**	
	(1.39)	**(3.28)*** **	**(1.86)* **	**(5.14)*** **	**(7.27)*** **	
ln(d)*t2	**0.0091**	**-**	**-0.0353**	**-**	**0.0507**	
	(0.54)		**(1.34)**		**(3.86)*** **	
ln(d)*cos(theta)	0.6129	0.6130	-0.7521	-0.7498	0.1791	
	(22.52)***	(22.54)***	(21.82)***	(21.87)***	(8.03)***	
ln(d)*sin(theta)	0.0300	0.0300	-0.1656	-0.1658	-0.0399	
	(1.71)*	(1.71)*	(6.56)***	(6.62)***	(2.94)***	
mean Y	1.44	1.44	-3.12	-3.12	-2.15	
st.dev. Y	2.50	2.50	3.21	3.21	1.68	
other 5% sig:	16	16	12	12	14	
other 10% sig:	0	0	0	1	1	
Min/Max yr:	1923	0	1944	0	2004	
AR1 rho	0.6557	0.6556	0.6193	0.6190	0.6884	
Log L	-4609.35	-4609.77	-6153.89	-6155.02	-3419.08	
3. PJP Landfill/etc. (NJ) profile code	222	123	222	321	421	

Location 4: Sayreville Landfill (NJ)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.093

N=372, tracts=93	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.8484	-0.9310	1.8397	1.8326	0.7425	0.7286
	(3.66)***	(3.94)***	(3.84)***	(3.89)***	(4.98)***	(5.22)***
ln(d)*t	**-0.2646**	**0.0397**	**-0.2092**	**-0.3266**	**-0.3066**	**-0.2722**
	(1.40)	**(0.41)**	**(0.51)**	**(1.67)***	**(1.87)***	**(4.30)*****
ln(d)*t2	**0.0973**	**-**	**-0.0448**	**-**	**0.0106**	**-**
	(1.84)*		**(0.39)**		**(0.22)**	
ln(d)*cos(theta)	0.2711	0.2716	-0.3293	-0.3320	-0.4091	-0.4086
	(4.43)***	(4.45)***	(3.89)***	(3.93)***	(10.87)***	(10.87)***
ln(d)*sin(theta)	-0.2055	-0.2049	0.2350	0.2408	-0.0179	-0.0179
	(3.16)***	(3.12)***	(2.11)**	(2.19)**	(0.47)	(0.47)
mean Y	2.60	2.60	-4.06	-4.06	-3.29	-3.29
st.dev. Y	1.93	1.93	2.55	2.55	1.36	1.36
other 5% sig:	8	8	7	7	11	11
other 10% sig:	0	0	0	0	0	0
Min/Max yr:	1984	0	1947	0	2115	0
AR1 rho	0.5506	0.5500	0.5028	0.5030	0.2634	0.2616
Log L	-350.47	-352.36	-557.64	-557.09	-281.47	-281.57
4. Sayreville L'fill (NJ) profile code	222	111	222	111	222	321

Location 5: Cinnaminson Landfill (NJ)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.195

N=708, tracts=177	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	0.2230		-0.7109		1.3955	
	(1.88)*		(2.56)**		(8.15)***	
ln(d)*t	**-1.0599**		**1.4996**		**-0.8123**	
	(7.86)* **		**(4.57)*** **		**(3.47)*** **	
ln(d)*t2	**0.1601**		**-0.2418**		**0.2060**	
	(3.82)* **		**(2.40)** **		**(2.79)*** **	
ln(d)*cos(theta)	1.1476		-1.8781		-0.6510	
	(14.54)***		(14.76)***		(9.45)***	
ln(d)*sin(theta)	-0.7709		0.7358		0.7046	
	(5.01)***		(3.14)***		(5.14)***	
mean Y	3.19		-4.66		-4.39	
st.dev. Y	2.37		3.16		1.99	
other 5% sig:	11		8		12	
other 10% sig:	1		2		1	
Min/Max yr:	2003		2001		1990	
AR1 rho	0.3973		0.4138		0.2305	
Log L	-934.50		-1267.54		-974.03	
5. Cinnaminson L'Fll (NJ) profile code	421		134		313	

Location 6: Old Bethpage Landfill (NY)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.124

N=588, tracts=147	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^*}{1-\%X_{it}^*}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-1.8525	-1.8540	2.6435	2.5697	0.1832	
	(7.23)***	(7.32)***	(5.04)***	(4.94)***	(1.59)	
ln(d)*t	**0.3796**	**0.3600**	**0.0303**	**0.4676**	**0.4600**	
	(1.68)*	**(3.21)*****	**(0.06)**	**(1.95)***	**(3.91)*****	
ln(d)*t2	**-0.0078**	**-**	**0.1540**	**-**	**-0.0716**	
	(0.12)		**(1.08)**		**(2.00)****	
ln(d)*cos(theta)	0.2397	0.2387	-0.8992	-0.9025	-0.1929	
	(4.71)***	(4.68)***	(7.70)***	(7.72)***	(7.15)***	
ln(d)*sin(theta)	-0.4314	-0.4299	0.3647	0.3613	0.0407	
	(7.51)***	(7.44)***	(2.75)***	(2.74)***	(1.26)	
mean Y	3.39	3.39	-6.02	-6.02	-3.43	
st.dev. Y	2.25	2.25	3.34	3.34	0.89	
other 5% sig:	6	6	4	4	5	
other 10% sig:	0	0	2	2	1	
Min/Max yr:	2213	0	1969	0	2002	
AR1 rho	0.3820	0.3836	0.4119	0.4106	0.3419	
Log L	-798.57	-798.35	-1188.37	-1188.93	-419.23	
6. Bethpage L'fill (NY) profile code	222	123	222	111	134	

Location 7: Ramapo Landfill (NY)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.093

N=120, tracts=30	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.8216	-0.8285	1.8539		0.2215	0.2179
	(1.67)*	(1.66)*	(2.69)***		(0.57)	(0.56)
ln(d)*t	**-0.0858**	**-0.0734**	**-0.8424**		**0.2179**	**0.4040**
	(0.51)	**(0.59)**	**(1.88)***		**(1.15)**	**(3.69)*****
ln(d)*t2	**0.0048**	**-**	**0.2581**		**0.0655**	**-**
	(0.13)		**(2.17)****		**(1.33)**	
ln(d)*cos(theta)	-0.6183	-0.6161	0.8726		0.3266	0.3281
	(4.29)***	(4.26)***	(4.83)***		(3.38)***	(3.32)***
ln(d)*sin(theta)	-0.2364	-0.2345	0.8722		0.4853	0.4909
	(1.14)	(1.12)	(2.91)***		(3.04)***	(2.91)***
mean Y	2.49	2.49	-3.52		-3.52	-3.52
st.dev. Y	1.57	1.57	2.25		0.90	0.90
other 5% sig:	7	6	5		2	3
other 10% sig:	2	3	2		0	0
Min/Max yr:	2060	0	1986		1953	0
AR1 rho	0.7463	0.7469	0.3624		0.6372	0.6647
Log L	-65.02	-65.05	-161.08		-64.60	-65.01
7. Ramapo Landfill (NY) profile code	222	111	313		222	123

Location 8: Silresim Chemical Corp/Iron Horse Park (MA)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.124

N=284, tracts=71	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-1.0524		1.6611	1.5664	0.5183	0.3885
	(2.42)**		(2.42)**	(2.36)**	(0.79)	(0.59)
ln(d)*t	**0.4873**		**-1.0371**	**-0.9879**	**-0.6456**	**-0.2875**
	(1.78)*		**(2.15)****	**(2.86)*****	**(1.71)***	**(0.91)**
ln(d)*t2	**-0.1579**		**0.0014**	**-**	**0.1156**	**-**
	(2.76)***		**(0.01)**		**(1.71)***	
ln(d)*cos(theta)	0.0462		0.0230	0.0212	-0.1160	-0.1199
	(0.71)		(0.18)	(0.17)	(1.00)	(1.02)
ln(d)*sin(theta)	0.7881		-0.9902	-0.9922	-0.4089	-0.4070
	(10.71)***		(7.99)***	(8.23)***	(3.37)***	(3.32)***
mean Y	3.73		-6.05	-6.05	-4.79	-4.79
st.dev. Y	2.00		2.34	2.34	2.10	2.10
other 5% sig:	6		6	6	2	2
other 10% sig:	0		1	0	2	2
Min/Max yr:	1985		5720	0	1998	0
AR1 rho	0.1943		0.0724	0.0616	0.2288	0.2344
Log L	-330.19		-503.90	-503.19	-433.21	-434.66
8. Silresim/IronHrse (MA) profile code	131		222	321	222	111

Location 9: CTS Printex Inc. (CA)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.195

N=416, tracts=104	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	1.1275	1.1229	-1.2919		-0.5102	
	(5.88)***	(5.89)***	(3.08)***		(3.68)***	
ln(d)*t	**-0.3984**	**-0.3920**	**0.4480**		**0.1338**	
	(3.63)*	**(4.72)***	**(1.69)**		**(1.84)**	
ln(d)*t2	**0.0017**	**-**	**-0.1425**		**-0.0453**	
	(0.08)		**(2.49)**		**(2.85)***	
ln(d)*cos(theta)	-0.2017	-0.2013	0.2966		0.7218	
	(1.92)*	(1.92)*	(1.18)		(6.87)***	
ln(d)*sin(theta)	-0.8265	-0.8270	1.6143		0.1395	
	(6.40)***	(6.39)***	(5.42)***		(0.77)	
mean Y	1.62	1.62	-4.75		-2.34	
st.dev. Y	1.28	1.28	2.50		1.04	
other 5% sig:	9	9	3		9	
other 10% sig:	0	0	3		0	
Min/Max yr:	3135	0	1986		1985	
AR1 rho	0.5372	0.5373	0.3583		0.6652	
Log L	-192.05	-192.06	-661.92		-206.85	
9. CTS Printex Inc. (CA) profile code	222	321	131		131	

Location 10: Montrose Chemical (CA)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.124

N=1084, tracts=271	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	0.5250		1.2565		-0.7666	-0.7506
	(5.65)***		(6.23)***		(9.70)***	(9.67)***
ln(d)*t	**-0.4041**		**-1.0863**		**0.1511**	**0.0825**
	(4.71)* **		**(5.42)*** **		**(2.62)*** **	**(3.06)*** **
ln(d)*t2	**0.1364**		**0.1535**		**-0.0214**	**-**
	(5.45)* **		**(2.62)*** **		**(1.30)**	
ln(d)*cos(theta)	0.2142		-0.5045		-0.0575	-0.0586
	(6.49)***		(8.11)***		(1.91)*	(1.95)*
ln(d)*sin(theta)	0.6981		-0.6822		-0.2024	-0.2044
	(11.67)***		(5.90)***		(3.27)***	(3.29)***
mean Y	0.29		-2.82		-1.32	-1.32
st.dev. Y	2.08		3.30		1.31	1.31
other 5% sig:	12		13		10	10
other 10% sig:	0		1		0	0
Min/Max yr:	1985		2005		2005	0
AR1 rho	0.5211		0.3824		0.7379	0.7377
Log L	-888.76		-1820.50		-553.62	-554.47
10. Montrose Chemical (CA) profile code	313		421		222	123

Location 11: Chem Central (MI)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.124

N=356, tracts=89	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.8215		0.7912	0.6204	-0.1765	-0.2173
	(4.26)***		(2.06)**	(1.70)*	(0.98)	(1.24)
ln(d)*t	**0.6960**		**-0.7683**	**-0.2480**	**0.0033**	**0.0955**
	(5.42)* **		**(2.36)** **	**(1.43)**	**(0.02)**	**(1.02)**
ln(d)*t2	**-0.1464**		**0.1647**	**-**	**0.0304**	**-**
	(4.56)* **		**(1.81)* **		**(0.56)**	
ln(d)*cos(theta)	-0.2231		0.7159	0.7256	-0.0445	-0.0473
	(1.75)*		(3.32)***	(3.40)***	(0.50)	(0.52)
ln(d)*sin(theta)	0.4966		-0.7775	-0.7748	-0.1387	-0.1386
	(8.56)***		(7.17)***	(7.16)***	(3.35)***	(3.32)***
mean Y	2.89		-4.32	-4.32	-4.15	-4.15
st.dev. Y	2.26		3.17	3.17	1.67	1.67
other 5% sig:	9		5	5	8	8
other 10% sig:	0		2	1	1	1
Min/Max yr:	1994		1993	0	1969	0
AR1 rho	0.4677		0.3518	0.3526	-0.1735	-0.1441
Log L	-371.56		-623.85	-625.45	-434.42	-432.60
11. Chem Central (MI) profile code	1343		222	111	222	111

Location 12: Kurt Manufacturing/McGillis & Gibbs Co (MN)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.195

N=760, tracts=190	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.0872		1.0172	0.9577	0.5890	
	(1.29)		(5.87)***	(5.79)***	(3.83)***	
ln(d)*t	**-0.0999**		**-0.5853**	**-0.3902**	**-0.8298**	
	(1.50)		**(3.00)*** **	**(5.00)*** **	**(4.11)*** **	
ln(d)*t2	**0.0398**		**0.0644**	**-**	**0.2129**	
	(2.01) **		**(1.09)**		**(3.38)*** **	
ln(d)*cos(theta)	-0.0242		0.0287	0.0269	-0.2431	
	(0.43)		(0.23)	(0.22)	(2.76)***	
ln(d)*sin(theta)	0.0829		-0.4530	-0.4528	0.0741	
	(1.07)		(3.61)***	(3.61)***	(0.78)	
mean Y	2.87		-4.77	-4.77	-4.88	
st.dev. Y	1.88		2.91	2.91	1.82	
other 5% sig:	9		7	7	8	
other 10% sig:	1		1	1	1	
Min/Max yr:	1983		2015	0	1989	
AR1 rho	0.5096		0.3068	0.3078	0.1300	
Log L	-662.89		-1225.68	-1225.89	-1049.59	
12. Kurt/McGillis (MN) profile code	313		222	321	313	

Location 13: Mercury Refining (NY)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.195

N=312, tracts=78	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X^*_{it}}{1-\%X^*_{it}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	0.0741	0.1149	-0.2786	-0.2498	0.9548	
	(0.26)	(0.42)	(0.70)	(0.64)	(3.59)***	
ln(d)*t	**-0.0156**	**-0.2278**	**0.3099**	**0.2144**	**-1.3919**	
	(0.09)	**(2.25)****	**(1.30)**	**(1.41)**	**(6.43)*****	
ln(d)*t2	**-0.0645**	**-**	**-0.0321**	**-**	**0.3641**	
	(1.45)		**(0.54)**		**(6.15)*****	
ln(d)*cos(theta)	0.0269	0.0357	-0.0245	-0.0257	0.1055	
	(0.27)	(0.36)	(0.14)	(0.15)	(0.83)	
ln(d)*sin(theta)	-0.1942	-0.1807	0.3769	0.3737	-0.1065	
	(2.75)***	(2.53)**	(3.22)***	(3.21)***	(1.44)	
mean Y	3.03	3.03	-3.95	-3.95	-4.83	
st.dev. Y	1.82	1.82	2.42	2.42	1.69	
other 5% sig:	4	4	3	3	3	
other 10% sig:	0	0	2	2	4	
Min/Max yr:	1969	0	2018	0	1989	
AR1 rho	0.5595	0.5561	0.5696	0.5675	0.3337	
Log L	-259.35	-259.19	-394.23	-394.32	-372.47	
13. Mercury Refining (NY) profile code	222	321	222	111	313	

Location 14: Niagara Mohawk Power Corp (Sarasota Springs Plant) (NY)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.124

N=48, tracts=12	Share White		Share Black		Share Hispanic	
$\log\left[\dfrac{\%X^*_{it}}{1-\%X^*_{it}}\right]$	quadratic	linear	quadratic	Linear	quadratic	linear
ln(d)	3.4972	3.8048	-6.8391	-6.7036	0.1926	0.3933
	(4.22)***	(5.01)***	(6.04)***	(5.87)***	(0.09)	(0.19)
ln(d)*t	**-0.7770**	**-0.9220**	**2.3396**	**1.9477**	**0.2921**	**0.3028**
	(2.17)**	**(2.92)*****	**(4.32)*****	**(3.82)*****	**(0.29)**	**(0.33)**
ln(d)*t2	**-0.0212**	**-**	**-0.1390**	**-**	**0.0267**	**-**
	(0.51)		**(1.89)***		**(0.30)**	
ln(d)*cos(theta)	-0.4439	-0.4898	0.2879	0.2899	0.1531	0.1426
	(3.41)***	(4.19)***	(1.76)*	(1.82)*	(0.69)	(0.63)
ln(d)*sin(theta)	-0.4078	-0.4267	1.0794	1.0739	2.4371	2.4498
	(2.68)***	(2.97)***	(2.23)**	(2.26)**	(4.47)***	(4.48)***
mean Y	4.03	4.03	-5.05	-5.05	-5.31	-5.31
st.dev. Y	1.16	1.16	1.97	1.97	1.75	1.75
other 5% sig:	8	9	9	8	6	6
other 10% sig:	2	2	2	3	1	1
Min/Max yr:	1786	0	2054	0	1915	0
AR1 rho	-0.0572	-0.1958	-0.2263	-0.2700	-0.3047	-0.2991
Log L	-3.21	-4.24	-35.16	-39.47	-48.93	-46.87
14. NIMO Sarasota Sp (NY) profile code	222	321	222	123	222	111

Location 15: Havertown PCP (PA)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.124

N=864, tracts=216	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	Linear	quadratic	linear
ln(d)	-2.2070	-2.1691	3.6741	3.6787	0.2688	
	(9.90)***	(9.46)***	(10.85)***	(10.85)***	(1.26)	
ln(d)*t	**0.7627**	**0.5618**	**-1.0726**	**-0.7970**	**-0.1329**	
	(4.61)* **	**(6.81)*** **	**(4.19)*** **	**(6.48)*** **	**(0.55)**	
ln(d)*t2	**-0.0680**	**-**	**0.0915**	**-**	**0.2289**	
	(1.39)		**(1.20)**		**(3.06)*** **	
ln(d)*cos(theta)	-0.9833	-0.9866	0.7620	0.7625	0.0744	
	(6.62)***	(6.73)***	(4.09)***	(4.12)***	(0.72)	
ln(d)*sin(theta)	-0.0280	-0.0365	-0.2732	-0.2738	-0.1597	
	(0.25)	(0.33)	(1.66)*	(1.66)*	(1.60)	
mean Y	1.78	1.78	-3.01	-3.01	-5.62	
st.dev. Y	3.51	3.51	4.06	4.06	1.93	
other 5% sig:	11	11	13	13	6	
other 10% sig:	1	1	0	1	2	
Min/Max yr:	2026	0	2029	0	1973	
AR1 rho	0.6897	0.6844	0.6151	0.6111	0.2127	
Log L	-1251.26	-1255.65	-1560.11	-1563.36	-1481.59	
15. Havertown PCP (PA) profile code	222	123	222	321	2124	

Location 16: North Penn (PA)

Radius=12 km; other distance effects linear in time; Auxiliary R-squared among distances=.093

N=256, tracts=64	Share White		Share Black		Share Hispanic	
$\log\left[\frac{\%X_{it}^{*}}{1-\%X_{it}^{*}}\right]$	quadratic	linear	quadratic	linear	quadratic	linear
ln(d)	-0.5887		0.8814	0.7485	-0.3350	-0.2367
	(2.17)**		(2.97)***	(2.50)**	(1.41)	(0.93)
ln(d)*t	**0.8923**		**-0.8357**	**-0.4685**	**0.1545**	**-0.1006**
	(3.94)* **		**(3.24)*** **	**(3.28)*** **	**(0.69)**	**(0.84)**
ln(d)*t2	**-0.1723**		**0.1192**	**-**	**-0.0781**	**-**
	(2.85)* **		**(1.68)* **		**(1.23)**	
ln(d)*cos(theta)	-0.2056		0.2697	0.2681	-0.1109	-0.1235
	(1.52)		(1.26)	(1.24)	(0.46)	(0.51)
ln(d)*sin(theta)	0.4617		-0.7693	-0.7700	0.0421	0.0437
	(4.98)***		(5.28)***	(5.28)***	(0.25)	(0.26)
mean Y	3.95		-5.48	-5.48	-5.62	-5.62
st.dev. Y	2.09		2.51	2.51	2.04	2.04
other 5% sig:	6		6	6	1	1
other 10% sig:	0		1	1	2	2
Min/Max yr:	1996		2005	0	1980	0
AR1 rho	0.1606		0.1478	0.1445	0.1754	0.1690
Log L	-285.49		-379.75	-382.64	-406.51	-408.54
16. North Penn (PA) profile code	1343		222	321	222	111

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