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Unequal Trajectories: Racial and Class Differences in Residential Exposure to Industrial Hazard

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Abstract

The unequal exposure to industrial hazards via differential residential attainment and/or differential sitings of toxic facilities is a long-standing environmental justice issue. This study examines individual trajectories of residential exposure to the risk of industrial hazard over nearly two decades. Using a latent class growth analysis on longitudinal geocoded data merged with the neighborhood-level pollution measures, we discover large racial differences in trajectories of pollution exposure. A majority of individuals are exposed to above-average pollution levels at some point during the study period, but blacks are more likely than whites to experience persistent exposure to high pollution. These differences are only partially explained by racial differences in suburban neighborhood attainment, socioeconomic status, and the frequency of inter-neighborhood moves. Immobile blacks also saw their exposure increase.

Introduction

Available evidence suggests that in the United States, poor minority households are disproportionately burdened by the geographic concentration of industrial hazards and toxic pollution (Ash and Fetter 2004; Brulle and Pellow 2006; Crowder and Downey 2010; Downey 2005, 2007; Hipp and Lakon 2010; Paster, Sadd, and Hipp 2001). On average, African Americans are exposed to industrial air pollution levels that are about twice as high as those experienced by whites, and while exposure to pollution tends to decline with higher socioeconomic status, racial disparities in exposure remain even among families with similar resources (Crowder and Downey 2010). These disparities by race and socioeconomic status are troubling, given the evidence that residential proximity to industrial hazards leads to poorer health outcomes, greater levels of psychological distress, impaired development and educational difficulties among children, perceptions of neighborhood disorder, and the

stagnation of housing values (Downey 2006; Downey and Van Willigen 2005; Evans and Kantrowitz 2002; Liu 2001; Pastor, Sadd, and Morello-Frosch 2002, 2004; Ross, Reynolds, and Geis 2000; Sadd et al. 1999).

While existing theoretical arguments suggest that the deleterious impacts of pollution exposure are likely to accumulate over time (cf. Pope et al. 2002), most environmental inequality research has focused on disparities in pollution exposure at a single point in time or within short observation periods. Some aggregate-level studies have examined temporal changes in pollution levels within neighborhoods (Been and Gupta 1997; Oakes, Anderton, and Anderson 1996; Saha and Mohai 2005), but aggregate-level research ignores the migration of households into and out of these neighborhoods, thereby limiting their utility for adjudicating competing theoretical explanations of environmental spatial inequality. Similarly, individual-level research on environmental inequality focuses on residential mobility patterns within short observation periods (Crowder and Downey 2010), thus failing to articulate how distinct points in time are linked together in ways that may produce longer spells of, or discontinuity in, exposure to pollution. This limitation makes it difficult if not impossible for researchers to assess whether there are considerable upward and/or downward changes in exposure, how these longer-term exposure trajectories might vary across social groups, or how these variations might be driven by individual characteristics and mobility patterns.

This research begins to address these questions by studying individual trajectories of residential exposure to the risk of industrial hazards. Using nearly two decades of longitudinal data from the Panel Study of Income Dynamics, merged with neighborhood-level pollution measures derived from the Environmental Protection Agency's (EPA's) Toxics Release Inventory (TRI), we apply a *latent class growth analysis* to investigate different kinds of risk trajectories experienced by individuals over an extended period of time. We then examine important social determinants of these unique risk trajectories, focusing on disparities by race and socioeconomic status.

Although we are unable to account for the level of ecological risk that individuals experience from the cradle to the grave, we are able to make considerable headway in this area of research. By taking a longitudinal approach to assessing residential pollution exposure, this study is uniquely situated to shed light on the importance of disparate patterns of residential mobility in exposing minority households to industrial hazards while conversely being able to assess changes in hazard exposure that are unrelated to migration. In doing so, we provide valuable insights into the structural dynamics through which inequality in long-term environmental risk unfolds.

Poverty and Exposure to Environmental Hazards over the Lifecourse

At any point in time, most of the US population occupies residential areas with little proximate exposure to industrial pollution. However, there is considerable geographic variation in the risk of exposure (Crowder and Downey 2010; Downey 2005). Moreover, in a cross-section of the population, the appearance of relatively low levels of risk could be misleading because many individuals, when monitored over time, likely experience

fluctuating risks to exposure. Indeed, exposure to industrial hazards is likely to be similar to individuals' experiences with poverty: When individuals are observed over the lifecourse, a considerably higher percentage experience poverty at some point during their lifetime relative to the percentage of the population that is poor at any given point in time (Corcoran 1995; Rank and Hirschl 2001; Timberlake 2007), and there is a typical array of individual trajectories into and out of poverty over the long run (McDonough, Sacker, and Wiggins 2005). Although it is an open question whether environmental risk is more or less variant than what longitudinal studies on poverty might indicate, given the established relationship between poverty and pollution exposure (Ash and Fetter 2004; Evans and Kantrowitz 2002), the extent of long-term individual risk to industrial hazards could be quite similar. Thus, the first objective of this research is to assess the individual-level heterogeneity in long-term trajectories of residential exposure to industrial hazards.

There are several recurrent hypotheses in the poverty literature that help guide our expectations concerning the types of risk trajectories that are most likely to occur (e.g., Andress and Schulte 1998). First, the *persistence hypothesis* posits that an individual's life chances are essentially fixed early in life and persist throughout the lifecourse. Parents' socioeconomic resources shape the types of neighborhoods and schools to which children are exposed, and in turn this exposure can affect children's development in ways that influence the next generation's socioeconomic attainments, including the quality of their neighborhoods (e.g., Sharkey 2008). According to the persistence hypothesis, there are two major groups of people: those who experience persistently low-quality neighborhoods, including those with high levels of industrial pollution, and those who are always safe from industrial hazards and other deleterious residential conditions. Therefore, we should expect at least two major risk trajectories to emerge from the longitudinal data on individual exposure to neighborhood pollution: (1) a flat trajectory of high exposure to industrial hazards over time; and (2) a flat trajectory of relatively low exposure to industrial hazards.

The second informative argument from the poverty literature suggests that exposure to neighborhood pollution might vary across the lifecourse (Dewilde 2003; Rank and Hirschl 2001). The *life-cycle hypothesis* maintains that many young adults start families with modest socioeconomic resources and, as a result, tend to live in more affordable housing typically located in poorer, more distressed neighborhoods. Over time, however, these families migrate out of these residential areas into better-quality neighborhoods as their careers and socioeconomic resources improve with age (South and Crowder 1997a). Based on the life-cycle perspective, we might expect that, in similar fashion, most families will start off in areas with exposure to relatively high industrial pollution but, over time, reduce this risk, primarily through the process of residential migration. Therefore, the life-cycle perspective suggests a single predominant trajectory of gradual decline over time to the residential exposure of industrial hazards.

Third, an emerging area of poverty research advances an *individualization hypothesis*, which suggests that experiences with poverty are becoming increasingly individualized in the modern era (Beck 1992; Leisering and Walker 1998). According to this perspective, social risks, such as poverty and exposure to disadvantaged residential environments, are shared by many in the population, but in ways that are contingent upon a vast confluence of individual

factors. For example, poverty can be a short-term and discontinuous phenomenon (e.g., life-cycle hypothesis), while for others, poverty, or the absence of poverty, is a continuous state (e.g., persistence hypotheses); and yet for many others, downward mobility or even seemingly recurrent oscillations between poor and non-poor states over time are real possibilities. This individualization hypothesis suggests that there is considerable heterogeneity with individuals' long-term experiences with exposure to neighborhood industrial hazards.

From previous longitudinal research on poverty, we know that the individualization thesis has limits. Rather than an unlimited array of individual experiences emerging when analyzing individual states of poverty over the lifecourse, researchers have identified a limited number of predominant categories of long-term experiences with poverty. For example, McDonough, Sacker, and Wiggins (2005) find four distinct individual poverty trajectories: always poor; never poor; began poor then became nonpoor; and began nonpoor then became poor. Similarly, for this research, we anticipate that longitudinal exposure to industrial hazard will follow a minimum of four major types (i.e., "classes") of trajectories: (c#1) persistently high exposure; (c#2) persistently low exposure; (c#3) high initial exposure then decreasing over time; and (c#4) low initial exposure then generally increasing over time. There is also a fifth possibility that is potentially more germane to industrial hazards than poverty exposure in general. Because exposure to industrial hazards is susceptible to changes in industrial production with the ebb and flow of economic cycles, a fifth likely category (c#5) could represent a subgroup whose exposure to industrial pollution oscillates between high and low hazardous exposures over time (cf. Elliott and Frickel 2013).

Racial Disparities of the Risk of Exposure to Industrial Hazards

Prior research has established the existence of environmental racial inequality (for a review, see Bowen 2002; Crowder and Downey 2010; Szasz and Meuser 1997). Although this literature provides a somewhat inconsistent picture of the extent of environmental inequality, most authors indicate that the distribution of industrial hazards—e.g., Superfund fund sites, hazardous waste sites, chemical spills, and manufacturing areas—are disproportionately located in neighborhoods occupied by racial minorities (Maranville, Ting, and Zhang 2009; Stretesky and Hogan 1998). There is continuing debate concerning the cause of this racial-environmental inequality, but there is a general consensus that racial minorities are disproportionately exposed to environmental hazards.

Based on past observations of racial disparities in environmental exposure using point-in-time measures, we anticipate that racial minorities will be overrepresented in the risk trajectories reflecting persistently high exposure to industrial hazards (c#1) and shifts from low exposure to high exposure over time (c#4). Correspondingly, racial minorities should be underrepresented in the trajectories characterized by persistently low exposure to industrial hazards (c#2) and shifts from high initial exposure to less exposure over the long run (c#3). How class-based and race-based factors intersect to create these environmental disparities is less clear.

According to the *racial income-inequality thesis* (Downey 2005; Oakes, Anderton, and Anderson 1996), racial differences in pollution-exposure trajectories largely reflect group differences in socioeconomic resources. Blacks in particular may be overrepresented in neighborhoods with a high risk of environmental hazard because they are more likely than whites to have low levels of income, education, and wealth, leaving them less able to afford higher-quality housing in safer neighborhoods. Previous research using aggregate-level data provides some support for this class-based perspective (e.g., Bowen et al. 1995). According to the racial inequality thesis, controlling for socioeconomic status should greatly attenuate, or possibly eliminate, the racial disparities in the odds of belonging to any of the latent class trajectories.

In contrast, proponents of the *racial residential discrimination thesis* (Bullard 1993; Mohai and Bryant 1992; Saha and Mohai 2005) argue that environmental hazards are disproportionately located in minority neighborhoods because (a) racial housing discrimination constrains the residential choices of racial minorities to neighborhoods with greater levels of environmental hazard; and/or (b) industrial sites are intentionally placed in disenfranchised areas by local power-brokers and decision-makers, and operated in these areas in ways that increase residents' risk of exposure. Both explanations are consistent with place-stratification theory, which describes ways in which real estate agents, mortgage lenders, local politicians, business elite, and other community actors exploit racial prejudices for the sake of urban development and economic growth (Logan and Molotch 1987). These place-stratification processes include overt factors, such as locating public housing in high-pollution areas, institutionalized mortgage discrimination, and residential steering of realtors; as well as indirect factors, such as differences in the ability of neighborhoods to oppose new industrial sitings, and/or the ability to curtail already existing sources of pollution. All of these factors lead to racial-spatial inequality, but not all factors are the direct byproduct of overt racial discrimination. The common denominator, however, is that these race-based factors will presumably continue to operate independently of socioeconomic considerations.

Although the racial residential discrimination thesis has received mixed support at the aggregate level with regard to environmental hazards, recent research at the individual level provides additional support. Crowder and Downey (2010) find that substantial racial differences in proximity to industrial hazards persist even after differences in education and income at the individual level are taken into account. Accordingly, we should expect that significant racial disparities in the odds of belonging to the most disadvantaged risk trajectories (c#1 and c#4) should persist after controlling for socioeconomic characteristics.

In general, neighborhood sorting processes are key to understanding racial spatial inequalities (cf. Sampson and Sharkey 2010) and suburbanization might be one mechanism through which structural forces, including socioeconomic factors and housing discrimination, produce racial differences in neighborhood pollution. Prior research demonstrates that blacks are less likely than whites to move to suburban neighborhoods (South and Crowder 1997b) and typically need greater socioeconomic resources than white households to attain suburban residence (Logan and Alba 1993). To the extent that industrial pollution is more concentrated in central city areas, the higher level of suburbanization of

whites might afford them some relative protection from trajectories involving high levels of exposure.

Nevertheless, other research suggests that differential rates of suburbanization may only partially explain environmental racial inequality. For instance, Friedman and Rosenbaum (2007) find that the neighborhood quality of the average black household in the suburbs is less than the neighborhood quality of the average white household in the suburbs. Moreover, suburban areas in recent decades have experienced considerable industrial development, and today many of the country's industrial production sites are located in industrial parks along major transportation routes that lie closer to suburban residential areas than to historic inner-city ghettos (Knox 2008). There is also emerging evidence of increasing levels of contamination in many newly industrialized suburban areas (Krieg 1998), with researchers finding evidence that minorities are disproportionately likely to live in polluted suburban areas in some metropolitan areas (Chi and Parisi 2011; Mennis and Jordan 2005) but not others (Downey 2005). These local findings raise a theoretically relevant empirical question as to whether differential trajectories of residential exposure to industrial hazard are driven primarily by differential suburbanization processes or whether differences in exposure trajectories persist regardless of differential suburban neighborhood attainment. A close examination of exposure trajectories will provide insight that may potentially move us beyond explanations based simply on historically differential rates of suburbanization for whites and blacks.

To advance place-stratification theory as it relates to environmental inequality, we have highlighted two main forces that could shape racial differences in individual trajectories of exposure to industrial hazards. On the one hand are the residential mobility processes that lead to racially differentiated neighborhood sorting. Place-stratification theory is often used to explain racial differences in residential mobility patterns that lead to different neighborhood attainments, like proximity to industrial hazard. On the other hand, a core aspect of place-stratification theory also emphasizes the broader political economy of urban development as a driver of spatial inequality, for which differential mobility is but one consequence (see Logan and Molotch 1987).

This broader aspect of place-stratification theory is important to consider because of the potentially biased political and economic decisions regarding the location and operation of industrial facilities throughout the US suburban and urban landscape (Been and Gupta 1997; Downey 2005; Grant et al. 2010; Hamilton 1995; Pastor, Sadd, and Hipp 2001; Shaikh and Loomis 1999). Even in the absence of significant disparities in residential mobility patterns, racial differences in neighborhood exposure trajectories may emerge if new industrial facilities are disproportionately opened in minority-populated areas, or if decisions about whether to maintain, and how to operate, existing facilities are correlated with the racial composition of the neighborhood. Therefore, racial differences in the likelihood of experiencing significant changes in exposure to industrial hazard over time (e.g., latent classes c#3 and c#4, possibly c#5) may reflect either racially differentiated mobility patterns or a political economy of industrial production that concentrates pollution in neighborhoods occupied by immobile minority-group members. Although we are unable to determine whether changes in the risk of residential exposure to industrial hazard are driven explicitly

by new facility sitings or changes in the production of toxins by old facilities, we are able to provide an empirical assessment of the contribution that residential mobility *and* the political economy of industrial production play in influencing individuals' risk trajectories by incorporating individual-level measures of residential mobility *and* immobility in our analyses.

Data and Methods

The data for this study come from the Panel Study of Income Dynamics (PSID) and the Environmental Protection Agency's (EPA) Toxics Release Inventory (TRI). The PSID is a longitudinal survey of approximately 5,000 US households that began in 1968. The PSID respondents were interviewed every year until 1997 and every two years thereafter. New households are added to the panel when children of the original families form their own household. The PSID is ideally suited to study trajectories of ecological risk to neighborhood pollution for several reasons. First, supplemental PSID geocode files allow us to link the addresses of individual PSID respondents to their corresponding census tract identifiers. This allows us to attach measures of neighborhood pollution to individual PSID respondents at each interview. Second, the longitudinal design of the PSID makes it possible to assess the level of ecological risk to neighborhood pollution for the same individuals over an extended period of time. These data then allow us to model the racial and class-based differences regarding the long-term ecological risk to industrial hazard. For this study, we focus on the data for 7,553 white and 5,236 black heads of PSID households interviewed in 1991 and followed through 2007—years that correspond with our data on neighborhood pollution. The PSID does not contain enough observations of other racial and ethnic groups over a long enough period of time to sustain a multi-ethnic comparison of exposure trajectories.

The data on neighborhood proximity to industrial hazards are based on the Toxic Release Inventory (TRI) data set collected by the EPA beginning in the late 1980s. The TRI is the most comprehensive and detailed record of industrial activity at the facility level in the United States. Industrial facilities with the equivalent of at least ten full-time employees and specializing in manufacturing, metal mining, coal mining, electricity-generating facilities that combust coal or oil, chemical wholesale distributors, petroleum terminals, and bulk storage facilities are required by law to submit to the TRI database the number of pounds of toxic chemicals they release into the environment each year. Our study uses TRI data from 1990 through 2007 (TRI data prior to 1990 are less reliable) and, in order to improve the accuracy of our hazard estimates, we include only those facilities for which, according to the EPA, the latitude and longitude provided in the TRI data are within 200 meters of the actual location of the facility.¹ As a result, we have data on a total of 30,309 unique facilities in the continental United States.

¹The locational accuracy variable provided by the EPA ranges from fifty meters (the facility is within fifty meters of the assigned coordinates) to 11,000 meters (the facility is within eleven kilometers of the assigned coordinates). We would have liked to have included only facilities for which the facility accuracy was fifty meters, but doing so would have resulted in the loss of 87.6 percent of the facilities in the data set (we would have lost 87.1 percent of the facilities had we included only facilities with locational accuracy estimates of 100 meters or less). By including facilities for which the locational accuracy was 200 meters or less, we were able to include 93.7 percent of all the TRI facilities in the data set.

Dependent Variable

The dependent variable for this study is the relative likelihood of experiencing various types of trajectories of exposure to proximate airborne industrial toxins released in and around neighborhoods of residence during the study period. Types of exposure trajectories are constructed from data on each respondent's biannual residential exposure to airborne industrial toxins. Unfortunately, a single source of pollution data that would allow us to also assess the ground-based legacy of industrial pollution and the role of air pollution generated by automobiles and from other sources does not exist. Despite these limitations, it is worth noting that a focus on contemporaneous levels of exposure to industrial hazard—for which the TRI data are the most widely used data source—is useful not only because of the harmful effects from frequent toxic emissions, but also because of the threat of industrial accidents these sites pose for local residents (e.g., toxic spills and catastrophic explosions).

The level of proximate industrial hazard in neighborhoods at each biannual interview is a continuous measure of the spatially weighted air pollution emitted by the TRI facilities within close proximity to the individual's census tract of residence. There are several steps to calculating this variable (see Downey [2006] for additional details). First, we overlay a map of the continental United States with a grid made up of 400- × 400-foot-square cells. Making use of the latitude and longitude information available in the TRI, we then calculate for each grid cell a distance-weighted sum of the pounds of air pollutants emitted that year by all TRI facilities located within 1.5 miles of the center of that grid cell. Inverse distance weights are used to calculate the weighted-sum grid cell values, with the weight declining from one to zero as the distance increases from zero feet to 1.5 miles. Finally, we use this weighted-sum grid to calculate the average grid cell value in each census tract in the country. Because many census tracts are located more than 1.5 miles away from the nearest industrial facility, the distribution of pollution proximity is positively skewed, with many tracts characterized by zero values. To reduce this skew, we add a small constant and take the natural log of the tract-level proximity measure. The resulting year-specific tract-level proximity measures are then attached to the individual geocoded records in the PSID data using each respondent's annual census tract identifiers.

Independent Variables

The key independent variables for this study are the respondent's demographic and socioeconomic characteristics; namely, the respondent's race (white or black), age, gender, homeownership status, educational attainment, and income. Differential suburbanization, residential mobility, and reliance on public housing also inform our understanding of who is exposed to the risk of industrial hazard over the long run. Because our interest is in the social characteristics associated with each type of unique risk trajectory as each latent trajectory emerges over time, we construct our independent variables to be time invariant. For race and gender, this is straightforward. For age, we use the respondent's age at the first observation in 1991. Homeownership is measured as the proportion of time from 1991 to 2007 that the individual spends living in an owner-occupied home. Educational attainment is measured as the highest level of schooling attained by 2007. Income is measured as the average level of income (in \$1,000s) between 1991 and 2007, adjusted for inflation using the CPI for the year 2000.

Potential effects of suburbanization are considered by incorporating measures of (a) the level of population density of the census tract for each respondent in 1991; and (b) the rate of change in tract-level population density for each respondent from 1991 to 2007. Data on tract-level population density are derived from the Neighborhood Change Database (Geo Lytics 2008). We also control for reliance on public housing with a measure indicating the proportion of time between 1991 and 2007 that the respondent lived in housing that was partially or fully subsidized by a government agency (e.g., in a housing project or receiving a Section 8 subsidy). Residential mobility is measured as the observed number of inter-neighborhood moves using two-year mobility intervals between 1991 and 2007.

Analytic Approach

We use a latent class growth analysis to assess variations in trajectories of exposure to neighborhood pollution. Latent class growth analysis offers researchers a classification tool that is useful for studying unobserved and potentially heterogeneous groupings of trajectories among a population of trajectories (Jung and Wickrama 2008; Muthén and Muthén 2000). When the trajectory of growth/change is suspected of being characterized by significant variation, and trajectory-group membership is unobserved, a latent class growth analysis is able to infer group membership from the observed patterns in the longitudinal data. Once an optimal number of growth trajectory classes are identified, further analysis can be conducted to study the social characteristics associated with individuals' likelihood of falling into any of the various trajectory classes.

More specifically, a latent class approach examines heterogeneity of trajectories by fitting models in a sequential order from the least complex model with only one average type of trajectory (i.e., a standard growth curve model) to more complex models that allow for many different types of average trajectories. Growth parameters are calculated for every individual (i.e., a unique intercept value and slope value for time for each individual), and then the distributions of those growth parameters are separated into groups based on (a) how many classes are theoretically justified by the researcher in advance; and (b) a mathematical decomposition of the pooled distribution that then groups similar individual-growth parameters into the same class. This approach is often referred to as a *finite mixture model*.

The validity of the methodology comes from the comparative process; the researcher starts by fitting a standard growth curve and then progresses to fitting a model where individuals are grouped into two different types of trajectories, then three different types of trajectories, four, five, and so forth. The model with the best *a priori* theoretical justification, the best model fit indices, and the least amount of classification error (i.e., highest entropy score) is determined to be the best solution to the data. Because a latent class growth analysis progresses through this comparative process, we know the results are methodologically and theoretically defensible; sensitivity checks are built into the procedure.

Formally, an unconditional latent class growth model with freely estimated growth parameters takes the following general form in SEM matrix notation:

$$y^{(c)} = \sum_{c=1}^C p_i^{(c)} [\Lambda^{(c)} \eta^{(c)} + r^{(c)}] \Rightarrow y^{(c)} = \begin{bmatrix} y_1^{(c)} \\ y_2^{(c)} \\ y_3^{(c)} \\ \vdots \\ y_9^{(c)} \end{bmatrix}; \Lambda^{(c)} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & \lambda_3^{(c)} \\ \vdots & \vdots \\ 1 & \lambda_9^{(c)} \end{bmatrix}; \eta^{(c)} = \begin{bmatrix} \alpha_i^{(c)} \\ \beta_i^{(c)} \end{bmatrix}; r^{(c)} = \begin{bmatrix} r_1^{(c)} \\ r_2^{(c)} \\ r_3^{(c)} \\ \vdots \\ r_9^{(c)} \end{bmatrix},$$

where $y^{(c)}$ is the level of risk to industrial hazard for individual i at time t ; $\sum_{c=1}^C p_i^{(c)}$ is the probability that the i th individual belongs to c th latent class; Λ is a matrix of constants and factor loadings; η is a vector of growth parameters (i.e., an intercept and a slope); and r is a vector of idiosyncratic errors. Here, the factor loadings $\lambda^{(c)}$ can be constrained for a linear specification or can be freely estimated to allow a trajectory to take a nonparametric functional form (as hypothesized for latent class $c=5$ above). For computational feasibility given the non-normality of the geographic distribution of industrial toxic release, this model specification also constrains the within-class variance components on the growth parameters to be zero (see Muthén and Muthén 2000; Bauer and Curran 2003). In order to incorporate all available information, missing data are handled via Full Information Maximum Likelihood (FIML) estimation (Enders and Bandalos 2001). To ensure that a global solution is reached, we follow the recommendations of Jung and Wickrama (2008).

The analysis proceeds as follows. First, the optimal number of latent classes is determined. In accordance with the above hypotheses, freely estimated growth trajectory models with one, two, three, four, five, and six latent classes are fitted consecutively to the data. A detailed discussion of the criteria used to determine the optimal number of latent class trajectories is provided in the results section. Second, because the number of latent classes identified in the preceding step is greater than two, a multinomial logistic regression model is employed to study the social characteristics associated with the odds of membership in each trajectory group.

Results

Figure 1 provides an illustration of the results from a latent class growth analysis. The fit statistics for each model solution are listed above each graphic. Following Collins and Lanza (2009, 82), we determine the best-fitting latent class solution based on statistical criteria, parsimony, and interpretability. To evaluate the latter two qualities (parsimony and interpretability), it is important to graphically display the various latent class solutions. Statistically, we rely on two fit statistics: (1) the Bayesian Information Criteria (BIC), which provides a relative gauge of model fit for competing model solutions with different numbers of parameters; and (2) an entropy measure that ranges from 0 to 1, with higher entropy values indicating less classification error and better latent class separation. Classification error emerges when there is low within-class homogeneity in the response pattern, and latent class separation refers to how well the latent class solution identifies distinct trajectories.

A total of six models are depicted in figure 1, starting with the optimal fitting model (as determined by the lowest BIC score) in the upper left-hand corner and moving to

decreasingly optimal models from panel (A) to panel (F). The six-class solution has the lowest BIC score (A), followed by the five-class solution (B), the four-class solution (C), the one-class solution (D), the three-class solution (E), and finally the two-class solution (F). It is important to note, however, that the BIC represent only one criterion. The BIC, like other fit statistics, may favor a greater number of latent classes when there is ample data, regardless of parsimony and interpretability of the results (Collins and Lanza 2009, 100–102).

Visually, there are several patterns in figure 1 that provide knowledge about the typical trajectories of individual exposure to the risk of residential industrial hazard over the long term. First, according to the one-class solution, we can tell that, on average, individuals' exposure to industrial pollution declined slightly over time. Although this may be attributable to the fact that, on average, individuals generally experienced upward spatial mobility over time, as posited by the *life cycle hypothesis* (c#3: high-to-low), it may also result from a general historical decline in reported TRI releases (EPA 2010). With the data at hand, we are unable to definitively distinguish between these two factors, but we will return to this issue in the regression analysis. This general decline in toxic release is apparent in each of the model solutions; even the latent trajectory characterized by continual exposure to high levels of neighborhood pollution (c#1: high-to-high) shows a modest decline in residential exposure over time.

Interestingly, the six-class solution and the five-class solution make more fine-grained distinctions between the different rates of declining exposure than does the four- or three-class solution. The five-class solution, which includes a latent trajectory of freely estimated factor loadings to allow for a nonlinear functional form as a test of whether an oscillating trajectory (c#5) is relevant, instead shows two latent high-to-low groups (c#3): one latent trajectory depicting a gradual improvement and the other nonlinear trajectory depicting rapid improvement. Latent class solutions six, five, and four also extract a latent class of people that see their exposure to industrial hazard increase over time. Thus, all three best-fitting model solutions support the *individualization hypothesis*, suggesting that there is significant heterogeneity in individuals' exposure to neighborhood industrial pollution. Overall, there appears to be one consistent class of individuals who experience persistently high levels of neighborhood pollution across time (c#1), a second group that experiences persistently low levels of exposure (c#2), a third group of individuals experiencing declines in exposure (c#3), and a fourth group that experiences increases in exposure to industrial hazards (c#4).

For further analysis, we selected the four-class solution for several reasons: First, the four-class solution is supported theoretically by the individualization hypothesis and the four general trajectories were also apparent in the higher-order solutions (five and six class solutions). Second, the extra classes in the higher-order solutions (five and six) do not provide any additional theoretical knowledge beyond the four-class solution. Third, the four-class solution has the best combination of fit statistics with the highest entropy score (0.826) among the models that are best fitting according to the BIC statistics. Therefore, the four-class solution has the best balance of model fit and classification error, it is more parsimonious than the six- and five-class solutions, and its interpretability is supported theoretically.

In table 1, we further examine the extent of heterogeneity in individuals' trajectories of exposure to industrial hazards using the four-class solution. First, note the average probabilities assigned to each latent class membership for the four-class solution. This information supplements the entropy statistic to more transparently assess the quality of the model solution in terms of within-class homogeneity and classification error. The average probabilities of class membership in table 1 are all above 0.80 (along the diagonal), which means that the probability of incorrect classification among individuals within their respective latent classes is low. Second is the prevalence of each class membership. According to table 1, 42 percent of the individuals in the PSID sample were exposed to neighborhoods with low levels of industrial pollution (c#2: low-to-low), 23 percent lived in neighborhoods with persistently high pollution exposures (c#1: high-to-high), another 23 percent began the study under high exposure but had their situation improve (c#3: high-to-low), and finally, 12 percent saw their exposure worsen over time (c#4: low-to-high). The weighted calculation using PSID sample weights to produce population values of these percentages is very similar to the unweighted version.²

Although the largest latent group has little exposure to industrial toxic release, it is also clear that a majority of individuals have trajectories that expose them to above average pollution levels at some point during the study period (58 versus 42 percent). There is also substantial variation in risk trajectories among the 58 percent of individuals who were exposed to high levels of pollution at some point during the study period. Here, a "high" level of neighborhood pollution is, on average, about a standard deviation above the mean for each year and "low" is essentially the equivalent of zero exposure.

Table 2 assesses the overall racial differences in TRI exposure during the study period. Here, we calculate the unadjusted racial difference in cumulative exposure to industrial hazard by using the growth parameters from each unique trajectory from the four-class solution estimated separately by race. The results reveal a racial disparity in cumulative exposure on the order of thirteen logged pounds of toxic release [33.91 ln(lb) for whites versus 46.70 ln(lb) for blacks] or nearly double the difference in poundage between whites and blacks (17,177 lb for whites versus 33,975 lb for blacks). The largest contributor to the overall cumulative racial disparity is the racial difference in pollution among those in the low-to-high category [41.47 ln(lb) for whites versus 47.11 ln(lb) for blacks]. Comparatively, in any given year (as if doing a cross-sectional analysis), the average residential exposure is between 2.9 and 4.8 logged pounds for whites versus 3.6 to 6.2 for blacks. Clearly, a point-in-time analysis masks a great deal of exposure heterogeneity and fails to specify the extent of racial spatial inequality that accumulates over time.

²We present the weighted descriptive statistics in table 1 and table 3 using the PSID survey weights provided for 1991. The weights capture the unequal probability of selection into the PSID sample and differential attrition. In the regression models, the use of weights is largely superfluous when also controlling for core socio-demographic characteristics because of the close association between socio-demographic characteristics (e.g., race, age, education, etc.) and sample selection/attrition. As a sensitivity check, we ran models with and without weights. The results change little, and the substantive conclusions are unaltered. In the supplemental analysis using the sampling weights, the residual racial gap is larger in all three contrasts than in the non-weighted models. However, the standard errors are generally larger in the weighted analysis than in the non-weighted analysis (although still statistically significant at a $p < .001$ level). This inefficiency suggests that the redundancy of the weights is unnecessary. We have elected to present the unweighted regression models because the net racial effects are more conservative and the standard errors are more efficient.

Table 3 provides weighted descriptive statistics by race for the variables used in a multinomial logistic regression analysis predicting the odds of latent class membership for the four-class solution. There are several notable differences by race in table 3. Foremost, a higher percentage of blacks (33 percent) than whites (20 percent) are classified in the trajectory characterized by persistent exposure to high levels of neighborhood pollution (c#1: high-to-high). Conversely, blacks (29 percent) are substantially less likely than whites (46 percent) to experience persistently low levels of neighborhood pollution during the study period (c#2: low-to-low). The average probability of membership in the other two latent trajectories (c#3: high-to-low and c#4: low-to-high) is more similar by race, although a slightly higher percentage of blacks (26 percent) than whites (22 percent) have residential trajectories characterized by declining pollution, likely reflecting the fact that blacks are more likely than whites to originate in highly polluted areas. Summing the means for trajectory classes 1 and 3 shows that 59 percent of black respondents, but only 42 percent of whites, were in trajectories characterized by high-pollution starting points.

Table 3 also documents substantial racial differences in individual- and family-level characteristics that might help explain these stark disparities. For instance, among whites the share of time spent in homeownership is over 25 percentage points greater than blacks (71 versus 43 percent, respectively). On average, whites have more than an additional year of schooling than blacks (13.95 versus 12.68 years) and reside in households with incomes that are almost \$30,000 (\$62,190 versus \$33,810) more than in black households. Additionally, the share of time the household was supported by subsidized housing is 14 percentage points greater for blacks compared to whites (17 versus 3 percent, respectively). On average, blacks resided in neighborhoods that were more densely populated in 1991 (over 7,000 people per square mile for blacks versus 3,650 per square mile for whites), and the rate of growth in population density over the study period was slightly positive for blacks but negative for whites. These factors could account for the observed racial disparities in exposure trajectories, and we turn to the regression analysis to assess that possibility.

Table 4 provides the logit coefficients from a multinomial regression analysis predicting the exposure trajectory experienced by individual PSID respondents. In these models, the reference category is the latent trajectory characterized by the persistence of low exposure to industrial hazard over the duration of the study period (c#2: low-to-low). The BIC fit statistics for the four models in table 4 indicate that each successive model gets incrementally better with the inclusion of new variables. Model 1 under columns 1, 5, and 9 shows the racial differences in the odds of belonging to the high-to-high (c#1), high-to-low (c#3), and low-to-high (c#4) trajectories relative to the low-to-low trajectory (c#2), adjusting for age and gender but without controls for socioeconomic status. The race coefficient in column 1 indicates that the odds of membership in the high-to-high trajectory relative to the low-to-low trajectory is 2.04 times higher ($\exp^{.711} = 2.04$) among blacks than among whites. The coefficients in column 5 show that blacks are 1.63 times ($\exp^{.487}$) more likely than whites to be in the high-to-low trajectory versus the low-to-low trajectory. In column 9, blacks are also more likely than whites to experience deterioration in their residential environment during the study period, with increasing exposure to pollution over time; the odds of being in the low-to-high pollution trajectory are 32 percent greater ($\exp^{.277}$) for blacks than for whites.

The second model under each contrast in table 4 (columns 2, 6, and 10) enters into the regression equation several key socioeconomic characteristics. According to the income-inequality thesis, these SES variables should account for the racial differences in neighborhood pollution trajectories. Several noteworthy findings emerge from these models. First, homeownership is negatively associated with membership in the high-to-high trajectory, the high-to-low trajectory, and the low-to-high trajectory relative to the low-to-low trajectory, indicating that individuals living in owner-occupied properties are less likely to be at risk for exposure to industrial hazard. Also as expected, both education and income are negatively associated with membership in the high-to-high exposure trajectory relative to the low-to-low trajectory. Conversely, in column 6 the effect of education on the odds of membership in the high-to-low trajectory is positive and the effect of income is not statistically significant. The positive effect of education in column 6 may reflect upward spatial mobility that tends to coincide with advancing levels of educational attainment, producing an increased likelihood of experiencing a downward pollution-exposure trajectory. On the other side of the socioeconomic spectrum, reliance on subsidized housing, net of other variables in the model, is positively associated with the odds of membership in the high-to-high pollution trajectory and the high-to-low trajectory, relative to membership in the low-to-low trajectory.

We also find in model 2 that the level of population density in the respondent's tract in 1991 is positively associated with being in the high-to-high trajectory relative to the low-to-low trajectory. A higher level of population density in 1991 and an increase in population density over the study period are also positively associated with being in the high-to-low trajectory relative to the low-to-low trajectory. Finally, a positive rate of change in density, but not the initial baseline level, is associated with being in a low-to-high trajectory relative to a low-to-low trajectory. Each of these findings is consistent with the argument that residence in dense urban locations tends to increase the likelihood of trajectories that entail higher than average exposure to neighborhood pollution.

The contrast between the *racial residential discrimination thesis* and the *racial income-inequality thesis* hinges on whether the relationship between racial status and pollution exposure is explained by socioeconomic status. In all three contrasts in table 4, we find that once we control for homeownership, education, income, time spent in government-subsidized housing, and differential suburbanization,³ racial differences in pollution-exposure trajectories are reduced but remain statistically significant at the .001 level. The largest reduction in the race effect is in column 2: controlling for SES explains 43 percent (.711 – .407/.711) of the initial racial disparity in the odds of experiencing a high-to-high pollution trajectory versus a low-to-low trajectory. Yet, even conditional on SES, the odds of experiencing persistently high pollution are still 1.5 times ($\exp^{.407}$) higher for blacks than for whites. A similar pattern emerges for the other two contrasts in columns 6 and 10. These findings provide qualified support for both the *racial residential discrimination thesis* and

³As an alternative measure of suburbanization, we included in a supplemental analysis a variable that captures the share of time an individual spent in a central-city neighborhood. Like population density, central-city location is positively associated with adverse exposure trajectories, and like population density, the central-city neighborhood measure attenuates but does not eliminate the racial disparities.

the *racial income-inequality thesis*; clearly, socioeconomic resources influence trajectories of exposure to neighbourhood pollution, but the residual racial gap also indicates that there are additional factors that cause racial disparities in these trajectories.

The final set of analyses address the role of residential mobility in shaping trajectories of exposure to industrial pollution. To examine this issue, we add to the regression model a measure that captures the number of inter-neighborhood moves observed over the study period. Frequent moves might signify the attempt to find suitable living conditions and has the potential of allowing families to escape dangerous environments. However, frequent movement might also be symptomatic of the vulnerability that households face in urban housing markets that lack affordable options in safe neighborhoods (Briggs, Popkin, and Goering 2010, 135–69). Thus, the expectation is that inter-neighborhood mobility will be predictive of both trajectories of change (high-to-low and low-to-high). Consistent with this expectation, the results in columns 3, 7, and 11 of table 3 show that the frequency of moves is positively associated with membership in the high-to-low and low-to-high trajectories. In other words, changes in pollution exposure at the individual level are not just driven by decisions about the location and operation of polluting industries; residential mobility itself also plays a significant role in determining a household's changing exposure to industrial hazard.

To further probe the impact of residential mobility, and to more fully examine the racially differentiated mobility dynamics that might be behind the racial disparities in exposure, the next step in the analysis examines whether the effects of residential mobility operate in a similar or different fashion for white and black households. Given the tenets of the racial-residential discrimination thesis, where residential constraints and housing vulnerability are likely to be greater among black households, we should expect the frequency of moves to have a stronger effect on the exposure trajectories for blacks. Model 4 in columns 4, 8, and 12 tests this hypothesis by adding an interaction term to assess the racial difference in the effect of residential mobility. Overall, we find significant racial differences in the effects of residential mobility on two of the three pollution-exposure contrasts. Specifically, in column 4, the coefficient for the number of inter-neighborhood moves ($-.109$) indicates that for whites a high level of mobility tends to decrease the probability of being in a high-to-high trajectory versus a low-to-low trajectory. In contrast, for blacks, frequent mobility actually increases this probability of exposure to the high-to-high trajectory ($-.109 + .181 = .072$). This effect for blacks is significantly different from whites and from zero at the .01 significance level. When black households move frequently, they are at a *higher* risk of being persistently exposed to industrial hazards. The opposite is true for white households. This finding is consistent with the housing vulnerability issue highlighted by the *racial-residential discrimination thesis*.

Additionally, we find in model 4, column 8, that the frequency of moves increases the likelihood of a high-to-low pollution trajectory for whites and blacks, but the effect for blacks is nearly twice as strong as it is for whites ($.103$ for whites versus $.103 + .087 = .190$ for blacks). Again, this finding reflects the tendency for black households to originate in high-pollution neighborhoods where migration can be a strategy to improve a household's neighborhood conditions over the long term, at least in terms of exposure to industrial

pollution. Thus, residential mobility is a mixed blessing for black households—migration provides a strategy to escape unsafe neighborhoods, but frequent mobility is also symptomatic of the vulnerability blacks face in trying to find and maintain suitable housing.

Interestingly, model 4 also provides the residual race effect for those households with no observed inter-neighborhood migration experience during the study period. This model provides evidence of whether the decisions of where to locate and how to operate industrial facilities differentially shapes individual-level changes in exposure to industrial pollution by race. The race coefficient in columns 4, 8, and 12 is the estimate of the racial difference in exposure trajectories for those households with zero inter-neighborhood migration during the study period, after controlling for socioeconomic characteristics at the individual level. We find that a statically significant residual racial gap remains for the low-to-high contrast: The odds of starting the observation period under low exposure to industrial pollution but ending the study period under high levels of exposure are 38 percent ($\exp^{.324}$) higher for *residentially immobile* black households than for immobile whites. The same pattern emerges in supplemental analyses (not shown) using an inverse coded measure of the share of time spent during the study in the same housing unit (i.e., 100 percent of time in the same house = zero migration). Explanations for this racial disparity among immobile households must, to some degree, involve the political economy of industrial production.

Conclusion

Environmental justice research has been limited in explaining the residential experiences of individuals that produce racial spatial inequalities in the aggregate. While the dangers of industrial hazard for human development increase with an individual's length of exposure, it was unclear from prior research whether, to what degree, and why residential exposure to industrial hazards changes over time. This research begins to address these questions by taking a longitudinal approach to studying residential exposure to industrial hazard, and as a result, several important findings emerge.

First, in support of the *individualization hypothesis*—which maintains that individual trajectories of exposure to pollution are heterogeneous but structured in patterned and predicable ways—this study finds multiple common trajectories of residential exposure to industrial hazards. The first trajectory (c#1: high-to-high) is characterized by persistent exposure to considerably higher-than-average levels of residential industrial pollution over the course of the sixteen-year study period. A second trajectory (c#2: low-to-low) involves living in neighborhoods with consistently low, to near zero, risk levels of industrial hazard. A third trajectory consists of households that began the study under high exposure but saw their exposure decline over time (c#3: high-to-low), and a fourth trajectory consists of households that went from low initial exposure to high levels of exposure by study's end (c#4: low-to-high). A majority of households experience, at least for a period of time, a greater than average exposure to industrial hazards, and among these households there is clearly substantial variation in their long-term risk profile that, if left unstudied, could obscure the overall magnitude of environmental burden borne by low-income and minority families.

A second set of important findings emerge that help us better understand the extent of, and reasons for, the racial disparity in exposure to industrial hazards. Specifically, we find that blacks are exposed to considerably higher than average levels of neighborhood pollution in much greater numbers than we would expect if race was inconsequential for environmental inequality research. Controlling for several important socioeconomic factors, we find, in support of the *racial income-inequality thesis*, that differences in socioeconomic status between whites and blacks account for a sizable share of the raw racial disparity. Yet, in support of the *racial residential discrimination thesis*, a significant residual racial gap in exposure remains even after controlling for socioeconomic differences between groups and differential levels of suburbanization.

A third set of findings probes deeper into the racial residential discrimination thesis than previous research by examining the role of residential mobility in generating trajectories of hazard exposure. Among some households, residential mobility provides an opportunity to improve one's living conditions, whereas for many other households, frequent mobility is symptomatic of residential vulnerability in tight housing markets. In support of this perspective, we find that frequent moves are both associated with a household's improved trajectory of exposure (c#3: high-to-low) as well as strongly associated with the more troubling trajectory of increasing exposure (c#4: low-to-high). Thus, residential mobility plays a significant role in affecting individual-level trajectories of changing exposure to industrial pollution, though in varying ways for different families. Importantly, our results also indicate that the effects of residential mobility operate differently by race, especially when examining the starkest contrast in exposure trajectories (i.e., high-to-high versus low-to-low): Frequent moves for white households increase the probability of maintaining persistently low levels of exposure, whereas for blacks, frequent moves increase the probability of being subjected to high levels of exposure over the long run.

Highlighting a second set of mechanisms driving environmental inequality, we also find sizable racial disparities in pollution-exposure experiences among immobile households, especially among those that began the study period under low levels of exposure but saw their exposure increase over the sixteen-year period. It is unclear given the available data whether the facility siting and operational decisions responsible for this finding result from racial bias among decision-makers, from the relative inability of black communities to defend against encroaching industrial land uses and operations (cf. Sampson 2012; Pastor, Sadd, and Hipp 2001), or from other factors (cf. Grant et al. 2010; Liu 2001). What is clear is that both frequent moves *and* immobility affect exposure trajectories differently for white and black households. The implication of this pattern resonates with what place-stratification and neighborhood-attainment researchers are beginning to discover (e.g., Briggs, Popkin, and Goering 2010): Poor minority households tend to move frequently for unexpected and involuntary reasons (e.g., landlord issues, evictions, caretaker responsibilities, etc.), which forces these households into limited or hasty housing and neighborhood choices. Conversely, when voluntary moves are being contemplated because of neighborhood safety issues, black households often lack access to, and/or clear evidence of, better neighborhood alternatives. This then often leads to apprehension and a decision not to move, despite the appearance, from an outsider's perspective, that a move would be in

the household's best interest. Thus, having to move too frequently, or not moving when it would seem one should, is emblematic of the larger struggle many black families face when trying to find and maintain housing in safe neighborhoods.

Of course, this study represents only a first step in developing a full understanding of lifecourse differences in pollution proximity and exposure, and there are limitations. For example, we rely on an environmental hazard indicator that, while superior to those used in much environmental inequality research, is still based on a single environmental hazard and a single spatial operationalization of exposure. Thus, our results do not account for potential racial differences in exposure to the ground-based legacy of industrial pollution or air pollution produced by automobiles. Finer spatial resolution to assess exposure is also something that warrants additional attention. While our strategy is consistent with much of the extant research on neighborhood stratification, to the extent that black and white populations are not equally distributed within census tracts, the focus on tract-based measures may mask some racial stratification that might be revealed with the use of smaller geographic units—census blocks or block-groups. In this regard, our estimates of racial differences in pollution-exposure trajectories should be viewed as somewhat conservative. We also acknowledge that racial differences in pollution-exposure trajectories might be related to broader patterns of population redistribution not captured here, as there could be aspects of mass migration flows and suburbanization processes other than changes in population density that could shape racial spatial disparities.

Future research should address these issues by examining pollution-trajectory differences for other hazards at different levels of spatial proximity and by investigating pollution-trajectory differences across the full lifecourse, with special attention paid to points in the lifecourse when people are particularly vulnerable to the risks posed by environmental hazards. Also, because one of the main arguments motivating environmental inequality research is that racial and ethnic variation in pollution exposure play a key role in producing other racially and ethnically inequitable outcomes, future research should determine whether lifecourse pollution trajectories are closely associated with educational, developmental, health, and employment outcomes, and if so, whether these correlates vary according to race/ethnic status. It is possible, for instance, that pollution exposure may produce health problems that disrupt educational attainment, skills acquisition, and socioeconomic accumulation in ways that undermine the ability to escape highly polluted areas, and these multiple effects may be especially pronounced among individuals experiencing high levels of pollution for extended periods of time, particularly during childhood. Conducting such research will greatly expand our understanding of the causes and consequences of environmental inequality in the United States.

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References

- Andress, Hans-Jürgen; Schulte, Katja. Empirical Poverty Research in Comparative Perspective, edited by Hans-Jürgen Andress. Brookfield, VT: Avebury Press; 1998. Poverty Risks and the Life Cycle: The Individualization Thesis Reconsidered; p. 331-356.
- Ash, Michael; Fetter, T. Robert Who Lives on the Wrong Side of the Environmental Tracks? Evidence from the EPA's Risk-Screening Environmental Indicators Model. *Social Science Quarterly*. 2004; 85:441-62.
- Bauer DJ, Curran PJ. Distributional Assumptions of Growth Mixture Models: Implications for Overextraction of Latent Trajectory Classes. *Psychological Methods*. 2003; 8(3):338. [PubMed: 14596495]
- Beck, Ulrich. Risk Society: Towards a New Modernity. London: SAGE; 1992.
- Been, Vicki; Gupta, F. Coming to the Nuisance or Going to the Barrios? A Longitudinal Analysis of Environmental Justice Claims. *Ecology Law Review*. 1997; 24:1-56.
- Bowen, William. An Analytic Review of Environmental Justice Research: What Do We Really Know? *Environmental Management*. 2002; 29:3-15. [PubMed: 11740620]
- Bowen, William M.; Salling, Mark J.; Haynes, Kingsley E.; Cyran, Ellen J. Toward Environmental Justice: Spatial Equity in Ohio and Cleveland. *Annals of the Association of American Geographers*. 1995; 85:641-663.
- Briggs, Xavier de Souza; Popkin, Susan J.; Goering, John M. Moving to Opportunity: The Story of an American Experiment to Fight Ghetto Poverty. Oxford: Oxford University Press; 2010.
- Bulle, Robert J.; Pellow, David N. Environmental Justice: Human Health and Environmental Inequalities. *Annual Review of Public Health*. 2006; 27:3.1-3.22.
- Bullard, Robert. Confronting Environmental Racism. Boston: South End Press; 1993.
- Chi, Guangqing; Parisi, Domenico. Highway Expansion Effects on Urban Racial Redistribution in the Post-Civil Rights Period. *Public Works Management & Policy*. 2011; 16(1):40-58.
- Collins, Linda M.; Lanza, Stephanie T. Latent Class and Latent Transition Analysis: with Applications in the Social, Behavioral, and Health Sciences. Hoboken, NJ: Wiley; 2009.
- Corcoran M. Rags to Rags: Poverty and Mobility in the United States. *Annual Review of Sociology*. 1995; 21:237-267.
- Crowder K, Downey L. Interneighborhood Migration, Race, and Environmental Hazards: Modeling Microlevel Processes of Environmental Inequality. *American Journal of Sociology*. 2010; 115:1110-1149.
- Dewilde, Caroline. A Life-Course Perspective on Social Exclusion and Poverty. *British Journal of Sociology*. 2003; 54:109-128. [PubMed: 12745821]
- Downey, Liam. The Unintended Significance of Race: Environmental Racial Inequality in Detroit. *Social Forces*. 2005; 83:971-1007.
- Downey, Liam. Environmental Racial Inequality in Detroit. *Social Forces*. 2006; 85:771-796.
- Downey, Liam. US Metropolitan-Area Variation in Environmental Inequality Outcomes. *Urban Studies*. 2007; 44(5/6):953-977. [PubMed: 21909171]
- Downey, Liam; Van Willigen, Marieke. Environmental Stressors: The Mental Health Impacts of Living Near Industrial Activity. *Journal of Health and Social Behavior*. 2005; 46:289-305. [PubMed: 16259150]
- Elliott, James R.; Frickel, Scott. The Historical Nature of Cities: A Study of Urbanization and Hazardous Waste Accumulation. *American Sociological Review*. 2013; 78(4):521-543.
- Enders CK, Bandalos DL. The Relative Performance of Full Information Maximum Likelihood Estimation for Missing Data in Structural Equation Models. *Structural Equation Modeling*. 2001; 8(3):430-457.
- Evans, Gary W.; Kantrowitz, Elyse. Socioeconomic Status and Health: The Potential Role of Environmental Risk Exposure. *Annual Review of Public Health*. 2002; 23:303-331.
- Friedman, Samantha; Rosenbaum, Emily. Does Suburban Residence Mean Better Neighborhood Conditions for All Households? Assessing the Influence of Nativity Status and Race/Ethnicity. *Social Science Research*. 2007; 36(1):1-27.

- Geo, Lytics. CensusCD Neighborhood Change Database 1970–2000 Tract Data. 2008 [Machine-Readable Database]. Available online at <http://www.geolytics.com/USCensus,Neighborhood-Change-Database-1970–2000,Products.asp>.
- Grant, Don; Trautner, Mary Nell; Downey, Liam; Thiebaud, Lisa. Bringing the Polluters Back In: Environmental Inequality and the Organization of Chemical Production. *American Sociological Review*. 2010; 75(4):479–504. [PubMed: 21921966]
- Hamilton, James T. Testing for Environmental Racism: Prejudice, Profits, Political Power? *Journal of Policy Analysis and Management*. 1995; 14:107–132.
- Hipp, John R.; Lakon, Cynthia M. Social Disparities in Health: Disproportionate Toxicity Proximity in Minority Communities over a Decade. *Health & Place*. 2010; 16(4):674–683. [PubMed: 20227324]
- Jung T, Wickrama KAS. An Introduction to Latent Class Growth Analysis and Growth Mixture Modeling. *Social and Personality Psychology Compass*. 2008; 2:302–317.
- Knox, Paul L. *Metropolitan, USA*. New Brunswick, NJ: Rutgers University Press; 2008.
- Krieg, Eric J. The Two Faces of Toxic Waste: Trends in the Spread of Environmental Hazards. *Sociological Forum*. 1998; 13(1):3–20.
- Leisering, Lutz; Walker, R. New Realities: The Dynamics of Modernity. In: Leisering, Lutz; Walker, R., editors. *The Dynamics of Modern Society: Poverty, Policy, and Welfare*. Bristol, UK: Polity Press; 1998. p. 3-16.
- Liu, Feng. *Environmental Justice Analysis: Theories, Methods, and Practice*. Boca Raton, FL: Lewis Publishers; 2001.
- Logan, John R.; Alba, Richard D. Locational Returns to Human Capital: Minority Access to Suburban Community Resources. *Demography*. 1993; 30:243–268. [PubMed: 8500639]
- Logan, John R.; Molotch, Harvey. *Urban Fortunes: The Political Economy of Place*. Berkeley: University of California Press; 1987.
- Maranville, Angela R.; Ting, Tih-Fen; Zhang, Yang. An Environmental Justice Analysis: Superfund Sites and Surrounding Communities in Illinois. *Environmental Justice*. 2009; 2(2):49–58.
- McDonough, Peggy; Sacker, Amanda; Wiggins, Richard D. Time on My Side? Life Course Trajectories of Poverty and Health. *Social Science & Medicine*. 2005; 61:1795–1808. [PubMed: 16029777]
- Mennis JL, Jordan L. The Distribution of Environmental Equity: Exploring Spatial Nonstationarity in Multivariate Models of Air Toxic Releases. *Annals of the Association of American Geographers*. 2005; 95(2):249–268.
- Mohai, Paul; Bryant, Bunyan. Environmental Racism: Reviewing the Evidence. In: Bryant, B.; Mohai, P., editors. *Race and the Incidence of Environmental Hazards*. Boulder, CO: Westview Press; 1992. p. 163-176.
- Muthén B, Muthén LK. Integrating Person-Centered and Variable-Centered Analyses: Growth Mixture Modeling with Latent Trajectory Classes. *Alcoholism: Clinical and Experimental Research*. 2000; 24:882–891.
- Oakes, John Michael; Anderton, Douglas L.; Anderson, Andy B. A Longitudinal Analysis of Environmental Equity in Communities with Hazardous Waste Facilities. *Social Science Research*. 1996; 25:125–148.
- Pastor, Manuel; Sadd, James L.; Morello-Frosch, Rachel. Who's Minding the Kids? Pollution, Public Schools, and Environmental Justice in Los Angeles. *Social Science Quarterly*. 2002; 83:263–280.
- Pastor, Manuel; Sadd, James L.; Morello-Frosch, Rachel. Reading, Writing, and Toxics: Children's Health, Academic Performance, and Environmental Justice in Los Angeles. *Environment and Planning C, Government and Policy*. 2004; 22:271–290.
- Pastor, Manuel; Sadd, James; Hipp, John. Which Came First? Toxic Facilities, Minority Move-In, and Environmental Justice. *Journal of Urban Affairs*. 2001; 23:1–21.
- Pope, Arden C., III; Burnett, Richard T.; Thun, Michael J.; Calle, Eugenia E.; Krewski, Daniel; Ito, Kazuhiko; Thurston, George D. Lung Cancer, Cardiopulmonary Mortality, and Long-Term Exposure to Fine-Particulate Air Pollution. *JAMA*. 2002; 287(9):1132–1141. [PubMed: 11879110]

- Rank, Mark R.; Hirschl, Thomas A. Poverty across the Life Cycle: Evidence from the PSID. *Journal of Policy Analysis and Management*. 2001; 20(4):737–755.
- Ross, Catherine; Reynolds, John; Geis, Karlyn. The Contingent Meaning of Neighborhood Stability for Residents' Psychological Well-Being. *American Sociological Review*. 2000; 65:581–597.
- Sadd, James L.; Pastor, Manuel, Jr; Boer, J. Thomas; Snyder, Lori D. 'Every Breath You Take...': The Demographics of Toxic Air Releases in Southern California. *Economic Development Quarterly*. 1999; 13:107–123.
- Saha, Robin; Mohai, Paul. Historical Context and Hazardous Waste Facility Siting: Understanding Temporal Patterns in Michigan. *Social Problems*. 2005; 52(4):618–648.
- Sampson, Robert J. *Great American City: Chicago and the Enduring Neighborhood Effect*. Chicago: University of Chicago Press; 2012.
- Sampson, Robert J.; Sharkey, Patrick. Neighborhood Selection and the Social Reproduction of Concentrated Racial Inequality. *Demography*. 2010; 45(1):1–29. [PubMed: 18390289]
- Shaikh S, Loomis J. An Investigation into the Presence and Causes of Environmental Inequity in Denver, Colorado. *Social Science Journal*. 1999; 36:77–92.
- Sharkey P. The Intergenerational Transmission of Context. *American Journal of Sociology*. 2008; 113:931–969.
- South, Scott J.; Crowder, Kyle D. Escaping Distressed Neighborhoods: Individual, Community, and Metropolitan Influences. *American Journal of Sociology*. 1997a; 102:1040–1084.
- South, Scott J.; Crowder, Kyle D. Residential Mobility between Cities and Suburbs: Race, Suburbanization, and Back-to-the-City Moves. *Demography*. 1997b; 34(4):525–538. [PubMed: 9545629]
- Stretesky, Paul; Hogan, Michael J. Environmental Justice: An Analysis of Superfund Sites in Florida. *Social Problems*. 1998; 45(2):268–287.
- Szasz, Andrew; Meuser, Michael. Environmental Inequalities: Literature Review and Proposals for New Directions in Research and Theory. *Current Sociology*. 1997; 45:99–120.
- Timberlake, Jeffrey M. Racial and Ethnic Inequality in the Duration of Children's Exposure to Neighborhood Poverty and Affluence. *Social Problems*. 2007; 54(3):319–342.

Figure 1.
Model fit statistics for a latent class growth analysis of residential exposure to the risk of industrial hazard

Average Latent Class Probabilities by Latent Class Membership for a Latent Class Growth Analysis of Residential Exposure to the Risk of Industrial Hazard

Table 1

Latent class trajectories	N	%	PSID weighted %	Average probability of latent class membership			
				c#1: High to high	c#2: Low to low	c#3: High to low	c#4: Low to high
				high	low	low	high
c#1: High to high	2,928	23	22	.89	.00	.07	.03
c#2: Low to low	5,320	42	43	.00	.94	.03	.07
c#3: High to low	2,992	23	23	.09	.02	.85	.06
c#4: Low to high	1,549	12	12	.02	.04	.04	.84
Total	12,789	100	100	1.00	1.00	1.00	1.00

Latent Class Growth Analysis Estimates of Yearly Airborne Industrial Toxic Released in the PSID's Respondents' Census Tract by Race and Latent Class Trajectory

Table 2

Year	White's TRI in logged lb				Black's TRI in logged lb			
	c#1: High to high	c#2: Low to low	c#3: High to low	c#4: Low to high	c#1: High to high	c#2: Low to low	c#3: High to low	c#4: Low to high
1991	9.94	1.08	8.62	2.05	10.23	1.33	9.13	3.37
1993	9.64	1.02	7.61	2.69	9.89	1.25	8.10	3.84
1995	9.34	.97	6.60	3.33	9.54	1.17	7.07	4.30
1997	9.04	.91	5.59	3.97	9.19	1.09	6.03	4.77
1999	8.74	.86	4.58	4.61	8.84	1.01	5.00	5.23
2001	8.44	.81	3.56	5.25	8.49	.93	3.97	5.70
2003	8.14	.75	2.55	5.89	8.14	.85	2.94	6.16
2005	7.84	.70	1.54	6.53	7.79	.77	1.91	6.63
2007	7.54	.64	.53	7.17	7.44	.69	.87	7.09
Column totals =	78.65	7.73	41.18	41.47	79.54	9.05	45.01	47.11
Cumulative totals =	ln(lb) = 33.91; lb = 17,177				ln(lb) = 46.70; lb = 33,975			

Note: To calculate cumulative totals, the column totals are weighted by the race-specific proportions for each class presented in table 3. Total cumulative pounds (lb) of airborne industrial toxins released in the respondents' census tract is calculated by first exponentiating the logged TRI values for each year then summing down the columns (and across the weighted column totals).

Table 3

Weighted Descriptive Statistics for Variables Used in a Multinomial Regression Analysis of Membership into Different Trajectories of Residential Exposure to the Risk of Industrial Hazard, Panel Study of Income Dynamics: 1991–2007

<i>Latent class trajectories</i>	<i>Whites</i>		<i>Blacks</i>	
	Means	Standard deviations	Means	Standard deviations
c#1: High to high	.20	.40	.33	.47
c#2: Low to low	.46	.50	.29	.45
c#3: High to low	.22	.42	.26	.44
c#4: Low to high	.11	.32	.13	.33
<i>Independent variables</i>				
Age in 1991	41.35	21.00	35.27	18.83
Women	.38	.48	.57	.50
Share of time as a homeowner	.71	.34	.43	.39
Highest level of education attained	13.95	3.30	12.68	3.03
Average inflation-adjusted income (\$1000)	62.19	57.52	33.81	25.29
Share of time spent in public housing or Section 8	.03	.13	.17	.27
Pop. density rate of change 1991–2007	−.26	.74	.03	3.76
Census tract pop. density in 1991 (1,000 per sq mi)	3.65	10.37	7.38	13.32
Frequency (#) of inter-neighborhood moves	1.70	1.79	2.32	2.14
<i>N</i> (head of households)	7,549		5,232	

Table 4

Logit Coefficients from a Multinomial Regression Analysis of Membership into Different Trajectories of Residential Exposure to the Risk of Industrial Hazard, Panel Study of Income Dynamics: 1991–2007

<i>Independent variables</i>	High to high (c#1) vs. low to low (c#2)				High to low (c#3) vs. low to low (c#2)				Low to high (c#4) vs. low to low (c#2)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Model 1 β (se)	Model 2 β (se)	Model 3 β (se)	Model 4 β (se)	Model 1 β (se)	Model 2 β (se)	Model 3 β (se)	Model 4 β (se)	Model 1 β (se)	Model 2 β (se)	Model 3 β (se)	Model 4 β (se)
Black (vs. white)	.711*** (.048)	.407*** (.053)	.409*** (.053)	.092 (.072)	.487*** (.048)	.289*** (.053)	.311*** (.053)	.143 (.075)	.277*** (.061)	.191** (.067)	.225*** (.068)	.324*** (.097)
Age in 1991	.001 (.001)	.000 (.001)	-.001 (.001)	-.001 (.001)	-.002* (.001)	.000 (.001)	.003* (.001)	.003* (.001)	-.009*** (.001)	-.008*** (.001)	-.004* (.001)	-.003* (.001)
Women (vs. men)	.210*** (.049)	.095 (.051)	.100* (.051)	.106* (.051)	.145** (.049)	.043 (.050)	.006 (.051)	.009 (.051)	.185** (.062)	.123 (.063)	.074 (.064)	.074 (.064)
Share time homeowner	-.226** (.078)	-.226** (.078)	-.245** (.081)	-.256** (.081)	-.422*** (.076)	-.422*** (.076)	-.164* (.082)	-.167* (.082)	-.331*** (.097)	-.331*** (.097)	.051 (.107)	.059 (.107)
High level education	-.040*** (.009)	-.040*** (.009)	-.039*** (.009)	-.041*** (.009)	.019* (.009)	.019* (.009)	.012 (.009)	.011 (.009)	.019 (.011)	.019 (.011)	.008 (.011)	.008 (.011)
Ave. income	-.003*** (.001)	-.003*** (.001)	-.003*** (.001)	-.003*** (.001)	-.001 (.001)	-.001 (.001)	-.002* (.001)	-.002* (.001)	-.001 (.001)	-.001 (.001)	-.001 (.001)	-.001 (.001)
Share time public housing	.415* (.138)	.399** (.136)	.399** (.136)	.330* (.136)	.280* (.141)	.280* (.141)	.357* (.142)	.313* (.143)	.181 (.183)	.181 (.183)	.282 (.188)	.307 (.187)
Pop. density rate of change	.056 (.029)	.063* (.030)	.063* (.030)	.064* (.029)	.065* (.029)	.065* (.029)	.074* (.029)	.075* (.029)	.067* (.030)	.067* (.030)	.077* (.030)	.077** (.030)
Pop. density in 1991	.015*** (.003)	.015*** (.003)	.015*** (.003)	.015*** (.003)	.015*** (.003)	.015*** (.003)	.016*** (.003)	.016*** (.003)	-.002 (.004)	-.002 (.004)	-.001 (.004)	-.001 (.004)
# Inter-neighborhood moves			-.017 (.015)	-.109*** (.021)			.138*** (.014)	.103*** (.018)		.186*** (.017)	.201*** (.021)	
# Moves $\times$ black			.181*** (.028)					.087*** (.025)				-.023 (.031)
Constant	-1.010*** (.045)	-.056 (.139)	-.015 (.143)	.176 (.146)	-.762*** (.043)	-.711*** (.135)	-1.119*** (.142)	-1.035*** (.145)	-1.162*** (.052)	-1.167*** (.169)	-1.735*** (.180)	-1.801*** (.184)
BIC Fit Statistics												
Model 1: 32919												

	High to high (c#1) vs. low to low (c#2)				High to low (c#3) vs. low to low (c#2)				Low to high (c#4) vs. low to low (c#2)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>Independent variables</i>	Model 1 β (se)	Model 2 β (se)	Model 3 β (se)	Model 4 β (se)	Model 1 β (se)	Model 2 β (se)	Model 3 β (se)	Model 4 β (se)	Model 1 β (se)	Model 2 β (se)	Model 3 β (se)	Model 4 β (se)
Model 2: 32799												
Model 3: 32620												
Model 4: 32592												

 $p < .001$
**
 $p < .01$
*
 $p < .05$ (two-tailed)