THE AIR IS ALWAYS CLEANER ON THE OTHER SIDE: RACE, SPACE, AND AMBIENT AIR TOXICS EXPOSURES IN CALIFORNIA

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ABSTRACT: *Environmental justice advocates have recently focused attention on cumulative exposure in minority neighborhoods due to multiple sources of pollution. This article uses U.S. EPA's National Air Toxics Assessment (NATA) for 1996 to examine environmental inequality in California, a state that has been a recent innovator in environmental justice policy. We first estimate potential lifetime cancer risks from mobile and stationary sources. We then consider the distribution of these risks using both simple comparisons and a multivariate model in which we control for income, land use, and other explanatory factors, as well as spatial correlation. We find large racial disparities in California's "riskscape" as well as inequalities by other factors and suggest several implications for environmental and land use policy.*

In 2000, Sunlaw Energy, a company seeking to build a new natural gas-powered power plant, approached the city of South Gate, an industrial suburb along the Alameda Corridor in Los Angeles County. While such plants often trigger resistance, partly because of fears of air pollution, the company promised to make use of a new cleaner pollution-control system that had only been deployed thus far in mini-generators. As this was to be the first test of whether the technology could be brought up to scale in a larger plant, many environmentalists from around the region and the state were supportive, particularly given that the statewide energy crisis in California was creating pressure for a rapid build-out of the power grid. Labor unions were also interested in the jobs that could be generated along with the electricity.

Some local community members and city leaders were not so enthusiastic. Invoking the notion of *cumulative exposure*, they argued that a new plant, no matter how clean, was an

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unfair burden in a heavily Latino community that was already the site of numerous pollution-emitting facilities and heavy truck traffic from local industry and nearby freeways. The company, eager to move forward, proposed that the matter be put to a city-wide referendum, confident that the combination of environmentalist and labor support, and promises to fund neighborhood improvements, provide local scholarships, and pay local taxes would yield a positive response from local voters. Despite an expensive long-term campaign that included ads, community picnics, and even a float in the city's Christmas parade, the referendum on March 6, 2001 produced a 2–1 landslide against the new plant; faced with this resounding "no," the company lived up to its earlier statements and withdrew its construction plans (Martin, 2001a, 2001b).

In recent years, advocates of environmental justice have suggested that such considerations of cumulative and inequitable exposure should figure into decisions about facility siting, freeway expansion, and other environmental disamenities. Such advocates have gained particular ground in California where 1999 legislation mandated environmental justice as a consideration for relevant state agencies and subsequent laws and agency actions have tried to better address community concerns about environmental disparities in the state. In this article, we determine whether the advocates have had a point, looking at the distribution of outdoor air toxic exposures and their estimated associated cancer risks in California. Simple comparisons indicate disparity by race and income, and multivariate analysis suggests an important association of race and income with the level of air toxics health measures even after controlling for other important factors, such as manufacturing presence, land use, population density, and region, that might explain the general level of air toxics. The results suggest that California policy makers and advocates have been right to be concerned about the intersection of cumulative exposure and environmental injustice.

There are several innovations in this article. First, we are among a very small group of authors using health risks based on estimated exposure rather than simply using proximity to particular point sources of pollution. Moreover, these health risks are based on pollution exposures from both point and mobile emission sources. Second, we control for land use, a variable that is usually eschewed in such analysis because of the difficulties of obtaining geographically broad and reliable coverage. Third, we subject the usual regressions to spatial tests to see whether the findings have been driven purely by geographic clustering; they are not, providing all the more reason to be concerned about potential issues of environmental inequity.

ENVIRONMENTAL JUSTICE FINDINGS

Environmental justice (EJ) research now has a long pedigree. Early ground-breaking studies on the siting of hazardous waste sites conducted by the GAO (U.S. General Accounting Office, 1983) and the United Church of Christ (United Church of Christ, 1987) seemed to suggest a disparity in proximity to hazards. In the mid-1990s, however, this pattern was disputed by a series of studies that seemed methodologically superior in both the choice of geographic scale (tracts versus zip codes) and the use of multivariate regression techniques to control for the other determinants that might influence hazard location (Anderton, Anderson, Oakes, & Fraser, 1994, Anderton et al., 1994). These early critiques prompted the adoption of increasingly sophisticated approaches in the field, including more careful choices around the regression methods and data (Been, 1995), consideration of the other sorts of hazards such as the emissions recorded in the Toxic Release Inventory (Sadd, Pastor, Boer, & Snyder, 1999), and the use of temporal analyses to see whether hazards were placed in minority communities or minorities moved in afterwards (Been & Gupta, 1997; Pastor, Sadd, & Hipp, 2001).

Many of these second-generation efforts have tended to square with the insights of environmental justice advocates, and a recent broad national study launched by three researchers initially skeptical of EJ claims also found evidence of disparities by race and class, depending on the geographic scale used (Lester, Allen, & Hill, 2001). Numerous other efforts have failed to find such a correlation. In an encyclopedic and very useful review of the field, Bowen (2001) points to a range of studies showing regional differences in patterns of environmental inequity, including Yandle and Burton's (1996) work on Texas and his own collaborative study of Ohio (Bowen, Salling, Haynes, & Cyran, 1995). Ash and Fetter (2002) also point to the importance of region, noting that disparities may exist within regions even if they do not show up in the broad national studies that aggregate populations from all over the country. Regardless of one's perspective on the national pattern, however, many have concluded that there does seem to be a consistent pattern of disparity in California, the area of focus in this article, and this may be one of the reasons why the state has become a leader in environmental justice activism and policy (Kelly, 2003).

Still, methodological disputes are rampant in the field. One important debate has to do with the consequences of pollution or proximity to exposure, with some arguing that a more explicit focus on risk should dominate the analysis (Foreman, 1998). This suggests the need to go beyond a focus on stationary sources and include analysis of the mobile sources and smaller emitters that may contribute a large share to the overall burdens of pollution and risk (Glickman & Hersh, 1995; Perlin, Setzer, Woodrow, Creason, & Sexton, 1995). Recent research on California does indicate that transportation emissions make significant contributions to estimated health risks associated with ambient pollutant concentrations, suggesting that a focus on stationary sources alone will likely distort any estimate of the distribution of environmental burdens (Morello-Frosch, Woodruff, Axelrad, & Caldwell, 2000, Morello-Frosch, Pastor, & Sadd, 2001). A risk modeling approach that considers all sources of pollution, including mobile sources, is also more consistent with the emerging policy focus on cumulative exposure.

Another methodological issue, brought to the debate with particular eloquence by Bowen (2001), is the need to pay more attention to potential spatial dependence into the analysis. That is because land uses tend to cluster together, and race and other variables are also clustered (due to socioeconomic drivers as well as the dynamics of residential choice and housing discrimination), correlations between hazards and race may be spurious. This suggests that regression techniques should introduce some control for spatial processes in order to clarify whether race and other socioeconomic and political variables are truly robust in multivariate analyses.

In other work, we have taken up some of these challenges. In Morello-Frosch, Pastor, and Sadd (2001), for example, we obtained cancer risk estimates from modeled concentrations of air pollutants, including mobile and small point sources, and explored the risk patterns for Southern California utilizing race, income, and land use. Using 1990 census data, we found that minority residents were far more likely to be living in areas of higher potential cancer risk from ambient air pollution than non-Latino white residents. More recently, we have conducted an analysis of proximity to facilities listed in the Toxic Release Inventory of the U.S. Environmental Protection Agency that attempted to control for spatial clustering through the use of spatial lag regressions (Pastor, Sadd, & Morello-Frosch, 2004). We found that race mattered in the distribution of environmental disamenties, although we were unable at that point to include a very important spatial characteristic, land use.

The goal in this analysis is to integrate risk data with census information and a new data set on land use, and then examine the patterns of environmental disparities in contemporary California. We also introduce some controls for the presence of immigrants based on the notion that newcomers might be either less aware of the effects of pollution or less willing or able to politically engage to resist the placement of environmental disamenities in their communities. Finally, we consider the spatial issues directly by introducing first regional dummy variables then attempting to control for spatially autocorrelated error terms. We turn below to the data and the methods before focusing on the results.

DATA SOURCES AND METHODS

The Dependent Variable: Air Toxics and Cancer Risks

To create measures of cumulative exposure and risk, we used annual average air toxics concentration estimates from the U.S. EPA's National Air Toxics Assessment (NATA) for 1996 (U.S. EPA, 2004). The underlying data on toxics comes from five primary information sources including: state and local toxic air pollutant inventories, existing databases related to EPA's air toxics regulatory program, EPA's Toxic Release Inventory (TRI) database, estimates using mobile source emissions estimates (developed by EPA's Office of Transportation and Air Quality), and other emission estimates generated from emission factors and activity data. Using the emissions data as inputs, an air dispersion model is used to estimate the annual average ambient concentration of each air toxic pollutant at the centroid of each census tract. The model is calculated after taking into account the impacts of atmospheric processes (winds, temperature, atmospheric stability, etc.) on pollutants. The 1996 NATA database includes estimates of concentrations for diesel particulates and 32 of the 188 air toxics listed under the 1990 Clean Air Act Amendments and takes account of both mobile and stationary sources.

We combined these air toxics concentration estimates with inhalation unit risk estimates for each carcinogenic compound to estimate overall cancer risks. First, estimated cancer risks for each pollutant in each census tract were derived with the formula

$$R_{ij} = C_{ij} \times IUR_j,$$

where R_{ij} is the estimate of individual lifetime cancer risk from pollutant j in census tract i, C_{ij} is the concentration in micrograms of pollutant per cubic meter of air ($\mu g/m^3$) of the air toxic j in census tract i, and IUR_j is the inhalation unit risk estimate for pollutant j. In accordance with California's AB2588 "Hot Spots" Guidelines (OEHHA, 2003) and EPA's cancer risk guidelines (U.S. EPA, 1986, 1990), cancer risks of each pollutant were assumed to be additive and were summed together in each tract to derive a total individual lifetime cancer risk. Source allocation estimates indicate that on average, mobile source emissions account for the largest proportion of estimated cancer risks (approximately 85%) followed by stationary sources (approximately 15%). Similarly, cumulative lifetime cancer risks were attributable to a handful of pollutants, especially diesel particulates (around 70%) followed by chromium, butadiene, polycyclic organic matter, formaldehyde, benzene, and carbon tetrachloride (approximately 30%).

The result of this work might be termed a *risk surface*. It offers a picture by tract of the estimated lifetime cancer risk associated with cumulative exposures to ambient air toxics with the hills and valleys of the risk surface indicating areas of higher or lower risk for residents. These risk estimates assume that residents live in the same area over their lifetime and do not represent actual cancer cases. However, the estimates allow for a broad scale geographical analysis of the potentially disparate health risks associated with air pollution borne by diverse communities in the state.

Before undertaking any analysis, however, we first needed to *reshape* the surface. That is, the 1996 risk surface from the NATA data is generated for the 1990 census tract shapes but any tests against demographics and income would probably be more appropriately performed using the 2000 census data. After all, the income variables in the 2000 census are actually from 1999, only three years newer than the risk data, and the demographics of 2000 are likely to be closer to 1996 than the 1990 data. We, therefore, intersected the 1990 and 2000 tracts and calculated risk values as attributes of the 2000 tracts based on the proportion of common area with 1990 tracts. This method makes the simplifying assumption that the 1990 risk value for any given tract is homogeneously distributed within that area, but 2000 tracts overlay two or more 1990 tracts in California in a relatively small number of cases. To our knowledge this is the first attempt at conducting an environmental justice analysis that combines U.S. EPA's 1996 NATA data with 2000 Census variables.

Independent Variables: Land Use, Market Dynamics, and Socioeconomics

We then derived a set of independent variables which corresponded to one of three non-exclusive explanations for the geographic pattern: land use considerations, market dynamics, and political power. The land use explanation suggests that excess pollution is the result of zoning, reflecting a potentially rational planning strategy of clustering uses together (such as industry, commerce, and transportation) to minimize impact on residents. The market explanation suggests that environmental pollution may reflect a mix of consumer and industry choices. Because the foregone income for poorer residents from illness is lower, one might expect such residents to be more likely to be near hazards and one might also, for reasons of market convenience, expect industrial firms and industrial workers to cluster together. A power-based explanation may accept or reject aspects of the rational planning and market choice view, but it forthrightly argues that marginalized groups will be less able to resist hazard placement, and companies and governments, seeking the path of least resistance, may seek to locate plants and environmental disamenities in their communities (Hamilton, 1995).

Land Use Variables

One of the most common variables utilized in the rational land use explanation is population density. This is based upon the notion being that denser areas will generate more traffic and pollution generating activities which increase cancer risk estimates. Such population density is measured as persons per square mile in the descriptive statistics below but in the regressions we follow the lead of Mennis (2002) and consider a natural log specification of population density. We do not expect that the shift from one person per square mile to 1000 per square mile to have the same effect on the likelihood of estimated cancer risk from ambient air pollution as the movement from 4000 to 5000 in the same square-mile area; there is a diminishing effect which is better captured by the log form. Alternative specifications (such as categorical variables for density) were explored but these did not improve the fits, are not standard in the literature, and did not square with our theoretical priors about the superior nature of the log form.

We also consider land use more explicitly. The first measure is indirect: we entered a dummy variable indicating whether a tract was urban (as indicated by whether more than 50% of the land area in each tract was designated urban by the Census). The assumption underlying the model was that urban tracts would have higher levels of air pollution. We were also fortunate to have direct estimates of land use. This is important because we have shown in earlier work that population density can actually be a stand-in for more direct measures of land use and so will decline in coefficient value and statistical significance once an appropriate proxy for actual land use is introduced into a regression (see Boer, Pastor, Sadd, & Snyder, 1997; Morello-Frosch, Woodruff, Axelrad, & Caldwell, 2000).

The first of our direct land use variables was the percentage of land devoted to industry, commerce, and transportation. The rationale behind this is that the former set of uses should be associated with higher levels of pollution from large point sources, small stationary sources (such as dry cleaners), and mobile sources. We also had a measure for the degree of land devoted to high density residential use. The assumption was that denser concentrations of residents will lead to more transport and more commerce, both of which will then yield more air pollution. This is also captured by population density; our regressions suggest that there is indeed some competition for significance and explanatory power due to collinearity. Because the density measure for residential housing is less exact than the actual population density from the Census (the former is interpreted from satellite imagery while the latter is directly calculated by using figures on people and land area from the Census), we expected that the general population density measure might dominate as an explanatory variable and found that to be the case.

The land use measures are taken from the 2001 U.S. Geologic Survey (USGS) Land Cover Characterization Program, an effort that uses aerial photo and satellite imagery interpretation to generate a 21-category classification of land use at a spatial resolution of 30 meters. To check accuracy, we compared a Southern California subset of this land use characterization with a higher resolution dataset generated by the Southern California Association of Governments (SCAG) that was based on city land use and zoning maps, as well as digital aerial imagery from three separate years. The match between the two datasets was quite good, although the USGS data tends to underestimate residential and commercial/industrial/transportation cover in a more urban setting. Still, the variables derived from each data source performed similarly in regression exercises limited to Southern California. Because we are interested in a statewide view, we present below only the results for the state that necessarily rely on the broader USGS dataset.

Market Dynamics Variables

The market dynamics view suggests that risk may be higher in areas of lower income, perhaps because lower-income residents are more willing to trade off health for less expensive housing. This suggests the need to introduce income into the analysis, a point we take up in more detail below. This view also suggests that firms may make locational decisions based on the proximity to large pools of workers. Anderton et al. (1994) first pointed the way to this insight by introducing a measure controlling for the percentage of census tract residents employed in manufacturing, and we follow suit in our analysis here (see also Been, 1993, 1995).

The income dynamics are, however, more complex than many first believe. While the usual assumption is that there will be a linear relationship between income and degree of risk, we have argued and demonstrated elsewhere that the relationship may be more

U-shaped (Boer et al., 1997). At very low levels of income, there may be few economic activities or assets and, therefore, no nearby sources of pollution from industry, commerce, or transport. On the other hand, at very high levels of income, residents may have the political power to resist riskier land uses and mitigation costs would be higher for polluters. Thus, we might expect the likelihood of both site location and air pollution to be higher at levels of income somewhere in the middle of the distribution. As it turns out, this pattern shows up in both our raw data and eventually in our regression analysis.

Power Variables

Finally, what about modeling empowerment? While income is one such measure of power, the more direct power measures used in traditional environmental justice analysis include race and home ownership. Race is, of course, exactly the focal point of many environmental justice advocates. From an analytical perspective, the notion is that if race is important, even after controlling for income, then perhaps calculations of differing political power and strength factor into hazard location (see Bullard, 1994; Hamilton, 1995; Pulido, 1996, 2000). We thus consider both the overall presence of people of color (derived by subtracting the percentage of the population that is non-Latino white) and separate measures for the percentage African American, Latino, and Asian Pacific, with the idea being that discriminatory intents or effects might be different depending on the group.

The home ownership variable attempts to pick up on the distinction between wealth and income, an issue that has emerged as important in the epidemiological literature but has been less well-addressed in the environmental justice research (Krieger & Fee, 1994). While income tends to reflect disposable cash, wealth measures family assets and hence a household's safety net in case of economic emergencies (Williams, 1996; Williams & Collins, 1995). Most game theory models suggest that those who have higher levels of economic security (due to existing assets) may be more willing and able to bargain strongly against, say, the location of a polluting facilities. In short, it is not just the flow of income but the stock of assets that matters. The Census has virtually no reliable measures of family wealth at the tract level but home ownership can be used as a crude indicator of wealth and assets (Krieger & Fee, 1994). We have also suggested that because homeowners tend to be more active politically, this variable may also serve as a crude measure of political engagement (Morello-Frosch, et al., 2001).

In this work, we also consider another variable in this category of power-based explanations–the presence of relatively recent immigrants. The notion is that newly arrived immigrants will tend to be less engaged in the political process by virtue of either their immigration status, which prevents them from voting, or simply because of their nascent experience with the US political system. A statistical problem is that the measure we use (the percentage of residents that arrived as immigrants in the 1980s and 1990s) is quite collinear with the percentage of residents that are Latino and Asian Pacific, particularly in California. To take account of this, we also constructed a dummy variable that took the value of one for census tracts where the presence of new immigrants was much higher than would have been expected. To determine this, we regressed the percentage of recent immigrants in a tract on the percentage of Latinos and Asian Pacifics in a tract then assigned the third of the state's tracts with the largest residuals (that is, where the actual presence of immigrants was much higher than the predicted value) a value of one. While an analytically superior strategy might have been to determine the percentage of Latinos and Asians that were recent immigrants, this is not available in the summary data available at the tract level. In any case, the resulting measure helps us to sort out the differential impact of race and ethnicity from immigration in our statistical model.

Regional Controls and Spatial Techniques

Finally, we also are concerned with spatial effects in terms of regional impacts and spatial autocorrelation. To look at these, we eventually turn to the use of spatial regression techniques. However, our first cut is simply to introduce dummy variables for various regions in California, specifically the five counties that make up the largest members of the Southern California Association of Governments (SCAG); the nine counties that make up the Association of Bay Area Governments (ABAG); California's most southern counties, San Diego and Imperial; the six counties around Sacramento; the eight counties that constitute the bulk of the San Joaquin Valley; the five counties on the state's central coast; the 11 counties that are in the eastern-most portion of the state and straddle the Sierra Nevada; and finally, the rest of the state.

Inclusion of such regional controls does change the coefficients and significance of some variables of interest as shown below. This led us to consider a different and more sophisticated way of modeling spatial effects, specifically attempting to control for spatial autocorrelation. Spatial autocorrelation refers to the tendency of variables to be influenced by their neighbors, a fact that will cause the errors in the regression analysis to not satisfy the independence conditions generally associated with ordinary least squares regression. Tests for such autocorrelations are much like the Durbin-Watson used in time series analysis; neighboring observations are defined in this case by space and not time. While there is generally one proximate lagged time period used in the temporal consideration of autocorrelation, there can be many such spatial neighbors. When such spatial autocorrelation is present, researchers tend to adopt either a spatial lag approach or a spatial errors approach with the latter usually considered methodologically superior for complex models such as that developed here.

Controlling for such spatial dependence requires that we construct an appropriate set of neighbor relationships. The archetypical strategy involves either a rook or the queen relationship–in the former case, units sharing boundaries are considered neighbors while in the latter case, any geographic unit that touches another unit is deemed to have an effect. In most testing, this also involves row standardization to determine weights–a unit with four neighbors will find that each has a one-fourth influence on the error. However, rook-style or queen-style relationships are most appropriate to square grids in which space is neatly arranged, hardly the geography typified by census tracts. Hence, we created a set of inverse distance weights such that neighbor effects, which are still required by row-standardization to sum up to one, decline with distance. Distance was measured from tract center to tract center with care taken to trim the tract shapes to account for coast lines. We specifically chose a power function of one with the maximum distance for a neighbor effect being 2.5 miles. This is a radius typically used as the maximum in the environmental justice literature and our results are robust to other reasonable choices of distance.

Finally, we should acknowledge that we are not offering a model with a wide and exhaustive range of variables. This, however, is intentional. Some earlier research, especially the path-breaking Anderton et al. (Anderton, Anderson, Oakes, et al., 1994; Anderton, Anderson, Rossi, et al., 1994) studies, tended to include many variables that were measuring nearly the same phenomenon and hence were likely to be highly collinear; the subsequent finding that some of these variables were not statistically significant was hardly surprising. By contrast, our strategy is to develop a parsimonious model that contains measures that capture and identify the important elements of various arguments about environmental justice.

RESULTS

Descriptive Statistics

How does the pattern of air toxics and cancer risk in California play out against the variables of interest described above? To understand the pattern visually, we utilize a two-by-two breakdown to split the state into census tracts of four types: (1) tracts where the estimated cancer risk is above the median for the state's tracts and the percentage minority is above the median for the state's tracts, (2) tracts where the estimated cancer risk is above the median and the percentage minority is below the median, (3) tracts where the estimated cancer risk is below the median and the percentage minority is above the median, and finally (4) tracts where the estimated cancer risk is below the median and the percentage minority is below the median. The resulting pattern is shown in Figure 1 and reveals the geographic clustering that leads us to consider spatial controls later in the analysis. As for demographics, about half the state's population lives in the tracts with above median-risk; those tracts contain only 39% of the state's Anglo population but 58% of the state's minority population.

Another approach to the demography involves considering various bands of tracts based on their risk estimates. While the breakout for Figure 1 considered only two sorts of tracts by level of pollution in order to simplify the mapping, we are less constrained by the challenges in visual representation when making tables and charts and therefore broke the state tracts into thirds, labeling the third with the lowest estimated cancer risk the *least polluted*, those in the middle third *moderately polluted*, and those in the top third *most polluted*. Tracts in the sample include only the 7,015 tracts (of the state's 7,049 tracts) for which we have all data eventually employed in our regression analysis; this constraint is imposed to maintain consistency through the analysis and the pattern is nearly identical if we change the sample for each variable to include all tracts where that variable is available.

Figure 2 shows the racial pattern in our three different pollution bands. As can be seen, the pattern is consistent with the usual suppositions of environmental justice advocates although in a slightly more complex way that is usually imagined. The percentage non-Latino white declines as we move from the least polluted tracts to the most polluted tracts but interestingly, the African American presence seems to rise as we move from the least polluted to the moderately polluted and stabilizes thereafter. Latino presence rises only slightly between least and moderately polluted areas but then move up rapidly as we drift into the most polluted areas. The Asian Pacific population is more similar to the African American pattern but there is still a sizable increase as we move from the moderately to the most polluted areas. In any case, the disproportionate presence of Latinos in highly areas with high pollution burdens may help to explain why California's environmental justice advocates have found such a ready audience in that community (see Pastor, Morello-Frosch, & Sadd, 2004).

Table 1 illustrates other variables of interest, including home ownership, household income, presence of manufacturing employees, percentage immigrants, and the various land use variables. We report the average value for each of these variables in the pollution bands described above. The exception is the population density measure for

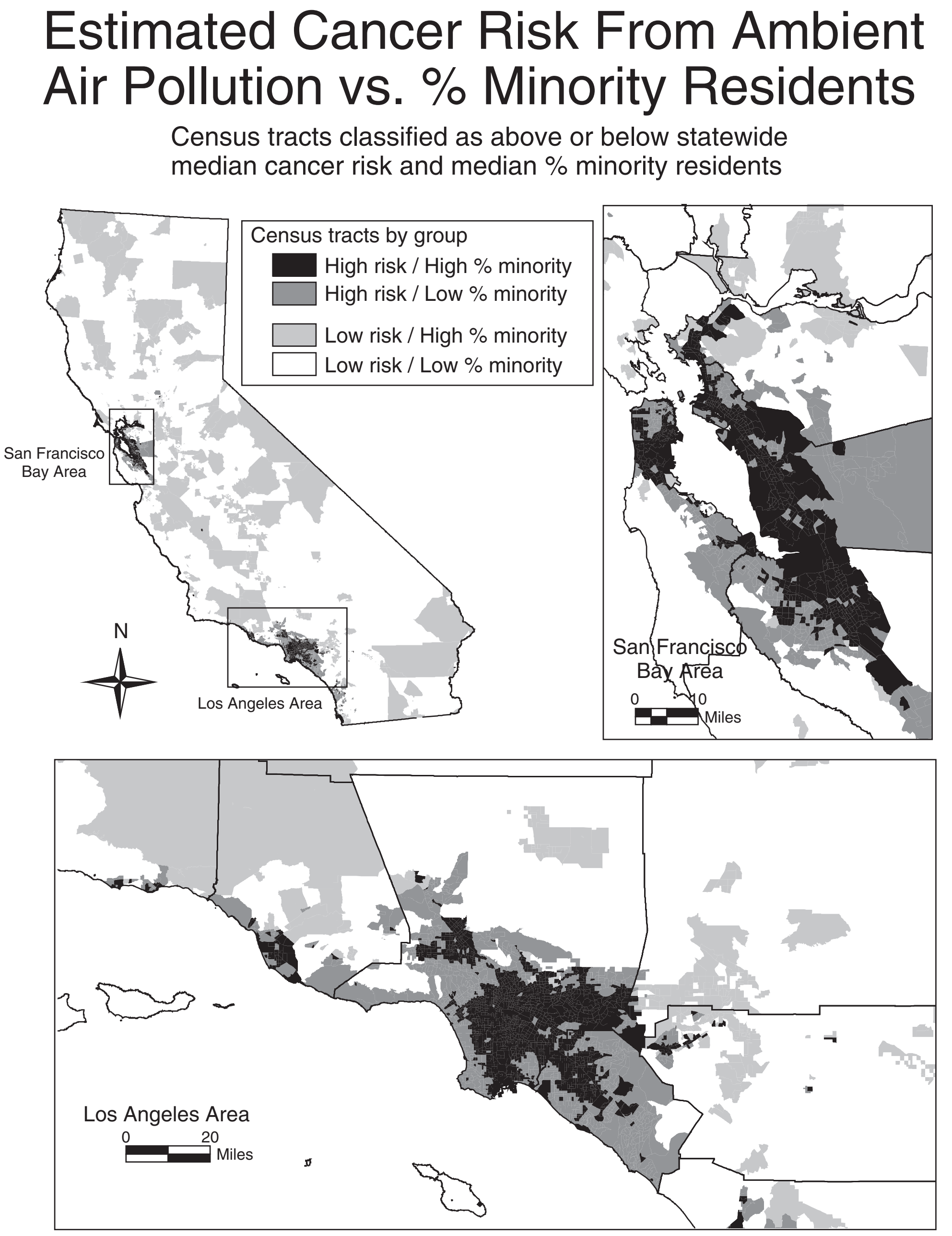

FIGURE 1

Estimated Cancer Risk and Demography in California

which we instead utilized the median in each pollution band given the potential for population density averages to be distorted by a few highly dense or very underpopulated outlier tracts. As might be expected, the proportion of home ownership declines as we move to the most polluted tracts, the percentage of the local labor

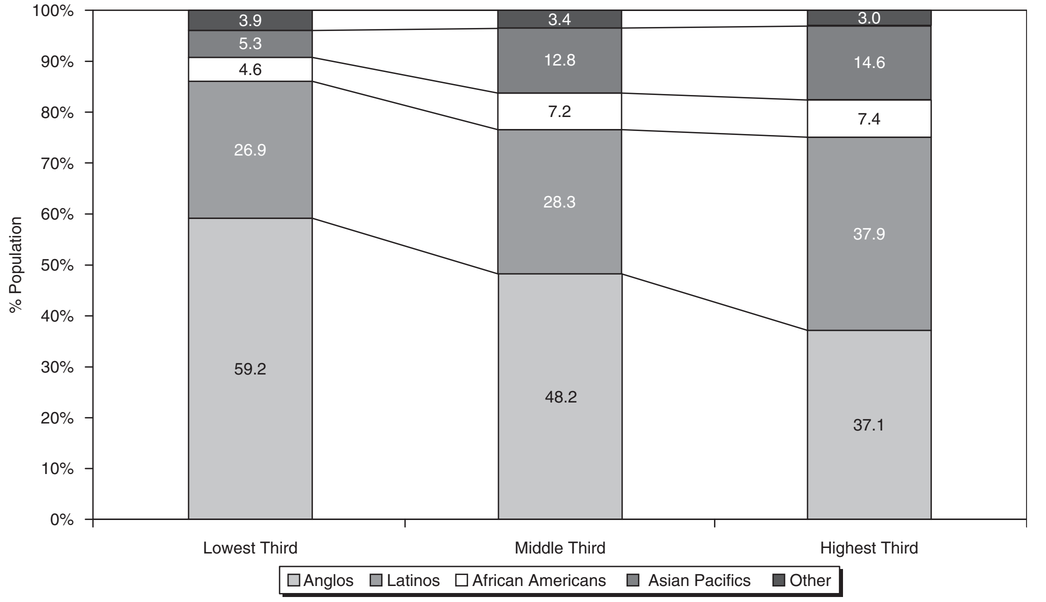

FIGURE 2

Racial/Ethnic Composition of California Census Tracts by Degree of Estimated Cancer Risk from Ambient Air Toxics

force in manufacturing rises, the percentage of immigrants rises dramatically, and population density is higher as is the degree of urbanization, the percentage of land devoted to industry, commerce, and transportation, and the percentage of land hosting high-density housing.

The exception to this monotonic pattern is median household income: as suggested above, it actually peaks in the middle band and is, in fact, somewhat higher for those living in the most polluted conditions than it is for those living in the least polluted conditions. While the latter finding might seem to contradict the usual assumptions about patterns of income inequities, it is important to keep in mind that these simple statistics have not yet been subjected to either multivariate analysis or spatial controls. It is possible that we are simply finding that denser, urban areas have more pollution and also have higher income levels than less urban areas. To explore these relationships in more detail, we must turn to multivariate analysis. The comparative examination does suggest that a U-shaped relationship might the most appropriate functional form.

The basic multivariate model regresses the log of estimated cancer risk on the independent variables discussed above; we use the log because this reduces extreme outliers and yields a normal-style distribution of the dependent variable that is more conducive to the standard regression requirements. Table 2 begins the analysis with a basic model that includes the following independent variables: the percentage people of color, the percentage home owners, median household income and its square (to reflect the assumption of a U-shaped relationship) (see Boer, et al., 1997), the percentage of the labor force in manufacturing, the log of population density, and a variable that takes the values of one if the tract is urban. All variables are signed as expected and the significance levels are high, with the lowest *t*-score being that for the urban dummy.

TABLE 1

Income, Density, and Other Characteristics of California Census Tracts by Degree of Estimated Cancer Risk from Ambient Air Pollution

	Percentage Home Owners	Relative Median Household Income (100 = state median)	Percentage of Labor Force in Manufacturing	Percentage Immigrated in the 1980s and 1990s	Population per Square Mile	Percentage Tracts Labeled Urban	Percentage Land Used by Industry, Commerce, or Transportation	Percentage Land Used by High Density Residential
Least polluted	64	95.3	9.2	10.5	2,174	62.6	6.7	3.1
Moderately polluted	58.1	122.1	13.6	18.7	6,800	92.1	12.9	10.4
Most polluted	50.3	108.8	16.6	23.5	9,672	97.9	17.2	18

The next column of Table 2 shows the basic model with a measure of commercial, industrial, and transportation land use. Compared to column one, we see that inclusion of this variable increases explanatory power (as measured by the adjusted R^2), appropriately reduces the coefficients on the measure for race, home ownership, income, and the percentage of the labor force in manufacturing, and causes the dummy variable indicating urbanization to be completely insignificant. Apparently, land use is important to consider in these analyses and failure to include it could lead to an attribution to racial and other dynamics that might be inappropriate. In the third column, we introduce our variable for high-density residential land use. As can be seen, this reduces the coefficient and significance for our population density measure, as might be expected, and the urbanization variable creeps up to quite anemic significance.

In Table 3, we introduce our first set of spatial controls: regional dummies set for various areas in the state. In the first column the coefficients for race and income fall dramatically as does the effect of the percentage of the labor force in manufacturing and the commercial/industrial/transportation land use variable. This suggests that the strong effects of those variables might be the result of spatial clustering for other reasons. Interestingly, this first use of spatial controls sharply reduces the statistical significance of the high-density residential variable. When we drop both it and the urban dummy in the second column, there are only very modest changes in coefficient values and significance levels for the other variables. Column three rounds out the picture by dropping the regional dummies and the urban and high-density residential variables, an exercise conducted in order to show how a very parsimonious regression would perform. Still, the most important implication from this table is the potential importance of spatial controls given their impact on the coefficients of other variables of interest.

Before investigating spatial effects more directly, we introduce the analysis of separate ethnic groups and immigration. The first column of Table 4, for example, shows the results when we enter the percentage African American, percentage Latino, and percentage Asian Pacific separately, including all land use measures. All of these measures are significant, although the coefficient for African American is much larger than for the other groups, suggesting a particular potential burden for that population. The second column introduces the percentage recent immigrants but the variable is only significant at the most marginal of levels. However, we suspect significant collinearity with percentage Latinos and Asians, a pattern reflected in the fact that the coefficients for Latinos and Asians decline when the immigration variable is introduced.

Given this issue, we instead created a variable, discussed earlier, which takes the value of one if the tract has a recent immigrant presence well beyond that usually associated with the presence of Latinos and Asians. We suggest that in such cases the tract is likely to be among those serving as receivers for newly arrived residents. This variable is quite significant in the regression analysis and its inclusion has only modest effects on other coefficients. Once we introduce regional controls, however, the measure of recent migration loses statistical significance, suggesting that it may be capturing a difference between regions rather than within regions. As before, the urban dummy and percentage high-residential decline in significance substantially when the regional controls are introduced.

What about a more systematic approach to controlling for spatial effects? The two standard regression approaches to spatial autocorrelation involve use of a spatial lag. This approach assumes that the autocorrelation is in the dependent variable. The spatial errors model assumes, as is more likely to be the case here, that the independent variables exhibit spatial dependence and the regression errors will be spatially dependent as well. While it is

TABLE 2

Determinants of the Level of Estimated Cancer Risk from Ambient Air Pollution: Testing Land Use Measures

	Basic Model		Model with Industrial, Commerce, and Transport Land Use		Model with Industrial and High-Density Residential Land Use	
Variables	Coefficient	*T*-stat	Coefficient	*T*-stat	Coefficient	*T*-stat
% People of color	0.608	17.23****	0.558	16.24****	0.538	15.82****
% Home owners	−1.073	−25.84****	−0.849	−20.31****	−0.753	−17.92****
Relative median household income (100 = state median)	0.016	29.84****	0.017	32.04****	0.017	33.84****
Relative median household income squared	−2.7E-05	−17.72****	−2.8E-05	−19.20****	−3.0E-05	−20.78****
% Labor force in manufacturing	1.422	14.37****	1.263	13.10****	1.149	12.00****
Log of population density	0.188	25.86****	0.190	26.85****	0.159	21.55****
Urban tract (yes or no)	0.090	2.86****	−0.024	−0.78	0.038	1.22*
% Land for industry, commerce, and transport			1.344	20.65****	1.324	20.57****
% Land used by high density residential					0.702	12.41****
Adjusted *R*-squared	0.540		0.567		0.576	
N	7015		7015		7015	
F-statistic	1179.6****		1148.2****		1060.0****	

*p < .20. **p < .10. ***p < .05. ****p < .01.

TABLE 3

Determinants of the Level of Estimated Cancer Risk from Ambient Air Pollution: Testing Land Use Measures and Introducing Regional Dummy Variables

	Model with Industrial and High-Density Residential Land Use, and Regional Controls		Model with Industrial Land Use, No Urban Dummy, and Regional Controls		Model with Industrial Land Use, No Urban Dummy, and no Regional Controls	
Variables	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
% People of color	0.299	9.59****	0.303	9.77****	0.561	16.41****
% Home owners	−0.680	−17.31****	−0.697	−18.47****	−0.853	−20.60****
Relative median household income (100 = state median)	0.011	23.22****	0.011	23.20****	0.017	32.07****
Relative median household income squared	−2.0E-05	−14.92****	−1.9E-05	−14.87****	−2.8E-05	−19.23****
% Labor force in manufacturing	0.663	7.82****	0.673	7.95****	1.266	13.16****
Log of population density	0.143	21.60****	0.143	34.63****	0.185	40.30****
Urban tract (yes or no)	−0.009	−0.34				
% Land used by industry, commerce, or transportation	0.989	17.12****	0.979	17.21****	1.335	20.85****
% Land used by high density residential	0.076	1.39*				
SCAG 5 County Area	0.952	21.21****	0.956	21.33****		
ABAG 9 County Area	0.783	16.44****	0.778	16.41****		
San Diego-Imperial Counties	0.632	13.43****	0.634	13.46****		
Sacramento 6 County Area	0.314	6.58****	0.309	6.50****		
San Joaquin 8 County Area	0.061	1.35*	0.057	1.26*		
Central Coast 5 Counties	0.109	2.14***	0.110	2.15***		
Sierra Nevada 11	0.064	1.05	0.064	1.06		
Adjusted *R*-squared	0.679		0.679		0.567	
N	7015		7015		7015	
F-statistic	926.7****		1058.8****		1312.2****	

*p < .20. **p < .10. ***p < .05. ****p < .01.

TABLE 4

Determinants of the Level of Estimated Cancer Risk from Ambient Air Pollution: Introducing Different Ethnicities and Immigration

	Model with Industrial and High-Density Residential Land Use, No Immigration		Model with Industrial and High-Density Residential Land Use, Simple Immigration Measure		Model with Industrial and High-Density Residential Land Use, Complex Immigration Dummy		Model with Industrial and High-Density Land Use, Complex Immigration Dummy, and Regional Controls	
Variables	Coefficient	*T*-stat	Coefficient	*T*-stat	Coefficient	*T*-stat	Coefficient	*T*-stat
% Latino	0.357	9.19****	0.315	6.41****	0.367	9.45****	0.143	4.00****
% African American	0.940	15.33****	0.943	15.38****	0.924	15.07****	0.431	7.77****
% Asian Pacific American	0.640	11.18****	0.565	7.24****	0.650	11.36****	0.584	11.41****
% Immigrated in the 1980s and 1990s			0.149	1.39*				
Higher than expected percentage recent immigrants					0.067	4.27****	0.007	0.51
% Home owners	−0.742	−17.62****	−0.718	−15.83****	−0.675	−15.06****	−0.666	−16.17****
Relative median household income (100 = state median)	0.017	31.67****	0.017	31.67****	0.017	31.31****	0.011	20.56****
Relative median household income squared	−3.0E-05	−20.10****	−3.0E-05	−20.14****	−2.9E-05	−20.04****	0.000	−13.47****
% Labor force in manufacturing	1.374	13.72****	1.353	13.35****	1.345	13.42****	7.9E-01	8.84****
Log of population density	0.153	20.68****	0.152	20.53****	0.151	20.47****	0.139	20.95****
Urban tract (yes or no)	0.040	1.29*	0.044	1.41**	0.046	1.48**	−0.009	−0.35
% Land used by industry, commerce, or transportation	1.302	20.35****	1.299	20.29****	1.294	20.24****	0.953	16.55****
% Land used by high density residential	0.758	13.38****	0.745	12.96****	0.743	13.10****	0.080	1.46*
SCAG 5 County Area							0.980	21.69****
ABAG 9 County Area							0.774	16.23****
San Diego-Imperial Counties							0.661	13.99****
Sacramento 6 County Area							0.320	6.72****
San Joaquin 8 County Area							0.094	2.08***
Central Coast 5 Counties							0.152	2.96****
Sierra Nevada 11							0.060	0.99
Adjusted *R*-squared	0.582		0.582		0.583		0.682	
N	7015		7015		7015		7015	
F-statistic	888.1****		814.4****		817.7****		793.3****	

*p < .20. **p < .10. ***p < .05. ****p < .01.

generally assumed that the spatial errors model is more appropriate in most circumstances, we began by testing the spatial lag; significance levels for our independent variables were nearly the same but the residuals still exhibited autocorrelation and so we turned to the spatial errors approach.

The results are shown in Table 5. Note that all regressions were conducted using a generalized moments procedure based on the approach of Kelejian and Prucha (1997). The first column shows the results for a full model, including all land use measures; the comparison regression conducted using OLS is in the third column of Table 2. In this spatial errors regression, coefficient values fall by about 35% for race, about 50% for home ownership and income, about 20% for manufacturing employee presence, and about 40% for commercial/industrial/transportation land use. The *t*-scores for these variables decline as well, however, all of these variables are easily significant at the .01 level. The adjusted R^2 also declines although it is unclear how much weight should be given to this measure after the iterated transformations necessary for this procedure. In any case, the decline in the coefficient values for the main variables noted above is exactly what we would have expected from introducing controls for spatial clustering and it is of analytical, if not social, comfort that the race variable still matters.

Interestingly, the percentage high-density residential is now insignificant, similar to that variable's performance when we introduced regional dummies as the spatial controls. The significance has clearly slipped over to the population density measure–its *t*-value has actually risen even though the coefficient fell. The dummy variable for urbanization is now significant at the 0.10 level and so the next regression (depicted in the second column) drops the high-density measure but retains the urban dummy. As can be seen, the pattern for all the other variables is essentially unchanged and so this is our base for further testing.

The next three columns enter the various ethnic groups separately then add first the percentage recent immigrants and then the recent immigrants dummy discussed above. We do not enter the regional dummies in any of these regressions because such spatial tags are generally considered inappropriate in a spatial regression. As with the general percentage people of color variables, coefficient values drop from the previous OLS model but the significance levels are surprisingly similar. The immigrant variable enters significantly, reducing the coefficient values for the Latino and Asian variables when entered as a direct measure. When entered as a dummy to avoid collinearity, the significance level rises and the other coefficients remain more stable. The bottom line of the analysis, however, is quite straightforward–even after controlling for spatial autocorrelation, we find a significant association of race with the estimated cancer risk in a particular tract.

CONCLUSIONS: IMPLICATIONS FOR POLICY-MAKING AND RESEARCH

This article has sought to advance the current state of environmental justice research by reexamining the distribution of environmental risk in the state of California using econometric and environmental health risk assessment tools. Utilizing pollutant concentration estimates, we estimated cancer risk from ambient air toxics and found a pattern of disproportionate exposure by race that persists even after controlling for other variables that predict ambient pollution burdens, such as land use, household income, population density, home ownership, and other variables normally used in the environmental justice literature. The pattern holds, moreover, even when we try to control for spatial factors through either the use of regional dummy variables or more sophisticated techniques that try to account for the presence of spatial autocorrelation.

TABLE 5

Determinants of the Level of Estimated Cancer Risk from Ambient Air Pollution: Results When Controlling for Spatial Autocorrelation, Full Set of Models

	Basic Full Model, Including All Land Use Variables, Spatial Error Specification		Basic Full Model, Including Industrial Land Use and Urban Dummy, Spatial Error Specification		Model with Ethnic Groups, Industrial Land Use and Urban Dummy, Spatial Error Specification		Model with Ethnic Groups, Industrial Land Use and Urban Dummy, Immigration Variable, Spatial Error Specification		Model with Ethnic Groups, Industrial Land Use and Urban Dummy, Immigration Dummy, Spatial Error Specification	
Variables	Coefficient	*T*-stat	Coefficient	*T*-stat	Coefficient	*T*-stat	Coefficient	*T*-stat	Coefficient	*T*-stat
% People of color	0.351	*10.80*****	0.351	*10.81*****						
% Home owners	−0.377	*−11.96*****	−0.377	*−12.13*****	−0.368	*−11.83*****	−0.349	*−10.65*****	−0.336	*−10.52*****
Relative median household income (100 = state median)	0.008	*21.80*****	0.008	*21.94*****	0.008	*21.15*****	0.008	*21.21*****	0.008	*21.04*****
Relative median household income squared	−1.2E-05	*−11.69*****	−1.2E-05	*−11.73*****	−1.2E-05	*−11.46*****	−1.2E-05	*−11.53*****	−1.2E-05	*−11.39*****
% Labor force in manufacturing	0.928	*10.32*****	0.928	*10.33*****	0.981	*10.75*****	0.959	*10.41*****	0.966	*10.58*****
Log of population density	0.144	*29.54*****	0.144	*30.88*****	0.141	*30.17*****	0.141	*30.03*****	0.141	*30.12*****
Urban tract (yes or no)	0.038	*1.94***	0.038	*1.93***	0.039	*1.98****	0.040	*2.06****	0.040	*2.04****
% Land used by industry, commerce, or transportation	0.792	*16.69*****	0.791	*16.80*****	0.785	*16.71*****	0.786	*16.72*****	0.786	*16.76*****
% Land used by high density residential	0.010	*0.19*								
% Latino					0.281	*8.01*****	0.226	*4.89*****	0.273	*7.81*****
% African American					0.640	*8.96*****	0.650	*9.08*****	0.641	*8.99*****
% Asian Pacific American					0.504	*8.20*****	0.424	*5.60*****	0.504	*8.21*****
% Immigrated in the 1980s and 1990s							0.162	*1.81***		
Higher than expected percentage recent immigrants									0.048	*4.40*****
Adjusted *R*-squared	0.270		0.269		0.279		0.281		0.282	
N	7015		7015		7015		7015		7015	

*p < .20. **p < .10. ***p < .05. ****p < .01.

It is important to note two empirical caveats before discussing the policy implications of this analysis. First, this is a pure cross-sectional analysis: we do not discuss whether environmental health conditions are worsening or improving over time nor can we establish with the data at hand whether the current allocation of pollutant burdens is a result of residential choice or the placement of polluting facilities and roadways in minority neighborhoods. While some of our earlier statistical work has been more consistent with the facility placement hypothesis (see Pastor, Sadd, & Hipp, 2001), historical analysis suggests that there are probably both facility placement and residential change dynamics affecting the inequitable pattern of environmental disamenities in Southern California (Boone & Modarres, 1999; Pulido, Sidawi, & Vos, 1996). However, we should stress that inclusion of income and land use does not explain away the racially disparate pattern of cancer risks associated with air toxics, suggesting that the pattern may not be related to a simple explanation of market dynamics or so-called "minority move-in."

The second caveat is that we do not offer a straightforward causal model of the cross-sectional pattern. Like much of the other research in this field, we are essentially establishing a multivariate mapping of potential explanatory factors. Still, the fact that the racial pattern persists in a multivariate setting does offer some insight into the potential casual factors at play. Specifically, the tendency for race and other variables most often associated with a power-based explanation of environmental risk to be highly significant and robust to various specifications (including spatial controls) suggests that more attention may need to be paid to insuring that the voices of underrepresented communities are present in future policy debates over environmental regulation and zoning decisions.

In any case, the results have several implications for politics and policy. First, this analysis contributes to the mounting body of evidence regarding environmental inequities in pollution burdens in California. This adds fuel to a movement that has recently secured a series of legislative and administrative changes in the state, including several state assembly and senate bills dealing with environmental justice, children's health, healthy schools, persistent bioaccumulative pollutants, and other issues. It specifically suggests the importance of addressing cumulative impacts, because our results are based on considering toxics from both mobile and stationary sources. Although data gaps pose challenges for estimating the cumulative health risks associated with multiple pollutants and emission sources, some researchers and regulatory agencies have at least begun to think about how to integrate existing information on multiple environmental hazards in certain neighborhoods (Morello-Frosch & Jesdale, 2003). More research is clearly needed in this arena, particularly so that cumulative estimates could be better developed and considering when making decisions about facility siting, freeway expansion, and other measures likely to worsen exposure.

Second, the results suggest the importance of considering land use. While we have demonstrated that race, income, and other variables matter even when one controls for land use, zoning is itself a decision that is not neutral in its process or outcome. For example, decisions that lead an area to be designated as an industrial zone may set the stage for elevated risks. Currently, environmental health and justice concerns do not figure significantly in land-use planning protocols. Some environmental justice advocates have consistently argued that any development project or siting decision that would worsen environmental inequities should at least trigger a more comprehensive review that could be incorporated into an Environmental Impact Statement (EIS). In addition to assessing the existing cumulative pollution exposures and associated health risks in an impacted area, such an EIS analysis would also require consideration of the demographic composition and linguistic capabilities of the surrounding community as well as data on land use patterns and proximity of schools, hospitals, and other facilities used by populations that are particularly vulnerable to environmental pollution. These integrated approaches will not only improve environmental regulation but can also better inform the development of land-use policy instruments that would include more systematic consideration of equity issues in zoning decisions and land-use planning (for related policy ideas, see Jackson, 2002, Northridge, Sclar, & Biswas, 2003; McCann & Ewing, 2003; Ewing, Schmid, Killingsworth, Zlot, & Rauderbush, 2003).

Finally, the analysis suggests that efforts to increase public participation in environmental decision-making should focus on those groups, including immigrants, which seem most likely to be disproportionately burdened by pollution sources. In this regard, outreach efforts should address barriers of language and community capacity to effectively engage in the policy arena. These approaches to leveling the playing field in terms of power and voice could benefit everyone: preliminary research indicates that disparities in political power and residential segregation affect not only those who bear the net costs and benefits of environmentally degrading activities, but also the overall magnitude of environmental degradation (e.g., air pollution) (Boyce, Klemer, Templet, & Willis, 1999) and health risks (e.g., individual estimated lifetime cancer risk). Our own research confirms this, suggesting that increased urban segregation (both in the nation and the state of California) exacerbates racial inequalities in cancer risks associated with air toxics and results in higher pollution levels overall across all demographic groups with risk gradients increasing for each racial group by increasing levels of segregation (Morello-Frosch & Jesdale, 2003).

The state of California does seem to be moving in several of the policy directions suggested above, many of which are embodied in a new set of recommendation for the California Environmental Protection Agency issued by an Advisory Committee on Environmental Justice (Cal-EPA, 2003). In particular, the state is considering improving community participation and assessing cumulative exposure and impact. Related legislation has also taken up the issue of the best way to incorporate environmental justice concerns into revisions of the local general plans that govern land use. In all these areas, the agency, advocates, and industry stakeholders are calling for more research to be conducted so that the patterns demonstrated here can be appropriately benchmarked and addressed.

As the research proceeds, it is likely that continuing debates about risk estimates, spatial controls, and independent variables will occupy the attention of the academic community. Nevertheless, it is important to remember that behind these methodological debates lies what we believe to be a shared goal: how best to facilitate a fair distribution of environmental amenities and disamenties. For many communities in contemporary California, the grass is always greener and the air is always cleaner on the other side; the hope for the state's future is that new policies and practices will ensure an opportunity for all residents to have access to a healthy environment.

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