Spatiotemporal Perspectives on Air Pollution and Environmental Justice in Hamilton, Canada, 1985–1996

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This article addresses two questions: (1) How do spatiotemporal changes in air pollution levels—specifically, total suspended particulates (TSP)—rise or fall with socioeconomic status? (2) A critical equity interpretation of environmental policy then motivates this question: does the pursuit of average regional reductions in pollution benefit those who need improvements least, benefit those who need improvements most, or maintain the status quo? TSP data are drawn from networks of monitoring stations operated in 1985, 1990, and 1995. The monitoring data are interpolated with a kriging algorithm to produce estimates of likely pollution distribution throughout Hamilton. Exposure is related to socioeconomic status (SES) variables at the census tract level for corresponding years—1986, 1991, and 1996—and associations are tested with ordinary least squares (OLS) and spatial regression models. The results show that whether TSP rises or falls, injustice persists but becomes less pronounced over time. Among all SES indicators, dwelling value consistently predicts TSP levels for all years, suggestive of a land-rent/spatial-externalities dynamic. As we move forward in time, it becomes increasingly difficult to differentiate air-pollution exposure among Hamilton neighborhoods, as industrial TSP sources become more dispersed in the region and transportation pollution becomes relatively more important. We conjecture that more equitable distributions of air pollution have resulted more from post-Fordist industrial and spatial restructuring than from environmental policy intervention. Injustice in Hamilton and its apparent relationship with changing industrial structure appear similar to results in the United States and speak to a continental, intraurban environmental-justice experience.

Key Words: air pollution, environmental justice, GIS, Hamilton, kriging.

The last two decades have seen rising concern over exposure to environmental health hazards and their effects (Eyles 1997). Some of this concern has come by way of the environmental-justice movement, which focuses on disparities in hazards exposure among different social groups. In the United States, where justice research has burgeoned, the poor and visible minorities have been the focus, giving rise to the concept of environmental racism (Bullard 1990; Pulido 2000). Earlier research in Hamilton, Canada, found a clear pattern of socioeconomic differentiation with respect to air pollution based on the neighborhood-status markers of dwelling value and unemployment rates (Jerrett et al. 2001). This appears to be related to environmental-justice observations elsewhere (Cutter, Hodgson, and Dow 2001). The purpose of this article is to build on earlier findings for Hamilton by examining environmental justice amidst changing air pollution levels over time.

From 1985 to 1995, levels of total suspended particulate (TSP) varied in Hamilton, falling slightly between 1985 and 1990 and then rising substantially between 1991 and 1995. These years frame the principal research question: as ambient TSP levels change, does environmental justice improve, worsen, or remain stable? In turn, a critical-equity interpretation of environmental policy motivates this question: does the pursuit of average regional reductions in pollution benefit those who need improvements least, benefit those who need improvements most, or maintain the status quo? To answer these questions, monitored TSP data are spatially interpolated and pooled in a GIS with data on socioeconomic status (SES) at the census-tract level. Use of air-pollution data and optimal spatial-interpolation techniques allows for an assessment of ambient TSP exposure at the neighborhood scale. Associations are then analyzed using regression analysis for the individual years and in pooled models. In addition to examining changes to air-pollution justice over time, these procedures also allow us to assess which SES markers best capture injustice in the local Hamilton context. Finally, by building on prior research in the local...
context, we broaden the justice literature by exploring similarities and differences in environmental justice between Canadian and American cities.

**Justice Research: Evidence and Debates**

The environmental-justice movement represents the politicized edge of environmental equity, focusing on the social inequality of human impacts of health-hazard exposure and promoting its abolition. Justice research has grown over the last thirty years to the point that its working hypothesis—that disadvantaged groups face “disproportionate” environmental health hazards—has influenced environmental policy in the United States (Bowen et al. 1995; Cutter 1995). It also dispels the myth of consensual environmentalism (Bullard 1990) that, some argue, preserves “white privilege” at the expense of poor and racial minorities (Pulido 2000). In this respect, bearing “disproportionate” environmental hazards takes on a particular meaning. As disadvantaged groups, the poor and racial minorities do not share proportionately in the benefits that come with economic growth and development. In consumption terms, therefore, they do not contribute as much to the production of pollution arising from economic activity as do advantaged groups. Yet the disadvantaged may bear more of the costs associated with economic development, including air-pollution exposure.

In the United States, where justice research has progressed furthest, racial minorities and persons of low SES constitute the most common foci. From the earliest landmark studies (Berry 1977; United Church of Christ 1987; U.S. General Accounting Office 1983; Bullard 1990), research has continually attempted to expose the social “processes” and “outcomes” of injustice (Cutter 1995; Pulido, Sidawi, and Vos 1996; Weinberg 1998; Haughton 1999). Process studies center on the apparent bias toward disadvantaged communities in the location of health hazards, usually in the siting process for noxious facilities. Outcome studies, such as this article, have focused on the presence and extent of injustice in terms of disparities in current exposure (e.g., Jerrett et al. 2001). Whether tracing the root of injustice or gauging its differential impact at one point in time, the studies have as their persistent theme exposure to environmental health risks to the disadvantage of racial minorities or the poor.

Justice research has not been without its debates and problems. Debates concern the root cause of the bias against disadvantaged groups, and questions surround data, research methods, and evidence. Although the former have unfolded among process studies, they provide a necessary context for this article. An early split in the debate, though one that is becoming more nuanced, saw environmental injustice explained by two contradictory processes: on the one hand, the evolution of “natural” market forces; on the other, a reflection of classism and racism as relations of power. The market argument posited that the siting of noxious facilities, for example, reflects least-cost location decisions among economic agents (Been 1993). Since these facilities tend to depress land rents over time, surrounding areas become occupied by disadvantaged groups reliant on inexpensive housing (Been and Gupta 1997; Mitchell, Thomas, and Cutter 1999; Szasz and Meuser 2000). Injustice thus reflects market forces in the first instance, rather than systematically biased decisions or racism in site selection. The counterargument pointed to unequal power relations surrounding, for example, exclusionary discourses such as “not in my backyard” (NIMBYism) and “locally unwanted land uses” (LULUs). White privilege represents one such relation, and this results in the exclusion of noxious facilities from areas occupied by citizens of influence (Hamilton 1993; Pulido 2000). By default, their spatial location lands with the disadvantaged (Pastor, Sadd, and Hipp 2001). This debate ultimately rests with establishing which came first: inexpensive housing and concomitant low-SES populations or the environmental hazard.

In addressing this criterion of “which came first,” the debate has become more nuanced, as researchers have engaged a number of alternative—and largely historical—strategies to explain injustice. Some have suggested that injustice has “two faces,” one driven by market forces and the other by unequal power relations (cf. Krieg 1998; Weinberg 1998); however, there is a more fundamental discontent with the notion that intentionality, whether in siting or in minority move-in, must be uncovered. Environmental justice and racism cannot be reduced to the motivation behind a single act. Rather, environmental justice results from a complex web of social relations, including planning practices, racialized job markets, and housing (Pulido 2000; Holifield 2001).

Outcome studies have also been questioned, due to data and methodological limitations. In a recent review, Bowen (2001) asks of the environmental-justice literature, “What do we really know?” To answer this question, he classifies the literature into three categories: poor-, medium-, and high-quality research. Research found to be methodologically lacking suffers a number of shortcomings, such as inadequate control tests for confounding relationships. Bowen’s answer—that justice research still has a long way to go—hinges on this and other shortcomings.

Lack of reliable data with which to measure hazards also challenges justice results (Perlin et al. 1995; Institute of
Medicine 1999). Pollution inventories are often inaccurate, either misplacing hazards in geographic information databases or simply not reporting smaller polluters below certain emissions thresholds, despite their significant aggregate impact (Jerrett et al. 1997). Even when emissions are known, it remains unclear how risk should be calibrated—for instance, in the relationship between toxicity and proximity to a hazard (cf. Bowen et al. 1995; Neumann, Forman, and Rothlein 1998; Sexton and Adgate 1999; Sheppard et al. 1999; Bolin et al. 2000). Constrained from working with measured exposure data, researchers have employed various methodological approaches to construct community-risk measurements: correlations of social group and hazard co-location within a jurisdiction (Greenberg 1993); zonation/buffering (Glickman 1994; Sui and Giardino 1995); plume-dispersion modeling (Chakraborty and Armstrong 2001; Karkazis and Boffey 2001) and toxicity indices (Bowen et al. 1995). Though some methods have been quite innovative, such as the cumulative hazards density index (Bolin et al. 2002), these approaches are generally not calibrated with monitoring data on ambient concentrations, data on indoor air quality, or personal-exposure data. In the one study that used personal monitoring and questionnaire data, some injustice was found for toxic metals, but not for pesticides (Pellizzari, Perritt, and Clayton 1999). Studies based on ambient exposure data are rare, and even these do not focus on all constituents of ambient pollution.

For these reasons, the environmental injustice discourse has evolved from intuitively appealing hypotheses to contested evidence (Sexton, Olden, and Johnson 1993; McMaster, Leitner, and Sheppard 1997; Bowen 2001). Other methodological debates center on issues of scale and study design, contributing to a rising consensus that injustice should not be taken for granted. Some (e.g., Anderton et al. 1994; Yandle and Burton 1996; Bowman and Crews-Meyer 1997) have argued that injustice has not been sufficiently shown in the literature, even among landmark studies. Others distinguish at-risk communities, arguing that evidence supports the presence of injustice based on race or class but not necessarily both (Bowen et al. 1995; Ringquist 1997; Hird and Reese 1998; Hockman and Morris 1998). Still, this growing literature supports the working hypothesis of injustice and, in some cases, argues that the situation is worsening (Krieg 1998; Neumann, Forman, and Rothlein 1998; Stretsky and Hogan 1998; Perlin, Sexton, and Wong 1999). Given these unresolved issues, Bowen (2001) answers his own question: Environmental-justice research, he concludes, lacks sustained and sound evidence—in short, the scientific rigor—to properly inform public policy and environmental law.

Our study attempts to address some of these methodological issues, particularly via actual monitored air-pollution data, the use of GIS and optimal spatial-interpolation techniques, and an intraurban census tract scale of analysis, all to examine changing levels of air-pollution injustice over time. This study also extends justice research by presenting another Canadian intraurban case that may be compared to the established American literature.

### A Canadian Test: Hamilton as Natural Experiment

As in the United States, research in Canada predates the rubric of “environmental justice” but is in its infancy (Draper and Mitchell 2001). Existing research points to similar lines of injustice in both process (Elliott et al. 1999) and outcome (Jerrett et al. 1997; Jerrett 2001) studies. The intraurban focus of the present article immediately raises the debate on North American urbanism. The debate has long been divided primarily between those who view Canadian and American cities as the same and those who view them as different (Goldberg and Mercer 1986; Yeates 1998), though others have suggested cross-border regionalism (Garreau 1981) and, most recently, the view that Canadian and American cities are on a path of convergence (Bourne and Ley 1993; Harris 2001). In a major research monograph on North American housing, using Hamilton as a case study, Doucet and Weaver (1988) argue that Hamilton can speak to the North American urban experience because of overlapping similarities not only in city-building but in urbanism generally. If these arguments are true, then examples of intraurban environmental injustice should permeate Canadian cities as well.

In this context, Hamilton provides a “natural experiment” for air-pollution justice. Known as Canada’s “steel city,” Hamilton is home to highly visible point-source polluters, with the country’s two largest steel producers located there (Figure 1). Located in the north-central part of the city, these companies and ancillary manufacturing facilities generate emissions that contribute approximately one-third of all air pollution in the region, with the remainder coming from transboundary, transportation, and residential sources (HAQI 1997). Hamilton’s steel industry has experienced waves of restructuring and diminishing importance in the region’s economy (Anderson 1987). To be sure, central-city point-source polluters remain highly visible. But over the last decade, the city has also seen the rise of suburban industrial complexes typical of industrial and spatial restructuring in North American urbanism generally (Scott 1988). While the exact nature...
of the creation of urban industrial districts is debated (Harris and Lewis 1998; Lewis 2000), the presence of suburban manufacturing nonetheless constitutes an important reconfiguration of air-pollution emissions in Hamilton.

The experiment centers on the use of the city’s air-pollution-monitoring network. Real and perceived concerns over air quality in the region have resulted in the installation of one of North America’s most extensive intraurban air-monitoring networks. This network permits a spatial analysis of localized variations in air pollution within the city. Early research found higher concentrations of air pollution in poorer areas (Handy 1977). Health studies have linked morbidity and mortality to the city’s air pollution to show that ill health can be significantly influenced by air pollution in the region (Kerigan, Goldsmith, and Pengelly 1986). And recent justice research on Hamilton has shown that both chronic and acute exposure to TSP affect disadvantaged groups significantly more than others (Jerrett et al. 2001). This study builds on these findings by examining changing air-pollution levels over time. The introduction of this temporal component allows us to test those social-theoretical constructs that persistently mark urban social disparities and to explore the possibility of a common intraurban environmental-justice experience in North America.

**Data and Methods**

The analysis relies on a GIS database containing air-pollution estimates and SES data for Hamilton. We integrated the database with ArcView 3.2 and S-Plus 6. The statistical and spatial analyses also relied on these software packages together with SPSS 10.1 and Minitab 12. Pollution estimates were based on TSP air-pollution data collected by the Ontario Ministry of the Environment (MOE) and the Urban Air Environment Group (UAEG) at McMaster University (see Figure 1). We attempted to include other criteria pollutants more closely associated with health effects (PM$_{2.5}$, SO$_2$, NO$_2$), but were restricted to TSP by sparse monitoring networks for these other pollutants in one or more periods. SES data were drawn from the censuses of Canada for 1986, 1991, and 1996. These data were combined into a geodatabase for an intraurban analysis using census tracts.

MOE and UAEG air pollution data were assembled from networks of hi-vol air-monitoring stations in Hamilton. Data were integrated with census data for each period to examine associations between SES and air-quality indicators. The analysis involved spatial regression models to assess the impact of pollution levels on the population of Hamilton. The results indicated significant associations between air pollution and health outcomes, particularly for vulnerable populations. The study also highlighted the need for ongoing monitoring and policy interventions to address environmental inequalities.
proxies for smaller and more hazardous particles of up to about 50 μm in size (PM10 and PM2.5) that are inhalable and have been associated in numerous studies with adverse cardiovascular effects and elevated mortality (e.g., Pope et al. 2002). In Hamilton, the ratio of PM10 to TSP can range from 0.31 to 0.50 across the city (Dobroff 1996; Kim and Jerrett 2001).

Various spatial-interpolation techniques were explored with the monitoring data for the three periods. First, trend surfaces were used to visualize the regional pattern of TSP in the city. Second- and third-order trend surfaces showed increasing complexity, though an improvement to the F-ratio test showed that the cubic order did not significantly improve upon the second-order surface. While useful for exploring global patterns in the distribution of TSP, trend-surface analysis is unlikely to yield local estimates that capture subregional differences (Burrough and McDonnell 2000). Moreover, trend-surface analysis assumes independence of the monitoring data, and, as noted below, this assumption does not hold in Hamilton. The residuals of the quadratic trend surface, therefore, were used in exploring a second interpolation technique, ordinary kriging. For each year, model variograms were constructed with robust estimation. Compared with linear and exponential function forms, the data were best summarized with a spherical form that also minimized the objective function in the S-Plus model variogram procedure. The semivariance structure of these variograms was the basis for all kriging procedures. As an optimal spatial-interpolation technique, kriging provided the best linear unbiased estimate (BLUE) of a spatially continuous process at any point in the study region (Burrough and McDonnell 2000).

Following trend-surface and ordinary kriging analyses, universal kriging was chosen for the analysis to address the presence of a trend from high pollution in the northeast, near the industrial core, to low pollution in the south and west. Our exploration of various approaches essentially parcels out the simultaneous estimation of global and local TSP variation in the universal kriging algorithm. Further, universal kriging with quadratic drift was employed: (1) it preserves the natural data units for analysis; (2) prior research has shown that TSP displays spatial dependency in Hamilton, which can be accounted for in simultaneous estimation of both the global first-order trend and local variations; and (3) the objective was to obtain estimates at unsampled locations rather than model the pollution surface per se.

While Hamilton's air-monitoring network is better than most others in North America, it is sparse in the suburbs. This problem is unlikely to influence the primary features of the surfaces: high levels in the north and east, more variable distributions below the Niagara Escarpment, and relatively homogeneous distributions in the suburban areas. Still, as we come forward in time, the distribution of TSP in Hamilton does become more varied. For this reason, and because the air-monitoring network was less dense in 1995, we conducted a number of tests to ensure that the estimated 1995 surface does capture the spatial process of TSP distribution in the city in that year. The first test was a cross-validation analysis of the TSP geometric means of the monitoring stations and of the surface estimates used in the analysis. We successively removed one air-monitoring station from the kriging estimation and produced a new surface in its absence, for a set of twenty new surfaces. We then compared the estimates with (1) the original monitored TSP values and (2) the estimated values used in the analysis as derived from the full set of monitors. The correlations for the former did not fall below $r = 0.93$; most exceeded $r = 0.98$. Also, the variance of all of the cross-validated surfaces was smaller than those of the monitored values. Similar results were obtained in comparisons with the estimated values using the full set of monitors. Our research suggests that no single station significantly distorts the characterization of the spatial process. Visualization of the new cross-validation surfaces showed that they largely resemble those of the complete set of monitoring stations. A second test of the reliability of the 1995 estimates involved the production of a new surface for 1994, based on the same number of stations as in 1990 ($n = 23$, though some in slightly different locations). The values of this new surface correlated with 1995 estimates...
at $r = 0.85$, in contrast to lower 1995 correlations with 1985 and 1990 estimates, as reported below.

In addition to separate annual TSP estimates, we also explored the possibility of spatiotemporal interpolation. This approach can accommodate a varying distribution of monitoring stations and may thus be applied retrospectively to monitoring data. However, spatiotemporal interpolation is subject to the same requirements related to the number and distribution of monitoring sites, plus an additional requirement of regular temporal data points. For instance, De Cesare, Myers, and Posa (1997) used this method with thirty-three spatial locations and thirty-six temporal observations (monthly averages over a three-year period). This method could not be implemented in our study, however: only annual mean and geometric mean data are available for 1985, and more generally, air quality is not sampled on the same days across all stations (as evidenced in our 1990 and 1995 data). These constraints made a spatiotemporal approach untenable. Our sensitivity checks on the individual surfaces suggest, however, that the 1995 estimates are both internally robust and representative of what appears to be an evolution toward more diffuse TSP distribution in Hamilton. Finally, we also undertook further sensitivity analyses, including removal of potentially aberrant estimates where kriging returned high standard errors. These are discussed in the Results section below (see also endnote 9).

To assemble a geodatabase of pooled pollution and SES data, TSP values were assigned to Hamilton census-tract centroids weighted for residential population, as measured by the distribution of housing stock. The number of tracts changed between 1986 and 1991, requiring the creation of a different set of centroids for 1986 versus 1991 and 1996. Pollution estimates were assigned directly to centroids during estimation via point-kriging in S-Plus. Point-kriging has the advantage of reducing the error propagation in polygon-to-point map overlay, specifically the assignment of estimates from a grid to centroid $(x, y)$ coordinates.

We pooled pollution estimates with corresponding SES variables for each census tract, as specified in Table 1. Most of these variables have been found to be significant in past environmental-justice research, including that done on Hamilton. Several of the variables, such as dwelling value and income, are accepted measures of SES in much of the justice literature. Low income and unemployment continue to be used as indicators of relative social deprivation (Langlois and Kitchen 2001). Less common in the justice literature but nonetheless important in urban studies are variables relating to family status and welfare-state reliance, specifically lone-parent families and income assistance (Bourne and Ley 1993; Valentine 2001). Education, significant in many of our models, is another common measure of SES in health studies (Jerrett et al. 1997) and has been found to be a significant modifier of the health effects of air pollution in the reanalysis of the American Cancer Society (ACS) study (Krewski et al. 2000) and subsequent analyses using extended follow-up periods (Pope et al. 2002). In the ACS study, Krewski and colleagues (2000) posit that modification of pollution’s effects on health may result, in part, from higher exposure in lower-education groups. We would expect, therefore, that these social-identity markers could be significant in environmental injustice.

Associations were tested with multiple ordinary least squares (OLS), simultaneous autoregressive (SAR), and

<table>
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<tr>
<th>Table 1. Variable Specification and Descriptive Statistics</th>
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<tr>
<td><strong>Census-Tract Variables</strong></td>
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<td>----------------------------</td>
</tr>
<tr>
<td>Mean</td>
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<tr>
<td>TSP, $Y_1$</td>
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<tr>
<td>Dwelling value, $X_1$</td>
</tr>
<tr>
<td>Low income, $X_2$</td>
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<tr>
<td>Low education, $X_3$</td>
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<tr>
<td>Median income, $X_4$</td>
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<td>Unemployment rate, $X_5$</td>
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<td>Manufacturing employment, $X_6$</td>
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<td>Lone-parent families, $X_7$</td>
</tr>
<tr>
<td>Government transfers, $X_8$</td>
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</table>


$Y_1$ = a variable representing estimates of total suspended particulate matter. $X_1$ = average dwelling value. $X_2$ = a variable representing percentage of economic families or unattached individuals over 15 years of age below Statistics Canada’s low-income cut-off. $X_3$ = percentage of population 15 years of age or older that has less than grade-nine education. $X_4$ = median household income. $X_5$ = unemployment rate among members of population who are 15 years of age or older. $X_6$ = percent of population employed in the manufacturing sector. $X_7$ = lone-parent families as a proportion of all families. $X_8$ = proportion of total income for the population 15 years of age or older, derived from government transfer payments.

$^a$ Canadian dollars.

$^b$ $X_4$ b $75,143$ $20,693$ $157,513$ $34,249$ $134,788$ $30,539$
generalized additive (GAM) models to assess whether Hamilton neighborhoods experience significant social disparities in ambient TSP at the census-tract level. We used regression techniques because they permit a robust method for testing multiple associations, including diagnostics and strength of relationships. Although we are modeling the entire “population” of census tracts in Hamilton, we may still approach the problem inferentially. Inferential significance tests can be applied because the population of areal units is not the only realization of spatial units that may be used. Following this logic, most geographical data should be treated as a sample, and it is reasonable to apply inferential statistics (see Norcliffe 1977 and Cliff and Ord 1981 for detailed discussion of this issue). In this instance, we are assessing whether the observed relationships from our regression analyses may have occurred by chance in a different random realization of the sampled population.

In using regression methods, we do not mean to imply that our sociodemographic variables “cause” TSP to vary throughout Hamilton. Rather, we use regression to test the existence and strength of associations. For instance, inclusion of the manufacturing-employment variable represents a control for the potential residential choice among lower-status populations living near high TSP zones (also heavy industrial zones) simply to reduce the journey to work—also a major theme in environmental-justice and urban studies (Anderton et al. 1994). Finding this variable to be nonsignificant allows us to be more confident that residential location close to a negative spatial externality is more likely to be the result of constraint, or lack of awareness of air pollution in residential location. More broadly, we cannot infer causality on the basis of one study alone, regardless of the modeling framework (Hill 1965; Bowen et al. 1995). Process studies are aimed at causality, usually taking a historically presentist approach to explain how injustice has been created in the siting of polluting facilities and other hazards (Holifield 2001). Outcome studies, on the other hand, gauge injustice at a point in time. In the context of the modeling framework of this study, the approach implies associations of complex relationships between SES and ambient air pollution, rather than causality (Helfand and Peyton 1999). Although we examine the issue at three points in time, this research targets outcomes and focuses on the presence and extent of change in injustice amidst changing TSP levels in the region. Our aim is not to focus on the mechanisms that create injustice, but to gauge the empirical magnitude of injustice in time and space. As in any “outcome” study, inferences about the processes that underlie injustice can only be tentative (Weinberg 1998). The results presented below are of chronic exposure to TSP at three time intervals to characterize changing injustice among those of different SES.

Modeling included all selected variables hypothesized to be significant based on past research, in a search for their complex associations with TSP. All variables were initially transformed to their closest approximation of the normal or Gaussian distribution. Manual forward selection of all significant bivariate predictors was used, accompanied by F-ratio improvement tests. Variables with the highest t-ratios were entered first, and this process was pursued until variables entered were insignificant. Each model was also tested by use of Mallow’s Cp to confirm that it represented the best subsets. Final models were then rerun with untransformed independent variables to ease interpretation. All models were tested with standard diagnostics and for significant spatial autocorrelation in the model residuals with Moran’s I statistic. If the residuals had significant autocorrelation, as in the 1986 OLS, a SAR model was run to ensure that significance tests did not violate the independent-observations assumption.

The above steps were also undertaken for a pooled model of Hamilton census tracts common to all three years. We did this by using yearly indicator variables and indexing monetary variables, such as dwelling value. Pooling enables us to assess the SES covariates that expose injustice for the entire period and to draw parallel comparisons as pollution levels change. Average pooled residuals of this model were found to be significantly spatially autocorrelated, and this could not be controlled via standard spatial regression, given the three time periods involved (i.e., there were three temporal periods, but only one spatial contiguity matrix). In light of this, we undertook a sensitivity analysis by filtering the spatial dependence of the residuals to help interpret the usefulness of the pooled OLS model. This was done via a GAM, including a loess function of census-tract centroid (see Burnett et al. 2001 for a discussion of this method). To target localized spatial dependence, a neighborhood span of 10 percent of all centroids was required in the loess smoother—a threshold at which the average pooled residuals were no longer found to be spatially autocorrelated in a Moran’s I test.

Results

Figure 2 shows estimated TSP surfaces and a broad regional view of TSP distribution. Surfaces are shown in the context of Hamilton’s spatial extent and in relation to the MOE’s TSP standards, in particular the nonexceedence objective—currently 60 μg/m$^3$ as annual geometric
Figure 2. Estimated TSP surfaces for Hamilton: (A) 1985; (B) 1990; (C) 1995.
mean. The annual averages shown in the surfaces indicate that the objective is often exceeded.

All surfaces reflect a high concentration of TSP in central Hamilton, peaking at 84 μg/m$^3$, 69 μg/m$^3$, and 76 μg/m$^3$ in 1985, 1991, and 1996 respectively. The mean estimated TSP levels for these years were similar, dropping slightly from 1985 to 1990 and then rising again in 1995. Visually, the surfaces for 1985 and 1990 are similar to one another, and the centroid estimates have a high correlation of $r = 0.93$. On the other hand, the TSP surface for 1995 is more varied, not displaying the well-defined peak in the northeast end of the city. Its centroid estimates correlate less strongly with those of 1985 and 1990 ($r = 0.71$ for each). This more varied TSP may have important implications for the changing picture of air-pollution justice in Hamilton. Contrary to official accounts (HAQI 1997), TSP levels have not fallen in absolute terms as we come forward in time. Nor can changes necessarily be attributed entirely to environmental interventions. Rather, these fluctuations likely reflect the ebb and flow of the economy—booming in the 1980s, in recession in the early 1990s, and flowing up once again toward the present. We also speculate that the changing pollution surface may reflect the shift in economic production toward a post-Fordist economy of restructured and decentralized manufacturing activities among agglomerated smaller and more flexible producers, though, as discussed in the conclusion, this contention requires further study.

Table 2 displays the zero-order correlations amongst the TSP and SES variables. We see that TSP is strongly correlated with a number of SES variables in the first two

<table>
<thead>
<tr>
<th>Year</th>
<th>TSP, $Y_1$</th>
<th>Dwelling Value, $X_1$</th>
<th>Low Income, $X_2$</th>
<th>Low Education, $X_3$</th>
<th>Median Income, $X_4$</th>
<th>Unemployment Rate, $X_5$</th>
<th>Manufacturing Employment, $X_6$</th>
<th>Lone-parent Families, $X_7$</th>
<th>Government Transfers, $X_8$</th>
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<td>1986</td>
<td>TSP, $Y_1$</td>
<td>$-0.74$</td>
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<td>$0.65$</td>
<td>$-0.61$</td>
<td>$0.62$</td>
<td>$0.26$</td>
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<td></td>
<td>Dwelling value, $X_1$</td>
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<td>$0.69$</td>
<td>$-0.64$</td>
<td>$-0.30$</td>
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<td></td>
<td>Low income, $X_2$</td>
<td>$-0.62$</td>
<td>$-0.73$</td>
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<td></td>
<td>Low education, $X_3$</td>
<td>$-0.62$</td>
<td>$0.65$</td>
<td>$0.48$</td>
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<td>Median income, $X_4$</td>
<td>$-0.67$</td>
<td>$-0.05$</td>
<td>$-0.63$</td>
<td>$-0.68$</td>
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<td>Unemployment rate, $X_5$</td>
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<td>$0.67$</td>
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<td></td>
<td>Manufacturing employment, $X_6$</td>
<td>$-$</td>
<td>$0.10$</td>
<td>$0.11$</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Lone-parent families, $X_7$</td>
<td>$-$</td>
<td>$0.54$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Government transfers, $X_8$</td>
<td>$-$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1991</td>
<td>TSP, $Y_1$</td>
<td>$-0.69$</td>
<td>$0.59$</td>
<td>$0.47$</td>
<td>$-0.64$</td>
<td>$0.62$</td>
<td>$0.26$</td>
<td>$0.60$</td>
<td>$0.65$</td>
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<tr>
<td></td>
<td>Dwelling value, $X_1$</td>
<td>$-0.61$</td>
<td>$-0.45$</td>
<td>$0.70$</td>
<td>$-0.61$</td>
<td>$-0.34$</td>
<td>$-0.58$</td>
<td>$-0.70$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Low income, $X_2$</td>
<td>$0.51$</td>
<td>$-0.72$</td>
<td>$0.80$</td>
<td>$0.17$</td>
<td>$0.82$</td>
<td>$0.67$</td>
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<tr>
<td></td>
<td>Low education, $X_3$</td>
<td>$-0.54$</td>
<td>$-0.58$</td>
<td>$0.40$</td>
<td>$0.37$</td>
<td>$0.73$</td>
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<td></td>
<td>Median income, $X_4$</td>
<td>$-0.59$</td>
<td>$-0.02$</td>
<td>$-0.56$</td>
<td>$-0.65$</td>
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<tr>
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<td>Unemployment rate, $X_5$</td>
<td>$0.27$</td>
<td>$0.74$</td>
<td>$0.65$</td>
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<tr>
<td></td>
<td>Manufacturing employment, $X_6$</td>
<td>$-$</td>
<td>$0.17$</td>
<td>$0.18$</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>Lone-parent families, $X_7$</td>
<td>$-$</td>
<td>$0.54$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Government transfers, $X_8$</td>
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<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1996</td>
<td>TSP, $Y_1$</td>
<td>$-0.35$</td>
<td>$0.12$</td>
<td>$0.02$</td>
<td>$-0.11$</td>
<td>$0.16$</td>
<td>$0.06$</td>
<td>$0.14$</td>
<td>$0.11$</td>
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<tr>
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<td>Dwelling value, $X_1$</td>
<td>$-0.49$</td>
<td>$-0.33$</td>
<td>$0.64$</td>
<td>$-0.50$</td>
<td>$-0.26$</td>
<td>$-0.49$</td>
<td>$-0.64$</td>
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<tr>
<td></td>
<td>Low income, $X_2$</td>
<td>$0.45$</td>
<td>$-0.74$</td>
<td>$0.79$</td>
<td>$0.07$</td>
<td>$0.88$</td>
<td>$0.69$</td>
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<td>Low education, $X_3$</td>
<td>$-0.46$</td>
<td>$0.48$</td>
<td>$0.45$</td>
<td>$0.27$</td>
<td>$0.64$</td>
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<tr>
<td></td>
<td>Median income, $X_4$</td>
<td>$-0.70$</td>
<td>$-0.06$</td>
<td>$-0.69$</td>
<td>$-0.82$</td>
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<tr>
<td></td>
<td>Unemployment rate, $X_5$</td>
<td>$-$</td>
<td>$-0.02$</td>
<td>$0.67$</td>
<td>$0.73$</td>
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<tr>
<td></td>
<td>Manufacturing employment, $X_6$</td>
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<td>$0.09$</td>
<td>$0.12$</td>
<td></td>
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<tr>
<td></td>
<td>Lone-parent families, $X_7$</td>
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<td></td>
<td>Government transfers, $X_8$</td>
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<td>$-$</td>
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<td>$-$</td>
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</tr>
</tbody>
</table>

Note: For variable specification, see Table 1.
periods, the highest being dwelling value. The coefficients also take the expected sign in all instances. Most striking, a major reduction in correlations between TSP and SES variables occurs in 1996. While dwelling value is most closely associated with TSP, its reduction in correlation to a low of $-0.347$ is representative of the change in TSP distribution. Most of the other SES variables show more precipitous declines in correlation with TSP.

Table 3 displays the results of the separate regression models for each year. For the 1986 OLS model, several SES indicators are significant, but the OLS model also produces significant spatially autocorrelated errors. A SAR model was used to adjust for significant spatial dependence among covariates; this reduced both the significance of some variables and the overall model fit. As found in earlier justice research on Hamilton (Jerrett et al., 2001), dwelling value remains the strongest covariate after control for spatial autocorrelation. The 1991 OLS regression presents roughly the same result as the 1986 model. Dwelling value is again the most robust variable. Owing to high intercorrelations, it is not surprising that unemployment and median income enter in place of family status and education. In contrast, the 1996 OLS model presents only a weak association between SES covariates and TSP. In fact, dwelling value enters as the only significant variable in 1996. As noted earlier, manufacturing employment was used in all models to control for the presence of residential location near to heavy-industrial point-source polluters, but was insignificant in all cases.

While strength and composition of each model varies, they can be generalized on the basis of the dwelling value variable. Dwelling value consistently captures the variation in TSP within Hamilton. Figure 3 displays the relative risks of exposure associated with the interquartile range of all significant variables employed in the analysis and the relative risks of dwelling value and education in each model. Focusing on dwelling value, the figure shows a diminishing association with TSP over time. By 1996, when the TSP surface is most varied, dwelling value comes closest to being nonsignificant and has a smaller point estimate. Therefore, two issues are key. First, dwelling value is the most important marker of SES for differentiating air-pollution exposure within Hamilton for the individual models. Second, sociospatial disparities in exposure appear to be less pronounced as we come forward in time.

To make direct comparisons with all three periods and to explicitly test the comparative statistics of injustice, the data were pooled for regression analysis. Using only the indicator variables, and treating 1986 ($b_0 = 3.91$) as the reference year, we found that average predicted TSP was insignificantly lower in 1991 ($b_1 = -2.44E-02, t = -1.09$), but significantly higher in 1996 ($b_2 = 0.11, t = 5.11$). This corroborates the overall similarity in the 1986 and 1991 TSP surfaces, which differ from the 1996 results.

Table 3 also shows the pooled OLS model with the inclusion of indicators and SES variables. In this form,

<table>
<thead>
<tr>
<th>Variable</th>
<th>OLS 1986 (n = 87)</th>
<th>OLS 1986 (n = 87)</th>
<th>OLS 1991 (n = 93)</th>
<th>OLS 1996 (n = 93)</th>
<th>OLS Pooled* (n = 249)</th>
<th>GAM Pooled* (n = 249)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.01 (40.22)</td>
<td>4.04 (45.22)</td>
<td>4.16 (135.73)</td>
<td>4.18 (92.00)</td>
<td>3.84 (92.00)</td>
<td>3.81 (92.00)</td>
</tr>
<tr>
<td>Dwelling value, $X_1$</td>
<td>-4.01E-06 (51.37)</td>
<td>-3.00E-06 (45.22)</td>
<td>-1.68E-06 (3.15)</td>
<td>-1.18E-06 (5.28)</td>
<td>-1.49E-06 (6.10)</td>
<td>-1.49E-06 (6.10)</td>
</tr>
<tr>
<td>Lone-parent families, $X_7$</td>
<td>4.47E-03 (2.24)</td>
<td>4.64E-03 (4.28)</td>
<td>3.54E-03 (4.13)</td>
<td>5.29E-03 (4.28)</td>
<td>5.00E-03 (4.13)</td>
<td></td>
</tr>
<tr>
<td>Low education, $X_3$</td>
<td>6.09E-03 (3.15)</td>
<td>4.84E-03 (2.79)</td>
<td>8.58E-03 (2.44)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment rate, $X_5$</td>
<td>3.28E-06 (2.23)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indicator, 1991</td>
<td></td>
<td>0.17 (5.40)</td>
<td>-2.48 (5.40)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indicator, 1996</td>
<td></td>
<td>0.28 (9.66)</td>
<td>1.28 (9.66)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model fit: adj. $R^2$</td>
<td>0.61 (p = 0.015)</td>
<td>0.27 (p = 0.712)</td>
<td>0.54 (p = 0.647)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moran’s I correlation</td>
<td>0.131 (p = 0.014)</td>
<td>0.01 (p = 0.933)</td>
<td>0.23 (p = 0.933)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* See text for a discussion of the indexing of dwelling value and testing of pooled residuals in this model.

* Pseudo-$R^2$
the indicators address predicted TSP between 1986 as the reference year and the later years, averaged across all SES variables. As such, the indicators capture significant differences in the average change in pollution across all variables from 1986 to 1991 and 1996—18 percent and 33 percent, respectively. A test for significant differences among the indicators found that 1991 and 1996 are also significantly different from each other ($t = 7.81$). In some respects, this is not surprising: the individual models for 1986 and 1991 were composed of different covariates, while the 1996 TSP surface was most distinct. That the 1991 indicator becomes significant speaks to the importance of adopting a temporal perspective in assessing the impact of SES on exposure. Also of note is the set of covariates that prove significant in their association with TSP across all three periods and, especially, the presence of indexed dwelling value as most robust. Its overall importance in association with TSP over the study period is borne in its negative relative risk ratio (Figure 3).

The pooled OLS model was extended via interaction terms of all significant SES variables and the yearly indicators. Interactions help to delineate whether the periodic differences are attributed to average TSP change across all SES variables, specific variables, or both. We can determine not only which set of SES measures are associated with air pollution injustice for the whole study period, but also which specific variables account for significant differences in exposure between periods. By including interaction terms, goodness of fit significantly improves ($adj. R^2 = 0.60, F = 47.43, p < 0.01$). The indicators now deal directly with differences in predicted TSP between the years, net of the other variables. Both indicators remained important in capturing absolute changes in TSP levels ($1991, b = -0.183, t = -1.74, p = 0.08; 1996, b = -0.146, t = -2.23, p = 0.03$), while 1991 and 1996 were no longer significantly different from each other ($t = 0.34$). Some predictive power is therefore transferred to key interaction terms, in particular those for dwelling value for 1991 and 1996 and for family status for 1991. In this model, air-pollution injustice in Hamilton is attributed to both absolute differences in predicted TSP between the years and to a differential impact of SES (mainly dwelling value) in predicting exposure within the models.

Having explored the pooled regression results, the final step was to test for spatial autocorrelation in the residuals, as discussed earlier. This was done for the pooled model shown in Table 3, including only yearly indicators, not the interaction terms. Residuals for each census tract were averaged over the three periods. These were tested and found to be significant. A GAM with a loess-smoothing term based on the coordinates of the centroids was used to reduce spatial dependency. Low education was the only covariate to add significantly to the loess term and
indicators in the GAM (F = 9.96, p < 0.01; improvement-to-F 23.30, p < 0.01), while dwelling value marginally improved the fit of this model (improvement-to-F 2.85, p = 0.09). Lone-parent families contributed less (F = 1.01, p = 0.31). An interaction term of low education and dwelling value was used to examine whether the pollution relationship of these two SES markers was conditional on each other. This would allow us to determine whether, for example, the relationship of low education is greater in low- versus high-status neighborhoods (measured by dwelling value). The interaction term did not add significantly to the GAM (improvement-to-F 1.01, p > 0.31), suggesting that each SES marker contributed additively to capturing TSP exposure. Use of the loess function in the final GAM, including yearly indicators and low education, did remove spatial dependency in the residuals with a low Moran's I correlation and p-value of 0.85. Thus, while dwelling value differentiates exposure among Hamilton neighborhoods in previous models, low education in the GAM model suggests that air-pollution awareness plays a role in conditioning exposure. If dwelling value speaks to constraint in the air-pollution awareness plays a role in conditioning exposure. Lower-status SES groups both are constrained to live in high exposure zones and, at the same time, may not be completely aware of the negative health effects from exposure. Lower-status residents tend to search out less-expensive accommodation while also placing less weight on the issue of air pollution. This interpretation agrees with earlier theoretical contributions in environmental economics that suggest that the demand for environmental quality has normal good properties, meaning the demand for higher quality goes up as a function of income (Baumol and Oates 1988). We may extend this interpretation to other markers of SES. In short, persons of low SES make a constrained choice in the air pollution/housing trade-off. Recent studies using large cohorts have reported educational effect modification in the health effects of air pollution (Pope et al. 2002). While controlling for possible confounders, researchers have found that subjects with less than a high-school education were observed to suffer the largest pollution health effects. Some of the health effects may be explained by the differential exposure observed here.

While these interpretations offer evidence of environmental injustice in Hamilton, they come with a number of caveats that suggest avenues for further inquiry. First, ambient TSP exposure alone does not constitute environmental injustice. Ill health has multiple determinants (Starfield 2001; Susser 2001), such as indoor air quality, many of which are important confounders in any attempt to assess the impact of pollution (Pengelly et al. 1984; Kerigan, Goldsmith, and Pengelly 1986; Wallace 1996). Confounders can be present in many forms. Ambient TSP levels, while representing potential exposure based on place/neighborhood of residence, do not necessarily reflect actual exposures. Personal monitors and a time-
geographical approach could shed light on actual exposures and the significance of assigning ambient levels to census tracts (cf. Pellizari, Perritt, and Clayton 1999). Another confounder relates to the use of controls for the location of social groups, as measured by covariates in the analysis. Having found that the presence of lone-parent families captures some injustice is important, because this often constitutes a “community of least resistance” in urban studies, but it has not been given due attention in justice research. Future work focused on this and other nontraditional groups should, however, include a control for residential location, as was done here with the manufacturing employment variable. We do not know whether lone-parent families are disproportionately found in high-exposure zones because their residential choice is influenced by the location of services for their particular family form in those areas.

A second caveat is that we have not been able to use a comparison spatial scale to assess whether the census-tract level of aggregation affects the finding of injustice. At the intraurban scale in Canada, the only alternative is enumeration areas (roughly three to four per census tract), but these data are often suppressed because of small numbers, and boundaries significantly change, making intertemporal analysis difficult. Anything larger than census tracts, such as forward sortation areas, yields areal units simply too large for an intraurban study. Similarly, although the air-pollution-monitoring network in Hamilton is better than most, the distribution and number of monitors does constrain the modeling of semivariance in regional TSP and thereby the kriging of TSP estimates. As in much of the environmental-justice literature, we have chosen to make use of available data and monitoring capacity, in the hope that census-tract aggregation captures reasonably discrete communities/neighborhoods and that the scale corresponds fairly well with the hazard field. In this context, future research using individual-level data and a more spatially extensive monitoring network is desirable, especially as the latter facilitates spatiotemporal interpolation for exposure characterization.

Further research can also extend the analysis in a number of ways. One extension would be to use the most recent census to examine whether dwelling value continues to be an important predictor of injustice, but with diminishing statistical significance. The GIS could also be augmented with the inclusion of a variable to control for the location of lone-parent families, with alternative air-pollution data in addition to TSP and with complementary environmental-hazards data. Integration of this could follow the use of the cumulative hazards density index (Bolin et al. 2002) for a broader assessment of the Hamilton “riskscape.” To bridge with the health effects of air-pollution exposure, we may also merge this analysis with existing morbidity and mortality data to determine if there are associations between TSP and other hazards and health outcomes at the local scale (cf. Burra et al. 2002). In particular, having found that dwelling value captures disparities and is arguably the most important indicator of social status, we might explore the presence of a “triple jeopardy” in the health effects of pollution: an accelerated, multiplicative effect as a result of both disproportionate exposure among lower-SES groups and their lack of social capital or superior health status to ameliorate its health effects. In these instances, we would expect to see greater health effects among lower SES groups because of exposure to pollution and SES.

Finally, these conclusions have a number of broader implications, which also open several avenues for further inquiry. The first is the issue of a continental urbanism. Given the rising consensus regarding a common North American urban type, the presence of injustice in Hamilton connects with the main lineaments of U.S. justice research and thereby builds on the small but growing literature that dispels Canadian urban exceptionalism (Jerrett et al. 1997; Jerrett et al. 2001; Wakefield et al. 2001). Urban environmental justice would appear to be as much a health and environmental policy issue in Canada as it is in the United States.

A second implication grows out of the apparently diminishing environmental injustice in Hamilton, also corroborated in U.S. studies. Several of these studies have suggested that, perhaps as a result of industrial and spatial restructuring, dispersed industrial complexes are redistributing environmental health hazards. Qualifying their conclusion on the basis of spatial scale, Bowen and colleagues (1995) suggested a U-shaped distribution of toxic emissions by income in Ohio. Some have gone further, arguing that post-Fordist economies are both diluting the centralized impact of large polluters such as Hamilton’s steel mills and introducing new sorts of hazards, such as highly toxic light-manufacturing emissions. Although they state that findings are inconclusive, Hird and Reese (1998) suggest an association between high income levels and low environmental quality across U.S. counties. Bolin and colleagues (2000) report a high-income bias in exposure to high-technology emissions in Phoenix, a city that skipped heavy industrialization but has more recently developed a post-Fordist light-manufacturing sector. They speculatively term this “Sunbelt justice.” Although evidence is anecdotal, it would seem that emerging industrial landscapes are blurring the clear picture of injustice that permeates the literature. However, as Bowen and colleagues (1995) argue, however, there is a need to engage theory and empirical evidence
regarding wider social processes, such as the spatial redistribution of manufacturing within urban regions, for this assertion to have a sound basis.

In the case of Hamilton, if we may extend this outcome study to hypothesize the underlying sociospatial process, the same may be true: industrial and spatial restructuring may have rebalanced aggregate particulate emissions away from the city and toward the suburbs, which can only be intensified by attendant vehicular trips and emissions. Perhaps the dynamics of industrial location, in addition to or in place of environmental-policy intervention, is bringing about air-pollution justice. As higher-status residents find it more difficult to insulate themselves from exposure, we can expect greater pressure on governments for intervention to control pollution, even in the face of average regional reductions. Further spatiotemporal analyses can elucidate the effect on air-pollution justice. It may also give clues about whether more diffuse pollution will lead to more concentrated political action aimed at reducing associated health impacts.

Acknowledgments

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Notes

1. These years provided the largest air-monitoring networks close to the years of the censuses.
2. In 1995, one station (station 29017) produced a suspect spike in the pollution surface. Inspection of the site reveals that the particulate matter was likely the effluence of local fugitive sources, including an asphalt plant. This kind of source is unlikely to produce hazardous particulate matter, due to a high proportion of large particles that are not inhalable. Frank Dobroff, an air quality analyst with MOE, confirmed this and suggested the data from this station be discarded (personal communication via email 29 November/3 December 2001). The station was shut down by the MOE the next year.
3. We began with a larger set of variables, but multicollinearity was found in tolerance tests of all potential predictors. We thus proceeded with the set of covariates shown in Table 1.
4. All variables measured in dollars were indexed to 1986 constant dollars for the pooled regression analysis.
5. All SAR models employed a first-order adjacency matrix.
6. As mentioned earlier, several other variables were removed from testing because they were found to be collinear in tolerance tests. Many of the variables included in the analysis also show high intercorrelations, though the modeling procedures guard against this. The improvement to F-ratio tests guard against inflated standard errors, a common symptom of collinear predictors. In addition, Mallow's Cp selects optimal models by including the strongest—and orthogonal—predictors.
8. The test for spatial autocorrelation in the pooled OLS model was based on the application of Moran's I to \( \Sigma (e_{1986} + e_{1991} + e_{1996}, i \ldots j)/3 \), for each i'th case and j'th year, representing the average residual of the error term for each tract.
9. As noted earlier, sensitivity analyses were undertaken with the 1996 data. The first involved the use of the suspect air-monitoring station (see endnote 2). The analysis showed that dwelling value remains the only significant covariate with a coefficient of \(-6.39E-07 (t = -3.53, p < 0.01)\), though model fit does diminish \((R^2 = 0.11)\). Given the results of other models and qualitative input from the MOE, it was decided to leave station 29017 out of the final analysis. The second sensitivity analysis of the reported 1996 model removed the suburban census tracts in Hamilton where the air-monitoring network is sparse and the kriging predictions show a rise in TSP (and standard errors) where this is unlikely. As a result, the dwelling-value variable actually diminished in significance \((b = -1.03e-06, t = -3.79)\) as compared with that reported in Table 3, suggesting that the reported model best captures disparities in TSP exposure.
10. Since the 1996 data form part of the pooled model, the sensitivity analysis using the suspect air-monitoring station was extended to this model. The analysis shows little change in the set of SES covariates, their relative significance, and their overall goodness of fit \((adj. R^2 = 0.51, F = 52.77, p < 0.01)\). For the second sensitivity analysis, most suburban tracts had already been removed, since they were not commensurate between the comparison years. Removal of three other suburban tracts changed neither model fit \((adj. R^2 = 0.52, F = 53.55, p < 0.01)\) nor the importance of the covariates.
11. The loess-smoothing term with a spatial span of 10 percent of observed points (centroids) slightly overfilters the spatial dependency of the covariates. Several other neighborhood spans were used for the loess term, but only a 10-percent span could remove spatial dependency. The resultant Moran's I is very small and negative \((> -0.000)\), and the dwelling-value variable changes sign in the final model. But this is unlikely to affect the relative importance of the covariates.

References


SPSS. Version 10.1. SPSS Inc., Chicago, IL.


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