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SINGLE MOTHER FAMILIES AND INDUSTRIAL POLLUTION IN METROPOLITAN AMERICA

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Abstract

Environmental inequality researchers have studied the distribution of social groups around a variety of environmental hazards. However, researchers have focused their attention primarily on race and class-based environmental inequality, largely ignoring the question of whether other subordinate groups—children, the elderly, women, welfare recipients, single mother families—are disproportionately burdened by environmental hazards. I address this gap in the literature by asking whether single mother families are overrepresented in environmentally hazardous neighborhoods, whether the percentage of single mother families in a neighborhood is a better predictor than a neighborhood's racial and income characteristics of environmental hazard presence levels, and whether the representation of single mother families in environmentally hazardous neighborhoods is similar to that of single father families and married parent families.

The 1980s and 1990s witnessed the rise of a new environmental movement, the environmental justice movement. Calling into question the mainstream environmental movement's assumption that environmental degradation affects everyone equally, environmental justice activists argued, among other things, that the poor, the working class, and people of color are disproportionately burdened by environmental hazards and that environmental inequality parallels other forms of inequality (Bryant and Mohai 1992; Szasz and Meuser 1997; Taylor 2000).

Responding to these claims, researchers have studied the distribution of social groups around a variety of environmental hazards, including hazardous waste sites, manufacturing facilities, superfund sites, and accidental chemical releases (Bowen 2002; Derezinski et al. 2003; Szasz and Meuser 1997). However, researchers have focused their attention primarily on race and class-based environmental inequality, largely ignoring the question of whether other subordinate groups—children, the elderly, women, welfare recipients, single mother families—are disproportionately burdened by environmental hazards (for exceptions see Chakraborty and Armstrong 2001; Pastor et al. 2002; Stretesky and Lynch 2002).

On the one hand, the field's focus on race and class-based environmental inequality makes sense: the field is relatively new and most environmental justice activism has focused on issues of race and class. On the other hand, this relatively narrow research focus is somewhat surprising given environmental justice activists' claims that environmental inequality parallels other forms of inequality and the fact that the impetus for much environmental justice activism has come from mothers concerned about the health and safety of their children (Bullard 1994; Hofrichter 1993; Taylor 2000).

Regardless of whether the field's focus is surprising or understandable, it has left a gap in our understanding of environmental inequality. We know, for example, that income and poverty are consistently associated with hazard presence in the expected direction: as environmental hazard presence increases, incomes decrease and poverty rates increase (Been 1994; Chakraborty and Armstrong 1997; Derezinski et al. 2003; Hamilton 1995; Krieg 1995; Lester et al. 2001; McMaster et al. 1997; Mohai and Bryant 1992; Morello-Frosch et al. 2001; Oakes et al. 1996; Ringquist 2000; Stretesky and Hogan 1998; Szasz and Meuser 1997). We also know that evidence regarding the existence of environmental racial inequality is mixed. Many studies have found strong evidence of environmental racial inequality (Been 1994; Downey 1998, 2003; Hamilton 1995; Krieg 1995; Mohai and Bryant 1992; Morello-Frosch et al. 2001; Ringquist 1997; Stretesky and Hogan 1998; Stretesky and Lynch 2002); some have found evidence of environmental racial inequality for some minority groups but not others (Brown et al. 1997; Pastor et al. 2002; Sadd et al. 1999); and some have found only weak evidence of environmental racial inequality, inconsistent evidence, or none at all (Anderton et al. 1994a, 1994b; Atlas 2002; Bowen et al. 1995; Clark et al. 1995; Derezinski et al. 2003; Oakes et al. 1996; Yandle and Burton 1996). Nevertheless, we know little about the representation of other subordinate groups in environmentally hazardous neighborhoods.

In this article, I address this gap in the literature by asking whether single mother families are overrepresented in environmentally hazardous neighborhoods and whether the percentage of single mother families in a neighborhood is a better predictor than a neighborhood's racial and income characteristics of environmental hazard presence levels. In addition, I ask whether the representation of single mother families in environmentally hazardous neighborhoods is similar to that of single father families and married parent families.

I focus on single mother families for several reasons. First, although mothers' concern for the health and safety of their children has provided the impetus for much environmental justice activism, environmental inequality researchers have only just begun to ask whether children are overrepresented in environmentally hazardous neighborhoods (Pastor et al. 2002; Stretesky and Lynch 2002) and have yet to examine the relationship between family structure and environmental hazard presence. Thus, by focusing on single mother families, I hope to shed light on a social group that has played an important role in environmental justice activism but been neglected in environmental inequality research.

Second, given the well-documented association between family structure, race, and income on the one hand (Franklin et al. 1995; Wilson 1987) and income, race, and environmental hazard presence on the other, it is likely that single mother families are overrepresented in environmentally hazardous neighborhoods. For example, in this study the percentage of single mother families in a census tract is strongly correlated with percent black ($r = .750$, $p < .01$), median family income ($r = -.633$, $p < .01$), and percent poverty ($r = .751$, $p < .001$), suggesting that single mother families may be overrepresented in environmentally hazardous neighborhoods due to their overrepresentation in black and lower income neighborhoods.

Third, although single mother families are overrepresented in poor and minority neighborhoods, they may not share the exact same housing stock as other poor and minority families, due perhaps to government policies or their particular housing needs and patterns of employment. Thus, it is possible that the percentage of single mother families in a neighborhood will be statistically associated with environmental hazard presence even after controlling for neighborhood income levels, neighborhood poverty levels, and neighborhood racial composition.

Fourth, it is likely that single mother families and children are particularly susceptible to the risks posed by environmental hazards. Research suggests that environmental hazards can negatively affect mental and physical health, neighborhood social organization, perceptions of local health risks, and psychological stress (Liu 2001; Mohai 1995; Sadd et al. 1999; Downey and Van Willigen 2005). For example, several studies document a negative association between residential proximity to environmental hazards and mental and physical health and development (Berry and Bove 1997; Croen et al. 1997; Evans and Kantrowitz 2002; Ross et al. 2000; Sadd et al. 1999) and a recent study (Downey and Van Willigen 2005) finds that residential proximity to industrial activity is positively associated with perceptions of neighborhood disorder, feelings of personal powerlessness, and depression among a sample of Illinois survey respondents.

Single mother families are likely to be particularly susceptible to these risks for a variety of reasons. First, research suggests that proximity-related physical health risks may be more pronounced for children than adults (Guzelian et al. 1992; Kaplan and Morris 2000; National Research Council 1993; Pastor et al. 2002; Schettler et al. 1999). Second, single mother families may have more trouble coping with physical and mental health problems than do other families because of their relative lack of resources, relatively low access to quality health care, and reliance on a single adult childcare provider (Small and Newman 2001; Williams and Collins 1995). Third, single mother families may be particularly vulnerable to the effects of neighborhood social disorganization.

Neighborhood social disorganization can negatively affect perceptions of neighborhood collective efficacy which, in turn, can impact “expectations for shared child control” (Sampson et al. 1999); parents’ monitoring of their own children; the number of unconventional friends youth have; and young people’s educational expectations, school grades, sense of personal efficacy, and problem behavior (Rankin and Quane 2002). These outcomes affect all families with children, but may be particularly problematic for single mother families because of their lack of resources and reliance on a single parent to counteract these effects.

Finally, research shows that women are more likely than men to express serious concern regarding environmental and technological risks, with minority women expressing the greatest concern and white men the least (Davidson and Freudenburg 1996). This concern gap shows up most clearly “for local facilities and / or ... technologies that are often seen as posing risks of contamination” and appears to be the result of gender and race differences in the degree to which individuals trust powerful institutions, are concerned about their children’s and community’s health and safety, and feel they have control over and benefit from technology (Davidson and Freudenburg 1996 p. 302; Finucane et al. 2000; Flynn et al. 1994; Marshall 2004). This research suggests not only that residential proximity to environmental hazards increases risk perceptions and stress among women more than men, but that the association between residential proximity and increased risk perceptions and stress may be particularly strong among single mothers and women of color.

Thus, it is particularly important that environmental inequality researchers determine whether single mother families are disproportionately represented in environmentally hazardous neighborhoods.

DATA

In order to determine whether single mother families are overrepresented in environmentally hazardous neighborhoods, I merged year-2000 tract-level census data for 14 U.S. metropolitan areas with year-2000 industrial facility pollution data drawn from the

Environmental Protection Agency's Toxic Release Inventory (TRI). I merged the data into a single dataset rather than into 14 separate datasets in order to increase sample size and reduce the number of regression analyses and tables that need to be presented. Increasing sample size is particularly important because the regression models employed in the article use maximum likelihood estimation techniques which require relatively large samples when the independent variables are correlated with one another (Long 1997). A list of the 14 metropolitan areas is provided in a subsequent section of the article as is a description of the method used to select metropolitan areas.

The census data are used to calculate the percentage of families in each tract that are *single mother families with children*, *single father families with children*, and *married couple families with children* (referred to from this point on as percent single mother families, percent single father families, and percent married parent families). The census data are also used to calculate *percent Hispanic*, *percent non-Hispanic black*, *median family income*, and *percent poverty* in each tract.

The TRI data are used to calculate the tract-level pollution proximity indicators used in this study (described below). Environmental inequality researchers generally use pollution proximity indicators rather than pollution exposure indicators because exposure data are extremely difficult to obtain. Thus, when environmental inequality researchers argue that environmental inequality exists in a study area what they usually mean is that some social group lives in closer proximity to a specified environmental hazard than we would expect if that social group were distributed randomly throughout the study area (Pollock and Vittas 1995; Sadd et al. 1999). This study uses this common standard.

The TRI records the number of pounds of specified toxic chemicals released into the environment each year by industrial facilities that employ the equivalent of ten or more full-time workers and manufacture, process, or otherwise use the specified chemicals in specified quantities.¹ TRI facilities were located on a map using an automated geographic information system (GIS) procedure called geocoding.²

Although used by many environmental inequality researchers, TRI data have several limitations. First, the toxic chemical emissions reported in the database represent only a small fraction of the toxic chemicals released into the environment each year by U.S. industrial facilities (Sadd et al. 1999). Second, TRI emissions are self-reported estimates and noncompliance rates are unknown. Finally, the database does not record actual or estimated exposure rates (Sadd et al. 1999; Szasz and Meuser 1997).

Despite these limitations, TRI-based studies make up a significant proportion of the environmental inequality literature (for example, see Bowen et al. 1995; Brown et al. 1997; Downey 1998; Pastor et al. 2001; Sadd et al. 1999). Researchers continue to use the TRI because the limitations described above are not as serious as they first appear. For example, although we do not know actual reporting compliance rates, it is likely that compliance rates

¹In 2000, the list of TRI chemicals included over 600 chemicals and chemical categories. The specified threshold quantities were 25,000 pounds for facilities that manufactured or processed TRI chemicals and 10,000 pounds for facilities that otherwise used TRI chemicals.

²Geocoding, which can be done in batch or interactive mode, is an automated process that requires a table of observations with known street addresses and a corresponding GIS street theme. Street theme streets are divided into segments and each segment is linked to a record that lists the odd and even street numbers at either end of the segment. Thus, the location of each observation is determined by matching the observation to the correct street segment and interpolating its placement along the segment based on its street number and the segment endpoint numbers. For example, if a facility's street address is 150 West 5th Street and it is matched to a street segment that runs from 100–200 West 5th Street, it will be placed midway along the segment. Because streets often serve as census tract boundaries, it is crucial that facilities are placed on the correct side of the street. Thus, you must specify an offset distance before running the procedure. Otherwise, the software places the facility directly on the street.

are high (Sadd et al. 1999). Moreover, regardless of its limitations, the TRI is still the most comprehensive and detailed national record of industrial facility pollution available to researchers. Finally, because of the difficulty of obtaining or deriving exposure and risk estimates, few of the datasets environmental inequality researchers currently use report such estimates. Thus, while it is important to acknowledge the limits of the TRI, it is also important to recognize that the TRI is as good a database for environmental inequality research as most of the other databases used by environmental inequality researchers.

MEASURING HAZARD PROXIMITY

Environmental inequality researchers generally create pollution proximity indicators by summing the pounds of pollutants released in each of their study area analysis units, summing the number of environmental hazards located in each of their study area analysis units, or creating a dummy variable set equal to one if a study area analysis unit contains an environmental hazard and zero otherwise. In addition, researchers sometimes consider analysis units that are adjacent to hazardous units to be hazardous as well (for example, see Anderton et al. 1994a, 1994b), but usually they do not.

These approaches are problematic in a number of respects. First, they force us to assume that environmental hazards are distributed evenly within analysis units. However, environmental hazards are not distributed evenly across space. Industrial facilities, for example, generally cluster near major transportation routes (Northam 1979), routes that often serve as census tract boundaries. Second, they force us to assume that environmental hazards either (1) do not impact people residing in adjacent analysis units or (2) impact every square inch of their home unit and specified adjacent units equally (Anderton et al. 1994a, 1994b). Third, simple summing fails to take analysis unit size into account. However, analysis units generally become larger as you move away from the urban core. In the Detroit metropolitan area, for example, distance from the central business district is significantly correlated with percent black and census tract area. As a result, in the Detroit metropolitan area, percent black is significantly and negatively correlated with tract area, a potentially important determinant of the number of facilities and pounds of emissions in a tract.

In order to overcome these problems, I converted each metropolitan area census tract map into a rectangular grid composed of 25-meter resolution square cells and then calculated (1) the number of TRI facilities located within a 0.25-Km radius of the center of each grid cell and (2) the total pounds of TRI pollutants emitted within a 0.25-Km radius of the center of each grid cell. Thus, all cells located within a 0.25-Km radius of a TRI facility, including cells in a different tract from that facility, are considered to be polluted and all cells in *each* tract that are outside a 0.25-Km radius of each TRI facility are considered to be unpolluted. Finally, I calculated the distance in meters from each grid cell to its nearest facility.

For each of these variables, I took the sum of the values of all the cells in each tract and divided this sum by the number of cells in each tract. The resulting variables, the pounds of TRI emissions within a 0.25-Km radius of the average tract cell (*average emissions*), the number of TRI facilities within a 0.25-Km radius of the average tract cell (*average facility presence*), and the distance from the average tract cell to its nearest facility (*average minimum distance*), take facility location and tract size into account. Average emissions and average facility presence allow facilities located within a 0.25-Km radius of a tract boundary to affect people living on the other side of that boundary without affecting every square inch of the adjacent tract and average minimum distance overcomes the boundary problem by measuring the distance to the nearest TRI facility regardless of where that facility is located. As a result, average emissions, average facility presence, and average minimum distance are more accurate indicators of pollution proximity than are the three most commonly used

pollution proximity indicators in the field: “the total pounds of emissions in an analysis unit,” “the total number of facilities in an analysis unit,” and “this analysis unit hosts a hazardous facility” (see Downey 2003 for a more detailed discussion of this variable construction technique).³

Average minimum distance, average facility presence, and average emissions each capture a different aspect of hazard proximity. Average emissions and average facility presence are density measures, the former measuring emissions density and the latter facility density. Information about facility density is valuable because facilities may be more visible than emissions and, as a result, may have a greater effect than emissions on residents’ perceptions of their neighborhoods and on local property values (several studies have found a relationship between hazard proximity and property values [Liu 2001]). Average minimum distance, on the other hand, tells us how far a tract is, on average, from TRI activity. This is important information because a neighborhood’s desirability, status, and property values may in part be a function of distance from industrial or hazardous activity.

STUDY AREA

Although this study only uses year-2000 census and TRI data, the data used in this study are drawn from a larger dataset I have compiled that includes 1990 and 2000 U.S. census and TRI data. Because it is more difficult to geocode 1990 TRI data than it is to geocode 2000 TRI data (due to improvements in street network maps from 1990 to 2000),⁴ the 14 metropolitan areas included in the dataset were selected using criteria shaped by the limitations of the 1990 data (the metropolitan areas are listed in Table 1). The metropolitan areas were chosen by (1) dividing the United States into 7 regions, the northwest, southwest, northern Midwest, southern Midwest, northeast, southeast, and mid-Atlantic; (2) allocating each of the 50 most populous metropolitan areas in the United States in 1990 to one of these regions; (3) ranking the metropolitan areas in each region, from highest to lowest, according to the total pounds of TRI pollutants emitted in each metropolitan area; and (4) moving down each list until I found two metropolitan areas in each region with a successful TRI facility geocoding rate of at least 75 percent.⁵ Unfortunately, only one metropolitan area in the southern Midwest (Houston) met these criteria. I made up for this by selecting an additional metropolitan area from the southwest (Phoenix). I chose Phoenix based on its relatively high geocoding rate.

³Like most proximity indicators used in environmental inequality research, including the number of facilities in a tract and total pounds of emissions in a tract, average emissions, average facility presence, and average minimum distance are limited in several respects. First, average emissions assumes that all chemical pollutants are equally hazardous and average facility presence and average minimum distance assume that all facilities are equally hazardous. Second, average emissions assumes an even dispersal of pollutants around each facility and average facility presence assumes an even dispersal of risk around each facility. Third, average emissions assumes there is no emissions decay within the 0.25-Km pollution radius and average facility presence assumes no risk decay within the 0.25-Km risk radius (if a facility emits 500 pounds of TRI pollutants, average emissions assigns a value of 500 to each cell within a 0.25-Km radius of it and average facility presence assigns a value of 1 to each cell within a 0.25-Km radius of it). Fourth, all three indicators assume that industrial facilities are more hazardous to those who live close to them than to those who live further away. Although these assumptions are all problematic, they underlie nearly all environmental inequality research. Moreover, the “no decay” assumption is less problematic for average emissions and average facility presence than it is for the three most commonly used proximity indicators in the literature, “the total pounds of emissions in an analysis unit,” “the total number of facilities in an analysis unit,” and “this analysis unit hosts a hazardous facility,” all of which assume that there is no emissions, pollution, or risk decay within the entire analysis unit that houses the hazard regardless of how big that analysis unit is or where the hazard is located within it (average minimum distance does not make a “no decay” assumption). Thus, average emissions, average facility presence, and average minimum distance rely on a slightly less limited set of assumptions than the commonly used proximity variables to which they most closely correspond (the total pounds of emissions in an analysis unit, the total number of facilities in an analysis unit, and “this analysis unit hosts a hazardous facility,” respectively).

⁴The 1990 TRI data were geocoded prior to the release of the 2000 street network data.

⁵While many of the metropolitan areas included in this study had successful geocoding rates well above 75% in 1990, several did not. Nevertheless, in my experience, 75% is a very good geocoding rate for 1990 data.

Successful geocoding rates for the 2000 TRI data used in this article were much better: approximately 94% of the TRI facilities in the 14 metropolitan areas were successfully geocoded.

While a random sample of major metropolitan areas would have been preferable to the sample used in this study, I was unable to generate a random sample of major metropolitan areas because so many of the 50 largest metropolitan areas had successful TRI facility geocoding rates below 75 percent in 1990. As a result, the findings reported in this article cannot be generalized to the 50 largest U.S. metropolitan areas or to a broader set of U.S. metropolitan areas. This is true, however, of all the regional and metropolitan area environmental inequality studies with which I am familiar, none of which use random sampling for case selection and almost all of which focus on a *single* region or metropolitan area. Thus, while not random, this study offers much broader metropolitan area coverage than virtually all previous urban environmental inequality studies.

ANALYTIC STRATEGY

In order to determine whether single mother families with children are overrepresented in environmentally hazardous neighborhoods, I regress each proximity indicator, in turn, on *percent single mother families* and its *squared term* (model 1, Tables 3, 4, and 5). Because the literature suggests that single mother families should be overrepresented in environmentally hazardous neighborhoods because they are overrepresented in minority and low income neighborhoods, I step *percent Hispanic*, *percent non-Hispanic black*, and their *squared terms* into the equation (Tables 3–5, model 2) and then *median family income*, *median family income squared*, and *percent poverty* into the equation (Tables 3–5, model 3). I step these variables in separately because the literature suggests that one reason minorities are overrepresented in environmentally hazardous neighborhoods is that they are overrepresented in low income neighborhoods. Finally, I step *percent single father families*, *percent married parent families*, and their *squared terms* into the equation to determine whether single mother families, single father families, and married parent families are similarly related to the dependent variable (Tables 3–5, model 4).

Squared terms are inserted into the regression models because the urban poverty and spatial mismatch literatures suggest that there is relatively little industrial activity in extremely poor, highly segregated, urban minority neighborhoods (Small and Newman 2001; Wilson 1987). In addition, other research I am currently conducting suggests that although environmental hazards tend to be located in lower income and minority neighborhoods, they are not always located in the poorest neighborhoods or the most heavily segregated minority neighborhoods. Since single mother families tend to be highly overrepresented in extremely poor neighborhoods and in heavily segregated minority neighborhoods (Small and Newman 2001; Wilson 1987), it is possible that environmental hazards tend to be located in neighborhoods with high percentages of single mother families, but not in neighborhoods with the highest percentages of single mother families.

Squared terms are dropped from specific regression models if they are not significantly associated with the dependent variable, and percent poverty squared is not included in any of the regression models because it is not significantly associated with any of the dependent variables. Descriptive statistics for the demographic and pollution proximity variables are listed in Table 2.

Including the three family structure variables in the same equation is potentially problematic because the sum of their values has an upper limit of 100% and they are, therefore, likely to be highly correlated. It turns out, however, that the sum of the three family structure variables is less than 54.3% in half of the census tracts in the sample and less than 62.8% in

75% of the tracts in the sample. Moreover, although *percent single mother families* is strongly correlated with *percent married parent families* ($r = -.528$, $p < .001$) and *percent single father families* ($r = .334$, $p < .001$; correlation results are not reported in table format), the regression analyses reported below show that the patterns of association between these variables and the three dependent variables vary according to which dependent variable is used, suggesting that results are not unduly influenced by multicollinearity.⁶

Finally, the regression models reported in this article control for unmeasured differences across metropolitan areas by including a dummy variable for each metropolitan area (except Seattle), set equal to one if a tract falls into that metropolitan area and zero otherwise. The coefficients for these dummy variables are not reported in any of the regression tables.

FINDINGS

Table 3, model 1 shows that the association between *average minimum distance* and *percent single mother families* is curvilinear: as *percent single mother families* increases, the distance from the average tract cell to its nearest facility decreases until percent single mother families reaches 43.37%, at which point the distance from the average tract cell to its nearest facility begins to increase (approximately 96.48% of all the tracts in the sample fall below the 43.37% turning point).⁷ Including percent Hispanic, percent Hispanic squared, and percent non-Hispanic black in the regression equation weakens the relationship between average minimum distance and percent single mother families (model 2), but the inclusion of the median family income, poverty, and family structure variables in models 3 and 4 does not.

Table 3, model 4 shows us that the family structure variables are not similarly associated with average minimum distance: unlike the association between percent single mother families and average minimum distance, which remains negative until percent single mother families equals 36.35%, average minimum distance increases, albeit at a declining rate, as percent married parent families increases *and* as percent single father families increases (percent single father family and its squared term are marginally significant, $p < .09$). The association between percent single father families and the dependent variable is positive until percent single father families equals 21.24% and the association between married parent families and the dependent variable is positive until percent married parent families equals 82.93%.

Thus, the association between single mother families and average minimum distance is negative for 93.69% of the tracts in the sample, the association between single father families and average minimum distance is positive for 99.84% of the tracts in the sample, and the association between married parent families and average minimum distance is positive for 99.89% of the tracts in the sample.

Finally, the last column in Table 3 lists standardized coefficients for model 4. These coefficients show that percent single mother families is more strongly associated with average minimum distance than is any other variable included in the model except percent Hispanic.

⁶In order to determine whether multicollinearity affected the variances of the regression coefficients, I ran a set of regression diagnostics after estimating each regression equation. The diagnostic tests showed that multicollinearity is not a problem.

⁷The following equation solves for the turning point at which the slope changes direction: $X = -b_1/2b_2$.

Average Facility Presence

Table 4 regresses average facility presence on the same set of independent variables as did Table 3. However, a tobit regression model is employed because average facility presence is left-censored at zero (average facility presence has a value of zero in approximately 77% of the tracts included in the sample), and as a result OLS estimates are biased and inconsistent.⁸

Table 4, model 1 shows that the association between percent single mother families and average facility presence is curvilinear: The association is positive until percent single mother families reaches 35.24%, at which point the association becomes negative. The association between percent single mother families and average facility presence is weakened when percent Hispanic, percent non-Hispanic black, and percent non-Hispanic black squared are inserted into the equation (model 2); and the main effect is no longer significant after percent poverty, median family income, and median family income squared are entered into the equation in model 3 (percent poverty is not significantly associated with the dependent variable in this model or in model 4).⁹

However, the curvilinear association between percent single mother families and the dependent variable becomes significant again when percent single father families, percent married parent families, and percent married parent families squared are inserted into the equation in model 4. When these variables are inserted into the equation, the association between percent single mother families and average facility presence remains positive until percent single mother families reaches 25.05%, at which point the association becomes negative (approximately 86% of all the tracts in the sample fall below the 25.05% turning point).

As in Table 3, the association between percent married parent families and the dependent variable is curvilinear and the opposite of the association between percent single mother families and the dependent variable: As percent married parent families increases, average facility presence decreases until percent married parent families reaches 41.94%, at which point the association becomes positive (approximately 65.45% of the tracts in the sample fall below the 41.94% turning point). Finally, the association between percent single father families and average facility presence is linear, positive, and marginally significant ($p < .065$).

The last column in Table 4 reports standardized coefficient estimates that are analogous to those used in OLS regression models (Roncek 1992). The standardized coefficients were calculated by dividing each coefficient in model 4 by the standard deviation of the error term and multiplying each of these quotients by the “standard deviation of the corresponding independent variable” (Roncek 1992, p. 506).

The standardized coefficients show that median family income is more strongly associated with the dependent variable than are any of the other independent variables. The next strongest predictor is percent non-Hispanic black, followed by percent married parent

⁸Because the tobit model combines a probit estimate for cases at the limit (average facility presence = 0) with an OLS estimate for cases not at the limit, tobit model coefficients can be decomposed to determine the effect that each independent variable has on the dependent variable when the dependent variable is at the limit and when it is not at the limit. However, tobit results will be biased if the effect of the independent variables on the dependent variable differs according to whether the dependent variable is at the limit. In order to determine whether this was a problem, I ran a series of probit models with the dependent variable set equal to 1 if average facility presence was greater than 0, and 0 otherwise. The pattern of results for these probit models is the same as the pattern of results listed in Table 4, supporting the use of tobit (Helms and Jacobs 2002). Tobit estimates will also be biased if the error terms are heteroskedastic. They are not heteroskedastic.

⁹Percent single mother families remains insignificant in model 3 even when I drop the squared term from the model.

families and percent Hispanic. However, percent non-Hispanic black and percent married parent families are both negatively associated with the dependent variable.

Average Emissions

Table 5 regresses average emissions on the same set of independent variables as did the previous regression models. A tobit regression model is used again because average emissions, like average facility presence, is heavily censored at zero.¹⁰

Table 5, model 1 shows that the association between percent single mother families and average emissions is statistically significant and curvilinear: The association is positive until percent single mother families reaches 28.67%, at which point the association becomes negative. Unlike the previous sets of regression models, inserting percent Hispanic and percent non-Hispanic black into the regression equation does not weaken the association between percent single mother families and average emissions (model 2). However, inserting median family income and percent poverty into the regression equation (model 3) weakens the relationship considerably (percent poverty is not significantly associated with the dependent variable in this model or in model 4).

Nevertheless, the curvilinear association between percent single mother families and average emissions is still statistically significant in models 3 and 4: as percent single mother families increases, average emissions increases until percent single mother families reaches 32.61% in model 3 and 38.44% in model 4, at which point the association becomes negative (approximately 91.7% of the tracts in the sample fall below the 32.61% turning point and approximately 94.7% fall below the 38.44% turning point). Moreover, the standardized coefficients for model 4 show that percent single mother families is more strongly associated with average emissions than are any of the other independent variables listed in Table 5 except percent non-Hispanic black and median family income; and, once again, percent non-Hispanic black is negatively associated with the dependent variable.

The results for the full model in Table 5 differ from the results for the full models in the previous tables in two respects. First, percent single mother families is the only family structure variable in Table 5 that is curvilinearly related to average emissions. Second, in Table 5, the coefficients for percent single mother families, percent single father families, and percent married parent families all have the same sign: they are all positively associated with average emissions.

DISCUSSION

The regression analyses reported above demonstrate that in the year 2000, single mother families were overrepresented in environmentally hazardous tracts in the 14 metropolitan areas included in this study: As the percentage of single mother families in a tract increased, the distance from the average tract cell to its nearest TRI facility decreased, albeit at a declining rate, and the number of TRI facilities and pounds of TRI emissions within a 0.25-Km radius of the average tract cell increased, again at a declining rate. These statistically significant curvilinear associations persist after stepping in percent Hispanic, percent non-Hispanic black, median family income, and percent poverty—the four demographic indicators most commonly used by environmental inequality researchers—and after stepping in percent single father families and percent married parent families. In addition, standardized coefficients show that of all the variables included in the regression models,

¹⁰A series of probit models, with the dependent variable set equal to 1 if average emissions is greater than 0, and 0 otherwise, produces the same pattern of results as the tobit models reported in Table 5, supporting the use of tobit. The error terms are not heteroskedastic.

percent single mother families is the second strongest predictor of average minimum distance and the third strongest predictor of average emissions (the second strongest predictor of average emissions is percent non-Hispanic black, which is associated with average emissions in the “wrong” direction: as percent non-Hispanic black increases, average emissions decreases).

The regression analyses reported above also suggest that single mother families, single father families, and married parent families are not equally represented in environmentally hazardous neighborhoods. For example, unlike single mother families, which are overrepresented in environmentally hazardous tracts according to all three proximity indicators, married parent families are underrepresented in tracts that are, on average, relatively close to and have a relatively high density of TRI facilities. Single father families, on the other hand, are neither over- nor underrepresented in tracts that are relatively close to or have a relatively high density of TRI facilities (recall that percent single father families is only marginally associated with average minimum distance and average facility presence). Moreover, the positive association that exists between single mother families and average emissions is much stronger than the positive associations that exist between average emissions and the other two family structure variables. Thus, the representation of single mother families in environmentally hazardous neighborhoods appears to be considerably different from that of married parent families and single father families.

As with any study, caution must be taken in interpreting the findings reported here. I noted earlier, for example, that the metropolitan areas included in this study were not selected randomly, preventing me from generalizing these findings to a broader set of metropolitan areas. I also pooled data from 14 metropolitan areas rather than examining these metropolitan areas separately. As a result, variation across metropolitan areas in the relationship between family structure and TRI proximity is ignored. In addition, I did not test causal hypotheses. Thus, we do not know why neighborhood family composition is associated with environmental hazard presence or why the statistically significant associations between the family structure variables and pollution indicators persist after controlling for neighborhood income levels, neighborhood poverty levels, and neighborhood racial composition. Similarly, even though these persistent associations appear to contradict the hypothesis that the overrepresentation of single mother families in environmentally hazardous neighborhoods is due solely to their overrepresentation in minority and low income neighborhoods, we cannot directly test this hypothesis without individual and family-level data. Finally, it is possible that findings would have differed if I had focused on a different set of hazards.

These caveats notwithstanding, this study suggests that neighborhood family composition is an important predictor of neighborhood environmental hazard levels and that living in neighborhoods that have an overrepresentation of single mother families may increase an individual's risk of living near environmental hazards. In addition, this study suggests that children are overrepresented in neighborhoods with high average TRI emissions levels, particularly children who are members of single mother families.

Evidence regarding the *consequences* of living in or near environmentally hazardous neighborhoods is mixed. Nevertheless, several studies suggest that residential proximity to environmental hazards negatively affects individuals' mental and physical health and development (Berry and Bove 1997; Croen et al. 1997; Evans and Kantrowitz 2002; Ross et al. 2000; Sadd et al. 1999; Downey and Van Willigen 2005). Research also suggests that the health risks associated with residential proximity to environmental hazards may be more pronounced for children than for adults (Guzelian et al. 1992; Kaplan and Morris 2000; National Research Council 1993; Pastor et al. 2002; Schettler et al. 1999).

Thus, residential proximity to environmental hazards is no insignificant matter and evidence that children may be overrepresented in polluted neighborhoods, and that some groups of children may bear a greater pollution burden than other groups of children, is of particular concern. This is the case not only because of children's potentially greater vulnerability to environmental pollution, but also because mental and physical health problems associated with environmental pollution likely hinder educational achievement and, therefore, future success in the job market (Diette et al. 2000; Pastor et al. 2002).

Given the public health and policy implications of the findings reported here, further research into the distribution of families and children around environmental hazards is clearly necessary. In addition to corroborating this study's findings, future research should more directly investigate whether membership in single mother, single father, and married parent families increases an *individual's* risk of living in an environmentally hazardous neighborhood and whether risk levels vary according to family income, family racial and ethnic status, or the type of environmental hazard under study. In other words, researchers should use individual and family-level data to investigate how family structure, gender, race, and income interact to shape residential proximity to environmental hazards. Finally, future research should investigate the effect that residential proximity to environmental hazards has on individuals, families, and neighborhoods. Investigating these issues will not only improve our understanding of environmental inequality, it will also shed light on the relationship between family structure, neighborhood context, and individual-level outcomes.

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References

- Anderton, Douglas L.; Anderson, Andy B.; Oakes, John Michael; Fraser, Michael R. Environmental Equity: The Demographics of Dumping. *Demography*. 1994a; 31:229–248. [PubMed: 7926187]
- Anderton, Douglas L.; Anderson, Andy B.; Rossi, Peter H.; Oakes, John Michael; Fraser, Michael R.; Weber, Eleanor W.; Calabrese, Edward J. Hazardous Waste Facilities: 'Environmental Equity' Issues in Metropolitan Areas. *Evaluation Review*. 1994b; 18:123–140.
- Atlas, Mark. Few and Far Between? An Environmental Equity Analysis of the Geographic Distribution of Hazardous Waste Generation. *Social Science Quarterly*. 2002; 83:365–378.
- Been, Vicki. Locally Undesirable Land Uses in Minority Neighborhoods: Disproportionate Siting or Market Dynamics? *The Yale Law Journal*. 1994; 103:1383–1422.
- Berry M, Bove F. Birth Weight Reduction Associated with Residence Near a Hazardous Waste Landfill. *Environmental Health Perspectives*. 1997; 105:856–861. [PubMed: 9347901]
- Bowen, William. An Analytic Review of Environmental Justice Research: What Do We Really Know? *Environmental Management*. 2002; 29:3–15. [PubMed: 11740620]
- Bowen, William M.; Salling, Mark J.; Haynes, Kingsley E.; Cyran, Ellen J. Toward Environmental Justice: Spatial Equity in Ohio and Cleveland. *Annals of the Association of American Geographers*. 1995; 85:641–663.
- Brown, Phil; Ciambone, Desiree; Hunter, Lori. Does "Green" Mask Grey? Environmental Equity Issues at the Metropolitan Level. *International Journal of Contemporary Sociology*. 1997; 34:141–158.
- Bryant, Bunyan; Mohai, Paul. *Race and the Incidence of Environmental Hazards*. Boulder, CO: Westview Press; 1992.
- Bullard, Robert D. *Unequal Protection: Environmental Justice and Communities of Color*. San Francisco: Sierra Club Books; 1994.

- Chakraborty, Jayajit; Armstrong, Marc P. Assessing the Impact of Airborne Toxic Releases on Populations with Special Needs. *Professional Geographer*. 2001; 53:119–131.
- Clark, Richard D.; Lab, Steven P.; Stoddard, Lara. Environmental Equity: A Critique of the Literature. *Social Pathology*. 1995; 1:253–269.
- Croen L, Shaw G, Sanbonmatsu L, Selvin S, Buffler P. Maternal Residential Proximity to Hazardous Waste Sites and Risk for Selected Congenital Malformations. *Epidemiology*. 1997; 8:347–354. [PubMed: 9209846]
- Davidson, Debra; Freudenburg, William. Gender and Environmental Risk Concerns: A Review and Analysis of Available Research. *Environment and Behavior*. 1996; 28:302–339.
- Derezinski, Daniel D.; Lacy, Michael G.; Stretesky, Paul B. Chemical Accidents in the United States, 1990–1996. *Social Science Quarterly*. 2003; 84:122–143.
- Diette, Gregory; Markson, Leona; Skinner, Elizabeth; Nguyen, Thereas; Algatt-Bergstrom, Pamela; Wu, Albert. Nocturnal Asthma in Children Affects School Attendance, School Performance, and Parents' Work Attendance. *Archives of Pediatrics and Adolescent Medicine*. 2000; 154:923–929. [PubMed: 10980797]
- Diette, Gregory; Markson, Leona; Skinner, Elizabeth; Nguyen, Thereas; Algatt-Bergstrom, Pamela; Wu, Albert. Environmental Injustice: Is Race or Income a Better Predictor? *Social Science Quarterly*. 1998; 79:766–778.
- Downey, Liam. Spatial Measurement, Geography, and Urban Racial Inequality. *Social Forces*. 2003; 81:937–954.
- Downey, Liam; Van Willigen, Marieke. Environmental Stressors: The Mental Health Impacts of Living near Industrial Activity. *Journal of Health and Social Behavior*. 2005; 46(3):289–305. [PubMed: 16259150]
- Evans, Gary W.; Kantrowitz, Elyse. Socioeconomic Status and Health: The Potential Role of Environmental Risk Exposure. *Annual Review of Public Health*. 2002; 23:303–331.
- Finucane, Melissa; Slovic, Paul; Mertz, C.; Flynn, James; Satterfield, Theresa. Gender, Race, and Perceived Risk: The 'White Male' Effect. *Health, Risk, & Society*. 2000; 2:159–172.
- Flynn, James; Slovic, Paul; Mertz, C. Gender, Race, and Perception of Environmental Health Risks. *Risk Analysis*. 1994; 14:1101–1108. [PubMed: 7846319]
- Franklin, Donna L.; Smith, Susan E.; McMiller, William EP. Correlates of Marital Status among African American Mothers in Chicago Neighborhoods of Concentrated Poverty. *Journal of Marriage and the Family*. 1995; 57:141–152.
- Guzelian, P.; Henry, C.; Olin, S. Similarities and Differences Between Children and Adults: Implications for Risk Assessment. Washington, DC: ILSI Press; 1992.
- Hamilton, James T. Testing for Environmental Racism: Prejudice, Profits, Political Power? *Journal of Policy Analysis and Management*. 1995; 14:107–132.
- Helms, Ronald; Jacobs, David. The Political Context of Sentencing: An Analysis of Community and Individual Determinants. *Social Forces*. 2002; 81:577–604.
- Hofrichter, Richard. *Toxic Struggles: The Theory and Practice of Environmental Justice*. Philadelphia: New Society Publishers; 1993.
- Kaplan, Sheila; Morris, Jim. Kids at Risk: Chemicals in the Environment Come Under Scrutiny as the Number of Childhood Learning Problems Soars. *US World and News Report*. 2000:128.
- Krieg EJ. A Socio-Historical Interpretation of Toxic Waste Sites: The Case of Greater Boston. *The American Journal of Economics and Sociology*. 1995; 54:1–14.
- Lester, James P.; Allen, David W.; Hill, Kelly M. *Environmental Injustice in the United States: Myths and Realities*. Boulder, CO: Westview Press; 2001.
- Liu, Feng. *Environmental Justice Analysis: Theories, Methods, and Practice*. Boca Raton, FL: Lewis Publishers; 2001.
- Long, Scott J. *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: Sage Publications; 1997.
- Marshall, Brent. Gender, Race, and Perceived Environmental Risk: The 'White Male' Effect in Cancer Alley, LA. *Sociological Spectrum*. 2004; 24:453–478.

- McMaster, Robert; Leitner, Helga; Sheppard, Eric. GIS-based Environmental Equity and Risk Assessment: Methodological Problems and Prospects. *Cartography and Geographic Information Systems*. 1997; 24:172–189.
- Mohai, Paul. The Demographics of Dumping Revisited: Examining the Impact of Alternate Methodologies on Environmental Justice Research. *Virginia Environmental Law Journal*. 1995; 13:615–653.
- Mohai, Paul; Bryant, Bunyan. Environmental Racism: Reviewing the Evidence. In: Bryant, B.; Mohai, P., editors. *Race and the Incidence of Environmental Hazards*. Boulder, CO: Westview Press; 1992. p. 163-176.
- Morello-Frosch, Rachel; Pastor, Manuel; Sadd, James. Environmental Justice and Southern ‘Riskscape’: The Distribution of Air Toxics Exposures and Health Risks among Diverse Communities. *Urban Affairs Review*. 2001; 36:551–578.
- National Research Council. *Pesticides in the Diets of Infants and Children*. Washington, DC: National Research Council; 1993.
- Northam, Ray M. *Urban Geography*. New York: John Wiley & Sons; 1979.
- Oakes, John Michael; Anderton, Douglas L.; Anderson, Andy B. A Longitudinal Analysis of Environmental Equity in Communities with Hazardous Waste Facilities. *Social Science Research*. 1996; 25:125–148.
- Pastor, Manuel; Sadd, James; Hipp, John. Which Came First? Toxic Facilities, Minority Move-In, and Environmental Justice. *Journal of Urban Affairs*. 2001; 23:1–21.
- Pastor, Manuel; Sadd, James L.; Morello-Frosch, Rachel. Who’s Minding the Kids? Pollution, Public Schools, and Environmental Justice in Los Angeles. *Social Science Quarterly*. 2002; 83:263–280.
- Pollock, Philip H., III; Elliot Vittas, M. Who Bears the Burden of Environmental Pollution? Race, Ethnicity, and Environmental Equity in Florida. *Social Science Quarterly*. 1995; 76:294–310.
- Rankin, Bruce H.; Quane, James M. Social Context and Urban Adolescent Outcomes: The Interrelated Effects of Neighborhoods, Families, and Peers on African-American Youth. *Social Problems*. 2002; 49:79–100.
- Rankin, Bruce H.; Quane, James M. Equity and the Distribution of Environmental Risk: The Case of TRI Facilities. *Social Science Quarterly*. 1997; 78:811–829.
- Ringquist, Evan. Equity and the Distribution of Environmental Risk: The Case of TRI Facilities. In: Vig, NJ.; Kraft, ME., editors. *Environmental Policy: New Directions for the 21st Century*. Vol. 4. Washington, DC: CQ; 2000.
- Roncek, Dennis. Learning More from Tobit Coefficients: Extending A Comparative Analysis of Political Protest. *American Sociological Review*. 1992; 57:503–507.
- Rosenbaum, JE.; Popkin, SJ. Employment and Earnings of Low-Income Blacks Who Move to Middle-Class Suburbs. In: Jencks, C.; Peterson, P., editors. *The Urban Underclass*. Washington, DC: The Brookings Institute; 1991. p. 342-356.
- Ross, Catherine; Reynolds, John; Geis, Karlyn. The Contingent Meaning of Neighborhood Stability for Residents’ Psychological Well-Being. *American Sociological Review*. 2000; 65:581–597.
- Sadd, James L.; Pastor, Manuel, Jr; Thomas Boer, J.; Snyder, Lori D. ‘Every Breath You Take...’: The Demographics of Toxic Air Releases in Southern California. *Economic Development Quarterly*. 1999; 13:107–123.
- Sampson, Robert J.; Morenoff, Jeffrey D.; Earls, Felton. Beyond Social Capital: Spatial Dynamics of Collective Efficacy for Children. *American Sociological Review*. 1999; 64:633–660.
- Schettler, T.; Solomon, G.; Valenit, M.; Huddle, A. *Generations at Risk: Reproductive Health and the Environment*. Cambridge, MA: MIT; 1999.
- Shaw, Clifford; McKay, Henry D. *Juvenile Delinquency and Urban Areas*. Chicago: The University of Chicago; 1942.
- Small, Mario Luis; Newman, Katherine. Urban Poverty after the Truly Disadvantaged: The Rediscovery of the Family, the Neighborhood, and Culture. *Annual Review of Sociology*. 2001; 27:23–45.
- Stretesky, Paul; Hogan, Michael J. Environmental Justice: An Analysis of Superfund Sites in Florida. *Social Problems*. 1998; 45:268–287.

- Stretesky, Paul; Lynch, Michael. Environmental Hazards and School Segregation in Hillsborough County, Florida, 1987–1999. *The Sociological Quarterly*. 2002; 43:553–573.
- Szasz, Andrew; Meuser, Michael. Environmental Inequalities: Literature Review and Proposals for New Directions in Research and Theory. *Current Sociology*. 1997; 45:99–120.
- Taylor, Dorceta. The Rise of the Environmental Justice Paradigm. *American Behavioral Scientist*. 2000; 43:508–580.
- Van Willigen, Marieke; Downey, Liam. Environmental Stressors: The Mental Health Impacts of Living Near Pollution Sources. *Journal of Health and Social Behavior*. Forthcoming
- Williams, David R.; Collins, Chiquita. US Socioeconomic and Racial Differences in Health: Patterns and Explanations. *Annual Review of Sociology*. 1995; 21:349–386.
- Wilson, William Julius. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago: The University of Chicago; 1987.
- Yandle, Tracy; Burton, Dudley. Reexamining Environmental Justice: A Statistical Analysis of Historical Hazardous Landfill Siting Patterns in Metropolitan Texas. *Social Science Quarterly*. 1996; 77:477–492.

Table 1

Metropolitan areas included in the analysis

Metropolitan areas	Number of tracts
<i>Southeast</i>	
Atlanta	660
Greensboro	263
<i>Mid-Atlantic</i>	
Baltimore	625
Philadelphia	1,329
<i>Northeast</i>	
Boston	1,176
Hartford	421
<i>Northern Midwest</i>	
Chicago	1,875
Detroit	1,275
<i>Southern Midwest</i>	
Houston	886
<i>Southwest</i>	
Los Angeles	2,786
Oakland	489
Phoenix	696
<i>Northwest</i>	
Portland	421
Seattle	527
<i>Total sample size</i>	13,429*

* The regression analyses reported below use 13,333 observations due to missing data values.

Table 2

Descriptive statistics for variables used in the analyses

	Mean	Standard deviation
<i>Dependent variables</i>		
Average minimum distance (in meters)	3,560.39	4,420.16
Average facility presence	0.02	0.07
Average emissions	415.02	4,606.63
<i>Independent variables</i>		
% Single mother families	13.77	11.95
% Single father families	3.85	3.17
% Married parent families	37.24	11.83
Median family income (in thousands of dollars)	58.94	27.06
% Hispanic	17.02	23.60
% Non-Hispanic black	15.70	27.05
% Poverty	12.59	12.23

Table 3
OLS models regressing average minimum distance on family structure and other demographic variables

	Model 1	Model 2	Model 3	Model 4	Model 4
	b	b	b	b	B
Family structure variables					
% Single mother families	-175.309 *** (7.604)	-105.687 *** (10.167)	-123.725 *** (11.358)	-124.751 *** (11.961)	-0.337 ***
% Single mother families squared	2.021 *** (.135)	1.238 *** (.146)	1.551 *** (.155)	1.716 *** (.165)	0.261 ***
% Single father families	—	—	—	33.779 [†] (18.525)	0.024 [†]
% Single father families squared	—	—	—	-0.795 [†] (.467)	-0.019 [†]
% Married parent families	—	—	—	73.145 *** (13.244)	0.196 ***
% Married parent families squared	—	—	—	-0.441 *** (.166)	-0.088 **
Control variables					
% Non-Hispanic black	—	-10.680 *** (2.376)	-9.851 *** (2.389)	-7.545 *** (2.441)	-0.046 **
% Non-Hispanic black squared	—	—	—	—	—
% Hispanic	—	-53.057 *** (6.444)	-60.182 *** (6.733)	-71.959 *** (6.836)	-0.384 ***
% Hispanic squared	—	0.237 *** (.070)	0.306 *** (.071)	.305 *** (.072)	0.131 ***
Median family income	—	—	-31.661 *** (7.765)	-38.291 *** (7.868)	-0.234 **
Median family income squared	—	—	0.111 ** (.038)	0.133 ** (.039)	0.128 **
% Poverty	—	—	-32.522 *** (6.247)	-23.012 *** (6.315)	-0.064 ***
Constant	6395.083 *** (188.977)	6123.865 *** (191.480)	8097.401 *** (447.937)	6198.862 *** (508.844)	—
R ²	0.128	0.144	0.147	0.154	—
N = 13,333					

[†] $t < .09$,

* $p < .05$,

** $p < .01$,

*** $p < .001$.

Note: Coefficients for the metropolitan area dummy variables are not reported.

Table 4
Tobit models regressing average facility presence on family structure and other demographic variables

	Model 1	Model 2	Model 3	Model 4	Model 4
	b	b	b	b	B
Family structure variables					
% Single mother families	0.00490*** (.00047)	0.00357*** (.00057)	0.00094 (.00064)	0.00147* (.000675)	0.1054*
% Single mother families squared	-0.00007*** (.00000)	-0.00004*** (.00000)	-0.00002* (.00000)	-0.00003*** (.00001)	-0.1184***
% Single father families	—	—	—	0.00131† (.00070)	0.0249†
% Single father families squared	—	—	—	—	—
% Married parent families	—	—	—	-0.00268*** (.00071)	-0.1901***
% Married parent families squared	—	—	—	0.00003*** (.00001)	0.1697***
Control variables					
% Non-Hispanic black	—	-0.00110*** (.00034)	-0.00115** (.00034)	-0.00123*** (.00034)	-0.1996***
% Non-Hispanic black squared	—	0.00000* (.00000)	0.00000* (.00000)	0.00000† (.00000)	0.0930†
% Hispanic	—	0.00180*** (.00011)	0.00126*** (.00013)	0.00126*** (.00014)	0.1779***
% Hispanic squared	—	—	—	—	—
Median family income	—	—	-0.00220*** (.00046)	-0.00197*** (.00047)	-0.3189***
Median family income squared	—	—	0.00000*** (.00000)	0.00000* (.00000)	0.1467—
% Poverty	—	—	-0.00014 (.00035)	-0.00034 (.00035)	-0.0246
Constant	-0.22814*** (.01241)	-0.21902*** (.01224)	-0.08011** (.02638)	-0.04504 (.02960)	—
Log-likelihood	-2810.92	-2626.96	-2588.81	-2579.82	—
Model χ^2	511.11***	879.03***	955.33***	973.31***	—
N = 13,333					

† < .065,

* p < .05,

** p < .01,

*** p < .001.

Note: Coefficients for the metropolitan area dummy variables are not reported.

Table 5
Tobit models regressing average emissions on family structure and other demographic variables

	Model 1	Model 2	Model 3	Model 4	Model 4
	b	b	b	b	B
Family structure variables					
% Single mother families	245.816 ^{***} (36.947)	256.146 ^{***} (43.759)	106.663 [*] (48.122)	112.638 [*] (48.883)	0.1112 [*]
% Single mother families squared	-4.287 ^{***} (.710)	-3.030 ^{***} (.692)	-1.635 [*] (.714)	-1.465 [*] (.719)	-0.082 [*]
% Single father families	—	—	—	119.164 [*] (53.572)	0.031 [*]
% Single father families squared	—	—	—	—	—
% Married parent families	—	—	—	39.740 [*] (18.486)	0.039 [*]
% Married parent families squared	—	—	—	—	—
Control variables					
% Non-Hispanic black	—	-57.042 ^{***} (10.299)	-58.814 ^{***} (10.365)	-59.683 ^{***} (10.401)	-0.134 ^{***}
% Non-Hispanic black squared	—	—	—	—	—
% Hispanic	—	63.447 ^{***} (8.866)	37.091 ^{***} (10.245)	23.378 [*] (11.488)	0.046 [*]
% Hispanic squared	—	—	—	—	—
Median family income	—	—	-69.565 ^{***} (10.816)	-69.337 ^{***} (11.076)	-0.156 ^{***}
Median family income squared	—	—	—	—	—
% Poverty	—	—	-7.073 (23.462)	-4.935 (23.746)	-0.005
Constant	-16734.89 ^{***} (928.764)	-17100.70 ^{***} (941.627)	-11165.43 ^{***} (1303.394)	-13105.91 ^{***} (1494.451)	—
Log-likelihood	-29242.04	-29173.33	-29149.33	-29145.50	—
Model χ^2	207.06 ^{***}	344.48 ^{***}	392.47 ^{***}	401.05 ^{***}	—
N = 13,333					

* p < .05,

** p < .01,

*** p < .001.

Note: Coefficients for the metropolitan area dummy variables are not reported.