Available online at www.sciencedirect.com
ScienceDirect
Environmental Research 106 (2008) 81–88
Environmental Research
www.elsevier.com/locate/envres

Does income inequality modify the association between air pollution and health?

Rana Charafeddine[a,*], Leslie I. Boden[b]

[a]*Léa-Roback Research Centre on Social Inequalities in Health of Montreal, Montréal, Québec, Canada H2L 1M3*
[b]*Department of Environmental Health, School of Public Health, Boston University, 715 Albany Street, Boston, MA 02118, USA*

Received 28 March 2006; received in revised form 31 August 2007; accepted 12 September 2007
Available online 22 October 2007

Abstract

Background: It has been hypothesized that socioeconomic status may act as an effect modifier of the association between air pollution and health. In this study, we investigated whether income inequality may modify the association between fine particulate pollution and self-reported health.
Methods: We combined several different sources of data. Demographic and socio-economic data, at the individual level, were drawn from the 2001 US Behavioral Risk Factor Surveillance System (BRFSS). County-level particulate pollution data for the year 2001 were provided by the US Environmental Protection Agency. State-level income inequality was measured by the Gini index using US census data from the year 2000. We used a hierarchical logistic regression to model the association between general self-reported health and fine particulate pollution accounting for income inequality as an effect modifier and controlling for the usual confounders.
Results: We found that when income inequality is low (10th percentile of the Gini distribution), the odds of reporting fair or poor health for a $10\,\mu g/m^3$ increase in particulate pollution is 1.34 (95% confidence interval 1.21–1.48). The analogous odds ratio for higher income inequality (60th percentile of the Gini distribution) is 1.11 (95% confidence interval 1.06–1.16).
Conclusions: Income inequality was found to be an effect modifier of the association between general self-reported health and particulate pollution. However, these findings challenged our hypothesis that people living in higher income inequality areas are more vulnerable to the impact of air pollution. We discuss the factors driving these results.

Keywords: Air pollution; Fine particulates; Income inequality; Socioeconomic factors; Self-reported health

1. Background

Individuals with low socioeconomic status (SES) have been hypothesized to be at elevated risk from air pollution compared to people with high SES due to higher exposure to environmental pollutants or to higher susceptibility to these pollutants (Lipfert, 2004; O'Neill et al., 2003). Several epidemiological studies, with varying target populations, study designs, health outcomes, and SES variables, have explored whether the effects of air pollution exposure are differently distributed by SES. O'Neill et al. (2003) reviewed many of these studies and concluded that findings vary according to the level of the socioeconomic factors used (individual-level or contextual-level). The majority of the studies looking at individual-level variables have found some effect modification by SES, with a stronger effect of air pollution among those with lower SES (Krewski et al., 2000; Pope et al., 2002). Studies using contextual-level SES (e.g. percent of people living below the poverty line, percent unemployed, percent minority) found mixed results (Jerrett et al., 2004; O'Neill et al., 2004; Ponce et al., 2005; Samet et al., 2000; Schwartz, 2000; Zanobetti et al., 2000). These contextual level studies have examined effect modification by a series of aggregate socioeconomic variables within a chosen study location. However, no study has looked at effect modification by income inequality.

*Corresponding author. Fax: +1 514 528 2441.
E-mail address: Rana.charafeddine@umontreal.ca (R. Charafeddine).

0013-9351/$ - see front matter © 2007 Elsevier Inc. All rights reserved.
doi:10.1016/j.envres.2007.09.005

1.1. Effect modification by income inequality

Similar to effect modification by SES, we postulate that individuals living in high-income inequality areas may be at elevated risks from air pollution compared to those living in more equal areas. On one hand, this may be due to higher exposure to environmental pollutants in high-income inequality areas as was suggested by a study that explored the association between US state-level income inequality and state-level environmental stress (Torras and Boyce, 1998). On the other hand, individuals living in high-income inequality areas may be more vulnerable to the adverse effects of air pollution due to two factors. First, income inequality is postulated to influence health through its effect on the social structure of communities which itself may increase individual susceptibility to air pollution. In a study using state-level ecologic variables of income inequality, social capital and violence, the authors found that violent crimes (homicide, assault, robbery) were consistently associated with high-income inequality and indicators of low social capital (Kawachi et al., 1999). Exposure to violence has been hypothesized to increase asthma morbidity and thereby increasing individuals' susceptibility to air pollution (Wright and Steinbach, 2001). In fact, exposure to violence may lead to increased psychosocial risk factors such as lack of control over one's life leading to great stress; which in turn increases asthma morbidity by triggering exacerbations through neuroimmunological mechanisms. Also, violence may affect asthma through influencing health promotion and health care seeking behaviors. For instance, a violent neighborhood may prevent an asthmatic from visiting a medical facility, a pharmacy or adhering to a prescribed walking regimen (Wright and Steinbach, 2001). Second, income inequality has been hypothesized to influence health through increased stressful social comparisons and the frustration inherent in an unequal society. Similarly to the effect of violence, chronic activation of the stress system is believed to lead to allostatic load, which is the "wear and tear" on organ systems resulting from stress (McEwen, 1998). Therefore stress may weakens the body's ability to defend against external challenges, including air pollution (Gee and Payne-Sturges, 2004).

1.2. Self-reported health (SRH)

General SRH has become a conventional method for measuring health in populations in the last two decades (Centers for Disease Control (CDC), 2001a; National Center for Health Statistics, 2001–2002; National Opinion Research Center (NORC), 1998). The utility of this measure derives from multiple factors. First, it is easily administered as it consists of asking individuals to rate their own health on a scale ranging from poor to excellent. Second, regardless of the semantic variations in the questions, this measure has been shown to be strongly and consistently predictive of mortality and of functional limitations (Burstrom and Fredlund, 2001; Idler and Benyamini, 1997; Idler and Kasl, 1995; Idler et al., 2000; Manderbacka et al., 1999; McGee et al., 1999). For instance, in a review of 27 studies comparing SRH and mortality, the authors concluded that in all but four of the 27 studies, general SRH reliably predicted survival in populations even after accounting for known risk factors (Idler and Benyamini, 1997). More recently, a meta-analysis between SRH and mortality was conducted (DeSalvo et al., 2006). The authors found that persons with poor SRH had a 2-fold higher mortality risk compared with persons with excellent SRH. Also, Jylha et al. (2006) have investigated the biological basis of SRH. They looked at the association between SRH and five biomarkers that are widely used in clinical practice as a proxy of poor health, namely albumin, white cell count, hemoglobin, HDL-cholesterol, and creatinine. All the biomarkers showed a graded relationship with SRH. When biomarkers and other indicators were adjusted for, self-rated health was still a significant predictor of mortality. Third, this measure provides a succinct way of addressing health from a broad perspective rather than assessing mortality or the absence of disease (Krause and Jay, 1994). It is suggested that this measure includes information about: diagnosed diseases and their severity as well as undiagnosed or early stage illness that might be missed by a physician, personal observation about functional status and performance in everyday life, sensation and perceptions about one's own body and mind (e.g. pain, tiredness), and individual understanding of their social and family history (Idler and Benyamini, 1997; Jylha et al., 2006).

1.3. Income inequality

The impacts of income inequality on health have been widely explored. Studies looking at this association have examined the effect of income inequality at different geographical levels such as states, metropolitan areas or counties (Blakely et al., 2002; Kennedy et al., 1998; Lopez, 2004; Soobader and LeClere, 1999; Subramanian et al., 2001). In the US, the most consistent association between income inequality and health appears to be at the level of the state where higher state-level income inequality has been linked to higher all-cause mortality risk, lower self-rated health, higher prevalence of depressive symptoms, as well as more adverse profile of health-related behaviors (Subramanian and Kawachi, 2006). Also, Wilkinson and Pickett (2006) have undertaken a review of the 155 papers reporting research findings on the association between income inequality and population health. They found that the studies of income inequality in large areas (states, regions, metropolitan areas) are more supportive of the association between inequality and health compared to those in small areas (counties, neighborhoods, zip codes). The authors suggest that this result reflect the fact that inequality in larger areas serves as a measure of the scale of social stratification, or how hierarchical a society is. They note that the smaller and more numerous the constituent areas used, the more of the income inequality in the larger areas gets converted into income differences *between* the small areas and the less that remains as inequality *within* them.

1.4. Fine particulate pollution

The influence of fine particulate matter (particulate matter with aerodynamic diameter less than or equal to 2.5 μm ($PM_{2.5}$)) on health has been widely explored. Particulate matter originates primarily from combustion sources (e.g. automobiles, power plants) and is formed from either the condensation of volatilized materials into primary particulate matter or from precursor gases reacting in the atmosphere to form secondary particles (Suh et al., 2000). $PM_{2.5}$ is considered as the component of the particulate matter that is most strongly associated with observed increase in mortality and morbidity (Suh et al., 2000). In the US and internationally, studies have shown consistent and significant association between exposure to ambient fine particulates and increased morbidity and mortality (Katsouyanni et al., 1997; Krewski et al., 2000; Pope and Dockery, 1999; Schwartz, 1999). However, the impacts of air pollution on self-rated health have been rarely explored except in case-control studies assessing the impact of one major industrial polluter or studies assessing the impact of environmental perceptions (Luginaah et al., 2002; Wilson et al., 2004). Epidemiologic studies have mainly assessed the association between air pollution and objective endpoints such as mortality or hospitalization (Krewski et al., 2000; Pope et al., 2002; Schwartz, 1999; Zanobetti et al., 2000). Yet, generic measures of health status have been proposed as potentially useful indicators to describe environmental-related morbidity (Curtis and Patrick, 2003). Moreover, SRH is a measure included in numerous population surveys which will enable researchers to relate environmental variables with detailed behavioral or socio-economic variables to study the interactions between environmental risk factors and other determinants of health.

In this analysis we will use county-level $PM_{2.5}$. Heterogeneity of exposure over space varies markedly by pollutant type. For $PM_{2.5}$, mean concentrations over large urban areas (county, city or metropolitan area) have been extensively used in the literature as a proxy for long-term exposure (Dominici et al., 2006; Krewski et al., 2000; Pope et al., 2002). This is because many studies have suggested that $PM_{2.5}$ have a homogenous distribution over large urban areas (Burton et al., 1996; DeGaetano and Doherty, 2004; Martuzevicius et al., 2004; Noble et al., 2003; Wilson and Suh, 1997).

Based on this background, the present study aims to build up knowledge on the differential impact of air pollution on health by exploring whether US state level income inequality is a significant effect modifier of the relation between SRH and fine particulate pollution.

2. Materials and methods

2.1. Data sources and modeled variables

2.1.1. Individual characteristics

Data pertaining to socio-economic, demographic and health-related characteristics were drawn from the 2001 survey of the US Behavioral Risk Factor Surveillance System (BRFSS). BRFSS is a state-based, continuous, random-digit-dialing telephone survey of the non-institutionalized US population aged 18 years or older. The data used in the present analyses were obtained from the Center for Disease Control website (Centers for Disease Control (CDC), 2001b). This survey is administered and supported by the Behavioral Surveillance Branch of the Center for Disease Control. For the year 2001, the survey consisted of over 212,510 telephone interviews from 50 states, the District of Columbia and certain US territories. We excluded respondents living in rural counties[1] because the county-level air pollution values used in our analysis are a proxy for personal exposure only in urban areas. We also excluded respondents with missing air pollution information as well as those with an unknown county of residence. Finally, we dropped all those living outside the continental USA. The final sample included 88,915 respondents distributed in 50 states and 375 counties.

General SRH status was used as the dependent variable in the analyses. In the BRFSS, the question was worded as follows: "Would you say that in general your health is excellent, very good, good, fair or poor?" The answer to this question was coded on a scale from 1 (excellent) to 5 (poor). The dichotomous outcome variable was assigned the value of 1 when the respondent rated his or her health as fair or poor and zero otherwise.

Demographic and socioeconomic variables potentially related to general self-reported health, as seen in previous studies, include race, age, sex, smoking, educational attainment and household income. Household income was adjusted for the number of people in the household using an equivalence parameter of 0.5; i.e., the total household income was divided by the square root of the number of people in the household (Daly and Valletta, 2006). The adjusted income was treated as a categorical variable: $<10\,000$, 10 000–14 999, 15 000–19 999, 20 000–24 999, 25 000–34 999, $>35\,000$. Also, we controlled for asthma, as this may be an important confounder in our model.

2.1.2. Particulate pollution

Data on fine particulates for the year 2001 were provided by the US Environmental Protection Agency which began only recently, in 1999, to measure fine particulates in the air on broad basis. Each respondent in the BRFSS was assigned an average annual $PM_{2.5}$ exposure based on his or her county of residence. Exposures are measurements taken at centrally located ambient air monitoring stations which reflect outdoor concentrations for $PM_{2.5}$. As $PM_{2.5}$ is measured in each county at multiple sites, an arithmetic average was computed and used in the analysis.

2.1.3. Income inequality and per-capita income

State income inequality data were computed using household income distribution extracted from the 2000 US Census. A variety of measures are used to determine the amount of inequality in an income distribution. We used the Gini index, which is the most commonly used measure of income inequality and is highly correlated with other income inequality measures (Kawachi and Kennedy, 1997). This index is derived from the Lorenz curve which displays graphically the cumulative share of total income accruing to successive income intervals in a population (Coulter, 1989). It measures the extent to which the actual distribution of income differs from a hypothetical distribution in which each person receives the same share.

[1]We used the definition of the US census to delineate rural areas. Rural consists of all territory, population, and housing units located outside of urbanized areas (UAs) and urban clusters (UCs). An UC consists of densely settled territory that has at least 2500 people but fewer than 50,000 people. An UA consists of densely settled territory that contains 50,000 or more people.

The Gini index ranges from 0 (absolute equality) to 1 (absolute inequality).

The Gini index was computed at the state level based on household income data from individuals living in both urban and rural areas. In this analysis, as respondents living in rural areas were dropped, the effect of state income inequality is examined only for people living in urban areas.

Finally, county per capita income was controlled for, in order to disentangle the effect of income inequality from that of the general poverty level. County per capita income data were also drawn from the year 2000 Census.

2.2. *Analysis of data*

Simple descriptive and bivariate analyses were performed to examine the relationship between self-reported health and the independent variables. These analyses were conducted with Stata (Stata Corp, 2001) using methods that account for the BRFSS's three stage sampling design. This complex design requires special statistical techniques to account for clustering, so the analysis was weighted and stratified as suggested by BRFSS documentation. For multivariate analysis, we conducted a hierarchical logistic regression to account for the hierarchical nature of the data (individuals nested within counties nested within states) using the HLM software (Bryk and Raudenbush, 1992) in order to avoid inaccuracies in point estimates or standard errors[2]. This logistic regression modeled the association between SRH, $PM_{2.5}$, the Gini index and their interaction (we allowed cross-level interaction between county particulate pollution and state level income inequality) while controlling for a series of individual level socio-demographic variables. All individual level characteristics were categorical variables. Fine particulate matter, income inequality and per capita income were all included in the final model as continuous variables.

As interaction between two continuous variables may lead to massive outliers that drive the association, we conducted a comparison analysis. We stratified our population by levels of income inequality (low, medium, high) and conducted three logistic regressions that modeled the association between self-reported heath and particulate pollution for each of these three populations, while controlling for a series of individual level socio-demographic variables.

3. Results

Table 1 displays the descriptive analysis and the bivariate relations between the individual characteristics of the respondents and those reporting fair or poor health. Percent reporting fair/poor health and the odds of reporting fair/poor health were consistent with what has been previously reported in the literature. Women were more likely than men to report fair or poor health. Older respondents were more likely to report fair or poor health. Whites had better self-rated health then other racial/ethnic groups, with Hispanics the most likely to report poor or fair health followed by African-Americans. Finally, people with lower income or educational level, smokers, self-reported asthmatics and those with no health insurance coverage were more likely to report fair or poor health.

Table 2 shows the descriptive analysis and the bivariate relations between the area level characteristics associated with the respondents and reporting health status. County

Table 1
Individual characteristics of the respondents, percentage reporting fair or poor health and the odds ratios of fair/poor health for all variables modeled independently ($N = 88.915$)

Variables	Number (%)	Percent reporting fair or poor health (non-weighted)	Odds ratio[a] (95% CI)
Demographic characteristics			
Gender			
Male	37,411(42.08)	11.88	0.83(0.77–0.89)
Female[b]	51,504(57.92)	14.06	1.00
Age Quartiles			
$\leqslant 32$	20,797	6.55	0.27(0.24–0.29)
33–43	22,428	8.06	0.36(0.32–0.39)
44–55	23,140	13.63	0.57(0.53–0.63)
>55	22,550	23.79	1
Race			
African American	9,664(10.87)	17.33	1.65(1.50–1.81)
Hispanic	6,916(7.78)	20.42	2.41(2.16–2.69)
Other minorities	5,388(6.06)	14.53	1.20(1.04–1.39)
White[b]	66,947(75.29)	11.68	1.00
Socio-economic characteristics			
Education			
Less than high school	7,462(8.39)	36.01	7.77(6.90–8.74)
High school diploma	24,244(27.27)	16.59	2.80(2.55–3.07)
Some college	24,877(27.98)	12.00	1.92(1.74–2.11)
College diploma[b]	32,332(36.36)	6.17	1.00
Household income adjusted for family size			
$<10\,000$	8,430(9.48)	33.89	7.50(6.71–8.39)
10 000–14 999	8,572(9.64)	23.78	4.89(4.38–5.47)
15 000–19 999	9,938(11.18)	17.08	3.06(2.73–3.42)
20 000–24 999	12,199(13.72)	13.50	2.43(2.17–2.73)
25 000–34 999	14,192(15.96)	9.94	1.84(1.64–2.05)
$>35\,000$[b]	35,584(40.02)	5.73	1.00
Health characteristics			
Current smoking status			
Smoker	20,524(23.08)	17.07	1.43(1.33–1.55)
Non-smoker[b]	68,391(76.92)	11.97	1.00
Do you have asthma now			
Yes	10,288(11.57)	21.67	1.81(1.66–1.99)
No[b]	78,627(88.43)	12.03	1.00
Health Insurance coverage			
Yes[b]	79,399(89.30)	12.55	1.00
No	9,516(10.70)	18.07	1.75(1.58–1.94)

[a]The odds ratios are from a series of weighted logistic regression models run independently.
[b]Referent category.

[2]To conduct the multivariate analysis, we used two methods. First using STATA we conducted a survey logistic regression using methods that account for the BRFSS's three stage sampling design as suggested by the BRFSS documentations. Second, we conducted a multilevel non-linear hierarchical logistic regression to account for the hierarchical nature of the data (individuals nested within counties nested within states) using the HLM software. The results were very comparable, thus we report only the results of the HLM analysis.

Table 2
Area-level characteristics associated with the respondents, percentage reporting fair or poor health and odds ratios of fair/poor health for all variables modeled independently ($N = 88{,}915$)

Variables	Number (%)	Percent reporting fair or poor health (non-weighed)	Odds ratios[a](95% CI)
Particulate matter quartiles ($\mu g/m^3$)			
First quartile ($\leqslant 10.58$)	22,220	12.44	1.20
Second quartile (>10.58–12.81)	21,812	12.50	(1.07–1.36)[b]
Third quartile (>12.81–14.92)	21,902	13.22	
Fourth quartile (>14.92)	22,981	14.37	
Gini index quartiles			
First quartile ($\leqslant 0.405$)	20,466	11.32	1.14
Second quartile (>0.405–0.415)	24,570	12.95	(1.10–1.18)[c]
Third quartile (>0.415–0.427)	19,452	13.39	
Fourth quartile (>0.427)	24,427	14.68	
Per capita income quartiles (USD)			
First quartile ($\leqslant 26{,}460$)	22,148	15.48	0.97 (0.94–1.00)[c]
Second quartile ($>26{,}460$–29,465)	21,851	13.82	
Third quartile ($>29{,}465$–34,236)	22,442	12.30	
Fourth quartile ($>34{,}236$)	22,474	11.03	

[a]The odds ratios are from a series of weighted logistic regression models run independently.
[b]The odds ratios represent a $10\,\mu g/m^3$ increase in particulate matter.
[c]The odds ratios represent a one standard deviation in these variables.

level $PM_{2.5}$ and state level income inequality show an association with reporting fair/poor health. An increase of $10\,\mu g/m^3$ of $PM_{2.5}$ is associated with 20% increase in the odds (95% CI, 1.07–1.36) of reporting fair or poor health. A one standard deviation increase in the Gini index is associated with 14% greater odds (95% CI, 1.10–1.18) of reporting fair or poor health. The per capita income of a respondent's county was not associated with the odds of reporting fair/poor health, although a strong gradient was observed between the quartile of per capita income and reporting worse health.

Table 3a shows the estimated coefficients and the confidence intervals of the Gini index, particulate pollution and their interaction terms. The 95% confidence interval associated with the interaction term excluded the null point (95% CI -1.26 to -0.04) which suggests that income inequality is an effect modifier for the association between particulate pollution and self-reported health. Thus, the effect of $PM_{2.5}$ on health changes for each value of the Gini index. This interaction is interpreted by adding the

Table 3a
Results from the hierarchical logistic regression model ($N = 88915$)

Variable	Adjusted estimated coefficient[a]	95% CI	
		Lower limit	Upper limit
Income inequality (state-level Gini index)	10.94	2.42	19.46
Particulate matter (county $PM_{2.5}$)	0.29	0.03	0.54
Interaction term between the Gini index and particulate matter	−0.65	−1.26	−0.04

[a]The estimated coefficients are from a hierarchical logistic regression modeling self-reported health with individual and area level characteristics (gender, age, race, education, household income, smoking status, having asthma, insurance coverage, annual average county $PM_{2.5}$, state-level Gini index and county per capita income), and a cross-level interaction between particulate pollution and the Gini index.

estimated coefficient of the main effect ($PM_{2.5}$) to the estimated coefficient of the interaction term multiplied by a specific value of the effect modifier (the Gini index). So, for example, the effect of $PM_{2.5}$ on self-reported health when the value of the Gini index is 0.395427 (10th percentile) is calculated as follows: $0.287214 + (-0.652596 \times 0.395427) = 0.029$. The corresponding odds ratio of reporting fair or poor health per $10\,\mu g/m^3$ increment of fine particulate matter is $e^{10 \times 0.029} = 1.34$. We calculate the confidence intervals manually from the variance–covariance matrix, as the statistical package used estimate the confidence intervals for models without interactions (Figueiras et al., 1998). Table 3b presents the odds ratios of reporting fair or poor health per $10\,\mu g/m^3$ increment of fine particulate matter in the final model for selected points of the income inequality distribution. These points are: 10th, 40th, 60th and 90th percentile. For respondents living in low-income inequality states (10th percentile of the Gini distribution), the odds of reporting fair or poor health for a $10\,\mu g/m^3$ increase in particulate pollution is 1.34 (95% CI 1.21–1.48). When income inequality increases, the odds ratios decrease. For instance, when income inequality is at the 60th percentile of the distribution, the odds of reporting fair or poor health for a $10\,\mu g/m^3$ increase in particulate pollution is 1.11(95% CI 1.06–1.16). When income inequality becomes higher, the effects of $PM_{2.5}$ on self-reported health becomes non-significant (OR = 1.06; 95% CI 0.99–1.13).

Table 4 shows the results of the three regressions undertaken on populations living in low, medium and high-income inequality states. Similar to results shown in Table 3, as the category of income inequality increases, the odds of reporting fair or poor health for a $10\,\mu g/m^3$ increase in particulate pollution decreases. No significant association was found between particulate pollution and self-reported health in the highest income inequality category (OR = 1.07; 95% CI 0.90–1.26).

Table 3b
Odds ratios for reporting fair or poor health per 10 μg/m^3 increment of $PM_{2.5}$ for selected points on the income inequality distribution ($N = 88{,}915$)

Selected points from the income inequality distribution (impact of $PM_{2.5}$ on self-reported health depends on the value of the Gini index)	Adjusted odds ratios[a]	95% CI	
		Lower limit	Upper limit
Gini = 0.395427 (10th percentile of the Gini distribution)	1.34	1.21	1.48
Gini = .4122883 (40th percentile of the Gini distribution)	1.20	1.12	1.28
Gini = .4238261 (60th percentile of the Gini distribution)	1.11	1.06	1.16
Gini = 0.431177 (90th percentile of the Gini distribution)	1.06	0.99	1.13

[a]The odds ratios for reporting fair/poor health are from a hierarchical logistic regression model that included individual and area level characteristics (gender, age, race, education, household income, smoking status, having asthma, insurance coverage, annual average county $PM_{2.5}$, state-level Gini index and county per capita income), and a cross-level interaction between particulate pollution and the Gini index.

Table 4
Odds ratios for reporting fair or poor health per 10 μg/m^3 increment of $PM_{2.5}$ for each income inequality category

The Gini index categories	Adjusted odds ratios[a]	95% CI	
		Lower limit	Upper limit
low[b] (⩽.4051705)	1.31	1.08	1.58
medium[c] (>.4051705–.4275475)	1.18	1.04	1.33
high[d] (>.4275475)	1.07	0.90	1.26

[a]The odds ratios for reporting fair/poor health are from three different hierarchical logistic regression models that included individual characteristics (gender, age, race, education, household income, smoking status, having asthma, insurance coverage), particulate pollution and per capita income. Each model was performed on a subsample of the respondents associated with one Gini index category.
[b]$N = 20{,}466$ nested in 69 counties.
[c]$N = 44{,}022$ nested in 197 counties.
[d]$N = 24{,}427$ nested in 109 counties.

4. Discussion

This study suggests a modest interaction between fine particulate concentrations in the air and income inequality as predictors of self-reported health status. After controlling for individual level characteristics, we find that individuals living in states with lower income inequality are significantly more likely to report fair or poor health if they lived in counties where particulate pollution is high. In states with high-income inequality, particulate pollution is not associated with reporting fair or poor health. These results contradict our hypothesis, as we posited that respondents living in states with higher levels of income inequality would be more likely to report fair or poor health associated with an increase in particulate pollution.

Higher risks from air pollution in more advantaged areas have been found elsewhere in the literature. Gouveia and Fletcher (2000) explored effect modification by area SES for the association between air pollution and mortality in Sao Paulo, Brazil. They found higher mortality risks from air pollution for people living in richer districts. One of the arguments used to explain their results is the presence of competing risk factors in poorer districts. Poorer people have lower mortality rates from air pollution because they have higher rates of mortality from risk factors such as violence or substance abuse. In this context, wealthier people appear more vulnerable to air pollution as they are relatively protected from other risk factors plaguing disadvantaged groups.

Such an argument may be pertinent to our results since studies have shown that state income inequality is socially corrosive and leads to more violence, lower levels of trust and lower social capital (Kawachi et al., 1999; Wilkinson and Pickett, 2006). Particulate pollution can be seen in this context as one of a series of competing determinants of health. It is, however, challenging to conduct a follow up that would confirm whether competing risks account for the deficit of poorer health from air pollution in high-income inequality areas since research has not yet uncovered competing risk factors for general self-reported health.

Another possible explanation for the observed results lies in the nature of the chosen environmental variable. Mean particulate pollution levels may be less valid as a proxy or measure for personal exposure of particulate pollution in high-income inequality states compared to low-income inequality states. In fact, although fine particulate matter is fairly homogenously distributed over large urban areas, it may have elevated concentrations near highly traveled roadways due to traffic sources (Zhu et al., 2002). One possibility is that in high-income inequality states, major roadways may be more often routed through socially disadvantaged neighborhoods due to their lower economic and political power. This would translate into higher within-group disparity in $PM_{2.5}$ exposures in these states. It is however complicated to test this hypothesis as complete data for the distribution of $PM_{2.5}$ in states of varying income inequality levels is not readily available. The limited number of air pollution monitors does not permit such a comprehensive study of the distribution of pollutants by income inequality status.

Another issue is the subjective nature of the dependent variable that can create systematic differences in health reporting across different social groups. Self-rated health is a strong predictor of mortality within groups; however, it may vary between groups (Blakely et al., 2002). For instance, it is suggested that people with higher education and income levels are inclined to give lower scores to topics such as environmental quality and their own health, and display more readiness to complain than people with lower SES (De Hollander, 2004). Thus the observed results are explained if populations in lower income inequality states are more likely to voice their health problems than those living in high-income inequality states. More investigation is needed to explore if health reporting may vary between groups with different income inequality contexts.

One concern in this study is the external validity of the findings. In order to check that our results are not specific to the BRFSS of the year 2001, we conducted the same analysis for the 1999, 2000 and 2002 BRFSS survey. The same Gini index was used for the four analyses. The results were comparable for the years 1999, 2001 and 2002, with the year 2001 results being the strongest. However, the year 2000 had different results in both direction and strength of the association between self-reported health and the $PM_{2.5}$ variable, the Gini index and the interaction factor. The association of all the individual variables with self-reported health was comparable for the 4 years. Intensive analysis has not revealed why results for the year 2000 differ from the other 3 years.

Finally, more studies are needed to explore the issue of effect modification by income inequality. One potential future study would be to assess if income inequality is an effect modifier of the relationship between air pollution and an objective outcome such as mortality or hospitalization. In fact, many of the earlier studies conducted on effect modification by contextual level SES examined the short-term effects of air pollution on daily mortality or hospitalization using standard methods in air pollution times series. These studies have mostly found no effect modification by contextual SES. Using similar methodologies as these studies, it would be interesting to compare if income inequality generates different findings. An interesting study would be to examine mortality for cardiovascular diseases (CVD). Air pollution is a known risk factor for CVD mortality; in addition, CVD risk factors such as high body mass index, hypertension, and sedentarism have been extensively studied. Finally, inequality in the distribution of income has been shown to be associated with the increased prevalence of CVD risk factors (Diez-Roux et al., 2000), making income inequality a potential effect modifier.

Acknowledgments

Rana Charafeddine holds a postdoctoral fellowship from the Canadian Health Services Research Foundation. We thank Nancy Maxwell, Tom Webster and Russel Lopez for insightful comments and critical review of the manuscript.

References

Blakely, T.A., Lochner, K., Kawachi, I., 2002. Metropolitan area income inequality and self-rated health—multi-level study. Soc. Sci. Med. 54, 65–77.

Bryk, A., Raudenbush, S., 1992. Hierarchial Liner Models: Applications and Data Analysis Methods. Sage Publications, Newbury Park CA.

Burstrom, B., Fredlund, P., 2001. Self rated health: is it as good a predictor of subsequent mortality among adults in lower as well as in higher social classes? J. Epidemiol. Community Health 55, 836–840.

Burton, R.M., Suh, H.H., Koutrakis, P., 1996. Spatial variation in particulate concentrations within metropolitan Philadelphia. Environ. Sci. Technol. 30, 400–407.

Centers for Disease Control (CDC), 2001a. Behavioral Risk Factor Surveillance System Survey Data. Department of Health and Human Services, Centers for Disease Control and Prevention, Atlanta, GA.

Centers for Disease Control (CDC), 2001b. Behavioral Risk Factor Surveillance System Survey Data, Available: 〈www.cdc.gov/brfss/technical_infodata/surveydata/2001.htm〉. [Accessed April 2003].

Coulter, P., 1989. Measuring Inequality: A Methodological Handbook. Westview Press, Boulder, CO.

Curtis, J.R., Patrick, D.L., 2003. The assessment of health status among patients with COPD. Eur. Respir. J. 21, 36S–45S.

Daly, M.C., Valletta, R.G., 2006. Inequality and poverty in United States: the effects of rising dispersion of men's earnings and changing family behavior. Economica 73, 75–98.

De Hollander, A.E.M., 2004. Assessing and evaluating the health impacts of environmental exposures. Ph.D. Thesis, Utrecht University, Utrecht.

DeGaetano, A.T., Doherty, O.M., 2004. Temporal, spatial and meteorological variations in hourly PM2.5 concentration extremes in New York City. Atmos. Environ. 38, 1547–1558.

DeSalvo, K.B., Bloser, N., Reynolds, K., He, J., Muntner, P., 2006. Mortality prediction with a single general self-rated health question. J. Gen. Intern. Med. 21, 267–275.

Diez-Roux, A.V., Link, B.G., Northridge, M.E., 2000. A multilevel analysis of income inequality and cardiovascular disease risk factors. Soc. Sci. Med. 50, 673–687.

Dominici, F., Peng, R.D., Bell, M.L., Pham, L., McDermott, A., Zeger, S.L., Samet, J.M., 2006. Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. J. Am. Med. Assoc. 295, 1127–1134.

Figueiras, A., Domenech-Massons, J.M., Cadarso, C., 1998. Regression models: calculating the confidence interval of effects in the presence of interactions. Stat. Med. 17, 2099–2105.

Gee, G.C., Payne-Sturges, D.C., 2004. Environmental health disparities: a framework integrating psychosocial and environmental concepts. Environ. Health Perspect. 112, 1645–1653.

Gouveia, N., Fletcher, T., 2000. Time series analysis of air pollution and mortality: effects by cause, age and socioeconomic status. J. Epidemiol. Community Health 54 (10), 750–755.

Idler, E.L., Benyamini, Y., 1997. Self-rated health and mortality: a review of twenty-seven community studies. J. Health Soc. Behav. 38, 21–37.

Idler, E.L., Kasl, S.V., 1995. Self-ratings of health—do they also predict change in functional ability. J. Gerontol. B 50, S344–S353.

Idler, E.L., Russell, L.B., Davis, D., 2000. Survival, functional limitations, and self-rated health in the NHANES I epidemiologic follow-up study, 1992. Am. J. Epidemiol. 152, 874–883.

Jerrett, M., Burnett, R.T., Brook, J., Kanaroglou, P., Giovis, C., Finkelstein, N., Hutchison, B., 2004. Do socioeconomic characteristics modify the short term association between air pollution and mortality? Evidence from a zonal time series in Hamilton, Canada. J. Epidemiol. Community Health 58, 31–40.

Jylha, M., Volpato, S., Guralnik, J.A., 2006. Self-rated health showed a graded association with frequently used biomarkers in a large population sample. J. Clin. Epidemiol. 59, 465–471.

Katsouyanni, K., Touloumi, G., Spix, C., Schwartz, J., Balducci, F., Medina, S., Rossi, G., Wojtyniak, B., Sunyer, J., Bacharova, L., Schouten, J.P., Ponka, A., Anderson, H.R., 1997. Short term effects of ambient sulphur dioxide and particulate matter on mortality in 12 European cities: results from time series data from the APHEA project. Br. Med. J. 314, 1658–1663.

Kawachi, I., Kennedy, B.P., 1997. The relationship of income inequality to mortality: does the choice of indicator matter? Soc. Sci. Med. 45, 1121–1127.

Kawachi, I., Kennedy, B.P., Wilkinson, R.G., 1999. Crime: social disorganization and relative deprivation. Soc. Sci. Med. 48, 719–731.

Kennedy, B., Kawachi, I., Glass, R., Prothrow-Stih, D., 1998. Income distribution, socioeconomic status, and self rated health in the United States:multilevel analysis. Br. Med. J. 317, 917–921.

Krause, N.M., Jay, G.M., 1994. What do global self-rated health items measure. Med. Care 32, 930–942.

Krewski, D., Burnett, R.T., Goldberg, M.S., Hoover, K., Siemiatycki, J., Jerrett, M., Abrahamowicz, M., White, W.H., 2000. Reanalysis of the Harvard Six Cities Study and the American Cancer Society Study of Particulate Air Pollution and Mortality. Health Effects Institute, Cambridge, MA.

Lipfert, F.W., 2004. Air pollution and poverty: does the sword cut both ways? J. Epidemiol. Community Health 58, 2–3.

Lopez, R., 2004. Income inequality and self-rated health in US metropolitan areas: a multi-level analysis. Soc. Sci. Med. 59, 2409–2419.

Luginaah, I.N., Taylor, S.M., Elliott, S.J., Eyles, J.D., 2002. Community reappraisal of the perceived health effects of a petroleum refinery. Soc. Sci. Med. 55, 47–61.

Manderbacka, K., Lundberg, O., Martikainen, P., 1999. Do risk factors and health behaviours contribute to self-ratings of health? Soc. Sci. Med. 48, 1713–1720.

Martuzevicius, D., Grinshpun, S.A., Reponen, T., Gorny, R.L., Shukla, R., Lockey, J., Hu, S.H., McDonald, R., Biswas, P., Kliucininkas, L., LeMasters, G., 2004. Spatial and temporal variations of PM2.5 concentration and composition throughout an urban area with high freeway density—the Greater Cincinnati study. Atmos. Environ. 38, 1091–1105.

McEwen, B.S., 1998. Protective and damaging effects of stress mediators. N. Engl. J. Med. 338, 171–179.

McGee, D.L., Liao, Y.L., Cao, G.C., Cooper, R.S., 1999. Self-reported health status and mortality in a multiethnic US cohort. Am. J. Epidemiol. 149, 41–46.

National Center for Health Statistics, 2001–2002. National Health and Nutrition Examination Survey (NHANES). Department of Health and Human Services, Centers for Disease Control and Prevention, Hyattsville, MD.

National Opinion Research Center (NORC), 1998. General Social Survey. National Opinion Research Center, Chicago, IL.

Noble, C.A., Mukerjee, S., Gonzales, M., Rodes, C.E., Lawless, P.A., Natarajan, S., Myers, E.A., Norris, G.A., Smith, L., Ozkaynak, H., Neas, L.M., 2003. Continuous measurement of fine and ultrafine particulate matter, criteria pollutants and meteorological conditions in urban El Paso, Texas. Atmos. Environ. 37, 827–840.

O'Neill, M.S., Jerrett, M., Kawachi, L., Levy, J.L., Cohen, A.J., Gouveia, N., Wilkinson, P., Fletcher, T., Cifuentes, L., Schwartz, J., 2003. Health, wealth, and air pollution: advancing theory and methods. Environ. Health Perspect. 111, 1861–1870.

O'Neill, M.S., Loomis, D., Borja-Aburto, V.H., 2004. Ozone, area social conditions, and mortality in Mexico City. Environ. Res. 94, 234–242.

Ponce, N.A., Hoggatt, K.J., Wilhelm, M., Ritz, B., 2005. Preterm birth: the interaction of traffic-related air pollution with economic hardship in Los Angeles neighborhoods. Am. J. Epidemiol. 162, 140–148.

Pope, C.A., Dockery, D.W., 1999. Epidemiology of particle effects. In: Holgate, S.T., Samet, J.M., Koren, H.S., Maynard, R.L. (Eds.), Air Pollution and Health. Academic Press, San Diego, pp. 673–705.

Pope, C.A., Burnett, R.T., Thun, M.J., Calle, E.E., Krewski, D., Ito, K., Thurston, G.D., 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. J. Am. Med. Assoc. 287, 1132–1141.

Samet, J.M., Dominici, F., Curriero, F.C., Coursac, I., Zeger, S.L., 2000. Fine particulate air pollution and mortality in 20 US Cities, 1987–1994. N. Engl. J. Med. 343, 1742–1749.

Schwartz, J., 1999. Air pollution and hospital admissions for heart disease in eight US counties. Epidemiology 10, 17–22.

Schwartz, J., 2000. Assessing confounding, effect modification, and thresholds in the association between ambient particles and daily deaths. Environ. Health Perspect. 108, 563–568.

Soobader, M.J., LeClere, F.B., 1999. Aggregation and the measurement of income inequality: effects on morbidity. Soc. Sci. Med. 48, 733–744.

Stata Corp, 2001. Stata 7 Reference Manual. Stata Corporation, College Station, TX.

Subramanian, S.V., Kawachi, I., 2006. Whose health is affected by income inequality? A multilevel interaction analysis of contemporaneous and lagged effects of state income inequality on individual self-rated health in the United States. Health Place 12, 141–156.

Subramanian, S.V., Kawachi, I., Kennedy, B.P., 2001. Does the state you live in make a difference? Multilevel analysis of self-rated health in the US. Soc. Sci. Med. 53, 9–19.

Suh, H.H., Bahadori, T., Vallarino, J., Spengler, J.D., 2000. Criteria air pollutants and toxic air pollutants. Environ. Health Perspect. 108, 625–633.

Torras, M., Boyce, J.K., 1998. Income, inequality, and pollution: a reassessment of the environmental Kuznets Curve. Ecol. Econ. 25, 147–160.

Wilkinson, R.G., Pickett, K.E., 2006. Income inequality and population health: a review and explanation of the evidence. Soc. Sci. Med. 62, 1768–1784.

Wilson, W.E., Suh, H.H., 1997. Fine particles and coarse particles: concentration relationships relevant to epidemiologic studies. J. Air Waste Manage. 47, 1238–1249.

Wilson, K., Elliott, S., Law, M., Eyles, J., Jerrett, M., Keller-Olaman, S., 2004. Linking perceptions of neighbourhood to health in Hamilton, Canada. J. Epidemiol. Community Health 58, 192–198.

Wright, R.J., Steinbach, S.F., 2001. Violence: an unrecognized environmental exposure that may contribute to greater asthma morbidity in high risk inner-city populations. Environ. Health Perspect. 109, 1085–1089.

Zanobetti, A., Schwartz, J., Dockery, D.W., 2000. Airborne particles are a risk factor for hospital admissions for heart and lung disease. Environ. Health Perspect. 108, 1071–1077.

Zhu, Y.F., Hinds, W.C., Kim, S., Shen, S., Sioutas, C., 2002. Study of ultrafine particles near a major highway with heavy-duty diesel traffic. Atmos. Environ. 36, 4323–4335.