NEIGHBORHOOD POLLUTION AND SUBJECTIVE HEALTH

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ABSTRACT

NIOBRA MONIQUE SAMUEL-PETERSON KEAH:
Neighborhood Pollution and Subjective Health
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In response to a call for more research documenting the association between pollution and subjective health, I use data collected by The Panel Study of Income Dynamics (PSID) between 1990 and 2007 to explore the association between neighborhood pollution and subjective health. Using regression analysis, I find that both neighborhood and individual level characteristics contribute to an association between neighborhood pollution and subjective health. Statistically, I also explore gender as a possible modifier in the proposed association and find minimal statistical support. Possible explanations for this finding are discussed in the conclusions. This research gives insight into how pollution may be associated with an individual's well-being. An addition, conclusions expand the implications of my findings on environmental justice campaigns and public health concerns.

DEDICATION

To God’s remarkable plan and marvelous purpose for my life;

&

To those who, when some fell silent, stood in the gap on my behalf and lent a hand.

TABLE OF CONTENTS

LIST OF TABLES

Table

Chapter One

STUDY AIMS

The following thesis responds to the need for more studies that document associations between environmental pollution and subjective health outcomes (Brulle and Pellow 2006). Within this particular study I seek to answer the following two questions:

- Is there statistical evidence for an association between subjective health and pollution in the tract of residence?
- Does gender moderate in the proposed relationship between subjective health and pollution the tract of residence?

Using data collected by The Panel Study of Income Dynamics (PSID) between 1990 and 2007 I explore the proposed association between neighborhood pollution and subjective health. In addition, I investigate the role of gender as a possible modifier within this projected relationship. The PSID is a longitudinal survey with rich information surrounding the income, family dynamics, socioeconomic background, and health of approximately 8,289 household heads (as of 2007).

Obtaining a better understanding of how neighborhood environmental conditions affect individual health outcomes such as subjective health is very important to sociologists, public health researchers, environmental scientists, and others for several reasons. Definitive evidence on an association between subjective health and pollution is not available in prior literature. On the most concrete level, this body of research allows scholars interested in issues affecting public health to gain better insight into the patterns, and disparities in health outcomes that exist across demographic characteristics such as race/ethnicity and socioeconomic status and neighborhood context. In addition, this research will move beyond past research which has examined pollution at the country, state, and city levels (Slama et al 2007; Lederman et al 2008; Wong et al 2008) by testing the influence of pollution exposure in a given tract of residence, thus acknowledging that pollution can greatly vary across small geographic areas (Boardman et al 2008; Stuart, Mudhasakul, and Sriwatanapongse 2009). Recent literature has also highlighted disparities in exposure to pollution (Boardman et al 2008; Stuart, Mudhasakul, and Sriwatanapongse 2009; Crowder and Downey 2010). These studies find instances of environmental injustice by age, race and class. This project will aid in informing environmental justice campaigns in identifying the implications of exposure to neighborhood pollution.

To be subjectively healthy is to be able to function in the world mentally, physically, and socially (Schultz and Lempert 2004). This project does not dig into how strongly subjective health is correlated with other health maladies in the data, therefore exploring a more physiological pathway by which pollution might be associated with individual-level health outcomes. Instead, this study rests on the existence of psychological connections between subjective health and pollution that may or may not develop as a result of physiological links with health and pollution. Prior research has shown that poor subjective health is associated with poor functioning throughout many institutions in life such as marriage and work (Ross et al, 1990; Ross and Mirowsky 1995; Ferrie et al, 1998; Stolzenberg 2001). Therefore, understanding the mechanisms by which health is influenced by the broader physical environment has vast implications for the social world.

Additionally, gender disparities in perception of health still exist, even though this difference is lessening as women increasingly enter the labor force and obtain higher levels of education (Cummings and Jackson 2008). Research also suggests gender disparities in patterns of neighborhood interaction (Campbell and Lee 1990; Ross and Jang 2000; Schultz and Lempert 2004). This study explores gendered trends surrounding neighborhood social environment on the theoretical level, thus, shedding light on a pathway in which the social environment may influence the health of men and women differently. On a statistical level, I examine whether gender is a modifier in the proposed association between subjective health and neighborhood-level pollution. Increased knowledge surrounding which social groups are most strongly affected by pollution will have important public policy implications for those involved in environmental justice as well as public health.

Chapter Two

THEORY

Past research has explored psychological health outcomes such as mental distress (Boardman 2008); however, this study focuses on subjective health. Subjective health is the chosen health outcome variable primarily because it has not yet been studied in conjunction with neighborhood-level pollution. This individual-level health outcome allows for the control of spuriousness and individual variation in the effects of pollution on health. Subjective health is also chosen because of the unique pathways in which it links pollution and general health.

There are two main mechanisms by which pollution might influence subjective health, one is physiological and the other is psychological in nature. The presence of pollution in a neighborhood may strengthen the likelihood of a greater number of reported and/or documented instances of poor health outcomes as a result of heightened amounts of exposure to ambient air pollutants (for reviews see Thurston and Ito 2001; Glinianaia et al 2004; Chen et al 2008; Ren and Tong 2008). Grineski et al (2007) suggest that ozone and toxic air releases at the zip-code level is connected to asthma prevalence in children. Barnett et al (2006) suggest a casual relationship between city-level concentrations of particulate matter, nitrogen dioxide, and carbon dioxide and complications within elderly patients with cardiovascular diseases. These studies lend support to the notion that through physiological pathways, the body is being exposed to harmful chemicals which adversely affect normal bodily processes resulting in poor health via diagnosed infection or disease.

The presence of neighborhood pollution may also spark one's perception of a harmful environment and therefore lead individuals to feel as though their health is affected adversely by their surroundings (Dalton 2003; Lederman et al 2008). Moreover, these perceptions of a harmful environment may spread and develop amongst a community via social networks. As individuals in a community begin to socialize with each other about issues affecting their neighborhoods, more residents become aware of possible environmental hazards as well as the effects of those hazards (if any) on others within in the community. This knowledge could lead individuals to judge their own health more harshly regardless of whether a particular illness has been diagnosed or not. This conclusion might strengthen the likelihood of poor health outcome reports even in the absence of overt physiological problems, ultimately highlighting the argument for a psychological mechanism connecting pollution to health.

The connection between neighborhood context and pollution to subjective health is also important to this study. Past literature has highlighted the role of neighborhood context and composition in predicting poor health (Diez-Roux 2001; Stafford et al 2004; Boardman, et al 2008; Do and Finch 2008; Ross and Mirowski 2008; Ruel and Robert 2009; Giatti et al 2010). Here, neighborhood context refers to the distribution of economic and social resources in a neighborhood. Neighborhood composition refers to racial composition, unemployment composition and other such characteristics of a neighborhood. Some researchers find statistically significant associations between neighborhood poverty, neighborhood affluence, unemployment, and racial composition of neighborhood arguing that place matters for the study of health. (Yen and Syme 1999; Stafford et al 2004; Boardman, et al 2008; Do and Finch 2008; Ross and Mirowski 2008; Ruel and Robert 2009). Other researchers find no association between neighborhood socioeconomic disadvantage and individual health arguing that individual factors matter (Browning and Cagney 2003; Giatti et al 2010). My study recognizes the importance of Ross and Mirowski (2008). The researchers find that neighborhood does matter, though neighborhood has a smaller impact on health than individual sociodemographic factors (Ross and Mirowski 2008). Ross and Mirowski also conclude that "40 percent of the association between neighborhood socioeconomic status and individual health is contextual and about 60 percent is compositional" (p168, 2008). Pollution too has notable associations with neighborhood context. Researchers have found that pollution emitting facilities are more likely to be located in poor, non-white neighborhoods where companies have gained inexpensive land and face the least resistance from residents for toxic emissions (Wing et al 2000; Lipfert 2004; Brulle and Pellow 2006; Strife and Downey 2009). As a result, race and class disparities in exposure to pollution exist (Boardman et al 2008; Stuart, Mudhasakul, and Sriwatanapongse 2009; Crowder and Downey 2010). Further, researchers have concluded that this disproportionate exposure to pollution is associated with higher rates of poor health (Wing et al 2000; Brulle and Pellow 2006).

Additionally, there are compelling theoretical arguments which suggest the relationship between pollution and perception of subjective health is moderated by gender (Boardman et al 2008); this body of research is largely centered on differences in social cohesion, perception of neighborhood, and concern with environmental risks. While this research cannot specifically address mechanisms connecting neighborhood to gender, theoretically these arguments aid in understanding how subjective health might be gendered. At the forefront of this argument is research done by Campbell and Lee in 1990 and 1992;

these studies find that women are better neighbors than men. Importantly, they arrive at this conclusion not because of popular notions that women spend more time in the neighborhood and work less than men (a notion that is decreasingly accurate), but instead because women in the United States are socialized to take on more social responsibility in their neighborhoods than men (Campbell and Lee 1990; 1992). While they find that both men and women exchange neighborhood goods and resources equally, when it comes to other recalled social interaction, women can name more of their neighbors, have talked with or visited with more neighbors, have a longer mean length of relationship with their neighbors and more often engage in brief "hello" interactions, as well as have longer conversations about neighborhood problems than men (Campbell and Lee 1990). As a result, Campbell and Lee (1992) provide support to the claim that women tend to have larger neighborhood networks than their counterparts and are "better neighbors" than men.

The gendered nature of social interaction patterns are important to the effects of pollution because they suggest that due to stronger networks, women may have better access to environmental information through more frequent interactions with neighbors. Increased neighborhood social interaction may make an individual more aware of pollution hazards in the neighborhood, more aware of possible effects of pollution on health and well-being, as well as more likely to interact locally with others who believe that local pollution influences poor health outcomes. An individual's own perception of his/her own health may be shaped by this increase in information. The knowledge of pollution exposure in a given area along with greater access to information regarding the consequences of exposure on health may lead individuals to report poorer self-rated health. Men's subjective health may not be as strongly affected by levels of pollution because knowledge of environmental harms is transmitted through neighborhood social networks which they are less connected to; as a result, men are less aware of the existence and probable danger of environmental harm in their neighborhood. Women, on the other hand, have stronger neighborhood ties and more neighborhood interaction which, in turn, increases the flow of information passed along social networks therefore expanding awareness of the presence and potential hazards of local pollution so that higher levels of pollution will more strongly affect women than men.

Differences in men's and women's social interactions in the home environment are important to the argument that perception of subjective health is gendered because perception of health may be shaped by more than just the individual. It is plausible that female labor force participation may alter the social networks of women. Despite labor force participation, women may still be more likely to maintain closer relationships with their neighbors. The literature surrounding women and the "second shift" supports this argument. Studies have shown that regardless of employment status, women still do more work taking care of the home and children (Bianchi et al 2000; Hoschild 2003; Milkie et al 2009). These at-home activities are more likely to put women in closer contact with neighbors. Due to the lack of data on neighboring within the PSID I am unable to test the empirical question of whether neighboring differences by gender arise as a result of neighborhood conditions; I do, however test the implication of these arguments on subjective health.

Literature also documents gender differences in environmental risk perception. In their 1993 article, Stern, Dietz, and Kalof discuss environmental perception as a function of socialization and social structure through the alteration of value orientations or attentiveness to information. They argue and support that gender differences are the results of varying beliefs about the effects of environmental problems (Stern et al 1993). Other studies suggest that women are more aware than men of their surroundings (Stern et al 1993; Schultz and Lempert 2004; Bevc, Marshall, and Picou 2007). Women talk about the advantages and disadvantages of living in a neighborhood, have opinions about neighborhood conditions and pay attention to the association between the environment and valued things (self, others, and the biosphere) regardless of whether they hold similar core values regarding environmental issues (Stern et al 1993; Schultz and Lempert 2004; Bevc, Marshall, and Picou 2007). Further, previous research finds that women tend to express more concern with technology and local[1] environmental hazards than men (Mohai 1992; Davidson and Freudenburg 1996). The implication of these findings is that even with access to the same information women may perceive greater danger from pollution, thus increasing the influence of local pollution on self-perception of health.

Based on theoretical arguments regarding the mechanisms by which pollution may affect health and variation in the influence of neighborhood and social interaction by gender, this study assesses whether an association between pollution and health exists as well as characterizes the conditioning role of gender within this association. I first examine whether subjective health tends to be lower for those in more polluted areas. After controlling for other individual factors such as, age and marital status, I expect for the association between pollution and poor subjective health to persist. Therefore, I hypothesize that subjective health is negatively influenced by increased concentrations of local pollution even after controlling for important individual and neighborhood factors. Second, I hypothesize that women's subjective health is more strongly affected by pollution than men's subjective health due to

[1] The terms local and neighborhood will be used interchangeably throughout this thesis.

[2] The sample will include the following years for which PSID health data is provided: 1990, 1991, 1992, 1993,

gendered characteristics mentioned in theory such as social cohesion, neighborhood functioning, and environmental concern.

Chapter Three

LITERATURE REVIEW

Existing evidence in the literature is consistent with the idea that neighborhood pollution affects health; however, this prior research does not provide definitive evidence for subjective health. There is a large body of research documenting the relationship between pollution and health (for reviews see Glinianaia et al 2004; Chen et al 2008; Ren and Tong 2008); however, very few studies analyze individual health outcomes and local level pollution. Much of this research examines the incidence and prevalence of various health outcomes as a function of pollution within specific populations and in large geographic areas. Childhood asthma is associated with pollution measured at the city-level in Copenhagen and the state-level in Arizona (Andersen et al 2007; Grineski et al 2007). Cardiovascular disease in the elderly is connected to pollution measured at the city-level in seven Australian cities and at the county-level across the United States (Dominici et al 2003; Barnett et al 2006). Low birth weight in newborns is linked to pollution measured at the county-level in Massachusetts and Connecticut, the city-level in Munich, and the industrial site level in Sydney, Nova Scotia, Canada (Burra et al 2006; Bell et al 2007; Slama et al 2007). Andersen et al (2007), find a correlation between hospital admissions for cardiovascular disease in the elderly and pediatric asthma, and ambient levels of total pollution as well as source allocated pollution at the city-level in Copenhagen, Denmark. Bell et al (2007), show an association between increased county-level air pollution and low birth weight in Massachusetts and Connecticut. Together, these articles lend strong support to a negative relationship between pollution and health outcomes and strengthen physiological arguments for the influence of pollution on subjective health.

While prior research is consistent with theoretical arguments connecting pollution to health, it falls short of testing the influence of local/neighborhood pollution exposure on an individual-level overall indicator of health. Past research controls for various characteristics of the population that may influence both pollution and health. This body of research, however, does not utilize neighborhood-level pollution measures nor does it explore subjective health as the main dependent variable. Further, past research does not examine gender disparities in the influence pollution on subjective health.

Prior research also misses the fact that pollution varies across small areas such as neighborhoods within cities, counties, states, and countries. Studies within the more general body of pollution and health literature focus on geographically limited case-studies which pin point population-level health in one or two large, highly polluted areas such as mortality in Hong Kong (Wong et al 2008), birth outcomes in post 9/11 New York City (Lederman et al 2008), and birth weight in Munich, Germany (Slama et al 2007). These studies examine pollution at the region, state, or county level which assumes that all residents are exposed to the same averaged levels of pollution. In truth, pollution is not stagnant or evenly distributed across space; there is dramatic variation over smaller geographical units such as neighborhoods (Boardman et al 2008; Stuart Mudhasakul, and Sriwatanapongse 2009).

A very small body of research examines subjective health and the interaction between socioeconomic characteristics and pollution. These few studies provide evidence of how neighborhood characteristics are correlated with individual health outcomes. A couple of these studies explore a relationship between pollution and subjective health as a function of economic development and economic inequality at the country and county levels. For example, Sun and colleagues (2008) find that air pollution significantly affects subjective health when controlling for sociodemographic and community economic development variables. Also, in their study of pollution and health in urban areas in the continental United States, Charafeddine and Boden (2008) find that respondents in states with lower income inequality are more likely to report poor/fair health in relation to increased levels of pollution. While these studies establish that there is a relationship between pollution and subjective health and the importance of neighborhood characteristics in determining individual health, they focus specifically on the elderly (Sun et al 2008) and urban residents (Charafeddine and Boden 2008). After finding that neighborhood characteristics influence subjective health, and asserting that neighborhood context matters, past research fails to study pollution at the neighborhood level.

Past literature does not assess the causal impact of neighborhood pollution and subjective health; it does, however, give indirect evidence for the notion that local pollution may affect subjective health irrespective of whether it directly affects physical health. For example, based on her findings that distance from a waste incinerator, perception of harm from the site, and the interaction between risk perception and environmental annoyance increase the prediction of poor psychological well- being, Lima (2004), concludes that "even if the incinerator has no negative [objective] consequences for those who live close to the site, the suspicion of threat produces augmented annoyance, which is related to symptoms of psychological discomfort" (p 81). In another study, Bevc, Marshall, and Picou (2007), find that perceived exposure to pollution is a predictor of both diagnosed and undiagnosed mental problems. These studies make evident the psychological argument for the influence of pollution on health.

The few studies that examine gender disparities in the relationship between pollution and health suggest that men and women may be affected by pollution differently; however, they have yet to address both neighborhood-level pollution and individual-level health on a national scale. In their 2005 Californian study, Chen et al find a statistically significant relationship between county-level pollution and risk of coronary heart disease mortality in females and not males. Chen et al (2005) focuses on a sample of mortality counts in the California area and uses county-level pollution data. Boardman and colleagues (2008) find that the negative relationship between increased industrial activity and poor mental health is more pronounced amongst women than men. Boardman et al (2008) observes solely mental health and uses neighborhood-level industrial activity data for the city of Detroit, Michigan.

Chapter Four

CONTRIBUTIONS

This research adds the present body of research by utilizing a large national sample of United States residents from a range of socioeconomic statuses, ages, races, and geographic residences to explore the possible relationship between neighborhood pollution and subjective health. Measurement issues are addressed by analyzing pollution across the nation at the neighborhood-level where a neighborhood is defined as a U.S. Census tract. The use of nationally representative data within this project allows for a sample distributed across a wide range of places. Neighborhood level pollution analysis brings forth dissimilarity in pollution exposure across smaller geographical units. This project observes the subjective health of PSID household heads, a health outcome that adds to both physiological and psychological arguments connecting pollution to health. Lastly, this study observes whether gender is a modifier in the proposed association between pollution and subjective health.

Moving beyond the work of Boardman et al (2008) which examines the association between pollution and mental health, this project uses subjective health as the main health outcome. In testing for a possible subjective health and pollution connection, this research explores a more general indicator of health that has documented associations with mental and physical health (Boardman et al 2008). Examining subjective health provides an opportunity to expound upon a health outcome in which, even in the absence of physiological ties to pollution exposure, will still have psychological ties to exposure to pollution. Because of the partially perceptive nature of subjective health, I am able to observe possible influences of aggregate measures of pollution as opposed to exploring specific chemical toxins (as would be done if the focus of the research were primarily on physiological pathways).

Aside from bringing forth a case in which the association between pollution and subjective health is tested, this study draws upon data that allows for a smaller and more precise census tract unit of analysis by which pollution is examined. Instead of proposing a new psychological pathway by which pollution might influence subjective health, this project provides a stronger base for existing arguments which link pollution to subjective health. While the physiological argument presented affirms that chemical factors contribute to the correlation between pollution and poor individual health maladies, the psychological argument presented in this thesis states that perception of environmental surroundings, neighboring, and concern with environmental hazards drive the association between pollution and subjective health.

While much research consistently supports a negative relationship between increased levels of pollution and physical/psychological health (Lima 2004; Bevc, Marshall, and Picou 2007; Boardman et al 2008; Sun and Gu 2008; Goldberg et al 2009), the need to account for potential confounders and selection processes that might help explain the association between pollution exposure and health problems has been brought up by several researchers (Brulle and Pellow 2006; Bevc, Marshall, and Picou 2007). A reason for this difficulty concerning statistical modeling lies in the fact that many factors that affect health also affect neighborhood selection and thereby exposure to environmental pollution. To address this issue, my study will control for other individual- and family-level factors which affect health and may also be associated with pollution exposure.

Chapter Five

DATA & STUDY DESIGN

The research questions presented in this study were addressed using data from the Panel Study of Income Dynamics due to its survey design and upkeep over the years; inclusion of important control variables which impact health; ability to be linked to extensive environmental data; and inquiry into respondents' health and well-being.

The PSID

The PSID, which began in 1968, is a large computer assisted interview survey of U.S. residents and their families. Data regarding respondents' finances, social behavior, family dynamics, have been collected annually until 1997 and biennially after 1997. In 37 years the PSID has maintained a response rate of 96%-98% from wave to wave and grown to nearly 9,000 household heads (psidonline.umich.edu). Such low attrition rates are beneficial to the proposed study because, with the sample weights provided by the PSID, findings using these data both reduce concerns about generalizability and enhance my sample's comparability to the PSID population as a whole. Fitzgerald et al, (1998) found that even though a large portion of the original PSID sample dropped out of the study, the representativeness of the study through 1989 was not compromised. Further, since 1989, there is no significant evidence that the PSID's cross sectional representativeness has been compromised (Fitzgerald et al 1998).

Due to the initial 1968 enumeration of the PSID, Asians and Hispanics are underrepresented in the original study population. In recent years, the PSID has added special samples of immigrant populations in order to remedy this issue. While caution should be used in generalizing about non-black and non-white populations, they will still be included in this project's sample population.

The PSID is well suited for the proposed study for a few key reasons. First, the PSID allows for longitudinal analysis using the individual as the unit of analysis. With this structure I will be able to utilize fixed effect modeling which will help me assess the potential role of neighborhood selection in supplemental sensitivity tests. Neighborhood selectivity refers to the individual characteristics associated with why one chooses to live in his/her neighborhood. The relationship between socioeconomic status and pollution exposure may complicate our ability to examine associations between subjective health and pollution because low socioeconomic status may reduce an individual's ability to select higher quality neighborhoods and lead him/her to live in more polluted areas. The primary statistical issue here is whether or not neighborhood selection will impact the parameter estimates of the association between pollution and health due to the inability to control for all individual factors (both observed and more importantly, unobserved) that affect both the likelihood of living in a polluted neighborhood and of reporting poor SRH. Individual fixed-effect modeling helps to minimize this bias by illuminating within person changes over multiple years of data collection.

Second, the PSID was originally designed to study poverty and economic opportunity. This content will assist the present project by providing important control variables which capture economic circumstance and try to isolate out confounding factors which might affect both residential location and health. Third, the PSID has great linkage potential with extensive neighborhood and environmental data. Given a PSID approved research plan, a Sensitive Data Protection Plan and a signed "Contract for Use of Sensitive Data" in order to protect the anonymity of the respondents, Geocode Match Files can be linked to the tract of resident for the PSID household. PSID Household- and individual-level data are then attached to neighborhood level data. Collectively, these data will contain PSID family and individual-level responses and neighborhood characteristics including information on environmental toxins.

The Sample

My study sample will include respondents classified as household heads and wives in individual-level and family-level waves of data collected between 1990 until 2007[2]. These years were chosen because they are years for which there are reliable pollution data and PSID data (Crowder and Downey 2010). Focus on data collected within these 17 years will provide a first look at the link between neighborhood pollution and individual health as well as the opportunity to utilize the longitudinal nature of the data. Respondents include household heads who responded for themselves and household heads' spouses for which the household heads also responded.[3] The household head is defined by the PSID as an individual who is at least 16, and holds the most financial responsibility in the household. The household heads and spouses sample is comprised of male and females ages 19-99 of various races/ethnicities. According to the PSID, a household head's "wife" or spouse includes partners in marital unions as well as live in partners of the household head for more than one year.

[2] The sample will include the following years for which PSID health data is provided: 1990, 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1999, 2001, 2003, 2005, 2007 (PSID 2009).

[3] Previous research utilizes fixed-effect models that cluster individuals at the family unit-level to account for bias associated with other-person reporting (Wagmiller 2009). Wagmiller (2009) found that fixed-effects statistical strategies reduced bias associated with other-person reporting in PSID respondents and their children.

This study's sample includes data collected over 17 years for 9,591 respondents. Table 1 shows the distribution of respondents by gender and household status. This population is made up 6, 396 males (6,014 that are heads of household) and 3, 195 females (1,849 that are heads of household). In total, the year-based sample includes 29,152 yearly (or repeated) observations over 13 data collection years. Not all respondents, however, have multiple years of data. In fact, the maximum number of years for which a respondent has multiple observations is 5 for females and 10 for males. Fifty percent of the females in the sample have between 3 and 5 years of data; whereas, 5% of males have between 5 and 10 years of data.

Neighborhood

The pollution data proposed within this study follows techniques used by Boardman et al (2008) and Crowder and Downey (2010). Because pollution is estimated at the Census tract-level, it makes sense for a neighborhood unit to be defined as a US Census tract. Census tracts are geographical areas within counties which contain between 1,500 and 8,000 persons. Census tracts typically coincide with population characteristics unique to counties and sometimes share administrative boundaries such as metropolitan areas. The spatial size of the geographic area is dependent upon an area's population density; as the population density increases, the geographic area decreases (http://www.census.gov/geo/www/cen_tract.html).

Throughout the proposal I use the term neighborhood level which can be defined as analysis done within a U.S. Census tract. Defining "neighborhood" as a Census tract is important to this study for two primary reasons. First, the cities and towns by which tracts are derived have a social context that may not necessarily be respected by tract lines; however, they do represent some level of population social homogeneity by taking economic and living circumstances into account (Census Bureau 2010). Second, the smallest level that individual-level PSID data in conjunction with Geocoded Match Files can be analyzed is the tract-level. Other pollution studies have also productively utilized this geographic level of analysis (Boardman et al 2008; Crowder and Downey 2010).

Due to the fact that this research is concerned with respondents' perception of their neighborhood surroundings and because theoretical arguments point to social context as a key part of the mechanism by which perception is formed, whether or not tracts can socially be considered neighborhoods is an issue that cannot be ignored. It is possible that the social contexts in which individuals live make up the boundaries of a neighborhood. Census tracts are designed with population density and geographical limits in mind; however, it is still relevant to note that even though these are physical boundaries, they are also residential environments to which respondents are exposed. Census tracts are widely accepted by researchers as an acceptable measurement tool when examining geographical neighborhood boundaries today (e.g. Boardman et al 2008; Crowder and Downey 2010) and therefore will be used in this study.

Self-Rated Health (The Dependent Variable)

Subjective health is the key dependent variable of interest within the study because it is a health measure which will likely capture both the psychological and physiological mechanisms by which local pollution may influence health outcomes. Also, this study will focus on subjective health responses because of its documented reliability in measuring an individual's well-being and its wide acceptance as a valid measure of actual health (Stolzenberg 2001; Schultz and Lempert 2004; Bevc, Marshall, and Picou 2007; Cummings and Jackson 2008). Responses to a general health status question using a 5-point scale have been collected every PSID interview year since 1987. This study will utilize responses from data collected between the years 1990 and 2007. The question specifically asks "..including any serious limitations you might have. Would you (HEAD) say your health in general is excellent, very good, good, fair, or poor?"

Pollution (The Focal Independent Variable)

The main independent variable of interest in the proposed study is pollution from industrial facilities in and around respondents' neighborhoods of residence for a given year. This study will utilize data collected over 17 years (1990-2007). Industrial activity data comes from the Environmental Protection Agency's Toxics Release Inventory (TRI). TRI data are noted as the most comprehensive publicly available industrial activity data (Boardman et al 2008). The data set is compiled of a wealth of information regarding the total number of pounds of specified chemicals emitted annually from facilities with 10 or more employees (Boardman et al 2008). This research will examine the sum influence of these chemicals rather than local concentrations of specific toxins. These data are particularly useful for the proposed study because they capture the theoretical mechanisms by which pollution may affect health. The level of emissions may have important physiological as well as psychological consequences. Overall concentrations of pollution are important for physiological effects on health; and the visibility of pollution sites is important for psychological effects. It is reasonable to think that overall pollution may be correlated with facility size because the size of the facility may affect visibility of pollution to local residents. For this study, a measure that taps into overall pollution in the area may add support to the theoretical linkage between pollution and subjective health through awareness, neighborhood social cohesion and the transmission of information. Measurements of total emissions combined with proximity to facility and facility size can help researchers estimate the status of pollution on individuals based on correlations between visual evidence of pollution, facility size and total emissions in relation to individuals within a tract of residence. The idea here is that while individuals may not know and discuss concrete levels of specific hazardous toxins, they do know and discuss visual evidence such as the size and proximity of industrial sites emitting pollution.

Pollution is measured using strategies employed by Boardman et al (2008), Downey (2006), and Crowder and Downey (2010). First, TRI facilities are located on a Census tract map of the U.S. and a 400 square foot rectangular grid is then placed over the map. Second, the distance from each TRI facility to the center of each grid cell is calculated. Third, weights are calculated using a distance decay function in which values decline from one to zero as distance between the facility and the grid cell increases. Weights are set to zero beyond 1.5 miles because facilities that are at 1.5 miles or more away from the center of a given tract are presumed not to influence health outcomes in that tract. Fourth, the grid weight is multiplied by the pounds of air pollution estimated to influence that grid cell. Finally, the grid cell values within a given tract are averaged together to provide a measure of proximate industrial pollution for all U.S. census tracts.

This measurement strategy produces tract-level measures of pollution that summarize the total pollution output of industrial facilities in the area, weighted by the distance between the PSID respondent's tract of residence and each facility. The dynamic nature of pollution may bring forth the proposed association between exposure to local pollution and subjective health when measures of pollution emissions are taken into account (especially at the census tract level). Further, the weighted proximity to industrial sites data may illuminate the possible association between perception of neighborhood pollution and subjective health. Thus, by measuring concentrations of pollution and simultaneously proximity to pollution emitting facilities, I am likely to capture both the physiological processes via exposure and the psychological processes via proxy for perception at work.

Additional Control Variables

The comprehensive nature of the PSID allows for further isolation of the effects of environmental pollution on health. I will explore the role of correlates of subjective health mentioned and used in past literature including: gender and race (Cummings and Jackson 2008), education (Ross and Huber 1985; Ross and Wu 1996; Mirowsky and Ross 1998; Reynolds and Ross 1998; Goesling 2007), marital and employment status (Ross and Mirowsky 1995; Ferrie et al 1998; Heard et al 2008), as well as income (which has a non-linear association with health) and age (Adler et al 1994; Ross and Wu 1996; Park 2005; Subramanian and Kawachi 2006).

Racial categories within the PSID include: White; Black, African-American, or Negro; Asian; and Native Hawaiian or Pacific Islander. While race will be controlled in this study, specific racial variations will be explored in future research. Age and education will be left as a continuous variable while income will be standardized to 2007-equivalent values in order to account for inflation.

The PSID asks respondents at each interview whether household heads are working, temporarily laid off or on leave, looking for work or unemployed, retired, disabled (permanently or temporarily), keeping house, student, or other (workfare in prison or jail). Therefore, I will include employment status. In addition, I will incorporate employment industry. It is plausible that those working in the manufacturing industry are more likely to live close to where they work (possibly more heavily polluted neighborhoods) and would therefore have a higher exposure to more pollution on the job. Marital status includes: married; never married; widowed; divorced/annulled; and separated.

This study uses select neighborhood variables with strong ties to the dependent variable and main independent variable. Neighborhood context is taken into account by examining respondents' neighborhood racial profile (percent minority), and income (average family income), all in the tract of residence.[4]

[4] There are statistically significant and relatively high correlations between neighborhood variables (see Table 6); however, adding each separately (meaning independent of the other neighborhood variables) significantly improves model fit. In addition, past research has found these variables to be instrumental in predicting self-rated health and/or pollution. (Diez-Roux 2001; Stafford et al 2004; Boardman, et al 2008; Do and Finch 2008; Ross and Mirowski 2008; Ruel & Robert 2009; Giatti et al 2010). Additional neighborhood level variables such as percent poverty and percent of female heads of household in the respondents' tract of residence were considered; however, these variables were too strongly correlated with each other to produce reliable coefficients (also see Table 6).

Chapter Six

ANALYTIC STRATEGY

To study the associations between local pollution and subjective health over PSID study years between 1990 and 2007, I use ordered logit regression models with robust standard errors for clustering at the individual level. Ordered logit models allow for regression analysis that is able to utilize the full five-response health variable. These regression models measure the variance across individuals but may produce biased results because they do not take into account selection processes and unobserved individual-level characteristics influencing both health and exposure to pollution. Despite these limitations, ordered logit regression models are preferred because they allow for full variance in the subjective health variable to be observed.[5] This study also utilizes multiple levels of analysis presented in the independent variables. Multilevel variables are useful to this study because they allow for the disaggregation of error structures over observational and individual levels of collection. Concerns regarding correlated error terms due to with-in person repeated observations are adjusted for by clustering observations on respondents' unique identifying variables.

[5] Methods for estimating fixed effects for ordered logit regression models are not yet established; therefore, in my analysis I will compare the sensitivity of ordered logit models with linear fixed effects models (see Table 5.).

Analytical models are estimated by first examining the association of pollution with health without controlling for confounding variables. Next, I add in sociodemographic variables which are mentioned in previous literature to have an influence health and pollution. Finally, racial profile (percent minority), and income (average family income) variables in the tract of residence are added to the models along with the sociodemographic variables to further isolate the association between pollution and health. Full models include the pollution and gender interaction term with both sociodemographic and neighborhood variables. These same steps are taken with a subset of the sample that includes only respondents identified as household heads. This analytic strategy will provide additional support to the proposed relationships using solely self-reported measures and exploring possible differences between male and female heads of household. If theoretical arguments linking local pollution to individual health outcomes are accurate, I expect to see a negative, statistically significant association between neighborhood pollution and subjective health for both the complete sample population as well as the subset of household heads. In addition, due to underlying theoretical mechanisms, I expect to find the influence of higher concentrations of pollution to be greater on women's poor health than men's poor health.

Chapter Seven

RESULTS

The study population incorporates 9,591 male and female PSID respondents and their spouses (see Table 1 and Table 1a). Sixty-three percent of household heads in the sample are male and 19% are female. There are 1,728 spouses in the sample; around 42% of females in the sample are spouses (see Table 1). Table 2 provides descriptive statistics for all of the variables used in this study. The age range of respondents in the sample spans from 16-98; the mean age of the population is 37. Average education attained in years is the equivalent of a high school education. The average respondent is married and working. Both characteristics are associated with better overall wellbeing. Sixty-two percent of the respondents report working in a manufacturing occupation that, in nature, may increase a respondents' exposure to pollution.

Table 2 provides descriptive statistics by gender and household status. These findings highlight differential experiences for male and female heads of household. The average age of female and male household heads is 40 and 39 respectively, while the average age for female and male spouses in the sample is 41 and 33, respectively. As one might expect, there are less female household heads working in manufacturing occupations (.36) than male household heads (.66), 36% to 66% respectively. Eighty-one percent of male household heads are married compared to .3% of female household heads. Over six percent of male spouses are married while 97% of female spouses are married. The educational level of men and women (household heads and spouses) in the sample are comparable, around 12 years. The median income for male heads of household ($34,005) is more than double the median income for female household heads ($16,900); however the median income for male and female spouses shows less of a gap ($31,875 and $28,653, respectively). Married heads of household report a median income of $38,294 while the median income for unmarried heads of heads of household is only $17,850.

Finally, in Table 2 we see relative differences in neighborhood characteristics. On average, females household heads in the sample live in neighborhoods with higher percentages of minorities (48%) compared to female spouses who tend to live in neighborhoods with lower percentages of minorities (36%). In addition, female household heads in the sample tend to live in neighborhoods with lower average family incomes than female spouses ($39,562 and $49,842, respectively), while male household heads in the sample live in neighborhoods with lower average family incomes than male spouses ($43,696 and $58,671, respectively). Differences in employment status of male and female spouses may contribute to differences in neighborhood average family incomes by raising the total household income and making higher income neighborhoods accessible. Table 2 shows that while 78% of male spouses are currently working, only 55% of female spouses are working. These results highlight the sample characteristics of respondents and their surrounding environments for which health is being predicted, however, I note that the female head sample is over-represented by single mothers in the sample, thus somewhat limiting the neighborhood variation for them.

In Table 3, average health descriptive statistics are displayed using the five response health variable where “1” is poor, “2” is fair, “3” is good, “4” is very good, and “5” is excellent. Also in Table 3 are frequencies of health status by sociodemographic characteristic. Overall, females more frequently report poorer subjective health than men 3.5 versus 3.8, respectively. Frequency distributions show that differences in average health of men versus women are due to the dearth of women reporting very good and excellent health. Minorities, except those classified as Asian and other race, report a .2 or greater difference in subjective health than whites. As age increases, health declines; this finding may be due to correlations with disabilities and the onset of illness and disease with increasing age. Differing levels of education also show variations in health status where higher levels of education are associated with better health reporting. In addition, average subjective health improves as income gets higher. Those within manufacturing occupations report a slightly lower average subjective health (3.70) than those who do not work in this sector of the economy (3.77). This finding might be explained by the security in having a job and a steady income. Or, it is possible that those who report working in the manufacturing industry are owners/managers and not solely blue collar workers. As a result, their exposure to pollution in the work place may be limited. Within this sample I also find that the mean age of individuals in the manufacturing industry is slightly lower than those in non-manufacturing occupations. Therefore age may also help explain the association between occupation and health status. The results for employment status show that working respondents and students have a higher average health status than any of the other occupations (3.79 and 3.75, respectively). Respondents that are disabled (2.35), retired (3.02), or temporarily laid-off (3.18), report the lowest health status. Respondents who are not married also report a lower health status (3.67) than persons who are married (3.77). These results are consistent with findings that gender, race, income, education, age, employment status and marital status influence subjective health (Ross and Huber 1985; Adler et al 1994; Ross and Mirowsky 1995; Ross and Wu 1996; Ferrie et al 1998; Mirowsky and Ross 1998; Reynolds and Ross 1998; Park 2005; Subramanian and Kawachi 2006; Goesling 2007; Cummings and Jackson 2008; Heard et al 2008).

Table 3a presents averages in subjective health by household status. Results show that for all racial groups, female heads of household have lower averages of subjective health than male heads of household. The same trend is present for all sociodemographic characteristics except for two employment status variables: temporarily laid off and homemaker, where female household heads have a higher average subjective health than male household heads.

In Table 4 I move forward to describe the association between pollution and subjective health using ordered logit models. Model 1 predicts subjective health using pollution. This model is estimated using 5 parameters, 1 independent variable and 4 cut points. The cut points numerically represents numerical thresholds between categorical outcomes. The pollution coefficient in this model confirms that excellent health is negatively correlated with increasing pollution. The log odds of reporting an increase in health status (i.e., better health) reduce by 0.1 percent with every 10,000 unit increase in pollution.[6] At the most basic level, this model supports the hypothesis that subjective health is negatively influenced by increased concentrations of local pollution.

Model 2 includes socio-demographic controls that are theoretically linked to both health status and exposure to pollution. With these additional controls, Model 2 shows that

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[6] Odds for subjective health as a function of pollution were derived using the following expression ($e^{.002}$-1) X 100.

pollution is still associated with health; however, some of this association can be explained by sociodemographic characteristics. Most specifically, Model 2 shows that nearly all of the added independent variables are important correlates of health. For example, in concert with theory, age has a negative association with health, whereas income and education have a positive association with health. Marital status also has a positive association with health. Black and Hispanic respondents are statistically significant correlates of health. Also in Model 2 I find that every $10,000 increase in individual level income is associated with a 0.4 percent (i.e., ($e^{.0037}$-1) X 100) increase in log odds of reporting good health.

While small, the effect size of pollution can more easily be seen in comparison with average family income in the census tract. For example, in Model 3, one standard deviation increase in pollution exposure is associated with a 0.000025 decrease in the ordinal scale of health while a one standard deviation increase in average family income in tract is associated with a .003 increase in the ordinal health scale. The association of neighborhood pollution with health is therefore quite small relative to the association of average neighborhood income with health, even with individual and other neighborhood characteristics taken into account.

Model 3 also helps to further isolate the association between pollution and health by adding in neighborhood characteristics. Percent minority has a negative association with good health. Average family income in a respondent's tract of residence is positively associated with good health. These findings are expected given arguments about the influence of neighborhood factors on health (Diez-Roux 2001; Stafford et al 2004; Boardman, et al 2008; Do and Finch 2008; Ross and Mirowski 2008; Ruel & Robert 2009; Giatti et al 2010).

BIC goodness of fit tests show that Models 2 and 3 are better able to predict health. Variance in BIC between Models 2 and 3 are very small. Psuedo R^2 also tells us that the most variation in health is explained in model 3 (0.0618). These statistical differences may be representative of the magnitude of neighborhood characteristics on self-rated health.

Results surrounding the role of gender in the association between pollution and subjective health are also explored in Table 4. In Model 4, the interaction between pollution and gender is added. In Model 4 the product term is statistically insignificant; however, the coefficient for the product term is in the negative direction. Supplemental statistical tests show that the addition of the product term does not significantly improve Model 3 (prob>chi2 = 0.4768)[7]. While females more often report having poorer health than men, there is not strong evidence that gender moderates the association between pollution and health.

In Table 4a I report results that estimate ordered logit models using solely PSID household heads in order to bring forth differences that may exist between male and female household heads and to test the sensitivity of spousal reporting of subjective health. Results show similarities in the direction of the association between pollution and subjective health in the sample of household heads and in the full sample of household heads and spouses.

Table 5 presents results using fixed effects linear regression models using the entire sample population to check the sensitivity of the ordered logit models (1-3) used within this study (see Table 5). This method of comparison treats self-rated health as a linear dependent variable. It is valid to think of self-rated health as linear because unlike other clearly ordered

[7] Wald tests were performed on ordered logit regression models to formally test whether the addition of the product term significantly improved the models. This method was taken because Stata is unable to produce valid likelihood ratio test statistics for ordered logit models due the ordered logit's robust standard errors.

measures (e.g. physical activity: never, monthly, weekly, daily), self-rated health is nearly linear in its 5-category construction. Using linear models to estimate models with the 5-category self-rated health indicator is not unusual (see Burgard, Brand and House 2007). By adding the fixed effect and random effect linear comparison, I am able to compare results that take account of unobserved variation within individuals across time (i.e., fixed effects) and their potential influence on self-rated health in the random effects models.

Table 5. displays the results of both fixed effect and random effect linear regressions. Results show that pollution is a significant predictor of subjective health in random effects models but not in the fixed effects models. This finding may suggest that unobservable selection factors contribute to the statistical significance found in the ordered logit models. Household status, individual income and being laid off, however, continue to be significant predictors of good health throughout both fixed effect and random effect models. Differences in statistical significance may also be attributed to low numbers of repeated observations per respondent. However, results show similarities in the direction of the associations between health and sociodemographic/neighborhood independent variables.

Chapter Eight

CONCLUSIONS

This study provides empirical evidence for an association between neighborhood pollution and subjective health. While some of this association can be explained by sociodemographic and neighborhood factors, as pollution exposure increases, the likelihood of reporting poor health increases This finding is consistent with documented associations between pollution and other psychological and physiological health outcomes (Lima 2004; Chen 2005; Bevc, Marshall, and Picou 2007; Boardman et al 2008; Charafeddine and Boden 2008; Sun et al 2008). In addition, this study adds further support to prior research that has found sociodemographic and neighborhood characteristics to be important factors contributing to health status (Ross and Huber 1985; Adler et al 1994; Ross and Mirowsky 1995; Ross and Wu 1996; Ferrie et al 1998; Mirowsky and Ross 1998; Reynolds and Ross 1998; Park 2005; Subramanian and Kawachi 2006; Goesling 2007; Cummings and Jackson 2008; Heard et al 2008). Though increases in average units of pollution in a tract are associated with very small declines in subjective health, these declines are significant, meaning it is highly unlikely that the decline shown in the results is by chance. This suggests that exposure to neighborhood pollution is correlated with one's well-being psychologically.

Though the interaction between gender and pollution is not found to be statistically significant in this study, the direction of the coefficient is negative as hypothesized. Employment and social ties may contribute to the finding that gender does not moderate the association between pollution and subjective health. First, the majority of the women in the sample were working or looking for a job. Results show that employment status does attenuate the association between pollution and subjective health (along with other factors). Perhaps the subjective health of working women is influenced by pollution in a similar manner to how men's subjective health is influenced by pollution. The gender effect is stronger in Table 4A (for female household heads) than in Table 4 (all women, household heads and spouses), but it is difficult to discern whether it is the employment status of female household heads or something else that matters.

Second, research has uncovered the importance of weak ties in the social world. Scholars have found that weak ties are important to social networks and the dissemination of information (Granovetter 1973; Thoits 2011). This suggests that weaker social ties within a neighborhood across men and women may more widely spread the word of environmental hazards than strong ties. Therefore, while women may have deeper social networks, men may still receive the same information through their weak social ties.

Limitations of this study include omitted variables such as smoking status and neighborhood interaction. Tobacco use has known associations with poor self-rated health and other adverse health outcomes (Pope et al 1993; Power et al 1998; Kawachi et al 1999; Vidrine et al 2009). Smoking may lessen the influence of pollutions emitted from facilities due to the very nature of tobacco as a pollutant. This variable was not used in the present study because it was not available for the whole 17 year study period. Future research will include survey questions pertaining to smoking status and social interactions surrounding one's place of residence and work environment should be included in future analyses.

In spite of non-statistically significant findings surrounding the role of gender in the association between pollution and health and limitations in the data, this research brings to light important thoughts on how environmental injustice may affect social groups differently. Pollution emitting facilities position themselves in areas with lower property values and where they will face the least community resistance (Wing et al 2000; Lipfert 2004; Brulle and Pellow 2006; Strife and Downey 2009). The question for researchers then becomes how does one assess the presence of these facilities on the community that is being exploited? This study may be one step in the right direction by exploring pollution at the neighborhood level and its role in a health outcome that has social, psychological, and physiological ties.

The findings of this study point to race, class and age inequities in subjective health and exposure to pollution. Research on environmental racism reports that minority and poor populations (especially in rural areas) are disproportionately exposed to higher concentrations of pollution (Wing et al 2000; Lipfert 2004; Brulle and Pellow 2006; Strife and Downey 2009). Upcoming studies should further explore the role of race/ethnicity, class, and age in the association between pollution and subjective health.

Many studies have been conducted to assess the effects of pollution on objective health outcomes such as cardiovascular diseases, asthma, mental health etc...(Pope 1993; Dominici et al 2003; Glinianaia et al 2004; Barnett et al 2006; Burra et al 2006; Andersen et al 2007; Bell et al 2007; Grineski et al 2007; Slama et al 2007; Chen et al 2008; Ren and Tong 2008; Boardman et al 2008). Most recent studies lend strong support to a causal relationship between pollution and various objective health outcomes such as respiratory morbidity and mortality (Delfino et al 2009; Jerrett et al 2009; Lepeule et al 2012). These studies broaden our knowledge about pollution effects but tend to ignore the role of social factors and subjective health within the association between pollution and health. For example, a recent relevant study by Lepeule et al (2012) follows a cohort from six cities in the US from 1974-2009 and finds chronic exposure to pollution yields significant associations with all-cause and cardiovascular mortality. However, many sociodemographic factors are left out of this analysis including marital status and income. Future research should explore the notion of subjective health, derived in part by social factors, as a salient participant in adverse objective health consequences as a result of pollution exposure. Research that examines the influence of pollution on a person's well-being in conjunction with objective health consequences will go far to define the accurate influence of social factors on pollution and outline key components of intervention strategies.

TABLES

Table 1. PSID Respondents by Household Status and Gender, N=9,591			
Household Status	Male	Female	Total
Head	6,014	1,849	7,863
Spouse	382	1,346	1,728
Total	6396	3,195	9,591

Table 1a. Percentage of PSID Respondents by Household Status and Gender, N=9,591			
Household Status	Male	Female	Total
Head	63%	19%	82%
Spouse	4%	14%	18%
Total	66%	34%	100%

Table 2. Descriptive Statistics for Variables in Models of Subjective Health – PSID, 1990-2007[8]										
	Total Population		**Females Household Heads**		**Female Spouses**		**Male Household Heads**		**Male spouses**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Dependent Variable										
Subjective Health	3.730	1.026	3.529	0.930	3.519	0.951	3.789	0.879	3.743	0.941
Independent Variables										
Total Pollution in Tract	64601.94	324777	72802.86	274601	62575.58	298094	60810.34	294733	34754.92	84957
Race (1=Yes)										
White	0.640	0.479	0.502	0.499	0.648	0.484	0.706	0.463	0.652	0.469
Black	0.286	0.452	0.439	0.494	0.305	0.467	0.221	0.423	0.284	0.445
Native Amer.	0.006	0.081	0.005	0.082	0.006	0.088	0.006	0.081	0.004	0.070
Asian	0.003	0.061	0.001	0.053	0.005	0.066	0.004	0.065	0.000	0.000
Hispanic	0.050	0.219	0.040	0.212	0.026	0.183	0.047	0.224	0.047	0.212
Other	0.011	0.106	0.010	0.117	0.007	0.086	0.013	0.118	0.011	0.111
Age	37	12	40	14	41	16	39	12	33	10
Education (years)	12.371	2.816	12.380	2.652	12.121	2.529	12.615	2.926	12.534	2.156
Income (Median)	29,297		16,900		28,653		34,005		31,875	
Manufacturing Occupation (1=yes)	0.625	0.483	0.362	0.462	0.652	0.428	0.666	0.438	0.993	0.060
Employment Status (1=yes)										
Working	0.870	0.335	0.930	0.239	0.556	0.448	0.952	0.215	0.781	0.378
Temporarily Laid Off	0.017	0.130	0.019	0.112	0.013	0.084	0.011	0.099	0.013	0.101
Looking for Work	0.021	0.144	0.014	0.108	0.047	0.177	0.010	0.099	0.074	0.273
Retired	0.028	0.167	0.016	0.120	0.082	0.23	0.017	0.139	0.051	0.139
Disabled	0.005	0.073	0.001	0.034	0.013	0.095	0.002	0.056	0.049	0.164
Homemaker	0.046	0.210	0.010	0.117	0.271	0.383	0.000	0.028	0.006	0.086
Student	0.007	0.085	0.006	0.068	0.014	0.106	0.003	0.042	0.022	0.149
Other	0.002	0.064	0.000	0.024	0.000	0.015	0.001	0.060	0.000	0.000
Marital Status (1=married)	0.625	0.484	0.003	0.053	0.971	0.209	0.812	0.390	0.069	0.14
Neighborhood Characteristics in Tract of Residence										
Percent minority	39.24	34.98	48.04	35.36	36.96	33.61	35.05	33.47	35.76	32.51
Average family income	41883.57	20298.06	39562.44	18816.09	49842.95	22048.93	43696.43	19304.27	58671.06	28827.67
N of observations		9,591		1,849		1,346		6,014		382

[8] Due to rounding, some totals may be slightly above or below 100.

Table 3. Average Health and Frequencies of Health Status of PSID Sample by Sociodemographic Characteristics (N=9,591)							
	Mean	SD	1=Poor	2=Fair	3=Good	4=Very	5=Excellent
Dependent Variable							
Subjective Health	3.730	1.026	195	944	2,690	3,186	2,576
Independent Variables							
Sex							
-Female	3.536	1.043	96	400	1,047	999	653
-Male	3.827	1.003	99	544	1,643	2,187	1,923
Race							
-White	3.836	1.000	114	475	1,552	2,164	1,837
-Black	3.532	1.034	61	372	935	808	575
-Native Amer.	3.453	1.082	2	10	22	17	13
-Asian	3.888	0.979	1	2	7	16	10
-Hispanic	3.542	1.080	14	72	146	146	109
-Other	3.720	1.088	3	13	28	35	32
Age							
16-30	3.965	0.914	23	172	765	1,230	1,065
31-40	3.783	0.981	38	251	904	1,026	855
41-50	3.618	1.050	38	211	499	523	398
51-64	3.347	1.131	63	209	375	306	218
65+	3.033	1.082	33	101	147	101	40
Education (years)							
0-12yrs	3.558	1.057	171	775	1,851	1,833	1,298
13-16yrs	4.007	0.906	24	169	839	1,353	1,278
Income							
<$15,000	3.456	1.117	93	336	660	592	452
>$15,000<$45,000	3.701	1.005	83	478	1,425	1,610	1,197
>$45,000	4.006	0.913	19	130	605	984	927
Occupation							
-Manufacturing	3.705	1.033	136	620	1,674	2,018	1,554
-Non-Manufacturing	3.771	1.012	59	324	1,016	1,168	1,022
Employment Status							
-Working	3.799	0.990	112	709	2,299	2,854	2,379
-Temporarily Laid Off	3.180	1.232	17	33	48	39	29
-Looking for Work	3.549	1.018	3	31	61	69	40
-Retired	3.021	1.081	22	67	98	65	26
-Disabled	2.346	1.202	16	14	13	6	3
-Homemaker	3.328	1.123	24	82	142	121	78
-Student	3.757	0.923	0	6	22	25	17
-Other	3.523	1.077	1	2	7	7	4
Marital Status							
-Married	3.767	1.022	117	544	1,661	1,967	1,707
-Not-Married	3.667	1.028	78	400	1,029	1,219	869

Table 3a. Average Health along Sociodemographic Characteristics, Household Status, and Gender (N=9,591)								
	Household Head		Spouse		Household Head		Spouse	
	Female	SD	Female	SD	Male	SD	Male	SD
Dependent Variable								
Subjective Health	3.546	1.036	3.523	1.053	3.831	1.007	3.746	0.940
Independent Variables								
Race								
-White	3.739	1.003	3.603	1.049	3.903	1.050	3.869	0.985
-Black	3.369	1.016	3.373	1.052	3.674	1.052	3.560	0.868
-Native Amer.	2.667	1.225	3.333	0.985	3.683	1.035	3.000	0.000
-Asian	3.667	0.577	4.286	0.756	3.808	1.059	0.000	0.000
-Hispanic	3.297	1.188	3.372	0.926	3.637	1.047	3.357	1.336
-Other	3.619	0.865	3.333	1.500	3.789	1.123	3.800	0.447
Age								
16-30	3.871	0.899	3.856	0.884	4.035	0.927	3.915	0.873
31-40	3.526	0.981	3.538	0.999	3.894	0.961	3.663	0.941
41-50	3.392	1.062	3.525	1.121	3.695	1.029	3.480	1.035
51-64	3.145	1.142	3.134	1.107	3.472	1.118	3.400	0.986
65+	3.037	1.084	2.797	1.069	3.272	1.045	2.800	1.304
Education (years)								
0-12yrs	3.406	1.054	3.362	1.059	3.659	1.051	3.559	0.963
13-16yrs	3.779	0.959	3.896	0.940	4.086	0.878	4.095	0.799
Income								
<$15,000	3.439	1.086	3.067	1.178	3.586	1.103	3.454	1.069
>$15,000<$45,000	3.595	0.991	3.554	0.988	3.768	1.014	3.693	0.916
>$45,000	3.864	0.915	3.842	0.945	4.036	0.909	4.015	0.843
Occupation								
-Manufacturing	3.594	1.036	3.410	1.094	3.787	1.013	3.763	0.942
-Non-Manufacturing	3.516	1.035	3.764	0.918	3.918	0.990	4.00	0.000
Employment Status								
-Working	3.581	1.025	3.744	0.934	3.871	0.980	3.821	0.921
-Temporarily Laid Off	3.352	1.097	3.523	0.928	3.056	1.337	3.200	0.447
-Looking for Work	3.273	0.977	3.441	0.983	3.746	1.079	3.625	0.942
-Retired	2.824	0.999	2.900	1.115	3.153	1.056	3.143	1.345
-Disabled	1.333	0.577	2.167	1.098	2.400	1.392	2.818	0.982
-Homemaker	3.229	1.140	3.349	1.125	2.200	0.447	3.667	0.577
-Student	3.438	0.964	3.695	0.876	3.857	1.014	4.200	0.632
-Other	3.000	0.000	5.000	0.000	3.473	1.073	0.000	0.000
Marital Status								
-Married	3.857	0.690	3.504	1.056	3.840	1.002	3.000	0.816
-Not-Married	3.544	1.036	3.840	0.959	3.800	1.025	3.778	0.937

Table 4. Ordered Logit Results for Health Status, PSID 1990-2007

Model	1	2	3	4
	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)
Average pollution in tract (*10,000s)	-0.0020***	-0.0012***	-0.0008*	-0.0011**
	0.0005	*0.0004*	*0.0004*	*.0005*
Sociodemographic Characteristics				
Female		-0.2947***	-0.2717***	-0.2772***
		-0.0476	*0.0477*	*0.0483*
Female*Pollution				*0.0008***
				0.0010
Household Head		0.0709	0.1574**	0.1563**
		0.0546	0.0553	0.0553
Race (white)				
Black		-0.4706***	-0.3484***	-0.3487***
		-0.0383	*0.0447*	*0.0447*
Native Am.		-0.3399	-0.2632	-0.2633
		0.2100	*0.2134*	*0.2134*
Asian		-0.3663	-0.4029	-0.4030
		0.3216	*0.3169*	*0.3169*
Latino		-0.1903**	-0.0945	-0.0945
		0.0861	*0.0878*	*0.0877*
Other		-0.1721	-0.0952	-0.1000
		0.1389	*0.1396*	*0.1402*
Age (squared)		0.0003***	0.0004***	0.0004***
		0.0000	*0.0000*	*0.0000*
Age		*-0.0678****	-0.0683***	-0.0684***
		0.0080	*0.0080*	*0.0080*
Education (in years)		0.1754***	0.1566***	0.1566***
		0.0071	*0.0074*	*0.0074*
Income (*10,000)		0.0037	0.0026	0.0026
		0.0024	*0.0017*	*0.0017*
Manufacturing		-0.0685*	-0.0668*	-0.0667**
		0.0337	*0.0339*	*0.0339*
Employment Status (working)				
Laid off temp.		-0.6809***	-0.6494***	-0.6488***
		0.1293	*0.1299*	*0.1299*
Looking for job		-0.2612***	-0.2437**	-0.2444**
		0.0889	*0.0885*	*0.0884*
Retired		-0.3285***	-0.3193**	-0.3188**
		0.1075	*0.1064*	*0.1064*
Disabled		-2.2789***	-2.2805***	-2.2816***
		0.2943	*0.2866*	*0.2862*
Home maker		-0.3369***	-0.3228***	-0.3253***
		0.0863	*0.0857*	*0.0858*
Student		-0.4303***	-0.4179**	-0.4175**
		0.1473	*0.1471*	*0.1471*
Other		-0.0797	-0.1567	-0.1572
		0.3212	*0.3241*	*0.3242*
Married		0.1594***	0.1684***	0.1685***
		0.0400	*0.0400*	*0.0400*
Neighborhood Context				
% Minority in tract			-0.0015**	-0.0015**
			0.0006	*0.0006*
Average family income in tract (/10,000)			0.00657***	0.0555***
			0.0086	*0.0096*
Cut Point 1	-3.9818	-4.2507	-4.1651	-4.1678
	0.0592	*0.2021*	*0.2034*	*0.2038*
Cut Point 2	-2.081	-2.2021	-2.1157	-2.1188
	0.0274	*0.1945*	*0.1961*	*0.1964*
Cut Point 3	-0.3853	-0.2883	-0.1960	0.1990
	0.0181	*0.1942*	*0.1957*	*0.1960*
Cut Point 4	1.0485	1.3029	1.4024	1.3995
	0.0202	*0.1949*	*0.1962*	*0.1965*
N of Individuals	9591	9591	9591	9591
Yearly Observations	29152	29152	29152	29152
Pseudo R2	0.0004	0.0612	0.0633	0.0633
Standard Errors in Italics	*** p<0.01, ** p<0.05, * p<0.1			
Goodness of Fit Measures	Model 1	Model 2	Model 3	Model 4
BIC Statistic	80004	75352	75202	75211
LR Statistic	35 (1)	4893 (21)	5062 (23)	5064 (24)

Table 4a. Ordered Logit Results for Health Status, PSID Household Heads (N=8,223) 1990-2007		
Model	3	4
	Coefficient (*SE*)	Coefficient (*SE*)
Average pollution in tract (*10,000s)	-0.0008*	-0.0012**
	0.0004	*0.0005*
Sociodemographic Characteristics		
Female	-0.3006***	-0.3156***
	0.0592	*0.0598*
Female*Pollution		*0.0021***
		0.0010[9]
Race (white)		
Black	-0.3428***	-0.3442***
	0.0485	*0.0485*
Native Am.	-0.1905	-0.1911
	0.2339	*0.2338*
Asian	-0.7089**	-0.7100**
	0.3139	*0.3140*
Latino	-0.0838	-0.0853
	0.0947	*0.0944*
Other	-0.1058	-0.1203
	0.1483	*0.1495*
Age (squared)	0.0005***	0.0005***
	0.0001	*0.0001*
Age	-0.0785***	-0.0786***
	0.0091	*0.0091*
Education (in years)	0.1564***	0.1564***
	0.0079	*0.0079*
Income (*10,000)	0.0028*	0.0028*
	0.0016	*0.0016*
Manufacturing	-0.0456	-0.0453
	0.0368	*0.0368*
Employment Status (working)		
Laid off temp.	-0.7309***	-0.7284***
	0.1545	*0.1545*
Looking for job	-0.0905	-0.0906
	0.1182	*0.1185*
Retired	-0.3722**	-0.3734**
	0.1240	*0.1240*
Disabled	-2.3875***	-2.3872***
	0.4231	*0.4231*
Homemaker	-0.3894	-0.3904
	0.2729	*0.2738*
Student	-0.3294	-0.3269
	0.2111	*0.2109*
Other	-0.3767	-0.3780
	0.3157	*0.3158*
Married	0.1555**	0.1549**
	0.0509	*0.0509*
Neighborhood Context		
% Minority in tract	-0.0013**	-0.0013**
	0.0006	*0.0006*
Average family income in tract (/10,000)	0.0637***	0.0638***
	0.0097	*0.0097*
Cut Point 1	-45963	-4.600
	0.2211	*0.2212*
Cut Point 2	-2.4420	-2.4484
	0.2111	*0.2111*
Cut Point 3	-0.5240	-0.5301
	0.2104	*0.2105*
Cut Point 4	1.0649	1.0590
	0.2107	*0.2108*
N of Individuals	8,223	8,223
Total Observations	24,467	24,467
Pseudo R2	0.0573	0.0574
Standard Errors in Italics	*** p<0.01, ** p<0.05, * p<0.1	
Goodness of Fit Measures	Model 1	Model 2
BIC Statistic	62876	62881
LR Statistic	3806 (22)	3811 (23)

[9] Wald test results show that the addition of a gender-pollution interaction term does not statistically improve statistical models within this sample of household heads (Prob>Chi Square = 0.06).

Table 5. Linear Regression Results for Health Status, PSID 1990-2007, N=9,591						
	Fixed Effect			Random Effect		
Model	1	2	3	1	2	3
	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)	Coefficient (*SE*)
Average pollution in tract (*10,000s)	-0.0002 *0.0003*	-0.0003 *0.0003*	-0.0002 *0.0003*	-0.0007** *0.0002*	-0.0005** *0.0001*	-0.0003* *0.0001*
Sociodemographic Characteristics						
Household Head		0.0987** *0.0412*	0.0988** *0.0412*		0.0750** *0.0247*	0.0977*** *0.0248*
Age		-0.0224*** *0.0034*	-0.0217*** *0.0036*		-0.0299*** *0.0038*	-0.0303*** *0.0038*
Education (in years)		0.0082 *0.0222*	0.0081 *0.0222*		0.0868*** *0.0032*	0.0788*** *0.0034*
Income (*10,000)		0.0007** *0.0003*	0.0007** *0.0003*		0.0008** *0.0004*	0.0008** *0.0004*
Manufacturing		0.0035 *0.0206*	0.0035 *0.0206*		0.01708 *0.0165*	0.0165 *0.0143*
Employment Status (working) Laid off temp.		-0.2365*** *0.0546*	-0.2364*** *0.0547*		-0.2950*** *0.0518*	-0.2912*** *0.0520*
Looking for job		-0.0484 *0.0476*	-0.0489 *0.0476*		-0.0905** *0.0401*	-0.0862** *0.0400*
Retired		-0.0241 *0.0451*	-0.0241 *0.0450*		-0.1058** *0.0395*	-0.1056** *0.0394*
Disabled		-0.0043 *0.1115*	-0.0042 *0.1116*		-0.4937*** *0.0964*	-1.5055*** *0.0951*
Homemaker		-0.0388 *0.0411*	-0.0386 *0.0411*		-0.0663*** *0.0335*	-0.0664** *0.0333*
Student		-0.0218 *0.0821*	-0.0202 *0.0820*		-0.0903 *0.0704*	-0.0849 *0.0704*
Other		-0.1787 *0.2612*	-0.1790 *0.2618*		-0.1354 *0.1642*	-0.1515 *0.1643*
Married		0.0161 *0.0292*	0.0158 *0.0292*		0.0594*** *0.0178*	0.0641*** *0.0177*
Neighborhood Context						
% Minority in tract			-0.0009 *0.0006*			-0.0008*** *0.0002*
Average family income in tract (/10,000)			0.0032 *0.0073*			0.0246*** *0.0037*
Constant	3.7198*** *0.0020*	4.6167*** *0.3155*	4.6373*** *0.3153*	3.7255*** *0.0094*	3.5831*** *0.0906*	3.5793*** *0.0909*
N of Individuals	9,591	9,591	9,591	9,591	9,591	9,591
Total Observations	29,152	29,152	29,152	29,152	29,152	29,152
R2	0.0012	0.0523	0.0596	0.0012	0.1578	0.1630
Number of Years	13	13	13	13	13	13
Standard Errors in Italics						
*** p<0.01, ** p<0.05, * p<0.1						

Table 6. Correlation Matrix for Neighborhood Level Variables (Tract of Residence)				
	% Minority	Avg. Family Income	% Female Heads of Household	% Poverty
% Minority	1			
Avg. Family Income	-0.3998*	1		
% Female Heads of Household	0.7045*	-0.4770*	1	
% Poverty	0.6416*	-0.6069*	0.7258*	1

* p<.05

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