THREE ESSAYS ON TOXIC CHEMICAL RELEASES, HOUSE VALUES,

HEALTH AND LABOR PRODUCTIVITY

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THREE ESSAYS ON TOXIC CHEMICAL RELEASES, HOUSE VALUES, HEALTH AND LABOR PRODUCTIVITY

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DISSERTATION ABSTRACT

THREE ESSAYS ON TOXIC CHEMICAL RELEASES, HOUSE VALUES,

HEALTH AND LABOR PRODUCTIVITY

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The Toxics Release Inventory is a public access database established under the Emergency Planning and Community Right-to-Know Act (EPCRA) to protect public health, safety and the environment from toxic chemical hazards. In 2002, industrial facilities in the US were required to report their annual environmental releases of approximately 650 toxic chemicals to the Environmental Protection Agency. Around 4 billion pounds of toxic chemicals were released into the environment in 2002 from industrial facilities. These toxic substances have the potential to impact morbidity and mortality in a significant way.

The City of Anniston in Calhoun County, Alabama is one of many places that have to deal with multiple environmental hazards. In the mid-1990s Anniston discovered that the city had been heavily contaminated with PCBs. Then, in the late-1990s, the US Army began the construction of Anniston Chemical Agent Disposal Facility to dispose of chemical weapons at the Anniston Army Depot, which is a Superfund site and generating a significant amount of toxic chemicals. To make the situation worse, lead contamination in Anniston was discovered in 2000, when EPA conducted tests for PCBs.

Impacts of toxic chemicals on human health may impose several types of costs to the society. The first type of these costs is the depreciation of values of residential properties in the area with high levels of toxic chemicals. The second type is the ultimate direct and indirect costs associated with health impacts of toxic substances.

The purpose of this dissertation is to investigate the impacts that toxic chemicals pose on the society. Specifically, we analyze how toxic substances affect property values, individual's health status and labor productivity losses. A number of economic models including hedonic price model and health capital models as well as econometric models including Full Information Maximum Likelihood model, generalized instrumental variable model and count model, are employed for the analysis.

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I. INTRODUCTION

The Emergency Planning and Community Right-to-Know Act (EPCRA) was enacted in 1986 by Congress to protect public health, safety and the environment from toxic chemical hazards. The law gives the public the right to know about toxic chemical releases in their community by requiring major industrial facilities in the U.S. to report their emissions of certain toxic chemical substances into the environment. Under EPCRA, the Toxics Release Inventory (TRI) program, managed by US Environmental Protection Agency (USEPA), was established to contain yearly information on toxic chemical releases and other waste management from industrial facilities.

In 2002, industrial facilities were required to begin reporting their annual environmental releases of approximately 650 toxic chemicals to USEPA. Around 4 billion pounds of toxic chemicals were released into the environment in 2002 from industrial facilities, of which 1.6 billion pounds were air releases, 0.2 billion pounds were water releases, and 2.2 billion pounds were land releases (RTK NET 2002). Water and land toxic chemical releases include a huge amount of arsenic and arsenic compounds, lead compounds, nickel and nickel compounds, chromium compounds, and cadmium compounds, which are either possible or proven human carcinogens, respiratory toxicants, developmental toxicants, skin and sense organ toxicants, or cardiovascular toxicants (EPA 2005). All these toxic substances have the potential to impact morbidity and mortality in a significant way.

The City of Anniston in Calhoun County, Alabama is one of many places that have to deal with multiple environmental hazards. National focus on Anniston began in the mid-1990s when it was discovered that the city has been heavily contaminated with PCBs. The contamination occurred gradually over several decades since the time PCBs were first produced at the Anniston Monsanto plant. Then, in the late 1990, the US Army began the construction of Anniston Chemical Agent Disposal Facility to dispose of chemical weapons at Anniston Army Depot. The chemical weapons include the nerve agents GB (known as sarin) and VX, and blistering agents HD and HT (know as mustard gas), which are very toxic. Residents of the area surrounding the disposal facility are concerned about the health risks in the case of leaking of chemical weapons during the process of disposal. The Anniston Army Depot is also a Superfund site and generating a significant amount of toxic chemicals. To make the situation worse, lead contamination in Anniston was discovered in 2000, when EPA conducted tests for PCBs. Unlike PCBs contamination, lead has been released into Anniston by a number of sources including several private enterprises. Both PCBs and lead are very toxic chemicals, which may cause a number of ill health effects.

There may be a number of economic impacts resulting from environmental health risks associated with toxic chemicals. The first type of costs is the depreciation of values of residential properties in areas where high levels of toxic chemicals are present. It is believed that property values are determined not only by the physical characteristics of the house such as its age, size and quality but also by environmental goods such as parks and beaches and environmental bads such as landfills, incinerators and all types of pollution. In this case, concerns about potential heath risks may drive people away from the area filled with toxic chemical releases depressing property values in the area as a result.

The second type of cost is related to the ultimate direct and indirect health impact costs associated with substances. People exposed to toxic chemical releases may develop some environmental illnesses including asthma, developmental problem, immune system damage, birth defects as well as cancer. Direct costs would be costs of treatments for these environmental illnesses. Indirect costs come from productivity losses associated with these illnesses, including sick days in bed, restricted activity days and especially loss of workdays.

The purpose of this dissertation is to investigate the economic impacts that toxic chemicals impose on the society. Specifically, we analyze how toxic substances affect property values, individual's health status and labor productivity. A number of economic models, including the hedonic price model and health capital model are investigated using econometric techniques such as Full Information Maximum Likelihood model, generalized instrumental variables and count model. The next three chapters of this dissertation present three independent studies. The last chapter concludes the findings in this dissertation and provides some recommendations.

In the second chapter, we explore how environmental health risks influence property values where environmental risks are represented by toxic chemical releases, Superfund sites and cancer mortality. A simultaneous Full Information Maximum Likelihood (FIML) approach is employed to control for endogeneity of toxic releases and cancer mortality using a county level dataset from the US. A comparison between Ordinary Least Squares and FIML models is performed. We also estimate the value of statistical life and predict the effect of an environmental cleanup and calculate net benefits of such a policy.

In the third chapter, we investigate how toxic chemical releases impact individual's health status and labor productivity losses. We begin by providing a theoretical model of health capital to explain how time lost due to illness is affected by toxic chemical exposure. We then construct a system of equations to simultaneously estimate impacts of toxics on workdays lost. A generalized instrument variable approach is employed using a unique dataset combining the 2002 National Health Interview Survey, TRI and other data.

In the fourth chapter, we examine the effects of multiple environmental hazards on health and labor productivity in Calhoun County, Alabama. This study is a modified version of the third chapter using micro level data. Another difference is that in this study we employ the maximum likelihood approach to solve simultaneously the system of equations instead of an instrumental variable approach. Environmental hazards include PCB contamination, lead contamination and the Army Depot. A survey was conducted to obtain individual characteristics, economic status, education status, health status and labor productivity losses. The dataset used for this study is created by merging survey data with PCB and lead levels from EPA office in Anniston and other data.

The results from these studies may be useful for environmental policy makers, especially in cost-benefit analysis. For example, the results of the first and second studies could be used in cost-benefit analysis for environmental cleanup of Superfund sites and reduction of toxic chemical releases at the aggregate level of county in the US. The results of the third study would inform policy makers about the health effects and indirect costs of environmental hazards and those results may be used for welfare estimates for environmental cleanup of the City of Anniston or other places that contaminated with PCBs or lead.

II. CANCER MORTALITY, TOXIC CHEMICAL RELEASES, AND HOUSE VALUES IN THE UNITED STATES

2.1 Introduction

Environmental health risks have attracted much public attention in recent decades. Environmental risks arise from air, water and land pollution that come from automobiles, agricultural activities or undesirable facilities such as hazardous waste sites and industries at the local or regional level. In this paper, we attempt to measure the economic impacts of environmental health risks originating from point sources such as waste sites and industrial facilities.

Concerns about environmental health risks may be reflected in lowered property values, with a resulting negative impact on individual economic welfare. The idea is that people are willing to pay more to reduce environmental risks. However, compensating differentials for risk are only indirectly observed in marketed goods. One method that has been developed to estimate the risk-money tradeoff is the hedonic price model (HPM) using housing market data (Rosen 1974). The model assumes that housing consists of a bundle of characteristics. Hedonic prices are defined as the implicit prices of characteristics and can be estimated from observed house prices and specific quantities of characteristics embodied in the houses. The effect of environmental risks on property values can thus be measured by regressing house values on characteristics, including environmental health risks.

The purpose of this paper is to estimate the effect of environmental health risks on property values in the United States. We include environmental disamenities, such as Superfund sites and toxic chemical releases, as proxies for environmental health risks. We also include cancer mortality as a factor that can impact house values; however, cancer mortality may also be a function of demographic characteristics and environmental disamenities. Further, toxic chemical releases may be explained by county demographic and economic characteristics such as percent male, percent white, percent with college degree and percent in the 35-54 age group. We hypothesize that house values, health risks and toxic releases are endogeneously determined. To test this, we employ a simultaneous Full Information Maximum Likelihood modeling approach to jointly estimate housing prices, cancer mortality, and total chemical releases using a county level dataset from the United States and compare the results to Ordinary Least Square models. The results indicate that a single model of house values significantly underestimates the effect of releases and cancer mortality. In addition, using the simultaneous model, we predict the effects of an environmental cleanup, estimating net benefits of such a policy.

2.2 Literature Review

There has been an intensive literature that uses the HPM to investigate the property value impacts of environmental goods as measured by proximity to toxic sites. Michaels and Smith (1990) use the hedonic model to investigate the impact of hazardous waste sites on house prices in Boston, finding that property values increase with distance from the house to the nearest site. Kohlhase (1991) studies the impact of toxic sites in Houston on property values before and after the sites were listed in the Superfund National Priorities List (NPL). Her study suggests that toxic sites have a significant impact on house prices once they are listed as NPL sites, with prices positively related to distance from toxic sites for up to 6.2 miles. Nelson, Genereux, and Genereux (1992) examine the effect of landfills on house sales in Minnesota and conclude that landfills have a negative impact on house values for homes within two miles and the value of a house located on a landfill boundary could be reduced more than 12 percent. Kiel and McClain (1995) use sale data from Massachusetts to examine the impact of an incinerator on sale prices and find that the impact of the incinerator is significant during the construction and ongoing operation stages. Hite et al. (2001) study the impact of the presence of four landfills in Ohio on the property values of nearby houses. The authors find that property values are negatively impacted by the proximity of both open and closed landfills. Anstine (2003) tests the influence of buyer information on house price, by examining how the presence of two very different noxious facilities impact property values in a semi-rural area of Tennessee. He finds that a visible noxious facility negatively affects home values while a non-visible disamenity does not.

A number of studies focus on the way environmental health risk beliefs affect property values. McClelland, Schulze, and Hurd (1990) estimate the effect of health risk beliefs on property values in the Los Angeles area. They find that health risk beliefs have a substantially negative correlation with property values, and risk beliefs decrease when moving away from hazardous waste sites. Gayer, Hamilton, and Viscusi (2000) examine the effect of cancer risk perceptions from Superfund sites on house prices in Grand Rapids, Michigan before and after the USEPA released its assessment of site risks. Total lifetime cancer risk is defined as the sum of soil and groundwater cancer risk from each site. They find that people are willing to pay more for houses with lower levels of exposure to cancer risk, and residents' willingness to pay to reduce risks decreases after release of the assessment. McCluskey and Rausser (2001) study the impact of perceived risks on property value, where perceived risk is assumed to be a function of lagged perceived risk and media coverage of certain hazardous waste sites in Dallas County, Texas. The authors find that perceived risk is negatively related to house prices, and media coverage increases perceived risk.

In contrast to previous studies that use house-level data, Chay and Greenstone (2005) used county-level data to investigate how total suspended particulates (TSPs) affect median values of owner occupied housing units in the county in 1970 and 1980. Their dataset consists of 988 counties, accounting for approximately 80 percent of the US population. They use two different models based on two measures of TSPs. In the first model, they regressed actual TSPs on median house values and find that the results are mixed. For 1970, correlation between housing prices and TSPs was significant and negative but for 1980, correlation between housing prices and TSPs was unexpectedly positive. In the second model, nonattainment status, which is defined by concentrations of TSPs that exceed a federally set ceiling, is used as an instrumental variable for TSPs. They estimate that a reduction of 1 mg/m3 in TSPs results in an increase of 0.2–0.4 percent in mean housing values, or a -0.20 to -0.35 elasticity, using the county-level regulations as an instrument. They also estimate aggregate welfare gain of $45 billion for homeowners for the late 1970s reductions in TSPs.

2.3 Empirical Model and Data

2.3.1 Environmental health risks

Sources of air, water, and land pollution are categorized into two groups: point and nonpoint. Point sources consist of stationary facilities or processes that generate a significant amount of pollution from their activities. Point sources include major industrial facilities like chemical plants, power plants, steel mills, oil refineries, and incinerators. Nonpoint sources arise from a large number of small and widely dispersed origins. Nonpoint sources include emissions from automobiles or runoff from land-disturbing activities like agriculture, forestry, mining, and urban development. The focus of this paper is environmental risks imposed by point sources, as there are currently policy prescriptions and regulatory infrastructure in place to measure these hazards.

Environmental exposure to toxic substances from hazardous waste sites or toxic chemical releases from industries poses human health risks. The potential health effects may be cancer or noncancer-related, such as birth defects, respiratory and immune system damage. Cancer is defined as a disease of heritable, somatic mutations affecting cell growth and differentiation, characterized by an abnormal, uncontrolled growth of cells. Cancer has been linked to exposure to toxic substances by means of carcinogenic chemicals.

In addition to direct indicators of health risks such as total toxic chemical releases, cancer mortality and cancer incidence form indirect cancer risk indicators. Individuals may form subjective measures of health risks by examining cancer statistics in their areas, since cancer mortality is observable and information is readily available.

2.3.2 Empirical model

We use the hedonic price model to investigate county-level cross-sectional relationships between median house values and environmental health risks. House value in each county reflects the value people place on a bundle of characteristics associated with a housing unit. The hedonic house price in equation 1 is assumed to be a function of house, neighborhood, county, and environmental characteristics

$$V = f\,(H, C, E) + \varepsilon \qquad (1)$$

where V is house value, H is a vector of the house characteristics, C is a vector of county socio-demographic characteristics, E is a vector of environmental disamenities with their attendant risks.

A number of previous studies have used individual house sale price as the dependent variable in hedonic price models (Gayer, et al. 2000a; Gayer, et al. 2000; Kiel and Zabel 2001; Kohlhase 1991; McCluskey and Rausser 2001; Nelson, et al. 1992). This paper, however, uses the county level median value of owner-occupied units obtained from the 2000 census as the dependent variable as we were unable to obtain cancer data at any lower level of aggregation. Review of the literature provides precedence for using median unit value to estimate the impact of environmental goods on housing (Nelson 1978; Schulze and King 2001; Zabel and Kiel 2000). In particular, as previously mentioned, Chay and Greenstone (2005) use the county level median value of owner-occupied housing units in their study. An advantage of using owners' self valuation of their house is that it provides values for houses whether or not they sell; therefore it eliminates the likelihood of sample selection bias (Kiel and Zabel 1997). Kiel and Zabel (1997) tests the accuracy of owner-estimated values and concluded that hedonic equations based on owners' valuation would provide unbiased estimates of changes in house prices.

People exposed to local environmental risks arising from Superfund sites and toxic chemical releases from industrial facilities suffer potential health impacts. We use several variables as proxies to measure environmental health risks, including total releases of toxics. Individuals may also be exposed to environmental health risks arising from hazardous waste sites. We thus include the number of Superfund sites on the National Priority List within a county to represent health risks.[1]

If individuals use publicly available statistics to assess local environmental health risks, we can assume cancer mortality or cancer incidence are potential candidates to represent environmental health risk proxies. Individuals' valuations of health effects of hazardous substances may therefore be reflected in house values, allowing us to include cancer incidence and death rates as an explanatory variable in the hedonic housing equation. County level cancer mortality data used in this analysis are the only publicly available data.

The effect of potential spatial correlation on house prices needs to be addressed in hedonic analysis. Several papers have used absolute location into econometric analysis

[1] Although we recognize that these are imperfect measures of actual health risk, perceived risks may be relevant for their impacts on individual willingness to pay to avoid exposure.

to control for spatial effects (Anselin 1988; Case 1991; Clapp 2003; Fik, et al. 2003; Pavlov 2000). Pavlov (2000), Clapp (2003), and Fik, Ling, and Mulligan (2003) incorporate geographic coordinates of individual housing units as explanatory variables in the hedonic house price model. Anselin (1988) uses neighborhood centroid coordinates to explain the variation in crime while Blair and Hite (2005) use geographic coordinates for county centroid to control for location effects on the landfill industry. Following these papers, county centroid geographic coordinates are included as explanatory variables in this analysis to control for spatial effects in house values.

The exponential specification of the hedonic price model with an additive error term is used in this paper. Within the hedonic framework, house value is assumed to be a function of environmental health risks including total chemical releases, number of Superfund sites, cancer mortality, and other explanatory variables.

We hypothesize that there are endogeneities in the system of equations. In 2000, 579 individual chemicals were tracked in the TRI database, of which 189 are classified as recognized carcinogens under the requirements of the Occupation Safety and Health Administration. Thus, total chemical releases may increase cancer mortality to exposed individuals; in addition, some Superfund sites may pose a risk. Some studies also find that cancer mortality is affected by local socioeconomic patterns (Burnley 1997; Faggiano et al. 1997; Singh et al. 2002). Singh et al (2002) show that cancer morality differs significantly among different age groups and Kesteloot (1994) finds there are highly significant positive correlations between cancer mortality and age, and a decrease in the rate of cancer incidence after 65 years of age. Thus it is important to control for these variables to the extent possible.

Other health-related characteristics within a county may also help explain differences in cancer death. We thus include county percent of obese individuals as an explanatory variable, since there is evidence that obesity and overweight positively affect cancer death rates, especially in women (Adderley-Kelly and Williams-Stephens 2003; Calle, et al. 2003). We also include the proportion of the population with any kind of health care coverage, since people with health care may be more likely to have cancer discovered early and are more likely to receive treatments in a timely manner. Tobacco use has been found a cause to lung cancer; hence percent of persons smoking on a daily basis is included as an explanatory variable in the cancer mortality equation. Since cancer mortality statistics used in this analysis covers all types of cancer, including skin cancer, average temperature is included as an explanatory variable[2].

Total chemical releases are probably endogenous to house values and cancer incidence. Toxic sites could be located in areas where poor people live (Hamilton 1993, 1995; Gayer, Hamilton, and Viscusi 2000). Further, Bui (2003) finds that TRI-emitting plants tend to locate in communities with more middle-aged residents, and where residents are more likely to be registered as Democrats.

The system of three equations is written as

$$V = \exp(\alpha_V + \beta\, DR + \chi\, H + \delta\, C + \sigma\, CM + \varphi_V\, TR + \gamma_V\, NPL + \iota X + \kappa Y) + \varepsilon_V \qquad (2)$$

$$CM = \exp(\alpha_{CM} + \lambda\, DR + \mu\, C + \nu\, HE + \varphi_{CM} TR + \gamma_{CM} NPL + \iota X + \kappa Y) + \varepsilon_{CM} \qquad (3)$$

$$TR = \exp(\alpha_{TR} + \theta\, DR + \vartheta\, C + \gamma_{TR}\, NPL + \iota X + \kappa Y) + \varepsilon_{TR} \qquad (4)$$

[2] Although skin cancer is associated with exposure to sunlight, increased exposure is correlated with warmer climates.

where V is the median value of a county's owner-occupied housing units; DR is a vector of dummy variables for regions, to control for unobserved heterogeneity in the data (e.g. differences in building material costs, job markets or tastes); H is a vector of house characteristics; C is a vector of county characteristics; CM is cancer mortality at county level in year 2000; TR is total release/ person for years 1987-2000 at the county level; NPL is the number of Superfund sites on the NPL /1000 sq mile within a county; X and Y are county centroid coordinates; where HE is a vector of health characteristics; and ε is the error term.

Each of the four environmental health risk variables is expected to have negative impacts on house values so that as environmental health risks increase, there will be a reduction in property values. House values are also expected to be positively related to desirable variables such as percent white, percent college degrees and household income.

Environmental hazards, such as total toxic releases and number of Superfund sites, are expected to increase cancer mortality. That is, the higher the total releases and the more Superfund sites within a given county the greater the potential exposure to carcinogens, which in turn increases incidence of cancer and cancer deaths. Total releases are assumed to be positively affected by the number of NPL sites and negatively related to household income. Certain regions are known to have particularly high concentrations of industrial activity; hence region dummy variables are included.

We first estimate the system of equations (2)-(4) using OLS. However if cancer mortality and total releases are endogenous, OLS parameter estimates will be biased and inconsistent. We thus also estimate a simultaneous FIML to compare with the OLS results. The FIML model is also useful for simulating outcomes of various policy alternatives, as it can capture feedback effects from endogenities in the system.

2.3.3 Data

The county-level data for this paper are obtained from several sources. House values and housing characteristics come from the 2000 decennial census, US Census Bureau. The crime rate is obtained from Federal Bureau of Investigation Uniform Crime Statistics. The number of Superfund sites on the Final National Priorities List is obtained from the CERCLIS database, Superfund Information System, EPA. Cancer mortality comes from the National Center for Health Statistics while health characteristics come from the Behavioral Risk Factor Surveillance System (BRFSS) 2000, Centers for Disease Control and Prevention.

Air, water, and land toxic releases are derived from the USEPA's TRI database, housed on the Right-to-Know network (www.rtknet.org). These are total releases of all chemicals into the air, water, and land reported to EPA by major industrial facilities in each county. Air releases include stack emissions, which occur through confined air streams, such as stacks, vents, ducts or pipes, and fugitive emissions such as equipment leak, evaporative losses from surface impoundments and spills, and releases from building ventilation systems (TRI). Water releases include surface water discharges to streams, rivers, lakes, oceans and other bodies of water and underground injection, which is the subsurface emplacement of fluids through wells. Land releases include all the chemicals disposed of on land within the boundaries of the reporting facility.

The total releases in the inventory cover about 582 individually listed chemicals accounting for less than 1% of the over 75,000 chemicals manufactured in the U.S., according to EPA's Toxic Substances Control Act Inventory (USEPA). However, TRI does not address all sources of releases and other waste management activities of TRI chemicals. The TRI releases contain annual data from its initial year, 1987, to 2000**.** Since it generally takes many years after exposure to a toxic substance for chemically-induced cancer to develop, we use cumulative TRI chemical releases from all sources from 1987 to 2000 as the explanatory variable in this paper.

Due to missing variables in Alaska, Hawaii and Washington DC, the final data set constructed from the different sources includes 3,106 counties in 48 states in the US.

Identification issues arise when we estimate parameters in a simultaneous equation model. Before estimating equations (2)-(4), we examine potential identification problem to determine whether we can obtain parameter estimates for the system. Regional dummies, county characteristics are included in all three equations. Proportion of county's population that is obese, proportion with any kind of health care coverage, and percentage of daily smokers are included only in the cancer mortality equation. Similarly, total earnings in manufacturing, percent of jobs in manufacturing, and percent Democratic votes in the 2000 Presidential election as a proportion of total population are included only in the total release equation. Housing characteristics included only in the house equation are number of rooms, year built, proportion of housing units with complete kitchen, real estate taxes, proportion of vacant houses and proportion of owner-occupied houses. To be sure that we exclude them reasonably, correlation coefficients are calculated (Table 2.1) between room and year built and age and gender of the owners since certain age and male or female may prefer houses of a certain age or with a certain number of rooms and year built. The correlation coefficients justify our exclusion. The results are similar for variables representing proportion of obese people, proportion of daily smokers, and proportion of people with health care. The correlation coefficients between them and 35-54 age group, gender, rooms, and year built are very small; therefore we exclude them from the house value and total release equations.

Table 2.2 presents descriptive statistics for all variables in the model. The mean value of county median owner-occupied housing units is $80,864 for the sample. The main explanatory variables are environmental health risks, represented by total releases, number of Superfund sites, counties with high chemical releases, and cancer mortality. The mean value of total releases is 626 pounds of toxic chemicals per person and the average number of Superfund sites is 0.79 per thousand square miles. The mean cancer mortality per county is 200 per hundred thousand persons.

Table 2.1 Correlation coefficient matrix

	Rooms	Year built	35-54 age	Male	Obese	Health	Dem00
Rooms	1						
Year built	-0.29	1					
35-54 age	0.23	0.17	1				
Male	-0.09	0.06	0.17	1			
Obese	-0.13	-0.06	-0.10	-0.08	1		
Health	0.44	-0.25	0.14	-0.03	-0.16	1	
Dem00	0.09	-0.14	0.17	-0.19	-0.06	0.24	1

Table 2.2 Variable definitions and descriptive statistics (N=3,106)

Variable	Mean	Std Dev
Median value of owner-occupied housing units ($1,000)	80,864.26	41,893.27
Cancer mortality (deaths/100,000 population)	200.3659	27.7276
Total releases (10,000 pounds/person)	0.0626	0.6903
Superfund sites (sites/1000sq mile)	0.7911	0.2236
Dummy for county with total release > 0.05	0.0959	0.2945
Household income($1,000)	40.7993	10.7805
Percent with college degrees (%)	10.9542	4.9238
Percent white (%)	84.7681	16.0126
Percent male (%)	49.5087	1.9389
Percent married people (%)	60.4018	5.3682
Percent people in 35-54 age group (%)	29.0931	2.5870
Percent employed in services (%)	23.2208	4.7242
Unemployment rate (%)	3.3901	1.4235
Crime rate (%)	3.2268	2.0785
Median rooms of housing units	5.9327	0.4479
Median year built of housing units	1969.3	11.2174
Percent house with complete kitchen %)	99.4231	0.9442
Real estates taxes ($1,000)	840.7414	634.2332
Percent vacant houses (%)	14.1438	9.5472
Percent owner occupied housed (%)	74.1038	7.5274
X coordinate of county's centroid	-91.6642	11.4803
Y coordinate of county's centroid	38.2790	4.8381
Percent jobs in manufacturing (%)	6.7768	5.1178
Dummy for Northwest region[3]	0.0637	0.2443
Dummy for Northeast region[4]	0.0698	0.2549
Percent votes for Democrat in 2000 election (%)	15.7034	5.0591
Percent population with health coverage (%)	86.6429	5.8989
Percent obese population (%)	19.6754	3.2329
Percent daily smoker (%)	18.0382	3.5531
Average temperature (^{o}F)	54.8480	8.3669

[3] Northwest region: Washington, Oregon, Idaho, Montana and Wyoming
[4] Northeast region: Maine, Vermont, New Hampshire, Massachusetts, Connecticut, Rhode Island, New York, New Jersey and Pennsylvania.

2.4 Model Estimates

Using the Breusch-Pagan test, we found that heteroscedasticity existed in the OLS model. After correcting for heteroscedasticity, the modified regression result showed that the chi-square statistics were calculated to be 0.52 for the first equation, 3.72 for the second equation , and 5.35 for the third equation, which are all smaller than the 5% critical value of significance of 7.81 (3 degrees of freedom). Therefore, we fail to reject the null hypothesis of homoscedasticity and concluded that heteroscedasticity is mitigated in the corrected model.

Tables 2.3, 2.4, and 2.5 present house value, cancer mortality, and total release regression results using OLS. In the house value equation, out of four variables for environmental health risks, parameter estimates for cancer mortality, total releases and county with high releases have the expected negative signs and are statistically significant. From the model specification, coefficients can be interpreted as the percentage impact of parameter on house values. For example, an increase of 1 cancer death per 100,000 in a county reduces house values by 0.07 percent, while an increase of 10,000 pounds of toxic releases per person reduces house values by 3.6 percent. The coefficient for number of Superfund sites is insignificant. The significantly positive coefficient for latitude is interpreted to mean that house values rise when moving to the North and a significantly negative coefficient of longitude indicates that property value increases when moving to the East. Holding latitude and longitude constant, house values are found to be higher in the Northeast and Northwest region. Housing characteristics include median number of rooms and median year built of housing units, in which median number of rooms has negative impact on house values and median year built has positive impact on house values. One additional room leads to a decrease of house values by 10.42 percent and one additional year in year built leads to an increase of house values by 0.75 percent. Neighborhood characteristics of household income, proportion of white, proportion population in the 35-54 age group, proportion employed in services and vacancy rate have positive effects on house values. An increase of 1 thousand dollars in household income raises house values 3.34 percent and an increase of 1 unit in proportions of white, population in the 35-54 age group, employed in services and vacant houses raise house values by 0.28, 0.93, 1.17 and 0.38 percent, respectively. Other neighborhood characteristics including proportion of college graduates, proportion of male, proportion of married people, unemployment rate and proportion of owner-occupied houses are negatively related to house values. One additional unit in these numbers leads to a decrease of house values by 0.36, 1.18, 0.94, 0.74 and 0.15, respectively.

In the cancer mortality equation, the coefficients for total releases, number of Superfund sites, and the dummy for county with high releases are unexpectedly insignificant. Counties with higher percent of daily smokers have a higher cancer death rate with a 1 percent increase in daily smoker increasing cancer mortality by 0.65 percent. County average temperature increases the rate of cancer mortality; each degree increase in average annual temperature is associated with a 0.24 percent increase in cancer mortality. One additional thousand in household income results in an increase of 0.12 in the cancer death rate. An increase of 1 unit in unemployment rate and crime rate raises cancer mortality rate by 0.42 and 0.43, respectively. Each percent increase in proportion of college graduates, males and married people reduces cancer death rate by 1.18, 0.55 and 0.63 percent, respectively.

In the total release equation, household income has an unexpectedly positive effect on total releases. An increase of household income by 1 thousand dollars raises toxic releases by 11.24 percent. This may be explained by recognizing that there are more jobs where there are more releases and that chemical factories provide high-paying jobs. Toxic chemical releases increase with unemployment rate, percent male and percent employed in services, but decrease with percent of college graduates, crime rate and percent of married people. Counties with a higher percentage of people voting Democratic in the 2000 President election have lower toxic chemical releases. Each percent increase in people voting Democratic is associated with a 15.62 percent decrease in total releases.

Table 2.3 Nonlinear OLS estimates for house value equation (N=3,106)

Variable	Parameter Estimate	Standard Error	t value
Intercept	-4.2224***	0.8818	-4.79
Household income	0.0334***	0.0007	46.86
Percent with college degrees	-0.0036***	0.0012	-2.95
Percent white	0.0028***	0.0004	7.61
Percent male	-0.0118***	0.0022	-5.27
Percent married people	-0.0094***	0.0011	-8.45
Percent people in 35-54 age group	0.0093***	0.0016	5.77
Percent employed in services	0.0117***	0.0012	9.87
Percent vacant houses	0.0038***	0.0005	8.45
Percent owner occupied housed	-0.0015**	0.0007	-2.02
Unemployment rate	-0.0074**	0.0035	-2.10
Crime rate (crimes per 1,000 population)	-0.0025	0.0019	-1.37
Median rooms of housing units	-0.1042***	0.0108	-9.69
Median year built of housing units	0.0075***	0.0005	16.58
Real estates taxes ($1,000)	-0.0001***	0.0000	-5.73
X coordinate of county's centroid	-0.0044***	0.0004	-10.86
Y coordinate of county's centroid	0.0084***	0.0012	6.90
Dummy for county with population > 100,000	0.0035	0.0116	0.30
Cancer death rate (death/100,000)	-0.0007***	0.0002	-4.16
Total releases (10,000 pounds/person)	-0.0358***	0.0085	-4.20
Superfund sites (sites/1000 sq mile)	0.0386	0.1584	0.24
Dummy for county with total release > 0.05	-0.0318**	0.0151	-2.11
Dummy for Northeast region	0.1860***	0.0175	10.61
Dummy for Northwest region	0.0919***	0.0168	5.46

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 2.4 Nonlinear OLS estimates for cancer mortality equation (N=3,106)

Variable	Parameter Estimate	Standard Error	t value
Intercept	5.5014***	0.0888	61.96
Household income	0.0012***	0.0004	3.25
Percent with college degrees	-0.0118***	0.0008	-14.65
Percent white	-0.0003*	0.0002	-1.69
Percent male	-0.0055***	0.0011	-4.96
Percent married people	-0.0063***	0.0006	-10.31
Percent people in 35-54 age group	0.0109***	0.0010	10.52
Percent employed in services	-0.0014*	0.0008	-1.80
Unemployment rate	0.0042**	0.0020	2.13
Crime rate (crimes per 1,000 population)	0.0043**	0.0011	3.84
Percent population with health coverage	-0.0005	0.0004	-1.20
Percent obese population	0.0010	0.0008	1.27
Percent daily smoker	0.0065***	0.0007	9.35
Average temperature	0.0024***	0.0004	6.81
Dummy for county with population > 100,000	-0.0204	0.0193	-1.06
Total releases (10,000 pounds/person)	0.0004	0.0034	0.10
Superfund sites (sites/1000 sq mile)	0.0306	0.1015	0.30
Dummy for county with total release > 0.05	0.0103	0.0079	1.30
Dummy for Northeast region	-0.0046	0.0104	-0.44
Dummy for Northwest region	0.0069	0.0109	0.64

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 2.5 Nonlinear OLS estimates for total releases equation (N=3,106)

Variable	Parameter Estimate	Standard Error	t value
Intercept	-5.5139***	1.7962	-3.07
Household income	0.1124***	0.0120	9.35
Percent with college degrees	-0.1908***	0.0305	-6.25
Percent white	0.0160*	0.0089	1.80
Percent male	0.0772***	0.0194	3.98
Percent married people	-0.0482***	0.0182	-2.65
Percent people in 35-54 age group	0.0129	0.0208	0.62
Percent employed in services	0.0798***	0.0119	6.69
Unemployment rate	0.1005***	0.0319	3.15
Crime rate (crimes per 1,000 population)	-0.1751***	0.0636	-2.75
Percent votes Democratic in 2000 election	-0.1562***	0.0245	-6.37
Percent jobs in manufacturing	-0.0776	0.0594	-1.31
Dummy for county with population>100000	-1.3486*	0.7204	-1.87
Superfund sites (sites/1000 sq mile)	1.6261	2.8117	0.58
Dummy for Northeast region	-0.9655	1.1945	-0.81
Dummy for Northwest region	-0.3629	0.3755	-0.97

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Our suspicion that endogeneities exist in the model means the OLS results are inconsistent. We thus performed a Hausman specification test (Hausman 1978) to test for endogeneity. The chi-squared statistics testing OLS against FIML is 10.42, which when compared with a critical value at the 5% level of significance of 3.84 (1 degree of freedom) suggests that there is endogeneity in the model, suggesting a simultaneous estimation method is appropriate. We thus employ a FIML model to jointly estimate the three equations.

Tables 2.6, 2.7 and 2.8 present the FIML model results corrected for heteroscedasticity. In the house value equation, coefficients for total releases and cancer mortality remain statistically significant. It is interesting to note that the magnitude of the significant coefficient for total releases is larger in the FIML model. Specifically, the percentage impact of total releases per person increases from 3.58 percent in the OLS model to 6.63 percent in the FIML model. Similarly to toxic releases, the negative effect of cancer mortality in the system model is greater than in the OLS model, increasing from 0.07 percent to 0.13 percent. This indicates that the OLS model underestimates the effect of toxic releases and cancer mortality. The coefficient for the dummy for counties with toxic releases greater than 500 pounds per person becomes insignificant. Coefficients for latitude, longitude and the Northeast and Northwest region remain statistically significant. The effects of other variables including housing characteristics and neighborhood characteristics remain the same in terms of the direction and magnitude of the effects.

In the cancer mortality equation, coefficients for total releases, number of Superfund sites and high release county dummy remain insignificant. The coefficients for economic and demographic characteristics including household income, percent college degrees, percent male, percent married people and percent in the 35-54 age group are consistent terms of signs and absolute values of the parameters with OLS model. Coefficients for percent white and percent employed in services become statistically significant at the 5 percent level. One percent increase in percent white and percent employed in services reduces cancer mortality by 0.03 and 0.15 percent, respectively. The insignificant coefficient for percent with health care coverage in the OLS becomes significant with the expected negative sign, with one additional percent of health care coverage reducing cancer mortality by 0.08 percent.

In the total release equation, the coefficient for number of Superfund sites remains insignificant. The effects of household income, proportion of college graduates, white and male, and unemployment rate, crime rate, percent voting Democratic in 2000 President election on house values are consistent with the OLS model in terms of the direction but are greater in absolute values. The coefficient for percent employed in services becomes insignificant in the system model.

Table 2.6 Nonlinear FIML Estimates for house value equation (N=3,106)

Variable	Parameter Estimate	Standard Error	t value
Intercept	-4.2276***	0.6335	-6.67
Household income	0.0334***	0.0004	84.31
Percent with college degrees	-0.0052***	0.0009	-5.57
Percent white	0.0027***	0.0003	8.94
Percent male	-0.0124***	0.0020	-6.11
Percent married people	-0.0100***	0.0008	-12.38
Percent people in 35-54 age group	0.0105***	0.0010	10.26
Percent employed in services	0.0116***	0.0008	14.87
Unemployment rate	-0.0067**	0.0031	-2.16
Crime rate (crimes per 1,000 population)	-0.0021	0.0018	-1.14
Median rooms of housing units	-0.1024***	0.0066	-15.57
Median year built of housing units	0.0076***	0.0003	23.12
Real estates taxes($1,000)	-0.0001***	0.0000	-9.76
Percent vacant houses	0.0037***	0.0003	13.37
Percent owner occupied housed	-0.0014***	0.0005	-2.90
X coordinate of county's centroid	-0.0043***	0.0002	-19.16
Y coordinate of county's centroid	0.0082***	0.0010	8.07
Dummy for county with population > 100,000	0.0035	0.0101	0.35
Cancer death rate (death/100,000)	-0.0013***	0.0002	-5.89
Total releases (10,000 pounds/person)	-0.0663**	0.0291	-2.27
Superfund sites (sites/1000 sq mile)	0.0315	0.2541	0.12
Dummy for county with total release > 0.05	-0.0260	0.0203	-1.28
Dummy for Northeast region	0.1856***	0.0133	14.00
Dummy for Northwest region	0.0915***	0.0134	6.85

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 2.7 Nonlinear FIML estimates for cancer mortality equation (N=3,106)

Variable	Parameter Estimate	Standard Error	t value
Intercept	5.5361***	0.0704	78.62
Household income	0.0011***	0.0004	2.88
Percent with college degrees	-0.0117***	0.0007	-15.87
Percent white	-0.0003**	0.0002	-2.01
Percent male	-0.0056***	0.0007	-7.90
Percent married people	-0.0065***	0.0005	-12.57
Percent people in 35-54 age group	0.0110***	0.0009	12.77
Percent employed in services	-0.0015**	0.0006	-2.32
Unemployment rate	0.0039***	0.0013	2.88
Crime rate (crimes per 1,000 population)	0.0044***	0.0012	3.74
Percent population with health coverage	-0.0008**	0.0004	-2.00
Percent obese population	0.0012*	0.0008	1.65
Percent daily smoker	0.0064***	0.0007	9.13
Average temperature	0.0023***	0.0003	7.96
Dummy for county with population > 100,000	-0.0205*	0.0126	-1.65
Total releases (10,000 pounds/person)	0.0030	0.0260	0.11
Superfund sites (sites/1000 sq mile)	0.0299	0.0976	0.31
Dummy for county with total release > 0.05	0.0099	0.0083	1.19
Interaction of DPOP and Superfund sites	1.9559	1.6615	1.18
Dummy for Northeast region	-0.0033	0.0151	-0.22
Dummy for Northwest region	0.0054	0.0109	0.49

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 2.8 Nonlinear FIML estimates for total releases equation (N=3,106)

Variable	Parameter Estimate	Standard Error	t value
Intercept	-7.5733	7.1406	-1.06
Household income	0.2030**	0.0371	5.47
Percent with college degrees	-0.3614**	0.0764	-4.73
Percent white	0.0732*	0.0412	1.78
Percent male	0.0703*	0.0407	1.73
Percent married people	-0.0862	0.0646	-1.34
Percent people in 35-54 age group	0.0802	0.0620	1.29
Percent employed in services	-0.0627	0.0382	-1.64
Unemployment rate	0.4393***	0.0859	5.11
Crime rate (crimes per 1,000 population)	-0.7795***	0.2399	-3.25
Percent votes for Democrat in 2000 election	-0.5702***	0.1298	-4.39
Percent jobs in manufacturing	-0.2268	0.1712	-1.32
Dummy for county with population>100000	-0.9286	9.1080	-0.03
Superfund sites (sites/1000 sq mile)	-14.5501	78.0084	-0.19
Interaction of DPOP and Superfund sites	37.8538	32.8000	0.01
Dummy for Northeast region	-0.1334	6.7000	0.00
Dummy for Northwest region	-4.1638	40.5903	-0.10

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

There are some significant differences when comparing OLS results with FIML results. In the house value equation, the coefficients for cancer mortality and total releases in the two models are significant and negative in both models, but the coefficients of the FIML are almost double in absolute value the coefficients of the OLS. The OLS coefficients for other variables are similar to the FIML results. In the cancer mortality equation, the estimates for total releases and number of Superfund sites are not significant in both the OLS and FIML models. The OLS coefficient for health care coverage is not significant while the FIML coefficient is significant. In the total release equation, number of Superfund sites does not have any impact on total toxic releases in both models.

2.5 Marginal Willingness to Pay and Value of Statistical Life

In the hedonic price model, the derivative of price with respect to a characteristic is equivalent to the marginal willingness to pay for changes in characteristic, which can be computed using the parameter estimates from Tables 2.3 and 2.6. The negative coefficients for cancer death and total releases in the house equation suggest that people are willing to pay higher prices for houses located in areas with lower cancer mortality rates and lower toxic chemical releases. Marginal willingness to pay for reducing cancer mortality and chemical releases is

$$\frac{\partial \text{ house value}}{\partial \text{ cancer mortality}} = \hat{\sigma} * \text{house value} \tag{5}$$

$$\frac{\partial \text{ house value}}{\partial \text{ total releases}} = \hat{\varphi}_{\mathrm{V}} * \text{house value} \tag{6}$$

where $\hat{\sigma}$ is the estimated coefficient for cancer mortality, and $\hat{\varphi}_{\mathrm{V}}$ is the estimated coefficient for total releases in the house value equation.

From the OLS parameter estimates in Table 2.3, the marginal willingness to pay for a reduction of 1 cancer death per 100 thousand persons is calculated to be \$55.05 and for a 1 pound reduction of total chemical releases to be \$0.29.

Taking endogeneity of cancer and total chemical releases into account, the equation to compute marginal willingness to pay for reducing cancer death is the same as in equation (5), but to compute marginal willingness to pay for reducing total releases as follow

$$\frac{\partial \text{ house value}}{\partial \text{ total releases}} = \hat{\varphi}_{\text{V}} \text{*house value} + \hat{\sigma} \text{* house value *} \hat{\varphi}_{\text{CM}}\text{*cancer death} \qquad (7)$$

where $\hat{\varphi}_{\text{CM}}$ is the estimated coefficient for total releases from equation 3. The FIML estimated parameters reported in Table 2.6 give the marginal willingness to pay for one cancer death reduction per 100 thousand persons to be $105.47 and for a 1 pound reduction of total chemical releases to be $0.54.

An important implication of the model estimated in this paper is that it can be used to calculate the value of statistical life based on the correlation between house values and cancer mortality. The assumption here is that there is a tradeoff between risk and property values, with mean willingness to pay for decreased cancer mortality using OLS and FIML estimated to be $55.05 and $105.47 respectively. However, this willingness to pay is for a representative household. To calculate the willingness to pay for an individual, the willingness to pay per household must be divided by the mean number of persons per household. With the mean household size of 2.586 at the county level, the mean willingness to pay per individual using OLS and FIML is estimated to be $21.29 and $40.79, respectively.

The value of statistical life is computed using the equation

$$\text{Value of statistical life} = \frac{\text{Willingness to pay}}{\text{Size of risk reduction}} \qquad (8).$$

For example, the willingness to pay estimates of $21.29 and $40.79 represent the amount of money an individual would be willing to pay to reduce cancer deaths by 1 per 100,000 persons. This results in an average value of statistical life per person of $2.13 million using OLS and $4.08 million using the FIML model in 2000 dollars.

There is a large difference in the value of statistical life between using OLS and FIML. Statistical life when cancer mortality and total releases are treated as exogenous is nearly half of the value of statistical life when they are treated as endogenous. However, the estimated value of statistical life from the simultaneous model seems to be more consistent with the findings of other studies in the housing market using hedonic price model to investigate the relationship between house prices and cancer risks. In their 2000 paper, Gayer, Hamilton, and Viscusi estimate the willingness to pay of residents to avoid cancer risks at Superfund sites and calculate the statistical value of cancer to be $4.6 million in 1996 dollars. Analyzing how changing information on cancer risk of Superfund sites affects house price, Gayer, Hamilton, and Viscusi (2002) report the value of a statistical cancer case to be $8.3 million. The range of our estimates is also similar to the calculations from the labor and automobile markets. Viscusi (1993) reviews labor market studies and reports a range for value of statistical life from $3 million to $7 million in 1990 dollars. Atkinson and Halvorsen (1990) calculate the value of statistical life at $3.4 million 1986 dollars using the hedonic price model for automobiles. Because we have imperfect measures of the correlation between total releases and cancer deaths, we suspect our measure is conservative. With better measures of specific carcinogenic releases, the links between releases and cancer should be more pronounced.

2.6 Welfare Estimates

In this section we conduct a rudimentary benefit cost analysis to estimate the welfare effects of cleaning up Superfund sites and reducing industrial point source releases. We use the simultaneous-equation model to perform this analysis. The assumption is that all Superfund sites are completely cleaned up and total toxic releases are decreased by half. The benefits and costs associated with our assumptions are calculated to obtain net benefits representing the welfare gain from reducing environmental health risks.

Predicted house values and cancer mortality rates are calculated by simultaneously solving the system represented by equations 2-4. We apply the Quasi-Newton method to simultaneously solve for predicted house value and cancer mortality under the baseline and different policy assumptions. The simulations are reported in Table 2.9. If a policy mandated elimination of Superfund sites and a reduction of total releases by half, the median house value would rise by $396.27 and cancer death rates would drop by 0.45 per 100,000 persons.

Table 2.9 House value and cancer mortality simulations

Variable	Original level of total releases and number of Superfund sites		Total releases decreased by 50% and clean-up of all Superfund sites	
	Mean	Std Error	Mean	Std Error
House value ($)	80,812.110	38,008.870	81,208.380	38,466.850
Cancer mortality (per 100,000 persons)	200.316	16.041	199.866	16.031

2.6.1 Benefits

Benefits from environmental risk reduction are estimated from the change in house value and cancer death rate. Table 2.10 presents estimated benefits for changes in house value and cancer rate that result from environmental improvement. The house value increase is multiplied by the total number of housing units in the sample to obtain benefits from the house value change. There are around 69 million owner-occupied housing units in the US and the net present value of benefits from changes in capitalized house values is $27.5 billion. Benefits from the cancer mortality decrease are calculated by multiplying the number of lives saved by the value of statistical life, where the number of lives saved is computed by multiplying the cancer rate reduction by the total number of persons living in owner-occupied houses. The cancer death rate decrease yields benefits of $3.3 billion per year. If we assume that such benefits will accrue over the foreseeable future, we can obtain a rough estimate of the net present value of all future benefits as a perpetuity. Based on a 3% interest rate, the net present value would be about $109.7 billion dollars. Therefore, the total benefits from cleaning up all Superfund sites and reducing toxic releases are $137.1 billion dollars.

Table 2.10 Estimated benefits

Variable	Change in Value	Sample Size	Benefits ($1,000)
Capitalized house value	396.270 ($/housing unit)	69,323,860 (housing units)	27,470,966
Annual cancer mortality	-0.450 (death/100,000)	179,271,502 (persons)	3,290,214
NPV cancer mortality in perpetuity			109,673,703
Total NPV benefit			137,144,669

2.6.2 Costs

Costs associated with the new level of toxic chemical releases and number of Superfund sites are costs from reducing total releases and cleanup of Superfund sites. Average cost of cleanup activities per Superfund site is presented in Table 2.11. The average cost of cleanup actions per site is around $31.6 million dollars. There are 1,152 Superfund sites in the final NPL and total cost of cleanup for all sites in the US is estimated to be $36 billion.

Costs for reduction of toxic chemical releases are not readily available. However, EPA annually spends about $7 billion in monitoring and regulatory costs for all US facilities. For the sake of expediency, we will assume that costs will increase incrementally by about $7 billion per year to reduce toxic chemical releases, adding a

NPV of about $233 billion to the total cost for cleanup of the NPL sites above, for a grand total cost of about $269 billion.

The net benefit of environmental health risk reduction is the difference in benefits and costs. In this case the difference between $137 billion in benefits is outweighed by the $269 billion in costs. However, as previously noted, our benefit estimate underestimates the true benefit significantly, as it includes only owner occupied house values and cancer mortality. Arguably, costs of lost value in rental housing and costs of treating cancer, as well as the other chronic illnesses related to toxic releases, such as respiratory diseases and birth defects will incur an even greater cost to society; further lost labor productivity is also not accounted for. Reductions in conditions associated with toxic releases might therefore result in an actual net benefit.

Table 2.11 Average cost of cleanup actions per NPL site

Cost category	Average total cost per site (US$)
Remedial investigation/Feasibility study	1,300,000
Remedial Design	1,500,000
Remedial Action	25,000,000
Net present value of operation and maintenance	3,770,000
Total	31,570,000

Source: Office of Program Management, Office of Superfund Remediation Technology Innovation, EPA.

2.7 Conclusions

In this paper, we investigate the effects of environmental health risks on house values in the US at the county level. A unique data set consisting of 3,106 counties in the US is used for the analysis. Several variables are used to represent environmental health risks including total chemical releases, number of Superfund sites, and cancer mortality. We assume that there are endogeneities in the model, using a system of equations to capture indirect impacts of variables. Both OLS and FIML are used to estimate the system. We go on to simulate cleanup of sites and toxic releases using a quasi-Newton method to solve the system. Our findings suggest that property value responds negatively to total releases and cancer mortality. The results of the FIML estimate indicate that a reduction of total releases by 1 pound per person leads to an estimated increase of $0.54 in house value and a decrease of cancer mortality by 1 death over 100,000 persons leads to an increase of $105.47 in housing values when cancer mortality and total chemical releases are endogenous. The value of statistical life is estimated to be $4 million with FIML model.

Based on the value of statistical life and capitalized house values, a simple cost benefit analysis is conducted. The results indicate that cleanup costs of $267 million exceed benefits of $137 million when only owner-occupied housing units and cancer mortality are accounted for. The findings suggest that in future research, we will need to include other kinds of health costs in order to estimate the true benefit of environmental cleanup, as reflected in housing markets. In addition, effects of releases, not just on cancer deaths but on morbidity associated with cancer and other diseases will be the subject of future research.

III. TOXIC CHEMICAL RELEASES, HEALTH EFFECTS, AND LABOR PRODUCTIVITY LOSSES

3.1 Introduction

The effects of pollution on human health have been investigated widely in the environmental and health literature. Pollutants may be linked to a wide range of effects on human health, including cancer or noncancer-related diseases, such as birth defects, respiratory and immune system damage. Since health is considered to be a capital good in the production process, health effects may impact labor productivity. As a result, exposure to pollution may contribute to productivity losses.

Although the relationship between pollution and morbidity has been investigated thoroughly in the health literature, almost all previous studies focused on air pollution alone (Bates and Sizto 1987; Ostro 1983; 1987; Ostro and Rothschild 1989; Pope-III 1991; Xu, et al. 1995). Two other types of pollution, including land and water pollution, which cause potentially more serious human health effects (Hopenhayn-Rich, et al. 1998; Lopez-Abente, et al. 2006; Smith, et al. 1998), have been neglected.

The focus of this analysis is to investigate the effects of pollution measured by aggregate levels of toxic chemical releases to air, land and water from industrial facilities on productivity losses represented by lost work days. The analysis uses a simultaneous equation count data model of work day lost and health status to estimate impacts of environmental factors on work days lost. Health instruments include toxic chemical releases, demographic and socioeconomic characteristics, a number of health conditions and behavior variables. A unique dataset combining the 2002 National Health Interview Survey (NHIS), TRI, US Census 2000 data and climatic data is used to estimate the impact of toxic releases on health status and lost labor productivity.

3.2 Literature Review

There is an extensive literature studying the impacts of pollution on human morbidity. Pollution has been linked to several kinds of diseases including respiratory symptoms, asthma, chronic bronchitis, and cancer by Mills *et al.*, 1991, Ostro *et al.*, 1991, Portney and Mullahy, 1986. A number of other papers have analyzed relationships between air pollution, hospital admissions and emergency room visits (Bates and Sizto 1987; Pope-III 1991; Samet, et al. 1981; Xu, et al. 1995). However, the focus of this section is to review some of the previous papers investigating the effects of pollution on labor productivity losses in the form of lost work days.

Ostro (1983) used 1976 NHIS data to study the effect of air pollution on morbidity measured by work loss days and restricted activity days. Two air pollution variables used were annual mean levels of particulates and sulfates (SO_4). The author found that there was a statistically significant relationship between particulates, work days lost and restricted activity days in three different functional forms tested including linear, Tobit, and logit-linear.

In another paper, Ostro (1987) replicated the previous analysis with four NHIS datasets from the year 1976 to 1981. Fine particles were used as a measure of air pollution instead of total suspended particulates. Another change from his previous study was that a Poisson distribution was used for work days lost and restricted activity days. The study reported that fine particles were positively and significantly associated with work loss days in 4 out of 6 years, and were positively related to restricted activity days in all 6 of the years.

Portney and Mullahy (1986) also used NHIS data to analyze health effects of air pollution. The dependent variable was the number of respiratory-related restricted activity days during survey respondents' 2-week recall periods with air pollution measured by ozone and sulfates during the same period. Maximum likelihood was used to estimate a Poisson model in the analysis. The authors found that there were positive and significant associations between ozone and respiratory-related restricted activity days. They also calculated the elasticity of respiratory-related restricted activity days with respect to ozone and evaluated the change in respiratory-related restricted activity days resulting from a change in ozone concentrations. The elasticity ranged from 0.005 to 0.5 and respiratory-related restricted activity days for urban adult population ranged from 240,000 to 22,000,000.

Ostro and Rothschild (1989) contributed to a series of studies on the relationship between health effects and air pollution by analyzing the health consequences of two air pollutants using 6 separate years of NHIS data. Respiratory-related restricted activity days and minor restricted activity days were used as indicators of acute morbidity. The results indicated that there was a positive and significant relationship between fine particles and respiratory-related restricted activity days in all six of the years. The association of fine particles with minor restricted activity days appeared to be weaker and the coefficient for fine particles was positive and significant in 4 out of the 6 years. The study found no relationship between ozone and respiratory-related restricted activity days but a weak association of ozone with minor restricted activity days.

Ostro (1990) used the 1979-1981 NHIS data to explore the association between acute respiratory morbidity and different measures of particulate matter, including sulfates, total suspended particulates, and fine and inhalable particulates. The author reported that of the alternative measures of particulate matter, sulfates appeared to have the greatest association with acute respiratory morbidity.

Samakovlis et al. (2005) investigated the impacts of NO_2 concentrations on incidence and duration of respiratory restricted activity days in Sweden using the 1999 National Environmental Health Survey. To handle the overdispersion problem in the Poisson model, the authors used a logit model to analyze how NO_2 concentrations affect incidence of respiratory problems and then used a Poisson model to investigate the relationship between NO_2 concentrations and number of respiratory restricted activity days. The results indicated that NO_2 level did not affect incidence of respiratory problems but positively affected respiratory restricted activity days.

3.3 Health Capital Model

This study follows the health capital model by Grossman (1970a,b) and Cropper (1981). A consumer maximizes the utility function

$$U = U(H_0, H_1, \dots, H_n, Z_0, Z_1, \dots, Z_n) \qquad (9)$$

where H_0 is initial stock of health, H_t is the stock of health in period t, and Z_t is total consumption of another commodity in period t.

Investments in health are given by the production function

$$I_t = D\ (M_t, X_t, TH_t; E_t) \tag{10}$$

where M_t is medical care, X_t is the market good input, TH_t, is time input, and E_t is the stock of human capital.

The increase in the stock of health is the net investment in health capital

$$dH_t/dt = H_{t+1} - H_t = I_t - \delta_t H_t \tag{11}$$

where I_t is gross investment and δ_t is the rate of health depreciation during the t^{th} period.

The marginal cost of gross investment in health capital is given by

$$\pi_t = N\ (PM_t, W_t) \tag{12}$$

where PM_t is price of purchased goods and W_t is wage rate.

The production function of healthy days is written as

$$h_t = F\ (H_t) \tag{13}$$

The stock of health and the number of healthy days are presented in Figure 3.1. At H_t=H_{min}, the number of healthy days equal zero. Along the curve, healthy time increases at a decreasing rate and approaches the 365-day line. The marginal product of the stock of health is $R_i = \partial h_t / \partial H_t > 0$.

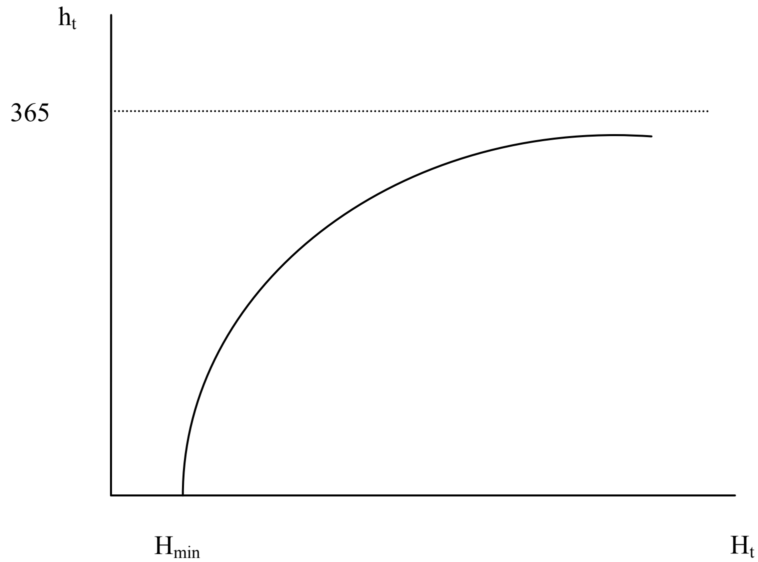


Figure 3.1 Stock of health and the number of healthy days

Sick time equals the total amount of time available in any period minus the number of healthy days in that period

$$TL_t = \Omega - h_t \tag{14}$$

where TL_t is time lost due to illness and Ω is total amount of time available.

The marginal product of health capital, the increase in the number of healthy days due to a one unit increase in the stock of health, equals the negative of the marginal product of lost health capital: $R_i = \partial h_t / \partial H_t = - \partial TL_t / \partial H_t$.

The optimal amount of sick time can be derived by equating the value of marginal product of lost health capital due to illness to the cost of health depreciation

$$W_t(\partial TL_t / \partial H_t) = - \pi_t \delta_t \qquad \text{or} \qquad \partial TL_t / \partial H_t = - \pi_t \delta_t / W_t \tag{15}$$

where π_t is the marginal cost of gross investment in health.

In Grossman's model, the rates of health depreciation are assumed to be exogenous. However, this paper follows Cropper (1981) by assuming that the rates of health depreciation are endogenous. If an individual is exposed to air, water, and land pollution, her/his health is degraded gradually. Beside, the rates of depreciation also are affected by age and stock of health. Therefore, the rate of depreciation of health capital is written as

$$\delta_t = G(t, P_t, S_t) \tag{16}$$

where t is time, P_t is pollution, and S_t is chronic illness or stress.

From (10), (15), and (16), we have

$$\partial TL_t / \partial H_t = Q(t, W_t, PM_t, P_t, S_t) \qquad (17).$$

This equation is interpreted to mean that pollution, along with wages, medical care, and other variables would affect health and time lost due to illness.

3.4 Empirical Model

3.4.1 Poisson regression and statistical tests for Poisson model

An empirical model is formulated to test whether toxic chemical releases have a positive impact on number of lost work days. We employ a Poisson regression model for count data to estimate discrete days of work lost, assuming number of lost work days, Y, follows a Poisson distribution with parameter λ

$$\Pr ob(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \qquad y = 0,1,2 \ldots n \tag{18}$$

Equation (18) gives the probability an individual has n work loss days in a given period of time. Both the expected value and variance of a Poisson distribution are equal to λ

$$E[y] = Var[y] = \lambda. \tag{19}$$

The Poisson regression model can be formulated as a loglinear model

$$\ln \lambda = \alpha X + \varepsilon_{\lambda} \tag{20}$$

where X is the vector of explanatory variables.

The Poisson model is a more restrictive version of the negative binomial in that $\lambda = E[y] = Var[y]$; it is thus necessary to test if the restrictions of the Poisson model hold. If the variance is greater than the mean, overdispersion exists and if the variance is smaller than the mean, underdispersion exists. Thus, a number of tests for the equality of the mean and the variance must be conducted (Cameron and Trivedi 1998). The first test is the likelihood ratio test based on Poisson and negative binomial regressions. In the negative binomial distribution

$$Var[y] = E[y] + k\,(E[y])^2$$

where k is a dispersion parameter; for the Poisson distribution $Var[y] = E[y]$ or $k=0$. The null hypothesis is $H_0 : k = 0$ and the alternative hypothesis is $H_a : k > 0$. The null hypothesis is rejected if the likelihood ratio statistic is greater than $\chi^2_{(1-2\alpha\,,\,1\ df)}$ where α is the significance level.

The second test for equality of the mean and the variance is the Wald test, which is conducted as a *t* test of dispersion parameter k using the one-sided test critical value of $z_{1-\alpha}$ where α is the level of significance.

3.4.2 Negative binomial

If the tests for equality of the mean and variance in the Poisson model fail, the negative binomial model is used. The probability mass function with a negative binomial distribution takes the following form

$$f(y) = \frac{\Gamma(k+y)}{y!\Gamma(k)} p^k (1-p)^y \tag{21}$$

where y is number of lost work days, y=0,1,2…, Γ is the gamma function, and p and k are parameters of the distribution.

In investigating how toxic chemicals affect labor productivity, losses are measured by number of work days lost. Based on the dataset created from the 2002 NHIS, the work-loss days equation is thus specified as

$$\ln \lambda = \zeta_0 + \zeta_1 \text{H} + \zeta_2 \text{I} + \zeta_3 \text{T} + \zeta_4 \text{CO} + \zeta_5 \text{WE} + \varepsilon_{\text{Y}} \tag{22}$$

where λ is expected value of work days lost, H is health status, I is a vector of individual's characteristics, T represents total toxic chemical releases, WE is a vector of weather condition including average temperature and precipitation, and CO is a vector of characteristics of the county of residence.

3.4.3 Sample selection bias

The dependent variable in this analysis is number of work days lost for those people who had a job in the past 12 months. Individuals with poor health might be systematically less likely to be employed; leading to potential selection bias in the model due to censoring of the data. Thus, a two-stage sample selection model developed by Heckman (1979) is used to control for selection bias.

A probit model using all observations in the dataset is employed to estimate probability of working

$$W = \varsigma_0 + \varsigma_1 H + \varsigma_2 I + \varsigma_3 T + \varsigma_4 CO + \varsigma_5 WE + \varepsilon_w \qquad (23)$$

where W is a binary variable for working status, H is health status, I is a vector of individual characteristics, T represents total toxic chemical releases, CO is a vector of characteristics of the county of residence, WE is a vector of weather condition and ε is the error term. A selection bias control variable, which is equivalent to the Inverse Mill's ratio, is calculated using the equation

$$\mu_i = \frac{\Theta(X_i, \omega)}{\Phi_i(X_i, \omega)} \qquad (24)$$

where Θ and Φ are the probability density function and the cumulative distribution function, X is the vector of explanatory variables in the employment equation, and ω is the conformable parameter vector. The inverse Mills ratio is then included as an additional explanatory variable in the main model to correct for selection bias between those working and those not working.

3.4.4 Endogenous health status

Previous studies show that pollution is positively related to a number of diseases (Mills, et al. 1991; Ostro, et al. 1993; Ostro, et al. 1991; Pope-III 1991; Portney and Mullahy 1986; Samakovlis, et al. 2005), which would lead to health deterioration. As a result of reduced health input, labor productivity would drop; not only would number of days worked drop, actual on-the-job performance may suffer as well. In the context of the effect of toxic chemical releases on productivity losses, health may be an endogenous variable. It follows that in the health literature, health status is hypothesized to be endogenous in a number of studies (Cai and Guyonne 2004; Dwyer and Mitchell 1999; Haveman, et al. 1994; Stern 1989). While Dwyer and Mitchell (1999) reject the endogeneity of self-reported health measures, Stern (1989), Haveman et al. (1994), Cai and Guyonne (2004) find health status to be endogenous.

We follow the literature and assume that health is an endogenous variable. The generalized instrumental variable method is used to control for the endogeneity of health status. First, health status is regressed against explanatory variables that affect health status and predicted values of health status are calculated from this regression. Then, health status is replaced by the predicted values in the sample selection equation and work-loss equation.

The instrument equation is written as

$$H^* = \beta_1 X + \varepsilon_H \tag{25}$$

where H^* is an unobservable latent variable, and X is a vector of explanatory variables including demographic and economic characteristics of an individual. The instrument equation of health status is estimated using a probit model.

3.5 Dependent and Independent Variables

Two measures of self-reported health status that have been used in the health literature are dichotomous (Dwyer and Mitchell 1999; Haveman, et al. 1994) and a multi-point scale of health status (Cai and Guyonne 2004; Lee 1982; Rivera 2001; Stern 1989). In this study, these two measures of health status are used to investigate how toxic chemical releases affect productivity loss.

The 5-point scale measure is respondents' self-reported health status, ranging from excellent, very good, good, fair and poor, and taken directly from the survey. A dichotomous health status measure is then created from 5-point scale by including excellent and very good in a "good health" category and good, fair and poor in a "fair health" category.

Determinants of self-reported health status include toxic chemical releases and other variables that affect employment status and work-loss days including demographic and socioeconomic variables; behavioral variables; employment conditions; and meteorological conditions. We also include health-related conditions, health care access and utilization, and health insurance as explanatory variables of health status. These variables are common in much of the literature modeling general health status (Cai and Guyonne 2004; Haveman, et al. 1994; Stern 1989).

Employment is assumed to be a function of demographic and socioeconomic characteristics including gender, age, race, education, marital status, income and home ownership (Bradley, et al. 2002; Cai and Guyonne 2004; Stern 1989) as well as health status. Annual mean precipitation and the annual minimum temperature are included as explanatory variables and differences in regions also are controlled using regional dummies. Other variables that may influence working status are toxic releases, behaviors such as drinking and smoking and living in an urban environment, controlled for by population density and a dummy for urban counties.

Work loss is hypothesized to be affected by environmental pollution measured by total toxic chemical releases at the county level. Ostro (1983, 1987 and 1989) found a positive relationship between air pollution and work loss and restricted activity days. Work loss is also assumed to be a function of general health status (Marmot, et al. 1995; Marmot, et al. 1993; North, et al. 1993). It is expected that good health status has a negative effect on work loss.

Biological variables such as gender, age, and race and of education and economic variables are believed to affect work loss. Women are expected to miss more work days since their labor may be valued more highly at home, and are more often required to care for sick children (Machnes 1992; Ostro 1987). People who are married or have children tend to miss more work days since they have to spend more time to take care of their family (Ostro 1987). People become less healthy as they age, so age is predicted to have a positive effect on work-loss days (Ostro 1987; Silver 1970). More highly-educated people tend to lose fewer work days since they have greater job responsibility, and may also have higher paying jobs (Grossman 1972; Stratmann 1999). High-income and wage rate are predicted to negatively impact lost work days since they represent higher opportunity costs (Meyer, et al. 1995; Ostro 1987). Likely because of limited access to health care, African-American individuals experience higher morbidity than whites, so they are expected to take more sick days than white workers (Ostro 1987; Stratmann 1999).

Other independent variables assumed to affect work days lost are behavior variables including lifestyle habits, work characteristics and meteorological conditions of the county of residence. Lifestyle habits including smoking and drinking are linked to a number of diseases and injuries, which results in losses of work days (Centers for Disease Control and Prevention 1994; Parrish, et al. 1993; Robbins, et al. 2000; Smith, et al. 1999; US Department of Health and Human Services 1982; 1983; 1984). Employment characteristics are included to control for the differences in working environments of respondents, since in service industries, workers are exposed to lower risk levels, while manufacturing and agricultural industries are riskier. Dummies for regions are also included since people in different regions have different culture, lifestyles, which may result in variations in health status and lost work days.

3.6 Data

3.6.1 Sources of data

As previously mentioned, we use a unique dataset, combining individual data from NHIS with county level TRI data, National Climatic data, and Census 2000 data, to investigate the effects of toxic release exposure on work loss.

The NHIS is conducted annually by the National Center for Health Statistics, Centers for Disease Control and Prevention (http://www.cdc.gov/nchs/nhis), and is the main source of health information for the American household population. The primary data in the NHIS consists of a Basic Module which is divided into three components: Family Core, Sample Adult Core, and Sample Child Core. The Family Core component collects information on household composition and socio-demographic characteristics, income and assets, health status and limitation of activity, injuries, and health care access and utilization and health insurance coverage for all family members. One sample adult and one sample child are randomly selected in each sample family and their detailed information is included in Sample Adult Core and Sample Child Core components. The Sample Adult component requires self-response to all questions and the Sample Child component requires response from a knowledgeable adult in the family. The Sample Adult component covers subjects that are included in the Family Core, in which the questions are more specific and some additional subjects, including adult health behaviors and occupation and employment status. Similarly, additional subjects are covered in the Sample Child Core component including child behavior and child immunization. The interviewed sample size of 2002 NHIS was 36,161 households with 93,386 persons in 36,831 families. The Sample Adult component consisted of 31,044 persons 18 years of age or older and the Sample Child component consisted of 12,524 children under 18 years old. The data used in this study are from the Sample Adult component of the 2002 NHIS including work loss, health status, demographic characteristics, economic status and education status.

Total toxic chemical releases at county level are derived from the TRI, USEPA (http://www.rtknet.org). Data for population density, urban county and population at county level are taken from Census 2000 Summary File 3, US Census Bureau, (http://www.census.gov/Press-Release/www/2002/sumfile3.html). Average temperature and precipitation data at the station level come from National Climatic Data Center, National Oceanic and Atmospheric Administration (http://www.ncdc.noaa.gov).

The individual-level NHIS data are then merged with county-level data from TRI, US Census 2000 and National Climatic Data Center using the county FIPS code. However, the public release of the NHIS dataset does not contain county codes because of confidentiality issues. Hence, our county-level dataset of environmental and other variables was sent to the Research Data Center, National Center for Health Statistics, CDC to be merged with individual-level NHIS data by the Research Data Center[5]. Data analysis conducted in this study is performed using remote access where SAS programs are submitted and outputs are received via email.

3.6.2 Data description

Working status is used as a dependent variable in the sample selection equation. Working status takes the value of 1 if response was 'had job last week' or 'had no job last week but had job past 12 months'. Data for this variable were taken from the responses to the question "Although you did not work last week, did you have a job or business at any time in the past 12 months". Data for work days lost is based on responses to the question "During the PAST 12 MONTHS, about how many days did you miss work at a job or business because of illness or injury (do not include maternity leave)?". Only those who had a job in the past 12 months were asked this question. General health status is self-reported, based on the response to the question "Would you say your health in general is excellent, very good, good, fair, or poor?" where 5 represents excellent health and 1 represents poor health.

[5] We would like to thank Negasi Beyene at the National Center for Health Statistics, CDC for his help on merging data and providing access to the dataset using the remote access system

Demographic characteristic variables used are race, age, sex and marital status socio-economic variables are education and income. Education attainment is represented by dummy variables where having a college degree is assigned a 1 and 0 otherwise. Income is a dummy variable taking a value of 1 if total combined family income was less than $45,000 and 0 otherwise.

A dummy for alcohol drinking is created from the current alcohol drinking status, taking the value of 1 if the respondent had more than 3 drinks per week. The current smoker dummy takes the value of 1 if the respondent currently smokes at least some days.

Employment conditions and characteristics include number of hours worked, number of years worked, a dummy variable for paid sick leave (1 if having paid sick leave on the current or most recent job), a dummy hourly worker at the current or most recent job, and a dummy for respondents who work more than one concurrent job. Dummies are also included for the type of industries in which respondents are employed. These include dummies for employment in service, manufacturing and agricultural industries.

Several health care access and utilization variables were used as determinants of health status, including the number of times the respondent had seen a doctor or other health care professional about his or her own health, number of emergency room visits, and if the respondent had a pneumonia shot during the past 12 months. A dummy is created taking the value of 1 if the respondent did not have any health insurance coverage at the time of interview.

Health-related conditions include existence of cancer, asthma and migraine, and body mass index. Data for the existence of cancer is based on response to the question "Have you ever been told by a doctor or other health professional that you had cancer or a malignancy of any kind?", existence of asthma is based on the question "Have you ever been told by a doctor or other health professional that you had asthma?" and existence of migraine is based on the question "During the past three months, did you have severe headache or migraine?".

Population density is the number of persons per square miles. The dummy for urban county takes the value of 1 if the county belongs to a Metropolitan statistical containing a core urban area of 50,000 or more population. The dummy for the Western region takes value of 1 if county of residence is in the Western region. The same applies for dummies for the Northeast and the Midwest regions[6].

Total toxic chemical releases are the sum of air, water, and land releases at the county level. Precipitation data are the annual average precipitation level per station. If a county has missing data, we use data from the nearest station of another county, based on distance from the county's centroid.

Of the original 31,044 observations in the Sample Adult component, 25,552 remain after eliminating data for item non-response. The sub-sample that excludes those who did not have a job in the past 12 months contains 14,632 observations. Table 3.1 contains definitions and Table 3.2 contains descriptive statistics of all the variables used

[6] Western region: Washington, Oregon, California, Nevada, New Mexico, Arizona, Idaho, Utah, Colorado, Montana, Wyoming, Alaska, and Hawaii. Northeast region: Maine, Vermont, New Hampshire, Massachusetts, Connecticut, Rhode Island, New York, New Jersey, and Pennsylvania. Midwest region: Ohio, Illinois, Indiana, Michigan, Wisconsin, Minnesota, Iowa, Missouri, North Dakota, South Dakota, Kansas, and Nebraska

in this study. The means of the two measures of health status of the sub-sample are statistically higher than those of the whole sample at the 1% level of significance. The means for binary and 5-point scale health status for the whole sample are 3.74 and 0.61, respectively and for the sub-sample are 4.02 and 0.72, respectively. Other variables which have significant differences at the 5% level between mean in the whole sample as compared to the sub-sample include DU, MALE, COLLEGE, MARRIED, INCOME45, DRINK and SMOKE. The mean work loss days is 3.5 days per year and average total toxic chemical releases is 10 pounds per person in 2001 for the sub-sample. Table 3.3 presents the frequencies of the three main categorical variables.

Table 3.1 Variable description

Variable	Description
NE	=1 if living in the Northeast region, =0 otherwise
WE	=1 if living in the West region, =0 otherwise
MW	=1 if living in the Midwest region, =0 otherwise
HEALTH5	General health status on a five-point scale (1=excellent, 5=poor)
HEALTH2	Binary general health status (1=good, 0=fair)
TOTREL	Total toxic releases in 2001 at county-level (10,000 pounds/person)
DU	=1 if county of residence is urban county, =0 otherwise
DENSITY	Thousand of persons/square mile
PRECIP	Annual mean precipitation (inch)
LOWTEMP	Lowest temperature (^{o}F)
MALE	=1 if male, =0 otherwise
AGE	Years of age
WHITE	=1 If white, =0 otherwise
COLLEGE	=1 If has a college degree, , =0 otherwise
MARRIED	=1 If married, =0 otherwise
INCOME45	=1 if income < $45,000, =0 otherwise
ASTHMA	=1 if having asthma, =0 otherwise
CANCER	=1 if having cancer, =0 otherwise
MIGRAINE	=1 if had severe migraine in past 3 months, =0 otherwise
BMI	Body Mass Index
NOINSUR	=1 if had no health insurance coverage, =0 otherwise
EMER	Number of times in a hospital emergency room
DOCVISIT	Number of times seeing a doctor
PNEUSHOT	=1 if ever had pneumonia shot,=0 otherwise
HOME50	=1 if respondent's home built before 1950, =0 otherwise
HOUSEOWN	=1 if owning a house, =0 otherwise
DRINK	=1 if current moderate or heavy drinker, =0 otherwise

Table 3.1 (continued)

Variable	Description
SMOKE	= 1 if current smoker, =0 otherwise
WORK	=1 if had a job in past 12 months, =0 otherwise
WORKLOSS	Number of work-loss days
SERVICE	=1 if working in service industry, =0 otherwise
MANUF	=1 if working in manufacturing industry, =0 otherwise
AGRI	=1 if working in agriculture, =0 otherwise
ONEJOB	=1 if having more than 1 job, =0 otherwise
HOURWORK	Number of hours worked in a week
YEARONJOB	Number of years on a current or recent job
PAIDSICK	=1 if had paid sick leave, =0 otherwise
PAIDHOUR	=1 if paid by hour, =0 otherwise
EMP500	=1 if working in place > 500 employees, =0 otherwise

Table 3.2 Descriptive statistics

Variable	The whole sample (N=25,552)		Subsample (those working) (N=14,632)	
	Mean	Std dev	Mean	Std dev
NE	0.1843	0.3878	0.1794	0.3837
WE	0.2058	0.4043	0.2068	0.4050
MW	0.2400	0.4271	0.2474	0.4315
HEALTH5	3.7405	1.0824	4.0167	0.9122
HEALTH2	0.6111	0.4875	0.7161	0.4509
TOTREL	0.0011	0.0041	0.0010	0.0039
DU	0.8350	0.3711	0.8504	0.3566
DENSITY	0.0221	0.0719	0.0214	0.0692
PRECIP	37.7165	17.4160	37.4308	17.2815
LOWTEMP	10.1479	13.5197	9.8939	13.6266
MALE	0.4435	0.4968	0.5004	0.5000
AGE	47.1817	17.7876	41.0985	12.6523
WHITE	0.7991	0.4007	0.8049	0.3962
COLLEGE	0.1623	0.3687	0.2027	0.4020
MARRIED	0.4930	0.5000	0.5224	0.4995
INCOME45	0.6500	0.4770	0.4678	0.4989
ASTHMA	0.1081	0.3106	0.1039	0.3052
CANCER	0.0770	0.2666	0.0430	0.2029
MIGRAINE	0.1527	0.3597	0.1515	0.3585
BMI	2.6976	0.5738	2.6988	0.5571
NOINSUR	0.1371	0.3440	0.1355	0.3423
EMER	0.3215	0.7752	0.2427	0.6263
DOCVISIT	2.6330	2.2690	2.2466	2.0636
PNEUSHOT	0.1787	0.3831	0.0863	0.2809
HOME50	0.3066	0.4611	0.2843	0.4511

Table 3.2 (continued)

Variable	The whole sample (N=25,552)		Subsample (those working) (N=14,632)	
	Mean	Std dev	Mean	Std dev
HOUSEOWN	0.6766	0.4678	0.6839	0.4649
DRINK	0.1918	0.3937	0.2272	0.4190
SMOKE	0.2258	0.4181	0.2412	0.4278
WORK	0.6951	0.4604	1	0
WORKLOSS			3.4950	12.2222
SERVICE			0.3952	0.4889
MANUF			0.1285	0.3347
AGRI			0.0210	0.1435
ONEJOB			0.0800	0.2713
HOURWORK			40.6040	12.8768
YEARONJOB			7.7776	8.5663
PAIDSICK			0.5947	0.4909
PAIDHOUR			0.5516	0.4973
EMP500			0.2129	0.4094

Table 3.3 Frequencies of health status and working status

Variable	Frequency
5-point scale health status	
Excellent	7,493
Very good	8,123
Good	6,585
Fair	2,516
Poor	835
Binary health status	
Good	15,616
Fair	9,936
Working status	
Working	17,762
Not working	7,790

3.7 Empirical Results

In this section, we present the empirical results of investigating how toxic chemical releases impact productivity losses. The first section reports the results for the model using binary health status.

3.7.1 Results using binary health status

The estimated coefficients of variables in the working status equation with exogenous health status are presented in Table 3.4. Respondents were more likely to work if they lived in the Midwest region or in areas experiencing lower minimum temperatures. Health status has a positive and significant association with the likelihood of working. The healthier the respondent, the more likely they are to have held a job in the past 12 months. The likelihood of working increased if respondents were male, young, had a college degree, or owned a house and decreased if family had an income less than $45,000 and were married. To correct for selection bias, the inverse Mill ratio is calculated and included as an explanatory variable in the work loss equation (Heckman 1979).

Results for work-loss days using the Poisson model and overdispersion tests of Poisson regression are presented in the Appendix A. Tests of overdispersion suggest the negative binomial is the appropriate model for days work lost (Appendix B).

Table 3.5 presents the parameter estimates from the negative binomial regression for the work loss model assuming binary health status is exogenous. The estimated coefficient for the inverse Mills ratio was statistically significant. General health status is significantly related to work days lost. It is estimated that being in good health reduces the number of work-loss days by 2.92 days per year. This result is consistent with other findings (Marmot, et al. 1995; Marmot, et al. 1993; North, et al. 1993). Levels of toxic chemical releases in county of residence are positively related to work days lost, which is similar to other studies (Ostro 1983; 1987; Ostro and Rothschild 1989). An increase in toxic releases by 1 pound/person would raise lost work days by 6.2 per year. Respondents in the Northeast and Midwest regions lost more days at work than respondent in other regions. An increase in population density of 100,000 persons/square mile decreases days on the job by 1.53 days. Higher minimum temperatures are associated with more work days lost, suggesting these conditions promote more rapid spread of diseases like colds and influenza. Coefficients for all six biological and socioeconomic variables are negative and statistically significant except for the white dummy. Women lost 0.88 more work days compared to men. Interestingly, an additional year in age lowers number of days missing from work by 0.04. Possible explanations for this finding are that the older workers rarely miss work because there is a possibility that they will be replaced by younger workers if they take days off and that they have more responsible jobs. Married people and people with college degrees have fewer days lost. Having family income less than $45,000 reduced number of days lost by 0.58. This is likely because they do not have sick leave or no health insurance. Behavior variables including smoking and drinking are both positively associated with number of days missed, with drinking contributing more to productivity loss by 0.35 days, in concurrence with other studies (Batenburg and Reinken 1990; Bush and Wooden 1995; Marmot, et al. 1993; North, et al. 1993). Working in a service industry decreased the work days missed by 0.58. Individuals who work for more years or work longer numbers of hours are also likely to miss fewer work days. Having paid sick leave, being paid by the hour and working in a place with more than 500 others is associated with increased work days lost.

Table 3.4 Results for working status equation with exogenous binary health status (Dependent variable = working status)

Variable	Parameter Estimate	Standard Error	Chi-Square
Intercept	2.3962****	0.0635	37.73
NEA	-0.0260	0.0309	-0.84
WE	-0.0560	0.0365	-1.53
MW	0.0707**	0.0317	2.23
HEALTH2	0.3455***	0.0201	17.13
TOTREL	0.3383	2.2464	0.15
DU	0.0183	0.0268	0.68
DENSITY	0.0163	0.1496	0.11
PRECIP	-0.0005	0.0007	-0.61
LOWTEMP	-0.0022**	0.0009	-2.28
MALE	0.4117***	0.0202	20.34
AGE	-0.0403***	0.0006	-64.65
WHITE	-0.0094	0.0248	-0.38
COLLEGE	0.2503***	0.0288	8.68
MARRIED	-0.1200***	0.0210	-5.70
INCOME45	-0.5620***	0.0233	-24.07
DRINK	0.1219***	0.0268	4.54
SMOKE	0.1058***	0.0241	4.38
HOUSEOWN	0.2140***	0.0239	8.95

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 3.5 Negative binomial results for work loss with binary exogenous health (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square	Discrete change (1 unit)
INTERCEPT	1.7140***	0.1479	134.32	
NEA	0.2348***	0.0584	16.18	0.8961
WE	0.0887	0.0681	1.70	0.3212
MW	0.1528***	0.0585	6.83	0.5630
HEALTH2	-0.7507***	0.0506	219.74	-2.9187
TOTREL	9.7839**	4.9265	3.94	62,626
DU	0.0173	0.0537	0.10	0.0607
DENSITY	-0.5670**	0.2866	3.91	-1.5274
PRECIP	-0.0026*	0.0015	3.02	-0.0090
LOWTEMP	0.0060***	0.0019	10.37	0.0211
MALE	-0.2530***	0.0501	25.55	-0.8836
AGE	-0.0109***	0.0031	11.99	-0.0381
WHITE	-0.0581	0.0476	1.49	-0.2084
COLLEGE	-0.1129**	0.0519	4.73	-0.3836
MARRIED	-0.0787**	0.0408	3.72	-0.2775
INCOME45	-0.1623***	0.0603	7.24	-0.5816
DRINK	0.2595***	0.0472	30.22	0.9866
SMOKE	0.1735***	0.0453	14.70	0.6371
SERVICE	-0.1677***	0.0415	16.29	-0.5808
MANUF	0.0193	0.0582	0.11	0.0686
AGRI	0.0674	0.1318	0.26	0.4380
ONEJOB	0.0516	0.0679	0.58	0.1862
HOURWORK	-0.0042***	0.0015	7.61	-0.0147
YEARONJOB	0.0087***	0.0026	11.25	0.0308
SDAYPAID	0.2841***	0.0408	48.36	0.9741
PBYHOUR	0.2241***	0.0396	31.96	0.7726
EMP500	0.1583***	0.0468	11.45	0.5829
INVERSE MILLS	1.6465***	0.4549	13.10	

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

The generalized instrumental variable method is used to estimate the working equation and the work loss equation, in order to account for the endogeneity of health status. A Hausman specification test (Hausman 1978) is used to test for endogeneity of health status. In this case, we conclude that health status is endogenous since the calculated statistic of 267.74 is greater than the critical value of 3.84 for a chi-square with 1 degree of freedom. However, it is necessary to test for the validity of any instrument used in instrumental variables estimation. The Nelson and Startz (1990) test is used in this analysis. The calculated Nelson and Startz statistic is 5,267, which is greater than critical value of 2. We conclude that the instruments are relevant.

The instrumental variable probit results for working status using binary health status are reported in Table 3.6. All of the coefficients that are statistically significant in the exogenous health model remain significant in the endogenous model and the Western dummy becomes significant as well. Health status still has positive but even greater effect on employment status. Coefficients for the other significant variables are slightly smaller in absolute values than those in the exogenous model. This means that the effect of explanatory variables is overestimated in the case of exogenous health status.

Table 3.6 Results for working status equation with endogenous binary health status (Dependent variable = working status)

Variable	Parameter Estimate	Standard Error	Chi-Square
INTERCEPT	2.1752***	0.0681	1,019.55
NEA	-0.0258	0.0309	0.70
WE	-0.0695**	0.0365	3.61
MW	0.0764***	0.0317	5.79
$HEALTH2^{IV}$	0.4111***	0.0247	278.13
TOTREL	0.7585	2.2357	0.12
DU	-0.0028	0.0270	0.01
DENSITY	0.0163	0.1495	0.01
PRECIP	-0.0006	0.0008	0.52
LOWTEMP	-0.0018*	0.0010	3.20
MALE	0.4056***	0.0202	402.35
AGE	-0.0371***	0.0007	2,880.79
WHITE	-0.0365	0.0250	2.12
COLLEGE	0.2267***	0.0288	61.80
MARRIED	-0.1307***	0.0211	38.51
INCOME45	-0.5094***	0.0238	456.74
DRINK	0.0916***	0.0270	11.50
SMOKE	0.1515***	0.0247	37.68
HOUSEOWN	0.2160***	0.0239	81.65

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

The instrumental variable estimation for the work days lost equation is presented in Table 3.7. Comparing the results in Table 3.7 and Table 3.5, there are some significant differences in the estimated coefficients. The coefficient for health status remains significant and of the expected negative sign but the magnitude of the effect of health status on work loss increases in a nontrivial way: when endogeneity of health status is controlled for, the negative impact on work loss nearly doubles. It is not surprising that the effect of health on work loss is understated in the case of exogenous health, which may result from measurement error on the health status variable. The coefficient for toxic releases remains significant, but less so. The coefficient for toxic chemical releases is smaller than that with exogenous health, but the marginal effect of toxic releases on work-loss days is greater. The likely reason for the increase in the effect is that in the case of endogenous health, toxic chemicals have direct and indirect impacts on work days lost, and toxic releases negatively affect health, which in turn negatively affects work loss. A 1 pound/person increase in toxic releases results in an increase of 8.7 days in work lost. The coefficient for the urban county dummy becomes significant and has the expected positive sign. Dummies for college, being married and smoking no longer have significant effects on work days lost. Coefficients for age and dummies for male, income of less than $45,000 and drinking remain significant. The effects of male and drinking dummies on work-loss days are almost the same but those for the age and income dummies triple. The coefficients for dummy variables for working in the service industry, number of years on job, having paid sick leave, being paid by the hour and working in a place of more than 500 people all remain significant and consistent.

Table 3.7 Negative binomial results for work loss with binary endogenous health (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square	Discrete change (1 unit)
INTERCEPT	2.7118***	0.1540	310.10	
NEA	0.2117***	0.0569	13.86	0.7938
WE	0.0280	0.0681	0.17	0.0987
MW	0.0942*	0.0575	2.69	0.3382
HEALTH2^{IV}	-1.4080***	0.0579	592.01	-7.4041
TOTREL	9.0982*	5.1710	3.10	87,489
DU	0.1963***	0.0529	13.80	0.6427
DENSITY	-1.0167***	0.2901	12.28	-2.2326
PRECIP	-0.0036***	0.0015	5.89	-0.0124
LOWTEMP	0.0030*	0.0018	2.73	0.0105
MALE	-0.2008***	0.0487	16.98	-0.6947
AGE	-0.0244***	0.0029	69.78	-0.0842
WHITE	0.1365***	0.0470	8.43	0.4602
COLLEGE	0.0020	0.0498	0.00	0.0071
MARRIED	-0.0479	0.0404	1.40	-0.1675
INCOME45	-0.4063***	0.0565	51.75	-1.5049
DRINK	0.3546***	0.0460	59.35	1.3832
SMOKE	-0.0195	0.0454	0.18	-0.0678
SERVICE	-0.2248***	0.0405	30.86	-0.7679
MANUF	-0.0288	0.0569	0.26	-0.0995
AGRI	-0.1679	0.1293	1.69	-0.5421
ONEJOB	-0.0453	0.0664	0.46	-0.1553
HOURWORK	-0.0044***	0.0015	9.21	-0.0154
YEARONJOB	0.0092***	0.0026	12.86	0.0324
PAIDSICK	0.2282***	0.0399	32.71	0.7797
PAIDHOUR	0.2282***	0.0386	34.98	0.7798
EMP500	0.1557***	0.0454	11.73	0.5681
INVERSE MILLS	2.0373***	0.4230	23.20	

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

3.7.2 Empirical results using a 5-point scale health status

The probit regression results for working status using an exogenous 5-point scale health status are reported in Table 3.8. The coefficients for the variables are consistent in terms of signs and magnitude when compared with the coefficients using binary health status. Health status is significantly positively associated with working status.

Testing for dispersion, it is obvious that the Poisson regression model is inadequate for lost work days since the calculated likelihood ratio is 127,552. Therefore, the negative binomial is used to model number of work days lost.

Table 3.9 shows the negative binomial regression results for work loss with an exogenous 5-point scale health status. As expected, health status has a significantly negative effect on work loss. Discrete changes in work days lost with a change in health status from one scale to another are not constant, increasing when health status gets worse. For example, a change in health status from excellent to very good results in an increase of work loss by 1.12 days while a change in health from fair to poor results in an increase of work loss by 4.19 days (Table 3.10). The coefficient for toxic releases is positive in sign and remains significant at the 10% level, suggesting pollution contributes to work days lost. However, the effect of toxic releases on work loss is reduced. An increase of toxic releases by 1 pound raises the number of work days lost by 1.63 compared with 6.26 days with exogenous binary health status. The rest of the coefficients have the same signs and levels of significance as using exogenous binary health status.

Table 3.8 Results for working status equation with exogenous 5-point scale health status (Dependent variable = working status)

Variable	Parameter Estimate	Standard Error	Chi-Square
INTERCEPT	1.7652***	0.0729	24.21
NEA	-0.0370	0.0310	-1.19
WE	-0.0627*	0.0367	-1.71
MW	0.0626**	0.0318	1.96
HEALTH5	0.2163***	0.0094	22.94
TOTREL	0.5754	2.2559	0.26
DU	0.0084	0.0270	0.31
DENSITY	-0.0011	0.1504	-0.01
PRECIP	-0.0004	0.0007	-0.49
LOWTEMP	-0.0023***	0.0009	-2.35
MALE	0.4184***	0.0207	20.55
AGE	-0.0390***	0.0006	-62.03
WHITE	-0.0250	0.0250	-1.00
COLLEGE	0.2291***	0.0289	7.92
MARRIED	-0.1227***	0.0211	-5.80
INCOME45	-0.5445***	0.0234	-23.21
DRINK	0.1008***	0.0269	3.74
SMOKE	0.1309***	0.0243	5.38
HOUSEOWN	0.1952***	0.0240	8.11

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 3.9 Negative binomial results for work loss with exogenous 5-point scale health (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square	Discrete change (1 unit)
Intercept	2.9664***	0.1765	282.60	
NEA	0.2276***	0.0580	15.40	0.7992
WE	0.0477	0.0674	0.50	0.1574
MW	0.1329**	0.0583	5.21	0.4490
HEALTH5	-0.4392***	0.0265	274.44	
TOTREL	8.5263*	4.8518	3.09	16,256
DU	0.0135	0.0534	0.06	0.0437
DENSITY	-0.6697***	0.2860	5.48	-1.5889
PRECIP	-0.0034**	0.0015	5.36	-0.0110
LOWTEMP	0.0068***	0.0018	13.82	0.0223
MALE	-0.2962***	0.0507	34.12	-0.9528
AGE	-0.0100***	0.0031	10.24	-0.0324
WHITE	-0.0381	0.0474	0.65	-0.1252
COLLEGE	-0.1123**	0.0512	4.80	-0.3515
MARRIED	-0.0658*	0.0405	2.64	-0.2139
INCOME45	-0.1396***	0.0592	5.56	-0.4610
DRINK	0.2813***	0.0466	36.44	0.9947
SMOKE	0.1656***	0.0454	13.34	0.5587
SERVICE	-0.1673***	0.0413	16.45	-0.5349
MANUF	-0.0098	0.0578	0.03	-0.0319
AGRI	0.0366	0.1311	0.08	0.1212
ONEJOB	0.0534	0.0673	0.63	0.1778
HOURWORK	-0.0029**	0.0015	3.67	-0.0094
YEARONJOB	0.0083***	0.0026	10.52	0.0271
SDAYPAID	0.2760***	0.0404	46.71	0.8725
PBYHOUR	0.2077***	0.0392	28.06	0.6625
EMP500	0.1467***	0.0464	10.00	0.4969
INVERSE MILLS	1.2650***	0.4595	7.58	

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 3.10 Discrete change of work loss with exogenous 5-point scale health status

Health status	Change	Discrete change in lost work days
From excellent to very good	$5 \rightarrow 4$	1.1230
From very good to good	$4 \rightarrow 3$	1.7423
From good to fair	$3 \rightarrow 2$	2.7032
From fair to poor	$2 \rightarrow 1$	4.1939

Table 3.11 presents probit regression results for working status using an endogenous 5-point scale health status, and the results are similar to those using the exogenous 5-point scale health status presented in Table 3.8 and to the results using binary health status in Table 3.6.

Table 3.12 and table 3.13 report the negative binomial regression results for work days lost when health status is endogenous. Compared to the work loss estimate with the HEALTH5 model in Table 3.7, coefficients for health status both have negative and statistically significant effect on work loss but the magnitude of the effect is quite different. The effect of health status on work loss is much stronger in the endogenous model than in the exogenous model. Moving from excellent health status to very good health status raises number of work days lost by 2.30 while raising work days lost only 1.12 days with exogenous health. Discrete changes in work loss when moving from one health status to another increase with endogenous health status. The change in work days lost resulting from a change in health status from excellent to very good is 2.30 days while from fair to poor is 15.46 days. The coefficient for toxic releases is insignificant in the endogenous health model while it is significant at the 10% level in the exogenous model. The dummy for urban county becomes significant in the case of endogenous health.   Lowest minimum temperature no longer has an effect on work days lost. The coefficient for dummy for white respondent becomes significantly positive with endogenous HEALTH5.

There are some similarities and differences when comparing estimated coefficients for explanatory variables in endogenous HEALTH2 with endogenous HEALTH5 model. Regardless of the way health status is measured, it has a significant and negative effect on work-loss. The significant coefficient for total releases in the endogenous HEALTH2 becomes insignificant in the endogenous HEALTH5 model. The dummies for urban county, white, male and income less than $45,000, age, drinking, population density and precipitation all have significant effects on work-loss in both models and the magnitude of those effects are consistent. The dummies for college and smoking become significant in the endogenous HEALTH5 model. The coefficients for other variables of employment status including the dummies for working in the service industry, having sick days paid, being paid by the hour, working place of more than 500 people, number of hour worked and years on the job remain significant and are consistent in terms of signs and absolute values in the endogenous HEALTH5 model.

Table 3.11 Results for working status with endogenous 5-point scale health status (Dependent variable = working status)

Variable	Parameter Estimate	Standard Error	Chi-Square
Intercept	1.7089***	0.1032	274.41
NEA	-0.0368	0.0308	1.42
WE	-0.0625*	0.0365	2.94
MW	0.0654**	0.0317	4.26
$HEALTH5^{IV}$	0.2100***	0.0182	133.71
TOTREL	0.4560	2.2313	0.04
DU	0.0084	0.0269	0.10
DENSITY	0.0204	0.1491	0.02
PRECIP	-0.0004	0.0008	0.25
LOWTEMP	-0.0023***	0.0010	5.71
MALE	0.4079***	0.0202	409.30
AGE	-0.0382***	0.0007	2,830.52
WHITE	-0.0311	0.0251	1.54
COLLEGE	0.2230***	0.0293	58.09
MARRIED	-0.1273***	0.0210	36.74
INCOME45	-0.5275***	0.0240	483.10
DRINK	0.1040***	0.0271	14.73
SMOKE	0.1366***	0.0248	30.21
HOUSEOWN	0.2202***	0.0239	85.24

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 3.12 Negative binomial results for work loss with endogenous 5-point scale health (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square	Discrete change (1 unit)
INTERCEPT	7.0100***	0.2250	970.51	
NEA	0.3213***	0.0560	32.92	1.2593
WE	0.1584***	0.0660	5.75	0.5839
MW	0.0884	0.0564	2.45	0.3190
HEALTH5^{IV}	-1.2778***	0.0388	1,083.11	
TOTREL	5.9586	4.6515	1.64	5,5339
DU	0.2425***	0.0518	21.92	0.7873
DENSITY	-0.9517***	0.2850	11.15	-2.1608
PRECIP	-0.0024*	0.0014	2.71	-0.0082
LOWTEMP	0.0025	0.0018	2.03	0.0089
MALE	-0.3524***	0.0476	54.72	-1.2165
AGE	-0.0291***	0.0030	95.92	-0.1009
WHITE	0.2381***	0.0463	26.41	0.7888
COLLEGE	0.1970***	0.0504	15.29	0.7449
MARRIED	-0.0157	0.0394	0.16	-0.0551
INCOME45	-0.4618***	0.0571	65.32	-1.7340
DRINK	0.4317***	0.0455	90.09	1.7455
SMOKE	-0.2495***	0.0454	30.20	-0.8397
SERVICE	-0.1905***	0.0397	23.00	-0.6569
MANUF	0.0643	0.0557	1.33	0.2318
AGRI	-0.0507	0.1260	0.16	-0.1742
ONEJOB	-0.0080	0.0651	0.01	-0.0279
HOURWORK	-0.0047***	0.0015	10.53	-0.0165
YEARONJOB	0.0082***	0.0025	10.62	0.0289
SDAYPAID	0.2491***	0.0391	40.65	0.8534
PBYHOUR	0.2023***	0.0380	28.40	0.6973
EMP500	0.1691***	0.0447	14.31	0.6226
INVERSE MILLS	0.6273	0.4281	2.15	

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 3.13 Discrete change of work loss with endogenous 5-point scale health status

Health status	Change	Discrete change in lost work days
From excellent to very good	$5 \rightarrow 4$	2.3037
From very good to good	$4 \rightarrow 3$	5.2671
From good to fair	$3 \rightarrow 2$	9.6674
From fair to poor	$2 \rightarrow 1$	15.4644

3.7 Conclusion

Although the Toxics Release Inventory program has been in operation since 1988, the Toxics Release Inventory data have not been widely used in health literature. This paper tries to take advantage of this rich dataset by investigating how air, water and land pollution all together impact productivity losses measured by work days lost using a unique dataset merging individual-level NHIS data and county-level Toxic Releases Inventory data.

A simultaneous equation model using a negative binomial regression for work days lost is built taking into account the endogeneity of health status. Instrumental variable estimation is used to estimate parameters of the model. This study also compares the effect of health status on work days lost using two different measures of self-reported health status: a binary and a 5-point scale. The results show that health status is negatively associated with work days lost, regardless of how health status is measured. The magnitude of the effect of health status on productivity loss increases when health status is endogenous. The estimations also indicate that air, water and land pollution have positive and significant impacts on work days lost with both exogenous and endogenous binary health status. Although the absolute value of the coefficient for toxic releases is reduced when binary health status is endogenous, the discrete change in work days lost from 1 pound reduction in toxic chemical releases increases. A 1 pound increase in toxic releases leads to an increase in work-loss by 6.26 days with exogenous binary health status and 8.75 days with endogenous binary health status. The coefficient for toxic releases is not significant in the case of endogenous 5-point scale status. The findings confirm that it is important to control for selection sample bias in the case of a censored sample.

As research on the effects of toxic chemicals on labor productivity has not received much attention, this paper may be useful for policy-makers. These results provide information on how industrial pollution including air, water and land pollution together impact individual productivity losses. The estimates of this study may be used for cost-benefit analysis for reducing industrial pollution. Benefits of pollution reduction would be increased significantly when taking into the account that toxic chemicals significantly increase productivity losses. It would help policy-makers decide what level of toxic chemical releases from industries is appropriate.

However, it is important to conduct future research at a sub-county level in order to better understand the impact of toxic chemical releases on health and productivity. Since air pollution is easily dispersed in the air, it is expected that the effect of toxic releases on work loss will be greater at the lower levels of aggregation. Future research should also be detected toward identifying which toxic chemicals contribute the most to work days lost, thus helping decision-makers to more efficiently target reductions of those chemicals.

IV. EFFECTS OF MULTIPLE ENVIRONMENTAL HAZARDS ON HEALTH AND LABOR PRODUCTIVITY IN CALHOUN COUNTY, ALABAMA

4.1 Introduction

Unique environmental characteristics have brought the City of Anniston into the spotlight in recent years. It is home to Anniston Army Depot and the Anniston Chemical Agent Disposal Facility, and is highly contaminated with polychlorinated biphenyls (PCBs) and lead, which resulted in several high-profile lawsuits. Furthermore, Anniston is located in a county that was ranked among the worst 30% of all counties in the United States in terms of total environmental releases, the worst 20% in terms of cancer risk and the worst 10% in terms of noncancer risk in 2002 (Scorecard 2006).

Anniston is located in Calhoun County, Alabama, about 90 miles west of Atlanta, Georgia and 65 miles east of Birmingham, Alabama. The city has a population of 24,000 with 49% African America and 48% white. The per capita income for the city in 2005 was about $18,800 and 23% of the population were below the poverty line. The city was founded in 1872 as a private enterprise when Samuel Noble and General Daniel Tyler formed the Woodstock Iron Company. Historically, Anniston was an industrialized manufacturing town where at least 23 major industrial facilities operated over the past one hundred years.

The purpose of this study is to analyze the relationship among environmental hazards, health status, and labor productivity in Calhoun County. Environmental hazards are represented by PCBs and lead contamination and the Depot. The theoretical framework from the previous essay is employed, in which labor productivity losses are measured by numbers of sick days, restricted activity days and lost work days and they are hypothesized to be adversely affected by environmental hazards. A direct mail survey was conducted to obtain data on individual characteristics, health status and productivity losses. Maximum likelihood estimation is employed to estimate a simultaneous system of equations.

4.2 PCBs Contamination and the Monsanto Anniston Plant

4.2.1 Background information

In 1929, PCBs were first produced by the Theodore Swann Company in Anniston. In 1935, the Swann Anniston PCB plant was purchased by the Monsanto Corporation. In 1971, the Monsanto Anniston plant stopped producing PCBs. In 1979, due to concerns about the environmental and health impacts of PCBs, the United States government banned the production of PCBs by the U.S. Environmental Protection Agency regulations under the Toxic Substances Control Act. In 1997, the Anniston plant under the name Solutia was spun off from Monsanto. Para-nitrophenol and polyphenyl compounds are now manufactured at the site (ATSDR 2000b). Solutia filed for bankruptcy in 2003.

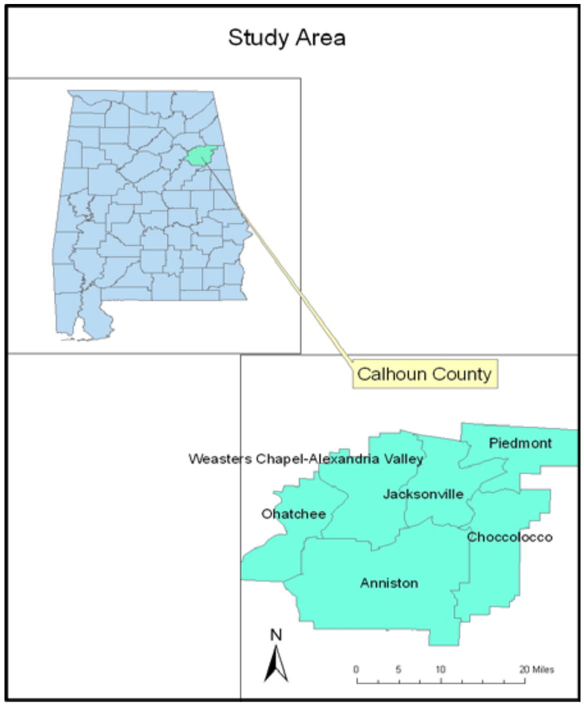


Figure 4.1: Map of the study area

The Solutia plant covers 70 acres located one mile west of downtown Anniston on State Highway 202 in Calhoun County, Alabama. The plant is bordered on the south by Highway 202, on the east by the Clydesdale Avenue extension, on the west by First Avenue, and on the north by the Norfolk Southern and Erie Railroads. The area north of the plant is surrounded by residential, commercial, and industrial properties. Residential properties are also located east and west of the plant.

During four decades of PCBs production at the Anniston Solutia plant, millions of pounds of PCB-containing waste may have been released into the environment through various pathways. These pathways include direct discharges to ditches, streams and other waterways, air emissions, dumping of PCB wastes into sewers, and the release of PCB wastes into unlined landfill sites. According to the company's July 1970 progress report, about 16 pounds of PCB waste were dumped daily into the town's waterways, while the year before, the company had been dumping about 250 pounds a day (Beiles 2000). The West End Landfill and the South Landfill located adjacent to the plant are the two unlined landfills where hazardous wastes from the Monsanto facility were disposed of (ATSDR 2000b). The West End Landfill comprises an area of six acres situated on the southwest side of the facility, north of Highway 202. The landfill was used for disposal of all wastes from the facility from the mid-1930s to 1961. In November 1961, the West End Landfill was closed and traded to the Alabama Power Company. With the closure of the West End Landfill, Monsanto began disposing of wastes at the South Landfill. The South Landfill was located southeast of the Monsanto facility, south of Highway 202, sitting on the lower northeast slope of Coldwater Mountain. The South Landfill was divided into 10 individual cells, each intended to hold a specific type of waste (ATSDR 2000b). Operations at the South Landfill ceased in 1988.

USEPA reported that PCBs migrated away from the Solutia facility during precipitation events as surface water flowed through areas containing PCBs during precipitation events and into various drainage ditches leading to Snow Creek, which flows north of the Solutia facility and through residential and business areas before emptying into Choccolocco Creek (EPA 2003). PCBs were also disseminated into the Anniston area through wind-blown dust, open burning and volatilization into the air.

4.2.2 Lawsuits

In Summer 1993, Anniston residents got their first glimpse of PCBs and Monsanto’s involvement (Beiles 2000). Largemouth bass with blistered scales were discovered in the nearby Choccolocco Creek and tests showed that the fish contained extremely high levels of PCBs. In November 1993, the Alabama Department of Public Heath issued a fish consumption advisory warning residents not to eat fish caught between the confluence of Snow Creek and Choccolocco Creek south of Oxford, downstream to where Choccolocco Creek flows into Lake Logan Martin (ADPH 2001). Around the same time, Alabama Power Company broke ground on land that previously belonged to Monsanto, breaching a PCB landfill that bled black tar (Beiles 2000).

Since the discovery of PCB contamination in Anniston, there have been a number of lawsuits filed against Monsanto by Anniston residents. In 1996, the Mars Hill Missionary Baptist Church, which was located across the street from Soluttia, filed a lawsuit against Monsanto over PCBs contamination. This case was settled in 1998 for $2.5 million. In 1996, the Owens v. Monsanto class action suit of 1,596 plaintiffs was filed over PCB contamination and was settled in April 2001 for $43 million. Also in 1996, Abernathy v. Monsanto was filed in Alabama state court on behalf of 3,500 plaintiffs in Anniston who have high levels of PCBs in their blood and on their properties, alleging that the company knew the hazards of introducing PCBs into the environment, failed to inform the community and tried to conceal what it had done (Beiles 2000). In 2001, more than 17,000 Anniston residents filed the Tolbert v. Monsanto suit against Monsanto in federal court over property and health damages associated with PCB contamination. In August 2003, lawyers for more than 20,000 plaintiffs in both the Abernathy v. Monsanto and Tolbert v. Monsanto cases and Solutia agreed to a $700 million settlement to resolve all outstanding Anniston PCB litigation (Centers 2003). The $700 million would include costs for cleanup, prescription drugs and $600 million in cash payments, of which Monsanto will provide $390 million in cash and $160 million in commercial insurance and Solutia will pay $50 million over 10 years. The $600 million was split between the two cases, with $350 million for 17,000 plaintiffs in the federal court case and $350 million for 3,500 plaintiffs in the state court case.

4.2.3 Responses from authorities

Several studies have been conducted by government agencies in response to the discovery of PCB contamination in Anniston. In 1996, the Alabama Department of Public Health studied the potential health effects of PCBs contamination and concluded that exposure to soil and sediment in the West End Landfill, Snow Creek and Choccolocco Creek presents a public health hazard (ADPH 1996b). Also in 1996, the Alabama Department of Public Health conducted an Exposure Investigation for the Cobbtown/Sweet Valley Community (ADPH 1996a). This is a neighborhood in West Anniston near the Solutia plant, where most houses have been purchased and demolished by Solutia. The Exposure Investigation found that PCB levels were elevated and concluded that PCB levels in soil, sediment, indoor dust and surface water in this neighborhood presented a public health hazard.

In February 2000, the Agency for Toxic Substances and Disease Registry (ATSDR) conducted an investigation on whether PCBs in soil, blood, and air in the area of Solutia are a threat to public health (ATSDR 2000b). The investigation has detected elevated blood PCB levels in many residents living around the Solutia plant as well as high PCB levels in soil in West Anniston. ATSDR concludes that soil concentrations of

PCBs in some areas of Anniston are high enough to present a public hazard in the form of cancer and non-cancer health impacts.

In October 2000 Solutia entered into an Administrative Order on Consent for a removal action at the Anniston PCB site (EPA 2006a). The purpose of the removal action is to reduce the short-term threat to public health and the environment caused by PCBs in the area around the Solutia facility and part of Oxford where they were contaminated with PCBs. The removal action includes sampling properties in these areas and cleanup for residential properties with PCBs level of 10 part per million (ppm) (EPA 2003). The cleanup includes the removal of the top three inches of soil from the impacted area. Additional composite sampling and removal of soils in these areas will continue until remaining soils within the next 9 inches of soil have PCB levels below 2 ppm. Soils in these areas below a depth of 12 inches will be removed until the PCBs level based on composite sampling is below 10 ppm (EPA 2001).

4.3 Lead Contamination

USEPA has determined that “the Anniston Lead Site consists of the entire geographic area in Anniston and its environs where lead has come to be located” (USEPA 2005). Lead contamination in Anniston was discovered in 2000, when USEPA conducted tests for PCBs. USEPA believes that lead has been released into Anniston’s environment through a number of pathways, including urban activities such as lead paint and leaded gasoline and through the operations of various private enterprises in the Anniston area, and it is also been found to be naturally occurring. For the last source of lead contamination, EPA's investigation indicated that lead had been released into the environment through air emissions, use of foundry sand as residential fill material, and through surface water runoff.

The USEPA responded to the lead contamination problem in the Anniston area in 2000, and cleanup activities began in April 2002 (USEPA 2006c). The USEPA has set 400ppm of lead as the cutoff level for cleanup for the Anniston area. Any house with lead level greater than 400ppm is subject for cleanup. USEPA has cleaned up 133 properties with elevated lead and 209 properties are waiting for cleanup.

4.4 The Anniston Army Depot

The Anniston Army Depot (ANAD), built in 1941 as an ammunition storage depot, covers an area of 15,200 acres in Calhoun County, and is located about 8 miles west of the city of Anniston. Currently, activities at the Depot include rebuilding and maintaining equipment such as tanks, missiles, and small arms.

4.4.1 Anniston Chemical Agent Disposal Facility

The ANAD is one of the eight Army Depots in the U.S. and has stored chemical weapons in on-site bunkers since 1961. Currently, the ANAD stores approximately 2,254 tons or 7.4 percent of the original U.S. stockpile of chemical weapons including projectiles, cartridges, rockets, ton containers and land mines containing the nerve agents GB (known as sarin) and VX, and blistering agents HD and HT (know as mustard gas).

In 1993, the United States was one of 120 countries that signed an international treaty called the Chemical Weapons Convention. The treaty required signatories to destroy their chemical weapons stockpiles by April 2007, with the possibility of a 5-year extension.

In 1996, the U.S Army contracted with Westinghouse Anniston to build, test, operate and close a facility to dispose of the ANAD stockpile. Facility construction was completed in 2001, and the Army began disposing of the chemical weapons at the Anniston Chemical Agent Disposal Facility (ANCDF) in August 2003. The facility operates 24 hours a day, 7 days a week and will be closed once all the chemical weapons have been destroyed. ANCDF uses high-temperature incineration technology to destroy the weapons.

Release of a chemical agent may affect different areas in different ways and at different times. The likelihood of being exposed to a chemical agent from a release decreases as the distance from the point of release increases. The extent of exposure also decreases with distance as the concentration of the agent becomes lower. Therefore, zones have been established to differentiate appropriate levels of response to a potential accidental chemical release. The zones are

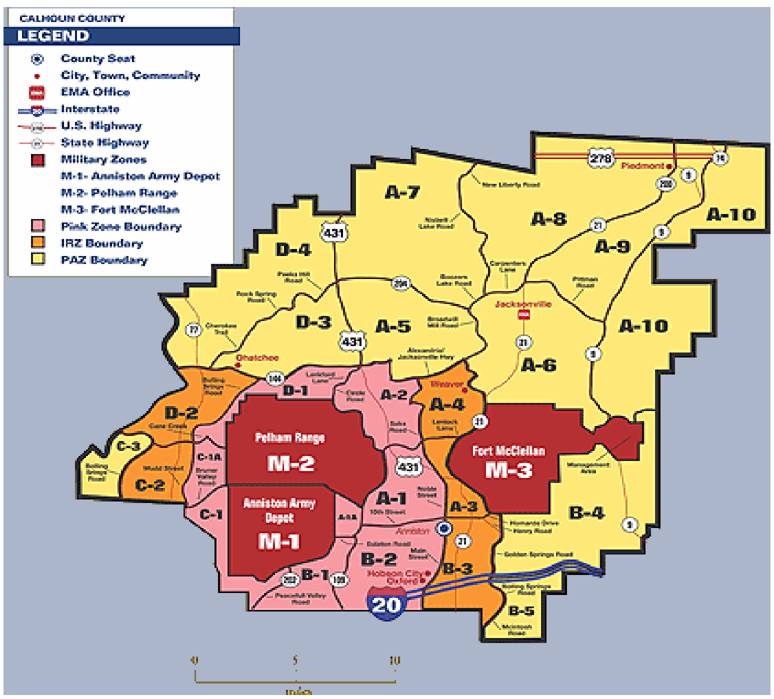
- Immediate response zone (pink zone): 6 miles from ANCDF
- Protective action zone (orange zone): 9 miles from ANCDF
- Precaution zone (yellow zone): 20-30 miles from ANCDF.

Approximately 116,000 residents of Calhoun County are impacted to varying degrees. The map and table below describe the affected areas and the population distribution among the affected zones in Calhoun County.

Table 4.1 Affected population by risk zones for Calhoun County, Alabama

Zone	Distance from ANAD (miles)	Number of Residents	% of residents
Pink Zone	6	35, 000	30.17
Orange Zone	9	40, 000	34.48
Yellow Zone	20-30	41, 000	35.35
TOTAL		116,000	100.00

Figure 4.2 Map of the risk zones of Calhoun County



Source: Alabama Emergency Management Agency

4.4.2 *The Superfund site and TRI facility*

The Anniston Army Deport was listed as a Superfund site in the final National Priority List Past in 1989 (EPA 2006d). Past activities at the Depot included vapor degreasing, metal cleaning, sandblasting, electroplating, and painting operations. The

Depot generated a significant amount of solid and liquid wastes including metals, cyanide, phenols, pesticides, herbicides, chlorinated hydrocarbons, petroleum hydrocarbons, solvents, acids, chelating agents, asbestos, and creosote, that were disposed of in trenches, lagoons, landfills, or other holding vessels from the 1940s through the late 1970s. Soil and groundwater in the area were contaminated as a result of the on-site disposal of wastes.

The Depot was ranked among the dirtiest 10% of all facilities in the US in terms of total environmental releases, cancer risk and non-cancer risk in 2002 (Scorecard 2006). In 2003 the Deport released into the environment 451,581 pounds of TRI chemicals.

4.5 Health Risks and Effects

4.5.1 PCBs

PCBs are mixtures of up to 209 individual chlorinated compounds (ATSDR 1999). There are no known natural sources of PCBs in the environment. PCBs are either oily liquids or solids and are colorless to light yellow, having no smell or taste. Due to their non-flammability, chemical stability, high boiling point and electrical insulating properties, PCBs were used widely as coolants and lubricants in transformers, capacitors, and other electrical equipment.

Upon entering the environment, PCBs may remain for a long period of time. They can easily cycle between soil, water, and air since they can evaporate from both soil and water. In the atmosphere, PCBs are present as solid particles or as a vapor.

PCBs are classified as probable human carcinogens by the USEPA and the International Agency for Research on Cancer (IARC) (ATSDR 1999; 2000a; IARC 1978;

1987; NCI 1978). Other studies link PCB exposure with health effects, including neurotoxicity,adverse reproductive and developmental effects, immune system suppression, liver damage, skin irritation, and endocrine disruption (ATSDR 1999; EPA 2006b; Gladen and Rogan 1991; Hagamar, et al. 1995; Jacobson, et al. 1990; Jacobson, et al. 1985; Taylor, et al. 1984; Taylor, et al. 1989; Tryphonas 1995).

The USEPA Office of Pollution Prevention and Toxics has created the TRI Chronic Human Health Indicators called toxicity weights in order to compare the relationship between various chemicals and chronic human health effects including cancer and non-cancer effects (Bouwes and Hassur 1997). Two toxicity weights are calculated for most TRI chemicals based on exposure pathway: oral toxicity weight and inhalation toxicity weight. PCB was assigned an oral toxicity weight of 100,000 and an inhalation toxicity weight of 1,000. It should be noted that the higher the weight, the more toxic the chemical.

4.5.2 Lead

Lead is described as "a heavy and low melting metal that occurs naturally" (ATSDR 2005). However, it is rarely found naturally as a metal but usually found combined with two or more other elements to form lead compounds.

Lead is a toxic element, which can cause a variety of adverse health effects ranging from reproductive or developmental effects to acute and chronic effects (EPA 2000). Reproductive or developmental effects include high likelihood of spontaneous abortion in pregnant women, increased risk of preterm delivery, low birth-weight, and impaired mental development (ATSDR 1992; 1997; DHHS 1993). Acute effects include death from lead poisoning, brain and kidney damage and gastrointestinal symptoms (ATSDR, 1992, 1997). Chronic effects include anemia, neurological symptoms and slowed conduction in peripheral nerves (ATSDR, 1992, 1997).

Lead has been assigned a toxicity weight of 100,000 for both inhalation and oral exposure pathways (Bouwes and Hassur 1997).

4.5.3 The chemical weapons

The chemical weapons in ANAD include GB and VX agents and mustard. When released into the air, GB and VX are broken down but persist for a few days. These agents tend to break down quickly in water and moist soil, but small amounts may evaporate or travel below the soil surface and contaminate groundwater (ATSDR 2002a). GB and VX are rapidly acting, lethal nerve agents which are extremely toxic chemical agents. Health effects of GB and VX include rhinorrhea and chest tightness, pinpoint pupils, shortness of breath, excessive salivation and sweating, nausea, vomiting, abdominal cramps, involuntary defecation and urination, muscle twitching, confusion, seizures, flaccid paralysis, coma, respiratory failure, and death.

HT and HD agents or mustard agents are not readily water soluble, but dissolve easily in oils, fats, and other solvents (ATSDR 2002b). Mustard agents can cause skin burns and blisters and damage to the respiratory airways.

4.5.4 TRI chemicals

TRI chemicals released by the Depot include very toxic chemicals such as lead compounds, chromium compounds, hexachloroethane, tetrachloroethylene and dichloromethane. A number of health effects including acute and chronic effects, reproductive and developmental effects and cancer are caused by these chemicals (ATSDR 1997; EPA 2007a; 2007b).

4.6 Data

4.6.1 Sources of data

Data for this analysis come from a number of sources. A direct mail survey provides data on perceived risks, health status, labor productivity and demographic and socioeconomic characteristics. Housing characteristics were taken from the Calhoun County Property Tax System, Calhoun County Administrative Offices. Toxic chemical releases at census block level and socioeconomic characteristics of block group are obtained from Toxic Release Inventory, USEPA (http://www.rtknet.org) and Census 2000, US Census Bureau (http://www.census.gov), respectively. Data on PCBs and lead levels in Anniston come from the regional EPA office in Anniston.

4.6.2 The survey

The survey instrument was developed and the targeted population determined after a research trip to Anniston in 2005 during which we met and discussed with citizen groups, county officers, newspaper reporters and Army personnel overseeing the incinerators. A mail survey entitled the 2006 Anniston Environmental Risk Survey was conducted to obtain the perceived risks from the incinerator and PCBs, health status, and labor productivity losses from residents in Calhoun County. The survey also obtained demographic and lifestyle data to control for confounding factors in order to isolate health and environmental effects on labor productivity.

Questions on health status and labor productivity losses were adapted from the National Health Interview Survey, Center for Disease Control and Prevention. Residents were asked about their general health status, and several diseases that may be linked with PCBs such as cancer, bronchitis and migraine. Labor productivity loss questions included how many hours a week residents work at their job, the number of days lost due to illness and injury, and the number of restricted activity days.

A cover letter accompanied the questionnaire stating the purpose of the survey and providing contact information to the respondents. The questionnaire and the cover letter were reviewed and approved by the Auburn Office of Human Subjects before being sent to Calhoun County residents. The cover letter and questionnaire are provided in Appendix C.

Although not the focus of this study, one of the purposes of the survey is to investigate if risk perceptions affect house prices in Calhoun County. Thus, the target population for the survey was individuals who purchased housed between 1993 and 2005 in Calhoun County. A total of 4,719 transactions that took place between 1993 and 2005 with complete addresses were taken from transactions records of the Calhoun County Property Tax System. A probability design to select addresses was used with stratified sampling by zone where each zone has a different sampling rate. The Pink Zone, which is the closest to the incinerator and contains the PCBs contaminated sites, was sampled at the highest rate. The Orange Zone, located 7-9 miles away from the incinerator, was sampled at the second highest rate and the Yellow Zone was sampled at the lowest rate.

A final sample of 3,492 house owners from 4,719 addresses were randomly selected using Excel. A map of the distribution of survey recipients is presented in Figure 4.3.

Questionnaires were first mailed to 3,492 residents in Calhoun County on January 20, 2006 using bulk rate mailing service. There were 480 responses or 13.7 percent within four weeks of the first mailing. On February 17, 2006, a total of 1,939 reminder postcards were randomly sent to residents those who did not respond. Subsequently, a second set of 1,550 questionnaires was mailed randomly to selected nonrespondents on March 18 and March 28. There were a total of 738 usable responses yielding a raw response rate of 21%. However, it should be noted that because surveys were mailed via bulk rate, there was no way to track bad addresses; thus the true response rate is likely higher.

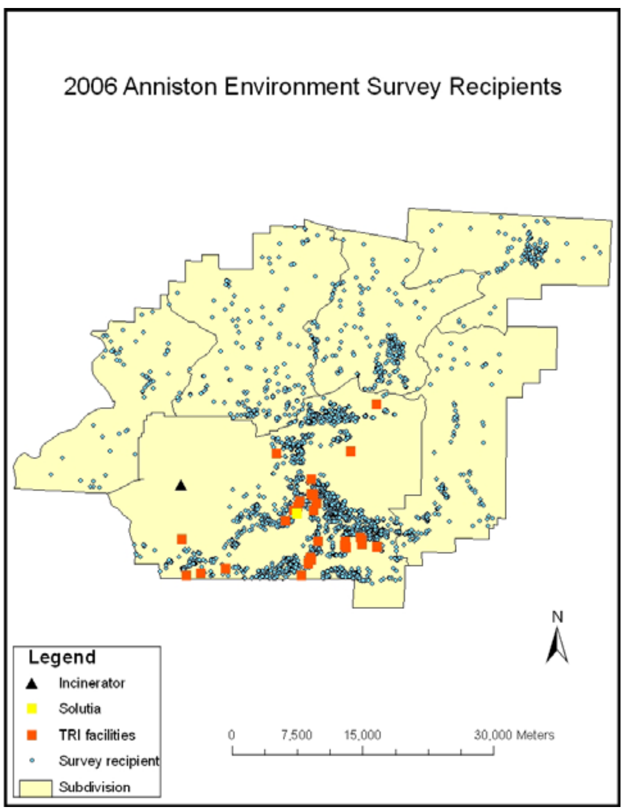


Figure 4.3 Map of survey recipients

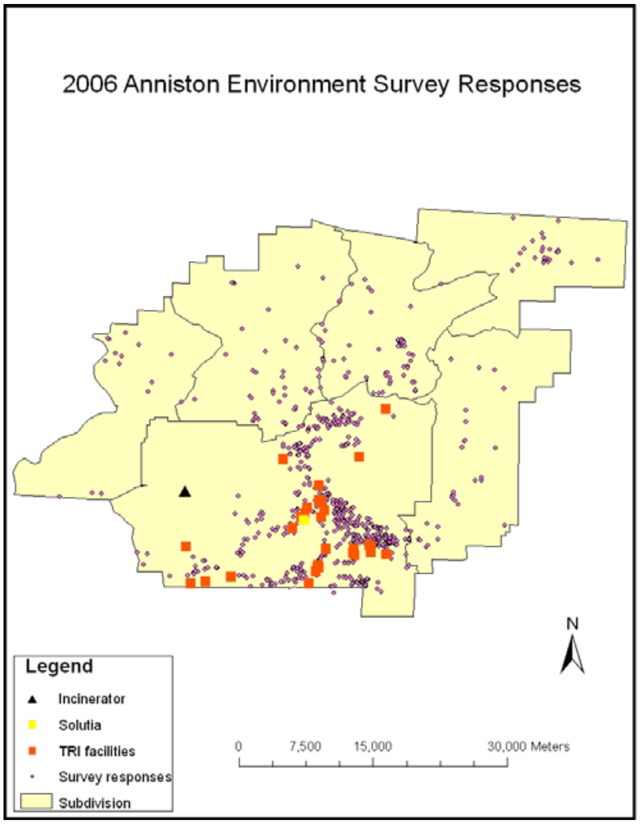


Figure 4.4 Map of the survey responses

4.6.3 Data

Demographic and economic characteristics of survey respondents are reported in Table 4.2. Almost two third of respondents are aged between 35 and 65 and about 85 percent are white. Respondents are divided rather evenly between male and female. Around 40 percent of respondents have college, professional and graduate degrees and 70 percent have family annual income of $40,000 or more.

Table 4.2 Demographic characteristics of survey respondents (N=738)

Variable	Number	Percentage
Age		
20-34	107	15
35-49	244	33
50-64	240	32
Over 65	147	20
Gender		
Male	392	53
Female	346	47
Race		
White	623	84
African-American	96	13
Other	19	3
Education		
Less than 12th grade	54	7
High school graduate	135	18
Associate or college, no degree	353	35
College degree	146	20
Graduate or professional degree	150	20
Income		
Under 20,000	86	11
20,000-39,999	145	20
40,000-59,999	169	23
60,000-99,999	237	32
100,000-150,000	79	11
Over 150,000	22	3
Marital status		
Single	45	6
Married	538	73
Other	155	21

There are 3,586 PCB soil samples with PCB levels in soil ranging from 0 to 5,501 ppm and 5,301 lead soil samples with lead levels in soil ranging from 0 to 52,000 ppm in Anniston. Table 4.3 presents descriptive statistics for PCBs and lead levels in soil samples. The mean value of PCB levels in soil is 5.37 ppm and the mean lead level is 247.90 ppm. Maximum values of PCB and lead levels are 5,501 ppm and 52,000 ppm, respectively, which are much higher than the baseline levels for cleanup actions.

Table 4.3 Statistics for PCBs and lead samples

	PCBs (ppm) (N=3,586)	Lead (ppm) (N=5,301)
Mean	5.37	247.90
Median	0	151
Standard Deviation	111.91	859.28
Minimum	0	0
Maximum	5,501.00	52,000.00
Skewness	42.45	44.85

Geographic Information System software (ArcGIS 9.0) is employed to estimate and assign calculated values of PCBs and lead to all unsampled locations. Specifically, we use interpolated kriging, an advanced geostatistical procedure that generates an estimated surface of PCB and lead levels from a scattered set of points. Kriging assumes that a local influence of an input point diminishes with distance; hence it weights the points closer to the processing cell greater than those farther away. Kriging assigns values to locations based on the surrounding measured values, mathematical formulas that determine the smoothness of the resulting surface, and statistical models that include the statistical relationship among the measured points. In this study, PCBs and lead levels are calculated for a square cell size of 30 meters for an area with a radius of 1,000 meters around the measured points.

Maps of PCB and lead levels in Anniston soil are presented in Figures 4.5 maps of PCB and lead kriging are presented in Figures 4.6. PCB and lead levels are assigned to each house using GIS by overlaying the PCB and lead kriging maps with the map of survey respondents' houses.

GIS is also used to measure proximity of each house to the incinerator and Solutia plant. Since x and y coordinates of the incinerator are not released to the public because of confidentiality issues, the centroid of the Army Depot is used instead.

The survey data were merged with data for census block group demographic characteristics, and with toxic chemical releases using the census block group code. The final dataset consists of 738 observations.

4.7 Empirical Models

This analysis employs the theoretical health model framework presented in the previous essay. An empirical model is designed to investigate health effects and productivity losses of the risks associated with the ANCDF, PCBs and lead levels in Anniston.

$$L = Q\ (I, E, W, E, H) \qquad (26)$$

where L is a vector of production loss measures, I represents a vector of individual demographic and economic characteristics, W is working condition, E is environmental characteristics and H is health status.

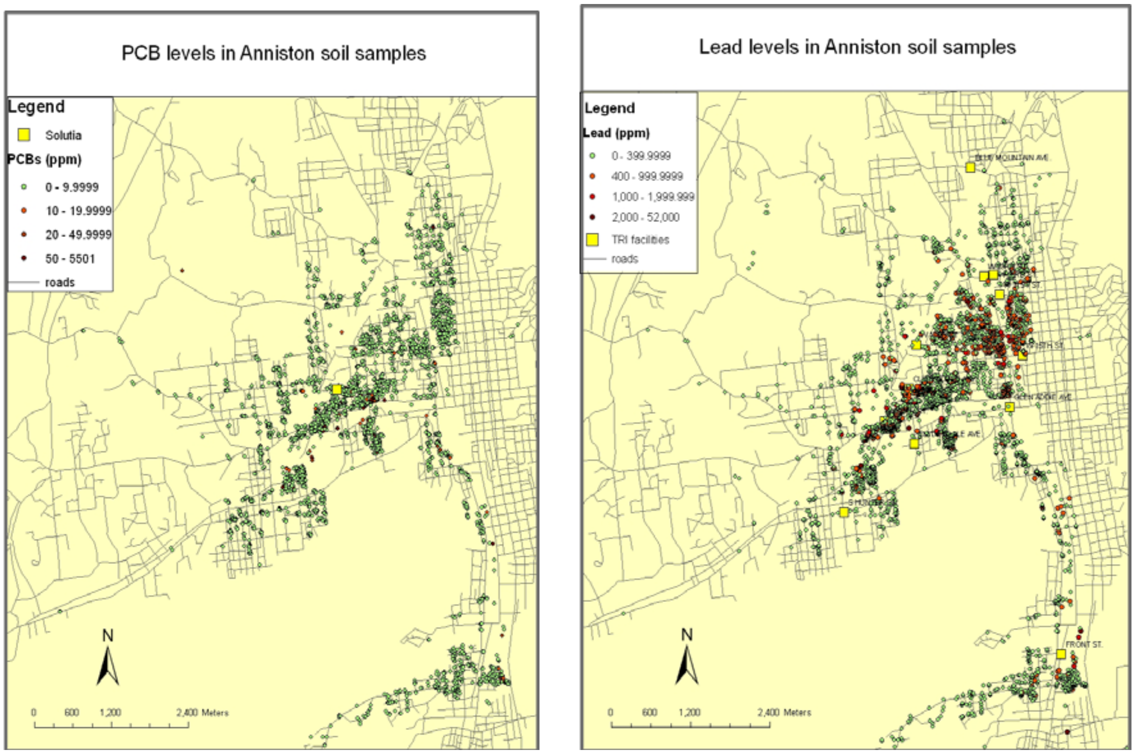


Figure 4.5: Maps of PCB and lead levels in Anniston soil samples

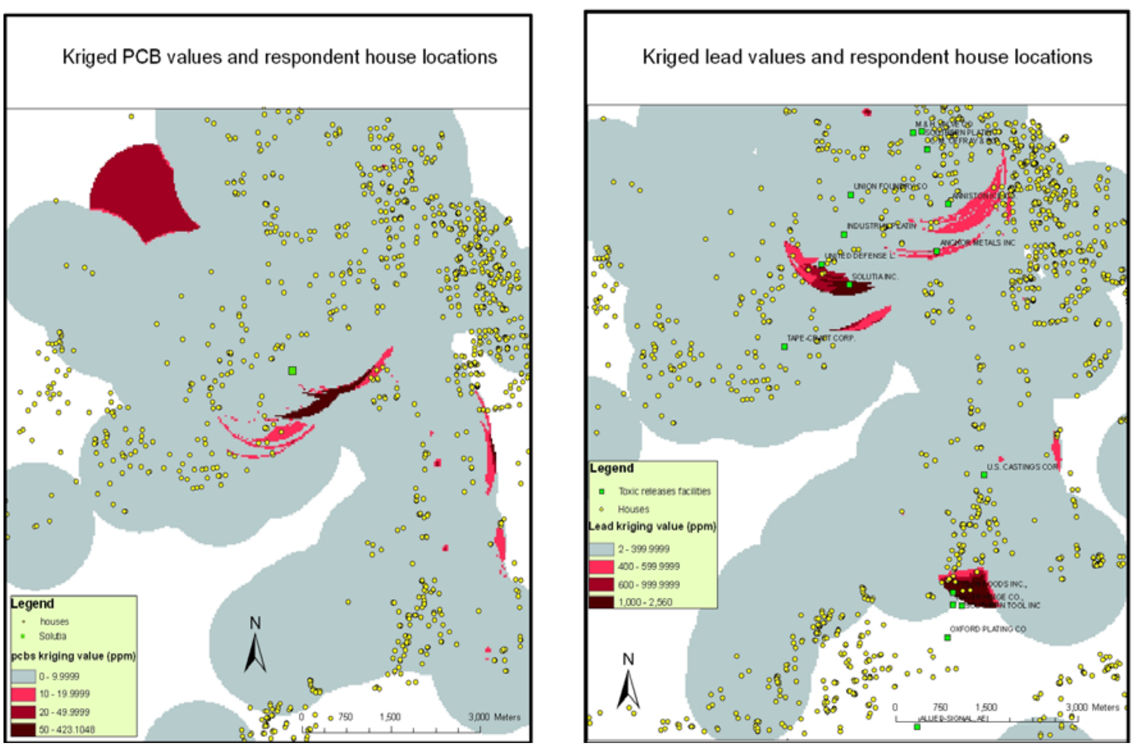


Figure 4.6 Maps of PCB and lead kriging

Three different types of measures of productivity losses are used, including sick days lost, restricted activity days and work days lost. Sick days lost is based on the question "During the past 12 months, how many days did illness or injury keep you in bed more than half of the day", restricted activity days is based on the question "During the past 12 months, about how many days were your activities restricted due to illness or injury" and work days lost based on the question "During the past 12 months, about how many days did you miss work at a job or business due to illness or injury. Health status is based on responses to the question "How do you evaluate your general health? Excellent, good, fair and bad". Health status is then recoded into binary variable where excellent and good take the value of 1 and fair and bad take the value of 0.

As presented in the previous section, there might be a number of health effects associated with PCBs, lead and the Depot. Therefore, we assume that health status is endogenous. A simultaneous-equations approach is employed to control for the endogeneity of health status, using maximum likelihood estimation of the simultaneous equations.

Three different systems of equation are set up based on three productivity loss measures. The simultaneous equations model is written as

$$\ln L = \alpha_D + \eta H + \gamma_L I + \zeta_L P + \tau_L A + \theta_L T + \delta_L D + \varepsilon_L \tag{27}$$

$$H = \alpha_H + \gamma_H I + \zeta_H P + \tau_H A + \theta_H T + \delta_H D + \varsigma S + \varepsilon_H \tag{28}$$

where L is productivity loss measured by sick days lost, restricted activity days and work days lost, H is health status, I is a vector of individual's characteristics, P is PCBs level, A is lead level, T is toxic release at census block group level, D is distance from each house to the centroid of the ANCDF and S is lifestyle characteristics.

To control for selection bias due to data censoring of those whose did not respond to the survey, the 2-stage Heckman sample selection model is used. In the first stage, a probit regression is used to estimate the individual probability of responding

$$R = \beta_0 + \beta_1 Z + \varepsilon_R \tag{29}$$

where R is a binary variable with survey respondents coded 1 and addresses from with a response not received are coded 0, X is a vector of explanatory variables including housing characteristics and demographic and socioeconomic characteristic at census block group level.

The inverse Mills ratio is calculated

$$\mu_i = \frac{\o_i \, (Z_i, \beta_1)}{\Phi_i \, (Z_i, \beta_1)} \tag{30}$$

where ø and Φ are the probability density function and the cumulative distribution function, Z is a vector of explanatory variables in the survey response equation, and β_1 is the conformable parameter vector of equation 4. In the second stage, the inverse Mills ratio is included as an explanatory variable in the main model to correct for selectivity bias.

The inverse Mills ratio is also calculated for working status to control for selection bias when estimating the lost work days model. Working status is assumed to be a function of individual demographic and socioeconomic characteristics and health status. The inverse Mills ratio for working is included in the lost work days model, along with the inverse Mill ratio for survey response.

A negative binomial equation for count data is employed to estimate productivity losses. The equation for productivity losses is written as

$$y = \alpha' X_1 + \varepsilon_y \tag{31}$$

where y is productivity losses, and X_1 is a vector of explanatory variables.

The probit equation for health status is given as

$$H^* = \beta' X_2 + \varepsilon H \tag{32}$$

$$H = 1 \text{ iff } H^* > 0,\ H = 0 \text{ iff } H^* \leq 0$$

where H* is a latent variable for health status.

The likelihood function for the simultaneous model represented in equations 31-32 is written as

$$L = \left[\frac{\Gamma(k+y)}{y!\Gamma(k)} p^k (1-p)^y \int_{-\infty}^{\beta X_2} \frac{1}{(2\pi)^{1/2}} \exp\left(\frac{-t^2}{2}\right) dt \right]^H \left[\frac{\Gamma(k+y)}{y!\Gamma(k)} p^k (1-p)^y \int_{\beta X_2}^{\infty} \frac{1}{(2\pi)^{1/2}} \exp\left(\frac{-t^2}{2}\right) dt \right]^{(1-H)}$$

where p=exp(X_1)/[exp(X_1)+k]

4.8 Empirical Results

A test for endogeneity of health status is conducted using a Hausman specification test (Hausman 1978). The calculated chi-squared statistic is 14.49, which when compared with a critical value at 5% level of significance of 3.84 (1 degree of freedom) suggests that there is endogeneity in the model and thus a simultaneous estimation method is appropriate. We employ a maximum likelihood approach to jointly estimate the two equations.

Dummy variables for PCB and lead levels are created, in which the PCB dummy takes a value of 1 for any positive PCB level and 0 otherwise, and the lead dummy takes the value of 1 if lead value is greater than 50 ppm and 0 otherwise. The cutoffs were chosen after testing a number of models that used different cutoff levels. Since PCBs and lead levels are positively correlated, the simultaneous model is estimated separately for the PCB and lead dummies.

Tables 4.4, 4.5 and 4.6 show definitions and descriptive statistics for the dependent and independent variables for the survey response model, sick days in bed model and work days lost model, respectively. There are 3,492 observations in the dataset for the survey response model, comprising demographic and socioeconomic characteristic data at the census block group level, along with individual housing characteristics. Data for the sick days in bed and restricted days models include 738 observations from the survey at individual level merged with the PCB and lead dummies at individual property level, and total releases at census block group level. The dataset for work days lost is a sub-sample of the dataset for sick days in bed, containing 530 observations for those who had held a job in the past 12 months.

Table 4.4 Descriptive statistics of variables for survey responding model (N=3,492)

Variable	Definition	Mean
Response	=1 if responding; 0 otherwise	0.2113
% white	Percent of white at census block group (%)	80.8464
% male	Percent of male at census block group (%)	47.4913
% never married	Percent of never married at census block group (%)	19.7185
% bachelor degree	Percent of bachelor degree at census block group (%)	10.9638
% poverty	Percent of household below poverty line census block group	9.7455
% rural population	Percent rural population at census block group (%)	22.6003
Year erected	Year the house was erected	1969
Basic area	Total basic area of the house (square feet)	1501
Total releases	Total toxic releases/person at census block group (pound/person) in 2005	1.4026
Distance to Solutia	Distance from the house to Solutia (mile)	6.3947
Distance to Depot	Distance from the house to Depot (mile)	9.8874

Table 4.5 Descriptive statistics of variables for sick days in bed and restricted days models (N=738)

Variable	Definition	Mean
Working status	=1 if had a job in the past 12 months; =0 otherwise	0.7182
Sick days in bed	Number of days in bed more than half of the day	8.1653
Restricted days	Number of days in which activity is restricted due to illness or injury	20.1043
Male	=1 if male; =0 otherwise	0.5312
Black	=1 if black; =0 otherwise	0.1301
Degree	=1 if has college or graduate or professional degree; =0 otherwise	0.3997
Married	=1 if married; =0 otherwise	0.7290
Age	Years of age	51.4472
Income	2005 household income ($10,000)	0.6263
Years at residence	Number of years at the current residence	7.9118
Pcbdum	=1 if PCBs level > 0 ppm; =0 otherwise	0.1640
Leaddum	=1 if lead level > ppm; =0 otherwise	0.1640
Total releases	Total toxic releases/person at census block group (pound/person)	0.1497
Distance to Depot	Distance from the house to Depot (mile)	9.9645
Health insurance	=1 if has health insurance; =0 otherwise	0.9309
Health status	=1 if health status is good; =0 otherwise	0.7480
Alcohol	=1 if daily alcohol drinker; =0 otherwise	0.0691
Smoke	=1 if daily smoker; =0 otherwise	0.1531
Cancer	=1 if has cancer; =0 otherwise	0.0650
Asthma	=1 if has asthma; =0 otherwise	0.1043
ER visits	Number of emergency room visits	1.2696
No adults	Number of adults in the household	1.1165
No kids	Number of kids in the household	0.7168

Table 4.6 Descriptive statistics of variables for work days lost model (N=530)

Variable	Definition	Mean
Working status	=1 if had a job in the past 12 months; =0 otherwise	1.0000
Sick days in bed	Number of days in bed more than half of the day	4.8962
Restricted days	Number of days in which activity is restricted due to illness or injury	10.1340
Work days lost	Number of days missed at a job or business due to illness or injury	5.2774
Male	=1 if male; =0 otherwise	0.5377
Black	=1 if black; =0 otherwise	0.1132
Degree	=1 if has college or graduate or professional degree; =0 otherwise	0.4453
Married	=1 if married; =0 otherwise	0.7623
Age	Years of age	46.2340
Income	2005 household income	0.6998
Years at residence	Number of years at the current residence	7.2582
Pcbdum	=1 if PCB level > 0 ppm; =0 otherwise	0.1453
Leaddum	=1 if lead level >50 ppm; =0 otherwise	0.1415
Total releases	Total toxic releases/person at census block group (pound/person)	0.1537
Distance to Depot	Distance from the house to Depot (mile)	10.1981
Health insurance	=1 if has health insurance; =0 otherwise	0.9340
Health status	=1 if health status is good; =0 otherwise	0.8226
Alcohol	=1 if daily alcohol drinker; =0 otherwise	0.0679
Smoke	=1 if daily smoker; =0 otherwise	0.1528
Cancer	=1 if has cancer; =0 otherwise	0.0415
Asthma	=1 if has asthma; =0 otherwise	0.0925
ER visits	Number of emergency room visits	1.2472
No adults	Number of adults in the household	1.2208
No kids	Number of kids in the household	0.8396
Construction	Percent of worker employed in construction at census block group level	9.5580
Work at Depot	=1 if working at Army Depot	0.0962

4.8.1 Results for survey response model

Regression results for the survey response equation are presented in Table 4.7. Percent male and never married at census block group level are negatively associated with the likelihood of responding to the survey but percent bachelor degree is positively associated with the likelihood of a survey response. The year a house was erected and the square footage of the house are positively associated with the likelihood of a survey response.

Table 4.7: Regression results for survey response equation (N=3,492)

Variable	Parameter Estimate	Std Error	Chi-Square
Intercept	-6.0559***	2.5315	5.72
% white	-0.0016	0.0024	0.44
% male	-0.0189**	0.0092	4.22
% never married	-0.0129**	0.0061	4.53
% bachelor degree	0.0087*	0.0048	3.32
% poverty	0.0077	0.0076	1.01
% rural population	-0.0005	0.0010	0.28
Year erected	0.0031***	0.0013	5.76
Basic area	0.0002***	0.0001	13.42
Total releases	0.0026	0.0031	0.69
Distance to Solutia	0.0102	0.0121	0.71
Distance to Depot	-0.0078	0.0122	0.40

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

The inverse Mills ratio is calculated from the survey response model in Table 4.7 and then is included as an additional independent variable for the simultaneous model using survey dataset.

4.8.2 Results of sick days in bed model

Table 4.8 provides maximum likelihood estimates for the sick days in bed model for PCB levels. The likelihood of good health is positively associated with college or graduate or professional degrees and income. This may be explained that those with college degree or better or higher income are more likely to have a healthy lifestyle, to consume healthy food and to have access to healthcare. As expected, good health is negatively associated with age. The number of years living at a residence has a negative impact on good health; the longer a resident's tenure, the lower the likelihood of good health. It should be noted that both PCB and lead are the chemicals that have very high toxicity weight in terms of chronic health effects on human. Hence, it may be the case for those who have been living in the area for a long period of time suffering chronic health effects that deteriorate their health over time. Another explanation is that children are very susceptible to PCB and lead, thus the longer respondents live in the area, the higher the chance their health was affected when they were young.

The PCB dummy, the variable of interest, was negatively associated with good health. This means that residents of a house with any positive kriged PCB level are less likely to enjoy good health. Distance to the Depot has a positive effect on the probability of good health; the closer a respondent lives from the Depot, the smaller the likelihood of good health. The Depot is the source of many toxic chemicals, thus those who live close to the Depot may suffer some health effects which result in bad health status or they may simply believe their health is worse because of the Depot. Working status is positively correlated with good health, possibly because the employ have better access to health care. Respondents with cancer are less likely to be in good health, and numbers of hospital emergency room visits are associated with poor health.

Table 4.8 Results for PCB sick days in bed model

Variables	Health status equation		Sick days in bed equation	
	Estimate	Std Error	Estimate	Std Error
Male	0.0197	0.1306	-0.5361***	0.1805
Black	-0.2467	0.1729	-0.1737	0.2637
Degree	0.3214**	0.1381	-0.5146***	0.1857
Married	0.0452	0.1453	0.4086**	0.2218
Age	-0.0159***	0.0054	0.0033	0.0077
Income	0.4684**	0.2251	-0.6454**	0.2877
Years at residence	-0.0193**	0.0083	0.0093	0.0153
PCBs dummy	-0.3329**	0.1723	0.4693**	0.2608
Toxic releases	0.0454	0.0525	-0.1741	0.1366
Distance to Depot	0.1121**	0.0579	0.0824	0.0781
Health status			-1.6808***	0.2199
Health insurance	0.2151	0.2326	0.1207	0.3521
Working	0.3987***	0.1551	-0.5543***	0.2228
Alcohol	-0.2291	0.2363		
Smoke	-0.2137	0.1591		
Cancer	-0.1788**	0.0783		
Asthma	-0.0966	0.0823		
Emergency room visit	-0.1853***	0.0285		
No of adults			0.1314	0.1034
No of kids			0.0779	0.0823
Inverse Mills - response	5.3779***	2.0676	-3.7958	2.8794

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

For the sick days in bed equation, males and those with a college or graduate or professional degree are likely to have fewer sick days in bed. A possible explanation is that those respondents are more likely to have a job; hence it is the opportunity cost that makes them less likely to stay in bed. Married respondents are more likely to have more sick days in bed. Income is also negatively associated with sick days in bed; possibly because of higher opportunity cost. Residents who had a job in the past 12 months have fewer sick days in bed; again possibly because of opportunity cost. The PCB dummy is positively associated with sick days in bed. Those living in a house with a positive kriged PCB level may experience health effects, so they are likely to stay in bed longer. As expected, good health is negatively associated with sick days in bed.

Maximum likelihood estimates for the sick days in bed model using the lead dummy are reported in Table 4.9. Except for the insignificant coefficient for distance to Depot, the results for the health status equation are similar to the PCB model, with the lead dummy negatively associated with health status. However, the magnitudes of the effects of PCBs and lead on health status are different; the coefficient for PCB in the health status equation is -0.3329 and for lead is -0.4187. A reasonable explanation is that the toxic weight for lead is greater than that for PCBs. This means that lead may cause more severe chronic health effects, which results in more severe health deterioration.

The sick days in bed equation results are similar to the model with PCBs, except that the lead dummy no longer has an effect on sick days in bed. It should be noted that sick days in bed is the measure of an individual's health that reflects how the individual can react to an acute condition. The finding of an insignificant effect of lead in the sick days in bed equation indicates that PCBs may cause more seriously acute health effects than lead does.

Table 4.9 Results for lead sick days in bed model

Variable	Heath status equation		Sick days in bed equation	
	Estimate	Std Error	Estimate	Std Error
Male	-0.0002	0.1314	-0.5583***	0.1838
Black	-0.2234	0.1743	-0.0846	0.2720
Degree	0.3268***	0.1385	-0.5571***	0.1873
Married	0.0484	0.1449	0.3613*	0.2196
Age	-0.0165***	0.0054	0.0038	0.0079
Income	0.4494**	0.2252	-0.6431**	0.2851
Years at residence	-0.0195**	0.0083	0.0101	0.0152
Lead dummy	-0.4187***	0.1765	-0.0579	0.2845
Toxic releases	0.0476	0.0524	-0.1591	0.1375
Distance to Depot	0.0930	0.0586	0.0535	0.0828
Health status			-1.7796***	0.2249
Health insurance	0.1941	0.2325	-0.0310	0.3628
Working	0.3860***	0.1549	-0.4609***	0.2206
Alcohol	-0.2342	0.2368		
Smoke	-0.2039	0.1588		
Cancer	-0.1825**	0.0786		
Asthma	-0.0962	0.0827		
Emergency room visit	-0.1879***	0.0286		
No of adults			0.1091	0.1042
No of kids			0.0858	0.0828
Inverse Mills - response	5.2457***	2.1076	-4.4623	3.0531

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

4.8.3 Results for restricted days model

Regression results for the PCB restricted days model are presented in Table 4.10. In the health equation, coefficients for the college degree or better dummy and income have significantly positive signs, while the coefficients for age and number of years at residence have significantly negative signs. The variable of interest, the PCB dummy, is negative and statistically significant. This indicates that residents at houses with non-zero PCB levels are less likely to enjoy good health. The coefficient for distance to Depot is positive and significant. Working status, cancer and number of emergency room visits are significantly associated with health status.

A restricted activity day are defined as a day in which usual activities are limited because of illness or injury, and reflect a loss of ability to perform one's social role at work, home or school. Restricted activity days are expected to be correlated to physical limitations (Scholes, et al. 1991). In the restricted days equation, those with college degree or better experience fewer restricted days, possibly because these respondents are more likely to have had better overall health care, thus preventing physical limitations. Good health significantly reduces the number of restricted days. This suggests that restricted days may be used as an indicator for health status. Working status is negatively correlated with restricted days, possibly because those without a job are likely to have some physical limitations that prevent them from doing so. However, PCBs do not have a significant role in restricting respondents' activities.

Table 4.10 Results for PCB restricted days model

Variable	Health status equation		Restricted days equation	
	Estimate	Std Error	Estimate	Std Error
Male	0.0203	0.1306	-0.0881	0.1834
Black	-0.2493	0.1728	-0.3989	0.2602
Degree	0.3339***	0.1382	-0.7776***	0.1747
Married	0.0425	0.1453	0.0639	0.2152
Age	-0.0161***	0.0054	0.0009	0.0076
Income	0.4701**	0.2244	-0.2129	0.2842
Years at residence	-0.0193**	0.0083	0.0104	0.0135
PCBs dummy	-0.3367***	0.1721	0.3758	0.2511
Toxic releases	0.0444	0.0519	0.0029	0.0588
Distance to Depot	0.1101**	0.0577	0.1301	0.0763
Health status			-1.5785***	0.2124
Health insurance	0.2091	0.2314	0.4324	0.3335
Working	0.3888***	0.1546	-0.8055***	0.2173
Alcohol	-0.2282	0.2364	-	
Smoke	-0.2201	0.1589	-	
Cancer	-0.1802**	0.0784	-	
Asthma	-0.0969	0.0823	-	
Emergency room visit	-0.1853***	0.0285	-	
No of adults			-0.0101	0.1018
No of kids			0.1267	0.0854
Inverse Mills - response	5.3834***	0.20612	-4.1986	2.7548

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 4.11 provides regression results for the restricted days model that includes the lead dummy. The results for this model are consistent with the results for restricted days model with PCBs. The coefficient for the lead dummy, the variable of interest, is of the expected negative sign and significant in the health status equation but is not significant in the restricted days equation. Once again, lead has a greater impact on health status than PCBs do; the coefficient for PCBs in the health status equation is -0.3367 compare with -0.4167 for lead. It is possible that lead has a more severe chronic effect on health status than PCBs do because of its higher toxic weight.

Table 4.11 Results for lead restricted days model

Variable	Health status		Restricted days	
	Estimate	Std Error	Estimate	Std Error
Male	0.0032	0.1315	-0.1521	0.1861
Black	-0.2173	0.1742	-0.3323	0.2714
Degree	0.3468***	0.1386	-0.8171***	0.1771
Married	0.0496	0.145	-0.1167	0.2178
Age	-0.0165***	0.0054	0.0008	0.0077
Income	0.4499**	0.225	-0.2085	0.2865
Years at residence	-0.0193***	0.0083	0.0132	0.0136
Lead dummy	-0.4167***	0.1765	-0.2074	0.2727
Toxic releases	0.0482	0.0526	0.0191	0.0601
Distance to Depot	0.0954*	0.0586	0.0974	0.0808
Health status			-1.6428***	0.2153
Health insurance	0.1981	0.2316	0.2900	0.3472
Working	0.3741**	0.1552	-0.7229***	0.2148
Alcohol	-0.2351	0.2369		
Smoke	-0.2094	0.1586		
Cancer	-0.1847***	0.0787		
Asthma	-0.0963	0.0826		
Emergency room visit	-0.1876***	0.0286		
No of adults			-0.0272	0.1019
No of kids			0.1163	0.0856
Inverse Mills - response	5.2383***	2.0839	-4.8204*	2.9535

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

4.8.4 Results for work days lost model

Among the three measures of productivity losses, number of work days lost is the most important variable. This variable represents a direct labor productivity loss, which may be readily quantifiable in economic terms, while sick days in bed and restricted days represent general productivity loss and are more difficult to measure. Table 4.12 reports maximum likelihood estimates of the work-loss days model using the PCB dummy. Those with college degree or better are more likely to enjoy good health. The older the respondents are, the higher the likelihood they will experience poor health. Asthma and the number of emergency room visits are negatively related to good health as expected. Surprisingly, the presence of PCBs does not have an effect on the health status of those who were employed. This is possibly because those who are affected by PCBs are less likely to work because of their sickness. At the same time those who had a job are likely to have access to health care, hence they would get treated if they have ever suffered any health effects from PCBs. In addition, those with jobs may live in areas of Calhoun County that are less likely to be contaminated.

In the work days lost equation, the coefficient for the college degree or better dummy is of the expected negative sign and is significant. This is consistent with the notion that those higher education levels have greater opportunity costs from missing work (Grossman 1972b; Stratmann 1999). Income is also negatively associated with lost work days; residents with higher income miss fewer days of work, which is similar to findings in the labor literature (Meyer, et al. 1995; Ostro 1987). The PCB dummy is significant and has a positive impact on missed work; that is, living in a house with positive PCB levels increases the number of lost work days. Like sick days in bed, lost work days reflect an outcome from acute health effects. The result shows that PCBs do acutely and negatively affect respondents' work histories. Good health is significantly and negatively associated with work days lost. Health insurance is positively related to lost work days; possibly because those with health insurance will also work for an employer who provides paid leave benefits. Percent employed in construction at the census block group level is also positively related to number of lost work days, possibly because those working in the construction industry are more likely to be exposed to dust and other air pollutants.

Table 4.13 presents maximum likelihood estimates for the lost work days model using the lead dummy, rather than PCB dummy as the explanatory variable of interest. The results for the health status equation are consistent with the equation using the PCB dummy, in which the coefficient for lead dummy is not significant. In the lost work days equation, the coefficients for college degree or better, health status, health insurance and construction remain statistically significant, but the coefficient for income becomes insignificant. The lead dummy is not significant in the work days lost equation. These results are consistent with the results in the sick days in bed model (these two measures reflect individual's react onto acute conditions) in which the coefficient for the lead dummy is not significant, but the coefficient for the PCB dummy is significant in the lost work days equation.

Table 4.12 Results for PCB work days lost model

Variables	Health status		Work days lost	
	Estimate	Std Error	Estimate	Std Error
Male	0.0446	0.1635	-0.1469	0.1817
Black	-0.2244	0.2371	-0.5586	0.3263
Degree	0.2985*	0.1691	-0.5922***	0.1622
Married	0.0784	0.1855	0.2001	0.2145
Age	-0.0263***	0.0073	-0.0173	0.0129
Income	0.4359	0.2759	-0.4354**	0.2191
PCBs dummy	-0.2233	0.2236	0.7158***	0.2877
Distance to Depot	0.0408	0.0586	0.0092	0.0754
Toxic releases	0.0588	0.0694	0.0505	0.0785
Health status			-0.6094***	0.2203
Health insurance	0.1633	0.2964	0.8395***	0.3295
Alcohol	-0.2686	0.2835		
Smoke	-0.2863	0.1987		
Cancer	-0.0928	0.0939		
Asthma	-0.426**	0.2134		
Emergency room visit	-0.1501***	0.0334		
Work at Depot	0.1064	0.4196	0.6248	0.2708
Construction	0.0591	0.0733	0.0367**	0.0179
No of adults			-0.0027	0.1051
No of kids			0.0017	0.0838
Inverse Mills-response	5.7674**	2.6476	-0.3831	2.6712
Inverse Mills-working	2.4581***	1.0329	2.1117***	1.1365

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table 4.13 Results for lead work days lost model

Variable	Health status		Work days lost	
	Estimate	Std Error	Estimate	Std Error
Male	0.0133	0.1650	-0.1518	0.1826
Black	-0.1742	0.2409	-0.2943	0.3338
Degree	0.3132***	0.1690	-0.6486***	0.1616
Married	0.0881	0.1841	0.1552	0.2177
Age	-0.0261***	0.0073	-0.0117	0.0130
Income	0.4421	0.2758	-0.4393	0.3038
Lead dummy	-0.3101	0.2342	0.0794	0.3221
Distance to Depot	0.0481	0.0701	-0.0105	0.0787
Toxic releases	0.0449	0.0596	0.0684	0.0841
Health status			-0.6308***	0.2207
Health insurance	0.1771	0.2973	0.8642***	0.3274
Alcohol	-0.2682	0.2846		
Smoke	-0.2679	0.1990		
Cancer	-0.0992	0.0944		
Asthma	-0.4290**	0.2141		
Emergency room visit	-0.1534***	0.0335		
Work at Depot	0.0951	0.2118	0.7823	0.6694
Construction	0.0367	0.1177	0.0273**	0.0174
No of adults			-0.0284	0.1066
No of kids			0.0075	0.0854
Inverse Mills - response	4.7476	2.6174	-1.7323	2.8858
Inverse Mills - working	1.9720***	0.8993	1.3875	1.0998

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

4.9 Discussion

The simultaneous system of equations and the inclusion of PCBs and lead in those two equations allow us to draw some conclusion about the extent of direct and indirect effects of labor productivity losses. PCB presence has both direct and indirect effects on the number of days in beds, has indirect effects on the number of restricted days and has direct effects on number of work days lost. Lead presence has indirect effects on the number of days in bed and restricted days, but has no effect on lost work days.

The coefficients for the PCB and lead dummies are used to calculate the marginal effects of those variables on productivity losses. The results are reported in Table 4.14. A discrete change in the PCB dummy from 0 to 1 results in an increase of sick days in bed by 0.77, an increase in restricted days by 0.15 and an increase in lost work days by 0.52 annually. Similarly, a discrete change in the lead dummy from 0 to 1 results in an increase of sick days in bed by 0.19 and restricted days by 0.17 annually.

In terms of toxic weight of chronic health effects, PCBs are less toxic than lead. In this study we find that PCBs have stronger effects on productivity losses than lead does. However, this result is not surprising if we consider that sick days in bed and lost work days both reflect mostly the effect of an acute conditions rather than a chronic condition. This indicates that PCBs are more toxic in terms of acute health effects than lead is. Further, the PCB effect may reflect the significant local and national media coverage, which raised Calhoun County residents' awareness level about the potential danger of PCBs.

We can use the marginal effects of PCB and lead on productivity losses to estimate welfare losses from lost days at work. However, costs for sick days in bed and restricted days are not available; we estimate here costs of labor productivity loss based on cost of one work day lost. The mean annual income for a household in the subsample of working respondents is $69,980. Under the assumption that the income comes from 2 people in the household, each working 250 days per year, one working day is worth $140 for the average household. The cost per work day lost as a result of the presence of PCBs is thus estimated to be $73 per working person. For the entire sample of working respondents this suggests a total loss of $38,690. If we extrapolate to numbers of employed persons in Calhoun County are 82,300 (71% working rate of 116,000 persons), the aggregate loss is $6 million, suggesting a significant economic loss given that the total annual value of labor in Calhoun County in 2002 was $959 million.

Table 4.14 Marginal effects for discrete change in PCB and lead dummies

Productivity loss	Discrete change in PCB (0→ 1)	Discrete change in lead (0→ 1)
Sick days in bed	0.77	0.19
Restricted days	0.15	0.17
Lost work days	0.52	

4.10 Conclusion

The empirical results presented here demonstrate that PCBs have significant and negative effects on the health status of residents in general, but no significant effect on the health status of working residents in particular. Similarly, lead is significantly and negatively associated with the health status of residents but is not associated with the health status of working residents. The effect of the chemical weapon incinerator on health status is inclusive since the coefficient for distance to Depot is significant in the model using PCB levels but insignificant in the model using lead levels. Since measurements of both PCBs and lead were generally taken at the same houses in the sample, this result is somewhat puzzling and worthy of further investigation.

PCBs are positively associated with all three measures of productivity loss. The presence of PCBs in the soil of respondents' house increases sick days in bed by 0.77, restricted days by 0.15 and lost work days by 0.52. Lead is positively related to only sick days in bed and restricted days. The presence of lead increases sick days in bed by 0.19 and restricted days by 0.17.

The evidence suggests that there are welfare losses associated with PCB and lead contaminations in Anniston City. Welfare losses come from the deterioration of residents' health status and labor productivity losses. Hence, it is necessary to carry out cleanup actions to restore worker productivity and limit welfare losses. Currently, the base level for PCB cleanup is 10 ppm and for lead is 400 ppm. As shown in this study, a positive level of PCB and a 50 ppm level of lead are associated negatively with health status and positively with productivity losses. Hence, the base levels of cleanup actions on PCBs and lead should be reduced since PCBs and lead are shown to have significant effects on health and productivity losses at levels smaller than the clean up level. It is also recommended that cleanup be accelerated since through 2006 USEPA has only mitigated 133 of the 209 properties with elevated lead levels in Anniston.

V. CONCLUSION

In this dissertation, we investigate economic impacts that toxic chemical hazards may impose on society, including losses in house values and indirect costs of health effects resulting from toxic chemicals. Specifically, we study how toxic chemicals impact property values, health status and labor productivity.

In the second chapter, we analyze the relationship between environmental health risks and property values in the US at the county level using a dataset with 3,106 counties. Several variables are used to represent environmental health risks including total chemical releases, number of Superfund sites, and cancer mortality. FIML is employed to control for the endogeneities of cancer mortality and toxic chemical releases in the model. Our findings indicate that house values are negatively associated with total releases and cancer mortality. The FIML estimates show that a reduction of total chemical releases by 1 pound per person results in an increase of $0.54 in house value and a decrease of cancer mortality by 1 death in 100,000 persons results in an increase of $105.47 in housing value. The value of statistical life is estimated to be $4 million with the FIML model. The value of statistical life and capitalized house values are used to estimate benefits of cleanup. Based on these estimates, a simple cost benefit analysis suggests that cleanup costs exceed benefits. However, it should be noted that the benefits are underestimated since only owner-occupied housing units and cancer mortality are accounted for in this study.

In the third chapter, we investigate how toxic chemical releases impact productivity losses measured by work days lost using a unique dataset merging individual-level NHIS data and county-level Toxic Releases Inventory data. A generalized instrumental variable estimation is used to account for the endogeneity of health status. The results reveal that health status is negatively associated with work days lost, regardless of how health status is measured, either in binary form or on a 5-point scale. The model underestimates the effect of health status on productivity loss when health status is exogenous. The estimations show that toxic chemical releases have positive and significant impacts on work days lost with both exogenous and endogenous binary health status. A 1 pound increase in toxic releases leads to an increase in lost work by 6.26 days with exogenous binary health status and 8.75 days with endogenous binary health status. The coefficient for toxic releases is not significant in the case of endogenous 5-point scale health status.

In the fourth chapter, we investigate how environmental hazards impact health status and labor productivity in Calhoun County, Alabama. Environmental hazards are represented by PCB contamination, lead contamination and distance to the Depot. A maximum likelihood approach is employed to simultaneously estimate the models of count and dichotomous data. A data set of direct mailing surveys, census block group data and kriged PCB and lead levels is used for the analysis. The results reveal that PCBs have significant and negative effects on the health status of residents in general, but no significant effect on the health status of working residents in particular. Similarly, lead is significantly and negatively associated with health status of respondents but is not associated with health status of working respondents. PCBs have positive impacts on all three measures of productivity losses. The presence of PCBs in the soil of respondents' houses increases sick days in bed by 0.77, restricted activity days by 0.15 and lost work days by 0.52. Lead has positive impacts only on sick days in bed and restricted days. The presence of lead increases sick days in bed by 0.19 and restricted days by 0.17. Welfare losses from the deterioration of residents' health status and lost work days associated with PCB contamination are estimated to be $6 million annually for Calhoun County.

Although the three essays in this dissertation are independent studies, they are connected by the main topic of environmental health risks. These studies may be useful for the general public since they provide information on how toxic chemicals impact their lives including their property values and health status. These studies are especially valuable to environmental policy-makers as they provide rich information on welfare losses associated with environmental hazards.

The results of the second chapter are important to decision makers as not only do they provide information on how property values respond to levels of toxic chemical releases, but also on how cancer mortality is associated with toxic chemicals. Along with the value of statistical life also estimated in this study, these results can be used for cost-benefit analysis for considering environmental cleanup of toxic releases. However, to estimate the true benefits of environmental cleanup, we suggest that in addition to cancer deaths, other health effects of toxic chemicals including cancer incidence, respiratory diseases, immune system damage and birth defects should be included in future research.

Costs of cancer treatment should also be included to calculate true benefits of reducing toxic chemical releases. It is also recommended that rental housing units should be included in future research.

The results of the third chapter provide information on how industrial pollution including air, water and land pollution together impact individual productivity losses. Like the results of the second chapter, the estimates of this study may be used for cost-benefit analysis for reducing toxic releases from industrial facilities. Benefits of pollution reduction would be increased significantly when taking into the account that toxic chemicals significantly deteriorate individual's health and increase productivity losses. However, it is important to conduct future research at a sub-county level in order to better understand the impact of toxic chemical releases on health and productivity because of the easily dispersed characteristics of air pollution. Future research should also be directed toward identifying which toxic chemicals contribute the most to work days lost, thus helping decision-makers to more efficiently target reductions of those specific chemicals.

The information in the fourth essay may be useful for policy makers in addressing areas that are contaminated with PCBs or lead. Currently, there are only a few studies investigating the economic impacts of PCBs and lead, therefore the results of this study may be used for cost-benefit analysis associated with the contamination. The study indicates that PCBs and lead affect not only individual's health status but also labor productivity. This is useful for policy makers to estimate the true cost of PCB and lead contamination. The results may also be used as a reference to establish a base level for cleanup action for contaminated areas. Currently in Anniston, the base level for PCB cleanup is 10 ppm and for lead it is 400 ppm. However, as shown in this study, a positive level of PCB and a 50 ppm level of lead are associated negatively with health status and positively with productivity losses. Hence, the base levels of cleanup actions on PCBs and lead should be reduced since PCBs and lead are shown to have significant effects on health and productivity losses at the level that is smaller than the clean up level.

REFERENCES

Adderley-Kelly, B. and E. Williams-Stephens. 2003. "The Relationship between Obesity and Breast Cancer." *ABNF Journal* 14: 61-66.

ADPH. 1996a. "Cobbtown/Sweet Valley Community PCB Exposure Investigation for the Monsanto Company Site, Anniston, Calhoun County, Alabama." Alabama Department of Public Health.

ADPH. 1996b. "Health Consultation for the Monsanto Company Site, Anniston, Calhoun County, Alabama." Alabama Department of Public Health.

ADPH. 2001. Alabama Department of Public Health. Public Health Assessment, Monsanto Company/Solutia Incorporated, Anniston, Calhoun County, Alabama. http://www.atsdr.cdc.gov/HAC/pha/solutia/mcs_p1.html.

Anselin, L. 1988. Spatial Econometrics: Methods and Models. Dordrecht, the Netherlands: Kluwer Academic Publishers.

Anstine, J. 2003. "Property Values in a Low Populated Area where Dual Noxious Facilities are Present." *Growth and Change* 34: 345-58.

Atkinson, S. and R. Halvorsen. 1990. "The Valuation of Risks to Life: Evidence from the Market for Automobiles." *The Review of Economics and Statistics* 72: 133-36.

ATSDR. 1992. Agency for Toxic Substances and Disease Registry. Case Studies in Environmental Medicine, Lead Toxicity.

ATSDR. 1997. Agency for Toxic Substances and Disease Registry. Toxicological Profile for Lead.

ATSDR. 1999. Agency for Toxic Substances and Disease Registry. Public Health Implications of Exposure to Plychlorinated Biphenyls (PCBs). http://www.atsdr.cdc.gov/DT/pcb007.html.

ATSDR. 2000a. Agency for Toxic Substances and Disease Registry, U.S. Department of Health and Human Services. Exposure Investigation Report. http://www.atsdr.cdc.gov/HAC/PHA/solutia/sol_toc.html.

ATSDR. 2000b. "Health Consultation: Evaluation of Soil, Blood, & Air Data from Anniston, Alabama." Agency for Toxic Substances and Disease Registry, U. S. Department of Health and Human Services.

ATSDR. 2002a. Agency for Toxic Substances and Disease Registry. Managing Hazardous Materials Incidents. Volume III - Medical Management Guidelines for Acute Chemical Exposures: Nerve Agents (GA, GB, GD, VX).

ATSDR. 2002b. Agency for Toxic Substances and Disease Registry. Managing Hazardous Materials Incidents. Volume III - Medical Management Guidelines for Acute Chemical Exposures: Blister Agents: Sulfur Mustard Agent H/HD, Sulfur Mustard Agent HT.

ATSDR. 2005. Agency for Toxic Substances and Disease Registry. Toxicological Profile for Lead. http://www.atsdr.cdc.gov/toxprofiles/tp13.pdf.

Batenburg, M. and J. Reinken. 1990. "The relationship between sickness absence from work and pattern of cigarette smoking." *The New Zealand medical journal* 103: 11-3.

Bates, D. and R. Sizto. 1987. "Air Pollution and Hospital Admissions in Southern Ontario: The Acid Summer Haze Effect." *Environmental Research* 43: 317-31.

Beiles, N. 2000. "What Monsanto Knew." *The Nation*: 18-22: New York.

Blair, B. and D. Hite. 2005. "The Impact of Environment Regulation on the Industry Structure of Lanndfills." *Growth and Change* 36: 529-50.

Boles, M., B. Pelletier, and Lynch. 2004. "The Relationship between Health Risks and Work Productivity." *Journal of Occupational and Environmental Medicine* 46: 737-45.

Bouwes, N. and S. Hassur. 1997. Office of Pollution Prevention and Toxics, U.S. Environmental Protection Agency. Toxics release inventory relative risk-based environmental indicators: Interim toxicity weighting summary document. http://www.epa.gov/opptintr/rsei/pubs/toxwght97.pdf.

Bradley, C., B. Heather, and D. Newmark. 2002. "Breast Cancer and Women's Labor Supply." *Health Services Research* 37.

Bui, L. T. M. and C. Mayer. 2003. "Regulation and Capitalization of Environmental Amenities: Evidence from the Toxic Release Inventory in Massachusetts." *The Review of Economics and Statistics* 85: 693-708.

Burnley, I. 1997. "Disadvantage and Male Cancer Incidence and Mortality in New South Wales." *Social Science & Medicine* 45: 465-76.

Bush, R. and M. Wooden. 1995. "Smoking and absence from work: Australian evidence." *Social Science and Medicine* 41: 437-46.

Cai, L. and K. Guyonne. 2004. "Health Status and Labor Force Participation: Evidence from the HILDA Data." *Melbourne Institute Working Paper* No. 4/04.

Calle, E., C. Rodriguez, K. Walker-Thurmond, and M. Thun. 2003. "Overweight, Obesity, and Mortality from Cancer in a Prospectively Studied Cohort of U.S. Adults." *The New England Journal of Medicine* 348: 1625-38.

Cameron, C. and P. Trivedi. 1998. Regression Analysis of Count Data. Cambridge, United Kingdom: Cambridge University Press.

Case, A. 1991. "Spatial Patterns in Household Demand." *Econometrica* 59: 953-65.

Centers for Disease Control and Prevention. 1994. "Cigarette Smoking among Adults-nited States, 1992, and Changes in the Definition of Current Cigarette Smoking." *Morbidity and Mortality Weekly Report* 43: 342-6.

Centers, J. 2003. Organic Consumers Association. Monsanto Fined $700 million for Poisoning People with PCBs. http://www.organicconsumers.org/Toxic/monsanto_pcbs.cfm.

Chay, K. and M. Greenstone. 2005. "Does Air Quality Matter? Evidence from the Housing Market." *Journal of Political Economy* 113: 376-424.

Clapp, J. 2003. "A Semiparametric Method for Valuing Residential Locations: Application to Automated Valuation." *Journal of Real Estate Finance and Economics* 27: 303-20.

Contoyannis, P. and A. Jones. 2004. "Socio-Economic Status, Health and Lifestyle." *Journal of Health Economics* 23: 965-95.

Cropper, M. 1981. "Measuring the Benefits from Reduced Morbidity." *American Economic Review* 71: 235-40.

Crossley, T. and S. Kennedy. 2002. "The Reliability of Self-Assesses Health Status." *Journal of Health Economics* 21: 643-58.

DHHS. 1993. Department of Health and Human Services. Hazardous Substances Data Bank.

Dwyer, D. and O. Mitchell. 1999. "Health Problems as Determinants of Retirement: Are Self-Rated Measures Endogenous?" *Journal of Health Economics* 18: 173-93.

EPA. 2000. Environmental Protection Agency. Lead Compounds. http://www.epa.gov/ttn/atw/hlthef/lead.html.

EPA. 2001. Environmental Protection Agency. Anniston PCB Site Administrative Order on Consent. http://www.epa.gov/Region4/waste/npl/nplal/annpcbaocremov.pdf.

EPA. 2003. "Proposed Plan Fact Sheet - Anniston PCB site." U. S. Environmental Protection Agency.

EPA. 2005. Toxics Release Inventory Program - Toxicity Information. http://www.epa.gov/tri/chemical/index.htm.

EPA. 2006a. U. S. Environmental Protection Agency. Alabama NPL/NPL Caliber Cleanup Site Summaries - Anniston PCB Site.

EPA. 2006b. Environmental Protection Agency. Health Effects of PCBs. http://www.epa.gov/pcb/pubs/effects.html.

EPA. 2006d. Alabama NPL/NPL Caliber Cleanup Site Summaries. http://www.epa.gov/Region4/waste/npl/nplal/annardal.htm.

EPA. 2007a. Chromium Compounds. http://www.epa.gov/ttn/atw/hlthef/chromium.html.

EPA. 2007b. Dichloromethane. http://www.epa.gov/ttn/atw/hlthef/methylen.html.

Ettner, S. 1996. "New Evidence on the Relationship between Income and Health." *Journal of Health Economics* 15: 67-85.

Faggiano, F., T. Partanen, M. Kogevinas, and P. Boffetta. 1997. "Socioeconomic Differences in Cancer Incidence and Mortality." *IARC Scientific Publications* 138: 65-176.

Fik, T., D. Ling, and G. Mulligan. 2003. "Modeling Spatial Variation in Housing Prices: A Variable Interaction Approach." *Real Estate Economics* 31: 623-46.

Gayer, T. 2000. "Neighborhood Demographics and the Distribution of Hazardous Waste Risks: An Instrumental Variables Estimation." *Journal of Regulatory Economics* 17: 131-55.

Gayer, T., J. Hamilton, and K. Viscusi. 2000. "Private Values of Risk Tradeoffs at Superfund Sites: Housing Market Evidence on Learning about Risk." *The Review of Economics and Statistics* 82: 439-51.

Gayer, T., J. Hamilton, and K. Viscusi. 2002. "The Market Value of Reducing Cancer Risk: Hedonic Housing Prices with Changing Information." *Southern Economic Journal* 69: 266-89.

Gladen, B. and W. Rogan. 1991. "Effects of prenatal polychlorinated biphenyls and dichlorodiphenyl dichloroethene on later development." *Journal of Pediatrics* 119: 58-63.

Grossman, M. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy* 80: 223-55.

Hagamar, L., T. Hallbery, and M. Leja. 1995. "High consumption of fatty fish from the Baltic Sea is associated with changes in human lymphocyte subset levels." *Toxicology Letters* 77: 335-42.

Hamilton, J. 1993. "Politics and Social Costs: Estimating the Impact of Collective Action on Hazadous Waste Facilities." *Rand Journal of Economics* 24: 101-25.

Hamilton, J. 1995. "Testing for Environmental Racism: Prejudice, Profits, Political Power?" *Journal of Policy Analysis and Management* 14: 107-32.

Hansen, A. and H. Selte. 2000. "Air Pollution and Sick-Leaves." *Environmental and Resource Economics* 16: 31-50.

Hausman, J. 1978. "Specification Tests in Econometrics." *Econometrica* 46: 1252-71.

Haveman, R., B. Wolfe, B. Kreider, and M. Stone. 1994. "Market Work, Wages and Men's Health." *Journal of Health Economics* 13: 163-82.

Heckman, J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47: 153-61.

Hite, D., W. Chern, F. Hitzhusen, and A. Randall. 2001. "Property-Value Impacts of an Environmental Disamenity: The Case of Landfills." *Journal of Real Estate Finance and Economics* 22: 185-202.

Hopenhayn-Rich, C., M. Biggs, and A. Smith. 1998. "Lung and kidney cancer mortality associated with arsenic in drinking water in Cordoba, Argentina." *International journal of epidemiology* 27: 561-69.

IARC. 1978. International Agency for Research on Cancer. Monograph on the Evaluation of the Carcinogenic Risk of Chemicals in Humans. Volume 18: Polychlorinated Biphenyls and Polybrominated Biphenyls.

IARC. 1987. International Agency for Research on Cancer. IARC Monographs on the Evaluation of Carcinogenic Risks to Humans. Supplement 7: Update of IARC Monographs.

Jacobson, J., S. Jacobson, and H. Humphrey. 1990. "Effects of in utero exposure to polychlorinated biphenyls and related contaminants on cognitive-functioning in young children." *Journal of Pediatrics* 116: 38-45.

Jacobson, S., G. Fein, and J. Jacobson. 1985. "The effect of intrauterine PCB exposure on visual recognition memory." *Child Development* 56: 956-60.

Kesteloot, H., S. Sasaki, G. Verbeke, and J. Joossens. 1994. "Cancer mortality and age: relationship with dietary fat." *Nutrition and Cancer* 22: 85-98.

Kiel, K. and K. McClain. 1995. "House Prices during Siting Decision Stages: The Case of an Incinerator from Rumor through Operation." *Journal of Environmental Economics and Management* 28: 241-55.

Kiel, K. and J. Zabel. 1997. "Evaluating the Usefulness of the American Housing Survey for Creating House Price Indices." *Journal of Real Estate Finance and Economics* 14: 189-202.

Kiel, K. and J. Zabel. 2001. "Estimating the Economic Benefits of Cleaning up Superfund Sites: The Case of Woburn, Massachusetts." *Journal of Real Estate Finance and Economics* 22: 163-84.

Kohlhase, J. 1991. "The Impact of Toxic Waste Sites on Housing Values." *Journal of Urban Economics* 30: 1-26.

Lee, L.-F. 1982. "Health and Wage: A Simultaneous Equation Model with Multiple Discrete Indicators." *International Economic Review* 23: 199-221.

Lopez-Abente, G., N. Aragones, R. Ramis, V. Hernandez-Barrera, B. Perez-Gomez, A. Escolar-Pujolar, and M. Pollan. 2006. "Municipal distribution of bladder cancer mortality in Spain: Possible role of mining and industry." *BMC Public Health* 6: 1-10.

Machnes, Y. 1992. "The Demand for Work-loss Days due to Illness." *Journal of Economic Behavior and Organization* 18: 283-86.

Malmstrom, M., J. Sundquist, and S.-E. Johansson. 1999. "Neighborhood Environment and Self-Reported Health Status: A Multilevel Analysis." *American Journal of Public Health* 89: 1181-86.

Marmot, M., A. Feeney, M. Shipley, F. North, and S. Syme. 1995. "Sickness absence as a measure of health status and functioning: from the UK Whitehall II study." *Journal of Epidemiology and Community Health* 49: 124-30.

Marmot, M., F. North, A. Feeney, and J. Head. 1993. "Alcohol consumption and sickness absence: from the Whitehall II study." *Addiction* 88: 369-82.

McClelland, G., W. Schulze, and B. Hurd. 1990. "The Effect of Risk Beliefs on Property Values: A Case Study of a Hazardous Waste Site." *Risk Analysis* 10: 485-97.

McCluskey, J. and G. Rausser. 2001. "Estimation of Perceived Risk and its Effect on Property Values." *Land Economics* 77: 42-55.

Meyer, B., K. Viscusi, and D. Durbin. 1995. "Workers' Compensation and Injury Duration: Evidence from a Natural Experiment." *American Economic Review* 85: 322-40.

Michaels, R. G. and V. K. Smith. 1990. "Market Segmentation and Valuing Amenities with Hedonic Models: the Case of Hazardous Waste Sites." *Journal of Urban Economics* 28: 223-42.

Mills, P., D. Abbey, L. Beeson, and F. Petersen. 1991. "Ambient Air Pollution and Cancer in California Seventh-day Adventists." *Archives of Environmental Health* 46: 271-80.

National Center for Health Statistics. 2002. Centers for Disease Control and Prevention.

National Health Interview Survey, 2002. http://www.cdc.gov/nchs/nhis.

National Climatic Data Center, N. O. a. A. A. 2005. http://www.ncdc.noaa.gov.

NCI. 1978. National Cancer Institute. Bioassay of Aroclor 1254 for possible carcinogenicity.

Nelson, A. C., J. Genereux, and M. Genereux. 1992. "Price Effects of Landfills on House Values." *Land Economics* 68: 359-65.

Nelson, C. and R. Startz. 1990. "The Distribution of the Instrumental Variables Estimator and Its *t*-Ration when the Instrument is a Poor One." *Journal of Business* 63: S125-40.

Nelson, J. 1978. "Residential Choice, Hedonic Prices, and the Demand for Urban Air Quality." *Journal of Urban Economics* 5: 357-69.

North, F., S. Syme, A. Feeney, J. Head, M. Shipley, and M. Marmot. 1993. "Explaining socioeconomic differences in sickness absence: the Whitehall II Study." *British medical journal* 306: 361-6.

Ostro, B. 1983. "The Effects of Air Pollution on Work Loss and Morbidity." *Journal of Environmental Economics and Management* 10: 371-82.

Ostro, B. 1987. "Air Pollution and Morbidity Revisited: A specification Test." *Journal of Environmental Economics and Management* 14: 87-98.

Ostro, B. 1990. "Associations between Morbidity and Alternative Measures of Particulate Matter." *Risk Analysis* 10: 421-27.

Ostro, B., M. Lipsett, J. Mann, A. Krupnick, and W. Harrington. 1993. "Air Pollution and Respiratory Morbidity among Adults in Southern California." *American Journal of Epidemiology* 137: 691-700.

Ostro, B., M. Lipsett, and M. Wiener. 1991. "Asthmatic Responses to Airborne Acid Aerosols." *American Journal of Public Health* 81: 694-702.

Ostro, B. and S. Rothschild. 1989. "Air Pollution and Acute Respiratory Morbidity: An Observational Study of Multiple Pollutants." *Environmental Research* 50: 238-47.

Parrish, K. M., M. C. Dufour, F. S. Stinson, and T. Harford. 1993. "Average Daily Alcohol Consumption during Adult Life among Decedents with and without Cirrhosis: the 1986 National Mortality Follow-back Survey." *Journal of Studies on Alcohol* 55: 450-6.

Pavlov, A. 2000. "Space-Varying Regression Coefficients: Semi-parametric Approach Applied to Real Estate Markets." *Real Estate Economics* 28: 249-83.

Pope-III, A. 1991. "Respiratory Hospital Admissions Associated with PM10 Pollution in Utah, Salk Lake, and Cache Valleys." *Archives of Environmental Health* 46: 90-97.

Portney, P. and J. Mullahy. 1986. "Urban Air Quality and Acute Respiratory Illness." *Journal of Urban Economics* 20: 21-38.

Rivera, B. 2001. "The Effects of Public Health Spending on Self-Assessed Health Status: an Ordered Probit Model." *Applied Economics* 33: 1313-19.

Robbins, A., V. Fonseca, S. Chao, G. Coil, N. Bell, and P. Amoroso. 2000. "Short Term Effects of Cigarette Smoking on Hospitalization and Associated Lost Workdays in a Young Healthy Population." *Tobacco Control* 9: 389-96.

Rosen, S. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy* 82: 34-55.

RTK NET. 2002. Toxic Release Inventory. http://www.rtknet.org.

Samakovlis, E., A. Huhtala, T. Bellander, and M. Svartengren. 2005. "Valuing Health Effects of Air Pollution - Focus on Concentration-Response Functions." *Journal of Urban Economics* 58: 230-49.

Samet, J., F. Speizer, and Y. Bishop. 1981. "The Relationship between Air Pollution and Emergency Room Visits in an Industrial Community." *Journal of the Air Pollution Control Association* 31: 236-40.

Scholes, D., A. LaCroix, E. Wagner, L. Grothaus, and J. Hecht. 1991. "Tracking progress toward National Health Objectives in the elderly: What do restricted activity days signify?" *American Journal of Public Health* 81: 485-88.

Schulze, S. and D. King. 2001. "The Use of Census Data for Hedonic Price Estimates of Open-Space Amenities and Land Use." *Journal of Real Estate Finance and Economics* 22: 239-52.

Scorecard. 2006. http://www.scorecard.org/env-releases/county.tcl?fips_county_code=01015.

Serxner, S., D. Gold, and K. Bultman. 2001. "The Impact of Behavior Health Risk on Worker Absenteeism." *Journal of Occupational and Environmental Medicine* 43: 347-54.

Silver, M. 1970. "An Economic Analysis of Variations in Medical Expenses and Work-loss Rates," in Empirical Studies in Health Economics. Herrert Klarman ed. Baltimore: The Johns Hopkins Press.

Singh, G. K., B. Miller, B. Hankey, and E. Fewer. 2002. "Changing Area Socioeconomic Patterns in U.S. Cancer Mortality, 1950-1998: Part I - All Cancer among Men." *Journal of the National Cancer Institute* 94: 904-15.

Smith, A., M. Goycolea, R. Haque, and M. Biggs. 1998. "Marked increase in bladder and lung cancer mortality in a region of Northern Chile due to arsenic in drinking water." *American journal of epidemiology* 147: 660-69.

Smith, G., C. Branas, and T. Miller. 1999. "Fatal Non-Traffic Injuries Involving Alcohol." *Annals of Emergency Medicine* 33: 659-68.

Stern, S. 1989. "Measuring the Effect of Disability on Labor Force Participation." *The Journal of Human Resources* 24: 361-95.

Stratmann, T. 1999. "What do Medical Services Buy? Effects of Doctor Visits on Work Day Loss." *Eastern Economic Journal* 25: 1-16.

Taylor, P., C. Lawrence, H. Hwang, and A. Paulson. 1984. "PCBs: influence on birthweight and gestation." *American Journal of Public Health* 74: 1153-4.

Taylor, P., J. Stelma, and C. Lawrence. 1989. "The relation of PCBs to birth weight and gestational age in the offspring of occupationally exposed mothers." *American Journal of Epidemiology*.

TRI. 2000. EPA. Toxic Release Inventory System Database. Http://www.rtknet.org.

Tryphonas, H. 1995. "Immunotoxicity of PCBs (Aroclors) in relation to Great Lakes." *Environmental Health Perspective* 103: 34-46.

US Census Bureau. 2000a. US Census Bureau. Census 2000 Database. Http://www.census.gov.

US Census Bureau. 2000b. US Department of Commerce. Census 2000 Summary File 3. http://www.census.gov/.

US Department of Health and Human Services. 1982. "The Health Consequences of Smoking: Cancer. A Report of the Surgeon General, 1982." Public Health Service, Office on Smoking and Health: Bethesda, Maryland.

US Department of Health and Human Services. 1983. "The Health Consequences of Smoking: Cardiovascular Disease. A Report of the Surgeon General, 1983." Public Health Service, Office on Smoking and Health: Rockville, Maryland.

US Department of Health and Human Services. 1984. "The Health Consequences of Smoking: Chronic Obstructive Lung Disease.. A Report of the Surgeon General, 1984." Public Health Service, Office on Smoking and Health: Rockville, Maryland.

Viscusi, K. 1993. "The value of Risks to Life and Health." *Journal of Economic Literature* 31: 1912-46.

Vistnes, J. 1997. "Gender Differences in Days Lost from work due to Illness." *Industrial and Labor Relations Review* 50: 304-23.

Xu, X., B. Xi, and H. Huang. 1995. "Air Pollution and Unscheduled Hospital Outpatient and Emergency Room Visits." *Environmental Health Perspectives* 103.

Zabel, J. and K. Kiel. 2000. "Estimating the Demand for Air Quality in Four U.S. Cities." *Land Economics* 76: 174-94.

APPENDICES

Appendix A: Poisson results for work loss days

Table A1: Poisson results for work loss days with binary exogenous health status (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square
HEALTH2	-0.6791***	0.0114	3,570.48
TOTREL	4.6635***	0.9884	22.26
DENSITY	-0.8585***	0.0788	118.78
PRECIP	-0.0038***	0.0004	106.20
LOWTEMP	0.0059***	0.0005	160.43
MALE	-0.1655***	0.0123	180.19
AGE	-0.0134***	0.0008	311.43
WHITE	-0.0138	0.0113	1.51
COLLEGE	-0.0684***	0.0136	25.21
MARRIED	-0.0848***	0.0099	73.52
INCOME45	-0.1667***	0.0145	131.87
DRINK	0.1737***	0.0112	239.92
SMOKE	0.2093***	0.0103	415.07
SERVICE	-0.1825***	0.0100	331.20
MANUF	0.0094	0.0137	0.47
ONEJOB	0.1041***	0.0164	40.23
HOURWORK	-0.0072***	0.0004	330.87
YEARONJOB	0.0090***	0.0006	224.19
SDAYPAID	0.2669***	0.0101	694.24
PBYHOUR	0.1784***	0.0099	321.43
EMP500	0.2051***	0.0106	373.52
INVERSE MILLS	1.9867***	0.1087	333.79

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table A2: Poisson results for work loss days with binary endogenous health status (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square
NEA	0.2266***	0.0142	254.74
MW	0.1378***	0.0148	86.61
HEALTH2[IV]	-1.4398***	0.0133	11,645.10
TOTREL	-0.0697	1.0219	0.00
DENSITY	-0.9738***	0.0796	149.64
PRECIP	-0.0039***	0.0004	109.47
LOWTEMP	0.0035***	0.0005	56.18
MALE	-0.1071***	0.012	80.14
AGE	-0.0281***	0.0007	1,741.32
WHITE	0.1197***	0.0114	109.91
COLLEGE	0.0708***	0.0136	27.18
MARRIED	-0.0516***	0.0099	27.17
INCOME45	-0.4543***	0.0136	1,111.89
DRINK	0.3351***	0.0112	898.41
SMOKE	-0.0236**	0.0106	4.99
SERVICE	-0.1930***	0.0100	369.13
MANUF	0.0345***	0.0137	6.34
AGRI	0.0965***	0.0341	8.04
ONEJOB	0.0129	0.0165	0.61
HOURWORK	-0.0068***	0.0004	300.63
YEARONJOB	0.0099***	0.0006	273.36
SDAYPAID	0.2357***	0.0101	544.23
PBYHOUR	0.1960***	0.0099	389.05
EMP500	0.2170***	0.0106	418.69
INVERSE MILLS	2.3702***	0.1031	528.19

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table A3: Poisson results for work loss days with 5-point exogenous health status (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square
NEA	0.2464***	0.0142	301.40
MW	0.1501***	0.0148	102.34
HEALTH5	-0.4397***	0.006	5,388.17
TOTREL	4.0768***	0.9948	16.79
DU	0.0974***	0.0135	52.22
DENSITY	-0.8692***	0.0791	120.79
PRECIP	-0.0038***	0.0004	107.85
LOWTEMP	0.0061***	0.0005	174.45
MALE	-0.1861***	0.0122	232.53
AGE	-0.0133***	0.0007	347.14
WHITE	0.0017	0.0113	0.02
COLLEGE	-0.0625***	0.0134	21.64
MARRIED	-0.0815***	0.0099	67.93
INCOME45	-0.1572***	0.0139	128.56
DRINK	0.1811***	0.0112	262.91
SMOKE	0.1789***	0.0103	299.46
SERVICE	-0.1761***	0.0100	307.69
MANUF	-0.0039	0.0137	0.08
AGRI	-0.0263	0.0341	0.60
ONEJOB	0.1045***	0.0164	40.57
HOURWORK	-0.0064***	0.0004	265.35
YEARONJOB	0.0095***	0.0006	250.94
SDAYPAID	0.2676***	0.0102	694.95
PBYHOUR	0.1686***	0.0099	287.61
EMP500	0.2145***	0.0106	407.81
INVERSE MILLS	1.6457***	0.1041	250.14

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Table A4: Poisson results for work loss days with 5-point endogenous health status (Dependent variable = work days lost)

Variable	Parameter Estimate	Standard Error	Chi-Square
Intercept	6.6252***	0.0485	18,691.80
NEA	0.2920***	0.0142	423.20
WE	0.0679***	0.0175	15.01
MW	0.1962***	0.0148	175.56
$HEALTH5^{IV}$	-1.2265***	0.0083	21,754.40
TOTREL	0.6769	1.0106	0.45
DU	0.2670***	0.0135	389.04
DENSITY	-0.8501***	0.0782	118.15
PRECIP	-0.0030***	0.0004	66.87
LOWTEMP	0.0046***	0.0005	94.75
MALE	-0.1309***	0.0123	114.10
AGE	-0.0304***	0.0007	1,776.78
WHITE	0.2142***	0.0114	351.97
COLLEGE	0.2387***	0.0135	310.53
MARRIED	-0.0100	0.0099	1.01
INCOME45	-0.4897***	0.0142	1,191.74
DRINK	0.4060***	0.0113	1,291.03
SMOKE	-0.1465***	0.0106	189.75
SERVICE	-0.1698***	0.0100	286.35
MANUF	0.0651***	0.0137	22.55
AGRI	0.1717***	0.0341	25.30
ONEJOB	0.0001	0.0164	0.00
HOURWORK	-0.0068***	0.0004	310.07
YEARONJOB	0.0089***	0.0006	223.09
SDAYPAID	0.2429***	0.0101	573.54
PBYHOUR	0.1959***	0.0099	390.92
EMP500	0.2082***	0.0106	385.61
INVERSE MILLS	1.4539***	0.1065	186.53

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Appendix B: Overdispersion tests

The likelihood ratio for Poisson and negative binomial models is calculated as

LR = -2 (LL (Poisson) – LL(negative binomial)) = 130,738.

Since the likelihood ratio test statistic is greater than the critical value of 5.41 at the 1% level, the null hypothesis is rejected, indicating the presence of overdispersion. The Wald test statistic is 4.2236/0.0682 = 61.92, which is greater than the 1% critical value of 2.33. We thus reject the null hypothesis of Poisson distribution of work-loss days. Hence, these two tests conclude that the Poisson model is inadequate for lost work days data and the negative binomial regression is used to model number of lost work days.

Appendix C: Information letter and survey questionnaire

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College of Agriculture

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INFORMATION SHEET
For Anniston Environmental Risk Survey

Dear Homeowner/Renter,

We, Sa Ho and Christophe de Parisot, two graduate students at Auburn University are asking you and other Calhoun County residents to help us better understand the ways in which you are affected by environmental conditions in your neighborhood. We hope to determine the impact of Anniston's incinerator and PCB contamination on housing prices, health, and labor productivity. This research will be used to help form public policy regarding environmental issues in Calhoun County, and it is important for you to make your opinion known.

In the 2005 *Anniston Environmental Risk Survey* which follows, we will be asking that the head of the household answer questions about perceived risks from the chemical weapons incinerator and PCB pollution in your neighborhood. If the person to whom this questionnaire was addressed has moved, then we ask you to fill it in. Please do not forward the questionnaire since it is important that the person currently living at the address on the envelope answer our questions. It is unnecessary for you to reveal your identity. Please take about fifteen to twenty minutes to answer our questions. Your participation in this project is extremely important, whether or not you are interested in these issues. A postage paid return envelope is enclosed. Your prompt response will be appreciated.

Your answers will be kept strictly confidential and will not be linked to you by name and/or address. No individual's name or address will ever be published in any of our studies, and only average statistics will be used. Your identity will never be divulged to any outside sources.

Should you have any questions about this questionnaire, please call or email us at either number or address below. You may also contact our faculty advisor, Dr. Hite at (334) 844-5655 or at hitedia@auburn.edu with questions. For more information regarding your rights as a research participant you may contact the Auburn University Office of Human Subjects Research or the Institutional Review Board by phone (334)-844-5966 or e-mail at hsubjec@auburn.edu or IRBChair@auburn.edu .

Sincerely,

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HUMAN SUBJECTS
OFFICE OF RESEARCH
PROJECT #05-223 EX 0510
APPROVED 10/30/05 TO 10/29/06

Page 1 of 1

A LAND-GRANT UNIVERSITY

Auburn University - Department of Agricultural Economics & Rural Sociology - 209B Comer Hall - Auburn, AL 36849 - Tel: (334) 844-5682

IMPORTANT DIRECTIONS FOR MARKING ANSWERS - PLEASE READ FIRST

- Please be sure to check the box when marking your response.
  Example: Incorrect marks: ■ Correct Marks: ☒ or ☑
- When checking boxes, please check only ONE box.

You have been randomly selected to participate in a research study and we invite you to please take the time to complete our survey and mail it back to us using the prepaid envelope. We ask that the survey be completed by an adult in the household.

Any information you provide will be strictly confidential. This data will be used only by persons engaged in this survey, and will not be disclosed or released to others for any purpose.

1. Do you own or rent your home?
   □ Own □ Rent →**GO TO 4**

2. If you own your home, to your best knowledge, what was the price asked by the previous owner or builder, and approximately how much did you actually pay for your house?
   Asking Price $________________ Purchase Price $________________

3. If you own your home, was it an existing structure or newly built when you bought it?
   □ Existing □ Newly Built

4. How long have you lived at your current address? _____Years _____Months

5. Did you move to your current home from
   □ Out of state □ Within Alabama but outside Calhoun County □ Within Calhoun County

6. Do you live on a farm and are you actively engaged in farming?
   □ Yes □ No

For questions 7 to 11, put a "1" next to the most important factor, a "2" next to the second most important factor, and so on down to "4".

7. When deciding where to live, locational factors are often taken into consideration. Please order the following four locational factors according to how important they were to you when you chose your current residence.
   ____ House is close to work place
   ____ House is close to friends and/or family
   ____ House is close to school
   ____ House is close to shopping and entertainment

8. When deciding where to live, neighborhood quality factors are often taken into consideration. Please order the following four neighborhood factors according to how important they were to you when you chose your current residence.
   ____ Neighborhood has lakes, trees, parks, etc.
   ____ Neighborhood has people with the same background
   ____ Chemical incinerator is not nearby
   ____ No nearby industrial pollution (PCBs and lead)

9. When deciding where to live, housing quality factors are often taken into consideration. Please order the following four housing quality factors according to how important they were to you when you chose your current residence.
   ____ This was the only place I could afford to live ____ The house has central air-conditioning
   ____ The house has up-to-date interior appliances ____ The size and numbers of rooms in the house

10. What potential environmental risk factors are you most concerned with? Please order the following four environmental risk factors according to how important they were to you when you chose your current residence.
   ____ Impact of Depot or Solutia on property value ____ Possible health risks from pollution of soil or water
   ____ Possible natural disaster affecting Army Depot ____ Possible terrorist attack at the Army Depot

11. Overall, please rank locational, neighborhood quality, housing quality and environmental risk factors in order of their importance to you when you chose your current residence.
   ____ Locational factors ____ Environmental risk factors
   ____ Neighborhood quality factors ____ Housing quality factors

12. If you were to consider moving to a new neighborhood in the Anniston area, would the operation of the incinerator at the Anniston Army Depot negatively influence your choice of neighborhoods?
   □ Yes □ No □ Do not know

13. Please rate your home in terms of general construction quality and quality of interior appliances
   □ Above average □ Average □ Below average

14. In your opinion, how much attention is given to environmental issues by local, state and federal government?
   □ Too much □ Too little □ Right amount

15. In your opinion, how much attention is given to environmental issues by the media?
   □ Too much □ Too little □ Right amount

16. Are you currently □ Employed □ Unemployed □ Retired □ Disabled

17. Even if you did not work last week, did you have a job or a business at any time in the PAST 12 MONTHS?
   □ Had a job last week □ No job last week, no job last 12 months → **GO TO 26**
   □ No job last week, had job last 12 months □ Do not know → **GO TO 26**

18. How many hours a week total do you work at (all of) your job(s)?________Hours

19. During the PAST 12 MONTHS, about how many days did you miss work at a job or business due to illness or injury (do not include maternity leave)? _________ days

20. Do you work at home for pay? □ Yes □ No

21. Do you work in downtown Anniston or Oxford? □ Yes □ No

22. Do you work at the Army depot? □ Yes □ No

23. Do you work at the Solutia plant? □ Yes □ No

24. Do you work on a farm? □ Yes □ No

25. How many minutes a day do you spend commuting to and from your job or jobs?_______ minutes

26. During the PAST 12 MONTHS, about how many days was your activity restricted due to illness or injury? _______ days

27. During the PAST 12 MONTHS, about how many days did illness or injury keep you in bed more than half of the day? ________days

28. How often do you drink any type of alcoholic beverage?
□ Never □ Daily □ Weekly □ Monthly □ Yearly □ Do not know

29. How often do you usually eat fruits and/or vegetables?
□ Never □ Daily □ Weekly □ Monthly □ Yearly □ Do not know

30. How often do you do any type of exercise or physical activity?
□ Never □ Daily □ Weekly □ Monthly □ Yearly □ Do not know

31. How often do you smoke cigarettes?
□ Every day □ Some days □ Not at all

32. Do you have any type of health insurance or health care coverage?
□ Yes □ No

33. Have you ever been told by a doctor or health professional that you have cancer or a malignancy of any kind?
□ Yes □ No → **GO TO 35** □ Do not know → **GO TO 35**

34. How old were you when cancer was first diagnosed? ___________ years

35. Have you ever been told by a doctor or other health professional that you have asthma?
□ Yes □ No → **GO TO 37** □ Do not know → **GO TO 37**

36. During the PAST 12 MONTHS, how many days were you UNABLE to work because of your asthma? ______ days

37. Have you ever been told by a doctor or other health professional that you have chronic bronchitis?
□ Yes □ No □ Do not know

38. During the PAST 12 MONTHS, did you have severe headaches or migraine?
□ Yes □ No □ Do not know

39. During the PAST 12 MONTHS, how many times have you had to visit an emergency room or urgent care center? _______ times

40. Do you have a well at home?
□ Yes □ No → **GO TO 42**

41. Do you rely on this well for drinking water?
□ Yes □ No

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42. How do you evaluate your general health?
    □ Excellent □ Good □ Fair □ Poor

43. How many persons 18 years of age or older, besides yourself, usually live in your household? ________

44. How many children under age 18 live in your household at least one-half of the time? ________

45. If you have children in elementary or high school, do the children attend
    □ Public Schools □ Private Schools □ Both

46. What is your age? ___________ Years

47. What is your race?
    □ White □ Asian or Pacific Islander □ American Indian, Eskimo or Aleut
    □ African-American □ Other race

48. How much school have you completed?
    □ Less than 9th grade □ 9th to 12th grade, no diploma □ High School Graduate or equivalent
    □ Associates Degree □ Some College, no degree □ Bachelors Degree
    □ Graduate or professional degree

49. What was the total household annual income earned before taxes in 2004 through wages, salary and bonuses by all persons in your household?
    □ Under $10,000 per year □ $10,000-19,999 per year □ $20,000-$29,999 per year
    □ $30,000-$39,999 per year □ $40,000-49,999 per year □ $50,000-$59,999 per year
    □ $60,000-$99,999 per year □ $100,000-149,999 per year □ Over $150,000 per year

50. What is your sex? □ Male □ Female

51. What is your marital status? □ Single, never married □ Married
    □ Divorced □ Widowed

52. Have you or has anyone in your household made a contribution of time or money in the past 2 years towards environmental causes such as the Sierra Club, National Wildlife Federation, or Community Against Pollution, etc.?
    □ Yes □ No

53. Did you vote in the last national election?
    □ Yes □ No