SPATIAL RESOLUTION, COSTS, AND EQUITY IN AIR TOXICS REGULATION

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Public Policy

Georgia Institute of Technology
August 2007

SPATIAL RESOLUTION, COSTS, AND EQUITY IN AIR TOXICS REGULATION

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ACKNOWLEDGEMENTS

Many individuals – teachers, family, friends, and relatives – supported me during this long and difficult journey. While I cannot name everyone here, I am grateful to each one of them.

I want to acknowledge the excellent guidance of the members of my dissertation committee – Drs. Ann Bostrom, Douglas Noonan, Armistead Russell, Michael Chang, and Marilyn Brown – who both challenged me and at the same time provided me with the right guidance to complete this research. It has been a wonderful learning experience working with my advisor, Dr. Ann Bostrom, over the past six years. Her critical feedback at various stages of this research, right from the conception to the end, proved to be invaluable. Dr. Douglas Noonan, as the Co-chair of my committee , has been a pillar of strength to me. I am grateful to him for listening to me patiently, for hours and hours together, as I struggled through my modeling for this research.

Dr. Michael Chang has been of source of constant support during the implementation of the Regional Air Impact Modeling Initiative (RAIMI), which is an important component of this research; his confidence in me always inspired me to get through several difficult steps in the implementation of RAIMI. I also want to thank him for his feedback on my draft dissertation. I want to thank Dr. Ted Russell for his guidance and encouragement to undertake the uncertainty analysis, which I believe, added important insights to my research. I am grateful to Dr. Marilyn Brown for agreeing to serve on my dissertation committee and for her valuable feedback on my dissertation draft.

My teachers and peers at the School of Public Policy (SPP) provided me constructive feedback at several stages of this dissertation research. I am grateful to the SPP community for their feedback and support.

I want to acknowledge funding support from the University of West Florida and the Environmental Protection Agency Region 4 Office through the Partnership for Environmental Research and Community Health (PERCH) project. I would also like to acknowledge a timely dissertation support fellowship from the Ivan Allen College and the School of Public Policy, Georgia Tech, and a research scholarship from the Georgia Chapter of the Air and Waster Management Association (AWMA).

Ryan Gesser was of great help with air dispersion modeling in RAIMI implementation. GAMS Development Corporation was very kind to me with their help in providing a fully functional GAMS software including non-linear programming solvers.

I am indebted to my parents and my three younger brothers for the sacrifices they made to let me come all the way from India to pursue a Ph.D. Their unconditional support and encouragement during the last two years have been of immense help during several difficult times. My in-laws have shown great confidence in my abilities and I am grateful for their constant support.

Words cannot describe the contribution of my wife Sreekanti in realizing this goal. None of this would have been possible if not for her unconditional love, patience, and encouragement. She also helped me, on several occasions, with her excellent software programming skills. I am very fortunate to have her enter my life at an important time.

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SUMMARY

Recent advances in technologies for monitoring and modeling coupled with concern about disproportionate impact on vulnerable communities in "hot spots" have been driving recent efforts to characterize risks from air toxics at finer spatial resolutions. However, few studies seek to understand the potential policy implications of regulating risks at increasingly finer spatial resolutions and the impact of resulting policies on distribution of risks and costs. To address this gap, this research poses two broad questions: (1) How could the choice of spatial resolution for regulation of risks from toxic air pollutants affect emission standards? and (2) What are the distributional consequences of regulation at different spatial resolutions?

To address the research questions, this research first develops a formal model of a hypothetical decision maker choosing emissions within a risk-based regulatory framework. The model follows the general outlines of the US Environmental Protection Agency (EPA) decision making processes under its current Residual Risk regulation and the Air Toxics "Hot Spots" program implemented by the California Air Resource Board (CARB). Within this framework, the decision maker chooses emissions to minimize net social costs (private industry costs and population health costs) subjected to the constraint that individual risk at any location should not exceed a certain threshold level of risk.

The model suggests that optimal emissions of air toxics could vary with the spatial resolution chosen to regulate risks depending on whether or not finer resolutions reveal local "hot spots" that are not apparent at coarse resolutions. Specifically, (a) spatial resolution of regulation does not matter to optimal emission levels when finer

spatial resolution does not capture new hotspots, (b) optimal emissions will decrease for sources that contribute most to hotspots captured at finer spatial resolutions, and (c) emission levels could increase for sources that do not contribute significantly to hotspots captured at finer resolutions. The model also suggests that net social costs are non-decreasing as one regulates risk at increasingly finer spatial resolutions.

An empirical application of the model using air toxic emission data for Escambia and Santa Rosa Counties in Pensacola, FL demonstrates the sensitivity of optimal emissions and net costs to the spatial resolution chosen for regulation. The empirical analysis is based on 15 "major" emission sources in seven industrial facilities in Pensacola, emitting six cancer-causing air toxics. Optimal emissions are estimated at three different spatial resolutions – census tract, census block group, and census block – and for three different threshold cancer risk values – 100 in a Million, 10 in a Million, and 1 in a Million.

The data for the analysis come from a variety of sources. An engineering cost methodology estimates abatement cost functions using data from regulatory impact analyses (RIAs) and background information documents (BIDs) of the EPA's Maximum Achievable Control Technology (MACT) standards. Air toxics exposures at the centroids of various census units were estimated by implementing an integrated risk assessment tool, the Regional Air Impact Modeling Initiative (RAIMI), recently developed by Region 6 of the EPA. RAIMI integrates an emission inventory, an air dispersion model, and a risk model and operates in a geographical information systems (GIS) environment. Population data come from the US Census Bureau; the value of statistical life (VSL) is based on prior estimates from various meta-analyses.

The empirical results are consistent with the predictions of the model. At a 100 in a million threshold risk, optimal emissions are exactly the same at the census block group and at the census tract resolutions, because regulation at the finer census block group resolution does not reveal any new hot spots. At the other risk thresholds and spatial resolution, emissions of pollutants such as acetaldehyde decrease for those sources that contribute the most to new hot spots identified at finer spatial resolutions. At a 100 in a Million risk threshold, the acetaldehyde emissions from a paper mill in Pensacola decrease from 135 to 69 ton per year (TPY) when regulated at the finer census block resolution. On the other hand, the optimal emissions of acetaldehyde increase from 4.2 to 10.7 for an organic chemical manufacturing facility because it contributes very little to the hot spot identified at the census block resolution.

The second part of the empirical analysis investigates the equity implications of regulating risks at finer spatial resolutions. The empirical results indicate that, consistent with the assumptions of the underlying decision model, regulation at finer resolutions reduces the maximum individual risk (MIR) of cancer in Pensacola. At a 10 in a Million risk threshold, MIR decreases from 17 in a Million at the census tract resolution to 10 in a Million at the finer census block resolution. The analysis, however, shows that the population risks, measured as expected excess cancer cases, might increase when risks are regulated at finer spatial resolutions. The expected excess cancer cases increase from 0.00215 at census tract level regulation to 0.00244 at census block regulation at the threshold risk of 100 in a Million.

The equity analysis also examined the environmental justice (EJ) implications of regulation at finer spatial resolutions by analyzing the correlations between changes in

cancer risk and percent nonwhite population. The correlations show improvements for nonwhites due to regulation at finer spatial resolutions at 10 in a Million risk threshold; at other risk thresholds the improvements occur in communities with higher proportion of whites. Thus the EJ analysis indicates that regulation at finer spatial resolutions might not address environmental injustice by itself.

Finally, this research conducted an uncertainty analysis taking into account uncertainties in abatement cost parameters, exposures estimated by air dispersion model, and cancer risk factors of toxic air pollutants. The results of the analysis demonstrate that uncertainties in input parameters introduce substantial uncertainty in choice of optimal emissions; the standard deviations and means of optimal emission distributions are of the same order of magnitude. However, spatial resolution at which air toxics risks are regulated could still matter in predictable ways even after taking into account the uncertainties that the decision maker faces.

The findings of this study have several policy implications. First, regulation at finer spatial resolutions involves a tradeoff between costs and equitable distribution of risks. At a threshold cancer risk of 100 in a million, regulating risks in Pensacola at the census block level resolution could be twice as costly as regulating risks at the census tract resolution, while reducing the MIR by almost half. Second, the MIR as a basis for risk-based regulation deserves further scrutiny, given the evidence from this research that decisions based on MIR could increase population risks. Third, regulation at finer spatial resolutions might not address environmental injustice by itself; EJ concerns may have to be incorporated more explicitly into emission control decisions. Future extensions of this research include formulating alternative decision models, relaxing assumptions such as

uniform susceptibility of population groups to toxic exposures, and fully characterizing the uncertainties in input parameters.

CHAPTER 1

INTRODUCTION

Environmental pollution is inherently spatial in nature, more so is air pollution. The fate and transport mechanism of air pollutants, after they are released from a source, is in part a function of source and emission characteristics, meteorological conditions, residence time of pollutants in the atmosphere, and physical features of the area into which pollutants are released. The complexity of this process produces variations in pollutant concentrations over a wide range of spatial scales from local to regional to global scales. Like any other spatial phenomenon, an implication is that patterns of pollutant concentrations observed at one scale[1] may not be apparent at other spatial scales (see Gibson, Ostrom, & Ahn, 2000). Thus global scale patterns in concentrations of greenhouse gases are not likely to be observed at local scales and localized concentrations of some air pollutants are unlikely to be apparent at larger scales.

The local scale concentrations or air pollution "hot spots" and their impacts in terms of health risks on exposed individuals and populations have been of recent concern in air quality management in the United States. A recent National Academies study on future air quality management in the United States recommended enhancement of exposure assessment in hot spots and design strategies to control sources contributing to

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[1] Scale has two attributes – extent and resolution. Spatial extent is the size of the geographical area under study and resolution is the density of measurement locations within the spatial extent. For example, national air toxics assessment (NATA) estimated cancer and non-cancer risks from air toxics in the US at the centroids of census tracts. According to the concepts of scale employed here, the spatial extent of this national scale study is the entire country and the spatial resolution is the census tract resolution.

hot spots (NRC, 2004). Risks in hot spots have especially been a concern with regards to air toxics[2] primarily because of the increasing concern that certain population groups may be disproportionately exposed to elevated risks in hot spots.

An initial policy response to deal with air toxics hot spots has been to increase local scale monitoring and develop modeling tools to characterize risks at finer spatial resolutions. Most of the U.S. Environmental Protection Agency (EPA)'s recent air toxics monitoring funds have been allocated to local scale monitoring projects, with a focus on characterization of air toxics exposures at community resolution. Advancements in Geographical Environmental Systems (GIS) tools are aiding in the development of new modeling tools capable of characterizing exposures at increasingly finer resolutions. In the context of this drive toward finer resolution information, a pertinent question is how could this information affect air toxics policy? This is the primary question for this dissertation research. In addition, this research also analyzes the distributional consequences of regulating risks at finer spatial resolutions.

1.1 Motivation for Research

1.1.1 Why Air Toxics "Hot Spots"?

The NRC study defined hot spots as "locales where pollutant concentrations are substantially higher than concentrations indicated by ambient outdoor monitors located in

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[2] Air toxics are one class of air pollutants regulated under the Clean Air Act (CAA). These pollutants include volatile organic compounds (VOCs) such as benzene and formaldehyde, semi-volatile compounds, and heavy metals such as nickel and mercury. Air toxics exposures are believed to cause cancer risks and a number of other non-cancer risks such as asthma and respiratory toxicity, central nervous system effects, systemic effects such as liver and kidney toxicity and immunotoxicity (Moller, Schuetzle, & Autrup, 1994).

adjacent or surrounding areas (NRC, 2004: 274).” Hot spots have been especially of concern in the context of air toxics[3], for reasons described below.

1.1.1.1 Localized Nature of Emissions

Air toxics are emitted not only from large stationary sources (e.g., oil refineries and organic chemical manufacturing facilities) and mobile sources, but also from smaller sources such as dry cleaners and gas stations. The smaller sources of air toxics are large in numbers and are typically distributed throughout densely populated urban areas, potentially posing very high, localized risks. Further, the concentrations of some air toxics tend to be highest within the first few meters from the source of release and flatten out quickly after that distance (EPA, 2004a). This nature of air toxics makes hot spots a concern in air toxics management.

1.1.1.2 Sparse Monitoring Network

The Clean Air Act Amendments (CAAA) listed 188 air toxics that should be regulated. Because of the large number of regulated air toxics, maintaining an extensive monitoring network is economically infeasible. Unlike the six criteria pollutants, there are no ambient air quality standards for air toxics. For criteria pollutants, EPA established a large network of monitoring stations including state and local air monitoring stations (SLAMS), national air monitoring stations (NAMS), special purpose monitoring stations (SPMS), and photochemical assessment monitoring stations (PAMS), all over the country to assess compliance with national ambient air quality standards (NAAQS). In case of air

[3] Air Toxics, Toxic Air Pollutants, and Hazardous Air Pollutants (HAPs) are used synonymously in this document.

toxics, however, the current national monitoring network for air toxics, called the National Air Toxics Trends Station (NATTS) network, has only 22 monitors across the country and monitors 18 toxic air pollutants (EPA, 2004a), mainly in large urban areas.

As some of the recent air quality modeling[4] studies of air toxics show, the spatial resolution of such a sparse monitoring network is unlikely to capture concentrations in localized hot spots. For example, Dolinoy & Miranda (2004) modeled concentrations of glycol ethers from lithographic printing units in Durham County, NC and found that modeling at finer resolutions (such as census blocks and block groups) reveals concentrations that are not apparent at coarser resolutions (census tracts and zip codes). Other studies (Ching et al., 2004; Majeed et al., 2004) modeled HAPs using the Community Multiscale Air Quality (CMAQ) model at various grid resolutions (36-, 12-, 4-, and 1-km grids) and found that coarser resolutions could not capture localized hot spots.

1.1.1.3 Environmental Justice Concerns

Perhaps the most important driver for the concern regarding air toxics hot spots is the evidence from the environmental justice literature that certain susceptible populations (low-income and minority groups) may be disproportionately subjected to high risks from air toxics (for e.g., see Morello-Frosch et al., 2001; Lopez, 2002; Morello-Frosch et al., 2002; Dolinoy & Miranda, 2004; Apelberg et al., 2005). Most of these studies have used national level assessments of air toxics such as the national air toxics assessment (NATA)

[4] Air quality models are computer models that are used to predict ambient concentrations, based on certain assumptions about the dispersion process, and use emission inventories, source and emission characteristics, local meteorology, and characteristics of local physical features as inputs.

and the cumulative exposure project (CEP) to analyze if minority and low income communities were subjected to greater risks than others. Some of these studies (e.g., Dolinoy & Miranda, 2004) used local scale estimation of risks and found evidence for environmental injustice.

1.1.2 Drive toward Increasing Spatial Resolution of Air Toxics Risks

Characterizing exposures in hot spots has been an explicit goal in many recent EPA air toxics strategy documents. The National Air Toxics Program or "Urban Air Toxics Strategy" (Federal Register, 1999a), developed in 1999, intended to "characterize exposure and risk distributions….(p: 38712)" in "geographic 'hot spots'…(p: 38712)" to achieve the goal of addressing disproportionate impacts of air toxics. EPA's Workplan for the National Air Toxics Program and Integrated Air Toxics State/Local/Tribal Program Structure (EPA, 2001) identified addressing risks in hot spots as part of its "near-source" and "community/neighborhood" goals. Finally, the second objective of EPA's proposed national air toxics monitoring program (EPA, 2004a) was to "characterize ambient concentrations (and depositions) in local communities (p: 14)."

At the level of implementation, EPA has been investing in local scale monitoring projects as well as modeling tools. For example, EPA allocated 60% of air toxics monitoring funding for the fiscal year 2004 to local-scale monitoring projects (EPA, 2004a). The aim of these projects, among other things, is to characterize the local concentration gradients of air toxics.

EPA has also been developing tools and guidance to model air toxics concentrations at finely resolved spatial scales, such as the community scale. An example of tool development is the recently developed integrated risk assessment tool called

Regional Air Impact Modeling Initiative (RAIMI) (EPA, 2006a). RAIMI is a GIS-based tool that can estimate cancer and non-cancer risks from multiple air toxics emitted from multiple sources at a community resolution. Recently, EPA has also published a detailed guidance document for conducting community-scale risk assessments as part of its Air Toxics Risk Assessment Reference Library series (EPA, 2006b).

Advances in GIS tools are also aiding the research efforts to characterize exposures at finer resolutions. In environmental health research, exposure models, which can estimate intra-urban variations in air quality based on the data on a limited number of monitoring stations are being developed (Nuckols, Ward, & Jarup, 2004; Jerrett et al., 2005). Jerrett et al., (2005) identified six such exposure models that are either under development or are already in use.

Recent research on air toxics modeling has also focused on developing methods that can model air toxics concentrations at spatially finely resolved local and neighborhood scales (see Touma et al., 2006 for a good review of this research). Full characterization of local scale ambient concentrations of air toxics requires modeling both long-range transport (transboundary air pollution) and local emissions. Large-scale air quality models such as CMAQ are capable of modeling long-range transport and chemical transformations but because of their limited spatial resolution, these models alone cannot fully characterize local scale concentrations. Air dispersion models such as the Industrial Source Complex Short Term (ISCST) model are designed to model local scale emissions, but they fall short of capturing the cumulative impacts from multiple sources. Recent modeling research has focused on developing techniques that can

combine large scale and local scale models to fully characterize local scale ambient concentrations (Touma et al., 2006; Isakov & Venkataram, 2006).

1.2 Research Questions

As the above discussion shows, characterizing risks from air toxics at fine spatial resolutions is an explicit goal in current air toxics policy and research, both as a strategic goal and with regard to implementation. This spatially finely resolved information will eventually be used federally or by states or local governments in policies to reduce risks from air toxics hot spots. In light of this, the question is how could finely resolved risk information affect the choice of a policy maker equipped with such information?

In framing the research question, this study makes a distinction between the effects of "resolution of information" and "resolution of regulation." Finer resolution of information could affect the decision maker's choice by providing additional information on risks. For example, a decision maker's policy choice could be affected if finely resolved information changes the uncertainty over the parameters in decision maker's objective function. Typically, such questions are studied under the value of information (VOI) framework (see Yokota & Thompson, 2004 for a review of VOI applications in environmental risk management).

Alternatively, finer resolution information could also be viewed as increasing the spatial resolution at which the decision maker could regulate risks. In this case, finer resolution information has no "informational" value and the policy choice is affected only by the number of spatial locations over which risks are regulated. This study focuses on the policy implications of increasing the "resolution of regulation."

As will be seen in later Chapters, regulation of emissions has been the primary policy instrument in air toxics risk management at all levels of government. In this context, the first question for this research is *how could increasing the spatial resolution at which risks are regulated affect emission controls on air toxics*?

As discussed earlier, the concern about hot spots is mainly driven by the evidence that certain susceptible groups (e.g., children, minorities and low-income groups) might be subjected to disproportionately higher risks from air toxics. Given this, the second question this research addresses is *what are the distributional consequences of regulating air toxics at finer spatial resolutions*?

1.3 Research Methodology

Based on a review of federal and state decision making in current risk-based air toxics policies, a formal decision model is proposed to study how regulation at finer spatial resolution could affect emission controls. In this model, a hypothetical social decision maker chooses emission levels to minimize net costs (net of costs of abatement to industry and population health costs) subject to the constraint that no spatial location should have more than a specific threshold risk. An empirical analysis then applies this model to air toxics emissions in two counties in Florida, Escambia and Santa Rosa, to demonstrate the results of the decision model.

1.4 Organization of Dissertation

This dissertation includes 11 chapters including this introduction. Chapter 2 provides a broad overview of air toxics management in the United States at the federal, state, and local levels. Chapter 3 reviews the decision making processes in risk-based regulation of air toxics. This chapter provides the rationale for the decision model in

Chapter 4. Chapter 4 formalizes the model and derives predictions regarding variation in emissions decisions depending on the spatial resolution chosen to regulate risks. Chapter 5 develops the detailed approach for the empirical application of the decision model developed in Chapter 4. The sixth chapter characterizes the data used to implement the empirical approach. Chapter 7 and Chapter 8 present the results of the empirical analysis of toxic air emissions in Pensacola. This analysis employs point estimates of model input parameters. Chapter 9 incorporates the uncertainties in model input parameters to draw implications for considering uncertainty in decision parameters. Chapter 10 draws broader implications of the results for environmental policy including cost-equity tradeoffs and the role of acceptable risk in resolving those tradeoffs, maximum individual risk as a basis for toxic regulations, and environmental injustice. Finally, Chapter 11 proposes some areas for future research.

CHAPTER 2

AIR TOXICS MANAGEMENT IN THE UNITED STATES

This chapter describes the primary policy tools used to manage air toxics at the federal, state, and local level in the United States. The first section discusses the federal air toxics policies followed by sections on state and local policies.

2.1 Federal Air Toxics Management

Control of air toxics at the federal level could be thought of as having two distinct phases – pre- and post 1990 Clean Air Act Amendments (CAAA).

2.1.1 Pre-1990 Air Toxics Control

The Section 112 of the Clean Air Act of 1970 required EPA to set standards, known as the National Emission Standards for Hazardous Air Pollutants (NESHAP), to control air toxics. Under this section, EPA had to first list the pollutant (s) considered hazardous, then promulgate proposed standards within 180 days of listing the pollutant, and finally, within the next 180 days, either set an emission standard or determine that the pollutant was not hazardous (Reitze, Jr. & Lowell, 2001).

NESHAPs under the CAA of 1970 were risk-based standards. EPA had to first establish, based on risk assessment, that the pollutant intended to be regulated posed substantial risk at ambient concentrations (Goldstein & Carruth, 2003). Then the emission standards were to be set by the EPA Administrator "at the level which in his judgment provides ample margin of safety to protect the public health from such hazardous air pollutant" (as quoted in Reitze, Jr. & Lowell, 2001). During the twenty

years prior to the 1990 CAA amendments, EPA listed eight pollutants and regulated only seven pollutants: asbestos, beryllium, mercury, radionuclides, inorganic arsenic, benzene, and vinyl chloride. Unrealistic timeframes required by the Act to develop standards, the agency's interpretation that the Act did not allow for consideration of costs and technological feasibility in determining the standards, and a number of lawsuits filed during this period all contributed to the slow pace of regulation (Reitze, Jr. & Lowell, 2001). This apparent lack of progress in setting standards to control air toxics led to a new section 112 in the 1990 amendments to the Clean Air Act.

2.1.2 Post-1990 CAAA Regulations

The 1990 amendments of the CAA listed 189 HAPs to be regulated under the amendments and required EPA to regulate sources that emit HAPs by developing standards. EPA had to list and develop emission standards for "major" [5] and "area" [6] source categories of stationary sources and develop separate standards for mobile sources. Four main types of standards have been developed by EPA since the promulgation of 1990 amendments: Maximum Achievable Control Technology (MACT), Area Source, Residual Risk, and Mobile Source. These standards are briefly described below:

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[5] Major sources are those that emit more than 10 tons per year (TPY) of any one of the 188 pollutants listed in the amendments or more than 25 TPY of a combination of pollutants.
[6] Area sources emit less than the threshold quantities specified for "major" sources.

MACT Standards

In response to the requirements of the 1990 CAAA amendments, in 1992, EPA published an initial list of 174[7] stationary source categories to be regulated under MACT standards and has since been developing standards for the listed sources in a phased manner. MACT standards are technology standards that are based on the best available technology for existing as well as new sources. MACT standards allow consideration of costs but only after ensuring a minimum standard or "floor." The MACT floor for existing sources is based on average emissions of the best performing 12% of existing units; for new sources, the floor is based on average emissions achieved by the best controlled source in the source category (Reitze Jr. & Lowell, 2001). The industries within each source category have three years to comply with the standards after the promulgation of the final rule. EPA completed the process of setting up standards for all listed source categories.

Residual Risk Standards

The MACT standards, as discussed earlier, are technology based standards and do not take into account the risks to public health and environment in setting the standards. The 1990 CAAA required EPA to review the risks remaining, eight years after the implementation of MACT standards, and set additional controls, if required. These standards are called Residual Risk Standards. EPA submitted a residual risk report (EPA, 1999a) to Congress in 1999 that outlined the approach EPA would take to determine whether additional controls would be required post-MACT implementation (see Chapter

[7] The initial list has been revised several times and it is an ongoing process.

3 for a more detailed explanation of the decision process involved in residual risk determination). EPA has so far completed residual risk standards for eight source categories (EPA, 2007a) although some of them did not require additional controls beyond MACT standards.

Area Source Standards

"Area" sources are smaller sources that emit less than the threshold emissions specified for "major" sources. Area sources categories are identified for regulation in several different provisions of 1990 CAAA. For example, the initial list of sources to be regulated under MACT standards identified five area source categories for regulation because EPA found a "threat of adverse health or environmental effects (Federal Register, 1992)" for these categories, as required by the CAAA. The CAAA also required EPA to identify at least 30 air toxics that pose the greatest potential health threat in urban areas and regulate the area source categories that represent 90% of the emissions of these 30 air toxics. In compliance with this requirement, EPA, in its Urban Air Toxics Strategy (EPA, 1999), identified those 30 urban air toxics. Currently, there are 70 area source categories, under three different listings, representing 90% of the emissions of the 30 urban air toxics (EPA, 2007b).

Some of the area sources are regulated under MACT Standards while a majority is regulated under Generally Available Control Technology Standards (GACT). GACT standards tend to be less stringent than MACT standards and they take into account the economic impact of employing those technologies and the technical capabilities of the firms to operate and maintain emission control systems.

Mobile Source Standards

Section 202 of the CAA requires EPA to set standards to control air toxics from mobile sources and their fuels. In 2001, EPA established the first mobile source air toxics rules (Federal Register, 2001) in which EPA identified 21 mobile source toxics to be regulated and established gasoline toxic emission performance standards. More recently, EPA finalized new mobile source rules that regulate benzene content in gasoline, set exhaust standards for vehicles at cold temperatures and evaporative emission standards from passenger vehicles, and set standards for gas cans to limit hydrocarbon emissions due to evaporation (Federal Register, 2007).

2.1.3 Air Toxics Assessments

In addition to the development of standards, the other major component of national air toxics management has been assessments of risks from air toxics. The objectives of this component are to identify geographical areas of high risks for priority action and track progress of regulatory programs in terms of their impact in reducing risks (Federal Register, 1999a). The assessment activities include the creation of a nation-wide monitoring network called the National Air Toxics Trends Stations (NATTS), the development of emission inventories, and the national air toxics assessments (NATA).

The NATTS network initially started with 13 monitoring stations across the country and now includes 22 stations, mainly located in urban areas. EPA has been compiling a national inventory of air toxics emissions since 1990, the most recent one being the 2002 NTI. This inventory, referred to as the national toxics inventory (NTI), is updated every three years. Two NATA studies have been conducted so far – one based on the 1996 NTI and the other based on the 1999 NTI. NATA studies estimate cancer and

non cancer risk from air toxics at the centroid of every census tract in the United States. The 1996 study estimated risks from 33 air toxics while the 1999 study estimated risks from 177 air toxics.

2.1.4 Integrated Urban Air Toxics Strategy

A key component of EPA's national air toxics program is the Integrated Urban Air Toxics Strategy (Federal Register, 1999a). This strategy was developed in response to the requirement in the 1990 CAAA that directs EPA to prepare "a comprehensive strategy to control emissions of hazardous air pollutants from area sources in urban areas (CAA: 74)." The strategy specifies three main goals: (1) attain 75% reduction in incidence of cancer risk attributable to stationary source air toxics, (2) attain a substantial reduction in public health risks from area source air toxics, and (3) address disproportionate impacts of air toxics risks across urban areas.

The urban strategy document provided details on four components of the strategy that EPA would implement to achieve the three goals. The first component was about the regulations that EPA would implement at the national scale and enforcement thereof; the second component focused on local and community-based initiatives to deal with cumulative risks in urban areas; the third component involved assessment activity including modeling tools and monitoring; and the final component was education and outreach to inform the public of risks and involve them in the implementation of the strategy.

Figure 2.1 shows an overview of current federal air toxics management reviewed in this section.

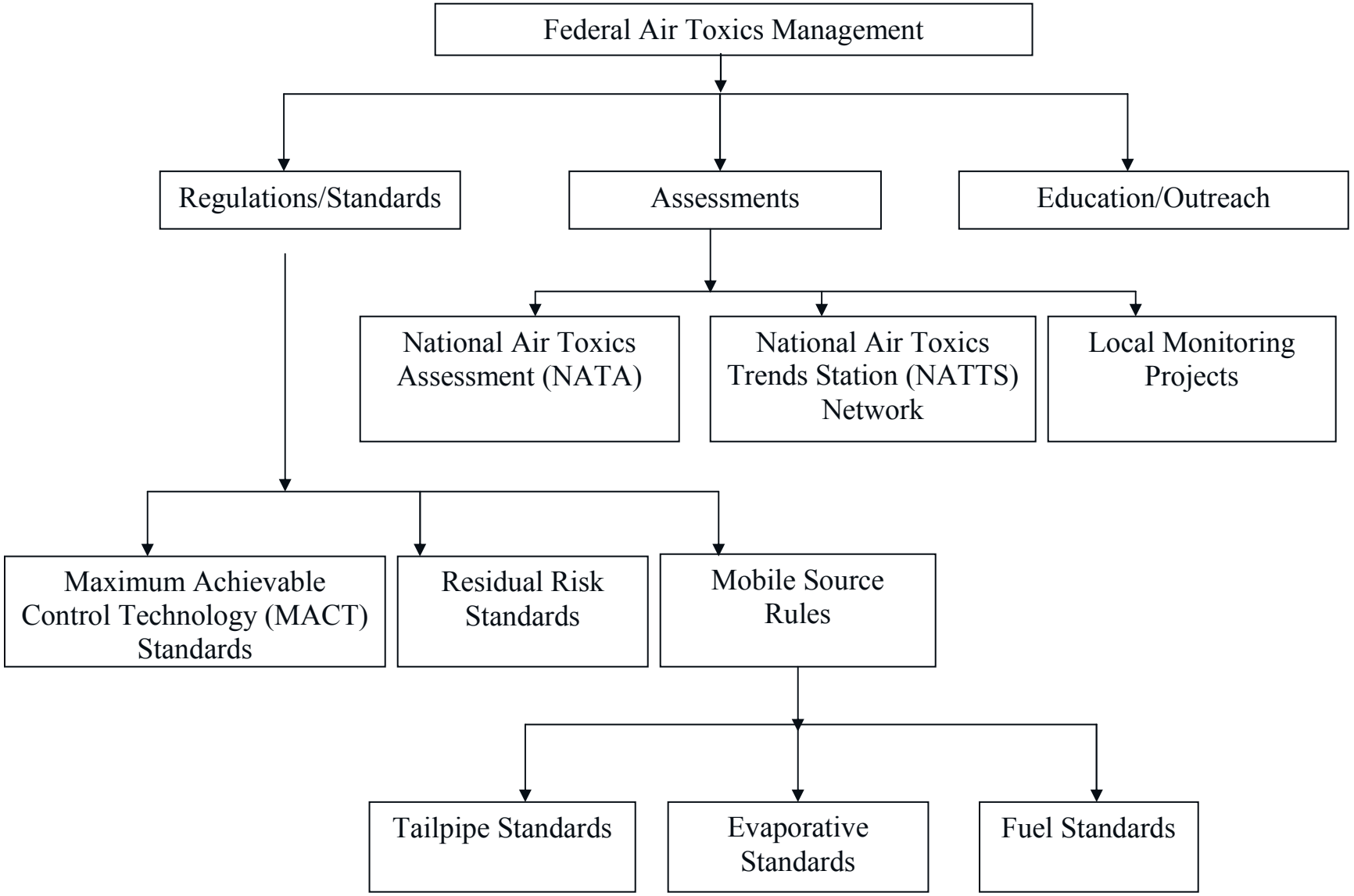

Figure 2.1 Federal Air Toxics Management in the United States
(Based on: Federal Register, 1999a)

2.2 State and Local Air Toxics Management

The slow pace of progress in federal regulation prior to the 1990 CAAA prompted many states to design their own air toxics programs to reduce emissions. The nature of the programs varies from state to state; while some states use technology based controls, some states use risk based standards, and a few others use ambient air toxics standards (Federal Register, 1999a). However, according to a survey conducted in 1995, 60% of the states that responded to the survey had risk based standards (EPA, 1999a). It is not clear how many of the state programs go beyond minimum federal regulations because no comprehensive study that compiles all the state air toxics programs is available. A recent GAO report (GAO, 2006), however, identified four state programs – California, New Jersey, Oregon, Wisconsin – and a local program, Louisville, KY that go beyond federal programs in many ways. Some of these programs are relatively new; for example, Oregon's program started in 2003 and the Louisville program was approved in 2005. The California program, which is one of the oldest and successful programs, and a local program, the Louisville program, are briefly reviewed below.

2.2.1 Air Toxics "Hot Spots" Program of California

California was among the first states to promulgate a state level air toxics regulation called The Air Toxics "Hot Spots" Information and Assessment Act (AB 2588), which came into effect in 1987. This is a risk-based regulation. Any stationary source that manufactures, formulates, uses, or releases one of the over 600 identified toxic substances is potentially subject to this Act. The Act has a number of components to it (see California ARB, 2007 for an overview). First, the facilities subjected to this Act have to submit an emission inventory reporting plan and, upon approval by the

appropriate air pollution control district (APCD), submit the emission inventory. This inventory must be updated every four years.

The APCD classifies the facilities as high, intermediate, and low priority risk, taking into account a number of relevant factors including toxic potency , the quantity of emissions of pollutants, and the location of the facility with respect to populated areas. Facilities that are prioritized as "high" risk facilities have to conduct a detailed health risk assessment to estimate the risks associated with their emissions. If the risks they pose are beyond the "notification" risk standard specified by the APCD, the facilities then must notify the people exposed to those risks. The 1992 amendments to the Act also requires high risk facilities to submit an emission reduction plan to reduce the risks below acceptable levels specified by the air quality district. This Act also prescribes penalties for violating any provisions of the Act or for intentionally submitting false information.

2.2.2 Louisville, KY Local Program

The Louisville Metro Air Pollution Control District Board recently approved implementation of a set of regulations under its Strategic Toxic Air Reduction (STAR) program (Louisville Metro, 2005). Based on extensive local monitoring and modeling studies, this program identified 37 air toxics released by various stationary sources in Louisville that pose or may pose risks above a specified health risk goal. The health risk goal is a 1 in a million cancer risk or higher than 1.0 non-cancer risk threshold. The STAR program identified 18 pollutants for action in its first phase. A total of 170 facilities are subject to regulation under this program. These facilities must conduct risk assessments to estimate cancer and non-cancer risks posed by their emissions and submit an emission reduction plan to reduce the risks below the health risk goal (Williams, n.d.).

The air pollution district increased the permit fees based on the size of the facility to partly fund the implementation of the STAR program. The federal EPA provided financial and technical assistance in designing the STAR program.

2.2.3 Role of Federal EPA in State/Local Air Toxics Programs

Many states, as discussed in the previous section, developed their own air toxics programs prior to the 1990 CAAA. After the development of federal standards such as MACT, there was a potential overlap of regulatory requirements for several facilities already regulated under a state regulation. In recognition of this potential overlap, Section 112(l) of the 1990 CAAA directed EPA to develop clear guidance to state and local (S/L) agencies on how agencies could seek approval for alternative standards or seek delegation authority to enforce federal standards. Section 112, however, makes it clear that EPA cannot approve any proposal by S/L agencies that is deemed less stringent than federal requirements.

The guidance developed by the EPA (Federal Register, 2000) in response to Section 112 (l) requirements proposes several alternatives for S/L agencies: (1) Agencies can request for straight delegation, without any changes in federal requirements, or (2) request approval of adjustments to federal rules, or (3) request approval of substitution for a particular federal rule, or (4) request an entirely independent program in lieu of federal rules. The guidance also specified timeframes and other procedures for approval process.

In addition to oversight of federal rule enforcement, EPA also works in partnership with S/L agencies to implement its overall national air toxics program, as outlined in the Integrated Urban Air Toxics Strategy (Federal Register, 1999a). As a

follow up to this commitment for partnership with S/L agencies, EPA created a workgroup in 2000 to discuss the role of state, local, and tribal (S/L/T) agencies in achieving the national air toxics program goals. The final Workplan, in its integrated S/L/T program structure, identified national, area-wide, near-source, and community/neighborhood goals and a four-step process (assessment, program development, program implementation, and audit/backstop) for addressing air toxics risks at each level (EPA, 2001). This document also discussed delegation of implementation and funding mechanisms for implementation of sub-national goals.

Finally, EPA funds local air toxics monitoring programs to help local agencies and communities address air toxics "hot spots." EPA has already funded a number of such projects in communities across the country and has been increasingly shifting its air toxics monitoring funds to local monitoring projects instead of expanding its national NATTS network (EPA, 2004a).

2.3 Summary

Review of air toxics management in the United States suggests that: (1) the predominant policy tool employed in air toxics management is regulation (2) current federal regulation has been moving increasingly towards risk based standards, in addition to implementation of technology based standards, (3) some state agencies have long been implementing risk based standards to reduce air toxics, and (4) local air toxics management is gaining prominence, with EPA actively encouraging such initiatives.

CHAPTER 3

DECISION MAKING IN RISK-BASED REGULATION OF TOXICS

This chapter reviews the regulatory decision making processes in the management of toxics. The first section reviews empirical research that analyzes EPA's regulatory decision making under various toxics laws. The next section focuses on risk-based air toxics regulation. Based on this review, the final section proposes a decision making model to study the primary question for this dissertation research.

3.1 Risk-based Regulation of Toxics

Risk-based regulation has a long history in the management of toxic pollutants in the United States. It has been widely used in regulatory decisions by a number of federal agencies including the EPA, the Food and Drug Administration (FDA), and the Occupational Safety and Health Administration (OSHA). Toxics regulations such as the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), the Toxics Substances Control Act (TSCA), the Superfund program under the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), and the regulation of toxic air pollutants under the Clean Air Act (CAA) – all base their regulatory decisions on assessment of risks to individuals and populations.

It is surprising, given the pervasiveness of risk assessment in regulatory decision making, that very limited empirical research systematically analyzes the actual decisions EPA and other agencies have made in a risk-based framework; the exception has been research on the Superfund program. Limited empirical research, mostly in political

economy, tests the influence of mainly three factors on EPA decisions. First, did EPA balance benefits and costs in its regulatory decision making; second, what is the role of maximum individual risk (MIR); and third, did political factors influence EPA decisions? The findings with regards to these three questions are briefly discussed below.

3.1.1 Balancing Benefits and Costs of Regulation

Economic efficiency suggests that decisions be made such that the marginal costs equal the marginal benefits of a regulation. Economic efficiency, however, is not a goal of environmental regulation in the US. While some regulations such as FIFRA and TSCA allow consideration of costs in regulatory decisions, the Superfund regulation and the Clean Air Act prohibit consideration of costs in standard setting. Balancing, in the context of this research, means testing whether a costly standard is less likely to be selected and a beneficial standard is more likely to be selected. An analysis of 242 regulatory decisions of EPA under FIFRA found that EPA did balance costs and benefits in deciding whether or not to allow continued use of a pesticide on food crops (Cropper et al., 1992).

TSCA is another regulation that allows balancing of costs and benefits. A study that analyzed EPA's decision to regulate the use of asbestos in 39 products found that EPA balanced costs and benefits, consistent with the TSCA mandate; products with low costs and high lives saved were banned most often while products with high costs and low lives saved were not banned (Van Houtven & Cropper, 1996). The Superfund law does not allow consideration of costs in setting cleanup target risk standards although costs may be considered in cleanup decisions once a target risk level is set. Empirical analysis of 110 soil contaminated superfund sites found that EPA's cleanup decisions

were consistent with Superfund law (Gupta, Van Houtven, & Cropper, 1995). Costs did not matter in selecting target risks while EPA did select lower cost technology options to achieve the target risks.

3.1.2 Maximum Individual Risk vs. Population Risk

A key feature of risk-based decision making in the regulation of toxic pollutants has been the focus on reducing individual risks. Individual risk typically means upper-bound[8] risk to a maximally exposed individual in a population. Population risk is measured either as the size of population exposed to risks above certain threshold risk values or the number of people in a population expected to develop a disease due to exposure to pollution.

In a study of 132 regulatory decisions made by federal agencies, no correlation was found between size of population exposed and likelihood of regulation whereas individual risk did matter in decisions (Travis et al., 1987). This study found that agency decisions revealed an implicit *de manefestis* and *de minimis* levels of individual risk; every chemical with an individual cancer risk above 4 in 1000 was regulated and no chemical with individual risk less than 1 in a million was regulated. Further, every pollutant with individual risks above *de manefestis* risk was regulated regardless of costs and pollutants for which individual risks fell between *de manefestis* and *de minimis* risks were regulated only when the cost per life saved was less than $ 2 million. EPA's guideline for Superfund cleanup is consistent with this finding. Whether or not a clean up

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[8] In the case of air toxics, upper-bound risk is based on the assumption that an individual subjected to estimated pollutant concentrations is exposed to those concentrations for 24 hours a day for 70 years.

action is required for a site is based on cumulative individual lifetime cancer risk. According to this guideline, no action is warranted for sites with less than 1 in a million individual lifetime cancer risk, action is warranted when individual risk exceeds 1 in 10,000, and action is discretionary for risks between these two values (Hamilton & Viscusi, 1999).

The above finding led to the "bright-line" hypothesis (Cropper et al., 1992), which says that regulatory agencies balance costs and benefits only after a threshold individual risk is achieved. Analysis of actual decisions made by EPA rejected this hypothesis for pesticide regulation (Cropper et al, 1992; Van Houtven & Cropper, 1996) but supported it for regulation of hazardous air pollutants (Van Houtven & Cropper, 1996).

3.1.3 Political Influence

In democratic decision making, voter interests, bureaucratic discretion, and interest group activities all influence environmental policies (Congleton, 1996). Tests of whether EPA was influenced by interests of different stakeholders in its risk-based regulation have used a number of different measures of political influence. In pesticide regulation decisions studied by Cropper et al., (1992), the influence of various stakeholder groups was measured by a dummy variable that indicated whether or not they commented on a regulatory proposal. Adding interest group variables "dramatically" increased the explanatory power of the model indicating that interest group activity was a significant predictor of the probability of cancellation of pesticide use. The study also found that "interventions by environmental groups have about twice the impact on the likelihood of cancellation as those by growers (p: 194)."

For the Superfund program, one of the most expensive efforts in US environmental policy, evidence is somewhat mixed. Hird (1994) studied the influence of House and Senate authorizing and appropriations subcommittees on a variety of Superfund outcome variables such as pace of cleanup and cleanup expenditures. His general finding was that the subcommittees did not affect outcomes. However, another study that used a different set of measures for political influence variables found strong evidence of their effects on stringency of cleanup targets (Viscusi & Hamilton, 1999). These measures included voter turnout, number of environmentalists in the state, and the environmental records of state senators.

3.2 Standard Setting Processes in Air Toxics Regulation

Prior to the Clean Air Act Amendments (CAAA) of 1990, regulation of air toxics was risk-based, as discussed in Chapter 2. EPA listed eight pollutants as hazardous and regulated seven pollutants before the 1990 CAAA. The most controversial among those seven pollutants was vinyl chloride. EPA first set standards for sources of Vinyl Chloride based on best available control technology because scientific uncertainty about risks restricted EPA's ability to determine a "safe" level for vinyl chloride, as mandated by the CAA. EPA argued that it had to take costs and technological feasibility into account because scientific uncertainty about "safe" quantities of vinyl chloride meant a zero emission standard (Reitze, Jr. & Lowell, 2001). This standard led to lawsuits, first by the Environmental Defense Fund (EDF) and later by the Natural Resources Defense Council (NRDC), claiming that Section 112 of the CAA of 1970 prohibits EPA from considering costs and technological feasibility (see Dankner, 1988 for an excellent legal review of this regulation).

In the lawsuit by NRDC, now known as the "Vinyl Chloride" case, the D.C. Circuit upheld EPA's view that the CAA did not explicitly prohibit consideration of costs but directed EPA to adopt a two-step process to setting up standards in case of hazardous air pollution regulation. In the first step, EPA should establish a "safe" level of risk without considering factors such as cost and technology. Once a safe level is assured, the second step should set the strictest feasible emission standard, taking into account costs and other factors. After the Vinyl Chloride case, EPA used this direction to set standards for regulation of sources of benzene (Federal Register, 1989).

One empirical study (Van Houtven & Cropper, 1996) that analyzed air toxics regulation prior to the 1990 CAAA concluded that the Vinyl Chloride case had an impact on how EPA made decisions in regulating air toxics. There was clear evidence in this study that EPA tried to balance costs and benefits before the Vinyl Chloride case but after the Vinyl Chloride verdict did not consider costs when maximum individual risk (MIR) was above 1 in 10,000.

The CAAA of 1990 required EPA to develop and enforce technology based standards, referred to as Maximum Achievable Control Technology Standards (MACT), in the first phase of implementation of air toxics regulation. Eight years after MACT implementation, EPA was required to the risks that remained and set additional controls, if necessary. This second phase of air toxics regulation, currently underway, entails the development and implementation of Residual Risk Standards. Under Section 112(f) of the CAAA, Congress directed that EPA should set residual risk standards to provide an "ample margin of safety" for public health. EPA submitted a report to Congress (EPA, 1999a) detailing its approach to conducting risk assessments and to set additional

controls, if required, under Residual Risk Standards. The following subsections discuss the decision process that EPA set forth to set regulation under residual risk standards, followed by a discussion of a relevant state act, the California "Hot Spots" program.

3.2.1 Residual Risk Regulation

Air toxics regulation under residual risk is no exception to the principle of protecting the individual exposed to maximum risk. The rationale behind this principle is "to ensure equitable protection across an exposed population (EPA, 2004b: 27)." Under this principle, decisions to control emissions are driven by the estimated upper-bound MIR[9] from a source category. Other factors such as costs and feasibility could be considered in control decisions only after ensuring that the MIR does not exceed a threshold value determined by the regulatory agency.

EPA adopted the two-step process suggested by the D.C. Circuit in the Vinyl Chloride case discussed earlier to set standards under the residual risk rule (EPA, 1999a). The two steps in the determination of additional control requirements under the residual risk regulation are:

1. In the first step, EPA determines an "acceptable risk" from air toxics for the exposed population. "Acceptable Risk" [10] is a judgment EPA makes by taking into account a number of factors including maximum individual risk (MIR), the overall incidence of cancer in the exposed population, the number of people exposed to different

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[9] MIR is "the highest estimated risk to an exposed individual in areas that people are believed to occupy (EPA, 1999b: 45)."

[10] The typical benchmark for risk acceptability under residual risk standards is a MIR of less than 1 in 10,000 (EPA, 1999a).

individual life time risk ranges, the uncertainties associated with risk estimates, weight of evidence for human health effects of toxic pollutants, and any other relevant health effects.

2. The second step is the determination of an "ample margin of safety." In making this determination, EPA "strives to provide protection to the greatest number of persons possible to an individual lifetime risk level no higher than approximately 1 in a million (Federal Register, 1989, p: 38046)." This step leads to establishment of controls to maintains "ample margin of safety." While establishing controls EPA takes into account not only all the health factors in the first step but also other factors such as cost and technical feasibility of controls, uncertainties, economic impact, and other relevant factors.

3.2.2 Identification of "Hot Spots"

A related regulation at the state level is the Air Toxics "Hot spots" Information and Assessment Act enacted by the California Air Resources Board (CAARB) in 1987 and later amended in 1992. This act requires that health risk assessments be conducted by those facilities that are identified to cause "significant" health risks and inform the public of those significant risks. The 1992 amendment also required that emissions of HAPs that contribute to significant risk be reduced within a specified timeframe. The Air Pollution Control Districts (APCD) set the risk threshold levels that trigger risk reduction requirements for the facilities. Facilities that exceed the threshold risk must submit a "risk audit and reduction plan" to bring the risks down to the threshold value. For example, South Coast Air Quality Management District requires facilities to submit a risk audit and

reduction plan if the cancer risk exceeds 25 in a million, the cancer burden exceeds 0.5, or the non cancer hazard index exceeds 3.0 (South Coast AQMD, 2007).

The identification of "hot spots" or "significant" risks that trigger requirements for risk reduction plans in this program is based on "point of maximum impact (PMI)" which is located using health risk assessment models. The California Air Resources Board issued detailed guidelines to facilities to determine the PMI (CalEPA, 2003). This PMI corresponds to MIR referred to earlier in residual risk regulation. Unlike federal residual risk standards where EPA determines how air toxics risk should be controlled by facilities, this state program allows flexibility, in terms of abatement options, to the industries to achieve the risk reductions. The APCDs do not specify the control technologies that the high-risk facilities must implement. However, in the risk audit and reduction plan submitted to APCDs for approval, the facilities must include a rationale for including or excluding identified abatement options.

3.3 A Model of Risk-based Air Toxics Decision Making

This section first reviews various approaches for modeling regulatory behavior and then proposes a model to address the questions for this research.

3.3.1 Modeling Regulatory Behavior

The review in Chapter 2 suggested that regulation is the primary instrument in air toxics management in federal as well as local agency policy making. Before proposing a decision model to address the research questions for this research, this section briefly reviews previous research on modeling regulatory decisions with special reference to environmental regulation.

The economic theory of regulation, first proposed by Stigler (1971), models regulators as maximizing their self-interest; the self-interest is generally the votes that

keep the regulators in power. This theory, referred to as "capture theory" of regulation, predicts that the benefits of regulation generally accrue to industry because of their ability to organize as powerful groups. Peltzman (1976) formalized and extended Stigler's theory and modeled regulator as maximizing the likelihood of reelection, given competing interest groups. Through this formulation, Peltzman's theory suggests that organized groups (such as consumers), in addition to the regulated industry, could also get a share of rents from a regulator maximizing the self-interest. Within this theoretical tradition, Becker (1983) modeled regulatory outcomes, specifically the political redistribution of income and other policies, as a result of competition for influence among pressure groups. One of Becker's main prediction is that governments will choose more efficient policies to less efficient policies in redistributing income from less powerful to more powerful groups.

Agency theory or principal-agent theory predicts that because elected institutions (Congress and President) create agencies and control their resources, regulatory behavior of the agencies should be shaped by the elected institutions (Wood, 1988). Many empirical studies of federal agency decisions show consistency with agency theory. Proposing a legislative choice model, Weingast & Moron (1983) modeled the Federal Trade Commission decisions as a function of preferences of Congressional oversight committees. The authors found that oversight committees held considerable influence on FTC decisions even in absence of systematic oversight hearings. Studying the core regulatory enforcement decisions of seven federal agencies including the Equal Employment Opportunity Commission (EEOC), the FTC, the Nuclear Regulatory Commission (NRC), the FDA, the National Highway Traffic Safety Administration

(NHTSA), the Office of Surface Mining (OSM), and the EPA, Wood & Waterman (1991) found that political events such as political appointments, resignations, and budget changes consistently affected agency decisions. Using similar theoretical approach to explain EPA's clean air enforcement decisions, Wood (1998) found limited evidence of political control in EPA decisions.

3.3.1.1 Modeling in Environmental Regulation

Two main approaches are reviewed here: public choice and political economy. The main emphasis of public choice approach in environmental policy is to explain the conditions under which policy makers choose different instruments. In one of the early studies, Buchanan & Tullock (1975) argued that firms favor emission standards to emission taxes because standards restrict entry of new firms leading to higher profits for the existing firms. This inference was based on the assumption that the industry, being more organized than consumers, can influence the choice of policy instrument. Hahn (1990) proposed a model of environmental regulator in which the regulator chooses a policy instrument and a level of environmental quality to maximize utility. The utility in the objective function was a linear combination of preferences of industry and environmental interest groups. Based on this model of environmental regulation, he author derives predictions for conditions under which the regulator chooses a market-based instrument as opposed to a standard. A more recent application of public choice approach to choice of environmental policy instruments proposed that the choice of instrument is a competitive equilibrium outcome of a "political market (Keohane, Revesz, & Stavins, 1997)." The proposed political market consists of utility maximizing legislators, who supply support for policy instruments based on their ideologies, and a

number of interest groups with a demand for particular types of policy instruments. Based on this modeling approach, the authors provide explanations for adoption of standards vs. market-based policy instruments.

Perhaps the approach most relevant to this research is the political economy approach that has already been discussed in Section 3.1. The political economy models reviewed here analyze *ex post* policy decisions of EPA to explain the determinants of EPA decision making. Cropper et al., (1992) modeled the probability of banning a pesticide as a function of costs and benefits of banning the pesticide and whether or not political interest groups participated in the regulatory process. The authors not only found that EPA did balance costs and benefits but also that participation of interest groups was a significant factor in banning decisions. In a study of Superfund decisions, Viscusi and Hamilton (1999) modeled regulatory stringency in site clean up decisions as a function of chemical risks and site-specific factors including voter turnout. The regulatory stringency was measured by target risk level for each chemical pathway and cost of clean up at each site. This study also found significant influence of political factors in EPA decisions.

3.3.2 Proposed Decision Model

The approaches reviewed in Section 3.3.1 suggests that the regulatory decision process is a complex political process largely influenced by political interests of various groups.

The decision model proposed for this research departs from the reviewed models in that this model assumes an idealized net social cost minimizing decision maker, who is not influenced by political considerations. The model proposed here reflects the decision process set forth by EPA and other state agencies under residual risk regulations. Based on the review in Section 3.2, the basic elements of the decision process in setting risk-based standards are:

1. Determine an acceptable level of maximum individual risk, and

2. Achieve the maximum feasible reduction in emissions taking into account the costs of controls and other factors only after risk to the maximally exposed individual is at or below the acceptable risk level determined in the first step. In this research this is translated as: balance the costs of compliance with the population health benefits of reducing emissions after ensuring that MIR is at or below an acceptable risk threshold.

Thus, in the model proposed here, ***a hypothetical decision maker chooses emission levels such that the net costs (net of costs to industry of abating emissions and population health costs) are minimized subjected to the constraint that no spatial location has an individual risk greater than a threshold value.*** This model is developed formally in Chapter 4.

CHAPTER 4

MODEL FORMULATION AND PREDICTIONS

This chapter formalizes the decision model proposed in section 3.3. The initial sections present the policy setting, the modeling choices, and the model assumptions. The later sections develop the mathematical form of the decision model to study the implications, for optimal emissions and net social costs, of regulating air toxics at finer spatial resolutions

4.1 Policy Setting

Let the baseline scenario be the current emissions of air toxics from various sources in a geographical area of interest such as a county. Suppose, a hypothetical decision maker made an assessment of risks based on current emissions and found that certain locations within the area of interest are subjected to high (or unacceptable) risks. The decision maker wants to act on this assessment and choose emission controls to reduce risks. Also suppose that the hypothetical decision maker can choose the spatial resolution over which to regulate risks. For example, the decision maker could regulate at census tract resolution (based on available national studies such as the national air toxics assessment) or at a finer resolution (such as a census block) based on a local scale modeling study. The question for this research is: how could the hypothetical decision maker's choice of emission levels vary depending on the spatial resolution the decision maker chooses to regulate risks?

4.2 Modeling Choices

The hypothetical decision maker's problem is to choose emission levels that minimize net social costs, subjected to the constraint that no individual is subjected to more than a certain threshold risk '*r'*. The net social costs consist of the net of private costs of abatement for firms and the human health costs of air toxics exposures.

4.2.1 Rationale for Modeling Choices

As explained in Chapter 3, in decisions such as the additional controls required under residual risk standards, a key factor for EPA is the risk to the maximally exposed individual, or the maximum individual risk (MIR). The constraint in the model, which says that no location should be subjected to more than a threshold risk '*r*,' reflects this principle. Further, after ensuring an acceptable level of MIR, EPA is allowed to consider costs and reduction of population risks while setting emission control standards. Thus the objective function of the model proposed here (i.e., net of private costs to industry and population health costs) is consistent with decision making processes as specified under risk-based air toxics emission control standards.

In risk-based regulations of air toxics, agencies implicitly choose the quantity of emissions. Although residual risk standards specify the technologies the regulated industries must adopt to reduce residual risks, these imply an allowable quantity of emissions. In California's "hot spots" program, the choice is more explicit. The industries that pose risks beyond the standard set by the Air Pollution Control District (APCD) must submit a detailed emission reduction program that reduces the maximum individual risk to within the specified limits. Thus, the choice variable in the decision model is emission levels.

4.3 Model Assumptions

The decision model assumes:

- The decision maker weighs private costs and social costs equally.
- Emissions are continuous and released at a constant rate.
- Value of statistical life (VSL) is constant across different population groups.
- Cancer risks are additive. That is, every pollutant imposes risk independent of other pollutants.
- The population is exposed to the estimated concentrations continuously during their entire lifetime (70 years).
- There is no chemical transformation of toxic air pollutants after they are released into air.
- Abatement costs are convex and increase at an increasing rate.
- The model includes costs of only cancer risks and does not include costs resulting from other endpoints such as non-cancer human health effects or ecological effects.

Implications of some of these assumptions and possible ways of relaxing the assumptions are discussed in Chapter 11.

4.4 Decision Maker's Problem Set-up

Let there be *'I'* sources, $S_1, S_2, \ldots, S_I$, each of which emit *'J'* toxic air pollutants $t_1, t_2, \ldots, t_J$. Let the excess lifetime cancer risk due to these *'J'* pollutants emitted by *'I'* sources be estimated at $k = 1,2,3,\ldots, K$ spatial locations. The cancer risk at any given location r_k is given by:

$$r_k = \sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ijk}u_j \quad \text{for all } k = 1,2,3,\ldots, K \qquad (4.1)$$

Where,

r_k Risk (expressed as increased probability of cancer) at *k* th location

Q_{ij} Emission rate (*g/s*) of pollutant *j* from *i* th source

β_{ijk} Exposure concentration, in [($\mu g / m^3$)/(g/s)], at location *k* due to a unit emission rate (1 *g/s*) of pollutant *j* from source *i* = *f* (meteorology, emission and source characteristics, site characteristics, location of the measurement point with respect to the source, and activity patterns of exposed population)

u_j Unit Risk Factor for *j* th pollutant, ($\mu g / m^3$)$^{-1}$ (represents the probability of cancer due to continuous exposure for 70 years to 1 $\mu g / m^3$ of pollutant *j*)

Cancer risk is expressed as '*n*' in a million probability. The interpretation is that if a million people are exposed to a risk of '*n*' in a million over 70 years, it is expected that there will be '*n*' additional cases of cancer due to air toxics exposure. So, if *m* th spatial location has p_m people and are exposed to a cancer risk of r_m, it is expected that there will be $p_m * r_m$ number of excess cancer cases. Thus for a geographic region with *m*=1,2,….,*M* population locations, the total number of expected additional cancer cases is given by:

$$R = \sum_{m=1}^{M} r_m p_m \qquad (4.2)$$

A component of the objective function is the health costs associated with cancer risks from toxics exposure. In a willingness to pay (WTP) framework, these costs could

be estimated as the number of additional cancer cases multiplied by the value of statistical life (V)[11]. Thus, this component of costs can be expressed as:

$$\text{Health Costs}, C_h = \sum_{m=1}^{M} r_m p_m . V \qquad (4.3)$$

The health costs are increasing in emissions. This is because the cancer risks increase as the air toxics emissions increase.

$$\frac{\partial C_h}{\partial Q_{ij}} > 0 \qquad (4.4)$$

The other component of the objective function is the private costs of abatement borne by polluting sources. This cost is in part a function of the industrial sector, the process and abatement technologies, and the type of toxic air pollutant being abated. If source *i* has to reduce emissions of a pollutant *j* from a baseline of Q^b_{ij} to Q_{ij}, and if MC_{ij} represents the marginal cost function for pollutant *j* from source *i*, then the private cost of abatement can be expressed as:

$$\text{Private Costs}, C_p = \sum_{i=1}^{I} \sum_{j=1}^{J} \int_{Q^b_{ij}}^{Q_{ij}} MC_{ij}(Q_{ij}) . dQ_{ij} \qquad (4.5)$$

The private costs decrease with increasing emissions. That is, the higher the allowable emissions, the lower are the abatement costs.

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[11]Value of statistical life (VSL) is the rate of tradeoff between money and the risk of dying (Hammitt, 2000). Its application here assumes that incidence of cancer results in mortality and that VSL is constant across additional cancer cases. VSL enters as a scalar in equation *(4.3)*, which assumes that there is no heterogeneity in willingness to pay to reduce risk of death across individuals. VSL is discussed further in Section 6.4.4.

$$\frac{\partial C_p}{\partial Q_{ij}} < 0 \qquad (4.6)$$

The constraint in the model is that the cancer risk at any of the spatial locations over which risks are regulated should not exceed a threshold value *r*. If the risks are regulated based on an assessment of risks over *k*=1,2,…,*K* spatial locations, the constraint in the model is given by:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ijk}u_j < r \qquad \forall \text{ k } = \text{ 1,2,3,….,K} \qquad (4.7)$$

It should be noted that the variable of interest for the question addressed in this research is *K*. Spatial resolution in this research refers to the number (or density) of locations over which risks are regulated. The number of locations increases as the spatial resolution becomes finer and finer. That is, *K* increases with increasing spatial resolution.

Putting everything together, the decision maker's problem then is:

$$\underset{Q_{ij}}{Min}\left\{\left(\sum_{i=1}^{I}\sum_{j=1}^{J}\int_{Q_{ij}^{b}}^{Q_{ij}} MC_{ij}\left(Q_{ij}\right).dQ_{ij}\right)+\left(\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} Q_{ij}\beta_{ijm}u_j p_m V\right)\right\} \qquad (4.8)$$

Subjected to the constraints that:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ijk}u_j < r \qquad \forall\ k\ =\ 1,2,3,\ldots.,K$$

$$Q_{ij} \geq 0$$

The goal is to derive the implications of regulating at finer spatial resolutions to optimal emissions and net costs, given the above problem set up. In order to achieve this, the first step is to solve the model for optimal emissions at any given resolution (i.e., at

any particular K) and then examine what happens to optimal emissions as we regulate at a finer spatial resolution (i.e., at any $K' > K$).

4.4.1 Optimal Emissions at a Specific Spatial Resolution (K)

Minimizing a function f is the same as maximizing – f . I will use this property to generate first order conditions for my problem. The Lagrangian is (Simon & Blume, 1994):

$$L = -\sum_{i=1}^{I}\sum_{j=1}^{J}\int_{Q_{ij}^{b}}^{Q_{ij}} MC_{ij}\left(Q_{ij}\right).dQ_{ij} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} Q_{ij}\beta_{ijm}u_j p_m V$$
$$-\lambda_1\left(\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ij1}u_j - r\right) - .... - \lambda_K\left(\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ijK}u_j - r\right) \qquad (4.9)$$

The first order conditions will be:

$$\frac{\partial L}{\partial Q_{ij}} = -MC_{ij}\left(Q_{ij}^{*}\right) - \sum_{m=1}^{M}\beta_{ijm}u_j p_m V - \sum_{k=1}^{K}\lambda_k\beta_{ijk}u_j \le 0 \qquad (4.10)$$

$$Q_{ij}\frac{\partial L}{\partial Q_{ij}} = -Q_{ij}^{*}MC_{ij}\left(Q_{ij}^{*}\right) - \sum_{m=1}^{M}Q_{ij}^{*}\beta_{ijm}u_j p_m V - \sum_{k=1}^{K}\lambda_k Q_{ij}^{*}\beta_{ijk}u_j = 0 \qquad (4.11)$$

$$\frac{\partial L}{\partial \lambda_1} = -(\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}^{*}\beta_{ij1}u_j - r) \ge 0, ..., \frac{\partial L}{\partial \lambda_K} = -(\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}^{*}\beta_{ijK}u_j - r) \ge 0 \qquad (4.12)$$

$$\lambda_1 \frac{\partial L}{\partial \lambda_1} = -\lambda_1 (\sum_{i=1}^{I} \sum_{j=1}^{J} Q_{ij}^* \beta_{ij1} u_j - r) = 0,$$

.

. *(4.13)*

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$$\lambda_K \frac{\partial L}{\partial \lambda_K} = -\lambda_K (\sum_{i=1}^{I} \sum_{j=1}^{J} Q_{ij}^* \beta_{ijK} u_j - r) = 0$$

$$\lambda_1 \geq 0, \ldots\ldots \lambda_K \geq 0 \qquad \textit{(4.14)}$$

In the above set of equations, *(4.10)* is a condition that the first derivative of the Lagrangian with respect to the choice variables should be non-positive. The set *(4.11)* is a condition that states that when $Q_{ij} > 0$, the condition *(4.10)* holds with equality. Equation *(4.12)* is just the constraint set, *(4.13)* is the complementary slackness condition, which says that either the constraints bind or the Lagrange Multipliers (LM) (λ) are zeros for those constraints that do not bind. The set of equations *(4.14)* says that the Lagrange Multipliers (LM) should be non-negative. The system of equations from *(4.10)* to *(4.14)* has (I*J+K) unknowns and (I*J+K) equations and hence is identified.

The choice variables, the emission quantities, are assumed non-negative. Given this, the condition in equation *(4.10)* holds with equality. It can thus be written as:

$$MC_{ij}(Q_{ij}^*) + \sum_{m=1}^{M} \beta_{ijm} u_j p_m V + \sum_{k=1}^{K} \lambda_k \beta_{ijk} u_j = 0 \qquad \textit{(4.15)}$$

Solving for Q_{ij}^{*} in this equation gives the optimal emissions for regulation at any spatial resolution *K*. Substituting all the Q_{ij}^{*} back into the objective function given by the equation *(4.8)* gives the net costs of regulation at any spatial resolution *K*.

4.4.2 Optimal Emissions at Finer Spatial Resolutions (*K′ > K)*

The question of interest is what happens to net costs and choice of emissions as one regulates risks at a finer resolution. That means the interest is in understanding how Q_{ij}^{*} and the objective function change if we add more constraints to the problem. Let the new optimal emissions for a pollutant *j* from source *i* be $Q_{ij}^{\prime *}$ and the number of locations over which the sources are regulated at the finer spatial resolution be K' (K'>K). As one regulates at this finer resolution, equation *(4.15)* becomes:

$$MC_{ij}(Q_{ij}^{\prime *}) + \sum_{m=1}^{M} \beta_{ijm} u_j p_m V + \sum_{k=1}^{K} \lambda_k' \beta_{ijk} u_j + \sum_{k=K+1}^{K'} \lambda_k' \beta_{ijk} u_j = 0 \qquad (4.16)$$

Here, λ_k' is LM or shadow price for any location *k* under regulation at a finer spatial resolution. For a pollutant *j* with positive emissions from a source *i*, $Q_{ij} \geq 0$, subtracting *(4.15)* from *(4.16)* gives:

$$MC_{ij}(Q_{ij}^{\prime *}) - MC_{ij}(Q_{ij}^{*}) + \sum_{k=1}^{K} (\lambda_k' - \lambda_k) \beta_{ijk} u_j + \sum_{k=K+1}^{K'} \lambda_k' \beta_{ijk} u_j = 0 \qquad (4.17)$$

4.4.2.1 Change in Optimal Emissions with Spatial Resolution

The first result of interest is the change in optimal emissions (Q^{*}_{ij}) when risks are regulated at finer spatial resolutions. In equation *(4.17)*, we have:

$$\lambda_k \geq 0, \lambda_k' \geq 0, \beta_{ijk} > 0, u_j > 0, MC_{ij}(Q_{ij}) < 0$$

Given this, we can derive the following set of conditions:

$$Q_{ij}'^{*} = Q_{ij}^{*} \; if \; \lambda_k' = \lambda_k \; \forall \, k = 1,2,....,K \; and \; \lambda_k' = 0 \; \forall \, k = K+1,..,K'$$

$$Q_{ij}'^{*} < Q_{ij}^{*} \; if \sum_{k=1}^{K} (\lambda_k' - \lambda_k)\beta_{ijk} + \sum_{k=K+1}^{K'} \lambda_k' \beta_{ijk} > 0 \qquad (4.18)$$

$$Q_{ij}'^{*} > Q_{ij}^{*} \; if \sum_{k=1}^{K} (\lambda_k' - \lambda_k)\beta_{ijk} + \sum_{k=K+1}^{K'} \lambda_k' \beta_{ijk} < 0$$

The first interpretation of the set of equations *(4.18)* is that regulating at finer spatial resolutions could result in increases in optimal emissions for some sources and reductions for some sources; and it might not matter for some sources. It is clear from the set of conditions *(4.18)* that two parameters – the Lagrange Multiplier (LM), λ_k , and exposure concentration at any location k, β_{ijk} – affect the change in emission levels. Before interpreting these conditions, it is important to interpret λ_k and β_{ijk} .

In an optimization problem, the LM or shadow price (λ_k here) represents the marginal change in the value function as one relaxes or tightens a constraint. In the problem presented here, λ_k represents the change in net costs due to a marginal change in threshold risk, *r*; in other words, λ_k indicates how costly it is to reduce the risk by an additional unit at the *k* th location. λ_k is zero for the spatial locations (*k*) for which the unregulated risk is below the threshold risk and is positive for locations for which the threshold risk constraint does bind. In other words, if we define "hotspot" as a location at which unregulated risk, r_k , would be above the threshold risk *r*, then $\lambda_k > 0$ for hotspots and $\lambda_k = 0$ for other non-hot spot locations.

The second parameter, β_{ijk}, represents the exposure concentration at the *k* th location due to a unit emission rate (1 *g/s*) of pollutant *j* from source *i*. As stated earlier, it is a function of several factors, including meteorological conditions, land use around the source, and distance of *k* th location from the source. Typically, β_{ijk} is highest closer to the source, in the downwind direction, and decreases with distance from the source (EPA, 2004a), which means that sources closer to hotspots typically contribute more to the risk at hotspots than sources away from the hotspots.

The interpretation of λ_k suggests that λ_k and hence λ'_k have non-zero (and non-negative) values only at hotspots. The set of conditions *(4.18)* indicates that the change in optimal emissions when risks are regulated at finer spatial resolutions is a function of (λ'_k - λ_k) and λ'_k, in addition to β_{ijk}. Hence, the change in optimal emissions of a pollutant *j* from source *i,* when regulated at finer resolutions, is a function of (1) what happens to hotspots when the sources are regulated at finer resolutions and (2) how much risk a pollutant/source combination contributes to hotspots (the value of β_{ijk} for any *ij* at hotspots, relative to β_{ijk} for any other source/pollutant combination $i'j' \neq ij$) at finer resolution. Given this, it is convenient to interpret the set of conditions *(4.18)* by constructing possible scenarios for what is likely to happen to hotspots as sources are regulated at finer spatial resolutions. The possible scenarios are:

1. Finer spatial resolution <u>*does not*</u> capture any new hotspots
2. Finer spatial resolution <u>*does*</u> capture new hotspots while some or all of the hotspots captured at coarser resolutions disappear

Under scenario 1, $\lambda'_k = 0 \; \forall \, k = K+1,..,K'$ and $\lambda'_k = \lambda_k \; \forall \, k = 1,2,....,K$, which means that the optimal emissions do not change for any source/pollutant combination, *ij*. Under scenario 2, for the sources that contribute most to hotspots captured at fine resolution, optimal emissions <u>*will*</u> be reduced because of high β_{ijk} and thus a higher absolute value for the term $\sum_{k=K+1}^{K'} \lambda'_k \beta_{ijk}$ compared to the term $\sum_{k=1}^{K} (\lambda'_k - \lambda_k)\beta_{ijk}$ [12] in *(4.18)*. For sources distant from hotspots captured at finer resolution, β_{ijk} tends to be low (EPA, 2004a). If λ'_k [13]is sufficiently lower than λ_k for hotspots captured at the coarser resolution so as to make the absolute value of the term $\sum_{k=1}^{K} (\lambda'_k - \lambda_k)\beta_{ijk}$ greater than the term $\sum_{k=K+1}^{K'} \lambda'_k \beta_{ijk}$, then the optimal emissions <u>*will*</u> increase for those sources when risks are regulated at a finer spatial resolution. Intuitively, an increase in optimal emissions is possible for sources distant from hot spots, because (i) the reduction in optimal emissions, for sources responsible for hot spots, creates slack in risks at other non-hot spot locations and (ii) because of this slack, the increase in costs, due to emission reductions by sources responsible for hot spots, could be offset by increasing the emissions for other sources that do not contribute to hot spots captured at finer resolution.

In summary, the set of conditions *(4.18)* indicate that (a) spatial resolution of regulation does not matter to optimal emissions when finer spatial resolution does not

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[12] Note that $\lambda'_k \leq \lambda_k \; \forall \, k = 1,2,....,K$ and hence this term is always negative.

[13] λ'_k =0 for hot spots that disappear under regulation at fine resolution

capture new hotspots, (b) optimal emissions will decrease for sources that contribute most to hotspots captured at finer spatial resolution, and (c) optimal emissions could increase for sources that do not contribute significantly to hotspots captured at finer resolution.

4.4.2.2 Change in Net Costs with Spatial Resolution

Net costs are non-decreasing when emissions are regulated at finer resolution. This comes from a standard result in optimization theory that the value function is non-decreasing with addition of constraints to the problem (Taha, 2003).

4.5 Sensitivity to Threshold Risk

The threshold risk 'r' in the model proposed here is an indicator of the individual risk that is considered acceptable in regulatory decisions. In a study of 132 federal regulatory decisions to control toxic substances, it was found that every chemical with a maximum individual cancer risk of 4000 in a million or higher was regulated by federal agencies (Travis et al., 1987). This study also found that the level of regulated risk varied depending on other factors such as expected number of additional cancer cases, costs of controls, and availability of control technologies. The current regulation of air toxics is consistent with these findings. EPA, in its Benzene NESHAP (Federal Register, 1989) and in its residual risk regulation (EPA, 1999a), set an acceptable risk of 100 in a million maximum individual risk (MIR) for its control decisions. While this is a goal for acceptable MIR, EPA has accepted higher MIR taking into account uncertainty, costs, and other factors. For example, in its first residual risk decision on coke oven emissions, the MIR was estimated to be 270 in a million after the implementation of proposed

controls. This risk was, however, considered by EPA to provide an "ample margin of safety" to public health and the environment.

Within the context of the decision process modeled here, it is possible to examine how optimal emissions will change with changes in acceptable MIR (or threshold risk, *r,* in the model) at any particular spatial resolution. Based on the discussion in Section 4.4.1, optimal emissions at any spatial resolution could be obtained by solving the equation *(4.15)*:

$$MC_{ij}(Q_{ij}^{*}) + \sum_{m=1}^{M} \beta_{ijm} u_j p_m V + \sum_{k=1}^{K} \lambda_k \beta_{ijk} u_j = 0$$

In this equation, λ_k is a function of *r*. λ_k increases with decreasing *r* i.e., the shadow prices for hotspots increase as the risk threshold is tightened. Further, new hotspots are likely to show up as the threshold risk is tightened i.e., more λ_k *s* with non-zero values. These two conditions will increase the value of the last term in equation *(4.15)* and thus reduce optimal emissions, Q_{ij}^{*}. Thus, optimal emissions are non-increasing as the risk threshold is tightened (i.e., for lower values of *r*). The opposite also holds true – the optimal emissions are non-decreasing as the risk threshold is relaxed (for higher values of *r*).

CHAPTER 5

EMPIRICAL APPROACH

This chapter describes the empirical approach adopted to illustrate the results of the model developed in Chapter 4. The first few sections describe various empirical choices made and the rationale behind those choices. The later sections outline the steps involved in analysis and the approach adopted for executing each step. The sources and quality of data are discussed separately in the next chapter.

5.1 Study Site

The site for empirical analysis in this research is a two-county (Escambia and Santa Rosa) area in Pensacola, FL. Community concerns about toxic contamination and the associated environmental justice issues and current focus of federal and local environmental agencies on this region's environmental health problems provide a suitable setting to analyze the questions this research seeks to address.

This two-county region has had problems with toxic contamination since the early 1990s – the most publicized case being the Superfund site of Escambia Treating Company. The dioxin contamination in groundwater and air from this waste site prompted citizen action (Wheeler, 1995) and eventually led to relocation of several families from the waste site by EPA (Hauserman & Olinger, 1996).

The two counties host a number of sources that emit toxic pollutants. According to the toxic release inventory (TRI) data of 2005, Escambia county was ranked top and Santa Rosa was ranked 9th in Florida in terms of total tons of toxics released into various media. Responding to public concern about potential impacts of poor local environmental

conditions on public health, the US Congress sponsored the Partnership for Environmental Research and Community Health (PERCH) to conduct a series of environmental health studies. PERCH is led by the University of West Florida in alliance with the Escambia and Santa Rosa County Health Departments. The environmental studies under this project include, among other things, multivariate analysis of health outcomes, assessment of contamination from dioxins, furans, mercury, and other pollutants in Escambia Bay, clinical studies of the population living around the superfund sites, and an assessment of air quality. Georgia Institute of Technology, University of South Florida, Florida State University, and other institutions are involved in conducting the environmental studies.

Georgia Institute of Technology conducted air quality studies in three phases under the PERCH project. The first phase of air quality studies compared risks from different air pollutants (particulate matter, ozone, and air toxics), based on available published data, to identify priorities for future research. Based on the assessment in the first phase, the second phase involved field monitoring studies to generate primary monitoring data on particulate matter and some air toxics. The third phase of air quality studies included (1) source apportionment studies to identify the contribution of regional and local sources to particulate matter pollution in Pensacola and (2) a comprehensive assessment of cancer and non cancer risks from stationary and mobile sources in the two county area using an integrated assessment tool, Regional Air Impact Modeling Initiative (RAIMI), developed by Region 6 of EPA.

This research utilizes the data from RAIMI implementation process in the third phase of the PERCH project. RAIMI data utilized for this empirical analysis include an

inventory of air toxics emission sources and their characteristics, population data, and estimated exposure concentrations using the Industrial Source Complex (ISC) (version 3) dispersion model.

5.2 Sample Selection

According to the National Toxics Inventory (NTI) of 1999, the two-county study area had 94 air toxics emission sources distributed across 43 facilities including manufacturing industries, utility plants, and waste landfills. These sources emitted 78 different air toxics. This research used a small subset of these 94 sources, selected based on the following two criteria, for empirical analysis.

1. The source is categorized as "major" [14] source according to the Clean Air Act. The rationale for this criterion is that most sources that are currently regulated under Maximum Achievable Control Technology Standards (MACT) are "major" sources.
2. The source emits at least one toxic air pollutant for which inhalation cancer risk can be quantified. This criterion is obvious because the model developed here quantifies only cancer risk.

Applying these two criteria resulted in a sample of 17 emission sources in eight facilities. It turned out that one of the eight facilities was not regulated under any MACT although it was classified as a "major" source. This facility was dropped out of the final sample because no abatement cost information was available for the sources within this

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[14] According to this definition, a "major" source of hazardous air pollutants (HAP) is one that emits more than 10 tons per year (TPY) of any one of the 188 regulated HAPs or more than 25 TPY of a combination of regulated HAPs.

facility. Thus the *final sample includes 15 emission sources from seven facilities that emit six different air toxics.*

5.3 Spatial Resolution Choices

The empirical application of the model developed in the earlier section requires estimating optimal emissions and total costs under regulation at different spatial resolutions. This study uses three spatial resolutions: census tract, census block group, and census block. The census tract is the biggest spatial unit and it is composed of several census block groups. The census block represents the finest spatial unit with a number of census blocks forming a census block group. The fact that population data and other demographic data of the US Census Bureau are available at these three resolutions make the empirical application of the model feasible.

In the context of these choices for spatial resolution, several analytical choices have been made. Firstly, the estimated risk at the geographical centroid of a census unit was assumed to represent the risk to any individual within that census unit. Thus, for example, regulation at census tract resolution means that the decision maker chooses emission levels such that the total costs are minimized subjected to the constraint that the *risk at the centroid of any census tract* does not exceed the threshold risk. Secondly, regulation at finer resolution assumed to include regulation of risks both at the existing locations (i.e., locations at which risk information was available when regulated at coarser resolution) and the new locations i.e., the locations where risk information has become available at finer spatial resolution. For example, regulation at census block group resolution, which is a finer spatial resolution than census tract, means that the decision maker chooses emission levels such that the total costs are minimized subjected

to the constraint that the *risk estimated at the centroid of any census block group and at the centroid of any census tract* does not exceed the threshold risk.

5.4 Empirical Analysis Steps

The empirical analysis includes three steps:

1. Estimate and/or obtain data on all input parameters to the model.
2. Run the optimization model at each of the three chosen spatial resolutions – census tract, census block group, and census block – and at three threshold risk values to estimate optimal emissions and total costs.
3. Analyze the spatial distribution of risks due to emissions under regulation at different spatial resolutions.

5.4.1 Estimation of Input Parameters to the Model

The objective function of the model has two components – private costs to industry and population health costs. The costs to industry are the costs of changing the emissions from a baseline quantity to a chosen quantity. Thus this component of the objective function required marginal cost functions (MC_{ij}) for each pollutant from each source and the baseline emissions (Q_{ij}^{b}).

The second component of the objective function is population health costs. Because the model developed here quantifies only cancers from inhalation pathway[15], these health costs include only a part of the costs of cancer due to exposure to air toxics.

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[15] In addition to direct inhalation, air toxics can cause cancer in humans though other pathways such as dermal absorption of soil contaminated by air toxics, ingestion of water, soil, and food (Cal EPA, 2003).

Cancer can be fatal or non fatal and costs vary accordingly. This empirical analysis assumes that all expected additional cancer cases due to exposure to air toxics result in fatal cancers. These costs are estimated in a willingness to pay (WTP) framework, which estimates costs as the number of fatal cancers multiplied by the value of a statistical life (VSL). The expected number of additional cancer cases is cancer risk in a spatial unit (m) multiplied by the population (p_m) in that spatial unit, summed over all spatial units (M) within the region under study. The spatial unit used for estimating additional cases of cancer is census block and cancer risk at the centroid of census block represents the cancer risk to which the population in the census block is exposed.

Cancer risk estimation is a function of quantity of emissions, exposure concentrations due to the unit emission rate (β)[16], and cancer potency of a toxic air pollutant (measured by unit cancer risk factor, u_j). In this analysis, cancer risk is estimated at a number of different spatial locations. As explained in the previous paragraph, estimation of costs of cancer in the objective function requires estimation of cancer risks at the centroid of every census block in the two-county area. In addition, the constraints in the model require estimation of cancer risks at a different set of spatial locations depending on the spatial resolution of regulation. Analysis at census tract resolution requires estimation of cancer risks at the centroids of the census tracts while analysis at the census block group resolution requires estimation of cancer risk at the centroids of the census block groups.

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[16] It should be noted that in this analysis the exposure concentrations due to emissions was estimated as a product of total emission rate and exposure concentration due to a unit emission rate (1 gram/second). Thus β represents the exposure concentrations due to a 1 g/s emission rate.

Hence, the input parameters required for empirical analysis are: marginal cost functions (MC_{ij}) for each pollutant from each source, baseline emissions (Q_{ij}^{b}), exposure concentration (β_{ijm}) at each of m=1,2,3,….,M locations due to a unit emission rate, exposure concentration (β_{ijk}) at each of k=1,2,3,….,K locations (K varies depending on the spatial resolution) due to a unit emission rate, unit cancer risk factor (u_j) for each pollutant, population (p_m) in each of M census block centroids, and the value of a statistical life (V).

Among these parameters, MC_{ij} and β_{ijm} or β_{ijk} require an empirical estimation strategy and hence are discussed in detail in this section. The details on remaining parameters are discussed in the next chapter on data collection.

5.4.1.1 Estimation of Marginal Cost (MC) Functions

Marginal cost (MC) functions represent the relationship between emissions and the cost of achieving an additional unit reduction at any given quantity of emissions. MC functions for pollution abatement have been estimated using three broad approaches:

1. Production cost approach: Estimation by relating production costs to environmental performance measures at the plant level
2. Direct cost approach: Econometric estimation by relating direct costs of pollution abatement, obtained through surveys, to emission quantities abated
3. Engineering cost approach: Engineering cost estimates of abatement technologies

Following a description of each of these approaches, the motivation for the approach used here is derived from a discussion of their strengths and weaknesses.

Production Costs Approach

Two different methods have been used in literature to estimate MC functions using this approach. In one type of studies, firms are assumed to minimize the cost of production subject to a constraint on the quantity of pollution that can be emitted. The production cost function is specified as a function of input prices, the quantity of output produced, the production technology, and the quantity of a pollution indicator (e.g., SO2 emissions from power plants or BOD from paper plants). The marginal cost function is the partial derivative of this cost function with respect to the pollution indicator. Gollop and Roberts (1985) used this approach to estimate MC functions of sulfur dioxide (SO_2) abatement for 56 electric utilities. Applying a similar approach, Carlson et al., (2000) derived MC functions for abatement of SO_2 in a sample of 734 fuel-switching electricity generating plants to estimate gains from SO_2 trading. McClelland and Horowitz (1999) estimated MC functions of biological oxygen demand (BOD) abatement in effluents of paper mills. A similar approach is used in the global climate change research for deriving MC curves for abatement of carbon dioxide (CO_2). An example application is the analysis of CO_2 emission trading under Kyoto protocol (Ellerman & Decaux, 1998). This study derived country level MC curves by estimating shadow prices for various levels of carbon controls using a computable general equilibrium model of global economy developed by the MIT Joint Program on the Science and Policy of Global Change.

A second type of studies uses an "output distance function" method. An output distance function is similar to a production function. While a traditional production function describes the production possibilities for a single output, an output distance function models the "joint production of multiple outputs (Fare et al., 1993, pp: 375)."

The idea behind this approach is that it is costless to dispose of goods (products) but it is not costless to dispose of bads (pollution) when the quantities of bads are regulated. Thus, under a "regulated" output distance function, the firm has to proportionally scale down (compared to an "unregulated" output distance function) its desirable outputs. Marginal costs are then the foregone revenues of "desirable" outputs due to an incremental reduction in undesirable outputs.

In this method, typically, the parameters of a translog output distance function are estimated using linear programming optimization. The shadow prices, which are the marginal costs of undesirable outputs, are derived using the estimated output distance function. This method is perhaps more widely used than the first method. This method has been applied to derive the marginal costs of pollution abatement in paper mills (Fare et al., 1993; Marklund, 2003), abatement of SO_2 emissions from power plants (Coggins & Swinton, 1996; Rezek & Blair, 2005), and controlling groundwater leaching and pesticide runoff in United States agriculture (Fare et al., 2006).

The production cost approach is a revealed cost method and thus avoids the problems of hidden costs and misallocated expenditures that are typically associated with the other two approaches (Pizer & Kopp, 2003). On the other hand, the main drawback of the production cost approach is that it is highly data-intensive. Establishment-level data on input costs and quantities and abatement volumes are not available for all types of pollutants and industrial sectors.

Econometric Estimation using Stated Direct Costs of Abatement

This approach is based on econometric estimation of direct abatement costs as a function of abated quantities. At least two studies in the literature (Hartman, Wheeler, &

Singh, 1997; Dasgupta et al., 2001) use this approach to estimate MC functions. The US Census Bureau collected pollution abatement and cost expenditure (PACE) data for a large number of firms in the United States. The Census Bureau collected PACE data annually between 1973 and 1994 (with the exception of 1987) and then in 1999, after a gap of five years (Ross et al., 2004). While PACE data has been used for a number of applications, only one study (Hartman, Wheeler, & Singh, 1997) has used it to estimate average and marginal costs of abatement for a variety of air pollutants – criteria as well as hazardous pollutants- and for a variety of industrial sectors. The authors estimated the costs of pollution abatement using a simple econometric model. The air pollution abatement cost was specified as a quadratic function of the quantity abated. They estimated a regression equation using ordinary least squares (OLS) for 37 industrial sectors[17] and for different pollutants using establishment level data.

$$C_{ij} = \beta_{0j} + \sum_i \beta_{jk} A_{ijk} + \sum_i \beta_{jjk} A^2_{ijk} + \varepsilon_{ij}$$

C_{ij} = Total air pollution abatement cost for plant i in sector j

A_{ijk} = Quantity of pollutant k abated by plant i in sector j

ε_{ij} = Error term

The marginal cost function based on the above estimated model was:

$$MC_{jk} = \beta_{jk} + 2\beta_{jjk} A_{ijk}$$

The econometric specification of this study ignores a number of other relevant independent variables that might be correlated with the level of abatement. For example,

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[17] Based on International Standard Industrial Classification (ISIC) codes

process- and abatement technologies vary across firms within any given industrial sector and have varying costs. To the extent that the level of abatement is correlated with the technology employed, the estimators in the above specification would be biased.

In contrast to this simple econometric specification, Dasgupta et al. (2001) specified a translog functional form in their study, in which they estimated the marginal abatement cost functions for four water pollutants in China, using direct costs of abatement.

The validity of abatement expenditures reported in surveys is suspect. This is the main drawback of the direct cost approach. For instance, the validity of PACE data to measure direct abatement costs has been criticized on several fronts. The questionnaire design does not make it clear the expenditures that must be included under environmental abatement expenditures. Jaffe et al., (1995) raises this question of misallocated expenditures: if a firm installs a production technology that has benefits in terms of both environmental improvements as well as product quality improvements, what part of the expenditure should be attributed to environmental improvements? The other criticism is that of hidden costs that go unreported in surveys, for example, costs of paper work and legal fees (Pizer & Kopp, 2003).

Engineering Cost Estimates

A more common approach to estimation of cost functions is *ex ante* engineering cost estimates of abatement technology options. In this approach, a suite of abatement technology options are identified for abatement of pollutants of concern and detailed costs of implementing those abatement options are estimated using engineering data. While specifics (such as assumptions about discount rates, the life of equipment, etc.,)

might differ from study to study, typically, capital costs of equipment and fixed and variable operation and maintenance (O&M) costs are included. In some cases, the costs of monitoring and record keeping are also estimated.

The first step in estimating marginal cost functions using this approach is to calculate the cost effectiveness of each identified abatement technology. Cost effectiveness is defined as the cost of abatement per unit of pollutant removed. The quantity of pollutant removed by a technology is the product of baseline emissions (uncontrolled emissions) and the removal efficiency of the technology. The cost of implementing that technology divided by the quantity of pollutant removed gives the cost effectiveness or the unit cost of that technology.

In this approach, the most cost-effective technology (lowest unit cost) is first applied to the source. Then, the technology with the lowest marginal cost among the remaining available options is applied. Marginal costs are calculated for each of the remaining available technologies as the difference in present value of costs between the technology under consideration and the existing technology, divided by the additional amount of pollutant removed by the new technology. Understandably, if the new technology has lower removal efficiency at higher costs compared to the existing technology, then that will not be applied. In this way, technologies with increasing marginal costs are successively applied.

For example, let us say that baseline emissions are 100 tons. Let us assume that the existing technology (or the most cost-effective technology that is applied first) has a removal efficiency of 50% at an annual cost of $50,000. Then the unit cost of this technology is $1000 per ton removed. If further abatement is required, and another

technology removes 60% at a cost of $90,000, the marginal cost of applying this second technology is then $4000 per ton ((90,000-50,000)/10). In this manner, it is possible to generate as many points as there are abatement technology options to generate a step function for MC. However, if a smooth MC function is required, one can choose a functional form such as a quadratic or an exponential form and fit a cost function with cost as the dependent variable and the level of abatement or emissions as the independent variable, using regression techniques. The slope of this cost function is the marginal cost function.

Specific examples of this approach include the study by the International Institute for Applied Systems Analysis under its Regional Air Pollution Information and Simulation (RAINS) model (Klimont, Amann, and Cofala, 2000), the tracking and analysis framework (TAF) model (U.S. Department of Energy, 1996) developed by Argonne National Laboratory, and a study on international analysis of methane and nitrous oxide abatement opportunities by US EPA (EPA, 2003a).

The engineering cost approach assumes that the only choice for firms confronted with pollution abatement is to employ end-of-the-pipe abatement technologies and ignores other possible adjustments the firms can make including reducing output and improving efficiency of existing processes (Hartman, Wheeler, & Singh, 1997). Further, this approach requires knowledge of specific processes within a firm to estimate cost functions and is more suitable to estimate cost functions for a small number of firms (Pizer & Kopp, 2003).

Selection of Approach for Estimation of Abatement Cost Functions

This research employs an engineering cost approach to estimate abatement cost functions. Each of the three approaches described above have their own strengths and weaknesses in estimating abatement cost functions. The direct abatement cost approach, although useful in estimating nationwide or region-wide costs of pollution abatement, suffers from problems associated with reported measures such as problems of survey design and uncounted costs of abatement (Pizer & Kopp, 2003). The production cost approach, being a revealed approach, reflects the costs of abatement more accurately, but fails to incorporate cost-efficient abatement technology options (Coggins & Swinton, 1996). Engineering cost estimates, on the other hand, can incorporate state-of-the-art abatement technology options, but fail to consider important alternatives for reducing pollution, for example, fuel switching in production processes, or scaling down output.

In selecting an approach for the empirical analysis in this research, however, the most critical criterion turned out to be the availability of data. The production cost approach requires extensive plant level data on input prices and quantities, output prices and quantities, and abatement volumes. Such data are readily available only for specific pollutants and industrial sectors, for example SO_2 in power plants. This type of data is not available for the toxic air pollutants of interest for this study, to the author's knowledge. For the direct abatement approach, the only data available in the US are the PACE data. There are two problems with these data: (1) plant level data are only publicly available with long lead times and (2) the most recent PACE data (for the year 1999) do not include data on volumes of pollution abatement, which are critical parameter for estimating cost functions. Thus, this research employs the engineering cost approach to estimate abatement cost functions.

The data on abatement technology options and costs are from Regulatory Impact Analyses (RIA) and background information documents (BID) that EPA developed to assess the cost impacts of various Maximum Achievable Control Technology (MACT) standards. For RIAs, EPA has to analyze the costs of various regulatory alternatives – typically control technology options to reduce emissions – in addition to the regulatory option selected.

The first step in the estimation of cost functions identified the specific MACT standards under which each of the 15 sources included in the empirical analysis is regulated. This step utilized air permit documents available from the Florida Department of Environmental Protection (FL DEP) to assign the 15 sources to the corresponding MACT standards. The next step thoroughly examined the RIAs to collect information on available emission control options, emission reductions associated with each technology, and annual costs of implementing the technology. Typically, the RIAs report these cost estimates at an aggregated sectoral level. However, they also report the number of industry sources on which these aggregate estimates are based. This information was used to obtain cost estimates for an "average" firm, which is the total sector-wise annual costs divided by the number of firms on which the aggregate estimates are based. *This is one of the important assumptions made in the estimation of cost functions – that the source in the analysis represents an "average" source.*

The MC function in the decision model is assumed to be continuous and hence the MC function estimated for empirical analysis must be a continuous function. In addition, the cost function in the model is a function of the level of emissions rather than the quantity of emissions abated. Hence, to fit the costs as a function of the level of

emissions, the emissions remaining after applying an abatement option are calculated as the difference between baseline emissions and the quantity of emissions abated by the technology option. For example, if the estimated baseline emissions for an "average" source are X ton/year and if an abatement option has a removal efficiency of 70%, then the emissions remaining after the application of the technology are calculated as X-0.7X=0.3X tons/year. If the annual costs of implementing that technology option are C, then (C, 0.3X) is a data point on the cost functions fitted for this analysis.

Previous estimates of MC functions have assumed either a quadratic functional form (Hartman, Wheeler, & Singh, 1997) or an exponential function (Mariam & Barre, 1996). In this analysis, an exponential function of the following form is fitted for cost functions.

$$C_{ij} = a_{ij} e^{b_{ij} Q_{ij}}$$

$C_{ij} = Annual\ costs\ of\ abatement\ for\ pollutant\ j\ from\ source\ i\ (\$)$
$Q_{ij} = Emission\ Levels\ of\ pollutant\ j\ from\ source\ i\ (Ton / Year)$
$a_{ij}, b_{ij} = Parameters\ to\ be\ estimated$

The exponential cost function was fitted with annual cost as the dependent variable and emission level (TPY) as the independent variable using a non-linear least square regression framework. The advantage of an exponential functional form is that it restricts the dependent variable, which is annual costs in this case, to positive values.

Finally, in almost all RIAs, the abatement technology options identified are not specific to abatement of any single toxic air pollutant; rather the technology abates a group of pollutants and there is no information in the RIAs on the removal efficiency of individual pollutants. Thus, in this analysis, the cost function developed for a given

source is applied separately to all the pollutants emitted from that source. The implication of this is that the costs to industry are potentially counted multiple times, once for each pollutant. For example, a single cost function is estimated for process vents in organic chemical manufacturing industry; that same function is applied for all pollutants emitted from process vents.

5.4.1.2 Estimation of Exposure Concentrations (β_{ijm} and β_{ijk})

Ambient air concentration of a pollutant at any location is typically the amount of pollutant estimated to be present in one m^3 of outdoor air, after the pollutant is released from a source. The exposure concentration, however, is the amount of pollutant people actually breathe and is not necessarily same as the ambient concentration. This is because people move from one place to the other (e.g., outdoors vs. indoors) and are involved in different types of activities that involve different breathing rates (e.g., exercising vs. watching a movie). Exposure models such as Hazardous Air Pollutant Exposure Model (HAPEM) have been developed to estimate exposure concentrations (Rosenbaum, 2005) from ambient concentrations. In this empirical analysis, however, ambient air toxics concentrations are used as surrogates for exposure concentrations because the integrated assessment tool, the Regional Air Impact Modeling Initiative (RAIMI), utilized in this analysis does not incorporate an exposure model such as HAPEM.

Regional Air Impact Modeling Initiative (RAIMI) Implementation

Annual average ambient air toxics concentrations are estimated using the air dispersion model integrated within RAIMI. The Region 6 office of EPA recently developed RAIMI, which consists of a set of tools designed "to evaluate the potential for

health impacts as a result of exposure to multiple contaminants from multiple sources, at a community level of resolution (EPA, 2006a).” RAIMI integrates an emission inventory, a dispersion model, and risk estimation in a Geographical Information System (GIS) environment, to support estimation and representation of risks from air toxics.

RAIMI uses the version 3 of the Industrial Source Complex Short Term (ISCST3) dispersion model to estimate ground-level ambient air toxics concentrations. Air dispersion models are computer models that predict ambient concentrations, based on assumptions about the dispersion process, and use as inputs, emission quantities, source and emission characteristics (e.g., temperature and velocity of gas flow), local meteorology (e.g., wind speed and direction and vertical temperature profile), and characteristics of local physical features (e.g., land use and cover). ISCST3 is a steady-state, multiple source, Gaussian dispersion model and has been the preferred regulatory model for industrial sources until it was replaced by AMS/EPA Regulatory Model (AERMOD) in 2005 (Federal Register, 2005).

The RAIMI system incorporated four primary tools. A conceptual diagram of implementation of RAIMI is shown in Figure 5.1. Appendix A provides more details on the implementation process.

1. ***Risk-MAP***: Risk-MAP is the core tool within RAIMI. Risk-MAP is used to import emission inventory information into a Geographic Information Systems (GIS) environment, perform risk analyses, present risk assessment results in tabular or graphical form, and perform supplemental analysis. Risk-MAP is designed as an extension within ArcGIS software.

2. ***Air Modeling Preprocessor (AMP)***: The main function of AMP is to prepare source-specific meteorological and ISCST3 air model input files. This tool is also designed as an extension in ArcGIS.
3. ***ISC Batch***: This tool is designed to execute multiple ISCST model runs in a single batch run.
4. ***AIR2GIS***: This tool organizes the output from the dispersion model into a format that can be imported into GIS.

Use of RAIMI first required importing emission inventory information into ArcGIS using the Risk-MAP tool. The inventory data include emission quantities of different pollutants from each source, emission characteristics such as temperature and exit velocity, and source characteristics such as the geographical location of sources. In this step, Risk-MAP generates a number of tables in *Microsoft Access* format to be used in later steps. The next two steps – the implementation of Air Modeling Preprocessor (AMP) tool to generate input files for the ISCST dispersion model and implementation of the ISCBatch tool to execute the ISCST dispersion model – are the steps that are most relevant to the estimation of annual average ambient concentrations and hence are explained in detail below.

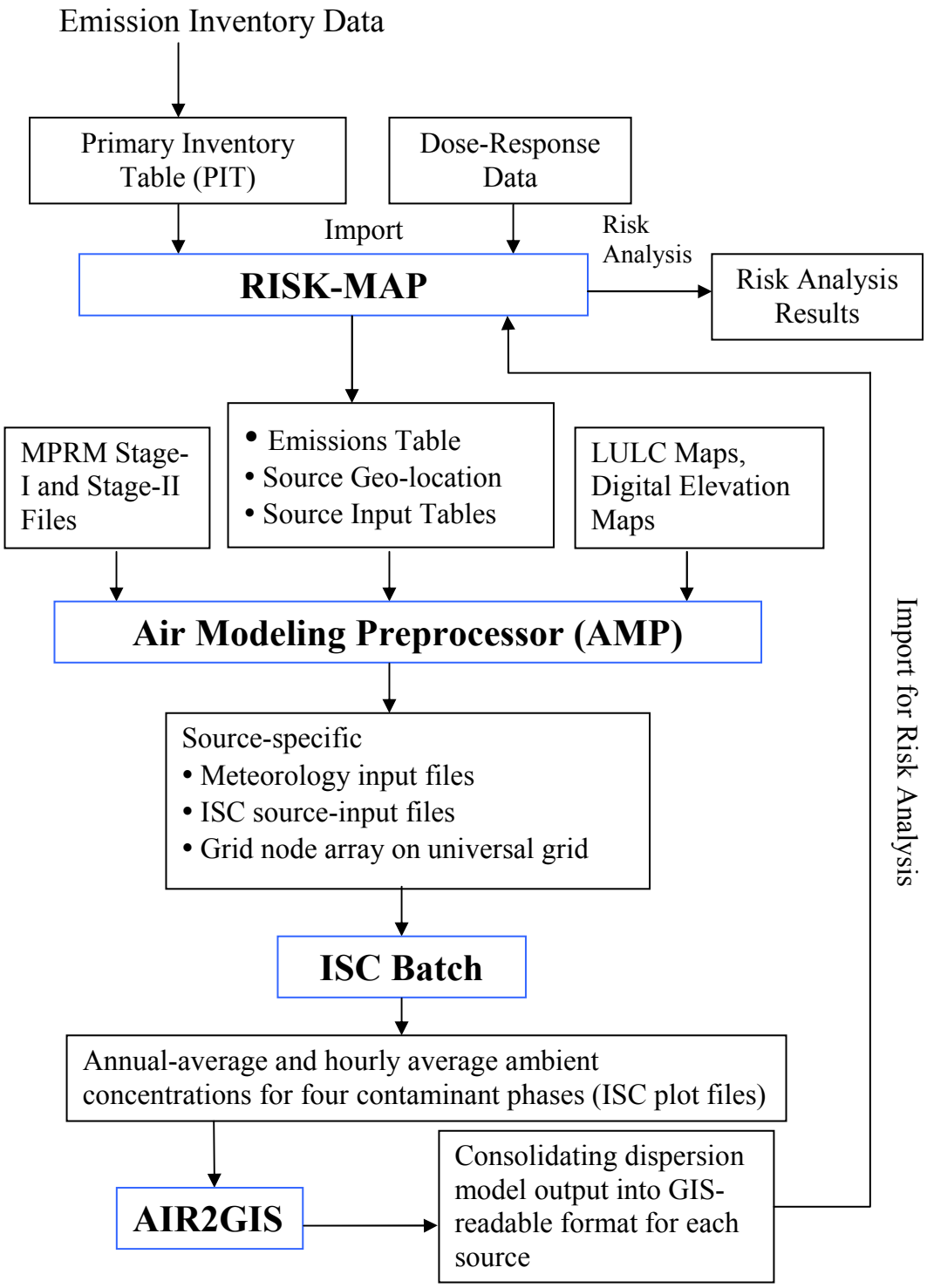

Figure 5.1 Conceptual Diagram of RAIMI Implementation

The second step in the RAIMI implementation is to generate input files using the AMP tool to execute the ISCST dispersion model. The ISCST model requires, for each source modeled: (a) meteorological conditions surrounding the source, (b) geographical coordinates of the receptor locations at which ambient concentrations are to be estimated, (c) source-specific inputs imported from the emission inventory, and (d) the land use characteristics and an elevation profile of the modeling domain.

Raw meteorological inputs were processed using EPA's Meteorological Preprocessor for Regulatory Models (MPRM). MPRM has three stages of execution. RAIMI requires stage 1 and stage 2 of MPRM as input so that it can complete stage 3 of MPRM and create an ISCST input meteorological data file for each source. Typically, five years of meteorological data at the nearest meteorological station are used for stage 1 and stage 2 MPRM. This study used the data collected at the Pensacola Regional Airport station for the years 1986 to 1990 to complete stage 1 and stage 2 of MPRM. Stage 3 processing of MPRM requires consideration of land use characteristics within the modeling domain. The effects of land use and land cover in a typical dispersion model are represented by three surface characteristics – surface roughness, the Bowen ratio, and Albedo, which may vary by wind direction and time of the year. This analysis used 1:250,000 USGS land use land cover maps in the form of a GIS shape file for the land use characteristics of the study area. AMP is capable of reading these spatial files to obtain the required parameters. Execution of stage 3 of MPRM generated a single 5-year (1986-1990) meteorological file with a .MET extension for each source.

RAIMI automatically generates an array of receptors throughout the modeling domain at which ISCST3 computes pollutant concentrations. RAIMI utilizes a universal

grid based in the Universal Transverse Mercator (UTM) coordinate projection system to generate 100-meter spaced receptors up to a distance of 5 km from each source, and 500-meter spaced receptors up to a distance of 10 km from each source. The ground-level terrain elevation of each receptor node is imported using the digital elevation model (DEM) data. However, the empirical analysis for this research required estimation of annual average concentrations at specific locations (i.e., centroids of various census units), that are different from the receptor locations generated by RAIMI. Thus, in the input to the dispersion model, the receptors generated by RAIMI were replaced with the appropriate centroid location coordinates. For example, for analysis at the census tract resolution, ambient concentrations were required at the centroids of census tracts and hence the RAIMI-generated receptors were replaced with census tract centroids.

Given all these inputs, the AMP tool within RAIMI automatically generates the source-specific formatted input files required for execution of the dispersion model. The third step then is to execute the ISCST dispersion model for all of the sources using the input files generated in the previous step. In a multi-source assessment, the dispersion model has to be executed once for each source. However, using the ISCBatch tool within RAIMI, the dispersion model can be executed for all sources in a single batch run. The ISCBatch tool produces output files that contain annual average ambient concentrations in microgram per cubic meter ($\mu g/m^3$) at specified locations due to 1 g/s emission of a pollutant released from each source. *For the empirical analysis here, it is assumed that the annual average concentration at any location due to a unit emission rate (1 g/s) is the same for every pollutant released from a particular source.*

5.4.2 Optimization Model Runs for Various Spatial Resolutions

The second step in the empirical methodology is to run the optimization model at the three chosen spatial resolutions – census tract, census block group, and census block. This study used the General Algebraic Modeling System (GAMS) (www.gams.com) version 22.3 to solve the optimization model. The GAMS is "a high-level modeling system for mathematical programming problems (McCarl, 2006, pp:2)." GAMS is capable of solving linear, nonlinear, and mixed integer programming problems. The optimization problem in this empirical analysis is a nonlinear programming problem. GAMS requires specific "solvers," in addition to the base GAMS program to solve nonlinear programming problems. Several solvers such as CONOPT, MINOS, and KNITRO are currently available within GAMS to solve nonlinear problems. Each of these solvers uses a specific routine to search for an optimal solution. This study relies on the CONOPT solver but tests the sensitivity of the solution to using the other solvers. A sample GAMS code written for optimization runs in this research is included in Appendix B.

The input data required for running the optimization program can be read in a specific file format called GDX in GAMS. All the input data are initially compiled in an *MS Excel* file and then imported into GDX format. GAMS program was instructed to write the solution to the optimization problem in *MS Excel* file format.

The solution to the optimization model gives a set of emission quantities for each source and pollutant at each resolution along with total costs (the value function). The optimization model is also solved at the three resolutions by varying the threshold risk. Emissions and net costs are estimated for the three resolutions at three different threshold

risks – 100 in a million cancer risk, 10 in a million cancer risk, and 1 in a million cancer risk. According to EPA, under its residual risk regulations, "…an MIR for cancer approximately 1 in 10 thousand should ordinarily be the upper end of the range of acceptability.. (EPA, 1999a, p:128)" and hence the choice of 100 in a million threshold cancer risk. State and local agencies typically use 1 in a million cancer risk as the health risk goal and hence the choice of 1 in a million threshold cancer risk. Ten in a million threshold cancer risk represents an intermediate value.

5.4.3 Analysis of Spatial Distribution of Risk

A key rationale for regulating risks at finer resolutions is to ensure protection for populations living in "hotspots" that are not apparent at coarse spatial resolutions. To demonstrate the equity implications of regulation at finer resolutions, risks are estimated at the centroids of census blocks by using both the optimal emissions that resulted from regulation at census tract resolution and the optimal emissions that resulted from regulation at census block resolution. Location and magnitude of maximum individual risk (MIR) at the two resolutions of regulation is then calculated to demonstrate the change in MIR with change in spatial resolution chosen for regulation. The spatial distribution of risk is then graphically represented on a map of the two county study area using ArcGIS software.

CHAPTER 6

DATA FOR EMPIRICAL ANALYSIS

This chapter discusses the data utilized in the empirical analysis, the sources of the data, and a few issues of quality of data used. The first section lists the industrial sources of air toxics selected for empirical analysis. The second section presents the data collected for the estimation of marginal cost (MC) functions and the fitted exponential cost functions for every source selected for analysis. The next section describes the data used for implementation of the Regional Air Impact Modeling Initiative (RAIMI) tools to estimate the exposure concentrations at various spatial locations. The remaining sections discuss the other input data such as baseline emissions, value of statistical life, and population data.

6.1 Sources Selected for Empirical Analysis

The two criteria used for selection of sources for empirical analysis are: (1) the source is a "major" source of air toxics and (2) at least one known carcinogen is released from the source. The first step in the selection process was to identify all the sources[18] that emit toxic air pollutants in Escambia and Santa Rosa. The National Toxics Inventory (NTI) data for 1999 complied by EPA was used to identify the entire population of sources. From this population, the second step identified all the "major" sources of air toxics using the Title V Operation Permits issued by the Florida Department of

[18] It is important to note that "sources" here refer to only stationary point sources.

Environmental Protection (FLDEP). Cancer toxicity information from EPA's Integrated Risk Information System (IRIS) was used to determine whether the "major" sources emitted at least one carcinogenic air pollutant.

Seventeen emission sources in eight industrial facilities satisfy the two selection criteria. Among these eight facilities that satisfied the two criteria, one facility – Armstrong World Industries – is not regulated under any Maximum Achievable Control Technology (MACT) standards although it is listed as a "major" source. Hence this facility was dropped from the final sample. *Thus the final sample includes 15 emission sources in seven facilities that emit six different air toxics*. The six air toxics are acetaldehyde, formaldehyde, benzene, acrylonitrile, nickel, and arsenic.

Table 6.1 shows the number of sources in each facility selected for empirical analysis, the industrial sector category of the facilities, and the cancer causing air toxics emitted from each facility.

Table 6.1 Facilities and Pollutants Selected for Empirical Analysis

Facility	**Industrial Sector**	**Number of Sources**	**Pollutants Emitted**
International Paper	Pulp, Paper, and Paperboard Mill	2	Formaldehyde, Acetaldehyde, Benzene
Gulf Power Company	Electric Power Generation, Transmission and Distribution	4	Formaldehyde, Acetaldehyde, Benzene, Nickel, Arsenic
Solutia, Inc.	Noncellulosic Organic Fiber Manufacturing	1	Formaldehyde, Acetaldehyde, Benzene
Air Products and Chemicals	Basic Chemical Manufacturing	1	Formaldehyde, Acetaldehyde, Benzene
Sterling Fibers	Noncellulosic Organic Fiber Manufacturing	3	Acrylonitrile

Facility	Industrial Sector	Number of Sources	Pollutants Emitted
Florida Gas Transmission Company	Pipeline Transportation of Natural Gas	1	Formaldehyde, Acetaldehyde, Benzene
Exxon Mobil (St. Regis plant)	Crude Petroleum and Natural Gas Extraction	3	Formaldehyde, Acetaldehyde, Benzene

6.2 Cost Functions

This section presents the data used for estimation of cost functions for each selected source. As explained in Chapter 4, Regulatory Impact Analyses (RIA) and Background Information Documents (BID) developed by EPA for MACT regulations are the sources of data for the estimation of cost functions. Before describing the details of data collected for each individual source, it is important to outline the general methodology used by EPA to estimate costs of abatement options in RIAs. The methodology for deriving abatement costs varies significantly from one regulation to another. The following steps, however, are typical:

- For an industrial sector to be regulated, identify the emission points or process units that should be regulated based on their emissions of hazardous air pollutants (HAPs).
- *Develop model process units for each process identified for regulation*: Model units are "parametric descriptions of the types of processes that exist and that are likely to be constructed in the future (EPA, 1993 pp: 4-1)." The idea behind these model units is to classify the entire population of firms potentially affected by regulation into a smaller number of representative units so that national cost estimates can be derived by aggregating the costs estimated for representative units. Typically, these model process units are developed based on an understanding of the process parameters that

affect emissions of HAPs. For example, in the development of MACT for pulping system emissions in pulp and paper mills, EPA classified paper units in the country into 18 model units based on the process parameters (e.g., process technology, wood type, digestion process, etc.) that affect HAP emissions (EPA, 1993). Each of the pulp and paper firms, affected by the MACT regulation, was assigned to one of these 18 model units.

- *Estimate baseline emissions for each model process unit*: The baseline emissions are usually estimated using emission factors developed for each model unit. If controls are already in place (even before the regulation), the reductions due to controls are taken into account in baseline emission estimations.
- *Identify control technology options for each process:* The number of control options considered varies widely from one RIA to another: anywhere between a single option and more than five options have been considered by EPA (GAO, 1997). At this step, information on the control efficiency of each identified technology is also collected. Control efficiency is the percentage of baseline emissions expected to be removed by the abatement option under consideration.
- *Estimate the costs of identified technology options for model mills using an engineering cost approach*: The estimated annualized costs include: (1) capital costs including capital recovery costs, taxes, insurance, administrative, and overhead charges, (2) equipment installation costs, and (3) direct operation and maintenance costs. The cost estimation includes a number of assumptions. The RIAs provide rationale for some of these assumptions, but others appear arbitrary. Example assumptions include installation costs as a percentage of purchased equipment costs,

life of technology (typically 10 years), interest rate, costs of fuels, labor requirement for operating pollution control equipment, and material maintenance costs as a fraction of maintenance material costs.

Two issues that are common to all the cost functions described later in this section deserve mention. Firstly, because the MACT rules were developed in different years for different source categories, the dollar years vary significantly from one RIA to another. In this analysis, however, all dollar years are converted to 1999 dollars using the Composite Price Index (CPI) Inflation Calculator of the Bureau of Labor Statistics. Secondly, "no control" was always considered as one of the abatement options irrespective of whether or not EPA considered such an option in its regulatory analysis. The costs of the "no control" option were assumed to be zero and the corresponding emission levels were assumed to be the baseline emissions. The remaining subsections provide details of fitted cost functions for all the sources.

6.2.1 International Paper

This facility manufactures paper and paperboards from wood pulp using Kraft process. The NTI data for 1999 listed 14 sources of air toxics at this facility. Among the air toxics emitted from these sources, acetaldehyde, benzene, and formaldehyde were the carcinogenic pollutants. Only two sources of the 14 listed emit carcinogenic pollutants.

This facility is subjected to National Emission Standards to control Hazardous Air Pollutants (NESHAP) emitted from Pulp and Paper Mills. The paper mill NESHAP has three parts MACT I (40 CFR 63 Subpart S), MACT II (40 CFR 63 Subpart M), and MACT III. Only MACT I and MACT II are applicable for this facility.

The background information document (BID) (EPA, 1993) on development of MACT I standards for paper mill includes information on two sources – pulping system vents and bleach lines vents. For the purpose of this analysis, it was assumed that the two NTI sources correspond to the two MACT I sources i.e., *pulping system vents and bleach line vents,* though there is insufficient information in the BID to verify this assumption.

The final version of the BID (EPA, 1997a) identified four abatement options for reducing emissions from the pulping system vents of Kraft process paper mills. The BID includes national aggregate estimates of costs for the four abatement options and suggests that the national aggregate estimates are based on 112 Kraft process paper mills. Hence dividing the national aggregate estimates by 112 gives the cost and emission estimates for an "average" source. One option costs more while reducing emissions less and was hence removed. Table 6.2 shows the data, including the "no control" option.

Table 6.2 Annual Costs and Emissions for Pulping System Vents of Paper Mills

Option	Annual Cost for "average" firm (1999 $/y)	Emission Reduction (Ton/year)	Emissions Remaining (Ton/year)
1. No control	0	0	1835
2	1,148,393	1211	624
3	1,216,518	1231	605
4	1,343,036	1240	595

Source: EPA. (1997). Pulp, Paper, and Paperboard Industry – Background Information for Promulgated Air Emission Standards: Manufacturing Processes at Kraft, Sulfite, Soda, Semi-chemical, Mechanical, and Secondary and Non-wood Fiber Mills, Final EIS, October 1997, EPA-453/R-93-050b

The BID (EPA, 1993) developed for MACT I proposed rule identified two options for bleach lines – (1) scrubbing and (2) incineration followed by scrubbing. The BID estimated control costs for a 1000 ton per day pulping capacity model mill with

certain process characteristics. The table below (Table 6.3) shows the costs and emissions data for bleach lines.

Table 6.3 Annual Costs and Emissions for Bleach Line Emissions of Paper Mills

Option	Annual Cost for "average" firm (1999 $/y)	Emission Reduction (Ton/year)	Emissions Remaining (Ton/year)
No Control	0	0	464
Scrubbing of Bleaching Vents	312,830	320	144
Incineration followed by Scrubbing	4,185,600	452	12

Source: EPA. (1993). Pulp, Paper, and Paperboard Industry – Background Information for Proposed Air Emission Standards: Manufacturing Processes at Kraft, Sulfite, Soda, and Semi-chemical Mills, October 1993, EPA-453/R-93-050a

6.2.2 Air Products Ltd.

This facility manufactures a number of chemicals such as methylamines, alkylamines, nitric acid, and ammonium nitrate. This facility is subject to National Emission Standards for Organic Hazardous Air Pollutants from the Synthetic Organic Chemical Manufacturing Industry.

The 1999 NTI lists six sources of HAPs within this facility. Only one of these six sources emits at least one carcinogenic air toxic. This source emits three carcinogenic air toxics – acetaldehyde, benzene, and formaldehyde. *Based on the information from the Title V Operating Permit of FLDEP, this source is most likely the process vent from methylamine plants*.

The RIA for Organic Chemicals NESHAP (EPA, 1994) identified regulatory options and estimated costs for five source categories – storage tanks, process vents,

equipment leaks, wastewater, and transfer operations – within this industrial sector. Based on the earlier discussion, the source category relevant to Air Products facility was process vents. The RIA for synthetic organic chemical industries MACT rule (EPA, 1994) considered five abatement options for process vents. The cost estimates for these five regulatory options are national aggregate estimates. However, according to the Background Information Document (BID) Volume 1A (EPA, 1992), the number of organic chemical manufacturing units considered in the national aggregate cost estimates are 729. The cost estimates and emission reductions are thus calculated for an "average" firm by dividing the national estimates by 729. The following table (Table 6.4) shows expected pollutant reduction for each option and the corresponding annual costs in 1999 dollars for an "average" firm.

Table 6.4 Annual Costs and Emissions for Process Vents in Synthetic Organic Chemical Manufacturing Industries

Option	Annual Cost for average firm (1999 $/y)	Emission Reduction (Ton/year)	Emissions Remaining (Ton/year)
1. No Control	0	0	395
2	101,097	355	40
3	106,612	357	38
4	113,964	360	35
5	121,317	361	34
6	178,299	364	31

Source: EPA. (1994). Regulatory Impact Analysis for The National Emissions Standards for Hazardous Air Pollutants for Source Categories: Organic Hazardous Air Pollutants from the Synthetic Organic Chemical Manufacturing Industry and Other Processes Subject to the Negotiated Regulation for Equipment Leaks. EPA Document Number EPA-453/R-94-019, March 1994

6.2.3 Solutia Inc.,

This facility manufactures nylon and nylon intermediate chemicals. This facility is subjected to the same NESHAP – *National Emission Standards for Organic Hazardous Air Pollutants from the Synthetic Organic Chemical Manufacturing Industry* – as Air Products facility. According to the Florida DEP air permit, the following sources within this facility are subject to NESHAP:

- Maleic Anhydride Plant: Emits VOCs
- Area 480 KA – Product Synthesis, Refining and Raw Material Recovery and all related ancillary equipment and systems: Emits VOCs and phenol
- Area 480 KA – Fugitive emissions

The 1999 National Toxics Inventory (NTI) lists four sources for this facility. Only one source emits carcinogenic pollutants – formaldehyde, acetaldehyde, and benzene. *This source is assumed to correspond to Maleic Anhydride Plant process emissions*. The same cost function developed earlier for Air Products (using data in Table 6.4) is used for this source as well because both facilities are regulated under the same NESHAP and emit the same carcinogenic air pollutants.

6.2.4 St. Regis

St. Regis is an oil and gas production facility owned by Exxon Mobil, and located in Santa Rosa County. This facility is subject to a variety of NESHAPs. According to FLDEP, the following are the sources of air toxics and the corresponding NESHAP to which they are subjected.

- Triethylene glycol (TEG) reboiler unit: subject to NESHAP for oil and natural gas production (40 CFR 63 Subpart HH)

- Two turbines: subject to NESHAP for Stationary Turbines (40 CFR 63 Subpart YYYY)
- One recompressor engine with catalytic converter and eight internal combustion (IC) engines: NESHAP for reciprocating internal combustion engines (40 CFR 63 Subpart ZZZZ)
- Gas-fired process heaters: subjected to NESHAP for Boilers and Heaters (40 CFR 63 Subpart DDDDD)

While the air permit lists a large number of sources of air toxics, the 1999 NTI lists only three sources for the St. Regis facility. One explanation for this discrepancy is that many of the sources have come under regulation only recently and thus were not listed as sources of air toxics in the 1999 inventory. It is not possible, however, to tell directly which of the sources listed in the air permit correspond to the three sources listed in the inventory. Two of the inventory sources emit the same pollutants – benzene, formaldehyde, acetaldehyde, and polycyclic organic matter. These two sources are likely to correspond to the two stationary turbine emissions because these are the pollutants of concern for natural-gas fired combustion turbines (Federal Register, 2004). For estimation of cost functions, *these two sources in the NTI are assumed to correspond to stationary turbine emissions*.

The third source in the NTI emits only benzene. This source likely corresponds to TEG reboiler unit that is subjected to oil and gas NESHAP. This is because benzene is the pollutant of primary concern for TEG reboiler unit (Federal Register, 1999b). Hence *the third source in the inventory was assumed to be TEG reboiler unit*.

Abatement Options for Stationary Turbines

The only control technology option considered for turbine NESHAP was oxidation catalyst to reduce emissions of formaldehyde, acetaldehyde, and benzene. The NESHAP requires new turbine units to install an oxidation catalyst. According to the RIA of turbine NESHAP, 44 new turbines are expected to install oxidation catalysts resulting in a total national HAP reduction of 98 ton per year (TPY) i.e., 2.227 TPY for an "average" turbine unit (EPA, 2003b). This emission reduction is based on an assumption of 95% removal efficiency of oxidation catalysts. Thus the baseline emissions for an average turbine are 2.344 TPY. The total estimated costs for installing and operating oxidation catalyst at these projected 44 units is $42.6 million ($1998) i.e., an average of $0.97 million per turbine unit. The table below (Table 6.5) shows the cost data including the "no control" option, after conversion to 1999 dollars.

Table 6.5 Annual Costs and Emissions for Stationary Turbines

Option	Annual Cost (1999$/y)	Emission Reduction (Ton/year)	Emissions Remaining (Ton/year)
No Control	0	0	2.3
Oxidation Catalyst	1,068,200	2.2	0.1

Source: EPA. (2003b). Economic Impact Analysis of the Final Stationary Combustion Turbines NESHAP: Final Report, August 2003, EPA Report No. EPA-452/R-03-014

Abatement Options for TEG Reboiler Unit

This analysis is based on Economic Impact Analysis (EIA) (EPA, 1999b) and Background Information Document (BID) (EPA, 1997b) of oil and gas NESHAP. The BID for oil and gas NESHAP identified four possible control options and the corresponding removal efficiencies for TEG reboiler emissions. The following are the control options.

- Condenser, with flash tank in dehydration system design (95% removal)

- Condenser without flash tank (50% removal)
- Combustion (98% removal)
- System optimization (Variable removal efficiency)

However, neither the BID nor the EIA estimate costs for all of the identified control options. The option selected for the final NESHAP rule was condenser with flash tank in dehydration system design. The EIA estimates costs only for this option. As in any typical EIA, model units were developed for TEG reboiler units in oil and gas production facilities. The model units were based on actual throughput of reboiler units. According to NTI, the actual throughput of the TEG reboiler unit in the St. Regis unit was 84 Million Cubic Feet per Day (MCFD). Under this classification St. Regis unit falls under the Model Unit TEG-D of the EIA (EPA, 1999b). The cost estimated for this model unit for the condenser with flash tank option is $12,790 (1993 $) per year. According to the oil and gas BID, the baseline emissions for a typical TEG reboiler unit is 120 Mg/year (132.6 TPY) and with a 95% reduction efficiency, the reduction in air toxics is 114 Mg/year (126 TPY). Thus the following data (Table 6.6) are used to fit a cost function for this source, after converting the costs into 1999 dollars.

Table 6.6 Annual Costs and Emissions for TEG Reboiler Emission Unit

Option	Annual Cost (1999$/yr)	Emission Reduction (Ton/year)	Emissions Remaining (Ton/year)
No Control	0	0	133
Condenser, with flash tank in dehydration system design	14,709	126	7

Source: EPA. (1999b). Economic Impact Analysis of the Oil and Natural Gas Production NESHAP and the Natural Gas Storage and Transmission NESHAP, Final Report, May, 1999, Office of Air Quality and Radiation, The Environmental Protection Agency

6.2.5 Florida Gas Transmission Company

This facility is part of a natural gas transmission pipeline system. It has six natural gas-fired internal combustion engines and two natural gas-fired turbine engines. Currently, according to FLDEP Title V Operating Permit, the internal combustion engines are subject to NESHAP for reciprocating internal combustion engines (RICE) and the turbines are subject to the turbine NESHAP.

The 1999 NTI, however, lists only one source for this facility. This source likely corresponds to turbine emissions because acetaldehyde, formaldehyde, benzene, and POM are the pollutants emitted from this source. Hence the same cost data developed earlier for turbine emissions (Table 6.5) in the St. Regis facility is used to fit cost function for this source.

6.2.6 Sterling Fibers

This facility manufactures acrylic fiber and is a major source of air toxics. This facility is subjected to the acrylic/modacrylic fiber manufacturing NESHAP (40 CFR 63 Subpart YY). Although this facility emits a number of air toxics, acrylonitrile is the only cancer-causing pollutant. According to the FLDEP air permit document, three regulated sources emit acrylonitrile – monomer process, acrylonitrile storage tanks, and polymer purification plant. The 1999 NTI also lists three sources of acrylonitrile. However, the three sources listed in the inventory are fugitive emission sources. The potential sources of fugitive emissions of acrylonitrile from this plant are storage tanks and plant-wide fugitive emissions from equipment leaks.

The EPA did not conduct a RIA for acrylic fiber NESHAP. However, an economic analysis (EPA, 1998) of the NESHAP for acrylic and modacrylic fiber is

available. This economic analysis estimated the cost of a leak detection and repair program at Sterling Fibers as $50,000 (1996 $) per year. The Title V permit document of Sterling Fibers has an attachment (Attachment 10) on leak detection and elimination program[19] submitted by the industry to FLDEP. According to this document, the estimated baseline plant-wide fugitive emissions are 1.25 pounds of acrylonitrile per hour of plant operation. Assuming continuous operation of the plant throughout the year, the estimated annual baseline emissions are 5.475 tons. The estimated efficiency of such leak detection programs is between 60 and 70 % (Klimont, Amann, & Cofala, 2000). Assuming an efficiency of 65%, the total reduction is 3.558 T/y and the emissions remaining are 1.916 T/y. Because no cost information is available for fugitive emissions from storage tanks, the same cost function is assumed for all sources. The data in Table 6.7 below show the annual cost and emission reductions assumed to fit the cost function for this source.

Table 6.7 Annual Costs and Emissions for Sterling Fibers Facility

Option	Annual Cost (1999$/yr)	Emission Reduction (Ton/year)	Emissions Remaining (Ton/year)
No Control	0	0	5.5
Leak Detection Program	53,000	3.6	1.9

Source: EPA. (1998). Economic impact analysis for the proposed national emission standard for hazardous air pollutants from the production of acrylic modacrylic fibers. Office of Air Quality Planning and Standards, Docket No. A-97-18, Item No. II-A-6, May 1998; Title V Renewal Application, Sterling Fibers, Inc. (Facility ID#113003), Pace, Florida. Attachment 10, Santa Rosa Plant Leak Detection and Elimination Program

[19] Title V Renewal Application, Sterling Fibers, Inc. (Facility ID#113003), Pace, Florida. Attachment 10, Santa Rosa Plant Leak Detection and Elimination Program

6.2.7 Gulf Power

This facility has seven boilers with varying heat input capacities. These boilers are the sources of air toxics. The carcinogenic pollutants are benzene, formaldehyde, acetaldehyde, and metals such as lead and nickel.

The RIA (EPA, 2002) of boilers and process heaters NESHAP, which is the relevant NESHAP to this source, developed model units based on the fuel type used and input heat capacity of boilers. All the boilers at this facility are in the existing solid fuel large boilers (>10 MMBtu/hr boilers using coal as the primary fuel) category. The selected regulatory option for NESHAP for this category is a combination of wet scrubber and typical fabric filter technologies. EPA considered two other regulatory alternatives – (1) a better designed and operated fabric filter (better than typically designed) and (2) packed bed scrubbers.

While the RIA itself did not provide details of costs of various alternatives, a separate cost memorandum[20] provided details of national aggregate costs of controls for various alternatives. The aggregate cost estimates are based on approximately 2300 boilers. Thus dividing the aggregate estimates by 2300 gives the estimates for an "average" unit. Table 6.8 gives the details for the category relevant to Gulf Power boilers (i.e., existing boilers with more than 10 MMBtu/hour input capacity using coal/solid fuel).

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[20] Memorandum to Jim Eddinger, USEPA, Office of Air Quality Planning and Standards (OAQPS) from Roy Oommen, Eastern Research Group, Inc., on Methodology for estimating Cost and Emission Impacts for Industrial, Commercial, Institutional Boilers and Process Heaters National Emission Standards for Hazardous Air Pollutants dated October 2002

Table 6.8 Annual Costs and Emissions for Gulf Power Boilers

Option	Annual Cost (1999$/yr)	Emission Reduction (T/y)	Emissions Remaining (T/y)
No Control	0	0	37
Combination of wet scrubbers and fabric filter	290,870	245	12
Packed Scrubbers	671,304	36	1

Source: Memorandum to Jim Eddinger, USEPA, Office of Air Quality Planning and Standards (OAQPS) from Roy Oommen, Eastern Research Group, Inc., on Methodology for estimating Cost and Emission Impacts for Industrial, Commercial, Institutional Boilers and Process Heaters National Emission Standards for Hazardous Air Pollutants dated October 2002

6.2.8 Fitted Cost Functions

The data presented above for each source are used to fit a continuous cost functions. As indicated in Chapter 4, the data are fitted to an exponential function of the form:

$$C_{ij} = a_{ij} e^{b_{ij} Q_{ij}}$$

The cost functions are fitted to this form in a nonlinear least square regression framework (Wooldridge, 2001) to estimate the parameters a_{ij} and b_{ij} with STATA 9.2 Table 6.9 shows estimated cost function parameters for each source in the analysis.

Table 6.9 Details of Cost Function Parameters Used in Empirical Analysis

Facility	Source	Source ID	Pollutants Emitted	Cost Parameters	
				a_{ij}	b_{ij}
International Paper	Bleaching Line Vent	IP01	Acetaldehyde	5303579	-0.019
	Pulping System Vent	IP02	Formaldehyde, Acetaldehyde, Benzene	27600000	-0.005

Facility	Source	Source ID	Pollutants Emitted	Cost Parameters	
				a_{ij}	b_{ij}
Gulf Power Company	Boiler	GP01	Formaldehyde, Acetaldehyde, Benzene	755887	-0.083
	Boiler	GP02	Formaldehyde, Acetaldehyde, Benzene	755887	-0.083
	Boiler	GP03	Formaldehyde, Acetaldehyde, Benzene	755886.9	-0.083
	Boiler	GP04	Nickel, Arsenic	755886.9	-0.083
Solutia, Inc.	Maelic Anhydride Plant Vent	SO01	Formaldehyde, Acetaldehyde, Benzene	1214368	-0.066
Air Products and Chemicals	Methylamine Plant Vent	AP01	Formaldehyde, Acetaldehyde, Benzene	1214368	-0.066
Sterling Fibers	Fugitive Emissions	SF01	Acrylonitrile	25600000	-3.225
	Fugitive Emissions	SF02	Acrylonitrile	25600000	-3.225
	Fugitive Emissions	SF03	Acrylonitrile	25600000	-3.225
Florida Gas Transmission Company	Turbine	FG01	Formaldehyde, Acetaldehyde, Benzene	2248523	-6.307
St. Regis plant	Turbine	SR01	Formaldehyde, Acetaldehyde, Benzene	2248523	-6.307
	Turbine	SR02	Formaldehyde, Acetaldehyde, Benzene	2248523	-6.307
	TEG Reboiler	SR03	Benzene	31863	-0.112

6.3 RAIMI Data

The implementation of RAIMI to estimate exposure concentrations involved collection of a variety of data from different sources. This section briefly presents the type of data collected and their sources.

6.3.1 Inventory Data

As discussed earlier (in Section 5.4.1.2), implementation of RAIMI required development of an emission inventory with physical characteristics of sources such as location and type (stack, fugitive, or flare), height of release, and velocity and temperature of the exit gas as well as emission characteristics such as pollutants released and emission rates. A few states in the United States developed their own inventories for air toxics. Florida, however, has not yet developed any such comprehensive state level database for air toxics. Hence this analysis uses a federal emission inventory developed by U.S. EPA. Specifically, I use a point source database from EPA's 1999 base year National Emission Inventory (NEI) (Version 3) for hazardous air pollutants (HAPs) (EPA, 2007c).

6.3.2 Geographical Information Systems (GIS) Data

RAIMI operates predominantly in a GIS environment. Thus, the implementation of RAIMI tools requires many GIS datasets. These GIS maps were primarily used to generate input files for dispersion modeling. The analysis for this study required the land use/land cover maps, digital elevation maps, and aerial photographs GIS to implement RAIMI.

6.3.2.1 Land Use/Land Cover Maps

Input to the ISCST3 dispersion model requires identification of land use category (urban or rural), dispersion coefficients, and surface roughness height parameters for each source selected for analysis. This study used 1:250,000 land use land cover (LULC) map of United States Geological Service (USGS) available from Florida Geographic Data

Library (FGDL) (www.fgdl.org) for Escambia and Pensacola counties. These maps were edited to correct for some inconsistencies.

6.3.2.2 Digital Elevation Maps (DEM)

The elevation of sources as well as receptors is an input for air dispersion modeling. In this study, 1:250,000 scale USGS digital elevation model (DEM) maps available from USGS (http://eros.usgs.gov/geodata) were used.

6.3.2.3 Aerial Photographs

Aerial photographs of the two-county study area were used for verifying source locations. The tool utilized for this purpose is called TerraServer Download ArcGIS 9.0 (Version 2) available from ESRI at http://arcscripts.esri.com/details.asp?dbid=13703. This tool has the ability to download aerial photograph imagery from TerraServer server (http://terraserver.microsoft.com) directly into ArcMap GIS software.

6.3.3 Upper Air and Surface Meteorological Data

The ISCST3 air dispersion modeling in RAIMI is executed using meteorological data for 1986 to 1990, based on surface observations taken from the Pensacola Regional Airport (WBAN 13899). During this period the observation station was located at 30.47 N, 87.20 W with a base elevation of 34.1 meters above mean sea level and anemometer height of 6.71 meters. Mixing heights and upper air data are from Apalachicola (WBAN 12832). The observation station at Apalachicola was located at 29.73 N, 85.02 W with a base elevation of 6.1 meters above mean sea level. It should be noted that precipitation data for wet deposition computations are not utilized in the analysis due to lack of a representative precipitation observation data set for the study period. This could

overestimate ambient air concentrations because removal of pollutants by precipitation is not taken into account. Surface and upper air data are obtained from U.S. EPA's archive of meteorological data for dispersion modeling (EPA, 2007d).

6.4 Other Input Data

6.4.1 Baseline Emissions

The baseline emissions represent the current emissions for sources selected for empirical analysis. These data are obtained from the 1999 National Toxics Inventory.

6.4.2 Unit Cancer Risk Factor

Unit Risk is defined as "the upper-bound excess lifetime cancer risk estimated to result from continuous exposure to an agent at a concentration of 1 µg/L in water, or 1 µg/m^3 in air (EPA, 2007e)." The URF is calculated using the following equation (Rood et al., 2001):

$$URF = \frac{SF.BR}{BW.CF}$$

where URF is Unit Risk Factor in (µg /m^3)$^{-1}$ SF = Slope Factor in mg/kg-day, BW = Body Weight in kg, BR = Breathing rate in m^3/day, and CF = Conversion factor to convert mg into µg = 1000. The slope factor in the above equation is defined by EPA as "an upper-bound, approximating a 95% confidence limit, on the increased cancer risk from a lifetime exposure to an agent (EPA, 2007e)."

Values of unit risk factors, u_j, for each of the six pollutants in the sample are from EPA's Integrated Risk Information System (IRIS) database. The following table (Table 6.10) shows the values of unit risk factors used in the analysis.

Table 6.10 Unit Risk Factors for Pollutants in Empirical Analysis

Pollutant	Unit Risk Factor
Benzene	0.0000078
Acetaldehyde	0.0000022
Formaldehyde	0.000013
Acrylonitrile	0.000068
Nickel	0.00024
Arsenic	0.0043

6.4.3 Population Data

The second term in the objective function requires population data for each census block to estimate population health risks. The census block population data were obtained from the US Census Bureau.

6.4.4 Value of Statistical Life

Value of statistical life is an extensively used measure for valuing mortality risks by regulatory agencies as well as environmental economics researchers. It represents the tradeoff individuals make between risk and wealth. VSL is often incorrectly interpreted as the value of an individual's life (Krupnick, 2004). For example, a VSL of $5 million does not mean that an individual will be willing to pay $5 million to avoid death; it rather means that 100,000 people in society would be willing to collectively pay $5 million to avoid a risk that randomly kills one among them (Hammitt, 2000).

Extensive research estimates VSL using either a revealed preference approach (hedonic-wage studies) or a stated preference approach (contingent valuation) (see Viscusi & Aldy, 2003 for a recent meta analysis of VSL estimates in a number of countries). A number of studies also examine the variation in VSL with income, age,

baseline risk, or risk aversion. This indicates that policy analyses should use different VSL for different population groups depending on their attributes. In this study, however, a uniform value is used for all population subgroups.

In addition to the issue of heterogeneity in individual willingness to pay to reduce risk of death, the other important policy debate with regard to VSL is the issue of benefit transfer. Because it is not feasible to estimate VSL for every context, VSL estimated within one context is used in analyzing policies in other contexts. Many of the VSL estimates in the literature are based on hedonic wage studies. The context for many of these studies is the risk of death in the work place due to accidents. Is it appropriate to apply VSL estimates derived from these studies to a context such as the risk of death due to cancer attributable to exposure to air toxics? A scientific advisory board (SAB) panel of EPA, while reviewing a white paper submitted by EPA on valuing the benefits of fatal cancer risk reduction, suggested that VSL estimates derived from wage-risk tradeoff studies "….should not be taken as accurate estimates of the value of reducing the risk of fatal cancers because of differences in both the nature of the risks being valued and in the socio-economic characteristics of the affected populations (EPA, 2000a, p: 19)." The SAB panel, however, recommended that EPA continue to use wage-risk VSL estimates because there was no theoretical or empirical basis to make any quantitative adjustments to wage-risk VSL estimates to reflect the differences in contexts. Thus, this study will use VSL estimates from the literature to estimate costs of cancer in the objective function.

Given that a large number of estimates of VSL exist in literature, EPA and other regulatory agencies utilize values from meta-analyses in their benefit cost assessments. EPA used a mean VSL of $4.8 million (in 1990$ or 5.5 million in 1999$) with a standard

deviation of $3.2 million in its benefit cost assessment of the Clean Air Act (EPA, 1999c) for 1990-2010. In its new proposed assessment for 1990-2020 (EPA, 2006c), EPA conducted another meta-analysis that yielded a mean of $5.4 million (2000$) and a standard deviation of $2.4 million. Mrozek & Taylor (2002) conducted a meta analysis of 33 studies and concluded that $2 million (1998$) was a reasonable mean estimate of VSL based on their analysis. Viscusi and Aldy (2003), in their meta analysis of a sample of US studies, estimated a mean value that varied between $5.5 million and $7.6 million (2000$).

Based on this review, this dissertation research uses a mean VSL of $5.5 million (1999$) because EPA has been using this value for most of its benefit assessments. However, because of the wide variation in mean VSL estimated by different meta analyses, a sensitivity analysis is also conducted by assuming two alternative values for the VSL: $2.04 million (1999$) (based on Mrozek & Taylor, 2002) representing the lower end of the mean VSL estimates and $7.35 million (1999$) (based on Viscusi & Aldy, 2003) representing the upper end of the available mean estimates.

CHAPTER 7

RESULTS: OPTIMAL EMISSIONS AND NET COSTS VS. SPATIAL RESOLUTION

The results of the empirical analysis are presented in two chapters. This chapter presents the results of the optimization runs discussed in Section 5.4.2. The next chapter, Chapter 8, discusses the potential distributional implications of regulating at finer spatial resolutions. The first section of this chapter discusses how choice of spatial resolution to regulate risks could affect the optimal emissions a hypothetical decision maker would choose, and then interprets the results in light of the model used for the analysis. The second section focuses on the costs of regulation at finer spatial resolutions. The last two sections present sensitivity of optimal emissions to risk thresholds and value of statistical life (VSL).

7.1 Optimal Emissions vs. Spatial Resolution

The optimal emissions a hypothetical decision maker might choose, based on the decision model developed in Chapter 4, are estimated at three different cancer risk thresholds. The following sub sections discuss the results at each threshold risk.

7.1.1 Risk Threshold of 100 in a Million Cancer Risk

Table 7.1 shows the baseline emissions and the optimal emissions at census tract, census block group (BG), and census block resolutions for each of the 34 source/pollutant combinations. The optimal emissions in Table 7.1 correspond to a risk threshold (r) of 100 in a million and at a value of statistical life (VSL) equal to $5.5 Million. One can

make two immediate observations from the table. First, the optimal emissions at the census block group regulation are exactly the same as those at the census tract regulation. Second, if the sources are regulated at a finer census block resolution instead of the census block group resolution, the optimal emissions are higher for a number of sources (for example, all pollutants and sources from Gulf Power) and lower for some sources (for example, acetaldehyde from IP02).

Table 7.1 Optimal Emissions for Regulation at Various Spatial Resolutions
(Threshold Risk = 1.0E-04; VSL=$5.5 Million)

Facility	Source ID	Pollutant	Baseline Emissions (T/Y)	Optimal Emissions (TPY)		
				Census Tract	Block Group	Block
International Paper	IP01	Acetaldehyde	5.5	149.6	149.6 ↔	196.4 ↑
	IP02	Formaldehyde	8.5	0	0	0
		Acetaldehyde	50.9	135.1	135.1 ↔	69.3 ↓
		Benzene	5.08	0	0	0
Solutia	SO01	Formaldehyde	0.0436	1.57	1.57 ↔	7.87 ↑
		Acetaldehyde	0.00575	28.6	28.6 ↔	34.9 ↑
		Benzene	0.00052	9.35	9.35 ↔	15.6 ↑
Sterling Fibers	SF01	Acrylonitrile	2.819	0.11	0.11 ↔	0.03 ↓
	SF02	Acrylonitrile	5.48	0.28	0.28 ↔	0.21 ↓
	SF03	Acrylonitrile	1.159	0.17	0.17 ↔	0.07 ↓
Air Products	AP01	Formaldehyde	0.869	0	0 ↔	0
		Acetaldehyde	0.073	4.25	4.25 ↔	10.7 ↑
		Benzene	0.03	0	0	0
St. Regis	SR01	Formaldehyde	30.52	1.02	1.02 ↔	1.07 ↑
		Acetaldehyde	2.561	1.30	1.30 ↔	1.35 ↑
		Benzene	1.0405	1.10	1.10 ↔	1.15 ↑
	SR02	Formaldehyde	0.01027	1.06	1.06 ↔	1.11 ↑
		Acetaldehyde	0.00135	1.34	1.34 ↔	1.39 ↑
		Benzene	0.000123	1.14	1.14 ↔	1.19 ↑
	SR03	Benzene	1.3	0	0	0
Florida Gas	FG01	Formaldehyde	78.8	1.15	1.15 ↔	1.20 ↑
		Acetaldehyde	6.615	1.43	1.43 ↔	1.48 ↑
		Benzene	2.687	1.23	1.23 ↔	1.28 ↑
Gulf Power	GP01	Formaldehyde	0.031	14.9	14.9 ↔	18.4 ↑
		Acetaldehyde	0.000006	36.3	36.3 ↔	39.8 ↑

Facility	Source ID	Pollutant	Baseline Emissions (T/Y)	Optimal Emissions (TPY)		
				Census Tract	Block Group	Block
		Benzene	0.00087	21.1	21.1 ↔	24.5 ↑
	GP02	Formaldehyde	0.00098	24.2	24.2 ↔	27.0 ↑
		Acetaldehyde	0.0000002	45.6	45.6 ↔	48.4 ↑
		Benzene	0.000028	30.4	30.4 ↔	33.1 ↑
	GP03	Formaldehyde	0.00228	37.8	37.8 ↔	40.2 ↑
		Acetaldehyde	0.0000004	59.2	59.2 ↔	61.6 ↑
		Benzene	0.0000621	44.0	44.0 ↔	46.4 ↑
	GP04	Nickel	0.4095	0	0	0
		Arsenic	0.438	0	0	0
Net Costs (Million $/y)				17.76	17.76	35.47

Note: ↑ - Increase in optimal emissions; ↓ - Decrease in optimal emissions; ↔ - No change in optimal emissions

Section 4.4.2.1 in Chapter 4 derived a set of conditions *(4.18)* to explain the direction of change of optimal emissions when risks are regulated at finer spatial resolution. According to these conditions, three parameters – λ_k, λ'_k, and β_{ijk} – affect the change in optimal emissions due to regulation at finer spatial resolution. The interpretation of the conditions in *(4.18)* suggested that (1) spatial resolution of regulation does not change optimal emissions when finer spatial resolution does not capture new hotspots, (2) optimal emissions will decrease for sources that contribute most to hotspots captured at finer spatial resolution, and (3) optimal emissions could increase for sources that do not contribute significantly to hotspots captured at finer resolution. The empirical results are consistent with these predictions, as described in the following.

Table 7.2a shows the optimal emissions of acetaldehyde (except for the source in the Sterling Fibers facility for which the pollutant is acrylonitrile) from a set of select sources when risks are regulated at two different resolutions: census tract and a finer census block group resolution. The results in Table 7.2a are for 100 in a million risk

threshold and $5.5 Million VSL. This first column in Table 7.2a shows the location of hot spots (k for which $\lambda_k \neq 0$), the second column shows the shadow price (λ_k) for hot spots at census tract resolution, and the third column shows the shadow price (λ'_k) for hot spots at the finer census block group resolution. The last column in Table 7.2a shows the exposure concentrations due to a unit emission rate (β_{ijk}) at hot spots for the select sources.

It can be observed from Table 7.2a that regulation at finer resolution does not capture any new hot spots. Location numbers 16 and 17 are the hot spots at both block group resolution and census tract resolution. Consistent with the interpretations of the conditions *(4.18)*, the optimal emissions are the same at both spatial resolutions.

Table 7.2b shows the results for regulation at census block group resolution and at a finer census block regulation. Regulation at the finer census block resolution captures two new hot spots, at location numbers 2503 and 9361 (shaded rows in Table 7.2b), but the two hot spots (location numbers 16 and 17) found at the census block group resolution disappear. The values of β_{ijk} for the sources indicate that source 1 of Sterling Fibers (SF01) has the maximum value (6.41 $\mu g / m^3$) at the hot spot 2503, much more than for any other source, and thus contributes most to the risk at that hot spot. Accordingly, the optimal emissions for this source reduce from 0.11 TPY at block group resolution to 0.03 TPY at census block resolution. Similarly, the second source of International Paper (IP02) has the highest exposure concentration (0.5218 $\mu g / m^3$, an order of magnitude higher than the next highest source Solutia) at hot spot location 9361 and thus the emissions of acetaldehyde from IP02 reduce from 135 TPY at block group

resolution to 69 TPY at block resolution. All the other sources contribute insignificant risk to hot spots at finer resolution and thus their optimal emissions increase. Again, this is consistent with the interpretation of the conditions *(4.18)*.

7.1.2 Risk Threshold of 10 in a Million Cancer Risk

The optimal emissions, at 10 in a million risk threshold, for all pollutant/source combinations at the three spatial resolutions are shown in Table 7.3. The optimal emissions, in general, either remain same or decrease for most sources, when regulated at block group resolution, except for acetaldehyde from IP01, which increases slightly. In case of regulation at census block resolution, the optimal emissions reduce for almost all the sources, with the exception of Florida Gas and Air Products, when compared to regulation at the coarser block group resolution.

Tables 7.4a and 7.4b explain these results. Table 7.4a shows that regulation at finer block group resolution as opposed to census tract resolution captures a new hot spot at location number 146. Acetaldehyde from two sources – Solutia and Air Products – has comparable exposure concentrations at the new hot spot captured by regulation at block group resolution. Thus, as expected, the emissions of acetaldehyde from Solutia reduce from 17.5 TPY to 17 TPY. In case of Solutia, regulation at census tract resolution itself does not allow any emissions and hence the regulation at finer resolution has zero optimal emissions. Because there is a reduction in optimal emissions for only one source, emissions for most of the other sources do not increase, except for a slight increase in acetaldehyde from IP01 (see Table 7.3).

Table 7.2a. Hot Spot Locations and Change in Optimal Emissions with Change in Spatial Resolution (Tract to Block Group Resolution; Risk Threshold: 100 in a Million)

Location No. (k)	λ_k (Tract)	λ'_k (BG)	$\beta_{ijk}(\mu g/m^3)$						
			IP02	**SO01**	**AP01**	**FG01**	**SR01**	**SF01**	**GP01**
16	1.1E+11	1.1E+11	0.2769	0.0219	0.0084	0.0019	0.0031	0.0062	0.007
17	2.5E+11	2.5E+11	0.0024	0.0087	0.1047	0.0022	0.0055	3.399	0.0024
Optimal Emissions (TPY)									
Tract			135	28.6	4.2	1.4	1.3	0.11	36.3
BG			135	28.6	4.2	1.4	1.3	0.11	36.3

Table 7.2b. Hot Spot Locations and Change in Optimal Emissions with Change in Spatial Resolution (Block Group to Block Resolution; Risk Threshold: 100 in a Million)

Location No. (k)	λ_k (BG)	λ'_k (Block)	$\beta_{ijk}(\mu g/m^3)$						
			IP02	**SO01**	**AP01**	**FG01**	**SR01**	**SF01**	**GP01**
16	1.1E+11	0	0.2769	0.0219	0.0084	0.0019	0.0031	0.0062	0.007
17	2.5E+11	0	0.0024	0.0087	0.1047	0.0022	0.0055	3.399	0.0024
2503	-	1.7E+11	0.0024	0.008	0.1007	0.0226	0.056	6.411	0.0024
9361	-	0.85E+11	0.5218	0.0265	0.0077	0.0019	0.0036	0.0059	0.0075
Optimal Emissions (TPY)									
BG			135	28.6	4.2	1.4	1.3	0.11	36.3
Block			69.2	34.9	10.7	1.5	1.35	0.03	39.8

IP02 – International Paper; SO01 – Solutia; AP01 – Air Products; FG01 – Florida Gas; SR01 – St. Regis; SF01 – Sterling Fibers; GP01 – Gulf Power
All emissions are for the pollutant acetaldehyde, except for SF01 for which the pollutant is acrylonitrile
Rows shaded in blue refer to hot spot locations at finer spatial resolution

Table 7.3 Optimal Emissions for Regulation at Various Spatial Resolutions
(Threshold Risk = 1.0E-05; VSL=$5.5 Million)

Facility	Source ID	Pollutant	Baseline Emissions (TPY)	Optimal Emissions (TPY)		
				Census Tract	Block Group	Block
International Paper	IP01	Acetaldehyde	5.5	112.0	113.9 ↑	96.9 ↓
	IP02	Formaldehyde	8.5	0	0	0
		Acetaldehyde	50.9	0	0	0
		Benzene	5.08	0	0	0
Solutia	SO01	Formaldehyde	0.0436	0	0	0
		Acetaldehyde	0.00575	17.5	17.0 ↓	16.4 ↓
		Benzene	0.00052	0	0	0
Sterling Fibers	SF01	Acrylonitrile	2.819	0	0	0
	SF02	Acrylonitrile	5.48	0.06	0.06 ↔	0.03 ↓
	SF03	Acrylonitrile	1.159	0	0	0
Air Products	AP01	Formaldehyde	0.869	0	0	0
		Acetaldehyde	0.073	0	0	0.54 ↑
		Benzene	0.03	0	0	0
St. Regis	SR01	Formaldehyde	30.52	0.90	0.90 ↔	0.86 ↓
		Acetaldehyde	2.561	1.2	1.19 ↔	1.14 ↓
		Benzene	1.0405	0.99	0.99 ↔	0.94 ↓
	SR02	Formaldehyde	0.01027	0.94	0.94 ↔	0.94 ↔
		Acetaldehyde	0.00135	1.22	1.22 ↔	1.22 ↔
		Benzene	0.000123	1.02	1.02 ↔	1.02 ↔
	SR03	Benzene	1.3	0	0	0
Florida Gas	FG01	Formaldehyde	78.8	1.03	1.03 ↔	1.06 ↑
		Acetaldehyde	6.615	1.31	1.31 ↔	1.35 ↑
		Benzene	2.687	1.11	1.11 ↔	1.14 ↑
Gulf Power	GP01	Formaldehyde	0.031	6.10	5.48 ↓	3.22 ↓
		Acetaldehyde	0.000006	27.5	26.9 ↓	24.6 ↓
		Benzene	0.00087	12.3	11.6 ↓	9.4 ↓
	GP02	Formaldehyde	0.00098	15.4	15.2 ↓	13.3 ↓
		Acetaldehyde	0.0000002	36.8	36.6 ↓	34.7 ↓
		Benzene	0.000028	21.6	21.4 ↓	19.5 ↓
	GP03	Formaldehyde	0.00228	29.0	29.1 ↑	27.4 ↓
		Acetaldehyde	0.0000004	50.4	50.5 ↑	48.8 ↓
		Benzene	0.0000621	35.2	35.2 ↔	33.5 ↓
	GP04	Nickel	0.4095	0	0	0
		Arsenic	0.438	0	0	0
Net Costs (Million $/y)				63.0	63.0	65.4

Note: ↑ - Increase in optimal emissions; ↓ - Decrease in optimal emissions; ↔ - No change in optimal emissions

Table 7.4b is more interesting. Regulation at the census block resolution revealed six new hot spots. The source Solutia (SO01) alone contributes significant amount of risk at three new hot spot locations and hence the acetaldehyde emissions from SO01 reduce from 17.0 to 16.4 TPY. Similarly, International Paper (IP02) has a value of β_{ijk} that is an order of magnitude higher than other sources at the new hot spot location 9353. Thus the emissions reduce from 0.1 to 0 TPY. The same holds for St. Regis (SR01) whose optimal acetaldehyde emissions slightly reduce from 1.19 to 1.14 TPY. St. Regis has β_{ijk} of 0.287 compared to 0.006 for the next highest source. There is a slight increase in optimal emissions for Air Products (AP01) and Florida Gas (FG01).

7.1.3 Risk Threshold of 1 in a Million Cancer Risk

The result in Section 4.5 showed that the optimal emissions are non-increasing, for regulation at any given spatial resolution, with decreasing (or stricter) threshold risk *r*. This result is evident from zero optimal emissions for a number of sources and relatively low optimal emissions for other sources, as shown in Table 7.5, for all spatial resolutions. Between census block group and census tract resolutions, Florida Gas and Gulf Power had their optimal emissions reduce for some pollutants while optimal emissions for most of the other sources remained the same across the two spatial resolutions. Acetaldehyde from Florida Gas (FG01) facility has a high value of β_{ijk}, compared to all other sources, at the hot spot captured at finer resolution (location number 85) and hence the reduction in optimal emissions, as seen in Table 7.6a.

Table 7.4a. Hot Spot Locations and Change in Optimal Emissions with Change in Spatial Resolution (Tract to Block Group Resolution; Risk Threshold: 10 in a Million)

Location No. (k)	λ_k (Tract)	λ'_k (BG)	$\beta_{ijk}(\mu g/m^3)$						
			IP02	**SO01**	**AP01**	**FG01**	**SR01**	**SF01**	**GP01**
16	2.4E+11	2.3E+11	0.2769	0.0219	0.0084	0.0019	0.0031	0.0062	0.007
17	5.2E+11	5.2E+11	0.0024	0.0087	0.1047	0.0022	0.0055	3.399	0.0024
146	-	13.0E+11	0.0076	0.055	0.0604	0.002	0.0048	0.0211	0.0188
Optimal Emissions (TPY)									
Tract			0	17.5	0	1.3	1.19	0	27.5
BG			0.096	17.0	0	1.3	1.19	0	26.9

Table 7.4b. Hot Spot Locations and Change in Optimal Emissions with Change in Spatial Resolution (Block Group to Block Resolution; Risk Threshold: 10 in a Million)

Location No. (k)	λ_k (BG)	λ'_k (Block)	$\beta_{ijk}(\mu g/m^3)$						
			IP02	**SO01**	**AP01**	**FG01**	**SR01**	**SF01**	**GP01**
16	2.3E+11	0	0.2769	0.0219	0.0084	0.0019	0.0031	0.0062	0.007
17	5.2E+11	0	0.0024	0.0087	0.1047	0.0022	0.0055	3.399	0.0024
146	13E+11	0	0.0076	0.055	0.0604	0.002	0.0048	0.0211	0.0188
979	-	6.8E+09	0.0018	0.003	0.002	0.0059	0.287	0.002	0.0015
2503	-	3.1E+11	0.0024	0.008	0.1	0.0023	0.0056	6.411	0.0024
9185	-	0.13	0.0149	0.091	0.021	0.002	0.004	0.0094	0.015
9261	-	1.7E+10	0.0137	0.096	0.024	0.002	0.004	0.011	0.016
9313	-	3.7E+10	0.008	0.055	0.047	0.002	0.005	0.021	0.023
9353	-	2.6E+011	0.31	0.024	0.007	0.002	0.004	0.005	0.007
Optimal Emissions (TPY)*									
BG			0.096	17.0	0	1.30	1.19	0	26.9
Block			0	16.4	0.53	1.34	1.14	0	24.6

IP02 – International Paper; SO01 – Solutia; AP01 – Air Products; FG01 – Florida Gas; SR01 – St. Regis; SF01 – Sterling Fibers; GP01 – Gulf Power
All emissions are for the pollutant acetaldehyde, except for SF01 for which the pollutant is acrylonitrile
Rows shaded in blue refer to hot spot locations at finer spatial resolution

Table 7.5 Optimal Emissions for Regulation at Various Spatial Resolutions
(Threshold Risk = 1.0E-06; VSL=$5.5 Million)

Facility	Source ID	Pollutant	Baseline Emissions (T/Y)	Optimal Emissions (T/Y)		
				Census Tract	Block Group	Block
International Paper	IP01	Acetaldehyde	5.5	15.6	15.8 ↑	12.0 ↓
	IP02	Formaldehyde	8.5	0	0	0
		Acetaldehyde	50.9	0	0	0
		Benzene	5.08	0	0	0
Solutia	SO01	Formaldehyde	0.0436	0	0	0
		Acetaldehyde	0.00575	0	0	0
		Benzene	0.00052	0	0	0
Sterling Fibers	SF01	Acrylonitrile	2.819	0	0	0
	SF02	Acrylonitrile	5.48	0.01	0.01 ↔	0 ↓
	SF03	Acrylonitrile	1.159	0	0	0
Air Products	AP01	Formaldehyde	0.869	0	0	0
		Acetaldehyde	0.073	0	0	0
		Benzene	0.03	0	0	0
St. Regis	SR01	Formaldehyde	30.52	0.01	0.02 ↑	0 ↓
		Acetaldehyde	2.561	0.29	0.30 ↑	0.28 ↓
		Benzene	1.0405	0.09	0.10 ↑	0.08 ↓
	SR02	Formaldehyde	0.01027	0.24	0.25 ↑	0.16 ↓
		Acetaldehyde	0.00135	0.52	0.53 ↑	0.44 ↓
		Benzene	0.000123	0.32	0.33 ↑	0.24 ↓
	SR03	Benzene	1.3	0	0	0
Florida Gas	FG01	Formaldehyde	78.8	0.59	0.11 ↓	0.06 ↓
		Acetaldehyde	6.615	0.87	0.39 ↓	0.34 ↓
		Benzene	2.687	0.67	0.19 ↓	0.14 ↓
Gulf Power	GP01	Formaldehyde	0.031	0	0	0
		Acetaldehyde	0.000006	5.41	5.55 ↑	6.51 ↑
		Benzene	0.00087	0	0	0
	GP02	Formaldehyde	0.00098	12.3	11.3 ↓	12.3 ↑
		Acetaldehyde	0.0000002	0	0	0
		Benzene	0.000028	0	0	0
	GP03	Formaldehyde	0.00228	0.38	0	0
		Acetaldehyde	0.0000004	21.8	19.8 ↓	20.7 ↑
		Benzene	0.0000621	6.53	4.55 ↓	5.51 ↑
	GP04	Nickel	0.4095	0	0	0
		Arsenic	0.438	0	0	0
Net Costs (Million $/y)				79.7	81.4	83.6

Note: ↑ - Increase in optimal emissions; ↓ - Decrease in optimal emissions; ↔ - No change in optimal emissions

Table 7.6a. Hot Spot Locations and Change in Optimal Emissions with Change in Spatial Resolution (Tract to Block Group Resolution; Risk Threshold: 1 in a Million)

Location No. (k)	λ_k (Tract)	λ'_k (BG)	$\beta_{ijk}(\mu g/m^3)$						
			IP02	**SO01**	**AP01**	**FG01**	**SR01**	**SF01**	**GP01**
2	4.1E+12	3.8E+12	0.0195	0.0034	0.0024	0.0054	0.255	0.0022	0.0016
16	1.5E+12	0	0.2769	0.0219	0.0084	0.0019	0.0031	0.0062	0.007
17	6.1E+11	6.1E+11	0.0024	0.0087	0.1047	0.0022	0.0055	3.399	0.0024
85	-	2.2E+12	0.0012	0.0025	0.0017	0.238	0.002	0.0017	0.001
126	-	1.3E+12	0.165	0.022	0.0092	0.0018	0.0034	0.0053	0.0064
Optimal Emissions (TPY)									
Tract			0	0	0	0.87	0.29	0	5.4
BG			0	0	0	0.39	0.30	0	5.5

Table 7.6b. Hot Spot Locations and Change in Optimal Emissions with Change in Spatial Resolution (Block Group to Block Resolution; Risk Threshold: 1 in a Million)

Location No. (k)	λ_k (BG)	λ'_k (Block)	$\beta_{ijk}(\mu g/m^3)$						
			IP02	**SO01**	**AP01**	**FG01**	**SR01**	**SF01**	**GP01**
2	3.8E+12	0	0.0195	0.0034	0.0024	0.0054	0.255	0.0022	0.0016
17	6.1E+11	0	0.0024	0.0087	0.1047	0.0022	0.0055	3.399	0.0024
85	2.2E+12	0	0.0012	0.0025	0.0017	0.238	0.002	0.0017	0.001
126	1.3E+12	0	0.165	0.022	0.0092	0.0018	0.0034	0.0053	0.0064
546	-	2.1E+12	0.0012	0.0021	0.0014	0.348	0.002	0.0015	0.008
979	-	3.9E+12	0.0018	0.003	0.002	0.006	0.286	0.002	0.0015
2503	-	3.3E+11	0.0024	0.008	0.1	0.0023	0.0056	6.411	0.0024
9353	-	1.2E+12	0.31	0.024	0.007	0.002	0.004	0.005	0.007
Optimal Emissions (TPY)*									
BG			0	0	0	0.39	0.30	0	5.5
Block			0	0	0	0.34	0.28	0	6.5

IP02 – International Paper; SO01 – Solutia; AP01 – Air Products; FG01 – Florida Gas; SR01 – St. Regis; SF01 – Sterling Fibers; GP01 – Gulf Power
All emissions are for the pollutant acetaldehyde, except for SF01 for which the pollutant is acrylonitrile; Rows shaded in blue are hot spot locations at finer spatial resolution

Between block group and census block resolution at 1 in a million risk threshold, most optimal emissions become zero while the reduction and the increase in optimal emissions for various sources is consistent with the interpretations of equation *(4.18)*. Table 7.6b shows the relevant results.

7.2 Net Costs vs. Spatial Resolution

This section discusses two types of costs – the net costs of regulation and the population health costs – resulting from regulation at three different spatial resolutions and at three different threshold risks. The net costs represent the net of private costs of abatement to industry and population health costs. The population health costs are costs due to residual risks remaining after the regulation and are discussed here in terms of number of expected additional cancer cases due to residual risks[21].

The result in Section 4.4.2 predicted that the net costs should be non-decreasing with spatial resolution. That is, the net costs cannot decrease as the risks are regulated at finer and finer spatial resolutions. The empirical results are consistent with that prediction. The last row of Table 7.1 shows the net costs of regulation at various spatial resolutions at 100 in a million risk threshold. Because the optimal emissions are the same for regulation at the census tract and at the census block group resolutions, the net costs are also the same at these two resolutions. However, regulation at the census block resolution result in net costs twice as high as those at the other resolutions ($35.5 Million at block resolution as opposed to $17.8 Million at census block group and census tract

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[21] The population health costs expressed in dollars are simply the product of number of expected additional cancer cases due to residual risks and the value of statistical life (VSL).

resolutions). This is because, at the census block resolution, although the optimal emissions increased marginally (compared to other resolutions) for a number of sources, there is a significant reduction in optimal emissions for two sources: International Paper (IP02) and Sterling Fibers. The abatement costs for these two sources together account for about 60% of additional net costs.

Figure 7.1 shows the variation of net costs as well as the number of additional cancer cases with spatial resolution when risks are regulated at 100 in a million cancer risk threshold. Net costs, as explained before, are the same at the tract and the block group resolutions but increase at the finest block resolution. The expected additional cancer cases due to air toxics exposures do not change between tract and block group regulation; but the expected cancer cases increase at the finer block resolution.

The increase in expected additional cancer cases at the finest resolution in the analysis is rather an unexpected, but important result. In the context of the decision model assumed in this paper, this result could be explained as follows. Under the regulation at finer resolutions, reducing risks at hotspots requires reduction in emissions from sources that contribute significantly to the hotspots. This reduction in emissions increases costs and not only reduces risks at hotspots, but potentially creates slack in risk at a number of other locations. In order to offset the increase in costs for some sources and due to the additional slack created by the reduction in emissions at these sources, a few other sources could be allowed to increase their emissions. If the increase in emissions from these other sources increases risk in areas that are highly populated, then the overall population risks might increase when risks are regulated at finer resolutions. The implications of this result are further explored in Chapter 10.

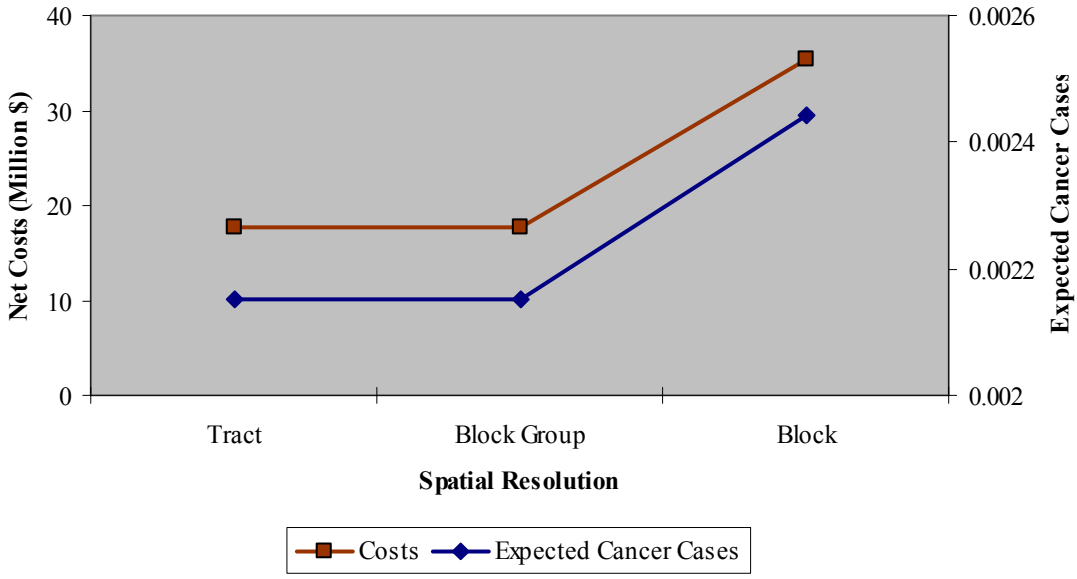

Figure 7.1 Variation of Net Costs and Expected Cancer Cases with Spatial Resolution (Threshold Risk: 100 in a Million)

Figure 7.2 shows the variation of net costs and expected additional cancer cases with spatial resolution when regulated at 10 in a million cancer risk threshold and Figure 7.3 shows the variation at 1 in a million cancer risk threshold. From Figures 7.1, 7.2, and 7.3, it can be observed that the increase in net costs when moving from a coarse resolution (track) to a finer resolution (block) is steepest at 100 in a million risk threshold while it flattens out at 10 in a million threshold, and flattens out further at 1 in a million risk threshold. The reason is: as the risk tolerance decreases, more and more sources have to be shut down even at coarse resolution and spatial resolution of regulation matters much less for net costs. We can see evidence for this reasoning by observing the optimal emissions at the three risk thresholds (in Tables 7.1, 7.3, and 7.5). The number of sources with zero optimal emissions increases as risk is regulated at tighter and tighter thresholds.

Unlike the regulation at 100 in a million threshold risk, the expected cancer cases due to residual risks drop with spatial resolution in case of regulation at 10 in a million and 1 in a million threshold risks.

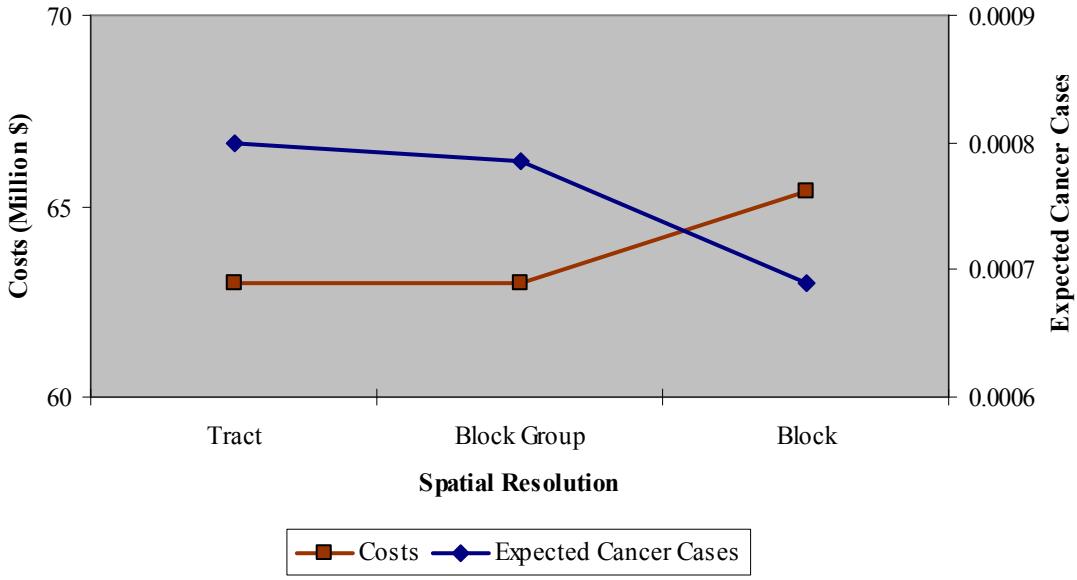

Figure 7.2 Variation of Net Costs and Expected Cancer Cases with Spatial Resolution (Threshold Risk: 10 in a Million)

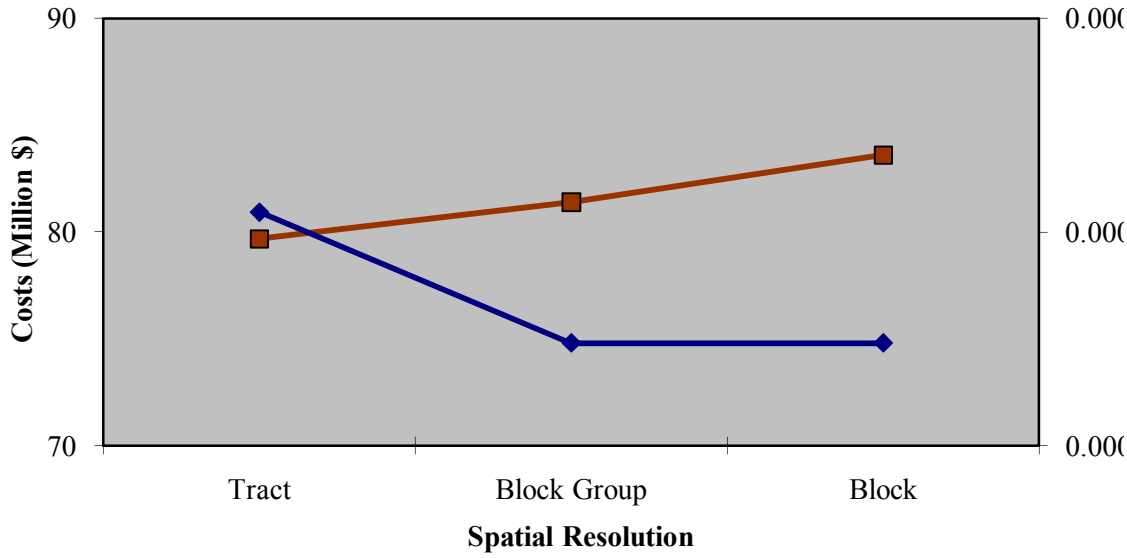

Figure 7.3 Variation of Net Costs and Expected Cancer Cases with Spatial Resolution (Threshold Risk: 1 in a Million)

7.3 Sensitivity of Optimal Emissions to Threshold Risks

The result in Section 4.5 predicted that, for regulation at any spatial resolution, the optimal emissions are non-increasing as the threshold risk *r* decreases. That is, the optimal emissions should decrease or remain unchanged when moving from 100 in a million risk threshold to 1 in a million risk threshold. Figures 7.4 and 7.5 show that the variation is in the expected direction – the optimal emissions decrease as the threshold risk decreases – for both census tract regulation and census block regulation.

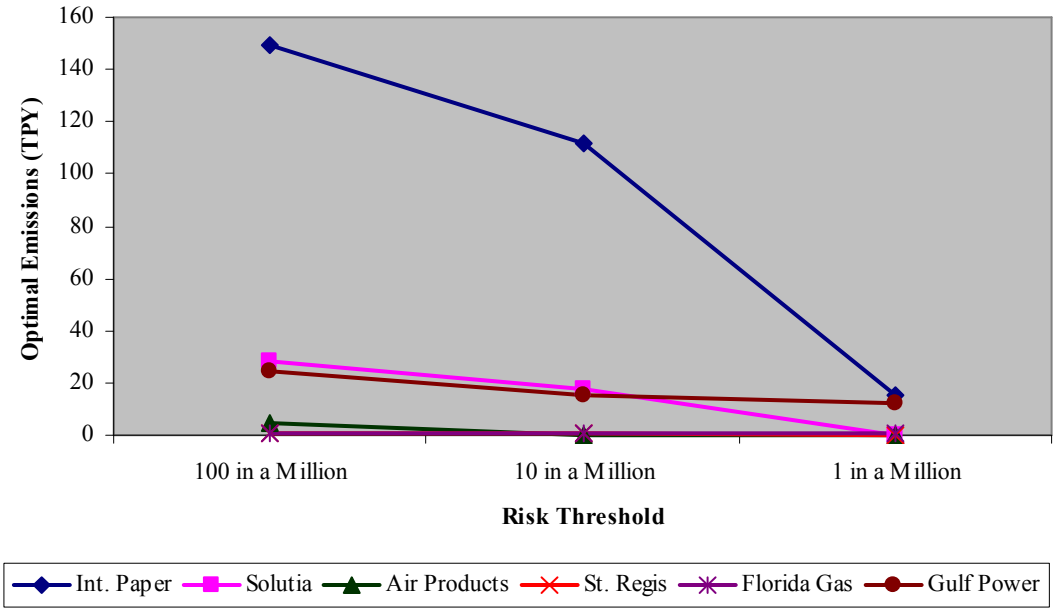

Figure 7.4 Variation of Optimal Emissions with Threshold Risk for Regulation at Census Tract Resolution

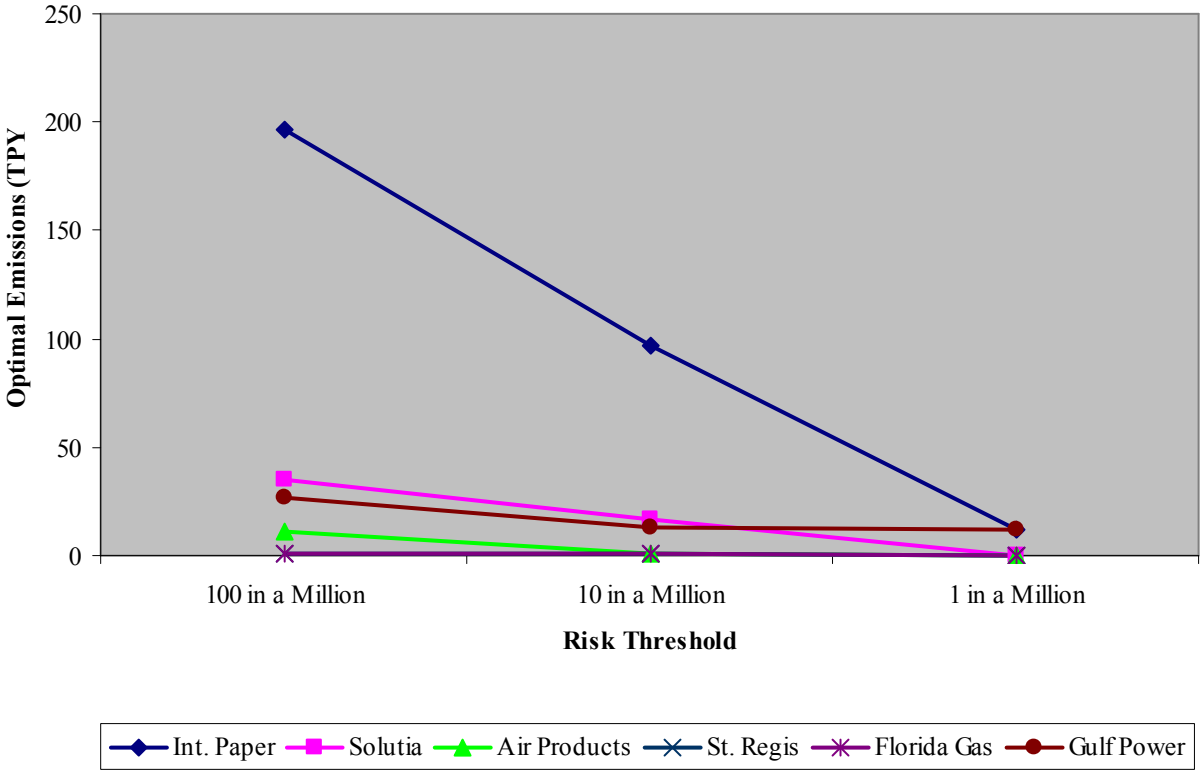

Figure 7.5 Variation of Optimal Emissions with Threshold Risk for Regulation at Census Block Resolution

7.4 Sensitivity to Value of Statistical Life (VSL)

Section 6.4.4 discussed in detail the need for analyzing the sensitivity of the results to estimates of VSL used in empirical analysis. The results presented in Tables 7.1, 7.3, and 7.5 are based on a VSL of $5.5 million (1999$). In this section, two other VSL estimates – $2.04 million (1999$) and $7.35 million (1999$) – are used to assess the sensitivity of optimal emissions to VSL for only a risk threshold of 100 in a million.[22]

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[22] Results were analyzed for other risk thresholds as well. Excluding the results from these risk thresholds do not change the conclusions of this section, however.

Table 7.7 shows the results of estimates of optimal emissions and net costs at the two estimates of VSL. First, the results are identical for $2.04 million VSL and $7.35 million VSL. Comparing the results in Table 7.7 with results in Table 7.1 (results of analysis based on $5.5 million VSL) reveals that alternative estimates of VSL have no effect on optimal emissions and net costs.

Table 7.7 Comparison of Optimal Emissions and Net Costs at Various Values of VSL (Risk Threshold: 100 in Million)

Facility	Source ID	Pollutant	Baseline Emissions (T/Y)	Optimal Emissions (TPY) (VSL=$2.04 million)			Optimal Emissions (TPY) (VSL=$7.35 million)		
				Census Tract	Block Group	Block	Census Tract	Block Group	Block
International Paper	IP01	Acetaldehyde	5.5	149.6	149.6	196.5	149.6	149.6	196.3
	IP02	Formaldehyde	8.5	0	0	0	0	0	0
		Acetaldehyde	50.9	135.1	135.1	69.2	135.1	135.1	69.3
		Benzene	5.08	0	0	0	0	0	0
Solutia	SO01	Formaldehyde	0.0436	1.6	1.6	7.9	1.6	1.6	7.85
		Acetaldehyde	0.00575	28.6	28.6	34.9	28.6	28.6	34.9
		Benzene	0.00052	9.37	9.37	15.7	9.37	9.37	15.6
Sterling Fibers	SF01	Acrylonitrile	2.819	0.11	0.11	0.03	0.11	0.11	0.03
	SF02	Acrylonitrile	5.48	0.28	0.28	0.21	0.28	0.28	0.21
	SF03	Acrylonitrile	1.159	0.17	0.17	0.07	0.17	0.17	0.07
Air Products	AP01	Formaldehyde	0.869	0	0	0	0	0	0
		Acetaldehyde	0.073	4.25	4.25	10.7	4.25	4.25	10.7
		Benzene	0.03	0	0	0	0	0	0
St. Regis	SR01	Formaldehyde	30.52	1.02	1.02	1.07	1.02	1.02	1.07
		Acetaldehyde	2.561	1.30	1.30	1.35	1.30	1.30	1.35
		Benzene	1.0405	1.10	1.10	1.15	1.10	1.10	1.15
	SR02	Formaldehyde	0.01027	1.06	1.06	1.11	1.06	1.06	1.11
		Acetaldehyde	0.00135	1.34	1.34	1.39	1.34	1.34	1.39
		Benzene	0.000123	1.14	1.14	1.19	1.14	1.14	1.19
	SR03	Benzene	1.3	0	0	0	0	0	0
Florida Gas	FG01	Formaldehyde	78.8	1.15	1.15	1.20	1.15	1.15	1.20
		Acetaldehyde	6.615	1.43	1.43	1.48	1.43	1.43	1.48
		Benzene	2.687	1.23	1.23	1.28	1.23	1.23	1.28
Gulf Power	GP01	Formaldehyde	0.031	14.9	14.9	18.4	14.9	14.9	18.4
		Acetaldehyde	0.000006	36.3	36.3	39.8	36.3	36.3	39.8
		Benzene	0.00087	21.1	21.1	24.5	21.1	21.1	24.5
	GP02	Formaldehyde	0.00098	24.3	24.3	27.0	24.2	24.3	27.0
		Acetaldehyde	0.0000002	45.6	45.6	48.4	45.6	45.6	48.4
		Benzene	0.000028	30.4	30.4	33.1	30.4	30.4	33.1

Facility	Source ID	Pollutant	Baseline Emissions (T/Y)	Optimal Emissions (TPY) (VSL=$2.04 million)			Optimal Emissions (TPY) (VSL=$7.35 million)		
				Census Tract	Block Group	Block	Census Tract	Block Group	Block
	GP03	Formaldehyde	0.00228	37.9	37.9	40.2	37.9	37.9	40.2
		Acetaldehyde	0.0000004	59.3	59.3	61.6	59.3	59.3	61.6
		Benzene	0.0000621	44.0	44.0	46.4	44.0	44.0	46.4
	GP04	Nickel	0.4095	0	0	0	0	0	0
		Arsenic	0.438	0	0	0	0	0	0
Net Costs (Million $/y)				17.75	17.75	35.47	17.75	17.75	35.47

CHAPTER 8

RESULTS: ANALYSIS OF DISTRIBUTION OF RISKS AND COSTS

This chapter presents the second set of results of empirical analysis. The first part of the chapter discusses how regulation at finer spatial resolutions affects the spatial distribution of cancer risks. This part also examines, through a correlation analysis, if regulation at finer resolutions addresses environmental justice (EJ) concerns. The final section of this chapter analyzes the distributional effects of regulation at finer resolutions on industry abatement costs.

8.1 Spatial Resolution and Spatial Distribution of Cancer Risks

One of the goals of characterizing air toxics risks at finer spatial resolutions is to address disproportionate impacts of air toxics exposures, as discussed in Chapter 1. It is expected that by regulating risks at finer and finer spatial resolutions, risks in hot spots that are not apparent at coarse resolution could be reduced, thus ensuring a more equitable distribution of risk. The empirical analysis carried out for this research could be used to demonstrate how the spatial distribution of risks changes with a change in the spatial resolution chosen for regulation.

8.1.1 Spatial Resolution and Maximum Individual Risk (MIR)

In order to demonstrate the impact of regulation at finer resolution on spatial distribution of risks, the analysis presented in this section estimates cancer risks at two

resolutions of regulation – census tract and census block[23] – and at two threshold risk levels (100 in a million and 10 in a million). Using the set of optimal emissions estimated at each resolution of regulation, cancer risks are estimated at the centroid of each census block.

Figure 8.1 shows the spatial distribution of cancer risks when risks are regulated at census tract resolution at the risk threshold of 100 in a million. The circled area in the figure is enlarged in the inset so that the blocks with risks greater than 100 in a million are clearly seen. The maximum individual risk (MIR) is 187 in a million when risks are regulated at the census tract resolution, although the risk threshold for the regulation is 100 in a million. The census blocks with MIR greater than 100 in a million, which are the hot spots in this case, are represented in red in Figure 8.1. Figure 8.2 shows spatial distribution due to regulation at the finer census block resolution at 100 in a million risk threshold. As expected, the MIR in this case is 100 in a million. The inset of Figure 8.2 shows that the hot spots that are seen in red blocks at census tract regulation (in Figure 8.1) disappear at the census block resolution. The spatial distribution of cancer risks in Figure 8.2 indicates that no census block in the two county area has a cancer risk greater than 100 in a million whereas the distribution in Figure 8.1 shows that a few blocks, represented in red, have cancer risks greater than 100 in a million with the maximum risk being 187 in a million.

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[23] Optimal emissions were also estimated for regulation at census block group resolution. However, the analysis in this chapter is restricted to tract and block level resolution because there was very little variation in optimal emissions between tract and block group level resolutions at all risk thresholds.

Figures 8.3 shows spatial distribution of risks when the risks are regulated at the census tract resolution with a threshold risk of 10 in a million. Again, the red blocks in the figure show the hot spots where cancer risk is above the 10 in a million threshold MIR. There are a few red blocks spread over the entire two county area and the inset shows the hot spots in the circled area. The MIR at the census tract regulation is 17 in a million, although the threshold risk is 10 in a million. Figure 8.4 shows spatial distribution of cancer risks when risks are regulated at the census block resolution. The MIR, not surprisingly, is 10 in a million and all the hot spots (the red blocks) that showed up in Figure 8.3 disappear here indicating that no census block has a risk greater than 10 in a million. Thus, regulation at finer spatial resolution can potentially reduce MIR.

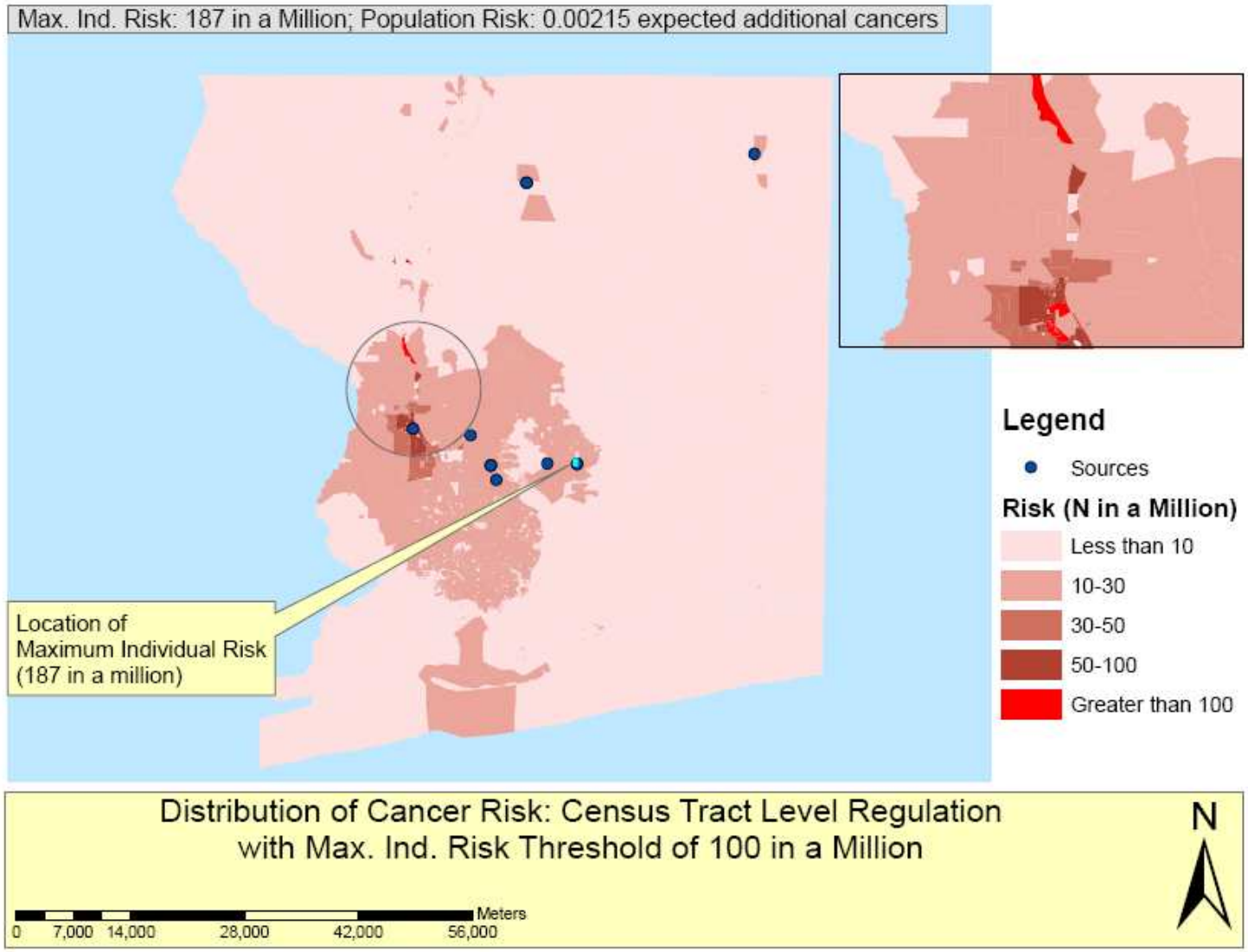

Figure 8.1 Spatial Distribution of Cancer Risks under Regulation at Census Tract Resolution (Cancer Risk Threshold of 100 in a Million)

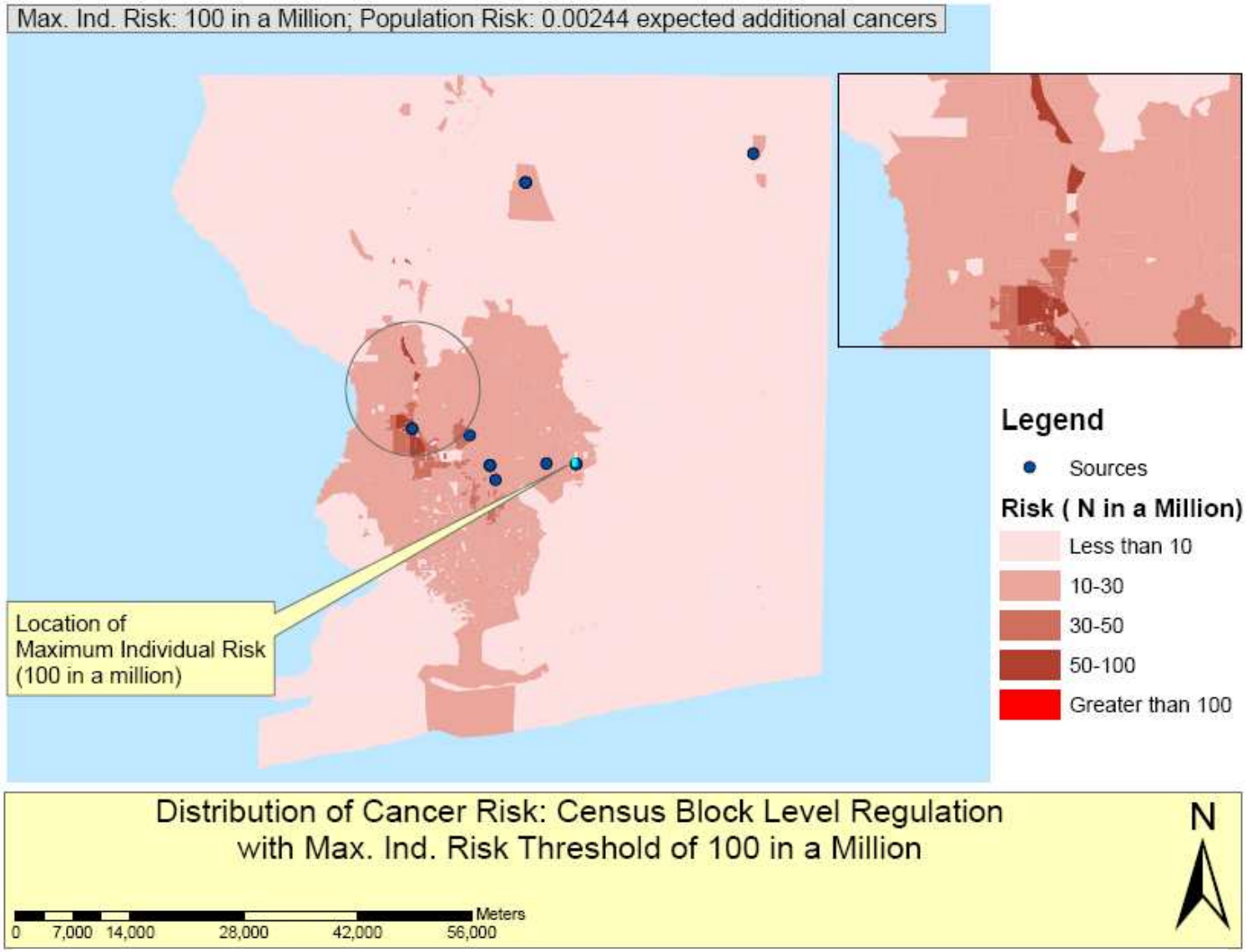

Figure 8.2 Spatial Distribution of Cancer Risks under Regulation at Census Block Resolution (Cancer Risk Threshold of 100 in a Million)

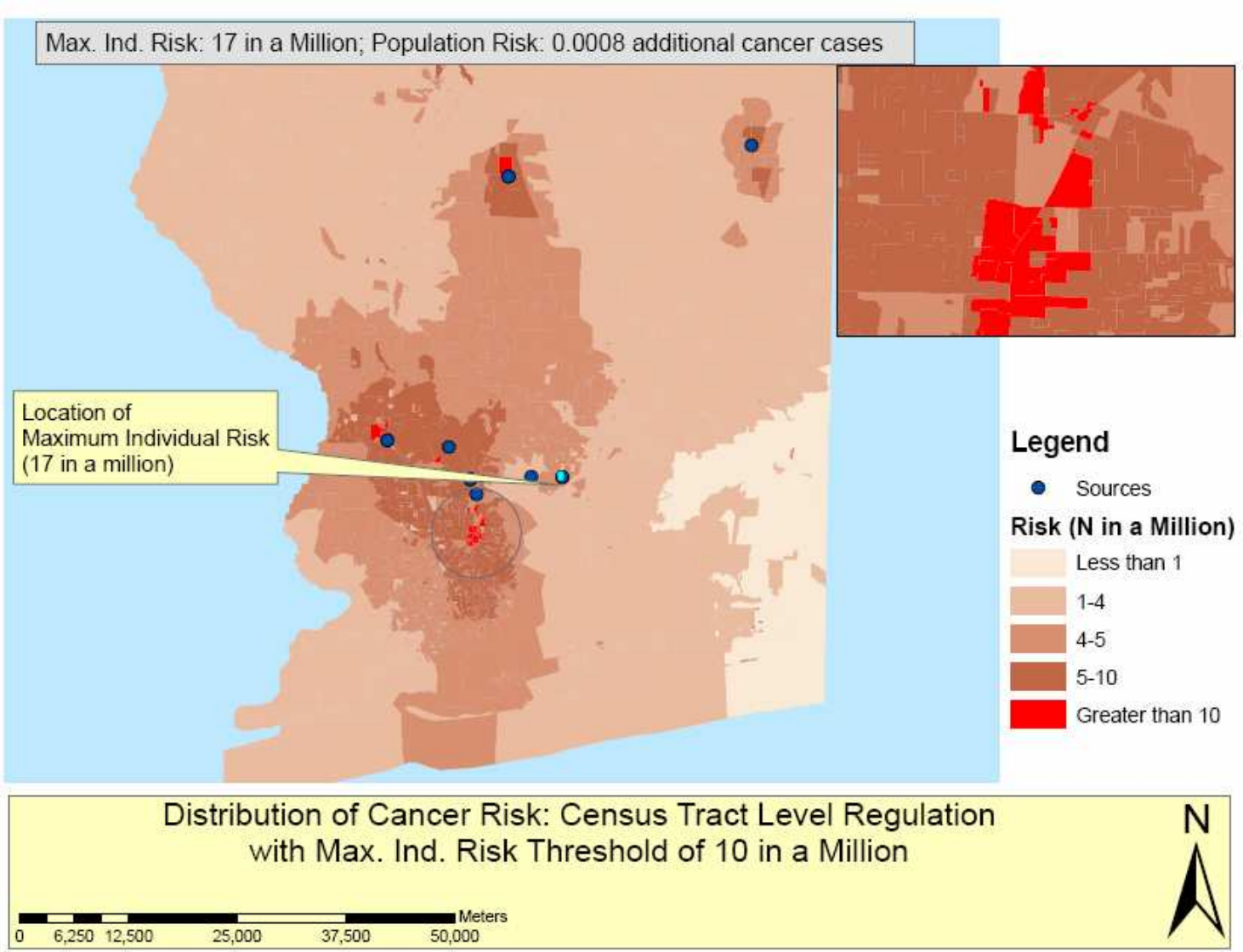

Figure 8.3 Spatial Distribution of Cancer Risks under Regulation at Census Tract Resolution (Cancer Risk Threshold of 10 in a Million)

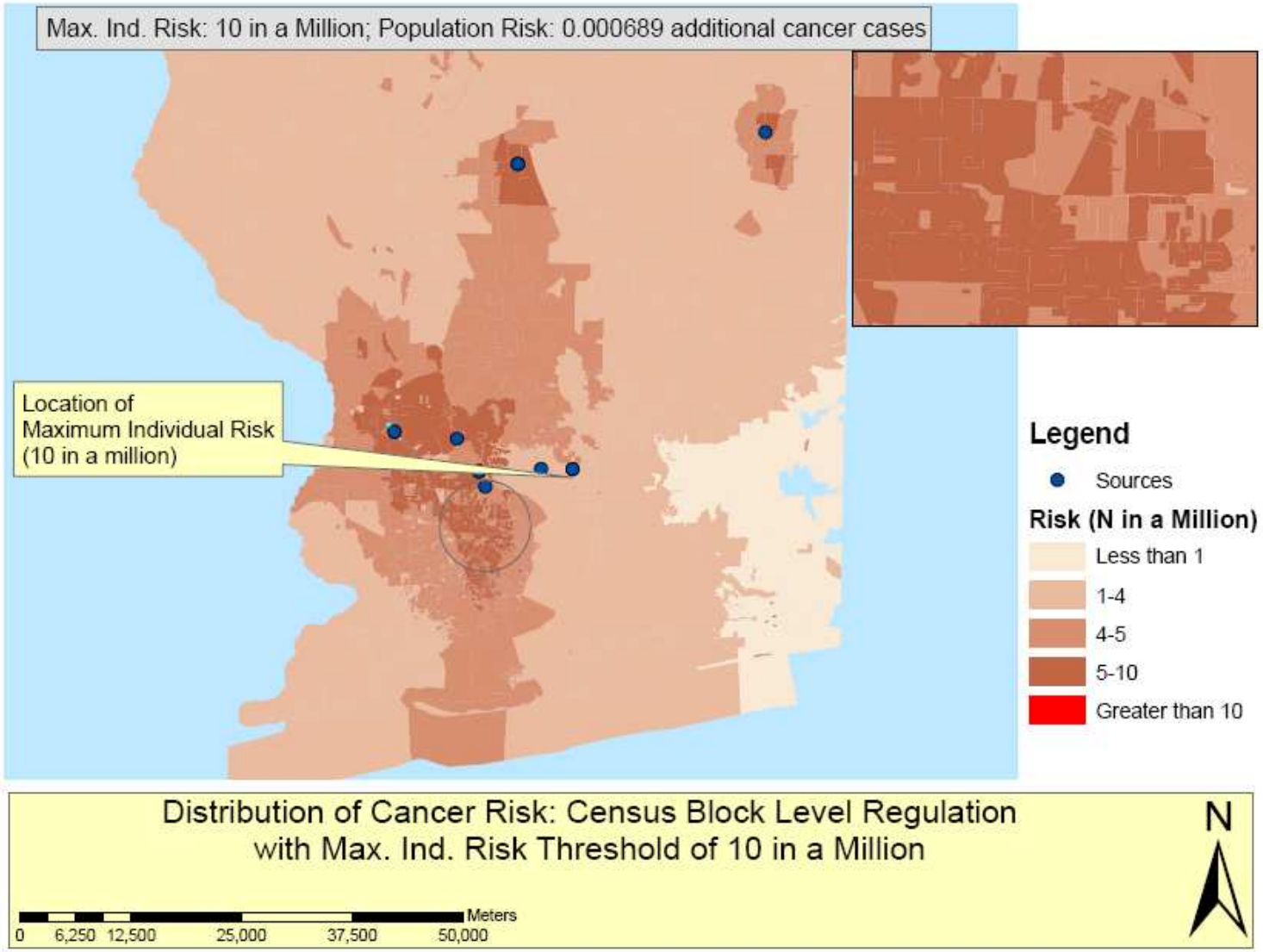

Figure 8.4 Spatial Distribution of Cancer Risks under Regulation at Census Block Resolution (Cancer Risk Threshold of 10 in a Million)

8.1.2 Spatial Resolution and Population Risks

Population risks in this research are measured as the expected additional cases of cancer due to air toxics exposures. The expected cancer cases are calculated as the product of cancer risk at the centroid of census block and population of the census block summed over all the 9881 census blocks in the two county study area.

In Chapter 7, while discussing expected additional cancers due to air toxics emissions remaining after regulation at 100 in a million threshold risk, it was found that the expected additional cancers were higher under regulation at the finer census block resolution (Refer to Figure 7.1). The expected cancers due to emissions remaining after regulation at census tract resolution were 0.00215 and the expected cancers at census block resolution were 0.00244. In the context of the decision model assumed in this paper, this result could be explained as follows. As discussed in Section 7.1.1, regulation at census block resolution, as opposed to census tract resolution, decreases emissions from some source and increases emissions from other sources. If the increase in emissions increases risk in areas that are highly populated, then overall population risks might increase.

Thus, while regulation at finer resolution (census block) results in a decrease in MIR from 187 in a million to 100 in a million, population risk increases. While this result might be an artifact of the specific empirical context studied here (that is, emission increases at finer resolutions occurring for those sources that are located in populated areas), the result still suggests that reduction in individual risks might come at the cost of increases in overall population risks. This is a criticism often put forward by public health

scholars against the focus on MIR in regulatory decision making (Goldstein, 1989; Goldstein & Carruth, 2003).

8.2 Environmental Justice (EJ) Analysis

The increasing evidence (Morello-Frosch et al., 2001; Lopez, 2002; Morello-Frosch et al., 2002; Dolinoy & Miranda, 2004; Apelberg et al., 2005) that low income and minority groups might be subjected to disproportionately high air toxics risks coupled with the likelihood that such groups are more susceptible than others to air pollution exposures (Rios, Poje, & Detels, 1993; O'Neill et al., 2003) due to a variety of biological and non-biological factors makes EJ an important policy concern. An important rationale for the increasing drive toward characterizing air toxics exposures at finer spatial resolutions has been the concern about environmental injustice.

The results in Section 8.1.1 show that regulation at finer spatial resolution can reduce MIR in hot spots. The analysis presented in Section 8.1.1, however, does not examine the association between reduction in risk due to regulation at finer spatial resolutions and population characteristics. This section presents a simple correlation analysis to test whether regulation at finer spatial resolutions addresses the EJ concerns.

8.2.1 Change in Cancer Risk and Race

The hypothesis tested here is that, if regulation at finer spatial resolutions were to address EJ concerns, change in risks due to regulation at finer resolution should be negatively correlated with EJ variables. In other words, regulation at finer resolutions would address EJ concerns if cancer risks attributable to air toxics decrease in areas with higher populations of minorities and low-income groups. The EJ variable for this analysis

is percent nonwhite population[24] and the association between change in risk and percent nonwhite is analyzed at the census block level.

Cancer risk is calculated at the centroid of each census block, according to equation *(4.1)*, reproduced below as equation *(8.1)*. Cancer risk at the centroid of each census block is calculated for regulation at each spatial resolution (census tract, census block group, and census block) for each risk threshold (100 in a Million, 10 in a Million, and 1 in a Million) based on optimal emissions presented in Tables 7.1, 7.3, and 7.5.

$$r_k = \sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ijk}u_j \qquad (8.1)$$

Where,

r_k Cancer risk at the k th census block

Q_{ij} Optimal Emissions (in *g/s*) of pollutant j from source i due to regulation at any given spatial resolution and risk threshold

β_{ijk} Exposure concentration, in [($\mu g/m^3$)/(g/s)], at any regulated location k due to unit emission rate (1 *g/s*) of pollutant j from source i

u_j Unit Risk Factor for j th pollutant, ($\mu g/m^3$)$^{-1}$ (represents the probability of cancer due to continuous exposure for 70 years to 1 $\mu g/m^3$ of pollutant j)

After calculating cancer risks at each census block due to regulation at each spatial resolution and each risk threshold, changes in cancer risk due to regulation at finer

[24] Association between change in cancer risk and income could not be tested because census data on median household income are not available at the census block level

spatial resolution is calculated at the centroid of each census block. The following table (Table 8.1) shows the pair-wise correlation between changes in risk due to regulation at finer resolutions and percent nonwhite population at census block level.

Table 8.1 Pair-wise Correlation between Change in Estimated Cancer Risk due to Regulation at Finer Resolutions and Percent Nonwhite (N = 7147)

Risk Threshold	Change in Risk due to change in Resolution of Regulation from Tract to Block Group	Change in Risk due to change in Resolution of Regulation from Tract to Block
100 in a Million	0	0.063**
10 in a Million	-0.27**	-0.31**
1 in a Million	0.028**	0.052**

** Correlations statistically significant at 1%

The results in Table 8.1 indicate mixed evidence for the effect of regulation at finer resolutions on environmental justice. At 100 in a million threshold risk, there was no change in the optimal emissions between census tract resolution and census block group resolution and hence there is no change in risk either, as indicated by the zero correlation in the first cell of Table 8.1. If the sources were to be regulated at the census block resolution instead of the census tract resolution, the correlation coefficient is positive indicating that blocks with increases in cancer risks have higher percentages of nonwhite population. In the context of the finding in Section 8.1.1 that MIR in hot spots decreases when risks are regulated at census block as opposed to census tract resolution, the positive correlation here indicates that decreases in cancer risk have not occurred in blocks with higher proportion of minorities. Although statistically significant, the correlation is weak (0.063).

At 10 in a million risk threshold, however, there is a relatively strong and statistically significant negative correlation between change in cancer risks and percent

nonwhite. This indicates that at 10 in a million risk threshold, regulation at finer resolution reduces risk in blocks with higher percentage of minorities. At 1 in a million risk threshold, the positive correlations resurface. The correlations, however, are weak although statistically significant. This result is not surprising. As discussed in Chapter 7, a 1 in a million risk threshold risk is so strict that the optimal emissions are zero for a number of sources even at the coarse census tract resolution. Because of this, changes in optimal emissions and hence cancer risks are very small when regulated at finer resolutions. The relative lack of variation in change in cancer risk between tract and block resolution is reflected in the weak correlation shown in the last row of Table 8.1.

In summary, at 100 in a million and 1 in a million threshold risk, regulation at finer resolution increases risk in areas with higher proportion of minorities. At 10 in a million threshold risk, the converse is true; regulation at finer resolution decreases risk in blocks with higher proportion of minority population. Overall, these results indicate that regulation at finer spatial resolutions might reduce MIR in hot spots; that reduction in MIR, however, need not automatically translate into reduction in risks for EJ communities. This result is somewhat expected because nothing in the decision model developed in Chapter 4 explicitly accounts for EJ concerns in the hypothetical decision maker's choice of optimal emissions. Possible ways in which EJ concerns could be incorporated into the decision model for the hypothetical decision maker are discussed in Chapter 11.

8.2.2 Expected Annual Cancer Incidence and Race

The analysis presented in the previous section examines the association between change in cancer risks and the *percentage* of nonwhite population. The *percentages* do

not adequately reveal the absolute number of people affected by the changes in cancer risks due to regulation at finer spatial resolutions. For example, consider two scenarios. In scenario 1, let us suppose that cancer risks decrease in blocks with very small population but very high *percentage* of minority population (that is, the few people that live in the block are minorities). The correlation coefficients for scenario 1 will show a strong negative correlation indicating that regulation at finer resolutions has a strong positive effect on EJ. In scenario 2, let us suppose that the cancer risks decrease by the same magnitude as in scenario 1 but in census blocks with large population and lower *percentage* of minorities (compared to scenario 1). The correlation analysis in this scenario 2 shows weaker relationships than in scenario 1, although the same decrease in cancer risks benefits a bigger minority population than in scenario 1. To overcome this drawback, this section replicates the correlation analysis of the previous section but uses the change in expected annual cancer incidence as the dependent variable. The change in expected annual cancer incidence weighs change in risk by the population affected by the change in risk. That is, change in expected annual cancer incidence in the *i* th census block = annual cancer risk at the centroid of the *i* th census block * total population of the *i* th census block. Table 8.2 shows the results of the correlation analysis.

Table 8.2 Pair-wise Correlation between Change in Expected Annual Cancer Incidence (= Change in Annual Cancer Risk * Population) due to Regulation at Finer Resolutions and Percent Nonwhite (N = 7147)

Risk Threshold	Change in Incidence from Tract Regulation to Block Group Regulation	Change in Incidence from Tract Regulation to Block Regulation
100 in a Million	0	-0.0034
10 in a Million	-0.0012	-0.0019
1 in a Million	0.0294	0.045**

** Correlations statistically significant at 1%

The results in Table 8.2 show that there is no statistically significant association between change in expected cancer incidence and percent minority, except in one case where the association is positive and statistically significant. This result is in sharp contrast to the results shown in Table 8.1. At 10 in a million threshold risk, for example, decrease in cancer risk due to regulation at finer resolutions was strongly associated with a higher proportion of minorities (Table 8.1), but when this decrease in risk was weighted by the size of population affected, there was no evidence of association with higher proportion of minorities. The implications of this result are discussed in detail in Chapter 10.

8.3 Spatial Resolution and Distribution of Abatement Costs

The empirical results in Tables 7.1, 7.3, and 7.5 indicate that optimal emissions decrease for some sources of air toxics, increase for some, and remain unchanged for others as the spatial resolution of regulation increases from census tract to census block resolution. The changes in optimal emissions at finer resolutions are associated with changes in abatement costs for regulated sources. Using the cost functions estimated for the empirical analysis, the changes in abatement costs corresponding to change in optimal emissions at finer spatial resolution are calculated. Table 8.1 shows the changes in abatement costs due to regulation at the census block resolution for the 15 sources selected for the analysis. Because the cost functions are assumed to be identical for every pollutant emitted from a source, the changes in costs in Table 8.1 are cumulative costs of abatement of all pollutants from a source. Changes in abatement costs are calculated for all the three threshold risks.

The results at 100 in a million threshold risk suggest that significant abatement costs would be imposed on two facilities or four sources (International Paper and Sterling Fibers) when risks are regulated at census block resolution instead of a coarser census tract resolution. Abatement costs would drop for all the other sources. At the other risk thresholds, however, costs would increase for all the sources except for one source. It should be noted that the zeros in the table reflect either unchanged non-zero levels of optimal emissions or zero emissions at both the coarse resolution and the finer resolution.

Table 8.3 Change in Abatement Costs Due to Regulation at Finer Spatial Resolution

Facility	Source ID	Change in Abatement Costs Due to Regulation at Census Block Resolution Instead of Tract Resolution ($)*		
		Risk Threshold		
		100 in a Million	10 in a Million	1 in a Million
International Paper	IP01	-169,560	203,125	287,180
	IP02	5,533,709	0	0
Solutia	SO01	-656,487	28,066	0
Sterling Fibers	SF01	5,284,603	0	0
	SF02	2,628,089	2,143,006	812,408
	SF03	5,630,810	0	0
Air Products	AP01	-316,063	-42,322	0
St. Regis	SR01	-1,734	4,362	243,933
	SR02	-13,473	0	576,383
	SR03	0	0	0
Florida Gas	FG01	-763	-1,067	2,636,622
Gulf Power	GP01	-972,413	217,830	-42,111
	GP02	-36,306	70,457	226
	GP03	-10,383	17,884	73,406
	GP04	0	0	0

* Negative values indicate decrease in abatement costs and positive values indicate increase in abatement costs

As expected, regulation at finer resolution not only affects the distribution of cancer risks, it also affects the distribution of abatement costs.

CHAPTER 9

UNCERTAINTY ANALYSIS

The model developed in Chapter 4 includes inputs around which significant uncertainties exist. The analysis presented in previous chapters was based on point estimates of input parameters. This chapter first reviews previous research on uncertainty in various input parameters to develop a rationale for the approach used in the uncertainty analysis. The later sections present the results of the uncertainty analysis and the final section discusses the interpretation of the results.

9.1 Approach for Uncertainty Analysis

Chapter 4 developed the model of a hypothetical decision maker choosing emission levels to minimize net social costs subjected to the constraint that cancer risk at no spatial location exceeds a threshold value. The following was the mathematical representation of the model.

$$\underset{Q_{ij}}{Min}\left\{\left(\sum_{i=1}^{I}\sum_{j=1}^{J}\int_{Q_{ij}^{b}}^{Q_{ij}} MC_{ij}\left(Q_{ij}\right).dQ_{ij}\right)+\left(\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} Q_{ij}\beta_{ijm}u_{j}p_{m}V\right)\right\} \qquad (9.1)$$

Subject to the constraints that:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ijk}u_{j} < r \qquad \forall\ k\ =\ 1,2,3,\ldots,K$$

$$Q_{ij} \geq 0$$

Q_{ij} Emission rate (*g/s*) of pollutant *j* from *i* th source

β_{ijm} Exposure concentration, in [($\mu g / m^3$)/(g/s)], at population location *m* due to a unit emission rate (1 *g/s*) of pollutant *j* from source *i* = *f* (meteorology, emission and source characteristics, site characteristics, location of the measurement point with respect to the source, activity patterns of exposed population, etc.,)

β_{ijk} Exposure concentration, in [($\mu g / m^3$)/(g/s)], at any regulated location *k* due to unit emission rate (1 *g/s*) of pollutant *j* from source *i*

u_j Unit Risk Factor for *j* th pollutant, ($\mu g / m^3$)$^{-1}$ (represents the probability of cancer due to continuous exposure for 70 years to 1 $\mu g / m^3$ of pollutant *j*)

p_m Population at location *m*

V Value of Statistical Life

The functional form assumed for the cost functions is exponential, as discussed in Section 5.4.1.1 in Chapter 5. Annual costs are expressed as:

$$C_{ij} = a_{ij} e^{b_{ij} Q_{ij}} \qquad (9.2)$$

C_{ij} = Annual costs of abatement for pollutant j from source i ($)
Q_{ij} = Emission Levels of pollutant j from source i (Ton/Year)
a_{ij}, b_{ij} = Cost Parameters to be estimated

Substituting this cost function in equation *(9.1)* gives the following form for the equation to be estimated.

$$\underset{Q_{ij}}{Min} \left\{ \left(\sum_{i=1}^{I} \sum_{j=1}^{J} (a_{ij} e^{b_{ij} Q_{ij}} - a_{ij} e^{b_{ij} Q_{ij}^{b}}) \right) + \left(\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{m=1}^{M} Q_{ij} \beta_{ijm} u_j p_m V \right) \right\} \qquad (9.3)$$

Subject to the constraints that:

$$\sum_{i=1}^{I}\sum_{j=1}^{J} Q_{ij}\beta_{ijk}u_j < r \qquad \forall\ k\ =\ 1,2,3,\ldots,K$$

$$Q_{ij} \geq 0$$

This research analyzes uncertainty in four parameters in equation *(9.3)* – annual average ambient concentrations (β_{ijm} and β_{ijk}), cancer unit risk factor (u_j), and cost parameters (a_{ij}, b_{ij}).

9.1.1 Uncertainty in Ambient Air Concentrations

The empirical analysis in this study used the Industrial Source Complex Short Term Version 3 (ISCST3) air dispersion model for estimating annual average ambient concentrations (β_{ijm} and β_{ijk}), as discussed in Chapter 5. The ISCST3 model is a steady state Gaussian Plume model and estimates hourly ambient air concentrations from point sources at a downwind distance *x* and crosswind distance *y* according to the following equation (reproduced from EPA, 1995).

$$C = \frac{QKVD}{2\pi u_s \sigma_y \sigma_z}\left[-0.5\left(\frac{y}{\sigma_y}\right)^2\right] \qquad (9.4)$$

Q Emission Rate (mass per unit time)

K Scaling Coefficient to Convert Units of Measurement

V Vertical Term, which is a function of such parameters as elevation of emission source, elevation of spatial location where concentration is estimated, mixing height, and plume rise

D Decay Term

$\sigma_y \sigma_z$ Standard Deviation of Lateral and Vertical Concentration Distribution (*m*)

u_s Mean Wind Speed (*m/s*) at Release Height

The total uncertainty in air dispersion models such as ISCST3 has three major components: model uncertainty, input parameter uncertainty, and stochastic uncertainty (Hanna, 1988; Rao, 2005). Model uncertainty arises if the mathematical representation of the model does not accurately capture the true dispersion process. For example, ISCST3 assumes that the dispersion of pollutants from an emission source follows a steady state Gaussian process. Model uncertainty represents the deviation of the true dispersion processes from this assumption.

Equation (9.4) indicates that ISCST3 requires a variety of input parameters to estimate ambient air concentrations all of which may have uncertainties in their measurement. This uncertainty is called input parameter uncertainty. Stochastic uncertainty arises from the inherently variable nature of atmospheric turbulence. This type of uncertainty is relevant for estimating concentrations for short averaging periods such as 1-hour averages and is not considered important for annual average concentrations (Rao, 2005).

9.1.1.1 Research on Uncertainties in the ISCST Model

Although quantification of uncertainties in air quality models has long been discussed (Fox, 1984), much of the empirical work has been more recent. The initial research focused on analytical techniques for propagating uncertainty in dispersion models (e.g., Freeman et al., 1986). However, with advances in computational power,

simulation techniques such as Monte Carlo (MC) simulations have become more common. The next few paragraphs review the studies of uncertainty in ISCST model predictions, with specific reference to estimation of ambient concentrations of toxic air pollutants, in order to provide a basis for the distributional assumptions made in this study.

A recent paper studied uncertainty of the ISCST3 and AERMOD models in predicting annual average concentrations of hexavalent chromium emitted from welding processes at a ship building and repair facility in California (Sax & Isakov, 2003). The study specified uncertainties in quantity of emissions, spatial and temporal allocation of emissions, model input parameters such as emission release parameters, building downwash, Bowen ratio, surface roughness, and interannual variability of meteorology. While the study did not indicate the number of Monte Carlo runs used for deriving the uncertainty estimates, the results indicated that the "95% confidence interval of predicted pollutant concentrations spanned roughly an order of magnitude at each receptor..(Sax & Isakov, 2003, p: 3487)." The uncertainty factor for 95% confidence interval (the ratio of 95% confidence upper bound to median and the ratio of median to 95% lower bound) ranged between two and three. This study found that emission uncertainties (Q in equation 9.4) contribute most to uncertainty in predicted ambient concentrations.

Using a different approach to evaluating uncertainty in ISCST model predictions, another study compared the monitored concentrations of nine volatile organic compounds (VOCs) to concentrations predicted by ISCST3 model in three communities in Minneapolis (Pratt et al., 2004). The study found that model predicted concentrations for all pollutants were within a factor of two of monitored concentrations.

A more recent study examined uncertainty in annual average concentrations of benzene and 1,3-butadiene predicted by two Gaussian models – ISCST3 and AERMOD – in Houston area (Hanna et al., 2006). This study specified uncertainties in several input parameters such as emissions, wind speed, wind direction, cloud cover, mixing height, surface roughness length, Bowen ratio, vertical temperature gradient, and vertical and horizontal dispersion parameters and studied uncertainties in predictions of pollutant concentrations by using 100 Monte Carlo runs. The predicted concentrations for 100 runs followed a log-normal distribution and the uncertainty factor (±geometric mean) for the 95% confidence range was between 2 and 3. This result was consistent across models and pollutants.

9.1.1.2 Distributional Assumptions for this Study

This analysis assumed a log-normal probability distribution for annual average air toxics concentrations. Log-normal distributions are generally suitable for physical quantities such as pollutant concentrations that are constrained to being non-negative (Morgan & Henrion, 1990). Further, empirical research on uncertainties in predicted pollutant concentrations shows that concentrations do follow log-normal distributions (Dabberdt & Miller, 2000; Hanna et al., 2001; Hanna et al., 2006).

A variable has a log-normal distribution if the logarithm of the variable has a normal distribution. Log-normal distribution are described by the mean (μ_{lnx}) of the logarithm of the variable and the standard deviation (σ_{lnx}) of the logarithm of the variable (Morgan & Heniron, 1990). Alternatively, log-normal distributions can also be described by their geometric mean (GM) and geometric standard deviation (GSD) (Limpert, Sahel, and Abbt, 2001). The GM is exp (μ) and GSD is exp (σ). GM is also the median of the

log-normal distribution. The uncertainty analysis in this study assumes that the annual average concentration predicted by ISCST3 model (used in deterministic analyses presented in chapter 7) represents the median (or GM) of the log-normal distribution. Research reviewed in Section 9.1.1.1 indicates that the uncertainty factor ranges from two to three. Consistent with that research, this analysis assumes an uncertainty factor of 2.5. This corresponds to a GSD of 1.6 and a $\sigma_{lnx} = 0.46$. Another important assumption made in characterizing uncertainty in ambient air concentrations in this study is that the correlations in concentrations across spatial locations are ignored. In Gaussian plume models, ambient concentrations predicted at one location are potentially correlated with concentrations predicted by the model at other locations in the modeling domain.

9.1.2 Uncertainty in Unit Risk Factor (URF)

EPA defines URF as "the upper-bound excess lifetime cancer risk estimated to result from continuous exposure to an agent at a concentration of 1 µg/L in water, or 1 µg/m^3 in air (EPA, 1999b, p: *xii*)." The URF is calculated using the following equation (Rood et al., 2001):

$$URF = \frac{SF * BR}{BW * CF} \qquad (9.5)$$

where URF is Unit Risk Factor in (µg /m^3)$^{-1}$ SF = Slope Factor in mg/kg-day, BW = Body Weight in kg, BR = Breathing rate in m^3/day, and CF = Conversion factor to convert mg into µg = 1000.

The slope factor in equation *(9.5)* is defined by EPA as "an upper-bound, approximating a 95% confidence limit, on the increased cancer risk from a lifetime exposure to an agent (EPA, 2007e)." The slope factor is derived using dose-response

assessments conducted based on either animal experiment studies or human epidemiological studies. Uncertainties exist in every step of dose-response assessments. Firstly, data on cancer incidence in experimental animals (such as mice and rats) are often used to derive response in humans. This is called inter-species extrapolation and the assumptions made in this extrapolation involve significant uncertainties[25]. Secondly, the doses or exposures of interest for human health risk assessments are much lower than the doses at which experimental animals respond in animal studies. This requires extrapolation to low doses based on dose-response data at higher doses. Typically, dose-response data at high doses are fitted to an assumed functional form and a point of departure (POD) for low-dose extrapolation is determined. From the POD, either a linear extrapolation (by drawing a line from POD to the origin) or, if sufficient evidence is available to assume a non-linear dose-response relationship at low doses, a non-linear extrapolation is used to derive the "slope factor." The assumption that dose-response relationship at high doses can be an indicator of a relationship at low doses and the assumption that a linear or non-linear extrapolation of some form sufficiently represents the relationship at low doses induce further uncertainty in the derivation of slope factors (EPA, 2005a).

Estimates of inhalation URF for different air toxics reported in EPA's Integrated Risk Information System (IRIS) are calculated based on upper-bound estimates of slope factors and a breathing rate of 20 m^3/day, and 70 kg body weight (EPA, 2005a). The

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[25] These uncertainties are not present when human data are used to derive slope factors. However, slope factors for most chemicals are based on animal data because of limited availability of data for epidemiological studies.

resulting value for the URF is an upper-bound estimate of cancer risk due to 1 μg /m^3 of lifetime (70 years) exposure to the pollutant. The assumption for breathing rate and body weight are based on an average adult individual and could vary considerably across population groups and individuals within a population group. For example, breathing rates and body weight could vary a great deal even within the adult population of a population group. Further, within a population group, breathing rates and body weight for children are significantly different from those of adults and thus these standard values are not appropriate when the assessed population is that of children. Thus this variability plays a role in determining an appropriate value for URFs.

Based on the discussion so far, an ideal uncertainty analysis for this study would specify a probability distribution for slope factors, to represent a range of possible values for each chemical (instead of a single upper bound estimate), and probability distributions for body weight and breathing rate in equation *(9.4)* and then use a Monte Carlo simulation to derive probability distributions for URFs for various chemicals. The major constraint in implementing such an approach is the difficulty in deriving distributions for slope factors. In spite of a great deal of research over the past few years on deriving probability distributions for cancer slope factors (see Boyce, 1998 for a comprehensive review), no standard approach has yet been developed to derive chemical-specific URF distributions (C.P. Boyce, personal communication, May 4, 2007) . Because of this, the distributions for URF are not readily available; rather, they have to be derived independently for each study.

The most commonly used and a relatively simple approach[26] for deriving probability distributions has been the statistical approaches that extend methods used by EPA to develop upper bound slope factors (e.g., Crouch et al., 1995). As discussed earlier in this section, uncertainty is encountered at various stages in the process of deriving cancer slope factors. Statistical approaches characterize the uncertainties at various stages to derive distributions for overall uncertainty in cancer slope factors (Boyce, 1998). Even this relatively simple approach is not so simple. This approach requires the original animal experimental data based on which EPA derived the point estimates of the slope factors reported in IRIS. This process is especially time-intensive if the distributions have to be derived for multiple chemicals, as required in this study. Hence an alternative approach that only characterizes the uncertainty in upper bound estimates of the URFs is used in this study.

9.1.2.1 Distributional Assumptions for URFs (u_j)

Although there is agreement between EPA and state agencies on the use of upper bound estimates for cancer risk assessments, the actual upper bound estimates used by agencies differ. For example, the upper bound URFs used by the California EPA, under its Air Toxics Hot Spots program, differ significantly from those used by federal EPA, for some air toxics. Appendix F of California EPA's "Technical Support Document for Describing Available Cancer Potency Factors" lists the air toxics for which the URFs of Cal EPA differ from those of U.S. EPA (Cal EPA, 2002). The basic approach used in

[26] Refer to Boyce (1998) for a review of various methods used in literature for deriving uncertainty distributions for slope factors

deriving the cancer slope factors is similar; however, differences in estimates of URFs "appear to be due mainly to differences in scientific judgment, differences in the interpretation of scientific data in individual cases, or to development of new scientific data…(Risk Assessment Advisory Committee, 1996, p: 4-10)."

Recognizing these differences in upper bound URFs between Cal EPA and U.S. EPA, the uncertainty analysis presented in this Chapter uses a uniform distribution with a lower bound corresponding to the lower estimate of the two agencies (Cal EPA and U.S. EPA) and an upper bound corresponding to higher estimate of the two agencies. Clearly, this is not the ideal approach for the analysis of interest here; but this approach is used because of the data constraints in developing a more comprehensive approach to characterizing uncertainty in URFs. The following table shows the lower bound and the upper bound URFs used in the uncertainty analysis conducted for this research.

Table 9.1 Assumed Distribution of URFs for Various Air Toxics

Air Toxic Chemical	Assumed Distribution	Point Estimate Used in Deterministic Analysis
Acetaldehyde	U (2.2E-06, 2.7E-06)	2.2E-06
Formaldehyde	U (0.6E-05, 1.3E-05)	1.3E-05
Benzene	U (0.78E-05, 2.9E-05)	0.78E-05
Acrylonitrile	U (0.68E-04, 2.9E-04)	0.68E-04
Arsenic	U (3.3E-03, 4.3E-03)	4.3E-03
Nickel	U (2.4E-04, 2.6E-04)	2.4E-04

Source: EPA's Integrated Risk Information System (IRIS) and Technical Support Document for Describing Available Cancer Potency Factors (Cal EPA, 2002)

9.1.3 Uncertainty in Cost Parameters

The cost functions for this research, discussed in Section 5.4.1 and Section 6.2, are estimated based on a number of assumptions that introduce significant uncertainties in

the estimation of the two cost parameters, a_{ij} and b_{ij} in equation *(9.2)*. First, the costs and the emission reductions associated with various abatement technology options are derived for an "average" source based on aggregate national estimates. These estimates can differ significantly for the specific sources analyzed in the empirical application, based on factors such as production capacity of the firm, process technology, and local input prices. Second, although a given abatement technology removes more than one toxic air pollutant, the empirical analysis assumes that the abatement technology is employed separately for each pollutant. This assumption results in multiple counting of costs, leading to potential overestimation of costs. Third, the background information documents (BID) and the regulatory impact analyses (RIA) used to identify the available abatement options, did not consider the full range of options for some source categories. For example, for some source categories, there were only two identified control options (including no control option). Thus the estimated cost functions for most of the sources are based on a very small sample size. Such a small sample size introduces huge uncertainties (very large standard errors in the non-linear least square estimation) in the estimation of the two cost parameters a_{ij} and b_{ij} .

The approach taken for quantifying uncertainty in cost parameters in this analysis is to utilize the estimates of means and standard errors on the parameters a_{ij} and b_{ij} , from the non-linear least square regression for each cost function, to generate a randomly drawn sample of values for each parameter. The random sample is drawn from a joint normal distribution with the correlation coefficient being empirically estimated from the non-linear least square regression estimation. The cost functions for Sterling Fibers, the TEG Reboiler of the St. Regis facility, and the turbines of Florida Gas and St. Regis

include only one abatement cost option listed in the respective RIAs. That is, including the "no control" option, the cost parameters are estimated based on two data points. The non-linear regressions do not generate standard errors for the cost parameters of these sources. Based on the largest standard errors among all sources, the standard errors for these three sources are assumed to be 80% of the mean value for the parameter a_{ij} and 25% of the mean value for the parameter b_{ij}.

Finally, an important assumption in the decision model regarding the cost functions is that the abatement costs increase at an increasing rate with abatement. This assumption means that the parameter a_{ij} is non-negative. However, when random samples are generated for the parameter a_{ij} from a joint normal distribution, because of the large standard errors on a_{ij} for some cost functions, a small percentage of the sample include negative values for a_{ij}. In order to be consistent with the assumptions of the model, the negative values on a_{ij} were constrained to have an arbitrarily small positive value of 0.1. This is clearly arbitrary and perhaps unrealistic. However, it illustrates the serious lack of data on abatement costs for air toxics.

9.2 Methodology for Uncertainty Analysis

The basic methodology followed for optimization runs in the deterministic analysis using point estimates of input parameters of the model was discussed in Section 5.4.2. The following were the steps involved in the implementation of uncertainty analysis presented in this chapter.

1. For each of the uncertain input parameters, a_{ij}, b_{ij}, u_j, β_{ijm}, and β_{ijk}, 500 samples – one for each simulation – were randomly drawn from the respective assumed probability distributions. There were 34 cost parameters – one for each combination of sources and pollutants (*I.J* in equation *9.3* = 34), 9881 ambient air concentration values (β_{ijm}) – one for each census block (M in equation *9.3* = 9881) – based on which population health costs are estimated in the objective function, six URFs (u_j) – one for each air toxic (*J*=6), and 77 constraints at census tract resolution, 317 constraints at census block group resolution, and 10198 constraints at census block resolution (i.e., K = 77 for census tract analysis, K = 317 for census block group analysis, and K = 10198 for census block analysis). Stata 9.2 was used to generate random samples.
2. As discussed in Section 5.4.2, to run General Algebraic Modeling System (GAMS), one needs to generate input files in GDX file format. The GDX format data are generated from data input into an *MS Excel* spreadsheet. Thus for this uncertainty analysis, 500 *MS Excel* input files and eventually 500 GDX input files – one for each simulation – were prepared using Macros in *MS Excel*. The decision to restrict the number of simulations to 500 was strictly based on the feasibility of generating input GDX files.
3. The GAMS optimization program with CONOPT solver for nonlinear programming was run in a batch mode with the 500 input GDX files. This batch run generated 500 output GDX files – one for each simulation – that contain optimal emissions and net costs. These outputs were then transferred into Stata 9.2 to conduct further statistical analyses presented in the next section.

The uncertainty analysis is carried out in two phases. In the first phase, costs are treated as known with certainty and the results of uncertainty in ambient air concentrations and URFs are analyzed. In the second phase, uncertainty in cost parameters is incorporated to examine the sensitivity of the results to uncertainty in cost estimates. The uncertainty analysis are carried out at one risk threshold – 10 in a million – for regulation at the three spatial resolutions (census tract, census block group, and census block). The analysis without uncertainty in cost parameters is carried out at one spatial resolution (census tract resolution) and at one risk threshold (10 in a million).

9.3 Results of Uncertainty Analysis[27]

9.3.1 Analysis without Uncertainty in Cost Parameters

9.3.1.1 Optimal Emissions

Table 9.2 shows the optimal emissions for select sources and pollutants at three spatial resolutions – census tract, census block group, and census block. For each spatial resolution, the table shows optimal emissions from the deterministic analyses (presented in Tables 7.1, 7.3, and 7.5) and six parameters – mean, standard deviation, median, 5th

[27] Because of the large number of pollutant/source combinations included in the analysis, results here are discussed based on a select set of source/pollutant combinations. These are selected such that the results based on these sources are generalizable across all combinations included in the analysis.

Table 9.2 Comparison of Optimal Emissions from Deterministic Analysis with Optimal Emissions from Uncertainty Analysis (Without Uncertainty in Cost Parameters) (Risk Threshold: 1E-05; VSL: $5.5 Million)

Resolution	Source	IP01	IP02	SO01	AP01	SF02	SR01	FG01	GP01	GP02	GP03
	Pollutant	**A**	**A**	**A**	**A**	**AN**	**A**	**F**	**A**	**B**	**F**
Census Tract	Deterministic Analysis	111.9	0	17.47	0	0.06	1.2	1.03	27.5	21.6	29.0
	Mean	91.3	2.77	12.83	2.6	0.022	1.0	1.08	23.47	9.07	30.1
	SD	25.7	4.18	4.78	3.6	0.024	0.2	0.07	3.62	5.37	4.9
	Median	90.6	1.2	13.1	0	0.018	1.04	1.08	23.6	8.34	29.8
	5th Percentile	50. 3	0.0	4.5	0	0	0.64	0.95	17.3	0.2	22.9
	95th Percentile	134.2	10.2	19.9	9.8	0.07	1.27	1.2	29.4	18.6	38.2
	99th Percentile	148.6	20.4	23.3	12.6	0.11	1.31	1.24	31.7	22.5	41.3
Census Block Group	Deterministic Analysis	113.9	0	17.0	0	0.06	1.19	1.03	26.9	21.4	29.1
	Mean	79.06	2.22	11.1	8	0.022	1.0	0.96	21.5	7.1	28.8
	SD	22.2	2.6	3.8	4.7	0.025	0.2	0.2	3.1	4.8	4.8
	Median	78.7	1.46	11.2	7.4	0.019	1.05	1.03	21.5	6.3	28.6
	5th Percentile	43.6	0	4.8	0.7	0	0.67	0.54	16.5	1.1	20.8
	95th Percentile	117.7	7.1	17.2	16.0	0.07	1.26	1.18	26.8	15.7	37.4
	99th Percentile	135.1	10.1	19.9	18.1	0.11	1.31	1.22	28.7	18.7	41.2
Census Block	Deterministic Analysis	96.9	0	16.4	0.54	0.03	1.14	1.06	24.6	19.5	27.4
	Mean	47.1	0.97	9.2	2.7	0.01	0.83	0.58	19.7	4.5	25.8
	SD	10.5	1.03	2.5	1.6	0.0096	0.17	0.17	2.4	3.9	4.3
	Median	47.2	0.75	9.3	3.1	0.009	0.8	0.56	19.8	3.7	25.9
	5th Percentile	29.9	0	5.2	0	0	0.6	0.33	15.6	0	19.0
	95th Percentile	63.7	2.8	13.5	4.9	0.03	1.18	0.9	23.3	12.2	33.3
	99th Percentile	71.2	3.6	15.1	5.7	0.04	1.2	1.02	24.6	16.1	35.4

Pollutants: A – Acetaldehyde; F – Formaldehyde; B – Benzene; AN – Acrylonitrile
Sources: IP – International Paper; SO – Solutia; SF – Sterling Fibers; SR – St. Regis; FG – Florida Gas; GP – Gulf Power

percentile, 95th percentile, and 99th percentile – that describe the distribution of optimal emissions derived from 500 simulations.

At census tract and census block group regulation, the optimal emissions from deterministic analysis generally fall between the median and the 95th percentile values of the distribution for most sources. The standard deviations are typically of the same order of magnitude as the mean except for the emissions from Gulf Power and Florida Gas. The 90% confidence range (range between 5th and 95th percentile) varies by an order of magnitude for most sources except for GP01 and GP03. This indicates a significant uncertainty in optimal emissions even without considering cost uncertainties.

The deterministic values, at the census tract and the census block group regulation, are typically closer to the 95th percentile than the median except for formaldehyde emissions from Florida Gas (FG01) and Gulf Power (GP03) and acetaldehyde emissions from International Paper (IP02) and Solutia (SO01). These results can be explained by going back to Table 9.1. This table (Table 9.1) shows the values of URFs used in the deterministic analysis as well as the bounds on URFs used in the uncertainty analysis. Among the four main pollutants, except in the case of formaldehyde, the deterministic analysis used the lower bound on the URF. All else equal, lower values of URF mean lower health costs and higher optimal emissions. Thus, for pollutants that used the lower bounds of the uncertainty distribution for deterministic analysis, the optimal emissions for most simulations are lower than the optimal emissions from deterministic analysis. This makes the deterministic optimal emissions fall into the upper tail of the simulated distributions. The opposite is true for formaldehyde for which

the deterministic analysis used the upper bound of the uncertainty distribution. In case of IP02 and SO01, the deterministic optimal emission is zero. As will be seen later in Figure 9.1, for acetaldehyde from IP02, more than half of the simulations result in zero optimal emissions and the remaining simulations show significant spread. Because of the large number of zeroes in the uncertainty simulation, the deterministic value (zero emissions) is closer to the median value than the 95th percentile value.

At the block resolution, however, the deterministic optimal emissions are not captured within the simulated distribution. The deterministic optimal emissions for most sources are well above the 99th percentile of the distribution. This potentially means that 500 simulations are not adequate to fully capture the range of possible optimal emissions at block regulation. This is likely because the number of constraints (K in the decision model) at the block resolution increase to 10,120 from 317 constraints at the block group resolution thus significantly increasing the number of input parameters. However, increasing the number of simulations would likely result in similar patterns explained for the case of census tract and census block group regulation.

Figure 9.1 shows histograms of optimal emissions for various pollutants from select sources. The distributions vary significantly across sources. Some of them approximate a normal distribution, some of them are skewed to the right, and some are skewed to the left. Acetaldehyde emissions from IP02 and acrylonitrile emissions from SF02 have large number of zeros in their distributions. These distributions are constrained in some sense because of the non-negativity constraint on emissions in the decision model.

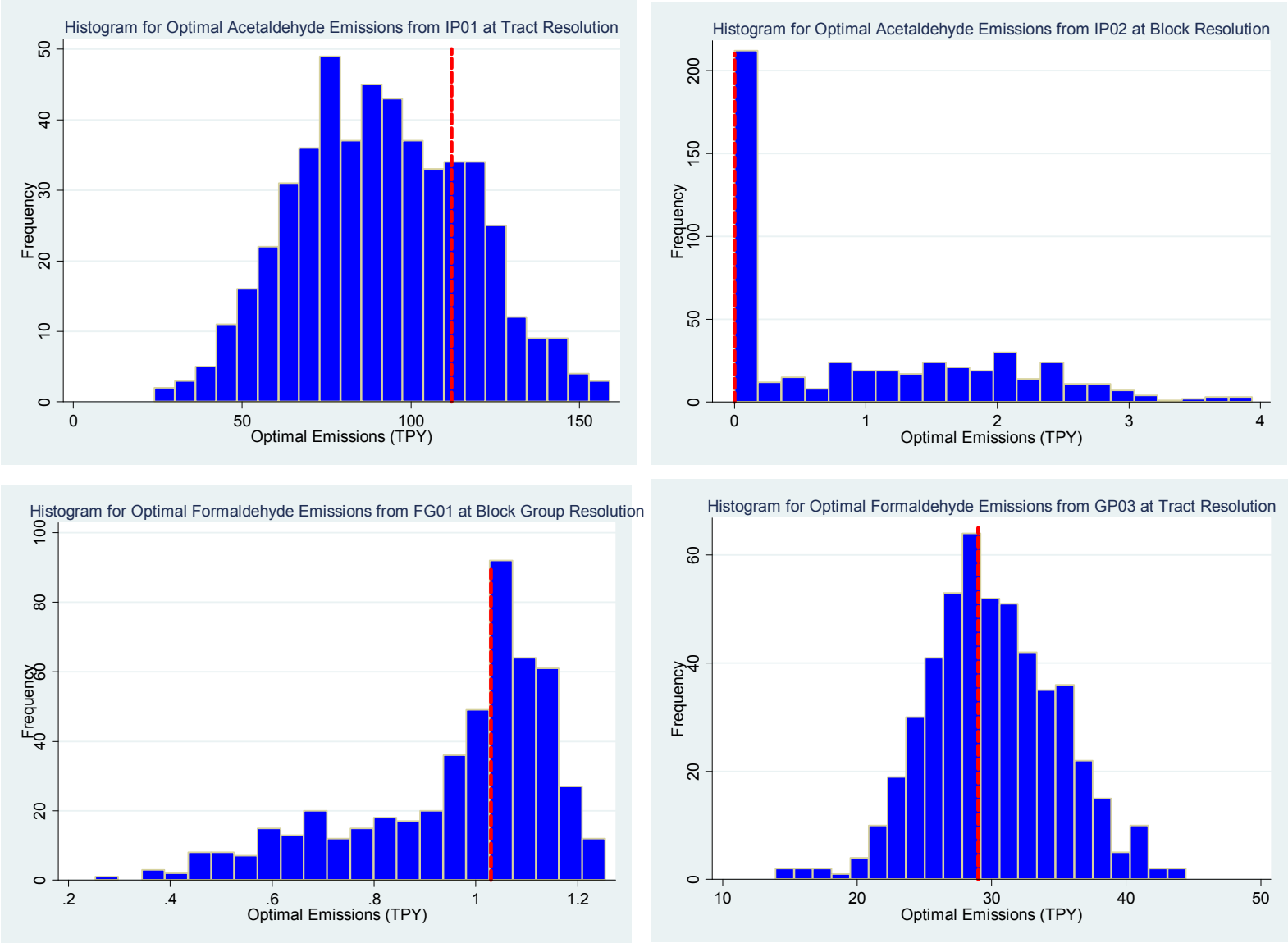


Figure 9.1 Histograms for Distribution of Optimal Emissions of Select Sources and Spatial Resolutions (Without Uncertainty in Cost Parameters) (*Deterministic optimal emissions are shown by red dashed lines*)

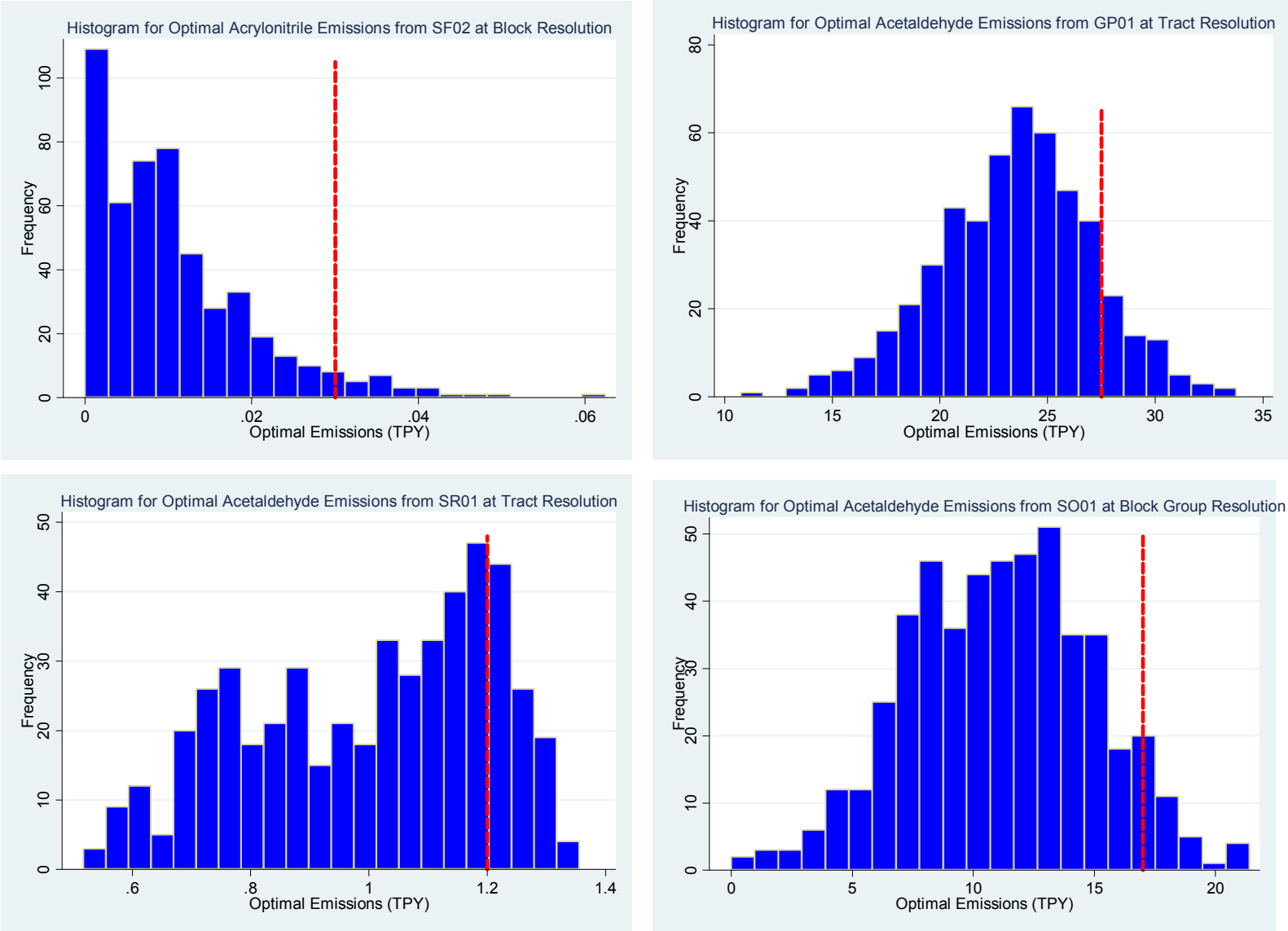


Figure 9.1 (cont'd) Histograms for Distribution of Optimal Emissions of Select Sources and Spatial Resolutions (Without Uncertainty in Cost Parameters) (*Deterministic optimal emissions are shown by red dashed lines*)

Optimal Emissions and Spatial Resolution under Uncertainty

The next question of interest is how uncertainty in ambient air concentrations and URFs affect optimal emissions across spatial resolutions of regulation. Again, Table 9.2 has some answers. First of all, the mean and the median of optimal emissions decrease as one regulates at finer resolutions. That is, emission standards become tighter and tighter at finer resolutions. This holds even for those sources that show a marginal increase in optimal emissions under the deterministic analysis. For example, under the deterministic analysis, the optimal emissions for IP01 increase at the finer census block group resolution compared to regulation at the census tract. However, the mean and the median optimal emissions of the simulated distributions decrease substantially at the finer resolution. Thus, if the hypothetical decision maker were to regulate acetaldehyde emissions from IP02 at the mean or the median of the distribution, the emission standards will be tighter at finer resolutions even if the deterministic choice relaxes the standards. This result also holds for other sources that show increases in optimal emissions at finer resolution. However, there are some sources (e.g., acrylonitrile from SF02 and acetaldehyde from SR01) for which deterministic analysis shows that the resolution at which these sources are regulated does not matter for optimal emissions and the uncertainty results are consistent with deterministic results. As seen from Table 9.2, the mean, median, and deterministic optimal emissions of SF02 and SR01 are the same at both tract and block group resolutions.

The second finding from Table 9.2 is that the standard deviation of the distribution of optimal emissions decreases from census tract resolution to the finer census block group and census block resolutions. This finding is generally consistent

across all sources. This means that the uncertainty in the choice of optimal emissions decreases as the sources are regulated at finer spatial resolutions.

The third finding from Table 9.2 is that there are significant overlaps in confidence ranges across spatial resolutions. That is, comparing the range of 5^{th} and 95^{th} percentile optimal emissions across spatial resolutions reveals that a particular range of optimal emissions are common across spatial resolutions. For example, the 5^{th} to 95^{th} percentile range for acetaldehyde emissions from IP01 is 50.3-134.2 at the census tract resolution, 43.6-117.7 at the census block group resolution, and 29.9-63.7 at the census block resolution. This shows that the range of optimal emissions from 50.3 to 63.7 is common to all the three resolutions. However, it is possible that the values within this overlapping region correspond to different confidence levels for different resolutions. The cumulative distributions functions (CDFs) can reveal if this is the case.

Figure 9.2 shows the CDFs of optimal emissions under regulation at the three spatial resolutions for a select set of sources. For most sources, the CDFs do not intersect, except at the tails of the distributions. Consistent with the findings from Table 9.2, the CDFs move to the left as the sources are regulated at finer resolutions. That is, at almost every confidence level, the optimal emissions decrease with increasing spatial resolution of regulation. There are a few exceptions, however. As discussed earlier, in two cases – acrylonitrile emissions from SF02 and acetaldehyde emissions from SR01 – the mean and the median of distributions were the same for the census tract and the census block group resolutions. The CDFs for these sources reinforce the finding; the two CDFs (tract and block group) for these two sources are indistinguishable (see Figure 9.2).

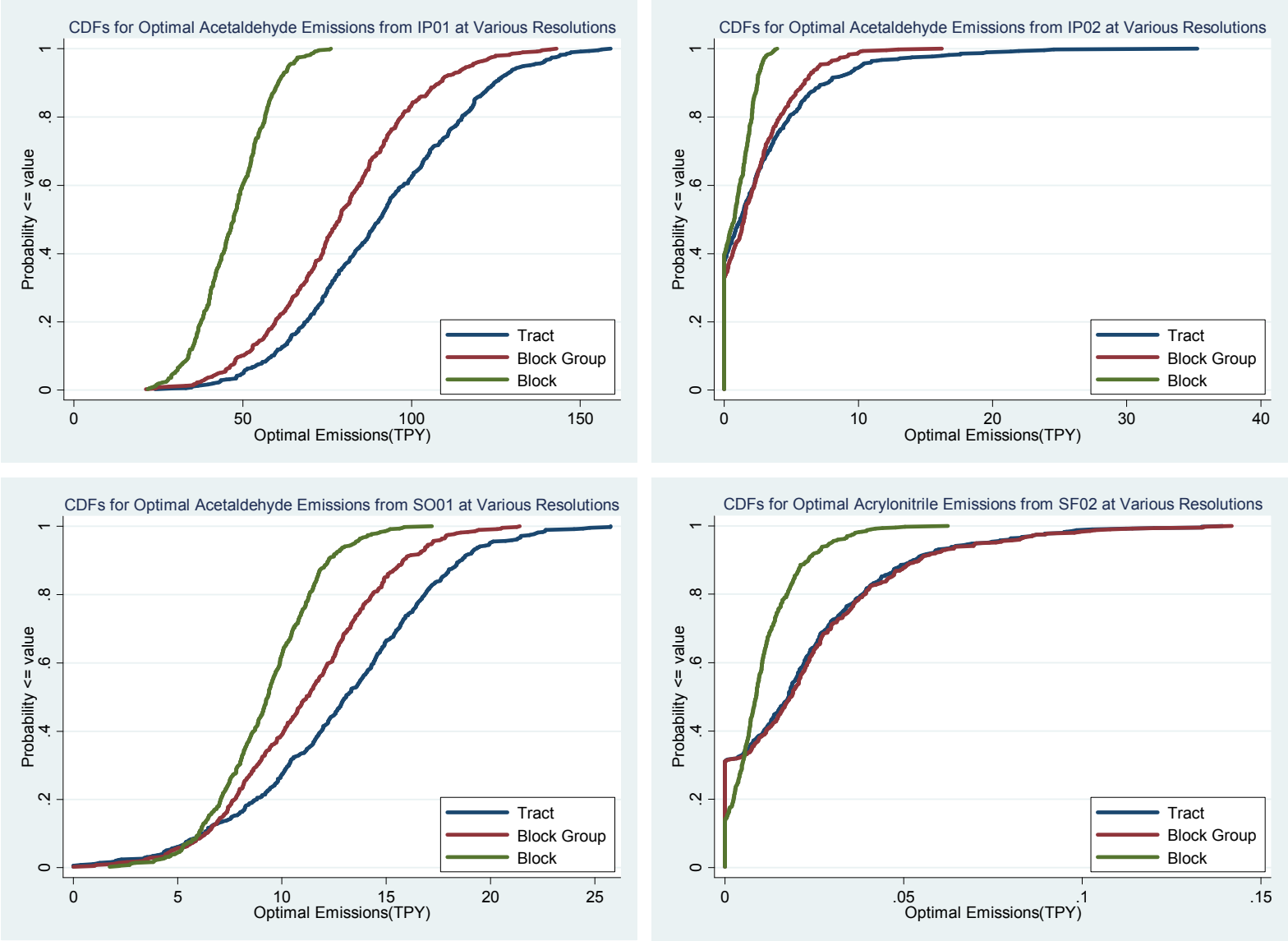


Figure 9.2 Cumulative Distribution Functions at Various Spatial Resolutions for Optimal Emissions of Select Sources (Without Uncertainty in Cost Parameters)

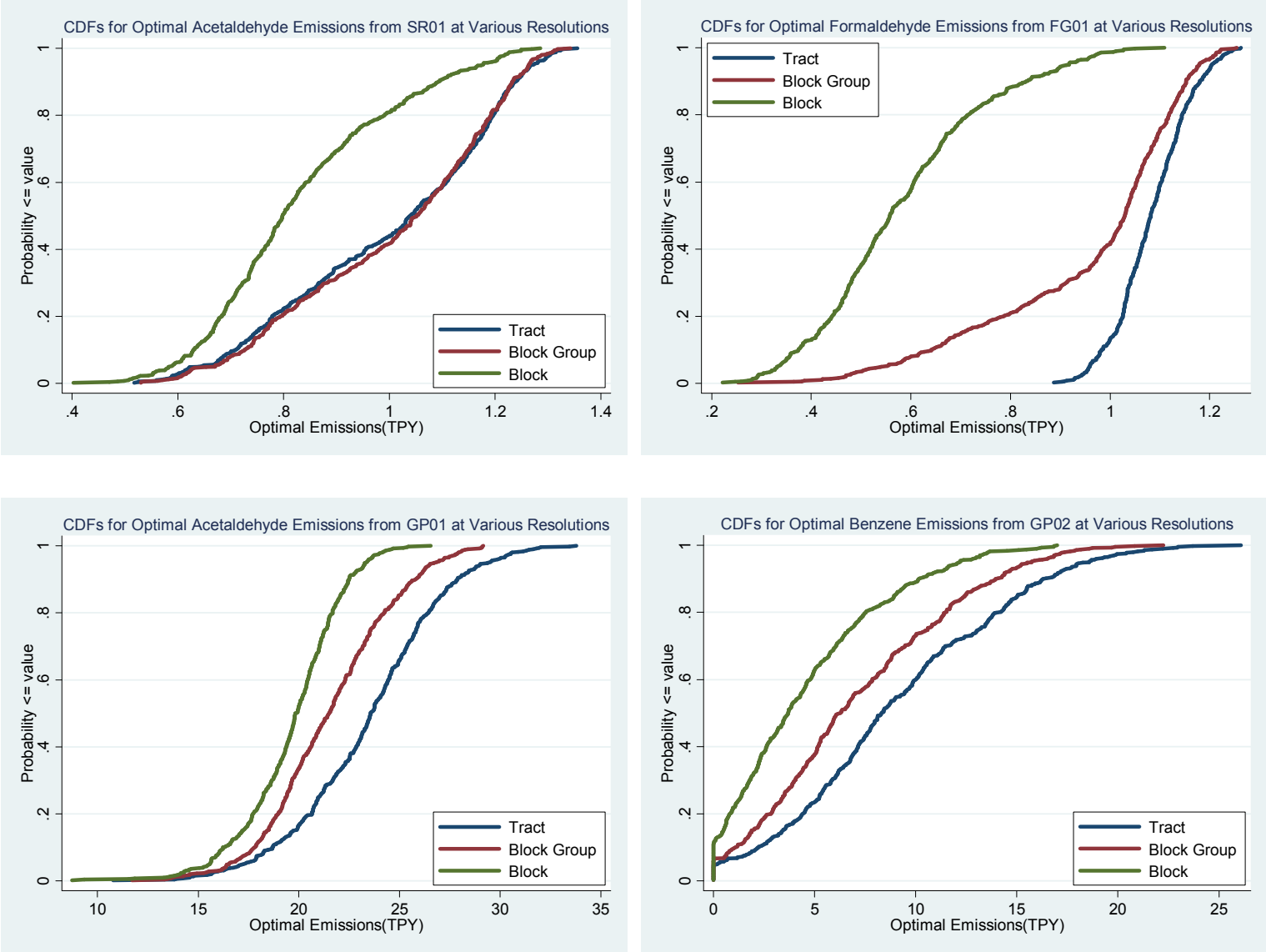


Figure 9.2 (cont'd) Cumulative Distribution Functions at Various Spatial Resolutions for Optimal Emissions of Select Sources (Without Uncertainty in Cost Parameters)

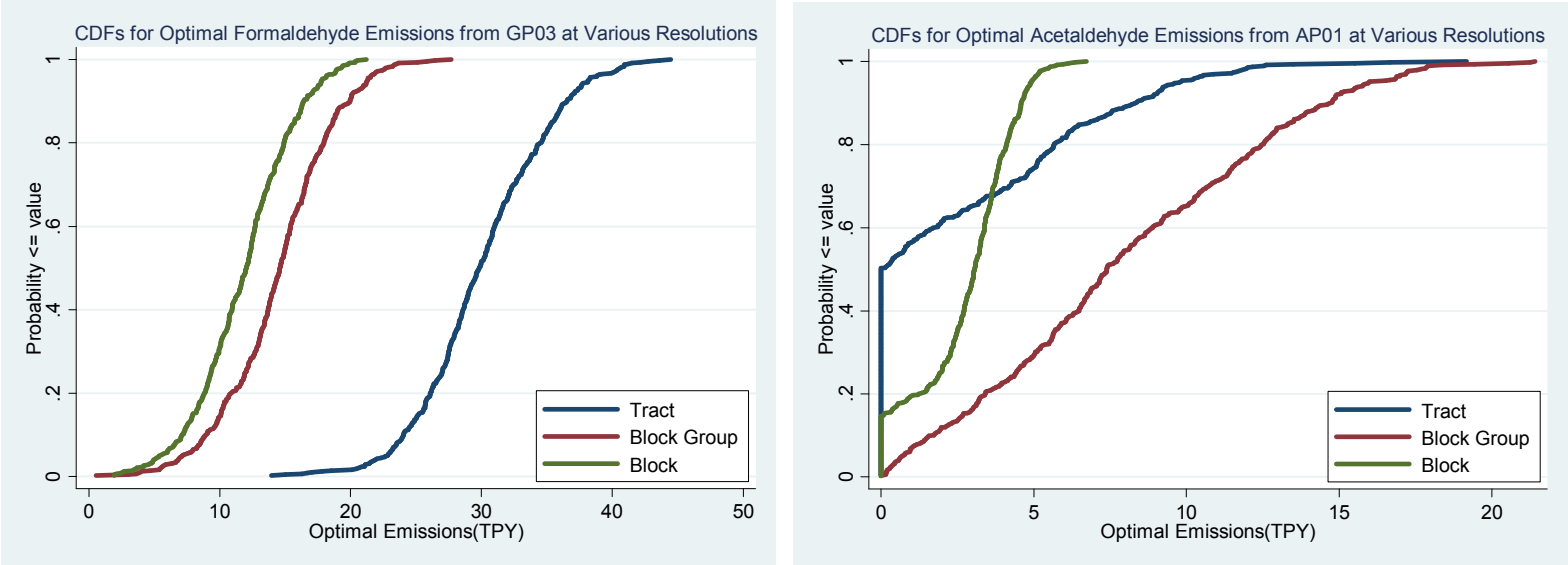


Figure 9.2 (cont'd) Cumulative Distribution Functions at Various Spatial Resolutions for Optimal Emissions of Select Sources (Without Uncertainty in Cost Parameters)

9.3.1.2 Net Costs without Uncertainty in Cost Parameters

The net costs are narrowly distributed at all the three resolutions with mean net costs increasing with increasingly finer spatial resolutions (mean = $65.9 million, SD = $73,736 for the census tract, mean = $66.5 million, SD = $74,659 for the census block group, and mean = $69.8 million, SD = $44,971 for census block. The difference in mean net costs between resolutions is statistically significant (Diff = $580, 800, $p<0.001$ between census tract and census block group; diff = $3,273,446, $p<0.001$ between census block group and census block).

Figure 9.3 shows the CDFs for net costs under regulation at the three spatial resolutions. The deterministic analysis predicted that net costs increase as the sources are regulated at finer resolutions. The CDFs move to the right with increasing resolution and they do not intersect, as expected, indicating that at any level of confidence, net costs are higher at finer spatial resolutions.

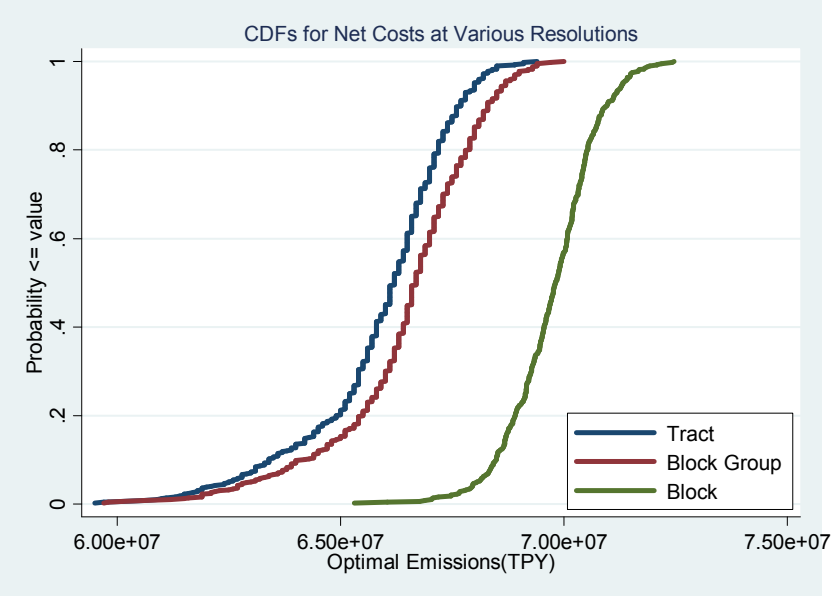


Figure 9.3 Net Costs of Regulation at Various Spatial Resolutions without Uncertainty in Cost Parameters

9.3.2 Analysis with Cost Uncertainties

The second phase of the analysis incorporated uncertainty in cost parameters, in addition to uncertainty in ambient air concentrations and URFs, and analyzed the results at one spatial resolution, the census tract resolution, and one risk threshold (10 in a million).

9.3.2.1 Optimal Emissions

Table 9.3 compares the results at census tract resolution with and without uncertainty in cost parameters. For about half of the sources shown in the table, there is a statistically significant difference in mean optimal emissions; one of the five sources shows an increase in mean optimal emissions when cost uncertainties are incorporated while for the other four the mean optimal emissions decrease. At the median level though, the optimal emissions decrease for all sources when cost uncertainties are incorporated into the analysis. That is, if the decision maker were to regulate the sources at the median of the distribution, she would choose stricter standards when cost uncertainties are incorporated into the analysis.

The second result from Table 9.3 is that the standard deviations of optimal emissions increase substantially when cost uncertainties are incorporated. This is not surprising because including uncertainties in more input parameters should typically increase (or at least should not decrease) the uncertainty in the output parameters.

Figure 9.4 compares the frequency distributions of optimal emissions with and without uncertainty in cost parameters. Because of the larger standard deviations, the values are spread over a bigger range when cost uncertainties are included. The shapes of the distributions appear generally similar with and without cost uncertainties with some

exceptions. In case of sources FG01 and SR01, the frequency distributions under cost uncertainties show a long bar at zero, which is not seen for distribution without cost uncertainties. This is because of the decision to constrain the sampled negative values on cost parameter a_{ij} to an arbitrary low value 0.1. A low value for a_{ij} indicates low abatement costs at any emission levels and this drives the optimal emission to zero because it is very cheap to abate pollution.

Finally, Figure 9.5 shows the CDFs of optimal emissions with and without cost uncertainties. The problem of constraining the cost parameter a_{ij} to 0.1 discussed in the previous paragraph shows up once again. In cases of those same sources (mainly FG01 and SR01), the CDFs with and without cost uncertainties start at very different locations on the emissions axis. Further, the CDF of optimal emissions with cost uncertainties included (red line) is much flatter than the CDF without the cost uncertainties (blue line), indicating much bigger uncertainty when cost parameters are incorporated in the analysis (see CDFs for formaldehyde and benzene emissions from FG01 and acetaldehyde emissions from SR01). For other sources, however, it appears from the CDFs that cost uncertainties might not matter a great deal. For most of the other sources, the CDFs with and without cost uncertainties almost merge.

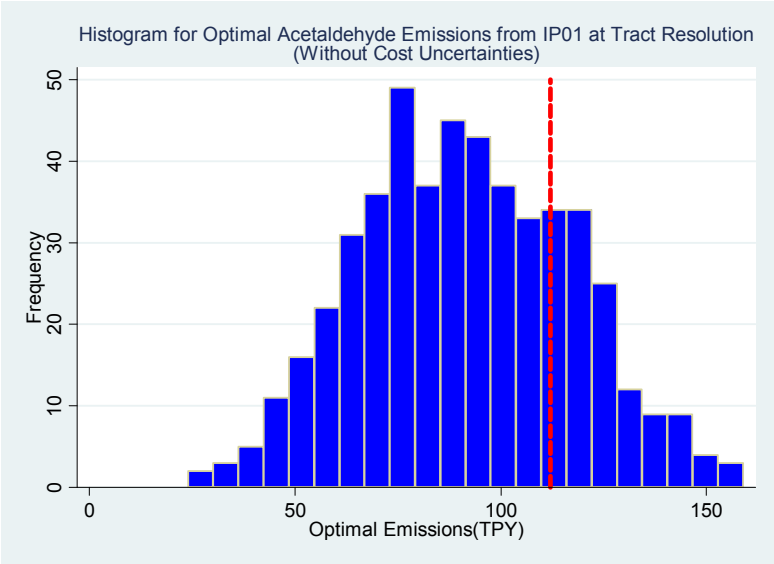
Table 9.3 Comparison of Optimal Emissions without Cost Uncertainties with Optimal Emissions from Uncertainty Analysis with Cost Uncertainties (Tract Resolution; Risk Threshold: 1E-05; VSL: $5.5 Million)

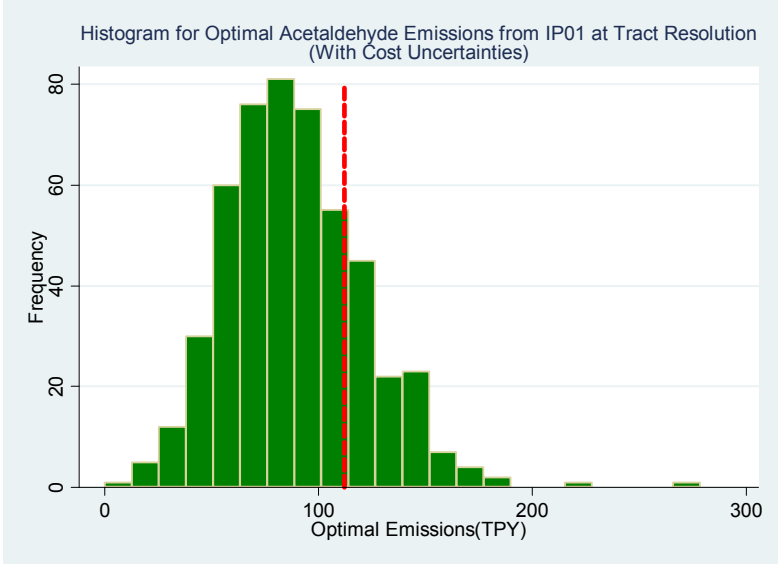
	Source	IP01	IP02	SO01	AP01	SF02	SR01	FG01	GP01	GP02	GP03
	Pollutant	**A**	**A**	**A**	**A**	**AN**	**A**	**F**	**A**	**B**	**F**
Deterministic Analysis		111.9	0	17.47	0	0.06	1.2	1.03	27.5	21.6	29.04
Without Cost Uncertainties	Mean	91.3	2.77	12.83	2.6	0.022	1.0	1.08	23.47	9.07	30.1
	SD	25.7	4.18	4.78	3.6	0.024	0.2	0.07	3.62	5.37	4.9
	Median	90.6	1.2	13.1	0	0.018	1.04	1.08	23.6	8.34	29.8
	5^{th} Percentile	50. 3	0.0	4.5	0	0	0.64	0.95	17.3	0.2	22.9
	95^{th} Percentile	134.2	10.2	19.9	9.8	0.07	1.27	1.2	29.4	18.6	38.2
	99^{th} Percentile	148.6	20.4	23.3	12.6	0.11	1.31	1.24	31.7	22.5	38.2
With Cost Uncertainties	Mean	88.8	3.3	11.0*	3. 5*	0.019	0.85*	0.91*	22.7*	8.7	29.8
	SD	32.6	5.9	5.9	4.6	0.024	0.37	0.36	5.1	5.9	6.4
	Median	85.3	0.93	11.7	0.4	0.013	0.93	1.02	23.3	7.9	29.6
	5^{th} Percentile	40.5	0	0	0	0	0	0	12.7	0	19.1
	95^{th} Percentile	145.8	13.5	19.5	13.1	0.07	1.3	1.25	30.0	19.3	40.9
	99^{th} Percentile	171.0	29.7	23.0	17.6	0.11	1.42	1.33	32.1	23.7	45.0

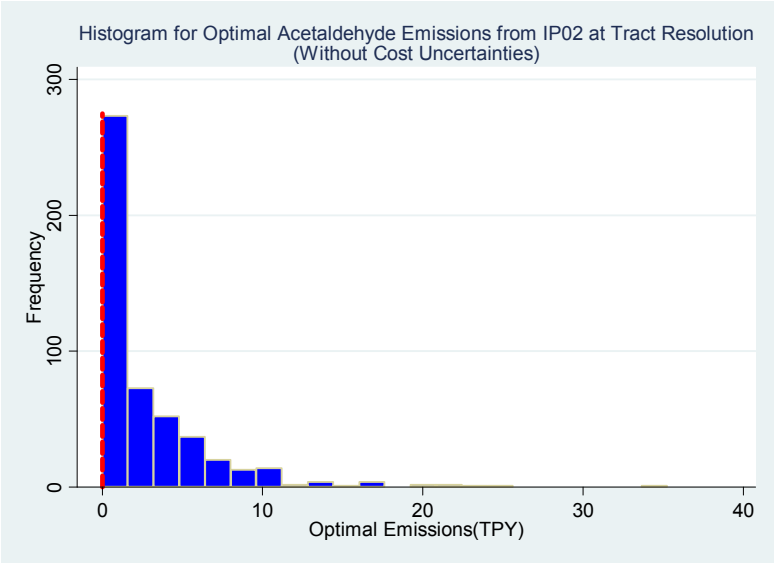
* Difference in means between optimal emissions with and without cost uncertainties is statistically significant at 5%

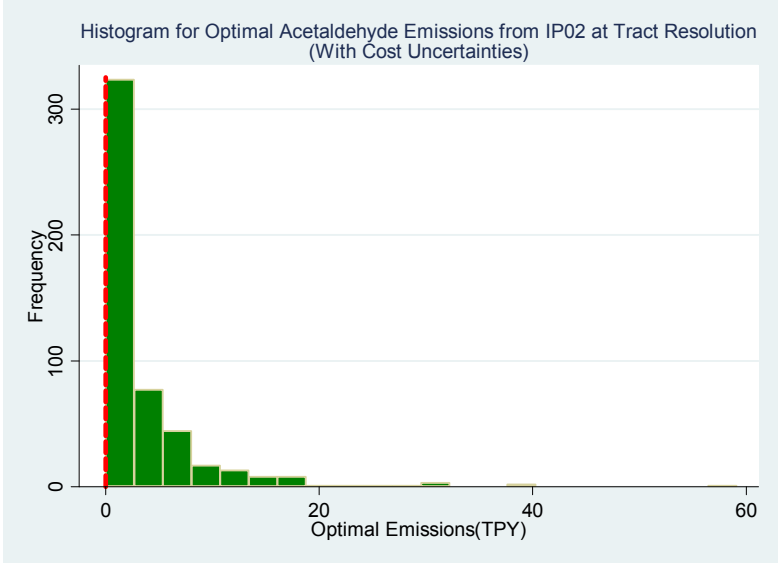
Pollutants: A – Acetaldehyde; F – Formaldehyde; B – Benzene; AN – Acrylonitrile

Sources: IP – International Paper; SO – Solutia; SF – Sterling Fibers; SR – St. Regis; FG – Florida Gas; GP – Gulf Power

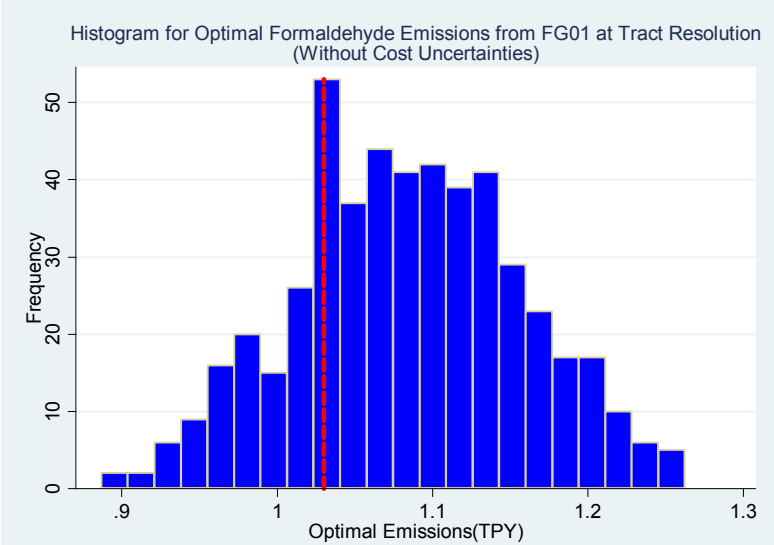


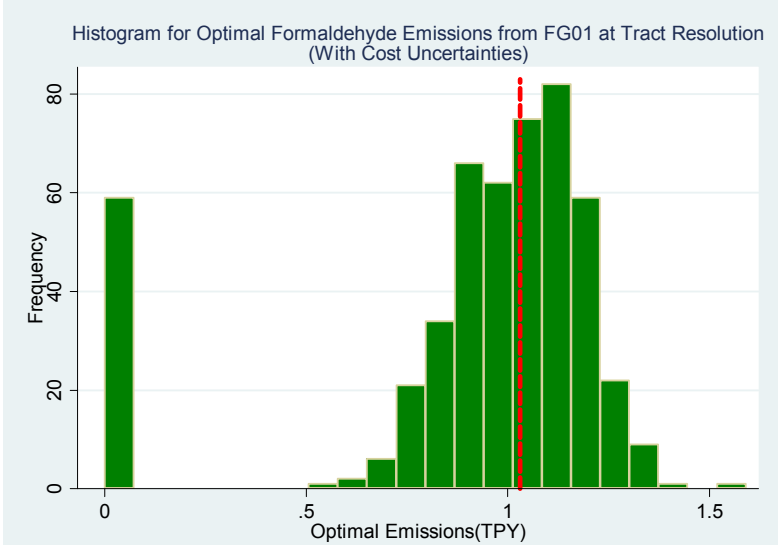


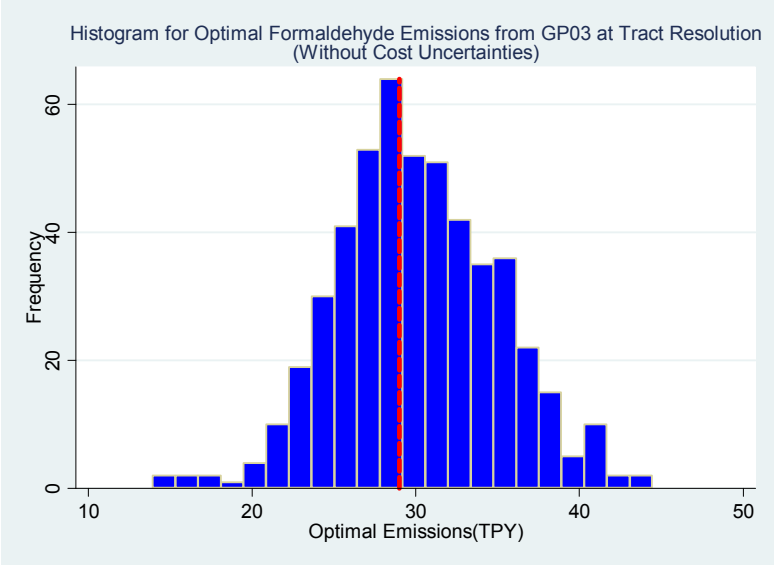


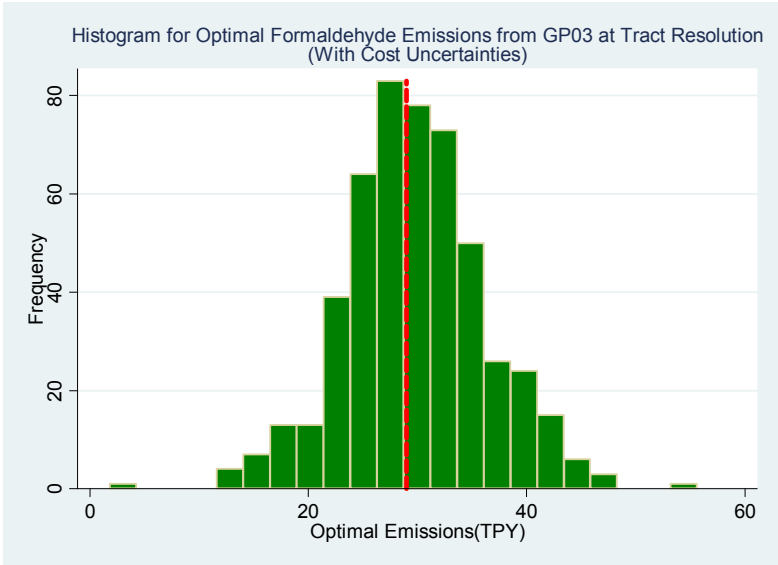


9.4 Histograms for Distribution of Optimal Emissions of Select Sources at Tract Resolution with and without Uncertainty in Cost Parameters (*Deterministic optimal emissions are shown by red dashed lines*)

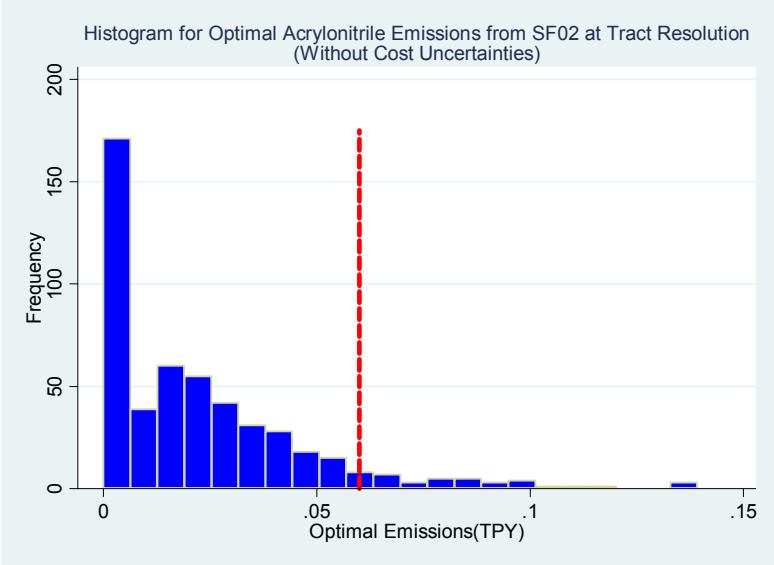


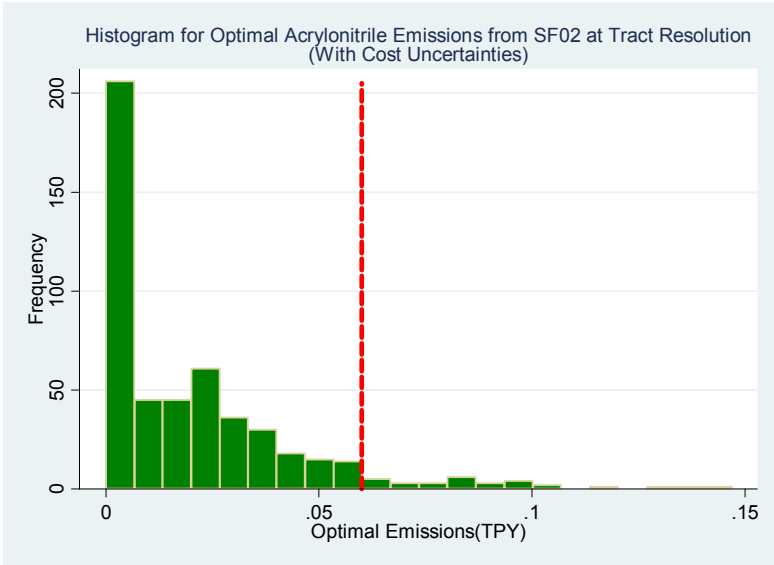


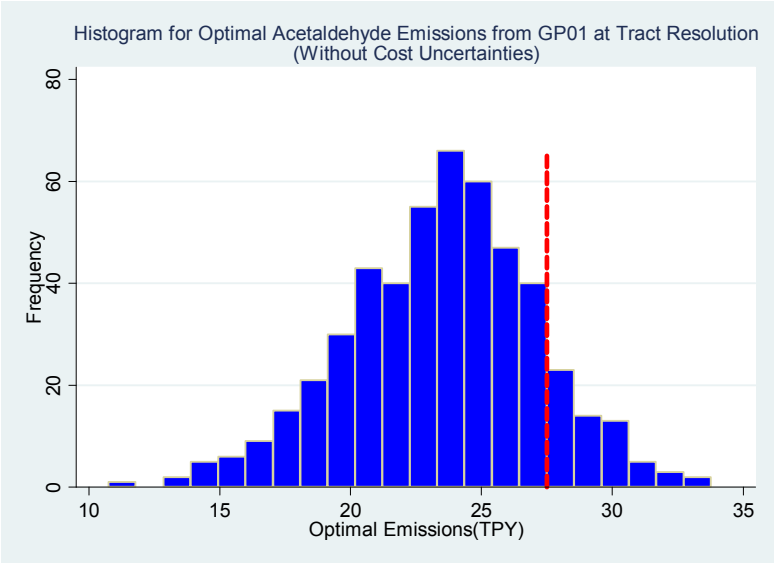


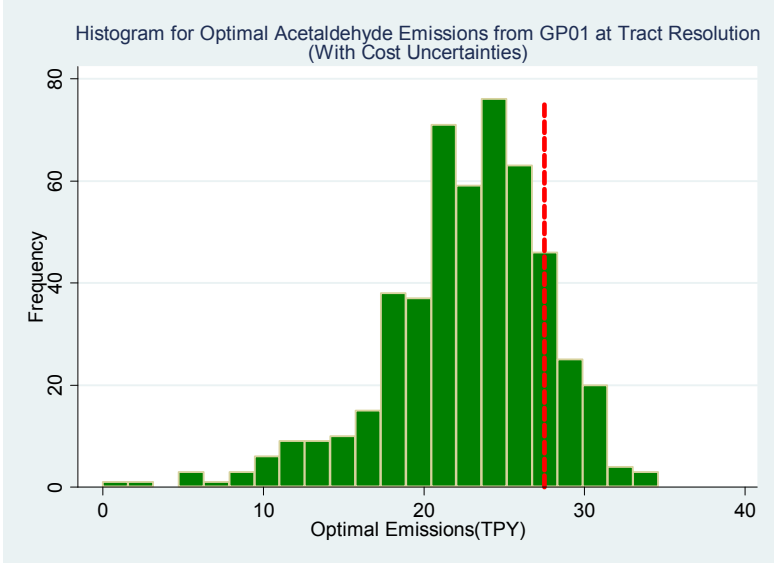


9.4 (Cont'd) Histograms for Distribution of Optimal Emissions of Select Sources at Tract Resolution with and without Uncertainty in Cost Parameters (*Deterministic optimal emissions are shown by red dashed lines*)

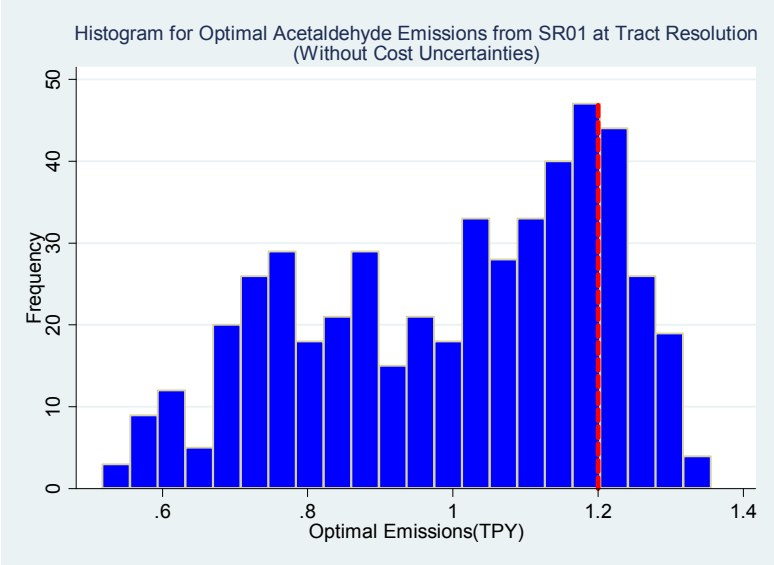


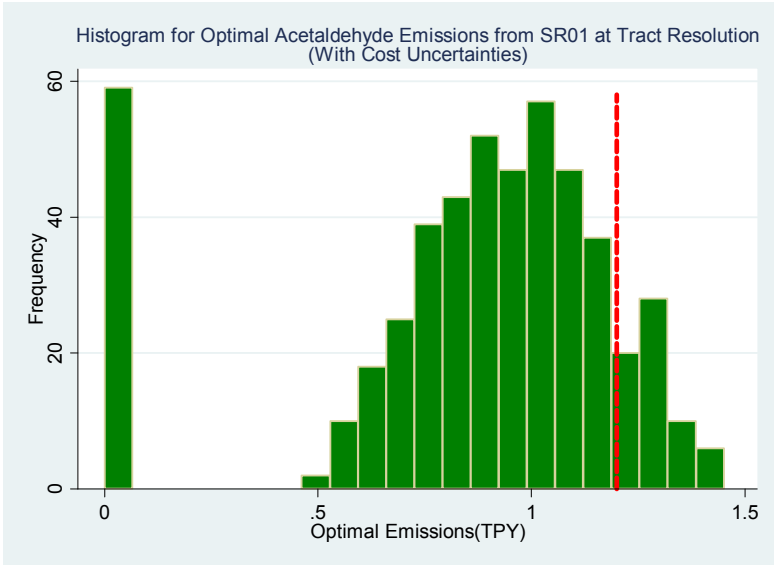


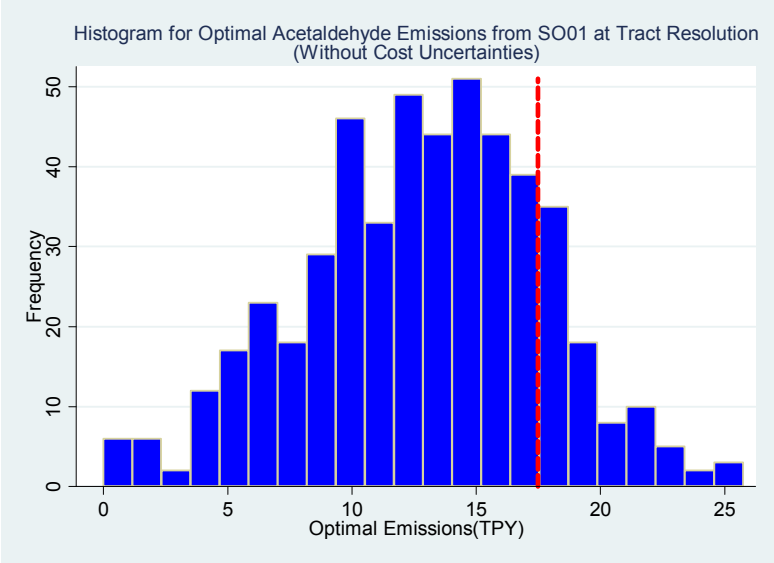


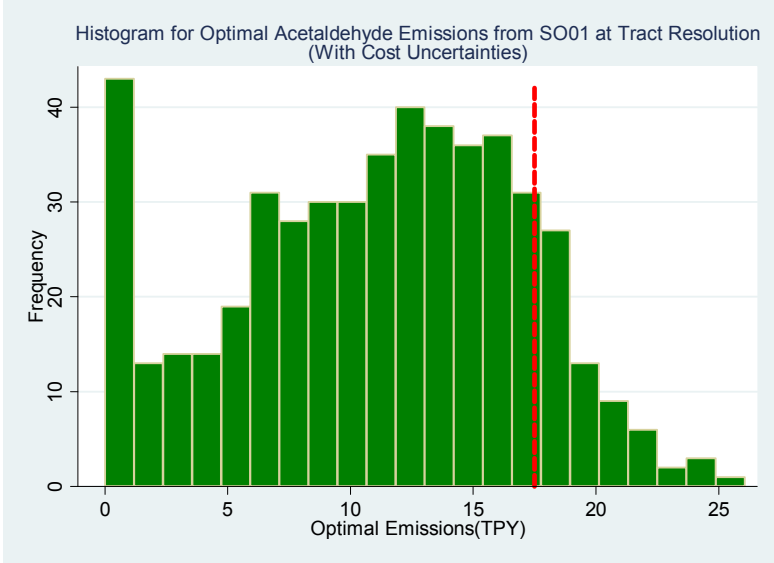


9.4 (Cont'd) Histograms for Distribution of Optimal Emissions of Select Sources at Tract Resolution with and without Uncertainty in Cost Parameters (*Deterministic optimal emissions are shown by red dashed lines*)









9.4 (Cont'd) Histograms for Distribution of Optimal Emissions of Select Sources at Tract Resolution with and without Uncertainty in Cost Parameters (*Deterministic optimal emissions are shown by red dashed lines*)

9.3.2.2 Net Costs

Figure 9.6 shows the frequency distribution of net costs with and without cost uncertainties included. The distribution on the right (with cost uncertainties) best captures the uncertainty in cost parameters. The net costs vary from negative values to as high as $200 million. The figure on the left that shows the distribution of net costs without cost uncertainties has a much narrower band – between $60 and $70 million. Again, the negative net costs that show up in the analysis with cost uncertainties can be explained by the constraint (a value of 0.1) placed on some of the sampled values for the cost parameter, a_{ij}. As explained before, this constraint drives the optimal emissions of all those sources with restricted a_{ij} values to zero, and at a very little cost. The zero emissions from these sources create slack in cancer risk at a number of spatial locations over which risks are regulated (in this case, the centroids of census tracts) and this slack allows higher emissions from other sources.

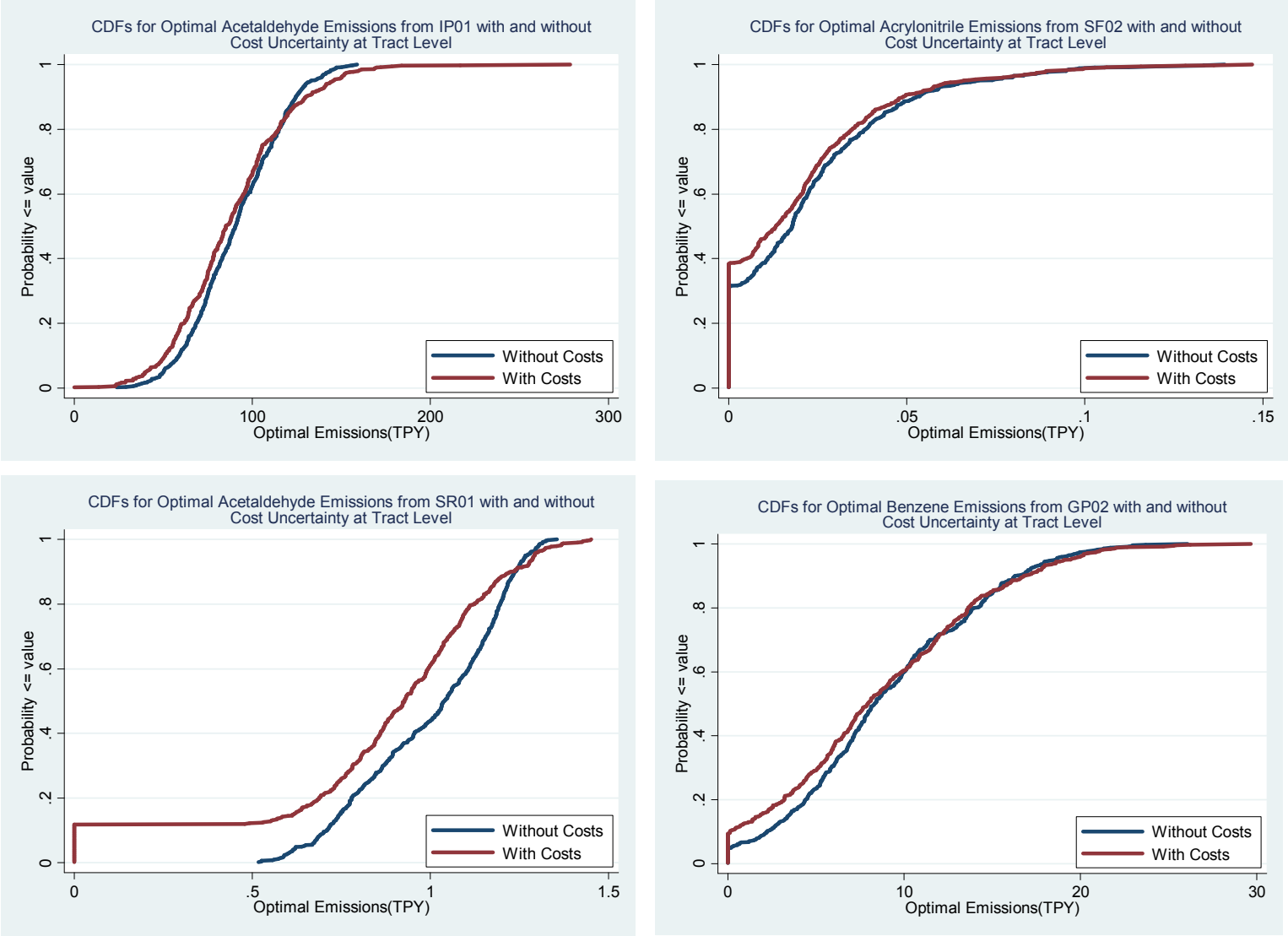
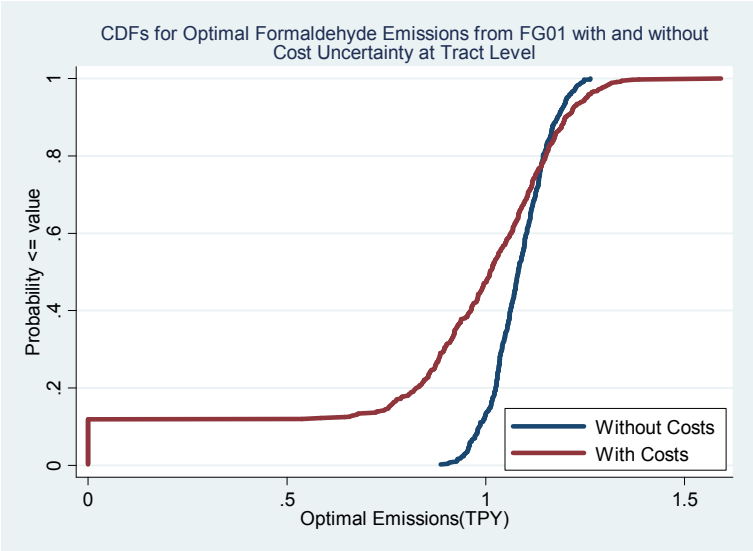
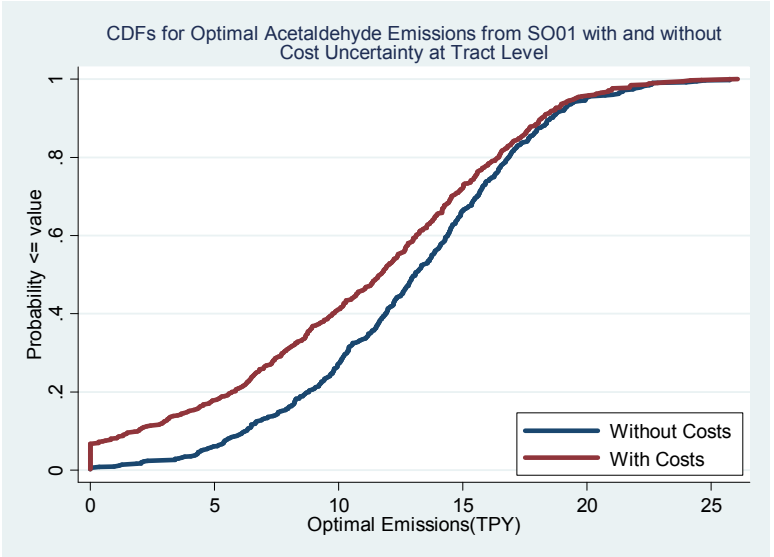
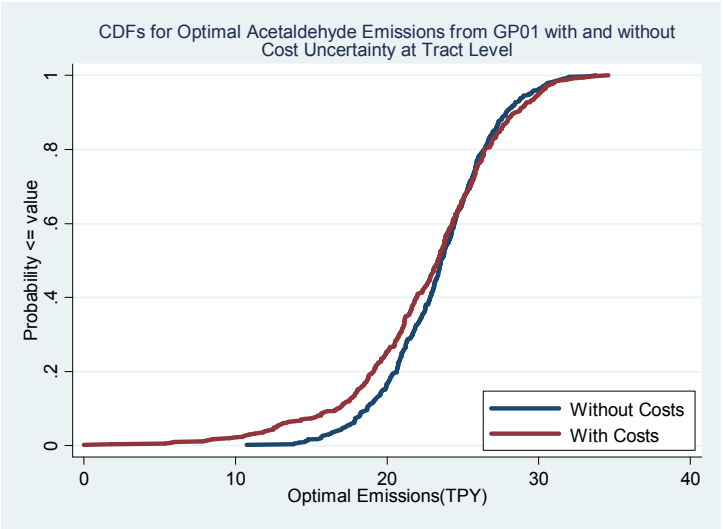


Figure 9.5 Cumulative Distribution Functions for Optimal Emissions of Select Sources at Tract Resolution with and without Uncertainty in Cost Parameters







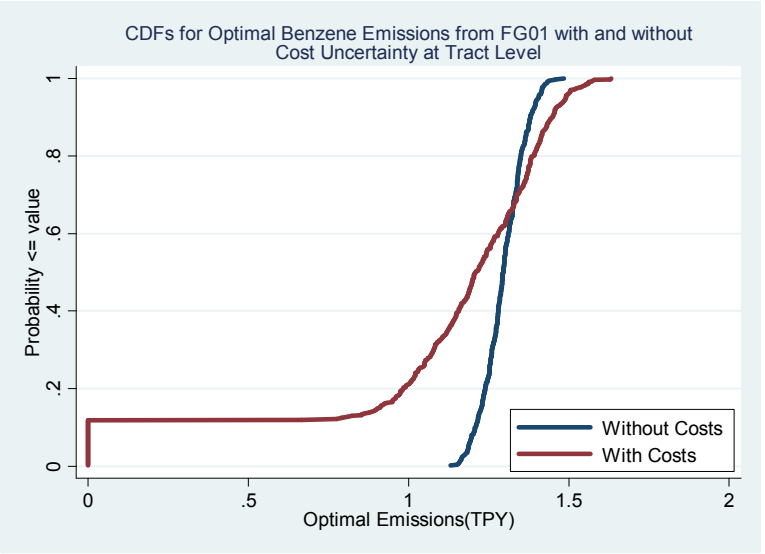
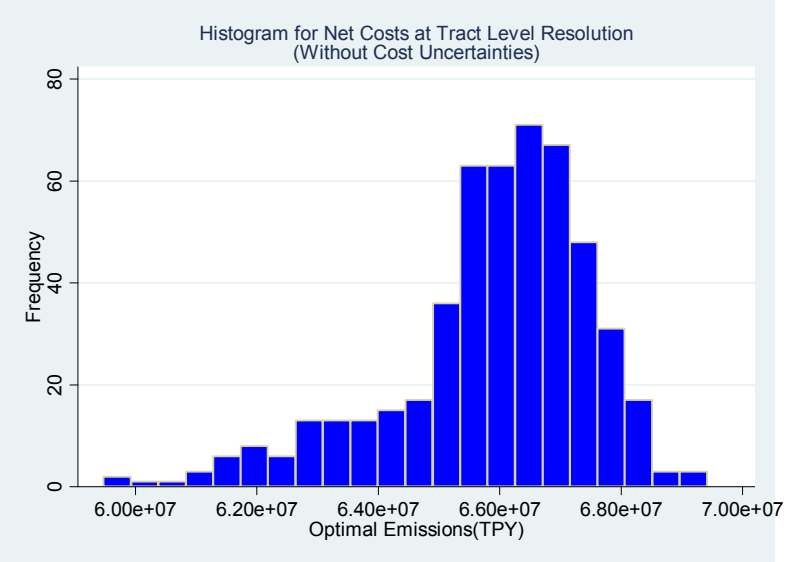


Figure 9.5 (cont'd) Cumulative Distribution Functions for Optimal Emissions of Select Sources at Tract Resolution with and without Uncertainty in Cost Parameters



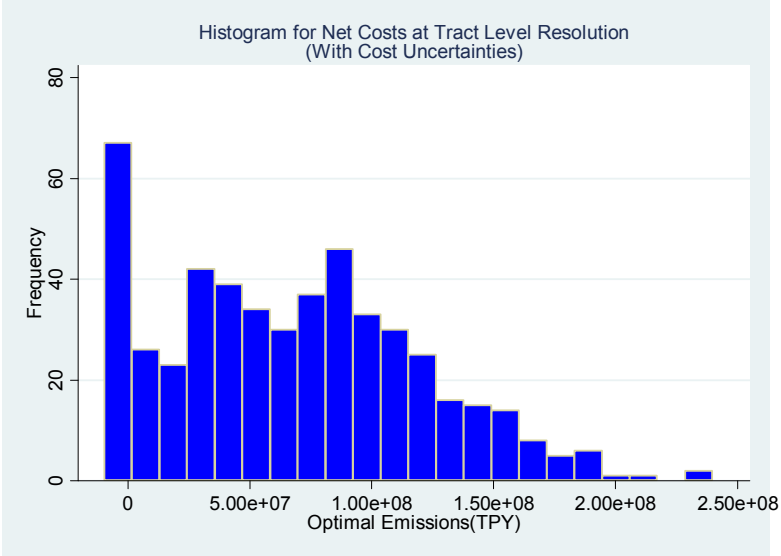


Figure 9.6 Histograms of Net Costs of Regulation at Tract Level Resolution with and without Cost Uncertainties

When these other sources are allowed to emit much more than their current baseline emissions, their costs decrease so much that the overall costs become negative. Finally, Figure 9.7 shows the CDFs for net costs at the census tract resolution with and without uncertainties in cost parameters. The CDF confirms the wider distribution of net costs with uncertainties in cost parameters compared to net cost distribution without uncertainties in cost parameters.

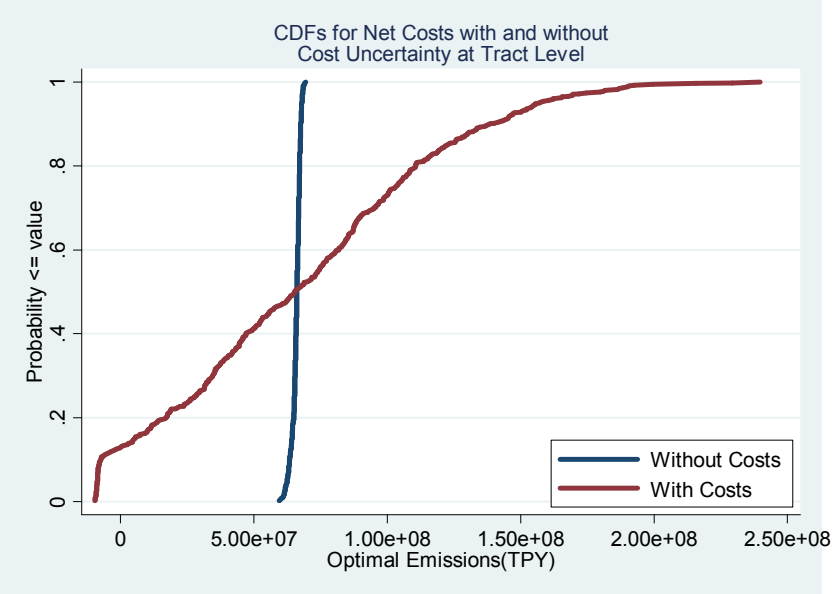


Figure 9.7 CDFs of Net Costs of Regulation at Tract Level Resolution with and without Uncertainties in Costs

9.3.3 Summary of Results

The uncertainty analysis presented here is by no means a complete analysis. First of all, the characterization of uncertainty in the input parameters of the decision model is inadequate. In characterizing uncertainty in ambient air concentrations, (a) the correlations in concentrations predicted by ISCST model across spatial locations

(receptors) were ignored and (b) in spite of some empirical evidence (Sax and Isakov, 2001) that the uncertainty in the prediction of Gaussian plume models could vary depending on the location of receptors with respect to sources, the analysis here assumes the uncertainty to be the same (constant $\sigma_{\ln x}$ for log-normal distribution) across all receptors. In the case of inhalation URFs, this analysis considered uncertainty in only the upper bound URF although a more complete characterization would characterize the entire range of plausible values. Finally, the characterization of cost uncertainties was limited to the uncertainty in parameters of the fitted cost functions. A more complete characterization should also include the uncertainty in the estimates of the abatement costs themselves. Secondly, as the analysis at block resolution indicated, the number of simulations used in the analysis might be inadequate to capture the complete range of possible optimal emission outcomes. Nevertheless, the analysis does provide some useful insights:

- In spite of the limited characterization, the uncertainty in input parameters introduces substantial uncertainty in the choice of optimal emissions; the standard deviations are of the same order of magnitude as the means of the distributions for most sources.
- Even after considering uncertainties, it appears that the empirical findings of deterministic analysis regarding variation of optimal emissions with spatial resolution generally hold, especially in the inter-quartile confidence range. That is, when the deterministic analysis found that the optimal emissions decrease when regulated at finer resolution, the uncertainty analysis also showed that the optimal emissions would be lower at finer resolutions. However, when the deterministic analysis found that the optimal emissions would increase at finer resolutions (for example, in Table

9.2, formaldehyde emissions from GP03 between tract and block group resolutions), the results from the uncertainty analysis still predicted a decrease in optimal emissions.

- In general, the uncertainty in the choice of optimal emissions decreases at finer spatial resolutions. This could be an artifact of an inadequate number of simulations, and a larger sample size for simulations might clarify this finding.
- Abatement cost uncertainties substantially influence results. The difference in means of the distributions with and without abatement cost uncertainties is statistically significant for a number of sources.

CHAPTER 10

POLICY IMPLICATIONS

This chapter discusses some of the major policy implications of the findings presented in Chapters 7, 8, and 9. The discussion is divided into a number of broad themes: costs vs. equity tradeoff, role of acceptable risk, regulation based on maximum individual risk, and environmental justice implications.

10.1 Costs vs. Equity Tradeoff

The central question for this research is how could regulation at finer spatial resolutions affect choices of emission standards and net social costs? The specific context for this study is the regulation of air toxics. The model developed to address this question and its empirical application demonstrates that the direction of change of choice of emissions is a function of whether or not regulation at finer resolutions identifies "hot spots" that are not apparent at coarser spatial resolutions. Sources that contribute to new hot spots identified at finer resolutions would be subjected to stricter emission standards while other polluting sources could be subjected to laxer emission standards. The results of the model and the empirical analysis also showed that net costs are non-decreasing with regulation at increasingly finer spatial resolutions.

The second question for this research is what are the distributional consequences of regulation at fine spatial resolutions? The results of the empirical analysis presented in Chapter 8 suggested that regulation at finer spatial resolutions could reduce "hot spots" where hot spots are defined as those locations at which unregulated risks exceed a certain "acceptable" level of risk. Thus, if the objective of regulation at finer spatial resolutions

is to address risk in "hot spots," it appears that finer resolution regulation could have the intended effect.

These findings imply that regulation at finer spatial resolutions could involve tradeoffs between costs and the goal of ensuring an equitable distribution[28] of risk. The results of the empirical analysis presented in Section 8.1.1 indicated, for example, that at 100 in a Million threshold risk, maximum individual risk (MIR) reduces from 187 in a Million at the census tract resolution, to 100 in a Million at the finer census block resolution. The size of the population that would benefit from this reduction in cancer risk is less than 0.1% of the total population of Escambia and Santa Rosa. On the other hand, the results in Table 7.1 show that regulation at the census block resolution costs twice as much as regulation at the census tract resolution and among the regulated entities, there will likely be both winners and losers, as indicated in Table 8.3. In the context of these results, the question is how can these tradeoffs be resolved?

The setting just described is a familiar setting in public policy making in which the eventual policy decision is an outcome of a political process involving the various groups likely to be affected by the policy. One line of empirical literature in environmental policy that is particularly relevant to the question here is the literature on the relation between polluting firms' abatement activity and characteristics of the community in which the firms are located. This literature consistently shows, in a variety of policy settings, that community characteristics have significant effects on the firm's pollution abatement behavior. Hazardous waste processing firms were unlikely to expand

[28] "Equitable distribution" here has no reference to environmental equity. This definition simply refers to the goal that no individual should be subjected to more than a certain level of "acceptable" risk

their capacity in locations where potential for collective action was high, as measured by voter turnout (Hamilton, 1993). Hamilton (1999) replicated this result for firms releasing carcinogenic air pollutants; firms located in high voter turnout areas reduced carcinogenic air emissions more. For Superfund, Hird (1993) found that Superfund clean up was more likely to benefit affluent and highly educated communities. Enforcement inspections were more likely in communities with higher per capita income (Helland, 1998); higher air pollution abatement expenditures were associated with communities with higher per capita income (Becker, 2004); and finally, manufacturing plants in areas with a politically active population emitted less air pollution (Gray & Shadbegian, 2004).

Thus, the empirical evidence in the literature indicates that the political power of the communities drives regulated firms' willingness to spend money on abatement activity. In the context of the findings of this dissertation research, this empirical evidence suggests that the risk reduction benefits of regulation at finer spatial resolution are likely to accrue to politically powerful groups because only those groups are capable of forcing regulated industries to pay for additional emission controls required by regulation at finer spatial resolutions. This presents a dilemma for regulation at finer spatial resolutions. An important rationale for regulating risks at finer spatial resolutions has been to protect minorities and low-income groups that are likely to live in hot spots. These groups, however, are also likely to possess limited political power, in which case regulation at finer resolutions is unlikely to benefit the targeted populations unless regulatory agencies ensure that the targeted populations have an influence in the policy process.

10.2 Role of Acceptable Risk

The preceding section argued that regulation at increasingly finer spatial resolution would involve tradeoffs between net costs of regulation and ensuring equitable distribution of risk. This argument, however, was conditional on a fixed threshold risk. The threshold risk represents an "acceptable level" of individual risk and reducing the individual risks across the population of interest to a level below this acceptable level would mean ensuring an "equitable distribution" of risks.

The concept of acceptable risk, however, is not a fixed quantity that is known *a priori* (Bostrom, Turaga, & Ponomariov, 2006). Research on technological risk perceptions suggests that risk acceptability is likely a function of perceived benefits of technology, perceived risks, and trust in institutions responsible for risk management (Siegrist, 2000). For example, when risks are regulated at 1 in a million threshold risk, Table 7.5 showed that a number of emission sources have to be shut down to achieve that level of risk. Under such situations, even for the local communities, the costs of achieving the "acceptable level" of risk (for example, in terms of loss of local employment) would likely be too high compared to the benefits of risk reductions, which in turn, might make higher risks acceptable.

Figure 10.1 shows the variation of net costs with threshold risk at each spatial resolution. The figure shows that as higher and higher risks become acceptable (as one moves to the right on the horizontal axis), the net costs decrease sharply. The implication is that "acceptable risk" could play a role in resolving the tradeoffs between costs and equity when risks are regulated at increasingly finer spatial resolutions.

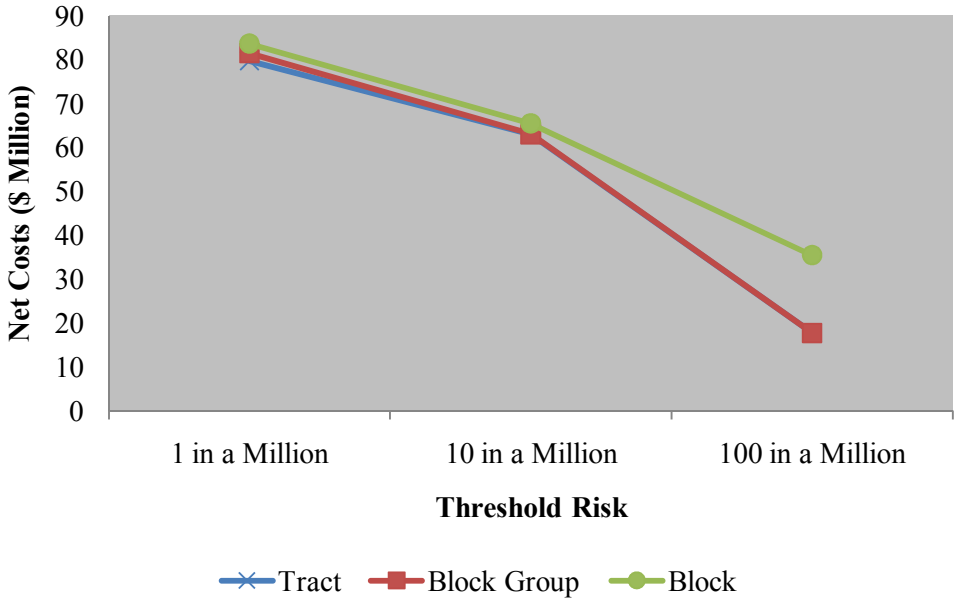


Figure 10.1 Variation of Net Costs with Threshold Risk

10.3 Maximum Individual Risk (MIR) in Risk-based Regulation

A key component that drives the results of the decision model developed for this study is the constraint that no spatial location should be subjected to more than a certain threshold risk. As finer resolutions reveal new hot spots, the constraint requires that risks be reduced in these new hotspots, which increases costs but ensures equity in risk. This constraint in the model was based on the principle of protection of the individual exposed to maximum risk. The rationale for this principle is "….to ensure equitable protection across an exposed population…(EPA, 2004b, p: 26)."

This principle of reducing MIR has been criticized both by economists and public health experts. The economists argue against this principle on the grounds of economic inefficiency of the policies that are based on this principle (Kopp, Krupnick, & Toman, 1996; Viscusi, 2000). The argument is that reducing small individual risk to large populations is likely to lead to greater benefits than reducing large individual risk to

smaller populations. The public health experts, although less concerned about economic inefficiency, also argue on similar lines. For public health experts, ignoring population in preference to individuals is against the historically accepted basis for public health decision making (Goldstein, 1989; Goldstein, 1995).

An interesting result found in the empirical analysis of this study illustrates the merit of the above arguments. At 100 in a Million risk threshold, regulation at the census block resolution instead of tract resolution reduced MIR from 187 in a Million to 100 in a Million (Figures 8.1 and 8.2); however, population risks, expressed as expected additional cancer cases, increased (Figure 7.1) when regulated at the finer resolution. This increase in population risk might just be an artifact of the empirical setting specific to this study but it does point to the possibility that by focusing on reducing the individual risk, one might just be achieving risk reductions to a few people[29] at the expense of a larger population. These results suggest the need for reexamining the principle of protecting individual risk as the basis in risk-based regulation.

10.4 Implications for Environmental Justice (EJ)

A 1994 executive order requires federal agencies to "…..make achieving environmental justice part of its mission by identifying and addressing, as appropriate, disproportionately high and adverse human health or environmental effects of its programs, policies, and activities on minority populations and low-income populations…(Executive Order 12898, 1994)." As discussed in Chapter 1 and Chapter 8,

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[29] Note that the reduction in individual risk from 187 in a Million to 100 in a Million benefits less than 0.1% of the population

the increasing emphasis on characterizing air toxics at finer resolutions is partly driven by the need to address disproportionate exposures to sensitive populations including minority and low-income populations.

The analysis presented in Chapter 8 showed that regulating risks at increasingly finer resolutions would reduce hot spots but the reduction in risks need not necessarily translate into reductions for minority communities. This result underlines the need for incorporating EJ concerns more explicitly in regulatory decisions in order to achieve desired EJ outcomes. This is especially important in light of a lack of clarity in EPA's current EJ practices. A recent General Accounting Office report (GAO, 2005), for example, reviewed three rules promulgated by EPA under the Clean Air Act (CAA) and found that EPA paid little attention to EJ in drafting the rules. The report also found that the working groups responsible for drafting the rules did not have any knowledge or guidance on incorporating EJ into rule making. Chapter 11 briefly discusses possible ways of modifying the model of decision making developed for this study to incorporate EJ concerns.

The analysis in Section 8.2.2 showed that even if the reductions in cancer risks due to regulation at finer resolution occurred in locations with a higher proportion of minority populations (see the case of 10 in a million threshold risk in Table 8.1), the population weighted change in risk (change in expected cancer incidence) had no association with the proportion of EJ population. This result demonstrates that assessment of environmental equity due to policy intervention should take the size of the population affected by the policy into account.

CHAPTER 11

FUTURE RESEARCH

The model developed to address the main research question in this dissertation was based on many assumptions, which were already discussed in Section 4.3. This chapter will (1) indicate possible ways of relaxing some of the model assumptions for future research and (2) suggests some additional data collection efforts that would improve the empirical analysis presented in this research.

11.1 Relaxing Modeling Assumptions

The model in Chapter 4 was based on a number of important assumptions. The earlier chapters discussed some of the assumptions in appropriate contexts. This section discusses two specific assumptions and indicates potential ways of relaxing those assumptions in light of current knowledge.

11.1.1 Variation in Susceptibility to Air Toxics Exposures

The health costs component of the model in Chapter 4 assumes uniform susceptibility to air toxics exposures irrespective of the individual characteristics of the population. However, susceptibility to toxics exposures could vary by age, race, gender, and health status (Zahm & Fraumeni, 1995). The population sub-groups of particular concern have been children and minority populations. The discussion that follows specifically focuses on these two groups and suggests possible ways of incorporating the variation in susceptibility within the decision model developed for this research.

11.1.1.1 Susceptibility in Children

The report (NRC, 1993) by the National Academy of Sciences in 1993 concluded that both exposure to toxics and chemical induced toxicity could differ between adults and children. More recent research indicates that accounting for variation in age related susceptibilities in risk assessments could lead to a 2.8 fold increase in mean risk estimates (Hattis, Globe, & Chu, 2005). The scientific evidence on age related susceptibilities, especially in children, led to an executive order in 1997 that requires federal agencies to "make it a high priority to identify and assess environmental health risks and safety risks that may disproportionately affect children (Executive Order 13045, 1997)."

The parameter in the decision model that could account for variation in susceptibilities is the unit risk factor (URF) u_j. As explained in Section 9.1.2, the URF is calculated by the equation:

$$URF = \frac{SF * BR}{BW * CF} \qquad (11.1)$$

Where, SF is cancer slope factor, BR is breathing rate, BW is body weight, and CF is a conversion factor equal to 1000.

The URF estimates the probability of cancer due to lifetime exposure to 1 $\mu g / m^3$ of pollutant. Typically, the values for the variables SF, BR, and BW are based on average adult characteristics. Accounting for differences in susceptibilities between adults and children requires adjusting for cancer potency as well as breathing rates and body weight. In case of cancer potency, in the most recent carcinogenic risk assessment guidelines, EPA developed a supplemental guidance for assessing susceptibility to early life exposures (EPA, 2005b). According to these guidelines, the cancer potency factor

should have an adjustment factor of 10 for individuals less than two years old and an adjustment factor of 3 for individuals between 2 and 16 years of age. These guidelines are specific to chemicals that cause cancer through mutagenic modes of action. EPA recommends no adjustment for other modes of action because of a lack of scientific evidence. The breathing rate and body weight are also obviously different for adults and children and that has an effect (based on equation *11.1*) on the URF that should be used for different life stages. The risk assessment guidelines for the Air Toxics Hot Spots program of California recommends using age-specific breathing rates and body weight to estimate risks (Cal EPA, 2003).

Thus, methods are available for accounting for variation in susceptibility between children and adults and future research should include such methods within the framework of the decision model and the empirical analysis. Ignoring this variation in susceptibility would overestimate the optimal emissions due to regulation at any given spatial resolution. However, the predictions of the model regarding the variation in optimal emissions with variation in spatial resolution would still hold unless the threshold risk constraints in the model are varied based on the population characteristics of the location at which risks are regulated.

11.1.1.2 Susceptibility based on Race

Section 8.2 briefly discussed the evidence on disproportionate risks to EJ communities as well as potentially greater susceptibility of these communities to cancer risks. It is important to understand the relation/difference between "variation in susceptibility to risk" and "disproportionate risk." If an individual within an EJ group and a non-EJ individual are both subjected to an equal level of air toxics exposure, the

variation in susceptibility to risks makes the EJ individual more prone to cancer risk than a non-EJ individual. This would lead to "disproportionate risk," which could be assessed by incorporating appropriate risk factors to each individual (the EJ individual will have a higher risk factor). Disproportionate risk, however, is also possible, even without considering the variation in susceptibility, when the two individuals are subjected to different levels of exposures of air toxics. Most of the empirical research that is concerned about "disproportionate risks" is based on the latter understanding of the term.[30] Unlike in case of risks to children, there is little guidance available from EPA on how to account for variation in susceptibility across racial groups in risk assessments.

In the context of this research, the constraint on threshold risk does address the concern of disproportionate risks because the constraint ensures that no individual is subjected to more than an "acceptable" risk. The model *does not* account for variation in susceptibility across racial groups or other sensitive groups. It is possible, however, to incorporate variation in susceptibility within the decision model. One possibility is to develop URFs that appropriately reflect the variation in susceptibilities across various population groups (children vs. adults, white vs. minority) and use the population group-adjusted URFs in the assessment of the population health costs component of the objective function. As explained in the previous paragraph, however, there is little guidance on how to quantify the differences in unit risk across racial groups. In light of this, an alternative is to assume that variation in susceptibility poses greater risks to

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[30] Actually most of the EJ research assumes presence of a polluting facility as a proxy for risk. It can be misleading especially in case of air pollution because some pollutants travel several miles from the location of emissions and could cause more impact in census units far away from the source.

minorities and vary the risk threshold conditional on the proportion of the EJ population in the location at which risk is regulated. That is, the threshold risk (which, in the current model, is constant across spatial locations over which risk is regulated) will be stricter for locations where the proportion of the EJ population is higher than some reference group.[31]

11.1.2 Valuation of Non-cancer and Ecological Effects

The decision model developed for this research does not quantify the costs of non cancer risk and ecological risk. Ignoring these risks underestimates the costs of residual risks remaining after regulation, and for any given spatial resolution of regulation, the optimal emissions will likely be overestimated (that is, ignoring the non cancer and ecological effects would relax the standards).

An important constraint in valuing non cancer and ecological risk is the lack of outcome measures in risk assessments that allow economic valuation. Typically economic valuations require quantification of probabilities of adverse outcomes so that stated preference methods such as willingness to pay (WTP) can be used to value the change in probabilities of those adverse outcomes due to a change in the exposure (Dockins et al., 2004). In case of non cancer risk assessments, the current method of quantification uses threshold models. Inhalation reference concentrations (RfC) or oral reference dose (RfD), used in non cancer risk assessments are defined "as an estimate,

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[31] A toolkit developed by EPA (EPA, 2004c) defines environmental justice communities as those communities where minorities or low income groups or children and elderly live at a higher percentage than the state average percentage. This definition of EJ communities could be used in differentiating the risk threshold across regulated locations.

with uncertainty spanning perhaps an order of magnitude, of an inhalation exposure or oral dose to the human population (including sensitive subgroups) that is likely to be without appreciable risks of deleterious effects during a lifetime (EPA, 1999a p: 50)." An index called hazard index (HI) is then calculated as a ratio of current exposures to RfC. If HI is above 1, it only indicates the potential for adverse non cancer risk but HI cannot clearly relate a change in exposures to a change in probability of an adverse effect. Efforts are underway (EPA, 2000b; Axelrad et al., 2005) to develop alternative non cancer risk assessment methods that allow valuation of non cancer health effects.

Quantifying and valuing ecological changes due to changes in pollutant concentrations is even more complex than valuing human health effects. Ecological risk assessment techniques have been in place for more than a decade now but there has been no systematic effort to link ecological risk assessment with economic valuation to develop valuation techniques for ecological effects. Recognizing this, EPA has recently developed a strategic plan to develop methods for ecological benefits assessment (EPA, 2006d). This document discusses several issues that need to be addressed and specific actions to achieve the goal of fully incorporating ecological effects valuation into benefit-cost analyses.

11.2 Improving Empirical Analysis

This section discusses three specific areas for future research where additional data could improve the empirical analysis.

11.2.1 Data for Estimation of Cost Functions

The limitations of data used for estimating cost functions have already been discussed at several places in the document, specifically in Chapter 6 and Chapter 9. The

approach for estimating cost functions relied on the regulatory impact analyses (RIA) and background information documents (BID) developed by EPA for various maximum achievable control technology (MACT) standards. This approach was selected because it was the only feasible approach. In hindsight, however, a primary data collection effort would have led to better estimation of cost functions. For example, for the sources selected for the analysis, one could have used an approach such as expert judgment to identify several alternative abatement options and the likely costs. The experts in such an approach would be engineering design firms that routinely design and construct pollution control devices. Such an approach lends itself to a more systematic quantification of uncertainties in cost parameters. Future research could explore such innovative alternatives to estimating costs in the face of an extremely limited amount of publicly available data.

11.2.2 Incorporating an Exposure Model

The integrated risk assessment tool, the Regional Air Impact Modeling Initiative (RAIMI), used for estimating exposure concentrations does not incorporate an exposure model. Because of this, the empirical analysis assumed ambient air concentrations to be surrogates for exposure concentrations. As discussed in Section 5.4.1.2, exposure models such as the Hazardous Air Pollutant Exposure Model (HAPEM) are available to estimate exposure concentrations from ambient air concentrations. These models use population activity pattern data. By making assumptions about the amount of time people live in different "microenvironments," such models can estimate exposures. Future research could incorporate an exposure model to improve the empirical analysis.

11.2.3 Improved Characterization of Uncertainty

The main limitations of the uncertainty analysis were summarized in Section 9.3.3. This is another area in empirical analysis that would benefit from additional data collection. Specifically, complete characterization of uncertainties in unit risk factors will clarify a number of conclusions made based on the limited analysis presented in Chapter 9.

APPENDIX A

RAIMI IMPLEMENTATION[32]

A.1 Background

The Regional Air Impact Modeling Initiative (RAIMI) consists of a set of tools designed "to evaluate the potential for health impacts as a result of exposure to multiple contaminants from multiple sources, at a community level of resolution[33]." RAIMI integrates emission inventory, dispersion model, and risk estimation in a GIS environment and allows estimation and representation of cancer and non-cancer risks from air toxics.

Conceptually RAIMI follows the typical steps involved in a multi-source multi-pollutant risk assessment of air toxics. Figure A1 shows a flowchart of steps involved in a typical risk assessment process. As a first step, an emission inventory of all sources and pollutants released in the community of interest is developed. An air dispersion model such as Industrial Source Complex (ISC) model predicts ambient air concentrations at a number of receptor locations using emission source characteristics (e.g., exit gas velocity, exit gas temperature, stack height), meteorological parameters (e.g., wind speed and direction, vertical temperature profile, atmospheric stability), land use, and terrain characteristics of the study area. An exposure model takes into account the activity patterns and demographic composition of the area to estimate the actual exposures from

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[32] This description is a slightly modified version of the write-up included in Gesser et al. "PERCH Air Quality Study, Midyear Progress Report;" Georgia Institute of Technology; August 11, 2006

[33] RAIMI – Regional Air Impact Modeling Initiative available at http://www.epa.gov/earth1r6/6pd/rcra_c/raimi/raimi.htm. Last updated March 3rd, 2006

ambient concentrations. In the next step, using the toxicity information for different pollutants, individual as well as cumulative cancer and non-cancer risks are estimated.

The RAIMI process generally follows this typical risk assessment process but with a few additional assumptions. First, RAIMI does not have an exposure model built into it and hence assumes ambient concentrations as surrogates to exposures. Second, the dispersion modeling in RAIMI estimates ambient concentrations for a unit emission rate (1 g/s). This assumes that pollutants are released at a constant rate over the entire year and the dispersion process for all pollutants is the same irrespective of their individual physical characteristics. Finally, RAIMI is currently capable of estimating cancer and non-cancer risks only from inhalation pathway. Future developments are likely to provide capabilities for considering other pathways such as ingestion.

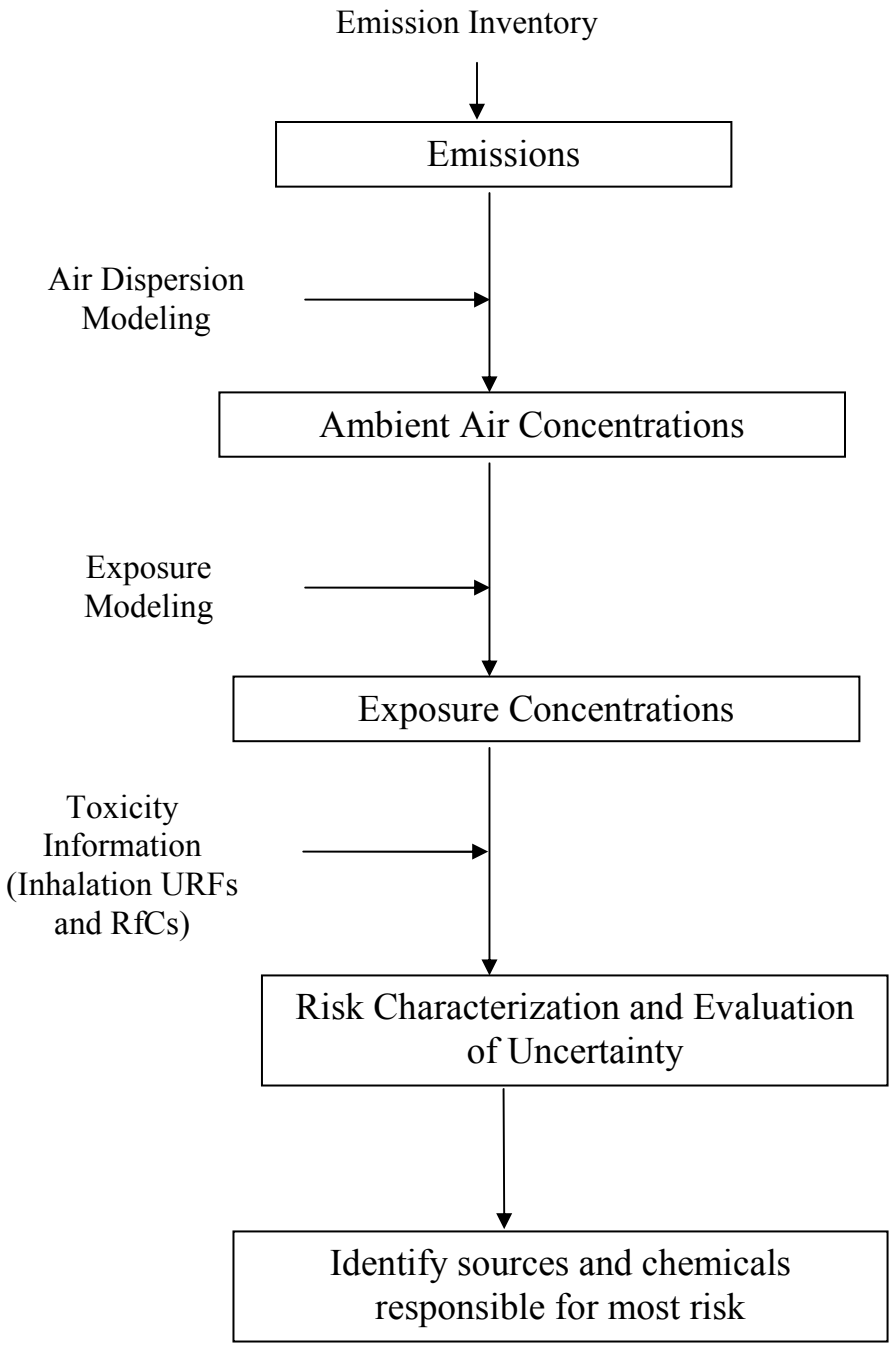

Figure A1. A Typical Inhalation Risk Assessment Process
(Source: EPA's Risk Assessment Reference Library – Volume 3)

A.2 RAIMI Components

The RAIMI system has five different tools that perform various functions.

1. **Risk-MAP**: Risk-MAP is the core tool within RAIMI. Risk-MAP is used to import emission inventory information into Geographic Information Systems (GIS) environment, perform risk analyses, present risk assessment results in tabular or graphical form, and perform supplemental analysis. Risk-MAP is designed as an extension within ArcMap GIS software.
2. **Air Modeling Preprocessor (AMP)**: The main function of AMP is to prepare source-specific meteorological and ISCST3 air model input files. This tool is also designed as an extension in ArcMap.
3. **ISC Batch**: This tool is designed to execute multiple ISCST model runs in a single batch run. In a multi-source risk assessment, the dispersion model has to be executed once for each source. Using this tool, one can run the dispersion model for a large number of sources in a single batch run.
4. **AIR2GIS**: This tool organizes the output from the dispersion model into a format that can be imported into GIS.
5. **Data Miner**: This tool has the capability to extract information from an existing inventory to prepare a table in a format that can be imported into the main Risk-MAP tool. Currently, this tool's use is restricted to Point Source Data Base (PSDB) format of Texas and was not used for this study.

A.2.1 Dispersion Model in RAIMI

Dispersion models predict downwind pollutant concentrations by simulating the evolution of the pollutant plume over time and space given data inputs including the quantity of emissions and the initial conditions (e.g., velocity, flowrate, and temperature) of the stack exhaust to the atmosphere. To estimate maximum ground-level

concentrations, RAIMI uses the latest version (02035) of the ISCST3 dispersion model, which was most recently upgraded by U.S. EPA on February 4, 2002. ISCST3 is a refined, steady-state, multiple source, Gaussian dispersion model and is a preferred model to use for industrial sources in this type of air quality analysis.[34]

It should be noted that RAIMI applications of ISCST3 do not allow for inclusion of building downwash parameters (i.e., dimensions of dominant building tiers), since the required data on buildings are typically not available. Building structures that obstruct wind flow near emission points may cause stack discharges to become caught in the turbulent wakes of these structures leading to downwash of the plumes. Wind blowing around a building creates zones of turbulence that are greater than if the building were absent. These effects generally cause higher ground level pollutant concentrations since building downwash inhibits dispersion from elevated stack discharges. The absence of building downwash analysis in this and any application of RAIMI is likely to affect the accuracy of model results to a certain degree that cannot be readily estimated since building dimensions (hence downwash effects) vary considerably from facility to facility.

A.2.2 Estimation of Cancer and Non cancer Risks in RAIMI

For chronic effects from carcinogenic compounds, risk is calculated from the inhalation unit risk (IUR), which represents upper-bound excess lifetime cancer risk estimated to result from continuous inhalation exposure of 1 g/m^3 over a lifetime. The chronic cancer risk is calculated simply as the product of the long-term modeled average

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[34] 40 CFR 51, Appendix W–*Guideline on Air Quality Models (April 2003 revision)*, Appendix A.5–Industrial Source Complex Model (ISC3). Note that since PERCH Phase III project inception, the U.S. EPA promulgated the AERMOD Modeling System on November 9, 2005 as the preferred regulatory dispersion model to replace ISCST3. However, RAIMI is not currently structured to utilize AERMOD, since this dispersion model requires different processing of meteorological data inputs than ISCST3. Future applications of RAIMI or refinement of risk assessment result should utilize AERMOD in favor of ISCST3.

concentration (MC) and the IUR. RAIMI calculates the chronic cancer risk attributable to each pollutant emitted from each source at each node, and making the assumption that all chronic risks are cumulative, adds the piecewise risks to quantify the total risks as summarized in equations A1 and A2.

$$\text{Risk}_i = MC_i \times \text{IUR}_i \qquad (A1)$$

$$\text{Cumulative Risk} = \sum_i \left(\text{Risk}\right)_i \qquad (A2)$$

Chronic non-cancer effects are expressed in terms of a reference concentration (RfC), which represents an estimate of the upper-bound continuous inhalation exposure without an adverse health effect. The chronic non-cancer risk is calculated simply as the division of the long-term *MC* by the RfC. The chronic non-cancer risk hazard quotient (*HQ*) attributable to each pollutant emitted from each source can be calculated at each receptor node, and making the assumption that all chronic risks are cumulative, adding the piecewise *HQ* yields the total hazard index (*HI*) as summarized in equations A3 and A4.

$$HQ_{\text{i}} = \frac{MC_i}{\text{RfC}_i} \qquad (A3)$$

$$HI = \sum_i \left(HQ\right)_i \qquad (A4)$$

A.3 Data

The implementation of RAIMI involved collection of a variety of data from different sources. This section briefly presents the type of data collected and their sources.

A.3.1 Emissions Data

RAIMI requires development of an emission inventory that should include physical characteristics of sources such as location and type (stack, fugitive, or flare), height of release, and velocity and temperature of exit gas as well as emission characteristics such as pollutants released, and the corresponding emission rates. Several states develop their own inventories for air toxics (for example, the point source database of Texas). Florida, however, has not yet developed any such comprehensive state level database for air toxics. Hence this research used a federal emission inventory developed by EPA. Specifically, we used the point source database of EPA's 1999 base year National Emission Inventory (NEI) (Version 3) for hazardous pollutants (HAPs) (http://www.epa.gov/ttn/chief/net/1999inventory.html).

The US EPA compiles the NEI for HAPs from a variety of sources. The first source of information for NEI is state and local air pollution control agencies. Identical information was also requested from the Emission Standards Division (ESD) for Maximum Achievable Control Technology (MACT) standards. EPA then uses Toxic Release Inventory (TRI) data to make sure that "all emissions data for facilities that report to TRI are included in NEI (EPA, 2003 p: 2-2)." Finally, for those states and counties that did not submit data in 1999, EPA used data submitted in 1996 to complete the 1999 base year NEI for HAPs.

Considerable manual, subjective quality assurance of data inputs was required to avoid misrepresentative modeling analyses. NEI data are compiled from emissions reports submitted by individual facilities whose emissions reports vary in completeness and quality. Common data entry errors that can have a significant impact on model results include source coordinates, emission rate, and stack parameters. Of these inputs, improper source coordinates were most evident when plotted in the RAIMI GIS system. Using NEI data, several facilities exhibited multiple point sources in distinct locations within the model domain. In these cases, aerial photographs and/or permit files obtained from the Florida Department of Environmental Protection were referenced to discern

appropriate source locations and parameters. The source inventory was also inspected for duplicate entries, which were removed if found.

A.3.2 Geographical Information Systems (GIS) Data

RAIMI predominantly operates in a GIS environment. Thus, the implementation of RAIMI tools requires several GIS maps. These GIS maps are primarily used in generating input files for dispersion modeling. In our study, we used the following GIS maps.

- *Land use/Land cover Maps*: Inputs to the ISCST3 dispersion model requires identification of land use category (urban or rural), dispersion coefficients, and surface roughness height parameters for each source. This study used a 1:250,000 land use / land cover (LULC) map (in the form of a GIS shapefile) from the United States Geological Service (USGS) available from the Florida Geographic Data Library (FGDL) (www.fgdl.org) for Escambia and Pensacola counties. These maps were edited to correct for some inconsistencies.
- *Digital Elevation Maps (DEM)*: The elevation of sources as well as receptors is an input for air dispersion modeling. This study used 1:250,000 scale USGS digital elevation model (DEM) maps available from http://eros.usgs.gov/geodata.
- *Aerial Photographs*: Aerial photographs of the two-county study area were used for verifying source locations. The tool utilized for this purpose is called TerraServer Download ArcGIS 9.0 (Version 2) (available from http://arcscripts.esri.com/details.asp?dbid=13703), which has the ability to download aerial photograph imagery from TerraServer server (http://terraserver.microsoft.com) directly into ArcMap GIS software.

A.3.3 Upper Air and Surface Meteorological Data

The ISCST3 air dispersion modeling in RAIMI was performed using 1986 through 1990 meteorological data based on surface observations taken from the Pensacola Regional Airport (WBAN 13899). During this period, the observation station was located at 30.47 N, 87.20 W with a base elevation of 34.1 meters above mean sea level and anemometer height of 6.71 meters. Mixing heights and upper air data were obtained from Apalachicola (WBAN 12832). The observation station at Apalachicola was located at 29.73 N, 85.02 W with a base elevation of 6.1 meters above mean sea level. It should be noted that precipitation data for wet deposition computations were not utilized in the analysis due to lack of a representative precipitation observation data set for the study period. Surface and upper air data were obtained from U.S. EPA's archive of meteorological data for dispersion modeling (http://www.epa.gov/scram001/metobsdata_databases.htm).

A.3.4 Toxicity Data

Unit Risk Factors (URFs) for cancer risk estimation and Reference Concentrations for non-cancer risk estimation for various air toxics were compiled by the US EPA Region 6 office from a variety of sources including EPA's Integrated Risk Information System (IRIS) (www.epa.gov/iris), California Air Resource Board (CA ARB) risk factors, and Health Effects Assessment Summary Tables (HEAST).

A.4 Implementation Methodology

This section describes the detailed implementation process of RAIMI for point sources in Pensacola and Santa Rosa counties (see Figure 5.1 for conceptual diagram of RAIMI implementation). The implementation involved the following broad steps.

- Creating PIT from 1999 National Toxics Inventory (NTI) database
- Setting up Emission Tracking Database (ETD)
    a. Importing PIT into Risk-Map

b. Identification and verification of geographical location of sources to be modeled
c. Preparation of source input table for AMP tool
d. Importing dose-response data as "contaminant table" into Risk-Map

- Implementing AMP tool to prepare source and meteorological input files for ISCST air dispersion model
- Executing ISCST model using RAIMI's ISC Batch tool to generate source-specific hourly and annual average plot files
- Importing air model results into Risk-Map tool for risk analysis on a GIS platform
- Analyzing cancer and non-cancer risks in the study area using Risk-Map tool

A.4.1 Creating Primary Inventory Table (PIT)

The PIT is one of the primary inputs into RAIMI. PIT is an *MS Access* table with each record containing information about a particular source. This information includes, among other things, a unique identifier for the source, the facility name, source location (in UTM coordinates), and emission characteristics such as temperature, exit velocity, height and diameter of emission stack. The PIT was generated from the NEI.

The first step in generating the PIT was to obtain point source NEI data for the entire state of Florida and then extracted data for Escambia (FIPS code – 12033) and Santa Rosa (FIPS code – 12113). The point source NEI for HAPs is an *MS Access* database organized in eight tables with the state facility identifier being the common field for all the tables. The data required for generating the PIT existed in three of those eight tables – "Site," "Emission Release Point," and "Emission." A set of *MS Access* queries extracted the required fields from the NEI database into the PIT. After extracting all the required fields, the *MS Access* table was formatted to comply with the specific requirements of the PIT. The User's Guide of RAIMI's Risk-Map tool (EPA Region 6, 2004) specifies the field name and field type for every field in the PIT. For example, the

name describing an emission point should have a field name "point_name" and it should be a text field with a width of 25 characters. Similarly, stack exit gas temperature should be named "temp" and that field should be an integer type.

It should be noted that not every field required for the PIT was available from the NEI database. For example, while fugitive source modeling ideally requires details about width and length of the fugitive source, the point source NEI does not report such information. In such cases, the fields in the PIT were left blank and the fugitive sources were modeled as if they were emitted from a stack.

The next step was to check for any inconsistencies in the compiled data. In the study area, the NEI reported duplicate data for some facilities. For example, although International Paper took over Champion International, the NEI data reports emissions data for both facilities separately. We removed data for Champion International and retained data for International Paper in the final PIT. Based on air permit documents from the Florida Department of Environmental Protection (DEP) as well as the draft 2002 NEI, the data for Champion International were excluded from the final PIT, while retaining the data for International Paper.

A.4.2 Setting up Emission Tracking Database (ETD)

The Risk-Map tool is developed as an extension of the ArcView GIS software. This step generates the information, in the form of several tables, necessary for running Air Modeling Preprocessor (AMP) tool and later for risk assessment. All these tables are generated by Emission Tracking Database (ETD) Manager – an *MS Access* database builder with imbedded queries. The tables are stored in the project-specific ETD. The ETD consists of (a) PIT, (b) Emissions, (c) Geolocation (d) Final Geolocation, (e) Sources_to_AM, (f) AM Sources, and (g) Contaminants tables.

The first step imported the PIT into the ETD. All the subsequent tables within ETD were generated using the information contained in the PIT. The first table generated

in ETD using information in the PIT is "emissions table." It simply contains the unique source ID, source name, and the emission value for each pollutant. Emissions table will be used as an input for risk assessment. The process behind the generation of all the ETD related tables are described below.

Geolocation

The Geolocation table generated in the ETD contains the source-specific location information that is taken from the PIT. The NEI collects information on coordinates of the source location and the corresponding reference datum. The reference datum was different for different source coordinates and for a few sources, no reference datum was specified[35]. The purpose of generating the Geolocation table was to project all the sources into a common reference datum. All the sources were projected into the UTM Zone 16 NAD 1983 coordinate system.

Final Geolocation

A crucial step in air dispersion modeling is accurate location of sources to be modeled. Before going any further, it was important to verify the accuracy of source locations in the Geolocation table. Before correcting the source locations, the "Geolocation" table was saved as "Final Geolocation" table.

As was generally described above, a number of independent sources of location information were used for this verification step. These information sources included:

- Location data for industrial facilities in Escambia supplied by the University of West Florida (UWF),
- Aerial Photographs,

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[35] In cases where no reference datum was specified, we assumed NAD 1927 projection system based on the recommendation of EPA Region 6 Office

- Air permit documents from the Florida Department of Environmental Protection (FL DEP),
- The Solid Waste Facility Locator of FL DEP[36], and
- Google Earth

Sources_ to_AM

The next table generated by the ETD Manager was Sources_to_AM table. This table contains the data on source-specific emission characteristics (such as exit gas temperature, velocity, and height and diameter of stack) as well as the source coordinates. The emission characteristic fields for this table come from the PIT and the source coordinate fields come from the Final Geolocation Table. In order to comply with the requirements of ISCST3 air dispersion model, some of the fields in the Sources_to_AM table had to be edited. These edits were made in AM Sources table, which was just a copy of Sources_to_AM table.

AM Sources

The NEI reports emission parameters such as exit gas velocity and temperature in English units whereas the ISCST3 model requires them in metric units. Thus, to meet these requirements, exit gas velocity was changed from *ft/s* to *m/s*, exit gas temperature from *degree Fahrenheit* to *degree Kelvin*, and stack diameter and height from *ft* to *m*. The ISCST3 model also places some restrictions on the minimum and maximum values for the above emission parameters. The following maximum and minimum values were used as per the recommendation of EPA Region 6 Office:

- Stack height:
    - Minimum: 1 m and Maximum: 91.44 m

[36] Available at http://gisweb.dep.state.fl.us/DEP/Regulatory/viewer.asp?SWFL=true

- Stack Diameter
    - Minimum: 0.01 m and Maximum: 30 m
- Stack gas temperature
    - Minimum: 273 K
- Stack gas exit velocity
    - Minimum: 0.01 m/s and Maximum: 165 m/s

After making these edits, the AM Sources table was imported into the ETD using the ETD Manager. This table was the source input table for AMP tool.

Contaminants

The contaminant table contains the dose-response data – unit risk factors (URF) for estimating cancer risks and reference concentrations (RfC) for estimating non-cancer risks – for various pollutants. EPA developed these values for various pollutants and they are primarily reported in the Integrated Risk Information System (IRIS) although a few other sources are also used. These are used as an input into risk assessment. As explained before, currently RAIMI only has the capability to estimate risk from the inhalation pathway. Eventually, capabilities to estimate risks from other pathways such as digestion will be developed.

A.4.3 Generating Input Files for ISCST Air Dispersion Model

The next step was to prepare input files for ISCST air dispersion model. This step is accomplished using the Air Model Preprocessor (AMP) tool. Similar to Risk-Map, AMP is also an extension in ArcGIS software. The AMP tool requires the following inputs to generate source-specific ISCST- and meteorological input files.

Source Input

AMP uses the AM_Souces table imported into Risk-MAP in the previous step for source input parameters.

MPRM Stage 1 and Stage 2 file:

Raw meteorological inputs were processed using U.S. EPA's MPRM which compiles surface and mixing height observations, calculates atmospheric stability, and estimates boundary layer profiles based on land use and cover surrounding the observation site. The AMP tool in RAIMI requires generation of quality checked surface and upper air meteorological data (stage 1 and stage 2 of MPRM)) so that it can complete stage 3 of MPRM and create an ISCST input meteorological data file for each source. Typically, five years of meteorological data at the nearest station is used for stage 1 and stage 2 MPRM. For this study, stage 1 and stage 2 of MPRM were completed for five years of available meteorological data between 1986 and 1990.

Land Use/Land Cover

Stage 3 processing of MPRM requires consideration of land use characteristics within the modeling domain. The effects of land use and land cover in typical dispersion model is represented by three surface characteristics – surface roughness, Bowen ratio, and Albedo that may vary by wind direction and time of the year. Completing stage 3 requires the definition of each surface characteristic in up to 12 wind sectors about the meteorological data observation point, varying by climatological season. This study used the 1:250,000 USGS land use land cover maps in the form of a GIS shape file for land use characteristics of the study area.

Elevation Data

RAIMI utilizes a universal grid based in the Universal Transverse Mercator (UTM) coordinate projection system to place receptors throughout the modeling domain at which ISCST3 computes pollutant concentrations. By default, RAIMI places 100-meter spaced receptors up to a distance of 5 km from each source, and 500-meter spaced up to a distance of 10 km from each source. The variation between the elevation of a

receptor grid node location and a source location significantly affects the dispersion modeling results. Because of this, the dispersion model input requires elevation of each receptor grid location relative to the source. Elevation data for the two-county study area was obtained from USGS Digital Elevation Model (DEM) maps. Our study area was covered by four DEM files – Pensacola East, Pensacola West, Andalusia East, and Andalusia West.

Using these inputs, AMP generated the following outputs:

- *Source-specific ISCST Input Files*: AMP can create model input files for each of the four contaminant phases – vapor, particle, particle-bound, and mercury vapor – for each source. In our study, however, we generated only vapor phase input files because we modeled only inhalation risks. This input file also includes source-centered universal grid node array with extracted terrain elevations.
- *Source-specific meteorological files*: Execution of stage 3 of MPRM generated a single 5-year (1986-1990) meteorological file with a .MET extension for each source.

A.4.4 Executing ISCST Model with ISC Batch Tool

The next step used the ISCST3 and meteorological input files generated for each source to execute the ISCST3 dispersion model. The output from this step is the estimation of 1-hour average and annual average concentrations at each point on the receptor grid for each source. This output is generated in the form of two plot files, one for each of the 1-hour and annual averages. The ISC Batch tool used in this step is capable of executing the ISCST3 model for a large number of sources in a single batch run. It should be noted again that the estimated ambient concentrations are based on a unit emission rate (1 g/s). That is, the emissions are modeled as if they are emitted at a constant rate over an entire year. The benefit of this approach is that risk estimations can

be carried out quickly for any emission scenario without having to run the dispersion model multiple times.

A.4.5 Importing Dispersion Model Results into Risk-Map Tool

The AIR2GIS tool used in this step merges the information in the two output plot files (for 1-hour and annual averages) generated in the previous step into one A2G file in a format importable to ArcGIS software. The AIR2GIS tool is capable of generating A2G files for several sources in a single run.

A.4.6 Risk Analysis

The final step in the implementation is the estimation of cancer and non-cancer risks in the study area by importing the ambient air concentrations (in the form of A2G files) into Risk-MAP tool. The Node Attribute Index Table (NAIT) layer, created during the process of importing A2G files into Risk-MAP, organizes and stores results of air dispersion model in "an efficient format designed to reduce file access and data read/write times[37]." The Risk-MAP tool then utilizes the toxicity information imported through "Contaminant" table and emission rates from "Emissions" table, created in earlier steps, to calculate cancer and non-cancer risks at various receptors in the study area. The NAIT layer enables Risk-MAP to calculate cumulative risks from individual risk calculations based on source, pollutant, or both.

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[37] Page 4-1 of RAIMI Tools – Risk-MAP User's Manual: Risk Management and Analysis Platform, US EPA Region 6, April 2004

APPENDIX B

GAMS MODEL CODE

```
* Decision Model for Mohan's Dissertation *
* GAMS Program for Optimization Run at Census Tract Resolution *
* Open the input GDX file *
$gdxin input.gdx
* Definition of Sets in the Model *
Sets
        i (*) sources
        j (*) pollutants
        k (*) locations
        m (*) pop-locations ;
* Reading the sets from the input gdx file *
$load i j k m
* Declaration of Parameters of the model *
Parameters
        u(j) Cancer Unit Risk Factors for pollutants
        QB (i,j) Baseline Emissions of Pollutant j from Source i
        Beta (i,j,m) Concentration at m from unit emission rate in obj function
        BetaR (m,i,j) Concentration at m in obj function with sets reversed for GDX input
        Gamma (i,j,k) Concentration at k from unit emission rate in constraint
        GammaR (k,i,j) Concentration at k in constraint with sets reversed for GDX input
        p(m) Population at location m
        b(i,j) Product term  for Cost Function
        c(i,j) Exponential term for Cost Function;
```

**** Load all the parameters from the input GDX file ****

$load u QB BetaR=Beta GammaR=Gamma p b c

option Beta<BetaR, Gamma<GammaR;

**** Close the input gdx file ****

$gdxin

**** Scalars in the model - threshold risk and value of statistical life ****

Scalars

V Value of Statistical Life in Dollars/5500000/

Z Threshold Risk/0.00001/;

**** Model Variables - Q is choice variable and TCOST is variable to be minimized ****

Positive variable Q(i,j) Emission of pollutant j from source i ;

Variable r(k) Risk at location k;

Variable LCOST Linear term in objective function;

Variable TCOST Total cost in dollars;

**** Declaration of equations for objective function and constraint ****

Equations

OBJ Objective Function for the Problem

Objl Equation for Linear term in objective function

CalRisk(k) Equation for Risk Calculation;

**** The factor 2116.8 below reflects conversion of Q from t/y to g/s and lifetime risk to annual risk ****

Objl.. LCOST =e= ((1/2116.8)(sum((i,j),(Q(i,j))*(sum (m, (Beta*

*(i,j,m)*p(m)*u(j)*V))))));*

OBJ .. TCOST =e= (sum ((i,j), ((b(i,j))(exp(c(i,j)*Q(i,j))-exp(c(i,j)*QB(i,j)))))+LCOST;*

*CalRisk(k) .. r(k)=e=sum((i,j), (Q(i,j)*Gamma(i,j,k)*u(j)));*

**** Risk Threshold Constraint ****

r.up(k)=Z;

**** Define the model – the model name is resolution ****

Model resolution Spatial Resolution Model /all/ ;

**** Declaration that this nonlinear optimization model should use CONOPT as the solver ****

Option nlp=CONOPT ;

**** Show slack in the constraints in the output ****

Option solslack=1;

**** Option file for CONOPT solver that specifies the maximum value any model parameter can reach in the optimization search ****

resolution.optfile=1;

**** Solve the non-linear optimization problem****

Solve resolution using nlp minimizing TCOST;

****Write optimized emissions and value function into a gdx file names "tract_output"****

execute_unload 'tract_output', Q, TCOST;

**** Write output from gdx file to Excel Spreadsheet ****

execute 'gdxxrw.exe tract_output.gdx var=Q.l rng=Sheet1!A1';

execute 'gdxxrw.exe tract_output.gdx var=TCOST.l rng=Sheet2!A1';

**** Display optimized emissions in the output LST file****

Display Q.l;

REFERENCES

Apelberg, B.J., Buckley, T.J., & White, R.H. (2005). Socio-economic and racial disparities in cancer risk from air toxics in Maryland. *Environmental Health Perspectives*, 113(6), 693-699

Axelrad, D.A., Baetcke, K., Dockins, C., Griffiths, C.W., Hill, R.N., Murphy, P.A., Owens, N., Simon, N.B., & Teuschler, L.K. (2005). Risk assessment for benefits analysis: Framework for analysis of a thyroid-disrupting chemical. *Journal of Toxicology and Environmental Health, Part A*, 68, 837-855

Becker, R.A. (2004). Pollution abatement expenditure by U.S. manufacturing plants: Do community characteristics matter? *Contributions to Economic Analysis & Policy*, 3(2), 1-21

Becker, G.S. (1983). A theory of competition among pressure groups for political influence. *The Quarterly Journal of Economics*, XCVIII (3), 371-400

Bostrom, A., Turaga, R.M.R., & Ponomariov, B. (2006). Earthquake mitigation decisions and consequences. *Earthquake Spectra*, 22(2), 313-328

Boyce, C.P. (1998). Comparison of approaches for developing distributions for carcinogenic slope factors. *Human and Ecological Risk Assessment*, 4(2), 527-577

Buchanan, J.M. & Tullock, G. (1975). Polluters' profits and political response: Direct control versus taxes. *The American Economic Review*, 65, 139-147

California ARB. (2007). Overview of the Air Toxics "Hot Spots" Information and Assessment Act. Last accessed on 16 April 2007 at http://www.arb.ca.gov/ab2588/overview.htm

Cal EPA. (2002). *Air Toxics Hot Spots Program Risk Assessment Guidelines Part II: Technical Support Document for Describing Available Cancer Potency Factors*. Office of Environmental Health Hazard Assessment, California Environmental Protection Agency, December 2002

Cal EPA. (2003). *The Air Toxics Program Guidance Manual for Preparation of Health Risk Assessments*. Office of Environmental Health Hazard Assessment, California Environmental Protection Agency, August 2003

Carlson, C., Burtraw, D., Cropper, M., & Palmer, K.L. (2000). Sulfur dioxide control by electric utilities: What are the gains from trade? *Journal of Political Economy*, 108(6), 1292-1325

Ching, J., Dupont, S., Herwehe, J., Otte, T., Lascer, A., Byun, D., & Tang, R. (2004). Air quality modeling at coarse-to-fine scales in urban areas. Preprints, 6th Conference on Atmospheric Chemistry: Air Quality in Megacities, 84th AMS Annual Meeting, Seattle, WA, January 11-15, 2004

Coggins, J. S. and J. R. Swinton. (1996). The price of pollution - a dual approach to valuing SO_2 allowances. *Journal of Environmental Economics and Management,* 30(1), 58-72.

Congleton, R.D. (1996). Introduction in *The Political Economy of Environmental Protection: Analysis and Evidence*, Congleton, R.D. eds., Ann Arbor, MI: University of Michigan Press

Cropper, M.L., Evans, W.N., Berardi, S.J., Ducla-Soares, M.M., & Portney, P.R. (1992). The Determinants of Pesticide Regulation: A Statistical Analysis of EPA Decision Making. *Journal of Political Economy*, 100(1), 175-197

Crouch, E.A.C., Lester, R.R., Lash, T.L., Armstrong, S.R., Green, L.C. (1995). *Report to the Commission on Risk Assessment and Risk Management: Health Risk Assessment Prepared per the Risk Assessment Reforms under Consideration in the U.S. Congress*. Cambridge Environmental Inc.,

Dabberdt. W.F., & Miller, E. (200). Uncertainty, ensembles and air quality dispersion modeling: applications and challenges. *Atmospheric Environment*, 34, 4667-4673

Dankner, R..S. (1988). Safety before feasibility: A two-step approach to regulating hazardous pollutants. *The George Washington Law Review*, 56, 799-803

Dasgupta, S., Huq, M., Wheeler, D., & Zhang, C. (2001). Water pollution abatement by Chinese industry: cost estimates and policy implications. *Applied Economics*, 33, 547-557

Dockins, C., Griffiths, C.W., Owens, N., Simon, N.B., & Axelrad, D.A. (2004). Linking economics and risk assessment. *Journal of Toxicology and Environmental Health, Part A*, 67, 611-620

Dolinoy, D.C., & Miranda, M.L. (2004). GIS modeling of air toxics releases from TRI reporting and non-TRI reporting facilities: Impacts for environmental justice. *Environmental Health Perspectives*, 112(17), 1717-1724

Ellerman, A.D., and A. Decaux. (1998). *Analysis of Post-Kyoto CO_2 Emissions Trading Using Marginal Abatement Curves, MIT Joint Program on the Science and Policy of Global Change* Report No. 40, Cambridge, MA

EPA. (1992). *Air Pollutant Emissions from Process Units in the Synthetic Organic Chemical Manufacturing Industry--Background Information for Proposed Standards. Volume 1A: National Impacts Assessment*. Emission Standards Division, office of Air Quality and Radiation

EPA. (1993). *Pulp, Paper, Paperboard Industry – Background Information for Proposed Air Emission Standards: Manufacturing Processes at Kraft, Sulfite, Soda, and Semi-chemical Mills*. Emission Standards Division, Office of Air and Radiation, EPA453/R-93-050a

EPA. (1994). *Regulatory Impact Analysis for the National Emission Standards for Hazardous Air Pollutants for Source Categories: Organic Hazardous Air Pollutants from the Synthetic Organic Chemical Manufacturing Industry and Other Processes Subjected to the Negotiated Regulation for Equipment Leaks*. EPA -453/R-94-019, March 1994

EPA. (1995). *User's Guide for the Industrial Source Complex (ISC3) Dispersion Models. Volume II – Description of Model Algorithms*. EPA-454/B-95-003b

EPA. (1997a). *Pulp, Paper, and Paperboard Industry – Background Information for Promulgated Air Emission Standards: Manufacturing Processes at Kraft, Sulfite, Soda, Semi-chemical, Mechanical, and Secondary and Non-wood Fiber Mills, Final EIS*, EPA-453/R-93-050b, October 1997

EPA. (1997b). *National Emissions Standards for Hazardous Air Pollutants for Source Categories: Oil and Natural Gas Production and Natural Gas Transmission and Storage - Background Information for Proposed Standards.* Emissions Standards Division, April, 1997

EPA. (1998). *Economic impact analysis for the proposed national emission standard for hazardous air pollutants from the production of acrylic modacrylic fibers. Office of Air Quality Planning and Standards.* Docket No. A-97-18, Item No. II-A-6, May 1998

EPA. (1999a). *Residual Risk Report to Congress*. Office of Air Quality Planning and Standards, Research Triangle Park, NC, March 1999

EPA. (1999b). *Economic Impact Analysis of the Oil and Natural Gas Production NESHAP and the Natural Gas Storage and Transmission NESHAP, Final Report.* Office of Air Quality and Radiation, May, 1999

EPA. (1999c). *The benefits and the costs of the Clean Air Act 1990 to 2010.* Office of Air and Radiation, Office of Policy, US EPA, EPA-410-R-99-001

EPA. (2000a). *An SAB Report on EPA's White Paper on Valuing the Benefits of Fatal Cancer Risk Reduction.* EPA-SAB-EEAC-00-013, July 27, 2000

EPA. (2000b). *Handbook for Non-cancer Health Effects Valuation*. Non-cancer Health Effects Valuation Sub-committee of the EPA Social Science Discussion Group, December 2000.

EPA. (2001). *U.S. Environmental Protection Agency Workplan for the National Air Toxics Program and Integrated Air Toxics State/local/tribal Program Structure*. Emission Standards Division, Office of Air Quality Planning and Standards, US EPA.

EPA. (2002). *Regulatory Impact Analysis of the Proposed Industrial Boilers and Process Heaters NESHAP: Final Report.* Office of Air Quality Planning and Standards, US EPA, November 2002

EPA. (2003a). *International Analysis of Methane and Nitrous Oxide Abatement Opportunities: Report to Energy Modeling Forum.* Working Group 21, June, 2003

EPA. (2003b). *Economic Impact Analysis of the Final Stationary Combustion Turbines NESHAP: Final Report.* EPA Report No. EPA-452/R-03-014, August 2003

EPA. (2004a). *National Monitoring Strategy: Air Toxics Component*. Office of Air Quality Planning and Standards, Research Triangle Park, NC, July 2004.

EPA. (2004b). *An examination of EPA risk assessment principles and practices. Staff Paper Prepared for the U.S. Environmental Protection Agency by members of the Risk Assessment Task Force*, Office of the Science Advisor, U.S. EPA, EPA/100/B-04/001

EPA. (2004c). *Toolkit for Assessing Potential Allegation of Environmental Injustice. Office of Environmental Justice*. EPA 300-R-04-002, November 2004

EPA. (2005a). *Guidelines and Carcinogenic Risk Assessment*. Risk Assessment Forum, US EPA, Washington, DC. EPA/630/P-03/001B

EPA. (2005b). *Supplemental Guidance for Assessing Susceptibility from Early-life Exposure to Carcinogens. Risk Assessment Forum.* US EPA, Washington, DC. EPA/630/R-03/003F

EPA. (2006a). *RAIMI – Regional Air Impact Modeling Initiative.* Last accessed on 12 March 2006 from http://www.epa.gov/earth1r6/6pd/rcra_c/raimi/raimi.htm

EPA. (2006b). *Air Toxics Risk Assessment Reference Library, Volume 3: Community-scale Assessment*. EPA-452/K-06-001C, April 2006

EPA. (2006c). *An Empirical Bayes Approach to Combining and Comparing Estimates of the Value of a Statistical Life for Environmental Policy Analysis, Appendix H of Benefits ant Costs of the Clean Air Act 1990-2020: Revised Analytical Plan for EPA's Second Prospective Analysis*

EPA. (2006d). *Ecological Benefits Assessment Strategic Plan*. EPA-240-R-06-001, October 2006

EPA. (2007a). *Risk and Technology Review*. Last accessed on 20 May 2007 from http://www.epa.gov/ttn/atw/rrisk/rtrpg.html

EPA. (2007b). *Area Source Standards*. Technology Transfer Network: Air Toxics Website. Last accessed on 15 April 2007 at http://www.epa.gov/ttn/atw/urban/arearules.html

EPA. (2007c). *1999 National Emission Inventory Documentation and Data –Final Version 3.0.* Last accessed on 31 March 2007 at http://www.epa.gov/ttn/chief/net/1999inventory.html

EPA. (2007d). *Surface and Upper Air Databases*. Last accessed on 31 March 2007 at http://www.epa.gov/scram001/metobsdata_databases.htm

EPA. (2007e). *Glossary of IRIS Terms*. Available from http://www.epa.gov/iris/gloss8.htm. Last accessed 12 March 2007

Executive Order 12898 (1994) Federal actions to address environmental justice in minority populations and low-income populations, issued February 11, 1994

Executive Order 13045 (1997) Protection of children from environmental health risks and safety risks, issued April 21, 1997

Fare, R., Grosskopf, S., Knox Lovell, C.A., Yaisawarng, S. (1993). Derivation of shadow process for undesirable outputs: A distance function approach. *The Review of Economics and Statistics*, 75(2), 374-380

Fare, R., Grosskopf, S., & Weber, W L. (2006). Shadow prices and pollution costs in U.S. agriculture. *Ecological Economics*, 56(1), 89-103

Federal Register. (1989). *National emission standards for hazardous air pollutants: Benzene*. 54(177):38044-38072

Federal Register. (1992). *Initial List of Categories of Sources Under Section 112 (c)(1) of the Clean Air Act Amendments of 1990*. July 16, 1992, 31576-91

Federal Register. (1999a). *Environmental Protection Agency National Urban Air Toxics Program: The Integrated Urban Air Toxics Strategy*. 64(137), 38706-38740

Federal Register. (1999b). *National Emission Standards for Hazardous Air Pollutants: Oil and Natural Gas Production and Natural Gas Transmission and Storage; Final Rule*, 64(116), 32609-62

Federal Register. (2000). *Hazardous Air Pollutants: Amendments to the Approval of State Programs and Delegation of Federal Authorities; Final Rule*. 65(179), 55809-46

Federal Register. (2001). *Controls of Emissions of Hazardous Air Pollutants from Mobile Sources: Final Rule*. 66(61), 17229-17273

Federal Register. (2004). *National Emission Standards for Hazardous Air Pollutants for Stationary Combustion Turbines; Final Rule*, 69(44), 10511-10548

Federal Register. (2005). *Revision to the Guideline on Air Quality Models: Adoption of a Preferred General Purpose (Flat and Complex Terrain) Dispersion Model and Other Revisions; Final Rule*, 70(216), 68217-68261

Federal Register. (2007). *Controls of Emissions of Hazardous Air Pollutants from Mobile Sources: Final Rule,* 71(60), 15803-15963

Fox, D.G. (1984). Uncertainty in air quality modeling. *Bulletin of American Meteorological Society*, 65(1), 27-36

Freeman, D.L., Egami, R.T., Robinson, N.F., & Watson, J.G. (1986). A method for propagating measurement uncertainties through dispersion models. *Journal of Air Pollution Control Association*, 36, 246-253

GAO. (1997). *Air Pollution: Information contained in EPA's regulatory impact analyses can be made clearer*. Resources, Community, and Economic Development Division, GAO/RCED-97-38

GAO. (2005). Environmental Justice: EPA should devote more attention to environmental justice when developing clean air rules. Report No. GAO-05-289, July 2005

GAO. (2006). *Clean Air Act: EPA should improve the management of its air toxics program*. Report no. GAO-06-669, June 2006

Gibson, C.C., Ostrom, E., & Ahn, T.K. (2000). The concept of scale and the human dimensions of global change: A survey. *Ecological Economics*, 32, 217-239

Goldstein, B.D. (1989). The maximally exposed individual: An inappropriate basis for public health decision making. *The Environmental Forum*, 6(1), 13-16

Goldstein, B.D. (1995). The need to restore the public health base for environmental control. *American Journal of Public Health*, 85(4), 481-483

Goldstein, B.D. & Carruth, R.S. (2003). Implications of the precautionary principle for environmental regulation in the United States: Examples from the control of hazardous air pollutants in the 1990 clean air act amendments. *Law and Contemporary Problems*, 66, 247-261

Gollop, F.M. & Roberts, M.J. (1985). Cost-minimizing regulation of sulfur emissions: Regional gains in electric power. *Review of Economics and Statistics*, 67(1), 81-90

Gray, W.B. & Shadbegian, R.F. (2004). 'Optimal' pollution abatement – whose benefits matter, and how much? *Journal of Environmental Economics and Management*, 47, 510-534

Gupta, S., Van Houtven, G., & Cropper,M.L. (1995). Do Benefits and Costs Matter in Environmental Regulation?: An Analysis of EPA Decisions Under Superfund," in *Analyzing Superfund: Economics, Science, and the Law*, Revez, R. & Stewart, R. eds., Washington DC, Resources for the Future Press

Hahn, R.W. (1990). The political economy of environmental regulation: Toward a unifying framework. *Public Choice*, 65, 21-47

Hamilton, J.T. & Viscusi, W.K. (1999). *Calculating Risks? The Spatial and Political Dimensions of Hazardous Waste Policy*, Cambridge, MA: The MIT Press

Hamilton, J.T. (1993). Politics and social costs: Estimating the impact of collective action on hazardous waste facilities. *The RAND Journal of Economics*, 24(1), 101-125

Hamilton, J.T. (1999). Exercising property rights to pollute: Do cancer risks and politics affect plant emission reductions? *Journal of Risk and Uncertainty*, 18(2), 105-124

Hammitt, J.K. (2000). Valuing mortality risk: Theory and practice. *Environmental Science & Technology*, 34(8), 1396-1400

Hanna, S.R. (1988). Air quality model evaluation and uncertainty. *Journal of Air Pollution Control Association*, 38, 406-412

Hanna, S.R., Lu, Z., Frey, H.C., Wheeler, N., Vukovich, J., Arunachalam, S., Fernau, M., & Hansen, D.A. (2001). Uncertainties in predicted ozone concentrations due to input uncertainties for UAM-V photochemical grid model applied to the July 1995 OTAG domain. *Atmospheric Environment*, 35, 891-903

Hanna, S.R., Paine, R., Heinold, D., Kintigh, E., & Baker, D. (2006). Uncertainties in air toxics calculated by the dispersion models AERMOD and ISCST3 in the Houston ship channel area. Revised manuscript RDK-602 submitted to the *Journal of Applied Meteorology*

Hartman, R., Wheeler, D., & Singh, M. (1997). The cost of air pollution abatement. *Applied Economics*, 29, 759-774

Hattis, D., Globe, R., & Chu, M. (2005). Age-related differences in susceptibility to carcinogenesis: II. Approaches for application and uncertainty analyses for individual genetically acting carcinogens. *Environmental Health Perspectives*, 113(4), 509-516

Helland, E. (1998). The enforcement of pollution control laws: Inspections, violations, and self-reporting. *The Review of Economics and Statistics*, 80(1), 141-153

Hird, J.A. (1993). Environmental policy and equity: The case of superfund. *Journal of Policy Analysis and Management*, 12(2), 323-343

Hird, J.A. (1994). *Superfund: The Political Economy of Environmental Risk*. Baltimore: John Hopkins University Press

Hauserman, J. & Olinger, D. (1996, October 4). *EPA to evacuate "Mount Dioxin*." St. Petersburg Times, p.1A

Isakov, V., & Venkataram, A. (2006). Resolving neighborhood scale in air toxics modeling: A case study in Wilmington, CA. *Journal of Air & Waste Management Association*, 56, 559-568

Jerrett, M., Arain, A., Kanaroglou, P., Beckerman, B., Potoglou, D., Sahsuvaroglu, T., Morrison, J., & Giovis, C. (2005). A review and evaluation of intraurban air pollution exposure models. *Journal of Exposure Analysis and Environmental Epidemiology*, 15, 185-04

Keohane, N.O., Revesz, R.L., & Stavins, R.N. (1997). The positive political economy of instrument choice in environmental policy, Discussion Paper 97-25, Washington D.C.: The Resources for the Future

Klimont, Z., Amann, M., & Cofala, J. (2000). *Estimating costs for controlling emissions of volatile organic compounds (VOC) from stationary sources*. Interim Report No. IR-00-51, International Institute for Applied Systems Analysis, Austria

Kopp, R., Krupnick, A.J., & Toman, M. (1996). Cost-benefit analysis and regulatory reform. White paper for the Commission on Risk Assessment and Risk Management.

Krupnick, A.J. (2004). *Valuing health outcomes: Policy choices and technical issues*. RFF Report, Resources for the Future, Washington, D.C.

Limpert, E., Stahel, W.A., & Abbt, M. (2001). Log-normal distribution across the sciences: Keys and clues. *Bioscience*, 51(5), 341-352

Lopez, R. (2002). Segregation and Black/White Differences in Exposure to Air Toxics in 1990. *Environmental Health Perspectives*, 110, Supplement 2, 289-295

Louisville Metro. (2005). *Board Approves Strategic Toxic Air Reduction Program to Protect Public Health, Enhance Quality of Life*. Available at http://www.louisvilleky.gov/APCD/STAR/

Majeed, M., Ching, J., Otte, T., Reynolds, L., & Tang, R. (2004). CMAQ Modeling for Air Toxics at Fine Scales: A Prototype Study, Extended Abstract: CMAS 2004 Workshop, Chapel Hill, NC.

Mariam, Y. & Barre, M. (1996). *VOCs's cost functions in the design of emission abatement strategies*. MPRA Paper No. 658. Available from http://mpra.ub.uni-muenchen.de/658/

Marklund, Per-Olov. (2003). *Analyzing Interplant Marginal Abatement Cost Differences: A Directional Output Distance Function Approach*. Umeå Economic Studies, Paper No. 618. Available at http://ideas.repec.org/p/hhs/umnees/0618.html

McCarl, B.A. (2006). *McCarl GAMS User Guide Version 22.4*, Developed in coordination with GAMS Development Corporation, pp:1-669

McClelland, J.D. & Horowitz, J.K. (1999). The costs of water pollution regulation in the pulp and paper industry. *Land Economics*, 75(2), 220-232

Moller, L. Schuetzle, D., & Autrup, H. (1994). Future research needs associated with the assessment of potential human health risks from exposure to ambient air pollutants. *Environmental Health Perspectives*, 102, Suppl 4, 193-210

Morello-Frosch, R., Pastor, M., & Sadd, J. (2001). Environmental justice and Southern California's "riskscape": The distribution of air toxics exposures and health risk among diverse communities. *Urban Affairs Review*, 36(4), 551-578

Morello-Frosch. R., Pastor, M Jr., Porras. C., Sadd, J. (2002). Environmental justice and regional inequality in southern California: implications for future research. *Environmental Health Perspectives*, 110, Supplement 2, 149-154

Morgan, M.G. & Henrion, M. (1990). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. New York: Cambridge University Press

Mrozek, J.R. & Taylor, L.O. (2002). *What determines the value of life? A Meta-Analysis. Journal of Policy Analysis and Management*, 21(2), 253-270

NRC (National Research Council). (1993). Pesticides in the diets of infants and children. Washington, DC: National Academy Press

NRC. (National Research Council) (2004). *Air Quality Management in the United States*. National Research Council of the National Academies. Washington, DC: National Academies Press.

Nuckols, J.R., Ward, M.H., Jarup, L. (2004). Using geographic information systems for exposure assessment in environmental epidemiology studies. *Environmental Health Perspectives*, 112(9), 1007-1015

O'Neill, M.S., Jerrett, M., Kawachi, I., Levy, J.I., Cohen, A.J., Gouveia, N., Wilkinson, P., Fletcher, T., Cifuentes, L, & Schwartz, J. (2003). Health, wealth, and air pollution: Advancing theory and methods. *Environmental Health Perspectives,* 111(16), 1861-1870

Peltzman, S. (1976). Toward a more general theory of regulation. *Journal of Law and Economics*, 19(2), 211-240

Pizer, W.A., & Kopp, R. (2003). Calculating the costs of environmental regulation. Discussion Paper 03-06, Washington, D.C, Resources for the Future

Pratt, G.C., Wu, C.Y., Bock, D., Adgate, J.L., Ramachandran, G., Stock, T.H., Morandi, M. Saxton, K. (2004). Comparing air dispersion model predictions with measured concentration of VOCs in urban communities. *Environmental Science & Technology*, 38, 1949-1959

Report of the Risk Assessment Advisory Committee. (1996). *A Review of the California Environmental Protection Agency's Risk Assessment Practices, Policies, and Guidelines*. Available at http://www.oehha.ca.gov/risk/pdf/RAACreport.pdf

Rao, S.K. (2005). Uncertainty analysis in atmospheric dispersion modeling. *Pure Applied Geophysics*, 162, 1893-1917

Reitze, Jr., A.W. & Lowell, R. (2001). Control of hazardous air pollution. *Boston College Environmental Affairs Law Review*, 28(2-3), 229-362

Rezek, J., & Blair, B.F. (2005). Abatement cost heterogeneity in phase I electric utilities. *Comparative Economic Policy*, 23(3), 324-340

Rios, R., Poje, G.V., & Detels, R. (1993). Susceptibility to environmental pollutants among minorities. *Toxicology and Industrial Health*, 9(5), 797-820

Rood, A.S., McGavran, P.D., Aanenson, J.W., & Till, J.E. (2001). Stochastic estimates of exposure and cancer risk from carbon tetrachloride released to the air from the Rocky Flats plant. *Risk Analysis*, 21(4), 675-695

Rosenbaum, A. (2005). *The HAPEM5 User's Guide: Hazardous Air Pollutant Exposure Model, Version 5*, Prepared for Office of Air Quality Planning and Standards, US EPA

Ross, M.T., Gallher, M.P., Murray, B.C., Throneburg, W.W., & Levinson, A. (2004). *PACE Survey: Background, applications, and data quality issues*. Working Paper # 04-09, National Center for Environmental Economics, US Environmental Protection Agency

Sax, T. & Isakov, V. (2003). A case study for assessing uncertainty in local-scale regulatory air quality modeling applications. *Atmospheric Environment*, 37, 3481-3489

Siegrist, M. (2000). The influence of trust and perceptions of risk and benefits on the acceptance of gene technology. *Risk Analysis*, 20(2), 195-203

Simon, C.P. & Blume, L. (1994). *Mathematics for Economists*. W.W. Norton & Company

South Coast AQMD. (2007). *Risk Reduction*. Last accessed on 19 April 2007 at http://www.aqmd.gov/prdas/AB2588/AB2588_B5.html

Stigler, G.J. (1971). The theory of economic regulation. *The Bell Journal of Economics and Management Science*, 2(1), 3-21

Taha, H.A. (2003). *Operations Research: An Introduction*. Upper Saddle River, NJ: Prentice Hall

Touma, J.S., Isakov, V., Ching, J., & Seigneur, C. (2006). Air quality modeling of hazardous pollutants: Current status and future directions. *Journal of Air & Waste Management Association*, 56, 547-558

Travis, C.C., Ritcher, S.A., Crouch, E.A.C., Wilson, R., & Klema, E.D. (1987). Cancer risk management: A review of 132 federal regulatory decisions. *Environmental Science & Technology*, 21(5), 415-420

U.S. Department of Energy. (1996). *Tracking and Analysis Framework (TAF) Model Documentation and User's Guide: An Interaction Model for Integrated Assessment of Title IV of the Clean Air Act Amendments*, Decision and Information Sciences Division, Argonne National Laboratory, December, 1996

Van Houtven, G. & Cropper, M.L. (1996). When is a life too costly to save? The evidence from U.S. environmental regulations. *Journal of Environmental Economics and Management*, 30(3), 348-368

Viscusi, W.K. & Hamilton, J.T. (1999). Are risk regulators rational? Evidence from hazardous waste cleanup decisions. *American Economic Review*, 89(4), 1010-1027

Viscusi, W.K. (2000). Risk equity. *The Journal of Legal Studies*. 29, 843-871

Viscusi, W. K. & Aldy, J.E. (2003). The value of a statistical life: A critical review of market estimates throughout the world. *Journal of Risk and Uncertainty*, 27(1), 5-76

Weingast, B.R., & Moran, M.J. (1983). Bureaucratic discretion or congressional control? Regulatory policy making by the Federal Trade Commission. *Journal of Political Economy*, 91(5), 765-800

Wheeler, L. (1995, October 2). *Pensacola activists take environmental concerns to Capitol Hill*. *Gannett News Service*

Wooldridge, J.M. (2001). *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA, The MIT Press

Williams, A. (n.d.). *Louisville 2005: STAR Adopted*. Last accessed on 16 April 2007 at http://www.louisvilleky.gov/APCD/STAR/

Wood, B.D. (1988). Principals, bureaucrats, and responsiveness in clean air enforcements. *The American Political Science Review*, 82(1), 213-234

Wood, B.D. & Waterman, R.W. (1991). The dynamics of political control of the bureaucracy. *The American Political Science Review*, 85(3), 801-828

Yokota, F. & Thompson, K.M. (2004). Value of information analysis in environmental health risk management decisions: Past, present, and future. *Risk Analysis*, 24(3), 635-650

Zahm, S.H. & Fraumeni, Jr. J.F. (1995). Environmental health issues. *Environmental Health Perspectives Supplements*, 103(S8), 283-286